MULTI-OBJECTIVE HYDROTHERMAL GENERATION SCHEDULING BASED ON HEURISTIC ALGORITHMS

A Thesis

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for the Degree of

DOCTOR OF PHILOSOPHY

Submitted by

NITIN NARANG
(Registration No. 950904010)

Under the supervision of

Dr. J. S. Dhillon
Professor
Department of Electrical &
Instrumentation Engineering
SLIET, Longowal,
Punjab, India

Dr. D. P. Kothari
Professor & Director- Research
MVSR, Engineering College,
Hyderabad
Andhra Pradesh, India

Department of Electrical & Instrumentation Engineering
Thapar University
Patiala-147004 (Punjab), INDIA

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Dedicated to

My Respected Father

Shri A. K. Narang

and

Respected Mother

Smt. Meena Narang

CERTIFICATE

Certified that the thesis entitled, "**Multi-Objective Hydrothermal Generation Scheduling based on Heuristic Algorithms**", which is being submitted by Nitin Narang in fulfillment of the requirements for the award of the degree of **Doctor of Philosophy**, to the Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, is a bona-fide record of the candidate's own work carried out by him under our supervision and guidance. The matter contained in this thesis has not been submitted, neither in part or in full to any other university or institute for award of any degree.

(Dr. J.S. Dhillon)
Professor,
Department of Electrical &
Instrumentation Engineering
Sant Longowal Institute of Engineering & Technology,
Longowal–148106, Distt. Sangrur, Punjab, India
Supervisor

(Dr. D.P. Kothari)
Professor & Director-Research
MVSR, Engineering College,
Hyderabad
Andhra Pradesh, India
Supervisor

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NOMENCLATURE

Main symbols and notations used in this study are listed below. Sometimes a symbol may have alternate meaning but in such a case; the context is sufficient to avoid confusion.

a_i , b_i	constants of predator-prey optimization algorithm for i^{th} unit
$a_{si}, b_{si}, c_{si}, d_{si}, e_{si}$	cost coefficients of i^{th} thermal unit
$\bar{a}_{si}, \bar{b}_{si}, \bar{c}_{si}$	expected cost coefficients of i^{th} thermal unit
A_h	the amount of information passed by the h^{th} objective
$\alpha_i, \beta_i, \gamma_i, \eta_i, \delta_i$	emission curve coefficients of i^{th} thermal unit
$\bar{\alpha}_i, \bar{\beta}_i, \bar{\gamma}_i$	expected emission curve coefficients of i^{th} thermal unit
B_{ij}, B_{io}, B_{oo}	loss coefficients
$\bar{B}_{ij}, \bar{B}_{io}, \bar{B}_{oo}$	expected loss coefficients
β	scaling factor of evolutionary programming algorithm
β_{init}	initial value of scaling factor
β_{final}	final value of scaling factor
β_{step}	step size of scaling factor
C_1, C_2	acceleration constants of predator-prey optimization algorithm
C_3, C_4	uniformly distributed scaled random numbers
$C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}\ C_{6j}$	power generation coefficients of the j^{th} hydro unit
$C(x)$, $C(y)$	coefficients of variation of random variables x and y, respectively
$C_i(0,1)$	Cauchy random variable generated for every value of i
D_i^j	j^{th} coordinate search direction for i^{th} dimension
Δp_{mh}	hydro power corresponding to residual volume during h^{th} slack sub-interval
Δp_{Dk}	residual power during k^{th} sub-interval
ΔV_j	residual volume of j^{th} hydro unit
E_d	Euclidean distance between predator and prey particle
f_l	fitness value of l^{th} individual
F_1, F_2, F_3	objective functions corresponding to economy, emission and inequality constraint, respectively
F_h	h^{th} objective function
F_{tot}	unified objective function
$\bar{F}_1, \bar{F}_2$	objective functions corresponding to expected economy and emission respectively
$\bar{F}_4, \bar{F}_5$	objective functions corresponding to expected power deviation and expected volume deviation, respectively.
$F_h^{\min}$, $F_h^{\max}$	minimum and maximum values of h^{th} objective function, respectively
ε	tolerance band

NOMENCLATURE (Continued)

g_j	water head correction factor of j^{th} hydro unit
G_i^t	global best prey position for i^{th} dimension for t^{th} movement
G_{pik}^t	global best thermal power prey position of i^{th} unit at k^{th} sub-interval for t^{th} movement
G_{qjk}^t	global best water discharge rate prey position of j^{th} hydro unit at k^{th} sub-interval for t^{th} movement
$G[.]$	generic element
$h_{11j}, h_{12j}, h_{13j}$	reservoir head variation coefficients of j^{th} hydro unit
$h_{21j}, h_{22j}, h_{23j}$	water discharge rate coefficients of j^{th} hydro unit
$\bar{h}_{11j}, \bar{h}_{12j}, \bar{h}_{13j}$	expected reservoir head variation coefficients of j^{th} hydro unit
$\bar{h}_{21j}, \bar{h}_{22j}, \bar{h}_{23j}$	expected water discharge rate coefficients of j^{th} hydro unit
H_{jk}	reservoir water head of j^{th} hydro unit at k^{th} sub-interval
H_{j0}, H_{jT}	initial and final hydraulic reservoir head, respectively of j^{th} hydro unit
$\bar{H}_{jk}$	expected effective reservoir head of j^{th} reservoir during k^{th} sub-interval
$\bar{H}_{j0}, \bar{H}_{jT}$	expected initial and final hydraulic reservoir head, respectively of j^{th} hydro unit
I_{jk}	natural inflow of j^{th} hydro unit at k^{th} sub-interval
$\bar{I}_{jk}$	expected natural inflow of j^{th} hydro unit at k^{th} sub-interval
IT_P	movement index for powell's pattern search metod
K	number of bounds on variables
$K_j, K_j^{'}$	constants of proportionality of j^{th} hydro unit
L	number of equality constraints
L_{il}^t	local best prey position for i^{th} dimension of l^{th} particle for t^{th} movement
L_{qjkl}^t	local best position representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
L_{pikl}^t	local best position representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
λ_i^*	step length for i^{th} variable (unit/sub-interval)
$\lambda_i^{\min}, \lambda_i^{\max}$	lower and upper limits of step length for i^{th} decision variable, respectively
M	number of inequality constraints
$\mu(F_h)$	membership function of h^{th} objective
$\mu(F_{hl})$	membership function of h^{th} objective of l^{th} particle
$\mu(F_1), \mu(F_2), \mu(F_3)$	membership functions of economy, emission and inequality constraint objectives, respectively
μ_D	cardinal priority ranking
$\mu_D^{\max}$	maximum value of cardinal priority ranking
N	number of generating units

NOMENCLATURE (Continued)

N_H	number of hydro units
N_T	number of thermal units
N_{ob}	number of objective functions
NP	population size
$N(0,1)$	normally distributed random number with mean 'zero' and standard deviation 'one'
$N_i(0,1)$	normalized random number with mean 'zero' and standard deviation 'one' for each variable of i^{th} variable
ν	scaling factor for velocity limits
p_{Dk}	power demand during k^{th} sub-interval
p_{ik}	power generation of i^{th} unit during k^{th} sub-interval
p_{Lk}	transmission loss during k^{th} sub-interval
$\bar{p}_{ik}$	expected real power generation of i^{th} unit during k^{th} sub-interval
$\bar{p}_{Lk}$	expected transmission loss during k^{th} sub-interval
p_{ik}^t	power generation of i^{th} unit at k^{th} sub-interval for t^{th} movement
P_{pikl}^t	prey positions/members representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
P_{qjkl}^t	Prey positions/members representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
$p_i^{\max}$, $p_i^{\min}$	upper and lower limits of i^{th} unit power generation, respectively
$\bar{p}_i^{\max}$, $\bar{p}_i^{\min}$	expected upper and lower limits of i^{th} unit power generation, respectively
pf	probability of fear
$pf_{\max}$	maximum probability of fear
PP_i^t	predator position for i^{th} dimension at t^{th} movement
PP_{pik}^t	predator position representing generation of i^{th} unit at k^{th} sub-interval for t^{th} movement
PP_{qjk}^t	predator position representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval for t^{th} movement
Pv_i^t	predator velocity for i^{th} dimension at t^{th} movement
Pv_{pik}^t	predator velocity representing generation of i^{th} unit at k^{th} sub-interval for t^{th} movement
Pv_{qjk}^t	velocity of a predator of j^{th} hydro unit at k^{th} sub-interval for t^{th} movement
q_{jk}	rate of water discharge of j^{th} hydro unit at k^{th} sub-interval
$\bar{q}_{jk}$	expected rate of water discharge of j^{th} hydro unit at k^{th} sub-interval
$q_j^{\max}$, $q_j^{\min}$	upper and lower limit of water discharge rate of j^{th} hydro unit, respectively
Q_j	non effective water discharge of the j^{th} hydro plant
r_p	penalty parameter
$rand()$	uniformly distributed random number

NOMENCLATURE (Continued)

$R(x,y)$	correlation coefficient of random variables x and y and varies from -1 to 1
S_j	surface area of reservoir of j^{th} hydro unit
SP_{jk}	spillage of j^{th} hydro unit at k^{th} sub-interval
σ_{il}	standard deviation of l^{th} parent member for i^{th} dimension
σ_{pikl}	standard deviation of parent member representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
σ_{qjkl}	standard deviation of parent member representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
$\sigma_{\mu(.)}$	standard deviation of membership function
t	movement count
$t_{\max}$	maximum number of movement
t_k	time duration of k^{th} sub-interval
t_{rj}	time delay from upstream reservoir 'r' to lower reservoir 'j'
T	total time interval for scheduling
U_j	upstream reservoirs on j^{th} reservoir
V_{errl}	total residual reservoir volume of l^{th} particle
V_{jk}	reservoir volume of j^{th} hydro unit at k^{th} sub-interval
V_{jF} , V_{jI}	final and initial reservoir storage volumes of j^{th} hydro unit, respectively
$\overline{V}_{jF}$	expected final reservoir volume of j^{th} hydro unit
$v_i^{\min}$, $v_i^{\max}$	minimum and maximum velocity limit, respectively for i^{th} generating unit
v_{il}^t	prey velocity of i^{th} dimension for l^{th} particle at t^{th} movement
$v_j^{\min}$, $v_j^{\max}$	minimum and maximum velocity limits for water discharge rate of j^{th} hydro unit, respectively
v_{pikl}^t	velocity of a prey particle/member representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
v_{qjkl}^t	velocity of a prey particle/member representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement
w	inertia weight constant of PPO algorithm
W_D , W_v	scaling factor for power balance and reservoir water balance constraint, respectively
W_h	weight assigned to h^{th} objective
W_h^*	best weight of h^{th} objective
Win_m	number of wins for randomly selected member m
x_i	i^{th} decision variable
$\bar{x}$, $\bar{y}$	expected values of variables x and y respectively
$x_i^{\max}$, $x_i^{\min}$	maximum and minimum values of x_i ,respectively

SYNOPSIS

Electric power today plays an exceedingly important role in the life of the community and in the development of various sectors of economy. In view of increase in the demand of electricity, considerable attention is given to interconnection between different systems. The hydro plants have high capital cost and low operating cost as compared to thermal plants. Hydro resources are considered to provide a clean and environment friendly energy option. Hydro plants are usually scheduled for peak load periods and thermal plants are normally scheduled for base-load period as hydro units are started-up and shut-down efficiently as compared to thermal units. Hence, the exploitation of hydro resources becomes important. The major concern of hydro resources is stochastic nature of availability. So, the integration between hydro and thermal systems is essential for the welfare, development and economic progress of our society. The fundamental requirement of *hydro-thermal generation scheduling* (HTGS) is to utilize the limited amount of water available to its fullest extent, such that the total system production cost and pollutants emission of thermal units are minimized while satisfying hydraulic and power system network constraints.

The integrated operation of the hydro-thermal system is split into long-term and short-term generation scheduling problems. The planning period is one or more years for long-term HTGS problems. For short-term HTGS, planning period is an hour or a day or a week as the load demand on the power system exhibits cyclic variations. The amount of water to be utilized for short-range HTGS problem is known from the solution of the long-range HTGS problem. Conventional hydroelectric plants are classified into run-of-river plants and storage plants. Run-of-river plants have little storage capacity, and utilize water as it becomes available. Storage plants are associated with reservoirs, during periods of low power requirements water is stored in the reservoirs and then released when the demand is high. Hydroelectric power plants are situated on different streams and on the same stream. The operation is different in case when the hydro plants are located on the same stream or on different streams. The operation of down steam plant depends on the immediate upstream plant. However, downstream plant influences the immediate upstream plant by its effect on tail water elevation and effective head.

Hydro-thermal generation scheduling is a large scale and complex problem owing to the large number of constraints, so it has been characterized as a nonlinear and non-convex optimization problem. The HTGS problem becomes difficult to solve due to stochastic nature of water availability. Various types of probabilistic variations are sources of uncertainties in HTGS problem, which leads to deviation from optimal operation and results rise in the production cost due to uncertain factors. Besides electric energy, thermal units also produce pollutant emissions, which deteriorate air quality. In general, a large-scale system typified by an electric power system also possesses multiple objectives to be achieved *viz*. economics operations, reliability, security, and environment. In essence, the HTGS is visualized as a multi-objective optimization problem.

Optimization techniques applied to solve HTGS problem are broadly divided into two main categories that are local search and global search techniques. Further, local search techniques are classified into gradient and direct search methods. Most of the gradient methods are applied to solve the HTGS problem with number of simplifying assumptions in order to make the optimization problem more tractable and simple. Sometimes implications may lead to false global optimum solution by virtue of simplifications. Direct search techniques do not require any information about the gradient and higher order gradients of the objective function whereby these techniques perform the search by explorative and pattern moves. One of the main disadvantages of direct search method is that when the search space is large or non-convex and function is multimodal, solution may converge to local solution. Global search techniques are a class of stochastic optimization also known adaption techniques, which are inspired, by natural evolution or nature. Global search techniques have multi-point search strategies as compared to local search techniques, which have single-point search strategies. Despite of number of advantages offered by global search techniques these are comparatively inefficient in fine tuning the solution.

Real-world multi-objective optimization problems give rise to set of optimal solutions called non-inferior solutions in place of single optimal solution. Mainly, multi-objective optimization techniques are grouped under two major categories: non-interactive and interactive. In the non-interactive method, a global performance function of the objectives is identified and optimized with respect to the constraints. On the other hand, in the interactive method, a local preference function or trade-off among objectives is identified by interacting with *decision makers* (DMs) and the solution process proceeds gradually towards the globally satisfactory solution. Solution methodologies for solving interactive multi-objective problem differ in two ways: the procedure used to generate non-inferior solution, the ways used to interact with the DMs, and the type of information made available to DM such as trade-offs. The main objective of DM is to fulfill the conflicting goals while satisfying the system constraints.

A hydro-thermal electric power system possesses multiple conflicting objectives to be achieved like economic operation and minimal impact on environment with due consideration of inaccuracies and uncertainties in the system data. The optimization techniques search the best possible solution with minimal effort that means there is a trade-off between the computational effort and the quality of the solution. When the dimension or search space of the problem is wide or problem is multimodal, the optimization techniques need different exploration and exploitation strategies. The local search techniques are more exploitation oriented whereas global search techniques are more explorative oriented. So, there is need of heuristic optimization technique that can provide a balance between exploration and exploitation to speed up the process of finding a satisfactory solution.

For multi-objective problems, various techniques are proposed to generate non-inferior solutions. Out of which weighting method is one of the most promising approaches, however in this method there is no rational basis to decide objective weights. So, there is a need to evaluate objective weights so that unified objective function should not lose any information. In previous studies of stochastic HTGS problem, expected volume deviations are not considered since hydro power output and coefficients of water discharge rate are random variables. So, there is a scope to study the effect of reservoir volume deviations.

In the thesis work, heuristic optimization techniques are proposed in which global and local search techniques are integrated to take advantages of both search techniques while offsetting their disadvantages. Global search techniques exploit the search area to identify parts with high quality solutions and local search techniques intensify the search in promising areas. The *predator-prey optimization* (PPO) and *evolutionary programming* (EP) are undertaken as global search techniques. The PPO technique is based on PSO with additional predator effect. In PPO, predators attract towards the global best prey particle that helps to explore the search area more effectively. In EP, chromosomes share information with each other and population moves like a one group towards an optimal area. Predator-prey optimization and EP update their information in different approaches. Predator-prey optimization does not have mutation operator as used in EP. The PPO and EP algorithms have excellent global search capabilities but these techniques have some limitations in local search. In proposed heuristic optimization techniques, *Powell's pattern search* (PPS) is taken as a local search technique. Powell's pattern search is based on conjugate direction method and is expected to speed up the convergence of nonlinear objective functions.

Further, the optimum operational strategies for integrated hydro-thermal electric power system has been explored by applying proposed heuristic optimization techniques using selective favourable features of PPO, EP and PPS. The proposed optimization techniques are applied to search optimum solution of fixed/variable-head and multi-chain short-term HTGS problems. The proposed optimization techniques are also validated on long-term HTGS problems. In the research work, two approaches are applied to solve multi-objective optimization problem. In one approach, objective functions are modeled using fuzzy set theory. The DM decides the solution interactively by considering unified affect of participating objectives by exploiting their membership functions. Highest cardinal priority ranking provides maximum satisfaction level of the participating objectives. In second approach, weighting method is explored to convert multi-objective optimization problem into scalar optimization problem. The best weight pattern is proposed to compute relevant weights. By applying best weight pattern evaluation, DM does not allow to skip the weight combination that actually corresponds to the 'best' compromising solution during simulation process. In practice, there are several inaccuracies and uncertainties in the input system information. So, the multi-objective HTGS problem has been posed as a stochastic multi-objective HTGS problem with explicit recognition of uncertainties and inaccuracies in system production cost, pollutant emission, rate of water discharge and system load.

The significant contributions of various authors related to HTGS problems and its relevant topics have been briefly reviewed in chapter 1. The requisite theoretical, mathematical, and computational backgrounds of different local and global optimization techniques are reviewed which are utilized in the present study to determine the solution of optimization problem.

In chapter 2, three heuristic optimization techniques are proposed whereby local and global optimization techniques are integrated. In first attempt, PPO and PPS techniques are integrated. The local best solutions obtained by PPO technique are considered as base points for PPS method to further improve the quality of solution locally. In second attempt, EP and PPS techniques are integrated whereby, members of EP technique acts as base points for PPS method. In third attempt, two global search techniques PPO and EP are implemented initially. Afterwards, local best solutions obtained from PPO and members of population obtained from EP are combined to form a pool. The pool of particles/members is arranged in ascending order according to their objective function value to select the base point for PPS. The proposed heuristic optimization techniques have advantage of exploration and exploitation property of global and local search techniques. Optimal operation of multi-objective hydro-thermal system is obtained using the proposed optimization techniques with due consideration of transmission losses of power system network. Hydro units having fixed and variable-head are engaged in HTGS problem. Valve-point loading effect is considered in operating characteristics of thermal generators. Multi-objective HTGS problem undertakes two conflicting objectives that are the operating cost and emission of gaseous pollutants Compromised solution is selected by finding the consolidated affect of participating objectives using their membership functions. Penalty method requires multiple runs to fine tune the penalty factor leading to a high computational cost. In this work, the constraints are satisfied by perturbing the decision variables in a systematic procedure. The proposed approach is tested on four electric power systems out of which three electric power systems have fixed-head hydro models and one system has variable-head hydro model.

In ensuing chapter, the proposed heuristic optimization techniques are applied on non-convex HTGS problem, considering multi-chain hydro model. The travel time between reservoirs is taken into account. Water discharge rate of the hydro units and power output of the thermal units are searched to find out the optimum solution. The variable elimination method is applied to satisfy the equality constraints. Inequality constraints are treated as objectives to maximize along with other objectives of the optimization problem. Inequality constraint is converted into objective by exploiting fuzzy set theory. The decision regarding the best solution of multi-objective HTGS problem is taken by applying max-min operator on membership functions of participating objectives.

In successive chapter, multi-objective HTGS problem is converted into single objective optimization problem by applying weighting method. Weight patterns are computed by conventional statistical measures, which characterize the correlation coefficients matrix evolution. The weights are updated, during the movement, according to best weight pattern using membership function of local best solutions of swarm or members of population obtained from proposed heuristic optimization techniques presented. The major advantage of weight pattern evaluation is that it provides rational basis of determining adequate weights. So, DM has all relevant weight combinations. The heuristics are applied to satisfy power balance, reservoir volume equality constraint, volume storage, and hydro power inequality constraint. The proposed optimization techniques with best weight pattern evaluation are applied to search optimum solution for four electric power systems.

In the succeeding chapter, proposed optimization techniques are extended for long-term multi-objective HTGS problems and are tested on two electric power systems which have scheduling period of one year. To handle equality constraints, variable elimination method is implemented. An objective function is included to handle inequality constraints by assigning their membership functions using fuzzy set theory. Highest cardinal priority ranking is computed to decide the best compromised solution. The proposed optimization techniques search the solution without taking any approximation and are proved to be computationally efficient.

In chapter 6, multi-objective HTGS problem is formulated with explicit recognition of uncertainties and inaccuracies in system production cost, pollutant emission, rate of water discharge and system load demand. The stochastic model is converted into its deterministic equivalent. The short-term fixed-head HTGS problem is solved in multi-objective framework in which main objectives such as operating cost, gaseous pollutant emission, expected power deviation, and expected volume deviation are minimized simultaneously. In this work, power generations have been considered as random and are correlated with each other. Further, operating cost, gaseous emission of pollutants and water discharge coefficients have been considered as random. The correlation between time-interval of hydro power generations is also considered. The results reveal that there is an additional cost and pollutant’s emission because of uncertainties and inaccuracies in system data.

In the thesis, the validity and effectiveness of the proposed heuristic techniques to solve multi-objective HTGS has been extensively verified and numerically tested by analyzing on small, medium, and large electric power systems. The eleven numerical examples in diverse situations having several thermal and hydro coordinated units are considered. The performance of each employed technique is compared with the reported results in literature. Finally, the main conclusions of thesis are presented and suggestions for future research in this area are indicated.

CHAPTER – 1

INTRODUCTION

Electrical energy is an essential ingredient for the industrial and all-round development of any country. It is a coveted form of energy, because it can be generated centrally in bulk and transmitted economically over long distances. Further, it can be adapted easily and efficiently to domestic and industrial applications. The efficient generation scheduling of available energy resources consists of determining the optimal operating strategy for the next scheduling period, subject to a variety of constraints on power systems. This task is becoming more involved as new competitive forces are impacting the power industry and are rapidly changing it as a marketplace. A coordinated worldwide action plan is, therefore, necessary to ensure that energy supply to humanity at large is assured for a long time and at low economic cost and with minimum emission. A modern power system consists of a number of thermal and hydro power units connected to different load centers through transmission network. Basically it is the optimum utilization of all energy sources in the most economical manner, so that an uninterrupted supply can be provided to the consumers. Due to electric and hydraulic coupling in hydro-thermal system, *hydro-thermal generation scheduling* (HTGS) is treated as multi-dimensional, non-linear, and non-convex problem. Therefore, generation scheduler faces a great challenge to search optimum solution, as there is a possibility of large infeasible and non-uniform search areas, and the presence of numerous local optima [341]. Economy was hitherto considers to be the sole criterion in the integrated operation of HTGS, but because of rigid environmental regulations [56] equal attention has also been focused to minimize the pollution in the air due to gaseous pollutants emission released by fuel of thermal units. Apart from fuel cost, emission control is another important objective and utility planners are trying to improve their operating strategies to reduce pollution simultaneously with operating cost [194]. Because of conflicting nature of emission and fuel cost, problem is viewed as *multi-objective optimization problem* (MOOP). To solve HTGS problem, many optimization methods have been used, such as *dynamic programming* (DP), network flow, *nonlinear programming* (NLP), and decomposition and coordination technique. The conventional methods usually require certain presumptions or simplifications to make the original model easy to solve, which may lead to local and sub-optimal solutions with great loss of revenue. In recent years, non-conventional global search techniques have aroused intense interest due to their flexibility, versatility and robustness in seeking the global optimal solution. Although global search techniques such as *evolutionary programming* (EP), *genetic algorithm* (GA), *evolutionary strategy* (ES), *simulated annealing* (SA), *particle swarm optimization* (PSO), *differential evolution* (DE) etc. are powerful search techniques; however, these techniques show slow converging characteristics, near optimum solution and sometimes struck to local optimum solution. To enhance the searching capability of global search techniques, local search methods can be hybridized with these.

1.1 OPTIMIZATION TECHNIQUE: A-STATE-OF-THE-ART

Optimization is the act of obtaining the best result under given circumstances. Optimization problems occur in many technical, economic, and scientific projects, like cost-, time-, and risk-minimization or quality-, profit-, and efficiency-maximization. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since, the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables. The optimization of power system is identical with the solution of a NLP problem characterized by large number of equality and inequality constraints. The objective function can be unimodal or multimodal function, but most of the practical system objective function represented by multimodal function.

Unimodal function: A unimodal function is one that has only one peak or valley in a specified boundary.

Multimodal function: An optimization problem is considered to be multimodal, when it contains more than one local optimal solution.

A scalar multi-variable constrained optimization problem is stated as follows:

Minimize $F(X)$ (1.1)

Subjected to:

Inequality constraints:

$$g_i(X) \le 0, \quad (i = 1,2,\ldots,M) \tag{1.2}$$

Equality constraints:

$$l_k(X) = 0, \quad (k = 1,2,\ldots,L) \tag{1.3}$$

Bound on variables:

$$x_j^L \le x_j \le x_j^U \quad (j = 1,2,\ldots,K) \tag{1.4}$$

where

$X = [x_1, x_2, \ldots, x_K]^T$ is an K-dimensional vector called the design vector

$F(X)$ is termed as objective function

M and L represent number of inequality and equality constraint, respectively

x_j^L and x_j^U represent lower and upper limits of decision variable, respectively

The optimization problem is solved to find optimal solution. The definitions of various solutions related to optimization are presented below [78]:

Feasible and Infeasible Solution: A solution is defined as a feasible solution if all equality and inequality constraints and variables bounds satisfied at that point. All other points those do not satisfy the equality and inequality constraints are infeasible solutions. Further feasible solution may be local optimal and global optimal solution.

Local optimal solution: A function $F(X)$ is said to have a relative or local minimum at $X = X*$ if $F(X*) \le F(X* \pm h)$ for all sufficiently small values of *h*.

Global optimal solution: A function $F(X)$ is said to be global or absolute minimum at $X*$ if $F(X*) \le F(X)$ for all X, and not just for all X close to $X*$, in the domain over which $F(X)$ is defined.

Necessary and sufficient conditions to check the validity of optimal solutions are given as:

Necessary condition: A necessary condition for a point to be an extreme point (maximum or minimum) at $X = X*$ if the first partial derivatives of $F(X)$ exists at $X*$ as:

$$\frac{\partial F}{\partial x_1}(X*) = \frac{\partial F}{\partial x_2}(X*) = \ldots = \frac{\partial F}{\partial x_n}(X*) = 0 \tag{1.5}$$

Sufficient condition: A sufficient condition for a stationary point (A point at which $F'(X*)$ is zero) $X*$ to be an extreme point is that the matrix of second partial derivatives (Hessian matrix) of $F(X)$ evaluated at $X*$ is (i) positive definitive when $X*$ is a relative minimum point, and (ii) negative definite when $X*$ is a relative maximum point.

Optimization techniques are classified as local search and global techniques. Local search techniques further divided into two categories: gradient based techniques and direct search techniques. Local search techniques follow some specific rule for moving from one solution to the other. These techniques have been in use for quite some time and have been successfully applied to many engineering design problems. Gradient based method uses the gradient of the function being optimized as the promising search direction. Examples of common gradient methods include steepest descent, Newton's, Fletcher-reeves, quasi-Newton etc. Even these techniques have been widely used for many optimization problems, it is difficult to apply them to the metabolic problem because the mathematical relationships between the modelling parameters and the modelling objectives. Gradient-based algorithms become ineffective in these applications due to the problem of local minima or the difficulty in calculating gradients. In case a function having more than one local minimum solution is to be optimized using a gradient-based search algorithm, the solution obtained may or may not be the global minimum solution. When the start point for a gradient based method is close to a local minimum, the algorithm will quickly move toward it and eventually converge. This means that if a different start point is used, a different solution may be found.

Another kind of local search method is direct search technique. Direct search techniques [4] were formally proposed and widely applied in the 1960s but fell out of favour with the mathematical optimization community by the early 1970s because these techniques lacked of coherent mathematical analysis. These techniques provide local solution because the solution moves from current to new position with small step size. The methods come under this search procedure are: random search method, simplex method, univariate method, pattern search method etc. Univariate algorithms perform search along each variable one at a time. These algorithms cannot usually solve functions having nonlinear interactions among design variables. This problem can be avoided by changing the directions of search in a favourable direction (pattern direction) instead of retaining them always parallel to the coordinate axis. The pattern search method works by creating a set of search direction iteratively. The created search directions should completely span the search space. Hooke-Jeeves method and Powell's pattern search come under the category of pattern search. Powell's method is an extension of basic pattern search method. It is most widely used pattern search method and can be proved to be a method of conjugate directions. A conjugate directions method will minimize a quadratic function in a finite number of steps. Since a general nonlinear function can be approximated reasonably well by a quadratic function near its minimum, a conjugate directions method is expected to speed up the convergence of even general nonlinear functions [78]. Direct search techniques so called non-gradient techniques are more robust in locating the optimum solution and are applicable in a broader set of problems.

One more advantage of non-gradient methods is that these do not require any derivatives of the objective function in order to find the optimum solution [103]. Hence, these are also known as black box method. One of the main disadvantages is that it is difficult to prove that the actual optimum is found [103]. By conducting several optimizations with different initial conditions, it could be made probable that the global optimum is truly found. Another disadvantage with non-gradient methods is that these usually require more function calls than gradient methods, and are thus more computationally expensive. However, as the capacities of the computers are increasing, this disadvantage is diminishing [80]. Furthermore, non-gradient methods are well suited for implementation on parallel processors [98].

The techniques of nonlinear, linear, geometric, quadratic or integer programming can be used for the solution of particular class of problems indicated by the nature of technique. Most of these methods are numerical techniques wherein approximate solution is sought by proceeding in an iterative manner by starting from initial solution. The *Linear Programming* (LP) approach has several advantages. Firstly, it is reliable, especially regarding the convergence properties. Secondly, it can quickly identify infeasibility. Nevertheless, despite a number of advantages, its range of application has remained somewhat restricted because of the inaccurate evaluation to find an exact solution. To solve a NLP problem, the first step in this method is to choose a search direction in the iterative procedure, which is determined by the first partial derivative. Therefore, these methods are referred to as the first-order methods such as the generalized reduced gradient method. Dynamic programming searches the solution space in forward or backward direction. The advantage of DP is its ability to maintain solution feasibility. Dynamic programming builds and evaluates the complete “decision tree” to optimize the problem at hand. Thus it suffers from the “curse of dimensionality” because of problem size increases rapidly with the number of decision variables, which results in an unacceptable solution time. Since, all the DP methods are based on the priority list, the solution obtained is sub-optimal. Although LP, NLP, and DP are promising techniques, a few shortcomings of these techniques may be worth mentioning: a) the multimodal, function needs to be continuously differentiable to attain optimal set point by NLP and DP techniques, which may be a restrictive assumption in real life problems. Moreover, heuristic and meta-heuristic technique may provide an alternative near-optimal condition, which is cost effective and reasonably acceptable for implementation rather than searching for exact optimal conditions based on LP, NLP or DP techniques.

Global search techniques are a class of stochastic optimization and adaption techniques are inspired by natural evolution or by nature inspired [103]. Each global search technique is designed along a different methodology. Despite their differences, all global search techniques are heuristic population based search procedures that incorporate random variation and selection. At a first glance, it seems that global search techniques, as multi-point search strategies, have other properties than local search techniques as single-point search strategies. Global search techniques are applied as a tool for the solution of complex optimization problems because of their exclusive advantages like robust and reliable performance, global search capability, ease of implementation, parallelism, no requirement of differentiable and continuous objective function. In the past decades, several global search techniques, such as GA, EP, SA, DE and PSO have been proven to be efficient in solving complex power system optimization problems. These techniques often provide a fast and reasonable solution, but do not ensure global optimal solutions in finite time. Bansal [222] has presented an overview of important mathematical optimization and artificial intelligence techniques used in power optimization problems till 2005.

1.1.1 Evolutionary Programming

Evolutionary programming is probably the oldest global search technique used to solve optimization problems. Evolutionary programming adapts the concept of natural evolution or survival of the fittest found in Darwinian Theory of evolution to enhance the population or “solutions” quality. It was first introduced by Fogel in 1964 [5] as findings of his doctorate work. The EP paradigm emphasizes the relationship between ancestors and their descendants and it relies exclusively on a mutation operator to produce offspring, i.e. there is no recombination operator. Back and Schwefel [79] discussed the history as well as the current state of EP. Kim *et al.* [131] have discussed two types of EP methods to handle non-linear constrained optimization problem. Kumar [91] has investigated EP for continuous parameter optimization problems and concluded that using a variety of mutation operators that is combined during evolution could hold the potential for producing better solutions with less computational effort. Yao *et al.* [128] and Wei *et al.* [68] have discussed slow convergence rates of EP on some function optimization problems and a *fast EP* (FEP) has been proposed which used Cauchy instead of Gaussian mutation as the primary search operator. Wang *et al.* [165] proposed a modified EP for optimization to avoid pre-mature convergence and balance of exploration and exploitation abilities of *classical EP* (CEP). Cho *et al.* [94] have suggested an algorithm that helps to accelerate convergence as well as enhance diversity of EP search technique. The factors responsible for its good performance include scaling, selection strategy, and use of age and search direction vector and multiple offspring per parent.

Research in power system has its share in applying EP to various optimization problems. The following are the major areas in which EP technique is applied: economic load dispatch, reactive power control and power loss reduction, optimal power flow, power system controller design and other power system areas. Somasundaram and Kuppusamy [221] have presented an algorithm, for solving security constrained economic load dispatch problem, through the application of EP. The EP techniques are used to minimize the production cost of thermal power generation by Kumarappan and Mohan [184]. Jayabarathi *et al.* [225] have aimed to explore the performance of three EP techniques with different types of mutation: Gaussian, Cauchy and combined Gaussian-Cauchy mutation for all kinds of economic load dispatch problem. Jayabarathi *et al.* [138] have presented the extension of EP method to include tie-line constraints in the multi-area economic load dispatch problems. Yang *et al.* [70] have developed an algorithm based on CEP of determining the global or near global optimal solutions of economic load dispatch problem. Jayabarathi *et al.* [127] have presented an approach using CEP technique for solving the economic load dispatch. Ravi *et al.* [233] have presented an attempt to explore the feasibility of modified FEP algorithm to solve non-convex economic load dispatch problem with transmission losses. Christober and Rajan [324] has developed an approach for solving the economic load dispatch problem using an integrated algorithm based on EP and SA on large scale power system. Somasundaram *et al.* [203] have proposed a solution approach for solving the economic load dispatch problem with units having prohibited operating zones. In this approach, the optimal solution and the corresponding optimum system incremental cost are determined using FEP technique without considering the prohibited operating zones. Then, a small set of decision spaces is formed by combining the feasible sub-regions of the fuel cost curve intervening the prohibited operating zones in the neighbourhood of the optimal system incremental cost. Wong and Yuryevich [96] have developed CEP based algorithm for solving the environmentally constrained economic load dispatch problem. Sinha *et al.* [185] have proposed various modifications to the basic EP method to enhance speed and robustness and these have been applied successfully on some benchmark mathematical problems and economic load dispatch problem.

Gnanadass *et al.* [206] have proposed modified EP for the solution of optimal power flow problem. In the proposed EP algorithm, mutation is changing non-linearly with respect to the number of generations to avoid premature condition. Somasundaram *et al.* [204] have presented an algorithm for solving security constrained optimal power flow problem through the application of EP. A modified EP has been applied to solve optimal power flow by Ongsakul and Tantimaporn [241]. They have divided the whole population into multiple sub-populations, which are used to perform the parallel search in divided solution space. Modified EP includes Gaussian and Cauchy mutation operators in different sub-populations to enhance the search diversity, selection operators with probabilistic updating strategy to avoid entrapping in local optimum and reassignment operator for every sub-population to exchange search information. Yuryevich and Wong [118] have developed CEP algorithm for solving the optimal power flow problem. Classical EP technique with adaptive mutation scale for the daily operation of a two-cogeneration system connected with auxiliary devices has been developed by Lai and Ma [99]. Tsay *et al.* [147] have studied the economical operation of cogeneration system under emission control and then CEP method was adopted to solve this problem. Park *et al.* [106] have proposed modified EP algorithm using domain mapping procedure and quadratic approximation technique for solving a generation expansion planning problem. Meza *et al.* [302] have presented a multi-objective EP algorithm to obtain an approximation of the Pareto front for generation expansion planning framework and to select the best alternative, analytical hierarchy process is applied.

Wu *et al.* [63] have concerned with application of CEP to optimal reactive power dispatch and voltage control of power systems. Ma and Li [71,85] have proposed an application of CEP to reactive power planning. Lee and Yang [97] have presented a comparative study for EP, ES and GA to the optimal reactive power planning problem. Jiang and Wang [212] have presented EP method with dynamic mutation and metropolis selection to solve the multi-objective reactive power optimization under the deregulation environment. A short-term HTGS algorithm based on the CEP technique is presented by Hota *et al.* [124]. Fast EP technique is applied for the solution of a short-term HTGS problem by Sinha *et al.* [186,187]. Yang *et al.* [76] have presented CEP based algorithm for the short-term HTGS problem. Cau and Kaye [171] have proposed constructive EP for minimizing the operational cost in the scheduling of hydro-thermal systems with multiple storages. Duo *et al.* [116] have proposed an approach which combines *Lagrangian relaxation* (LR) principle and EP for short-term thermal unit commitment. Jeong *et al.* [322] have presented an approach for solving unit commitment problems using a quantum-inspired EP. Juste *et al.* [119] have formulated the unit commitment problem and then employs the EP technique in which populations of contending solutions are evolved through random changes, and selection. Evolutionary programming is designed to encode each unit's operating schedule with regards to its minimum up/down time. An EP based algorithm is developed for the combined heat and power dispatch problem for cogeneration systems by Wong and Algie [158]. Lai *et al.* [98] have proposed an application of CEP to fault-section estimation in power systems.

The Gray correlation analysis method is proposed by Tsai and Hsu [344] for feeder reconfiguration. The proposed method is used to integrate different objectives and provide a relative measure to a particular switching plan associated with a chromosome without any prior knowledge of the system under reconfiguration. Song *et al.* [90] have proposed a fuzzy controlled EP, based on heuristic information. The mutation fuzzy controller adaptively adjusts the mutation rate during the simulated evolutionary process. Kim and Myung [83] have proposed two phase EP method for handling nonlinear constrained optimization problems. The first phase uses the standard EP, while an EP formulation of the augmented Lagrangian method is employed in second phase to solve the problem. Chen *et al.* [299] have tried to improve the performance of EP via exploring selection strategy. Three selection rules have been presented to encourage both fitness diversity and solution diversity. Two solution exchange rule have been introduced to further exploit the preserved genetic diversity. Alam *et al.* [367] have presented a recurring two-stage EP to balance the explorative and exploitative features of the conventional EAs.

1.1.2 Particle Swarm Optimization and its Variants

Particle swarm optimization is a global search technique originally introduced by Kennedy and Eberhart [59]. The most attractive features of PSO are its simple concept, easy implementation, fast computation, and robust search ability [215]. It simulates the social evolvement knowledge through, probing the optimum by evolving the population which may include candidate solutions. Compared with the other global search techniques, PSO shows incomparable advantages in searching speed and precision [215].

Despite several advantages of PSO, it has some shortcomings. Particle swarm optimization convergence behaviour depends upon its parameters. Wrong choice of PSO parameters may result in divergent particle trajectories and it causes trapping into local minimum value [311]. On applying PSO to high-dimensional optimization problems, it suffers from premature convergence problem resulting in a low optimization precision or even failure [321].

Many researchers have attempted to improve the performance of PSO either through mathematical analysis or in modifying PSO algorithm [161, 232, 240, 353, 360]. Clerc and Kennedy [161] have explored the working of PSO from the individual particle's point of view. They have analyzed, the way a particle searches a complex problem space. Bergh and Engelbrecht [232] have analyzed the convergence behaviour of PSO and concluded that the PSO algorithm does not guarantee to converge to the global optimum by fixing the parameters. Kadirkamanathan *et al.* [240] have analyzed the stability of particle dynamics using Lyapunov stability analysis and the concept of passive systems. Chen and Jiang [353] have analyzed the behaviour of PSO on the basis of social model and then derived the upper and lower bounds of the expected particle norm. Gao and Xu [360] have investigated the behaviour of particles in the PSO using a Monte Carlo method. The results reveal the essence of the trajectory of particles during iterations and documents the reasons of failure of global search ability of PSO in the last stage of iterations. Particle swarm optimization researchers also aim to improve the PSO algorithm in various ways.

These amelioration and development have been placed into five categories:

- Inertial weight varying strategy, such as constant inertial weight [108], linearly decreasing inertial weight [129], fuzzy inertia weight [152, 368], and random inertial weight [148]; Adaptive inertia weight [314, 384].
- Parameter selection and convergence analysis [109, 161, 265, 304, 391].
- Swarm topology structure [117, 125, 234].
- Discrete PSO [395].
- Particle swarm optimization combined with some evolutionary computation operators and other methods, such as selection [102], mutation [174, 183, 191, 229] breeding [146], chaos [211, 216, 250, 318] cooperative approach [194], orthogonal experimental design [283], deflection and stretching techniques [197], Gaussian probability distribution linked with chaotic sequences [269], Chaotic

mapping with the Gaussian probability distribution [318], wavelet mutation [284], bacterial foraging effect [385], iteration index [355].

In the process of the conventional PSO algorithm, particles in the swarm come together at a step and then, it becomes difficult for particles to escape from the accumulation point. After that, the algorithm loses its global search ability. To overcome this deficiency of PSO, Silva *et al.* [154] have developed a *predator-prey optimization* (PPO) model. The motivation was mainly introduced diversity in the swarm at any moment during the run of the algorithm, not depending on the level of convergence already achieved. Silva *et al.* [155] and Higashitani *et al.* [237] have validated the PPO method through numerical simulations with several benchmark problems comparing to PSO method. They have concluded that PPO performed significantly better than the standard PSO in the optimization of benchmark multimodal functions, either by findings, on average, better solutions at the end of the runs, or by finding solutions of similar quality but with a higher convergence rate. Johnson and Sahin [317] have discussed the application of four variants of PSO to data clustering. They have concluded that predator-prey PSO method would be more beneficial to the clustering, as keeping the particles moving would be highly important because a good position could be now, may not be a good position in future. A detailed overview of the basic concepts of PSO and its variants was presented by Del Valle *et al.* [286].

There are various applications of PSO in power system reported in literature. Abido [159] has applied PSO algorithm for optimal power flow problem. Jeyakumar *et al.* [231] have described a successful adaptation of the PSO algorithm to solve various types of ELD problems. Arya *et al.* [336] have presented a PSO for scheduling of reactive power control variables for voltage stability enhancement. The security constrained optimal active power dispatch is solved by applying PSO technique by EI-Ela *et al.* [260]. Mandal *et al.* [266] have applied PSO to determine the optimal hourly schedule of power generation in a hydro-thermal power system. Alrashidi and El-Hawary [238] have presented a comprehensive coverage of PSO applications in solving optimization problems in the area of electric power system. Badar *et al.* [383] have presented PSO algorithm with dynamic weights, applied to reduce the real power loss in a system. Arya *et al.* [336] have described co-ordinated based PSO algorithm for rescheduling of reactive power control variable to obtain an adequate loadability margin for operating point. Arya *et al.* [252] have described an algorithm for computing shortest distance to voltage collapse using PSO technique. Bhattacharyya *et al.* [296] presented an approach to the optimal reactive power planning based on fuzzy logic and PSO. The objectives are to be minimized real power loss and to improve the voltage profile of a given interconnected power system. Arya *et al.* [305] have described a viewpoint for static voltage stability enhancement based on a modified PSO technique. Arya *et al.* [393] have described coordinated aggregation based PSO for optimum modifications for failure rate and repair time for a radial electrical distribution system.

Zhao *et al.* [229] have proposed an extension of the standard PSO which uses more particles information to control the mutation operation. The proposed algorithm is applied for power system unit commitment .Coelho and Lee [269] have proposed an approach to PSO which are based on Gaussian probability distribution linked with chaotic sequences. The use of chaotic sequence in PSO could be helpful to escape from local optima, while the Gaussian distribution could provide a faster convergence in local search. The proposed algorithm has been tested on economic load dispatch problems. Baskar and Mohan [265] have applied constriction factor approach in velocity equation of PSO. They have tested this approach to solve economic load dispatch problem and found satisfactory. Chaturvedi *et al.* [304] solved economic load dispatch problem using PSO with a novel parameter automation strategy in which time varying acceleration coefficients are employed to effectively control local and global search. A self adaptive inertia weight PSO is applied to determine the optimal generation schedule of real operated cascaded hydro-electric system by Mahor and Rangnekar [384]. Selvakumar and Thanushkodi [262] have modelled and embedded anti-predatory activity of particle (bird) in the classical PSO to form anti-predator PSO and applied to solve economic load dispatch problem. Saber *et al.* [295] have proposed modified PSO consists of problem dependent variable number of promising values (in velocity vector), unit vector and error-iteration dependent step length. Benchmark data sets and methods are used to show the effectiveness of the proposed method. Acharjee and Goswami [314] have developed adaptive PSO for power flow analysis under critical conditions and multiple power flow solutions. Particle swarm optimization parameters *i.e.*, inertia weight and learning factors are made adaptive on the basis of objective functions of the current and best solutions in the present generation. Safari and Shayeghi [355] have incorporated iteration best index in classical PSO to enrich the searching behaviour, solution quality. Proposed method has been applied to determine the feasible optimal solution of the economic load dispatch. Zhou *et al.* [358] have introduced a novel PSO with random position to guide the flying particles with a probability that depends on the difference of the fitness between the particles with the maximum absolute fitness value and the minimum one.

Hota *et al.* [315] have presented an approach to the solution of optimal power generation to short-term HTGS problem, using modified PSO technique. Arumugam *et al.* [312] have proposed a competitive approach of PSO to solve various optimization problems. Jiang *et al.* [380] have formulated a dynamic economic load dispatch model with wind power and then a modified PSO approach is developed for solving the dynamic economic load dispatch problem.

1.1.3 Hybrid Optimization Techniques

Literature on optimization techniques reveal that, there are generally two types of optimizing techniques: global and local. Although global search techniques have proven their ability to explore large search spaces, they are comparatively inefficient in fine tuning the solution. On the other hand, local optimizing methods are designed to exploit a local area, but these methods are usually not good at exploring wide area and hence not applied alone for global optimization. Due to their respective strength and weakness, there is motivation for the hybridization of global and local search methods. The key to achieving high performance for any heuristic algorithm is to maintain a good balance between exploitation and exploration during search [420].

Classical LP and NLP methods are often either unsuitable or impractical when applied to constrained problems. Evolutionary computation techniques are constructed to cope effectively with the difficulties of constrained problems. Salomon [103] has compared the evolutionary algorithms (EAs) and gradient search methods. Classical gradient methods and EAs represent two very different classes of optimization techniques. He explored the extent a hybrid method, consisting of evolutionary gradient-search procedure, and it is beneficial in the field of continuous parameter optimization. Wu and Ma [63] have proposed an enhanced EP algorithm, which incorporates the gradient descent mechanism in generation of offspring.

Seki *et al.* [350] have proposed local search method for improving the feasible solution obtained by the LR technique to search optimum solution for unit commitment problem. Rajan and Mohan [247] have presented an EP based SA method to solve the short-term unit commitment problem. Rajan [356] has presented an approach to solve the hydro-thermal unit commitment problem using SA embedded EP approach. Rajan and

Mohan [192] have presented an approach based on EP and Tabu search method to solve the short-term unit commitment problem. Victoire and Jeyakumar [209] have presented an integrated technique based on PSO and *sequential quadratic programming* (SQP) technique for solving the economic load dispatch problem. A multi-agent based hybrid PSO technique is applied to solve economic load dispatch problem by kumar *et al.* [371]. The algorithm integrates the deterministic search, the multi-agent system, PSO algorithm and bee decision-making process. Ramesh *et al.* [351] have presented a hybrid approach that includes DE with PSO, for the solution of economic load dispatch problems. Basu [417] has proposed a hybrid methodology integrating bee colony optimization with SQP for solving dynamic economic load dispatch problem. Attaviriyanupap *et al.* [166] have solved the dynamic economic load dispatch problem by applying EP as a base level search, which gives a direction to the optimal global region, and then a local search SQP technique is used to fine tune the optimal solution. Victoire and Jeyakumar [223] presented a modified hybrid EP–SQP method to solve the dynamic economic load dispatch problem. Titus and Jeyakumar [285] have presented hybrid EP, PSO and SQP methods to solve the dynamic economic load dispatch problem of generating units considering non-convex features. A deterministic guided PSO algorithm has been presented to solve the dynamic economic load dispatch problem by Victoire and Jeyakumar [224]. The deterministic guided PSO method is a two-phase optimizer: in the first phase the PSO technique is explored the space freely. In the second phase, SQP is used only when there is an improvement of solution. Vaisakh *et al.* [392] have presented a heuristic optimization methodology based on Bacterial foraging PSO-DE algorithm to solve dynamic economic load dispatch problem. Wong and Duan [335] have proposed a hybrid algorithm of DE and EP to reduce the required population size. The proposed algorithm has been applied to solve reactive power flow problem. Attaviriyanupap *et al.* [188] have proposed a hybrid method using LR and EP techniques to help Generation Company to make a decision, regarding power dispatch and reserve should be sold in markets. Liang *et al.* [370] have presented a fuzzy based hybrid PSO approach for solving the optimal power flow problem with uncertainties.

Chang [352] has presented an approach of combined SQP and PSO to optimize the planning of large-scale passive harmonic filters. Tseng and Lin [308] have proposed a hybrid genetic local search algorithm to solve permutation flowshop scheduling problem. A memetic PSO algorithm which combines the canonical PSO with a Chaotic and Gaussian local search procedure is proposed by Jia *et al.* [357]. Coelho and Alotto [268] have applied an optimization method inspired by an artificial immune network combined with Nelder-Mead simplex method for designing of Loney's solenoid benchmark problem. Noman and Iba [277] have presented a crossover-based adaptive local search operation for enhancing the performance of standard DE. Derbel *et al.* [388] have illustrated GA combined with an iterative local search to solve location routing problem. The main idea behind the hybridization is to improve the solutions generated by the GA, by applying iterative local search. The combination of an EA, a clustering process, and a local-search procedure to the evolutionary design of product-unit neural networks has been proposed by Martinez-Estudillo *et al.* [230]. Tseng and Chen [307] have addressed a two-phase GA search algorithm that combines the GA and local search method to solve resource-constrained project scheduling problem. Duan *et al.* [420] have presented results of a comparative study with the objective to identify the most effective and efficient way of applying a local search method embedded in a hybrid algorithm. Harman and McMinn [342] have illustrated results from a large empirical study that compares the behaviour of both global and local search based optimization on real word problems, and suggested that a hybrid global-local search may be appropriate. So, there is a need of heuristic optimization technique based on integration of global and local search technique to achieve speed, efficiency and reliable convergence.

1.1.4 Multi-Objective Optimization

One of the inherent characteristics associated with complex real-world decision making problems is their inescapably multifarious nature. One of the multifarious features of such problems is their multiple objectives that are often in conflict. Owing to the conflicting nature of objectives, an optimal solution that simultaneously maximizes/minimizes all the criteria is usually not attainable. Real-world, decision making problems, thus, often leads to a MOOP formulation [156]. Generally MOOPs require the computation of a set of decision variables that provide the best possible solution to a predefined scalar objective function or a set of optimal trade-off values in case of two or more conflicting objectives.

Pareto optimal solutions and front: With multiple objectives, there is generally not one unique solution which is best with respect to all objectives but a set of solutions which cannot be dominated by any other solutions in the search space. These solutions are known as Pareto-optimal solutions or non-dominated solutions [16]. The curve formed by joining these solutions is known as Pareto-optimal front.

For MOOPs, finding the best solution means trading off between the different objectives. Methodologies used for solving MOOPs, principally differ in two ways, the procedure used to generate non-inferior solutions and the ways and means used to interact with *Decision-maker* (DM) and the type of information made available to the DM such as trade-offs. There are various techniques for generating non-inferior solutions, e.g. weighting method, ε-constraint method, and non-inferior set estimation method etc. The multiple objectives are often combined using objective function weights. The final solution can be highly sensitive to the weights used in the scalarization process. The main difficulty with using utility theory, for many practitioners, is the determination of meaningful utility functions. In such methods, the value of the weights chosen or the utilities used dictates the final solution. The ε-constraint method optimizes the most preferred objective and considers the other objective as constraints bounded by some allowable levels ε. The most obvious weakness of this approach is that it is time consuming.

Weighting method has been used for converting MOOP into single-objective one, by various researchers [151, 172, 181, 208, 226, 227, 236, 258, 272, 276]. A DE based technique to solve optimal power flow problem with multiple and competing objectives has been presented by Varadarajan and Swarup [276]. Tsay [281] has presented a multi-objective approach based on EP to solve the economical operation of cogeneration system under emission constraints. An optimization technique based on progressive articulation of preference information has been presented to solve the multi-objective environmental economic load dispatch by Yalcinoz and Koksoy [258]. Bath *et al.* [208] have explored the use of GA to search for the assigned weightage pattern of objectives to obtain the best compromised thermal power generation schedule in the multi-objective framework. Nangia *et al.* [151] have formulated a multi-objective optimal power flow problem and a number of noninferior solutions are generated in 3D space. Singh and Dhillon [272] have presented best weight pattern evaluation approach to solve multi-objective load dispatch problem which determines the allocation of power demand among the committed generating units, to minimize a number of objectives. The evolutionary optimization technique has been employed in which the preferred weightage pattern has been searched to get the best optimal solution in non-inferior domain by Brar *et al.* [172]. Bath *et al.* [227] have used the weighting method to generate non-inferior solutions for the DM and the best compromised solution has been obtained by searching for the optimal weight pattern using evolutionary optimization method. The proposed method has been applied to solve multi-objective load dispatch problem. Singh *et al.* [236] have proposed a solution methodology for the determination of best objective weights to solve multi-objective thermal power dispatch problem. The weights are calculated by conventional statistical measures, which characterize the correlation coefficients matrix evolution.

To generate non-inferior solutions to the MOOP, the ε-constraint method is used [133,313]. Osman *et al.* [313] have presented a multi-objective GA approach for multi-objective economic emission dispatch problem. The algorithm maintains a finite-sized archive of non-dominated solutions which get iteratively updated in the presence of new solutions based on the concept of ε-dominance. A price penalty factor has been widely used for converting MOOP into single-objective problem [210, 329, 347, 386]. Chen and Ke [210] have proposed a projection-based two-layer SA method to solve multi-objective reactive power planning problem for large-scale power systems. Raglend *et al.* [329] have done a comparative study on the solutions obtained by applying different intelligent techniques on multi-objective economic emission dispatch problem considering line flow constraints. Hota *et al.* [347] have presented an optimization approach involving a modified bacterial foraging algorithm applied for the solution of the multi-objective economic emission dispatch problem. Shaw *et al.* [386] have proposed an opposition-based gravitational search algorithm for multi-objective economic emission dispatch problem.

In almost all decision making problems, there are several criteria for judging the possible alternatives. The main concern of DM is to fulfil the conflicting goals while satisfying the constraints of the system. Hwang and Masud [10] have classified the methods according to the participation of the DM in the solution process and given as:

No preference method: In no preference methods, the MOOP is solved and the solution obtained is presented to the DM. The DM may either accept or reject the solution. It seems quite unlikely that the solution best satisfying the DM could be found with these methods.

Posteriori method: In posteriori methods, after the Pareto optimal set has been generated, it is presented to the DM, who selects the most preferred among the alternatives. The inconveniences here are that the generation process is usually computationally expensive and sometimes in part, at least, difficult. On the other hand, it is hard for the DM to select a large set of alternatives.

Priori method: In the case of priori methods, the DM must specify her or his preferences, hopes and opinions before the solution process. The difficulty is that the

DM does not necessarily know beforehand what it is possible to attain in the problem and how realistic her or his expectations are.

Interactive method: In the interactive methods, interacting with the DM identifies a local preference function or trade-off among objectives, and the solution process proceeds gradually towards the globally satisfactory solution. The interactive method can be characterized by the following procedure:

- Find a non-inferior solution by applying weighting method, ε-constraint method etc.
- Interact with DM to obtain his reaction response to the solution, and
- Repeat above steps until satisfaction is reached or until some other termination criterion is met [34].

Interactive methods are presumed to produce the most satisfactory results. Because only part of the Pareto optimal points has to be generated and evaluated, and the DM can specify and correct her or his preference and selections as the solution process continue and s(he) gets the know the problem and its potentialities better. This also means that the DM does not to know any global preference structure.

The recent direction is to handle all the objectives simultaneously as competing objectives. Global search techniques seem particular suitable to solve MOOPs because they deal simultaneously with a set of possible solutions which allows to find an entire set of Pareto optimal solution in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of the traditional mathematical programming techniques. Additionally, global search techniques are less suitable to the shape of continuity of the Pareto front, whereas these two issues are a real concern for mathematical programming techniques [113]. Some of the recent evolutionary approaches to solve MOOP, are *non-dominated sorting genetic algorithm* (NSGA-II), *strength Pareto evolutionary algorithm* (SPEA), *Pareto archived evolution strategy* (PASE), *multi-objective differential evolution* (MODE), *multi-objective particle swarm optimization* (MOPSO) and others. Coello [113] has reviewed some of the most popular multi-objective evolutionary optimization techniques reported in literature till 1998.

A MOPSO technique for environmental/economic dispatch problem is proposed by Abido [309]. Wang and Singh [273] have formulated a stochastic model for combined heat and power dispatch and then MOPSO method is developed to deal with the economic combined heat and power dispatch by simultaneously considering multiple conflicting objectives. Piperagkas *et al.* [359] have proposed stochastic multi-objective model for economic load dispatch that incorporates in the optimization process heat and power from combined heat and power units and expected wind power. Wang and Singh [254] have proposed fuzzified MOPSO algorithm and implemented to dispatch the electric power considering both economic and environmental issues.

The concept of robust optimal solution is incorporated into multi-objective optimal reactive power dispatch for the consideration of uncertain load perturbations during system operations [340] and then NSGA-II has been adopted to search for the robust Pareto solutions for robust multi-objective optimal reactive power dispatch. Jeyadevi *et al.* [374] have addressed an application of modified NSGA-II by incorporating controlled elitism and dynamic crowding distance strategies in NSGA-II to solve multi-objective optimal reactive power dispatch problem.

A multi-objective harmony search algorithm is applied for multi-objective optimal power flow problem by Sivasubramani and Swarup [378]. Sivasubramani and Swarup [376] have presented a multi-objective harmony search algorithm for EED problem. A SPEA based approach has been widely used to form the Pareto-optimal set. Kumari and Maheswarapu [343] have combined a decoupled quadratic load flow solution with enhanced GA to solve the optimal power flow problem and SPEA based approach has been used to form the Pareto-optimal set. Abido [176] has presented a multi-objective EA for environmental/economic power dispatch problem.

A multi-objective EP technique has been applied by Abido and Bakhashwain [219] for optimal reactive power dispatch problem where real power loss and the bus voltage deviations are able to minimize simultaneously. Cai *et al.* [331] have developed a multi-objective chaotic ant swarm optimization method for solving the multi-objective environmental/economic dispatch which considers both economic and environmental issues. Wu *et al.* [338] have presented a MODE algorithm for environmental/economic power dispatch problem. The proposed MODE approach adopts an external elitist archive to retain non-dominated solutions found during the evolutionary process. A multi-objective hybrid evolutionary strategy by hybridizing GA and SA techniques for the solution of optimal power flow has been presented by Das and Patvardhan [178]. Gong *et al.* [326] have discussed a hybrid multi-objective algorithm based on PSO and DE to solve environmental/economic dispatch problem. A crowding distance-based approach is introduced to assign the particles' leaders and to update the external archive. Silva *et al.* [387] have proposed a multi-objective biogeography-based optimization, combined with a

PPO approach. The proposed technique is validated in the constrained design of a brushless dc wheel motor. Shi and Xu [145] have solved multi-objective optimal operation problem by applying self-adaptive mutation operator in EP technique.

The weighting method is the most common method used for solving multi-objective optimization problems until recently. A major drawback of weighting method is that there is no rational basis of determining adequate weights. Another limitation with the simulated weight problem is that the decision maker may skip the weight combination that actually corresponds to the 'best' compromising solution during simulation procedure because of step size taken. So, there is a need to evaluate the best weight pattern so that decision maker evaluates the 'best' solution among the presented non-inferior solutions.

1.2 HYDRO-THERMAL GENERATION SCHEDULING

Since the sources of energy are so diverse (coal, oil or gas, river water, marine tide etc.), the choice of one or the other is made on economic, technical or geographic basis. As there are few facilities to store electrical energy, the net production of utility must clearly track its load. The idea of integrated operation is the optimum utilization of all energy sources in the most economical manner, so that an uninterrupted supply can be made available to the consumers. The operating cost of thermal plant is very high, though their capital cost is low. On the other hand, the operating cost of hydroelectric plant is low but their capital cost is high. The hydroelectric plant can be started quickly and it has high reliability and greater speed of response. Hence hydro plants can take up fluctuating loads. In contrast to hydro plants, the starting of thermal plant is slow and their speed of response is slow as well. So it has become economical as well as convenient to have both thermal and hydro on the same grid. Normally the thermal plant is preferred as a base load plant whereas hydroelectric plant is run as a peak load plant. In the present set-up of large system with hydro and thermal power stations, the integrated operation of these power stations is inevitable and the economic aspects of such an operation are of great importance. In hydro-thermal integration, it is essential to use the total quantity of water available from the hydro system to the fullest extent. In a hydro system, fixed charges continue regardless of the amount of power generated, as there is no fuel cost associated with hydro power. Therefore, minimum overall cost is achieved by maximum exploration of hydro resources, *i. e.* water available over a period of time. Most hydro-electric plants are multi-purpose and it is necessary to meet certain obligations other than power generation. These may include a maximum for-bay elevation, not to be exceeded because of danger of flooding, and a minimum plant discharge and spillage to meet irrigational and navigational commitments. Distinctions among hydro power systems depend on the number of hydro stations, their locations, operating characteristics and time horizons.

Hydro plants are classified on the basis of time horizons: short-term hydro scheduling encircles a time horizon of 1 day to 1 week, usually discretized in hourly intervals [24]. Short-term HTGS must use the water storage and release schedules from long-term scheduling solutions [17,109], with the necessary modification based on short-term rainfall, water inflow, and load predictions. The Long-term hydro scheduling encircles a time horizon of one or more years, discredited in weekly or monthly intervals [27]. The cyclic nature of reservoir water inflows and seasonal load demand and corresponding scheduling period of one year or more years is used. The solution of the long-range problem considers the dynamics of head variations through the water flow continuity equation.

1.2.1 Short-Term Hydro-Thermal Generation Scheduling

The short-term hydro-thermal generation scheduling problem is classified on different criteria. One criterion can be considered as reservoir capacity. For large capacity reservoirs water head considered as fixed, generated power does not depends on water head. If reservoir capacity is not sufficiently high, power generated by hydro plant is affected by variation of head. Another criterion is on the basis of location of hydro plants. It can be located on same stream or different stream. Short-term HTGS is an important optimization task in power system operation. A good generation schedule reduces the production cost, increases the system reliability, and maximizes the energy capability of reservoirs [27]. The optimal scheduling of hydro-thermal power system is basically a complex programming problem involving nonlinear objective function and a mixture of linear and nonlinear constraints. The objective of hydro-thermal scheduling is to generate the power economically, whereas satisfying various constraints. The equality constraints include generation-demand balance and balance of available volume-water discharge. The inequality constraints include generation limit on thermal and hydro power unit, limit on discharge rate and reservoir storage level limit.

In the short-term scheduling of a fixed water head, power generation depends only on the discharge of water [13, 21, 30, 180, 220]. Several conventional methods have been used for fixed-head HTGS under practical constraints such as DP [244], mixed integer programming [75], LR technique [100], Lagrangian multiplier, gradient search techniques [157], and an efficient method [30]. Most of the applied methods make a number of assumptions to simplify the optimization problem, but that may lead to a sub-optimal solution. The recent trend is to apply more realistic models for hydro and thermal units. The nature of these models is represented by non-smooth, non-convex characteristics. Such models require a fast, accurate and robust solution methodology as it cannot be handled effectively by mathematical programming based optimization methods. Generally, heuristic search techniques are used as tool for solution of complex optimization problems because of their strength to overcome the shortcoming of traditional optimization methods.

Various heuristic search techniques have been reported in the literature pertaining to short-term fixed-head HTGS. Basu has applied Hopfield neural networks [180], EP [201], SA [220] and RCGA [365] for solving fixed-head HTGS. The artificial immune system technique has been applied for optimal scheduling of thermal plants in coordination with fixed-head hydro units by Basu [366]. Sasikal and Ramaswamy [334] have presented an optimal gamma based algorithm for fixed-head HTGS using GA.

The head of reservoir is variable if the hydro-plants are having reservoir of small capacity. Hydro-thermal scheduling algorithm which accounted for head variations is first presented by Ricard [1]. Ricard's model neglects transmission losses. Glimn and Kirchmayer [2] and later Arismunander [3] used variational calculus to solve the HTGS which included transmission losses. Rashid and Nor [39] have presented an algorithm for the optimum scheduling of variable-head hydro and thermal plants. El-Hawary and Ravindranath [20] have applied Newton-Raphson method for optimal operation of variable-head hydro-thermal system. Within the LR framework, the hydro river catchment sub-problems are difficult to solve. The head-dependent water power conversion adds another dimension of difficulty since the objective function of hydro sub-problems are no longer stage-wise additive with respect to water discharge. It is difficult to solve the sub-problems by relaxing the reservoir limits or the hydraulic coupling among units. Ni *et al.* [115] have proposed an algorithm with a relaxation structure to solve hydro river catchment sub-problems. A river catchment sub-problem is further decomposed into two sets of sub-problems: a continuous-variable optimization problem determining the generation levels of all units in the entire river catchment, and a number of pure integer problems determining the hydro commitment status, one for each unit.

The continuous problem is solved by a nonlinear network flow algorithm, and the integer problems are solved by DP with a small number of states and well-structure transitions.

Several researchers have tried to investigate the dependency of variable-head of hydro units. Emad and braham [86] have solved dynamic hydro-thermal economic dispatch with variable-head using NLP technique in conjunction with successive approximation method. Catalão *et al.* [218, 332, 333] have proposed a nonlinear approach to solve the short-term HTGS problem, considering hydro-electric power generation a function of water discharge and of the head. Borghetti *et al.* [261] have discussed a unit commitment problem of a multi-unit pump-storage hydro power station, for a short-term period in which electricity priced are forecasted. They have presented a model that takes into account the water head effects on power production through an enhanced linearization technique. Kanakasabapathy and Shanti Swarup [346] have developed bidding strategy for operating multiunit pumped-storage power plant in a day-ahead electricity market. They have applied evolutionary tri-state PSO based approach, combining PSO with tri-state coding technique and genetics-based mutation operator to maximize the expected profit of the pumped-storage plant.

In multi-chain hydro model, hydro plants are located on different streams as well as on the same stream. The operation of a downstream plant depends on the immediate upstream plant. The travel time between reservoirs must be taken into account if the transposition delays are not negligible. Time-delay is a difficult issue, depending on the distance between reservoirs and on the water discharge [341]. But downstream plant influences the immediate upstream plant by its effect on tail water elevation and effective head. The number of research papers in this field is so large that a critical review of all of them is beyond the scope of this thesis due to space consideration. An extensive bibliography is presented in [93, 142, 301]. Brief reviews of certain latest selected and representative papers in the area of HTGS, however, are presented here.

Lagrangian relaxation has been widely used for the HTGS of power systems. The idea is to use Lagrangian multipliers to relax system-wide demand and reserve requirements, and decompose the problem into unit-wise sub-problems that are easier to solve. Yan *et al.* [44] have solved a hydro unit sub-problem by a merit order allocation method, and a thermal unit sub-problem is solved by using DP without discretizing generation levels. Guan *et al.* [88] have concentrated on the solution methodology for hydro sub-problems with cascaded reservoirs and discrete hydro constraints. The key idea is to substitute out the reservoir dynamics and to relax the reservoir level constraints by using another set of multipliers, making a hydro sub-problem unit-wise and stage-unit decomposable. Dynamic programming is then applied to optimize the operating states across the planning horizon with a small number of well-structured transitions. Salam *et al.* [100] have solved the thermal sub-problem by using DP without discretizing generation levels. Instead of solving hydro sub-problems independently, the HTGS uses the commitment status of thermal units obtained from the thermal sub-problem. Rakic and Marovic [53] have considered a unified problem of short-term operation planning and power exchange scheduling of large hydro-thermal power systems. The problem is solved using LR technique. Decomposition technique is applied to solve the dual and primal problem. Dynamic programming, feasible direction method and LP method are used for the solution of sub-problems.

A two layer approach to solve the unit commitment problem of a hydro-thermal power system has been applied by Rudolf and Bayrleithner [111]. The first layer uses a GA to decide the on/off status of the unit and the second layer uses a NLP formulation solved by LR technique to perform the economic load dispatch problem. Wang and Shahidehpour [41] have decomposed the HTGS problem into thermal and hydro sub-problems. The coordination between these sub-problems is the system Lagrange multiplier. For the hydro sub-system, network flow concepts are adopted to coordinate water usage over the entire study time span and reduced gradient method is used to obtain optimal solution. Ngundam *et al.* [132] have described a method for scheduling large-scale hydro-thermal power systems based on the LR technique.

Guan and Zhang [65] have discussed the basic idea of LR method, and then two-level structure is formed. The low level consists of individual thermal, hydro, pumped-storage and schedulable contract sub-problems. The high level dual problem is to update the multipliers so as to maximize the dual function. The difficulty with the Lagrangian multipliers is that it is updated most commonly by using a sub-gradient method. Since the high level dual function is non-differential with many ridges, sub-gradient method may zig-zag across riders resulting in slow convergence and the solutions of these sub-problems may oscillate between minimum and maximum generations with slight changes of the multipliers. To overcome this difficulty a nonlinear approximation method is presented, which utilizes nonlinear functions, to approximate relevant linear cost functions by Guan and Zhang [65]. Luh *et al.* [101] have presented an algorithm that utilizes a reduced complexity bundle method to update the multipliers at the high level. This method is a kind of bundle method that show faster convergence compared to sub-gradient method, and has much reduced complexity as compared to a conventional bundled method. Zhang *et al.* [114] have presented an algorithm that utilizes the bundle trust region method to update the multipliers within the LR framework. In the framework of the LR, Redondo and Conejo [123] have provided a non-oscillating and efficient multiplier updating procedure that shows better results as compared to procedures such as sub-gradient and bundled methods to solve HTGS problem.

A second-order network flow algorithm designed for HTGS has been presented by Oliveira and Soares [58] .The algorithm is based on the truncated Newton method and also applied heuristic strategies for variable partition into basic-super-basic–non-basic sets to improve the algorithm's efficiency. Tang and Luh [61] have proposed a method based on differential DP and mixed coordination to address short-term scheduling of hydro-thermal systems. Initially, problem is decomposed into thermal and hydro sub-problems, the thermal sub-problem is solved analytically and then extended differential DP and mixed coordination are used to solve the hydro sub-problem. Skugge *et al.* [49] have described an approach for solving the seasonal planning problem of a hydro-thermal system where part of the thermal capacity consists of energy constrained natural gas units. They have decomposed the problem into two parts: one part performs a traditional production costing given a gas schedule. The other part makes use of weekly marginal costs with first order information from the production costing algorithm in order to schedule the gases.

Ferreira [51] has studied the convergence properties of the classical hydro-thermal optimization algorithm. He has proposed a relaxation coefficient to show the guaranteed convergence and also demonstrate the sensitivity of relaxation coefficient depends on the hydro and thermal scheduling functions. Rajakovic and Ruzic [47] have dealt with the sensitivity analysis of an optimal short-term hydro-thermal schedule. They have also presented some results of sensitivity calculations concerning relevant errors in thermal cost coefficients, hydro plant characteristics, forecasted water inflows and forecasted system demands.

Al-Agtash and Su [105] have discussed an augmented Lagrangian approach to HTGS. It adds to the standard Lagrangian function a quadratic penalty function which associates generation-load balance, spinning reserve and emission constraints. Heredia and Nabona [57] have used a nonlinear network flow model with linear side constraints to solve the HTGS. Hydro generation is linearized with respect to network variables and a thermal generation and transmission network is introduced.

Fadil and Yasar [149] have proposed a pseudo spot price algorithm for short-term HTGS. The proposed technique has two parts: In the first part, pseudo active generation incremental cost values of hydraulic units are determined. In the second part, active generation, in all time intervals are determined by using unit's active generation incremental costs and pseudo spot price of bought active powers. Petcharaks and Ongsakul [256] have proposed a hybrid enhanced LR method and quadratic programming. Dynamic programming and coordination equation techniques have been applied to solve short-term operation of hydro-thermal system by Al-Shakarchi and Al-Hassany [137]. Werner and Verstage [126] have reported an approach based on evolution strategies to determine the optimal schedule of all hydro-electric and thermal plants. Differential evolution [267] and DE with SQP based algorithm [337] are applied for optimum HTGS. Yuan *et al.* [288,290] have proposed an enhanced DE algorithm for optimal hydro generation scheduling. In the proposed method, chaos theory is applied to obtain self-adaptive parameter setting in DE. Mandal and Chakrabotry [416] have conducted a study of control parameters of DE based optimal scheduling of hydro-thermal system with cascaded reservoir.

Chen and Chang [77] have presented an approach to the 24-hour ahead generating scheduling of hydraulically coupled plant based on the GA. A two-phase neural network technique has been presented by Naresh and Sharma [170]. Swain *et al.* [372] have applied optimization procedure based on clonal selection algorithm. Kumar and Mohan [379] have presented a technique for solving the HTGS through the application of GA. They have solved hydro sub-problem using GA and then thermal sub-problem is solved by applying incremental cost (lemda) iteration technique. Zoumas *et al.* [193] have solved hydro-thermal coordination problem with an enhanced GA that features a set of problem-specific genetic operators. Genetic algorithm based technique [217] and a diploid genotype based GA [140] are applied to solve short-term HTGS. Wong [150] has applied hybrid technique based on SA and GA for short-term HTGS. Gil *et al.* [179] have introduced a model that handles simultaneously the sub-problems of the short-term hydro-thermal coordination, unit commitment and economic load dispatch and GA is applied for optimum generation scheduling.

Evolutionary programming based technique [124,171] and fast EP technique [186,187] have been applied to solve short-term HTGS by various researchers. Mandal *et al.* have applied PSO [266,362] technique to solve short-term economic generation scheduling of hydro-thermal system. A modified PSO [315], adaptive PSO [345] and self adaptive PSO [408] have been applied to solve daily HTGS. In self adaptive PSO the evolution direction of each particle is redirected dynamically by adjusting the parameters of PSO in the evolution process. Hinojosa and Leyton [402] have applied a mixed-binary evolutionary particle swarm optimizer to solve HTGS problem. They have considered water discharge rate as continuous and thermal states as binary decision variable. Zhang *et al.* [390] have proposed a small population-based PSO approach. In proposed method, a mutation operation that selects the flying guides for each individual is employed to enhance the diversity of the small population. Liao *et al.* [421] have applied an adaptive chaotic artificial bee colony algorithm to solve the HTGS. In this method, chaotic search is applied to guide artificial bee colony algorithm to escape from a local optimum effectively. Roy [419] has presented a teaching learning based optimization technique to solve short-term HTGS considering nonlinearities like valve point loading effect of thermal unit and prohibited discharge zone of water reservoir of the hydro plants. Zhang *et al.* [414] have integrated SA technique into cultural DE. They have used adaptive crossover rate to control the population convergence. They have tested integrated technique on various benchmark problems and then it is applied to solve HTGS problem and found satisfactory. Wang *et al.* [407] have presented a differential real-coded quantum-inspired evolutionary algorithm to solve short-term HTGS problem.

Santos and Diniz [319] have applied multistage benders decomposition technique to solve HTGS problems. They proposed a different strategy to decompose the problem, where each stage comprises all variables and constraints of several time periods. Sifuentes *et al.* [259] have presented a decomposition method that includes the network through ac modelling within the HTGS optimization process including the losses. Parastegari *et al.* [418] have applied benders decomposition method improved by bacterial foraging oriented by PSO to solve AC constrained HTGS problem.

A dual approach has been used by Mezger and Almeida [243] to solve short-term HTGS for systems under pool-bilateral markets. First of all, the bilateral transactions and the spot market trades are discriminated in the short-term hydro-thermal system model. Subsequently, the resulting problem is decomposed into one hydro and a set of electrical and thermal sub-problems. The sub-problems are solved analytically by a primal-dual interior point method, whereas the dual problem is solved using bundle method. Singh *et al.* [363] have proposed a congestion management strategy for a pool based electricity market considering combined operation of hydro and thermal generator companies. The proposed method is applied to minimize the cost of re-dispatching the hydro and thermal generator companies to alleviate congestion. Bisanovic *et al.* [281] have addressed the self-scheduling problem of determining the unit commitment status for power generation companies before submitting the hourly bids in a day-ahead market. The hydro-thermal model is formulated as a deterministic optimization problem where expected profit is maximized using the 0/1 mixed-integer LP technique. Parrila and Garcia-Gonzalez [214] have presented a branch and bound algorithm to solve the weekly scheduling problem of a large-scale hydro-thermal power system.

1.2.2 Long-Term Hydro-Thermal Generation Scheduling

The long-term hydro scheduling which encircle a time horizon of one or more years, discretized in weekly or monthly intervals. In a hydro-thermal power system with significant percentage of hydro generation, a long–term multi reservoir management has a great impact on the production cost of the thermal units. Additionally, the long-term scheduling is strongly influenced by the water inflow uncertainty [136], and it is a stochastic problem [84]. A non-uniform composite representation of hydro-electric systems has been applied in long-term HTGS by Cruz Jr. and Soares [69]. This representation was developed from reservoir operational rules based on optimal reservoir trajectories obtained with a deterministic HTGS algorithm. Ferrero *et al.* [104] have proposed an algorithm based on DP for long-term HTGS of multi-reservoir systems. The proposed method minimizes the sum of operation cost in two consecutive periods, formulating the HTGS problem as a function of reservoirs water content in one period. Martinez and Soares [160] have applied stochastic dynamic programming to long-term HTGS problem. Stochastic DP has ability to cope with the nonlinear and stochastic characteristics of long-term HTGS problem, and the fact that it provides a closed-loop feedback control policy. A software package is proposed by Castro and Gonzalez [196] for solving long-term hydro-thermal coordination problem. The problem is solved through either Minos or Snopt, two state-of-the-arts nonlinear optimization packages.

Santos *et al.* [310] and Goncalves *et al.* [397] have applied progressive hedging method to solve the medium-term operation planning. Santos *et al.* [310] have discussed two important aspects of the progressive hedging method: the use of warm start and the choice of a suitable penalty parameter. A suitable decomposition schemes is applied to reduce the processing time [397]. A semidefinite programming is presented to solve medium-term hydro-thermal coordination problem by Fuentes-Loyola and Quintana

[169]. The convex quadratic constraints have been replaced by nonconvex integer value constraints and then semidefinite programming is implemented. Wu *et al.* [275] have elaborated a stochastic midterm risk constrained HTGS algorithm in a generation company. The objective of a generation company is to maximize payoffs and minimize financial risks when scheduling in midterm generation of thermal, cascaded hydro, and pumped-storage units. Ahmadi *et al.* [382] have presented a method for hydro-thermal self scheduling problem in a day-ahead joint energy and reserve market. The problem is modelled in the form of multi-objective framework to simultaneously maximize generation company profit and minimize emissions of thermal units. Baslis *et al.* [298] have presented a model for the simulation of the optimal medium-term operation of a hydro-thermal system. System stochastic parameters are modelled by Monto Carlo scenarios, which are solved on distributed processors.

1.2.3 Multi-Objective Hydro-Thermal Generation Scheduling

In recent years, rigid environmental regulation forced the utility planners to consider emission control as an important objective and to modify their operating strategies to reduce pollution and atmospheric emissions of the thermal power plants [133,175]. Because of conflicting nature of emission and fuel cost, problem is viewed as MOOP. Multi-objective HTGS has been undertaken by several researches till now. Many different techniques such as EP [199], DE [303] and modified quantum-behaved PSO [348] have been applied with weighted sum method to solve the problem. The important aspect of the weighted sum method is that a set of Pareto-optimal solutions can be obtained by varying the assigned weights to objectives [120]. In comparison to aforementioned weighted approach, researchers are exploring other methods to handle MOOP.

Zhou *et al.* [404] have proposed a DE algorithm based on ε-domination and orthogonal design method for HTGS considering economy and emission as objectives. Basu [341] presented MODE for economic-environmental dispatch of hydro-thermal power system where both cost and emission objectives have been treated simultaneously as competing objectives. Lu *et al.* [381] have proposed an integrated DE algorithm into the framework of cultural algorithm model to implement the evolution of population space. A hybrid multi-objective cultural algorithm is applied to deal with short-term environmental/economic HTGS by optimizing both objectives simultaneously. Zhang *et al.* [415] have proposed three chaotic sequences based MODE technique to solve short-term hydro-thermal optimal scheduling with economic emission. They have utilized elitist archive mechanism to retain the non-dominated individual solution. Selvakumar [409] has presented a solution technique for multi-objective HTGS through civilized swarm optimization, which is based on hybridization of society-civilization algorithm and PSO. Zhang *et al.* [413] have integrated culture belief into MODE and chaotic sequence is imported to improve evolution population diversity. The integrated method is applied for short-term HTGS. A price penalty factor is applied to convert bi-objective problem into a single objective one. Various different techniques such as quantum PSO [325], quadratic approximation based DE [375], self-organizing hierarchical PSO technique with time varying acceleration coefficients [391] have been applied for combined economic-emission scheduling of cascaded hydro-thermal systems by using price penalty factor. A goal-attainment method is used to convert a MOOP into a single-objective one and then SA technique is applied for economic emission load dispatch problem for fixed-head [220] and cascaded reservoir [200] hydro-thermal system by Basu.

Various techniques have been proposed by many researchers to deal with multi-objective HTGS considering fixed-head hydro model. A modified GA has been applied by Chiang [248] for optimal multi-objective economic emission dispatch. The ε-constraint technique is employed to manage the MOOP. Basu has presented EP based method [201] and NSGA-II [365] for economic environmental dispatch of fixed-head hydro-thermal power system.

1.3 FUZZY SET THEORY IN POWER SYSTEM

Analytical approaches have been used over the years for many power system operation, planning and control problems. However, the mathematical formulations of real world problems are derived under certain restrictive assumptions and even with these assumptions, the solution of large scale power system problems are not trivial. On the other hand, there are many uncertainties in various power system problems because power systems are large, complex, geographically widely distributed systems and influenced by unexpected events. These facts make it difficult to effectively deal with many power system problems through strict mathematical formulations alone [89]. To address uncertainty and imprecision, fuzzy logic was developed by Lotfi Zadeh in 1964 [6]. Fuzzy logic offers a new way of representing inaccuracies and uncertainties in data for machine realization. In fuzzy logic, a statement is true to various degrees, ranging from completely true through half-true to completely false which differs from the traditional set theory's true/false approach. The principle objective is the treatment of inaccuracies and uncertainties embedded in data by defining a fuzzy set comprising membership functions representing the degree of belonging to the set [9].

The application of fuzzy set theory is extended over wide range in power system problems. Ruey-Hsun and Jian-Hao [251] have used various membership functions to take into account the uncertainties due to the prediction of: speed of wind, solar radiation, load prediction, etc. Similar approach was also proposed by Attaviriyanupap [202]. They have used fuzzy sets to take into account uncertainties due to: demand and reserves required in each market, prices cleared in each market, and the probability by which reserves are called upon in actual operation. The factors that affect the feasibility and optimality of the solutions to the economic dispatch problem, using fuzzy sets, are examined by Han *et al.* [152]. Yan and Luh [82] have developed a fuzzy optimization algorithm based on symmetric approach of fuzzy optimization and the LR technique. They have considered system demand, reserve requirements and prices of future purchase transactions as uncertain values. A fuzzy model for power system operation is presented by Miranda and Saraiva [37]. Uncertainties in load and generations are modelled as fuzzy numbers and system behaviour under known injections is dealt with by a DC fuzzy power flow model. El-Sharkh and El-Keib [181] have presented a fuzzy model for and a solution approach to the integrated maintenance scheduling of problem generation and transmission systems. The fuzzy model accounts for load uncertainty over the maintenance horizon, and the cost variation due to market price changes. Djukanovic *et al.* [73] have modelled the blending/transloading facilities using an interactive fuzzy LP, in order to allow the DM to solve the problem of uncertainty of input information within the fuel scheduling optimization.

The modelling of power system contains differential equations with nonlinear parameters. These nonlinear functions may not be known but some linguistic information is known. Utilizing this information, fuzzy logic systems can be designed to model the system behaviour. Hosseinzadeh and Kalam [121] have developed fuzzy power system stabilizer using the concept of fuzzy basis functions. They have used linguistic rules regarding the dependence of the plant output on the controlling signal to build fuzzy power system stabilizer. Zadeh and Kalam [163] have developed indirect adaptive fuzzy power system stabilizer using the concept of fuzzy basic functions. They have carried out the simulation studies for an industrial co-generator and utilize a one-machine infinite-bus model and concluded that the performance of indirect adaptive fuzzy power system stabilizer is better than linear power system stabilizer. Hosseinzadeh and Kalam [122] have developed fuzzy power system stabilizer using speed and active power deviations as the controller input variables and scaling parameters of stabilizer is tuned by neural network. Hosseinzadeh and Kalam [164] have developed a fuzzy-logic power system stabilizer using speed deviation and accelerating power as the controller input variables. They have tested the stabilizer by performing nonlinear simulation using a synchronous machine infinite bus model. Shi *et al.* [50] have presented optimization and implementation of fuzzy controllers to improve the stability of power systems. A number of research articles indicate applicability of fuzzy systems to power system for wider operating conditions. Bansal [168] has presented a comprehensive set of references on fuzzy set theory applications in power system from 1994 till 2001.

The fuzzy optimization procedure is another aspect of fuzzy-set theory. It provides a framework for handling optimization problems. In fuzzy optimization, the objective may not be optimized exactly, and constraints can be satisfied to varying degrees. This is opposed to crisp optimization where an optimal solution is sought satisfying all the constraints crisply. Fuzzy optimization reported in the literature can roughly be classified into two categories. In the first category, problems have crisp coefficient in their objective functions and constraints, however, constraints can be satisfied to varying degrees. Most methods reported in literature transform a fuzzy problem into a crisp one by using the symmetric approach of Bellman and Zadeh [7]. The basic idea is that the objective function should be essentially smaller than or equal to some “aspiration level,” and this can be regarded as constraint. Bellman and Zadeh treat this “objective constraint” and other constraints symmetrically, and define fuzzy optimization as maximizing the minimum degree of satisfaction among all the objectives. Problems in the second category have fuzzy coefficients in their objectives and/or constraints. The presence of fuzzy coefficients makes the optimization problems much more difficult. In the literature, these problems are generally transformed into problems of the first category, by converting into multi-objective as has been done by Lai and Hwang [38], or by using alpha cut considered by Sakawa [45]. The converted problems are then transformed into crisp optimization based on the symmetric approach. Berredo *et al.* [369] have presented the result of research into the use of Bellman-Zadeh approach to decision making in a fuzzy environment for solving multi-criteria power engineering problems. Mekhamer *et al.* [189] have introduced an algorithm that combines fuzzy and heuristic methods to determine the exact optimal solution for capacitor allocation in radial distribution feeders. They have also discussed the effect of varying some parameters in the membership functions to obtain better results.

Several applications of fuzzy optimization in power systems have been reported in the literature. A recursive fuzzy DP method has been developed to obtain the commitment and dispatch of thermal and hydro units [31]. Fuzzy optimization methods for problems of first category have been developed for optimal power flow with uncertain system loads by Miranda and Saraiva [37], for multi-area scheduling with fuzzy demand and tie capacity limits by Wang *et al.* [36], and for power system scheduling with fuzzy reserve requirements by Guan *et al.* [66]. Venkatesh *et al.* [245] have formulated unit commitment problem using fuzzy linear optimization and then solved it by applying a mixed integer linear programming routine.

Somasundaram and Swaroopan [368] have proposed fuzzified PSO algorithm based on the combined application of fuzzy logic strategy incorporated in the PSO algorithm and an adaptive inertia weight is obtained from the fuzzy logic strategy. The proposed algorithm is applied to solve economic load dispatch problem. Blaže and Marko [414] have proposed a multi-objective method for solving the dynamic multi-objective economic emission dispatch. They have introduced fuzzy membership functions to handle constraint violations. Venkatesh *et al.* [130] have proposed a multi-objective fuzzy linear programming to solve optimal reactive power scheduling. In this programming, each objective and each violated constraint of the problem are associated with their respective fuzzy sets and their corresponding satisfaction parameters. The multi-objective fuzzy linear programming maximizes the minimum of these satisfaction parameters and achieves the optimum.

Real-world applications usually involve simultaneous optimization of multiple objectives, which are generally non-commensurable and conflicting with each other. In view of the development of multi-objective techniques the role of fuzzy set theory in decision making is increasing day by day. Brar *et al.* [226] have proposed the use of fuzzy logic approach for modelling the conflicting objectives for secure, economical and environmental clean operation. They have applied fuzzy interactive process using weighted min-max formulation by regulating the weights in a systematic order. Chen [141] has presented an interactive fuzzy-norm satisfying method for multi-objective reactive power source planning, by considering that the DM has fuzzy goals for each of the objective functions. Huang *et al.* [81] have applied a fuzzy satisfaction-maximizing decision approach to solve the bi-objective power dispatch problem regarding both minimum fuel cost and minimum environmental impact of NOx emission. Singh and Dhillon [270, 271] have dealt with the MOOP relaying to real and reactive power scheduling of thermal power generating units. They have implemented ε-constraint method to generate the non-inferior solutions along with the trade-off function between the conflicting objectives. Fuzzy set theory has been exploited to access the indifferent band and interaction with the DM is obtained via surrogate worth trade-off functions of the objectives. Basu [199, 201] has presented an interactive fuzzy satisfying method for multi-objective generation scheduling. Dhillon *et al.* [60] have applied the fuzzy decision making theory to obtain the compromised solution of stochastic multi-objective load dispatch problem. Srinivasan *et al.* [48] have incorporated fuzzy logic technique in a knowledge based system to solve multi-criteria problem involving multiple conflicting objectives. The proposed approach treats economy, security, emission and reliability as competing objectives for optimal dispatch of the local system generating units. Bath *et al.* [207] have presented an interactive fuzzy satisfying method to decide the generation schedule with explicit recognition of statistical uncertainties in system production cost data, NOx pollutant emission data and system load demand. Dhillon *et al.* [157] have exploited fuzzy decision making methodology to decide the generation schedule of a short-range fixed-head hydro-thermal problem. Srinivasan *et al.* [48] have presented a multi-objective technique for dynamic generation scheduling. Fuzzy logic approach is used to transform MOOP into single objective and then it is solved by maximizing this function. Brar *et al.* [172] have solved MOOP by searching the optimal weightage pattern of objectives and fuzzy set theory has been exploited to decide the preferred optimal operating point. Brar *et al.* [291] have proposed the utility of GA to search for the active and reactive power scheduling for a multi-objective load dispatch problem. Fuzzy decision-making methodology has been applied to decide the fitness function corresponding to each string of active and reactive power generations.

Chalermchaiarbha and Ongsakul [400] have proposed elitist MOPSO for solving multi-objective power dispatch. The proposed method utilizes fuzzy multi-attribute decision making, including maximizing the diversity of Pareto-optimal solutions, limiting the number of Pareto-optimal solutions to a manageable size as well as extracting the best compromise solution. A fuzzy clustering-based PSO algorithm has been proposed to solve the economic-emission dispatch by Agrawal *et al.* [280]. The proposed fuzzy clustering technique, manages the size of the repository within limits without distorting the characteristics of the Pareto front. Ramesh and Li [87] have developed a fuzzy formulation for a multi-objective optimal power flow problem. They utilized the fuzzy model for obtaining a Pareto curve reflecting the tradeoff between conflicting objectives.

Moeini *et al.* [373] have presented a fuzzy rule-based model for operation of hydro power reservoirs. The proposed fuzzy rule-based model presents a set of suitable operating rules for release from the reservoir based on ideal or target storage levels. Venkatesh and Ranjan [228] have developed a fuzzy model of the objective function for optimal capacitor allocation in radial distribution system in the EP framework. Brar *et al.* [242] have used fuzzy logic for modelling the conflicting objectives for secure, economical and environmentally clean power system operation. Weighting method is employed to generate trade-off among objectives. Venkatesh *et al.* [112] have solved nonlinear programming problem of optimal reactive power planning using successive multi-objective fuzzy LP framework. Using fuzzy models, all the violated load bus voltage constraints are fuzzified and their enforcements are maximized. In multi-objective problem, objectives are conflicting in nature. No solution can satisfy all the objectives in all respect. So, there is a need to apply fuzzy methodology to choose best compromise solution, which provides maximum satisfaction level from the participating objectives.

1.4 STOCHASTIC METHODS IN POWER SYSTEM

Conventional power system problem uses deterministic models, which are however not able to reflect some real situations in practical applications. Since certain inaccurate and uncertain factors are normally involved in system operations, stochastic models are more suited for investigating some of the power dispatch problems. Zhang and Lee [205] have proposed a method to compute a probabilistic optimal load flow. The proposed method combines the concept of Cumulants and Gram-Charlier expansion theory to obtain probabilistic distribution functions of transmission line flows. Su [213] have applied a probabilistic load-flow approach to take uncertainty of nodal data and line parameters into account in the load flow computations. Morales and Pérez-Ruiz [253] have considered four different Hong’s point estimate [95] schemes on the probabilistic power flow problem. Li *et al.* [289] have presented a probabilistic optimal load flow algorithm taking account of the variation of load power. They have taken system load as a random vector, which allows them to consider uncertainties and correlations of load. Yu *et al.* [300] have proposed a sampling method, Latin hypercube sampling combined with cholesky decomposition method, into Monte Carlo simulation for solving the probabilistic load flow problem. Tamtum *et al.* [293] have introduced two extensions to the cumulant method for probabilistic optimal load flow; the first is an enhancement to provide improved handling of limits within the probabilistic optimal load flow problems and the second is a way to include corrected variables.

In order to maintain desired levels of voltage and reactive power flow under various conditions and network configurations, power system operators may utilize a number of control tools such as switching reactive power sources, changing generator voltage, and/or adjusting transformer tap-settings. A probabilistic constrained load flow is applied to the optimal selection of the tap positions on the generator step-up and auxiliary unit transformer in order to maximize the generator reactive supply and absorption capabilities by Hatziargyriou and Karakatsanis [138]. Hu *et al.* [354] have proposed a chance-constrained programming formulation for optimal reactive power dispatch that considered uncertain nodal power injections and random branch outages.

