

Thesis

on

# **Generation Scheduling of Coordinated Power System Using Heuristic Optimization Technique**

Submitted in fulfillment of the requirements

of

**DOCTOR OF PHILOSOPHY**

*Submitted by*

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June, 2024

*Dedicated to*  
*My*  
*Respected Father*  
**S. Kewal Singh**  
*and*  
*Respected Mother*  
**Smt. Sudesh Kumari**

## CERTIFICATE

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Certified that the thesis entitled, "**Generation Scheduling of Coordinated Power System Using Heuristic Optimization Technique**", which is being submitted by Arunpreet Kaur in fulfillment of the requirements for the award of the degree of **Doctor of Philosophy**, to the Department of Electrical and Instrumentation Engineering, Thapar Institute of Engineering & Technology, Patiala, is a bonafide records of the candidate's own work carried out by her under our supervision and guidance.

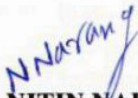
The matter contained in this thesis has not submitted, neither in part or in full to any other university or institute for the award of any degree.



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**ARUNPREET KAUR**

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# NOMENCLATURE

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The main symbols and notations used in this thesis are listed below. Sometimes a symbol may have alternate meaning, but in such a case, the context is sufficient to avoid confusion.

## Indices

$i$	Index for the total number of generating units
$j$	Index for the cogeneration unit
$k$	Index for heat unit
$l$	Index for hydro unit
$m$	Index for solar unit
$t$	Index for sub-interval (hour)
$it$	Current iteration

## Input Data

$N^{TH}, N^{HY}, N^{CHP}, N^H, N^{PV}$

$T$

$it^{max}$ ,

$N^P, N^D, N^{OB}$

$C_{1i}(PT_{it})$

$C_{2j}(PC_{jt}, HC_{jt})$

$C_{3k}(H_{kt})$

$C_{4m}(PS_{mt})$

$E_{1i}(PT_{it})$

$E_{2j}(PC_{jt}, HC_{jt})$

$E_{3k}(H_{kt})$

$PT_{it}$

$PC_{jt}$

$HC_{jt}$

$H_{kt}$

$q_{lt}$

$PH_{lt}$

$PS_{mt}$

$V_{lt}$

$PT_i^{\min}, PT_i^{\max}$

$PC_j^{\min}, PC_j^{\max}$

$HC_j^{\min}, HC_j^{\max}$

$H_k^{\min}, H_k^{\max}$

$q_l^{\min}, q_l^{\max}$

$PH_l^{\min}, PH_l^{\max}$

$V_l^{\min}, V_l^{\max}$

$V_l^{ini}, V_l^{fin}$

$IN_{lt}$

$S_{lt}$

$\tau_{ml}$

$UP_l$

$a_i, b_i, c_i, d_i, e_i$

$\alpha_k, \beta_k, \gamma_k$

## Description

Total number of thermal, hydro, CHP, heat, PV units

Time-interval

Time interval, maximum iterations,

Population size, decision variables, objective functions

Cost function of thermal units

Cost function of CHP units

Cost function of heat units

Cost functions of PV units

Emission function of thermal units

Emission function of CHP units

Emission function of heat units

Power output of  $i^{th}$  thermal unit at  $t^{th}$  sub-interval

Power output of  $j^{th}$  CHP unit at  $t^{th}$  sub-interval

Heat output of  $j^{th}$  CHP unit at  $t^{th}$  sub-interval

Heat output of  $k^{th}$  heat unit at  $t^{th}$  sub-interval

Water discharge rate at  $l^{th}$  hydro unit at the  $t^{th}$  sub-interval

Power output of  $l^{th}$  hydro unit at the  $t^{th}$  sub-interval

Power output of  $m^{th}$  PV units at  $t^{th}$  sub-interval

Reservoir volume stored at  $l^{th}$  hydro unit at  $t^{th}$  sub-interval

Power output limits of  $i^{th}$  thermal unit

Power output limits of  $j^{th}$  CHP unit

Heat output limits of  $j^{th}$  CHP unit

Heat output limits of  $k^{th}$  heat unit

Water discharge rate limits of  $l^{th}$  hydro unit

Power output limits of  $l^{th}$  hydro unit

Reservoir volume limits of  $l^{th}$  hydro unit

Initial and final sub-interval reservoir volume at  $l^{th}$  hydro unit

Inflow of  $l^{th}$  hydro unit at  $t^{th}$  sub-interval

Spillage discharge rate of the  $l^{th}$  hydro unit at  $t^{th}$  sub-interval

Water transportation delay from  $m^{th}$  to  $l^{th}$  hydro unit

Upstream reservoirs from  $l^{th}$  hydro unit

Cost coefficients of  $i^{th}$  thermal unit

Fuel cost coefficients of  $k^{th}$  heat unit

## NOMENCLATURE (Continued)

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$\varepsilon_j, \varphi_j, \eta_j, \mu_j, \delta_j, \zeta_j$	Fuel cost coefficients of $j^{\text{th}}$ CHP unit
$C_{1l}, C_{2l}, C_{3l}, C_{4l}, C_{5l}, C_{6l}$	Coefficients of power output of $l^{\text{th}}$ hydro unit
$a_{l_i}, b_{l_i}, c_{l_i}, d_{l_i}, e_{l_i}$	Emission coefficients of $l^{\text{th}}$ thermal unit
$\varepsilon_{l_j}, \varphi_{l_j}$	Emission coefficients of $j^{\text{th}}$ CHP unit
$\alpha_{l_k}, \beta_{l_k}$	Emission coefficients of $k^{\text{th}}$ heat unit
$K_m$	Per unit cost of $m^{\text{th}}$ PV unit
$U_{mt}$	On/off (0/1) status of $m^{\text{th}}$ PV unit at $t^{\text{th}}$ sub-interval
$P_m^{\text{rated}}$	Rated power of PV units
$T^{\text{ref}}$ and $T^{\text{amb}}$	Reference and ambient temperature
$\alpha$	Temperature coefficient
$SR^{\text{in}}$	Incident solar radiation
$S^{\text{share}}$	Solar share
$X_{dt}$	$d^{\text{th}}$ decision variable at $t^{\text{th}}$ sub-interval
$X_d^{\text{min}}, X_d^{\text{max}}$	Bounds on $d^{\text{th}}$ decision variable
$P_{mt}$	Power generation of $m^{\text{th}}$ power unit at $t^{\text{th}}$ sub-interval
$PT_{\text{dep}}^t$	Power output of the dependent unit at $t^{\text{th}}$ sub-interval
$H_{\text{dep}}^t$	Heat output of the dependent heat unit at $t^{\text{th}}$ sub-interval
$PD_t$	Power demand at $t^{\text{th}}$ sub-interval
$HD_t$	Heat demand at $t^{\text{th}}$ sub-interval
$PL_t$	Transmission loss at $t^{\text{th}}$ sub-interval
$B_{mn}, B_{Omt}, B_{oo}$	Transmission loss coefficients
$EP_t^{\text{DEP}}, EH_t^{\text{DEP}}$	Error for dependent power and heat unit
$EV_1^{\text{FI}}$	Error for final reservoir volume
$EVO_{lt}, EPH_{lt}$	Error for reservoir volume and hydro power of $l^{\text{th}}$ hydro unit at $t^{\text{th}}$ sub-interval
$r$	Exterior penalty factor
$X_P, X_{GW}$	Position of prey and grey wolf
$Z$	Encircling strategy of grey wolves
$z$	Control parameter of the GWO algorithm
$A, B$	Coefficient vectors of GWO algorithm
$X_{1d}, X_{2d}, X_{3d}$	Positions by Cauchy, Gaussian and opposition-based mutation, respectively
$cau(0,s)$	Random number based on the Cauchy distribution
$gau(0,h)$	Random number based on the Gaussian distribution
$s$	Control parameter of the Cauchy distribution
$h$	Standard deviation of the Gaussian distribution
$rand, R_1, R_2, \eta$	Uniformly distributed random number between [0, 1]
$\Gamma$	Gamma function
$pd$	Discovery probability of QCSA algorithm
$S_{it}$	Step size of $it^{\text{th}}$ iteration
$\alpha, \beta, \delta$	Scaling factor, distribution factor ( $1 \leq \beta \leq 2$ ), learning regulator factor of QCSA algorithm
$p, q$	Normally distributed random numbers with variance $\sigma p$ and $\sigma q = 1$
$X_{gb}$	Current best solution
$X_x, X_y$	Randomly chosen positions from the population
$\bar{X}$	Mean of positions

## NOMENCLATURE (Continued)

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$\psi(\gamma)$	Wave function
$ \psi(\gamma) ^2$	Probability density function
$L$	Distance between the current nest position and mean position
$c_1, c_2$	Chaotic tent map sequence
$\mu(F_d)$	Membership function
$\mu_d$	Cardinal priority ranking

# GLOSSARY OF ACRONYMS

Acronym	Description
ABC	Artificial bee colony
AIS	Artificial immune system
BA	Bat algorithm
BCO	Bee colony optimization
BD	Benders decomposition
CHP	Combined heat and power
CHPGS	Combined heat and power generation scheduling
CHP-PV-GS	Combined heat and power-photo-voltaic generation scheduling
CPS	Coordinated power system
CPSGS	Coordinated power system generation scheduling
CO	Crisscross optimization
CPR	Cardinal priority ranking
CSA	Cuckoo search algorithm
CTM	Chaotic tent map
CTM-QCSA-GWO	Chaotic tent map- quantum-cuckoo search algorithm- grey wolf optimizer
CSO	Civilized swarm optimization
DE	Differential evolution
DP	Dynamic programming
ELD	Economic load dispatch
EP	Evolutionary programming
FOR	Feasible operating region
GA	Genetic algorithm
GS	Generation scheduling
GSA	Gravitational search algorithm
GSO	Group search optimization
GWO	Grey wolf optimizer
GWO-MS	Grey wolf optimizer-mutation strategies
HDE	Hybrid differential evolution
HSA	Harmony search algorithm
HT	Hydro-thermal
HTGS	Hydro-thermal generation scheduling
LR	Lagrangian relaxation
MCDE	Modified chaotic differential evolution
MCSA	Modified cuckoo search algorithm
MDE	Modified differential evolution
MHDE	Modified hybrid differential evolution
MIP	Mixed integer programming
MO	Multi-objective
MOABC	Multi-objective artificial bee colony
MOCDE	Multi-objective cultural differential evolution
MODE	Multi-objective differential evolution
MOGS	Multi-objective generation scheduling
MOGSA	Multi-objective gravitational search algorithm
MOP	Multi-objective problem
MO-CHPGS	Multi-objective combined heat and power generation scheduling
MO-HTGS	Multi-objective hydro-thermal generation scheduling

## GLOSSARY OF ACRONYMS (Continued)

Acronym	Description
MS	Mutation strategies
NFLT	No free lunch theorem
NSGA	Non-dominated sorting genetic algorithm
ORCCRO	Opposition real coded chemical reaction-based optimization
OTLBO	Oppositional teaching learning-based optimization
PPO	Predator-prey optimization
PPS	Powell's pattern search
PSO	Particle swarm optimization
PV	Photo-voltaic
RC	Real coded
RCGA	Real coded genetic algorithm
RCCRO	Real coded chemical reaction-based optimization
SA	Simulated annealing
SOP	Single-objective problem
SQP	Sequential quadratic programming
TLBO	Teaching learning-based optimization
TVAC	Time-varying acceleration coefficient
QOBL	Quasi-opposition-based learning
QPSO	Quantum-particle swarm optimization
QCSA	Quantum-cuckoo search algorithm
QCSA-GWO	Quantum-cuckoo search algorithm-grey wolf optimizer
QCSA-MS	Quantum-cuckoo search algorithm-mutation strategies