Siahkali and Vakilian [327] have developed a solution method based on mixed integer NLP for generation scheduling of power system, while taking into account the stochastic behaviour of the load magnitude and the wind power generation. An interactive fuzzy satisfying method has been presented to decide the generation schedule with explicit recognition of statistical uncertainties in system production cost data, NO_x pollutant emission data and system load demand by Bath *et al.* [207]. Wang and Singh [274] have formulated deterministic and stochastic models and then modified PSO method has been developed to deal with the economic load dispatch while simultaneously considering the environmental impact. Bath *et al.* [239] have formulated stochastic multi-objective generation scheduling problem with explicit recognition of statistical uncertainties in the thermal generation cost, gaseous emission curves, real and reactive power demand and voltage magnitude at each bus. The problem is solved sequentially in the decoupled form and Hooke-Jeeves method has been employed to generate non-inferior solutions. Dhillon *et al.* [60] have formulated stochastic MOOP where operating cost and variance of generation mismatch are two non-commensurable objectives. Weighted sum technique is used to simulate trade off relation among the conflicting objectives and finally, fuzzy set theory is applied to choose optimal operating point over the trade-off curve. Attaviriyanupap *et al.* [202] have proposed a fuzzy-optimization approach to dynamic dispatch, considering the uncertainties in deregulated energy and reserve markets. Fuzzy numbers is used to handle uncertainties. Chang and Fu [92] have presented a stochastic formulation of multi-objective optimization for combined heat and power dispatch. Both the power and heat demands are treated as random variables. Wang and Singh [273] have formulated a stochastic model for combined heat and power dispatch, and then a modified PSO method is developed to deal with economic combined heat and power dispatch by simultaneously considering multiple conflicting objectives.

For hydro-thermal systems, the limited energy storage capability of water reservoirs, along with stochastic nature of their availability, makes their solution more difficult job than for purely thermal systems [361]. For HTGS, it becomes necessary to account for random nature of load, river inflow and uncertainties in input from various sources and a stochastic representation of these must be used. El-Hawary and Mbamalu [26] have presented a technique that deals with the hydro-thermal optimal power dispatch problem accounting for the effects of uncertainty in predicting active power demand. The method relates the probability distribution of the uncertain factors in the system active power generation, bus voltages, and phase angles to the probability distribution of errors resulting from the forecast of the active power demand. Contaxis and Kavatza [29] have presented a sub-optimal optimization method for solving the annual HTGS considering the stochastic nature of inflows to the reservoirs and forced outage rates of the thermal units. Cerisola *et al.* [399] have applied stochastic dual DP decomposition to a nonconvex multistage stochastic hydro-thermal model where the nonlinear water head effects on production and the nonlinear dependence between the reservoir head and the reservoir volume are modelled. Dhillon *et al.* [361] have formulated the stochastic multi-objective HTGS problem with explicit recognition of uncertainties in the system production cost coefficients and system load, which are treated as random variable and real coded genetic algorithm has been applied for scheduling. Fuzzy methodology has been exploited for solving a decision making problem involving multiplicity of objectives and selection criterion for best compromised solution. Dhillon *et al.* [157] have analyzed the hydro-thermal short-range fixed-head problem with explicit recognition of uncertainties in production cost, NOx, SO_2 and CO_2 emission and load demand. The weighting method is used to simulate the trade-off relation between the conflicting objecting and finally, fuzzy decision-making methodology is exploited to decide the generation schedule. Dhillon *et al.* [144] have presented a fuzzy decision making methodology to decide the generation schedule of long-term hydro-thermal problems with explicit recognition of statistical uncertainties in system production cost data, NO_x emission data, system load demand and hydro reservoir water inflows. Jiekang *et al.* [287] have proposed a model for short-term scheduling optimization of cascaded hydro plants, which includes uncertainties, such as water inflows, electricity prices, unit status, and so on, etc. A strategy for optimal scheduling based on PSO and chance-constrained programming is presented to maximize the expected profit at a given risk level. Rebennack *et al.* [401] have solved stochastic HTGS considering CO_2 emission constraints using stochastic dual DP. A risk-constrained stochastic midterm hydro-thermal price-based unit commitment problem is solved by Wu *et al.* [275]. The approach considers market price uncertainties for energy and ancillary services, natural water inflow and generator forced outage uncertainties. Uncertainties are simulated by the Monte Carlo method at different scenarios and LR technique is applied to decompose the original stochastic problem into several tractable scenarios.

Production costing models are widely used in the electric power industry to forecast the cost of producing electricity. These models account for the expected load variation over time and the uncertainty in the utilization of generating units. Mazumdar and Kapoor [62] have suggested that, in order to obtain a more detailed characterization of the probability distribution of production cost beyond the expected value, a model involving the stochastic processes underlying the generator outage is necessary. A stochastic model is considered as an enhancement to the traditional Baleriaux model and it has also shown that Monte Carlo simulation can be used on the enhanced model. Kapoor and Mazumdar [67] have proposed markovian model of the generation system together with a deterministic time-varying demand to compute the mean and the variance of the production costs. Chiang *et al.* [134] have proposed a stochastic model to quantify the variation of the estimated production cost that is directly affected by the load uncertainty. They have used a Gauss-Markov stochastic model of load with a chronological production simulation model. Bo and Li [316] have proposed the concept of probabilistic location marginal price and formulate the probability mass function of random load. Street *et al.* [263] have developed a model for pricing flexible gas supply contracts, taking into account the uncertainty associated to the supply-dependent on the dispatch of the thermal power plants, which have priority of the use of the gas-and the risk profile of potential consumers. The price-base unit commitment problem with uncertain market prices has been modelled as a stochastic mixed integer linear program by Li *et al.* [257].

Restructured power systems signify generation and transmission participants that are unbundled as self-interested entities which are also responsible in a competitive environment. In such environments, independent system operator is responsible for the optimal coordination of maintenance for generating units and transmission lines which would ensure the security of power systems and maximize the social welfare. Wu *et al.* [339] have presented a stochastic model for the independent system operator's optimal coordinated long-term maintenance scheduling of generation units and transmission lines with short-term security-constrained unit commitment. Random disturbances of power systems including forced outages of generating units and transmission lines, load forecast errors, and fuel price fluctuations are modelled as scenario trees using the Monte Carlo simulation. Wu *et al.* [255] have presented a stochastic model for the long-term solution of a security-constraint unit commitment. In this model, random disturbances are modelled as scenario trees using the Monte Carlo simulation method.

Electricity planning is subjected to a large degree of uncertainty, due to various aspects i.e., demand growth, price and elasticity of electricity, cost and availability of fuels and technologies, reliability of generating groups, inflation rates, interest rates, environmental regulation etc. Kasangaki *et al*. [64] have presented a method for stochastic electric power system production costing and operations planning. In this method, a stochastic Hopfield/Chua-Kennedy neural network in which unit availability and system load demand are random parameter with known statistics and unit outages are modelled as Markov processes. Zareipour *et al.* [328] have reported the economic impact of price forecasts to short-term operation scheduling. They have used electricity market price forecasts to determine the expected next-day electricity prices, optimal operating schedules and the associated cost for each load. Linares [167] has presented an electricity planning model which deals with uncertainty and its associated risk at two levels. At the first level, environmental risk is minimized through a multiple-criteria model and at the second level, by performing a risk analysis consistent with the multiple criteria model. Since certain inaccurate and uncertain factors are normally involved in hydro-thermal system operations, stochastic models are more suited for investigating the hydro-thermal scheduling problems.

1.5 OUTLINES OF THE THESIS

This thesis proposes heuristic optimization techniques to solve hydrothermal scheduling problem. Designing of proposed heuristic optimization techniques are based on a diversification phase followed by intensification. So, to fulfil this objective integration of global and local search technique is proposed. The basic idea is to start from an initial solution obtained from global search technique and to search for successive improvement by examining neighbouring solutions using local optimization method. Proposed heuristic optimization techniques are tested on various multi-objective hydro-thermal scheduling problems. The thesis also addresses inaccuracies and uncertainties in system production cost, system demand, water inflow of hydro unit and reservoir head by converting expected model into its deterministic equivalent. Fuzzy set theory is explored for decision making methodology.

The considerable contribution of various researchers related to advances of hydro-thermal generation scheduling problem and solution methodologies have been briefly reviewed in the present chapter. The chapter also reviews the fuzzy set theory and stochastic methods in power system applications.

Chapter 2 proposes three heuristic techniques that hybridize global search and local search techniques. Powell's search method is proposed to be applied as a local search technique. Predator-prey optimization and evolutionary programming are selected as global search technique. The proposed heuristic optimization techniques perform optimization in two phases. In the first phase, the particles/members of predator-prey optimization/evolutionary programming techniques, explore the solution space freely. In the second phase, the Powell's pattern search will be invoked after a certain number of movements. The proposed heuristic optimization techniques have advantage of fast search property of global search technique and the local refining property of local search technique. The proposed heuristic optimization techniques have been applied for optimal operation of multi-objective hydro-thermal system, considering fixed and variable-head hydro model, valve-point loading effect of thermal generators and transmission losses. The minimum operating cost and the minimum pollutants of gaseous emission are considered as two objectives. Heuristics are applied to handle equality constraints whereby equality constraints are satisfied by perturbing the decision variables systematically. Fuzzy set theory is explored to choose the best compromised solution.

In chapter 3, heuristic optimization techniques are proposed for multi-objective hydro-thermal generation scheduling, considering multi-chain hydro model. Multi-objective hydro-thermal generation scheduling problem minimizes number of objectives viz. thermal unit operating cost and pollutant's emission together. The travel time of water between two reservoirs is taken into account. The variable elimination method is applied to satisfy the equality constraints. An objective is introduced to take care of inequality constraint and fuzzy decision index is applied to provide the best-compromised solution among all objectives. The validity of proposed heuristic optimization techniques is demonstrated on small, medium and large electric power systems. Comparison of results is performed with existing solution methodologies.

In, chapter 4, multi-objective hydro-thermal scheduling problem is converted into single objective constrained optimization problem by applying weighting method to generate non-inferior solutions. The weight patterns are computed by conventional statistical measures, which characterize the correlation coefficients matrix evolution. The weights are updated, during the movement, according to best weight pattern using membership function of best solution of each particle/member obtained from heuristic search techniques. The heuristic penalty-less constraint handling technique is applied to satisfy power balance and reservoir volume equality constraints. Volume storage and hydro power inequality constraints are satisfied by another heuristic search technique. Finally, four electric power systems are tested for economic, emission and multi-objective scheduling and obtained results are compared with reported results.

In chapter 5, heuristic proposed heuristic optimization techniques are extended for long-term hydro-thermal generation scheduling. The variable elimination method is applied to satisfy the equality constraints and inequality constraints are taken care by another objective using fuzzy set theory. The effectiveness of proposed techniques is demonstrated on two electric power systems. The scheduling period of electric power systems is taken as one year and divided into weekly and monthly sub-intervals. The proposed heuristic optimization techniques provide the improved results without taking any approximation in very less computational burden.

The intent of the chapter 6 is to formulate stochastic multi-objective optimization problem. The uncertainties and inaccuracies in the system product cost coefficients, polluting gaseous emission curve coefficients, water discharge rate coefficients and system load are precisely considered in stochastic problem formulation. The expected model is converted into its deterministic equivalent. The hydro-thermal short-range fixed-head scheduling problem is solved in multi-objective framework in which main objectives such as operating cost, gaseous pollutant emission, expected power deviation and expected volume deviation are taken up together. Proposed heuristic optimization techniques are applied to search compromised solution. The objectives are quantified by eliciting the corresponding membership function. The best compromised solution is one, which provides maximum satisfaction level from the participating objectives.

The last chapter summarizes the significant conclusion of the research carried out for the preparation of the present thesis. Both the contribution and utilization of proposed heuristic search optimization techniques are symmetrically presented on multi-objective hydro-thermal generation scheduling problem. Some new directions for further research efforts are also presented.

CHAPTER – 2

MULTI-OBJECTIVE SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING USING HEURISTIC SEARCH TECHNIQUES

2.1 INTRODUCTION

Optimization methods are generally classified into two main groups: local search and global search techniques. To search the optimum solution, local search techniques apply gradient based techniques, and follow a single path search. Most of the local search techniques used to solve the *hydro-thermal generation scheduling* (HTGS) problem make a number of simplifying assumptions in order to make the optimization problem more tractable, but the conduct of linearization causes non-optimal solutions resulting in huge loss of revenue [186]. Global search techniques use stochastic techniques and include randomness in moving from one solution to the next. Some recent global search techniques are *genetic algorithm* (GA), *evolutionary programming* (EP), *differential evolution* (DE) and *particle swarm optimization* (PSO) techniques etc. Particle swarm optimization is one of the most promising global search techniques. Kennedy and Eberhart have introduced PSO technique [59]. The most attractive features of PSO are its simple concept, easy implementation, fast computation, and robust search ability [215]. It simulates the social evolvement knowledge through probing the optimum by evolving the population which may include candidate solutions. Compared with the other global search techniques, PSO shows incomparable advantages in searching speed and precision [215]. Particle swarm optimization does not possess the mutation operator used in EP; it finds the optimum solution by swarm following the best particle. Compared with EP, the information sharing mechanism in PSO is significantly different. In EP, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. However, in PSO, only particle best and global best give out the information to others. It is a one way information sharing mechanism.

Despite several advantages of PSO, it has some shortcomings. Particle swarm optimization convergence behaviour depends upon its parameters. Wrong choice of PSO parameters may result in divergent particle trajectories and it causes trapping into local minimum solution [311]. On applying, PSO to high-dimensional optimization problems, it suffers from premature convergence problem resulting in a low optimization precision or even failure [321]. Zhou *et al.* [358] have discussed one of the main deficiencies of PSO algorithm, in the process to search optimum solution, particles in the swarm would come together at a step and then, it must be difficult for particles to escape from the accumulation point. After that, the algorithm would lose its global search ability. To overcome this deficiency of PSO, Silva *et al.* [154] have developed a predator-prey model. The motivation was mainly introduced diversity in the swarm at any moment during the run of the algorithm, not depending on the level of convergence already achieved. The predator-prey concept is one of the most important concepts in nature, in order to improve the ability of PSO. In *predator prey optimization* (PPO) technique, particles are divided into two categories, predator and prey. Predators always try to catch global best prey, while preys always try to escape from them. Predators play the role of searching around global best in a concentrated manner, whereas preys explore on a solution space escaping from predators, so predators prevent pre-mature convergence and preys play the role of diversification. Predator prey optimization has successfully applied to various test problems [154]. Silva *et al.* [387] have proposed a multi-objective biogeography optimization, combined with a predator-prey approach and validated in the constrained design of a brushless dc wheel motor.

To enhance the searching capability of global search techniques, local search methods are hybridized with global search techniques [264]. Harman and McMinn [342] have discussed theoretical exploration of global search techniques and have suggested that hybridization of global and local search may be appropriate. Noman and Iba [277] have proposed a crossover-based adaptive local search operation for enhancing the performance of standard DE algorithm. Global search techniques are comparatively inefficient in fine tuning the solution. To overcome this deficiency of global search technique, Martinez-Estudillo *et al*. have presented a hybrid global search technique that combines global search technique and local optimization procedure [230]. Jia *et al.* [357] have proposed a memetic PSO algorithm which combines the canonical PSO with a chaotic and Gaussian local search procedure to overcome the premature convergence problem of PSO.

The aim of hydro-thermal scheduling is to minimize fuel cost of thermal units by allocating generation to hydro and thermal units optimally within a specified period. As the source of hydro power is the natural water resources, the operational cost of hydro-electric units is insignificant. Apart from heat, thermal units produce particulates and gaseous emissions. A number of substances such as SO_2, NOx, dust particles etc. are emitted during the operation of thermal units. Now days, emission control is also an important objective to be considered along with fuel cost and utility planners are trying to improve their operating strategies to reduce pollution [194]. Hydro-thermal scheduling can be recognized as a multi-objective constrained optimization problem with two conflicting objectives, *i.e.*, the minimum fuel cost and the minimum gaseous emission effects.

Multi-objective HTGS has been undertaken by several researches till date. Many different techniques such as fuzzy decision satisfying method [144,157,199], goal-attainment method [220], DE [303] and *quantum PSO* (QPSO) [348] have been applied to solve multi-objective optimization problem that has been converted into a single objective optimization problem by linear combination of different objectives as a weighted sum. Lu *et al.* [381] have presented hybrid multi-objective cultural algorithm to deal with short- term environmental/economic HTGS. The proposed method integrates DE algorithm into the framework of cultural algorithm model. Basu has presented multi-objective DE [341] and *non-dominated sorting algorithm-II* (NSGA-II) [365] for economic-environmental dispatch of hydro-thermal power system. Swain *et al.* have developed an optimization procedure based on clonal selection algorithm for the solution of short-term HTGS [372]. Wang *et al.* [408] have applied a self-adaptive PSO with a strategy to handle the various constraints to solve hydro-thermal scheduling. Artificial immune system has been used for optimal scheduling of fixed-head hydro-thermal system [366]. Lu *et al.* [375] have developed quadratic approximation based DE with valuable trade off approach to solve bi-objective HTGS problem.

In majority of the research work reported in the literature for solving HTGS, penalty function approach has been applied for constraint handling. Main difficulty of using penalty parameter is its appropriate selection for better performance. Manoharan *et al.* [278] have employed a penalty parameter-less constraint handling scheme, which eliminates the trial and error method to select penalty parameter. Deb [135] has proposed a penalty parameter less constraint handling scheme. Park *et al.* [330] have proposed a constraint handling scheme to improve the solution quality without scarifying computational efficiency.

The aim of the chapter is to propose three heuristic techniques by hybridizing global and local search optimization techniques. To exploit the property of solutions, PPO and EP techniques are undertaken as global search techniques and to enhance the performance of solutions obtained from global search techniques, *Powell's pattern search* (PPS) technique is undertaken as local search technique. In first attempt, PPO and PPS are integrated. In second attempt, EP and PPS are integrated and in third attempt PPO, EP and PPS are integrated to realize their performance. The multi-objective HTGS problem has been solved by applying proposed heuristic optimization techniques. In HTGS problem, fixed/variable-head hydro model, valve-point loading effect of thermal generators and transmission losses of power system network are considered. Hydro-thermal scheduling is recognized as a multi-objective constrained optimization problem with two conflicting objectives, *i.e.*, the minimum fuel cost and the minimum gaseous pollutants' emission. To satisfy the equality constraints, a heuristic approach is applied in which decision variables are perturbated in a systematic manner. Because, a penalty method requires multiple run to fine tune the penalty factor leading to a high computational cost. The objectives are quantified by obtaining the corresponding membership function and max-min operator is applied to extract the best compromised non-dominated solution.

2.2 PROPOSED HEURISTIC OPTIMIZATION TECHNIQUES

Designing of proposed heuristic optimization techniques are based on a diversification phase followed by intensification. Heuristic search techniques do not purely follow the concept of one single traditional metaheuristics; rather these combine various algorithmic ideas. The integration of different algorithm concepts is motivated by the desire to obtain better performing systems that exploit and unite advantages of the individual pure strategies. The combined use of different search algorithm enhances the robustness of global search. There are generally two types of optimization methods: global and local. Global optimization methods are designed to explore the search space and typically use a lot of time to find an optimal/near optimal solutions if used alone. On the other hand, local optimization methods are designed to exploit a local area, but these are usually not good at exploring wide search area and hence not applied for global optimization. Due to their respective strength and weakness, there is motivation for the integration of global search and local search methods. The key to achieve high performance for heuristic algorithm is to maintain a good balance between exploitation and exploration during search. The basic idea is to start from an initial solution obtained from global search technique and to search for successive improvements by examining neighbouring solutions using local optimization method. Pattern search technique is a popular paradigm in direct search methods. Direct search methods, are often called derivative-free as these do not require any information about the gradient or higher derivatives of the objective function to search for an optimal solution. Therefore direct search methods may very well be used to solve non-continuous, non-differentiable and multimodal optimization problems.

In this chapter, three heuristic search techniques are proposed ahereby local and global optimization techniques are integrated. To maintain the diversity in population, Powell's search method is applied after a set number of movements of global search technique. A number of trials are done and it is observed that proposed heuristic optimization techniques produce optimum result when Powell's search method is applied after 50 movements of global search technique.

ALGORITHM 2.1: Proposed heuristic optimization technique-I

1. Read Input data and parameters of algorithm
2. Randomly initialize the prey positions and velocities.
3. Randomly initialize the predator position and velocity.
4. Set movement counter t=1.
5. Set IT=50
   DO
   - 5.1 Update predator velocity and position.
   - 5.2 Randomly generate the probability fear between 0 and 1.
   - 5.3 *IF* (probability fear > maximum probability fear) *THEN*
     - Predator affects the prey.

     ENDIF
   - 5.4 Update prey velocities and positions.
   - 5.5 Update local best positions.
   - 5.6 *IF*(t MOD IT=0) *THEN*
     - Apply Powell's method to modify local best positions
     - *IF* (modified local best positions generate improved solution) *THEN*
       - Update local best positions

       ENDIF

     ENDIF
   - 5.7 Update global best position.
   - 5.8 Increment the movement counter t=t+1

   WHILE ($t \leq t_{max}$)
   STOP

- ***Proposed Heuristic Optimization Technique-I*** **(PHOT-I)**: It is based on integration of predator-prey optimization and Powell's pattern search method.

Predator-prey optimization is used as global search technique and Powell's pattern search is applied as a local search technique. The PHOT based on PPO and PPS is elaborated in Algorithm-2.1.

- ***Proposed Heuristic Optimization Technique-II*** **(PHOT-II)**: It is based on integration of evolutionary programming and Powell's pattern search method. Evolutionary programming is used as a global search technique and Powell's pattern search is applied as a local search technique. The PHOT based on EP and PPS is elaborated in Algorithm-2.2.

ALGORITHM 2.2: Proposed heuristic optimization technique-II

1. Read Input data and parameters of algorithm.
2. Randomly initialize *NP* member population.
3. Set movement counter *t*=1.
4. Set *IT*=50.

DO

4.1 Create three offspring vectors using Gaussian, Cauchy and mean of Gaussian and Cauchy mutation operator.
4.2 Combine parent and offspring to form a pool of 4*NP* members
4.3 Apply competition for survival
4.4 Select *NP* members population on the basis of most number of win
4.5 *IF*(t MOD IT=0) *THEN*
  Apply Powell's method to modify members
  IF (modified members generate improved solution) *THEN*
    Update members
  ENDIF
ENDIF
4.6 Update global best solution on basis of objective function
4.7 Update scaling factor
4.8 Increment the movement counter *t*=*t*+1

WHILE ($t \leq t_{max}$)
STOP

- ***Proposed Heuristic Optimization Technique-III*** **(PHOT-III)**: It is based on integration of predator-prey optimization, evolutionary programming and Powell's pattern search method. It is proposed that initially two global search techniques PPO and EP are implemented, which have different information sharing mechanism. Since, PPO does not possess the mutation operator as used in EP; it finds the optimum solution by predator chasing the global best prey and preys try to escape from predator. In EP, chromosomes share information with each other. So, the whole population moves like a one group towards an optimal area. The population of EP and best local positions of prey particles are combined to decide the best possible solution and then Powell's pattern search is applied to enhance the search capability of the proposed heuristic techniques. After that the pool is arranged in ascending order to select base points for Powell's pattern search. The PHOT based on PPO, EP and PPS is elaborated in Algorithm-2.3.

ALGORITHM 2.3: Proposed heuristic optimization technique-III

1. Read Input data and parameters of algorithms.
2. Randomly initialize the *NP* prey positions and velocities of PPO technique.
3. Randomly initialize the predator position and velocity of PPO technique.
4. Randomly initialize *NP* member population of EP technique.
5. Set movement counter *t*=1.
6. Set *IT*=50.

DO

- 6.1 Apply steps 5.1 to 5.5 of algorithm 2.1 of PHOT-I.
- 6.2 Apply steps 4.1 to 4.4 of algorithm 2.2 of PHOT-II
- 6.3 Form a pool of *NP* local best positions and *NP* members of population.
- 6.4 Arrange in ascending order and select *NP* solutions on the basis of objective function.
- 6.5 *IF*(t MOD IT=0) *THEN*
  - Apply Powell's method to modify *NP* solutions
  - *IF* (modified solutions generate improved solution) *THEN*
    - Update solutions
  - *ENDIF*
- *ENDIF*
- 6.6 Update global best solution.
- 6.7 Update scaling factor of EP technique.
- 6.8 Increment the movement counter *t*=*t*+1

WHILE ($t \leq t_{max}$)

STOP

2.3 MULTI-OBJECTIVE SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING PROBLEM

The aim of multi-objective HTGS is to minimize the thermal operating cost and gaseous pollutant emission level of thermal plants simultaneously, while satisfying various operational constraints. The thermal generator cost is usually approximated using quadratic function. However, it is more practical to consider the valve-point loading for fossil–fuel-based unit. In this context, a cost function is obtained based on the ripple curve for more accurate modelling. This curve contains higher order nonlinearity and discontinuity due to the valve-point loading effect. One way of representing this effect is to use a rectified sinusoidal function in the cost function [215]. Operating cost function for thermal unit is expressed over the optimization interval given as:

$$F_1 = \sum_{k=1}^{T} \sum_{i=1}^{N_T} \left(a_{si} p_{ik}^2 + b_{si} p_{ik} + c_{si} + \left| d_{si} \sin\left\{ e_{si} \left(p_i^{\min} - p_{ik} \right) \right\} \right| \right) \tag{2.1}$$

where

a_{si} , b_{si} , c_{si} , d_{si} and e_{si} are cost coefficients of i^{th} thermal unit

p_{ik} is real power generation of i^{th} thermal unit during k^{th} sub-interval

N_T is the number of thermal units

T is total time interval for scheduling

$p_i^{\min}$ is the lower power generation limit of i^{th} thermal unit

Apart from heat, thermal units produce particulates and gaseous emissions. The amount of emission from each unit is given as sum of a quadratic and an exponential function. The total emission in the system can be expressed as [8]:

$$F_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\alpha_i p_{ik}^2 + \beta_i p_{ik} + \gamma_i + \eta_i \exp(\delta_i p_{ik})\right) \tag{2.2}$$

where

α_i , β_i , γ_i , η_i and δ_i are emission curve coefficients of i^{th} thermal unit

In short-term HTGS problem, an insignificant fuel cost is incurred in the operation of hydro-units. The input-output characteristic of a hydro-generator is expressed by the variation of water discharge, q_{jk} which is a function of power output, p_{mk} and net head H_{jk} . According to Glimn- Kirchmayer model [20], the discharge of j^{th} hydro unit at k^{th} sub-interval is

$$q_{jk} = K_j \varphi(p_{mk})\psi(H_{jk}) \quad (j = 1,2,\ldots,N_H ; m = j + N_T ; k = 1,2,\ldots,T) \tag{2.3}$$

where

H_{jk} and q_{jk} and are water head and rate of water discharge, respectively of j^{th} hydro unit at k^{th} sub-interval

p_{mk} is hydro power of m^{th} unit at k^{th} sub-interval

$\varphi(p_{mk})$ and $\psi(H_{jk})$ are represented by quadratic functions:

$$\psi(H_{jk}) = h_{11j} H_{jk}^2 + h_{12j} H_{jk} + h_{13j} \quad (j = 1,2,\ldots,N_H ; m = j + N_T ; k = 1,2,\ldots,T) \tag{2.4}$$

$$\varphi(p_{mk}) = h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j} \quad (j = 1,2,\ldots,N_H ; m = j + N_T ; k = 1,2,\ldots,T) \tag{2.5}$$

with

h_{11j} , h_{12j} , h_{13j} are head variation coefficient of j^{th} hydro unit

h_{21j} , h_{22j} , h_{23j} are hydro power generation coefficient of j^{th} hydro unit

It is presumed that head is constant over the optimization interval for a large capacity reservoir whereas for a small capacity reservoir; the effective head is variable over the optimization interval. The discharge equation is stated as [20]:

$$q_{jk} = \begin{cases} K_j^{'}\varphi(p_{mk}) & ;\text{fixed head} \\ K_j\varphi(p_{mk})\psi(H_{jk}) & ;\text{variable head} \end{cases} \quad (j = 1,2,\ldots,N_H; m = j + N_T; k = 1,2,\ldots,T) \tag{2.6}$$

where

K_j and $K_j^{'}$ are constant of proportionality of j^{th} hydro unit

The effective head is obtained by assuming that j^{th} hydro unit's reservoir has vertical sides and small capacity. Spillage occurs only when the reservoir storage limit is exceeded. Effective head continuity equation is stated as:

$$H_{j(k+1)} = H_{jk} + \frac{t_k}{S_j}\left(I_{jk} - q_{jk}\right) \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \tag{2.7}$$

where

H_{jk} is water head of j^{th} hydro unit at k^{th} sub-interval

N_H is the number of hydro units

q_{jk} is rate of water discharge of j^{th} hydro unit at k^{th} sub-interval

I_{jk} is natural inflow of j^{th} hydro unit at k^{th} sub-interval

t_k is time duration of k^{th} sub-interval

S_j is surface area of reservoir of j^{th} hydro unit

The net water head over the planned time interval is given by:

$$H_{jT} = H_{j0} + \frac{1}{S_j}\sum_{k=1}^{T} t_k\left(I_{jk} - q_{jk}\right) \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \tag{2.8}$$

with

H_{j0} and H_{jT} are initial and final hydraulic reservoir head, respectively of j^{th} hydro unit

Multi-objective short-term HTGS problem is described as minimization of total fuel cost and emission simultaneously subjected to various constraints. There are two types of constraint in this problem: equality constraint and inequality constraint. The equality constraints include: total generation should meet load demand and losses in each sub-interval and hydro-unit is also constraint by the amount of water available. Inequality constraints comprise of discharge rate and power limits.

Mathematically objectives are stated as:

Minimize $\left[F_1, F_2\right]^T$ (2.9)

Subjected to following set of constraints:

(i) The load demand equality constraint during each sub-interval

$$\sum_{i=1}^{N_T} p_{ik} + \sum_{j=1}^{N_H} p_{mk} = p_{Dk} + p_{Lk} \;\left(m = j + N_T ; k = 1,2,\ldots,T\right) \tag{2.9a}$$

where

p_{Dk} is the power demand and p_{Lk} is the transmission loss during k^{th} sub-interval

p_{ik} is power generation of i^{th} thermal unit at k^{th} sub-interval

p_{mk} is hydro power generation of m^{th} unit at k^{th} sub-interval

(ii) Total water discharge rate of each hydro-unit should be same as available volume

$$\sum_{k=1}^{T} t_k q_{jk} = V_{jF} \;\left(j = 1,2,\ldots,N_H\right) \tag{2.9b}$$

where

V_{jF} is volume of water available of j^{th} hydro unit

(iii) The power limits are imposed on thermal and hydro-units

$$p_i^{\min} \le p_{ik} \le p_i^{\max} \;\left(i = 1,2,\ldots,N; k = 1,2,\ldots,T\right) \tag{2.9c}$$

where

$p_i^{\max}$, $p_i^{\min}$ are upper and lower power limit of i^{th} unit, respectively

(iv) The discharge rate limits are imposed on hydro-units

$$q_j^{\min} \le q_{jk} \le q_j^{\max} \;\left(j = 1,2,\ldots,N_H ; k = 1,2,\ldots,T\right) \tag{2.9d}$$

where

$q_j^{\max}, q_j^{\min}$ are upper and lower limit of water discharge rate of j^{th} hydro unit, respectively

Transmission losses in the system during k^{th} sub-interval are represented by Kron's loss formula through B-coefficient [30] is:

$$p_{Lk} = \sum_{i=1}^{N}\sum_{j=1}^{N} p_{ik} B_{ij} p_{jk} + \sum_{i=1}^{N} p_{ik} B_{io} + B_{oo} \;\left(k = 1, 2,\ldots,T\right) \tag{2.9e}$$

where

B_{ij}, B_{io}, B_{oo} are loss coefficients

2.4 CARDINAL PRIORITY RANKING

Fuzzy optimization provides a robust framework for handling multi-objective optimization problems. In Fuzzy satisfying method, different objectives are easily integrated because all membership function values of these objectives are in the range of 0 to 1. It is assumed that membership function $\mu(F_h)$ is a strictly monotonic linearly decreasing and continuous function, defined as [233]:

$$\mu(F_h)=\begin{cases}1 & ;F_h \le F_h^{min} \\ \dfrac{F_h^{max}-F_h}{F_h^{max}-F_h^{min}} & ;F_h^{min} < F_h < F_h^{max} \\ 0 & ;F_h \ge F_h^{max}\end{cases} \qquad (h=1,2,\ldots,N_{ob}) \tag{2.10}$$

where

F_h^{min}, F_h^{max} are minimum and maximum values of h^{th} objective function, respectively

F_h is objective function corresponding to h^{th} objective

$\mu(F_h)$ is membership function of h^{th} objective

N_{ob} is number of objective functions

The *multi-objective Problem* (MOP) is formulated considering conflicting objectives: economy and emission of pollutants. Minimum value of the economy is obtained by considering only cost function and vice versa. Owing to the conflicting nature of objectives, emission will have maximum value when economy has the minimum value and vice versa. The combined effect of all participating objectives using their membership functions is obtained in multi-objective problem. The decision regarding the best solution is taken by applying max-min operator of the membership functions. Mathematically, unified objective function or cardinal priority ranking is defined as:

$$\mu_D = \min\left(\mu(F_h); h=1,2,\ldots,N_{ob}\right) \tag{2.11}$$

The maximum value of μ_D is the desirable solution.

2.5 CONSTRAINT HANDLING

The movement of particles/members is not always guaranteed to satisfy the constraints. The constraint treatment procedure is performed to get feasible solution. In most of the cases, penalty function method is used for constraint handling. It requires multiple run to fine tune the penalty factor leading to a high computational cost [408]. The inclusion of the penalty function also distorts the objective function. The distortion in objective function is small for small values of penalty parameter. For a large value of penalty parameter, the optimum function may have artificial local optimal solutions [135]. In this chapter penalty method is not applied for constraint handling. The decision variables are perturbated to satisfy equality constraints and perturbations of decision variables do not allow violation of inequality constraints [330].

Two search moves are performed, in first move; water balance equality constraint is satisfied for each hydro-unit by perturbing hydro power randomly. In second move, power balance equality constraint is satisfied for each sub-interval by perturbing thermal power randomly. This whole process continues until both equality constraints have been satisfied.

To satisfy reservoir volume equality constraint given by Eq. (2.9b), water discharge rate is computed by Eq. (2.3) and then residual volume ΔV_j is computed as:

$$\Delta V_j = \sum_{k=1}^{T} t_k q_{jk}^t - V_{jF} \quad (j = 1,2,\ldots,N_H) \tag{2.12}$$

where

q_{jk}^t is water discharge rate of j^{th} hydro unit for k^{th} sub-interval at t^{th} movement

t_k is time duration of k^{th} sub-interval

If residual volume is less then tolerance band, then constraint is satisfied; otherwise residual hydro power Δp_{mh} corresponding to residual volume is computed as:

$$T_{jk}\left(h_{21j}\Delta p_{mh}^2 + h_{22j}\Delta p_{mh} + h_{23j}\right)t_k = \Delta V_j \quad (j = 1,2,\ldots,N_H; m = j + N_T) \tag{2.13}$$

$$T_{jk} = \begin{cases} K_j^{'} & ;\text{fixed head} \\ K_j\,\psi\left(H_{jk}\right) & ;\text{variable head} \end{cases}$$

The generation at h^{th} slack sub-interval of all hydro units is perturbated as:

$$p_{mh}^t = \begin{cases} p_{mh}^t - \min\left\{\Delta p_{mh}, \left(p_{mh}^t - p_m^{\min}\right) \times rand()\right\} & if\ \Delta p_{mh} > 0 \\ p_{mh}^t - \max\left\{\Delta p_{mh}, \left(p_{mh}^t - p_m^{\max}\right) \times rand()\right\} & if\ \Delta p_{mh} < 0 \end{cases} \quad (m = N_T + 1, N_T + 2, \ldots, N) \tag{2.14}$$

where

p_{mh}^t is power generation of m^{th} hydro unit for h^{th} slack sub-interval at t^{th} movement

This process continues until water-balance equality constraint is satisfied.

To satisfy power balance equality constraint given by Eq. (2.9a), residual power Δp_{Dk} is computed as:

$$\Delta p_{Dk} = \sum_{i=1}^{N} p_{ik}^{t} - p_{Dk} - p_{LK} \quad (k = 1,2,\ldots,T, l = 1,2,\ldots,NP) \tag{2.15}$$

If residual power is less then tolerance band, then constraint is satisfied; otherwise out of total number of thermal generating unit those act as decision variables, one generation of slack thermal unit 's' is perturbated during each sub-interval as:

$$p_{sk}^{t} = \left\{ \begin{array}{ll} p_{sk}^{t} - \min\left\{\Delta p_{Dk}, \left(p_{sk}^{t} - p_{s}^{\min}\right)\times rand\right\} & ;\Delta p_{Dk} > 0 \\ p_{sk}^{t} - \max\left\{\Delta p_{Dk}, \left(p_{sk}^{t} - p_{s}^{\max}\right)\times rand\right\} & ;\Delta p_{Dk} < 0 \end{array} \right\} \quad (k = 1,2,\ldots,T) \tag{2.16}$$

where

p_{sk}^{t} is power generation of s^{th} slack thermal unit for k^{th} sub-interval at t^{th} movement

Transmission loss is computed after evaluating the slack thermal unit power.

This process continues until power balance equality constraint is satisfied. The elaborated steps are given in Algorithm-2.4.

ALGORITHM 2.4: Constraint handling

1. Check the limits of thermal and hydro power.
2. *IF* $(p_{ik} > p_{i}^{\max})$ *THEN*

   $p_{ik} = p_{i}^{\max}$

   ENDIF
3. *IF* $(p_{ik} < p_{i}^{\min})$ *THEN*

   $p_{ik} = p_{i}^{\min}$

   ENDIF
4. Select a slack sub-interval *h* randomly.
5. Compute water discharge rate by using Eq. (2.6).
6. Compute the residual volume, ΔV_j as given in Eq. (2.12).
7. *IF* $\left|\Delta V_j\right| < \varepsilon$ (ε is residual volume tolerance) *THEN*

   GOTO step 11.

   ENDIF
8. Compute residual hydro power Δp_{mh} as given by Eq. (2.13).
9. Modify the hydro power at h^{th} sub-interval to satisfy reservoir volume equality constraint as given in Eq. (2.14).
10. Select a slack sub-interval that has not selected so far and GOTO step 5.
11. Select a slack thermal unit'*s*' randomly.
12. Compute the transmission loss using kron's formula.
13. Compute the residual power, Δp_{Dk} as given in Eq. (2.15).
14. *IF* $\left|\Delta p_{Dk}\right| < \varepsilon$ (ε is residual power tolerance)*THEN*

    GOTO step 17.

    ENDIF
15. Modify s^{th} thermal unit power generation for all sub-intervals to satisfy power balance equality constraint as per Eq. (2.16).
16. Select a slack thermal unit that has not selected so far and GOTO step 12.
17. *STOP*

2.6 SOLUTION METHODOLOGY

Multi-objective HTGS is solved using proposed heuristic optimization techniques as discussed in section 2.2 that embed global and local search techniques. Fuzzy methodology has been exploited to find the best compromised solution. In this work, heuristic approach is used to satisfy the equality constraints, in which constraints are not augmented in the objective function.

2.6.1 Short-term Hydro-thermal Generation Scheduling using Proposed Heuristic Optimization Technique-I

Predator-prey optimization and Powell's pattern search methods are integrated where PPO is used to perform search globally and PPS method performs search locally. After applying a fixed number of movements of PPO algorithm, PPS method is applied to fine tune the local optimum solution. Elaborative steps are presented in ensuing sub-sections.

2.6.1.1 Initialization of prey position and velocity

The prey population is randomly initialized between upper and lower limits of decision variables. The position and velocity of prey for thermal and hydro generations are given as:

$$p_{pikl}^{0} = p_i^{\min} + \left(p_i^{\max} - p_i^{\min}\right) \times rand() \;\; \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T, l = 1,2,\ldots,NP\right) \tag{2.17}$$

$$v_{pikl}^{0} = v_i^{\min} + \left(v_i^{\max} - v_i^{\min}\right) \times rand() \;\; \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T, l = 1,2,\ldots,NP\right) \tag{2.18}$$

where

p_{pikl}^{0} are initial prey positions representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle

v_{pikl}^{0} are initial prey velocity of i^{th} generating unit at k^{th} sub-interval of l^{th} particle

$v_i^{\min}$ and $v_i^{\max}$ are minimum and maximum velocity limit, respectively for i^{th} generating units

The maximum and minimum velocity limits for thermal generation is taken as [265]:

$$v_i^{\max} = 0.5\left(\sum_{i=1}^{N_T} p_i^{\max} - \sum_{i=1}^{N_T} p_i^{\min}\right) \times 0.01 \tag{2.19}$$

$$v_i^{\min} = -v_i^{\max} \qquad \left(i = 1,2,\ldots,N_T\right) \tag{2.20}$$

The maximum and minimum velocity limit for hydro power is taken as:

$$v_m^{\max} = 0.5\left(\sum_{m=N_T+1}^{N} p_m^{\max} - \sum_{m=N_T+1}^{N} p_m^{\min} \right) \tag{2.21}$$

$$v_m^{\min} = -v_m^{\max} \qquad (m = N_T+1, N_T+2,\ldots,N) \tag{2.22}$$

2.6.1.2 Initialization of predator position and velocity

Single predator position and velocity for thermal and hydro generation is randomly initialized within their respective limits for each sub-interval as:

$$PP_{pik}^{0} = p_i^{\min} + \left(p_i^{\max} - p_i^{\min}\right)\times rand() \; (i=1,2,\ldots,N;\, k=1,2,\ldots,T) \tag{2.23}$$

$$Pv_{pik}^{0} = v_i^{\min} + \left(v_i^{\max} - v_i^{\min}\right)\times rand() \quad (i=1,2,\ldots,N;\, k=1,2,\ldots,T) \tag{2.24}$$

where

PP_{pik}^{0} are initial predator position representing generation of i^{th} unit at k^{th} sub-interval

Pv_{pik}^{0} are initial predator velocity of i^{th} generating units at k^{th} sub-interval

2.6.1.3 Objective function evaluation

Multi-objective HTGS problem is solved to find the unified affect of participating objectives using their membership functions. The cardinal priority ranking or objective function is evaluated to select best solution.

$$\mu_{Dl} = \min\left(\mu(F_h); h=1,2,\ldots,N_{ob}\right) \; (l=1,2,..NP) \tag{2.25}$$

Maximum value of cardinal priority provides maximum satisfaction level from the participating objectives.

2.6.1.4 Update predator velocity and position

The Predator's objective is to influence the global best prey in a controlled manner. The updated predator velocity and position for thermal and hydro power at *(t+1)*th movement is given as:

$$Pv_{pik}^{t+1} = C_4\left(G_{pik}^{t} - PP_{Pik}^{t}\right) (i=1,2,\ldots,N;\, k=1,2,\ldots,T) \tag{2.26}$$

$$PP_{pik}^{t+1} = PP_{pik}^{t} + Pv_{pik}^{t+1} \; (i=1,2,\ldots,N;\, k=1,2,\ldots,T) \tag{2.27}$$

where

G_{pik}^{t} is global best prey position representing generation of i^{th} unit at k^{th} sub-interval for t^{th} movement

PP_{pik}^{t} is predator position representing generation of i^{th} unit at k^{th} sub-interval for t^{th} movement

Pv_{pik}^{t} is predator velocity of i^{th} generating unit at k^{th} sub-interval for t^{th} movement

C_4 is uniformly distributed scaled random number

The elements of predator position and velocity may violate its limit. This violation is corrected by fixing at their corresponding values.

2.6.1.5 Update prey velocity and position

The updated prey velocity and position for thermal and hydro power at $(t+1)^{th}$ movement is given as:

$$v_{pikl}^{t+1} = \begin{cases} wv_{pikl}^{t} + C_1\left(L_{pikl}^{t} - P_{pikl}^{t}\right)\times rand() + C_2\left(G_{pik}^{t} - P_{pikl}^{t}\right)\times rand() & ; P_f \le P_{f\max} \\ wv_{pikl}^{t} + C_1\left(L_{pikl}^{t} - P_{pikl}^{t}\right)\times rand() + C_2\left(G_{pik}^{t} - P_{pikl}^{t}\right)\times rand() + C_3 \times a_i \exp\left(-b_i \times E_d\right) & ; P_f > P_{f\max} \end{cases}$$
$$\left(i = 1,2,\ldots,N; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \qquad (2.28)$$

$$P_{pikl}^{t+1} = P_{pikl}^{t} + v_{pikl}^{t+1} \quad \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \qquad (2.29)$$

where

a_i , b_i are constant of PPO algorithm for i^{th} generating unit

v_{pikl}^{t} is velocity of a prey particle of i^{th} generating unit respectively at k^{th} sub-interval of l^{th} particle for t^{th} movement

P_{pikl}^{t} is prey position representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

L_{pikl}^{t} is local best position representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

C_3 is uniformly distributed scaled random number

Inertia weight w is varied from 0.9 to 0.4 linearly with respect to movement

E_d is Euclidean distance between predator and prey particle

The elements of prey position and velocity may violate its limit. Such violation is corrected by fixing at its corresponding limit.

2.6.1.6 Upgrade local and global best position

To fine tune the local best position, Powell's pattern search is elaborated in two steps. In first step, local best hydro power is upgraded and in second step, local best thermal power is upgraded. The constraints are satisfied after each step by perturbing the decision variables as discussed in sub-section 2.5. During upgrading process of local best hydro power, each sub-interval is considered as coordinate direction '*j*' (sub-interval) and it is modified once at a time along coordinate search direction as:

$$L^t_{pmkl} = L^t_{pmkl} + \lambda^*_k D^j_k \;\left(m = N_T + 1, N_T + 2, \ldots, N; k = 1,2,\ldots,T; j = 1,2,\ldots,T+1; l = 1,2,\ldots,NP\right) \quad (2.30)$$

where

λ^*_k is step length for k^{th} sub-interval

D^j_k is j^{th} search direction for k^{th} sub-interval

L^t_{pmkl} is local best position representing hydro power generation of m^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

Local best thermal power is modified along any one selected coordinate search direction '*j*' (thermal power) during each sub-interval and given as:

$$L^t_{pikl} = L^t_{pikl} + \lambda^*_i D^j_i \quad \left(i = 1,2,\ldots,N_T; j = 1,2,\ldots,N_T + 1; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \quad (2.31)$$

where

λ^*_i is step length for i^{th} thermal unit

D^j_i is j^{th} search direction for i^{th} thermal unit

L^t_{pikl} is local best position representing generation of i^{th} thermal unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

After modifying local best solutions by applying Powell's pattern search, objective function is evaluated. If modified local best solutions improve the solution quality, then modified local best solutions is updated. Powell's Patten Search procedure elaborated in Appendix-C is followed to improve the local best variables. Finally, global best solution is updated from local best solutions on the basis of objective function. The proposed heuristic optimization technique based on PPO and PPS to solve multi-objective HTGS is elaborated in Algorithm-2.5.

ALGORITHM-2.5 Proposed technique-I for multi-objective HTGS

1. Read Input data. Set maximum and minimum values of all objectives and constant of proposed algorithm.
2. Randomly initialize the prey positions and velocities as given by Eq. (2.17) and Eq. (2.18), respectively.
3. Randomly initialize the predator position and velocity as given by Eq. (2.23) and Eq. (2.24), respectively.
4. Apply constraint handling scheme by given in algorithm 2.4
5. Start the movement count t=0.
6. Set *IT*=50.
   DO
   - 6.1 Increment the movement count $t=t+1$
   - 6.2 Update predator velocity and position by using Eq. (2.26) and Eq. (2.27), respectively.
   - 6.3 Randomly generate probability fear between 0 and 1.
   - 6.4 *IF*(probability fear >maximum probability fear) *THEN*
     Predator affects the prey.
     ENDIF
   - 6.5 Update prey velocities and positions by using Eq. (2.28) and Eq. (2.29), respectively.
   - 6.6 Apply constraint handling scheme as given in algorithm 2.4
   - 6.7 Compute fuzzy membership function for all objectives by using Eq. (2.10).
   - 6.8 Apply max-min operator to find cardinal priority ranking by using Eq. (2.25).
   - 6.9 Update local best positions.
   - 6.10 *IF*((t MOD IT)=0) *THEN*
     Apply Powell's method to modify local best positions as given in section 2.6.1.4.
     Apply Constraint handling scheme as given in algorithm 2.4.
     IF (modified local best position generate improved solution) *THEN*
     Update local best position
     ENDIF
     ENDIF
   - 6.11 Update global best position.

   WHILE ($t \le t_{max}$)
   STOP

2.6.2 Short-term Hydro-thermal Generation Scheduling using Proposed Heuristic Optimization Technique-II

Evolutionary programming is used as a base level search in the global search space and Powell's method as a local search technique. The population obtained from EP algorithm is updated by applying Powell's search method after a fixed number of movements of EP algorithm to avoid possible local optimum solutions. Elaborative steps are presented in ensuing sub-sections.

2.6.2.1 Initialization of population

The members of population are randomly initialized between upper and lower limits of decision variables. The members representing thermal and hydro generations are given as:

$$p_{pikl}^{0} = p_i^{\min} + \left(p_i^{\max} - p_i^{\min}\right) \times rand() \; \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T, l = 1,2,\ldots,NP\right) \tag{2.32}$$

where

P_{pikl}^{0} is initial parent representing generation of i^{th} unit at k^{th} sub-interval of l^{th} member.

2.6.2.2 Evaluation of offspring and selection

The three offspring from each parent are generated by applying Gaussian mutation, Cauchy mutation and mean of Gaussian and Cauchy mutation operator. The offspring for thermal and hydro power are generated as:

$$P_{pik(l+NP)}^{t} = P_{pikl}^{t} + \sigma_{pikl} N_{ik}(0,1) \; \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \tag{2.33}$$

$$P_{pik(l+NP)}^{t} = P_{pikl}^{t} + \sigma_{pikl} C_{ik}(0,1) \; \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \tag{2.34}$$

$$P_{pik(l+NP)}^{t} = P_{pikl}^{t} + \sigma_{pikl} \left(\frac{N_{ik}(0,1) + C_{ik}(0,1)}{2}\right) \; \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \tag{2.35}$$

where

P_{pikl}^{t} is parent representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

$P_{pik(l+NP)}^{t}$ is offspring representing generation of i^{th} unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

σ_{pikl} is standard deviation for P_{pikl}^{t}

$N_{ik}(0,1)$ is normally distributed random number for i^{th} unit at k^{th} sub-interval

$C_{ik}(0,1)$ is a Cauchy random number for i^{th} unit at k^{th} sub-interval

The standard deviation indicates the range of the offspring created around the parent vector. The standard deviation is given as:

$$\sigma_{pikl} = \frac{\beta \mu_D^{\max}}{\mu_D}\left(p_i^{\max} - p_i^{\min}\right) \quad \left(i = 1,2,\ldots,N; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \tag{2.36}$$

where

$\mu_D^{\max}$ is maximum value of cardinal priority ranking

β is scaling factor

After mutation, the elements of offspring may violate constraints. The violation is corrected by applying constraint handling scheme discussed in section 2.5.

2.6.2.3 Competition and selection

Parents and offspring generated by Gaussian, Cauchy and mean of Gaussian and Cauchy are combined to form a pool of 4*NP* members. The cardinal priority of 4*NP* members is computed. Each member of a pool has to compete with some other members to select set of parents for next generation. The score for each trial vector after stochastic competition is given by:

$$Win_l = \sum_{m=1}^{R} win_m \tag{2.37}$$

$$Win_m = \begin{cases} 1, & rand() < \dfrac{\mu_{Dl}}{\mu_{Dl} + \mu_{Dc}} \\ 0 & otherwise \end{cases} \tag{2.38}$$

$$c = \text{int}(4 \times NP \times rand() + 1) \tag{2.39}$$

where

μ_{Dc} is cardinal priority ranking of randomly selected c^{th} competitor in the pool

$rand()$ is uniformly distributed random number

μ_{Dl} is cardinal priority ranking of l^{th} member

Win_l is number of wins of randomly selected member *l*

After competing, the trial *4NP* solutions, including parents and offspring are ranked in descending order of score. The first *NP* trial solutions survive and are selected as population for next generation.

2.6.2.4 Upgrade population

To fine tune the population, process is elaborated in two steps. In first step, hydro power is upgraded and then thermal power is upgraded by applying PPS method as discussed in sub-section 2.6.1.6.

2.6.2.5 Upgrade global best solution

The cardinal priority ranking is evaluated as given in Eq. (2.25) to find global best member. Maximum value of cardinal priority ranking represents global best solution.

2.6.2.6 Scaling factor

In general, the scaling factor is fixed throughout the whole search processing. The solution converges prematurely if a small fixed scaling factor is set while the search with a large fixed scaling factor does not converge. So in this work, adaptive scaling factor is applied [99]. The scaling factor changes as follows:

$$\beta = \begin{cases} \beta - \beta_{step} & if \ \mu_D^{\max} \ unchanged \\ \beta & if \ \mu_D^{\max} improved \\ \beta_{final} & if \ \beta - \beta_{step} < \beta_{final} \end{cases} \tag{2.40}$$

$$\beta(0) = \beta_{init} \tag{2.41}$$

where

β is scaling factor

β_{init} is initial value of scaling factor

β_{final} is final value of scaling factor

β_{step} is step size of scaling factor

$\mu_D^{\max}$ is maximum value of cardinal priority ranking

The scaling factor decreases as the process goes on. Such a scaling factor not only prevents convergence but also produces a smooth convergence.

The proposed heuristic optimization technique based on EP and PPS to solve multi-objective HTGS is elaborated in Algorithm-2.6.

2.6.3 Short-term Hydro-thermal Generation Scheduling using Proposed Heuristic Optimization Technique-III

The proposed methodology introduces a heuristic algorithm combining PPO and EP to improve the quality of solutions. Also, to improve the solution quality, locally PPS method is implemented. The third PHOT consists of two phases. In the first phase, the particles/members of PPO/EP will explore the solution space freely. In the second phase, the PPS will be invoked after a certain number of movements. In this proposed heuristic technique favorable features of PPO, EP and PPS are merged. So that PHOT-III has advantages of fast and diverse search properties of global search techniques and the local refining property of Powell’s search method. The third PHOT based on integration of PPO, EP and PPS to solve multi-objective HTGS is elaborated in Algorithm-2.7.

2.7 ELECTRIC POWER SYSTEMS AND RESULTS

The proposed heuristic optimization techniques have been applied to solve HTGS problem on four electric power systems to demonstrate the effectiveness of the techniques. Results are obtained by implementing on electric power system for three cases. Initially economic HTGS problem is undertaken and then minimum emission HTGS problem is solved. Finally, PHOTs are applied to solve a multi-objective HTGS problem. It is presumed that water head is constant over the optimization interval for first three electric power systems. Fourth electric power system has variable reservoir head.

ALGORITHM-2.6: Proposed technique-II for multi-objective HTGS

1. Read Input data. Set maximum and minimum values of all objectives and constant of proposed algorithm.
2. Randomly initialize member of population using Eq. (2.32)
3. Apply constraint handling scheme as given in algorithm 2.4.
4. Start the movement count t=0.
5. Set IT=50.

DO

 5.1 Increment the movement count $t=t+1$
 5.2 Create three offspring vectors using Gaussian, Cauchy and mean of Gaussian and Cauchy mutation operator using Eq. (2.33) to Eq. (2.35).
 5.3 Apply constraint handling scheme as given in algorithm 2.4.
 5.4 Combine parent and offspring to form a pool of 4*NP* members
 5.5 Compute fuzzy membership function for all objectives using Eq. (2.10).
 5.6 Apply max-min operator to find cardinal priority ranking using Eq. (2.25).
 5.7 Apply competition for survival as given in section 2.6.2.3.
 5.8 Select *NP* members population on the basis of most number of win
 5.9 *IF*((t MOD IT)=0) *THEN*
  Apply Powell's method to modify population as given in section 2.6.2.4
  Apply Constraint handling scheme as given in algorithm 2.4.
  IF (modified population generate improved solution) *THEN*
   Update population
  ENDIF
 ENDIF
 5.10 Update the scaling factor using Eq. (2.40).
 5.11 Update global best member on the basis of objective function.

WHILE ($t \le t_{max}$)
STOP

2.7.1 Electric Power System-I

The electric power system-I comprises of two thermal and two hydro units [365]. A fixed-head hydro-thermal load scheduling problem of 24 h duration has been undertaken. The optimization period has been divided into 3 sub-intervals of eight hours each. Operating characteristics of hydro units are given in Table E.1 (Refer Appendix E, Section E.1). The thermal power generation limits, cost coefficients and emission coefficients of thermal units are given in Table E.2 (Refer Appendix E, Section E.1) and Table E.3 (Refer Appendix E, Section E.1), respectively. Load demand is mentioned in

Table E.4 (Refer Appendix E, Section E.1) and loss coefficient matrix is given in section E.1 of Appendix E.

ALGORITHM-2.7: Proposed technique-III for multi-objective HTGS

1. Read Input data and constant of algorithms.
2. Randomly initialize the *NP* prey positions and velocities using Eq. (2.17) and Eq. (2.18), respectively.
3. Randomly initialize the predator position and velocity using Eq. (2.23) and Eq. (2.24), respectively.
4. Randomly initialize *NP* members of population using Eq. (2.32).
5. Apply constraint handling scheme to *NP* prey position and *NP* member of population as given in algorithm 2.4.
6. Set movement count t=0
7. Set IT=50

    DO

    7.1 Increment the movement counter $t=t+1$

    7.2 Apply steps 6.2 to 6.9 of algorithm 2.5 of PHOT-I for multi-objective HTGS.

    7.3 Apply steps 5.2 to 5.8 of algorithm 2.6 of PHOT-II for multi-objective HTGS.

    7.4 Form a pool of *NP* local best positions and *NP* members of population.

    7.5 Arrange in ascending order and select *NP* solutions on the basis of objective function

    7.6 *IF* (t MOD IT =0) *THEN*

    Apply Powell's method to modify *NP* solutions.

    Apply Constraint handling scheme as given in algorithm 2.4.

    IF (modified solutions improve the quality of solution) *THEN*

    Update solutions

    ENDIF

    ENDIF

    7.7 Update global best solution on the basis of objective function.

    7.8 Update scaling factor of EP technique using Eq. (2.40).

    WHILE ($t \le t_{\max}$)

    STOP

2.7.1.1 Parameter setting and selection of population size

To find best parameters of PHOT-I, a series of experiments are conducted with different parameter values. Acceleration coefficients C_1 and C_2 are varied between 1.0 and 2.0 with a step size of 0.5. This range is widely applicable for PSO applications [330]. Predator-prey optimization constant 'a_i' is varied between $\left(0.05\times p_i^{\max}\right)$and $\left(0.2\times p_i^{\max}\right)$ with a step size of 0.01 and another constant 'b_i' is varied between $\left(5/p_i^{\max}\right)$ to $\left(15/p_i^{\max}\right)$ with step size of 1.0 as suggested by Silva *et al.* [154]. The simulation experiments are performed for various values of pf_{max}, C_4 and C_3, in the range of 0.05-1.5 with a step size of 0.05. For Powell's method, the upper and lower limit of promising search area is selected from numbers of experiments conducted by various step lengths in the step of $\left(\pm 0.01\times p_i^{\min}\right)$.

Finally, after number of trials, the parameters are tuned. Numerical values of the best parameters for PHOT-I followed to achieve the solution are given in Table 2.1. For PHOT-II, the values of various scaling parameters for EP like $\beta_{init}, \beta_{final}$ and β_{step} are adjusted as 1, 0.05 and 0.01, respectively. For Powell's search method upper and lower limit of promising search area is same as set for PHOT-I. For PHOT-III, parameters setting are same as set for PPO, EP and PPS algorithms in PHOT-I and II.

Table 2.1: Parameter values for PHOT-I

Constant	λ_i^{max}	λ_i^{min}	a_i	b_i	C_1	C_2	C_3	C_4	Pf_{max}
Value	$0.1\times p_i^{min}$	$-0.1\times p_i^{min}$	$0.1\times p_i^{max}$	$\left(\frac{10}{p_i^{max}}\right)$	2	2	1	0.1	0.95

Note: p_i^{max}, p_i^{min} : Upper and lower limit of i^{th} decision variables.

Table 2.2: Effect of population size on objective function values: Electric power system-I

Population Size	Economic Scheduling		Emission Scheduling		Multi-objective Scheduling		
	Cost ($)	CPU Time (sec)	Emission (lb)	CPU Time (sec)	Cost ($)	Emission (lb)	CPU Time (sec)
30	64793	13.41	571.34	13.26	65190	605.34	13.52
40	64669	14.21	568.70	14.11	65143	600.39	14.39
50	64614	15.89	564.92	15.45	65058	594.18	16.74
60	64696	16.72	565.34	16.73	65059	594.23	17.92

To find the optimal size of population, a simulation study is carried out with different population size as shown in Table 2.2. It is observed from Table 2.2 that higher population's size is not preferable sometimes to obtain the optimal result but increase the execution time. Final generation schedule is obtained by taking population size as 50 and maximum movement is set to 400.

2.7.1.2 Effect of penalty parameter

In generation scheduling problem, choice of constraint handling method is an important task. In penalty method approach, residual power and residual volume are penalized by exterior penalty parameter (r_p) and inequality constraint violation is corrected by fixing these to their corresponding limit. To highlight the influence of the choice of penalty parameters on the performance of PHOT-I, on electric power system-I, a simulation study is carried out with different values of penalty parameters while maximum number of movements and other parameters remain fixed. The obtained results are given in Table 2.3 and it is observed that the selection of an appropriate value for the penalty parameter is very important for better performance. The cumulative residual power of all sub-interval ($C\Delta P_D$) and cumulative residual volume of all hydro-units ($C\Delta V$) are shown in Table 2.3. It is concluded that power balance and reservoir volume equality constraint is satisfied when penalty parameter is set to 1000 or 10000. It is observed from Table 2.3 that, small value of penalty parameter cannot force the solution to become feasible. With large value of penalty parameter, more emphasis is assigned for solutions to become feasible and solution may converge near optimum solution.

Table 2.3: Effect of penalty parameter on objective function values: Electric power system-I

r_p	Economic Scheduling			Emission Scheduling			Multi-objective Scheduling			
	Cost ($)	$C\Delta P_D$ (MW)	$C\Delta V$ (MCF)	Emission (lb)	$C\Delta P_D$ (MW)	$C\Delta V$ (MCF)	Cost ($)	Emission (lb)	$C\Delta P_D$ (MW)	$C\Delta V$ (MCF)
1	64624	2.781	3.832	568.33	2.512	3.931	65068	596.62	2.956	3.1053
10	64628	1.590	2.017	570.22	2.012	2.419	65077	699.23	1.590	2.412
100	64633	0.913	1.045	571.39	1.076	1.034	65082	602.29	0.892	1.232
1000	64689	0.008	0.003	568.78	0.005	0.008	65089	600.24	0.001	0.002
10000	64697	0.001	0.000	570.64	0.001	0.002	65095	605.87	0.001	0.000

Table 2.4: Comparison of results: Electric power system-I

Technique Applied	Economy Scheduling			Emission Scheduling			Multi-objective Scheduling			
	Cost ($)	Emission (lb)	CPU time (s)	Cost ($)	Emission (lb)	CPU time (s)	Cost ($)	Emission (lb)	μ_D	CPU time (s)
RCGA[365]	66603	681.16	21.63	66892	586.14	20.27	--	--	--	--
NSGA-II [365]	--	--	--	--	--	--	66331	618.08	0	27.85
MODE [365]	--	--	--	--	--	--	66354	619.42	0	30.71
SPEA-II [365]	--	--	--	--	--	--	66332	618.45	0	34.87
PHOT-I	64614	669.56	15.89	65793	564.92	15.45	65058	594.18	0.623	16.74
PHOT-II	64639	668.11	17.47	65856	571.25	17.42	65085	595.15	0.600	17.83
PHOT-III	64615	669.43	21.25	65882	567.13	21.53	65060	594.43	0.621	21.67

Note: RCGA: Real coded genetic algorithm; MODE: Multi-objective differential evolution; SPEA-II: Strength Pareto evolutionary algorithm-II

2.7.1.3 Comparison of results

The PHOTs are implemented to obtain the generation schedule for short-term hydro-thermal systems. The optimum results obtained by applying proposed techniques are compared with results reported in literature as depicted in Table 2.4. It is observed from Table 2.4, the minimum value of cost function $F_1^{\min}$ and minimum emission $F_2^{\min}$ are found to be 64,614$ and 564.92 lb, respectively are obtained by PHOT-I and are chosen as desired levels. Because of conflicting nature of cost and emission objectives, the desired level of one objective can be achieved only at the expense of unacceptable level of other objective. The unacceptable levels F_1^{max} and F_2^{max} are found to be 65,793 $ and 669.56 lb, respectively to achieve desired levels. To compare multi-objective HTGS, results obtained by various techniques, cardinal priority ranking is computed by considering desired and unacceptable levels obtained by PHOT-I. Maximum cardinal priority achieved by PHOT-I is 0.623, as depicted in Table 2.4. So, it shows higher satisfaction level of objective functions for multi-objective HTGS. Proposed heuristic optimization technique-II and III also shows great potential to avoid local optimum points. Power generation schedules and water discharge rate corresponding to minimum cost, minimum emission and multi-objective HTGS are depicted in Table 2.5.

In order to give a graphical view, the convergence behaviour of the PHOTs and PPO technique for minimum cost and minimum emission HTGS are shown in Fig 2.1 and 2.2, respectively for the electric power system-I. The convergence characteristic for multi-objective scheduling is shown in Fig 2.3. It is evident from Figs 2.1 to 2.3, Powell's pattern search not only improves the quality of the final solution but significantly improve the convergence of the search space process.

Table 2.5: Power generation and water discharge rate for HTGS: Electric power system-I

	k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)		Water discharge rate (MCF/h)	
				p_{1k}	p_{2k}	p_{3k}	p_{4k}	q_{1k}	q_{2k}
Economic Scheduling	1	900.0	28.5542	171.0031	421.8305	240.172	95.54856	703.4565	501.5868
	2	1200.0	51.9370	221.3387	576.1409	297.044	157.4132	895.4741	849.5465
	3	1100.0	43.2372	197.3291	507.3441	298.6531	139.9107	901.0695	748.8669
	k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)		Water discharge rate (MCF/h)	
				p_{1k}	p_{2k}	p_{3k}	p_{4k}	q_{1k}	q_{2k}
Emission Scheduling	1	900.0	32.0417	300.00	358.8672	207.8891	65.2854	599.4330	339.4003
	2	1200.0	54.2380	300.00	438.8036	316.8604	198.5740	965.0065	1093.269
	3	1100.0	45.6328	300.00	411.6112	308.5150	125.5060	935.5605	667.3302
	k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)		Water discharge rate (MCF/h)	
				p_{1k}	p_{2k}	p_{3k}	p_{4k}	q_{1k}	q_{2k}
Multi-objective Scheduling	1	900.0	29.538	230.956	369.675	233.390	95.516	233.39	95.516
	2	1200.0	53.321	294.313	493.180	304.411	161.416	304.411	161.416
	3	1100.0	44.391	265.673	445.231	297.635	135.850	297.635	135.85

From Figs 2.1 to 2.3, it is concluded that the PHOT-III, shows good convergence characteristics as compared to PHOT-I, PHOT-II and PPO technique. According to Table

2.3, the PHOT-I showed the best performance in terms of CPU time to search the optimum solution as compared to PHOT-II and PHOT-III. Proposed heuristic optimization techniques-I and III, use PPO technique as one of the global search techniques in which predator effects of PPO helps to avoid the premature convergence.

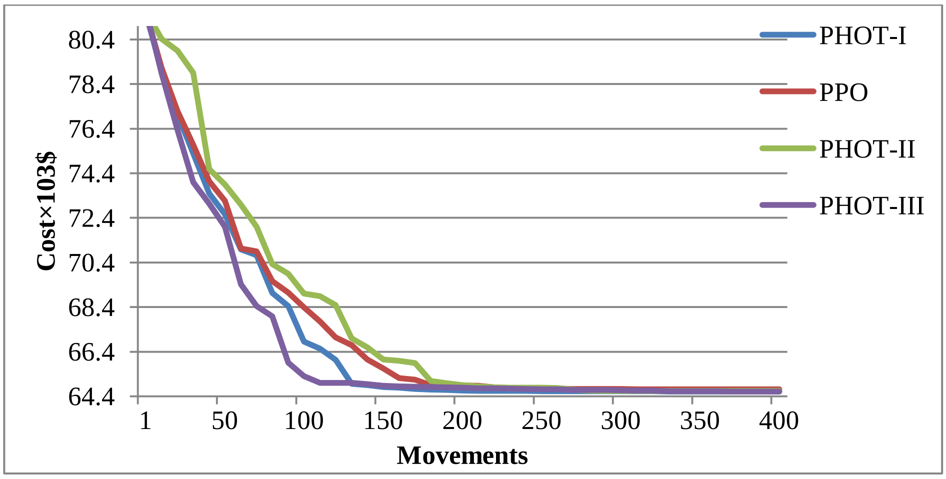

Figure 2.1: Convergence characteristics for minimum cost HTGS: Electric power system-I

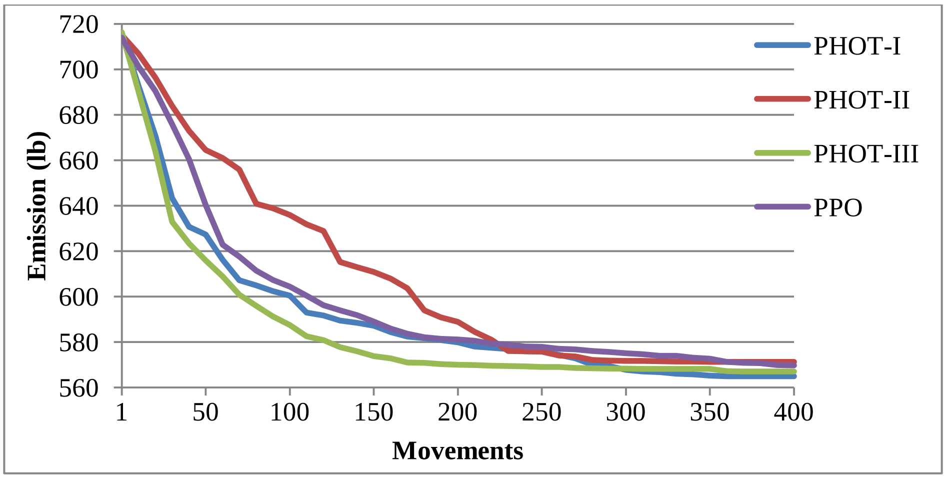

Figure 2.2: Convergence characteristics for minimum emission HTGS: Electric power system-I

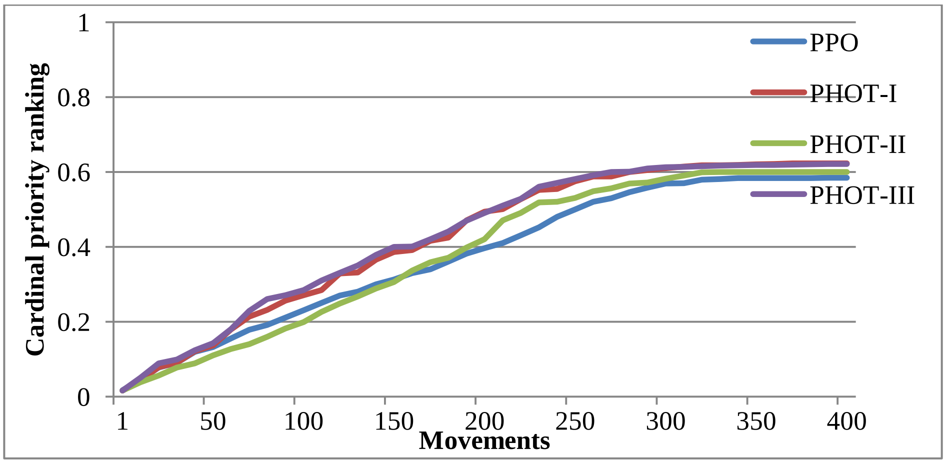

Figure 2.3: Convergence characteristics for cardinal priority ranking of multi-objective HTGS: Electric power system-I

Table 2.6: Analysis of parameters variation of PHOT-I for minimum operating cost HTGS: Electric power system-I

Best Parameter-Δ	Best	Average	Worst	Best Parameter + Δ	Best	Average	Worst
$v_i^{\min} = 0.8 \times v_i^{\min}$	64649 0.054%	64678 0.099%	64691 0.119%	$v_i^{\min} = 1.2 \times v_i^{\min}$	64631 0.026%	64666 0.080%	64692 0.120%
$v_i^{\max} = 0.8 \times v_i^{\max}$	64620 0.009%	64637 0.035%	64651 0.057%	$v_i^{\max} = 1.2 \times v_i^{\max}$	64628 0.023%	64646 0.049%	64681 0.103%
$v_m^{\min} = 0.8 \times v_m^{\min}$	64638 0.037%	64651 0.057%	64679 0.100%	$v_m^{\min} = 1.2 \times v_m^{\min}$	64632 0.027%	64653 0.060%	64689 0.116%
$v_m^{\max} = 0.8 \times v_m^{\max}$	64641 0.041%	64667 0.082%	64699 0.131%	$v_m^{\max} = 1.2 \times v_m^{\max}$	64637 0.035%	64651 0.057%	64674 0.092%
$\lambda_i^{\min} = -0.08 \times p_i^{\min}$	64712 0.151%	64788 0.269%	64891 0.428%	$\lambda_i^{\min} = -0.12 \times p_i^{\min}$	64630 0.024%	64656 0.065%	64691 0.119%
$\lambda_i^{\max} = 0.08 \times p_i^{\min}$	64703 0.137%	64761 0.227%	64834 0.340%	$\lambda_i^{\max} = 0.12 \times p_i^{\min}$	64651 0.057%	64682 0.105%	64711 0.150%
$\lambda_k^{\min} = -0.08 \times p_k^{\min}$	64680 0.102%	64711 0.150%	64790 0.272%	$\lambda_k^{\min} = -0.12 \times p_k^{\min}$	64660 0.071%	64696 0.126%	64710 0.148%
$\lambda_k^{\max} = 0.08 \times p_k^{\min}$	64713 0.153%	64759 0.218%	64812 0.306%	$\lambda_k^{\max} = 0.12 \times p_k^{\min}$	64684 0.108%	64694 0.123%	64719 0.162%
$a_i = 0.08 \times p_i^{\max}$	64669 0.085%	64754 0.216%	64799 0.286%	$a_i = 0.12 \times p_i^{\max}$	64633 0.029%	64672 0.089%	64740 0.195%
$b_i = 8/p_i^{\max}$	64731 0.181%	64787 0.267%	64832 0.337%	$b_i = 12/p_i^{\max}$	64651 0.057%	64693 0.122%	64739 0.193%
C_1=1.6	64623 0.013%	64632 0.027%	64671 0.088%	C_1=2.4	64649 0.054%	64691 0.119%	64741 0.196%
C_2=1.6	64621 0.010%	64634 0.030%	64656 0.065%	C_2=2.4	64632 0.027%	64680 0.102%	64721 0.165%
C_3=0.8	64678 0.099%	64729 0.177%	64781 0.258%	C_3=1.2	64631 0.026%	64652 0.058%	64680 0.102%
C_4=0.08	64690 0.117%	64721 0.165%	64762 0.229%	C_4=0.12	64639 0.038%	64685 0.109%	64731 0.181%
Pf_{max}=0.76	64810 0.303%	64891 0.428%	64943 0.509%	Pf_{max}=1.14	65241 0.970%	65260 0.999%	65289 1.044%
$w_{\max}$=0.72	64691 0.119%	64754 0.216%	64791 0.273%	$w_{\max}$=1.296	64649 0.054%	64681 0.103%	64730 0.179%
$w_{\min}$=0.32	64631 0.026%	64678 0.099%	64711 0.150%	$w_{\max}$=0.48	64629 0.023%	64690 0.117%	64741 0.196%
All (down)	64823 0.323%	64891 0.428%	64954 0.526%	All (up)	65032 0.647%	65128 0.795%	65281 1.032%

Figure 2.4 shows the distribution of the Pareto optimal solutions in terms of membership functions of emission and cost obtained by PHOT-I. Each feasible solution is compared with every other solution in the swarm to check it is dominated by any solution in the swarm. If the solution is found to be dominated by any solution, this means that there exists at least one solution in the swarm which is better than this solution in all objectives. Hence this solution cannot belong to the non-dominated set. However, if no solution is found to dominate this solution, it is a member of non-dominated set. After

finding non-dominated solutions, the curve is formed by joining these solutions to draw the Pareto-optimal front.

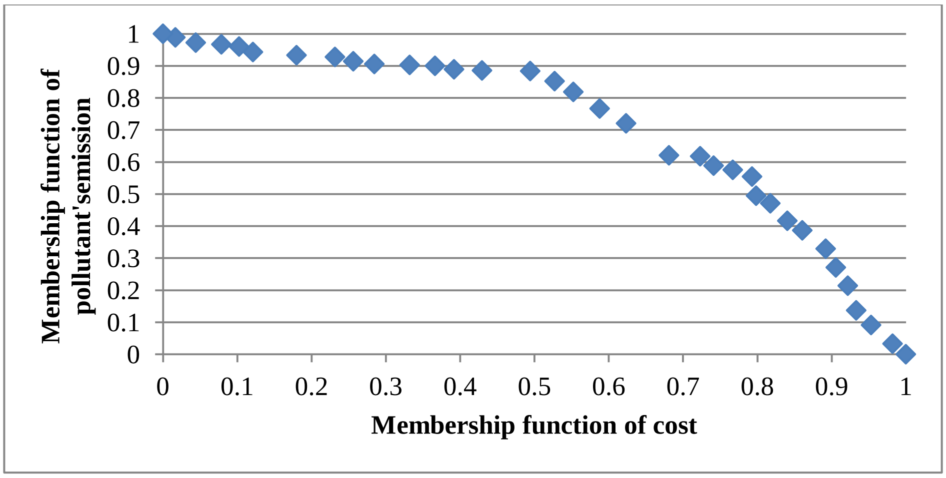

Figure 2.4: Pareto optimal front obtained by PHOT-I: Electric power system-I

2.7.1.4 Parameter sensitivity analysis and robustness of techniques

The sensitivity analysis is also performed by perturbing parameters around their original values for electric power system-I to find minimum value of cost by applying PHOT-I. Twenty runs are given to find best, average and worst value of objective function. Individual parameter is perturbated (Δ) by ±20% while rest of parameters remains fixed. Parameters have also been perturbed, simultaneously ±20% of their original values. It is observed from Table 2.6 that maximum variation from optimal values of operating cost obtained by PHOT-I are (0.970%), (0.999%) and (1.044%) for best, average and worst results, respectively. The sensitivity analysis is also done for PHOT-II and PHOT-III as the procedure adopted for PHOT-I and it is observed that parameters are very less sensitive to the variations.

To investigate the effect of initial solutions, and to verify the robustness of the PHOTs, the best, average and worst results obtained by the PHOTs, PPO and PSO techniques have been compared in Table 2.7. It is concluded that the best, average and worst results of PHOT-I are less than the results obtained by other considered techniques. The standard deviation (S.D.) of any statistical data measures the variability. The S.D. is computed for twenty trials of minimum cost, minimum emission and maximum value of cardinal priority ranking. It is evident from the results reported in Table 2.7, that S.D. of solutions obtained by PHOT-III is minimum for economy, emission and multi-objective scheduling. Small value of S.D. indicates most of the results have probably succeeded.

Table 2.7: The best, average and worst values of objectives: Electric power system-I

Technique Applied	Scheduling		Best	Average	Worst	S.D.
PHOT-I	Economy	F1 ($)	64614	64627	64639	6.550
	Emission	F2(lb)	564.92	568.32	572.76	3.078
	Multi-objective	μ_D	0.623	0.602	0.574	0.0110
PHOT-II	Economy	F1 ($)	64639	64663	64699	7.139
	Emission	F2(lb)	571.25	579.43	585.31	4.420
	Multi-objective	μ_D	0.600	0.578	0.543	0.0019
PHOT-III	Economy	F1 ($)	64615	64644	64670	5.964
	Emission	F2(lb)	567.13	573.85	583.62	3.002
	Multi-objective	μ_D	0.621	0.601	0.574	0.0009
PPO	Economy	F1 ($)	64718	64731	64750	7.236
	Emission	F2(lb)	569.73	573.34	579.31	3.124
	Multi-objective	μ_D	0.587	0.551	0.536	0.0158
PSO	Economy	F1 ($)	65241	65312	65449	10.424
	Emission	F2(lb)	579.56	591.65	603.71	4.653
	Multi-objective	μ_D	0.502	0.486	0.445	0.0177

2.7.2 Electric Power System-II

The data of electric power system-II is taken from [201]. The system under study comprise of two fixed-head hydro units and four thermal units. The optimization period of 48 h has been divided into 4 sub-intervals. Operating characteristics of hydro units are given in Table E.5 (Refer Appendix E, Section E.2). The thermal power generation limits, cost coefficients and emission coefficients of thermal units are given in Table E.6 (Refer Appendix E, Section E.2) and Table E.7 (Refer Appendix E, Section E.2), respectively. Load demand is given in Table E.8 (Refer Appendix A, Section E.2) and loss coefficient matrix is given in section E.2 of Appendix E.

2.7.2.1 Comparison of results

For electric power system-II, it is observed from Table 2.8, the minimum value of cost function $F_1^{\min}$ is found to be 65,567 $ obtained by PHOT-I and minimum emission $F_2^{\min}$ is found to be 22817 lb obtained by PHOT-III. Minimum cost and emission are taken as chosen desired values for multi-objective HTGS. The unacceptable levels $F_1^{\max}$ and $F_2^{\max}$ are found to be 88,858 $ and 40,731 lb, respectively to achieve desired levels. To compare multi-objective HTGS, results obtained by various techniques, cardinal priority ranking is computed by considering desired and unacceptable levels. Maximum cardinal priority achieved by PHOT-III is 0.8814, as depicted in Table 2.8. So, it shows higher satisfaction level of objective functions for multi-objective HTGS. Power generation schedule and water discharge rate for minimum cost, minimum emission and multi-objective HTGS are depicted in Table 2.9.

Table 2.8: Comparison of results: Electric power system-II

Technique Applied	Economy Scheduling			Emission Scheduling			Multi-objective Scheduling			
	Cost ($)	Emission (lb)	CPU time (s)	Cost ($)	Emission (lb)	CPU time (s)	Cost ($)	Emission (lb)	μ_D	CPU time (s)
SA[220]	70718	37778	--	89094	23200	--	73612	26080	0.6545	1492
RCGA [365]	66516	35218	40.36	89320	23222	41.98	--	--	--	--
NSGA-II [365]	--	--	--	--	--	--	68333	25278	0.8626	45.42
MODE [365]	--	--	--	--	--	--	68388	25792	0.8339	46.76
SPEA-2 [365]	--	--	--	--	--	--	68392	26005	0.8220	57.02
EP [201]	70732	37778	--	89055	23200	--	74397	27573	0.7345	884
GA-MU [248]	67751	29470	90.15	89254	23223	78.27	68521	26080	0.8178	96.10
IGA-MU [248]	66539	29503	51.63	89316	23223	42.87	68492	26080	0.8178	53.54
PHOT-I	65567	40731	22.00	88774	22828	21.98	66951	25596	0.8449	22.76
PHOT-II	66283	33469	23.51	88728	22926	23.57	66748	25765	0.8354	23.83
PHOT-III	66164	33463	30.61	88858	22817	30.64	68329	24637	0.8814	30.61

Note: SA: Simulated annealing; GA-MU: Genetic algorithm with the multiplier updating; IGA-MU: Improved GA-MU

Table 2.10: Comparison of results: Electric power system-III

Technique Applied	Economy Scheduling			Emission Scheduling			Multi-objective Scheduling			
	Cost ($)	Emission (kg)	CPU Time (s)	Cost ($)	Emission (kg)	CPU Time (s)	Cost ($)	Emission (kg)	μ_D	CPU Time (s)
PHOT-I	451925	337940	23.43	453602	336448	23.92	452417	336767	0.6609	23.61
PHOT-II	452329	338252	25.61	453516	336654	25.64	452191	337353	0.3428	25.73
PHOT-III	452073	338164	30.57	453376	336228	30.51	452352	337254	0.4007	30.63

2.7.3 Electric Power System-III

Electric power system-III comprises of four fixed-head hydro units and five thermal units [20].The optimization period has been divided into 24 sub-intervals of 1 h each. Operating characteristics of hydro units are given in Table E.9 (Refer Appendix E, Section E.3). The thermal power generation limits, cost coefficients and emission coefficients of thermal units are given in Table E.10 (Refer Appendix E, Section E.3).

Load demand is given in Table E.11 (Refer Appendix E, Section E.3) and loss coefficient matrix is given in section E.3 of Appendix E.

Table 2.9: Power generation and water discharge rate for HTGS: Electric power system-II

	k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)				Hydro generation (MW)		Water discharge rate (acre-ft/h)	
				p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	q_{1k}	q_{2k}
Economic Scheduling	1	900.0	15.2628	20.00	30.00	124.8733	229.5038	249.9155	260.9702	36001.39	43006.93
	2	1100.0	23.900	20.00	30.00	209.5578	139.7506	241.6096	482.9821	34671.13	91710.27
	3	1000.0	18.9545	20.00	30.00	209.3928	229.5091	165.3033	364.7495	23214.05	64094.71
	4	1300.0	32.7122	97.788	112.043	209.801	229.5135	218.8744	464.6917	31113.43	87188.11
	k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)				Hydro generation (MW)		Water discharge rate (acre-ft/h)	
				p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	q_{1k}	q_{2k}
Emission Scheduling	1	900.0	15.8092	72.23866	133.783	135.6704	91.3094	169.7273	313.0802	23840.67	53227.25
	2	1100.0	23.9609	79.1889	142.0427	147.5734	100.1406	247.2240	407.7909	35568.54	73705.15
	3	1000.0	19.6495	75.5778	137.9659	141.61	95.6865	208.7983	360.0108	29575.79	63067.61
	4	1300.0	33.7924	102.0282	167.6162	184.6640	129.4837	250.00	500.00	36015.00	96000.00
	k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)				Hydro generation (MW)		Water discharge rate (acre-ft/h)	
				p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	q_{1k}	q_{2k}
Multi-objective Scheduling	1	900.0	16.0666	98.4916	113.9015	124.9093	52.5380	217.2761	308.9501	30867.92	52390.13
	2	1100.0	24.3824	91.3920	113.1964	124.9080	139.5779	185.2532	470.0547	26076.41	88504.60
	3	1000.0	19.3069	93.4729	113.8913	124.9082	138.8096	224.8758	323.3489	32040.66	55328.88
	4	1300.0	33.3842	98.5381	164.5417	205.3402	139.7588	250.00	475.2056	36015.00	89776.39

2.7.3.1 Comparison of results

For electric power system-III, it is observed from Table 2.10, the minimum value of cost function $F_1^{\min}$ is found to be 45, 1925 \$ obtained by PHOT-I and minimum emission $F_2^{\min}$ is found to be 33,6228 kg obtained by PHOT-III. Minimum cost and minimum emission are taken as chosen desired values for multi-objective HTGS. The unacceptable levels $F_1^{\max}$ and $F_2^{\max}$ are found to be 45,3376 \$ and 33,7940 kg, respectively to achieve desired levels. To compare multi-objective HTGS, results obtained by various techniques, cardinal priority ranking is computed by considering desired and unacceptable levels. Maximum cardinal priority achieved by PHOT-I is 0.6609, as depicted in Table 2.10. It shows higher satisfaction level of objective functions for multi-objective HTGS. Power generation schedule and reservoir water discharge rate for minimum cost is depicted in

Table 2.11 and Fig. 2.5, respectively. Power generation schedule and reservoir water discharge rate for minimum emission is depicted in Table 2.12 and Fig. 2.6, respectively. Power generation and water discharge rate for the given load demand while solving the multi-objective HTGS problem for electric power system-III are illustrated in Table 2.13 and Fig. 2.7, respectively by applying PHOT-I.

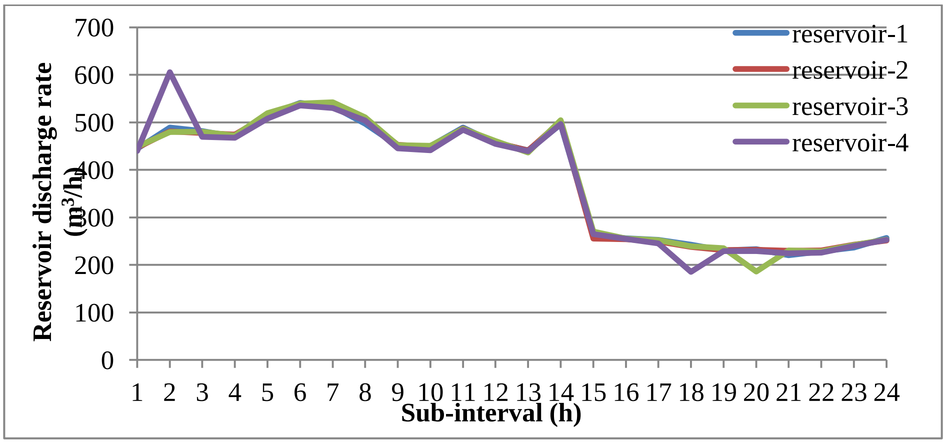

Figure 2.5: Reservoir discharge rate for minimum cost HTGS: Electric power system-III

2.7.4 Electric Power System-IV

Electric power system-IV comprises of four variable reservoir head hydro units and five thermal units [20]. The optimization period, divided into 24 sub-intervals of 1 h each has been undertaken. Operating characteristics of hydro units, thermal unit cost coefficients, emission coefficients, load demand and loss coefficients are same as used for electric power system-III. Reservoir head variation and reservoir details of hydro plants are given in Table E.12 (Refer Appendix E, Section E.4) and E.13 (Refer Appendix E, Section E.4), respectively.

2.7.4.1 Comparison of results

For electric power system-IV, it is observed from Table 2.14, the minimum value of cost function is obtained by PHOT-III and minimum emission is obtained by PHOT-I. Minimum cost and emission are taken as chosen desired levels for multi-objective HTGS and corresponding maximum value of other objective is taken as unacceptable levels. To compare multi-objective HTGS, results obtained by various techniques, cardinal priority ranking is computed by considering desired and unacceptable levels. Maximum cardinal priority achieved by PHOT-III is 0.6795, as depicted in Table 2.14. Results obtain by PHOT-III, shows higher satisfaction level of objective functions for multi-objective HTGS.