## ABSTRACT

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The modern electrical power system focuses on acquiring an economical and environmentally favourable operation with high operating efficiency. The optimum generation scheduling is an essential research study for economic operation of power system. The primary objective of generation scheduling (GS) problem is to allocate the load demand to the generating units with minimal fuel cost while satisfying all the operational constraints. In the existing power system, thermal power generation contributes to the significant amount of total power generation in the world. However, power generation plants using fossil fuels release pollutant emissions in the atmosphere. Thus, reducing the pollutant emissions along with cost-effective power generation is one of the foremost challenges for electric utilities. The combined heat and power (CHP) generation (or cogeneration) has been proven very efficient not only due to the concurrent production of heat and electricity from a single source of fuel but also because of high fuel conversion efficiency, saving the generation cost and reducing the greenhouse gas emissions as compared to thermal plants. Thus, CHP units have been considered as a promising substitute for conventional thermal power units for saving fuel and protecting the environment. Referable to the huge requirement of high temperature for hot water in the household and industrial fields, heat units can be incorporated along with CHP units to fulfil the heat demand.

The increasing concern for global warming and environment-friendly energy requirement has prompted the utilization of high-efficiency renewable energy sources like solar, wind and hydro power in the energy sector. Though renewable energy sources provide pollution-free energy but the power generation capacity is comparatively less and these alone may not supply sufficient power to the electric load. Hydro plants are extensively preferred due to their competence to fulfill peak load demand, insignificant pollutant emissions, and fuel costs. However, due to uncertainty and reliability concerns of hydro resources, it is difficult to rely solely on hydro units to provide all the electrical energy demand. Thus, the hydro plants must coordinate with other reliable energy sources like thermal, CHP and heat units to fulfill the power and heat demands at minimum

operating cost and pollutant emissions. To achieve the maximum utilization of all the energy sources economically, the use of an interconnected or coordinated power system (CPS) is beneficial to the suppliers and society. Since simultaneously minimizing the fuel cost and pollutant emissions are conflicting in nature, hence, the problem is treated as a multi-objective (MO) generation scheduling problem.

Researchers have investigated conventional or mathematical and global search techniques for searching the optimum generation schedule of the CPS for achieving economic and environmental benefits. The conventional optimization techniques undertake a few assumptions to solve the optimization problem and able to search only local optimal solutions and these are not able to find the global best solution. The conventional techniques are effective to solve differentiable and continuous optimization problems and may fail to perform for solving complex, discontinuous, non-differentiable, non-linear, non-convex and large-scale problems, since the search space increases exponentially with the size of the problem. Due to these limitations of conventional techniques, researchers have given more attention to the global search optimization techniques. The performance of global search optimization techniques is superior to conventional optimization techniques in terms of better exploration capability, robustness, derivative-free nature and avoiding local optima. Thus, these can be applied to solve non-differential and discontinuous optimization problems. Despite the numerous advantages of global search techniques, these techniques still lack in exploitation capability and have high computational complexity when applied to solve complex, multi-dimensional and multi-modal optimization problems. Considering the ‘no free lunch theorem (NFLT)’ which says that no single optimization technique can optimally resolve all the optimization problems, the researchers have proposed and implemented hybrid/modified optimization techniques to solve complex multi-dimensional optimization problems. The hybrid/modified optimization techniques may be more efficient, flexible and effective for attaining better performance for complex optimization problems. Moreover, hybrid optimization techniques maintain a balance between exploration and exploitation abilities.

The intent of the thesis is to formulate the single and MO coordinated power system generation scheduling (CPSGS) problem incorporating thermal, CHP, heat and hydro units. The CHP-photo-voltaic (PV) generation scheduling (CHP-PV-GS) problem has also been formulated considering CHP, heat, and PV units. The CPSGS, MO-CPSGS and CHP-PV-GS scheduling problems are high constrained, complex, non-convex, multi-modal, multi-dimensional optimization problems. Thus, three heuristic optimization techniques have been proposed and implemented to these problems. The effectiveness of the proposed optimization techniques has been validated by using small, medium, and large-sized test systems. The results obtained by the proposed optimization techniques have been compared with the reported results and found satisfactory.

The thesis work is organized into seven chapters. The brief discussion regarding each chapter is given as follows:

The Chapter-1 reviews the significant contributions of researchers to single-objective and MO hydro-thermal generation scheduling (HTGS), combined heat and power generation scheduling (CHPGS) and CPSGS problems. The computational and theoretical backgrounds of conventional and global search optimization techniques and their implementation to optimization problems have been presented. A brief introduction and implementation of hybrid and MO optimization techniques is also presented.

In Chapter-2, the CPSGS problem is formulated. For solving the CPSGS problem, a heuristic optimization technique- I, i.e., grey wolf optimizer (GWO) with mutation strategies (MS) (GWO-MS) is proposed. In proposed optimization technique (POT)-I, the GWO is used for its best exploitation ability and three mutation strategies, i.e., Cauchy, Gaussian and opposition based-mutation have been used to enhance the exploration and exploitation. The POT-I have been tested on four test systems, considering one HTGS and three CPSGS problems and the results have been compared with the other well-established techniques. The results attained by POT-I illustrate that it is better than the state-of-art techniques. To validate the statistical performance of the POT-I, t-

test and Mann-Whitney tests have been performed on all the test systems, which shows the superiority of POT-I over traditional GWO technique.

In Chapter-3, a heuristic optimization technique-II, i.e., quantum-cuckoo search algorithm (QCSA) with MS (QCSA-MS) has been proposed. The POT-II integrated QCSA technique with three mutation strategies, i.e., Cauchy, Gaussian and opposition-based mutation. The QCSA has been used to explore the search space due to its excellent exploration quality and MS has been used for enhancing the good exploitation of the algorithm, which makes it a well-balanced algorithm for solving the complex optimization problem. The POT-II has been implemented to HTGS and CPSGS problems. The POT-II outperforms the QCSA technique in terms of outcomes, convergence characteristics, and distribution diversity. The POT-II achieved significant economic cost while dealing with complex joint constraints of CPSGS problem as compared to optimal cost obtained by QCSA, GWO and POT-I and other established methods. Further, statistical t-test confirms the robustness of the POT-II.

In Chapter-4, a heuristic optimization technique-III namely chaotic tent map (CTM) based QCSA with GWO (CTM-QCSA-GWO) has been proposed for finding an optimal solution to the CPSGS problem. The POT-III fully utilizes the diversification ability of QCSA to explore a broader range of search space and exploitation ability of GWO for searching the optimal result by enhanced convergence rate. Further CTM strategy has been applied to hybrid QCSA-GWO technique to reduce the dependency on algorithm parameters and to improve the solution quality and the convergence speed. Three test systems of generation scheduling problems verify the performance of the POTs and the results are compared with published results. The outcomes of the POT-III are compared with the results obtained by the GWO, QCSA, POT-I and II and found satisfactory and cost-effective. Further, the POT-III is validated by t-test to investigate statistical performance.

In Chapter-5, the CHP-PV-GS problem is formulated including thermal, CHP, heat and PV units. The CHPGS and CHP-PV-GS problems are solved using POT-II and III. The

incorporation of PV units with thermal, CHP and heat units significantly saves the fuel cost. The results obtained by POT-III are better than results obtained of GWO, QCSA, QCSA-GWO and POT-II.

In Chapter-6, the MO-CPSGS problem has been formulated considering fuel cost and emission as two objectives to be minimized simultaneously. The POT-II and III have been applied to three test systems, including the MO-HTGS and small and medium-sized MO-CPSGS problems, to demonstrate their applicability and efficacy. The cardinal priority method has been utilized for searching the most satisfying non-dominated solution. All the test systems have been solved for three cases, i.e., economic generation, emission generation scheduling and MO generation scheduling. The POT-II and III outperformed the published findings from recent contemporary techniques. Further, the POT-III outperforms the POT-II.

Finally, the Chapter-7 concludes the contributions, and future scope of this research work in the field of generation scheduling and optimization techniques.





# CHAPTER-1

## INTRODUCTION

### 1.1 INTRODUCTION

The optimum generation scheduling of existing energy resources for fulfilling the load demand at economical fuel cost and emission is one of the most challenging and demanding tasks in modern power systems. The generation of electric energy using thermal, gas and oil facilities has been very popular over the last few decades. The traditional thermal generation plants rely on non-renewable resources like fossil fuels. The fossil-fuelled power units facilitate the high demand for electric energy. However, various harmful pollutant emissions like carbon dioxide (CO<sub>2</sub>), nitrogen oxides (NO<sub>x</sub>) and sulfur dioxide (SO<sub>2</sub>) caused by the fossil fuels used in these units account for high proportion. Also, thermal generation plants are not the ideal solution to meet the world's growing energy demand, due to their poor efficiency, high emission levels and significant heat loss. Due to growing awareness of global warming and protecting the environment from emission pollutants, society demands clean energy with the least possible cost and emissions. Thus, the requirement for alternatives to thermal generation plants is obvious. In recent years, combined heat and power (CHP) or co-generation plants have been playing a significant part in the utility industry. The CHP units produce electric power and heat simultaneously from a single fuel source and utilize the wasted heat for industrial or household purposes. The CHP units not only save fuel and attain energy efficiency of around 90%, which is 36%-40% for conventional thermal power plants but also decrease the emission by 13-18% (Zou *et al.*, 2019). The CHP units consume 10-30% less fuel for producing a specific amount of power and heat than it takes for producing the same amount of power and heat by power and heat units separately (Rong and Lahdelma, 2007). Thus, CHP units have been considered as a promising substitute for conventional thermal power units for saving fuel and protecting the environment. In the modern-day scenario, there is a considerable demand for hot water and heated households, especially in the western world. Hence, to satisfy the

heat demand, CHP units and heat units are required. The CHP unit's integration into the generation scheduling of the power systems is complicated by the heat-power mutual dependencies.

Furthermore, hydroelectric plants can be an economical alternative to conventional thermal units because of the comparatively negligible operating cost and emission. The increasing concern for global warming and environment-friendly energy requirement has prompted the utilization of high-efficiency renewable energy sources like solar, wind and hydro power in the energy sector. Though renewable energy sources provide pollution-free energy but the power generation capacity is comparatively less and also these alone may not supply sufficient power to the electric load. The other major issue with renewable energy sources is uncertainty. As the primary concern with hydro units is the uncertain availability and inconsistent accessibility of water resources at all places. The power system operators may face difficulties due to the unpredictable characteristics of renewable energy sources and fluctuating load requirements. Hence, renewable energy sources like hydro, solar or wind units may coordinate with thermal, heat and CHP units for supplying the expected power and heat demands in the utmost cost-effective and environment friendly way.

Each type of energy sources has their pros and cons. Hence to achieve the maximum utilization of all the energy sources economically, the use of an interconnected or coordinated power system (CPS) is beneficial to the suppliers and society. Emission control has become one of the significant tasks, along with minimizing electricity generation costs. Since economic and emission generation scheduling are two different objectives that need to be minimized simultaneously, the problem becomes a multi-objective (MO) generation scheduling (GS) (MOGS) problem. The MOGS problem aims to satisfy the system load requirements of all the generating units while satisfying all the constraints with minimum fuel cost and emission.