Table 2.11: Power generation for minimum operating cost HTGS: Electric power system-III

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generations (MW)					Hydro generations (MW)			
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}	p_{8k}	p_{9k}
1	5448	604.0338	817.5491	807.4575	788.6330	771.0928	758.5027	526.9594	528.566	530.1838	523.0897
2	5776	683.3798	852.016	846.9409	823.8555	814.2776	798.2091	562.7820	556.0198	555.2790	650.00
3	5664	658.3933	854.2844	835.7048	818.4056	805.8012	795.4096	556.6741	553.5120	555.6776	546.9238
4	5624	648.1528	845.2495	834.7252	809.7546	799.0984	790.5722	547.0032	550.9557	5459.3761	545.4178
5	5928	730.2869	892.7570	885.8636	863.2420	849.6722	837.9036	583.0996	582.2878	585.9355	577.5257
6	6064	767.5391	913.9250	900.5635	882.8217	870.7418	859.5569	602.6314	601.3550	601.3640	598.5802
7	6088	778.3518	975.000	897.9778	879.4199	867.2001	853.8795	597.0212	597.9110	603.4795	594.4628
8	5856	710.1639	882.2450	871.1468	850.5220	838.7947	826.1120	568.7570	575.2917	579.2441	574.0504
9	5480	611.6718	820.7684	809.6669	793.0319	777.7543	764.5095	531.9022	533.5291	532.9861	527.5227
10	5464	607.9019	821.6401	808.6915	784.9968	774.8265	764.9997	531.0172	529.8663	531.5428	524.3207
11	5728	675.0901	857.8895	849.7112	824.8745	820.6400	807.1425	562.3447	560.8671	560.5168	559.1038
12	5536	625.9609	833.5082	817.1113	801.9359	785.5154	774.4416	536.4600	537.7742	540.1734	535.0409
13	5400	591.9825	812.0743	796.4722	776.9926	764.7157	752.3130	523.9412	523.3034	519.9767	522.1932
14	5828	702.6562	879.4672	867.1851	846.3588	832.7900	821.5433	567.7214	572.5560	574.6591	568.3757
15	3928	295.8950	587.0774	572.5679	555.9677	536.7990	526.8971	361.2469	352.7177	368.0957	362.5258
16	3840	281.8704	577.1167	563.8469	536.7307	524.2663	510.4288	353.6073	351.3641	352.6132	351.8966
17	3784	272.9841	566.8200	549.1547	529.4777	520.0345	504.0140	349.6389	346.4115	349.1129	342.3201
18	3608	249.0656	547.1159	529.0480	510.9995	502.7836	483.7110	339.0818	333.7555	335.5702	275.000
19	3584	242.9951	538.0841	519.8586	497.6196	485.2604	478.1340	325.8737	326.7451	330.9095	324.5101
20	3544	239.8951	542.5927	522.2203	503.4365	486.6451	473.1560	328.7996	327.3528	275.00	324.6922
21	3528	235.0259	526.7766	515.3481	495.7559	475.3950	464.0564	314.6700	325.0719	326.2746	319.6776
22	3552	238.5014	534.0040	515.7517	496.3376	485.0836	464.8907	323.7821	325.8695	323.7715	321.0109
23	3688	258.5152	551.4586	535.9003	519.1322	504.5973	489.0724	332.3770	338.9165	338.5067	336.5545
24	3840	282.1788	574.0575	562.2787	541.0647	529.1385	512.4004	354.1391	348.6351	350.3441	350.1208

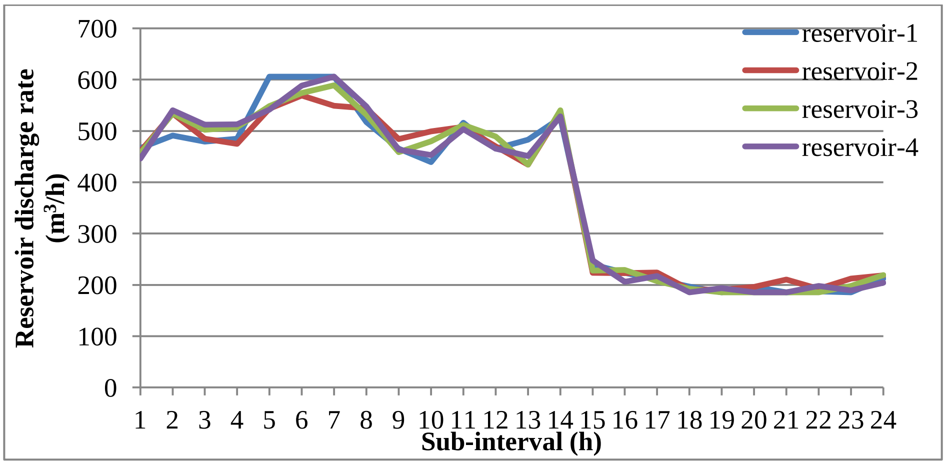

Figure 2.6: Reservoir discharge rate for minimum emission HTGS: Electric power system-III

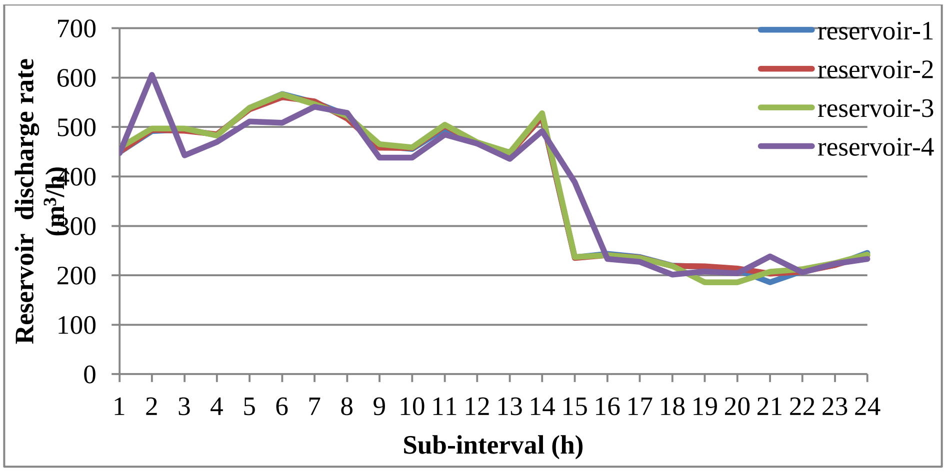

Figure 2.7: Reservoir discharge rate for multi-objective HTGS: Electric power system-III

Table 2.12: Power generation for minimum emission HTGS: Electric power system-III

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generations (MW)					Hydro generations (MW)			
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}	p_{8k}	p_{9k}
1	5448	600.2234	773.3821	784.1882	792.1128	769.6326	779.6902	544.5909	539.6443	536.6392	528.3431
2	5776	679.1198	804.3201	822.1423	824.2918	825.7036	817.7112	564.1190	597.5203	597.1501	602.1611
3	5664	653.1886	806.1109	817.1985	799.2354	815.9506	810.9520	554.5776	559.3074	573.0643	580.7913
4	5624	641.1950	792.5866	808.1279	803.6129	798.4856	794.0438	559.3589	551.1170	576.5911	581.2709
5	5928	717.6230	824.2847	834.4464	836.9894	841.3034	843.5976	650.00	604.2219	607.9589	602.8206
6	6064	754.7580	848.5500	854.5877	861.6543	858.6307	857.4618	650.00	623.4243	627.1619	637.2872
7	6088	761.9835	853.0963	856.5048	866.5188	859.6221	867.6608	650.00	608.6290	637.9517	650.00
8	5856	701.0899	814.3242	842.8876	834.9007	831.6636	841.1309	584.6202	604.8499	595.2548	607.4583
9	5480	606.4852	763.2147	785.5002	786.5553	788.3170	779.8686	543.8334	558.7260	538.3398	542.1303
10	5464	602.2501	770.3927	776.8394	799.5469	763.7353	773.6732	522.5846	570.3815	555.4619	533.6347
11	5728	668.3137	808.9763	810.9109	815.4253	814.3876	831.7219	583.4150	577.3952	580.0052	574.0763
12	5536	621.4569	779.2963	805.3213	782.3171	791.3439	801.3574	543.8502	547.0721	562.8810	544.0174
13	5400	588.7401	762.7182	779.3828	779.4846	777.9637	763.0826	557.5760	518.1304	518.1048	532.2968
14	5828	692.9013	818.7568	841.3888	820.7729	829.7155	825.1024	590.4993	599.3289	602.0883	593.2485
15	3928	305.0214	580.4052	580.9160	584.9506	585.5354	579.1383	336.2244	318.0956	323.1633	344.5930
16	3840	293.1516	558.5697	586.7235	585.9666	568.3872	574.1494	318.4368	317.9892	324.4742	298.4550
17	3784	284.4217	554.2547	573.5044	563.7203	570.9548	572.4066	303.3905	318.8483	300.0634	311.2789
18	3608	260.4633	535.9421	550.9192	554.2260	555.4268	544.3658	288.0594	281.4514	283.0728	275.00
19	3584	257.1183	535.5395	545.9879	561.7162	541.9227	540.3766	275.0141	281.0218	275.00	284.5396
20	3544	248.9812	532.5049	532.9520	536.6108	531.4193	534.9551	287.0695	287.4695	275.00	275.00
21	3528	245.8857	516.7941	528.4753	528.9979	531.4012	539.5534	275.000	303.6638	275.00	275.00
22	3552	250.5197	526.9604	542.8653	543.8042	539.0821	525.8542	276.9426	282.8462	275.00	289.1648
23	3688	273.5823	558.2054	563.3559	560.0701	568.4070	561.8107	275.000	305.8669	289.6525	279.2137
24	3840	295.8180	576.7412	583.9794	584.0244	571.7917	590.1202	305.7641	312.9232	313.7284	296.7457

Table 2.14: Comparison of result: Electric power system-IV

Technique Applied	Economy Scheduling			Emission Scheduling			Multi-objective Scheduling			
	Cost ($)	Emission (kg)	CPU Time (s)	Cost ($)	Emission (kg)	CPU Time (s)	Cost ($)	Emission (kg)	μ_D	CPU Time (s)
PHOT-I	458555	345890	24.38	459211	344175	25.47	458897	344414	0.39152	25.82
PHOT-II	458570	345784	25.57	459828	344940	25.61	458587	345042	0.36343	25.81
PHOT-III	458409	345537	31.57	459904	344316	31.82	458666	344523	0.67955	31.86

Note: PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

Table 2.13: Power generation for multi-objective HTGS: Electric power system-III

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generations (MW)					Hydro generations (MW)			
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}	p_{8k}	p_{9k}
1	5448	601.699	790.928	788.564	782.370	781.267	777.530	530.700	530.866	538.177	529.284
2	5776	680.439	825.192	828.288	820.639	819.040	812.820	564.777	566.827	568.854	650.000
3	5664	656.818	819.494	825.102	822.084	816.840	810.150	567.462	565.286	569.073	525.322
4	5624	644.784	812.187	813.620	808.475	808.487	802.427	558.795	559.704	557.664	547.422
5	5928	724.622	858.927	854.878	858.302	851.486	848.528	600.445	598.750	601.346	579.957
6	6064	763.786	883.145	879.023	876.791	876.241	874.159	621.857	617.039	621.487	578.041
7	6088	774.489	868.149	871.285	975.00	857.675	861.246	609.217	610.773	606.428	602.712
8	5856	703.856	845.846	845.422	837.471	838.473	836.208	589.915	584.205	588.864	593.450
9	5480	609.649	793.204	794.083	787.974	788.495	782.065	540.781	537.713	543.599	521.731
10	5464	605.952	792.897	796.267	785.486	784.274	777.397	535.738	537.367	538.765	521.757
11	5728	671.507	828.736	829.962	821.367	822.695	820.619	569.097	572.811	574.832	559.385
12	5536	622.364	803.164	799.635	791.271	790.970	790.276	544.799	546.500	546.880	544.865
13	5400	589.825	784.306	778.093	774.712	776.569	767.752	530.055	528.503	530.165	519.666
14	5828	697.496	838.649	845.266	840.935	836.351	833.112	586.499	587.280	592.653	564.747
15	3928	296.252	555.164	557.082	550.466	543.664	541.995	332.102	331.202	333.212	479.361
16	3840	285.972	556.112	564.460	556.984	553.803	551.021	339.819	337.309	337.316	329.144
17	3784	277.391	559.120	551.721	546.467	545.908	540.182	333.070	331.395	331.153	322.370
18	3608	251.739	532.918	532.141	523.009	520.900	517.516	314.002	313.072	313.123	293.054
19	3584	250.069	528.384	531.902	528.050	523.741	522.208	311.755	312.323	275.00	300.703
20	3544	244.207	528.210	527.395	520.123	515.596	513.030	304.489	307.687	275.010	296.663
21	3528	240.050	521.989	518.837	507.407	510.570	503.656	275.00	295.934	299.991	334.664
22	3552	243.883	520.836	523.624	518.088	514.620	513.333	301.389	299.856	305.656	298.478
23	3688	263.386	537.643	541.413	538.979	531.864	532.837	315.515	315.470	319.671	317.990
24	3840	285.816	562.270	563.226	556.897	550.081	547.359	342.211	336.482	338.599	328.687

Table 2.15 and 2.16 depicted the variation in reservoir head and power generation schedule for minimum cost, respectively. Water discharge rate for minimum cost is

shown in Fig. 2.8. Table 2.17 and 2.18 depicted the variation in reservoir head and power generation for minimum emission, respectively. Water discharge rate for minimum emission is shown in Fig. 2.9.

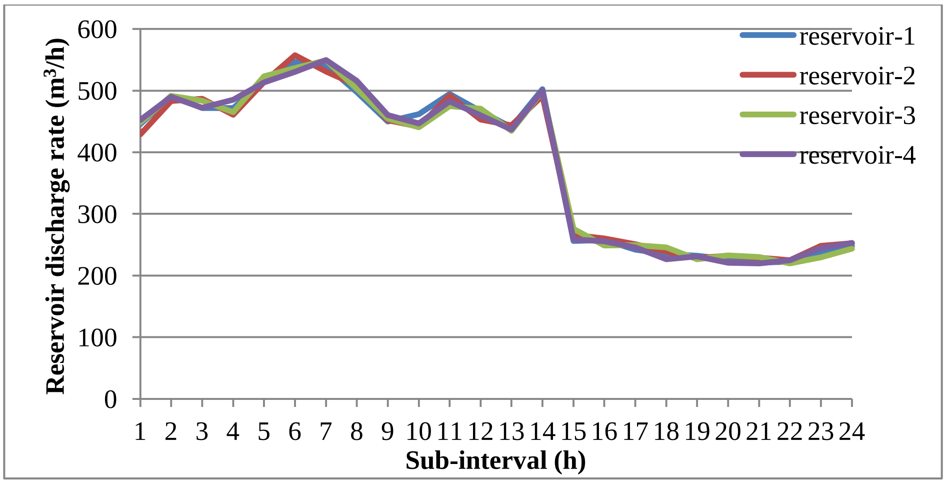

Figure 2.8: Reservoir discharge rate for minimum cost HTGS: Electric power system-IV

Table 2.15: Reservoir head variation for minimum operating cost HTGS: Electric power system-IV

k	p_{Dk} (MW)	Head Variation (m)			
		H_{1k}	H_{2k}	H_{3k}	H_{4k}
1	5448	179.8320	180.1370	180.4420	180.7460
2	5776	179.8319	180.1369	180.4419	180.7459
3	5664	179.8319	180.1369	180.4419	180.7458
4	5624	179.8318	180.1368	180.4418	180.7458
5	5928	179.8317	180.1367	180.4417	180.7457
6	6064	179.8316	180.1366	180.4416	180.7456
7	6088	179.8316	180.1365	180.4416	180.7455
8	5856	179.8315	180.1365	180.4415	180.7455
9	5480	179.8314	180.1364	180.4414	180.7454
10	5464	179.8313	180.1363	180.4413	180.7453
11	5728	179.8313	180.1362	180.4413	180.7453
12	5536	179.8312	180.1362	180.4412	180.7452
13	5400	179.8311	180.1361	180.4411	180.7451
14	5828	179.8311	180.1360	180.4411	180.7450
15	3928	179.8310	180.1360	180.4410	180.7450
16	3840	179.8309	180.1359	180.4409	180.7449
17	3784	179.8309	180.1359	180.4409	180.7449
18	3608	179.8309	180.1358	180.4409	180.7448
19	3584	179.8308	180.1358	180.4408	180.7448
20	3544	179.8308	180.1358	180.4408	180.7448
21	3528	179.8308	180.1357	180.4408	180.7448
22	3552	179.8307	180.1357	180.4408	180.7447
23	3688	179.8307	180.1357	180.4407	180.7447
24	3840	179.8307	180.1357	180.4407	180.7447

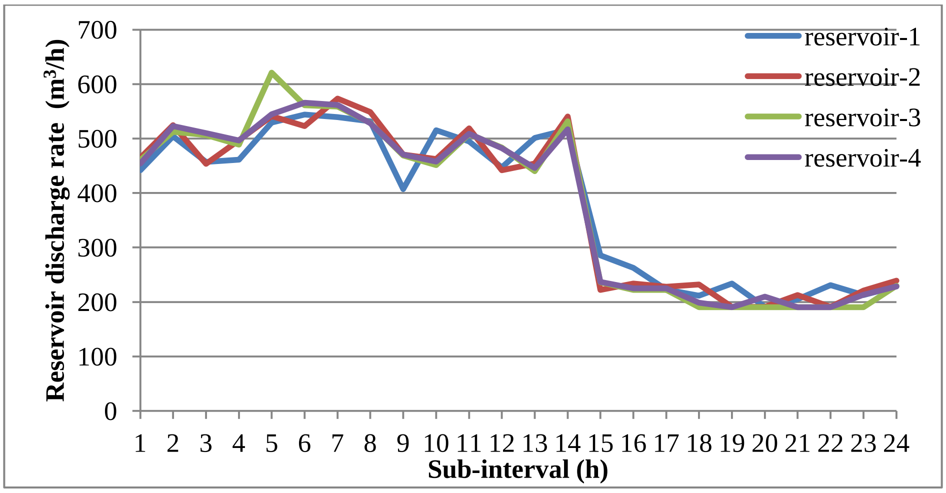

Figure 2.9: Reservoir discharge rate for minimum emission HTGS: Electric power system-IV

Table 2.16: Power generation for minimum operating cost HTGS: Electric power system-IV

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generations (MW)					Hydro generations (MW)			
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}	p_{8k}	p_{9k}
1	5448	608.1601	819.0781	811.9865	803.2371	790.6931	764.1047	517.5182	504.3597	520.5586	524.6239
2	5776	693.9811	881.8567	872.0223	843.0676	843.9636	818.9765	553.5280	547.6770	554.6838	554.2056
3	5664	661.9536	854.5434	849.8563	824.8496	814.9296	803.7206	538.2079	550.4629	548.9765	540.4070
4	5624	652.4731	854.2045	852.3586	817.7537	807.9401	791.1620	538.2079	530.1779	534.0567	550.4803
5	5928	734.1139	897.6662	891.7860	868.3497	868.0821	842.1893	571.6481	571.2252	578.9753	572.1924
6	6064	770.9321	910.6186	912.2760	897.4600	870.5507	870.4909	595.0645	603.8167	589.3293	585.3263
7	6088	779.2521	915.2037	920.4031	903.1723	886.7221	868.6107	590.9912	584.4330	598.3881	599.3278
8	5856	713.7991	885.5482	871.3244	872.7269	838.9901	837.5227	558.5351	567.4523	563.5346	574.1645
9	5480	614.0402	824.8049	811.3058	789.7902	785.7314	781.6330	520.7222	522.9466	525.9763	531.1299
10	5464	611.5284	824.8391	814.9493	796.6945	787.8324	771.1854	530.4159	514.8735	514.6399	520.0984
11	5728	679.4252	858.0414	859.2665	840.9539	832.8546	815.0060	556.2565	554.8429	541.7133	548.4895
12	5536	628.0228	823.1244	827.5105	807.5155	791.9189	786.5696	534.1668	524.0807	538.4914	530.6453
13	5400	595.5540	814.3719	801.1407	789.1837	776.8361	762.0698	513.4376	516.5563	509.9258	512.0323
14	5828	707.3828	877.0757	875.4044	859.8198	848.8755	835.8695	562.0330	554.115	560.4141	561.7760
15	3928	297.6937	587.5994	587.8477	555.2162	542.6555	533.5727	345.7441	356.5529	366.5464	349.9586
16	3840	283.6322	583.4196	567.9129	544.9324	528.7305	515.3672	347.2929	350.3114	339.0229	346.6424
17	3784	275.5135	559.1346	567.4846	543.1456	528.4923	513.0466	331.5045	340.7798	339.6731	336.2524
18	3608	247.3524	544.0960	529.1791	496.8083	488.3839	493.1203	323.7988	328.3607	335.8041	315.8010
19	3584	245.1261	540.9530	535.9339	503.7840	486.8062	487.4742	320.8553	317.3709	315.2048	320.7440
20	3544	238.5922	525.5095	523.8505	499.4573	483.5351	482.3020	314.9069	321.0767	322.2452	309.7093
21	3528	236.7419	528.4611	520.0372	496.3672	480.5284	484.6162	309.0125	317.9204	319.3415	308.4574
22	3552	241.4599	529.9286	538.2577	506.9287	489.2808	483.3864	310.0963	313.3268	308.2575	313.9967
23	3688	260.2055	547.7534	549.9955	514.6767	517.0348	499.6150	326.8652	338.2242	318.7423	335.2985
24	3840	285.1940	576.1362	569.8654	554.3906	534.7609	532.5380	337.3603	342.7692	333.7167	343.6569

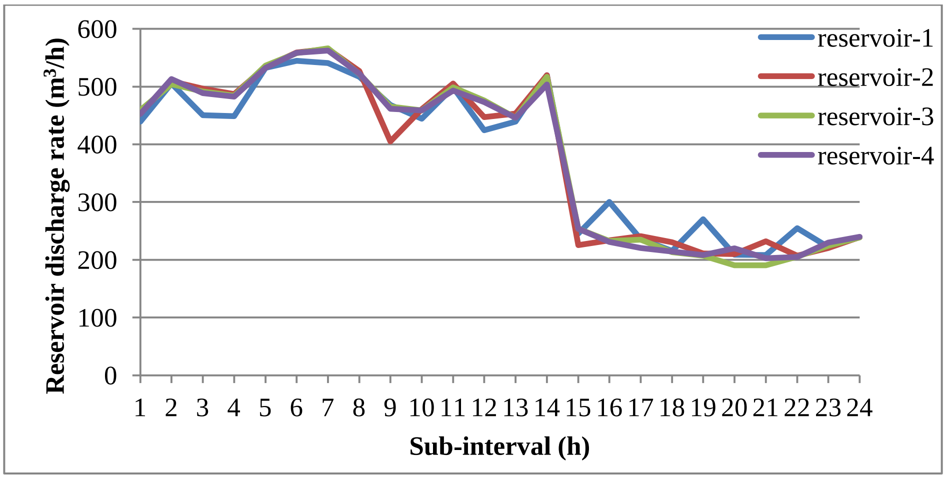

Figure 2.10: Reservoir discharge rate for multi-objective HTGS: Electric power system-IV

For multi-objective HTGS, Table 2.19 and 2.20 depicted the variation in reservoir head and power generation schedule, respectively obtained by PHOT-III. Water discharge rate for best multi-objective scheduling is shown in Fig. 2.10.

Table 2.17: Reservoir head variation for minimum emission HTGS: Electric power system-IV

k	p_{Dk} (MW)	Head Variation (m)			
		H_{1k}	H_{2k}	H_{3k}	H_{4k}
1	5448	179.8320	180.1370	180.4420	180.7460
2	5776	179.8319	180.1369	180.4419	180.7459
3	5664	179.8319	180.1368	180.4418	180.7458
4	5624	179.8318	180.1368	180.4418	180.7458
5	5928	179.8317	180.1367	180.4417	180.7457
6	6064	179.8316	180.1366	180.4416	180.7456
7	6088	179.8316	180.1365	180.4415	180.7455
8	5856	179.8315	180.1364	180.4414	180.7454
9	5480	179.8314	180.1364	180.4413	180.7454
10	5464	179.8313	180.1363	180.4413	180.7453
11	5728	179.8313	180.1362	180.4412	180.7452
12	5536	179.8312	180.1361	180.4411	180.7451
13	5400	179.8311	180.1361	180.4411	180.7451
14	5828	179.8311	180.1360	180.4410	180.7450
15	3928	179.8310	180.1359	180.4409	180.7449
16	3840	179.8309	180.1359	180.4409	180.7449
17	3784	179.8309	180.1359	180.4409	180.7449
18	3608	179.8309	180.1358	180.4408	180.7448
19	3584	179.8308	180.1358	180.4408	180.7448
20	3544	179.8308	180.1358	180.4408	180.7448
21	3528	179.8308	180.1357	180.4407	180.7447
22	3552	179.8307	180.1357	180.4407	180.7447
23	3688	179.8307	180.1357	180.4407	180.7447
24	3840	179.8307	180.1357	180.4406	180.7446

Table 2.18: Power generation for minimum emission HTGS: Electric power system-IV

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generations (MW)					Hydro generations (MW)			
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}	p_{8k}	p_{9k}
1	5448	604.0599	794.787	791.227	789.5435	786.1047	785.9872	514.1564	533.4908	530.6468	526.1162
2	5776	684.7303	839.2689	836.6797	830.9923	835.2359	824.6890	563.3539	579.7719	571.0946	579.6442
3	5664	660.9614	834.5913	832.3647	824.4910	826.0392	820.2056	526.6666	524.2366	566.5549	569.8113
4	5624	647.0891	819.6705	818.5185	814.2478	811.1710	806.8472	529.9758	558.6415	552.8257	559.1910
5	5928	721.3712	852.4152	851.8340	845.1415	841.7821	838.1865	582.6295	591.6973	650.00	595.6852
6	6064	770.6016	873.4385	870.3005	865.0169	975.000	860.5799	593.2219	578.1703	607.4374	611.4363
7	6088	775.5277	872.7860	869.6856	975.00	861.8514	865.0674	589.7752	615.4254	605.6654	608.2715
8	5856	704.6236	849.7007	845.1373	844.8420	836.4819	835.7422	704.6236	584.1931	597.5468	583.6971
9	5480	614.1755	804.0124	802.5355	798.1909	796.7639	791.9288	485.8955	538.1757	537.3607	539.3122
10	5464	604.1957	786.8539	788.9373	780.7546	780.1840	776.2838	571.9149	531.4028	522.9766	528.8879
11	5728	672.2787	831.5380	832.6155	825.0972	821.6677	821.0645	556.3316	575.08	567.96	568.9243
12	5536	627.5927	814.8495	812.2022	803.9078	800.0943	801.3873	518.8188	514.9986	548.6947	548.6394
13	5400	589.1194	786.2678	777.3307	772.5013	769.4009	764.5325	561.2277	524.7695	513.9084	519.1809
14	5828	698.0519	844.7893	844.6060	844.0721	833.1622	834.2916	572.7604	591.6335	585.5835	575.1540
15	3928	303.8314	584.7547	587.9740	576.3944	573.4130	570.6232	375.4856	310.5275	325.6881	326.9710
16	3840	289.5540	567.9760	574.7611	569.4417	562.2122	554.7147	352.2834	322.8112	310.7655	314.5882
17	3784	282.6635	570.0783	566.8869	561.0605	560.9818	556.0121	310.3787	316.4035	310.5791	314.2824
18	3608	256.0713	539.7837	544.5776	539.0723	531.2858	530.2014	298.0707	321.2406	275.00	284.8395
19	3584	254.4207	543.9490	543.4588	540.6746	532.3846	530.2443	322.7063	275.0025	275.0009	275.00
20	3544	249.1135	539.9570	537.5110	538.8480	530.4177	523.9955	275.0036	275.0618	275.00	297.3187
21	3528	244.6955	530.7932	531.3372	526.3850	523.0643	520.0590	291.3068	299.7041	275.0005	275.0459
22	3552	248.9179	541.3368	540.7293	527.2593	526.7661	520.5127	319.2710	275.0423	275.00	275.0004
23	3688	270.2874	566.1733	559.8697	551.9951	550.1451	544.9121	299.5647	309.2323	275.00	301.3951
24	3840	290.8054	573.5770	577.2871	568.8212	563.8954	563.9493	317.2156	328.4334	319.2935	318.3329

Table 2.19: Reservoir head Variation for multi-objective HTGS: Electric power system-IV

k	p_{Dk} (MW)	Head Variation (m)			
		H_{1k}	H_{2k}	H_{3k}	H_{4k}
1	5448	179.832	180.137	180.442	180.746
2	5776	179.8319	180.1369	180.4419	180.7459
3	5664	179.8319	180.1368	180.4418	180.7458
4	5624	179.8318	180.1368	180.4418	180.7458
5	5928	179.8317	180.1367	180.4417	180.7457
6	6064	179.8317	180.1366	180.4416	180.7456
7	6088	179.8316	180.1365	180.4415	180.7455
8	5856	179.8315	180.1364	180.4414	180.7454
9	5480	179.8314	180.1364	180.4414	180.7454
10	5464	179.8314	180.1363	180.4413	180.7453
11	5728	179.8313	180.1362	180.4412	180.7452
12	5536	179.8312	180.1361	180.4411	180.7451
13	5400	179.8312	180.1361	180.4411	180.7451
14	5828	179.8311	180.136	180.441	180.745
15	3928	179.831	180.1359	180.4409	180.7449
16	3840	179.831	180.1359	180.4409	180.7449

Table 2.19: Reservoir head Variation for multi-objective HTGS: Electric power system-IV (continued)

k	p_{Dk} (MW)	Head Variation (m)			
		H_{1k}	H_{2k}	H_{3k}	H_{4k}
17	3784	179.8309	180.1359	180.4409	180.7449
18	3608	179.8309	180.1358	180.4408	180.7448
19	3584	179.8309	180.1358	180.4408	180.7448
20	3544	179.8308	180.1358	180.4408	180.7448
21	3528	179.8308	180.1357	180.4407	180.7447
22	3552	179.8308	180.1357	180.4407	180.7447
23	3688	179.8307	180.1357	180.4407	180.7447
24	3840	179.8307	180.1357	180.4406	180.7446

Table 2.20: Power generation for multi-objective HTGS: Electric power system-IV

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generations (MW)					Hydro generations (MW)			
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}	p_{8k}	p_{9k}
1	5448	605.3269	804.8343	806.1125	790.7953	783.7454	775.1503	512.36	525.6976	529.8646	524.767
2	5776	687.2997	857.1655	849.0758	833.5508	829.7787	824.6896	564.2415	567.8189	564.6651	572.3141
3	5664	660.8362	843.215	842.0234	824.2828	818.1516	809.0485	521.4921	558.3763	554.762	553.4839
4	5624	650.436	834.4604	834.0058	818.3953	812.0565	806.7805	520.0321	550.8104	549.3394	548.5557
5	5928	728.0032	876.0565	870.8894	862.8345	853.9873	844.6497	584.989	586.7444	589.0648	586.7875
6	6064	766.6346	899.0086	896.7968	882.3359	873.1719	869.0084	594.0618	605.2236	604.998	606.0295
7	6088	773.6465	902.3975	898.8162	885.2406	881.2452	873.0551	590.9217	609.7814	611.2705	608.9182
8	5856	708.334	867.6758	860.0159	850.3071	841.9048	831.9557	573.3499	581.4741	578.3959	579.2546
9	5480	615.6968	814.0108	814.2347	802.4796	791.0512	787.403	535.5518	484.4022	534.3538	532.2094
10	5464	608.741	807.0409	807.2391	788.8845	784.4838	779.6791	516.2861	530.4576	529.0566	529.613
11	5728	674.9957	848.9973	839.7027	830.0797	825.1182	817.4443	559.2276	564.8259	560.6219	556.978
12	5536	630.6313	826.5414	825.1428	806.4193	806.7957	798.5248	500.0483	519.1444	542.8004	541.2139
13	5400	593.0958	796.6964	795.5512	783.3294	772.2832	770.4922	512.3005	524.1758	518.7709	519.4959
14	5828	701.5439	861.9116	853.9294	846.1575	839.8719	837.0095	575.3232	575.8794	574.3613	565.1002
15	3928	303.6928	595.5078	591.0925	575.7062	567.1483	564.3621	334.8729	313.8644	344.3224	344.8165
16	3840	285.7924	571.56	563.5509	550.2832	544.9559	540.2892	389.7621	322.6099	322.1488	320.6326
17	3784	279.7317	568.7297	566.4774	555.7913	543.944	539.8676	324.9572	330.5381	324.2092	309.2175
18	3608	252.4186	542.1639	538.7997	527.1546	515.3392	511.8757	302.5461	319.2603	300.959	302.32
19	3584	247.0955	535.1507	529.8638	512.9549	505.8624	499.2833	360.3882	298.2066	293.9423	295.4432
20	3544	244.8815	540.1061	530.4098	522.693	513.046	506.5785	295.3606	296.8592	275	308.8283
21	3528	241.8735	531.4125	534.4259	514.1335	507.8134	501.8371	294.4817	321.2059	275	289.5634
22	3552	243.1199	529.3552	526.0626	514.073	504.3017	499.0952	344.5636	293.5375	292.4589	291.6721
23	3688	264.8528	556.1717	554.7111	536.8777	529.1722	524.8228	310.1661	308.2315	313.0153	319.6845
24	3840	288.2482	579.4543	571.2313	562.0526	553.6483	546.5283	328.1293	328.6743	328.6694	329.8603

2.8 CONCLUSIONS

In this chapter, global search characteristics of PPO and EP and local search characteristics of Powell's search technique are combined to develop heuristic search techniques. Local search PPS technique is implemented as a neighborhood search, where it intends to explore the promising search area obtained by PPO or EP technique to improve the quality of solution. Proposed heuristic optimization techniques are explored to solve fixed and variable-head HTGS problem. In the multi-objective framework, it is realized that cost and emissions are conflicting objectives and are subjected to mutual interface. Moreover, heuristic constraint handling technique, which do not require penalty factor, is applied to handle the constraints. The solutions obtained from PHOTs are having better quality in terms of minimum operating cost, gaseous pollutants' emission level and computation time.

The practical viability of the formulation is illustrated through four numerical examples in different systems. The first, second and third system has sufficient reservoir capacity so reservoir head is fixed for these systems. Fourth system has variable reservoir head. The results reveal that the PHOTs are very effective in reaching an optimal generation schedule. The parameter sensitivity analysis is also performed and it is observed that parameters are less sensitive to the variations. The best, average and worst results are obtained by PHOTs to investigate the effect of initial solutions, and to verify the robustness of these techniques. It is concluded that PHOTs produce good quality solutions on every execution. The inclusion of local search speed-up the search process and also helps in obtaining a fine-grained value for the objective.

CHAPTER – 3

MULTI-OBJECTIVE SHORT-TERM MULTI-CHAIN HYDRO-THERMAL GENERATION SCHEDULING USING HEURISTIC SEARCH TECHNIQUES

3.1 INTRODUCTION

In recent years, multi-objective hydro-thermal generation scheduling is recognized as one of the most significant problems in the interconnected electric system operation. The objective of *hydro-thermal generation scheduling* (HTGS) is to find the optimal solutions of the water discharge rates of the hydro units and power output of the thermal units so to minimize the total production cost and emission simultaneously, while subjected to a series of constraints. Hydro resources are considered to provide a clean and environment friendly energy option, while thermal units' particular fossil fuel-based resources are considered to provide an environmentally aggressive energy option. Because of cyclic nature of reservoir inflows coordination between thermal and hydro units are necessary. In multi-chain hydro model, hydro plants are located on different streams as well as on the same stream. The operation of a downstream plant depends on the immediate upstream plant. The travel time between reservoirs must be taken into account if the transposition delays are not negligible. Time-delay is a difficult issue, depending on the distance between reservoirs and on the water discharge [107]. Downstream plant influences the immediate upstream plant by its effect on tail water elevation and effective head. In multi-chain hydro-thermal model, the equality constraints include generation-demand balance and balance of available volume-water discharge. The inequality constraints include generation limits on thermal and hydro power units, limits on discharge rate and reservoir storage level limits.

Generally, traditional optimization methods, such as equal incremental cost equations, *dynamic programming* (DP), *network flow programming* (NFP), nonlinear programming, progressive optimality algorithm and mathematical decomposition method are less prominent to find the optimum results because generation scheduling problems have too many variables and constraints, which influence the calculation precision [292]. Network flow programming is the most widely used method for HTGS as compared to other approaches. Since, it is more effective in dealing with the water travelling time between stations in a river. However, when some convex branches exist in the flow network, the computational efforts required by NFP technique drastically increased [40]. Decomposition is a method based on Lagrange multiplier, it may encounter difficulties when deal with the operation limits and non-convexity. For the HTGS problem, DP provides accurate modelling of the majority of hydro-electric plant characteristics [244]. The "curse of dimensionality" still remains the main drawback of DP for a realistic system with multiple river basins and cascaded hydro plants. In order to make, DP more practical, some approximations have to be made. Among these methods, dual DP [35] and DP with successive approximation [23] have gained much popularity. The dual DP overcomes the dimensionality problem of traditional DP by approximating the further cost function. The DP with successive approximation starts with an initial "feasible scheduling" for every reservoir, and each reservoir is successively scheduled while the others are fixed. Since, successive approximation belongs to a class of greedy search algorithms, the solution usually got stuck at a local optimum rather than at the global optimum. In recent years, global search techniques are applied as a tool for the solution of complex optimization problems because of number of advantages.

Multi-objective hydro-thermal generation scheduling has been undertaken by several researchers till date. Lu *et al.* [375] have developed quadratic approximation based differential evolution with valuable trade-off approach to solve bi-objective HTGS problem. Xu *et al.* [404] have proposed a DE algorithm based on ε-domination and orthogonal design method for HTGS, considering economy and emission as objectives. Coelho *et al.* [282] and Sun *et al.* [325] have applied quantum particle swarm optimization for short-term combined economic-emission HTGS problem. Mandal *et al.* [391] have applied self-organizing hierarchical PSO with time varying acceleration coefficients for combined economic-emission scheduling of cascaded hydro-thermal systems.

The intent of this chapter is to apply proposed heuristic optimization techniques as described in section 2.2 of chapter 2, for optimal operation of hydro-thermal system, considering multi-chain hydro model. *Proposed heuristic optimization techniques* (PHOTs) integrate global and local search techniques. Powell's search method is applied as a local search technique. *Predator-prey optimization* (PPO), *evolutionary programming* (EP) and integrated technique of PPO and EP are selected as global search technique, respectively in heuristic techniques. The heuristic techniques first exploit the property of global search techniques, and then Powell's pattern search has been used to improve the solutions locally, by examining neighbouring solutions.

The objective of multi-objective HTGS is to find the optimal solutions in terms of the water discharge rates of the hydro units and power output of the thermal units to minimize the total operating cost and emission of gaseous pollutants simultaneously, while satisfying a series of constraints. The variable elimination method is implemented to handle the equality constraints, whereby dependent variables are determined from the equality constraint. Inequality constraints of dependent variables are incorporated as an additional objective function represented by the fuzzy membership index of constraints in the optimization problem. Fuzzy methodology has been applied to solve multi-objective optimization problem involving the multiple conflicting objectives and is treated as selection criteria to decide the best compromised solution. The PHOTs are applied to HTGS problem considering only economic criteria, only emission of gaseous pollutants and multi-objective HTGS. The validity of the PHOTs is demonstrated on various electric power systems and performing comparison analysis economic and gaseous emission simultaneously with existing techniques.

3.2 MULTI-OBJECTIVE HYDRO-THERMAL GENERATION SCHEDULING PROBLEM FORMULATION

The aim of multi-objective HTGS is focused on the optimal use of water resources for minimizing the production cost and emission of gaseous pollutants simultaneously, while satisfying various constraints of hydro-thermal system.

3.2.1 Multi-Chain Hydro Model

A multi-chain hydro model is undertaken, in which lower reservoir volume depends on upper reservoir discharge. The power generated from a hydro plant is related to the reservoir characteristics as well as the water discharge rate. A number of models [52] have been used to represent this relationship. In general, the hydro generator power output is a function of the net hydraulic head reservoir volume and the rate of water discharge given as:

$$p_m = f(q_j, V_j) \qquad (j = 1,2,\ldots,N_H; m = j + N_T) \tag{3.1}$$

and $V_j = f(H_j) \qquad (j = 1,2,\ldots,N_H)$ (3.2)

where

p_m is hydro generator power output of m^{th} unit

H_j is net hydraulic head of j^{th} hydro unit

V_j, q_j are reservoir volume and rate of water discharge of j^{th} hydro unit, respectively

The model can also be written in terms of reservoir volume instead of the reservoir net head, and is a function of power generation characteristics as [107]:

$$p_{mk} = C_{1j}V_{jk}^2 + C_{2j}q_{jk}^2 + C_{3j}V_{jk}q_{jk} + C_{4j}V_{jk} + C_{5j}q_{jk} + C_{6j}$$
$$(j = 1,2,\ldots,N_H; k = 1,2,\ldots,T; m = j + N_T) \tag{3.3}$$

where

p_{mk} is power generation of m^{th} unit at k^{th} sub-interval

$C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}$ and C_{6j} are the power generation coefficients of the j^{th} hydro unit

N_H and N_T represent the number of hydro and thermal units, respectively.

T is total time interval for scheduling

q_{jk}, V_{jk} are rate of water discharge and reservoir volume, respectively of j^{th} hydro unit at k^{th} sub-interval

Water storage at the end of k^{th} sub-interval can be obtained from volume dynamics for the hydro reservoir network as:

$$V_{j(k+1)} = V_{jk} + I_{jk} - q_{jk} - SP_{jk} + \sum_{r=1}^{U_j}\left(q_{r(k-t_{rj})} + SP_{r(k-t_{rj})}\right) \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \tag{3.4}$$

where

I_{jk}, SP_{jk} are water inflow and spillage, respectively of j^{th} hydro unit at k^{th} sub-interval

U_j is upstream reservoir

t_{rj} is representing time delay from upstream reservoir ‘r’ to lower reservoir ‘j’

3.2.2 Multi-objective Hydro-thermal Generation Scheduling

The thermal unit cost function F_1 and amount of pollutant emission Function F_2 are same as discussed in chapter 2, section 2.3. The equality constraints comprises: total generation should meet load demand and loss in each sub-interval and hydro unit is also constrained by the amount of water available. Inequality constraints comprise of discharge, volume and power generation limits. Mathematically multi-objective HTGS is stated as:

Minimize $[F_1, F_2]^T$ (3.5)

Subjected to

(i) The final reservoir volume equality constraint for each hydro unit as [107] :

$$V_{jF} = V_{jI} + \sum_{k=1}^{T} I_{jk} - \sum_{k=1}^{T} q_{jk} - \sum_{k=1}^{T} SP_{jk} + \sum_{k=1}^{T}\sum_{r=1}^{U_j}\left(q_{r(k-t_{rj})} + SP_{r(k-t_{rj})}\right)$$

$$(j = 1,2,\ldots,N_H) \qquad (3.5a)$$

where

V_{jF} , V_{jI} are the final and initial reservoir storage volumes of j^{th} hydro unit respectively

(ii) The load demand equality constraint during each sub-interval

$$\sum_{i=1}^{N_T} p_{ik} + \sum_{j=1}^{N_H} p_{mk} = p_{Dk} + p_{Lk} \quad (m = j + N_T; k = 1,2,\ldots,T) \qquad (3.5b)$$

where

p_{Dk} is the power demand and p_{Lk} is the transmission loss during k^{th} sub-interval

(iii) The rate of discharge limits are imposed on each hydro unit

$$q_j^{\min} \le q_{jk} \le q_j^{\max} \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \qquad (3.5c)$$

where

$q_j^{\max}$ and $q_j^{\min}$ are the upper and lower limits of rate of water discharge of j^{th} hydro unit, respectively

(iv) The volume limits are imposed on each hydro unit

$$V_j^{\min} \le V_{jk} \le V_j^{\max} \quad (j = 1,2,\ldots,N_H; k = 1,2,..T) \qquad (3.5d)$$

where

V_j^{max} and V_j^{min} are the upper and lower limits of reservoir volume of j^{th} hydro unit, respectively

(v) The generating power limits are imposed on each hydro and thermal unit

$$p_i^{min} \le p_{ik} \le p_i^{max} \; (i = 1,2,\ldots,N; k = 1,2,..T) \tag{3.5e}$$

where

p_i^{max} and p_i^{min} are the upper and lower limits of power generation of i^{th} unit, respectively

3.3 CONSTRAINT HANDLING TECHNIQUE

Variable elimination method is applied to handle the equality constraints. The variables to be eliminated are known as dependent variable and the remaining variables are known as independent variable. Dependent thermal generating unit is introduced to meet the equality constraint given by Eq. (3.5b) during each sub-interval. Water discharge rate of a sub-interval so called dependent sub-interval is computed to satisfy the available water constraint given by Eq. (3.5a) for each hydro unit. Inequality constraints are handled using exterior penalty method.

3.3.1 Power Balance Equality Constraint

A dependent thermal unit is selected arbitrarily from thermal units and other thermal units act as independent variables in each sub-interval. The power of the dependent thermal unit during k^{th} sub-interval (p_{dk}) is computed as:

$$\sum_{i=1}^{N} p_{ik} = p_{Dk} + \sum_{i=1}^{N}\sum_{j=1}^{N} p_{ik} B_{ij} p_{jk} + \sum_{i=1}^{N} p_{ik} B_{io} + B_{oo} \; (k = 1,2,..T) \tag{3.6}$$

where B_{ij}, B_{io}, B_{oo} are loss coefficients

The above equation is rewritten as:

$$p_{dk} + \sum_{\substack{i=1 \\ i \ne d}}^{N} p_{ik} = p_{Dk} + \sum_{\substack{i=1 \\ i \ne d}}^{N}\sum_{\substack{j=1 \\ j \ne d}}^{N} p_{ik} B_{ij} p_{jk} + \sum_{\substack{j=1 \\ j \ne d}}^{N} p_{jk}\left(B_{jd} + B_{dj}\right) p_{dk} + B_{dd} p_{dk}^2 + \sum_{\substack{i=1 \\ i \ne d}}^{N} B_{io} p_{ik} + B_{do} p_{dk} + B_{oo}$$

$$(k = 1,2,..T) \tag{3.7}$$

The above equation is rewritten in quadratic form as:

$$X_k p_{dk}^2 + Y_k p_{dk} + Z_k = 0 \ (k = 1, 2, \ldots, T) \tag{3.8}$$

where

$$X_k = \begin{cases} 0 & ; p_{Lk} = 0 \\ B_{dd} & ; p_{Lk} \neq 0 \end{cases}$$

$$Y_k = \begin{cases} -1 & ; p_{Lk} = 0 \\ \sum_{\substack{j=1 \\ j \neq d}}^{N} \left(B_{jd} + B_{dj}\right) p_{jk} + B_{do} - 1 & ; p_{Lk} \neq 0 \end{cases}$$

$$Z_k = \begin{cases} p_{Dk} - \sum_{\substack{i=1 \\ i \neq d}}^{N} p_{ik} & ; p_{Lk} = 0 \\ p_{Dk} + B_{oo} + \sum_{\substack{i=1 \\ i \neq d}}^{N} \sum_{\substack{j=1 \\ j \neq d}}^{N} p_{ik} B_{ij} p_{jk} + \sum_{\substack{i=1 \\ i \neq d}}^{N} B_{io} p_{ik} - \sum_{\substack{i=1 \\ i \neq d}}^{N} p_{ik} & ; p_{Lk} \neq 0 \end{cases}$$

The positive root of Eq. (3.8) gives the dependent generation of thermal unit at k^{th} sub-interval.

3.3.2 Water Balance Equality Constraint

The dependent sub-interval 'h' is arbitrarily selected to meet the water balance equality constraint and other sub-intervals act as independent variables for each hydro unit. The water discharge rate (q_{jh}) for dependent sub-interval of j^{th} hydro unit is computed as:

$$q_{jh} = V_{jI} - V_{jF} + \sum_{k=1}^{T} I_{jk} - \sum_{\substack{k=1 \\ k \neq h}}^{T} q_{jk} - \sum_{k=1}^{T} SP_{jk} + \sum_{\substack{k=1 \\ k \neq h}}^{T} \sum_{r=1}^{U_j} q_{r(k-t_{rj})} + \sum_{k=1}^{T} \sum_{r=1}^{U_j} SP_{r(k-t_{rj})} \ \left(j = 1, 2, \ldots, N_H\right) \tag{3.9}$$

Reservoir volume and hydro power for j^{th} hydro unit during h^{th} sub-interval are computed by Eq. (3.4) and Eq. (3.3) respectively.

3.3.3 Inequality Constraint Handling

Every violation of inequality constraint is penalized by exterior penalty factor 'r_p' and cumulative effect of all inequality constraints violation is included in another objective function F_3 as:

$$F_3 = r_p \left(\sum_{k=1}^{T} \langle p_{dk} \rangle + \sum_{j=1}^{N_H} \langle q_{jh} \rangle + \sum_{k=1}^{T} \sum_{j=1}^{N_H} \langle V_{jk} \rangle + \sum_{k=1}^{T} \sum_{m=N_T+1}^{N} \langle p_{mk} \rangle \right) \tag{3.10}$$

First term of Eq. (3.10) represents the total violation of inequality constraint of dependent thermal unit power in each sub-interval, where $\langle p_{dk} \rangle$ is computed as:

$$\langle p_{dk} \rangle = \begin{cases} \left(p_{dk} - p_d^{\min}\right)^2 & ;if \quad p_{dk} < p_d^{\min} \\ \left(p_d^{\max} - p_{dk}\right)^2 & ;if \quad p_{dk} > p_d^{\max} \\ 0 & ;if \quad p_d^{\min} \le p_{dk} \le p_d^{\max} \end{cases} \tag{3.10a}$$

Second term of Eq. (3.10) represents the total violation of inequality constraint of water discharge rate during h^{th} dependent sub-interval for all hydro units, where $\langle q_{jh} \rangle$ is computed as:

$$\langle q_{jh} \rangle = \begin{cases} \left(q_{jh} - q_j^{\min}\right)^2 & ;if \quad q_{jh} < q_j^{\min} \\ \left(q_j^{\max} - q_{jh}\right)^2 & ;if \quad q_{jh} > q_j^{\max} \\ 0 & ;if \quad q_j^{\min} \le q_{jh} \le q_j^{\max} \end{cases} \tag{3.10b}$$

Third and fourth term of Eq. (3.10) represents the total violation of inequality constraint on water storage volume and hydro power, respectively of all hydro units in each sub-interval, where $\langle V_{jk} \rangle$ and $\langle P_{mk} \rangle$ are computed as:

$$\langle V_{jk} \rangle = \begin{cases} \left(V_{jk} - V_j^{\min}\right)^2 & ;if \quad V_{jk} < V_j^{\min} \\ \left(V_j^{\max} - V_{jk}\right)^2 & ;if \quad V_{jk} > V_j^{\max} \\ 0 & ;if \quad V_j^{\min} \le V_{jk} \le V_j^{\max} \end{cases} \tag{3.10c}$$

$$\langle p_{mk} \rangle = \begin{cases} \left(p_{mk} - p_m^{\min}\right)^2 & ;if \quad p_{mk} < p_m^{\min} \\ \left(p_m^{\max} - p_{mk}\right)^2 & ;if \quad p_{mk} > p_m^{\max} \\ 0 & ;if \quad p_m^{\min} \le p_{mk} \le p_m^{\max} \end{cases} \tag{3.10d}$$

3.4 FORMULATION OF UNIFIED OBJECTIVE FUNCTION

Fuzzy optimization provides a robust framework for handling *multi-objective problems* (MOPs). In fuzzy satisfying method, different objectives are easily integrated because all membership function values of these objectives are in range of 0 to 1. It is assumed that membership function $\mu(F_h)$ is a strictly monotonic linearly decreasing and continuous function, defined as [157]:

$$\mu(F_h)=\begin{cases}1 & ;F_h \le F_h^{min} \\ \dfrac{F_h^{max}-F_h}{F_h^{max}-F_h^{min}} & ;F_h^{min} < F_h < F_h^{max} \qquad (h=1,2,\ldots,N_{ob}) \\ 0 & ;F_h \ge F_h^{max}\end{cases} \tag{3.11}$$

where

N_{ob} is number of objectives

Minimum value of objective function F_h^{min} is achieved by giving full weightage to h^{th} objective and neglecting others and maximum value of h^{th} objective F_h^{max} is achieved by exploiting conflicting nature of objectives.

Multiple objectives of HTGS and objective function corresponding to inequality constraint are clubbed to find the unified affect of all the objectives simultaneously using membership functions. Decision regarding the best solution is made by maximizing the satisfaction level. It is represented by cardinal priority ranking or unified objective function and defined mathematically as:

$$\mu_D = \min(\mu(F_1),\mu(F_2),\mu(F_3)) \tag{3.12}$$

where

$$\mu(F_3)=\frac{1}{1+F_3}$$

$$\mu(F_3)=\begin{Bmatrix}1; & F_3 \le \varepsilon \\ 0; & F_3 > \varepsilon\end{Bmatrix}$$

with

μ_D is cardinal priority ranking

F_1, F_2 and F_3 are objective functions corresponding to economy, emission and inequality constraint, respectively

ε is the tolerable criterion

$\mu(F_1),\mu(F_2),\mu(F_3)$ are membership functions of economy, emission and inequality constraint objectives, respectively.

On violation of inequality constraint, the satisfaction level of safe operation becomes zero. Tolerable constraint criterion ε has been set in the desired range of accuracy like 0.001 or 0.0001.

3.5 SOLUTION METHODOLOGY

Multi-objective HTGS is transformed to a max-min optimization problem in fuzzy form. The heuristic PHOTs as discussed in section 2.2 of Chapter 2 that embeds global and local search technique are explored to solve the problem. Fuzzy methodology has been exploited to find the best compromised solution.

3.5.1 Proposed Heuristic Optimization Technique-I

In this technique, first PPO method is applied for known number of movements and then Powell's method is explored for further improvement of local best positions obtained from PPO technique. This process continues up to the maximum number of movements, to achieve maximum value of unified objective function. Elaborative steps to initialize prey, and predator position and velocity, update predator and prey velocity and position and upgrading of local best positions are presented in ensuing sub-sections.

3.5.1.1 Initialization of prey position and velocity

The prey positions are randomly initialized between upper and lower limits of thermal generation as given by Eq. (2.17) of chapter 2. The prey positions representing water discharge rate of hydro generating units are randomly initialized as:

$$P_{qjkl}^{0} = q_j^{\min} + \left(q_j^{\max} - q_j^{\min}\right) \times rand\,() \qquad \left(j = 1,2,..,N_H; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \tag{3.13}$$

where

p_{qjkl}^{0} is initial prey position representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle

The heuristic random search strategy is applied that converts initial prey population into feasible solutions. Two search moves are performed successively to satisfy both the equality constraints. One move meets the load demand constraint during each sub-interval and second move meets the available water constraint for every hydro unit. The whole process is repeated till both the constraints are satisfied.

Mathematically these moves are represented below. Initial water discharge position is updated as:

$$P^0_{qjkl} = \begin{cases} P^0_{qjkl} + W_v \times rand() \times \left(q_j^{\max} - q_j^{\min}\right)\left|\Delta V^0_{jl}\right| & if\left(\Delta V^0_{jl} < 0\right) \\ P^0_{qjkl} - W_v \times rand() \times \left(q_j^{\max} - q_j^{\min}\right)\left|\Delta V^0_{jl}\right| & if\left(\Delta V^0_{jl} > 0\right) \end{cases}$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \quad (3.14)$$

where

$$\Delta V^0_{jl} = V_{jF} - V_{jI} + \sum_{k=1}^{T} I_{jk} + \sum_{k=1}^{T}\sum_{r=1}^{Uj}\left(q_{r\left(k-t_{rj}\right)l} + SP_{r\left(k-t_{rj}\right)}\right) - \sum_{k=1}^{T} SP_{jk} - \sum_{k=1}^{T} P^0_{qjkl}$$

$$\left(j = 1,2,\ldots,N_H; l = 1,2,\ldots,NP\right) \quad (3.15)$$

with

P^0_{qjkl} is initial prey position representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle

ΔV^0_{jl} is residual volume of j^{th} hydro unit of l^{th} initially generated water discharge position particle

W_v is scaling factor for reservoir water balance equality constraint

If water discharge violates the limit, then it has been set to its corresponding limit. This process is repeated till water balance equality constraint is satisfied.

In second move, initial thermal power generation position is updated as

$$P^0_{pikl} = \begin{cases} P^0_{pikl} - W_D \times rand() \times \left(p_i^{\max} - p_i^{\min}\right)\left|\Delta p^0_{Dkl}\right| & if\left(\Delta p^0_{Dkl} < 0\right) \\ P^0_{pikl} + W_D \times rand() \times \left(p_i^{\max} - p_i^{\min}\right)\left|\Delta p^0_{Dkl}\right| & if\left(\Delta p^0_{Dkl} > 0\right) \end{cases} \left(i = 1,2,\ldots,N_T; k = 1,2,..T; l = 1,2,..NP\right) \quad (3.16)$$

where

$$\Delta p^0_{Dkl} = p_{Dk} + p_{Lk} - \sum_{i=1}^{N} P^0_{pikl} \quad \left(i = 1,2,\ldots,N_T; k = 1,2,..T; l = 1,2,..NP\right) \quad (3.17)$$

with

p^0_{pikl} is initial prey position representing power generation of i^{th} thermal unit at k^{th} sub-interval of l^{th} particle

Δp^0_{Dkl} is residual power for k^{th} sub-interval of l^{th} initially generated position particle

W_D is scaling factor for power balance equality constraint

If updated thermal power violates the limit, then it has been set to its corresponding limit. This process is repeated till both power balance equality is satisfied.

The prey velocity for thermal power generation is randomly initialized as given by Eq. (2.18) of chapter 2. The prey velocity for water discharge rate of hydro generating units is randomly initialized within their respective upper and lower limits.

$$v_{qjkl}^{0} = v_{q}^{\min} + \left(v_{q}^{\max} - v_{q}^{\min}\right) \times rand() \ \left(j = 1,2,..,N_H; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \quad (3.18)$$

where

v_{qjkl}^{0} is initial prey velocities of j^{th} hydro units at k^{th} sub-interval of l^{th} particle

The maximum and minimum velocity limit for thermal unit generation is same as given by Eq. (2.19) and (2.20), respectively of chapter 2. The maximum and minimum velocity limit for water discharge rate is taken as [265]:

$$v_{j}^{\max} = 0.5\left(\sum_{j=1}^{N_H} q_{j}^{\max} - \sum_{j=1}^{N_H} q_{j}^{\min}\right) \times \upsilon \quad (3.19)$$

$$v_{j}^{\min} = -v_{j}^{\max} \quad (3.20)$$

The scaling factor for velocity limits υ is set to 0.01 as discussed in sub-section 2.6.1.1 of chapter 2. Selection of velocity limits is an important aspect in PPO technique. The maximum allowed velocity actually controls the maximum exploration ability of particles in the search area. In the initial stage, high maximum velocity helps to search different regions of the solution space; at the final stage, small value of maximum velocity is preferred for the final search. Hence the initial search is started with high maximum velocity and if no improvement is observed in the global best solution for the same number of movements, velocity limits are squeezed by a factor α.

3.5.1.2 Initialization of predator position and velocity

The single predator position and velocity are randomly initialized between upper and lower limits for thermal generation as given by Eq. (2.23) and Eq. (2.24) of chapter 2. The position and velocity for rate of water discharge are randomly initialized as:

$$PP_{qjk}^{0} = q_{j}^{\min} + \left(q_{j}^{\max} - q_{j}^{\min}\right) \times rand() \ \left(j = 1,2,..,N_H; k = 1,2,\ldots,T\right) \quad (3.21)$$

$$Pv_{qjk}^{0} = v_{j}^{\min} + \left(v_{j}^{\max} - v_{j}^{\min}\right) \times rand() \ \left(j = 1,2,\ldots,N_H; k = 1,2,\ldots,T\right) \quad (3.22)$$

where

PP_{qjk}^{0} is initial predator position representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval

Pv_{qjk}^{0} is initial predator velocity of j^{th} hydro units at k^{th} sub-interval

3.5.1.3 Objective function evaluation

Multi-objective HTGS problem is solved to find the combined effect of participating objectives using their membership functions. The cardinal priority ranking or unified objective function is evaluated to select local and global best positions.

$$\mu_{Dl} = \min(\mu(F_h); h = 1,2,\ldots,N_{ob}) \; (l = 1,2,\ldots NP) \tag{3.23}$$

Maximum value of cardinal priority provides maximum satisfaction level from the participating objectives.

3.5.1.4 Update predator velocity and position

The predator velocity and position for generation of thermal unit are evaluated as given by Eq. (2.26) and Eq. (2.27) of chapter 2. The predator velocity and position for water discharge rate are updated as:

$$Pv_{qjk}^{t+1} = C_4\left(G_{qjk}^{t} - PP_{qjk}^{t}\right) \; (j = 1,2,..,N_H; k = 1,2,\ldots,T; k \neq h) \tag{3.24}$$

$$PP_{qjk}^{t+1} = PP_{qjk}^{t} + Pv_{qjk}^{t+1} \; (j = 1,2,..,N_H; k = 1,2,\ldots,T; k \neq h) \tag{3.25}$$

where

C_4 is a uniformly random number between 0 and upper limit

G_{qjk}^{t} is global best water discharge rate prey position of j^{th} hydro unit at k^{th} sub-interval for t^{th} movement

PP_{qjk}^{t} is predator position representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval for t^{th} movement

Pv_{qjk}^{t} is velocity of a predator of j^{th} hydro unit at k^{th} sub-interval for t^{th} movement

The predator position PP_{qjk}^{t} and velocity Pv_{qjk}^{t} may violate its limit. This violation is overcome by fixing their values at their corresponding limit.

3.5.1.5 Update prey velocity and position

The prey velocity and position for generation of thermal unit are evaluated as given by Eq. (2.28) and Eq. (2.29) of chapter 2, except for d^{th} dependent thermal unit. The velocity and position of a prey particle for water discharge rate are updated as:

$$v_{qjkl}^{t+1} = \begin{cases} wv_{qjkl}^{t} + C_1\left(L_{qjkl}^{t} - P_{qjkl}^{t}\right)\times rand() + C_2\left(G_{qjk}^{t} - P_{qjkl}^{t}\right)\times rand() & ;P_f \le P_{f\max} \\ wv_{qjkl}^{t} + C_1\left(L_{qjkl}^{t} - P_{qjkl}^{t}\right)\times rand() + C_2\left(G_{qjk}^{t} - P_{qjkl}^{t}\right)\times rand() + C_3 \times a_j \exp\left(-b_j \times E_d\right) & ;P_f > P_{f\max} \end{cases}$$

$$\left(j = 1,2,..,N_H ; k = 1,2,\ldots,T; k \ne h; l = 1,2,\ldots,NP\right) \quad (3.26)$$

$$P_{qjkl}^{t+1} = P_{qjkl}^{t} + v_{qjkl}^{t+1} \left(j = 1,2,..,N_H ; k = 1,2,\ldots,T; k \ne h; l = 1,2,\ldots,NP\right) \quad (3.27)$$

where

C_1 and C_2 are acceleration constant

C_3 is a uniformly distributed random number between 0 and upper limit

PPO constant 'a_j' provides the maximum amplitude of the predator effect over a prey

PPO constant 'b_j' control the effects of predator

w is inertia weight and it is varied from 0.9 to 0.4 linearly with respect to movement

v_{qjkl}^{t} is velocity of a prey particle of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

P_{qjkl}^{t} is prey positions representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

L_{qjkl}^{t} is local best position for water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

E_d is The Euclidean distance between predator and prey water discharge rate position

The elements of prey positions p_{qjkl}^{t} and velocities v_{qjkl}^{t} may violate their limits. This violation is overcome by fixing at their corresponding limits.

ALGORITHM-3.1: Proposed heuristic optimization technique-I for multi-objective HTGS

1. Read Input data. Set maximum and minimum values of all objectives and constant of proposed optimization technique.
2. Randomly initialize the prey positions and velocities as depicted in sub-section 3.5.1.1.
3. Heuristic search technique is applied to satisfy equality constraints as depicted in sub-section 3.5.1.1.
4. Randomly initialize the predator position and velocity as mentioned in sub-section 3.5.1.2.
5. Set the movement count t=0.
6. Set IT=50.
7. Set the movement counter for velocity limit m=0.
   DO
   - 7.1 Increment the iteration count $t=t+1$
   - 7.2 Compute water discharge rate for slack sub-interval as given in Eq. (3.9).
   - 7.3 Compute reservoir volume and hydro power for slack sub-interval by applying Eq. (3.4) and Eq. (3.3), respectively.
   - 7.4 Compute slack thermal unit power as given in Eq. (3.8).
   - 7.5 All inequality constraint violation is included in another objective function as given in Eq. (3.10).
   - 7.6 Update predator velocity and position as mentioned in sub-section 3.5.1.4.
   - 7.7 Randomly generate probability fear between 0 and 1.
   - 7.8 *IF*(probability fear >maximum probability fear) *THEN*
     - Predator affects the prey.

     ENDIF
   - 7.9 Update prey velocities and positions as mentioned in sub-section 3.5.1.5.
   - 7.10 Compute fuzzy membership function for all objectives by applying Eq. (3.11).
   - 7.11 Apply max-min operator to find cardinal priority ranking by applying Eq. (3.23).
   - 7.12 Update local best position.
   - 7.13 *IF*((t MOD IT)=0) *THEN*
     - Apply Powell's method to modify local best position by applying Eq. (3.28) and Eq. (3.29).
     - *IF* (modified local best position generate improved solution) *THEN*
       - Update local best position

       ENDIF

     ENDIF
   - 7.14 Update global best position.
   - 7.15 *IF*(global best position updated)*THEN*
     - *m=0*

     ELSE
     - *m=m+1*
     - *IF* ($m>m_{max}$) *THEN*
       - Squeeze the velocity limits by α factor
       - *m=0*

       ENDIF

     ENDIF

   WHILE ($t \le t_{max}$)
8. Solution corresponding to maximum cardinal priority ranking is the best solution.
   STOP

3.5.1.6 Upgrade local and global best position

Two steps are followed to improve the local best solutions obtained from PPO by applying Powell's pattern search. In first step, local best positions representing water discharge rate are selected as base points for PPS algorithm as mentioned in Appendix-C, and is also presented here.

During upgrading process of local best water discharge rate, each sub-interval is considered as coordinate direction *'i'* for all hydro units. It is modified once at a time along the coordinate search direction as:

$$L^t_{qjkl} = L^t_{qjkl} + \lambda^*_k D^i_k \qquad \left(j = 1,2,\ldots,N_H; k = 1,2,\ldots,T; k \neq h; i = 1,2,\ldots,T+1; l = 1,2,\ldots,NP\right) \tag{3.28}$$

where

λ^*_k is step length for k^{th} sub-interval

D^i_k is i^{th} search direction for k^{th} sub-interval

L^t_{qjkl} is local best position for water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

In next step, local best thermal power is modified along any one selected coordinate search direction '*j'* (thermal power) during each sub-interval and given as:

$$L^t_{pikl} = L^t_{pikl} + \lambda^*_i D^j_i \quad \left(i = 1,2,\ldots,N_T; j = 1,2,\ldots,N_T+1; k = 1,2,\ldots,T; l = 1,2,\ldots,NP\right) \tag{3.29}$$

where

λ^*_i is step length for i^{th} thermal unit

D^j_i is j^{th} search direction for i^{th} thermal unit

L^t_{pikl} is local best position for power generation of i^{th} thermal unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

After modifying local best solutions by applying Powell's pattern search, objective function is evaluated. If modified local best solutions improve the solution quality, then solutions are updated. Finally, global best solution is updated from local best solutions. The first PHOT based on PPO and PPS to solve multi-objective HTGS is elaborated in Algorithm-3.1.

3.5.2 Proposed Heuristic Optimization Technique-II

Evolutionary programming explores the search space quickly in the beginning, but its performance is slow as the search progresses. Thus, there is a possibility that EP converges at local best optimal solution. Adding a suitable local search technique has the potential to boost the performance significantly. In PHOT-II, initial search is performed by EP technique and after reaching a set number of movements, Powell's method is applied to avoid possible local optimum solutions. Elaborative steps are presented in ensuing sub-sections.

ALGORITHM-3.2: Proposed heuristic optimization technique-II for multi-objective HTGS

1. Read Input data. Set maximum and minimum values of all objectives and constant of proposed optimization technique.
2. Randomly initialize population as mentioned in sub-section 3.5.2.1.
3. Heuristic search technique is applied to satisfy equality constraints.
4. Start the movement counter t=0.
5. Set IT=50

   DO

   5.1 Increment the movement count t=t+1
   5.2 Compute water discharge rate for slack sub-interval by applying Eq. (3.9).
   5.3 Compute reservoir volume and hydro power for slack sub-intervals by using Eq. (3.4) and Eq. (3.3), respectively.
   5.4 Compute slack unit thermal power for all sub-intervals as given by Eq. (3.8).
   5.5 All inequality constraint violation is included in another objective function as given by Eq. (3.10).
   5.6 Create three offspring vectors using Gaussian, Cauchy and mean of Gaussian and Cauchy mutation operator as mentioned in sub-section 3.5.2.2.
   5.7 Combine parent and offspring to form a pool of 4*NP* members.
   5.8 Compute fuzzy membership function for all objectives and cardinal priority ranking by applying Eq. (3.11) and Eq. (3.23), respectively.
   5.9 Apply competition for survival.
   5.10 Select new *NP* member population on the basis of most number of wins.
   5.11 *IF*(t MOD IT=0) *THEN*
   Apply Powell's method to modify population
   IF (modified population generate improved solution) *THEN*
   Update population
   ENDIF
   ENDIF
   5.12 Update the scaling factor of EP.
   5.13 Update global best member on the basis of objective function.

   WHILE ($t \le t_{max}$)
6. Solution corresponding to maximum cardinal priority ranking is the best solution.

   STOP

3.5.2.1 Initialization of population

The members of population representing generation of thermal unit are initialized as given by Eq. (2.32) in chapter 2. The members representing water discharge rate of hydro units, are given as:

$$p_{qjkl}^{0} = q_j^{\min} + \left(q_j^{\max} - q_j^{\min}\right) \times rand() \;\; \left(j = 1,2,\ldots,N_H; k = 1,2,\ldots,T, l = 1,2,\ldots,NP\right) \quad (3.30)$$

After initializing, equality constraints are satisfied as discussed in section 3.5.1.1.

3.5.2.2 Evaluation of offspring and selection

The offspring represents generation of thermal units using Gaussian, Cauchy and mean of Gaussian and Cauchy mutation operator are given by Eq. (2.33) to Eq. (2.35), respectively in chapter 2. The offspring representing water discharge rate of hydro units are represented as:

$$P^t_{qjk(l+NP)} = P^t_{qjkl} + \sigma_{qjkl} N_{jk}(0,1)\;(j=1,2,\ldots,N_H; k=1,2,\ldots,T; k \neq h; l=1,2,\ldots,NP) \tag{3.31}$$

$$P^t_{qjk(l+NP)} = P^t_{qjkl} + \sigma_{qjkl} C_{jk}(0,1)\;(j=1,2,\ldots,N_H; k=1,2,\ldots,T; k \neq h; l=1,2,\ldots,NP) \tag{3.32}$$

$$P^t_{qjk(l+NP)} = P^t_{qjkl} + \sigma_{qjkl}\left(\frac{N_{jk}(0,1)+C_{jk}(0,1)}{2}\right)\;(j=1,2,\ldots,N_H; k=1,2,\ldots,T; k \neq h; l=1,2,\ldots,NP) \tag{3.33}$$

where

P^t_{qjkl} is member representing water discharge rate of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

σ_{qjkl} is standard deviation for P^t_{qjkl}

$P^t_{qjk(l+NP)}$ is offspring representing generation of j^{th} hydro unit at k^{th} sub-interval of l^{th} particle for t^{th} movement

$N_{jk}(0,1)$ is normally distributed random number of j^{th} hydro unit at k^{th} sub-interval

$C_{jk}(0,1)$ is a Cauchy random number of j^{th} hydro unit at k^{th} sub-interval

The standard deviation for thermal unit generation is given by Eq. (2.36) in chapter 2. The standard deviation for water discharge rate is computed as:

$$\sigma_{qjkl} = \frac{\beta\mu_D^{\max}}{\mu_D}\left(q_j^{\max} - q_j^{\min}\right)\quad (j=1,2,\ldots,N_H; k=1,2,\ldots,T; l=1,2,\ldots,NP) \tag{3.34}$$

where

$\mu_D^{\max}$ is maximum value of cardinal priority ranking.

After generating offspring, parents and offspring are combined to form a pool of 4*NP* members. The cardinal priority of 4*NP* members is computed and competition and selection process is done to select parents for next generation as discussed in sub-section 2.6.2.3 of chapter 2. To fine tune the selected population, Powell's search method is applied as discussed in section 3.5.1.6. Global best solution is decided by comparing cardinal priority ranking of members and scaling factor of evolutionary programming is updated during each movement as mentioned in section 3.5.1.7. The PHOT-II, to solve multi-objective HTGS is elaborated in Algorithm-3.2.

3.5.3 Proposed Heuristic Optimization Technique-III

The stochastic procedures are adopted by global search techniques that help to explore the search space quickly in the beginning but performance of these techniques become slow while the run progress. Predator-prey optimization and evolutionary programming techniques show high possibility to overcome local best solutions. But to fine tune the search process local search technique is integrated with global search techniques. Proposed heuristic optimization technique-III, introduces a heuristic algorithm that integrates PPO and EP techniques and to further improve the solution quality, Powell's pattern search method is implemented after certain movement of global search techniques. The PHOT-III to solve multi-objective HTGS is elaborated in Algorithm-3.3.

3.6 ELECTRIC POWER SYSTEMS AND RESULTS

The proposed heuristic optimization techniques have been applied on four electric power systems to demonstrate the effectiveness. The hydro sub-system configuration and network matrix includes the water time delays. The HTGS problem is initially solved for economic generation scheduling (case-I) where only operating cost is considered ignoring emission objective. In second attempt, HTGS problem is undertaken where only emission objective is considered (case-II) and economy objective is ignored. Finally, it is solved as a multi-objective HTGS (case-III) considering both the objectives, simultaneously. For each case, twenty runs are given to find the best results.

3.6.1 Electric Power System-V

The data of electric power system-V has been referred from [199]. The electric power system-V comprises 4-hydro and 3-thermal units. The scheduling period is 24 h with one hour sub-intervals. The hydro sub-system configuration and network matrix including the water time delay are shown in Fig E.1 (Refer Appendix E, Section E.5). The hydro unit power generation coefficients are given in Table E.14 (Refer Appendix E, Section E.5). The hydro reservoir storage capacity limits, plant discharge limits, initial and final storage capacity limits, rate of water discharge limits and hydro plant generation limits are given in Table E. 15 (Refer Appendix E, Section E.5). The reservoirs inflows are given in Tables E.16 (Refer Appendix E, Section E.5). The thermal power generation limits, cost coefficients and emission coefficients are given in Table E.17 (Refer Appendix E, Section E.5) and Table E.18 (Refer Appendix E, Section E.5), respectively. The load demand is tabulated in Table E.19 (Refer Appendix E, Section E.5).

ALGORITHM-3.3: Proposed heuristic optimization technique-III for multi-objective HTGS

1. Read Input data and constant of algorithms.
2. Randomly initialize the *NP* prey positions and velocities as mentioned in sub-section 3.5.1.1.
3. Randomly initialize the predator position and velocity of PPO technique as mentioned in sub-section 3.5.1.2.
4. Randomly initialize *NP* member of population of EP technique as mentioned in sub-section 3.5.2.1.
5. Heuristic search technique is applied to satisfy equality constraints for prey positions and member of population as mentioned in sub-section 3.5.1.1.
6. Movement count t=0.
7. Set *IT*=50.
8. Start the movement counter for velocity limit $m=0$.
   DO
   - 8.1 Increment the movement counter t=t+1
   - 8.2 Compute water discharge rate for slack sub-interval by applying Eq. (3.9).
   - 8.3 Compute reservoir volume and hydro power for slack sub-interval by applying Eq. (3.4) and Eq. (3.3), respectively.
   - 8.4 Compute slack thermal unit power as given by Eq. (3.8).
   - 8.5 All inequality constraint violation is included in another objective function as given by Eq. (3.10).
   - 8.6 Apply steps 7.6 to 7.12 of algorithm 3.1 of PHOT-I for multiobjective HTGS.
   - 8.7 Apply steps 5.6 to 5.10 of algorithm 3.2 of PHOT-II for multiobjective HTGS.
   - 8.8 Form a pool of *NP* local best positions and *NP* members of population.
   - 8.9 Arrange in ascending order and select *NP* solutions on the basis of objective function
   - 8.10 *IF* (t MOD IT =0) *THEN*
     - Apply Powell's method to modify *NP* solutions.
     - *IF* (modified solutions generate improved solution) *THEN*
       - Update solutions
     - *ENDIF*
   - *ENDIF*
   - 8.11 Update global best solution on the basis of objective function.
   - 8.12 Update scaling factor of EP technique.
   - 8.13 *IF*(global best position updated)*THEN*
     - $m=0$
   - *ELSE*
     - $m=m+1$
     - *IF* ($m>m_{max}$) *THEN*
       - Squeeze the velocity limit of PHOT-I by α factor
       - $m=0$
     - *ENDIF*
   - *ENDIF*

   WHILE ($t \le t_{\max}$)
9. Solution corresponding to maximum cardinal priority ranking is the best solution.
   STOP

3.6.1.1 Parameter Setting

The PHOTs as discussed in section 3.5 are applied to search the optimum solution. The procedure opted to find the best parameter of PHOT-I is same as discussed in sub-section 2.7.1.1 of chapter 2. The different values of best parameters of PHOT-I, are tabulated in Table 3.1. The velocity squeezing factor α has been set to 0.9. The scaling factors W_v and W_D are set to 0.05. For PHOT-II, the values of various scaling factors for EP like β_{init}, β_{final} and β_{step} are adjusted as 1, 0.01 and 0.005, respectively. For Powell's search method upper and lower limit of promising search area is same as set for PHOT-I. For PHOT-III, parameters setting are same as set for PPO, EP and PPS algorithms in PHOT-I and PHOT-II. Final generation schedule is obtained by taking population size as 50 in 1000 movements.

Table 3.2: Comparison of results: Electric power system-V

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost ×(10^3) ($)	Emission ×(10^3) (ton)	CPU time (s)	Cost ×(10^3) ($)	Emission ×(10^3) (ton)	CPU time (s)	Cost ×(10^3) ($)	Emission ×(10^3) (ton)	CPU time (s)
QADEVT [375]	41.76	30.71	--	45.97	16.65	--	42.94	17.92	--
ε-ODEM [404]	--	--	--	--	--	--	44.67	16.65	--
NSGA-II [404]	--	--	--	--	--	--	46.05	17.08	--
SPEA-II [404]	--	--	--	--	--	--	45.53	16.97	--
PESA-II [404]	--	--	--	--	--	--	45.43	16.84	--
QPSO [325]	42.36	31.30	--	45.27	17.77	--	44.26	18.23	--
SOHPSO-TVAC[391]	41.98	24.48	112.0	44.43	16.80	112.6	43.04	17.00	120.0
EP[199]	45.06	48.80	--	59.29	16.55	--	47.90	26.23	4582
Clonal SA[372]	42.44	--	109.1	--	--	--	--	--	--
DE [303]	43.50	21.09	72.96	51.45	18.26	72.73	44.91	19.61	74.97
Modified DE[235]	42.61	33.32	125.0	48.72	15.73	--	43.20	20.38	--
PSO [362]	42.47	28.13	123.5	48.26	16.93	124.7	43.28	17.90	132.4
PSO [266]	44.74	--	232.7	--	--	--	--	--	--
SA [266]	45.47	--	246.2	--	--	--	--	--	--
MOCA-PSO[398]	42.00	16.84	--	44.96	16.24	--	43.87	16.22	--
HMOCA[381]	41.80	16.84	--	46.74	15.91	--	43.59	16.20	--
PPO	42.11	26.17	31.04	48.90	16.00	30.82	44.11	17.47	31.62
PHOT-I	41.52	28.76	29.22	48.95	15.72	29.00	42.90	17.22	30.87
PHOT-II	42.04	29.96	32.54	48.94	15.73	32.14	43.65	16.96	32.98
PHOT-III	41.05	29.35	43.51	48.90	15.71	42.65	43.22	16.93	42.51

Note: QADEVT: quadratic approximation based differential evolution with valuable trade-off; ε-ODEMO: DE algorithm based on ε-domination and orthogonal design; NSGA-II: Non-dominated sorting genetic algorithm; SPEA-II: Strength Pareto evolutionary algorithm-II; PESA-II: Pareto envelope-based selection algorithm-II;

QPSO: quantum PSO; SOHPSO-TVAC: self-organizing hierarchical PSO with time varying acceleration coefficients; SA: Simulated annealing; MOCA-PSO: Multi-objective cultural algorithm based on PSO; HMOCA: Hybrid multi-objective cultural algorithm; PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III;

Table 3.1: Parameters of PHOT-I

Constant	$\lambda_i^{\max}$	$\lambda_i^{\min}$	a_i	b_i	C_1	C_2	C_3	C_4	Pf_{max}
Value	$0.1\times x_i^{\min}$	$-0.1\times x_i^{\min}$	$0.08\times x_i^{\max}$	$\left(\frac{1}{x_i^{\max}}\right)$	1.5	2	1	0.1	0.95

Note: $x_i^{\max}$, $x_i^{\min}$: Upper and lower limit of i^{th} decision variables.

Table 3.3: Power generation for minimum operating cost HTGS: Electric power system-V

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	20	209.8112	229.5185	86.05116	67.22905	5.37521	131.9956
2	780	22.14277	124.9861	319.3513	93.53946	48.44854	34.93351	136.6046
3	700	20	124.9789	229.5664	91.34644	66.54964	41.92976	125.6333
4	650	20	124.9269	229.5199	69.19142	58.87887	22.4668	125.0182
5	670	20	209.8342	139.7768	78.76998	59.23806	22.96437	139.4134
6	800	20	124.9188	319.295	60.88238	51.57577	47.51851	175.8134
7	950	20.13303	209.8154	319.2793	71.51664	67.28381	50.2962	211.6672
8	1010	20.10021	294.7606	229.5287	76.45585	66.57201	52.16999	270.4198
9	1090	175	294.733	319.2594	73.96664	56.89139	14.65829	155.4983
10	1080	20.04648	209.8195	409.0684	77.46165	69.32432	45.70537	248.5734
11	1100	20	294.7267	319.3718	77.57712	69.7243	12.7966	305.8026
12	1150	175	209.8129	319.2423	66.34325	52.33335	43.70031	283.567
13	1110	102.997	209.8218	319.304	77.31557	66.15308	37.94117	296.4663
14	1030	20.11513	209.8221	319.3055	81.82079	77.388	48.86378	272.6838
15	1010	20	209.8151	319.2874	75.08722	49.59625	34.65756	301.5553
16	1060	174.9785	209.8141	229.5133	64.33231	51.20493	36.74653	293.409
17	1050	20	209.8115	319.3003	80.52615	70.74669	45.24568	304.3683
18	1120	102.748	209.8145	319.2792	74.97269	71.15762	38.82349	303.2032
19	1070	102.4314	294.7206	229.5263	57.90852	49.4118	49.95577	286.0441
20	1050	175	40.00165	319.2888	81.37874	83.52309	50.58377	300.2226
21	910	20	209.8167	229.643	79.09409	71.09576	54.33576	246.0137
22	860	20	124.912	229.5161	70.18434	74.9859	55.34354	285.0569
23	850	20	124.892	229.5313	55.61242	58.21323	56.20169	305.5479
24	800	20	40.01196	229.5323	80.49236	76.59854	57.87459	295.5007

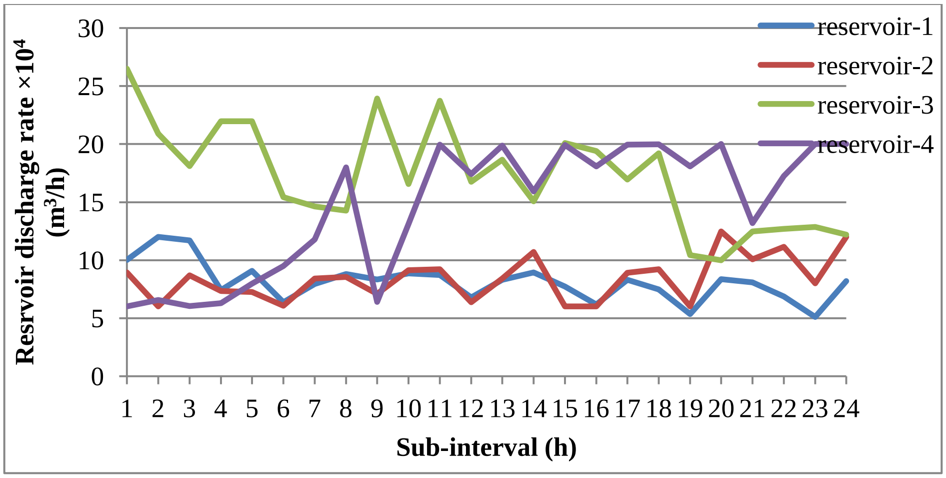

Figure 3.1: Reservoir discharge rate for minimum cost HTGS: Electric power system-V

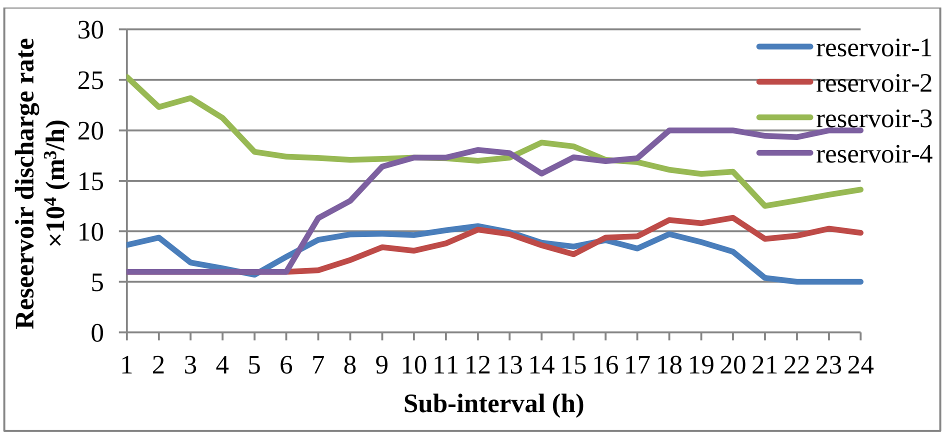

Figure 3.2: Reservoir discharge rate for minimum emission HTGS: Electric power system-V

3.6.1.2 Comparison of results

The results obtained from PHOTs, are compared with the results reported in literatures. To validate the feasibility of PHOTs, the result obtained from these techniques are also compared with PPO with same constraint handling technique. Table 3.2 represents cost and emission corresponding to economic, emission and multi-objective HTGS and CPU time to achieve the results by PHOTs and other techniques reported in literature. It is observed from Table 3.2 that PHOT-III, yields better result for minimum cost and minimum emission by achieving lower objective values, for electric power system-V. Conflicting nature of the two objectives is evident from the results. Table 3.3 and Fig. 3.1 represents power generation schedule and reservoir water discharge rate, respectively for minimum cost. Table 3.4 and Fig 3.2 represents power generation schedule and reservoir water discharge rate, respectively for minimum emission. The minimum value of each objective function is obtained by applying economy HTGS and emission HTGS problem separately. Because of conflicting nature of cost and emission objectives, minimum value of one objective is obtained at the expense of maximum value of other objective. To compare the multi-objective result among various reported results, membership function is computed by considering best minimum objective function value among results reported in Table 3.2, and corresponding maximum value. It is evident from Fig 3.3, that maximum value of cardinal priority ranking is achieved by the solution obtained from the PHOT-I. Results reported in [303,391] consumes more or less water than the available storage of water. However, in this study better results have been obtained which strictly satisfy all constraints of the electric power system. Table 3.5 and Fig 3.4 represent power generation schedule and reservoir discharge rate, respectively while solving the multi-objective generation scheduling problem for electric power system-V as obtained by PHOT-I.

Table 3.4: Power generation for minimum emission HTGS: Electric power system-V

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	170.3386	180.7346	124.2185	78.97171	49	14.85658	131.88
2	780	174.2169	186.7124	128.5317	83.5061	50.16399	27.84203	129.0269
3	700	158.7148	166.1443	113.2124	68.05759	51.296	16.83122	125.7437
4	650	144.516	145.3552	97.72334	63.92107	52.934	23.92518	121.6253
5	670	148.5772	152.3873	102.4075	59.04089	54.5	37.26503	115.8221
6	800	175	191.5078	133.6074	72.63052	55.504	38.06233	133.688
7	950	175	224.6215	159.982	82.64479	57.13809	37.99563	212.618
8	1010	175	236.6158	170.6672	85.07034	63.88784	37.61285	241.1459
9	1090	175	253.575	188.6871	85.11608	71.73107	36.63482	279.256
10	1080	175	246.4506	180.7477	84.6378	69.54841	35.85921	287.7563
11	1100	175	253.0228	186.863	87.29477	74.24285	35.8128	287.7638
12	1150	175	269.2969	204.3868	89.71402	81.44177	36.87877	293.2817
13	1110	175	254.1619	188.6813	86.90556	78.06869	37.20275	289.9798
14	1030	175	230.181	164.5223	81.74662	71.21379	33.77924	273.5572
15	1010	175	213.4662	150.4763	80.28062	65.9886	36.73051	288.0578
16	1060	175	230.9539	165.2787	84.67104	76.1051	42.92596	285.0653
17	1050	175	226.0401	161	79.91669	76.08318	44.85448	287.1057
18	1120	175	243.7635	177.294	88.34782	82.10271	47.49237	305.9996
19	1070	175	221.818	158.0176	83.57138	77.57684	49.24802	304.7683
20	1050	175	215.4683	152.1838	77.2487	77.2546	49.72006	303.1247
21	910	158.7055	165.3265	112.3301	56.94061	65.56329	54.25594	296.878
22	860	143.9627	146.1351	99.08579	53.89813	67.02986	56.51808	293.3703
23	850	138.5551	140.8989	94.48265	54.29103	69.90886	58.07764	293.7859
24	800	128.0008	122.8806	80.32928	54.6973	66.39808	58.68149	289.0125

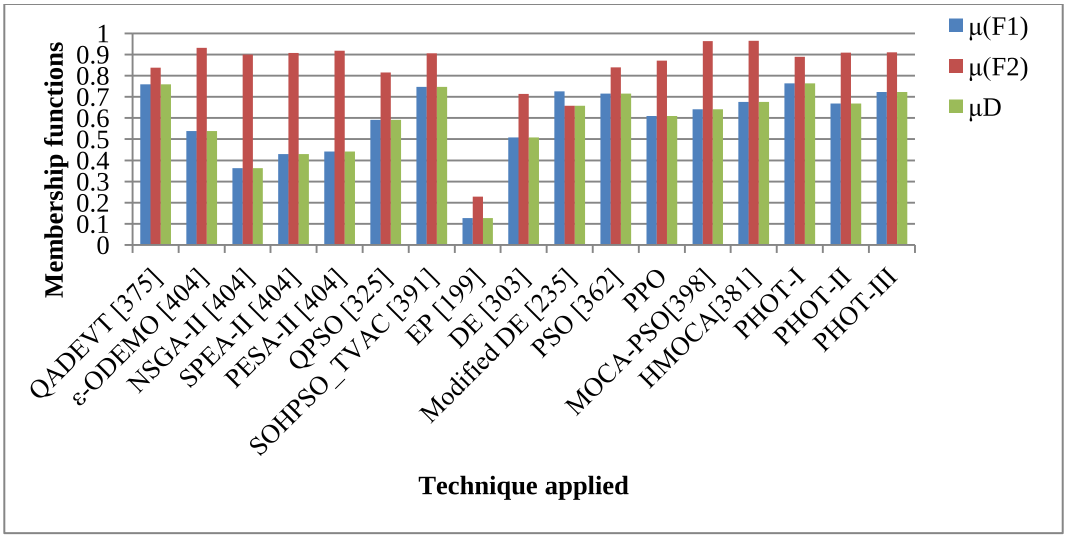

Figure 3.3: Comparison of cardinal priority ranking of multi-objective HTGS: Electric power system-V

Table 3.5: Power generation for multi-objective HTGS: Electric power system-V

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	175	209.423	50	88.392	52.745	40.555	133.883
2	780	174.215	208.049	139.539	59.562	49.852	19.887	128.892
3	700	175	124.877	138.791	62.397	50.993	22.333	125.606
4	650	103.618	125.136	137.177	84.172	52.692	25.688	121.513
5	670	102.862	126.022	139.86	87.02	63.746	32.698	117.789
6	800	175	209.865	139.456	53.126	54.529	35.316	132.706
7	950	175	209.966	214.143	80.749	65.115	19.081	185.944
8	1010	175	209.889	189.806	58.141	58.7	27.15	291.312
9	1090	175	210.088	229.33	88.333	74.994	44.07	268.181
10	1080	175	209.893	228.07	69.869	73.144	43.844	280.177
11	1100	173.9	209.765	225.296	94.266	79.428	44.212	273.130
12	1150	175	224.748	228.956	95.341	81.071	38.881	306.002
13	1110	175	283.54	229.467	77.042	60.527	35.547	248.876
14	1030	175	209.852	218.081	54.654	51.905	26.392	294.115
15	1010	103.939	209.852	228.877	81.46	69.675	38.59	277.735
16	1060	175	209.434	229.157	81.283	69.641	41.136	254.348
17	1050	175	209.684	170.648	75.655	82.183	49.493	287.331
18	1120	175	215.124	230.887	84.493	76.32	35.25	302.925
19	1070	175	209.634	189.319	87.362	55.434	49.383	303.866
20	1050	175	210.609	142.886	95.194	71.811	52.113	302.387
21	910	175	124.914	139.139	63.51	84.19	54.245	269.001
22	860	112.39	124.699	137.78	65.163	77.198	56.23	286.539
23	850	102.311	124.787	121.64	84.114	64.320	56.367	296.46
24	800	102.208	124.84	139.452	54.823	46.173	47.117	285.387

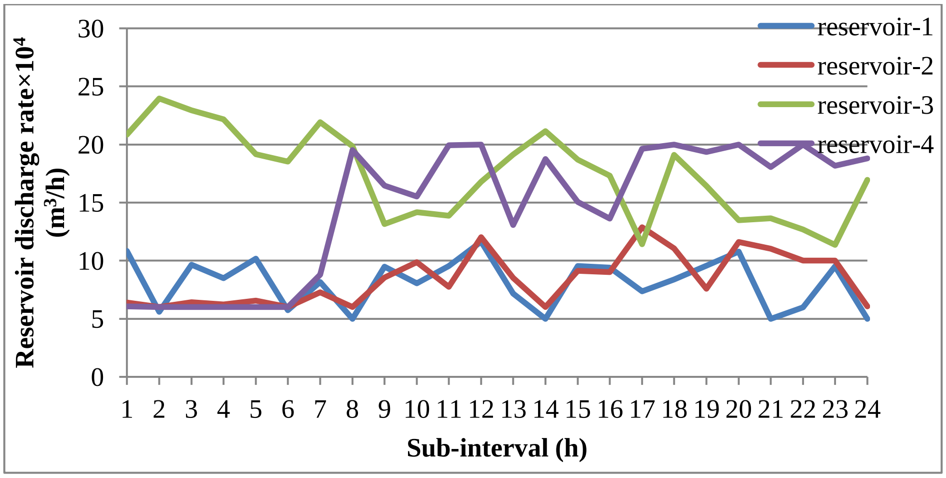

Figure 3.4: Reservoir discharge rate for multi-objective HTGS: Electric power system-V

The convergence behavior of the PPO technique and PHOTs, while solving minimum cost and minimum emission HTGS are shown in Figs 3.5 and 3.6, respectively for the electric power system-V. The convergence characteristic for multi-objective generation scheduling is shown in Fig 3.7. It is evident from Figs 3.5 to 3.7, Powell's pattern search not only improves the quality of the final solution but significantly improve the convergence of the search space process. From Fig 3.5 and Fig 3.7, it is observed that the PHOT-III, shows good convergence characteristics as compared to PHOT-I, PHOT-II and PPO technique.

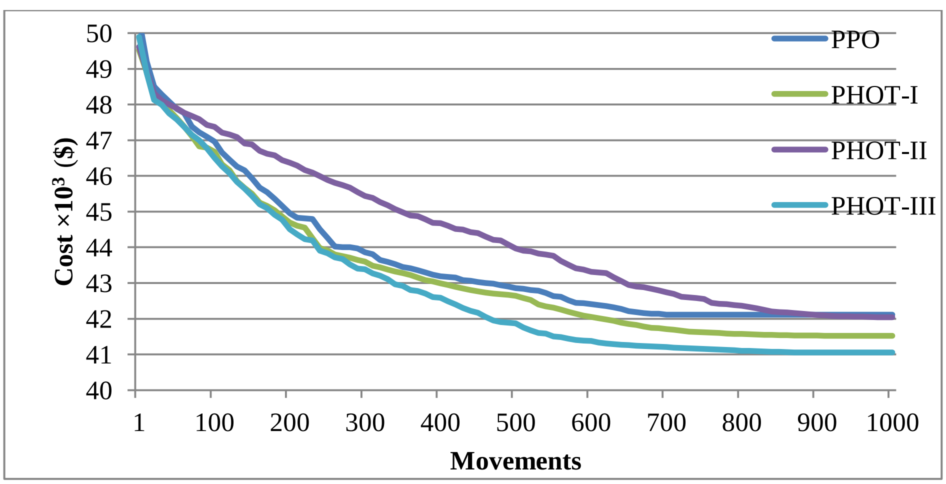

Figure 3.5: Convergence characteristics for minimum cost HTGS: Electric power system-V

From Table 3.2, the PHOT-I take less time to achieve the optimum solution as compared to PHOT-II and PHOT-III. Although PHOT-II take less time than PHOT-III, but sometimes struck in to local optimum solution.