The researchers have applied various optimization techniques to search optimum generation schedule of the CPS for achieving economic and environmental benefits. The optimization techniques are categorized into two groups, namely conventional or mathematical and global search optimization techniques. The conventional techniques are effective to solve

differentiable and continuous optimization problems. Most of the conventional optimization techniques take several assumptions to make the problem tractable and able to search only local optimal solutions. These techniques may fail to perform for solving complex, discontinuous, non-differentiable, non-linear, non-convex and large-scale problems, since the search space increases exponentially with the size of the problem (Rashedi *et al.*, 2009). Due to these limitations of conventional techniques, researchers have given more attention to the global search optimization techniques.

The global search techniques have become quite popular in the past few decades because they are simple, robust, flexible, derivative-free and avoid local optima. The global search techniques do not need convexity and differentiability of the optimization problem and are not sensitive to the initial solutions. The global search techniques explore the search space extensively for the optimum solution by generating a population of candidate solutions at the beginning of the search process, whereas the conventional approaches follow a single-path search process (Farhat and El-Hawary, 2009). The global search techniques have better search ability and a faster convergence rate than the traditional conventional approaches. The global search have superior abilities to avoid local optima because these techniques use stochastic procedures and incorporate unpredictability in moving from one solution to the next, whereas conventional methods adhere to deterministic transition rules (Mirjalili *et al.*, 2014). The global search techniques have shown promising performance for solving non-convex, multi-modal and non-linear problems. However, these techniques take much computational time to solve large-scale problems (Fang *et al.*, 2014). Besides, the global search techniques face the premature convergence problem for multi-modal problems due to numerous local minima. The optimization algorithm must balance the exploration and exploitation during the search process to avoid premature convergence problems and to achieve an optimal solution for multi-modal and multi-dimensional problems (Wu *et al.*, 2019). The ‘no free lunch theorem (NFLT)’ logically proves that no single optimization technique can optimally resolve all the optimization problems (Wolpert and Macready, 1997). Thus, NFLT

allows researchers to use the concept of ‘hybridization or modification’ by combining the best capabilities of two or more techniques or by modifying the existing approaches to develop a hybrid technique for solving a more comprehensive range of optimization problems. The hybrid/modified optimization techniques may be more efficient, flexible and effective for attaining better performance for complex optimization problems (Deep and Bansal, 2009).

In order to solve the MOGS problems, various MO optimization techniques have been implemented by the researchers to solve decision-making problems with multiple objectives. The MO techniques are generally classified as single-objective and multi-objective techniques. In single-objective techniques, the multi-objective problem (MOP) is altered to a single-objective problem (SOP) by weights or price penalty factor. A single compromised solution is generated instead of a set of non-dominated solutions. For non-convex optimization problems, the weighting techniques may not obtain the actual Pareto optimal solutions. However, searching the uniformly distributed set of Pareto optimal solutions in a SOP is difficult. In MO techniques, multiple objectives can be handled concurrently and Pareto optimal solution set can be generated in a single attempt. Yet, the MO techniques face premature convergence problem and computational burdens for large-scale and non-convex problems. Thus, more effective heuristic techniques must be explored to solve MO optimization problems (Feng *et al.*, 2017).

## **1.2 OPTIMUM GENERATION SCHEDULING**

The optimum generation scheduling of electric power system has been extensively investigated due to its substantial economic and environment impacts. The main objective of the optimum generation scheduling problem is to determine the generation schedule of the generating units while satisfying all the constraints in pre-defined time-period for achieving the optimal fuel cost and emission. The hydro-thermal generation scheduling (HTGS) and CHP generation scheduling (CHPGS) play a significant role in the power system for optimizing the fuel cost and emission. The literature study of HTGS, CHPGS and CPSGS problems is presented here:

### 1.2.1 Hydro-thermal Generation Scheduling

Hydro-thermal generation scheduling is a vital optimization task in power system operation. The fuel cost of hydro units is negligible; therefore, the HTGS problem is focused on minimizing the fuel cost of thermal units by optimizing the water discharge rate of hydro units and power output of thermal units over a known scheduling horizon. The hydro-thermal (HT) system needs to satisfy hydraulic and power system network constraints, *i.e.*, power load balance, thermal and hydro power generation capacity bounds on thermal and hydro units, water discharge rate and reservoir volume capacity limits and initial and terminal reservoir volume limits in a given scheduled time (Yin *et al.*, 2020). The transmission losses and valve point loading effect of thermal units increase the complexity and degree of optimization problem difficulty for the HTGS problem. Thus, HTGS is a complex, non-linear, high-constrained, multi-dimensional and multi-modal optimization problem with a set of linear and non-linear constraints.

Many researchers have made contributions to solve the HTGS problem by using conventional methods such as Lagrangian relaxation (LR) (Guan *et al.*, 1995), decomposition technique (Habibollahzadeh and Bubenko, 1986), dynamic programming (DP) (Chang *et al.*, 1990), network flow (Oliveira and Soares, 1995), mixed-integer programming (MIP) (Nilsson and Sjelvgren, 1996), dual DP (Pinto *et al.*, 2013), benders decomposition (BD) (López-Salgado *et al.*, 2016), outer approximation method (López-Salgado *et al.*, 2016) and nested BD (Santos *et al.*, 2017). The DP can suitably handle non-linear objective functions and constraints directly, however, it is not appropriate for high-dimensional problems like HTGS as the programming complexity and computational time increases with the size of the system (Dias *et al.*, 2013). A few approximations need to be taken to make the DP more practical to solve the HTGS problem (Yang and Chen, 1989). On the other hand, LR is suitable for handling high-dimensional problems with less computation time, however, the efficiency of the LR method is affected by the size of the duality gap (Yin *et al.*, 2020). In the network flow method, the presence of convex branches in the flow network increases the complexity and computational efforts (Oliveira and Soares, 1995).

Due to the obvious limitations of the conventional techniques to solve large-scale and non-convex problems like HTGS, a wide variety of global search techniques have been suggested by the researchers which are more flexible, versatile, and robust for finding the global optimum solution.

Among the global search techniques, simulated annealing (SA) (Wong and Wong, 1994), genetic algorithm (GA) (Gil *et al.*, 2003), differential evolution (DE) (Mandal and Chakraborty, 2008), particle swarm optimization (PSO) (Mandal *et al.*, 2008) and evolutionary programming (EP) (Sinha *et al.*, 2003) have been widely utilized in the past decades for solving the HTGS problem. The researchers have developed and explored few other global search algorithms such as artificial immune system (AIS) (Basu, 2011a), clonal selection algorithm (Swain *et al.*, 2011), teaching learning-based optimization (TLBO) (Roy, 2013), gravitational search algorithm (GSA) (Yuan *et al.*, 2014) and ant lion optimization (Mohan *et al.*, 2016a) for the solution of HTGS problem. Trung *et al.* (2014) proposed a cuckoo search algorithm (CSA) for solving the HTGS problem. Roy *et al.* (2018) presented krill herd algorithm and Das *et al.* (2018) proposed sine cosine algorithm for solving the HTGS problem. Yin *et al.* (2020) proposed crisscross optimization for finding the optimal schedule of HTGS problem. Thirumal *et al.* (2023) developed turbulent water flow optimization technique to solve the cascaded HTGS problem.

Several improved or hybrid/improved versions of existing optimization techniques have been proposed and implemented by researchers for solving the HTGS problem for improving the search ability, convergence characteristics and achieving more effective solutions. Wu *et al.* (2000) employed genotype-based GA to get the optimal solution to the HTGS problem in which convergence speed and overall performance are enhanced. Yin and Wong (2001) combined GA with SA to solve the HTGS problem. The other modified/hybrid versions of GA which exhibit effective performance for HTGS problem are real-coded (RC) genetic algorithm (RCGA) with arithmetic average bound blend crossover and wavelet mutation operator (Dhillon *et al.*, 2011), RCGA-artificial fish swarm (Fang *et al.*, 2014), RCGA with random transfer vectors-based mutation (Haghrah *et al.*, 2015) and RCGA based on improved Muhlenbein mutation (Nazari-

Heris *et al.*, 2017). Lakshminarasimman and Subramanian (2006), (2008) introduced improved or hybrid versions of DE, *i.e.*, modified differential evolution (MDE) and modified hybrid DE, to accelerate the convergence speed for solving the HTGS problem. Basu (2014) offered improved DE using Gaussian random variable to improve DE's search capability to solve the HTGS problem. Sivasubramani and Swarup (2011) proposed hybrid DE and sequential quadratic programming (SQP) for obtaining the solution of the HTGS problem.

For PSO variants, an improved PSO has been proposed by Hota *et al.* (2009) for attaining good solution quality and fast convergence speed for the HTGS problem. A modified adaptive PSO has been developed for solving HTGS by utilizing the tree topology for varying the inertia weight and acceleration coefficients of the PSO (Amjady and Soleymanpour, 2010). Immune algorithm-based PSO has been presented for achieving a better global solution with lesser computational efforts by Fu *et al.* (2011). Zhang *et al.* (2012) proposed a small population-based PSO for diversifying the swarm and speeding up the convergence of small populations by using mutation, DE and migration operators to solve the HTGS problem. Narang *et al.* (2014a) presented predator-prey optimization (PPO) for finding the optimal solution to the HTGS problem. Akhijahani and Ivatloo (2015) presented modified dynamic neighborhood learning-based PSO and Fakhar *et al.* (2015) proposed a fully-informed PSO for solving the HTGS problem. Cavazzini *et al.* (2018) suggested two swarm-based PSO for the solution of HTGS problem. Wu *et al.* (2019) presented a couple-based PSO focusing on overcoming the early convergence problems to solve the HTGS problem. Patwal and Narang (2020b) presented modified crisscross PSO and improved binary PSO to solve the HTGS problem.

Roy *et al.* (2013) incorporated quasi-opposition-based learning (QOBL) in TLBO to develop a quasi-oppositional-TLBO technique for enriching the search ability of TLBO and getting better results for HTGS problem. The opposition real coded chemical reaction-based optimization has been presented by integrating the concepts of QOBL and RC chemical reaction-based optimization (RCCRO) for accelerating the convergence speed of RCCRO to solve HTGS

by Bhattacharjee *et al.* (2014). To avoid the premature convergence problem of artificial bee colony (ABC) technique, adaptive chaotic ABC (Liao *et al.*, 2013) and binary- real coded (RC) bee colony optimization (BCO) (Lu *et al.*, 2015) has been proposed and applied for the optimum solution of HTGS problem. In another attempt, Narang (2017) proposed improved predator-influenced civilized swarm optimization (CSO) for solving HTGS problem. Narang (2018) integrated GSA and PPO techniques to achieve the optimal schedule of the HT units. Nazari-Heris *et al.* (2018) presented an improved harmony search algorithm (HSA) to solve the HTGS problem. Naik *et al.* (2020) suggested modified social group optimization for solving the HTGS problem, in which modification has improved both exploration and exploitation abilities compared to conventional social group optimization technique.

### **1.2.2 Combined Heat and Power Generation Scheduling**

A well-established co-generation system, combined heat and power (CHP) generation outperforms other sources of energy in terms of energy efficiency and environmental benefits. The main aim of the CHPGS problem is to minimize the overall production cost of CHP, heat and thermal units while satisfying all the constraints. Combined heat and power problem need to satisfy different operational constraints such as power demand balance of CHP and power units, heat demand balance of heat and CHP units, capacity limits of power, CHP and heat units. Dual dependency between power and heat outputs of CHP units increases the difficulty of the CHPGS problem. Thus, these challenges make the CHPGS problem non-convex, non-differentiable and non-linear optimization problem.