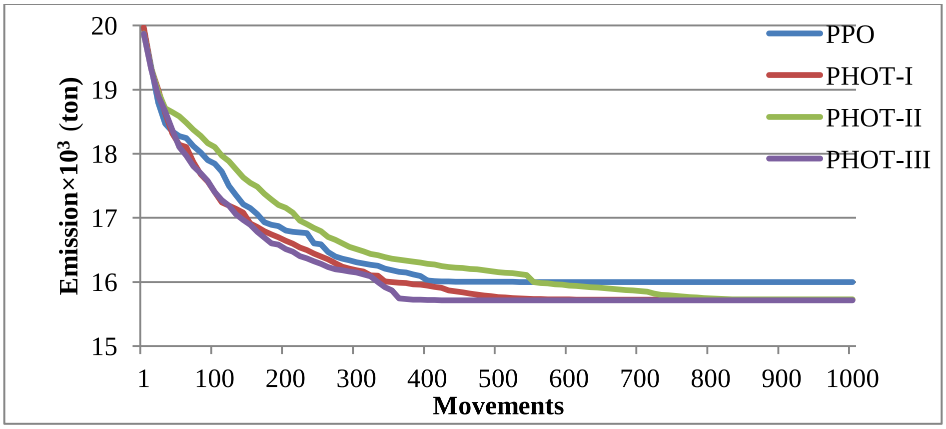

Figure 3.6: Convergence characteristics for minimum emission HTGS: Electric power System-V

Table 3.6: Obtained results with perturbed parameter of PHOT-I for minimum operating cost HTGS: Electric power system-V

Best Parameter-Δ	Best cost ×(10^3) (\$)	Average cost×(10^3) (\$)	Worst cost×(10^3) (\$)	Best Parameter + Δ	Best cost×(10^3) (\$)	Average cost×(10^3) (\$)	Worst cost×(10^3) (\$)
$v_i^{\max} = 0.8 \times v_i^{\max}$	41.57 0.130%	41.61 0.223%	41.73 0.513%	$v_i^{\max} = 1.2 \times v_i^{\max}$	41.52 0.007%	41.59 0.175%	41.66 0.344%
$v_i^{\min} = 0.8 \times v_i^{\min}$	41.56 0.108%	41.67 0.370%	41.75 0.561%	$v_i^{\min} = 1.2 \times v_i^{\min}$	41.54 0.055%	41.62 0.245%	41.67 0.373%
$v_j^{\max} = 0.8 \times v_j^{\max}$	41.52 0.130%	41.60 0.223%	41.71 0.513%	$v_j^{\max} = 1.2 \times v_j^{\max}$	41.53 0.007%	41.61 0.175%	41.67 0.344%
$v_j^{\min} = 0.8 \times v_j^{\min}$	41.58 0.108%	41.65 0.370%	41.73 0.561%	$v_j^{\min} = 1.2 \times v_j^{\min}$	41.55 0.055%	41.63 0.245%	41.68 0.373%
$\lambda_k^{\max} = 0.08 \times x_k^{\min}$	41.54 0.053%	41.61 0.223%	41.70 0.431%	$\lambda_k^{\max} = 0.12 \times x_k^{\min}$	41.58 0.146%	41.64 0.296%	41.69 0.416%
$\lambda_k^{\max} = -0.08 \times x_k^{\min}$	41.53 0.031%	41.60 0.190%	41.70 0.356%	$\lambda_k^{\max} = -0.12 \times x_k^{\min}$	41.53 0.036%	41.61 0.209%	41.70 0.419%
$\lambda_i^{\max} = 0.08 \times x_i^{\min}$	41.52 0.053%	41.62 0.223%	41.72 0.431%	$\lambda_i^{\max} = 0.12 \times x_i^{\min}$	41.59 0.146%	41.65 0.296%	41.73 0.416%
$\lambda_i^{\min} = -0.08 \times x_i^{\min}$	41.55 0.031%	41.63 0.190%	41.71 0.356%	$\lambda_i^{\min} = -0.12 \times x_i^{\min}$	41.54 0.036%	41.62 0.209%	41.72 0.419%
$a_i = 0.064 \times x_i^{\max}$	41.58 0.151%	41.64 0.286%	41.71 0.469%	$a_i = 0.096 \times x_i^{\max}$	41.58 0.154%	41.68 0.392%	41.76 0.578%
$a_j = 0.064 \times x_j^{\max}$	41.61 0.151%	41.66 0.286%	41.72 0.469%	$a_j = 0.096 \times x_j^{\max}$	41.59 0.154%	41.67 0.392%	41.75 0.578%
$b_i = 0.8 / x_i^{\max}$	41.53 0.019%	41.57 0.127%	41.63 0.269%	$b_i = 1.2 / x_i^{\max}$	41.54 0.055%	41.60 0.197%	41.67 0.368%
$b_j = 0.8 / x_j^{\max}$	41.54 0.019%	41.58 0.127%	41.63 0.269%	$b_j = 1.2 / x_j^{\max}$	41.53 0.055%	41.59 0.197%	41.65 0.368%
C_1=1.2	41.59 0.171%	41.64 0.296%	41.72 0.486%	C_1=1.8	41.54 0.048%	41.60 0.192%	41.65 0.320%
C_2=1.6	41.57 0.127%	41.64 0.286%	41.72 0.484%	C_2=2.4	41.55 0.074%	41.60 0.185%	41.64 0.291%
C_3=0.8	41.54 0.050%	41.60 0.199%	41.67 0.368%	C_3=1.2	41.54 0.045%	41.59 0.173%	41.70 0.440%
C_4=0.08	41.56 0.103%	41.63 0.272%	41.74 0.537%	C_4=0.12	41.55 0.086%	41.61 0.219%	41.69 0.414%
Pf_{max}=0.76	41.62 0.250%	41.69 0.416%	41.75 0.556%	Pf_{max}=1.14	41.60 0.197%	41.65 0.320%	41.69 0.414%
All (down)	41.61 0.223%	41.67 0.370%	41.73 0.517%	All (up)	41.59 0.178%	41.64 0.286%	41.68 0.395%

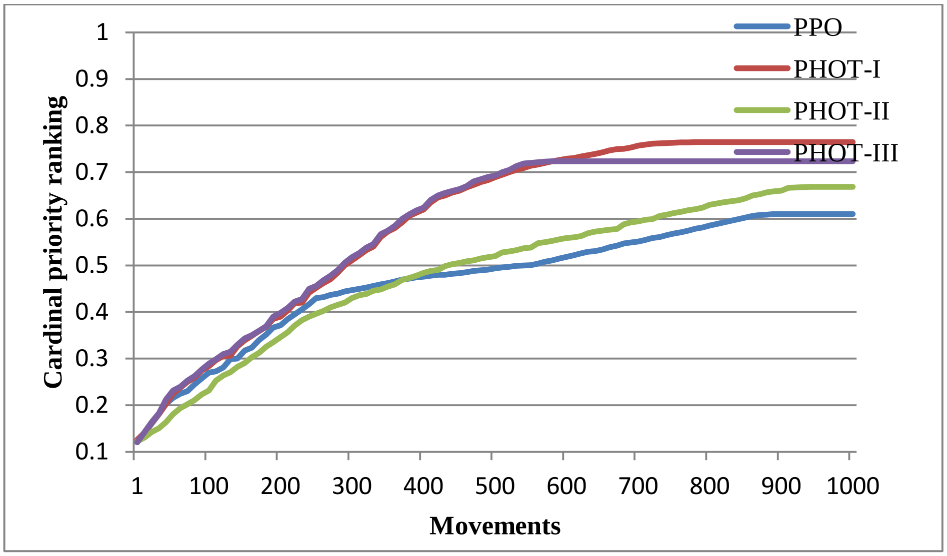

Figure 3.7: Convergence characteristics for cardinal priority ranking of multi-objective HTGS: Electric power System-V

3.6.1.3 Parameter sensitivity analysis and robustness of techniques

The parameters of PHOT-I is perturbed (Δ) around their original values by ±20% for electric power system-V for minimum cost HTGS. In this procedure one parameter is perturbed at a time and others remain fixed. The parameters are also perturbed simultaneously ±20% of their original values. The cumulative effects of the parameters' perturbations for PHOT-I, are shown in Table 3.6. Maximum variation from optimal values of the cost has been observed as (0.250%), (0.370%) and (0.578%) for best, average and worst results, respectively for PHOT-I. The sensitivity analysis is also done for PHOT-II and PHOT-III as the procedure adopted for PHOT-I and it is observed that parameters are very less sensitive to the variations. The best, average and worst results obtained by PHOTs have been compared in Table 3.7 to investigate the effect of initial solutions, and to verify the robustness of the PHOTs. It is concluded that the best, average and worst results of PHOT-III are less than solutions of other proposed techniques for minimum cost and minimum emission scheduling. The standard deviation (S.D.) is computed for twenty trials of minimum cost, minimum emission and cardinal priority ranking. It is observed from the results given in Table 3.7, that solutions obtained by PHOT-III show minimum standard deviation. So results obtained by PHOT-III have high precision.

Table 3.7: The best, average and worst values of objectives: Electric power system-V

Technique Applied	Scheduling		Best	Average	Worst	S. D.
PHOT-I	Economy	$F_1 \times 10^3$ ($)	41.52	41.92	42.45	0.22376
	Emission	$F_2 \times 10^3$ (ton)	15.72	15.95	16.32	0.20340
	Multi-objective	μ_D	0.76433	0.73782	0.70982	0.01421
PHOT-II	Economy	$F_1 \times 10^3$ ($)	42.04	42.57	42.96	0.25751
	Emission	$F_2 \times 10^3$ (ton)	15.73	15.98	16.46	0.21309
	Multi-objective	μ_D	0.66879	0.62784	0.59842	0.01632
PHOT-III	Economy	$F_1 \times 10^3$ ($)	41.05	41.44	41.85	0.22005
	Emission	$F_2 \times 10^3$ (ton)	15.71	15.89	16.26	0.20102
	Multi-objective	μ_D	0.72356	0.70998	0.69025	0.01398

3.6.2 Electric Power System-VI

The data of electric power system-VI has been referred from [341]. The electric power system-V comprises 4-hydro and 3-thermal units. The scheduling period is 24 h with one hour sub-intervals. The hydro sub-system configuration and network matrix is same as for electric power system-V. The operating characteristics of hydro units are same as for electric power system-V. The generation limits, cost coefficients and emission coefficients of thermal units are given in Table E.20 (Refer Appendix E, Section E.6) and Table E.21 (Refer Appendix E, Section E.6).

3.6.2.1 Comparison of results

The proposed heuristic techniques based on PPO, EP and PPS methods have been applied for scheduling of hydro-thermal electric power system-VI. The results obtained from PHOTs are compared with the results reported in literature. It is observed from Table 3.8, that PHOT-I yields better result for minimum cost and PHOT-III yields better results for minimum emission by achieving lower objective values, for electric power system-VI. Table 3.9 and

Fig. 3.8 represents power generation schedule and reservoir water discharge rate, respectively for minimum cost. Table 3.10 and Fig. 3.9 represents power generation schedule and reservoir water discharge rate, respectively for minimum emission.

Table 3.8: Comparison of results: Electric power system-VI

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost $\times(10^3)$ ($)	Emission (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission (ton)	CPU time (s)
DE [341]	110.8	51.37	2554	161.4	11.50	2424	--	--	--
RCGA [341]	112.9	49.87	3156	160.0	11.62	3261	--	--	--
NSGA-II [341]	--	--	--	--	--	--	127.2	18.96	4301
MODE [341]	--	--	--	--	--	--	126.8	17.7	2957
MO [411]	--	--	--	--	--	--	84.40	14.69	170
PPO	72.15	137.26	31.44	143.2	10.71	30.46	108.4	11.81	31.08
PHOT-I	68.35	163.67	29.10	139.6	10.04	29.24	81.28	18.41	29.23
PHOT-II	69.95	168.54	31.52	147.20	10.52	32.04	82.11	17.04	32.14
PHOT-III	68.80	166.01	36.36	109.29	9.93	36.51	81.00	21.69	36.72

Note: MODE: Multi objective differential evolution; RCGA: Real coded GA; PHOT-I: Proposed heuristic optimization technique-I, PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

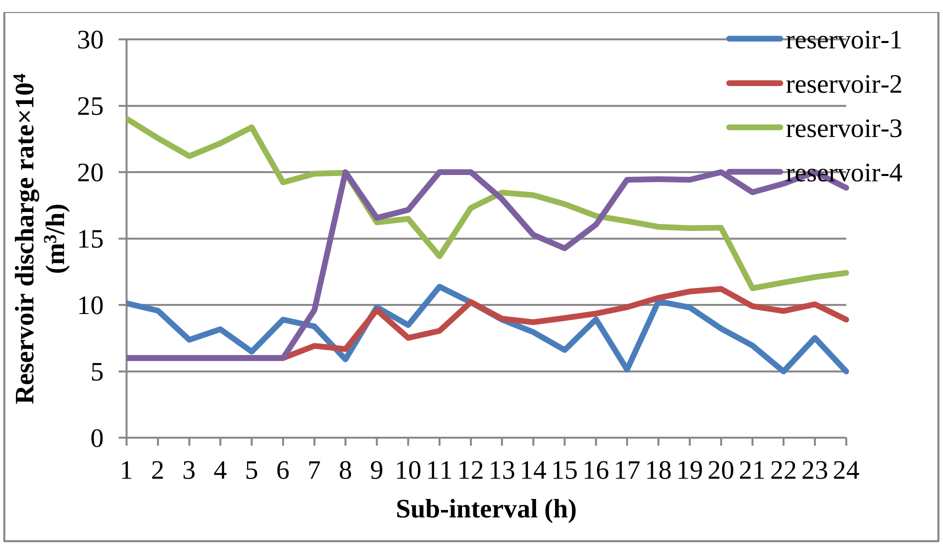

Figure 3.8: Reservoir discharge rate for minimum cost HTGS: Electric power system-VI

Table 3.9: Power generation for minimum operating cost HTGS: Electric power system-VI

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	175	216.1481	67.96017	86.51125	49	23.41882	131.9616
2	780	175	243.2021	71.85533	83.89906	50.16399	26.85806	129.0215
3	700	175	196.4234	51.90971	70.77339	51.296	28.85934	125.7381
4	650	175	153.8452	50	76.10054	52.934	20.50068	121.6196
5	670	175	197.6652	51.93653	64.30942	54.5	10.77271	115.8161
6	800	175	253.7845	72.71069	79.81113	55.504	30.58958	132.6001
7	950	175	300	116.3196	76.32051	62.42183	27.06911	192.8675
8	1010	175	300	96.44483	59.07971	60.30555	24.80943	294.3589
9	1090	175	300	141.1296	84.8748	78.14814	37.45928	273.3847
10	1080	175	299.3771	141.4453	77.84274	65.26163	36.38211	284.6912
11	1100	175	299.9999	116.4963	92.23231	69.32962	40.94184	306.0004
12	1150	175	299.993	165.4715	87.73459	81.55592	34.35542	305.89
13	1110	175	299.9672	156.0467	81.15952	73.88136	31.40851	292.5371
14	1030	175	299.9785	103.6399	76.08267	71.9131	34.06467	269.3214
15	1010	175	299.6205	95.07458	67.4544	73.83719	37.717	261.2967
16	1060	175	300	106.6571	84.01828	75.63562	42.14732	276.5421
17	1050	175	300	95.45847	55.77336	77.33215	43.99036	302.4443
18	1120	175	299.9728	126.6218	92.41142	78.86996	45.33386	301.7906
19	1070	175	288.017	92.16486	89.63143	78.05987	46.93369	300.1935
20	1050	175	288.0111	82.48449	79.65659	76.22659	46.80181	301.8199
21	910	175	201.9511	53.98308	70.29713	68.31708	51.56929	288.8828
22	860	175	169.1499	50	54.24346	66.08044	54.5752	290.9514
23	850	175	132.5839	50	75.08877	67.97675	56.874	292.4771
24	800	175	120.0492	50	54.70451	60.90932	58.39619	280.9413

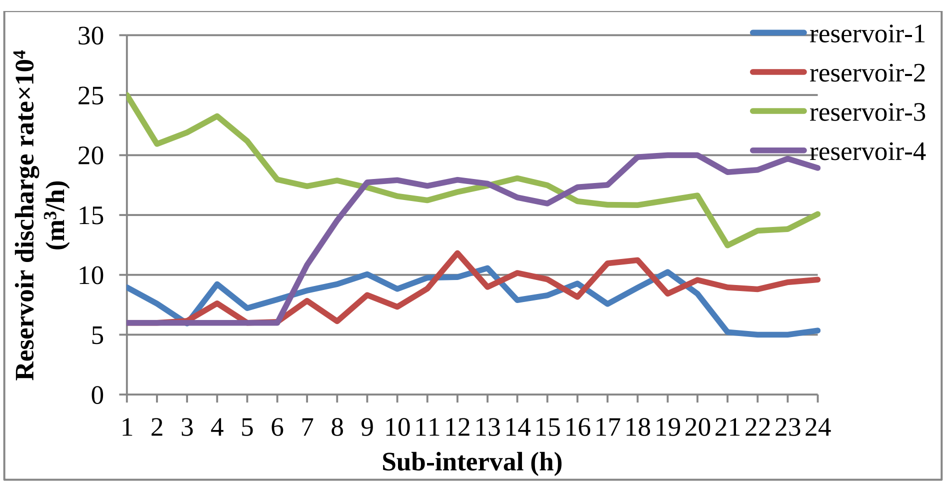

Figure 3.9: Reservoir discharge rate for minimum emission HTGS: Electric power system-VI

Table 3.10: Power generation for minimum emission HTGS: Electric power system-VI

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	160.3281	125.2704	186.1409	80.79861	49	16.58197	131.88
2	780	160.0455	127.1057	205.6094	72.74972	50.16399	35.29882	129.0269
3	700	149.4945	122.0642	164.0062	60.92272	52.41294	25.35566	125.7437
4	650	124.9931	108.2179	134.5737	83.59737	63.80873	13.1839	121.6253
5	670	129.3181	115.4813	162.8922	70.62269	53.57454	22.28919	115.8221
6	800	169.5298	128.7566	203.7671	75.11158	55.21868	34.13667	133.4796
7	950	173.0214	143.6741	244.063	79.22583	67.3334	36.63108	206.0512
8	1010	173.7902	143.5465	266.9585	82.02292	55.14112	35.15089	253.3899
9	1090	174.8716	148.0159	287.5473	85.93348	69.80547	36.36777	287.4585
10	1080	172.7993	147.5876	286.4033	79.66492	63.44158	37.95412	292.1492
11	1100	174.8842	151.3985	286.8046	85.29433	73.52844	39.43906	288.6508
12	1150	173.8798	155.6798	316.3059	86.30243	87.48102	37.9459	292.4051
13	1110	174.0408	150.9374	295.7934	89.78851	72.20834	37.12992	290.1017
14	1030	174.8104	144.8924	239.4682	75.66808	77.69881	36.53716	280.925
15	1010	173.9402	137.727	228.066	79.23335	74.41249	39.91618	276.7048
16	1060	174.9375	142.8473	256.1696	85.71431	66.03015	46.43026	287.8709
17	1050	174.7435	144.5615	238.6771	75.14538	80.05499	47.99173	288.8257
18	1120	174.7087	148.1759	280.3955	84.17756	78.53958	49.52587	304.4768
19	1070	174.3649	145.4639	243.4627	90.98424	61.71864	50.27843	303.7272
20	1050	174.7759	141.2277	236.3972	80.23406	66.71527	49.54435	301.1055
21	910	165.6411	123.2439	159.2023	55.69606	62.58212	55.32306	288.3115
22	860	132.3709	117.4963	150.064	53.96029	61.73132	57.66133	286.7158
23	850	133.8674	110.0033	139.1592	54.34213	64.8496	58.68994	289.0884
24	800	121.5077	101.738	115.047	57.89888	64.9727	58.12233	280.7134

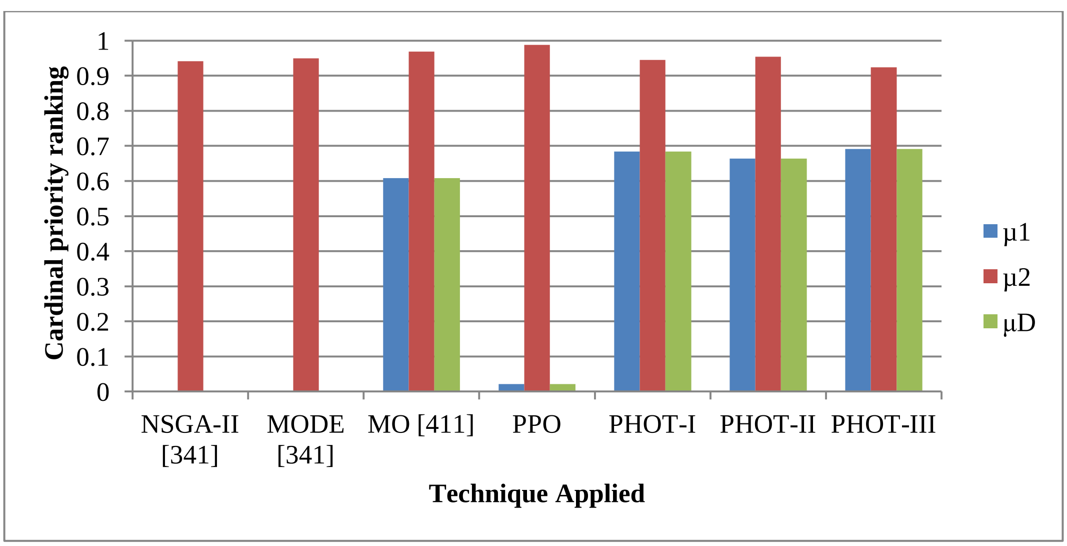

Figure 3.10: Comparison of cardinal priority ranking of multi-objective HTGS: Electric power system-VI

Table 3.11: Power generation for multi-objective HTGS: Electric power system-VI

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	169.0538	168.646	124.8562	82.63612	49	23.92789	131.88
2	780	173.8442	202.102	126.2074	63.5256	50.16399	35.12986	129.0269
3	700	156.2333	157.7403	94.44338	77.49546	51.296	34.79621	127.9954
4	650	167.5731	115.4983	72.83981	83.24074	75.5594	13.15911	122.1296
5	670	133.587	176.5746	107.2176	68.4146	57.93536	10.66555	115.6053
6	800	171.1213	187.1514	135.7681	79.8637	53.20619	39.78868	133.1006
7	950	174.9252	215.6372	198.482	76.86702	65.35725	33.94724	184.7841
8	1010	174.9997	220.5471	201.5547	69.17191	56.71503	31.17833	255.8331
9	1090	174.7383	230.7453	208.3769	86.45596	64.18206	35.96238	289.539
10	1080	174.9351	219.1322	215.1868	76.54132	71.32777	37.58062	285.3229
11	1100	175	221.9189	204.3968	89.17872	78.48754	38.15733	292.8854
12	1150	174.207	226.4811	244.0614	79.56036	85.14428	37.76443	302.8099
13	1110	174.313	231.8872	224.4657	82.42532	63.70275	36.33256	296.9014
14	1030	172.9149	215.1131	168.4219	74.77925	80.99804	33.54134	284.2583
15	1019	174.2001	211.9989	156.313	80.07381	66.38801	40.71779	280.3349
16	1060	174.7817	222.1078	185.4736	89.56802	54.55672	47.04234	286.4968
17	1050	174.879	212.5875	162.747	71.62569	81.68773	48.84551	297.6558
18	1120	174.9918	225.7384	215.9123	83.94884	64.01913	51.30117	304.1177
19	1070	174.3734	214.0644	177.678	92.33225	58.37968	51.47423	301.7273
20	1050	174.2184	208.8403	176.0752	78.85174	60.72824	50.86191	300.4541
21	910	174.4003	181.7336	55.6747	79.90627	69.3288	53.99635	294.9905
22	860	171.7203	167.7443	86.84328	53.99868	62.37427	53.31626	264.0313
23	850	162.3943	168.6708	58.87868	58.41236	58.1188	57.41761	286.1385
24	800	174.7401	131.4051	61.63054	56.31063	50.42179	58.46914	267.0527

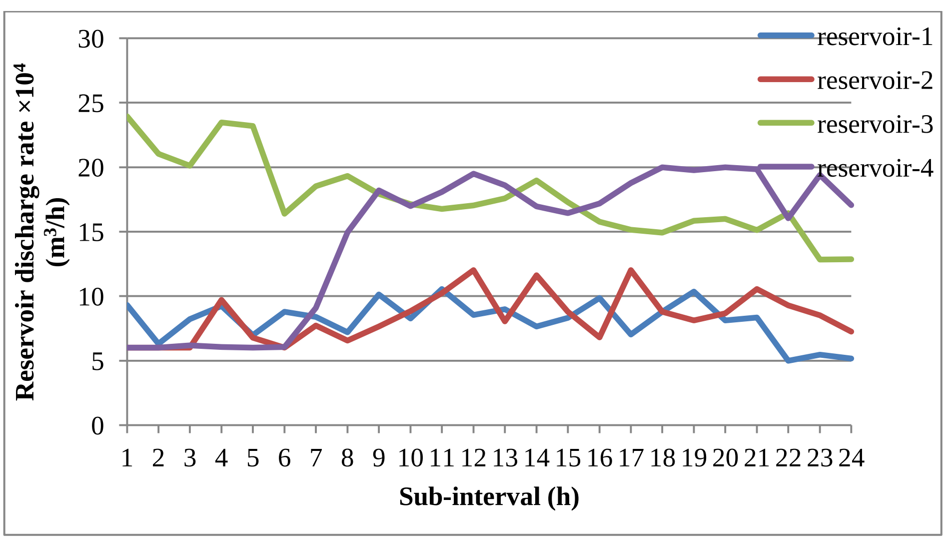

Figure 3.11: Reservoir discharge rate for multi-objective HTGS: Electric power system-VI

To select better multi-objective solution, cardinal priority ranking is computed. It is evident from Fig 3.10, that maximum value of cardinal priority ranking is achieved by solution obtained from PHOT-III. It is observed from Table 3.8, that a relatively large difference of cost exists among the results obtained by PHOTs as compared to NSGA-II, MODE. So, it is concluded that solutions obtained by NSGA-II and MODE struck to a local optimum solution. Table 3.11 and Fig. 3.11 represent power generation schedule and reservoir discharge rate, respectively while solving the multi-objective generation scheduling problem by applying PHOT-III for power system system-VI.

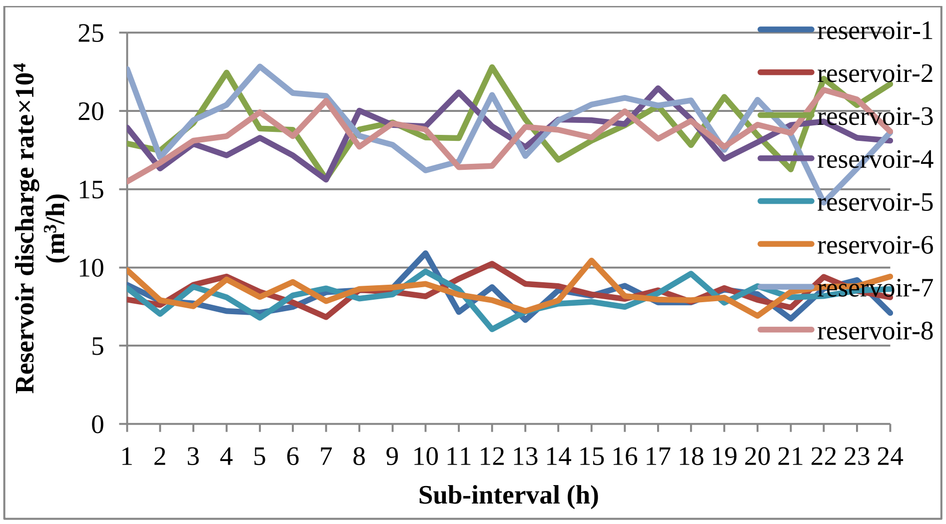

Figure 3.12: Reservoir discharge rate for minimum cost HTGS: Electric power system-VII

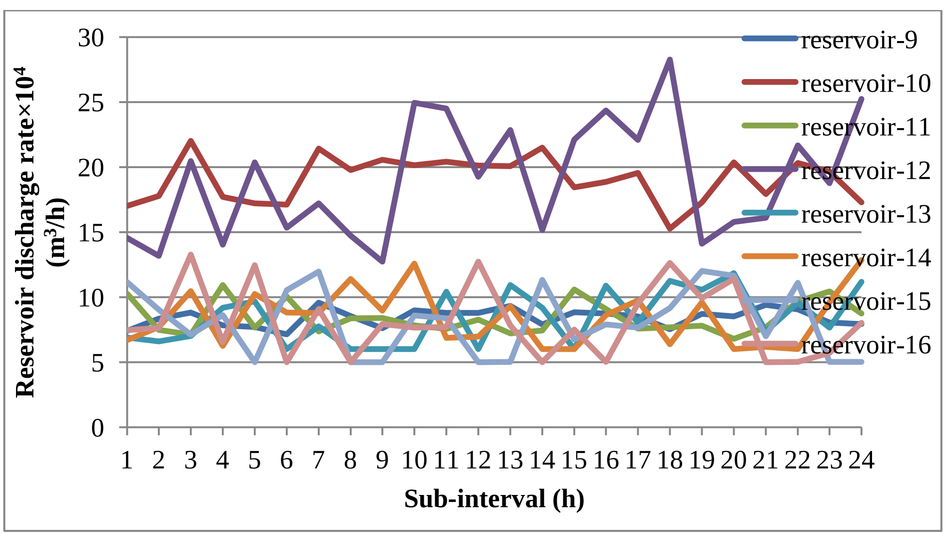

Figure 3.12: Reservoir discharge rate for minimum cost HTGS (Continued)

3.6.3 Electric Power System-VII

Electric power system-VII is comprised of 16 hydro units and 6 thermal units, and scheduling period is of 24 h having a 1 h sub-interval. The hydro plant data has been taken from [217], and thermal unit characteristics are obtained from [364]. The hydro sub-system configuration is shown in Fig E.2 (Refer Appendix E, Section E.7). The hydro unit power generation coefficients are given in Table E.22 (Refer Appendix E, Section E.7). The hydro reservoir storage capacity limits, plant discharge limits, initial and final storage capacity limits, rate of water discharge limits and hydro plant generation limits are mentioned in Table E.23 (Refer Appendix E, Section E.7). The reservoirs inflows are given in Tables E.24 (Refer Appendix E, Section E.7). The thermal power generation limits, cost coefficients and emission coefficients of thermal units are given in Table E.25 (Refer Appendix E, Section E.7). The load demands are given in Table E.26 (Refer Appendix E, Section E.7).

3.6.3.1 Comparison of results

Three proposed heuristic optimization techniques have been applied for scheduling of hydro-thermal electric power system-VII. The results obtained from PHOTs are compared with the result from PSO and PPO technique. It is observed from Table 3.12 that PHOT-III, yields minimum cost and minimum emission by achieving lower objective values, for electric power system-VII. Thermal and hydro power corresponding to minimum cost is tabulated in Table 3.13 and Table 3.14, respectively. Figure 3.12 represents reservoir discharge rate for minimum cost.

Table 3.12: Comparison of results: Electric power system-VII

Technique Applied	Economy Scheduling			Emission Scheduling			Multi-objective Scheduling		
	Cost (×10^3) ($)	Emission (×10^3) (ton)	CPU time (s)	Cost (×10^3) ($)	Emission (×10^3) (ton)	CPU time (s)	Cost (×10^3) ($)	Emission (×10^3) (ton)	CPU time (s)
PSO	1365.7	26.236	75.32	1390.5	24.871	75.91	1364.0	25.340	77.31
PPO	1349.8	26.967	37.24	1391.4	23.711	38.53	1360.1	25.064	38.56
PHOT-I	1337.5	27.225	31.35	1406.2	23.184	31.52	1359.1	24.289	31.57
PHOT-II	1337.3	27.218	34.25	1405.1	23.181	34.16	1361.8	24.390	34.61
PHOT-III	1337.2	27.231	40.31	1404.9	23.180	40.36	1358.8	24.305	40.52

Note: PHOT-I: Proposed heuristic optimization technique-I, PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

Table 3.13: Thermal power generation for minimum operating cost HTGS: Electric power system-VII

k	p_{Dk} (MW)	Thermal Power (MW)					
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}
1	1374	80.03328	80.92334	210	225	315	325
2	1278	44.80622	28.61169	202.0368	225	315	325
3	1372	79.23453	76.35205	210	225	315	325
4	1058	33.10393	15.72363	151.0953	155.7763	270.2789	290.1988
5	1358	71.28413	69.17517	210	225	315	325
6	1282	47.86977	28.53577	210	214.1622	315	325
7	1130	33.5168	17.80811	148.9509	185.9722	293.8396	305.285
8	1200	40.24189	18.37122	176.0171	184.7561	315	325
9	1248	48.04558	25.03442	193.5279	200.2576	315	325
10	1364	74.34255	70.09363	210	225	315	325
11	1146	36.03767	18.7688	170.3712	174.4029	299.0776	306.3999
12	1262	45.86384	30.26245	198.2336	211.2117	315	325
13	1246	44.80364	27.23096	193.345	201.1044	315	325
14	1140	33.76936	16.15369	157.0767	154.962	310.2666	325
15	1226	42.19844	18.75867	177.7306	205.4189	315	325
16	1314	57.07966	39.29211	210	225	315	325
17	1426	100.0573	106.4093	210	225	315	325
18	1028	33.46978	13.07068	130.4037	131.9281	285.2457	290.8114
19	1148	36.17852	19.77429	160.5272	164.5192	306.0236	313.164
20	1256	46.4886	25.87061	198.7144	199.8521	315	325
21	1348	73.0806	61.55066	210	225	315	325
22	1424	98.80446	106.6074	210	225	315	325
23	1070	34.51646	13.08569	141.8033	140.4382	304.5619	293.9638
24	1118	35.05403	12.84106	161.2208	169.0477	297.3492	303.8364

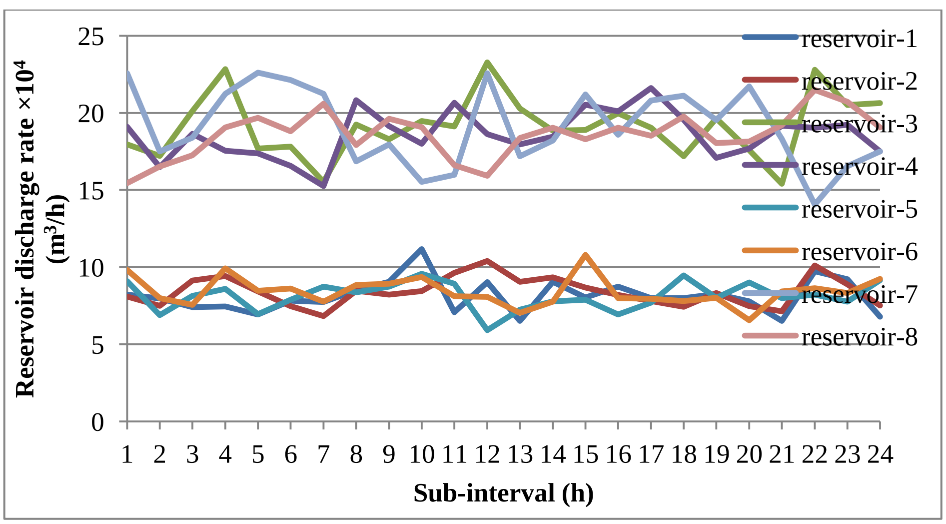

Figure 3.13: Reservoir discharge rate for minimum emission HTGS: Electric power system-VII

Thermal and hydro power corresponding to minimum emission is tabulated in Table 3.15 and Table 3.16, respectively. Figure 3.13 represents reservoir discharge rate for minimum emission.

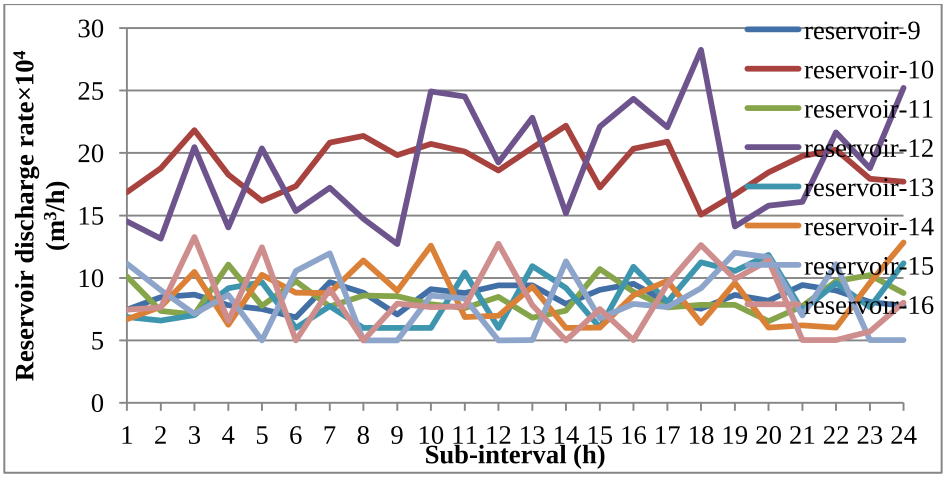

Figure 3.13: Reservoir discharge rate for minimum emission HTGS (Continued)

Table 3.15: Thermal power generation for minimum emission HTGS: Electric power system-VII

k	p_{Dk} (MW)	Thermal Power (MW)					
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}
1	1374	125	150	192.605	194.4246	289.8864	284.063
2	1278	125	150	178.0116	177.693	254.7702	255.4394
3	1372	125	150	196.5217	194.5533	283.526	281.5323
4	1058	123.8023	119.5558	135.7305	133.9768	199.0411	203.3096
5	1358	125	150	193.8163	191.7475	282.4031	272.4921
6	1282	125	150	175.6987	177.3264	256.527	257.1793
7	1130	124.7236	139.0999	148.2515	147.7628	211.392	214.4529
8	1200	125	150	159.9923	160.2985	232.3845	230.9637
9	1248	125	150	172.3945	168.1656	246.5855	243.8896
10	1364	125	150	192.8096	191.2117	278.9838	282.2477
11	1146	125	145.0962	148.4095	149.97	218.9381	217.6766
12	1262	125	150	172.856	173.215	255.4077	249.7468
13	1246	125	150	168.7661	171.0995	244.0602	248.5037
14	1140	125	144.954	148.4993	149.2303	216.2265	213.5105
15	1226	125	150	167.7489	162.2038	238.4852	239.5126
16	1314	125	150	183.2628	183.4859	265.5992	263.8384
17	1426	125	150	205.8977	205.2553	296.9672	299.063
18	1028	112.0845	112.8311	135.5016	132.5312	194.0038	197.7397
19	1148	125	141.2722	151.9596	150.9742	215.4131	215.5331
20	1256	125	150	170.9432	171.201	245.6266	249.5791
21	1348	125	150	192.812	189.1661	276.7571	275.9596
22	1424	125	150	205.355	202.8559	299.5066	297.1405
23	1070	119.6586	125.2717	135.8603	142.541	200.9779	203.5143
24	1118	125	133.7079	144.0969	146.1287	215.8977	214.2292

Table 3.14: Hydro power generation (MW) for minimum operating cost hydro-thermal scheduling: Test system-VII

k	p_{7k}	p_{8k}	p_{9k}	p_{10k}	p_{11k}	p_{12k}	p_{13k}	p_{14k}	p_{15k}	p_{16k}	p_{17k}	p_{18k}	p_{19k}	p_{20k}	p_{21k}	p_{22k}
1	8.0409	6.1731	5.2140	25.4936	7.9194	7.1835	3.1721	23.2196	5.8388	5.4491	7.3880	5.8400	5.5036	5.3722	9.0779	7.1578
2	7.4568	5.9592	5.5035	24.0487	6.8971	6.0320	5.5373	25.2445	6.4312	5.5662	5.7527	6.2023	5.3851	6.0988	8.0808	7.3492
3	7.3795	6.7291	5.1243	25.5118	8.0682	5.8061	4.9799	26.4957	6.6726	4.0868	5.5426	4.9908	5.7358	7.5773	6.8867	9.8264
4	7.0657	7.0156	3.7246	25.3718	7.6500	6.8608	4.6235	27.0037	6.1252	5.7737	7.6755	6.3602	7.1347	5.0859	7.8760	6.4764
5	6.9880	6.4665	5.1794	26.7106	6.7252	6.2398	3.3772	28.1296	6.1232	5.9051	5.8835	5.2409	7.3707	7.5550	5.2087	9.4372
6	7.2027	6.0368	5.2045	26.0327	7.6596	6.7636	4.1163	27.5499	5.7791	5.9227	7.1815	6.3469	5.0547	6.7051	8.8024	5.0739
7	7.7872	5.4022	5.9368	25.0400	7.8937	5.9409	4.2111	29.1592	7.1713	4.4741	5.5278	6.1445	6.2671	6.5712	9.1460	7.9544
8	7.8498	6.4048	5.2626	27.9705	7.4851	6.2614	5.1561	27.4329	6.3935	5.1787	6.0274	6.4455	5.0127	7.5888	5.0448	5.0993
9	7.9439	6.2312	5.1237	27.3212	7.6808	6.2042	5.3351	28.4786	5.7544	4.8944	5.9523	6.4147	5.0700	6.1879	5.1509	7.3912
10	9.0623	6.0448	5.4046	27.2911	8.5295	6.2740	5.7107	28.0878	6.5607	4.9253	5.6048	3.1376	5.1820	7.5947	7.8805	7.2737
11	7.0022	6.6999	5.4520	28.3278	7.9438	5.8986	5.6734	26.1498	6.4528	4.7599	5.5227	3.2352	7.9469	4.6459	7.8206	7.4103
12	8.1665	7.1468	3.5055	26.8748	6.2632	5.7515	4.2803	26.2480	6.4783	4.7930	6.0319	5.5400	5.2683	4.8627	5.3744	9.8433
13	6.7716	6.3720	4.9986	26.4840	7.2056	5.3362	5.5075	28.4412	6.7046	4.8345	5.3869	4.0374	8.2054	6.2558	5.4542	7.5205
14	8.1781	6.2292	5.7450	27.7664	7.6357	5.8049	4.8587	28.1237	5.8300	4.2111	5.5762	6.3026	7.2006	4.2059	9.7122	5.3919
15	8.0225	5.9479	5.5223	27.4402	7.7826	7.1834	4.4273	27.8673	6.4307	5.3847	7.3324	4.4118	5.2082	4.4057	6.9998	7.5270
16	8.4641	5.8333	5.2486	27.1600	7.5849	5.9429	4.2559	29.1110	6.3896	5.2179	6.5145	3.0933	8.1741	6.2201	7.9127	5.5055
17	7.7848	6.1442	4.7837	28.2903	8.2327	5.8028	4.3805	28.1341	6.2188	4.9491	5.5866	4.2246	6.5627	6.7674	7.7431	8.9282
18	7.8032	5.6218	5.5799	27.1814	9.0082	5.7209	4.1841	29.0767	5.5541	5.9439	5.6166	0.0000	8.0840	4.6284	8.7725	10.2951
19	8.3539	6.0000	4.4845	25.4047	7.8066	5.6852	5.2851	28.1312	6.1215	5.7017	5.5730	6.1157	7.4595	6.4765	10.1412	9.0729
20	8.1470	5.4534	5.3369	26.5643	8.5042	4.8991	4.1087	29.0482	5.8901	4.7323	4.8976	6.0218	7.7198	4.1847	9.8910	9.6752
21	6.9683	5.1728	5.8305	27.2965	7.9991	5.8875	4.8663	28.8695	6.3160	5.4280	5.5339	5.9209	5.2828	4.4410	7.1329	5.4228
22	8.3319	6.3560	3.8079	27.0936	8.0437	6.1056	5.7364	30.4378	6.1169	4.6352	6.6949	4.1437	6.6093	4.5034	9.5247	5.4472
23	8.6549	5.8669	4.5615	26.7981	8.2645	6.1392	5.5622	29.3276	5.5677	4.7919	6.9921	5.1957	5.5363	6.8384	5.4395	6.0939
24	7.2511	5.5953	3.8825	26.9076	8.3412	6.3936	5.0098	27.6884	5.4970	5.4874	5.9990	1.9050	7.2949	7.9877	5.4803	7.9302

Table 3.16: Hydro power generation (MW) for minimum emission hydro-thermal Scheduling: Test system-VII

k	p_{7k}	p_{8k}	p_{9k}	p_{10k}	p_{11k}	p_{12k}	p_{13k}	p_{14k}	p_{15k}	p_{16k}	p_{17k}	p_{18k}	p_{19k}	p_{20k}	p_{21k}	p_{22k}
1	7.6436	6.2505	5.2052	25.5799	8.1516	7.1700	3.2345	23.1886	5.8647	5.4840	7.3189	5.8418	5.4971	5.3655	9.0739	7.1503
2	7.5463	5.8903	5.5527	24.1448	6.7896	6.0848	5.4376	25.1046	6.4942	5.2784	5.6720	6.2001	5.3789	6.0933	8.0753	7.3215
3	7.2033	6.8555	4.7851	25.9082	7.6870	5.8145	5.3170	26.0029	6.5801	4.1563	5.5416	4.9825	5.7375	7.5789	6.8880	9.8275
4	7.2506	7.0025	3.4821	25.5776	7.9529	7.1953	4.2540	27.4544	6.1086	5.6151	7.7541	6.3573	7.1362	5.0875	7.8772	6.4777
5	6.8629	6.4412	5.5022	26.0694	6.8460	6.3869	3.5332	28.0647	5.9942	6.0723	5.9523	5.2381	7.3722	7.5565	5.2100	9.4383
6	7.4568	5.8505	5.4847	25.5259	7.4514	6.4450	3.6735	27.8789	5.6035	5.8663	7.0439	6.3459	5.0563	6.7066	8.8035	5.0752
7	7.3814	5.4068	5.9652	24.6446	7.9299	5.8516	4.0740	29.2567	7.2385	4.7163	5.7681	6.1398	6.2685	6.5727	9.1471	7.9555
8	7.8708	6.3506	5.1283	28.2663	7.6906	6.3432	5.5559	27.7236	6.5738	4.5064	6.1545	6.4454	5.0142	7.5901	5.0462	5.1005
9	8.1929	6.1115	5.4254	27.1989	7.9310	6.2639	5.3381	28.6850	5.4353	5.1394	6.0220	6.4154	5.0714	6.1894	5.1522	7.3924
10	9.1873	6.2256	5.0393	26.4067	8.4126	6.4144	5.8589	28.1842	6.6689	4.6513	5.6200	3.1420	5.1833	7.5959	7.8816	7.2747
11	6.9750	6.8846	5.1876	28.0793	8.1248	5.7303	5.8804	26.1421	6.4946	4.8312	5.5091	3.2422	7.9481	4.6474	7.8216	7.4113
12	8.3392	7.2014	3.2258	26.7935	6.1332	5.7687	3.6131	25.5538	6.8274	5.2887	6.1287	5.5476	5.2696	4.8640	5.3756	9.8441
13	6.6739	6.3899	4.6720	26.8908	7.2387	5.1281	5.5492	28.0097	6.7437	4.7040	5.0809	4.0493	8.2065	6.2571	5.4553	7.5214
14	8.4916	6.4575	5.1843	27.4703	7.6809	5.6373	5.3062	28.2996	5.8407	3.8731	5.5180	6.3053	7.2017	4.2072	9.7128	5.3929
15	7.9026	6.0901	5.2306	28.6965	7.8273	7.2511	4.1675	27.7358	6.5305	5.6899	7.3689	4.4139	5.2093	4.4069	7.0007	7.5278
16	8.4144	5.8478	4.8674	28.2848	7.1604	5.7397	5.2109	28.5215	6.7704	4.6842	6.3967	3.0996	8.1750	6.2211	7.9135	5.5065
17	7.9361	5.6158	5.1788	29.0036	7.7778	5.7107	4.3210	28.1527	5.8813	4.3963	5.6122	4.2258	6.5636	6.7683	7.7439	8.9289
18	7.9561	5.3245	5.6733	27.6895	8.9367	5.5699	4.0811	29.1527	5.5034	5.9369	5.7011	0.0000	8.0848	4.6295	8.7732	10.2956
19	8.1352	5.7543	4.9397	25.8736	7.9971	5.5565	4.7051	28.2089	6.0285	5.8014	5.5742	6.1202	7.4602	6.4773	10.1417	9.0736
20	7.7911	5.1709	5.5383	26.5645	8.6287	4.5998	3.6516	28.4475	5.6673	5.3894	4.7002	6.0273	7.7205	4.1856	9.8915	9.6757
21	6.8142	4.9978	5.9207	27.4745	7.9266	5.8234	4.9229	29.4975	6.3105	4.8485	5.5639	5.9216	5.2836	4.4418	7.1337	5.4238
22	8.9854	6.7232	3.3765	26.9622	8.0658	5.9836	5.7426	30.6693	6.0627	4.6195	6.7185	4.1454	6.6099	4.5042	9.5252	5.4482
23	8.6673	6.0546	4.4816	27.5085	7.7550	5.8368	5.5164	29.4605	5.5686	5.3309	6.8860	5.1988	5.5370	6.8390	5.4405	6.0948
24	7.0177	5.2127	4.3946	26.5699	8.6675	6.2962	5.3037	28.0746	5.3793	5.3964	6.0287	1.9026	7.2953	7.9880	5.4812	7.9308

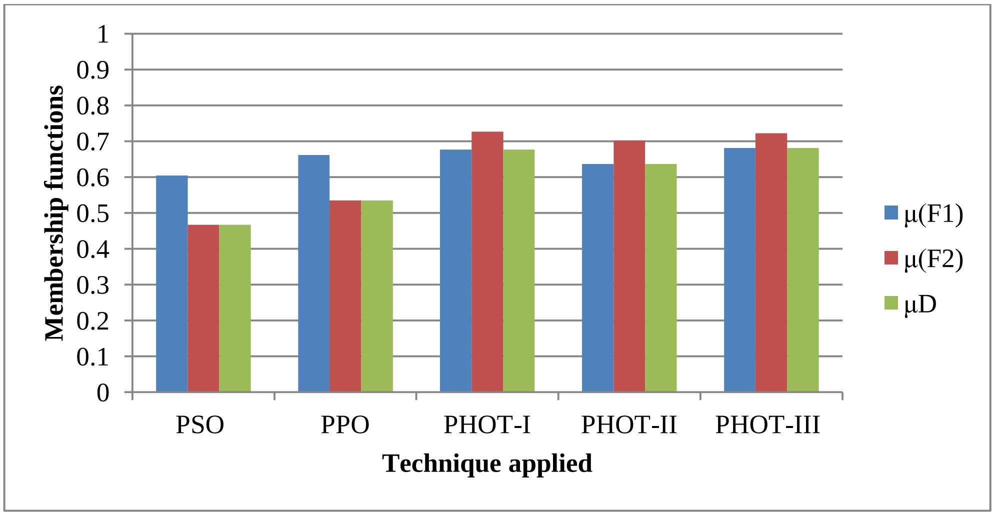

Figure 3.14: Comparison of cardinal priority ranking of multi-objective HTGS: Electric power system-VII

Table 3.17: Thermal power generation for multi-objective HTGS: Electric power system-VII

k	p_{Dk} (MW)	Thermal Power (MW)					
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}
1	1374	106.3831	108.7232	201.0465	201.4621	305.927	312.2643
2	1278	94.80019	97.48705	185.596	188.4585	286.9619	287.1703
3	1372	105.4608	111.5999	198.0986	200.9364	307.6092	306.7363
4	1058	71.1206	68.05984	152.9827	151.5766	234.4042	236.9631
5	1358	104.3318	109.5935	195.7471	197.2901	303.6037	304.3164
6	1282	97.3614	98.94363	183.1138	187.8935	289.5271	284.2186
7	1130	78.48325	80.91372	161.6203	160.0654	250.8158	254.1675
8	1200	86.35062	85.81328	175.7325	173.5076	268.4681	270.1423
9	1248	92.08745	94.78484	177.4692	184.7142	279.5286	278.9878
10	1364	106.2406	110.2213	198.9448	199.6707	301.4286	303.4763
11	1146	83.55067	80.63504	165.28	164.3477	253.1755	257.792
12	1262	95.81621	96.48337	181.2163	184.5962	280.8364	286.5553
13	1246	92.13856	93.89933	176.9897	183.1257	279.6301	280.8188
14	1140	79.53202	80.92395	163.9215	162.7147	252.2608	257.4506
15	1226	89.79489	88.61724	176.8069	179.839	274.1077	274.8215
16	1314	94.10664	103.4145	188.4226	193.3452	295.0298	296.8899
17	1426	111.043	118.4191	208.5652	212.7955	315	315.5177
18	1028	67.90099	64.74178	147.0731	148.0104	228.3093	228.9035
19	1148	80.83471	82.24616	165.2886	163.824	254.9727	253.4438
20	1256	91.57018	98.61461	180.088	183.2335	278.9362	278.3907
21	1348	102.5377	105.9049	193.2206	203.7319	302.7145	301.1013
22	1424	110.4519	114.9587	208.1856	211.9824	312.6646	322.3882
23	1070	68.38815	71.30368	150.0353	155.7299	242.3728	240.6703
24	1118	75.62015	75.76195	162.0106	164.3902	250.0944	251.4285

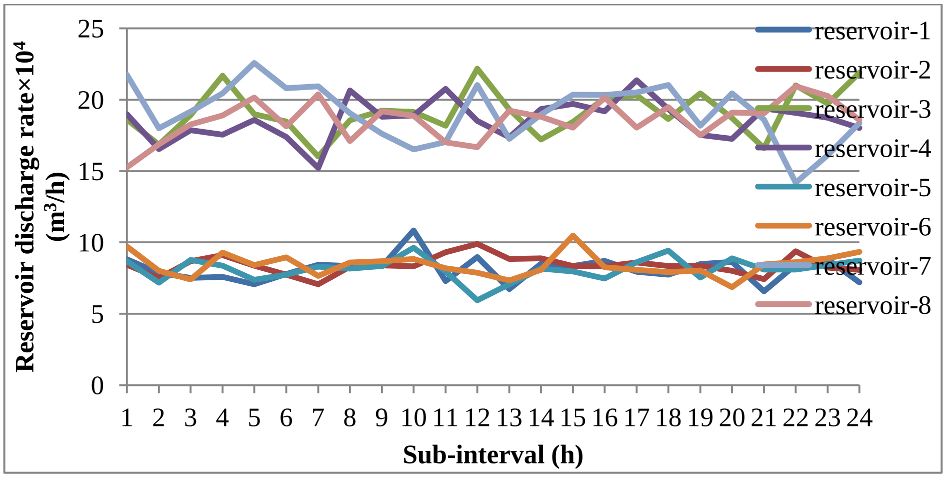

Figure 3.15: Reservoir discharge rate for multi-objective HTGS: Electric power system-VII

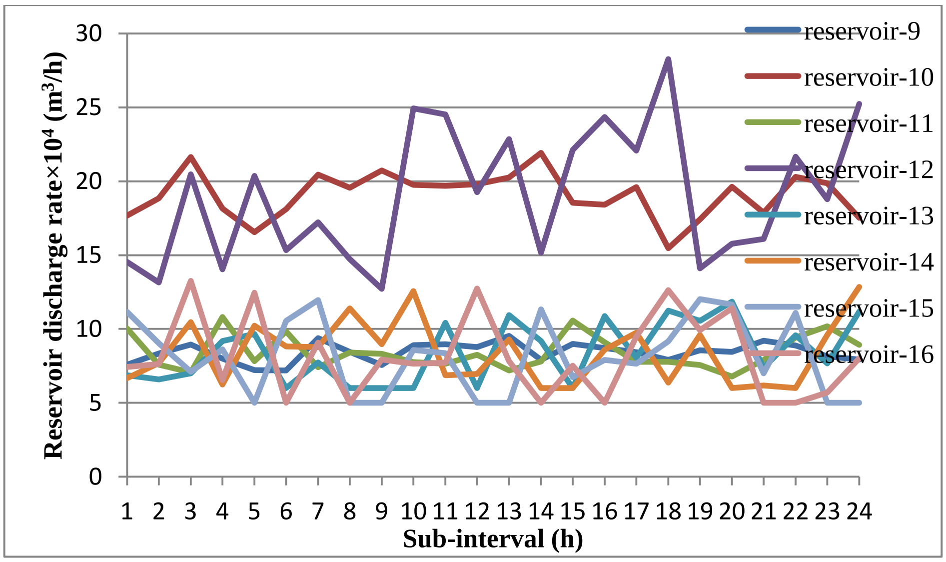

Figure 3.15: Reservoir discharge rate for multi-objective HTGS (Continued)

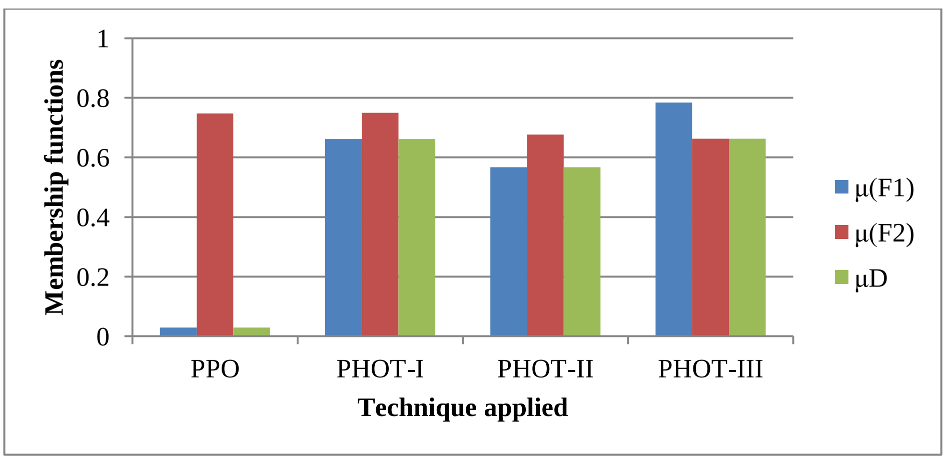

Figure 3.16: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-VIII

Table 3.18: Hydro power generation (MW) for multi-objective HTGS: Electric power system-VII

k	p_{7k}	p_{8k}	p_{9k}	p_{10k}	p_{11k}	p_{12k}	p_{13k}	p_{14k}	p_{15k}	p_{16k}	p_{17k}	p_{18k}	p_{19k}	p_{20k}	p_{21k}	p_{22k}
1	8.0028	6.4464	5.0017	25.5183	7.9269	7.1297	3.6741	23.0563	5.9476	5.2846	7.2767	5.8418	5.4971	5.3655	9.0739	7.1504
2	7.4545	5.8685	5.6392	24.2760	7.0038	6.0968	5.3122	25.2984	6.4254	5.2453	5.8175	6.1989	5.3790	6.0933	8.0753	7.3422
3	7.2671	6.6007	5.2300	25.4697	8.0704	5.7312	5.0682	26.6085	6.7323	4.2310	5.5297	4.9879	5.7375	7.5790	6.8880	9.8275
4	7.3223	6.8378	4.1303	25.5760	7.8055	6.8990	4.6072	27.2844	6.2093	5.6424	7.6415	6.3586	7.1363	5.0876	7.8772	6.4777
5	6.9475	6.4283	5.1708	26.7111	7.1308	6.4169	3.5437	28.1516	5.7931	6.0089	6.0008	5.2368	7.3723	7.5566	5.2100	9.4383
6	7.4126	6.0407	5.3194	25.9985	7.3415	6.6845	4.3190	27.2491	5.8242	5.6694	7.0960	6.3454	5.0563	6.7066	8.8035	5.0753
7	7.7901	5.5698	5.9065	24.4748	7.6674	5.8123	4.2585	28.8661	7.0659	4.8544	5.5837	6.1406	6.2686	6.5727	9.1471	7.9556
8	7.7234	6.2579	5.3724	28.1023	7.5694	6.2532	4.9692	26.8900	6.3527	5.2232	6.0774	6.4434	5.0142	7.5902	5.0462	5.1006
9	7.7249	6.2190	5.1596	26.8698	7.7056	6.1890	5.3982	28.4738	5.7360	4.8005	5.9320	6.4142	5.0714	6.1894	5.1522	7.3923
10	9.0429	6.1604	5.1535	26.9663	8.4632	6.2306	5.6610	28.1072	6.5373	5.0414	5.5880	3.1304	5.1833	7.5960	7.8816	7.2748
11	7.1103	6.7337	5.4785	27.9806	7.5544	5.8798	5.6190	26.6098	6.5784	5.0136	5.6041	3.2286	7.9481	4.6474	7.8217	7.4113
12	8.3042	7.0037	3.8468	26.4623	6.1880	5.7599	4.2498	26.3654	6.4754	4.9089	6.0438	5.5349	5.2696	4.8640	5.3756	9.8440
13	6.8273	6.3365	5.0678	26.1464	7.1265	5.4441	5.4496	28.5495	6.8164	4.7632	5.4006	4.0296	8.2065	6.2571	5.4553	7.5214
14	8.1506	6.3082	5.6906	27.6080	7.9741	5.9325	4.9775	28.0779	5.8368	4.0063	5.8202	6.2993	7.2017	4.2072	9.7128	5.3929
15	8.1087	6.0286	5.4338	27.5562	7.8920	7.2098	4.4456	27.6029	6.5110	5.3457	7.3211	4.4128	5.2093	4.4069	7.0007	7.5278
16	8.3931	6.0546	4.8823	27.1258	7.5819	5.9960	4.4895	29.1307	6.3664	5.3531	6.5089	3.0931	8.1750	6.2211	7.9135	5.5065
17	7.8970	6.1763	4.7775	28.3190	8.3974	5.8678	4.3325	27.8713	6.1531	4.9344	5.7030	4.2254	6.5636	6.7683	7.7439	8.9289
18	7.7722	5.9416	5.3339	27.1928	8.9120	5.7045	4.0416	29.0401	5.7660	5.9210	5.6522	0.0000	8.0848	4.6295	8.7732	10.2956
19	8.2769	5.7829	4.6659	25.9951	7.6482	5.6486	5.1053	27.9133	6.0018	5.6765	5.4015	6.1214	7.4602	6.4773	10.1417	9.0736
20	8.3661	5.4916	5.2446	26.1410	8.5553	4.8640	4.2179	29.0449	5.8404	5.0214	4.8831	6.0233	7.7205	4.1856	9.8915	9.6757
21	6.8391	5.1436	5.7612	27.6549	8.0048	5.8858	4.8283	29.1523	6.2007	5.4613	5.6515	5.9225	5.2836	4.4418	7.1337	5.4238
22	8.1975	6.3318	4.3108	27.1503	7.9896	6.0062	5.7297	30.1872	6.0230	4.6540	6.5503	4.1511	6.6099	4.5042	9.5252	5.4482
23	8.4307	5.7003	4.8206	27.1683	8.1931	6.1803	5.5890	29.0833	5.6353	4.7124	6.8793	5.1962	5.5370	6.8390	5.4405	6.0948
24	7.3343	5.5890	3.8064	26.8257	8.4057	6.3536	5.0912	27.6432	5.4984	5.4344	6.1200	1.8970	7.2953	7.9880	5.4812	7.9308

Table 3.19: Comparison of results: Electric power system-VIII

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost $\times(10^3)$ ($)	Emission $\times(10^3)$ (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission$\times$ (10^3) (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission $\times(10^3)$ (ton)	CPU time (s)
CSA[372]	3503.50	--	67.34	--	--	--	--	--	--
PPO	3514.90	13746.4	68.21	3531.2	9808.35	67.83	3530.6	10013.30	66.42
PHOT-I	3495.10	13655.0	65.56	3532.70	9741.89	64.73	3506.95	10004.9	65.83
PHOT-II	3508.41	13482.5	69.73	3530.52	9972.31	69.80	3510.50	10308.0	69.31
PHOT-III	3494.30	13147.4	87.21	3531.7	8953.22	86.41	3502.38	10366.6	85.48

Note: CSA: Clonal selection algorithm; PHOT-I: Proposed heuristic optimization technique-I, PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

Table 3.20: Hourly power demand, thermal and hydro generations and corresponding cost and emission for minimum operating cost HTGS: Electric power system-VIII

k	Power Demand (MW)	Total Thermal Generation (MW)	Total Hydro Generation (MW)	Cost$\times(10^3)$ ($/h)	Emission$\times(10^3)$ (ton/h)
1	18166.9	12233.77	5933.132	138.3405	353.6112
2	18198	12206.94	5991.064	137.9164	347.5102
3	17921.1	12088.04	5833.059	136.822	333.0151
4	17944.4	12109.99	5834.413	137.3259	377.7824
5	18257.4	12527	5730.398	140.855	576.9252
6	18472.4	12534.56	5937.842	140.6493	566.8969
7	18971	12707.4	6263.596	142.331	580.1546
8	19389.4	13029.69	6359.712	145.5375	587.7829
9	19437	12945.5	6491.503	144.5854	590.1154
10	20426.6	14044.16	6382.441	159.3195	643.4984
11	19936.5	13369.62	6566.884	149.6893	600.3918
12	20500.5	13826.99	6673.512	156.1742	633.973
13	20296.6	13621.2	6675.399	152.9942	612.8391
14	20281.5	13675.82	6605.68	153.8002	624.0008
15	19755	12881.22	6873.78	144.1849	588.6559
16	20170.6	13283.77	6886.828	148.4552	599.7657
17	19917.1	12981.35	6935.75	145221.4	597.3044
18	20033.5	13027.44	7006.061	145.5329	587.936
19	20427.4	13519.34	6908.061	151.4691	615.1364
20	20398	13446.17	6951.828	151.023	601.5498
21	20157.9	13175.91	6981.99	147.1772	599.0607
22	19709	12759.39	6949.611	143.2871	586.6675
23	19426.8	12786.89	6639.914	143.3965	588.4405
24	19266.3	12186.58	7079.725	138.2896	354.4138

To select better multi-objective solution, cardinal priority ranking is computed. It is evident from Fig 3.14, that maximum value of cardinal priority ranking is achieved by solution obtained from PHOT-III. Thermal and hydro power generation corresponding to this solution is tabulated in Tables 3.17 and 3.18, respectively. Figure 3.15 represents reservoir water discharge rate for multi-objective scheduling by applying PHOT-III.

Table 3.21: Hourly power demand, thermal and hydro generations and corresponding cost and emission for minimum emission HTGS: Electric power system-VIII

k	Power Demand (MW)	Total Thermal Generation (MW)	Total Hydro Generation (MW)	Cost×(10^3) ($/h)	Emission×(10^3) (ton/h)
1	18166.9	12236.62	5930.276	140.4026	166.6622
2	18198	12206.69	5991.306	139.622	155.5765
3	17921.1	12080.98	5840.116	137.718	142.0233
4	17944.4	12108.82	5835.576	138.1409	145.4351
5	18257.4	12527.52	5729.883	144.0319	201.5649
6	18472.4	12532.22	5940.182	144.0656	203.003
7	18971	12707.76	6263.24	145.7648	238.678
8	19389.4	13031.03	6358.368	146.9451	343.8816
9	19437	12945.31	6491.695	146.8064	312.5879
10	20426.6	14044.04	6382.556	160.4933	613.0591
11	19936.5	13366.79	6569.714	149.8371	599.9226
12	20500.5	13827.84	6672.66	157.0735	604.952
13	20296.6	13620.54	6676.064	153.9492	601.4058
14	20281.5	13675	6606.499	154.7313	602.2285
15	19755	12878.56	6876.438	146.6236	290.5091
16	20170.6	13284.94	6885.66	148.7191	599.776
17	19917.1	12981.71	6935.393	146.8588	330.1894
18	20033.5	13027.16	7006.344	146.9713	357.084
19	20427.4	13519.59	6907.814	152.3982	600.7946
20	20398	13448.25	6949.75	151.0463	600.3446
21	20157.9	13178.45	6979.449	147.7349	467.9953
22	19709	12763.26	6945.737	145.6326	299.0531
23	19426.8	12786.64	6640.164	145.8338	284.8226
24	19266.3	12186.17	7080.128	140.3246	191.6718

3.6.4 Electric Power System-VIII

Electric power system-VIII is comprised of 54 hydro units and 44 thermal units. The scheduling period is divided into 24 sub-interval of 1 h each. The data of electric power system-VIII has been referred from [372]. The emission coefficients for electric power system-VIII are adopted from [364], by simply adding together two existing thermal systems 40 unit and 10 unit and forming 50 thermal units. The emission coefficients of 51 to 54th

thermal unit are identical to 50th thermal unit of the combined system. The hydro sub-system configuration and network matrix including the water time delay are shown in Fig E.3 (Refer Appendix E, Section E.8). The hydro unit power generation coefficients are given in Table E.27 (Refer Appendix E, Section E.8). The hydro reservoir storage capacity limits, plant discharge limits, initial and final storage capacity limits, rate of water discharge limits and hydro plant generation limits are mentioned in Table E. 28 (Refer Appendix E, Section E.8).

Table 3.22: Hourly power demand, thermal and hydro generations and corresponding cost and emission for multi-objective HTGS: Electric power system-VIII

k	Power Demand (MW)	Total Thermal Generation (MW)	Total Hydro Generation (MW)	Cost×(10^3) (\$/h)	Emission×(10^3) (ton/h)
1	18166.9	12235.06	5931.84	137.711	293.2057
2	18198	12204.72	5993.285	137.3751	310.9663
3	17921.1	12073.57	5847.528	136.4644	305.0854
4	17944.4	12113.05	5831.351	137.2144	252.9427
5	18257.4	12529.34	5728.062	141.1897	307.4538
6	18472.4	12535.07	5937.334	141.7306	305.3524
7	18971	12708.4	6262.603	143.5705	321.9366
8	19389.4	13032.08	6357.316	146.0436	386.4727
9	19437	12944.83	6492.167	145.2853	376.1799
10	20426.6	14045.58	6381.017	159.2841	626.2045
11	19936.5	13371.94	6564.557	149.7387	600.0666
12	20500.5	13827.48	6673.023	156.1498	620.2876
13	20296.6	13620.72	6675.876	153.0781	612.9997
14	20281.5	13679.35	6602.152	154.0027	621.7499
15	19755	12881.52	6873.484	144.8585	344.3759
16	20170.6	13282.35	6888.251	148.6983	599.8208
17	19917.1	12979.9	6937.203	145.909	376.9803
18	20033.5	13028.42	7005.085	146.0525	385.242
19	20427.4	13518.66	6908.741	151.5488	615.5178
20	20398	13447.66	6950.337	151.5488	620.0262
21	20157.9	13177.61	6980.295	147.618	482.4367
22	19709	12764.89	6944.114	144.2924	358.4181
23	19426.8	12786.44	6640.363	144.2708	337.5181
24	19266.3	12188.79	7077.508	138.7153	305.3942

The reservoirs inflows are given in Tables E.29 (Refer Appendix E, Section E.8). The thermal power generation limits, cost coefficients and emission coefficients of thermal units are given in Table E.30 (Refer Appendix E, Section E.8) and Table E.31 (Refer Appendix E, Section E.8), respectively. The load demand is mentioned in Table E.32 (Refer Appendix E, Section E.8) respectively. Reservoir inflows of 25th and 26th hydro units are equal to the half of discharged water of 20th hydro unit. The reservoir inflows of 29th, 30th, 33th, 37th and 38th hydro units are computed in the same way. In this electric power system, apart from power generation, 10×10^4 m^3/h, water released by *36th* and *40th* hydro unit is utilized for domestic and irrigation purposes, respectively.

3.6.4.1 Comparison of results

To check the validity of the PHOTs, electric power system-VIII has been taken under consideration which has 98 units. Apart from the results reported in literature, results obtained from PHOTs are compared with the result from PPO technique with same constraint handling technique. It is observed from Table 3.19 that PHOT-III yields better result for minimum cost and minimum emission, by achieving lower objective values. The CPU time to execute the PHOTs for electric power system-VIII is not exponentially increased as compared to time taken for electric power system-V, which has 4 hydro and 3 thermal units. It is concluded that high number of decision variables, does not affect the performance of PHOTs. Tables 3.20, 3.21 and 3.22 provide the hourly load demand, hydro, thermal power generation, corresponding cost and emission of electric power system-VIII for minimum cost, minimum emission and multi-objective HTGS, respectively.

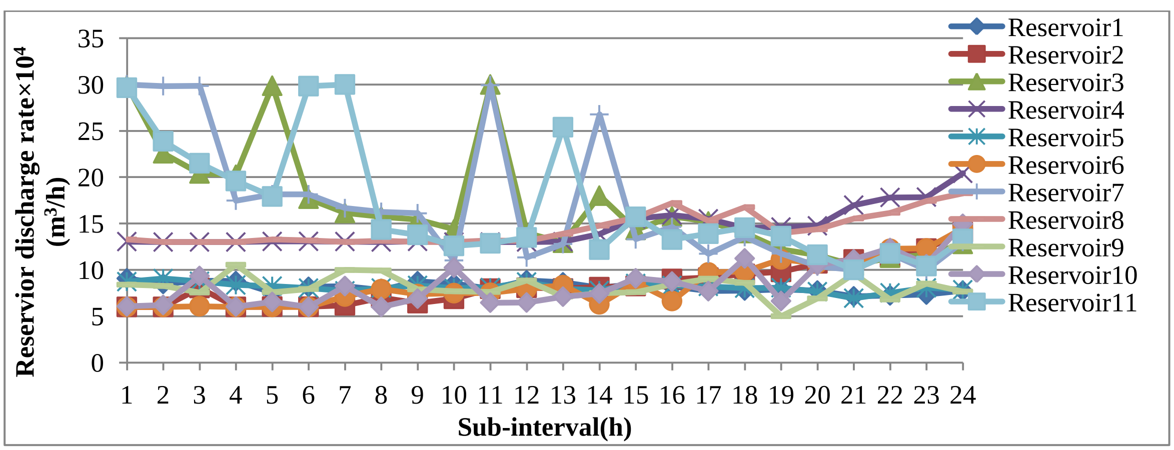

Figure 3.17: Reservoir discharge rate for multi-objective HTGS: Electric power system-VIII

Cardinal priority ranking and membership function of electric power system-VIII is presented in Fig 3.16. It is evident from Fig 3.16, that maximum value of cardinal priority ranking is achieved by solution obtained from PHOT-III. Thermal power generation for multi-objective HTGS is tabulated in Table 3.23 and water discharge rate is shown in Fig 3.17.

Table 3.23: Thermal power generation (MW) for multi-objective HTGS: Electric power system-VIII

k / Unit	1	2	3	4	5	6	7	8	9	10	11	12
1	112.1298	112.0002	112.0003	111.9990	112.0001	112.0003	111.9990	110.4794	111.9990	112.0003	112.0021	111.9990
2	112.1104	112.0001	112.0031	110.8516	111.9998	112.0012	112.0019	111.7307	111.9990	111.9983	112.0004	112.0004
3	97.8227	97.4172	98.0002	97.9981	98.0005	97.9984	97.2956	97.9989	98.0019	98.0006	98.0003	98.0031
4	179.9990	180.0006	80.0042	130.2529	179.9983	129.8047	180.0069	180.0002	180.0003	179.9908	179.9980	180.0023
5	88.9076	88.0009	87.9985	87.9981	88.0021	88.0013	88.0005	87.9993	88.0009	87.9990	87.9990	88.0029
6	105.0535	139.8452	138.9901	140.0000	105.9023	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000
7	261.1004	259.8633	261.0002	261.0002	258.4707	261.0006	258.4365	260.9999	260.9998	299.5854	260.9991	261.0039
8	285.5754	284.6869	283.9985	286.1574	283.1085	289.9998	290.0002	287.7208	290.0002	289.9999	290.0004	290.0031
9	286.0003	284.8154	286.0003	285.9998	285.9990	285.9998	285.9990	285.9996	286.0006	286.0002	285.9991	286.0036
10	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0020
11	94.0000	94.0000	94.0000	94.0000	94.0000	94.0000	94.0000	95.0000	94.0000	243.2783	95.0000	246.8486
12	169.2002	168.9991	169.0003	169.0001	169.0002	168.9990	166.0578	169.0004	169.0004	243.3008	168.9999	228.9386
13	215.0003	214.9990	215.0004	215.0003	214.9990	214.9990	214.0004	215.0019	215.0031	393.8154	215.0039	308.2607
14	305.0004	214.7676	304.9999	304.9990	305.0004	304.9990	305.0003	304.9991	304.9991	393.5107	304.9990	394.1670
15	395.1205	394.3369	394.2278	395.0023	395.0003	394.5400	395.0002	394.9991	395.0002	395.0002	395.0020	395.0004
16	395.0007	394.3047	394.9990	395.0003	395.0003	394.9991	391.8174	395.0002	395.0002	395.0003	395.0001	394.9990
17	400.1003	399.4922	399.9999	400.0006	399.6328	399.9991	399.9998	400.0001	399.9999	489.3096	400.0002	489.7383
18	489.2353	489.2607	400.8154	489.3535	399.3466	489.9996	488.7711	490.0002	489.9998	489.9991	490.0002	490.0003
19	512.1201	510.7816	510.5986	421.8616	511.9999	511.9990	509.2728	511.9987	510.4453	511.9998	512.0006	512.0009
20	510.6513	511.2504	510.9387	508.5820	510.7913	510.9941	505.1428	511.9990	511.9991	512.0007	512.0031	511.9991
21	433.2910	519.9538	516.2460	520.0566	522.1733	511.2930	510.0062	523.9991	523.9999	524.0009	524.0027	523.9991
22	524.0005	519.1973	522.9698	434.2793	434.2640	509.8737	520.0752	524.0004	523.1582	523.9991	524.0026	524.0009
23	522.8672	521.4336	523.9990	523.0137	521.9957	502.9180	514.7031	524.0006	518.4951	523.9991	523.9991	524.0008
24	520.6611	523.9999	524.0002	433.6240	523.9990	512.2354	512.3252	524.0006	523.1318	524.0002	524.0043	523.9999
25	523.8504	523.2216	522.5400	517.7967	520.2878	514.9086	523.9990	524.0004	524.0003	524.0004	524.0048	524.0009
26	523.9146	433.6787	523.1240	432.6252	523.9990	517.5830	513.8692	518.9872	520.3039	524.0004	524.0008	524.0005
27	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	11.0007	11.0005	11.0008	11.0033

Table 3.23: Thermal power generation (MW) for multi-objective hydro-thermal scheduling: Test system-VIII (Continued)

k / Unit	1	2	3	4	5	6	7	8	9	10	11	12
28	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.9991	10.9990	11.0062	11.0071
29	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.9991	11.0009	11.0083
30	97.0000	87.7578	88.1016	97.0000	97.0000	86.9658	93.8594	97.0000	91.5801	97.0000	97.0000	97.0000
31	159.5410	160.2271	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
32	190.0000	159.8984	190.0000	190.0000	161.1904	160.5879	190.0000	190.0000	172.7588	190.0000	190.0000	190.0000
33	159.8604	190.0000	190.0000	189.7568	159.6279	163.7139	189.9990	190.0000	190.0000	190.0000	190.0000	190.0000
34	164.9270	165.3447	164.6360	200.0000	200.0000	200.0000	200.0000	200.0000	182.6582	200.0000	200.0000	200.0000
35	167.5976	165.6995	164.8418	164.9473	164.6680	164.4941	168.0001	167.9990	168.0009	199.9971	191.6328	167.9991
36	165.1708	165.2837	164.5054	165.4602	165.3558	164.1440	164.8691	167.9991	168.0002	200.0000	200.0000	199.9971
37	88.8710	89.1036	88.8964	88.6612	94.4084	88.7697	88.0046	95.1274	92.0918	110.0000	110.0000	110.0000
38	90.0100	89.2584	88.4380	90.7428	90.5355	91.3217	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000
39	90.7194	89.7076	89.3421	93.0366	91.2529	96.2978	99.0234	110.0000	110.0000	110.0000	110.0000	110.0000
40	331.4816	510.7532	420.8314	510.9111	511.1035	507.8555	495.7453	509.9049	512.0001	512.0001	512.0006	512.0003
41	447.6232	448.7803	363.6924	449.7146	469.3235	446.6523	447.0713	535.1309	528.3613	629.9999	630.0002	629.9989
42	300.7986	299.2529	300.4453	299.0830	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000
43	300.2179	224.7258	150.0698	74.3799	360.0000	298.6230	227.5703	360.0000	360.0000	360.0000	360.0000	360.0000
44	160.9989	160.0469	160.1943	159.6758	161.0002	110.5381	161.3008	161.1001	161.0001	179.6699	171.7451	161.0001
45	109.7194	109.8494	161.3909	159.2343	160.2630	159.6485	159.6933	161.0009	160.9999	180.0000	161.0001	161.0010
46	109.6809	109.8604	160.3780	160.3004	111.0459	110.6914	160.3001	160.0009	159.9998	160.1021	160.0049	159.9991
47	160.5374	159.5505	109.8242	161.3003	160.9189	161.0005	161.2001	161.0009	160.6914	176.1914	161.0010	160.9991
48	160.0931	110.3027	160.7285	159.8429	161.0005	110.4912	160.0908	160.9999	161.0008	161.2008	161.0028	161.0008
49	160.1208	160.0009	160.3091	160.3003	112.6758	160.0001	160.1008	159.9991	159.9998	160.1200	160.0028	160.0009
50	79.1099	79.0001	79.2011	40.0000	40.0000	77.6836	78.0742	78.9991	40.3086	114.7881	114.5039	113.0068
51	114.8083	115.0003	77.2568	115.3004	115.0007	115.0002	115.0065	114.9991	76.5156	115.2229	115.0325	117.5491
52	55.0000	55.0000	55.0000	55.0000	55.5144	93.0005	93.0009	92.8286	92.9991	119.4961	119.9609	119.9629
53	93.1034	93.0004	93.0001	93.2004	92.4854	93.0002	92.6270	92.9991	93.0002	120.0000	115.0234	119.9707
54	55.3412	55.0001	55.0056	118.7633	120.0000	93.4431	55.0068	54.9999	95.3300	120.0000	120.0000	120.0000

Table 3.23: Thermal power generation (MW) for multi-objective hydro-thermal scheduling: Test system-VIII (Continued)

k / Unit	13	14	15	16	17	18	19	20	21	22	23	24
1	112.0004	112.0009	112.0009	112.0002	111.9990	111.9993	112.0002	112.0014	111.9990	110.3555	111.9992	112.0001
2	112.0003	111.9983	112.0030	112.0145	111.9986	111.9989	112.0048	112.0081	112.0019	112.0006	110.9746	111.9991
3	106.8673	98.0004	97.9973	98.0075	97.9985	98.0006	119.9972	98.0015	98.0006	97.9991	97.9991	98.0005
4	179.9991	179.9990	174.7501	180.0036	180.0003	180.0015	180.0001	180.0030	180.0013	179.9990	179.9990	180.0018
5	88.0020	88.0049	88.0002	88.0002	87.9991	87.9991	89.6233	88.0004	88.0003	87.9990	88.0006	87.9991
6	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000
7	261.0003	261.0010	257.5020	261.0078	261.0004	260.9999	292.9192	261.0004	261.0008	261.0002	260.9999	260.9991
8	290.0049	290.0003	288.7998	290.0013	289.9991	289.9990	293.3587	290.0079	289.9990	289.9990	289.9999	290.0001
9	286.0049	286.0002	285.9990	286.0018	286.0003	285.9998	285.9991	286.0087	283.7021	286.0004	286.0002	285.9990
10	130.0000	191.2158	130.0000	130.0020	130.0000	130.0000	130.0010	130.0059	130.0000	130.0000	130.0000	130.0000
11	168.8633	169.4268	94.0000	95.0059	94.0000	94.0000	95.0000	159.1807	95.0000	94.0000	95.0000	94.0000
12	169.0004	242.5352	168.9991	168.9991	168.9991	168.9991	168.9991	242.3428	168.9688	169.0006	169.0005	169.0005
13	214.9998	215.0003	214.9990	215.0001	215.0005	215.0005	215.0010	214.9990	215.0005	214.6367	214.9990	214.9998
14	304.9990	305.0004	304.9980	305.0042	304.9991	305.0004	304.9990	304.9990	305.0004	304.5254	304.9987	304.3965
15	395.0010	394.9990	394.9990	395.0020	394.9990	395.0006	395.0020	394.9980	394.0938	394.9987	394.9994	394.9990
16	395.0024	394.9990	395.0002	395.0029	395.0004	394.9991	395.0005	395.0034	394.1387	394.9987	394.9994	394.9707
17	489.9998	489.2754	399.9990	400.0010	400.0003	399.9990	489.9991	418.4258	400.0006	399.9989	400.0004	399.5234
18	489.9991	490.0002	488.1592	489.9991	490.0005	489.9999	489.9991	490.0004	489.9989	489.9990	490.0005	489.7646
19	511.9999	512.0009	505.8584	511.9979	511.9918	509.8965	512.0002	511.9987	511.9980	511.3406	511.3047	511.9989
20	512.0008	512.0010	512.0014	512.0056	500.6056	512.0001	512.0002	511.9989	511.9980	495.9449	511.9991	512.0004
21	523.9991	523.9987	521.3809	524.0008	523.7832	524.0007	523.9980	524.0003	523.9980	523.9986	523.9990	523.9991
22	523.9987	523.9990	524.0004	523.9989	524.0003	523.9989	523.9974	524.0006	522.6572	523.9989	445.2715	353.3477
23	523.9989	524.0012	524.0004	524.0020	516.9824	523.9990	524.0014	523.9990	521.1572	524.0005	517.6738	524.0007
24	523.9980	523.9991	523.9999	524.0036	524.0021	523.9979	524.0001	524.0001	524.0006	521.5820	521.3340	523.9999
25	523.9990	523.9991	516.8291	523.9999	524.0011	523.9981	524.0013	524.0009	524.0002	523.9987	524.0001	524.0007
26	523.9990	524.0027	504.8203	523.9980	523.5059	522.9727	523.9998	526.1484	524.0005	495.8809	523.1543	515.2910
27	11.0055	11.0009	10.0000	11.0030	10.0000	11.0005	11.0020	11.0021	10.0000	11.0008	10.0000	10.0000

Table 3.23: Thermal power generation (MW) for multi-objective hydro-thermal scheduling: Test system-VIII (Continued)

k / Unit	13	14	15	16	17	18	19	20	21	22	23	24
28	11.0008	11.0039	10.0000	11.0011	10.0000	11.0007	11.0033	11.0003	10.0000	11.0001	10.0000	10.0000
29	10.9998	10.9998	10.0000	11.0033	10.9999	10.9999	11.0052	11.0000	10.0000	10.0000	10.0000	10.0000
30	97.0000	97.0000	97.0000	97.0000	97.0000	97.0000	97.0000	97.0000	97.0000	97.0000	80.0244	97.0000
31	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
32	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
33	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
34	200.0000	200.0000	163.2862	200.0000	200.0000	200.0000	200.0000	200.0000	200.0000	200.0000	181.8965	200.0000
35	199.9961	167.9991	164.4873	168.0010	168.0003	163.7207	168.0001	169.9258	168.0001	168.0001	165.4004	164.9434
36	171.4063	199.9971	168.0002	168.0010	168.0009	168.0009	200.0000	171.6641	168.0001	164.0732	165.4395	167.9999
37	110.0000	110.0000	110.0000	110.0000	110.0000	91.8705	110.0000	110.0000	110.0000	110.0000	110.0000	84.8779
38	110.0000	110.0000	107.4711	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	89.5752	99.4258	110.0000
39	110.0000	110.0000	110.0000	110.0000	110.0000	109.9990	110.0000	110.0000	110.0000	110.0000	101.6510	102.5542
40	511.9999	512.0002	511.9991	512.0004	512.0004	512.0003	511.9998	516.3455	511.9980	497.7093	512.0001	422.0010
41	630.0007	629.9985	448.5146	630.0007	524.6934	529.9854	629.9989	632.7673	598.8281	525.7500	479.3486	449.7754
42	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	359.9990	360.0000	151.2773
43	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	355.2842	360.0000	221.6367
44	161.0006	161.0005	161.0001	161.0004	160.9991	161.0005	161.0010	168.9521	161.0006	160.3633	160.7002	161.0005
45	179.9932	179.9727	160.0635	161.0009	161.0004	160.9991	180.0000	162.8193	160.0664	160.0801	161.0001	150.0332
46	179.9951	160.0009	159.9999	160.0004	160.0005	158.9014	160.7480	160.0010	160.0004	112.3184	112.5586	146.7588
47	179.9854	169.9893	159.3877	161.0004	160.9991	159.9893	161.0007	175.9453	160.9999	161.0001	161.0001	161.0005
48	179.9887	161.0001	161.0003	160.9999	160.6973	160.6982	161.2310	179.0692	160.9989	160.3936	161.0001	111.6367
49	179.9706	159.9998	160.0004	179.9718	160.0001	160.0004	160.5621	160.0008	160.0004	113.4531	158.7803	160.0007
50	119.9717	119.9785	73.9209	119.9639	40.0000	79.0004	119.9736	79.0059	79.0002	40.0000	73.8574	79.0001
51	114.6966	119.9720	115.0006	78.9991	114.2773	78.0498	116.2561	79.0042	115.0005	79.4850	40.0000	55.5147
52	119.9648	119.9746	93.0003	119.9648	55.0000	93.0004	120.0000	115.0186	93.0007	93.0001	93.0001	57.8133
53	120.0000	120.0000	93.0005	102.3848	82.4111	93.0004	120.0000	120.0000	92.9989	72.1397	92.4277	93.0007
54	120.0000	120.0000	63.2906	120.0000	94.9443	93.3278	120.0000	120.0000	120.0000	55.0001	118.2174	93.6731

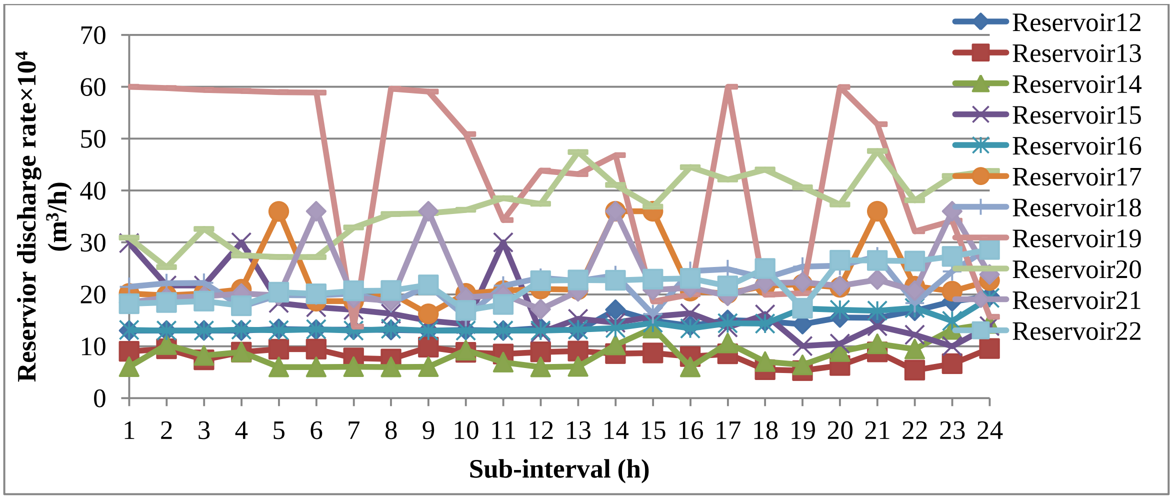

Figure 3.17: Reservoir discharge rate for multi-objective HTGS (Continued)

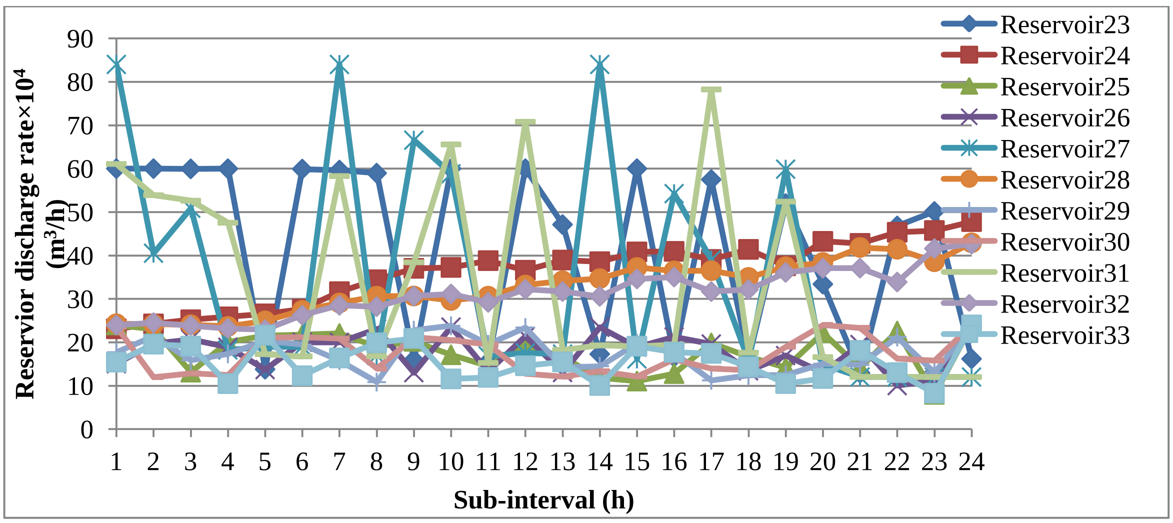

Figure 3.17: Reservoir discharge rate for multi-objective HTGS (Continued)

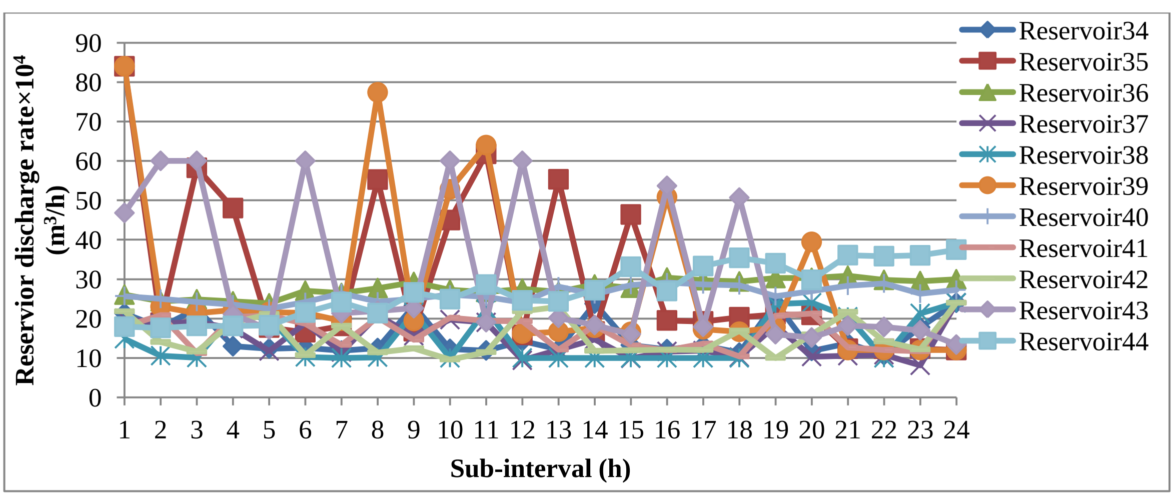

Figure 3.17: Reservoir discharge rate for multi-objective HTGS (Continued)

3.7 CONCLUSIONS

In this chapter, proposed heuristic optimization techniques based on global search techniques and PPS method are implemented on multi-chain HTGS problems. Multi-chain hydro plants have a hydraulic connection in series or parallel, which affects reservoir levels of downstream hydro power plants. The short-term hydro-thermal scheduling with the consideration of multiple objectives is a complex non-linear constrained optimization problem having non-smooth and non-convex characteristics. Therefore, hydro-thermal scheduling problem is a complicated constraint optimization problem whose feasible solution space is large. Global search techniques are applied as a tool for the solution of complex optimization problems because of their exclusive advantages. In proposed heuristic optimization techniques, Powell's search method is integrated with EP, PPO and with combination of EP and PPO technique. Powell's search method improves the quality of global solutions obtained by PPO or EP technique. Proposed heuristic optimization techniques have been applied to solve three different types of hydro-thermal generation scheduling problems; economic, gaseous pollutant's emission and multi-objective scheduling.

The PHOTs have been tested on four hydro-thermal electric power system. Fifth and sixth electric power system has 4-hydro and 3-thermal units. Seventh electric power system has 16-hydro and 6-thermal units. Finally, to demonstrate the effectiveness proposed heuristic techniques, these have been applied on eighth hydro-thermal system which has 44-hydro units and 54-thermal units. The results reveal that the PHOTs are very effective in reaching an optimal generation schedule. It is found that the PHOTs produce better results by achieving better objective values. To decide the 'best' generation schedule for multi-objective scheduling problem, fuzzy cardinal priority ranking is compared to various reported results. Higher value of cardinal priority ranking represents higher the satisfaction level of all the objectives and it is achieved by proposed heuristic optimization techniques for all the electric power systems. The analysis of parameter variation is performed. It is concluded that parameters are less sensitive to the variations. The best, average and worst results are obtained by PHOTs to investigate the effect of initial solutions and to verify the robustness of these and it is observed that PHOTs produce better solutions on every execution. The proposed heuristic optimization techniques are easy to implement and take less time to achieve the good quality solution.

CHAPTER – 4

WEIGHT PATTERN EVALUATION FOR MULTI-OBJECTIVE SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING

4.1 INTRODUCTION

Generally real world optimization problems require the computation of a set of decision variables that provide the best possible solution to a predefined scalar objective function or a set of optimal trade-off values in case of two or more conflicting objectives. With multiple objectives, there is not one unique solution which is best with respect to all objectives but there is a set of solutions which cannot be dominated by any other solutions in the search space. These solutions are known as Pareto-optimal solutions or non-dominated solutions. Methodologies used for solving *multi-objective optimization problem* (MOOP), principally differ in two ways, the procedure used to generate non-inferior solutions and the ways and means used to interact with *decision-maker* (DM) and the type of information made available to the DM such as trade-offs. There are various techniques for generating noninferior solutions [236,404], e.g. weighting method, ε-constraint method, and noninferior set estimation method etc. In weighting method, a number of runs are required to get a set of non-dominated solutions, and when the objective function is nonconvex then it may fail in yielding the true optimal solutions [176]. Other methods have been opted by various researchers *i.e.* ε-constraint method, interactive fuzzy based method, goal attainment method, and price penalty method etc. to get a set of non-dominated solutions in a single run. The most obvious weakness of ε-constraint method is that it is time-consuming and trends to find weakly non-dominated solutions [176]. An extension of fuzzy interactive method to include more objectives is a very qualm fact. The main disadvantage of goal programming is that it demands a higher effort from the DM. Researchers [303,362] have applied price penalty factor to bundle the fuel cost and emission in *hydro-thermal generation scheduling* (HTGS) problem. Price penalty factor does not address the conflict issue between different objectives. Global search techniques seem suitable to solve MOOPs because they deal simultaneously with a set of possible solutions which allows finding an entire set of Pareto optimal solution in a single run of the algorithm. Additionally, global search techniques are less suitable to the shape of continuity of the Pareto front. *Non-dominated sorting genetic algorithm* (NSGA-II) encompasses advanced concepts like elitism, fast non-dominated sorting approach and diversity maintenance along the Pareto-optimal front; it still falls short in maintaining lateral diversity and obtaining Pareto-optimal with high uniformity [374]. *Multi-objective differential evolution* (MODE) can deal with simple low-dimensional problem with a fast convergence rate. However, when applied to cope with complicated problems with multiple local optimal fronts, MODE may end up with premature convergence because of the significantly decreasing of population diversity caused by their fast convergence rate [381]. In *multi-objective evolutionary algorithm* (MOEA) approach, for large the number of objectives of multi-objective problem, Pareto dominance-based ranking procedures become ineffective in sorting out the quality of solutions. Villalobos-Arias *et al.* [394] have proposed a mechanism to spread the solutions generated by a multi-objective evolutionary algorithm. The approach is based on the use of stripes that are applied in objective function space and it is independent of the search engine adopted. A multi-objective programming algorithm may find multiple non-dominated solutions. If these solutions are scattered more uniformly over the Pareto frontier in the objective space, they are more different choices and so their quality is better. Leung and Wang [190] have proposed a quality measure to measure the uniformity of a given set of non-dominated solutions over the Pareto frontier.