A wide range of research studies have been carried out for the optimum solution to the CHPGS problem. Various conventional techniques like dual and quadratic programming (Rooijers and Amerongen, 1994), LR (Sashirekha *et al.*, 2013), DP (Facci *et al.*, 2014), BD (Abdolmohammadi and Kazemi, 2013), branch and bound algorithm (Rong and Lahdelma, 2007) and mixed integer non-linear programming (Kim and Edgar, 2014) have been implemented for attaining optimal generation schedule of CHPGS problem. Owing to many advantages, the global

search techniques like HSA (Vasebi *et al.*, 2007), PSO (Ramesh *et al.*, 2009), DE (Basu, 2010a), BCO (Basu, 2011b), AIS (Basu, 2012), firefly algorithm (Yazdani *et al.*, 2013), invasive weed optimization (Jayabarathi *et al.*, 2014) and affinely adjustable robust optimization (Zugno *et al.*, 2016) have been widely applied to solve the CHPGS problem. Some other global search approaches have also been explored by researchers. Basu (2016) applied group search optimization (GSO) inspired by animal search behavior for solving the CHPGS problem. Hagh *et al.* (2014) presented improved GSO for improving the searchability of GSO of giving a nearly optimal solution instead of the optimal one for the CHPGS problem. Further, Basu (2015) has proposed an opposition-based GSO for resolving the CHPGS problem to enhance the solution's effectiveness and quality. Ghorbani (2016) proposed exchange market algorithm for solving the CHPGS problem. Beigvand *et al.* (2016) presented GSA for the optimal solution to the CHPGS problem. PSO with time-varying acceleration coefficient (TVAC) (Mohammadi-ivatloo *et al.*, 2013) has been implemented for the CHPGS problem to improve solution quality and avoid the premature convergence of actual PSO by adaptive variation of the acceleration coefficient throughout iterations. TLBO and oppositional-TLBO have been applied to CHPGS by Roy *et al.* (2014). Meng *et al.* (2015) suggested crisscross optimization algorithm and Nguyen *et al.* (2016) implemented CSA to obtain the optimal schedule of CHPGS problem. Narang *et al.* (2017) integrated CSO with a local search technique Powell's pattern search (PPS) for solving the CHPGS problem. The hybridization of bat algorithm (BA) and ABC with chaotic based self-adaptive search strategy has been introduced by Murugan *et al.* (2018) for solution of CHPGS problem. Zhou *et al.* (2020) proposed deep reinforcement learning approach to solve CHPGS problem. Yang *et al.* (2022) suggested CSA with DE mutation to solve CHPGS problem.

### 1.2.3 Coordinated Power System Generation Scheduling

The significant extension of interconnections among different energy systems has become necessary to meet the rapidly growing power demand. The integration of different energy sources such as thermal, CHP, heat, hydro, wind, solar, *etc.* has considerable advantage of adaptability in

adjusting demand and supply discrepancies (Rajpurohit *et al.*, 2008). The power system researchers have been extensively working to achieve the optimum generation scheduling of CPS, considering renewable energy sources for mitigating the carbon impact (Singh and Singh, 2009).

Pereira *et al.* (2012) addressed the short-term scheduling problem consisting of thermal, hydro and wind power plants and solved it using the binary mixed integer non-linear optimization technique. Azizipanah-Abarghooee *et al.* (2015) coordinated CHP units with wind and PV units to solve the economic load dispatch (ELD) problem using chance constrained programming and jointly distributed random variables methods. Banerjee *et al.* (2016) presented optimum hourly schedule of power generation in HT-wind system using PSO. Dubey *et al.* (2016b) used ant lion optimization technique with composite ranking index to achieve the solution of generation scheduling problem having integrated HT-wind units. Das *et al.* (2018) proposed and solved the generation scheduling problem of hybrid energy systems, including hydro, thermal, wind and photo-voltaic (PV) units by crow search algorithm. Ming *et al.* (2018) optimized the power generation of a large-scale hydro-PV hybrid power plant using direct search algorithm. Patwal *et al.* (2018) incorporated solar units into pumped storage HT units for the optimal generation schedule and obtained the optimal solution by TVAC-PSO based mutation strategies. Liu *et al.* (2018) proposed a scheduling framework consisting of thermal, CHP, heat, wind units and thermal energy storage system using modified PSO technique. Faridnia *et al.* (2019) implemented PSO to the optimal scheduling model of a microgrid with tidal generation. He *et al.* (2019) proposed an integrated scheduling model of hydro, thermal, wind and spinning reserve and implemented improved DE to solve it. Basu (2019) suggested chaotic fast convergence EP technique to solve the multi-region GS problem of HT, solar and wind units including pumped hydro energy storage. Basu (2019b) suggested squirrel search algorithm for the solution of generation scheduling of CHP units integrated with renewable energy sources. Ojeda-Esteybar *et al.* (2020) suggested the solution of HTGS problem including solar generating units using mathematical non-linear programming model. Patwal and Narang (2020b) modelled the generation scheduling problem

with integrated wind and pumped storage HT units and proposed modified crisscross PSO algorithm to solve it. Basu (2020) recommended chaotic fast convergence EP for resolving the GS problem considering hydro units, pumped storage hydro units and renewable energy sources (wind turbine and PV units). Mu *et al.* (2021) proposed the economic dispatch problem of joint operation of the wind farm and CHP plant considering energy flexibilities in heating networks. Zhang (2021) proposed a short-term optimum scheduling model for hybrid generation system considering wind, solar, hydro and thermal plants while considering the dynamic frequency response of the hybrid generation power system and solved by mixed integer linear programming method. Bruno *et al.* (2022) suggested incorporation of operating reserve constrains in the generation scheduling of energy and storage resources in small islands (Bruno *et al.*, 2022). Ebeed *et al.* (2023) incorporated renewable energy sources into stochastic optimal reactive power dispatch problem and proposed enhanced artificial gorilla troops optimizer to solve it. Mohamed *et al.* (2023) suggested optimal reactive power dispatch including electric vehicles using enhanced transient search optimization algorithm.