The weighting method [396] is the most common method used for solving MOOPs until recently. It simply assigns different weights to each objective function based on its importance and combines different objectives into single objective function. In most of the previous research work, weights were uniformly formed and simulated using a suitable step size variation. But, the number of non-inferior solutions of MOOP increases exponentially with the increase in the number of participating objectives. So, generation of complete non-inferior surface is time consuming. A major drawback of weighting method is that there is no rational basis of determining adequate weights. The objective function so formed may lose significance due to combining non-commensurable objectives. Another limitation with the simulated weight problem is that the decision maker may skip the weight combination that actually corresponds to the 'best' compromising solution during simulation procedure because of step size taken. In other words, the decision maker seeks the 'best' solution only among the presented non-inferior solutions. The above cited problem is overcome by evaluating the best weight pattern. Diakoulaki *et al.* [55] have proposed a method for determination of objective weights, based on the quantification of two fundamental notions of multi-objective decision method: the contrast intensity and the conflicting character of the evaluation criteria. The extraction and exploitation of these two features is beneficial in the decision making. Singh *et al.* [236] have evaluated the best weight pattern for multi-objective load dispatch.

The intent of this chapter is to solve the multi-objective short-term HTGS problem, exploiting weighting method. The proposed heuristic optimization techniques (PHOTs) as discussed in chapter 2, have been applied for optimal operation of hydro-thermal system, considering multi-chain hydro model with valve-point effect of thermal generators. In weighting method, there is a need to determine adequate weights and the objective function so formed should not lose any significant information due to combining non-commensurable objectives. Statistical measures which characterize the correlation coefficient matrix evolution have been applied to compute weight patterns. The information extract from membership function of best solutions of each particle/member obtained from proposed technique is used to update the weights, during the movement. The heuristic penalty less constraint handling technique is applied to satisfy power balance and reservoir capacity constraints. Volume storage and hydro power generation limits are satisfied by another heuristic search technique. The PHOTs are applied to four HTGS problems for economic and minimum emission level of gaseous pollutants being multi-objective HTGS. The solutions obtained from these proposed techniques are compared with solutions of existing techniques and results are found satisfactory.

4.2 MULTI-OBJECTIVE HYDRO-THERMAL GENERATION SCHEDULING

The aim of multi-objective hydro-thermal generation scheduling is to optimize the thermal operating cost and gaseous pollutant emission level of thermal plant simultaneously, while satisfying the various constraints. The thermal unit cost function F_1 and amount of pollutant emission function F_2 are discussed in chapter 2, section 2.3 and multi-chain hydro model is discussed in section 3.2.1 in chapter-3.

To generate the non-inferior solutions, the MOOP is converted into scalar optimization problem using weighting method and problem is stated as [172]:

Minimize $$F_{tot} = \sum_{h=1}^{N_{ob}} W_h F_h \quad (4.1)$$

Subjected to

(i) $$\sum_{h=1}^{N_{ob}} W_h = 1.0, \qquad W_h \geq 0.0 \quad (4.1a)$$

(ii) The reservoir volume constraint for each hydro unit

$$V_{jF} = V_{jI} + \sum_{k=1}^{T} I_{jk} - \sum_{k=1}^{T} q_{jk} - \sum_{k=1}^{T} SP_{jk} + \sum_{k=1}^{T}\sum_{r=1}^{U_j}\left(q_{r(k-t_{rj})} + SP_{r(k-t_{rj})}\right) \; (j = 1,2,\ldots,N_H) \quad (4.1b)$$

(iii) The load demand equality constraint during each sub-interval

$$\sum_{i=1}^{N} p_{ik} = p_{Dk} + p_{Lk} \quad (k = 1,2,..T) \quad (4.1c)$$

(iv) The discharge limits are imposed on hydro unit

$$q_j^{\min} \leq q_{jk} \leq q_j^{\max} \; (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \quad (4.1d)$$

(v) The volume limits are imposed on hydro unit

$$V_j^{\min} \leq V_{jk} \leq V_j^{\max} \; (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \quad (4.1e)$$

(vi) The power limits are imposed on thermal and hydro unit

$$p_i^{\min} \leq p_{ik} \leq p_i^{\max} \; (i = 1,2,\ldots,N; k = 1,2,\ldots,T) \quad (4.1f)$$

where

N_H and N_T are number of hydro and thermal units, respectively

N is total number of units

T is total time interval for scheduling

F_{tot} represents unified objective function

W_h is weight assigned to h^{th} objective

N_{ob} represents number of objective functions

V_{jF} and V_{jI} are the final and initial reservoir storage volumes of j^{th} hydro unit respectively

p_{Dk} and p_{Lk} are the power demand and transmission loss during k^{th} sub-interval, respectively

$p_i^{\max}$ and $p_i^{\min}$ are the upper and lower limits of i^{th} unit power generation, respectively

$q_j^{\max}$ and $q_j^{\min}$ are the upper and lower limits of water discharge rate of j^{th} hydro unit, respectively

I_{jk}, q_{jk}, V_{jk} and SP_{jk} are water inflow, water discharge rate, reservoir volume and spillage of j^{th} hydro unit at k^{th} sub-interval, respectively

$V_j^{\max}$ and $V_j^{\min}$ are the upper and lower limits of j^{th} hydro unit, respectively

U_j is upstream reservoir

t_{rj} is representing time delay from upstream reservoir '*r*' to lower reservoir '*j*'

4.3 CONSTRAINTS HANDLING

The movement of particles is not always guaranteed to satisfy the constraints. The constraint handling procedure is performed to get feasible solution. Mostly, penalty function method is used for constraint handling. Penalty function method converts a constrained optimization problem into an unconstraint optimization problem. But this method requires multiple run to fine tune the penalty factor leading to a high computational cost. The inclusion of the penalty function also distorts the objective function. The distortion in objective function is small for small values of penalty parameter. For a large value of penalty parameter, the optimum of objective function may have artificial local optimal solutions [143]. In this work, the heuristic penalty less constraint handling technique is applied to satisfy power balance and reservoir volume equality constraints [330] by perturbing the generations of thermal unit and water discharge rates, respectively systematically. Volume storage and hydro power inequality constraints are satisfied by another heuristic search technique [278].

4.3.1 Equality Constraints

To satisfy reservoir volume equality constraint given by Eq. (4.1b), residual volume ΔV is computed as:

$$\Delta V_{jl} = V_{jF} - V_{jI} - \sum_{k=1}^{T} I_{jk} + \sum_{k=1}^{T} q_{jkl}^{t} + \sum_{k=1}^{T} SP_{jk} - \sum_{k=1}^{T}\sum_{r=1}^{U_j}\left(q_{r(k-t_{rj})l}^{t} + SP_{r(k-t_{rj})} \right)$$
$$(j = 1,2,\ldots,N_H ; l = 1,2,\ldots,NP) \quad (4.2)$$

If residual volume is less then tolerance band, then constraint is satisfied; otherwise out of total number of sub-intervals, water discharge rate at h^{th} slack sub-interval of hydro unit is evaluated as:

$$q_{jhl}^{t} = \begin{cases} q_{jhl}^{t} - \min\left\{\Delta V_{jl}, \left(q_{jhl}^{t} - q_{j}^{\min}\right)\times rand\right\} & ;\Delta V_{jl} > 0 \\ q_{jhl}^{t} - \max\left\{\Delta V_{jl}, \left(q_{jhl}^{t} - q_{j}^{\max}\right)\times rand\right\} & ;\Delta V_{jl} < 0 \end{cases} \quad (j = 1,2,\ldots,N_H ; l = 1,2,\ldots,NP) \quad (4.3)$$

where

q_{jhl}^{t} is water discharge rate of j^{th} hydro unit for h^{th} sub-interval at t^{th} movement of l^{th} particle.

This process continues until water-balance equality constraint is satisfied.

After satisfying the reservoir volume equality constraint, hydro power is computed from obtained water discharge rate. To satisfy power balance equality constraint given by Eq. (4.1c), residual power (Δp_D) is computed as:

$$\Delta p_{Dkl} = \sum_{i=1}^{N} p_{ikl}^{t} - p_{Dk} - p_{LK} \qquad (k = 1,2,\ldots,T, l = 1,2,\ldots,NP) \quad (4.4)$$

If residual power is less then tolerance band, then constraint is satisfied; otherwise out of total number of thermal generating unit those act as decision variables, one generation of slack thermal unit 's' is evaluated during each sub-interval as:

$$p_{skl}^{t} = \begin{cases} p_{skl}^{t} - \min\left\{\Delta p_{Dkl}, \left(p_{skl}^{t} - p_{s}^{\min}\right)\times rand\right\} & ;\Delta p_{Dkl} > 0 \\ p_{skl}^{t} - \max\left\{\Delta p_{Dkl}, \left(p_{skl}^{t} - p_{s}^{\max}\right)\times rand\right\} & ;\Delta p_{Dkl} < 0 \end{cases} \quad (k = 1,2,\ldots,T, l = 1,2,\ldots,NP) \quad (4.5)$$

where

p_{skl}^{t} is power generation of s^{th} slack thermal unit for k^{th} sub-interval at t^{th} movement of l^{th} particle.

The whole process is continued until both the equality constraints are satisfied. The elaborated steps are given in Algorithm-4.1.

ALGORITHM 4.1: Equality Constraint handling

1. Check the limits of water discharge rate.
2. *IF* $(q_{jk} > q_j^{\max})$ *THEN*

   $q_{jk} = q_j^{\max}$

   ENDIF
3. *IF* $(q_{jk} < q_j^{\min})$ *THEN*

   $q_{jk} = q_j^{\min}$

   ENDIF
4. Set a slack sub-interval counter, h=1.

   DO

   4.1 Compute the residual volume, ΔV_{jl} as depicted in Eq. (4.2)

   4.2 If $\left|\Delta V_{jl}\right| < \varepsilon$, GOTO step 6; ε is residual volume tolerance.

   4.3 Modify the water discharge rate at h^{th} sub-interval to satisfy equality constraint as depicted in Eq. (4.3).

   4.4 Increment the sub-interval counter, $h=h+1$

   WHILE (h<T)
5. Compute corresponding reservoir volume and hydro power as mentioned in sub-section 3.2.1 of chapter 3.
6. Check the limits of thermal power.
7. *IF* $(p_{ik} > p_i^{\max})$ *THEN*

   $p_{ik} = p_i^{\max}$

   ENDIF
8. *IF* $(p_{ik} < p_i^{\min})$ *THEN*

   $p_{ik} = p_i^{\min}$

   ENDIF
9. Set a slack thermal unit counter $s=1$

   DO

   9.1 Compute the transmission loss using kron's formula.

   9.2 Compute the residual power, Δp_{Dkl} as depicted in Eq. (4.4).

   9.3 If $\left|\Delta p_{Dkl}\right| < \varepsilon$, GOTO step 10, ε is residual power tolerance.

   9.4 Modify s^{th} thermal unit power generation to satisfy power balance equality constraint as per Eq. (4.5).

   9.5 Increment the thermal unit counter $s=s+1$

   WHILE (s<N)
10. *STOP*

4.3.2 Inequality Constraints

All feasible solutions have zero constraint violation but sometimes, during the search, solutions may become infeasible. In this scheme, total residual volume of l^{th} particle V_{errl} is computed as:

$$V_{errl} = \begin{cases} V_{jkl} - V_j^{\max} & ; V_{jkl} > V_j^{\max} \\ 0 & ; V_j^{\min} \geq V_{jkl} \geq V_j^{\max} \\ V_j^{\min} - V_{jkl} & ; V_{jkl} < V_j^{\min} \end{cases} \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T; l = 1,2,\ldots,NP) \tag{4.6}$$

The pair-wise comparison is done to select smaller volume constraint violation solution by comparing two infeasible solutions. When two feasible solutions are computed, the one with better objective function value is chosen. In case one feasible and another infeasible solution are compared, then feasible solution is chosen. The same procedure is applied to satisfy hydro power inequality constraint.

4.4 Weight Pattern Evaluation

Owing to imprecise nature of *decision maker's* (DM) judgment, it is presumed that DM has fuzzy or imprecise goal of each objective function. Minimum and maximum values for each of the multiple objectives, is carried out by giving full weightage to one objective and neglecting other objectives. It is assumed that membership function $\mu(F_{hl})$ is a strictly monotonic linearly decreasing and continuous function, defined as [157]:

$$\mu(F_{hl}) = \begin{cases} 1 & ; F_{hl} \leq F_h^{\min} \\ \dfrac{F_h^{\max} - F_{hl}}{F_h^{\max} - F_h^{\min}} & ; F_h^{\min} < F_{hl} < F_h^{\max} \\ 0 & ; F_{hl} \geq F_h^{\max} \end{cases} \quad (h = 1,2,\ldots,N_{ob}; l = 1,2,\ldots,NP) \tag{4.7}$$

Information contained in multi-objective decision method, problem is related to the measure of better alternatives in order to show both unlikeness and conflict of the decision objective.

The process is started by constructing matrix of relative scores with membership function and standard deviation, which quantifies the strength of the h^{th} objective of the generated *NP* best solution of particles obtained while implementing PHOT. The standard deviation of membership function $\sigma_{\mu(F_{hl})}$ is a measure of the value of that objective to the decision making process [55]. A symmetrical matrix of correlation coefficients is constructed. A generic element, which is the linear correlation coefficient between the membership functions, is computed as:

$$G[\mu(F_{hl}), \mu(F_{ml})] = \frac{Cov[\mu(F_{hl}), \mu(F_{ml})]}{\sigma_{\mu(F_{hl})}\sigma_{\mu(F_{ml})}}; \quad (h = 1,2,\ldots,N_{ob}; m = 1,2,\ldots,N_{ob}; l = 1,2,\ldots,NP) \tag{4.8}$$

The more disagreeable the scores of the alternatives in objectives, lower are the values of generic elements. Mathematically, a measure of the conflict by objective $\mu(F_{hl})$ with respect to the decision situation set forth the rest of objectives is given by [55]:

$$\sum_{h=1}^{N_{ob}} \left[1 - G\{\mu(F_{hl}), \mu(F_{ml})\}\right] \qquad (m = 1,2,\ldots,N_{ob}) \tag{4.9}$$

The amount of information A_h given by the h^{th} objective can be evaluated by measures of agreement reached which quantify the opinions as:

$$A_h = \sigma_{\mu(F_{hl})} \sum_{h=1}^{N_{ob}} \left[1 - G\{\mu(F_{hl}), \mu(F_{ml})\}\right] \quad (m = 1,2,\ldots,N_{ob}) \tag{4.10}$$

The higher is the value of A_h, larger is the amount of information transmitted by the corresponding objectives and the higher is its relative importance for the decision making process. Objective weight pattern W_h^* is evaluated by normalizing the weights as given below [55]:

$$W_h^* = \frac{A_h}{\sum_{m=1}^{N_{ob}} A_m} \quad (h = 1,2,\ldots,N_{ob}) \tag{4.11}$$

The steps of best weight pattern evaluation method are elaborated in Algorithm-4.2.

ALGORITHM 4.2: Evaluation of best weight Pattern

1. Present with non-inferior solutions obtain from proposed technique.
2. Compute membership function of non-inferior solutions using Eq. (4.7).
3. A symmetrical matrix of correlation coefficient is formed and generic element is computed by Eq. (4.8).
4. A measure of conflict with respect to the decision situation set forth the rest of objectives is computed by Eq. (4.9).
5. The amount of information A_h given by the h^{th} objective is evaluated by Eq. (4.10).
6. Compute best normalized weights by Eq. (4.11).
   STOP

4.5 SOLUTION METHODOLOGY

Economic emission HTGS posed as a MOOP, and weighting method are used to convert it into a single objective problem. To start with movement process initially equal weights have been given to all objectives. Heuristic techniques based on integration of PPO, EP and PPS is explored to find optimum solution. The weights are updated, during the movement, according to best weight pattern using membership function of local best position of swarm or member of population obtained from integrated technique. This process continues up to the maximum number of movements, to achieve optimum solution.

ALGORITHM 4.3: Weight pattern evaluation with PHOT-I for multi-objective HTGS

1. Read input data, set maximum and minimum values of all objective function, maximum number of movement t_{max} and constant of proposed optimization technique, initial weights.
2. Randomly initialize prey position and velocity as discussed in sub-section 3.5.1.1 of chapter 3.
3. Randomly initialize a single predator position and velocity within the set limits as discussed in sub-section 3.5.1.2 of chapter 3.
4. Apply constraint handling procedure as discussed in section 4.3
5. Set movement counter as t=0
6. Set IT=50

   DO

   6.1 Increment the movement counter t=t+1
   6.2 Update predator velocity and position as discussed in sub-section 3.5.1.4 of chapter 3.
   6.3 Randomly generate the probability fear (pf) between 0 and 1.
   6.4 *IF* (pf>$pfmax$), *THEN*
   Update prey velocity including predator effect.
   ELSE
   Update prey velocity without predator effect.
   ENDIF
   6.5 Update prey position as discussed in sub-section 3.5.1.5 of chapter 3.
   6.6 Apply constraint handling procedure as discussed in section 4.3.
   6.7 Update local best position.
   6.8 *IF* ((t MOD IT)=0), *THEN*
   Apply Powell's pattern search to modify local best positions by applying Eq. (3.28) and Eq. (3.29), respectively.
   Apply constraint handling procedure as discussed in section 4.3
   IF (modified local best position generate improved solutions) *THEN*
   Update local best position.
   ENDIF
   ENDIF
   6.9 Update global best positions.
   6.10 Compute best normalized weights using local best solutions by applying, weight pattern evaluation as depicted in Algorithm-4.2.

   WHILE ($t<t_{max}$)
7. Positions corresponding to minimum value of objective function are the best compromised solution.

STOP

4.5.1 Proposed Heuristic Optimization Technique-I

Predator-prey optimization technique and Powell's search method are integrated in PHOT-I as discussed in chapter 2, section 2.2. The steps of PHOT-I, *i.e.* initialization of prey and predator position and velocity are same as discussed in sub-section 3.5.1.1 and 3.5.1.2 of chapter 3. After initialization of particles, constraint handling procedure as discussed in section 4.3 is applied to make the solution feasible. The objective function is evaluated and local and global best positions are updated. The velocity and position of predator and prey particles are updated for each thermal and hydro unit and for each sub-interval as discussed in sub-section 3.5.1.4 and 3.5.1.5 of chapter 3.

The weights are updated, during the movement, according to best weight pattern using membership function of local best position of swarm obtained from integrated technique. After a set number of movements, to improve the local and global best solutions obtained from PPO technique, Powell's pattern search method is applied as discussed in sub-section 3.5.1.6 of chapter 3. This process continues up to the maximum number of movements, to achieve optimum solution. The stepwise procedure to solve multi-objective HTGS is given in Algorithm-4.3.

4.5.2 Proposed Heuristic Optimization Technique-II

Evolutionary programming and Powell's search method are integrated in PHOT-II as discussed in chapter 2, section 2.2. The parent population is initialized as discussed in sub-section 3.5.2.1 of chapter 3. The offspring from each parent are generated for each thermal and hydro unit and for each sub-interval, by applying Gaussian mutation, Cauchy mutation and mean of Gaussian and Cauchy mutation operator as discussed in sub-section 3.5.2.2. After generating three sets of offspring, parents and offspring form a pool of 4*NP* member. Each member in the combined pool has to compete with other members to have a chance to select for next generation. The number of wins for each member after stochastic competition is given as:

$$Win_l = \sum_{m=1}^{R} win_m \tag{4.12}$$

$$Win_m = \begin{cases} 1, & rand() > \dfrac{F_{totl}}{F_{totl} + F_{totc}} \\ 0 & otherwise \end{cases} \tag{4.13}$$

$$c = \mathrm{int}(4 \times NP \times rand() + 1) \tag{4.14}$$

where

F_{totc} is objective function value of randomly selected c^{th} competitor in the pool

$rand()$ is uniformly distributed random number

F_{totl} is objective function value of l^{th} member

Win_l is number of wins of randomly selected member *l*.

ALGORITHM 4.4: Weight pattern evaluation with PHOT-II for multi-objective HTGS

1. Read input data, set maximum and minimum values of all objective function, maximum number of movement t_{max} and constant of proposed optimization technique, initial weights.
2. Randomly initialize population as discussed in sub-section 3.5.2.1 of chapter 3.
3. Apply constraint handling treatment procedure as discussed in section 4.3.
4. Set movement counter as t=0.
5. Set *IT*=50

   DO

   5.1 Increment the movement counter t=t+1

   5.2 Create three offspring vectors using Gaussian, Cauchy and mean of Gaussian and Cauchy mutation operator as discussed in sub-section 3.5.2.2 of chapter 3.

   5.3 Apply constraint handling Scheme as discussed in section 4.3.

   5.4 Combine parent and offspring to form a pool of 4*NP* members.

   5.5 Apply competition for survival as discussed sub-section 4.5.2.

   5.6 Select new *NP* member population on the basis of most number of win as discussed in sub-section 4.5.2.

   5.7 *IF* ((t MOD IT)=0), *THEN*

   Apply Powell's method to modify population.

   Apply constraint handling treatment procedure as discussed in section 4.3.

   IF (modified population generate improved solution) *THEN*

   Update population

   ENDIF

   ENDIF

   5.8 Update global best solution.

   5.9 Update scaling factor of EP.

   5.10 Compute best normalized weights by applying weight pattern evaluation as depicted in Algorithm-4.2.

   WHILE ($t<t_{max}$)
6. Member corresponding to minimum value of objective function is the best compromised solution.

   STOP

After competing, the trial 4*NP* solutions are ranked in descending order of score and first *NP* solutions are selected for next generation. The weights are updated, during the movement, according to best weight pattern using membership function of member of population obtained from integrated technique. After a set number of movements, to improve the members of population obtained from EP technique, Powell's pattern search method is applied as discussed in sub-section 3.5.1.6 of chapter 3. Global best solution is obtained by comparing objective function value and scaling factor is updated during movement as mentioned in sub-section 3.5.1.7 of chapter 3. This process continues up to the maximum number of movements, to achieve optimum solution. The stepwise procedure to solve multi-objective HTGS is given in Algorithm-4.4.

ALGORITHM 4.5: Weight pattern evaluation with PHOT-III for multi-objective HTGS

1. Read input data, set maximum and minimum values of all objective function, maximum number of movement t_{max} and constant of proposed optimization technique, initial weights.
2. Randomly initialize the *NP* prey positions and velocities as discussed in sub-section 3.5.1.1 of chapter 3.
3. Randomly initialize the predator position and velocity as discussed in sub-section 3.5.1.2 of chapter 3.
4. Randomly initialize *NP* members of population as discussed in sub-section 3.5.2.1 of chapter 3.
5. Apply constraint handling scheme to *NP* prey position and *NP* member of population as discussed in section 4.3.
6. Set movement counter as t=0
7. Set *IT*=50

   DO

   7.1 Increment the movement counter t=t+1
   7.2 Apply steps 6.2 to 6.7 of algorithm 4.3 of weight pattern evaluation with PHOT-I for multi-objective HTGS.
   7.3 Apply steps 5.2 to 5.6 of algorithm 4.4 of weight pattern evaluation with PHOT-II for multi-objective HTGS.
   7.4 Form a pool of *NP* local best positions and *NP* members of population.
   7.5 Arrange in ascending order and select *NP* solutions on the basis of objective function
   7.6 *IF* ((t MOD IT)=0), *THEN*

   Apply Powell's method to modify *NP* solutions.

   Apply constraint handling treatment procedure as discussed in section 4.3.

   IF (modified solutions improve the quality of solution) *THEN*

   Update solutions

   ENDIF

   ENDIF

   7.7 Update global best solution.
   7.8 Update scaling factor of EP technique.
   7.9 Compute best normalized weights by applying weight pattern evaluation as depicted in Algorithm-4.2.

   WHILE ($t<t_{max}$)
8. Solution corresponding to minimum value of objective function is the best compromised solution.

   STOP

4.5.3 Proposed Heuristic Optimization Technique-III

Evolutionary programming technique, predator-prey optimization and Powell's search method is integrated in PHOT-III as discussed in chapter 2, section 2.2. Weights are computed as discussed in section 4.4. The steps of PHOT-III are followed as mentioned in section 3.5.3 of chapter 3. The stepwise procedure to solve multi-objective HTGS is given in Algorithm-4.5.

4.6 ELECTRIC POWER SYSTEMS AND RESULTS

Proposed heuristic optimization techniques along with weight pattern evaluation are tested on four multi-chain hydro-thermal electric power systems to demonstrate the effectiveness of proposed solution approach. The HTGS problem is initially solved for economic generation scheduling (case-I) where only operating cost is considered ignoring emission objective. In second attempt, HTGS problem is undertaken where only emission objective is considered (case-II) ignoring economy objective. Finally, it is solved as a multi-objective HTGS (case-III) considering both the objectives simultaneously. Parameters setting of all PHOTs are same as discussed in section 3.6.1. For each system, twenty runs are given to find the best results. Electric power system-V, VI, VII and VIII has been taken from sub-section 3.6.1, 3.6.2, 3.6.3 and 3.6.4, respectively of chapter 3. A comparison has been made among the results obtained from the different search techniques applied.

Table 4.1: Parameters of PHOT-I

Constant	$\lambda_i^{\max}$	$\lambda_i^{\min}$	a_i	b_i	C_1	C_2	C_3	C_4	Pf_{max}
Value	$0.1\times x_i^{\min}$	$-0.1\times x_i^{\min}$	$0.05\times x_i^{\max}$	$\left(\frac{1.5}{x_i^{\max}}\right)$	1.5	2	1	0.1	0.95

Note: $x_i^{\max}$, $x_i^{\min}$: Upper and lower limit of i^{th} decision variables.

4.6.1 Parameter Setting

The proposed heuristic optimization techniques as discussed in section 4.5.1 are applied to search the optimum solution. To find the best parameters of PHOT-I, the same procedure is opted as discussed in sub-section 2.7.1.1 of chapter 2. The different values of best parameters of PHOT-I, are tabulated in Table 4.1. The parameters of PHOT-II, like β_{init}, β_{final} and β_{step} are set to 1, 0.01 and 0.005, respectively. The other parameters of PHOT-II are upper and lower limit of promising search area for Powell's search method and these values are same as set for PHOT-I. The parameters setting for PHOT-III are same as mentioned for PHOT-I and PHOT-II. Final generation schedule is obtained by taking population size as 50 in 1000 movements.

4.6.2 Electric Power System-V

The results obtained from PHOTs, are compared with the results reported in literature. It is observed from Table 4.2 that PHOT-III, yields better result for minimum cost and minimum emission by achieving lower objective values, for electric power system-V. Conflicting nature of the two objectives (minimum fuel cost and minimum emission) is evident from the results. Table 4.3 and Fig 4.1 represent power generation schedule and water discharge rate for minimum cost, respectively for electric power system-V. Table 4.4 and Fig 4.2 represent power generation schedule and water discharge rate for minimum emission, respectively for electric power system-V.

Table 4.2: Comparison of results: Electric power system-V

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost×(10^3) ($)	Emission ×(10^3) (ton)	CPU time (s)	Cost×(10^3) ($)	Emission ×(10^3) (ton)	CPU time (s)	Cost×(10^3) ($)	Emission ×(10^3) (ton)	CPU time (s)
QADEVT [375]	41.76	30.71	--	45.97	16.65	--	42.94	17.92	--
ε-ODEM [404]	--	--	--	--	--	--	44.67	16.65	--
NSGA-II[404]	--	--	--	--	--	--	46.05	17.08	--
SPEA-II [404]	--	--	--	--	--	--	45.53	16.97	--
PESA-II[404]	--	--	--	--	--	--	45.43	16.84	--
QPSO [325]	42.36	31.30	--	45.27	17.77	--	44.26	18.23	--
SOHPSO-TVAC [391]	41.98	24.48	112.0	44.43	16.80	112.6	43.04	17.00	120.0
EP[199]	45.06	48.80	--	59.29	16.55	--	47.90	26.23	4582
Clonal SA[372]	42.44	--	109.1	--	--	--	--	--	--
DE[303]	43.50	21.09	72.96	51.45	18.26	72.73	44.91	19.61	74.97
MDE[235]	42.61	33.32	125.0	48.72	15.73	--	43.20	20.38	--
PSO[362]	42.47	28.13	123.5	48.26	16.93	124.7	43.28	17.90	132.4
PSO[266]	44.74	--	232.7	--	--	--	--	--	--
SA[266]	45.47	--	246.2	--	--	--	--	--	--
MOCA-PSO [398]	42.00	16.84	--	44.96	16.24	--	43.87	16.22	--
HMOCA [381]	41.80	16.84	--	46.74	15.91	--	43.59	16.20	--
PHOT-I	41.19	26.50	33.63	48.99	15.71	33.87	43.18	17.05	34.06
PHOT-II	41.70	27.86	35.87	48.95	15.74	34.52	43.11	18.78	35.72
PHOT-III	41.06	25.36	41.66	49.00	15.70	40.63	42.45	17.85	42.69

Note: NSGA-II: Non-dominated sorting genetic algorithm; SPEA-II: Strength Pareto evolutionary algorithm-II; PESA-II: Pareto envelope-based selection algorithm-II; SA: Simulated annealing; MDE: Modified DE; MOCA-PSO: Multi-objective cultural algorithm based on PSO; HMOCA: Hybrid multi-objective cultural algorithm; PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique

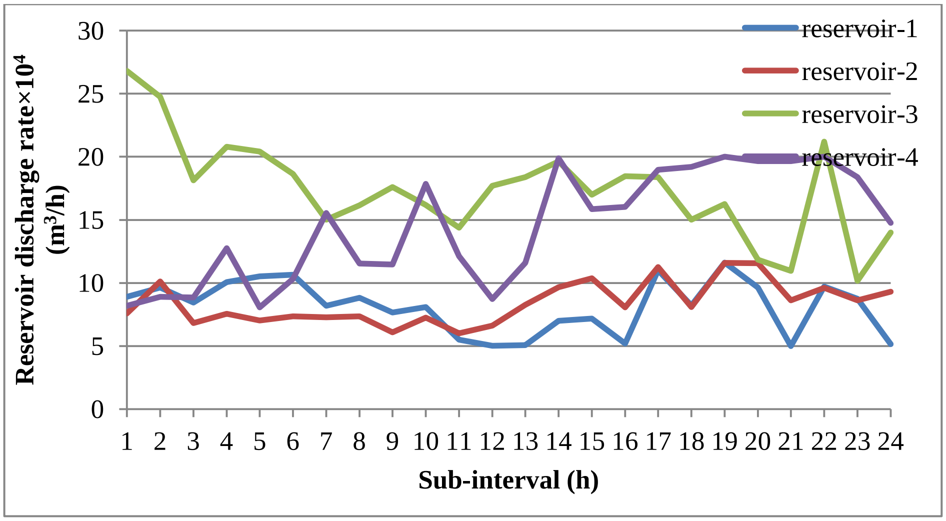

Figure 4.1: Reservoir discharge rate for minimum cost HTGS: Electric power system-V

Table 4.3: Power generation for minimum operating cost HTGS: Electric power system-V

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	102.6761	294.7265	50	80.35799	59.38971	2.97768	159.8744
2	780	102.6847	294.7206	50	84.63087	73.38538	11.25809	163.3202
3	700	102.6765	40	229.5076	77.9901	53.5644	40.34626	155.915
4	650	20.0946	40	229.5185	86.26375	59.69323	26.7201	187.7098
5	670	102.7228	40	229.5227	87.08694	57.06072	27.99981	125.6071
6	800	102.7783	294.7246	50	85.74612	59.77713	36.24513	170.7287
7	950	102.8459	294.731	139.7739	72.38196	59.13011	47.18691	234.1224
8	1010	102.6764	294.8125	229.5227	75.81071	58.85821	47.0027	201.3182
9	1090	102.678	294.8517	319.3082	69.11443	50.21103	44.27077	209.5698
10	1080	102.6786	294.6906	229.5005	72.57951	59.07178	47.75263	273.7314
11	1100	102.6688	294.7148	319.3123	55.2663	51.63632	51.09985	225.2972
12	1150	102.6323	294.594	408.9694	52.73675	57.53553	44.49763	188.9944
13	1110	102.6328	294.7275	319.2665	54.2439	68.84573	41.64904	228.5934
14	1030	102.6171	209.8115	229.513	70.99278	76.30776	36.16244	304.5395
15	1010	102.6261	209.8181	229.5451	73.12679	79.29623	43.50726	272.0328
16	1060	102.6261	294.72	229.4988	56.8224	66.39847	37.84199	272.0448
17	1050	102.6361	294.8341	139.782	97.38248	82.34283	37.66064	295.3083
18	1120	102.618	209.861	319.2802	81.27762	63.93846	46.91727	296.0522
19	1070	20.0105	294.7473	229.5284	99.49173	79.51711	45.2725	301.3773
20	1050	102.6298	294.7665	139.7824	89.24329	76.25378	51.06413	296.2042
21	910	102.5524	294.707	50	54.67036	60.29953	52.72979	294.9846
22	860	20	124.9322	229.542	89.33318	65.64651	34.99471	295.5509
23	850	101.9827	40	229.511	83.45525	60.18685	54.40572	280.3987
24	800	101.9186	40	229.5103	55.92641	63.33237	57.87224	250.6843

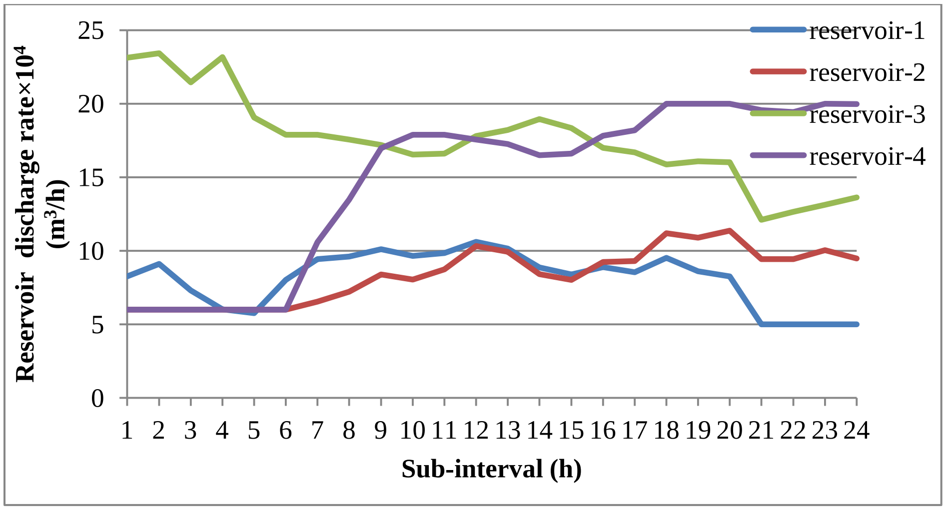

Figure 4.2: Reservoir discharge rate for minimum emission HTGS: Electric power system-V

Table 4.4: Power generation for minimum emission HTGS: Electric power system-V

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	168.8721	179.2278	122.5968	78.19643	49	20.20853	131.889
2	780	174.9794	185.952	129.2607	80.94304	50.16399	29.67562	129.0263
3	700	157.0607	162.8772	111.0893	71.42938	51.296	20.50546	125.7431
4	650	146.7988	149.9298	99.82744	61.20544	52.934	17.68011	121.6247
5	670	149.1988	152.7736	103.0595	59.21851	54.5	35.42837	115.8214
6	800	174.9991	189.9781	130.8055	75.76727	55.504	39.92052	133.0256
7	950	174.9885	228.8264	165.2967	84.39729	60.00095	38.32892	198.1618
8	1010	174.9945	235.1725	171.2808	84.228	63.61686	33.33599	247.3719
9	1090	174.9994	252.144	186.8541	86.51394	70.94662	34.45685	284.0854
10	1080	175	248.3811	181.9715	85.14668	70.13103	35.87766	283.4923
11	1100	174.9989	253.9957	186.1155	86.28246	74.5959	37.24011	286.7716
12	1150	174.9989	269.8691	203.1158	89.92627	81.34631	35.53172	295.2119
13	1110	175	253.2438	187.6312	87.14091	77.71713	34.02715	295.2398
14	1030	174.9985	226.6875	162.3227	81.59984	69.98373	32.95723	281.4503
15	1010	174.9986	215.5129	153.2263	79.46341	67.06902	36.63287	283.0966
16	1060	175	229.8262	164.6151	83.64581	75.0808	42.72073	289.1118
17	1050	174.9989	222.9307	156.652	81.59543	74.76266	44.98724	294.0735
18	1120	174.9993	243.7468	178.7712	86.94183	81.92899	47.6131	305.9991
19	1070	174.9993	223.5797	159.0291	81.58618	77.85289	48.09058	304.8627
20	1050	174.9993	215.3478	151.1611	79.00725	77.07207	49.27418	303.1389
21	910	160.0295	166.4344	112.4369	53.60759	66.00429	53.82433	297.6634
22	860	145.5172	146.8616	98.04182	53.91011	66.05943	56.20654	293.4037
23	850	142.4606	140.0153	93.30808	54.3009	68.68867	58.04031	293.1866
24	800	128.082	123.8087	80.4547	54.70436	65.28333	58.77308	288.8895

The minimum value of each objective function is obtained by applying economy HTGS and emission HTGS problem separately. Because of conflicting nature of cost and emission objectives, minimum value of one objective is obtained at the expense of maximum value of other objective. To compare the multi-objective solution among various reported results, a max-min function is applied in fuzzy form. The overall membership function is represented as cardinal priority ranking $\mu_D = \{\min\{\mu(F_h); h = 1,2,\ldots,Nob\}\}$. Maximum value of cardinal priority ranking represents best Pareto optimal solution. Membership function is computed by considering best minimum objective function value among results reported in Table 4.2, and corresponding maximum value. It is evident from Fig 4.3, that maximum value of cardinal priority ranking is achieved by the solution obtained from the PHOT-III. Results reported in [303, 391] consumes more or less water than the available storage of water. However, in this study better results have been obtained which strictly satisfy all constraints of the electric power system.

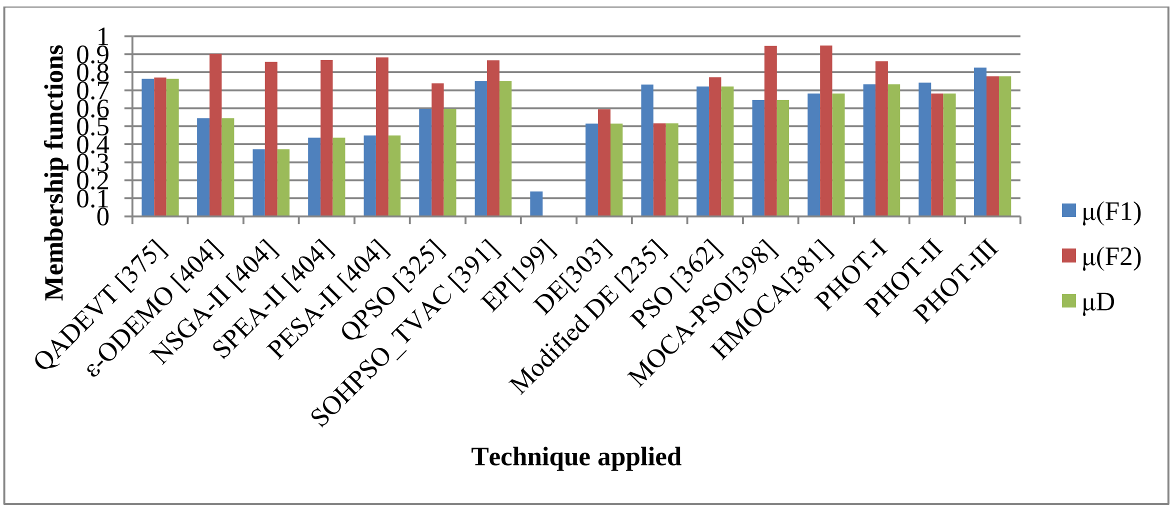

Figure 4.3: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-V

Table 4.5 and Fig 4.4 represent power generation schedule and water discharge rate, respectively while solving the multi-objective generation scheduling problem by applying PHOT-III. The convergence behavior of PHOTs, for minimum cost and minimum emission hydro-thermal generation scheduling are shown in Fig 4.5 and Fig 4.6, respectively. From Fig 4.5 and Fig 4.6, it is concluded that the PHOT-III, shows good convergence characteristics as compared to PHOT-I and PHOT-II. From Table 4.2, it is concluded that the PHOT-I take less time as compared to PHOT-II and PHOT-III.

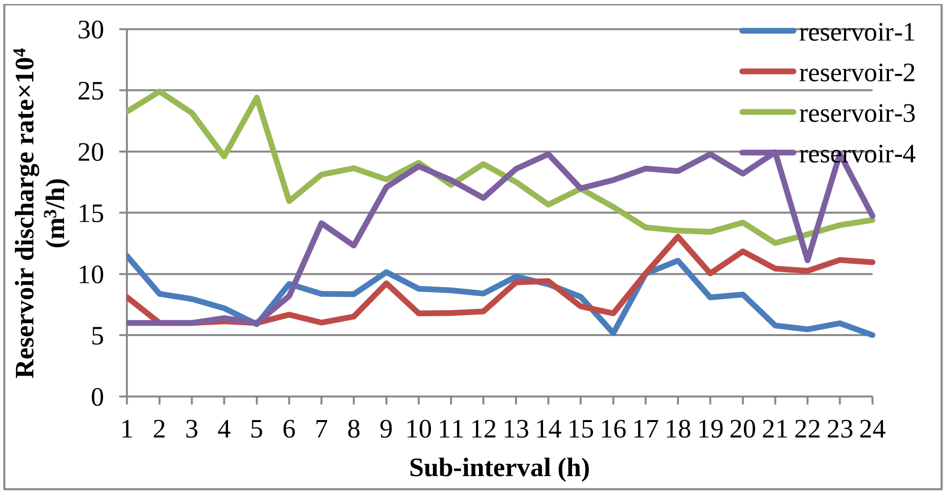

Figure 4.4: Reservoir discharge rate for multi-objective HTGS: Electric power system-V

Table 4.5: Power generation for multi-objective HTGS: Electric power system-V

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	174.9959	209.9817	50.22676	91.94212	62.64083	28.18809	132.0142
2	780	159.1761	125.1714	229.1866	76.90804	48.95867	11.58225	129.0179
3	700	167.1554	125.7736	139.8382	74.64578	50.09938	16.75408	125.7345
4	650	102.7204	125.2264	139.9984	69.71262	52.66987	32.87454	126.7975
5	670	172.6441	124.857	139.8374	59.87226	53.33961	4.02698	115.422
6	800	107.8276	209.7929	139.8965	81.74015	59.19523	41.91518	159.6323
7	950	104.4324	209.816	229.4091	76.37688	54.7121	35.87646	238.6457
8	1010	175	209.1711	229.0444	76.15341	58.25633	32.62112	229.7858
9	1090	175	209.9844	229.5625	85.65249	75.19206	35.43488	279.1726
10	1080	175	209.7701	228.7515	78.8678	59.69049	29.42167	298.504
11	1100	174.9807	210.0144	252.9167	78.89139	60.93381	34.6112	287.726
12	1150	174.9362	209.4661	319.0896	78.33183	62.93463	28.3808	276.9429
13	1110	175	209.7026	229.5429	86.43924	77.84691	34.45018	297.0242
14	1030	175	209.8376	139.5235	83.50295	77.66013	40.55617	303.9257
15	1010	105.8843	209.1011	229.3759	78.21192	65.44982	38.07549	283.9854
16	1060	174.1035	209.0476	226.4977	55.8223	62.39845	42.9743	289.2419
17	1050	174.9552	209.8176	147.9174	90.74586	82.10973	47.33862	297.2033
18	1120	175	273.309	139.7492	95.40857	92.39112	49.44913	294.6947
19	1070	140.2388	209.9025	214.1414	78.64972	76.43646	49.83895	300.885
20	1050	174.8534	209.7086	165.2656	80.00385	82.05151	50.50898	287.6982
21	910	174.3182	125.9645	125.4614	60.939	73.83755	53.63919	295.9368
22	860	102.8324	124.9106	229.423	58.33748	72.08745	56.17256	216.3143
23	850	102.4492	124.8951	136.3897	62.90695	74.92184	57.47473	291.0611
24	800	102.8262	125.5291	139.469	54.705	71.99294	58.19738	248.1794

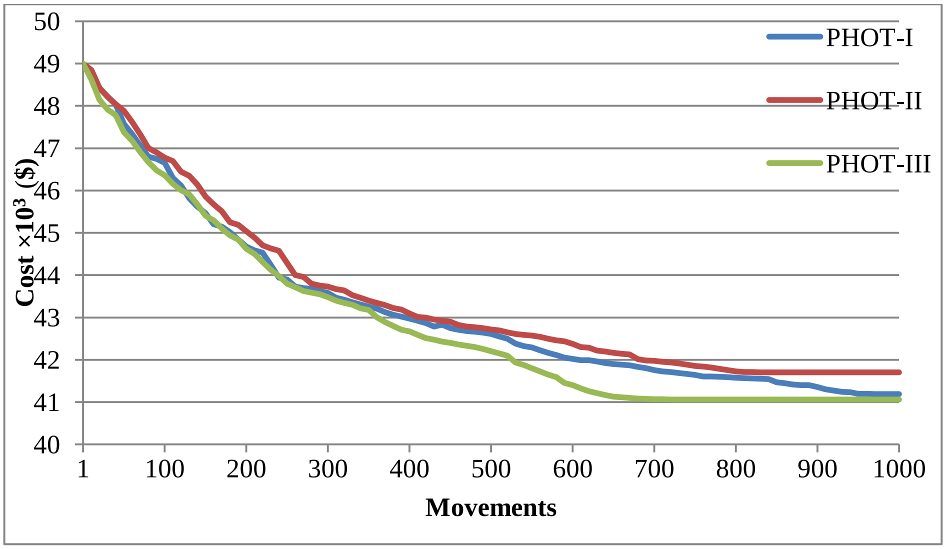

Figure 4.5: Convergence characteristics for minimum cost HTGS: Electric power system-V

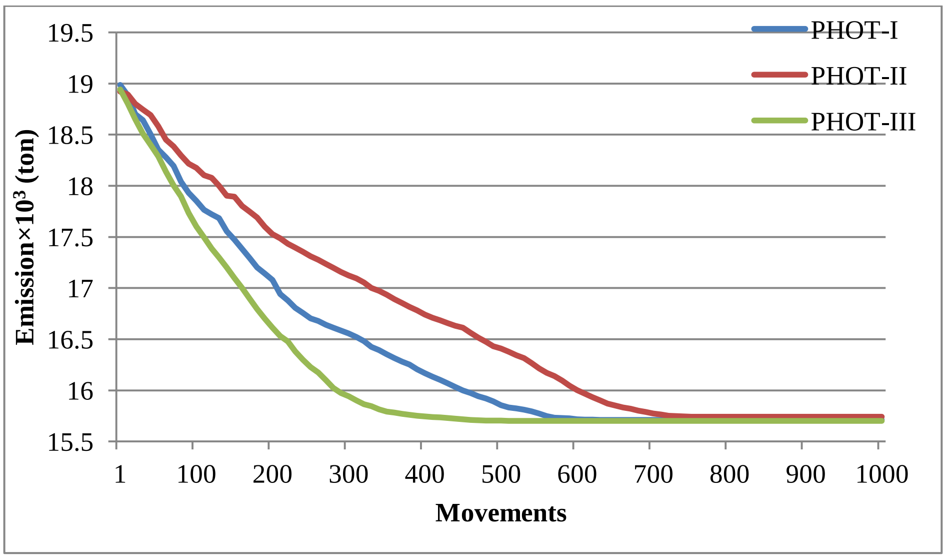

Figure 4.6: Convergence characteristics for minimum emission HTGS: Electric power system-V

4.6.2.1 Robustness of proposed heuristic optimization techniques

To investigate the effect of initial solutions, and to verify the robustness, proposed heuristic techniques are tried 20 times and the best, average and worst results are compared as given in Table 4.6. It is evident from Table 4.6 that best, average and worst results obtained by PHOT-III are better than solutions of PHOT-I and PHOT-II for minimum cost and minimum emission scheduling. Minimum standard deviation is obtained by solutions from PHOT-III, so it is concluded that PHOT-III generate more precise solutions.

Table 4.6: The best, average and worst values of objectives: Electric power system-V

Technique Applied	Scheduling		Best	Average	Worst	S. D.
PHOT-I	Economy	$F_1 \times 10^3$ ($)	41.19	41.56	42.23	0.23561
	Emission	$F_2 \times 10^3$ (ton)	15.71	15.98	16.42	0.20018
PHOT-II	Economy	$F_1 \times 10^3$ ($)	41.70	42.13	42.99	0.25438
	Emission	$F_2 \times 10^3$ (ton)	15.74	16.11	16.64	0.21009
PHOT-III	Economy	$F_1 \times 10^3$ ($)	41.06	41.45	42.02	0.22908
	Emission	$F_2 \times 10^3$ (ton)	15.70	15.87	16.37	0.20002

Note: PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

Table 4.7: Comparison of results: Electric power system-VI

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost $\times(10^3)$ ($)	Emission (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission (ton)	CPU time (s)
DE[341]	110.8	51.37	2554	161.4	11.50	2424	--	--	--
RCGA[341]	112.9	49.87	3156	160.0	11.62	3261	--	--	--
NSGA-II [341]	--	--	--	--	--	--	127.2	18.96	4301
MODE[341]	--	--	--	--	--	--	126.8	17.7	2957
Multi-objective [411]	--	--	--	--	--	--	84.40	14.69	170
PHOT-I	68.20	127.5780	33.26	128.264	9.7676	33.52	83.737	16.0500	33.41
PHOT-II	69.00	129.3084	36.35	128.909	9.8114	36.46	84.746	15.4473	34.76
PHOT-III	67.82	157.1964	41.46	129.674	9.7592	42.01	81.279	18.4126	40.94

Note: PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

4.6.3 Electric Power System-VI

The proposed heuristic optimization techniques based on PPO, EP and PPS methods have been applied for scheduling of hydro-thermal electric power system-VI. The results obtained from PHOTs are compared with the results reported in literature. It is observed from Table 4.7 that PHOT-III yields better result for minimum cost and minimum emission by achieving lower objective values, for electric power system-VI. Table 4.8 and Fig 4.7 represent power generation schedule and water discharge rate for minimum cost. Table 4.9 and Fig 4.8 represent power generation schedule and water discharge rate for minimum emission, respectively.

Table 4.8: Power generation for minimum operating cost HTGS: Electric power system-VI

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	175	226.4696	69.30706	80.83319	49.00138	17.50733	131.8814
2	780	175	229.6126	69.82634	85.7841	50.19024	40.55991	129.0268
3	700	175	200.0066	52.54795	73.2895	51.2944	22.11721	125.7444
4	650	175	161.7362	50	64.64568	52.93187	24.06111	121.6251
5	670	175	187.9575	50.16137	54.40566	54.5011	32.15248	115.8219
6	800	175	251.826	72.82669	73.06157	55.50188	38.41805	133.3659
7	950	175	296.1935	94.365	85.45012	58.78429	41.65107	198.556
8	1010	175	299.6447	116.1878	70.81816	58.23852	32.47977	257.6311
9	1090	175	300	145.8546	92.645	68.74273	34.55677	273.1935
10	1080	175	299.9851	138.1128	88.96972	72.92738	34.57156	270.4334
11	1100	175	299.9822	145.0499	88.32513	68.96738	30.92311	291.7522
12	1150	175	299.9882	149.1465	92.47434	91.61156	37.62405	304.1554
13	1110	175	300	136.3342	89.80864	81.27925	33.43137	294.1397
14	1030	175	294.3552	94.32473	71.57233	67.33393	31.92478	295.489
15	1010	175	294.152	93.90325	81.78401	69.89561	36.93756	258.3275
16	1060	175	299.9539	101.2104	85.13914	73.57013	43.23193	281.8962
17	1050	175	292.5967	93.69643	73.50224	74.37176	45.68969	295.145
18	1120	175	299.968	129.0284	84.66232	77.58289	48.30416	305.4561
19	1070	175	292.7823	93.68328	76.21352	77.3704	49.67922	305.2732
20	1050	175	288.486	91.48695	64.83896	76.38506	50.31794	303.487
21	910	175	205.353	54.73128	53.60355	68.09872	54.33893	298.8764
22	860	175	160.9185	50	53.9065	66.94061	56.34746	296.8889
23	850	175	148.3213	50	54.29793	71.21848	57.83879	293.3256
24	800	175	113.4186	50	54.70223	60.81875	58.70907	287.3533

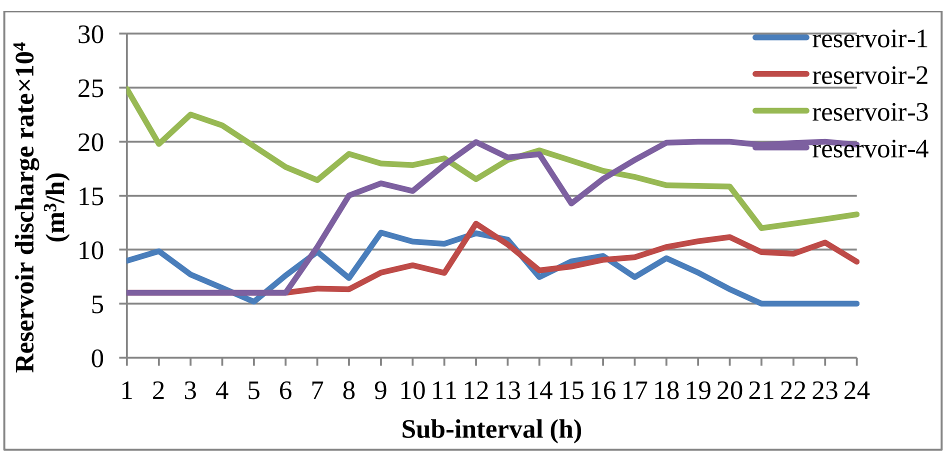

Figure 4.7: Reservoir discharge rate for minimum cost HTGS: Electric power system-VI

Table 4.9: Power generation for minimum emission HTGS: Electric power system-VI

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	132.2957	113.4767	207.4401	87.65639	49	28.24995	131.8811
2	780	141.4768	118.5682	230.3665	80.88081	50.17029	29.51072	129.0268
3	700	119.1497	105.7695	182.2221	75.26218	51.29746	40.5555	125.7436
4	650	112.6777	101.8359	167.7845	75.90524	52.93338	17.22941	121.6252
5	670	119.4989	106.6156	182.9029	60.68757	54.4994	29.97435	115.822
6	800	146.1494	121.0146	242.7986	59.63435	55.50343	42.96571	131.9346
7	950	158.6056	128.6413	277.7756	89.95547	57.83504	41.38243	195.8052
8	1010	152.1512	124.5728	258.3658	85.81805	55.86959	44.28298	288.9398
9	1090	170	140.0716	367.6883	85.853	77.69215	30.54061	218.1545
10	1080	170	133.5195	306.864	86.16939	68.46223	36.55326	278.4317
11	1100	170	137.4528	339.7065	77.7878	76.9311	37.2619	260.8601
12	1150	170	142.7117	377.5307	58.11695	84.65708	36.29022	280.6936
13	1110	168.8484	134.0635	311.4881	83.01701	76.31609	35.13407	301.1329
14	1030	157.3468	128.5773	272.9875	75.24233	70.14373	35.21827	290.4843
15	1010	149.9493	124.878	249.3653	88.6981	66.08016	40.78262	290.2467
16	1060	162.8764	132.233	287.1466	57.95984	79.65474	44.41612	295.7135
17	1050	156.2554	127.1576	263.8829	88.64543	74.64147	45.12205	294.2954
18	1120	166.8223	131.0865	304.7245	83.13089	80.55434	47.87803	305.8038
19	1070	156.4678	125.4897	275.3166	84.43459	76.20351	47.21614	304.872
20	1050	153.081	123.334	263.5085	83.87254	75.58091	48.66135	301.9621
21	910	123.1111	110.7191	203.9628	55.86545	66.30974	53.69194	296.3403
22	860	114.6554	102.344	172.147	61.53082	64.83659	56.05444	288.4323
23	850	86.21698	100.0767	181.8974	64.92908	67.62898	57.91014	291.3412
24	800	97.81207	94.34241	140.9919	54.71283	65.11475	58.53088	288.5013

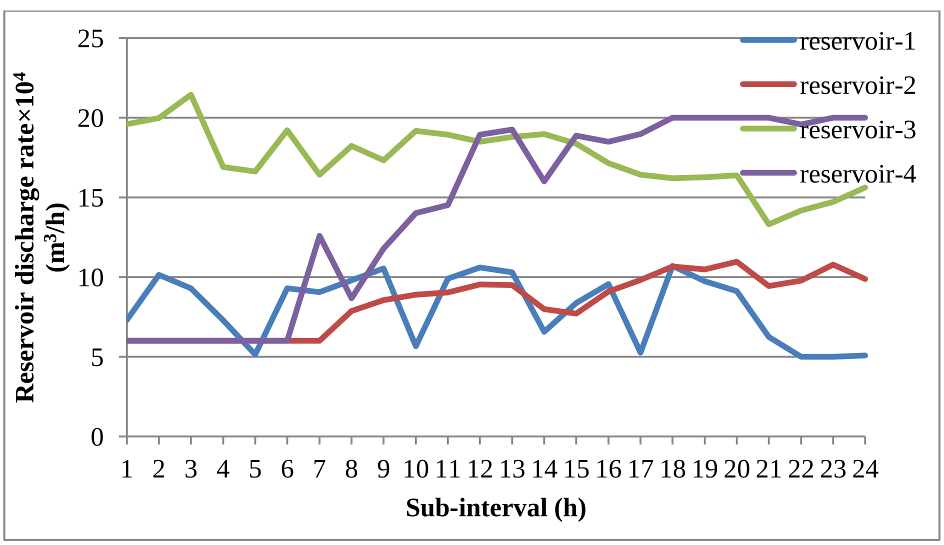

Figure 4.8: Reservoir discharge rate for minimum emission HTGS: Electric power system-VI

To select better multi-objective solution, cardinal priority ranking is computed. It is evident from Fig 4.9, that maximum value of cardinal priority ranking is achieved by solution obtained from PHOT-III. It is observed from Table 4.7, that a relatively large difference of cost exists among the results obtained by PHOTs as compared to NSGA-II, MODE. So, it is concluded that solutions obtained by NSGA-II and MODE struck to a local optimum solution. Table 4.10 and Fig 4.10 represent power generation schedule and water discharge rate, respectively while solving the multi-objective generation scheduling problem by applying PHOT-III for electric power system-VI.

Table 4.10: Power generation for multi-objective HTGS: Electric power system-VI

k	p_{Dk} (MW)	Thermal Power (MW)			Hydro Power (MW)			
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	750	175	183.046	108.0089	88.31781	49	14.7473	131.88
2	780	175	197.3535	134.1913	79.80272	50.16399	14.46153	129.0269
3	700	175	168.9277	81.59935	63.78952	51.296	33.64208	125.7453
4	650	175	149.1283	66.36676	76.14845	52.934	8.79738	121.6252
5	670	175	157.9083	75.86449	66.3908	54.5	24.5144	115.822
6	800	175	193.8123	127.8591	74.66971	55.504	39.44686	133.7081
7	950	175	208.7466	168.6029	74.06817	63.62491	38.25471	221.7027
8	1010	175	208.5272	191.9742	75.13754	61.238	34.38149	263.7416
9	1090	175	216.7612	219.2977	82.12404	73.65841	36.69477	286.4639
10	1080	175	214.126	219.8893	79.10375	71.65534	40.08371	280.1418
11	1100	175	212.1266	220.2446	91.82561	71.19698	34.67644	294.9297
12	1150	175	223.8185	253.3237	87.65299	86.99977	37.64789	285.5571
13	1110	174.8015	213.7266	241.2154	79.64764	76.68832	34.01618	289.9043
14	1030	175	208.9457	185.1667	71.74955	74.16203	38.54002	276.436
15	1010	175	199.6219	176.2915	83.16051	59.17162	36.52859	280.2259
16	1060	175	209.2917	191.05	89.20254	71.79465	44.13405	279.5269
17	1050	175	212.4672	153.6749	72.79185	82.63218	47.4742	305.9596
18	1120	175	207.3544	230.442	76.22388	78.92469	48.12501	303.9301
19	1070	175	197.3063	202.0573	82.95993	71.12085	49.70339	291.8522
20	1050	175	196.8746	174.8991	79.31705	72.40724	50.36244	301.1395
21	910	175	177.5856	75.65332	82.69734	67.34196	53.95778	277.764
22	860	175	146.4553	76.39114	54.09494	63.81091	55.79632	288.4513
23	850	175	137.5937	56.29187	66.05156	65.5568	57.10628	292.3998
24	800	175	122.5507	50	54.70427	58.95538	57.18139	281.6083

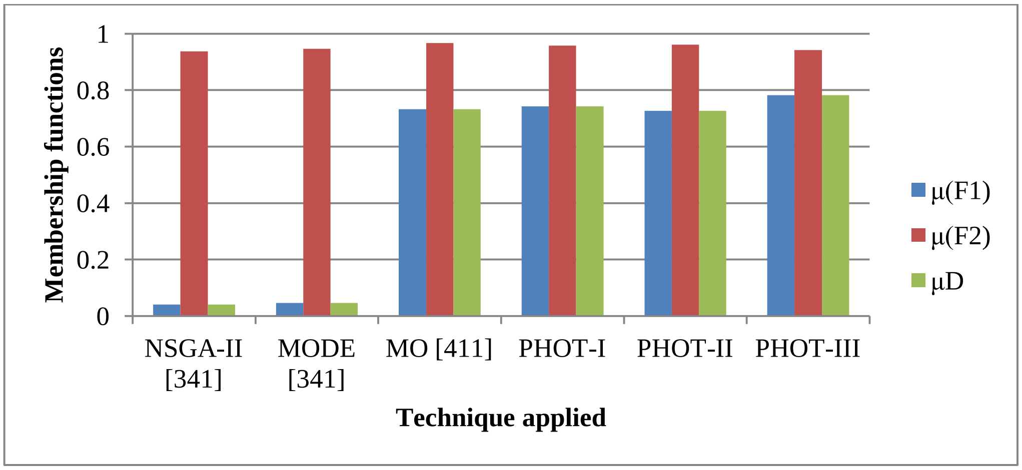

Figure 4.9: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-VI

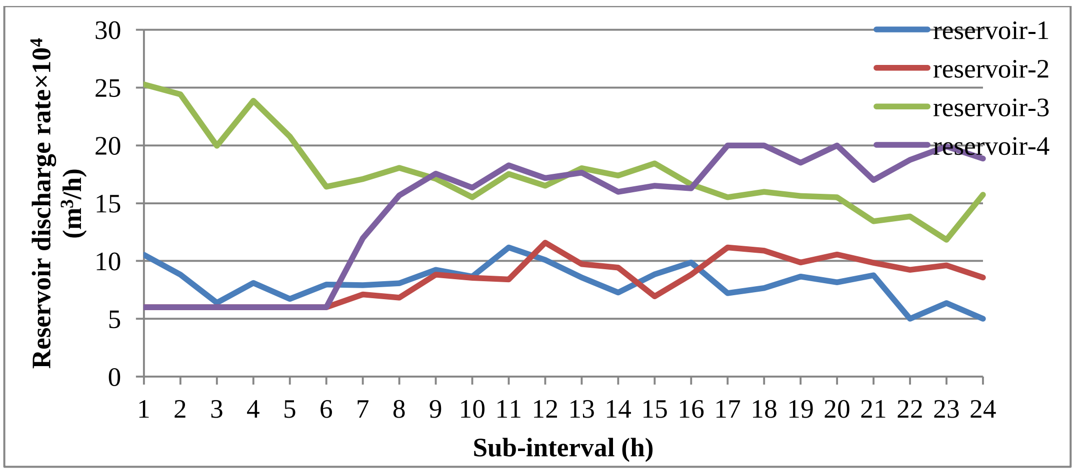

Figure 4.10: Reservoir discharge rate for multi-objective HTGS: Electric power system-VI

4.6.4 Electric Power System-VII

Three proposed heuristic optimization techniques have been applied for scheduling of hydro-thermal electric power system-VII. The results obtained from PHOTs are compared with the result from PSO and PPO technique. It is observed from Table 4.11 that PHOT-III, yields minimum cost and PHOT-I, yields minimum emission by achieving lower objective values, for electric power system-VII. Tables 4.12 and 4.13 represent thermal and hydro power generation schedule, respectively while, Fig 4.11 represents water discharge rate for minimum cost for electric power system-VII. Tables 4.14 and 4.15 represent thermal and hydro power generation schedule, respectively while, Fig 4.12 represents water discharge rate for minimum emission for electric power system-VII.

Table 4.11: Comparison of results: Electric power system-VII

Technique Applied	Economy Scheduling			Emission Scheduling			Multi-objective Scheduling		
	Cost ($\times10^3$) ($)	Emission ($\times10^3$) (ton)	CPU time (sec)	Cost ($\times10^3$) ($)	Emission ($\times10^3$) (ton)	CPU time (sec)	Cost ($\times10^3$) ($)	Emission ($\times10^3$) (ton)	CPU time (sec)
PSO	1365.71	26.236	75.32	1390.50	24.871	75.91	1364.0	25.340	77.31
PPO	1349.80	26.967	37.24	1391.41	23.711	38.53	1360.10	25.064	38.56
PHOT-I	1336.91	27.124	36.42	1400.20	23.056	36.51	1356.61	24.420	36.68
PHOT-II	1336.50	27.118	38.93	1403.91	23.174	37.43	1366.70	23.930	37.44
PHOT-III	1333.90	27.028	45.35	1400.11	23.059	46.32	1357.71	24.351	46.03

Note: PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

Table 4.12: Thermal power generation for minimum operating cost HTGS: Electric power system-VII

k	p_{Dk} (MW)	Thermal Power (MW)					
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}
1	1374	91.91113	79.62451	209.954	224.1085	314.3269	324.025
2	1278	46.70972	38.52124	208.2869	211.6427	314.3915	324.025
3	1372	80.30859	76.15356	210	224.3878	314.9974	324.025
4	1058	35.94104	10.42859	149.3945	157.3087	294.9407	272.7128
5	1358	75.28247	65.2406	209.4225	224.264	315	324.025
6	1282	49.44568	23.21423	208.3019	223.7675	314.2295	324.025
7	1130	39.13281	13.09729	163.032	167.6844	287.3875	316.1348
8	1200	36.85339	25.57349	176.4245	182.475	314.5554	324.025
9	1248	40.81287	23.51892	209.9985	191.9906	314.2032	324.025
10	1364	74.54541	68.20691	209.6891	224.9968	314.2397	324.025
11	1146	38.88989	17.74365	151.1114	178.8461	297.5299	319.0751
12	1262	45.78589	29.35803	208.0663	203.3397	314.3266	320.6312
13	1246	49.38049	20.13086	192.4028	201.7516	313.3047	324.025
14	1140	30.36438	21.32593	162.2432	171.6985	301.1544	305.5356
15	1226	45.26343	26.0249	174.7786	195.585	312.9943	324.025
16	1314	56.46423	38.20593	208.3793	224.9861	312.1841	324.025
17	1426	97.0509	104.1481	209.2841	223.6555	314.9932	324.6004
18	1028	35.31952	10.01477	144.6109	142.5923	265.6652	281.9894
19	1148	40.49304	10.05261	157.2366	174.3817	311.7108	299.8006
20	1256	46.74658	35.22632	180.1129	207.9073	312.4946	324.025
21	1348	71.60181	62.81604	210	223.0763	312.4407	324.025
22	1424	96.70032	105.0007	209.5707	224.9954	312.6771	324.5557
23	1070	30.44067	10.01111	144.1699	165.4721	282.9147	287.434
24	1118	33.92847	17.15918	153.0522	159.9282	296.3169	312.8819

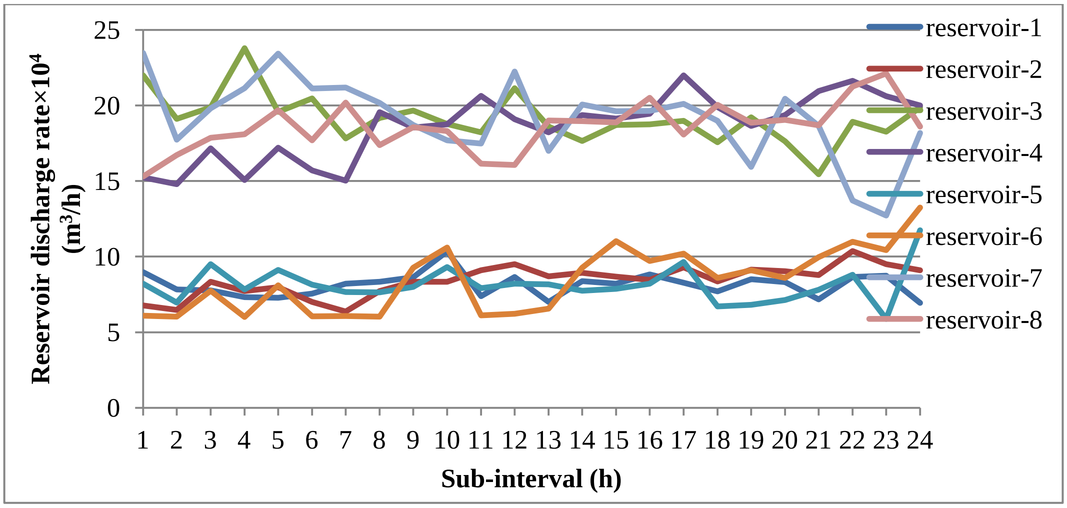

Figure 4.11: Reservoir discharge rate for minimum cost HTGS: Electric power system-VII

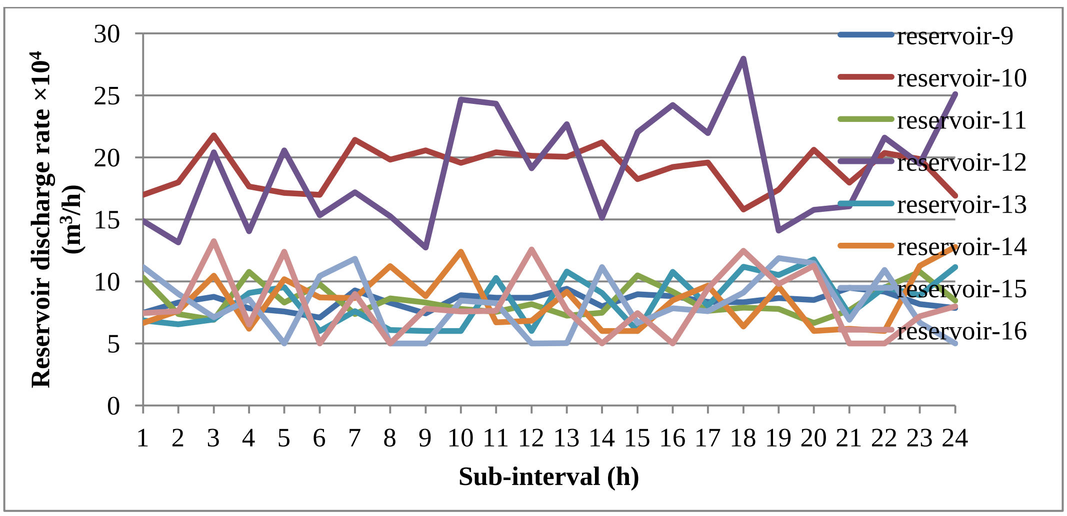

Figure 4.11: Reservoir discharge rate for minimum cost HTGS (Continued)

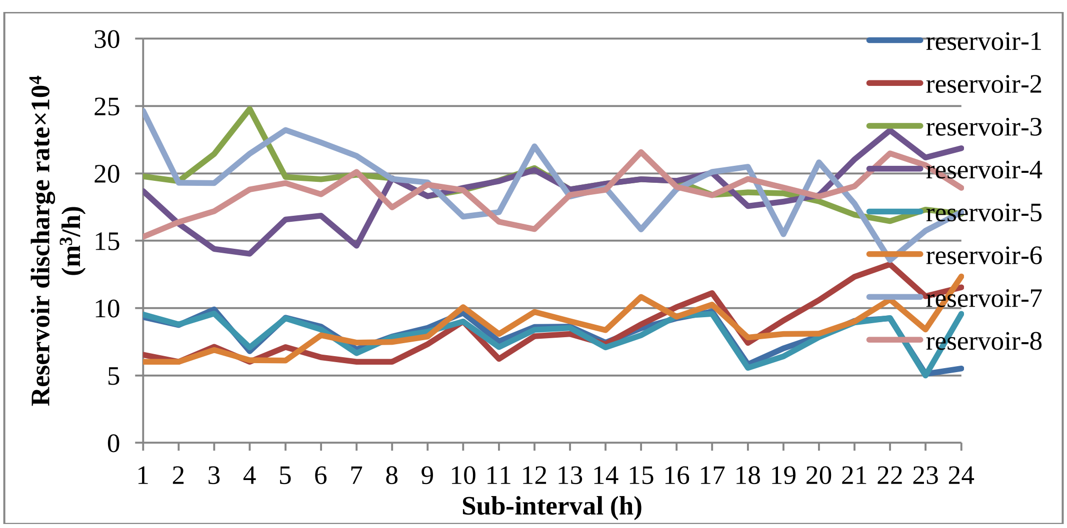

Figure 4.12: Reservoir discharge rate for minimum emission HTGS: Electric power system-VII

Table 4.13: Hydro power generation (MW) for minimum operating cost HTGS: Electric power system-VII

k	p_{7k}	p_{8k}	p_{9k}	p_{10k}	p_{11k}	p_{12k}	p_{13k}	p_{14k}	p_{15k}	p_{16k}	p_{17k}	p_{18k}	p_{19k}	p_{20k}	p_{21k}	p_{22k}
1	8.0776	5.4243	3.5470	23.0264	7.6357	4.9583	2.6905	23.0789	5.8808	5.4583	7.3982	5.8111	5.4832	5.3541	9.0750	7.1504
2	7.4359	5.3002	4.8791	23.7230	6.8618	5.0372	5.2336	25.3700	6.3996	5.5167	5.6818	6.1980	5.3386	6.0652	8.0590	7.3231
3	7.4281	6.5600	4.6781	26.2677	8.4889	6.2827	4.6284	26.5336	6.6491	4.1968	5.4229	5.0049	5.6950	7.5770	6.8896	9.8249
4	7.1344	6.2470	2.6696	25.0875	7.4642	5.1923	4.0848	27.0792	6.1362	5.7868	7.6290	6.3551	7.0810	5.0400	7.8368	6.4500
5	7.0971	6.4750	4.6195	27.6607	8.2138	6.7412	2.6693	28.3849	6.0461	5.9221	6.2902	5.1452	7.3276	7.5374	5.2111	9.4244
6	7.2508	5.8574	4.2091	26.7210	7.5553	5.3836	3.8344	27.5401	5.7518	5.9470	7.0403	6.3458	5.0774	6.6643	8.7607	5.0774
7	7.6452	5.4317	5.1216	26.5680	7.2062	5.4548	3.7152	29.4634	7.0257	4.4773	5.5307	6.1421	6.1985	6.5265	9.1158	7.9085
8	7.7209	6.2942	4.6715	30.2562	7.2123	5.4162	4.0426	27.7694	6.2844	5.1512	6.1876	6.4146	5.1003	7.5628	5.0530	5.1048
9	7.9173	6.6119	4.4477	29.5615	7.4806	7.4930	4.4743	28.8807	5.6859	4.8766	5.8895	6.4130	5.0958	6.1516	5.1574	7.3180
10	8.8324	6.6010	4.7340	29.8185	8.2910	8.0654	4.7986	28.7234	6.5798	5.1259	5.5766	3.2907	5.2068	7.6000	7.8220	7.2335
11	7.1814	7.0587	4.9389	30.9691	7.5354	5.3733	4.9563	27.0620	6.4753	4.7508	5.5106	3.3403	7.9167	4.6143	7.7618	7.3637
12	8.1181	7.2649	3.7444	29.7935	7.8352	5.5976	2.8523	27.1274	6.4825	4.7814	5.9728	5.5747	5.2989	4.8535	5.3797	9.8233
13	7.0436	6.7448	4.7704	29.4238	7.8443	5.9287	4.8360	29.8759	6.8271	4.8261	5.4031	4.1185	8.1912	6.2763	5.4601	7.4408
14	8.0745	6.8289	5.0929	30.2128	7.6189	7.6695	3.8089	29.6502	5.9626	4.3331	5.5990	6.3028	7.1868	4.2922	9.6538	5.3994
15	8.0236	6.6897	4.8376	29.8903	7.7935	8.4972	3.9926	29.7093	6.5705	5.4412	7.2822	4.4568	5.2511	4.4888	6.9216	7.4917
16	8.4740	6.5890	4.8577	30.0513	8.0680	7.7795	4.0649	30.7692	6.4923	5.1003	6.5603	3.1722	8.1776	6.2435	7.8664	5.4981
17	8.1392	7.0153	4.7946	31.3529	8.9716	7.9162	3.8789	29.1504	6.1759	4.9346	5.6157	4.2823	6.6010	6.8247	7.7212	8.9016
18	7.7504	6.3602	5.2507	29.9329	6.9751	6.8960	4.3931	30.6323	6.0773	5.8717	5.7263	0.0758	8.1270	4.7305	8.7419	10.2764
19	8.2937	6.6331	4.7362	28.9255	7.0791	7.0159	5.2045	29.7732	6.1095	5.6771	5.5396	6.1281	7.5117	6.5723	10.1113	9.0227
20	8.1496	6.4318	5.2313	29.4371	7.3282	6.6119	3.7587	29.6083	5.9120	4.6268	4.7877	6.0358	7.7762	4.2920	9.8500	9.6598
21	7.3177	6.2341	5.6992	30.1409	7.8099	7.2895	4.3733	29.5136	6.3791	5.4123	5.5178	5.9385	5.3419	4.5461	7.0941	5.4412
22	8.3295	7.0187	4.9162	29.8376	8.4538	7.6711	5.4444	31.0140	6.1836	4.6027	6.6075	4.1849	6.6813	4.6040	9.4934	5.4629
23	8.3678	6.5234	5.1849	29.0422	6.2779	7.3008	5.6648	30.5875	5.6466	4.6984	7.1401	4.9657	6.3067	7.6712	6.8751	7.3106
24	7.1340	6.2097	4.6420	28.4501	9.9769	8.1321	4.9498	27.6827	5.4454	5.5666	5.8301	1.9936	7.2860	7.9623	5.4705	7.9025

Table 4.14: Thermal power generation for minimum emission HTGS: Electric power system-VII

k	p_{Dk} (MW)	Thermal Power (MW)					
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	P_{6k}
1	1374	125	149.9983	199.302	192.9835	286.9235	287.0942
2	1278	125	150	179.2543	176.9034	258.4175	253.3643
3	1372	125	149.7411	202.798	189.5121	279.1191	285.2789
4	1058	115.3011	122.7895	139.7717	149.5697	199.0645	198.2064
5	1358	125	149.6013	188.1306	189.6885	286.3832	276.1356
6	1282	125	149.609	179.8949	174.9156	252.3496	258.3048
7	1130	123.6351	145.3427	151.6709	143.688	209.4202	214.1918
8	1200	124.0774	149.3942	167.4779	157.8712	233.0072	227.9784
9	1248	123.7412	147.9355	175.9958	164.4363	245.0328	248.8798
10	1364	124.2799	149.9862	190.6338	194.1809	276.1428	279.5135
11	1146	117.7883	143.1715	150.504	149.9019	225.2336	217.6337
12	1262	124.1321	149.0282	174.0145	168.0026	248.6642	253.7563
13	1246	125	145.9169	173.2203	165.4586	241.9705	247.299
14	1140	121.5015	148.9455	148.3214	146.7639	217.4596	211.8097
15	1226	120.98	148.2504	170.9869	160.2211	237.5731	236.3794
16	1314	123.645	149.8243	179.2123	184.5648	259.2985	266.2447
17	1426	122.2499	150	201.0527	202.5547	298.2064	298.2454
18	1028	107.6056	116.6133	137.9664	134.9863	197.8816	191.3021
19	1148	118.4866	137.0918	154.7528	147.6986	218.1042	215.9772
20	1256	123.3208	149.9897	172.0587	167.3055	246.546	247.4192
21	1348	124.4204	149.9567	194.0792	180.8914	273.3879	278.0225
22	1424	124.8253	150	204.0144	202.3932	289.9358	298.6696
23	1070	120.679	128.0162	140.5563	139.8329	202.1968	197.0097
24	1118	120.6833	135.6597	144.3905	144.1382	211.05	215.1516

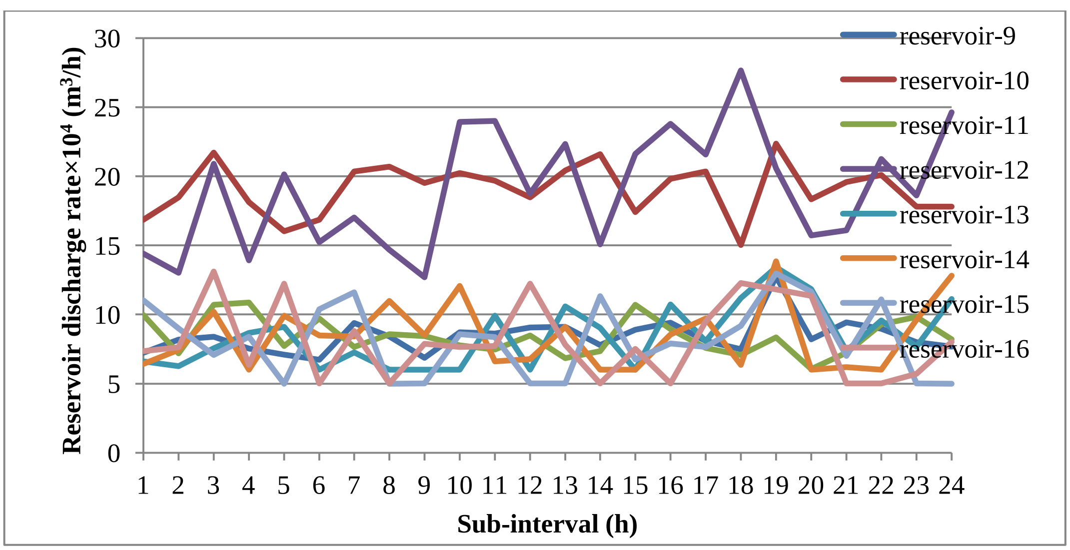

Figure 4.12: Reservoir discharge rate for minimum emission HTGS (Continued)

Table 4.15: Hydro power generation (MW) for minimum emission hydro-thermal scheduling: Test system-VII

k	p_{7k}	p_{8k}	p_{9k}	p_{10k}	p_{11k}	p_{12k}	p_{13k}	p_{14k}	p_{15k}	p_{16k}	p_{17k}	p_{18k}	p_{19k}	p_{20k}	p_{21k}	p_{22k}
1	8.2785	5.2661	4.5729	25.3535	8.3745	4.9000	1.9242	23.0749	5.7296	5.4834	7.2470	5.8513	5.3261	5.1932	9.0323	7.0910
2	7.9749	4.9880	4.8254	24.2481	7.9899	5.0164	4.7271	25.2563	6.3519	5.3727	5.5855	6.1957	5.1648	5.9617	8.0578	7.3445
3	8.5878	5.8746	4.0625	23.3623	8.4263	5.7447	4.8402	26.4050	6.4614	4.2044	7.5019	4.8028	6.1236	7.4883	6.8646	9.8006
4	6.6650	5.2032	2.0712	23.9334	6.8782	5.3334	3.9411	27.8836	5.9979	5.6477	7.4520	6.3877	6.8615	4.9548	7.7501	6.3364
5	8.2189	6.1286	4.5165	27.1380	8.1962	5.4703	2.7668	28.4537	5.7935	6.0868	5.7301	5.3625	7.1194	7.4669	5.2177	9.3950
6	7.7480	5.6471	4.5749	27.6653	7.6217	6.8190	3.1395	28.3639	5.6149	5.9555	6.8224	6.3855	5.1173	6.6006	8.7520	5.0985
7	6.6385	5.4445	4.4263	26.0545	6.4368	6.4195	3.6145	29.7878	7.1976	4.9077	5.5209	6.2120	6.0321	6.4673	9.0655	7.8259
8	7.2983	5.4523	4.4114	30.3767	7.2675	6.3790	4.2511	28.2073	6.4660	4.8009	5.9463	6.4697	5.1024	7.5665	5.0693	5.1290
9	7.7088	6.3948	4.7829	29.5031	7.5676	6.6029	4.2801	29.5621	5.4383	5.2583	5.7578	6.4194	5.1582	6.1150	5.1745	7.3912
10	8.3602	7.4384	4.5846	29.9277	8.0514	7.7948	5.0199	29.3211	6.6208	4.8575	5.3426	3.8040	5.2674	7.6568	7.9107	7.3037
11	7.1807	5.6908	4.3444	30.2294	6.9325	6.6670	5.0326	27.4171	6.5833	5.0041	5.2513	3.6291	7.8054	4.7224	7.8483	7.4380
12	7.9850	6.9565	3.7946	30.7356	7.9001	7.6079	3.0114	27.0392	6.8396	5.3439	5.9491	5.7688	5.3773	4.9846	5.3887	9.7433
13	8.0423	7.0569	4.3860	29.8407	8.0299	7.1492	4.6043	29.5666	6.7982	4.7105	4.9305	4.4077	8.1759	6.4277	5.4634	7.5603
14	7.3288	6.5745	4.2865	30.1228	7.1228	6.7230	4.4794	29.8249	5.9938	4.1688	5.3336	6.3738	7.2651	4.4739	9.7361	5.4151
15	8.1330	7.5552	4.1042	30.3320	7.8544	7.9982	5.3136	31.4567	6.6982	5.6603	7.1841	4.7547	5.3497	4.6678	7.0119	7.5520
16	8.6335	8.2481	4.1734	30.2650	8.7796	7.2000	4.6793	29.3979	6.9695	4.9033	6.2424	3.5767	8.2615	6.4615	7.9236	5.5139
17	8.9202	8.6142	4.6208	30.6258	8.8923	7.5511	4.2389	28.9753	6.1571	4.6541	5.4003	4.6165	6.7199	7.0242	7.7514	8.9494
18	6.2001	6.4196	4.6981	28.8196	5.9957	6.0568	4.1261	29.9181	5.7387	5.9640	5.0533	0.5570	8.2356	4.9000	8.7841	10.2174
19	7.1831	7.3168	4.6141	29.1550	6.7552	6.0951	5.4932	29.6121	8.0371	3.7558	5.7347	4.7812	8.6541	8.2962	10.4766	9.9567
20	7.8389	7.9384	4.7625	29.5487	7.8395	6.0331	3.8109	28.8231	5.6818	5.4139	4.2048	6.0544	7.7171	4.1833	9.8908	9.6556
21	8.5309	8.4573	5.0914	31.1284	8.5260	6.5324	4.8683	29.5778	6.3094	4.9054	5.1210	5.9366	5.2800	4.4394	7.1355	5.4241
22	8.5917	8.5201	5.3743	31.6637	8.6859	7.3042	5.6415	30.8247	6.0406	4.6933	6.4012	4.3449	6.6057	4.5002	9.5254	5.4478
23	5.5469	7.4103	5.3817	30.0272	5.4757	6.1022	5.6143	29.5101	5.5090	5.3679	6.6303	5.2534	5.5333	6.8361	5.4393	6.0946
24	5.9469	7.4578	5.4532	29.9146	8.9118	7.7975	5.3047	28.0193	5.3289	5.3703	5.6733	2.3162	7.2727	7.9702	5.4705	7.9301

To select better multi-objective solution, cardinal priority ranking is computed. It is evident from Fig 4.13, that maximum value of cardinal priority ranking is achieved by solution obtained from PHOT-I. Tables 4.16 and 4.17 represent thermal and hydro power generation schedule, respectively while, Fig 4.14 represents water discharge rate for multi-objective scheduling applied by PHOT-I for electric power system-VII.

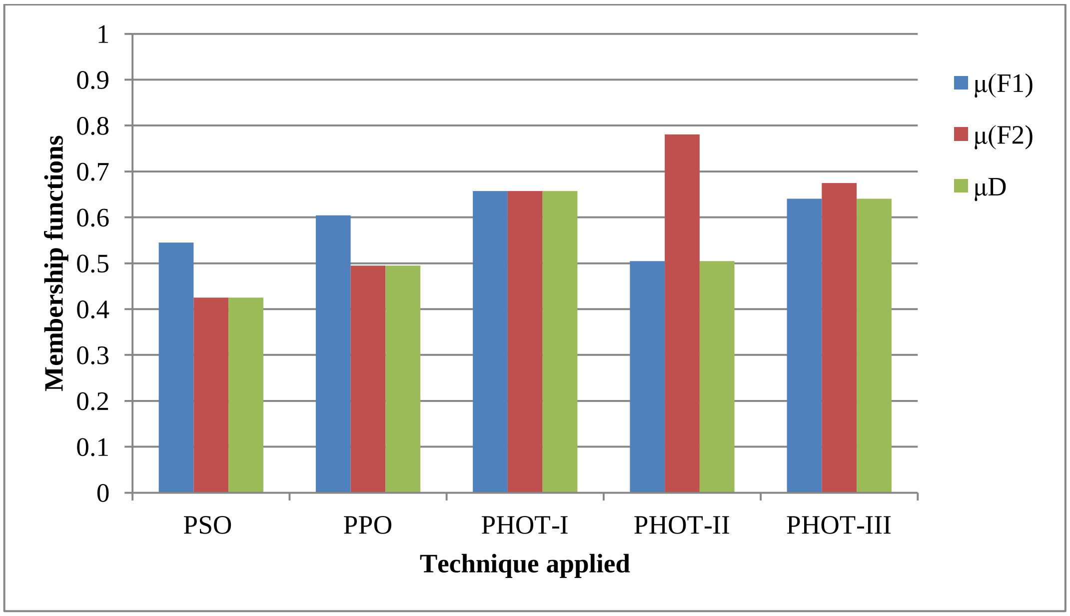

Figure 4.13: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-VII

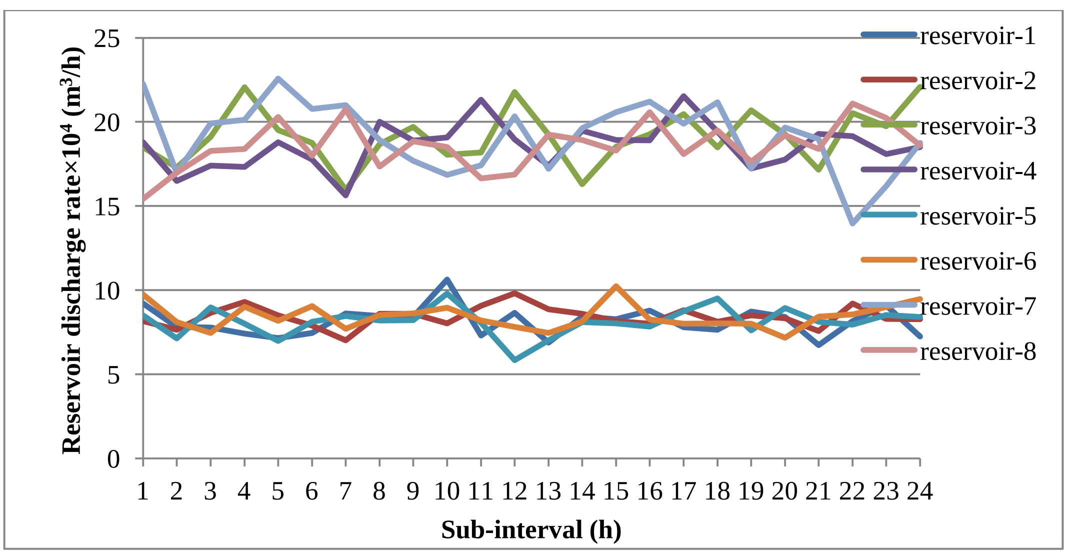

Figure 4.14: Reservoir discharge rate for multi-objective HTGS: Electric power system-VII

Table 4.16: Thermal power generation for multi-objective HTGS: Electric power system-VII

k	p_{Dk} (MW)	Thermal Power (MW)					
		p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}
1	1374	101.4174	105.6209	198.8253	204.2949	312.2443	313.5845
2	1278	94.5589	95.17957	181.6809	187.5959	288.8577	292.0348
3	1372	103.0743	107.4173	195.3361	199.8138	310.1913	314.8561
4	1058	70.35676	65.16376	152.8743	152.2311	238.068	237.1762
5	1358	100.6527	106.0727	196.6334	198.2206	309.0666	304.3649
6	1282	96.19144	93.77625	185.9648	190.1021	283.3113	291.0319
7	1130	76.98482	75.18919	159.2731	163.6406	253.6029	256.7957
8	1200	83.34796	87.36343	175.9523	176.2867	266.7187	270.2243
9	1248	88.66454	88.52698	180.5443	184.5404	280.9733	284.3155
10	1364	101.9385	103.1466	200.2493	203.5581	307.8362	302.8618
11	1146	78.8429	78.75239	164.1256	167.2106	257.1747	258.6761
12	1262	91.17973	93.55078	184.1998	186.8327	285.1432	284.511
13	1246	87.7348	92.70252	178.8151	183.5376	281.6346	281.7572
14	1140	80.01115	75.37178	165.6281	165.5194	254.5254	255.6481
15	1226	86.09624	86.2745	181.0832	178.2163	274.6749	278.6546
16	1314	96.9752	98.34728	189.2902	193.045	295.1714	298.1803
17	1426	108.1468	118.5824	207.0369	210.6078	315	321.281
18	1028	61.71114	66.14772	151.0441	145.889	229.4508	230.7518
19	1148	79.49866	79.84103	165.917	162.205	256.2671	256.4067
20	1256	90.68072	92.9446	179.8676	183.7447	281.8439	281.4617
21	1348	100.2926	104.1523	193.6467	198.2049	308.395	305.0604
22	1424	106.4711	113.5072	210	210.9941	314.9173	324.6317
23	1070	72.0282	67.30132	153.2743	155.9368	236.996	243.4543
24	1118	80.08872	74.20216	160.8959	162.678	247.9824	253.0978

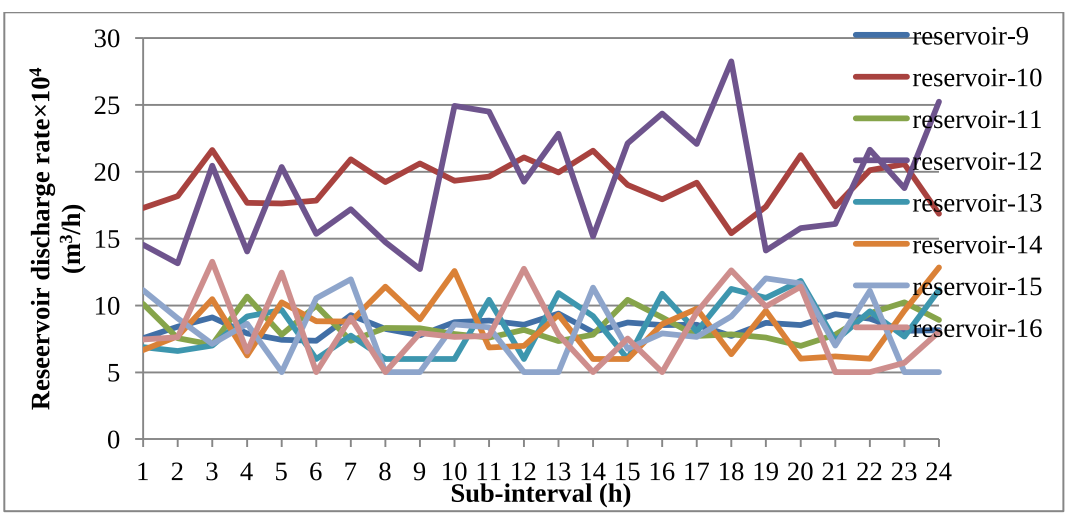

Figure 4.14: Reservoir discharge rate for multi-objective HTGS (Continued)

Table 4.17: Hydro power generation (MW) for multi-objective HTGS: Electric power system-VII

k	p_{7k}	p_{8k}	p_{9k}	p_{10k}	p_{11k}	p_{12k}	p_{13k}	p_{14k}	p_{15k}	p_{16k}	p_{17k}	p_{18k}	p_{19k}	p_{20k}	p_{21k}	p_{22k}
1	8.2112	6.2913	5.0412	25.4061	7.8100	7.1323	3.4019	23.1751	5.9244	5.3804	7.3104	5.8418	5.4971	5.3655	9.0735	7.1504
2	7.4164	5.9814	5.5465	24.2511	6.9679	6.1480	5.5588	25.4054	6.4717	5.4582	5.7969	6.1998	5.3790	6.0933	8.0753	7.3426
3	7.4299	6.5877	5.1619	25.2398	8.1925	5.7515	4.8020	26.5301	6.8147	4.2596	5.5206	4.9885	5.7375	7.5790	6.8884	9.8274
4	7.1912	6.9532	3.9327	25.5682	7.5845	6.7481	4.7358	26.9681	6.1479	5.7855	7.5768	6.3590	7.1363	5.0876	7.8772	6.4777
5	6.9907	6.5056	4.9788	27.0462	6.8676	6.2794	3.5342	28.2421	5.9157	5.8207	5.9964	5.2345	7.3723	7.5566	5.2100	9.4383
6	7.1745	6.1137	5.2163	26.4817	7.5970	6.7530	4.3092	27.1570	5.9050	5.7530	7.1759	6.3440	5.0563	6.7066	8.8035	5.0753
7	7.8843	5.5152	5.8962	25.0225	7.7670	5.8683	4.2135	29.0583	6.9819	4.6805	5.5415	6.1410	6.2686	6.5727	9.1469	7.9552
8	7.7777	6.4065	5.3156	27.9575	7.5980	6.2308	5.0019	27.0330	6.2122	5.3481	6.0313	6.4432	5.0142	7.5902	5.0462	5.1006
9	7.7572	6.2943	4.9738	27.1760	7.6279	6.1722	5.3719	28.2049	5.8501	4.8618	5.9258	6.4141	5.0714	6.1894	5.1522	7.3920
10	8.9377	5.9403	5.4714	27.3837	8.5509	6.3153	5.5803	27.8623	6.4281	5.2170	5.6578	3.1283	5.1833	7.5960	7.8816	7.2756
11	7.1061	6.5788	5.4706	28.4138	7.6324	5.9050	5.5151	26.3876	6.5065	5.0647	5.5797	3.2282	7.9481	4.6474	7.8224	7.4113
12	8.1000	6.9422	4.0428	26.8319	6.0940	5.7449	4.5371	26.6470	6.3513	4.4039	6.0021	5.5329	5.2696	4.8640	5.3756	9.8437
13	6.9474	6.3421	5.0872	26.1673	7.1019	5.5286	5.4499	28.5986	6.7545	4.8793	5.4952	4.0258	8.2065	6.2571	5.4541	7.5225
14	8.0890	6.1378	5.8662	27.6686	7.9242	5.9730	4.7294	28.1788	5.9070	4.1759	5.8331	6.2985	7.2017	4.2072	9.7129	5.3929
15	8.0560	5.9193	5.4143	26.9871	7.9400	7.1089	4.3213	27.8586	6.3729	5.2057	7.2593	4.4118	5.2093	4.4069	7.0007	7.5283
16	8.4292	5.8924	5.1931	26.9238	7.8507	6.0164	4.0480	29.4427	6.2862	5.4774	6.5248	3.0896	8.1750	6.2211	7.9144	5.5059
17	7.8025	6.3361	4.7245	28.2915	8.4821	5.8615	4.5416	28.0325	6.2726	5.0858	5.6891	4.2219	6.5636	6.7683	7.7430	8.9285
18	7.7002	5.8384	5.3964	27.1411	8.9481	5.8044	3.9416	29.1176	5.6882	5.9376	5.7080	0.0000	8.0848	4.6295	8.7740	10.2957
19	8.4382	5.9030	4.5673	25.6761	7.6931	5.6535	5.3320	28.0668	6.1330	5.6881	5.4426	6.1188	7.4602	6.4773	10.1413	9.0734
20	8.2090	5.6974	5.0673	26.4281	8.5800	5.0851	4.5334	29.0739	5.9169	4.3562	5.0148	6.0214	7.7205	4.1856	9.8915	9.6759
21	6.9786	5.2381	5.6422	27.5286	8.0062	5.8727	4.7162	28.5999	6.3054	5.5558	5.5965	5.9241	5.2836	4.4418	7.1347	5.4238
22	8.0155	6.2427	4.5157	27.2107	7.8829	5.9914	5.7529	30.2475	6.1135	4.7203	6.5474	4.1511	6.6099	4.5042	9.5252	5.4482
23	8.5989	5.7440	4.8043	26.7147	8.2622	6.2546	5.5868	29.0050	5.6222	4.4134	6.8971	5.1959	5.5370	6.8390	5.4405	6.0940
24	7.3669	5.7171	3.7025	27.1645	8.1945	6.4264	4.9780	27.6109	5.6285	5.5701	6.1024	1.8976	7.2953	7.9880	5.4812	7.9311

4.6.5 Electric Power System-VIII

The proposed heuristic techniques along with weight pattern evaluation are applied on electric power system-VIII to search global optimum solutions for different types of scheduling. It is observed from Table 4.18 that PHOT-I yields better result for minimum cost and PHOT-III yields better results for minimum emission, by achieving lower objective values, for electric power system-VIII. It is observed from tables 4.2, 4.7, 4.11 and 4.18 that CPU time to execute the PHOTs does not exponentially increases as the number of decision variables increases.

Table 4.18: Comparison of results: Electric power system-VIII

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost $\times(10^3)$ ($)	Emission $\times(10^3)$ (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission $\times(10^3)$ (ton)	CPU time (s)	Cost $\times(10^3)$ ($)	Emission $\times(10^3)$ (ton)	CPU time (s)
CSA[372]	3503.50	--	67.34	--	--	--	--	--	--
LR[406]	4137.80	--	89.25	--	--	--	--	--	--
QEA[406]	4079.40	--	66.41	--	--	--	--	--	--
NLP[406]	4062.70	--	104.6	--	--	--	--	--	--
PSO [406]	3980.30	--	56.34	--	--	--	--	--	--
DE[406]	3863.90	--	58.78	--	--	--	--	--	--
RQEA[406]	3817.80	--	57.63	--	--	--	--	--	--
CRQEA[406]	3490.50	--	62.48	--	--	--	--	--	--
PHOT-I	3489.90	13458.7	68.17	3512.74	9474.367	70.98	3503.41	10941.45	67.86
PHOT-II	3502.60	13832.92	70.53	3529.0	9784.800	68.97	3512.23	9508.105	70.38
PHOT- III	3491.30	13460.3	92.77	3535.39	9039.65	92.53	3505.58	10597.87	92.60

Note: CSA: Clonal selection algorithm LR: Lagrange relaxation; QEA: Quantum-inspired evolutionary algorithm; RQEA: Real-coded QEA; CRQEA: Clonal RQEA with Cauchy mutation; PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

Cardinal priority ranking and membership function of electric power system-VIII is presented in Fig 4.15. It is evident from Fig 4.15, that maximum value of cardinal priority ranking is achieved by solution obtained from PHOT-III. Tables 4.19, 4.20 and 4.21 provide the hourly load demand, hydro, thermal power generation, corresponding cost and emission of electric power system-VIII for economic, emission and multi-objective HTGS scheduling, respectively. Thermal power generation for multi-objective HTGS is presented in Table 4.22 and water discharge rate is shown in Fig 4.16.

Table 4.19: Hourly power demand, thermal and hydro generations and corresponding cost and emission for minimum cost HTGS: Electric power system-VIII

k	p_{Dk} (MW)	Total Thermal Generation (MW)	Total Hydro Generation (MW)	Cost×(10^3) ($/h)	Emission×(10^3) (ton/h)
1	18166.9	12244.38	5922.52	136472.4	346259.4
2	18198	12216.68	5981.32	137456.8	340046.9
3	17921.1	12075.31	5845.79	136989.6	351518.7
4	17944.4	12119.96	5824.44	134240.1	549400.4
5	18257.4	12556.93	5700.47	139016.2	579121.3
6	18472.4	12550.79	5921.61	139282.5	574740.1
7	18971	12727.79	6243.21	141124.5	583867.9
8	19389.4	13046.38	6343.02	145476.3	588791.8
9	19437	12942.52	6494.48	144200	585837.9
10	20426.6	14051.74	6374.86	159454.5	643961.5
11	19936.5	13419.36	6517.14	150292.1	600320.6
12	20500.5	13853.63	6646.87	156531.8	634178.8
13	20296.6	13637.22	6659.38	153318.4	613904.1
14	20281.5	13695.8	6585.7	154163.1	624319.7
15	19755	12893.76	6861.24	144083	594501.5
16	20170.6	13292.42	6878.18	148733.3	599807.9
17	19917.1	12990.28	6926.82	144818.4	590792
18	20033.5	12996.45	7037.05	145689.4	597493.1
19	20427.4	13501.29	6926.11	151260.5	614469.8
20	20398	13462.35	6935.65	151261.3	630702.8
21	20157.9	13216	6941.9	147938.7	599875.1
22	19709	12782.09	6926.91	143858.6	596154.4
23	19426.8	12814.08	6612.72	144160.8	592687.1
24	19266.3	12242.23	7024.07	140070.3	425990.6

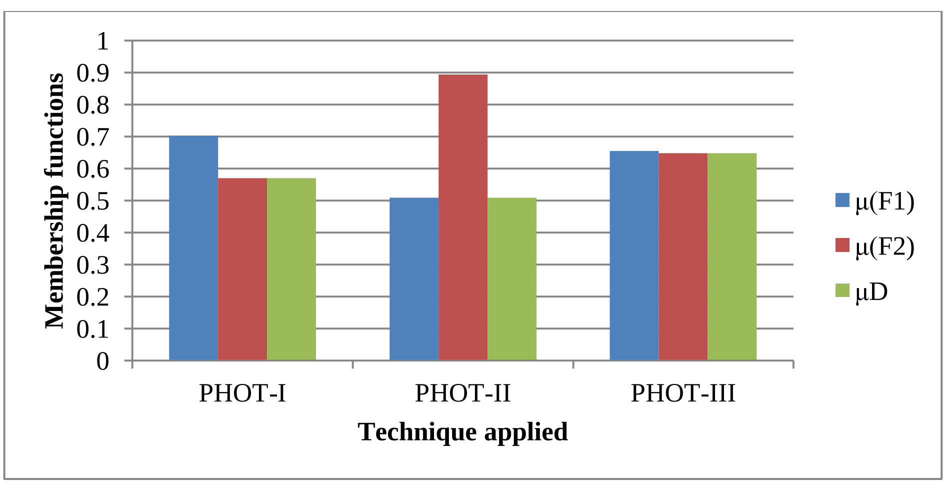

Figure 4.15: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-VIII

Table 4.20: Hourly power demand, thermal and hydro generations and corresponding cost and emission for minimum emission HTGS: Electric power system-VIII

k	p_{Dk} (MW)	Total Thermal Generation (MW)	Total Hydro Generation (MW)	Cost×(10^3) ($/h)	Emission×(10^3) (ton/h)
1	18166.9	12244.64	5922.262	140.3623	159.8989
2	18198	12214.05	5983.955	139.7574	155.9426
3	17921.1	12077.91	5843.192	137.9019	142.0035
4	17944.4	12117.89	5826.513	138.4126	146.7715
5	18257.4	12553.49	5703.906	144.2553	206.6533
6	18472.4	12549.75	5922.65	144.2379	206.4531
7	18971	12727.41	6243.593	145.8188	247.4106
8	19389.4	13045.96	6343.437	146.9951	351.0282
9	19437	12944.09	6492.915	146.8231	309.1882
10	20426.6	14050.13	6376.469	160.5285	613.8194
11	19936.5	13420.11	6516.391	150.9119	601.3093
12	20500.5	13846.8	6653.699	157.3628	612.3169
13	20296.6	13633.63	6662.968	153.7881	602.1704
14	20281.5	13696.4	6585.097	154.7323	605.5112
15	19755	12896.22	6858.782	146.7386	291.7133
16	20170.6	13295.55	6875.053	148.7792	599.7662
17	19917.1	12988.55	6928.55	146.850	327.2114
18	20033.5	13005.05	7028.449	146.9159	335.0398
19	20427.4	13492.65	6934.753	151.6488	601.2968
20	20398	13474.89	6923.111	151.6973	601.8773
21	20157.9	13224.48	6933.417	148.0409	599.7342
22	19709	12784.76	6924.243	145.6831	283.715
23	19426.8	12819.42	6607.381	146.4093	269.2047
24	19266.3	12243.17	7023.135	140.7363	169.6133

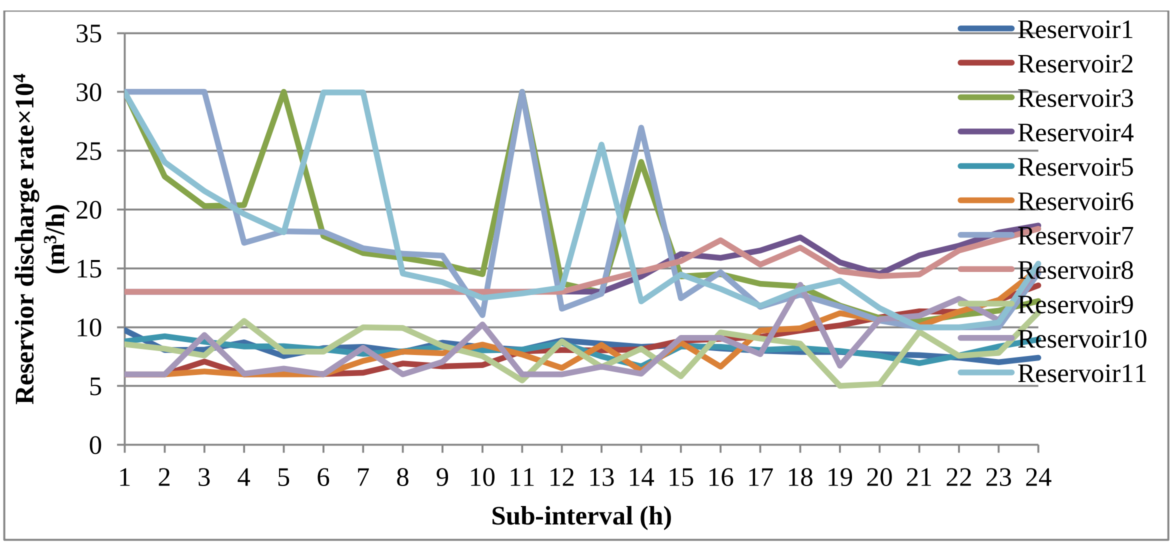

Figure 4.16: Reservoir discharge rate for multi-objective HTGS: Electric power system-VIII

Table 4.21: Hourly power demand, thermal and hydro generations and corresponding cost and emission for multi-objective hydro-thermal scheduling: Electric power system-VIII

k	p_{Dk} (MW)	Total Thermal Generation (MW)	Total Hydro Generation (MW)	Cost×(10^3) (\$/h)	Emission×(10^3) (ton/h)
1	18166.9	12242.6	5924.304	138.1629	295.7403
2	18198	12213.98	5984.016	137.6477	298.9017
3	17921.1	12075.12	5845.984	137.1134	314.9294
4	17944.4	12118.73	5825.668	136.0163	253.8407
5	18257.4	12555.45	5701.946	140.8845	292.6037
6	18472.4	12549.16	5923.244	140.4457	329.1128
7	18971	12727.17	6243.832	142.3992	345.0574
8	19389.4	13050.36	6339.039	146.5807	376.6048
9	19437	12945.6	6491.402	145.7481	355.7551
10	20426.6	14053	6373.6	159.4565	648.4268
11	19936.5	13420.05	6516.455	150.3825	600.4332
12	20500.5	13847.31	6653.189	156.6361	622.2411
13	20296.6	13638.87	6657.727	153246.5	615.2126
14	20281.5	13718.19	6563.313	154.8592	616.4427
15	19755	12890.65	6864.352	144.8608	377.3526
16	20170.6	13295.52	6875.085	149.057	602.3213
17	19917.1	12975.06	6942.037	145.740	380.3026
18	20033.5	13003.07	7030.428	146.0121	390.6788
19	20427.4	13496.65	6930.746	151.9374	627.0118
20	20398	13479.38	6918.625	151.262	613.2405
21	20157.9	13223.71	6934.193	148042.9	599.7413
22	19709	12785.11	6923.886	144675.6	319.8962
23	19426.8	12816.36	6610.444	144232.2	382.0787
24	19266.3	12257.16	7009.145	140179	339.9442

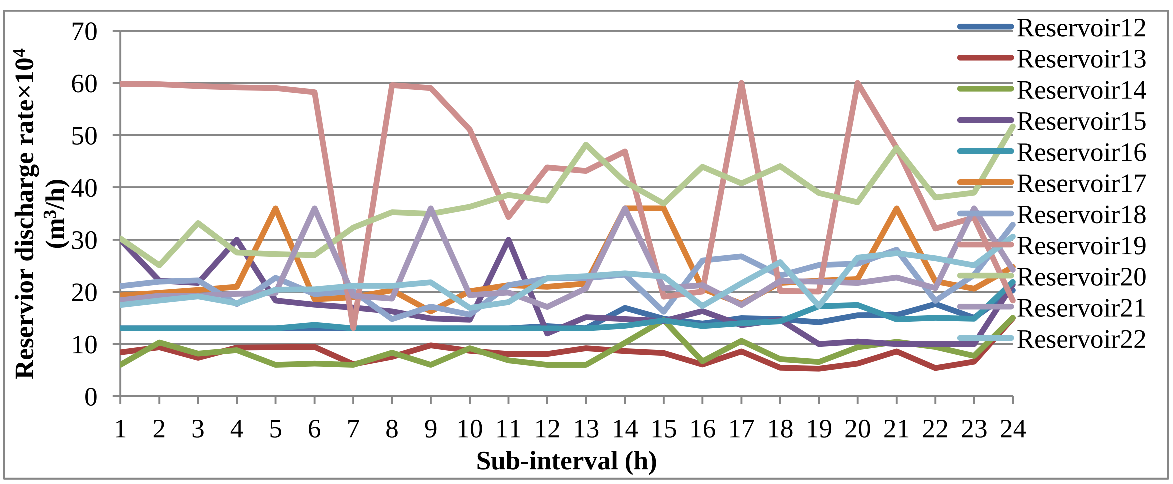

Figure 4.16: Reservoir discharge rate for multi-objective HTGS (Continued)

Table 4.22: Thermal power generation (MW) for multi-objective HTGS: Electric power system-VIII

k / Unit	1	2	3	4	5	6	7	8	9	10	11	12
1	111.9990	111.9980	110.8218	112.0005	112.0003	111.9950	112.0051	112.0011	112.0021	111.9972	112.0028	112.0011
2	111.9989	111.9988	112.0020	103.6133	112.0005	112.0040	111.9991	112.0021	112.0022	111.9979	111.9969	112.0004
3	97.4028	98.0002	97.8668	97.9989	98.0009	98.0001	97.9989	97.9989	98.0005	98.0005	98.0001	97.9974
4	179.9645	129.8105	178.3643	180.0004	179.9989	179.9989	179.9991	179.9991	179.9995	179.9959	179.9992	179.9992
5	88.0001	87.9991	88.0005	88.0006	88.0001	87.9989	87.9991	87.9995	88.0007	88.0002	88.0002	87.9988
6	140.0000	140.0000	140.0000	105.6885	140.0000	140.0000	140.0000	140.0000	110.0006	140.0000	140.0000	140.0000
7	259.5296	260.2950	259.6260	260.9978	260.9989	261.0004	260.9979	261.0002	261.0002	300.0000	261.0001	260.9989
8	284.3784	284.6733	284.7283	287.3861	289.9991	289.9992	290.0001	290.0001	290.0003	290.0004	289.9991	290.0001
9	283.9750	284.6501	284.6005	284.7577	286.0001	285.9998	286.0004	286.0001	275.9992	286.0002	285.9998	286.0002
10	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	204.5064	130.0000	130.0000
11	94.0000	94.0000	94.0000	94.0000	94.0000	94.0000	94.0000	94.0000	94.0000	318.0490	168.8232	243.2666
12	168.7288	168.8664	169.0003	168.8322	168.9991	169.9995	119.0005	169.0006	169.0002	243.9221	168.9996	317.9533
13	215.0001	214.8760	214.4148	215.0002	215.0001	214.9991	214.9990	214.9989	215.0010	304.0865	215.0010	304.2562
14	304.3493	304.5029	304.9615	305.0003	304.9989	305.0003	305.0004	305.0003	304.9989	304.9989	304.9989	304.9996
15	394.1329	393.6481	394.4919	214.6494	395.0002	394.9989	394.0001	394.9982	393.7559	395.0005	395.0009	394.9990
16	393.8400	394.2531	393.8205	215.3051	215.4502	125.0001	213.7822	394.9989	394.9989	483.9132	394.9989	395.0001
17	399.5872	399.5736	399.5688	400.0001	399.9981	399.9992	399.9992	400.0002	399.5879	489.1388	400.0002	489.4878
18	487.3452	488.2901	489.2559	489.1253	490.0004	489.9992	489.4912	490.0004	490.0002	489.9991	489.9992	490.0005
19	511.2421	421.3147	510.3714	331.7432	420.0004	338.4561	511.9989	510.9978	502.0005	512.0005	511.9999	512.0006
20	510.0229	511.0255	508.7272	510.6590	502.0006	512.0008	512.0011	511.9979	511.9979	512.0004	512.0001	511.9969
21	522.8341	519.6377	522.3235	523.0264	524.0003	523.9995	513.7490	523.1641	513.9991	524.0007	524.0005	523.9996
22	522.4262	523.2893	520.9800	433.6768	524.0002	524.0004	523.9997	514.0003	514.0004	524.0005	524.0003	523.9997
23	523.1976	519.0046	519.3502	523.0762	523.9999	523.9991	524.0004	514.0001	513.9997	523.9998	523.9997	523.9999
24	512.4408	519.3417	522.3528	523.1286	524.0005	524.0008	524.0004	513.9998	513.9997	523.9998	524.0005	524.0004
25	521.0724	520.9825	521.2442	503.4346	524.0007	524.0008	524.0007	523.9999	523.9999	524.0007	524.0006	524.0006
26	432.6108	519.9633	433.5251	433.6357	433.6309	524.0003	523.9998	514.0005	524.0006	524.0007	523.9997	524.0005
27	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	11.0003	10.9998	11.0001

Table 4.22: Thermal power generation (MW) for multi-objective HTGS: Electric power system-VIII (Continued)

k / Unit	1	2	3	4	5	6	7	8	9	10	11	12
28	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	11.0001	10.9996	11.0002
29	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.0000	10.9997	11.0004	10.9997
30	87.8027	88.1173	88.2564	97.0000	97.0000	86.9995	87.0001	87.0005	86.9998	97.0000	97.0000	97.0000
31	159.7597	187.3277	189.8872	190.0000	190.0000	160.0001	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
32	159.7519	190.0000	190.0000	160.2188	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
33	189.8020	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000
34	164.7031	164.9131	200.0000	200.0000	188.1279	200.0000	200.0000	200.0000	200.0000	200.0000	200.0000	200.0000
35	168.0004	165.0782	165.7295	168.0004	167.9999	167.9998	168.0001	167.9998	167.9989	200.0000	198.0645	199.8506
36	166.4863	164.8281	165.2627	168.0001	167.9998	168.0005	168.0005	168.0004	167.9989	198.8994	200.0000	200.0000
37	109.7078	89.1408	89.2738	110.0000	110.0000	110.0000	88.1172	90.0004	110.0000	110.0000	110.0000	110.0000
38	110.0000	89.2383	110.0000	110.0000	110.0000	110.0000	90.0001	110.0000	110.0000	110.0000	110.0000	110.0000
39	89.3199	88.8091	89.4046	95.4803	97.6533	110.0000	89.9991	110.0000	110.0000	110.0000	110.0000	110.0000
40	421.4076	421.3244	511.3048	512.0003	422.9998	512.0002	511.9999	511.6768	511.9989	512.0002	512.0007	511.9999
41	449.1261	450.6194	359.5264	369.5859	463.5879	445.7041	455.0313	545.5195	523.4395	630.0004	629.9989	629.9989
42	225.4074	224.6875	224.3871	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000
43	302.2490	299.0020	224.0527	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000
44	161.0004	160.9998	109.8984	160.7070	160.9997	161.0003	161.0001	161.0002	161.0002	161.0001	160.9998	179.9238
45	161.0001	109.8203	109.9463	160.9999	160.9991	160.9998	160.9989	160.9999	161.0001	161.0001	161.0001	161.0003
46	109.9281	109.8780	160.0004	159.9998	159.9991	160.0001	160.0004	160.0030	159.9992	160.0001	159.9991	159.9991
47	159.8606	159.9108	159.9178	161.0002	160.9993	161.0002	161.0002	161.0001	160.9993	160.9992	161.0004	161.0002
48	110.1750	159.4606	110.3320	161.0004	160.9995	160.9992	161.0004	161.0002	161.0002	160.9998	161.0003	174.3127
49	110.7988	160.0004	110.0537	160.0001	159.9990	159.9994	159.9997	159.9993	160.0004	160.0003	159.9986	160.0004
50	77.9258	40.0000	40.0000	79.0004	79.0001	79.0002	78.9992	78.9993	78.9994	114.8286	114.9170	115.1829
51	40.0000	77.7055	40.0000	115.0002	114.9992	115.0002	114.9995	114.9992	114.9992	114.9078	115.2358	79.0004
52	93.0001	92.9998	55.0000	93.0001	93.0002	93.0002	92.9998	92.9998	92.9746	120.0000	120.0000	120.0000
53	93.0002	93.0003	92.9998	92.9999	83.0003	92.0002	92.9998	83.0001	55.0002	120.0000	92.9994	120.0000
54	92.3194	55.0003	55.5044	120.0000	120.0000	120.0000	120.0000	120.0000	94.8418	120.0000	120.0000	120.0000

Table 4.22: Thermal power generation (MW) for multi-objective hydro-thermal scheduling: Test system-VIII (Continued)

k / Unit	13	14	15	16	17	18	19	20	21	22	23	24
1	112.0002	114.0000	111.9981	112.0043	112.0025	112.0001	114.0000	112.0022	111.9989	111.9987	112.0021	112.0022
2	112.0019	114.0000	112.0009	112.0001	112.0001	112.0002	111.9979	112.0018	112.0003	112.0002	111.9989	111.9989
3	97.9968	98.0021	98.0009	98.0001	97.9989	97.9989	98.7725	98.0021	98.0002	97.9795	98.0002	97.1826
4	180.0002	180.0002	179.9990	180.0005	180.0005	180.0005	180.0001	180.0001	180.0001	179.8027	180.0001	177.0449
5	88.0001	88.0002	87.9991	87.9991	88.0004	88.0003	97.0000	88.0003	88.0002	87.9994	87.9992	87.5957
6	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	140.0000	99.9998
7	300.0000	300.0000	261.0002	298.6367	260.9989	260.9989	280.9385	261.0001	261.0002	261.0001	260.9990	251.0000
8	289.9995	300.0000	280.0005	290.0002	280.0002	289.9992	290.0004	289.9991	290.0002	280.0004	280.0010	280.0003
9	285.9992	286.0001	276.0002	285.9995	276.0003	286.0004	292.6418	286.0004	285.9989	285.9990	275.4521	284.3760
10	130.0000	205.4199	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000	130.0000
11	168.2402	168.8555	94.0000	95.0000	94.0000	94.0000	95.0000	95.0000	95.0000	94.0000	94.0000	94.0000
12	169.0051	243.9727	168.9899	168.9987	169.0005	169.0002	169.0002	243.5684	169.0001	148.9979	158.9989	158.9989
13	214.9989	214.9989	214.9989	215.0002	215.0002	214.9989	215.0002	215.0002	215.0002	214.9993	214.9990	205.0002
14	305.0005	305.0004	305.0002	304.9924	305.0015	305.0004	304.9989	304.9989	305.0002	305.0001	304.9990	304.9991
15	394.9990	395.0002	395.0001	394.9999	395.0001	395.0001	395.0001	395.0001	395.0001	394.9989	394.9989	395.0004
16	395.0001	395.0002	395.0002	395.0002	394.9979	394.9979	394.9982	395.0002	395.0001	395.0002	394.9992	394.9983
17	489.5967	399.9989	400.0002	400.0001	399.9989	400.0002	490.0004	489.9979	399.9989	399.9994	400.0001	399.9994
18	490.0002	490.0002	469.9998	489.9929	490.0032	489.9976	489.9993	490.0001	490.0005	489.9992	480.3018	478.2324
19	512.0004	511.9999	512.0004	512.0001	501.9998	502.0004	516.2295	511.9997	512.0004	501.9997	511.9990	494.9268
20	511.9998	511.9999	501.9999	512.0006	502.0001	502.0003	514.3105	511.9999	512.0006	512.0006	512.0002	488.6201
21	523.9997	523.9999	514.5293	523.9968	524.0007	524.0008	530.0001	524.0002	523.9989	514.0020	523.9998	513.9999
22	524.0009	523.9999	524.0005	523.9991	524.0003	524.0002	525.6279	523.9999	523.9978	514.0010	524.0007	524.0001
23	523.9999	524.0005	523.9998	524.0008	524.0004	524.0008	525.6299	523.9999	523.9998	513.9990	523.9999	523.9999
24	523.8889	524.0006	524.0007	523.9999	523.9998	524.0001	526.9326	524.0005	523.9998	514.0010	523.9997	524.0005
25	524.9997	524.0001	524.0004	523.9995	523.9998	524.0005	527.5294	524.0007	524.0005	503.9990	523.9998	514.0007
26	523.9998	523.9998	523.9999	524.0007	524.0008	524.0006	525.3135	524.0007	524.0001	513.9990	524.0001	514.0001
27	10.9998	11.0001	10.0000	11.0001	10.0000	10.0000	11.0005	11.0001	10.9996	10.0000	10.0010	10.0000

Table 4.22: Thermal power generation (MW) for multi-objective hydro-thermal scheduling: Test system-VIII (Continued)

k / Unit	13	14	15	16	17	18	19	20	21	22	23	24
28	11.0004	10.9999	10.0000	10.9999	10.0000	10.0000	10.9997	11.0007	10.9997	10.0000	10.0000	10.0000
29	11.0004	11.0004	10.0000	10.9996	10.0000	10.0000	10.9998	11.0001	10.9996	10.0000	10.0000	10.0000
30	97.0000	97.0000	86.9997	97.0000	97.0000	97.0000	97.0000	97.0000	97.0000	85.7666	86.8145	85.6094
31	190.0000	190.0000	159.9998	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	180.0010	190.0000
32	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	180.0005	190.0000
33	190.0000	190.0000	160.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	190.0000	179.9997	189.6328
34	200.0000	200.0000	169.9998	200.0000	200.0000	200.0000	200.0000	200.0000	200.0000	200.0000	198.1230	199.8994
35	199.0001	200.0000	165.7969	168.0007	167.9998	167.9998	185.9404	168.0001	168.0039	168.0001	167.0273	166.9111
36	200.0000	200.0000	165.3047	175.7930	168.0004	167.0957	182.4668	167.9999	167.9998	168.0001	166.5938	166.2559
37	110.0000	110.0000	107.1826	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	108.2158	108.1318
38	110.0000	110.0000	86.8555	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	108.0684	108.0264
39	110.0000	110.0000	107.2709	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	110.0000	108.7920	108.3267
40	511.9996	512.0001	510.1670	511.9997	512.0002	512.0002	511.9999	512.0007	512.0001	502.0006	511.9998	511.9998
41	630.0002	630.0001	549.9997	630.0002	531.6914	543.6182	629.9997	630.0002	630.0001	452.8271	536.1553	521.4180
42	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	176.2480
43	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	360.0000	358.8643	226.0488
44	180.0000	180.0000	161.0002	160.9987	160.9991	161.0001	180.0000	167.8926	161.0001	161.0001	160.1572	131.3438
45	160.9997	160.9997	160.9998	161.0001	161.0001	160.9998	160.9998	161.0002	161.0002	161.0002	160.6016	156.2568
46	160.0002	180.0000	160.0002	162.5361	160.0001	159.9992	159.9997	160.0002	160.0001	158.5967	159.4590	111.1123
47	160.1992	180.0000	160.1436	165.1367	161.0003	161.0003	176.9688	174.2637	161.0003	161.0004	161.0003	160.4941
48	180.0000	161.0004	161.0004	164.4688	160.9999	160.9992	179.3486	179.3799	160.9993	160.9992	160.9999	156.1367
49	180.0000	160.0002	159.9991	162.6855	160.0003	159.9998	180.0000	160.0004	159.9992	159.6699	159.6357	158.3291
50	120.0000	120.0000	40.0000	78.9991	78.3682	79.0003	79.0004	120.0000	78.9992	40.0000	40.0000	40.0000
51	115.0332	117.9424	115.0002	79.0003	115.0004	81.3565	79.0002	78.9993	78.9993	113.2510	81.0996	40.0000
52	120.0000	120.0000	92.9998	120.0000	55.0000	85.0001	120.0000	120.0000	114.9994	85.0004	55.0000	55.0000
53	120.0000	120.0000	81.4004	118.2529	93.0004	92.9992	120.0000	116.2754	109.7061	85.2158	55.0003	54.9992
54	120.0000	120.0000	120.0000	120.0000	55.0003	54.9994	120.0000	120.0000	120.0000	54.9991	55.0004	55.0004

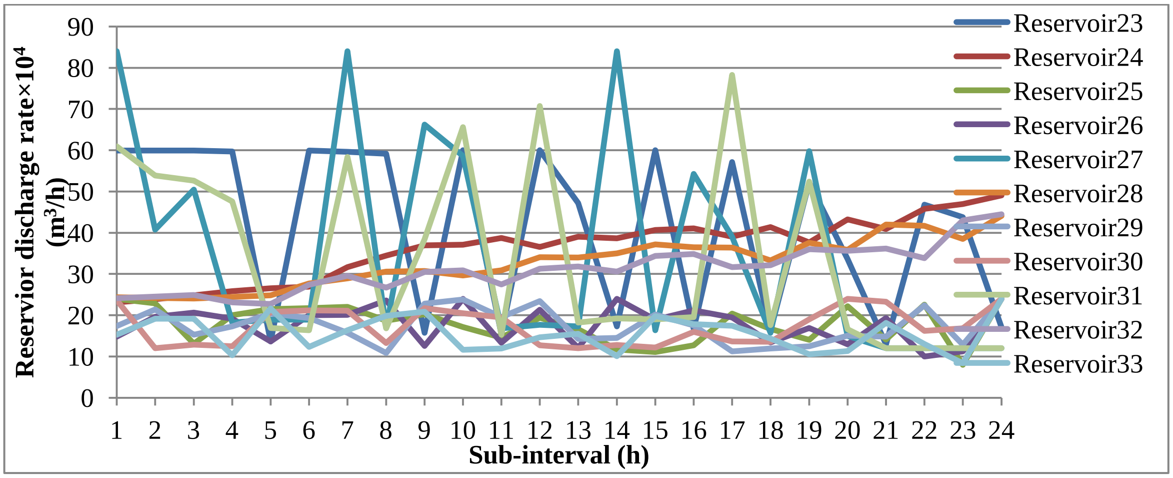

Figure 4.16: Reservoir discharge rate for multi-objective HTGS (Continued)

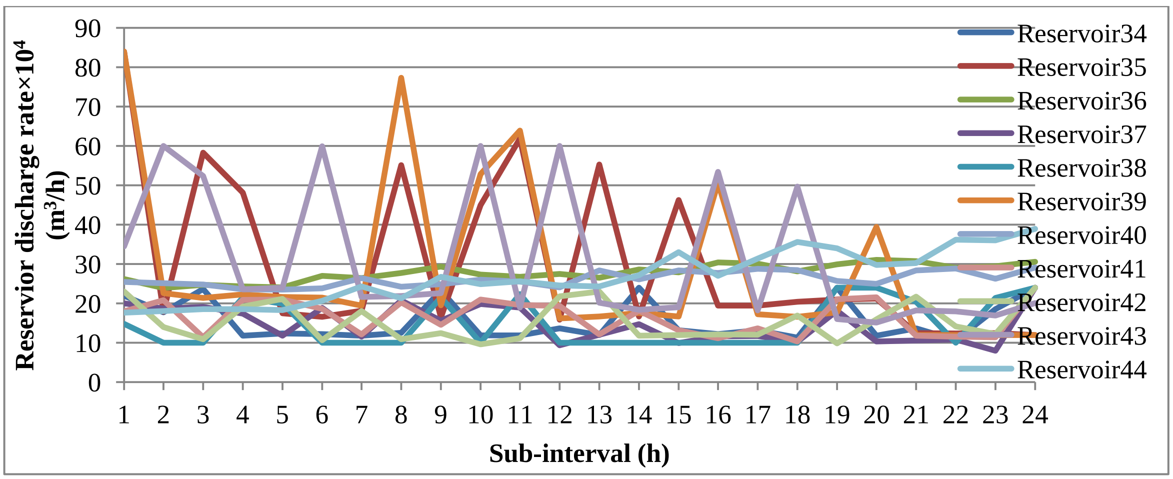

Figure 4.16: Reservoir discharge rate for multi-objective HTGS (Continued)

4.7 CONCLUSIONS

In this chapter, the weight pattern evaluation is applied to multi-objective HTGS problems. Two fundamental concepts of multi-objective decision method are considered which are contrast intensity of the alternative's performance with respect to single objective and the conflicting nature of the objectives with each other. Objective weights derived in this work are found to embody the information which is transmitted from all the objectives participating in the multi-objective problem. Further, in this work, proposed heuristic optimization techniques are explored involving global search technique(s) and Powell's pattern search technique. Predator prey optimization technique shows great potential to escape from local optimum solutions due to predator fear effect. Powell's pattern search further improves the local best solutions obtained during the implementation of global search techniques. Being a mechanism of evaluation of weights, it can handle any number of objectives to optimize simultaneously.

The practical viability of the formulation is illustrated through four numerical examples in diverse situations. Two small electric power systems have 4-hydro and 3-thermal units. Another medium system has 16-hydro and 6-thermal units, and finally one large electric power system is undertaken which has 44-hydro and 54-thermal units. For each electric power system the optimization period has been divided into 24 sub-intervals of one hour each. The results reveal that the PHOTs are very effective in reaching an optimal generation schedule. It is found that the PHOTs produce better results in terms to achieve better objective values. To decide the 'best' generation schedule for multi-objective scheduling problem, fuzzy cardinal priority ranking is compared of various reported results. Higher value of cardinal priority ranking represents higher the satisfaction level of all the objectives and it is achieved by PHOTs for all the considered electric power systems.

CHAPTER – 5

LONG-TERM MULTI-OBJECTIVE HYDRO-THERMAL GENERATION SCHEDULING

5.1 INTRODUCTION

The objective of the long-term *hydro-thermal generation scheduling* (HTGS) is to determine the hydraulic and thermal power generation for each step of the study period such that the system's resources (fuel and water) be efficiently used, obtaining thus higher economy in the current period and the future ones. Another goal of long-term HTGS is to obtain a generation scheduling that matches the long-term generation targets for each hydro plant and optimizes the efficiency of hydro power conversion. Due to the complexity, the HTGS problem has usually been organized as a hierarchical chain, in which the optimization is solved for different time scopes and different system's representation details *i.e.* long-term HTGS and short-term HTGS. The long-term HTGS covers a planning period of one or more years, divided into monthly intervals, with the month being divided into weeks. The short-term hydro-thermal scheduling covers the next week ahead usually divided into hourly intervals. The long-term HTGS problem plays an important role in power system that heavily depends on hydro electricity, since reservoir capacities are limited, there is a strong link between today's operating decisions and further consequences. If too much water is used at an early stage, shortage may occur in subsequent stages, possibly leading to load curtailment. Conversely, storing too much water may lead to spillage, imposing loss of energy in the system.

To solve long-term HTGS, several methods have been proposed in the literature. A widely used one is *dynamic programming* (DP). The success of this technique is due to the fact that the non linear and stochastic variables characteristics can be properly handled [104, 244]. Ferrero *et al.* [104] and Cruz Jr. and Soares [69] have proposed an algorithm based on

DP for long-term HTGS of multi-reservoir systems. However, when there are more than three or four reservoirs, exact DP method become intractable, and solution methods resort to approximations. To overcome this problem many techniques have been proposed. The long-term HTGS problem can be formulated as a stochastic DP problem, in which the inflows to reservoir are assumed to be random variable with a known probability distribution and the other parameters are assumed to be known with certainty [32]. Martinez and Soares [160] have applied stochastic DP to long- term HTGS problem. Stochastic DP has ability to cope with the nonlinear and stochastic characteristics of long-term HTGS problem, and the fact that it provides a closed-loop feedback control policy. Dias *et al.* [410] have employed parallel processing techniques to improve of the stochastic DP allied to the long-term operational planning of electrical power system. They have grouped hydroelectric plants into energy equivalent reservoirs and the expected cost functions are modelled by a piecewise linear approximation, by means of Convex Hull algorithm.

Methods based on linear programming technique [244], are also used for solving the long-term HTGS problem and it permits the model representation by: (1) a set of equations which describe the constraints of the system under study and (2) the objective function expressing the parameter to be maximized or minimized. The linear programming permits the linearization of the system constraints close to the nominal operating point or the modelling of the non linear ones by using linear segments. Helesth and Warland [323] have presented a methodology to solve the long-term HTGS problem as a sequence of time-dependent two-stage stochastic linear programming problems. The stochastic nature of reservoir inflow is represented as a fan of scenarios, where each scenario corresponds to a historical inflow record.

Another solution procedure of long-term HTGS is based on a deterministic model [33, 46, 72]. In this approach, the solution of the stochastic problem is obtained from the solutions of the deterministic model for a set of different scenarios representing the stochastic nature of inflows [294]. The advantage of this approach is that it does not require simplification for the handling of multi-reservoir systems. Several techniques have been proposed for the solution of this problem, including non-linear programming, network flow approaches, interior point method, which are especially efficient for solving large scale optimization problem, has arise. Azevedo *et al.* [294] have solved deterministic version of the long-term HTGS problem for large-scale HTGS, by considering nonlinear functions for hydroelectric generation and non-hydraulic operational costs. Matos and Finardi [403] have presented a computational model for solving the long-term HTGS of the Brazilian hydro-thermal power system. Mantawy *et al.* [173] have applied an algorithm based on using the short-term memory of tabu search approach to solve long-term HTGS problem. Liao *et al.* [405] have presented an adaptive artificial bee colony algorithm for long-term dispatch of cascaded hydro power systems.

The contributions of the electric energy industry to environmental pollution raise questions concerning environmental protection and methods of eliminating or reducing pollution from power plants either by design or by operational strategies. The Clean Air Act of 1990 mandated control of emissions of all coal fired power plant by the year 2000 [56]. Dispatch the power generation to minimize emissions instead of or as a supplement to the usual cost objective of economic dispatch. Hydro-thermal scheduling is recognized as a multi-objective constrained optimization problem with two conflicting objectives, *i.e.*, the minimum fuel cost and the minimum gaseous emission effects. Dhillon *et al.* [144]have presented a fuzzy decision making methodology to decide the generation schedule of long-term multi-objective hydro-thermal problems with explicit recognition of statistical uncertainties in system production cost data, NO_x emission data, system load demand and hydro reservoir water inflows.

This chapter proposes heuristic optimization techniques combining predator-prey optimization, evolutionary programming and Powell's pattern search as discussed in chapter 2, to solve the long-term multiobjective HTGS. The multi-objective long- term HTGS problem aims to define the generation of each power unit in a power system of hydroelectric reservoir and thermal plants in order to meet the demand for electricity over a long-term planning time horizon at minimum operating cost and minimizes pollutant emissions of thermal plants. To satisfy power load balance and reservoir volume equality constraints variable elimination method is implemented, whereby dependent variables are determined from the equality constraint. Multiple objectives and inequality constraints are formulated by exploring fuzzy set. The membership value indicates the degree to which an objective is satisfied, so higher the membership the greater is the satisfaction with a solution. The results obtained from the *proposed heuristic optimization techniques* (PHOTs) are compared with results reported in literature are found satisfactory.

5.2 MULTI-OBJECTIVE LONG-TERM HYDRO-THERMAL GENERATION SCHEDULING

The goal of multi-objective long-term HTGS is to minimize the thermal operating cost and gaseous pollutant emission level of thermal units simultaneously, while considering various constraints simultaneously. The thermal unit cost is usually approximated using quadratic functions. However, advanced thermal power units consist of generating units having multiple flow turbines in order to include flexible operational facilities. Because of that ripple curve is added in quadratic function of cost function and it is represented as [215]:

$$F_1 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(a_{si}\,p_{ik}^2 + b_{si}\,p_{ik} + c_{si} + \left|d_{si}\sin\left\{e_{si}\left(p_i^{\min} - p_{ik}\right)\right\}\right|\right) \tag{5.1}$$

where

a_{si}, b_{si}, c_{si}, d_{si} and e_{si} are cost coefficients of i^{th} thermal unit

p_{ik} is real power generation of i^{th} thermal unit during k^{th} sub-interval

N_T is the number of thermal units

T is total time interval for scheduling

$p_i^{\min}$ is the lower power generation limit of i^{th} thermal unit

Apart from heat, thermal units produce particulates and gaseous emissions. A number of substances such as gaseous pollutants SO_2 ,NOx and dust particles etc. are emitted during the operation of thermal units. The amount of pollutant emission is given as [364]:

$$F_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\alpha_i\,p_{ik}^2 + \beta_i\,p_{ik} + \gamma_i + \eta_i \exp(\delta_i\,p_{ik})\right) \tag{5.2}$$

where

α_i, β_i, γ_i, η_i and δ_i are emission curve coefficients of i^{th} thermal unit

5.2.1 Hydro Model-I

The average hydro generation during each sub interval depends on the water discharge through the turbine and on the average head, which is also a function of the storage. The average hydro generation during the k^{th} sub-interval is given as [144]:

$$p_{mk} = H_j\left[1 + 0.5g_j\left(2V_{jk} + I_{jk} - q_{jk} - SP_{jk}\right)\right]\left(q_{jk} - Q_j\right) \quad \left(j = 1,2,\ldots,N_H;\, m = j + N_T;\, k = 1,2,\ldots,T\right) \tag{5.3}$$

where

H_j is reservoir head of the j^{th} hydro unit

g_j is the water head correction factor to account for variation in head with storage of the j^{th} hydro unit

Q_j is non effective water discharge of the j^{th} hydro unit

The volume dynamics for the hydro reservoir network is given as:

$$V_{j(k+1)} = V_{jk} + I_{jk} - q_{jk} - SP_{jk} + \sum_{r=1}^{U_j}\left(q_{r(k-t_{rj})} + SP_{r(k-t_{rj})}\right)\left(j = 1,2,\ldots,N_H; k = 1,2,\ldots,T\right) \quad (5.4)$$

where

I_{jk}, q_{jk}, V_{jk} and SP_{jk} are the water inflow, rate of discharge, reservoir volume and spillage, respectively of j^{th} hydro unit at k^{th} sub-interval

U_j is number of upstream reservoir

t_{rj} is representing time delay from upstream reservoir '*r*' to lower reservoir '*j*'.

5.2.2 Hydro Model-II

For hydro model-II, volume dynamics for the hydro reservoir network is same as given by Eq. (5.4). The hydro power generation is a function of water discharge rate and reservoir storage and it is given as [107]:

$$p_{mk} = C_{1j}V_{jk}^2 + C_{2j}q_{jk}^2 + C_{3j}V_{jk}q_{jk} + C_{4j}V_{jk} + C_{5j}q_{jk} + C_{6j}$$
$$\left(j = 1,2,\ldots,N_H; m = j + N_T; k = 1,2,\ldots,T\right) \quad (5.5)$$

where

p_{mk} is hydro power generation of m^{th} unit at k^{th} sub-interval

$C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}$ and C_{6j} are the power generation coefficients of the j^{th} hydro unit

5.3 PROBLEM FORMULATION AND SOLUTION APPROACH

Multi-objective HTGS is stated that minimize operating cost and pollutants emission of thermal units subjected to operational and system constraints.

Mathematically problem can be represented as:

$$\text{Minimize} \quad [F_1, F_2]^T \quad (5.6)$$

Subjected to

(i) The final reservoir volume equality constraint for each hydro unit as [107]:

$$V_{jF} = V_{jI} + \sum_{k=1}^{T} I_{jk} - \sum_{k=1}^{T} q_{jk} - \sum_{k=1}^{T} SP_{jk} + \sum_{k=1}^{T}\sum_{r=1}^{U_j}\left(q_{r(k-t_{rj})} + SP_{r(k-t_{rj})}\right) \quad (j = 1,2,\ldots,N_H) \tag{5.6a}$$

(ii) The load demand equality constraint during each sub-interval

$$\sum_{i=1}^{N} p_{ik} = p_{Dk} + p_{Lk} \quad (k = 1,2,\ldots,T) \tag{5.6b}$$

(iii) The rate of discharge limits are imposed on each hydro unit

$$q_j^{\min} \le q_{jk} \le q_j^{\max} \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \tag{5.6c}$$

(iv) The volume limits are imposed on each hydro unit

$$V_j^{\min} \le V_{jk} \le V_j^{\max} \quad (j = 1,2,\ldots,N_H; k = 1,2,..T) \tag{5.6d}$$

(v) The power limits are imposed as on each hydro and thermal unit

$$p_i^{\min} \le p_{ik} \le p_i^{\max} \quad (i = 1,2,\ldots,N; k = 1,2,..T) \tag{5.6e}$$

where

$p_i^{\max}$ and $p_i^{\min}$ are the upper and lower limits of i^{th} unit power generation, respectively

$q_j^{\max}$ and $q_j^{\min}$ are the upper and lower limits of rate of water discharge of j^{th} hydro unit, respectively

p_{Dk} is the power demand and p_{Lk} is the transmission loss during k^{th} sub-interval

p_{mk} is hydro power generation of m^{th} unit at k^{th} sub-interval

V_{jF}, V_{jI} are the final and initial reservoir storage volumes respectively

Thermal power generation and water discharge rate of hydro unit are searched to find optimum solution. The multi-objective problem is formulated considering conflicting objectives: economy, emission of pollutants. Minimum values of cost and emission are obtained by considering economy and emission HTGS, respectively. The proposed heuristic optimization techniques as discussed in section 2.2 of chapter 2, has been applied to search the optimum solution of long-term HTGS. Predator-prey optimization technique and Powell's search method are integrated in first PHOT. The steps of first PHOT *i.e.* initialization of prey and predator position and velocity, predator and prey velocity and position evaluation, up-gradation of local best position are followed as mentioned in section 3.5.1 of chapter 3. In another attempt, EP technique and Powell's search method is integrated and step *i.e.* initialization of member of population, evaluation of offspring and selection of members for next generation and up-gradation of members are followed as mentioned in section 3.5.2 of chapter 3. Heuristic technique based on two natures inspired methods PPO and EP and direct search Powell's method are integrated in PHOT-III. The steps of third PHOT are followed as mentioned in section 3.5.3 of chapter 3. During the search, movement of particles/members is not always guaranteed to satisfy the constraints. Variable elimination method is applied to handle the equality constraints. The variables to be eliminated are known as dependent variable. Dependent thermal generating unit is introduced to meet the equality constraint given by Eq. (5.6b) during each sub-interval as discussed in sub-section 3.3.1 of chapter 3. Water discharge rate of a sub-interval so called dependent sub-interval is computed to satisfy the available water constraint given by Eq. (5.6a) for each hydro unit as discussed in sub-section 3.3.2 of chapter 3. Fuzzy logic approach is applied to satisfy inequality constraints, in which all inequality constraints are clubbed to form another objective as discussed in sub-sections 3.3.3 and 3.4 of chapter 3. The decision regarding the best solution is made to maximize the satisfaction level or cardinal priority ranking. Owing to the conflicting nature of objectives, emission objective has maximum value while operating cost has minimum value and vice-versa.

5.4 ELECTRIC POWER SYSTEMS AND RESULTS

The PHOTs are applied on three different scheduling problems. In first case, long-term HTGS problem is solved for economic generation scheduling, and in second case problem is solved for emission generation scheduling. Finally, both the objectives are considered simultaneously in third case. The PHOTs have been applied on two electric power systems. One electric power system is formed by integrating first hydro model and thermal units and another electric power system is the integration of second hydro model with thermal units. For PHOTs population size is taken as 50 and maximum movements are set to 1000 to achieve the optimum solution and for each case, simulation is performed twenty times to justify the results.

5.4.1 Parameter Setting

The procedure opted to find the best parameters of first PHOT are the same as adopted and discussed in sub-section 2.7.1.1 of chapter 2. The different values of best parameters of first PHOT are tabulated in Table 5.1. For second PHOT, the values of various scaling parameters for EP like β_{init}, β_{final} and β_{step} are adjusted as 1.1, 0.01 and 0.005, respectively and Powell's pattern search limits are same as set for first PHOT. For third PHOT, parameters setting are same as set for PPO, EP and PPS algorithms in first and second PHOTs.

Table 5.1: Parameters of PHOT-I

Constant	$\lambda_i^{\max}$	$\lambda_i^{\min}$	a_i	b_i	C_1	C_2	C_3	C_4	*Pfmax*
Value	$0.1\times x_i^{\min}$	$-0.1\times x_i^{\min}$	$0.05\times x_i^{\max}$	$\left(\dfrac{1.5}{x_i^{\max}}\right)$	2	2	1	0.1	0.95

Note: $x_i^{\max}$, $x_i^{\min}$: Upper and lower limit of i^{th} decision variables.

5.4.2 Electric Power System-IX

The data of electric power system-IX has been referred from [144]. The electric power system-IX comprises 3-hydro and 4-thermal units. The scheduling period is 12 months with one month sub-intervals. The hydro unit data are given in Table E.33 (Refer Appendix E, Section E.9). The thermal power generation limits, cost coefficients and emission coefficients are given in Table E.34 (Refer Appendix E, Section E.9). The load demand is given in Table E.35 (Refer Appendix E, Section E.9) and loss coefficient matrix is depicted in section E.9 of Appendix E.

5.4.2.1 Comparison of results

The results obtained from PHOTs, are compared with the results reported in literature. It is observed from Table 5.2 that PHOT-I, yields better result for minimum cost and PHOT-III yields minimum emission by achieving lower objective values, for electric power system-IX. Minimum cost is obtained only when emission level is reached at its maximum value and vice-versa. Conflicting nature of the two objectives (minimum fuel cost and minimum emission) is evident from the results. Table 5.3 represents power generation schedule and Fig

5.1 represents water discharge rate for minimum cost. Table 5.4 represents power generation schedule and Fig 5.2 represents water discharge rate for minimum emission.

Table 5.2: Comparison of results: Electric power system-IX

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost ($)	nission (kg)	CPU time (s)	Cost ($)	Emission (kg)	CPU time (s)	Cost ($)	Emission (kg)	CPU time (s)
CR[144]	6800.13	--	--	--	--	--	--	--	--
PHOT-I	6793.96	12500.69	12.43	8319.63	11787.22	12.46	7024.15	12146.19	12.45
PHOT-II	6859.03	12505.49	13.21	8056.74	11916.58	13.42	6916.97	12234.36	13.35
PHOT-III	6802.80	12501.30	20.21	8303.55	11784.74	20.40	7038.02	12137.05	20.44

Note: CR: Conjugate gradient; PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

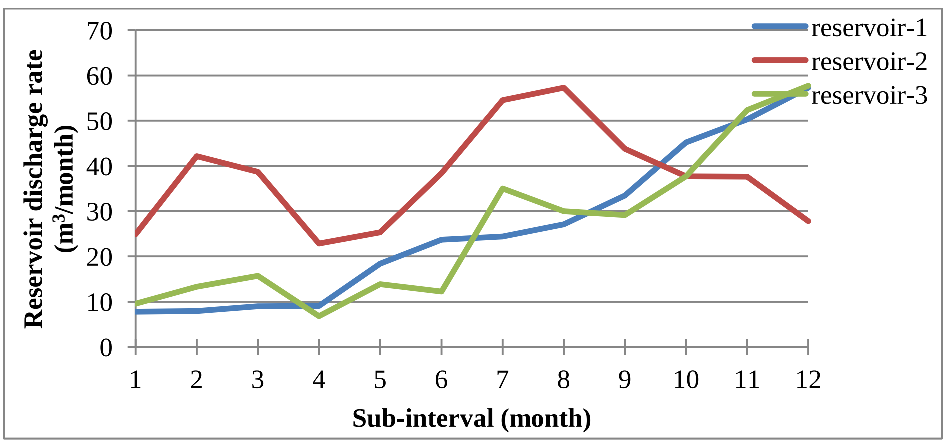

Figure 5.1: Reservoir discharge rate for minimum cost HTGS: Electric power system-IX

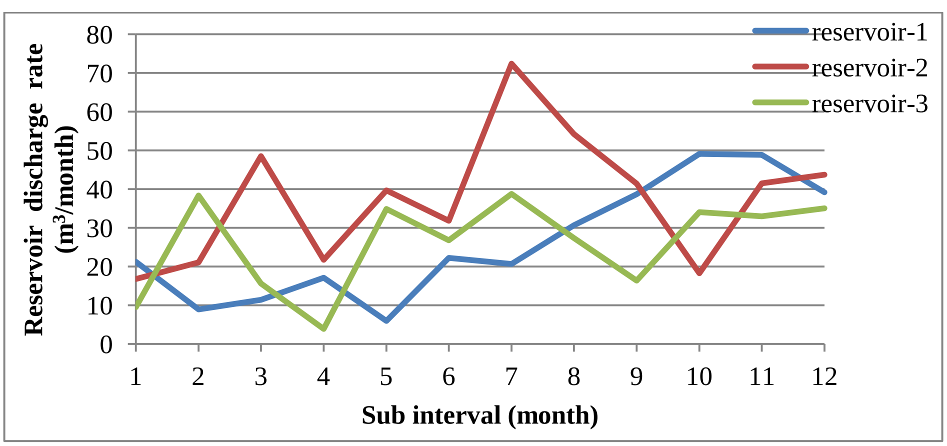

Figure 5.2: Reservoir discharge rate for minimum emission HTGS: Electric power system-IX

Table 5.3: Power generation for minimum operating cost HTGS: Electric power system-IX

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal Power (MW)				Hydro Power (MW)		
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	200	4.71891	55.70757	46.29123	33.03105	33.04792	10.59878	16.13989	9.9024
2	210	4.90133	54.38578	45.28344	32.14844	32.08683	10.6857	26.77476	13.53637
3	205	4.57837	52.30946	43.48045	31.18779	30.96692	12.20084	23.59159	15.84132
4	180	3.80874	50.24699	41.46648	29.46828	29.89235	12.39149	13.48162	6.86147
5	195	4.02799	48.31065	39.89467	28.28921	28.4972	25.17414	14.70938	14.15271
6	200	4.12194	45.78505	37.64974	26.91699	26.70112	32.17461	22.24896	12.64548
7	220	5.02957	41.87623	33.88577	24.4172	24.14743	32.98229	31.57647	36.14418
8	204	4.39233	35.58862	29.29635	20.78535	20.52216	37.69711	33.28529	31.21747
9	189	4.23953	29.24609	23.80921	16.53223	16.35337	49.18712	25.95181	32.15968
10	199	6.06157	24.10503	19.67398	13.48896	13.7081	67.93868	22.8931	43.2537
11	207	7.76317	20.46989	16.97642	11.0701	11.19414	73.19019	23.37027	58.49215
12	198	8.44943	16.6217	13.29275	8.74171	8.53529	79.88181	17.77095	61.60524

Table 5.4: Power generation for minimum emission HTGS: Electric power system-IX

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal Power (MW)				Hydro Power (MW)		
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	200	4.9449	34.19248	34.73442	43.5	43.5	28.25832	10.95504	9.80465
2	210	5.60671	31.97297	33.6733	43.5	43.5	11.54885	13.77542	37.63617
3	205	5.02516	30.3028	32.72981	43.5	43.5	14.76087	30.72959	14.50201
4	180	4.35667	28.21726	30.35036	43.5	43.5	21.89776	13.2421	3.64923
5	195	5.00757	23.1671	26.44948	43.49964	43.5	7.644	23.56125	32.18613
6	200	4.9087	22.14278	24.33075	43.5	43.5	29.06933	18.7249	23.64088
7	220	6.11276	17.3704	19.30884	43.5	43.5	27.13849	42.21972	33.07523
8	204	5.59793	11.8733	14.21926	43.5	43.5	41.60374	31.31989	23.58172
9	189	5.80404	5.9923	7.12008	43.49988	43.49841	54.75357	24.49529	15.44452
10	199	7.67144	1.15031	2.19764	43.5	43.5	70.4513	11.27196	34.60018
11	207	7.7268	0.00	0.0706	43.49791	43.49985	67.46954	26.50732	33.68164
12	198	6.75197	0.00	0.00	43.4994	43.49153	53.22209	28.31441	36.22458

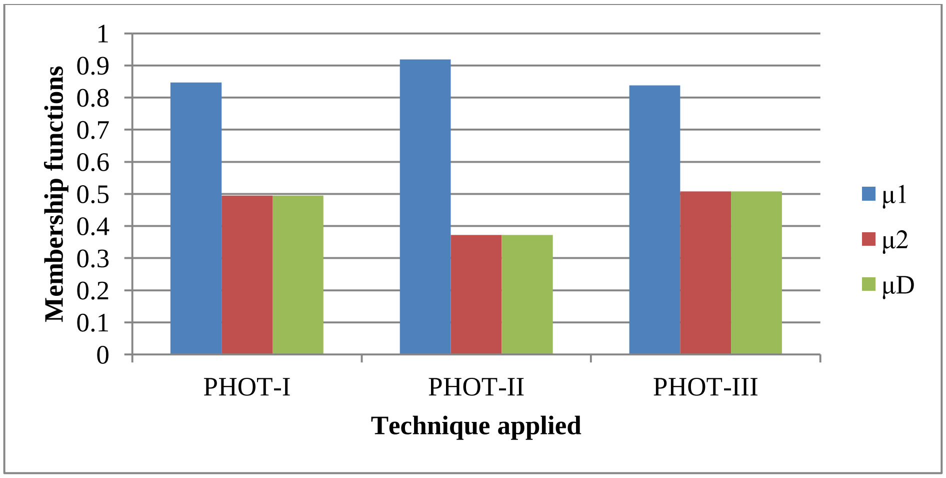

Figure 5.3: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-IX

Table 5.5: Power generation for multi-objective HTGS: Electric power system-IX

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal Power (MW)				Hydro Power (MW)		
			p_{1k}	p_{2k}	p_{3k}	p_{4k}	p_{5k}	p_{6k}	p_{7k}
1	200	4.82093	45.46053	38.98787	40.65684	40.39914	12.21399	17.15902	9.94355
2	210	5.03487	44.28222	37.78262	39.82132	39.985	11.71086	26.89021	14.56266
3	205	4.73631	42.05979	36.38757	38.70861	38.654	11.85046	23.17445	18.90138
4	180	3.97797	40.32639	34.1815	37.61829	37.57263	14.17868	14.78815	5.31229
5	195	4.2064	38.34238	32.85513	36.35487	36.53667	22.60988	13.78656	18.72092
6	200	4.25815	36.11034	30.50742	34.80301	34.80477	30.14656	22.24105	15.64502
7	220	5.13025	32.37712	27.51511	32.83697	32.91666	36.86855	33.8842	28.73163
8	204	4.55055	26.73459	22.49096	29.72431	29.31005	39.29914	33.84955	27.14193
9	189	4.38115	20.48596	16.91299	25.73206	25.97907	47.93538	23.76179	32.57384
10	199	6.14571	15.85464	13.02001	22.90472	22.8954	66.7874	20.4736	43.21
11	207	7.64861	12.09501	9.5022	20.8858	20.73544	70.39734	23.46131	57.57151
12	198	8.28793	8.32667	6.71547	18.40973	18.17461	76.82059	16.64544	61.19545

To compare the multi-objective solution among various results, membership function is computed by considering best minimum objective function value among results reported in Table 5.2, and corresponding maximum value. It is evident from Fig 5.3, that maximum value of cardinal priority ranking is achieved by the solution obtained from PHOT-III. Table 5.5 represents power generation schedule and Fig 5.4 represents water discharge rate while solving the multi-objective generation scheduling for electric power system-IX corresponding to maximum cardinal priority solution.

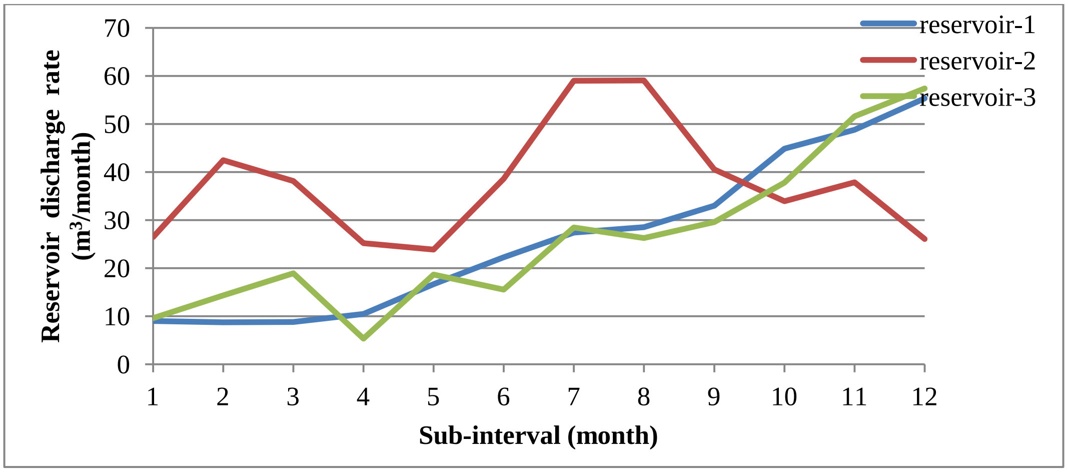

Figure 5.4: Reservoir discharge rate for multi-objective HTGS: Electric power system-IX

Table 5.6: The best, average and worst values of objectives: Electric power system-IX

Technique Applied	Scheduling		Best	Average	Worst	S. D.
PHOT-I	Economy	F_1 ($)	6793.96	6882.43	6982.21	56.641
	Emission	F_2 (kg)	11787.22	11914.52	12035.32	75.901
	Multi-objective	μ_D	0.4951	0.4674	0.4008	0.02569
PHOT-II	Economy	F_1 ($)	6859.03	6904.63	6980.74	58.453
	Emission	F_2 (kg)	11916.58	11987.67	12105.41	78.905
	Multi-objective	μ_D	0.3943	0.3653	0.3003	0.02612
PHOT-III	Economy	F_1 ($)	6802.80	6876.56	6915.65	55.781
	Emission	F_2 (kg)	11784.74	11868.53	11945.73	74.352
	Multi-objective	μ_D	0.5079	0.4814	0.4542	0.02543

Note: PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

5.4.2.2 Robustness of proposed heuristic optimization techniques

The twenty trials are given for minimum cost, minimum emission and multiobjective generation scheduling to examine the effect of initial solutions, and to verify the robustness of the PHOTs. To investigate the probability of success, standard deviation is computed of minimum cost, minimum emission and cardinal priority ranking results. The best, average and worst results and their standard deviations are tabulated in Table 5.6. It is observed from Table 5.6 that standard deviation is minimum for results obtained by third PHOT for all types of scheduling.

5.4.3 Electric Power System-X

The data of electric power system-X has been referred from [104] except for emission coefficients. The electric power system-X comprises 4-hydro and 1-thermal units. The scheduling period is 52 week with one week sub-intervals. The hydro sub-system configuration and network matrix including the water time delay are shown in Fig E.4 (Ref Appendix E, Section E.10). The hydro unit power generation coefficients are given in Table E.36 (Ref Appendix E, Section E.10). The hydro reservoir storage capacity limits, plant discharge limits, initial and final storage capacity limits, rate of water discharge limits and hydro plant generation limits are mentioned in Table E.37 (Ref Appendix E, Section E.10). The reservoirs inflows are given in Tables E.38 (Ref Appendix E, Section E.10). The thermal power generation limits, cost coefficients and emission coefficients are given in Table E.39 (Ref Appendix E, Section E.10) and Table E.40 (Ref Appendix E, Section E.10), respectively. The load demand is tabulated in Table E.41 (Ref Appendix E, Section E.10).

5.4.3.1 Comparison of results

The results obtained from PHOTs, are compared with the results reported in literature. It is observed from Table 5.7 that PHOT-I, yields better result for minimum cost and minimum emission by achieving lower objective values, for electric power system-X. Conflicting nature of the two objectives (minimum fuel cost and minimum emission) is evident from the results. Table 5.8 represents power generation schedule and Fig 5.5 represents water discharge rate for minimum cost.

Table 5.9 represents power generation schedule and Fig 5.6 represents water discharge rate for minimum emission scheduling. To compare the multi-objective solution among various results, membership function is computed. Membership function is computed by considering best minimum objective function value among results reported in Table 5.7, and corresponding maximum value. It is evident from Fig 5.7, that maximum value of cardinal priority ranking is achieved by the solution obtained from PHOT-I.

Table 5.7: Comparison of results: Electric power system-X

Technique Applied	Case-I Economic Scheduling			Case-II Emission Scheduling			Case-III Multi-objective Scheduling		
	Cost ×10^6 ($)	Emission ×10^6 (lb)	CPU time (sec)	Cost ×10^6 ($)	Emission ×10^6 (lb)	CPU time (sec)	Cost ×10^6 ($)	Emission ×10^6 (lb)	CPU time (sec)
Two stage [104]	45.44	--	442.8	--	--	--	--	--	--
SA [104]	46.08	--	537.6	--	--	--	--	--	--
SA (Fine grid) [104]	45.80	--	1896	--	--	--	--	--	--
PHOT-I	41.57	4.567	18.64	42.06	4.538	18.12	41.71	4.544	18.42
PHOT-II	41.61	4.618	19.86	42.45	4.541	19.57	41.86	4.545	19.63
PHOT-III	41.59	4.576	25.72	42.20	4.542	25.61	41.80	4.546	25.73

Note: SA: Successive approximation; PHOT-I: Proposed heuristic optimization technique-I; PHOT-II: Proposed heuristic optimization technique-II; PHOT-III: Proposed heuristic optimization technique-III

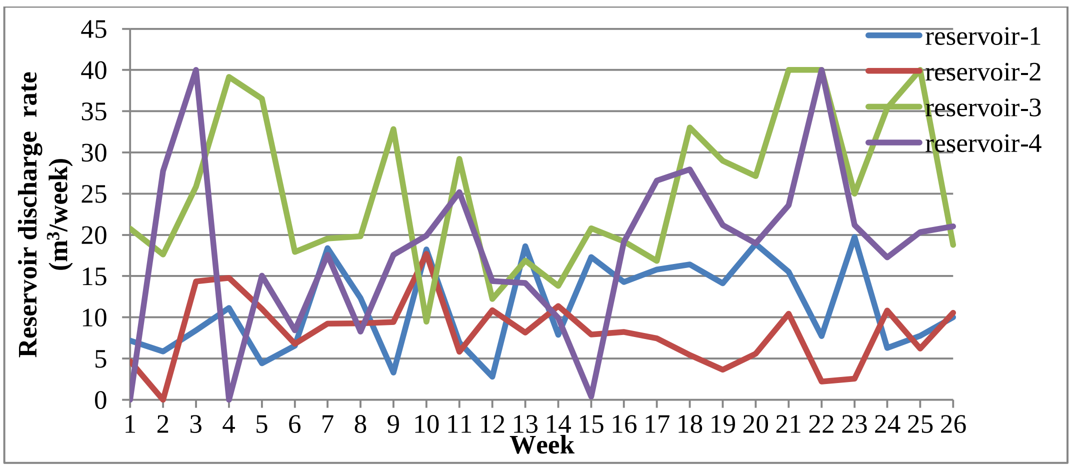

Figure 5.5: Reservoir discharge rate for minimum cost HTGS: Electric power system-X

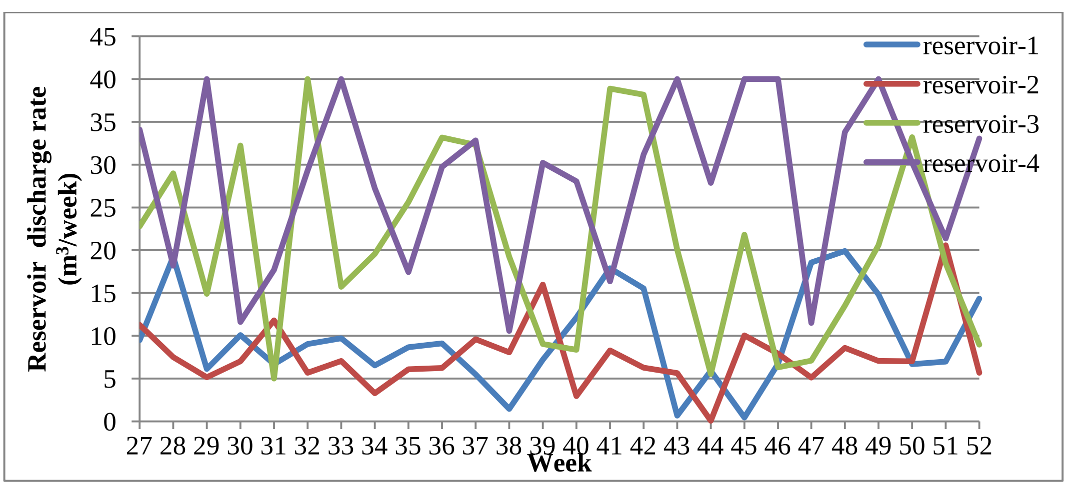

Figure 5.5: Reservoir discharge rate for minimum cost HTGS: Electric power system-X (Continued)

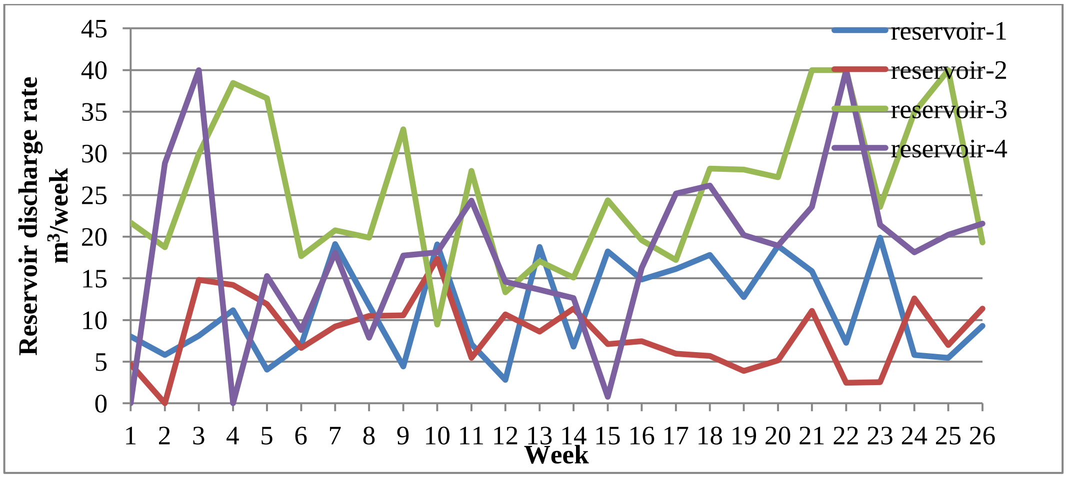

Figure 5.6: Reservoir discharge rate for minimum emission HTGS: Electric power system-X

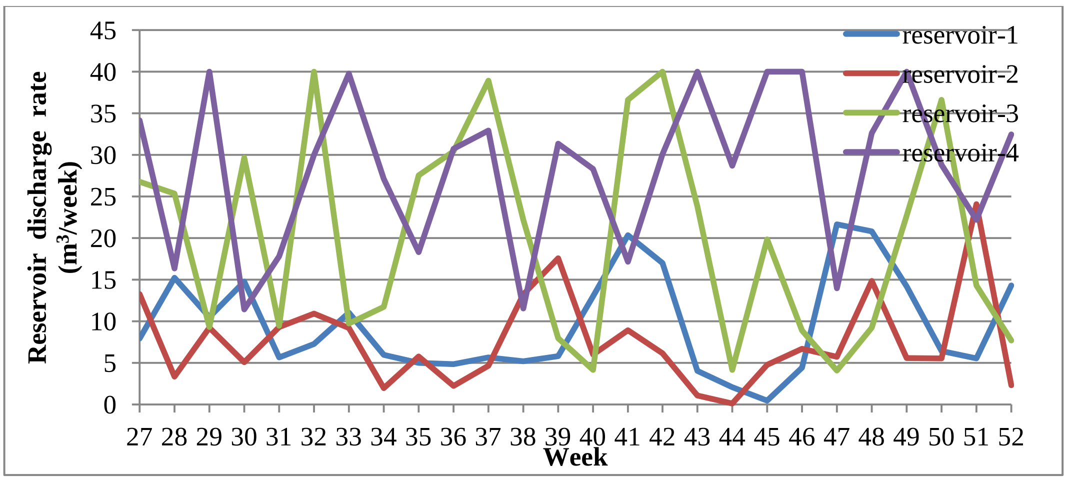

Figure 5.6: Reservoir discharge rate for minimum emission HTGS: Electric power system-X (Continued)

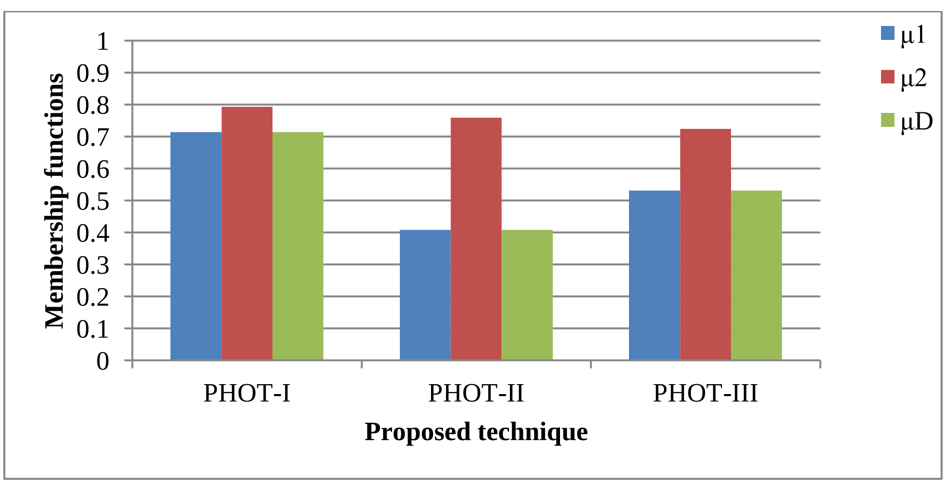

Figure 5.7: Comparison of cardinal priority ranking for multi-objective HTGS: Electric power system-X

Table 5.8: Power generation and load demand (MW) for minimum cost HTGS: Electric power system-X

k		1	2	3	4	5	6	7	8	9	10	11	12	13
p_{Dk}		870	890	900	910	910	900	910	900	890	885	880	875	875
Thermal	p_{1k}	582.5292	375.5284	293.1578	548.9770	376.4841	457.0549	294.6035	396.4366	315.0474	246.8948	231.9454	372.2126	291.4839
Hydro	p_{2k}	69.6295	60.7589	80.5459	95.4844	49.2303	68.8359	108.5856	101.5400	37.7805	108.8627	71.8567	32.2088	110.1349
	p_{3k}	48.9289	4.4410	103.9787	100.7473	84.1492	58.6289	73.2515	72.1357	71.7443	91.5828	41.8340	71.2601	55.7887
	p_{4k}	110.4125	99.6679	113.2209	104.9718	105.7586	90.2596	95.7522	103.3687	120.2068	64.2827	131.7584	83.8610	105.7876
	p_{5k}	58.5000	349.6038	309.0966	59.8197	294.3779	225.2208	337.8073	226.5190	345.2212	373.3768	402.6055	315.4576	311.8049
k		14	15	16	17	18	19	20	21	22	23	24	25	26
p_{Dk}		877	880	882	885	890	890	890	885	880	870	870	865	850
Thermal	p_{1k}	374.1714	501.4869	225.6983	188.6705	164.6230	222.8762	231.2085	148.5425	186.3951	228.5540	226.6428	216.0009	181.7059
Hydro	p_{2k}	79.1961	110.0473	106.4749	106.6156	104.3613	100.5234	94.5860	94.2953	68.4694	82.4749	55.3850	65.7575	77.3877
	p_{3k}	70.7608	51.9361	53.9149	49.4385	36.6269	24.5296	42.5251	72.1731	14.3011	20.4328	78.7216	50.8437	75.9030
	p_{4k}	96.0101	125.9232	122.1597	113.4072	157.4162	152.1301	148.0332	155.3616	152.5862	137.9329	147.8271	136.4566	111.9312
	p_{5k}	256.8616	90.6065	373.7523	426.8681	426.9728	389.9409	373.6472	414.6273	458.2481	400.6055	361.4236	395.9413	403.0722
k		27	28	29	30	31	32	33	34	35	36	37	38	39
p_{Dk}		850	850	845	845	840	840	820	780	770	780	785	790	790
Thermal	p_{1k}	93.7786	213.6135	177.3082	302.8111	299.7324	145.3591	122.2753	146.1349	171.6381	85.2863	87.5291	351.3996	110.4963
Hydro	p_{2k}	74.3837	76.1686	48.7778	70.8833	52.9407	67.0053	69.8427	52.9629	66.6233	69.2303	47.5097	11.4743	65.1423
	p_{3k}	76.4620	54.8443	38.9317	53.4030	78.1365	42.9087	54.2943	27.2266	52.7905	55.7953	78.1970	69.7681	100.2662
	p_{4k}	123.6094	132.4632	97.7558	132.0962	42.5015	124.0722	94.7420	107.7488	115.9989	112.0678	103.5881	87.6295	50.2448
	p_{5k}	481.7664	372.9104	482.2267	285.8065	366.6889	460.6547	478.8457	445.9268	362.9493	457.6204	468.1762	269.7285	463.8505
k		40	41	42	43	44	45	46	47	48	49	50	51	52
p_{Dk}		810	820	830	840	820	820	825	830	830	835	830	830	840
Thermal	p_{1k}	193.1620	216.6674	134.0674	230.5765	287.3035	211.8220	236.2939	366.8627	191.4639	222.0118	234.7354	230.8582	277.9194
Hydro	p_{2k}	88.9474	88.3297	87.0359	2.1132	56.3272	2.9610	67.5614	100.0786	92.1646	95.6949	63.8409	67.5657	99.1548
	p_{3k}	28.9874	72.7138	60.0828	56.5747	6.1989	90.1371	77.2538	57.0327	82.6303	72.4165	72.1458	111.7326	56.4328
	p_{4k}	52.3402	95.0760	89.3485	86.2475	28.9998	84.7562	31.5827	39.6916	75.3336	103.7907	114.8551	94.0348	61.1676
	p_{5k}	446.5631	347.2131	459.4655	464.4882	441.1705	430.3237	412.3083	266.3344	388.4077	341.0861	344.4229	325.8087	345.3254

Table 5.9: Power generation and load demand (MW) for minimum emission HTGS: Electric power system-X

	k	1	2	3	4	5	6	7	8	9	10	11	12	13
	p_{Dk}	870	890	900	910	910	900	910	900	890	885	880	875	875
Thermal	p_{1k}	550.0244	331.1065	295.4424	560.0079	362.3978	418.4238	279.2382	369.6466	264.2555	283.2999	291.2499	363.4592	282.0668
Hydro	p_{2k}	85.1881	64.5978	65.6240	98.7982	54.8860	92.9142	100.6530	104.2398	75.0775	97.4502	55.4720	28.1576	106.1164
	p_{3k}	58.7408	26.7197	105.6335	86.9742	95.0835	47.1472	78.0599	78.2847	77.1448	73.1881	10.5360	58.5672	68.3428
	p_{4k}	117.5468	112.0211	113.8775	99.6808	105.6764	98.6602	103.7972	99.4907	120.8034	68.0876	114.4817	104.4590	109.1775
	p_{5k}	58.5000	355.5550	319.4225	64.5390	291.9563	242.8547	348.2518	248.3382	352.7188	362.9742	408.2604	320.3571	309.2966
	k	14	15	16	17	18	19	20	21	22	23	24	25	26
	p_{Dk}	877	880	882	885	890	890	890	885	880	870	870	865	850
Thermal	p_{1k}	357.6750	517.6501	266.4827	185.8484	171.8381	229.4660	248.6691	166.0193	175.7151	205.9732	210.8446	227.3654	186.9873
Hydro	p_{2k}	60.4549	102.7003	101.2062	94.8945	90.8704	84.2417	92.6137	81.1238	45.8795	82.5080	45.8239	50.5637	47.4576
	p_{3k}	59.0137	27.9770	42.7413	40.0669	57.1972	38.4778	39.8760	66.6066	34.6952	48.1963	86.5018	57.7631	84.5231
	p_{4k}	121.0072	135.0180	134.3535	133.1465	137.0150	146.4312	141.4532	147.5746	145.0369	124.5144	141.4410	134.7036	112.4779
	p_{5k}	278.8491	96.6546	337.2164	431.0436	433.0793	391.3834	367.3881	423.6756	478.6734	408.8081	385.3888	394.6043	418.5540
	k	27	28	29	30	31	32	33	34	35	36	37	38	39
	p_{Dk}	850	850	845	845	840	840	820	780	770	780	785	790	790
Thermal	p_{1k}	89.4316	274.4881	147.2432	320.6729	295.5645	124.7891	127.8787	192.3924	186.4756	138.9747	130.0068	277.4956	120.0835
Hydro	p_{2k}	66.5883	85.8260	74.2035	79.3101	44.2347	56.5482	73.8994	48.0052	42.3660	43.0490	51.6249	49.4499	56.0783
	p_{3k}	81.6228	21.9252	64.6794	37.3760	65.9459	72.6877	63.3623	11.1858	47.3034	19.9812	44.9409	95.2087	100.5596
	p_{4k}	124.4985	120.9476	66.3852	127.4014	68.0606	116.8638	66.3280	78.9035	120.6898	113.9448	88.4605	83.8566	41.3449
	p_{5k}	487.8589	346.8131	492.4888	280.2397	366.1944	469.1111	488.5317	449.5132	373.1651	464.0504	469.9671	283.9893	471.9337
	k	40	41	42	43	44	45	46	47	48	49	50	51	52
	p_{Dk}	810	820	830	840	820	820	825	830	830	835	830	830	840
Thermal	p_{1k}	186.5846	208.2676	143.9658	228.9799	324.4723	246.9712	248.8755	358.0679	185.3429	231.1154	251.7513	254.4769	312.1759
Hydro	p_{2k}	92.7275	82.0858	85.5449	36.5288	19.7020	3.1838	48.0440	89.8680	87.4973	94.0112	61.4500	56.0370	99.1464
	p_{3k}	52.3050	73.0220	55.8218	12.9788	5.7951	53.6632	70.0018	63.3415	110.5601	60.4281	60.6835	104.2015	26.5591
	p_{4k}	26.8498	99.4296	87.7535	93.7079	21.2026	79.8711	41.0283	19.3123	55.2074	110.2851	111.1022	79.7080	54.9286
	p_{5k}	451.5331	357.1951	456.9141	467.8046	448.8280	436.3108	417.0504	299.4103	391.3923	339.1602	345.0130	335.5766	347.1899

Table 5.10: Power generation and load demand (MW) for multi-objective HTGS: Electric power system-X

k		1	2	3	4	5	6	7	8	9	10	11	12	13
p_{Dk}		870	890	900	910	910	900	910	900	890	885	880	875	875
Thermal	p_{1k}	574.6017	370.3353	291.6088	549.7090	375.1523	450.3645	289.2789	399.4077	297.5045	266.0416	237.0957	364.8618	295.3774
Hydro	p_{2k}	75.4020	60.3474	78.4257	95.5460	45.2746	72.7517	106.8807	99.1320	49.5719	106.4980	72.7082	32.4588	108.7758
	p_{3k}	48.9289	4.4410	105.0180	99.1678	87.7307	57.2961	72.9017	77.6762	75.9012	89.2596	37.6159	68.8048	56.8958
	p_{4k}	112.5674	102.9313	114.3645	103.1694	102.3320	87.5594	96.4792	101.7633	118.0503	63.8195	130.2755	89.0367	106.0899
	p_{5k}	58.5000	351.9450	310.5830	62.4079	299.5104	232.0283	344.4595	222.0208	348.9722	359.3812	402.3047	319.8379	307.8611
k		14	15	16	17	18	19	20	21	22	23	24	25	26
p_{Dk}		877	880	882	885	890	890	890	885	880	870	870	865	850
Thermal	p_{1k}	339.6694	493.6202	258.4152	200.7888	173.2614	231.6628	234.9391	145.2005	181.5500	231.6335	215.2662	229.4583	177.2314
Hydro	p_{2k}	70.8209	108.2730	106.2551	105.2053	100.9572	95.7592	92.1038	91.7227	63.8910	79.0249	50.0413	48.6872	73.7690
	p_{3k}	68.7264	45.2235	48.2184	39.2254	39.0629	26.6941	39.3204	75.3313	16.3812	20.1959	85.1607	54.5964	77.2288
	p_{4k}	101.7201	134.9467	122.7014	114.3983	149.6802	150.0616	147.6211	154.3851	151.9126	134.0959	147.7831	137.0472	113.5128
	p_{5k}	296.0632	97.9366	346.4099	425.3821	427.0382	385.8224	376.0157	418.3604	466.2652	405.0499	371.7488	395.2110	408.2580
k		27	28	29	30	31	32	33	34	35	36	37	38	39
p_{Dk}		850	850	845	845	840	840	820	780	770	780	785	790	790
Thermal	p_{1k}	90.4301	249.5665	178.5893	307.1213	308.0375	135.7293	122.3718	153.0728	174.6066	91.3479	95.3483	323.5425	107.0237
Hydro	p_{2k}	72.0201	76.3771	52.9643	73.4483	46.2469	68.4809	72.0601	46.9621	62.7576	63.4337	45.2441	22.2145	65.1255
	p_{3k}	77.5847	43.5818	31.9409	48.4622	74.2079	41.6189	55.0628	25.9959	51.2239	47.7301	76.0222	71.2423	100.1513
	p_{4k}	125.3924	126.1124	96.2729	133.3466	43.8566	125.6110	89.6134	107.9021	119.1350	115.5022	98.7483	88.1565	48.5079
	p_{5k}	484.5726	354.3622	485.2327	282.6217	367.6510	468.5600	480.8918	446.0671	362.2770	461.9861	469.6372	284.8441	469.1915
k		40	41	42	43	44	45	46	47	48	49	50	51	52
p_{Dk}		810	820	830	840	820	820	825	830	830	835	830	830	840
Thermal	p_{1k}	203.1519	202.6293	138.8936	228.7733	290.3160	191.9550	265.6592	358.8210	203.2601	223.2640	235.4266	239.9687	284.6107
Hydro	p_{2k}	88.6003	87.5699	87.1019	5.3001	47.9717	21.3241	59.6330	98.2883	92.3614	95.3979	67.6714	62.4207	99.9846
	p_{3k}	24.4519	77.2568	62.1099	48.3357	9.3723	88.8548	71.4451	58.0297	74.0630	71.0505	67.8117	111.0027	51.0246
	p_{4k}	45.1524	96.3878	86.2004	91.5694	24.7480	83.2699	10.3218	35.0440	70.7198	104.1948	114.4427	92.5679	58.0895
	p_{5k}	448.6436	356.1563	455.6942	466.0215	447.5920	434.5963	417.9410	279.8169	389.5957	341.0928	344.6476	324.0401	346.2906

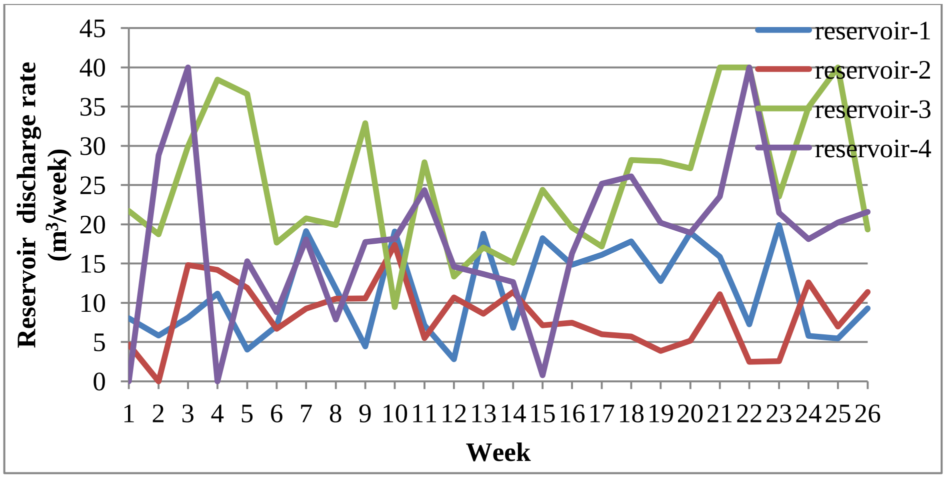

Figure 5.8: Reservoir discharge rate for multi-objective HTGS: Electric power system-X

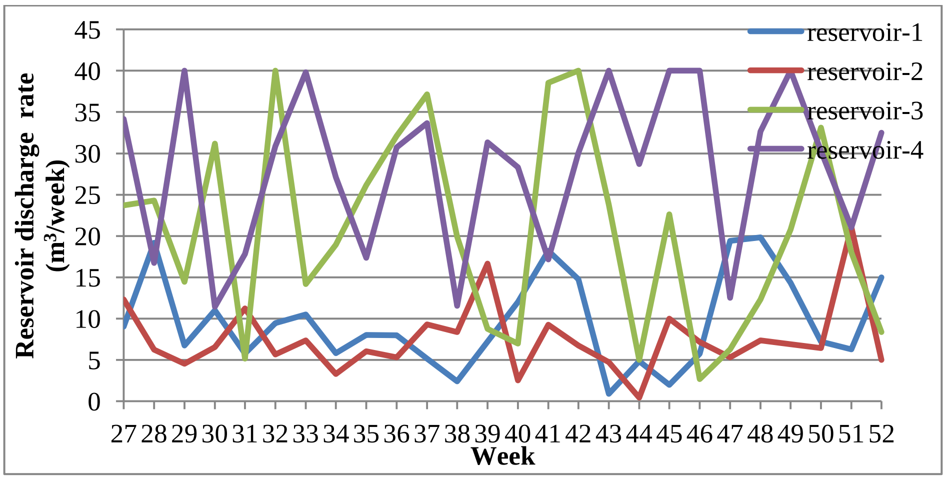

Figure 5.8: Reservoir discharge rate for multi-objective HTGS: Electric power system-X (Continued)

Table 5.10 represents power generation schedule and Fig 5.10 and 5.11 represents water discharge rate while solving the multi-objective generation scheduling for electric power system-X corresponding to maximum cardinal priority solution.

5.5 CONCLUSIONS

The proposed heuristic optimization techniques applied to solve the long-term multi-objective HTGS are presented in this chapter. The PHOTs have been tested on two hydro-thermal electric power systems. One electric power system consist hydro model-I and thermal units. The scheduling period is one year with one month sub-intervals. Another system has hydro model-II and thermal units and scheduling period is one year with one week sub-intervals. The results reveal that the PHOTs are very effective to search an optimal generation schedule. The minimum cost obtained by PHOT-II and PHOT-III, is high as compared to cost obtained by conjugate gradient method. Because some approximations are taken in conjugate gradient method to make the problem more traceable but approximations can lead to inaccurate optimal solutions. The tremendous amount of annual fuel cost and gaseous pollutant emission in thermal plants is associated so a small percentage of saving or achievement in any objective is considered significant. Thus it fully justifies the need for more accurate analysis. The robustness of proposed optimization techniques are also tested by taking best, average and worst results and it is observed that good quality results are achieved on every execution. The execution time to achieve optimal solution by PHOTs is very less as compared to result reported in literature without taking any approximation.

CHAPTER – 6

STOCHASTIC SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING

6.1 INTRODUCTION

With economic development, population growth and urban expansion, energy plays an increasingly significant role in modern economic development and human activities for achieving sustainable development of society and economy. It is well known that energy consumption can result in air pollutants, which are extremely harmful to both public health and environment. Besides, climate change is considered to be one of the most challenging problems in the 21st century. In power industry, power generation scheduling is an important decision-making problem, which is closely associated with economical and environmental issues. In real world applications, energy system is subjected to a variety of social, economic, environmental and technical factors, which are highly uncertain and interrelated. The nature of uncertainty in generator's cost characteristics, network parameters, load model coefficients, and limits on voltages, flow and generations, are generally of non-probabilistic type. It is well known that load forecast is always subject to certain errors. Network parameter errors arise due to imprecise data used for reactance calculations and aging. Resistances also vary with temperature. Generator cost curves are determined from heat rate curves, which are not even updated regularly. Fuel prices also fluctuate continuously. Hence the input data for optimization studies is rarely available with complete certainty [412]. Uncertainties in the system data must be addressed in any analysis. Unfortunately, this problem is acute in power systems because of the geographical spread, size, and complexity of power systems. But most of the times, it is implicitly assumed that the problem is refrained from both intrinsic and extrinsic disturbance and inaccuracy. However, this ideal assumption is not true in real world applications, and the deviations are even quite considerable in certain conditions. The uncertainties may come from the internal parameter changes as well as the external continuously varying factors. Conventional power system problem uses deterministic models, which are however not able to reflect some real situations in practical applications. Since certain inaccurate and uncertain factors are normally involved in system operations, stochastic models are more suited for investigating the power dispatch problems. In order to solve stochastic scheduling problem, starting from the early seventies different computational methodologies for power system uncertainty analysis were introduced. One common approach is that variations in system parameters and variables are modeled mathematically using their variance and covariance.

Viviani and Heydt, [12] have outlined the computational details of the stochastic optimal energy dispatch algorithm using the multi-variate Gram-Charlier series. El-Hawary and Mbamalu [19, 25,26] have investigated the perturbations in the system thermal fuel cost, in power demand and in system equality constraints as stochastic and normally distributed with zero mean and a given variance. Dhillon *et al.* [43] have considered the uncertainties in the system production cost and in load demand and have formulated a stochastic economic emission load dispatch problem. A stochastic formulation of multi-objective optimization for combined heat and power system dispatch has been done by Chang and Fu [18] by considering both power and heat demands as random variables. Uncertainties in the system production cost data and generator outputs have been taken into account by Selvi *et al.* [198] to solve economic dispatch problem of thermal generation using genetic algorithm. Wu *et al.* [255] have presented the method to estimate the uncertainty in the load-flow solution and have presented a stochastic model for the long-term solution of security-constrained unit commitment problem. Li *et al.* [289] have presented a probabilistic optimal power flow algorithm taking account of the variation of load power. They have taken system load as a random vector.

For hydro-thermal systems, the limited energy storage capability of water reservoirs, along with stochastic nature of their availability, makes their solution more difficult job than for purely thermal systems [361]. El-Hawary and Mbamalu [26] have presented a technique that deals with the hydro-thermal optimal power dispatch problem accounting for the effects of uncertainty in predicting active power demand. A sub-optimal optimization method is presented by Contaxis and Kavatza [29] to solve the annual *hydro-thermal generation* *scheduling* (HTGS) considering the stochastic nature of inflows to the reservoirs and forced outage rates of the thermal units. Dhillon *et al.* [361] have formulated the stochastic multi-objective HTGS problem with explicit recognition of uncertainties in the system production cost coefficients and system load, which are treated as random variable and real coded genetic algorithm has been applied for scheduling. Dhillon *et al.* [157] have analyzed the hydro-thermal short-range fixed-head problem with explicit recognition of uncertainties in production cost, NOx, SO_2 and CO_2 emission and load demand. The weighting method is used to simulate the trade-off relation between the conflicting objectives and finally, fuzzy decision-making methodology is exploited to decide the generation schedule. Dhillon *et al.* [144] have presented a fuzzy decision making methodology to decide the generation schedule of long-term hydro-thermal problems with explicit recognition of statistical uncertainties in system production cost data, NO_x emission data, system load demand and hydro reservoir water inflows. Jiekang *et al.* [287] have proposed a strategy for optimal scheduling of cascaded hydro plants, which includes uncertainties, such as water inflows, electricity prices, and unit status. The proposed strategy is based on particle swarm optimization and chance-constrained programming and is presented to maximize the expected profit at a given risk level. Rebennack *et al.* [401] have solved stochastic HTGS considering CO_2 emission constraints using stochastic dual dynamic programming.

In previous studies of stochastic models, deviation in reservoir volume is not considered. Since, hydro power output and coefficients of water discharge rate are treated as random variables, so there is a need to consider volume deviations. In view of the above, the intent of the chapter is to formulate multi-objective HTGS problem as a stochastic multi-objective optimization problem with explicit recognition of uncertainties and inaccuracies in system production cost, pollutant emission, water discharge rate and system load. The hydro-thermal scheduling problem is solved in multi-objective framework in which objectives such as operating cost, gaseous pollutant emission, variance of generation and variance of reservoir volume are minimized together. The correlation between hydro power generations of present sub-interval with hydro power generations of next sub-interval is also considered. Proposed heuristic optimization techniques based on *predator-prey optimization* (PPO), *evolutionary programming* (EP) and *Powell's pattern search* (PPS) are applied to search compromised solution. The objectives are quantified by eliciting the corresponding membership function.

The best compromised solution is one, which provides maximum satisfaction level from the participating objectives. Further, heuristic approach is used to satisfy the constraints, by perturbing the decision variables in systematic manner.

6.2 MULTI-OBJECTIVE STOCHASTIC SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING PROBLEM

The aim of multi-objective stochastic hydro-thermal optimum generation scheduling is to optimize the thermal operating cost, gaseous pollutant emission levels of thermal unit and expected deviations simultaneously, while satisfying the various operational constraints. Stochastic thermal and hydro model is converted into its deterministic model.

6.2.1 Expected Thermal Model

A fuel cost function is given as:

$$F_1 = \sum_{k=1}^{T} \sum_{i=1}^{N_T} \left(a_{si} p_{ik}^2 + b_{si} p_{ik} + c_{si} \right) \tag{6.1}$$

where

a_{si} , b_{si} and c_{si} are cost coefficients of i^{th} thermal unit

p_{ik} is real power generation of i^{th} thermal unit during k^{th} sub-interval

N_T is the number of thermal units

T is total time interval for scheduling

Thermal units produce particulates and gaseous emissions, such as gaseous pollutants SO_2 ,NOx, CO_2 and dust particles etc. The amount of total emission can be defined as:

$$F_2 = \sum_{k=1}^{T} \sum_{i=1}^{N_T} \left(\alpha_i p_{ik}^2 + \beta_i p_{ik} + \gamma_i \right) \tag{6.2}$$

where

α_i , β_i and γ_i are emission curve coefficients of i^{th} thermal unit

The expected model of multi-objective problem is formulated by considering cost coefficients, emission coefficients and load demand as random variables. Then the generator output automatically becomes random. Random variables are considered as normally distributed and statistically dependent to each other. By taking expectations, the expected model can be converted into its deterministic equivalent. The expected value of a function is obtained by expanding the function, employing Taylor's series, about the mean. Deterministic equivalent of stochastic thermal model is stated as:

Expected cost

$$\overline{F}_1 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\overline{a}_{si}\,\overline{p}_{ik}^2 + \overline{b}_{si}\,\overline{p}_{ik} + \overline{c}_{si} + \overline{a}_{si}\ \mathrm{var}(\,\overline{p}_{ik}) + 2\,\overline{p}_{ik}\ \mathrm{cov}(a_{si}, p_{ik}) + \mathrm{cov}(b_{si}, p_{ik})\right) \qquad (6.3)$$

Expected total emission

$$\overline{F}_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\overline{\alpha}_i\,\overline{p}_{ik}^2 + \overline{\beta}_i\,\overline{p}_{ik} + \overline{\gamma}_i + \overline{\alpha}_i\ \mathrm{var}(\,p_{ik}) + 2\,\overline{p}_{ik}\ \mathrm{cov}(\alpha_i, p_{ik}) + \mathrm{cov}(\beta_i, p_{ik})\right) \qquad (6.4)$$

where

$\overline{a}_{si}, \overline{b}_{si}$ and $\overline{c}_{si}$ are expected cost coefficients of i^{th} thermal unit

$\overline{\alpha}_i, \overline{\beta}_i$ and $\overline{\gamma}_i$ are the expected emission curve coefficients of i^{th} thermal unit

$\overline{p}_{ik}$ is expected real power generation of i^{th} unit during k^{th} sub-interval

In this study, variance and covariance are replaced by the coefficients of variation and correlation coefficient respectively. In general variance and covariance are defined as:

$$\mathrm{var}(x) = C^2(x)\overline{x}^2 \qquad (6.5)$$

$$\mathrm{cov}(x, y) = R(x, y)C(x)C(y)\,\overline{x}\,\overline{y} \qquad (6.6)$$

where

$C(x)$ and $C(y)$ are the coefficients of variation of random variables x and y, respectively

$\overline{x}$ *and* $\overline{y}$ are the expected values of variables x and y respectively

$R(x, y)$ is correlation coefficient of random variables x and y and varies from -1 to 1

The zero value of coefficient of variation implies no randomness, in other words, the complete certainty about the value of random variables. Using Eq. (6.5) and Eq. (6.6), the stochastic economy and emission objectives can be represented as:

$$\overline{F}_1 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left([1 + C^2(p_{ik}) + 2R(a_{si}, p_{ik})C(a_{si})C(p_{ik})]\overline{a}_{si}\,\overline{p}_{ik}^{\,2} + [1 + R(b_{si}, p_{ik})C(b_{si})C(p_{ik})]b_{si}\,\overline{p}_{ik} + \overline{c}_{si}\right) \qquad (6.7)$$

$$\overline{F}_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left([1 + C^2(p_{ik}) + 2R(\alpha_i, p_{ik})C(\alpha_i)C(p_{ik})]\overline{\alpha}_i\,\overline{p}_{ik}^2 + [1 + R(\beta_i, p_{ik})C(\beta_i)C(p_{ik})]\overline{\beta}_i\,\overline{p}_{ik} + \overline{\gamma}_i\right) \qquad (6.8)$$

6.2.2 Expected Hydro Model

In short-term HTGS, an insignificant fuel cost is incurred in the operation of hydro-units. The input-output characteristic of a hydro-generator is expressed by the variation of water discharge rate, q_{jk} which is a function of power output, p_{mk} and net head h_{jk}. According to Glimn- Kirchmayer model, the discharge of j^{th} hydro unit at k^{th} subinterval is

$$q_{jk} = K_j \varphi(p_{mk})\psi(H_{jk}) \ \ (j = 1,2,\ldots,N_H; m = j + N_T; k = 1,2,\ldots,T) \tag{6.9}$$

where

H_{jk} and q_{jk} are reservoir head and rate of water discharge, respectively of j^{th} hydro unit at k^{th} sub-interval

p_{mk} is hydro power of m^{th} unit at k^{th} sub-interval

$\varphi(p_{mk})$ and $\psi(H_{jk})$ are represented by quadratic functions:

$$\psi(H_{jk}) = h_{11j} H_{jk}^2 + h_{12j} H_{jk} + h_{13j} \ \ (j = 1,2,\ldots,N_H; m = j + N_T; k = 1,2,\ldots,T) \tag{6.10}$$

$$\varphi(p_{mk}) = h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j} \ \ (j = 1,2,\ldots,N_H; m = j + N_T; k = 1,2,\ldots,T) \tag{6.11}$$

with

$h_{11j}, h_{12j}, h_{13j}$ are head variation coefficient of j^{th} hydro unit

$h_{21j}, h_{22j}, h_{23j}$ are hydro power generation coefficient of j^{th} hydro unit

It is presumed that head is constant over the optimization interval for a large capacity reservoir whereas for a small capacity reservoir; the effective head is variable over the optimization interval. The discharge equation can be stated as:

$$q_{jk} = \begin{cases} K'_j \varphi(p_{mk}) & ;\text{fixed head} \\ K_j \varphi(p_{mk}) \psi(H_{jk}) & ;\text{variable head} \end{cases} \ \ (j = 1,2,\ldots,N_H; m = j + N_T; k = 1,2,\ldots,T) \tag{6.12}$$

where

K_j and K'_j are constant of proportionality of j^{th} hydro unit

A stochastic model of function $\varphi(p_{mk})$ is obtained deeming the hydro-generation and hydro power generation coefficients to be random variables. Similarly, stochastic model of function $\psi(H_{jk})$ is obtained deeming the water inflows, available water for hydro-generation and effective head variation coefficients to be random variables. The random variables are assumed to be normally distributed and dependent, so the expected value of water head and hydro power function becomes

$$\psi\left(\overline{H}_{jk}\right)=\bar{h}_{11j}\overline{H}_{jk}^{2}+\bar{h}_{12j}\overline{H}_{jk}+\bar{h}_{13j}+\bar{h}_{11j}\,\mathrm{var}(H_{jk})+2\overline{H}_{jk}\,\mathrm{cov}(h_{11j},H_{jk})+\mathrm{cov}(h_{12j},H_{jk})$$

$$\left(j=1,2,\ldots,N_H;m=j+N_T;k=1,2,\ldots,T\right) \quad (6.13)$$

$$\varphi\left(\bar{p}_{mk}\right)=\bar{h}_{21j}\bar{p}_{mk}^{2}+\bar{h}_{22j}\bar{p}_{mk}+\bar{h}_{23j}+\bar{h}_{21j}\,\mathrm{var}(p_{mk})+2\bar{p}_{ik}\,\mathrm{cov}(h_{21},p_{mk})+\mathrm{cov}(h_{22j},p_{mk})$$

$$\left(j=1,2,\ldots,N_H;m=j+N_T;k=1,2,\ldots,T\right) \quad (6.14)$$

where

$\bar{h}_{11j}$, $\bar{h}_{12j}$, $\bar{h}_{13j}$ are expected effective head variation coefficient of j^{th} hydro unit

$\bar{h}_{21j}$, $\bar{h}_{22j}$, $\bar{h}_{23j}$ are expected hydro generation coefficient of j^{th} hydro unit

$\bar{p}_{mk}$ is expected hydro power generation of m^{th} unit during k^{th} sub-interval

$\overline{H}_{jk}$ is expected effective head of j^{th} reservoir during k^{th} sub-interval

The expected discharge is given by

$$\bar{q}_{jk}=K_j\varphi\left(\bar{p}_{mk}\right)\psi\left(\overline{H}_{jk}\right)\ \left(j=1,2,\ldots,N_H;m=j+N_T;k=1,2,\ldots,T\right) \quad (6.15)$$

where

$\bar{q}_{jk}$ is expected rate of water discharge of j^{th} hydro unit during k^{th} sub-interval

Using equations (6.5) and (6.6), the stochastic function of reservoir head function given by Eq. (6.16) and hydro power function given by Eq. (6.17) can be represented as:

$$\psi\left(\overline{H}_{jk}\right)=[1+C^2(H_{jk})+2R(h_{11j},H_{jk})C(h_{11j})C(H_{jk})]\bar{h}_{11j}\overline{H}_{jk}^{2}+[1+R(h_{12j},H_{jk})C(h_{12j})C(H_{jk})]\bar{h}_{12j}\overline{H}_{jk}+\bar{h}_{13j}$$

$$\left(j=1,2,\ldots,N_H;m=j+N_T;k=1,2,\ldots,T\right) \quad (6.16)$$

$$\varphi\left(\bar{p}_{mk}\right)=[1+C^2(p_{mk})+2R(h_{21j},p_{mk})C(h_{21j})C(p_{mk})]\bar{h}_{21j}\bar{p}_{mk}^{2}+[1+R(h_{22j},p_{mk})C(h_{22j})C(p_{mk})]\bar{h}_{22j}\bar{p}_{mk}+\bar{h}_{23j}$$

$$\left(j=1,2,\ldots,N_H;m=j+N_T;k=1,2,\ldots,T\right) \quad (6.17)$$

Reservoir dynamics

The effective head is obtained by assuming that j^{th} hydro unit's reservoir has vertical sides and small capacity. Spillage occurs only when the reservoir storage limit is exceeded. Effective head continuity equation is stated as:

$$H_{j(k+1)}=H_{jk}+\frac{t_k}{S_j}\left(I_{jk}-q_{jk}\right)\ \left(j=1,2,\ldots,N_H;k=1,2,\ldots,T\right) \quad (6.18)$$

where

H_{jk} , q_{jk} , I_{jk} are reservoir head, water discharge rate and natural inflow of j^{th} hydro unit at k^{th} sub-interval, respectively

t_k is time duration of k^{th} sub-interval

S_j is surface area of reservoir of j^{th} hydro unit

The net water head over the planned time interval is given by:

$$H_{jT} = H_{j0} + \frac{1}{S_j}\sum_{k=1}^{T} t_k \left(I_{jk} - q_{jk}\right) \left(j = 1,2,\ldots,N_H ; k = 1,2,\ldots,T\right) \tag{6.19}$$

where

H_{j0} and H_{jT} are initial and final hydraulic reservoir head, respectively of j^{th} hydro unit

Since the thermal generations and load demand are random, the hydro-generations also become random. Natural inflow is also random during k^{th} subinterval so water discharge will become random and hence the effective head will also be random. The expected overall effective head is represented below

$$\overline{H}_{jT} = \overline{H}_{j0} + \frac{1}{S_j}\sum_{k=1}^{T} t_k \left(\bar{I}_{jk} - \bar{q}_{jk}\right) \left(j = 1,2,\ldots,N_H ; k = 1,2,\ldots,T\right) \tag{6.20}$$

where

$\overline{H}_{j0}$ and $\overline{H}_{jT}$ are expected initial and final hydraulic reservoir head, respectively of j^{th} hydro unit

$\bar{q}_{jk}$, $\bar{I}_{jk}$ are expected water discharge rate and expected natural inflow of j^{th} hydro unit at k^{th} sub-interval, respectively

Continuity equation giving expected effective head can be written as

$$\overline{H}_{jk+1} = \overline{H}_{jk} + \frac{t_k}{S_j}\left(\bar{I}_{jk} - \bar{q}_{jk}\right) \quad \left(j = 1,2,\ldots,N_H ; k = 1,2,\ldots,T\right) \tag{6.21}$$

where

$\overline{H}_{jk}$ is expected water head of j^{th} hydro unit at k^{th} sub-interval

Corresponding variances are:

$$var\left(H_{jk+1}\right) = E\left[\left(H_{jk+1} - \overline{H}_{jk+1}\right)^2\right] \qquad \left(j = 1,2,\ldots,N_H ; k = 1,2,\ldots,T\right) \tag{6.22}$$

On simplification, above equation can be rewritten as:

$$var\left(H_{jk+1}\right) = var\left(H_{jk}\right) + \frac{t_k}{S_j}\left(var\left(I_{jk}\right) - var\left(q_{jk}\right)\right) \left(j = 1,2,\ldots,N_H ; k = 1,2,\ldots,T\right) \tag{6.23}$$

Similarly covariance is

$$cov\left(H_{jk+1}, H_{mk+1}\right) = E\left[\left(H_{jk+1} - \overline{H}_{jk+1}\right)\left(H_{mk+1} - \overline{H}_{mk+1}\right)\right]$$

$$\left(j = 1, 2, \ldots, N_H; m = 1, 2, \ldots, N_H; j \neq m; k = 1, 2, \ldots, T\right) \tag{6.24}$$

After simplification, covariance is

$$cov\left(H_{jk+1}, H_{mk+1}\right) = cov\left(H_{jk}, H_{mk}\right) + \frac{t_k}{S_j}\left[cov\left(I_{jk}, I_{mk}\right) - cov\left(q_{jk}, q_{mk}\right)\right]$$

$$\left(j = 1, 2, \ldots, N_H; m = 1, 2, \ldots, N_H; j \neq m; k = 1, 2, \ldots, T\right) \tag{6.25}$$

6.2.3 Expected Transmission Loss

A common approach to model transmission losses in the system is to use Kron's loss formula through B- coefficients.

$$p_{Lk} = \sum_{i=1}^{N}\sum_{j=1}^{N} p_{ik} B_{ij} p_{jk} + \sum_{i=1}^{N} p_{ik} B_{io} + B_{oo} \tag{6.26}$$

where

B_{ij}, B_{io} and B_{oo} are B-coefficients

With normally distributed random variables, the expected transmission losses $\overline{P}_{Lk}$ are given below. It is presumed that random variables are independent during the interval.

$$\begin{aligned}\overline{p}_{Lk} = &\sum_{i=1}^{N}\sum_{j=1}^{N} \overline{p}_{ik} \overline{B}_{ij} \overline{p}_{jk} + \sum_{i=1}^{N} \overline{B}_{io} \overline{p}_{ik} + \overline{B}_{oo} + \sum_{i=1}^{N} \overline{B}_{ii} \operatorname{var}\left(p_{ik}\right) + \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} 2\,\overline{B}_{ij} \operatorname{cov}\left(p_{ik}, p_{jk}\right) + \sum_{i=1}^{N} 2.\overline{p}_{ik} \operatorname{cov}\left(p_{ik}, B_{ii}\right) \\ &+ \sum_{i=1}^{N}\sum_{\substack{j=1 \\ j\neq i}}^{N} 2.\overline{p}_{jk} \operatorname{cov}\left(p_{ik}, B_{ij}\right)\end{aligned} \tag{6.27}$$

$$\overline{p}_{Lk} = \sum_{i=1}^{N}\sum_{j=1}^{N} \overline{p}_{ik}\, U_{ijk}\, \overline{p}_{jk} + \sum_{i=1}^{N} \overline{B}_{io} \overline{p}_{ik} + \overline{B}_{oo} \tag{6.28}$$

with

$$\overline{U}_{ijk} = \begin{cases} \left(1 + R(p_{ik}, p_{jk}) C(p_{ik}) C(p_{jk}) + 2R(p_{ik}, B_{ij}) C(p_{ik}) C(B_{ij})\right)\overline{B}_{ij} & (i \neq j) \\ \left(1.0 + C^2(p_{ik}) + 2.0\, R(p_{ik}, B_{ii}) C(p_{ik}) C(B_{ii})\right)\overline{B}_{ii} & (i = j) \end{cases}$$

6.2.4 Equality and Inequality Constraints

The equality constraint includes the hydro-unit is constraint by the amount of water available as:

$$\sum_{k=1}^{T} t_k \bar{q}_{jk} = \bar{V}_{jF} \quad (j = 1,2,\ldots,N_H) \tag{6.29}$$

where

$\bar{V}_{jF}$ is expected volume of water available of j^{th} hydro unit

The expected load demand equality constraint is expressed as

$$\sum_{i=1}^{N} \bar{p}_{ik} = \bar{p}_{Dk} + \bar{p}_{Lk} \quad (k = 1,2,\ldots,T) \tag{6.30}$$

Inequality constraints comprise of discharge rate and power limits as given below:

$$q_j^{\min} \le \bar{q}_{jk} \le q_j^{\max} \quad (j = 1,2,\ldots,N_H; k = 1,2,\ldots,T) \tag{6.31}$$

$$p_i^{\min} \le \bar{p}_{ik} \le p_i^{\max} \quad (i = 1,2,\ldots,N; k = 1,2,\ldots,T) \tag{6.32}$$

6.2.5 Expected power deviations

Thermal and hydro unit power generation is taken as random variable. So there is a need to convert the stochastic model into its deterministic equivalent by taking its expected value. Further, active power loss, system fuel, emission curves and hydro power curve are quadratic functions of decision variables and randomness in decision variables will affect it. By virtue of the above consideration, there will be a mismatch in load demand. The expected mismatch can be estimated through minimization of the squared error of the unsatisfied power demand [207].

$$E\left[\left(\bar{p}_{Dk} + \bar{p}_{Lk} - \sum_{i=1}^{N} p_{ik}\right)^2\right] \tag{6.33}$$

p_{ik} is the actual power generation required to meet the load, which is considered to be random. Using Eq. (6.30) above equation can be rewritten as:

$$E\left[\left(\sum_{i=1}^{N} \bar{p}_{ik} - \sum_{i=1}^{N} p_{ik}\right)^2\right] \tag{6.34}$$

The expected deviations are considered as another objective to be minimized.

$$\bar{F}_4 = \sum_{k=1}^{T}\left(\sum_{i=1}^{N} \mathrm{var}(p_{ik}) + \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} 2\,\mathrm{cov}(p_{ik}, p_{jk})\right) \tag{6.35}$$

$$\overline{F}_4 = \sum_{k=1}^{T}\left(\sum_{i=1}^{N}\sum_{j=1}^{N}\overline{p}_{ik}\,T_{ijk}\,\overline{p}_{jk}\right) \tag{6.36}$$

with

$$T_{ijk} = \begin{cases} C^2(p_{ik}) & (i = j) \\ R(p_{ik}, p_{jk})\,C(p_{ik})\,C(p_{jk}) & (i \neq j) \end{cases}$$

6.2.6 Expected volume deviations

The hydro power generations are treated as random variables and the stochastic model is converted into its deterministic equivalent by taking its expected value. The water discharge rate curve is quadratic function of decision variable, hydro power and there variances quantify the degree of uncertainties associated with the expected values. So, the solution will provide only the expected values of water discharge rate. By virtue of the above consideration, there will be a mismatch in reservoir volume. So, the expected mismatch can be estimated through minimization of the squared error of the unsatisfied reservoir volume.

$$E\left(V_j - \overline{V}_j\right)^2 \qquad \left(j = 1,2,\ldots,N_H\right) \tag{6.37}$$

$$= E\left(\sum_{k=1}^{T} t_k q_{jk} - \sum_{k=1}^{T} t_k \overline{q}_{jk}\right)^2 \qquad \left(j = 1,2,\ldots,N_H\right) \tag{6.38}$$

This mismatch can be treated as another objective function.

$$\overline{F}_5 = \sum_{k=1}^{T} t_k^2 \operatorname{var}(q_{jk}) + \sum_{k=1}^{T-1}\sum_{l=k+1}^{T} 2t_k t_l \operatorname{cov}(q_{jk}, q_{jl}) \quad \left(j = 1,2,\ldots,N_H\right) \tag{6.39}$$

Variance of water discharge rate is computed as:

$$\operatorname{var}(q_{jk}) = E\left[\left(q_{jk} - \overline{q}_{jk}\right)^2\right] \qquad \left(j = 1,2,\ldots,N_H; k = 1,2,..T\right) \tag{6.40}$$

For fixed-head hydro system, water discharge is given by Eq. (6.12), so variance of water discharge is computed as:

$$\operatorname{var}(q_{jk}) = E\left[\left((h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j}) - \overline{q}_{jk}\right)^2\right] \qquad \left(j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T\right) \tag{6.41}$$

$$\operatorname{var}(q_{jk}) = E\left[\left((h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j})^2 + \overline{q}_{jk}^2 - 2(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j})\right)\overline{q}_{jk}\right]$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T\right) \tag{6.42}$$

$$\text{var}(q_{jk}) = E\left[\left(\begin{matrix}(h_{21j}^2 p_{mk}^4 + h_{22j}^2 p_{mk}^2 + h_{23j}^2 + 2h_{21j}h_{22j}p_{mk}^3 + 2h_{21j}h_{23j}p_{mk}^2 + 2h_{22j}h_{23j}p_{mk}) \\ +\bar{q}_{jk}^2 - 2(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j})\end{matrix}\right)\bar{q}_{jk}\right]$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T\right) \tag{6.43}$$

The variance of water discharge rate is represented in terms of variance and covariance of hydro power and water discharge rate coefficients and it is represented as:

$$\begin{aligned}&\text{var}(q_{jk}) = \bar{p}_{mk}^4 \,\text{var}(h_{21j}) + [6\bar{h}_{21j}^2\bar{p}_{mk}^2 + \bar{h}_{22j}^2 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk} + 2\bar{h}_{21j}\bar{h}_{23j} - 2\bar{q}_{jk}\bar{h}_{21j}]\,\text{var}(p_{mk}) + \bar{p}_{mk}^2\,\text{var}(h_{22j}) + \text{var}(h_{23j}) + \\ &[8\bar{h}_{21j}\bar{p}_{mk}^3 + 6\bar{h}_{22j}\bar{p}_{mk}^2 + 4\bar{h}_{23j}\bar{p}_{mk} - 4\bar{q}_{jk}\bar{p}_{mk}]\,\text{cov}(h_{21j}, p_{mk}) + [4\bar{h}_{22j}\bar{p}_{mk} + 6\bar{h}_{21j}\bar{p}_{mk}^2 + 2\bar{h}_{23j} - 2\bar{q}_{jk}]\,\text{cov}(h_{22j}, p_{mk}) + \\ &[2\bar{p}_{mk}^3]\,\text{cov}(h_{21j}, h_{22j}) + [4\bar{h}_{21j}\bar{p}_{mk} + 2\bar{h}_{22j}]\,\text{cov}(h_{23j}, p_{mk}) + [2\bar{p}_{mk}^2]\,\text{cov}(h_{21j}, h_{23j}) + [2\bar{p}_{mk}]\,\text{cov}(h_{22j}, h_{23j})\end{aligned}$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T\right) \tag{6.44}$$

After replacing variance and covariance by the coefficients of variation and correlation coefficient respectively, the variance of water discharge rate is represented as:

$$\begin{aligned}&\text{var}(q_{jk}) = \bar{p}_{mk}^4\bar{h}_{21j}^2 C^2(h_{21j}) + [6\bar{h}_{21j}^2\bar{p}_{mk}^2 + \bar{h}_{22j}^2 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk} + 2\bar{h}_{21j}\bar{h}_{23j} - 2\bar{q}_{jk}\bar{h}_{21j}]\bar{p}_{mk}^2 C^2(p_{mk}) + \\ &\bar{p}_{mk}^2\bar{h}_{22j}^2 C^2(h_{22j}) + \bar{h}_{23j}^2 C^2(h_{23j}) + [8\bar{h}_{21j}^2\bar{p}_{mk}^4 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk}^3 + 4\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk}^2 - 4\bar{h}_{21j}\bar{q}_{jk}\bar{p}_{mk}^2]R(h_{21j}, p_{mk})C(h_{21j})C(p_{mk}) + \\ &[4\bar{h}_{22j}^2\bar{p}_{mk}^2 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk}^3 + 2\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk} - 2\bar{h}_{22j}\bar{p}_{mk}\bar{q}_{jk}]R(h_{22j}, p_{mk})C(h_{22j})C(p_{mk}) + \\ &[2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk}^3]R(h_{21j}, h_{22j})C(h_{21j})C(h_{22j}) + [4\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk}^2 + 2\bar{h}_{22j}\bar{h}_{23j}\bar{p}_{mk}]R(h_{23j}, p_{mk})C(h_{23j})C(p_{mk}) + \\ &[2\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk}^2]R(h_{21j}, h_{23j})C(h_{21j})C(h_{23j}) + [2\bar{h}_{22j}\bar{h}_{23j}\bar{p}_{mk}]R(h_{22j}, h_{23j})C(h_{22j})C(h_{23j})\end{aligned}$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T\right) \tag{6.45}$$

The covariance of water discharge rate is computed as:

$$\text{cov}(q_{jk}, q_{jl}) = E\left[\left(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j} - \bar{q}_{jk}\right)\left(h_{21j}p_{ml}^2 + h_{22j}p_{ml} + h_{23j} - \bar{q}_{jl}\right)\right]$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T-1; l = k+1; m = j + N_T\right) \tag{6.46}$$

$$= E\left[\left(\begin{matrix}h_{21j}^2 p_{mk}^2 p_{ml}^2 + h_{21j}h_{22j}p_{mk}p_{ml}^2 + h_{21j}h_{23j}p_{ml}^2 + h_{21j}h_{22j}p_{mk}^2 p_{ml} + h_{22j}^2 p_{mk}p_{ml} + h_{22j}h_{23j}p_{ml} + \\ h_{21j}h_{23j}p_{mk}^2 + h_{22j}h_{23j}p_{mk} + h_{23j}^2 - g_1\bar{q}_{jm} - g_2\bar{q}_{jk} + \bar{q}_{jk}\bar{q}_{jm}\end{matrix}\right)\right]$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T-1; l = k+1; m = j + N_T\right) \tag{6.47}$$

where

$$g_1 = \left[\left(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j}\right)\right]$$

$$g_2 = \left[\left(h_{21j}p_{ml}^2 + h_{22j}p_{ml} + h_{23j}\right)\right]$$

$$\begin{aligned}&\text{cov}(q_{jk}, q_{jl}) = A_1\,\text{var}(p_{mk}) + A_2\,\text{var}(h_{21j}) + A_3\,\text{var}(p_{ml}) + A_4\,\text{var}(h_{22j}) + A_5\,\text{var}(h_{23j}) + A_6\,\text{cov}(p_{mk}, p_{ml}) + \\ &A_7\,\text{cov}(p_{mk}, h_{21j}) + A_8\,\text{cov}(p_{ml}, h_{21j}) + A_9\,\text{cov}(p_{mk}, h_{22j}) + A_{10}\,\text{cov}(p_{ml}, h_{22j}) + A_{11}\,\text{cov}(p_{mk}, h_{23j}) + A_{12}\,\text{cov}(p_{ml}, h_{23j}) + \\ &A_{13}\,\text{cov}(h_{21j}, h_{22j}) + A_{14}\,\text{cov}(h_{21j}, h_{23j}) + A_{15}\,\text{cov}(h_{22j}, h_{23j})\end{aligned}$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T-1; l = k+1; m = j + N_T\right) \tag{6.48}$$

After replacing variance and covariance by the coefficients of variation and correlation coefficient respectively, the variance of water discharge rate is represented as:

$$\begin{aligned}
\text{cov}(q_{jk}, q_{jl}) &= A_1 p_{mk}^2 C^2(p_{mk}) + A_2 h_{21j}^2 C^2(h_{21j}) + A_3 p_{ml}^2 C^2(p_{ml}) + A_4 h_{22j}^2 C^2(h_{22j}) + A_5 h_{23j}^2 C^2(h_{23j}) \\
&+ A_6 p_{mk} p_{ml} R(p_{mk}, p_{ml}) C(p_{mk}) C(p_{ml}) + A_7 p_{mk} h_{21j} R(p_{mk}, h_{21j}) C(p_{mk}) C(h_{21j}) + A_8 p_{ml} h_{21j} R(p_{ml}, h_{21j}) C(p_{ml}) C(h_{21j}) + \\
& A_9 p_{mk} h_{22j} R(p_{mk}, h_{22j}) C(p_{mk}) C(h_{22j}) + A_{10} p_{ml} h_{22j} R(p_{ml}, h_{22j}) C(p_{ml}) C(h_{22j}) + A_{11} p_{mk} h_{23j} R(p_{mk}, h_{23j}) C(p_{mk}) C(h_{23j}) + \\
& A_{12} p_{ml} h_{23j} R(p_{ml}, h_{23j}) C(p_{ml}) C(h_{23j}) + A_{13} h_{21j} h_{22j} R(h_{21j}, h_{22j}) C(h_{21j}) C(h_{22j}) + A_{14} h_{21j} h_{23j} R(h_{21j}, h_{23j}) C(h_{21j}) C(h_{23j}) + \\
& A_{15} h_{22j} h_{23j} R(h_{22j}, h_{23j}) C(h_{22j}) C(h_{23j})
\end{aligned}$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T-1; l = k+1; m = j + N_T\right) \qquad (6.49)$$

with

$$A_1 = [\bar{h}_{21j}^2 \bar{p}_{ml}^2 + \bar{h}_{21j} \bar{h}_{22j} \bar{p}_{ml} + \bar{h}_{21j} \bar{h}_{23j} - \bar{h}_{21j} \bar{q}_{jl}]$$

$$A_2 = [\bar{p}_{mk}^2 \bar{p}_{ml}^2]$$

$$A_3 = [\bar{h}_{21j}^2 \bar{p}_{mk}^2 + \bar{h}_{21j} \bar{h}_{22j} \bar{p}_{mk} + \bar{h}_{21j} \bar{h}_{23j} - \bar{h}_{21j} \bar{q}_{jk}]$$

$$A_4 = [\bar{p}_{mk} \bar{p}_{ml}]$$

$$A_5 = [1]$$

$$A_6 = [4\bar{h}_{21j}^2 \bar{p}_{mk} \bar{p}_{ml} + 2\bar{h}_{21j} \bar{h}_{22j} \bar{p}_{ml} + 2\bar{h}_{21j} \bar{h}_{22j} \bar{p}_{mk} + \bar{h}_{22j}^2]$$

$$A_7 = [4\bar{h}_{21j} \bar{p}_{mk} \bar{p}_{ml}^2 + \bar{h}_{22j} \bar{p}_{ml}^2 + 2\bar{h}_{22j} \bar{p}_{mk} \bar{p}_{ml} + 2\bar{h}_{23j} \bar{p}_{mk} - 2\bar{p}_{mk} \bar{q}_{jl}]$$

$$A_8 = [4\bar{h}_{21j} \bar{p}_{ml} \bar{p}_{mk}^2 + \bar{h}_{22j} \bar{p}_{mk}^2 + 2\bar{h}_{22j} \bar{p}_{mk} \bar{p}_{ml} + 2\bar{h}_{23j} \bar{p}_{ml} - 2\bar{p}_{ml} \bar{q}_{jk}]$$

$$A_9 = [\bar{h}_{21j} \bar{p}_{ml}^2 + 2\bar{h}_{21j} \bar{p}_{mk} \bar{p}_{ml} + 2\bar{h}_{22j} \bar{p}_{ml} + \bar{h}_{23j} - \bar{q}_{jl}]$$

$$A_{10} = [2\bar{h}_{21j} \bar{p}_{mk} \bar{p}_{ml} + \bar{h}_{21j} \bar{p}_{mk}^2 + 2\bar{h}_{22j} \bar{p}_{mk} + \bar{h}_{23j} - \bar{q}_{jk}]$$

$$A_{11} = [2\bar{h}_{21j} \bar{p}_{mk} + \bar{h}_{22j}]$$

$$A_{12} = [2\bar{h}_{21j} \bar{p}_{ml} + \bar{h}_{22j}]$$

$$A_{13} = [\bar{p}_{mk} \bar{p}_{ml}^2 + \bar{p}_{mk}^2 \bar{p}_{ml}]$$

$$A_{14} = [\bar{p}_{ml}^2 + \bar{p}_{mk}^2]$$

$$A_{15} = [\bar{p}_{mk} + \bar{p}_{ml}]$$

Aggregating above equations, the multi-objective stochastic hydro-thermal problem is stated as:

$$\text{Minimize} \quad \left[\bar{F}_1, \bar{F}_2, \bar{F}_4, \bar{F}_5\right]^T \qquad (6.50)$$

Subjected to equality and inequality constraints given by Eq. (6.29) to Eq. (6.32).

6.3 Solution Approach

The multi-objective problem is formulated considering conflicting objectives: economy, emission of pollutants and expected deviations. Minimum value of objective is obtained by considering one objective at a time. Thermal and hydro power generations are searched to find optimum solution. Stochastic models are converted into their equivalent deterministic models by taking their expected values. During the search, movement of particles/evolution of members is not always guaranteed to satisfy the constraints. Water balance equality constraint is satisfied for each hydro-unit by distributing residual volume to hydro units randomly as discussed in sub-section 2.5 of chapter 2. To satisfy power balance for each sub-interval, residual power is randomly distributed among the thermal units as discussed in sub-section 2.5 of chapter 2. Multiple objectives of stochastic HTGS problem are organized by assuming that decision maker (DM) has fuzzy goals for each of the objective functions. The fuzzy goals of the DM have been quantified by eliciting the corresponding membership function as discussed in section 2.4 of chapter 2. The cardinal priority ranking is computed to select the best-compromised solution among all objectives. To express the effect of variance and covariance of the random variables to each other, different cases have been considered. The effect of coefficients of variation of operating cost and gaseous emission coefficients has been studied by Bath *et al.* [207, 208]. They have also considered expected power deviation as one objective. But reservoir volume deviations are not considered in previous studies. In this study, expected volume deviations are considered because hydro power output and coefficients of water discharge rate are treated as random variables. Power generations of each hydro unit are also correlated with next sub-interval hydro power generation.

The *proposed heuristic optimization techniques* (PHOTs) as discussed in section 2.2 of chapter 2, have been applied to search the optimum solution. Predator-prey optimization technique and Powell's search method are integrated in PHOT-I. The steps of PHOT-I, *i.e.* initialization of prey and predator position and velocity, predator and prey velocity and position evaluation, up-gradation of local best position is followed as mentioned in sub-section 2.6.1 of chapter 2. Evolutionary programming technique and Powell's search method are integrated in PHOT-II. The steps of PHOT-II, *i.e.* initialization of members, evaluation of offspring and selection of parents for next generation and up-gradation of members is followed as mentioned in section 2.6.2 of chapter 2. Heuristic technique based on two random search methods PPO and EP and direct search Powell's method are integrated in PHOT-III. The steps of PHOT-III, is followed as mentioned in section 2.6.3 of chapter 2.

6.4 Electric Power System and Results

The stochastic HTGS problem is initially solved by considering one objective at a time while other objectives are ignored. After achieving minimum and maximum values of objectives, it is solved as a multi-objective HTGS considering all the objectives simultaneously. Parameters setting of all PHOTs are same as discussed in section 2.7.1.1. For each system, twenty runs are given to find the best results. Results are obtained by taking population size as 50 in 400 movements for all PHOTs.

6.4.1 Electric Power System-XI

The system under study comprises of two thermal units and two hydro units [157]. A short-term hydro-thermal load scheduling problem of 24 h duration has been undertaken. The optimization period has been divided into 24 sub-intervals of one hour each. Operating characteristics of hydro units are given in Table E.42 (Refer Appendix E, section E.11). Operating characteristics of thermal units are given in Table E.43 (Refer Appendix E, section E.11). Load demand is mentioned in Table E.44 (Refer Appendix E, section E.11) and loss coefficient matrix is given in section E.11 of Appendix E. Five different cases expressing diverse conditions are considered to realize the effect of variance and covariance of the random variables to each other (pair wise). There is a need to use exact values of coefficients of variation and correlation coefficients as and when required. But here in this study, assumed values of these coefficients are undertaken.

Case I: Operating cost, gaseous emission and water discharge coefficient of hydro unit are considered deterministic. Power generations have been considered as random but independent and uncorrelated pair wise.

$$C(a_{si}) = C(b_{si}) = 0.0,\ R(a_{si}, p_i) = R(b_{si}, p_i) = 0.0 \qquad (i = 1, 2, \ldots, N_T)$$

$$C(h_{21j}) = C(h_{22j}) = C(h_{23j}) = 0.0,\ R(h_{21j}, p_m) = R(h_{22j}, p_m) = R(h_{23j}, p_m,) = 0.0$$

$$(j = 1, 2, \ldots, N_H; m = j + N_T)$$

$C(\alpha_i) = C(\beta_i) = 0.0,\ R(\alpha_i, p_i) = R(\beta_i, p_i) = 0.0\ \ (i = 1, 2, \ldots, N_T)$

$C(P_i) = 0.0,\ R(p_i, p_j) = 0.0\ \ (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$

$C(B_{ij}) = 0.0,\ R(p_i, B_{ij}) = 0.0\ \ (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$

Case II: Operating cost, gaseous emission and water discharge coefficient of hydro unit are considered deterministic. Power generations have been considered as random and correlated with each other pair wise.

$C(a_{si}) = C(b_{si}) = 0.0,\ R(a_{si}, p_i) = R(b_{si}, p_i) = 0.0\ \ (i = 1, 2, \ldots, N_T)$

$C(h_{21j}) = C(h_{22j}) = C(h_{23j}) = 0.0,\ R(h_{21j}, p_m) = R(h_{22j}, p_m) = R(h_{23j}, p_m,) = 0.0$

$(j = 1, 2, \ldots, N_H;\ m = j + N_T)$

$C(\alpha_i) = C(\beta_i) = 0.0,\ R(\alpha_i, p_i) = R(\beta_i, p_i) = 0.0\ \ (i = 1, 2, \ldots, N_T)$

$C(P_i) = 0.05,\ R(p_i, p_j) = 0.05\ \ (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$

$C(B_{ij}) = 0.0,\ R(p_i, B_{ij}) = 0.0\ \ (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$

Case III: Power generations have been considered as random and correlated with each other pair wise. Further operating cost and gaseous emission have been considered as random and correlated with power generation pair wise.

$C(a_{si}) = C(b_{si}) = 0.01,\ R(a_{si}, p_i,) = R(b_{si}, p_i,) = 0.05\ \ (i = 1, 2, \ldots, N_T)$

$C(h_{21j}) = C(h_{22j}) = C(h_{23j}) = 0.0, R(h_{21j}, p_m,) = R(h_{22j}, p_m,) = R(h_{23j}, p_m,) = 0.0$

$(j = 1, 2, \ldots, N_H;\ m = j + N_T)$

$C(\alpha_i) = C(\beta_i) = 0.01,\ R(\alpha_i, p_i,) = R(\beta_i, p_i,) = 0.05\ \ (i = 1, 2, \ldots, N_T)$

$C(P_i) = 0.05,\ R(p_i, p_j) = 0.05\ \ (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$

$C(B_{ij}) = 0.0,\ R(p_i, B_{ij}) = 0.0\ \ (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$

Case IV: Power generations have been considered as random and correlated with each other pair wise. Water discharge coefficients have been considered as random and correlated with power generation pair wise. Power generations of each hydro unit are correlated with next sub-interval hydro power generation.

$C(a_{si}) = C(b_{si}) = 0.00,\ R(a_{si}, p_i,) = R(b_{si}, p_i,) = 0.00\ \ (i = 1, 2, \ldots, N_T)$

$C(h_{21j}) = C(h_{22j}) = C(h_{23j}) = 0.01,\ R(h_{21j}, p_m,) = R(h_{22j}, p_m,) = R(h_{23j}, p_m,) = 0.05$

$(j = 1, 2, \ldots, N_H;\ m = j + N_T)$

$$C(\alpha_i) = C(\beta_i) = 0.00,\ R(\alpha_i, p_i,) = R(\beta_i, p_i,) = 0.00 \quad (i = 1, 2, \ldots, N_T)$$

$$C(P_i) = 0.05,\ R(p_i, p_j) = 0.05 \quad (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$$

$$C(B_{ij}) = 0.0,\ R(p_i, B_{ij}) = 0.0 \quad (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$$

$$R(p_{jk}, p_{jl}) = 0.05 \quad (j = 1, 2, \ldots, N_H; k = 1, 2, ..T; l = k + 1)$$

Case V: Power generations have been considered as random and correlated with each other pair wise. Further operating cost, gaseous emission and water discharge coefficients have been considered as random and correlated with power generation pair wise. Power generations of each hydro unit are correlated with next sub-interval hydro power generation.

$$C(a_{si}) = C(b_{si}) = 0.01,\ R(a_{si}, p_i,) = R(b_{si}, p_i,) = 0.05 \ (i = 1, 2, \ldots, N_T)$$

$$C(h_{21j}) = C(h_{22j}) = C(h_{23j}) = 0.01,\ R(h_{21j}, p_m,) = R(h_{22j}, p_m,) = R(h_{23j}, p_m,) = 0.05$$

$$(j = 1, 2, \ldots, N_H; m = j + N_T)$$

$$C(\alpha_i) = C(\beta_i) = 0.01,\ R(\alpha_i, p_i,) = R(\beta_i, p_i,) = 0.05 \quad (i = 1, 2, \ldots, N_T)$$

$$C(P_i) = 0.05,\ R(p_i, p_j) = 0.05 \quad (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$$

$$C(B_{ij}) = 0.0,\ R(p_i, B_{ij}) = 0.0 \quad (i = 1,\ 2,\ \ldots, N;\ j = 1, 2, \ldots, N)$$

$$R(p_{jk}, p_{jl}) = 0.05 \quad (j = 1, 2, \ldots, N_H; k = 1, 2, ..T; l = k + 1)$$

6.4.2 Comparison of Results

The economy, environmental impact, variance of power and variance of volume are the four objectives considered, respectively. The cost, emission and hydro power generation coefficients are treated as random variables. The thermal and hydro powers are taken as random decision variables. The minimum and maximum values of the objectives are calculated by performing hydrothermal scheduling to minimize the single objective one by one and exploiting conflicting nature of objectives. Minimum and maximum values are given in Tables 6.1 to 6.3 by applying PHOT-I, II and III, respectively. For case-I and II, it is evident from the Tables 6.1 to 6.3, minimum value of all objectives obtained by PHOT-III is better than the objective value obtained by other PHOTs. For case-III, minimum value of cost obtained by PHOT-I is better than the cost obtained by PHOT-II and PHOT-III. For other objectives, PHOT-III outperforms other PHOTs and by achieving lower objective function value. For case-IV and V, expected deviation of volume obtained by PHOT-I is better than the expected deviation of volume obtained by other PHOTs. For other objectives, PHOT-III outperforms other PHOTs by achieving lower objective function value. Better objective value is chosen as desired levels and corresponding maximum values are taken as unacceptable levels.

Table 6.1: Minimum and Maximum values of the objectives by PHOT-I

		Case-I	Case-II	Case-III	Case-IV	Case-V
$\overline{F}_1$ (Rs/h)	Minimum	53109	53160	53155	53152	53183
	Maximum	54322	54128	54098	54704	54490
$\overline{F}_2$ (kg/h)	Minimum	22581	23588	23894	23850	23459
	Maximum	29179	32127	31891	32494	37684
$\overline{F}_4$ $(MW)^2$	Minimum	-	21745	21744	21748	21742
	Maximum	-	24304	24219	24428	26277
$\overline{F}_5$ $(m^3)^2$	Minimum	-	1527	1529	1817	1814
	Maximum	-	1866	1827	2299	2312

Table 6.2: Minimum and Maximum values of the objectives by PHOT-II

		Case-I	Case-II	Case-III	Case-IV	Case-V
$\overline{F}_1$ (Rs/h)	Minimum	53112	53166	53361	53163	53166
	Maximum	54294	54219	54220	54196	53848
$\overline{F}_2$ (kg/h)	Minimum	22690	23833	23835	24589	24532
	Maximum	29131	32460	30526	36603	36606
$\overline{F}_4$ $(MW)^2$	Minimum	-	21899	21896	21900	21899
	Maximum	-	24402	23803	25966	25966
$\overline{F}_5$ $(m^3)^2$	Minimum	-	1517	1518	1857	1857
	Maximum	-	1868	1868	2195	2175

Table 6.3: Minimum and Maximum values of the objectives by PHOT-III

		Case-I	Case-II	Case-III	Case-IV	Case-V
$\overline{F}_1$ (Rs/h)	Minimum	53105	53150	53208	53134	53143
	Maximum	54353	54518	54504	54140	54103
$\overline{F}_2$ (kg/h)	Minimum	22511	23028	23067	23838	23197
	Maximum	29161	37305	36849	33628	33630
$\overline{F}_4$ $(MW)^2$	Minimum	-	21665	21663	21666	21669
	Maximum	-	26118	26017	24821	24821
$\overline{F}_5$ $(m^3)^2$	Minimum	-	1476	1479	1841	1841
	Maximum	-	1976	1967	2228	2272

The multi-objective results obtained by PHOTs are depicted in Table 6.4 for five different cases. To compare the multi-objective solution among various results obtained by PHOTs, membership function is computed for all objectives by considering desired level of objective function and unaccepted level. The max-min operator has been applied to decide the ‘best’ compromised solutions. The overall membership function is represented as cardinal priority ranking $\mu_D = \max\{\min\{\mu(F_h); h = 1,2,\ldots,Nob\}\}$; where Nob is number of objectives. Maximum value of cardinal priority ranking represents best non-inferior solution. It is evident from figures 6.1 to 6.5, that result obtained by PHOT-III achieve highest cardinal priority ranking for all cases. So, it shows higher satisfaction level of objective function for multi-objective HTGS. Tables 6.5 to 6.9 shows power generation for multi-objective scheduling obtained by PHOT-III for case-I, II, III, IV and V, respectively.

Table 6.4: Comparison of results for multi-objective HTGS

		Case-I	Case-II	Case-III	Case-IV	Case-V
$\overline{F}_1$ (Rs/h)	PHOT-I	53562	53518	53360	53428	53827
	PHOT-II	53564	53601	53387	53219	53721
	PHOT-III	53552	53524	53340	53245	53634
$\overline{F}_2$ (kg/h)	PHOT-I	23663	24570	26396	25482	25079
	PHOT-II	23600	24267	26029	29748	25527
	PHOT-III	23829	24772	26518	28035	25965
$\overline{F}_4$ $(MW)^2$	PHOT-I	-	22048	22565	22280	22167
	PHOT-II	-	21971	22469	23596	22336
	PHOT-III	-	22095	22592	23040	22422
$\overline{F}_5$ $(m^3)^2$	PHOT-I	-	1800	1717	2112	2156
	PHOT-II	-	1825	1737	1976	2167
	PHOT-III	-	1782	1700	2020	2114

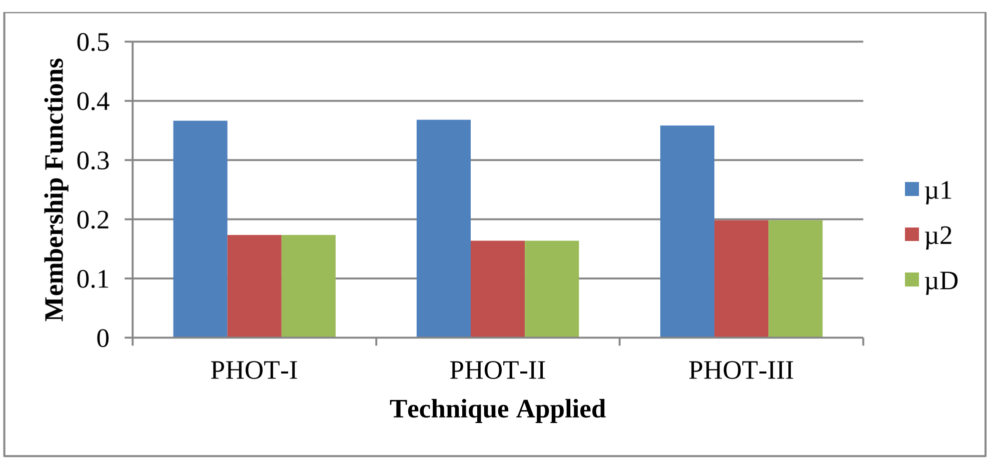

Figure 6.1: Comparison of cardinal priority for Electric power system-XI, case-I

Table 6.5: Power generation for multi-objective HTGS: Electric power system-XI, case-I

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)	
			p_{1k}	p_{2k}	p_{3k}	p_{4k}
1	400	5.7095	109.3102	158.2036	138.1958	0.00
2	300	3.2554	74.07259	91.18277	138	0.00
3	250	2.34928	50.85029	63.49902	138	0.00
4	250	2.3338	48.28611	65.55639	138	0.491
5	250	2.35265	51.25026	63.1024	138	0.00
6	300	3.22583	71.43671	93.78915	138	0.00
7	450	7.39658	131.8154	187.4976	138.0835	0.00
8	900	29.66262	233.6304	357.8741	234.6275	103.5305
9	1230	56.34835	286.3358	466.2	340.7335	193.0791
10	1250	58.37367	289.817	469.0186	347.5063	202.0318
11	1350	68.29391	308.3434	519.1732	375.9902	214.7872
12	1400	73.92741	333.9883	541.3097	393.3103	205.3193
13	1200	53.38615	291.2776	480.6025	305.0319	176.4742
14	1250	58.69687	291.4445	456.3484	346.656	214.2479
15	1250	58.39458	297.2751	474.6507	340.1822	196.2865
16	1270	60.5738	292.4992	467.3684	345.7414	224.9647
17	1350	68.44241	314.3965	515.985	380.608	207.4529
18	1470	81.54984	345	584.3348	395	226.9239
19	1330	66.70869	294.2214	484.7691	384.7945	232.9237
20	1250	58.48985	301.114	474.8752	330.607	201.8937
21	1170	50.78885	285.5136	452.4465	332.6068	150.2219
22	1050	40.45519	254.574	409.2977	296.1547	130.4289
23	900	29.6684	231.129	347.9138	244.7978	105.8276
24	600	13.03692	135.5806	196.53	218.2591	62.6672

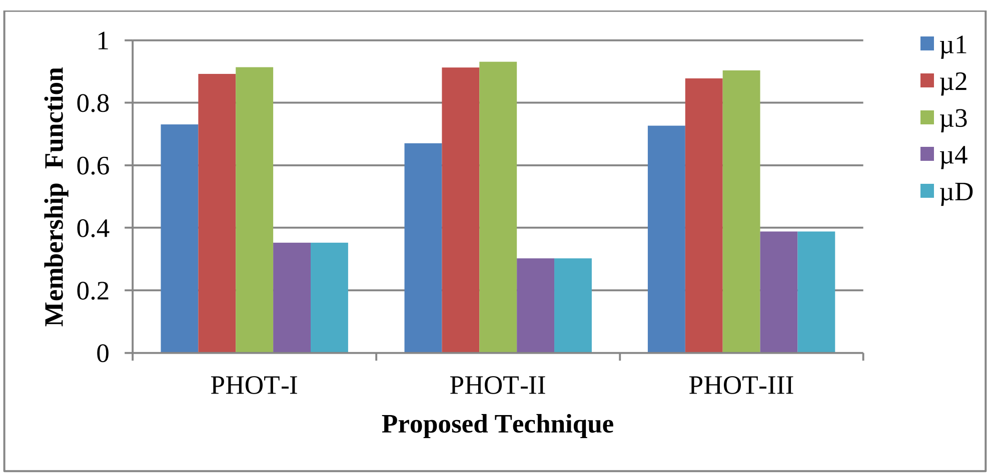

Figure 6.2: Comparison of cardinal priority for Electric power system-XI, case-II

Table 6.6: Power generation for multi-objective HTGS: Electric power system-XI, case-II

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)	
			p_{1k}	p_{2k}	p_{3k}	p_{4k}
1	400	5.82346	98.88348	123.3789	142.0789	41.48222
2	300	3.39871	69.94006	75.60309	143.6316	14.22389
3	250	2.46769	48.81428	53.69175	138	11.96165
4	250	2.46107	51.42761	53.63404	138	9.39939
5	250	2.34707	49.98925	64.35784	138	0.00
6	300	3.52094	60.62043	66.71394	138	38.18653
7	450	7.43276	111.2445	136.5809	144.1277	65.47973
8	900	29.46267	208.5512	337.0952	255.6453	128.1711
9	1230	56.27245	280.6061	467.3087	367.5009	170.8569
10	1250	58.54319	285.1564	464.3041	341.398	217.6845
11	1350	68.03092	313.5081	550.6522	345.1573	208.7132
12	1400	73.91951	332.715	546.6298	395	199.5747
13	1200	53.57832	290.4397	469.6691	317.1343	176.3353
14	1250	57.94745	287.7874	497.5583	333.8401	188.7616
15	1250	58.32708	287.9077	473.1908	358.5309	188.6977
16	1270	60.0629	284.6036	485.324	380.7764	179.3589
17	1350	68.30587	319.8412	539.8014	350.8839	207.7792
18	1470	81.31468	342.8899	609.7408	379.0751	219.6088
19	1330	66.141	309.8492	524.0136	369.9813	192.2968
20	1250	57.75834	281.7122	501.4898	344.877	179.6793
21	1170	50.33701	263.9352	464.742	327.3178	164.3419
22	1050	40.49592	246.5927	401.5394	298.3268	144.037
23	900	29.57704	215.3117	335.0284	254.8921	124.3447
24	600	13.34506	176.8726	256.9538	175.856	3.66263

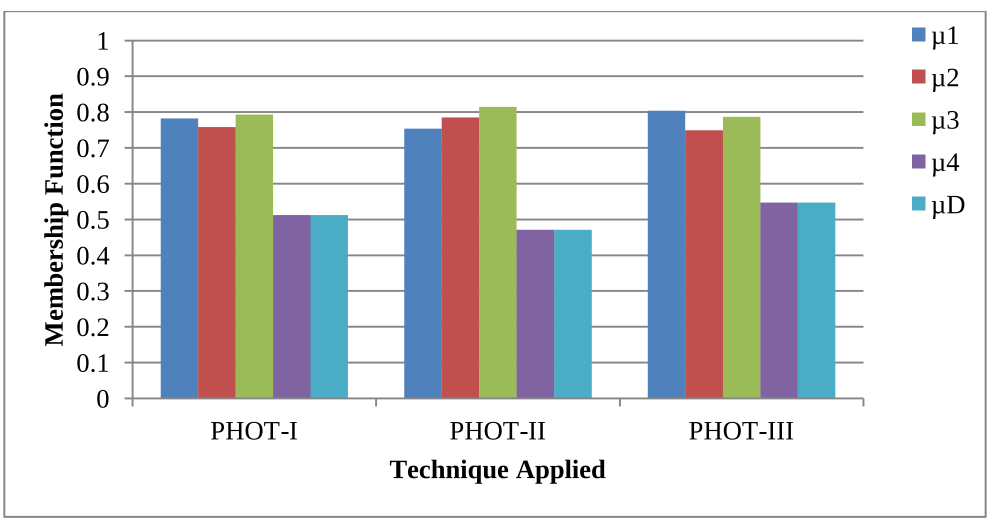

Figure 6.3: Comparison of cardinal priority for Electric power system-XI, case-III

Table 6.7: Power generation for multi-objective HTGS: Electric power system-XI, case-III

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)	
			p_{1k}	p_{2k}	p_{3k}	p_{4k}
1	400	5.75545	86.49161	125.6799	154.6671	38.91675
2	300	3.46841	15	106.2848	138	44.18359
3	250	2.5334	15	72.15646	138	27.37689
4	250	2.36977	15	88.17651	138	11.19333
5	250	2.5864	15	67.88579	138	31.70061
6	300	3.41625	15	111.3544	144.2051	32.85677
7	450	7.30357	95.13376	142.1209	171.6909	48.35794
8	900	29.14362	190.4144	348.5165	260.2182	129.9945
9	1230	55.39606	263.7159	514.1136	334.8152	172.7513
10	1250	57.3765	268.0269	518.6469	332.4908	188.2119
11	1350	67.26155	289.7512	576.6987	357.6336	193.1782
12	1400	72.62391	303.6934	603.1712	368.9501	196.8091
13	1200	52.70535	261.3389	496.7109	326.9701	167.6855
14	1250	57.35767	267.3706	517.9182	339.1352	182.9336
15	1250	57.21183	267.6058	529.7544	341.7215	168.1302
16	1270	59.32396	274.2779	527.0339	343.9893	184.0229
17	1350	67.3823	279.7533	552.5078	395	190.1213
18	1470	81.29083	345	610.622	395	200.6689
19	1330	65.17464	282.7721	564.8859	354.5286	192.9881
20	1250	57.37561	270.919	519.8261	338.7361	177.8945
21	1170	49.87465	246.7723	486.3042	318.6817	168.1165
22	1050	39.96748	223.1055	419.7677	299.5346	147.5595
23	900	29.05924	187.3996	353.7319	260.4085	127.5193
24	600	12.79245	125.7692	215.1883	199.6232	72.21176

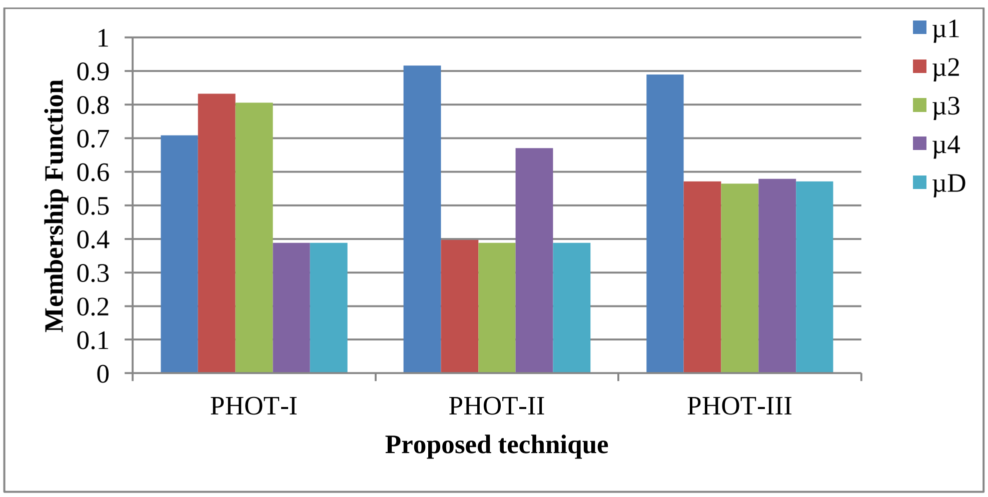

Figure 6.4: Comparison of cardinal priority for Electric power system-XI, case-IV

Table 6.8: Power generation for multi-objective HTGS: Electric power system-XI, case-IV

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)	
			p_{1k}	p_{2k}	p_{3k}	p_{4k}
1	400	5.96568	62.81174	115.957	182.1977	44.99922
2	300	3.80459	40.08162	58.96788	168.8019	35.95315
3	250	2.93233	31.08227	32.82602	154.3528	34.6712
4	250	2.72647	34.29327	42.36925	143.4428	32.62117
5	250	2.81162	54.35485	29.29748	153.1158	16.04348
6	300	3.79686	45.04008	56.43396	167.7512	34.57156
7	450	7.63864	86.25266	121.138	184.4087	65.83935
8	900	28.94615	181.159	360.4012	263.1452	124.2409
9	1230	55.05122	245.4428	532.1798	330.8114	176.6172
10	1250	57.12269	260.6271	536.1005	325.0198	185.3754
11	1350	66.9857	281.6136	600.3668	347.1611	187.8443
12	1400	72.27416	292.874	627.5052	367.4708	184.4241
13	1200	52.4541	248.1217	510.1842	314.388	179.7603
14	1250	56.9836	252.6868	537.766	341.281	175.2498
15	1250	56.96724	256.971	541.9817	345.1548	162.8597
16	1270	58.91956	254.6974	551.0982	327.1455	195.9785
17	1350	66.92632	267.7383	584.9879	366.3871	197.8129
18	1470	80.16399	309.795	668.0797	371.5848	200.7044
19	1330	64.72707	263.2804	600.9337	337.5104	193.0026
20	1250	57.15334	253.7405	524.3749	339.9926	189.0454
21	1170	49.6207	245.3675	522.9058	302.4763	148.871
22	1050	39.93217	209.8607	416.8009	304.4984	158.7721
23	900	28.77258	174.1607	374.8641	263.6265	116.1213
24	600	12.79499	128.0867	214.6596	215.1774	54.87129

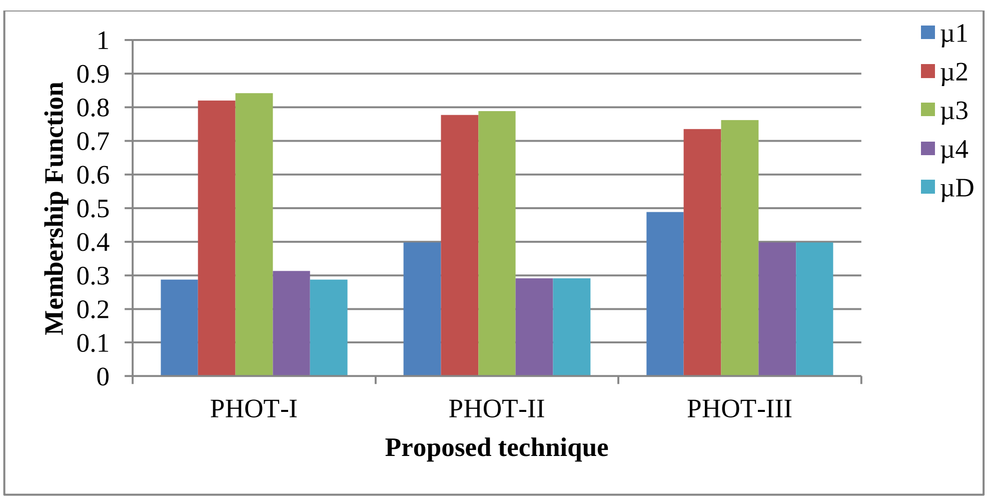

Figure 6.5: Comparison of cardinal priority for Electric power system-XI, case-V

Table 6.9: Power generation for multi-objective HTGS: Electric power system-XI, case-V

k	p_{Dk} (MW)	p_{Lk} (MW)	Thermal generation (MW)		Hydro generation (MW)	
			p_{1k}	p_{2k}	p_{3k}	p_{4k}
1	400	5.83946	15	219.388	142.7511	28.70045
2	300	3.31786	76.23706	85.52078	140.9137	0.646
3	250	2.84903	15	51.53787	186.3111	0.00
4	250	2.4438	15	80.84235	155.2808	1.32049
5	250	2.71011	50.72912	36.22744	148.06	17.6936
6	300	3.31512	15	124.0861	164.229	0.00
7	450	8.61342	69.29372	85.7888	242.8394	60.69162
8	900	29.3444	180.9347	332.0116	277.2856	139.1124
9	1230	55.68016	279.4595	506.7979	343.785	155.6378
10	1250	58.15693	301.2147	511.5865	294.0426	201.3131
11	1350	68.88467	345	561.9478	304.1542	207.7826
12	1400	73.13391	324.1732	594.697	359.267	194.9966
13	1200	53.35909	294.054	513.0734	277.4482	168.7834
14	1250	57.193	276.5667	554.9041	334.6119	141.1104
15	1250	59.03086	303.1439	449.3405	395	161.5466
16	1270	60.4716	303.775	484.8475	343.2016	198.6475
17	1350	67.94542	305.6627	543.8163	360.0459	208.4205
18	1470	81.83437	344.9873	580.2954	390.2415	236.3102
19	1330	66.91218	317.5236	493.5158	375.104	210.7689
20	1250	58.35382	316.4572	542.0959	299.1686	150.6321
21	1170	50.93878	285.8739	452.2007	314.1753	168.6889
22	1050	40.50156	229.4845	393.3831	276.8574	190.7767
23	900	30.35377	191.1163	285.5917	308.4475	145.1982
24	600	13.00499	144.6081	207.5929	175.6124	85.19171

6.4.2.1 Robustness of proposed heuristic optimization techniques

The 20 independent runs are made to obtain best, average and worst solutions by applying PHOTs. The standard deviation (S.D.) is also computed from the solutions to investigate the probability of success. The best, average, worst results and standard deviation are tabulated in Table 6.10 for case-II. It is concluded from Table 6.10 that standard deviation of results obtained by PHOT-III, is lower as compared to S.D. obtained by other two PHOTs. So, the result obtained by PHOT-III is more precise.

Table 6.10: The best, average and worst values of objectives: Electric power system-XI, case-II

Technique	Scheduling	Best	Average	Worst	S. D.
PHOT-I	$\bar{F}_1$ (Rs/h)	53160	53193	53214	6.424
	$\bar{F}_2$ (kg/h)	23588	23602	23633	5.783
	$\bar{F}_4$ $(MW)^2$	21745	21762	21784	3.731
	$\bar{F}_5$ $(m^3)^2$	1527	1558	1572	2.190
	μ_D	0.3521	0.3324	0.3010	0.0142
PHOT-II	$\bar{F}_1$ (Rs/h)	53166	53198	53219	6.983
	$\bar{F}_2$ (kg/h)	23833	23854	23886	6.021
	$\bar{F}_4$ $(MW)^2$	21899	21934	21962	3.902
	$\bar{F}_5$ $(m^3)^2$	1517	1542	1574	2.223
	μ_D	0.3022	0.2889	0.2774	0.0157
PHOT-III	$\bar{F}_1$ (Rs/h)	53150	53189	53222	6.213
	$\bar{F}_2$ (kg/h)	23028	23045	23088	5.452
	$\bar{F}_4$ $(MW)^2$	21665	21691	21723	3.665
	$\bar{F}_5$ $(m^3)^2$	1476	1499	1515	2.009
	μ_D	0.3884	0.3692	0.3599	0.0140

6.5 CONCLUSIONS

Conventional hydro-thermal generation scheduling method allocates generation schedule to the individual thermal and hydro generating units based upon deterministic operating cost, pollutants' emission function and hydro models ignoring inaccuracies and uncertainties. Moreover, load demand is considered constant, but in practice it varies randomly. Such generation schedule may result in the lowest cost. However, additional operating cost and pollutant's emission are associated with such a schedule because of variance and covariance. Conventional scheduling therefore renders the non-optimal solution to a power system analyst. This chapter discusses the hydro-thermal generation scheduling problem as the multi-objective optimization problem considering expected cost coefficients, expected pollutants emission coefficients, and expected hydro power generation coefficients. The correlation between hydro power generations of present sub-interval with hydro power generations of next sub-interval is also considered. The proposed heuristic optimization techniques based on integration of random search and local search method is applied to search the optimum solution. The local search enhances the search in promising search areas. The practical viability of the formulation is illustrated through a numerical example. Because of the tremendous annual fuel cost, emissions in thermal units, a small percentage saving is considered significant in either case, thus justifying the need for more accurate analysis and consideration of randomness invariables.

CHAPTER – 7

CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

7.1 INTRODUCTION

This chapter presents the salient and significant contributions of the thesis as well as brief statement concerning some recommendations for further research. The significant original contributions are listed and discussed.

7.2 SIGNIFICANT CONTRIBUTIONS

The content presented in this thesis is to propose techniques which are based on integration of global search and local search techniques. The integrated techniques are applied to solve multi-objective hydro-thermal generation scheduling problem so as to minimize a number of conflicting objectives while allocating the electricity demand among the committed generating units subject to physical and technological constraints of electric power system.

The following significant contributions result from this research.

1. Global search techniques are applied as a tool for the solution of complex optimization problems because of their exclusive advantages. Despite of many advantages, most of the global search techniques have some major shortcomings. To improve the exploration and exploitation capability of search technique, integration of random search and local search techniques is proposed. In proposed heuristic optimization techniques, Powell's search method is integrated with predator-prey optimization, evolutionary programming and with combined evolutionary programming and predator-prey optimization technique. The evolutionary programming technique come under the category of evolutionary algorithms and predator-prey optimization technique is a part of swarm based optimization techniques. Both these techniques have different information sharing mechanism. In

evolutionary programming solution is updated through selection and mutation operator and in predator-prey optimization technique solution is updated by information shared by global and local best solutions. Integration of these two global search techniques in effective manner improves the chance to search the optimum solution. In proposed heuristic optimization techniques, local search Powell's pattern search technique is implemented as a neighbourhood search, where it intends to explore the promising search area obtained by predator prey optimization or evolutionary programming technique to improve the quality of solution. Proposed heuristic optimization techniques have been applied to solve three different types of scheduling problems; economic, gaseous pollutant's emission and multi-objective scheduling.

2. Multi-objective fixed/variable-head hydro-thermal generation scheduling problem is solved by proposed techniques. The practical viability of the formulation is illustrated through numerical examples in different systems. The results reveal that proposed techniques are able to search optimum solution. The proposed heuristic optimization techniques are simple, easy to implement and robust. Predator-prey optimization technique also shows great potential to escape from local optimum solutions due to predator fear factor. Powell's pattern search further improves the local best solutions obtained during the implementation of global search techniques.
3. The proposed heuristic optimization techniques based on global search technique and Powell's pattern search method are tested on multi-chain *hydrothermal generation scheduling* (HTGS) problems. The water transport delays between connected reservoirs as well as the valve-point loading effects of thermal units are taken into account to formulate the problem. The objectives are quantified by eliciting the corresponding membership function. The feasibility and effectiveness of the proposed techniques are demonstrated on four electric power hydro-thermal systems. Fifth and sixth electric power system has 4- hydro and 3- thermal units. Seventh electric power system has 16- hydro and 6- thermal units. Finally, large generating size power system is undertaken which has 44-hydro units and 54-thermal units. To decide the 'best' generation schedule for multi-objective scheduling problem, fuzzy cardinal priority ranking is compared of various reported results. The results reveal that,

proposed techniques produce better quality solutions by reducing cost and emission. The proposed heuristic optimization techniques are easy to implement and take less time to achieve the good quality solution.

4. The multi-objective problem is converted into scalar problem by applying weighting method. In which, fundamental concepts of multi-objective decision method are undertaken. One important concept is contrast intensity of the alternative's performance with respect to single objective and another concept is the conflicting nature of objectives with each other. The information transmitted by objectives is considered to evaluate the objectives weight and weights are updated, during the movement, using membership function of local best position of swarm or member of population obtained from proposed technique. The major advantage of weight pattern evaluation is that objective function so formed does not lose any significant information and decision maker will not skip the weight combination that actually corresponds to the best compromised solution. The practical viability of the formulation is illustrated through numerical examples in diverse situations.
5. The proposed heuristic optimization techniques are applied to solve long-term multi-objective hydro-thermal scheduling problem. Two hydro-thermal electric power systems have been taken into account, both systems has scheduling period of one year and divided into monthly and weekly sub-intervals. From the computational results reported it can be stated that proposed optimization techniques produce satisfactory results as compared to some conventional methods without taking any approximation. Approximations can lead to stick the solution that may not be true optimal solution. In generation scheduling, a small percentage of saving is significant because tremendous amount of annual fuel cost and gaseous pollutant emission are associated. Thus it fully justifies the need for more accurate analysis when advanced computing techniques are available.
6. Conventional hydro-thermal generation scheduling method allocates generation schedule to the individual thermal and hydro generating units based upon deterministic cost, emission function and hydro models ignoring inaccuracies and uncertainties. Moreover, load demand is considered constant, but in practice it varies randomly. Such generation schedule may result in the lowest cost. However

additional cost is associated with such a schedule having relatively large variance and covariance. Conventional scheduling therefore renders the non-optimal solution to a power system analyst. In multi-objective framework, the analysis of stochastic hydro-thermal short-range fixed-head is undertaken and expected operating cost, expected emissions, expected power deviation and expected volume deviation has been taken as conflicting objectives to be minimized. The practical viability of the formulation is illustrated through a numerical example.

7. There are various techniques to handle constraints; out of which penalty function method is commonly used to convert a constrained optimization problem into an unconstraint optimization problem. But this method requires multiple run to fine tune the penalty factor leading to a high computational cost. The inclusion of the penalty function also distorts the objective function. The distortion in objective function is small for small values of penalty parameter. For a large value of penalty parameter, the optimum of objective function may have artificial local optimal solutions. In this work, heuristic constraint handling technique, which do not require penalty factor, is explored to handle the constraints.

7.3 SUGGESTIONS FOR FURTHER RESEARCH

The presented results have demonstrated the effectiveness of the proposed heuristic optimization techniques to solve multi-objective hydro-thermal generation scheduling; still there is a lot of scope to improve the performance of heuristic optimization techniques and these heuristic techniques can be applied to solve different optimization problems. Some of the possible further research directions are listed below:

1. The combined operation of conventional and non-conventional energy sources can be included in the study. Combined cycle plant can be undertaken.
2. Memtic algorithms can be applied to solve hydro-thermal generation scheduling problem.
3. Exponential membership function can be considered.
4. The proposed heuristic optimization techniques can be applied to solve unit commitment problem.

5. The stochastic model of multi-chain hydro model can be implemented.
6. AC constraint hydro-thermal generation scheduling can be solved by proposed optimization techniques.
7. In deregulated environment the generation company (GENCO) refers to optimization of generation resources in order to maximize the profit. In deregulated ambient satisfying load is not mandatory, therefore objective of GENCO is solely to maximize the profit. Security would be unbundled from energy and priced as an ancillary service and can also be competitive. The further scope of research may be to investigate optimal hydro-thermal scheduling in a competitive environment which require comprehensive model of the GENCO production capacities.
8. Due to physical operating restriction, thermal units cannot operate in specific restriction and consequently their fuel cost function is of a discrete function. Proposed heuristic optimization techniques can be applied for hydro-thermal scheduling, considering prohibited operating zones.

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APPENDIX – A

PREDATOR-PREY OPTIMIZATION TECHNIQUE

Predator-prey optimization is a form of PSO including predator's effect. Particle swarm optimization is a population based search technique and uses swarm intelligence such as bird flocking, fish schooling. Particle changes its position with time based on its own experience and experience of neighboring particles. The position mechanism of the particle in the search space is updated by adding the velocity vector to its position vector as given by Kennedy and Eberhart [59]. In PPO model, predator population is also included with prey swarm. Predators are attracted to global best prey particle, while the prey particles are repelled by their presence [154]. The interactions between predator and prey help to avoid convergence at local optimum solutions, maintain diversity in the population. Let's say particle fly in 'N' dimensional search space. The updated predator velocity Pv_i^{t+1} and position PP_i^{t+1} for i^{th} dimension and $(t+1)^{th}$ movement is represented as:

$$Pv_i^{t+1} = C_4\left(G_i^t - PP_i^t\right)\ (i = 1,2,\ldots,N) \tag{A.1}$$

$$PP_i^{t+1} = PP_i^t + Pv_i^{t+1}\ (i = 1,2,\ldots,N) \tag{A.2}$$

where

C_4 is a uniform random number which gives quickness of predator to catch the global prey.

G_i^t is global best prey position for i^{th} dimension for t^{th} movement.

The updated prey velocity v_{il}^{t+1} and position P_{il}^{t+1} for i^{th} dimension, l^{th} particle and $(t+1)^{th}$ movement is represented as:

$$v_{il}^{t+1} = \begin{cases} wv_{il}^t + C_1\left(L_{il}^t - P_{il}^t\right)\times rand() + C_2\left(G_i^t - P_{il}^t\right) rand\times() & ;pf \le pf_{\max} \\ wv_{il}^t + C_1\left(L_{il}^t - P_{il}^t\right)\times rand() + C_2\left(G_i^t - P_{il}^t\right)\times rand() + C_3 a_i \exp(-b_i E_d) & ;pf > pf_{\max} \end{cases}$$

$$(i = 1,2,\ldots,N; l = 1,2,\ldots,NP) \tag{A.3}$$

$$P_{il}^{t+1} = P_{il}^t + v_{il}^{t+1}\ (i = 1,2,\ldots,N; l = 1,2,\ldots,NP) \tag{A.4}$$

where

C_1 and C_2 are the acceleration constant

C_3 is uniformly distributed scaled random number which influences the effect of predator on prey

a_i provides the maximum amplitude of the predator effect over a prey

b_i is controlling effect of predator over prey

w is inertia weight

L_{il}^{t} is local best prey position for i^{th} dimension of l^{th} particle for t^{th} movement

pf is probability of fear which controls the influence of predator on any individual in the swarm

$pf_{\max}$ is maximum probability of fear

E_d is Euclidean distance between predator and prey

$rand()$ is uniformly distributed random number

The basic PPO algorithm is elaborated in Algorithm-A.1.

ALGORITHM A.1: Predator-prey optimization

1. Read Input data and constants of algorithm.
2. Compute objective function for all prey population.
3. Assign all prey positions as their local best position.
4. Compute global best position among local best position of prey.
5. Set movement counter t=1

   DO

   5.1 Update predator velocity and position.
   5.2 Randomly generate the probability fear between 0 and 1.
   5.3 *IF* (probability fear > maximum probability fear) *THEN*
       Predator affects the prey.
       ENDIF
   5.4 Update prey velocity and position.
   5.5 Compute objective function for prey population.
   5.6 Update particles local and global best positions.
   5.7 Increment the counter *t=t+1*

   WHILE ($t \le t_{\max}$)
6. STOP

APPENDIX – B

EVOLUTIONARY PROGRAMMING TECHNIQUE

Evolutionary programming is one of the main avenues of research in evolutionary computation in the early 1990's like genetic algorithm along with genetic programming, and evolution strategies. Evolutionary programming technique is based on natural evolution, *i. e.* for a given population of individuals, the environmental pressure causes natural selection based on survival of fitness and thus causes rise in the fitness of the new population [63]. A set of candidate solutions is randomly created initially, within the domains of elements of functions and some of better candidates based on fitness are chosen to seed the next generation by applying mutation on them. Mutation is applied to one candidate and one new candidate is resulted. Execution of mutation leads to a set of new candidates. The offspring competes based on their fitness with the old ones for a place in next generation. Optimization by EP is summarized into two major steps:

1. Mutate the solutions in the current population.
2. Select the next generation from the mutated and the current solutions.

The three EP techniques of mutation are Gaussian, Cauchy and mean of Gaussian and Cauchy mutation. The conventional EP employs the Gaussian mutation operator is called as classical EP. The EP using Cauchy mutation operator is called as fast EP as it converges faster than classical EP. The EP technique is also applying mean of Gaussian and Cauchy mutation operators.

Gaussian Mutation

It is performed on each vector element by adding a normally distributed random number $N(0,1)$ and standard deviation σ_{il} . This result in

$$x_i = [x_{i1}, x_{i2}, \ldots, x_{iNP}] \; (i = 1,2,..N) \qquad \text{(B.1)}$$

$$x_{i,l+NP}^{t+1} = x_{il}^{t} + \sigma_{il}^{t} N_i(0,1) \; (i = 1,2,..N; l = 1,2,..NP) \qquad \text{(B.2)}$$

where

$N(0,1)$ is normally distributed random number with zero mean and unit standard deviation

$N_i(0,1)$ denotes the normalized random number with zero mean and unit standard deviation for each variable of i^{th} variable

x_i^t is i^{th} decision variable at t^{th} movement

σ_{il}^t is standard deviation of l^{th} particle and i^{th} dimension at t^{th} movement

Cauchy Mutation

Using, Cauchy mutation, an offspring is created by

$$x_{i,l+NP}^t = x_{il}^t + \sigma_{il}^t C_i(0,1) \quad (i = 1,2,\ldots,N; l = 1,2,..NP) \tag{B.3}$$

where

$C_i(0,1)$ is a Cauchy random number that is generated for every value of *i*.

ALGORITHM-B.1: Evolutionary Programming

1. Read Input data, parameters of EP.
2. Start the movement counter *t*=1

   DO

   2.1 Compute the fitness value of all parent vectors and compute the minimum objective function among the parent population.
   2.2 Generate offspring vectors by applying mutation operator.
   2.3 Evaluate the fitness value with offspring vectors.
   2.4 Competition among parent and offspring for survival.
   2.5 Selection of new population for parents.
   2.6 Increment the movement counter *t*=*t*+1
   2.7

   WHILE ($t \le t_{max}$)

3 STOP

Combined Gaussian and Cauchy Mutation

In this method, offspring is generated from parents by applying mean of Gaussian and Cauchy mutation operators as:

$$x_{i,l+NP}^t = x_{il}^t + \sigma_{il}^t \left(\frac{N_i(0,1) + C_i(0,1)}{2} \right) \; (i = 1,2,\ldots,n; l = 1,2,..NP) \tag{B.4}$$

In each of these methods, the standard deviation σ_{il}^t is given by the expression

$$\sigma_{il}^t = \frac{\beta f_l}{f^{\min}} \left(x_i^{\max} - x_i^{\min} \right) \; (l = 1,2,..NP) \tag{B.5}$$

where

NP is members in a population

β is the scaling factor which has to be tuned during the process of search for the optimum around the initial points

f_l is the fitness value of l^{th} individual derived from objective function, $F(x)$

$f^{\min}$ is minimum fitness among the NP parents

$x_i^{\max}$ and $x_i^{\min}$ are maximum and minimum values of x_i ,respectively

Each individual x_{il} in the combined population has to compete with some other individuals to select set of parents for next generation. The score for each trial vector after stochastic competition is given by:

$$Win_l = \sum_{m=1}^{R} win_m \tag{B.6}$$

$$Win_m = \begin{cases} 1, & rand() > \dfrac{f_l}{f_l + f_c} \\ 0 & otherwise \end{cases} \tag{B.7}$$

$$c = \text{int}(4NP \times rand() + 1) \tag{B.8}$$

where

f_m is fitness value of randomly selected m^{th} competitor in the combined population

$rand$ is uniformly distributed random number

f_l is fitness value l^{th} particle

Win_m is number of wins of m^{th} particle

After completing the trial *2NP* solutions, including parent and offspring are ranked in descending order of score. The first *NP* trial solutions survive and are selected as new parents for next generation.

The basic EP algorithm is elaborated in Algorithm-B.1.

Scaling factor

In general, the scaling factor is fixed throughout the whole search processing. However, in practical applications, a small fixed scaling factor can only result in premature convergence, while the search with a large fixed scaling factor will not converge. A scaling factor is given to change the scaling factor to solve the problem as follows [99]:

$$\beta = \begin{cases} \beta - \beta_{step} & if \ \ f^{\min} \ unchanged \\ \beta & if \ \ f^{\min} \ improved \\ \beta_{final} & if \ \beta - \beta_{step} < \beta_{final} \end{cases} \tag{B.9}$$

$$\beta(0) = \beta_{init} \tag{B.10}$$

where

$f^{\min}$ is minimum value of fitness function

The scaling factor will decrease as the process goes on. Such a scaling factor not only prevents convergence but also produces a smooth convergence.

APPENDIX – C

POWELL'S PATTERN SEARCH METHOD

Powell's pattern search method is a direct search method for finding the solutions to numerical problems. The procedure of going from a given point to the next improved point is called a move. A move is termed a *success* if the value of objective function improves; otherwise, it is a *failure*. The initial move designed to minimization of the function by moving in the coordinate search direction and after that search is performed in pattern direction. The point from which a pattern move is initiated, is designated a *base point*, and the direct search procedure is conceived as fundamentally proceeding from one base point to the next generated point which is considered as the new base point. A new point is found by jumping from the current best point along a direction connecting the previous best point [306]. Powell's pattern search is based on conjugate direction method and is expected to speed up the convergence of nonlinear objective functions. A nonlinear function can be approximated by a quadratic function, so function can be optimized in finite number of steps using PPS [78]. The pattern search index, '*m*' is set to 1. Initial coordinate directions as:

$$D_i^j = \begin{cases} 1 \; ; i = j \\ 0 \; ; i \neq j \end{cases} \left(i = 1,2,\ldots,N;\; j = 1,2,\ldots,N\right) \quad \text{(C.1)}$$

where

D_i^j is j^{th} coordinate search direction for i^{th} dimension

Save decision variable x_i as Z_i .The decision variable x_i is modified once along the coordinate direction *(j)* as:

$$x_i = x_i + \lambda_i^* D_i^j \; \left(i = 1,2,\ldots,N\right) \quad \text{(C.2)}$$

Step length for i^{th} decision variable (λ_i^*) is randomly generated as:

$$\lambda_i^* = \lambda_i^{\min} + \left(\lambda_i^{\max} - \lambda_i^{\min}\right) \times rand() \; \left(i = 1,2,..,N\right) \quad \text{(C.3)}$$

where

λ_i^{min} and λ_i^{max} are lower and upper limits of step length for i^{th} decision variable, respectively

The decision variable is updated based on objective function:

$$x_i = \begin{Bmatrix} x_i + \lambda_i^* D_i^j & ; F\left(x_i + \lambda_i^* D_i^j\right) < F(x_i) \\ x_i & ; else \end{Bmatrix} \; (i = 1,2,..,N) \tag{C.4}$$

This process is continued for all '*N'* coordinate directions. To optimization cycle; pattern search direction is obtained considering saved decision variable Z_i as:

$$D_i^j = x_i - Z_i \; (i = 1,2,\ldots,N;\, j = N+1) \tag{C.5}$$

One of the coordinate directions is discarded in favor of the pattern direction '*m*' as:

$$D_i^m = D_i^j \;\; (i = 1,2,\ldots,N;\, j = N+1) \tag{C.6}$$

Pattern search index is updated by one.

This process continues until all the coordinate directions have been discarded. It can be restarted along one of the coordinate direction till the desired solution is achieved. The steps are given in Algorithm-C.1.

ALGORITHM-C.1: Powell's pattern search

1. Set movement counter $IT_P=1$

DO

- 2. The initial search direction is set for *N* coordinate directions by implying Eq. (C.1)
- 3. Set pattern search direction index m*=1*

  DO

  - 4. Set coordinate search direction index *j=0*
  - 5. Save decision variable for pattern search direction as Z_i .

    DO

    - 6. Increment, coordinate search direction index, *j=j+1*
    - 7. Randomly generate the step length λ_i by implying Eq. (C.3)
    - 8. *IF (j =N+1)*
      - 8.1 Pattern search direction is obtained using Eq. (C.5)
      - 8.2 One of the coordination directions discarded following Eq. (C.6)
      - 8.3 *m=m+1*

      ENDIF
    - 9. Decision variable modified as per Eq. (C.2)
    - 10. If objective function converges, update variable by implying Eq. (C.4)

    WHILE (j< N+1)

  WHILE (m < N)
- 11. Increment movement counter, $IT_P= IT_P+1$

WHILE $(IT_p \leq IT_{pmax})$

STOP

Direct Search methods are used to provide solutions to some problems, which can't be solved using classical (gradient) methods [306].

- Search methods work even if the objective function is discontinuous and non-differentiable at some points.
- Search methods provide faster solutions to problems as compared to classical methods.
- Search methods are easily implemented on computers being repetitions of identical arithmetic operations with simple logic.
- Search methods are capable of providing approximate solutions at every step during the process of problem solving.
- Search methods are used to find the global minimum when the objective function possesses several relative minima.

APPENDIX – D

DERIVATION OF EXPECTED VALUES OF FUNCTIONS

D.1 DERIVATION OF EXPECTED COST OBJECTIVE FUNCTION

The total operating cost for thermal power generating units in the system is given as:

$$F_1 = \sum_{k=1}^{T}\sum_{i=1}^{N}\left(a_{si}p_{ik}^2 + b_{si}p_{ik} + c_{si}\right) \tag{D.1}$$

where

a_{si}, b_{si} and c_{si} are cost coefficients of i^{th} thermal unit

p_{ik} is real power generation of i^{th} thermal unit during k^{th} sub-interval

N is the number of thermal units

T is total time interval for scheduling

The expected value of operating cost $\overline{F}_1$ in above equation is written as:

$$\overline{F}_1 = E\left\{F_1\left(\overline{a}_{si}, \overline{b}_{si}, \overline{c}_{si}, \overline{p}_{ik}\right)\right\} + \frac{1}{2}\sum_{k=1}^{T}\sum_{i=1}^{N}\frac{\partial^2 F_1}{\partial p_{ik}^2}\operatorname{var}\left(p_{ik}\right) + \sum_{k=1}^{T}\sum_{i=1}^{N}\frac{\partial^2 F_1}{\partial p_{ik}\partial a_{si}}\operatorname{cov}\left(a_{si}, p_{ik}\right) + \sum_{k=1}^{T}\sum_{i=1}^{N}\frac{\partial^2 F_1}{\partial p_{ik}\partial b_{si}}\operatorname{cov}\left(b_{si}, p_{ik}\right) \tag{D.2}$$

where

$\overline{a}_{si}, \overline{b}_{si}$ and $\overline{c}_{si}$ are expected cost coefficients of i^{th} thermal unit

$\overline{p}_{ik}$ is the expected generation of i^{th} generator at k^{th} sub-interval

The partial derivatives are evaluated about mean of random variables a_{si}, b_{si} and c_{si}

$$\frac{\partial^2 F_1}{\partial p_{ik}^2} = 2\overline{a}_{si} \tag{D.3}$$

$$\frac{\partial^2 F_1}{\partial p_{iK}\partial a_{si}} = 2\overline{p}_{ik} \tag{D.4}$$

$$\frac{\partial^2 F_1}{\partial p_{ik}\partial b_{si}} = 1 \tag{D.5}$$

The partial derivatives represented by Eqs. (D.3) - (D.5) are substituted in Eq. (D.2).

$$\overline{F}_1 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\overline{a}_{si}\overline{p}_{ik}^2 + \overline{b}_{si}\overline{p}_{ik} + \overline{c}_{si} + \overline{a}_{si}\,\mathrm{var}(\overline{p}_{ik}) + 2\overline{p}_{ik}\,\mathrm{cov}(a_{si}, p_{ik}) + \mathrm{cov}(b_{si}, p_{ik})\right) \tag{D.6}$$

In this study, variance and covariance are replaced by the coefficients of variation and correlation coefficient respectively.

$$\mathrm{var}(p_{ik}) = C^2(p_{ik})\overline{p}_{ik}^2 \tag{D.7}$$

$$\mathrm{cov}(a_{si}, p_{ik}) = R(a_{si}, p_{ik})C(a_{si})C(p_{ik})\overline{a}_{si}\overline{p}_{ik} \tag{D.8}$$

$$\mathrm{cov}(b_{si}, p_{ik}) = R(b_{si}, p_{ik})C(b_{si})C(p_{ik})\overline{b}_{si}\overline{p}_{ik} \tag{D.9}$$

where

$C(a_{si})$ and $C(b_{si})$ are the coefficients of variation of random parameters a_{si} and b_{si} respectively.

$C(p_{ik})$ is the coefficient of variation of random active power generation, p_{ik}

$R(a_{si}, p_{ik})$ is the correlation coefficient between cost coefficient a_{si} and active power generation p_{ik} of i^{th} generator at k^{th} sub-interval.

$R(b_{si}, p_{ik})$ is the correlation coefficient between cost coefficient b_{si} and active power generation p_{ik} of i^{th} generator at k^{th} sub-interval.

Substitute Eqs. (D.7), (D.8) and (D.9) in Eq. (D.6) to get:

$$\overline{F}_1 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left([1 + C^2(p_{ik}) + 2R(a_{si}, p_{ik})C(a_{si})C(p_{ik})]\overline{a}_{si}\overline{p}_{ik}^2 + [1 + R(b_{si}, p_{ik})C(b_{si})C(p_{ik})]b_{si}\overline{p}_{ik} + \overline{c}_{si}\right) \tag{D.10}$$

D.2 DERIVATION OF EXPECTED EMISSION OBJECTIVE FUNCTIONS

Thermal units produce particulates and gaseous emissions, such as gaseous pollutants SO_2, NO_x, CO_2 and dust particles etc. The amount of emission can be defined as:

$$F_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\alpha_i p_{ik}^2 + \beta_i p_{ik} + \gamma_i\right) \tag{D.11}$$

where

α_i, β_i and γ_i emission of i^{th} thermal unit

$$\overline{F}_2 = E\{F_2(\overline{\alpha}_i, \overline{\beta}_i, \overline{\gamma}_i, , \overline{p}_{ik})\} + \frac{1}{2}\sum_{k=1}^{T}\sum_{i=1}^{N}\frac{\partial^2 F_2}{\partial p_{ik}^2}\mathrm{var}(p_{ik}) + \sum_{k=1}^{T}\sum_{i=1}^{N}\frac{\partial^2 F_2}{\partial p_{ik}\partial\alpha_i}\mathrm{cov}(\alpha_i, p_{ik}) + \sum_{k=1}^{T}\sum_{i=1}^{N}\frac{\partial^2 F_2}{\partial p_{ik}\partial\beta_i}\mathrm{cov}(\beta_i, p_{ik}) \tag{D.12}$$

where

$\bar{\alpha}_i$, $\bar{\beta}_i$ and $\bar{\gamma}_i$ are the expected emission curve coefficients of i^{th} thermal unit

The partial derivatives are evaluated about mean of random variables α_i, β_i, γ_i and p_{ik}.

$$\frac{\partial^2 F_2}{\partial p_{ik}^2} = 2\bar{\alpha}_i \tag{D.13}$$

$$\frac{\partial^2 F_2}{\partial p_{ik}\partial \alpha_i} = 2\bar{p}_{ik} \tag{D.14}$$

$$\frac{\partial^2 F_2}{\partial p_{ik}\partial \beta_i} = 1 \tag{D.15}$$

The partial derivatives represented by Eqs. (D.13) - (D.15) are substituted in Eq. (D.12).

$$\bar{F}_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left(\bar{\alpha}_i \bar{p}_{ik}^2 + \bar{\beta}_i \bar{p}_{ik} + \bar{\gamma}_i + \bar{\alpha}_i \operatorname{var}(p_{ik}) + 2\bar{p}_{ik}\operatorname{cov}(\alpha_i, p_{ik}) + \operatorname{cov}(\beta_i, p_{ik})\right) \tag{D.16}$$

In this study, variance and covariance are replaced by the coefficients of variation and correlation coefficient respectively.

$$\operatorname{var}(p_{ik}) = C^2(p_{ik})\bar{p}_{ik}^2 \tag{D.17}$$

$$\operatorname{cov}(\alpha_i, p_{ik}) = R(\alpha_i, p_{ik})C(\alpha_i)C(p_{ik})\bar{\alpha}_i \bar{p}_{ik} \tag{D.18}$$

$$\operatorname{cov}(\beta_i, p_{ik}) = R(\beta_i, p_{ik})C(\beta_i)C(p_{ik})\bar{\beta}_i \bar{p}_{ik} \tag{D.19}$$

where

$C(\alpha_i)$ and $C(\beta_i)$ are the coefficients of variation of random parameters α_i and β_i respectively.

$R(\alpha_i, p_{ik})$ is the correlation coefficient between cost coefficient α_i and active power generation p_{ik} of i^{th} generator at k^{th} sub-interval.

$R(\beta_i, p_{ik})$ is the correlation coefficient between cost coefficient β_i and active power generation p_{ik} of i^{th} generator at k^{th} sub-interval.

Substitute Eqs. (D.17), (D.18) and (D.19) in Eq. (D.16) to get:

$$\bar{F}_2 = \sum_{k=1}^{T}\sum_{i=1}^{N_T}\left([1 + C^2(p_{ik}) + 2R(\alpha_i, p_{ik})C(\alpha_i)C(p_{ik})]\bar{\alpha}_i \bar{p}_{ik}^2 + [1 + R(\beta_i, p_{ik})C(\beta_i)C(p_{ik})]\bar{\beta}_i \bar{p}_{ik} + \bar{\gamma}_i\right) \tag{D.20}$$

D.3 DERIVATION OF EXPECTED TRANSMISSION LOSS

A common approach to model transmission losses in the system is to use Kron’s loss formula through B- coefficients.

$$p_{Lk} = \sum_{i=1}^{N}\sum_{j=1}^{N} p_{ik} B_{ij} p_{jk} + \sum_{i=1}^{N} p_{ik} B_{io} + B_{oo} \tag{D.21}$$

where

B_{ij}, B_{io} and B_{oo} are B-coefficients

With normally distributed random variables, the expected transmission losses $\overline{P}_{Lk}$ are given below. It is presumed that random variables are independent during the interval.

$$\overline{p}_{Lk} = \sum_{i=1}^{N}\sum_{j=1}^{N}\overline{p}_{ik}\overline{B}_{ij}\overline{p}_{jk} + \sum_{i=1}^{N}\overline{B}_{io}\overline{p}_{ik} + \overline{B}_{oo} + \sum_{i=1}^{N}\overline{B}_{ii}\ \mathrm{var}\ (p_{ik}) + \sum_{i=1}^{N-1}\sum_{j=i+1}^{N}2\,\overline{B}_{ij}\ \mathrm{cov}\ (p_{ik}, p_{jk}) + \sum_{i=1}^{N}2.\overline{p}_{ik}\ \mathrm{cov}\ (p_{ik}, B_{ii})$$
$$+ \sum_{i=1}^{N}\sum_{\substack{j=1 \\ j\neq i}}^{N}2.\overline{p}_{jk}\ \mathrm{cov}\ (p_{ik}, B_{ij}) \quad \text{(D.22)}$$

$$\overline{p}_{Lk} = \sum_{i=1}^{N}\sum_{j=1}^{N}\overline{p}_{ik}\,U_{ijk}\ \overline{p}_{jk} + \sum_{i=1}^{N}\overline{B}_{io}\overline{p}_{ik} + \overline{B}_{oo} \quad \text{(D.23)}$$

with

$$\overline{U}_{ijk} = \begin{cases} \left(1 + R(p_{ik}, p_{jk})C(p_{ik})C(p_{jk}) + 2R(p_{ik}, B_{ij})C(p_{ik})C(B_{ij})\right)\overline{B}_{ij} & (i \neq j) \\ \left(1.0 + C^2(p_{ik}) + 2.0\,R(p_{ik}, B_{ii})\,C(p_{ik})\,C(B_{ii})\right)\overline{B}_{ii} & (i = j) \end{cases}$$

where

$\overline{B}_{ij}, \overline{B}_{io}$ and $\overline{B}_{oo}$ are expected B-coefficients

D.4 DERIVATION OF EXPECTED POWER DEVIATION

The expected mismatch can be estimated through minimization of the squared error of the unsatisfied power demand.

$$E\left[\left(\overline{p}_{Dk} + \overline{p}_{Lk} - \sum_{i=1}^{N}p_{ik}\right)^2\right] \quad \text{(D.24)}$$

p_{ik} is the actual power generation required to meet the load, which is considered to be random. Above equation can be rewritten as:

$$E\left[\left(\sum_{i=1}^{N}\overline{p}_{ik} - \sum_{i=1}^{N}p_{ik}\right)^2\right] \quad \text{(D.25)}$$

The expected deviations are considered as another objective to be minimized.

$$\overline{F}_4 = \sum_{k=1}^{T}\left(\sum_{i=1}^{N}\mathrm{var}(p_{ik}) + \sum_{i=1}^{N-1}\sum_{j=i+1}^{N}2\,\mathrm{cov}(p_{ik}, p_{jk})\right) \quad \text{(D.26)}$$

$$\overline{F}_4 = \sum_{k=1}^{T}\left(\sum_{i=1}^{N}\sum_{j=1}^{N}\overline{p}_{ik}\,T_{ijk}\,\overline{p}_{jk}\right) \quad \text{(D.27)}$$

with

$$T_{ijk} = \begin{cases} C^2(p_{ik}) & (i = j) \\ R(p_{ik}, p_{jk})C(p_{ik})C(p_{jk}) & (i \neq j) \end{cases}$$

D.5 DERIVATION OF EXPECTED VOLUME DEVIATION

The expected mismatch can be estimated through minimization of the squared error of the unsatisfied reservoir volume.

$$E\left(V_j - \overline{V}_j\right)^2 \quad (j = 1,2,\ldots,N_H) \tag{D.28}$$

$$= E\left(\sum_{k=1}^{T} t_k q_{jk} - \sum_{k=1}^{T} t_k \overline{q}_{jk}\right)^2 \quad (j = 1,2,\ldots,N_H) \tag{D.29}$$

This mismatch can be treated as another objective function.

$$\overline{F}_5 = \sum_{k=1}^{T} t_k^2 \operatorname{var}(q_{jk}) + \sum_{k=1}^{T-1} \sum_{l=k+1}^{T} 2 t_k t_l \operatorname{cov}(q_{jk}, q_{jl}) \quad (j = 1,2,\ldots,N_H) \tag{D.30}$$

Variance of water discharge rate is computed as:

$$\operatorname{var}(q_{jk}) = E\left[\left(q_{jk} - \overline{q}_{jk}\right)^2\right] \qquad (j = 1,2,\ldots,N_H; k = 1,2,..T) \tag{D.31}$$

For fixed head hydro system, water discharge is given by Glimn- Kirchmayer model, so variance of water discharge is computed as:

$$\operatorname{var}(q_{jk}) = E\left[\left((h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j}) - \overline{q}_{jk}\right)^2\right] \; (j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T) \tag{D.32}$$

$$\operatorname{var}(q_{jk}) = E\left[\left((h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j})^2 + \overline{q}_{jk}^2 - 2(h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j})\right)\overline{q}_{jk}\right]$$

$$(j = 1,2,\ldots,N_H; k = 1,2,..T; m = j + N_T) \tag{D.33}$$

Let's take $g_1 = h_{21j}^2 p_{mk}^4$ (D.34)

$$E(g_1) = \frac{1}{2}\frac{\partial^2 g_1}{\partial h_{21j}^2}\operatorname{var}(h_{21j}) + \frac{1}{2}\frac{\partial^2 g_1}{\partial p_{mk}^2}\operatorname{var}(p_{mk}) + \frac{\partial^2 g_1}{\partial h_{21j}\partial p_{mk}}\operatorname{cov}(h_{21j}, p_{mk}) \tag{D.35}$$

$$E(g_1) = \frac{1}{2}(2\overline{p}_{mk}^4)\operatorname{var}(h_{21j}) + \frac{1}{2}(12\overline{h}_{21j}^2 \overline{p}_{mk}^2)\operatorname{var}(p_{mk}) + (8\overline{h}_{21j}\overline{p}_{mk}^3)\operatorname{cov}(h_{21j}, p_{mk}) \tag{D.36}$$

Let's take $g_2 = h_{22j}^2 p_{mk}^2$ (D.37)

$$E(g_2) = \frac{1}{2}\frac{\partial^2 g_2}{\partial h_{22j}^2}\operatorname{var}(h_{22j}) + \frac{1}{2}\frac{\partial^2 g_2}{\partial p_{mk}^2}\operatorname{var}(p_{mk}) + \frac{\partial^2 g_2}{\partial h_{22j}\partial p_{mk}}\operatorname{cov}(h_{22j}, p_{mk}) \tag{D.38}$$

$$E(g_2) = \frac{1}{2}(2\overline{p}_{mk}^2)\operatorname{var}(h_{22j}) + \frac{1}{2}(2\overline{h}_{22j}^2)\operatorname{var}(p_{mk}) + (4\overline{h}_{22j}\overline{p}_{jk})\operatorname{cov}(h_{22j}, p_{mk}) \tag{D.39}$$

Let's take $g_3 = h_{23j}^2$ (D.40)

$$E(g_3) = \mathrm{var}(h_{23j}) \quad \text{(D.41)}$$

Let's take g4= $2h_{21j}h_{22j}p_{mk}^3$ (D.42)

$$E(g_4) = \frac{1}{2}\frac{\partial^2 g_4}{\partial p_{mk}^2}\mathrm{var}(p_{mk}) + \frac{\partial^2 g_4}{\partial h_{21j}\partial h_{22j}}\mathrm{cov}(h_{21j},h_{22j}) + \frac{\partial^2 g_4}{\partial h_{21j}\partial p_{mk}}\mathrm{cov}(h_{21j},p_{mk}) + \frac{\partial^2 g_4}{\partial h_{22j}\partial p_{mk}}\mathrm{cov}(h_{22j},p_{mk}) \quad \text{(D.43)}$$

$$E(g_4) = \frac{1}{2}(12\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk})\mathrm{var}(p_{mk}) + (2\bar{p}_{mk}^3)\mathrm{cov}(h_{21j},h_{22j}) + (6\bar{h}_{22j}\bar{p}_{mk}^2)\mathrm{cov}(h_{21j},p_{mk}) + (6\bar{h}_{21j}\bar{p}_{mk}^2)\mathrm{cov}(h_{22j},p_{mk}) \quad \text{(D.44)}$$

Let's take g5= $2h_{21j}h_{23j}p_{mk}^2$ (D.45)

$$E(g_5) = \frac{1}{2}\frac{\partial^2 g_5}{\partial p_{mk}^2}\mathrm{var}(p_{mk}) + \frac{\partial^2 g_5}{\partial h_{21j}\partial h_{23j}}\mathrm{cov}(h_{21j},h_{23j}) + \frac{\partial^2 g_5}{\partial h_{21j}\partial p_{mk}}\mathrm{cov}(h_{21j},p_{mk}) + \frac{\partial^2 g_5}{\partial h_{23j}\partial p_{mk}}\mathrm{cov}(h_{23j},p_{mk}) \quad \text{(D.46)}$$

$$E(g_5) = \frac{1}{2}(4\bar{h}_{21j}\bar{h}_{23j})\mathrm{var}(p_{mk}) + (2\bar{p}_{mk}^2)\mathrm{cov}(h_{21j},h_{23j}) + (4\bar{h}_{23j}\bar{p}_{mk})\mathrm{cov}(h_{21j},p_{mk}) + (4\bar{h}_{21j}\bar{p}_{mk})\mathrm{cov}(h_{23j},p_{mk}) \quad \text{(D.47)}$$

Let's take g6= $2h_{22j}h_{23j}p_{mk}$ (D.48)

$$E(g_6) = \frac{\partial^2 g_6}{\partial h_{22j}\partial h_{23j}}\mathrm{cov}(h_{22j},h_{23j}) + \frac{\partial^2 g_6}{\partial h_{22j}\partial p_{mk}}\mathrm{cov}(h_{22j},p_{mk}) + \frac{\partial^2 g_6}{\partial h_{23j}\partial p_{mk}}\mathrm{cov}(h_{23j},p_{mk}) \quad \text{(D.49)}$$

$$E(g_6) = (2\bar{p}_{mk})\mathrm{cov}(h_{22j},h_{23j}) + (2\bar{h}_{23j})\mathrm{cov}(h_{22j},p_{mk}) + (2\bar{h}_{22j})\mathrm{cov}(h_{23j},p_{mk}) \quad \text{(D.50)}$$

Let's take g7= $\bar{q}_{jk}^2$ (D.51)

$$E(g_7) = \bar{q}_{jk}^2 \quad \text{(D.52)}$$

Let's take

$$g_8 = \left[\left(-2(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j})\right)\bar{q}_{jk}\right] \quad \text{(D.53)}$$

$$E(g_8) = -2\bar{q}_{jk}E\left[\left(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j}\right)\right] \quad \text{(D.54)}$$

$$E(g_8) = -2\bar{q}_{jk}\left[\left(\bar{h}_{21j}\,\mathrm{var}(p_{mk}) + (2\bar{p}_{mk})\mathrm{cov}(h_{21j},p_{mk}) + \mathrm{cov}(h_{22j},p_{mk})\right)\right] \quad \text{(D.55)}$$

$$\mathrm{var}(q_{jk}) = \bar{p}_{mk}^4\,\mathrm{var}(h_{21j}) + [6\bar{h}_{21j}^2\bar{p}_{mk}^2 + \bar{h}_{22j}^2 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk} + 2\bar{h}_{21j}\bar{h}_{23j} - 2\bar{q}_{jk}\bar{h}_{21j}]\mathrm{var}(p_{mk}) + \bar{p}_{mk}^2\,\mathrm{var}(h_{22j}) + \mathrm{var}(h_{23j}) +$$
$$[8\bar{h}_{21j}\bar{p}_{mk}^3 + 6\bar{h}_{22j}\bar{p}_{mk}^2 + 4\bar{h}_{23j}\bar{p}_{mk} - 4\bar{q}_{jk}\bar{p}_{mk}]\mathrm{cov}(h_{21j},p_{mk}) + [4\bar{h}_{22j}\bar{p}_{mk} + 6\bar{h}_{21j}\bar{p}_{mk}^2 + 2\bar{h}_{23j} - 2\bar{q}_{jk}]\mathrm{cov}(h_{22j},p_{mk}) +$$
$$[2\bar{p}_{mk}^3]\mathrm{cov}(h_{21j},h_{22j}) + [4\bar{h}_{21j}\bar{p}_{mk} + 2\bar{h}_{22j}]\mathrm{cov}(h_{23j},p_{mk}) + [2\bar{p}_{mk}^2]\mathrm{cov}(h_{21j},h_{23j}) + [2\bar{p}_{mk}]\mathrm{cov}(h_{22j},h_{23j})$$

$$\left(j = 1,2,\ldots,N_H;\, k = 1,2,\ldots T;\, m = j + N_T\right) \quad \text{(D.56)}$$

$$\mathrm{var}(q_{jk}) = \bar{p}_{mk}^4 \bar{h}_{21j}^2 C^2(h_{21j}) + [6\bar{h}_{21j}^2 \bar{p}_{mk}^2 + \bar{h}_{22j}^2 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk} + 2\bar{h}_{21j}\bar{h}_{23j} - 2\bar{q}_{jk}\bar{h}_{21j}]\bar{p}_{mk}^2 C^2(p_{mk}) +$$
$$\bar{p}_{mk}^2 \bar{h}_{22j}^2 C^2(h_{22j}) + \bar{h}_{23j}^2 C^2(h_{23j}) + [8\bar{h}_{21j}^2 \bar{p}_{mk}^4 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk}^3 + 4\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk}^2 - 4\bar{h}_{21j}\bar{q}_{jk}\bar{p}_{mk}^2]R(h_{21j}, p_{mk})C(h_{21j})C(p_{mk}) +$$
$$[4\bar{h}_{22j}^2 \bar{p}_{mk}^2 + 6\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk}^3 + 2\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk} - 2\bar{h}_{22j}\bar{p}_{mk}\bar{q}_{jk}]R(h_{22j}, p_{mk})C(h_{22j})C(p_{mk}) +$$
$$[2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk}^3]R(h_{21j}, h_{22j})C(h_{21j})C(h_{22j}) + [4\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk}^2 + 2\bar{h}_{22j}\bar{h}_{23j}\bar{p}_{mk}]R(h_{23j}, p_{mk})C(h_{23j})C(p_{mk}) +$$
$$[2\bar{h}_{21j}\bar{h}_{23j}\bar{p}_{mk}^2]R(h_{21j}, h_{23j})C(h_{21j})C(h_{23j}) + [2\bar{h}_{22j}\bar{h}_{23j}\bar{p}_{mk}]R(h_{22j}, h_{23j})C(h_{22j})C(h_{23j})$$

(D.57)

where

$C(h_{21j})$, $C(h_{22j})$ and $C(h_{23j})$ are the coefficients of variation of hydro power coefficients h_{21j}, h_{22j} and h_{23j} respectively

$C(p_{mk})$ is the coefficient of variation of random parameters, p_{mk}

$R(h_{21j}, p_{mk})$ is the correlation coefficient between hydro power coefficient h_{21j} and hydro power generation p_{mk} of m^{th} generator at k^{th} sub-interval

$R(h_{22j}, p_{mk})$ is the correlation coefficient between hydro power coefficient h_{22j} and hydro power generation p_{mk} of m^{th} generator at k^{th} sub-interval

$R(h_{23j}, p_{mk})$ is the correlation coefficient between hydro power coefficient h_{23j} and hydro power generation p_{mk} of m^{th} generator at k^{th} sub-interval

$R(h_{21j}, h_{22j})$ is the correlation coefficient between hydro power coefficients h_{21j} and h_{22j}

$R(h_{21j}, h_{23j})$ is the correlation coefficient between hydro power coefficients h_{21j} and h_{23j}

$R(h_{22j}, h_{23j})$ is the correlation coefficient between hydro power coefficients h_{22j} and h_{23j}

The covariance of water discharge rate is computed as:

$$\mathrm{cov}(q_{jk}, q_{jl}) = E\left[\left(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j} - \bar{q}_{jk}\right)\left(h_{21j}p_{ml}^2 + h_{22j}p_{ml} + h_{23j} - \bar{q}_{jl}\right)\right]$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T-1; l = k+1; m = j + N_T\right) \quad \text{(D.58)}$$

$$= E\left[\begin{pmatrix} h_{21j}^2 p_{mk}^2 p_{ml}^2 + h_{21j}h_{22j}p_{mk}p_{ml}^2 + h_{21j}h_{23j}p_{ml}^2 + h_{21j}h_{22j}p_{mk}^2 p_{ml} + h_{22j}^2 p_{mk}p_{ml} + h_{22j}h_{23j}p_{ml} + \\ h_{21j}h_{23j}p_{mk}^2 + h_{22j}h_{23j}p_{mk} + h_{23j}^2 - g_9\bar{q}_{jm} - g_{10}\bar{q}_{jk} + \bar{q}_{jk}\bar{q}_{jm} \end{pmatrix}\right]$$

$$\left(j = 1,2,\ldots,N_H; k = 1,2,..T-1; l = k+1; m = j + N_T\right) \quad \text{(D.59)}$$

where

$$g_9 = \left[\left(h_{21j}p_{mk}^2 + h_{22j}p_{mk} + h_{23j}\right)\right]$$

$$g_{10} = \left[\left(h_{21j}p_{ml}^2 + h_{22j}p_{ml} + h_{23j}\right)\right]$$

Let's take $g_{11} = h_{21j}^2 p_{mk}^2 p_{ml}^2$ (D.60)

$$E(g_{11}) = \frac{1}{2}\frac{\partial^2 g_{11}}{\partial h_{21j}^2}\text{var}(h_{21j}) + \frac{1}{2}\frac{\partial^2 g_{11}}{\partial p_{mk}^2}\text{var}(p_{mk}) + \frac{1}{2}\frac{\partial^2 g_{11}}{\partial p_{ml}^2}\text{var}(p_{ml}) + \frac{\partial^2 g_{11}}{\partial p_{mk}\partial p_{ml}}\text{cov}(p_{mk}, p_{ml}) + \frac{\partial^2 g_{11}}{\partial h_{21j}\partial p_{mk}}\text{cov}(h_{21j}, p_{mk}) + \frac{\partial^2 g_{11}}{\partial h_{21j}\partial p_{ml}}\text{cov}(h_{21j}, p_{ml})$$

(D.61)

$$E(g_{11}) = \frac{1}{2}(2\bar{p}_{mk}^2 \bar{p}_{ml}^2)\text{var}(h_{21j}) + \frac{1}{2}(2\bar{h}_{21j}^2 \bar{p}_{ml}^2)\text{var}(p_{mk}) + \frac{1}{2}(2\bar{h}_{21j}^2 \bar{p}_{mk}^2)\text{var}(p_{ml}) + 4\bar{h}_{21j}^2 \bar{p}_{mk}\bar{p}_{ml}\,\text{cov}(p_{mk}, p_{ml}) + (4h_{21j} p_{mk} p_{ml}^2)\text{cov}(h_{21j}, p_{mk}) + (4h_{21j} p_{mk}^2 p_{ml})\text{cov}(h_{21j}, p_{ml})$$

(D.62)

Let's take $g_{12} = h_{21j} h_{22j} p_{mk} p_{ml}^2$ (D.63)

$$E(g_{12}) = \bar{h}_{21j}\bar{h}_{22j}\frac{1}{2}\frac{\partial^2 g_{12}}{\partial p_{ml}^2}\text{var}(p_{ml}) + \bar{h}_{21j}\bar{h}_{22j}\frac{\partial^2 g_{12}}{\partial p_{mk}\partial p_{ml}}\text{cov}(p_{mk}, p_{ml}) + \frac{\partial^2 g_{12}}{\partial h_{21j}\partial h_{22j}}\text{cov}(h_{21j}, h_{22j}) + \frac{\partial^2 g_{12}}{\partial h_{21j}\partial p_{mk}}\text{cov}(h_{21j}, p_{mk}) + \frac{\partial^2 g_{12}}{\partial h_{21j}\partial p_{ml}}\text{cov}(h_{21j}, p_{ml}) + \frac{\partial^2 g_{12}}{\partial h_{22j}\partial p_{mk}}\text{cov}(h_{22j}, p_{mk}) + \frac{\partial^2 g_{12}}{\partial h_{22j}\partial p_{ml}}\text{cov}(h_{22j}, p_{ml})$$

(D.64)

$$E(g_{12}) = \bar{h}_{21j}\bar{h}_{22j}\frac{1}{2}(2\bar{p}_{mk})\text{var}(p_{ml}) + 2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{ml}\,\text{cov}(p_{mk}, p_{ml}) + (\bar{p}_{mk}\bar{p}_{ml}^2)\text{cov}(h_{21j}, h_{22j}) + (\bar{h}_{22j}\bar{p}_{ml}^2)\text{cov}(h_{21j}, p_{mk}) + (2\bar{h}_{22j}\bar{p}_{mk}\bar{p}_{ml})\text{cov}(h_{21j}, p_{ml}) + (\bar{h}_{21j}\bar{p}_{ml}^2)\text{cov}(h_{22j}, p_{mk}) + (2\bar{h}_{21j}\bar{p}_{mk}\bar{p}_{ml})\text{cov}(h_{22j}, p_{ml})$$

(D.65)

Let's take $g_{13} = h_{21j} h_{23j} p_{ml}^2$ (D.66)

$$E(g_{13}) = \frac{1}{2}\frac{\partial^2 g_{13}}{\partial p_{ml}^2}\text{var}(p_{ml}) + \frac{\partial^2 g_{13}}{\partial h_{21j}\partial h_{23j}}\text{cov}(h_{21j}, h_{23j}) + \frac{\partial^2 g_{13}}{\partial h_{21j}\partial p_{ml}}\text{cov}(h_{21j}, p_{ml}) + \frac{\partial^2 g_{13}}{\partial h_{23j}\partial p_{ml}}\text{cov}(h_{23j}, p_{ml})$$

(D.67)

$$E(g_{13}) = \frac{1}{2}(2\bar{h}_{21j}\bar{h}_{23j})\text{var}(p_{ml}) + (\bar{p}_{ml}^2)\text{cov}(h_{21j}, h_{23j}) + (2\bar{h}_{23j}\bar{p}_{ml})\text{cov}(h_{21j}, p_{ml}) + (2\bar{h}_{21j}\bar{p}_{ml})\text{cov}(h_{23j}, p_{ml})$$

(D.68)

$g_{14} = h_{21j} h_{22j} p_{mk}^2 p_{ml}$ (D.69)

$$E(g_{14}) = \frac{1}{2}\frac{\partial^2 g_{14}}{\partial p_{mk}^2}\text{var}(p_{mk}) + \frac{\partial^2 g_{14}}{\partial h_{21j}\partial h_{22j}}\text{cov}(h_{21j}, h_{22j}) + \frac{\partial^2 g_{14}}{\partial h_{21j}\partial p_{mk}}\text{cov}(h_{21j}, p_{mk}) + \frac{\partial^2 g_{14}}{\partial h_{21j}\partial p_{ml}}\text{cov}(h_{21j}, p_{ml}) + \frac{\partial^2 g_{14}}{\partial h_{22j}\partial p_{mk}}\text{cov}(h_{22j}, p_{mk}) + \frac{\partial^2 g_{14}}{\partial h_{22j}\partial p_{ml}}\text{cov}(h_{22j}, p_{ml}) + \frac{\partial^2 g_{14}}{\partial p_{mk}\partial p_{ml}}\text{cov}(p_{mk}, p_{ml})$$

(D.70)

$$E(g_{14}) = \frac{1}{2}(2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{ml})\text{var}(p_{mk}) + (\bar{p}_{mk}^2\bar{p}_{ml})\text{cov}(h_{21j}, h_{22j}) + (2\bar{h}_{22j}\bar{p}_{mk}\bar{p}_{ml})\text{cov}(h_{21j}, p_{mk}) + (\bar{h}_{22j}\bar{p}_{mk}^2)\text{cov}(h_{21j}, p_{ml}) + (2\bar{h}_{21j}\bar{p}_{mk}\bar{p}_{ml})\text{cov}(h_{22j}, p_{mk}) + (\bar{h}_{21j}\bar{p}_{mk}^2)\text{cov}(h_{22j}, p_{mk}) + (2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk})\text{cov}(p_{mk}, p_{ml})$$

(D.71)

Let's take $g_{15} = h_{22j}^2 p_{mk} p_{ml}$ (D.72)

$$E(g_{15}) = \frac{1}{2}\frac{\partial^2 g_{15}}{\partial h_{22j}^2}\text{var}(h_{22j}) + \frac{\partial^2 g_{15}}{\partial h_{22j}\partial p_{mk}}\text{cov}(h_{22j}, p_{mk}) + \frac{\partial^2 g_{15}}{\partial h_{22j}\partial p_{ml}}\text{cov}(h_{22j}, p_{ml}) + \frac{\partial^2 g_{15}}{\partial p_{jk}\partial p_{ml}}\text{cov}(p_{mk}, p_{ml}) \quad \text{(D.73)}$$

$$E(g_{15}) = \frac{1}{2}(2\bar{p}_{mk}\bar{p}_{ml})\text{var}(h_{22j}) + (2\bar{h}_{22j}\bar{p}_{ml})\text{cov}(h_{22j}, p_{ml}) + (2\bar{h}_{22j}\bar{p}_{mk})\text{cov}(h_{22j}, p_{ml}) + \bar{h}_{22j}^2\text{cov}(p_{mk}, p_{ml}) \quad \text{(D.74)}$$

Let's take $g_{16} = h_{22j} h_{23j} p_{ml}$ (D.75)

$$E(g_{16}) = \frac{\partial^2 g_{16}}{\partial h_{22j}\partial h_{23j}}\text{cov}(h_{22j}, h_{23j}) + \frac{\partial^2 g_{16}}{\partial h_{22j}\partial p_{ml}}\text{cov}(h_{22j}, p_{ml}) + \frac{\partial^2 g_{16}}{\partial h_{23j}\partial p_{ml}}\text{cov}(h_{23j}, p_{ml}) \quad \text{(D.76)}$$

$$E(g_{16}) = (\bar{p}_{ml})\text{cov}(h_{22j}, h_{23j}) + (\bar{h}_{23j})\text{cov}(h_{22j}, p_{ml}) + (\bar{h}_{22j})\text{cov}(h_{23j}, p_{ml}) \quad \text{(D.77)}$$

Let's take $g_{17} = h_{21j} h_{23j} p_{mk}^2$ (D.78)

$$E(g_{17}) = \frac{1}{2}\frac{\partial^2 g_{17}}{\partial p_{mk}^2}\text{var}(p_{mk}) + \frac{\partial^2 g_{17}}{\partial h_{21j}\partial h_{23j}}\text{cov}(h_{21j}, h_{23j}) + \frac{\partial^2 g_{17}}{\partial h_{21j}\partial p_{mk}}\text{cov}(h_{21j}, p_{mk}) + \frac{\partial^2 g_{17}}{\partial h_{23j}\partial p_{mk}}\text{cov}(h_{23j}, p_{mk}) \quad \text{(D.79)}$$

$$E(g_{17}) = \frac{1}{2}(2\bar{h}_{21j}\bar{h}_{23j})\text{var}(p_{mk}) + (\bar{p}_{mk}^2)\text{cov}(h_{21j}, h_{23j}) + (2\bar{h}_{23j}\bar{p}_{mk})\text{cov}(h_{21j}, p_{mk}) + (2\bar{h}_{21j}\bar{p}_{mk})\text{cov}(h_{23j}, p_{mk}) \quad \text{(D.80)}$$

Let's take $g_{18} = h_{22j} h_{23j} p_{mk}$ (D.81)

$$E(g_{18}) = \frac{\partial^2 g_{18}}{\partial h_{22j}\partial h_{23j}}\text{cov}(h_{22j}, h_{23j}) + \frac{\partial^2 g_{18}}{\partial h_{22j}\partial p_{mk}}\text{cov}(h_{22j}, p_{mk}) + \frac{\partial^2 g_{18}}{\partial h_{23j}\partial p_{mk}}\text{cov}(h_{23j}, p_{mk}) \quad \text{(D.82)}$$

$$E(g_{18}) = (\bar{p}_{mk})\text{cov}(h_{22j}, h_{23j}) + (\bar{h}_{23j})\text{cov}(h_{22j}, p_{mk}) + (\bar{h}_{22j})\text{cov}(h_{23j}, p_{mk}) \quad \text{(D.83)}$$

Let's take $g_{19} = h_{23j}^2$ (D.84)

$$E(g_{19}) = [\text{var}(h_{23j})] \quad \text{(D.85)}$$

$$g_9\bar{q}_{jm} = [(h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j})q_{jm}] \quad \text{(D.86)}$$

$$E(g_9\bar{q}_{jm}) = E[(h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j})q_{jm}] \quad \text{(D.87)}$$

$$E(g_9\bar{q}_{jm}) = \bar{q}_{jm}E[(h_{21j} p_{mk}^2 + h_{22j} p_{mk} + h_{23j})] \quad \text{(D.88)}$$

$$E(g_9\bar{q}_{jm}) = \bar{q}_{jm}[\bar{h}_{21j}\text{var}(\bar{p}_{mk}) + (2\bar{p}_{mk})\text{cov}(p_{mk}, h_{21j}) + (1)\text{cov}(p_{mk}, h_{22j})] \quad \text{(D.89)}$$

$$g_{10}\bar{q}_{jk} = [(h_{21j} p_{ml}^2 + h_{22j} p_{ml} + h_{23j})q_{jk}] \quad \text{(D.90)}$$

$$E(g_{10}\bar{q}_{jk}) = E[(h_{21j} p_{ml}^2 + h_{22j} p_{ml} + h_{23j})q_{jk}] \quad \text{(D.91)}$$

$$E(g_{10}\bar{q}_{jk}) = \bar{q}_{jk}E[(h_{21j} p_{ml}^2 + h_{22j} p_{ml} + h_{23j})] \quad \text{(D.92)}$$

$$E(g_{10}\bar{q}_{jk}) = \bar{q}_{jk}[\bar{h}_{21j}\text{var}(\bar{p}_{ml}) + (2\bar{p}_{ml})\text{cov}(p_{ml}, h_{21j}) + (1)\text{cov}(p_{ml}, h_{22j})] \quad \text{(D.93)}$$

Let's take $g_{20} = \bar{q}_{jk}\bar{q}_{jm}$ (D.94)

$$E(g_{20}) = \bar{q}_{jk}\bar{q}_{jm} \tag{D.95}$$

$$\mathrm{cov}(q_{jk}, q_{jl}) = A_1 \,\mathrm{var}(p_{mk}) + A_2 \,\mathrm{var}(h_{21j}) + A_3 \,\mathrm{var}(p_{ml}) + A_4 \,\mathrm{var}(h_{22j}) + A_5 \,\mathrm{var}(h_{23j}) + A_6 \,\mathrm{cov}(p_{mk}, p_{ml}) + A_7 \,\mathrm{cov}(p_{mk}, h_{21j}) + A_8 \,\mathrm{cov}(p_{ml}, h_{21j}) + A_9 \,\mathrm{cov}(p_{mk}, h_{22j}) + A_{10} \,\mathrm{cov}(p_{ml}, h_{22j}) + A_{11} \,\mathrm{cov}(p_{mk}, h_{23j}) + A_{12} \,\mathrm{cov}(p_{ml}, h_{23j}) + A_{13} \,\mathrm{cov}(h_{21j}, h_{22j}) + A_{14} \,\mathrm{cov}(h_{21j}, h_{23j}) + A_{15} \,\mathrm{cov}(h_{22j}, h_{23j}) \tag{D.96}$$

$$\mathrm{cov}(q_{jk}, q_{jl}) = A_1 p_{mk}^2 C^2(p_{mk}) + A_2 h_{21j}^2 C^2(h_{21j}) + A_3 p_{ml}^2 C^2(p_{ml}) + A_4 h_{22j}^2 C^2(h_{22j}) + A_5 h_{23j}^2 C^2(h_{23j}) + A_6 p_{mk} p_{ml} R(p_{mk}, p_{ml}) C(p_{mk}) C(p_{ml}) + A_7 p_{mk} h_{21j} R(p_{mk}, h_{21j}) C(p_{mk}) C(h_{21j}) + A_8 p_{ml} h_{21j} R(p_{ml}, h_{21j}) C(p_{ml}) C(h_{21j}) + A_9 p_{mk} h_{22j} R(p_{mk}, h_{22j}) C(p_{mk}) C(h_{22j}) + A_{10} p_{ml} h_{22j} R(p_{ml}, h_{22j}) C(p_{ml}) C(h_{22j}) + A_{11} p_{mk} h_{23j} R(p_{mk}, h_{23j}) C(p_{mk}) C(h_{23j}) + A_{12} p_{ml} h_{23j} R(p_{ml}, h_{23j}) C(p_{ml}) C(h_{23j}) + A_{13} h_{21j} h_{22j} R(h_{21j}, h_{22j}) C(h_{21j}) C(h_{22j}) + A_{14} h_{21j} h_{23j} R(h_{21j}, h_{23j}) C(h_{21j}) C(h_{23j}) + A_{15} h_{22j} h_{23j} R(h_{22j}, h_{23j}) C(h_{22j}) C(h_{23j}) \tag{D.97}$$

where

$$A_1 = [\bar{h}_{21j}^2 \bar{p}_{ml}^2 + \bar{h}_{21j}\bar{h}_{22j}\bar{p}_{ml} + \bar{h}_{21j}\bar{h}_{23j} - \bar{h}_{21j}\bar{q}_{jl}]$$

$$A_2 = [\bar{p}_{mk}^2 \bar{p}_{ml}^2]$$

$$A_3 = [\bar{h}_{21j}^2 \bar{p}_{mk}^2 + \bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk} + \bar{h}_{21j}\bar{h}_{23j} - \bar{h}_{21j}\bar{q}_{jk}]$$

$$A_4 = [\bar{p}_{mk}\bar{p}_{ml}]$$

$$A_5 = [1]$$

$$A_6 = [4\bar{h}_{21j}^2 \bar{p}_{mk}\bar{p}_{ml} + 2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{ml} + 2\bar{h}_{21j}\bar{h}_{22j}\bar{p}_{mk} + \bar{h}_{22j}^2]$$

$$A_7 = [4\bar{h}_{21j}\bar{p}_{mk}\bar{p}_{ml}^2 + \bar{h}_{22j}\bar{p}_{ml}^2 + 2\bar{h}_{22j}\bar{p}_{mk}\bar{p}_{ml} + 2\bar{h}_{23j}\bar{p}_{mk} - 2\bar{p}_{mk}\bar{q}_{jl}]$$

$$A_8 = [4\bar{h}_{21j}\bar{p}_{ml}\bar{p}_{mk}^2 + \bar{h}_{22j}\bar{p}_{mk}^2 + 2\bar{h}_{22j}\bar{p}_{mk}\bar{p}_{ml} + 2\bar{h}_{23j}\bar{p}_{ml} - 2\bar{p}_{ml}\bar{q}_{jk}]$$

$$A_9 = [\bar{h}_{21j}\bar{p}_{ml}^2 + 2\bar{h}_{21j}\bar{p}_{mk}\bar{p}_{ml} + 2\bar{h}_{22j}\bar{p}_{ml} + \bar{h}_{23j} - \bar{q}_{jl}]$$

$$A_{10} = [2\bar{h}_{21j}\bar{p}_{mk}\bar{p}_{ml} + \bar{h}_{21j}\bar{p}_{mk}^2 + 2\bar{h}_{22j}\bar{p}_{mk} + \bar{h}_{23j} - \bar{q}_{jk}]$$

$$A_{11} = [2\bar{h}_{21j}\bar{p}_{mk} + \bar{h}_{22j}]$$

$$A_{12} = [2\bar{h}_{21j}\bar{p}_{ml} + \bar{h}_{22j}]$$

$$A_{13} = [\bar{p}_{mk}\bar{p}_{ml}^2 + \bar{p}_{mk}^2\bar{p}_{ml}]$$

$$A_{14} = [\bar{p}_{ml}^2 + \bar{p}_{mk}^2]$$

$$A_{15} = [\bar{p}_{mk} + \bar{p}_{ml}]$$

with

$R(p_{mk}, p_{ml})$ is the correlation coefficient between hydro power generation p_{mk} of m^{th} generator at k^{th} sub-interval and hydro power generation p_{ml} of m^{th} generator at l^{th} sub-interval

APPENDIX-E

ELECTRIC POWER SYSTEMS

E.1 DATA FOR ELECTRIC POWER SYSTEM-I

Electric power system-I consists of 2-hydro and 2-thermal units, having 24-hour scheduling period divided into 3 sub-intervals of 8 hour each. A set of operating characteristics of 2-hydro unit are given in Table E.1. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 2-thermal units used in the study undertaken are given in Table E.2 and E.3 respectively. Load demand and loss coefficient for the given study is tabulated in Table E.4.

Table E.1: Operating characteristics of 2-hydro unit: Electric power system-I

Hydro unit (j)	h_{21j} (MCF/MW^{2}h)	h_{22j} (MCF/MWh)	h_{23j} (MCF/h)	K'_j Factor	$p_j^{\min}$ (MW)	$p_j^{\max}$ (MW)	V_{jF} (MCF)
1	0.000216	0.306	1.980	1	0	400	2500
2	0.000360	0.612	0.936	1	0	300	2100

Table E.2: Operating characteristics of 2-thermal generator: Electric power system-I

Thermal Unit (i)	Operating cost coefficients					$p_i^{\min}$ (MW)	$p_i^{\max}$ (MW)
	a_{si} ($/MW^{2}h)	b_{si} ($/MWh)	c_{si} ($/h)	d_{si} ($/h)	e_{si} (1/MW)		
1	0.0025	3.2	25	0	0	50	300
2	0.0008	3.4	30	0	0	50	700

Table E.3: Emission coefficients of 2-thermal unit: Electric power system-I

Thermal Unit (i)	Emission coefficients				
	α_i (lb/MW^{2}h)	β_i (lb/MWh)	γ_i (lb/h)	η_i (lb/h)	δ_i (1/MW)
1	0.0000419	0.0032767	1.38593	0	0
2	0.0000683	0.0054551	4.02669	0	0

Table E.4: Load demand: Electric power system-I

Sub-interval (k)	Duration (h)	p_{Dk} (MW)
1	8	900
2	8	1200
3	8	1100

The loss coefficient loss matrix is given below:

$$\begin{bmatrix} 0.000140 & 0.000010 & 0.000015 & 0.000015 \\ 0.000010 & 0.000060 & 0.000010 & 0.000013 \\ 0.000010 & 0.000010 & 0.000068 & 0.000065 \\ 0.000015 & 0.000013 & 0.000065 & 0.000070 \end{bmatrix}$$

E.2 DATA FOR ELECTRIC POWER SYSTEM-II

Electric power system-I consists of 2-hydro and 4-thermal units, having 48-hour scheduling period divided into 4 sub-intervals of 12 hour each. A set of operating characteristics of 2-hydro unit are given in Table E.5. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 4-thermal units used in the study undertaken are given in Table E.6 and E.7 respectively. Load demand and loss coefficient for the given study is tabulated in Table E.8.

Table E.5: Operating characteristics of 2-hydro unit: Electric power system-II

Hydro unit (j)	h_{21j} (acre-ft/MW^{2}h)	h_{22j} (acre-ft/MWh)	h_{23j} (acre-ft/h)	K'_j Factor	p_j^{min} (MW)	p_j^{max} (MW)	V_{jF} (acre-ft)
1	0.00986	8.5	260	1	0	250	125,000
2	0.01140	9.8	250	1	0	500	286,000

Table E.6: Operating characteristics of 4-thermal unit: Electric power system-II

Thermal Unit (i)	Operating cost coefficients					p_i^{min} (MW)	p_i^{max} (MW)
	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	d_{si} (\$/h)	e_{si} (1/MW)		
1	0.0030	1.8	60	140	0.040	20	125
2	0.0012	2.1	100	160	0.038	30	175
3	0.0010	2.0	120	180	0.037	40	250
4	0.0015	1.8	40	200	0.035	50	300

Table E.7: Emission coefficients of 4-thermal unit: Electric power system-II

Thermal Unit (i)	Emission coefficients				
	α_i (lb/MW^{2}h)	β_i (lb/MWh)	γ_i (lb/h)	η_i (lb/h)	δ_i (1/MW)
1	0.0150	-0.555	50	0.5773	0.02446
2	0.0105	-1.355	60	0.4968	0.02270
3	0.0080	-0.600	45	0.4860	0.01948
4	0.0120	-0.555	30	0.5035	0.02075

Table E.8: Load Demand: Electric power system-II

Sub-interval (k)	Duration (h)	p_{Dk} (MW)
1	12	900
2	12	1100
3	12	1000
4	12	1300

The loss coefficient loss matrix is given below:

$$\begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000017 \\ 0.000014 & 0.000045 & 0.000016 & 0.000020 & 0.000015 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 \\ 0.000015 & 0.000020 & 0.000010 & 0.000040 & 0.000010 \\ 0.000020 & 0.000018 & 0.000012 & 0.000014 & 0.000011 \\ 0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000036 \end{bmatrix}$$

E.3 DATA FOR ELECTRIC POWER SYSTEM-III and IV

Electric power system-III and IV consists of 4-hydro and 5-thermal units, having 24-hour scheduling period divided into 24 sub-intervals of 1 hour each. A set of operating characteristics of 4-hydro unit are given in Table E.9. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 5-thermal units used in the study undertaken are given in Table E.10. Load demand and loss coefficient for the given study is tabulated in Table E.11

Table E.9: Operating characteristics of 4-hydro unit: Electric power system-III and IV

Hydro unit (j)	h_{21j} (m^3/MW^{2}h)	h_{22j} (m^3/MWh)	h_{23j} (m^3/h)	K'_j	p_j^{min} (MW)	p_j^{max} (MW)	V_{jF} (m^3)
1	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	96.74445	275	650	9175
2	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	96.74239	275	650	9175
3	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	96.74036	275	650	9175
4	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	96.73837	275	650	9175

Table E.10: Operating characteristics of 5-thermal unit: Electric power system-III and IV

Thermal Unit (i)	Operating cost coefficients			Emission coefficients			p_i^{min} (MW)	p_i^{max} (MW)
	a_{si} ($/MW²h)	b_{si} ($/MWh)	c_{si} ($/h)	α_i (kg/MW²h)	β_i (kg/MWh)	γ_i (kg/h)		
1	0.003	2.7	150.0	0.006483	-0.79027	28.82488	325	975
2	0.003	2.8	150.0	0.006483	-0.79027	28.82488	325	975
3	0.003	3.0	150.0	0.006483	-0.79027	28.82488	325	975
4	0.003	3.1	150.0	0.006483	-0.79027	28.82488	325	975
5	0.003	3.2	150.0	0.006483	-0.79027	28.82488	325	975

Table E.11: Load Demand (MW): Electric power system-III and IV

k	p_{Dk}	k	p_{Dk}	k	p_{Dk}	k	p_{Dk}
1	5448	7	6088	13	5400	19	3584
2	5776	8	5856	14	5828	20	3544
3	5664	9	5480	15	3928	21	3528
4	5624	10	5464	16	3840	22	3552
5	5928	11	5728	17	3784	23	3688
6	6064	12	5536	18	3608	24	3840

The loss coefficient loss matrix is given below:

$$10^{-03} \times \begin{bmatrix} 0.143 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.143 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.143 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.143 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.143 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.143 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.143 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.143 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.143 \end{bmatrix}$$

E.4 DATA FOR ELECTRIC POWER SYSTEM-IV

For electric power system-IV, set of operating characteristics of 4-hydro unit are given in Table E.9. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 5-thermal units used in the study undertaken are given in Table E.10. Load demand and loss coefficient for the given study is tabulated in Table E.11. A set of reservoir operating characteristics used in the study undertaken are given in Table E.12 and Table E.13.

Table E.12: Reservoirs head variation of 4-hydro unit: Electric power system-IV

Hydro unit (j)	h_{11j} (m^{-2})	h_{12j} (m^{-1})	h_{13j}	Initial Head, H_{j0} (m)
1	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	179.8320
2	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	180.1370
3	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	180.4420
4	7.729×10^{-6}	4.42887×10^{-3}	1.17265×10^{-1}	180.7460

Table E.13: Reservoir details of 4-hydro unit: Electric power system-IV

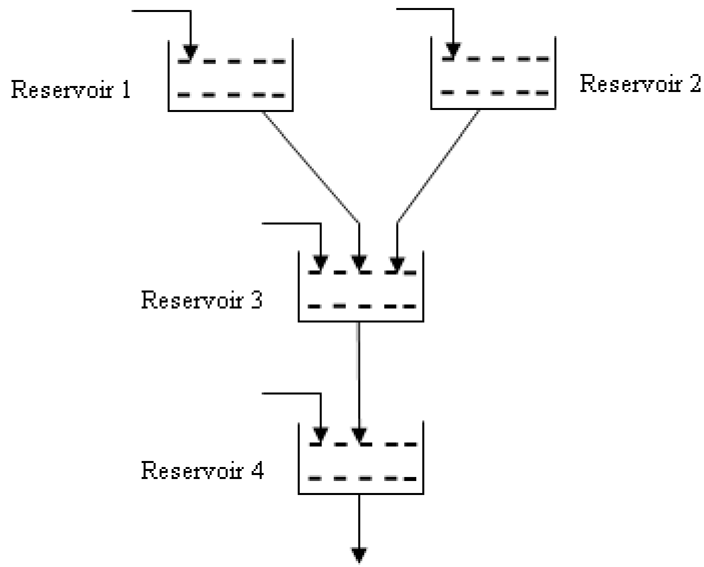
Hydro unit (j)	S_j ($\times10^6$), (m^2)	I_j (m^3)
1	6.4748	7.0
2	6.4748	7.1
3	6.4748	7.2
4	6.4748	7.3

E.5 DATA FOR ELECTRIC POWER SYSTEM-V

Electric power system-V consists of 4-hydro and 3-thermal units, having 24-hour scheduling period divided into 24 sub-intervals of 1 hour each. A hydraulic system network along with number of upstream reservoir and time delay between upstream and downside reservoir are shown in Fig E.1. Hydro power generation coefficients are given in Table E.14. A set of operating characteristics of hydro unit and reservoirs inflow are given in Table E.15 and E.16, respectively. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 3-thermal units used in the study undertaken are given in Table E.17 and E.18 respectively. Load demand and loss coefficient for the given study is tabulated in Table E.19.

Table E.14: Hydro power generation coefficients: Electric power system-V

Unit (j)	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C_{5j}	C_{6j}
1	-0.0042	-0.42	0.030	0.90	10.0	-50
2	-0.0040	-0.30	0.015	1.14	9.5	-70
3	-0.0016	-0.30	0.014	0.55	5.5	-40
4	-0.0030	-0.31	0.027	1.44	14.0	-90



Plant	1	2	3	4
U_j	0	0	2	1
t_{rj}	2	3	4	0

Figure E.1: Hydraulic system network: Electric power system-V

Table E.15: Reservoir storage capacity limits, initial and final storage capacity limits, plant discharge limits, and hydro plant generation limits: Electric power system-V

Unit (j)	V_j^{min}	V_j^{max}	V_{jI}	V_{jF}	q_j^{min}	q_j^{max}	p_j^{min} (MW)	p_j^{max} (MW)
	($\times 10^4$ m^3)				($\times 10^4$ m^3/h)			
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	6	20	0	500

Table E.16: Reservoir inflows ($\times 10^4$ m^3/h): Electric power system-V

k	Reservoir				*k*	Reservoir				*k*	Reservoir			
	1	2	3	4		1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	9	10	8	1	0	17	9	7	2	0
2	9	8	8.2	2.4	10	11	9	1	0	18	8	6	2	0
3	8	9	4	1.6	11	12	9	1	0	19	7	7	1	0
4	7	9	2	0	12	10	8	2	0	20	6	8	1	0
5	6	8	3	0	13	11	8	4	0	21	7	9	2	0
6	7	7	4	0	14	12	9	3	0	22	8	9	2	0
7	8	6	3	0	15	11	9	3	0	23	9	8	1	0
8	9	7	2	0	16	10	8	2	0	24	10	8	0	0

Table E.17: Cost coefficients and operating limits of thermal units: Electric power system-V

Unit(i)	a_{si} ($/MW^{2}h)	b_{si} ($/MWh)	c_{si} ($/h)	d_{si} ($/h)	e_{si} (1/MW)	p_i^{min} (MW)	p_i^{max} (MW)
1	0.0012	2.45	100	160	0.038	20	175
2	0.0010	2.32	120	180	0.037	40	300
3	0.0015	2.10	150	200	0.035	50	500

Table E.18: Emission coefficients: Electric power system-V

Unit (i)	α_i (lb/MW^{2}h)	β_i (lb/MWh)	γ_i (lb/h)	η_i (lb/h)	δ_i (1/MW)
1	0.0105	-1.355	60	0.4968	0.01925
2	0.0080	-0.600	45	0.4860	0.01694
3	0.0120	-0.555	30	0.5035	0.01478

Table E.19: Load demand (MW): Electric power system-V

k	p_{Dk}	k	p_{Dk}	k	p_{Dk}
1	750	9	1090	17	1050
2	780	10	1080	18	1120
3	700	11	1100	19	1070
4	650	12	1150	20	1050
5	670	13	1110	21	910
6	800	14	1030	22	860
7	950	15	1010	23	850
8	1010	16	1060	24	800

E.6 DATA FOR ELECTRIC POWER SYSTEM-VI

Electric power system-VI consists of 4-hydro and 3-thermal units, having 24-hour scheduling period divided into 24 sub-intervals of 1 hour each. A hydraulic system network along with number of upstream reservoir and time delay between upstream and downside reservoir are shown in Fig E.1. Hydro power generation coefficients are given in Table E.14. A set of operating characteristics of hydro unit and reservoirs inflow are given in Table E.15 and E.16, respectively. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 3-thermal units used in the study undertaken are given in Table E.20 and E.21 respectively. Load demand and loss coefficient for the given study is tabulated in Table E.19.

Table E.20: Cost coefficients and operating limits of thermal units: Electric power system-VI

Unit (i)	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	d_{si} (\$/h)	e_{si} (1/MW)	p_i^{min} (MW)	p_i^{max} (MW)
1	0.0037	2.00	10	18	0.0370	20	175
2	0.0175	1.75	10	16	0.0380	40	300
3	0.0625	1.00	20	14	0.0400	50	500

Table E.21: Emission coefficients: Electric power system-VI

Unit (i)	$\alpha_i \times 10^{-6}$ (ton/MW^{2}h)	$\beta_i \times 10^{-4}$ (ton/MWh)	$\gamma_i \times 10^{-2}$ (ton/h)	$\eta_i \times 10^{-4}$ (ton/h)	$\delta_i \times 10^{-2}$ (1/MW)
1	6.490	-5.554	4.091	2.0	2.857
2	5.638	-6.047	2.543	5.0	3.333
3	4.586	-5.094	4.258	0.01	0.8

E.7 DATA FOR ELECTRIC POWER SYSTEM-VII

Electric power system-VII consists of 16-hydro and 6-thermal units, having 24-hour scheduling period divided into 24 sub-intervals of 1 hour each. A hydraulic system network along with number of upstream reservoir and time delay between upstream and downside reservoir are shown in Fig E.2. Hydro power generation coefficients are given in Table E.22. A set of operating characteristics of hydro unit and reservoirs inflow are given in Table E.23 and E.24, respectively. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 6-thermal units used in the study undertaken are given in Table E.25. Load demand and loss coefficient for the given study is tabulated in Table E.26.

Table E.25: Cost coefficients, emission coefficients and operating limits of thermal units: Electric power system-VII

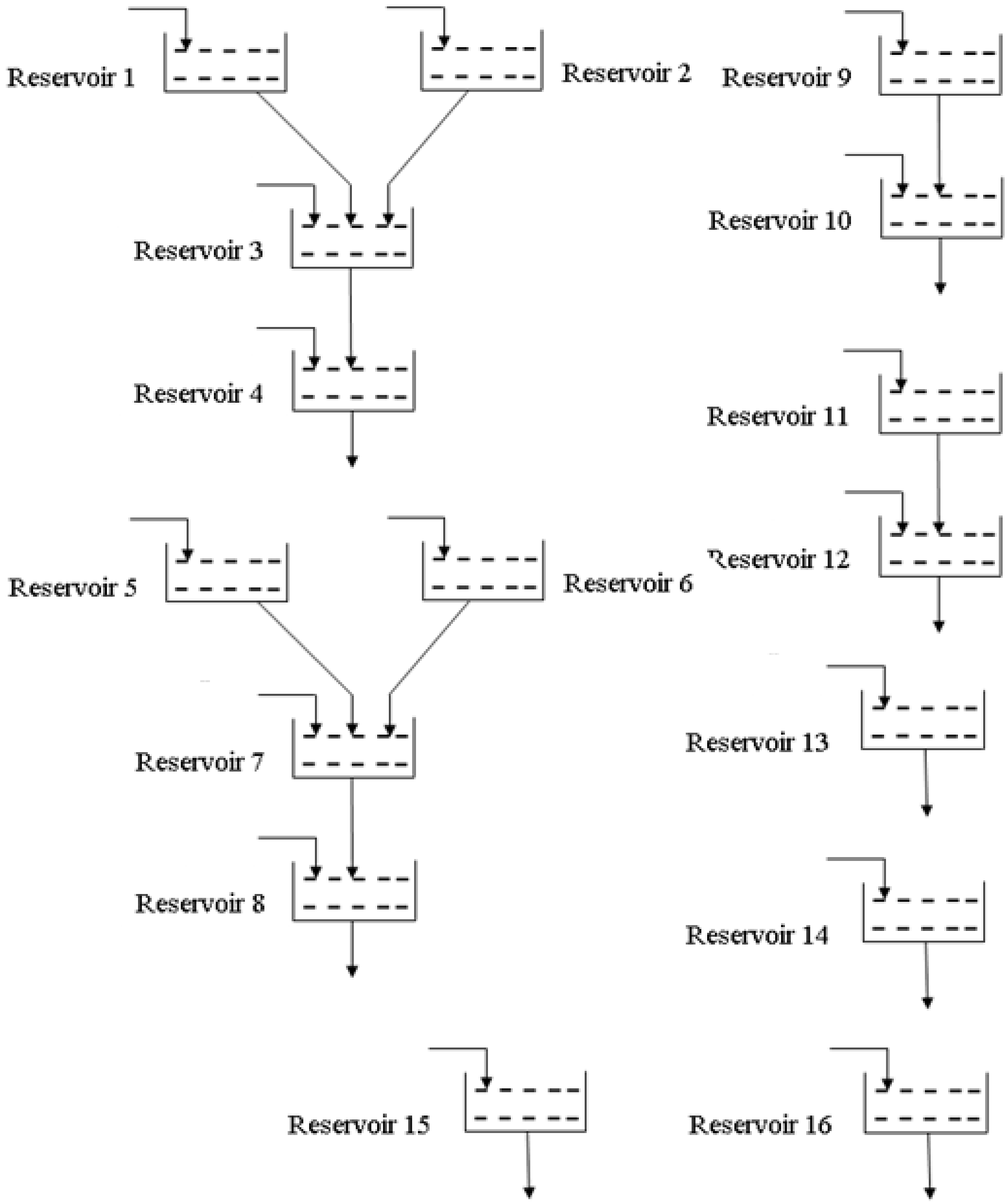
Unit (i)	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	α_i (ton/MW^{2}h)	β_i (ton/MWh)	γ_i (ton/h)	p_i^{min} (MW)	p_i^{max} (MW)
1	0.15247	38.5390	756.7988	0.00419	0.32767	13.8593	10	125
2	0.10587	46.1591	451.3251	0.00419	0.32767	13.8593	10	150
3	0.03546	38.3055	1243.5311	0.00683	-0.54551	40.2669	35	210
4	0.02803	40.3965	1049.9977	0.00683	-0.54551	40.2669	35	225
5	0.01799	38.2704	1356.6592	0.00461	-0.51116	42.8955	125	315
6	0.02111	36.3278	1658.5696	0.00461	-0.51116	42.8955	130	325

Table E.22: Hydro power generation coefficients: Electric power system-VII

Plant (j)	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C_{5j}	C_{6j}
1	-0.00042	-0.042	0.0030	0.090	1.0	-5
2	-0.00040	-0.030	0.0015	0.114	0.95	-7
3	-0.00016	-0.030	0.0014	0.055	0.55	-4
4	-0.00030	-0.031	0.0027	0.144	1.4	-9
5	-0.00042	-0.042	0.0030	0.090	1.0	-5
6	-0.00040	-0.030	0.0015	0.114	0.95	-7
7	-0.00016	-0.030	0.0014	0.055	0.55	-4
8	-0.00030	-0.031	0.0027	0.144	1.4	-9
9	-0.00040	-0.030	0.0015	0.114	0.95	-7
10	-0.00016	-0.030	0.0014	0.055	0.55	-4
11	-0.00040	-0.030	0.0015	0.114	0.95	-7
12	-0.00016	-0.030	0.0014	0.055	0.55	-4
13	-0.00040	-0.030	0.0015	0.114	0.95	-7
14	-0.00040	-0.030	0.0015	0.114	0.95	-7
15	-0.00042	-0.042	0.0030	0.090	1.0	-5
16	-0.00042	-0.042	0.0030	0.090	1.0	-5

Table E.23: Reservoir storage capacity limits, initial and final storage capacity limits, plant discharge limits, and hydro plant generation limits: Electric power system-VII

Plant (j)	V_j^{min}	V_j^{max}	V_{jI}	V_{jF}	q_j^{min}	q_j^{max}	p_j^{min}	p_j^{max}
	($\times 10^4$ m^3)				($\times 10^4$ m^3/h)		(MW)	(MW)
1	80	150	100	120	5	15	0	100
2	60	120	80	70	6	15	0	100
3	100	240	170	170	10	30	0	100
4	70	160	120	140	13	25	0	100
5	80	150	100	120	5	15	0	100
6	60	120	80	70	6	15	0	100
7	100	240	170	170	10	30	0	100
8	70	160	120	140	13	25	0	100
9	60	120	80	70	6	15	0	100
10	100	240	170	170	10	30	0	100
11	60	120	80	70	6	15	0	100
12	100	240	170	170	10	30	0	100
13	60	120	80	70	6	15	0	100
14	60	120	80	70	6	15	0	100
15	80	150	100	120	5	15	0	100
16	80	150	100	120	5	15	0	100



Plant	1	2	3	4	5	6	7	8
U_j	0	0	2	1	0	0	2	1
t_{rj}	0	0	0	0	0	0	0	0
Plant	9	10	11	12	13	14	15	16
U_j	0	1	0	1	0	0	0	0
t_{rj}	0	0	0	0	0	0	0	0

Figure E.2: Hydraulic system network: Electric power system-VII

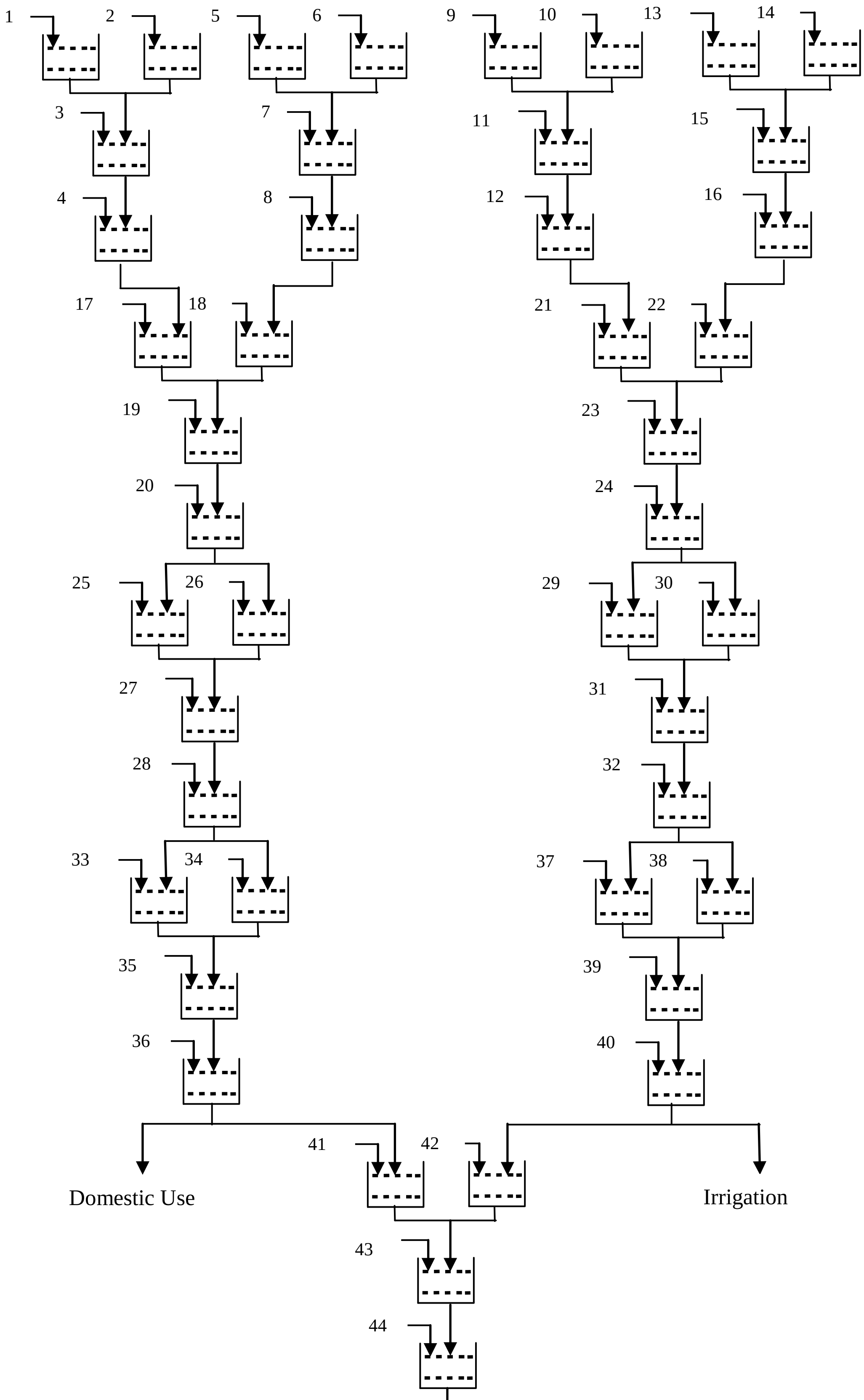
Table E.26: Load demand (MW): Electric power system-VII

k	p_{Dk}	k	p_{Dk}	k	p_{Dk}
1	1374	9	1248	17	1426
2	1278	10	1364	18	1028
3	1372	11	1146	19	1148
4	1058	12	1262	20	1256
5	1358	13	1246	21	1348
6	1282	14	1140	22	1424
7	1130	15	1226	23	1070
8	1200	16	1314	24	1118

Table E.24: Reservoir inflows ($\times 10^4$ m^3/h): Electric power system-VII

k	Reservoir (j)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	10.0	8.0	8.1	2.8	10.0	8.0	8.1	2.8	8.0	23.1	8.0	23.1	8.0	8.0	10.0	10.0
2	9.0	8.0	8.2	2.4	9.0	8.0	8.2	2.4	8.0	15.2	8.0	15.2	8.0	8.0	9.0	9.0
3	8.0	9.0	4.0	1.6	8.0	9.0	4.0	1.6	9.0	17.0	9.0	17.0	9.0	9.0	8.0	8.0
4	7.0	9.0	2.0	0.0	7.0	9.0	2.0	0.0	9.0	11.0	9.0	11.0	9.0	9.0	7.0	7.0
5	6.0	8.0	3.0	0.0	6.0	8.0	3.0	0.0	8.0	9.3	8.0	9.3	8.0	8.0	6.0	6.0
6	7.0	7.0	4.0	0.0	7.0	7.0	4.0	0.0	7.0	9.7	7.0	9.7	7.0	7.0	7.0	7.0
7	8.0	6.0	3.0	0.0	8.0	6.0	3.0	0.0	6.0	12.6	6.0	12.6	6.0	6.0	8.0	8.0
8	9.0	7.0	2.0	0.0	9.0	7.0	2.0	0.0	7.0	12.4	7.0	12.4	7.0	7.0	9.0	9.0
9	10.0	8.0	1.0	0.0	10.0	8.0	1.0	0.0	8.0	6.6	8.0	6.6	8.0	8.0	10.0	10.0
10	11.0	9.0	1.0	0.0	11.0	9.0	1.0	0.0	9.0	8.7	9.0	8.7	9.0	9.0	11.0	11.0
11	12.0	9.0	1.0	0.0	12.0	9.0	1.0	0.0	9.0	8.0	9.0	8.0	9.0	9.0	12.0	12.0
12	10.0	8.0	2.0	0.0	10.0	8.0	2.0	0.0	8.0	12.3	8.0	12.3	8.0	8.0	10.0	10.0
13	11.0	8.0	4.0	0.0	11.0	8.0	4.0	0.0	8.0	11.0	8.0	11.0	8.0	8.0	11.0	11.0
14	12.0	9.0	3.0	0.0	12.0	9.0	3.0	0.0	9.0	12.7	9.0	12.7	9.0	9.0	12.0	12.0
15	11.0	9.0	3.0	0.0	11.0	9.0	3.0	0.0	9.0	8.0	9.0	8.0	9.0	9.0	11.0	11.0
16	10.0	8.0	2.0	0.0	10.0	8.0	2.0	0.0	8.0	9.0	8.0	9.0	8.0	8.0	10.0	10.0
17	9.0	7.0	2.0	0.0	9.0	7.0	2.0	0.0	7.0	9.0	7.0	9.0	7.0	7.0	9.0	9.0
18	8.0	6.0	2.0	0.0	8.0	6.0	2.0	0.0	6.0	13.0	6.0	13.0	6.0	6.0	8.0	8.0
19	7.0	7.0	1.0	0.0	7.0	7.0	1.0	0.0	7.0	9.4	7.0	9.4	7.0	7.0	7.0	7.0
20	6.0	8.0	1.0	0.0	6.0	8.0	1.0	0.0	8.0	6.0	8.0	6.0	8.0	8.0	6.0	6.0
21	7.0	9.0	2.0	0.0	7.0	9.0	2.0	0.0	9.0	9.7	9.0	9.7	9.0	9.0	7.0	7.0
22	8.0	9.0	2.0	0.0	8.0	9.0	2.0	0.0	9.0	7.0	9.0	7.0	9.0	9.0	8.0	8.0
23	9.0	8.0	1.0	0.0	9.0	8.0	1.0	0.0	8.0	10.0	8.0	10.0	8.0	8.0	9.0	9.0
24	10.0	8.0	0.0	0.0	10.0	8.0	0.0	0.0	8.0	5.0	8.0	5.0	8.0	8.0	10.0	10.0

E.8DATA FOR ELECTRIC POWER SYSTEM-VIII



Unit (j)	1,5,9,13	2,6,10,14	3,7,11,15,19,23, 27,31,35,39,43	4,8,12,16,20,24, 28,32,36,40,44	17,21,25,29, 33,37,41	18,22,26,30, 34,38,42
U_j	0	0	2	1	1	1
t_{rj}	2	3	4	0	2	3

Figure E.3: Hydraulic system network: Electric power system-VIII

Electric power system-V consists of 44-hydro and 54-thermal units, having 24-hour scheduling period divided into 24 sub-intervals of 1 hour each. A hydraulic system network along with number of upstream reservoir and time delay between upstream and downside reservoir are shown in Fig E.3. Hydro power generation coefficients are given in Table E.27. A set of operating characteristics of hydro unit and reservoirs inflow are given in Table E.28 and E.29, respectively. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 3-thermal units used in the study undertaken are given in Table E.30 and E.31 respectively. Load demand and loss coefficient for the given study is tabulated in Table E.32.

Table E.27: Hydro unit power generation coefficients: Electric power system-VIII

Unit (j)	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C_{5j}	C_{6j}
1,5,9,13,17,21,25,29,33,37,41	-0.0042	-0.42	0.030	0.90	10.0	-50
2,6,10,14,18,22,26,30,34,38,42	-0.0040	-0.30	0.015	1.14	9.5	-70
3,7,11,15,19,23,27,31,35,39,43	-0.0016	-0.30	0.014	0.55	5.5	-40
4,8,12,16,20,24,28,32,36,40,44	-0.0030	-0.31	0.027	1.44	14.0	-90

Table E.28: Reservoir storage capacity limits, initial and final storage capacity limits, plant discharge limits, and hydro plant generation limits: Electric power system-VIII

Unit (j)	$V_j^{\min}$	$V_j^{\max}$	V_{jI}	V_{jF}	$q_j^{\min}$	$q_j^{\max}$	$p_j^{\min}$	$p_j^{\max}$
	($\times 10^4$ m^3)				($\times 10^4$ m^3/h)		MW	
1,5,9,13	80	150	100	120	5	15	0	500
2,6,10,14	60	120	80	70	6	15	0	500
3,7,11,15	100	240	170	170	10	30	0	500
4,8,12,16	70	160	120	140	13	25	0	500
17,21	100	230	150	160	8	36	0	500
18,22	80	180	130	140	12	36	0	500
19,23	120	370	270	320	10	60	0	500
20,24	130	360	290	310	18	60	0	500
25,29,33,37	140	350	240	260	8	24	0	500
26,30,34,38	100	300	180	200	10	24	0	500
27, 31, 35, 39	270	500	400	400	12	84	0	500
28, 32, 36, 40	200	450	350	360	12	60	0	500
41	100	300	170	200	5	24	0	500
42	100	300	160	180	6	24	0	500
43	170	400	300	300	12	60	0	500
44	100	350	250	280	12	50	0	500

Table E.30: Cost coefficients and operating limits of thermal units: Electric power system-VIII

Unit (i)	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	d_{si} (\$/h)	e_{si} (1/MW)	p_i^{min} (MW)	p_i^{max} (MW)
1	0.00690	6.73	94.705	100	0.084	36	114
2	0.00690	6.73	94.705	100	0.084	36	114
3	0.02028	7.07	309.54	100	0.084	60	120
4	0.00942	8.18	369.03	150	0.063	80	190
5	0.0114	5.35	148.89	120	0.077	47	97
6	0.01142	8.05	222.33	100	0.084	68	140
7	0.00357	8.03	287.71	200	0.042	110	300
8	0.00492	6.99	391.98	200	0.042	135	300
9	0.00573	6.6	455.76	200	0.042	135	300
10	0.00605	12.9	722.82	200	0.042	130	300
11	0.00515	12.9	635.20	200	0.042	94	375
12	0.00569	12.8	654.69	200	0.042	94	375
13	0.00421	12.5	913.40	300	0.035	125	500
14	0.00752	8.84	1760.4	300	0.035	125	500
15	0.00708	9.15	1728.3	300	0.035	125	500
16	0.00708	9.15	1728.3	300	0.035	125	500
17	0.00313	7.97	647.85	300	0.035	220	500
18	0.00313	7.95	649.69	300	0.035	220	500
19	0.00313	7.97	647.83	300	0.035	242	550
20	0.00313	7.97	647.81	300	0.035	242	550
21	0.00298	6.63	785.96	300	0.035	254	550
22	0.00298	6.63	785.96	300	0.035	254	550
23	0.00284	6.66	794.53	300	0.035	254	550
24	0.00284	6.66	794.53	300	0.035	254	550
25	0.00277	7.10	801.32	300	0.035	254	550
26	0.00277	7.10	801.32	300	0.035	254	550
27	0.52124	3.33	1055.1	120	0.077	10	150
28	0.52124	3.33	1055.1	120	0.077	10	150
29	0.52124	3.33	1055.1	120	0.077	10	150
30	0.01140	5.35	148.89	120	0.077	47	97
31	0.00160	6.43	222.92	150	0.063	60	190
32	0.00160	6.43	222.92	150	0.063	60	190
33	0.00160	6.43	222.92	150	0.063	60	190
34	0.0001	8.95	107.87	200	0.042	90	200
35	0.0001	8.62	116.58	200	0.042	90	200
36	0.0001	8.62	116.58	200	0.042	90	200
37	0.0161	5.88	307.45	80	0.098	25	110
38	0.0161	5.88	307.45	80	0.098	25	110
39	0.0161	5.88	307.45	80	0.098	25	110
40	0.00313	7.97	647.83	300	0.035	242	550

Table E.30: Cost coefficients and operating limits of thermal units: Electric power system-VIII (Continued)

Unit (i)	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	d_{si} (\$/h)	e_{si} (1/MW)	p_i^{min} (MW)	p_i^{max} (MW)
41	0.00028	8.10	550	300	0.035	0	680
42	0.00056	8.10	309	200	0.042	0	360
43	0.00056	8.1	307	200	0.042	0	360
44	0.00324	7.74	240	150	0.063	60	180
45	0.00324	7.74	240	150	0.063	60	180
46	0.00324	7.74	240	150	0.063	60	180
47	0.00324	7.74	240	150	0.063	60	180
48	0.00324	7.74	240	150	0.063	60	180
49	0.00324	7.74	240	150	0.063	60	180
50	0.00284	8.6	126	100	0.084	40	120
51	0.00284	8.6	126	100	0.084	40	120
52	0.00284	8.6	126	100	0.084	55	120
53	0.00284	8.6	126	100	0.084	40	120
54	0.00284	8.6	126	100	0.084	40	120

Table E.29: Reservoir inflows (×10^4 m^3/h): Electric power system-VIII

Unit (j)	Sub-interval (k)											
	1	2	3	4	5	6	7	8	9	10	11	12
1,5,9,13,17,21	10	9	8	7	6	7	8	9	10	11	12	10
2,6,10,14,18,22	8	8	9	9	8	7	6	7	8	9	9	8
3,7,11,15,27,31,35,39,43	8.1	8.2	4	2	3	4	3	2	1	1	1	2
4,8,12,16,20,24	2.8	2.4	1.6	0	0	0	0	0	0	0	0	0
19,23	16.2	16.4	8	4	6	8	6	4	2	2	2	4
28,32,36,40,44	1.4	1.2	0.8	0	0	0	0	0	0	0	0	0
25,29	1	1	0	0	1	0	0	0	0	0	0	0
26,30,33,34,37,38,41,42	0	0	0	0	0	0	0	0	0	0	0	0
Unit (j)	Sub-interval (k)											
	13	14	15	16	17	18	19	20	21	22	23	24
1,5,9,13,17,21	11	12	11	10	9	8	7	6	7	8	9	10
2,6,10,14,18,22	8	9	9	8	7	6	7	8	9	9	8	8
3,7,11,15,27,31,35,39,43	4	3	3	2	2	2	1	1	2	2	1	0
4,8,12,16,20,24,25,26,28,29,30,32,33,34,36,37,38,40,41,42,44	0	0	0	0	0	0	0	0	0	0	0	0
19,23	8	6	6	4	4	4	2	2	4	4	2	1

Table E.31: Emission coefficients and operating limits of thermal units: Electric power system-VIII

Unit (i)	α_i (ton/MW^{2}h)	β_i (ton/MWh)	γ_i (ton/h)	η_i (ton/h)	δ_i (1/MW)
1	0.0480	-2.20	60	1.31	0.0569
2	0.0480	-2.20	60	1.31	0.0569
3	0.0762	-2.36	100	1.31	0.0569
4	0.0540	-3.14	120	0.9142	0.0454
5	0.0850	-1.89	50	0.9936	0.0406
6	0.0854	-3.08	80	1.31	0.0569
7	0.0242	-3.06	100	0.655	0.02846
8	0.0310	-2.32	130	0.655	0.02846
9	0.0335	-2.11	150	0.655	0.02846
10	0.4250	-4.34	280	0.655	0.02846
11	0.0322	-4.34	220	0.655	0.02846
12	0.0338	-4.28	225	0.655	0.02846
13	0.0296	-4.18	300	0.5035	0.02075
14	0.0512	-3.34	520	0.5035	0.02075
15	0.0496	-3.55	510	0.5035	0.02075
16	0.0496	-3.55	510	0.5035	0.02075
17	0.0151	-2.68	220	0.5035	0.02075
18	0.0151	-2.66	222	0.5035	0.02075
19	0.0151	-2.68	220	0.5035	0.02075
20	0.0151	-2.68	220	0.5035	0.02075
21	0.0145	-2.22	290	0.5035	0.02075
22	0.0145	-2.22	285	0.5035	0.02075
23	0.0138	-2.26	295	0.5035	0.02075
24	0.0138	-2.26	295	0.5035	0.02075
25	0.0132	-2.42	310	0.5035	0.02075
26	0.0132	-2.42	310	0.5035	0.02075
27	1.8240	-1.11	360	0.9936	0.04060
28	1.8240	-1.11	360	0.9936	0.04060
29	1.8240	-1.11	360	0.9936	0.04060
30	0.0850	-1.89	50	0.9936	0.04060
31	0.0121	-2.08	80	0.9142	0.04540
32	0.0121	-2.08	80	0.9142	0.04540
33	0.0121	-2.08	80	0.9142	0.04540
34	0.0120	-3.48	65	0.6550	0.02846
35	0.0120	-3.24	70	0.6550	0.02846
36	0.0120	-3.24	70	0.6550	0.02846
37	0.0950	-1.98	100	1.42	0.0677
38	0.0950	-1.98	100	1.42	0.0677
39	0.0950	-1.98	100	1.42	0.0677
40	0.0151	-2.68	220	0.5035	0.02075
41	0.0151	-2.68	220	0.5035	0.02075

Table E.31: Emission coefficients and operating limits of thermal units: Electric power system-VIII (Continued)

Unit (i)	α_i (ton/MW^{2}h)	β_i (ton/MWh)	γ_i (ton/h)	η_i (ton/h)	δ_i (1/MW)
42	0.0151	-2.68	220	0.5035	0.02075
43	0.0151	-2.68	220	0.5035	0.02075
44	0.0151	-2.68	220	0.5035	0.02075
45	0.0151	-2.68	220	0.5035	0.02075
46	0.0151	-2.68	220	0.5035	0.02075
47	0.0151	-2.68	220	0.5035	0.02075
48	0.0151	-2.68	220	0.5035	0.02075
49	0.0151	-2.68	220	0.5035	0.02075
50	0.0151	-2.68	220	0.5035	0.02075
51	0.0151	-2.68	220	0.5035	0.02075
52	0.0151	-2.68	220	0.5035	0.02075
53	0.0151	-2.68	220	0.5035	0.02075
54	0.0151	-2.68	220	0.5035	0.02075

Table E.32: Load demand (MW): Electric power system-VIII

k	p_{Dk}	k	p_{Dk}	k	p_{Dk}
1	18166.90	9	19437.00	17	19917.10
2	18198.00	10	20426.60	18	20033.50
3	17921.10	11	19936.50	19	20427.40
4	17944.40	12	20500.50	20	20398.00
5	18257.40	13	20296.60	21	20157.90
6	18472.40	14	20281.50	22	19709.00
7	18971.00	15	19755.00	23	19426.80
8	19389.40	16	20170.60	24	19266.30

E.9 DATA FOR ELECTRIC POWER SYSTEM-IX

Electric power system-IX consists of 3-hydro and 4-thermal units, having 1-year scheduling period divided into 12 sub-intervals of 1 month each. A set of operating characteristics of hydro unit is given in Table E.33. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 4-thermal units used in the study undertaken are given in Table E.34. Load demand and loss coefficient for the given study is tabulated in Table E.35.

Table E.33: Operating characteristics of 3-hydro unit: Electric power system-IX

Hydro unit (j)	1	2	3
H_{j0} (m)	0.98	0.50	0.75
g_j water head correction factor	0.004	0.002	0.004
Q_j non-effective water discharge	0.0	0.0	0.0
V_{jI} (m^3/month)	100	150	100
V_{jF} (m^3/month)	100	150	100
q_j^{max} (m^3/month)	73	75	80
q_j^{min} (m^3/month)	3.334	4.353	3.543
p_j^{max} (MW)	89.03	57.61	75
p_j^{min} (MW)	0	0	0

Table E.34: Operating characteristics of 4-thermal unit: Electric power system-IX

Thermal Unit	Operating unit coefficients			Emission Coefficients		
(i)	a_{si} (Rs/MW^{2}h)	b_{si} (Rs/MWh)	c_{si} (Rs/h)	α_i (kg/MW^{2}h)	β_i (kg/MWh)	γ_i (kg/h)
1	0	0.10	2.5	0.00767	0.80507	363.7048
2	0	0.12	2.6	0.00767	0.80507	363.7048
3	0	0.16	2.8	0.01378	-1.24885	137.3701
4	0	0.16	2.8	0.01378	-1.24885	137.3701

Table E.35: Load demand (MW): Electric power system-IX

Month (k)	p_{Dk}	Month (k)	p_{Dk}	Month (k)	p_{Dk}
1	200	5	195	9	189
2	210	6	200	10	199
3	205	7	220	11	207
4	180	8	204	12	198

The loss coefficient loss matrix is given below:

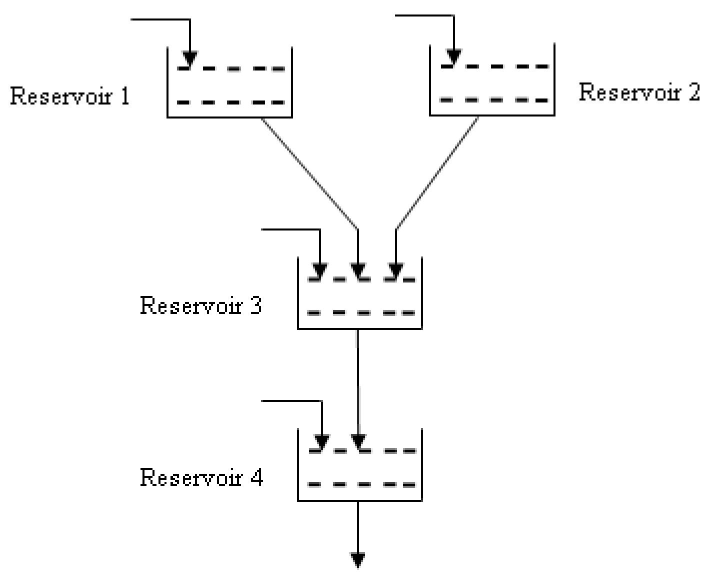
$$\begin{bmatrix} 0.0005 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0005 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0008 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0008 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0007 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0007 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0009 \end{bmatrix}$$

E.10 DATA FOR ELECTRIC POWER SYSTEM-X

Electric power system-X consists of 4-hydro and 1-thermal units, having 1-year scheduling period divided into 52 sub-intervals of 1 week each. A hydraulic system network along with number of upstream reservoir and time delay between upstream and downside reservoir are shown in Fig E.4. Hydro power generation coefficients are given in Table E.36. A set of operating characteristics of hydro unit and reservoirs inflow are given in Table E.37 and E.38, respectively. Thermal unit cost coefficients and gaseous pollutant emission coefficients of 1-thermal units used in the study undertaken are given in Table E.39 and E.40 respectively. Load demand and loss coefficient for the given study is tabulated in Table E.41.

Table E.36: Hydro power generation coefficients: Electric power system-X

Unit (j)	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C_{5j}	C_{6j}
1	-0.0042	-0.42	0.030	0.90	10.0	-50
2	-0.0040	-0.30	0.015	1.14	9.5	-70
3	-0.0016	-0.30	0.014	0.55	5.5	-40
4	-0.0030	-0.31	0.027	1.44	14.0	-90



Plant	1	2	3	4
U_j	0	0	2	1
t_{rj}	0	0	0	0

Figure E.4: Hydraulic system network: Electric power system-X

Table E.37: Reservoir storage capacity limits, initial and final storage capacity limits, plant discharge limits, and hydro plant generation limits: Electric power system-X

Unit (j)	V_j^{min}	V_j^{max}	V_{jI}	V_{jF}	q_j^{min}	q_j^{max}	p_j^{min}	p_j^{max}
	($\times 10^4$ m^3)				($\times 10^4$ m^3/h)		(MW)	(MW)
1	0	200	100	100	0	30	0	500
2	0	200	100	100	0	30	0	500
3	0	350	150	150	0	40	0	500
4	0	350	150	150	0	40	0	500

Table E.38: Reservoir inflows ($\times 10^4$ m^3/h): Electric power system-X

Sub-interval (k)	Reservoir 1	2	3	4	Sub-interval (k)	Reservoir 1	2	3	4	Sub-interval (k)	Reservoir 1	2	3	4
1	12	6	3	3	19	9.8	8	7.6	0	37	9.9	10.0	3.0	0
2	12	6	4	2	20	9.7	7.9	7.0	0	38	10.0	10.0	3.0	0
3	11.8	6.5	5	1	21	9.6	7.6	6.0	0	39	10.5	10.0	2.0	0
4	11.7	6.7	6	0	22	9.4	7.5	5.5	0	40	10.7	9.8	2.2	0
5	11.7	6.8	7	0	23	9.0	7.5	4.0	0	41	10.9	9.6	2.3	0
6	11.6	6.9	8	0	24	8.5	7.4	3.0	0	42	11.0	9.5	2.4	0
7	11.5	7	8.8	0	25	8.7	7.0	2.0	0	43	11.5	9.3	2.5	0
8	11.4	7.2	8.9	0	26	8.5	7.0	1.0	0	44	11.7	9.2	3.0	0
9	11.3	7.3	9	0	27	8.0	7.3	1.0	0	45	11.9	9.0	3.5	0
10	11.2	7.5	8.98	0	28	8.0	7.4	2.0	0	46	11.7	8.5	3.5	0
11	11	7.8	8.7	0	29	8.5	7.7	1.0	0	47	11.8	8.0	4.0	0
12	11	7.7	8.6	0	30	8.7	8.0	2.0	0	48	12.0	7.5	4.0	0
13	10.9	7.9	8.5	0	31	8.8	8.5	1.0	0	49	12.0	7.0	3.5	0
14	10.85	8.0	8.4	0	32	9.0	9.0	1.2	0	50	12.0	6.5	3.5	1.0
15	10.7	8.2	8.3	0	33	9.2	9.2	1.3	0	51	12.0	6.0	3.0	2.0
16	10.6	8.4	8.2	0	34	9.3	9.5	1.5	0	52	12.0	6.0	4.0	3.0
17	10.5	8.3	8.0	0	35	9.5	9.7	2.0	0					
18	10	8.2	8.2	0	36	9.7	9.9	2.5	0					

Table E.39: Cost coefficients and operating limits of thermal units: Electric power system-X

Unit (i)	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	p_i^{min} (MW)	p_i^{max} (MW)
1	0.0120	14.994	24.587	0	1000

Table E.40: Emission coefficients of thermal units: Electric power system-X

Unit (i)	α_i (lb/MW^{2}h)	β_i (lb/MWh)	γ_i (lb/h)
1	0.0105	-1.355	60

Table E.41: Load demand (MW): Electric power system-X

k	p_{Dk}	k	p_{Dk}	k	p_{Dk}
1	870	19	890	37	785
2	890	20	890	38	790
3	900	21	885	39	790
4	910	22	880	40	810
5	910	23	870	41	820
6	900	24	870	42	830
7	910	25	865	43	840
8	900	26	850	44	820
9	890	27	850	45	820
10	885	28	850	46	825
11	880	29	845	47	830
12	875	30	845	48	830
13	875	31	840	49	835
14	877	32	840	50	830
15	880	33	820	51	830
16	882	34	780	52	840
17	885	35	770		
18	890	36	780		

E.11 DATA FOR ELECTRIC POWER SYSTEM-XI

Electric power system-XI consists of 2-hydro and 2-thermal units, having 24-hours scheduling period divided into 24 sub-intervals of 1 hour each. A set of operating characteristics of hydro units are given in Table E.42. The thermal unit cost and emission coefficient are given in Table E.43. Load demand and loss coefficients for the given study are tabulated in Table E.44.

Table E.42: Operating characteristics of 2-hydro unit: Electric power system-XI

Hydro unit (j)	h_{21j} (Mm^3/MW^{2}h)	h_{22j} (Mm^3/MWh)	h_{23j} (Mm^3/h)	$K_j^{'}$ Factor	P_j^{min} (MW)	P_j^{max} (MW)	V_{jF} (Mm^3)
1	6.116×10^{-6}	8.66494×10^{-3}	5.606727×10^{-2}	1	0	1000	71
2	1.0194×10^{-5}	1.732988×10^{-2}	2.650452×10^{-2}	1	0	1000	60

Table E.43: Operating characteristics of 2-thermal unit: Electric power system-XI

Thermal Unit (i)	Operating unit coefficients			Emission coefficients			p_i^{min} (MW)	p_i^{max} (MW)
	a_{si} (\$/MW^{2}h)	b_{si} (\$/MWh)	c_{si} (\$/h)	α_i (kg/MW^{2}h)	β_i (kg/MWh)	γ_i (kg/h)		
1	0.00250300	3.20128	25.0	0.00649078	-0.7905861	28.82488	0	1000
2	0.00080096	3.40136	30.0	0.00649078	-0.7905861	28.82488	0	1000

Table E.44: Load demand: Electric power system-XI

Sub-interval (k)	P_{Dk} (MW)	Sub-interval (k)	P_{Dk} (MW)	Sub-interval (k)	P_{Dk} (MW)
1	400.00	9	1230.0	17	1350.0
2	300.00	10	1250.0	18	1470.0
3	250.00	11	1350.0	19	1330.0
4	250.00	12	1400.0	20	1250.0
5	250.00	13	1200.0	21	1170.0
6	300.00	14	1250.0	22	1050.0
7	450.00	15	1250.0	23	900.0
8	900.00	16	1270.0	24	600.0

The loss coefficient loss matrix is given below:

$$\begin{bmatrix} 0.0001401 & 0.0000100 & 0.0000150 & 0.0000150 \\ 0.0000100 & 0.0000600 & 0.0000100 & 0.0000130 \\ 0.0000150 & 0.0000100 & 0.0000680 & 0.0000650 \\ 0.0000150 & 0.0000130 & 0.0000650 & 0.0000700 \end{bmatrix}$$

CURRICULUM VITAE OF AUTHOR

1. **Name:** Nitin Narang
2. **Father's name:** Shri. A. K. Narang
3. **Date of Birth:** August 04, 1976
4. **Academic Background:**

	Degree	Specialization	University	Year
i.	B. E.	Electrical Engineering	MITS, Gwalior	1998
ii.	M. Tech	Electrical Engineering	IIT, Chennai	2000

5. **Publications:** (Related to Ph.D. Work)

International Journals

1. **Nitin Narang, J.S. Dhillon and D.P. Kothari**, Multi-objective Short-term Hydrothermal Generation Scheduling Using Predator-prey Optimization, *Electric Power Components and Systems*, vol. 40, no. 15, 2012, pp. 1708-1730.
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