#### 1.2.4 Multi-Objective Hydro-thermal Generation Scheduling

The power companies are more interested in minimizing the cost of power production, whereas reducing emissions is desired for social welfare. The global search optimization techniques are the most suitable methods for achieving the non-dominated or Pareto optimal solution for the MO-HTGS problem. The researchers have utilized the price penalty factor approach for converting the MO-HTGS problem into a SOP and solved it with different techniques like DE (Mandal and Chakraborty, 2009), improved quantum behaved PSO (QPSO) (Sun and Lu, 2010), PSO (Mandal and Chakraborty, 2011) and hybrid chemical reaction optimization-DE (Roy, 2014). Dhillon *et al.* (2001) presented a fuzzy decision-making methodology for deciding the MOGS of HT units and utilized weighted minimax approach to simulate the trade-off relationship among the contradictory objectives in the non-inferior domain. The MO-HTGS problem is solved using conjugate gradient method. Basu (2004), (2006) converted the MO-HTGS problem into the SOP by the interactive

fuzzy satisfying method and then resolved it by EP and PSO, respectively. Basu (2005) proposed a goal-attainment method for transforming MOP into SOP and then solved the SOP using the SA technique. Chiang (2007) and (Lasemi *et al.*, (2020) utilized the  $\epsilon$ -constraint technique for optimizing the MOGS of the HT power system. Lu and Sun (2011) presented quadratic approximation-based DE with a valuable trade-off method for the solution of the MO-HTGS problem, in which the MOP is integrated to SOP by price penalty factor and valuable trade-off ratio. The MO-HTGS problem has been combined into SOP problem using the cardinal priority ranking (CPR) method and the resulting SOP has been solved by using PPO (Narang *et al.*, 2012), integrated PPO-PPS (Narang *et al.*, 2012), modified CSA (MCSA) (Nguyen and Vo, 2017), crisscross PSO (Patwal and Narang, 2018), fuzzy-based surrogate worth trade-off approach (Patwal and Narang, 2020a). Selvakumar (2013) utilized the global criterion function concept based on Euclidean distance for formulating the SOP from the economic and emission objectives of MO-HTGS and solving it by CSO technique. Narang *et al.* (2014b) used a weight pattern evaluation method for obtaining the SOP problem from MOP and implemented a hybrid PPO-PPS technique to get the MO-HTGS problem's solution. Nezhad *et al.* (2014) applied an augmented  $\epsilon$ -constraint approach to generate the Pareto optimal front and implemented fuzzy decision-making and lexicographic optimization for selecting the most dominating Pareto solution for the MO-HTGS problem. Tian *et al.* (2015) converted the MO-HTGS problem into SOP by utilizing variable weights based on the time intervals and implemented improved GSA for obtaining the generation and emission schedule of the HT system. Kumar and Dhillon (2022) employed price penalty approach to transform the MO-HTGS problem to a SOP and then SOP is addressed using intensified water cycle technique.

The researchers have proposed and implemented different MO global search techniques for solving the MO-HTGS problem. Basu (2011c) proposed non-dominated sorting genetic algorithm (NSGA)-II to solve the non-linear constrained MO-HTGS problem. Yuan *et al.* (2015) presented extended NSGA-III for solving the MO-HTGS problem in which dominance

relationship criterion based on constraint violation is introduced for selecting a new generation. Basu (2010b) presented multi-objective differential evolution (MODE) for handling MO-HTGS problem. Qin *et al.* (2010) presented DE with adaptive Cauchy mutation to solve MO-HTGS problem to avoid premature convergence and preserve the diversity of the population. Hybrid MO cultural algorithm has been proposed by Lu *et al.* (2011) for solving the MO-HTGS problem. Zhang *et al.* (2013) presented culture belief-based MO hybrid DE algorithm to solve MO-HTGS problem. Zhang *et al.* (2013) proposed SA-based MO cultural DE (MOCDE), Glotić and Zamuda (2015) developed surrogate DE and Zhang *et al.* (2017) proposed gradient descent-based MOCDE for solving the MO-HTGS problem. Feng *et al.* (2017) combined the advantages of parallel technology and MODE to develop parallel-MODE algorithm to find the optimum schedule of MO-HTGS problem. In order to solve MO-HTGS problem, Zhang *et al.* (2012) presented MO cultural algorithm-based PSO. Feng *et al.* (2017) proposed multi-objective QPSO for the MO generation schedule of HT units. Zhou *et al.* (2014) presented MOABC for solving the MO-HTGS problem. Tian *et al.* (2014) proposed non-dominated sorting GSA with chaotic mutation for obtaining Pareto optimal solutions for the MO-HTGS problem. Li *et al.* (2015) introduced improved MOGSA for the MO-HTGS problem by utilizing chaotic mutation to enhance the search mechanism. Ahmadi *et al.* (2015) used lexicographic optimization and the normal boundary intersection method for generating the Pareto optimal front for the MO-HTGS problem. Nguyen and Vo (2017) proposed MCSA for the MO-HTGS problem. Though the MO optimization techniques can attain the optima for solving the non-convex MOGS of the HT system, however these techniques may stuck into local optima to a certain degree which may cause premature convergence problem, especially when solving large-scale optimization problems (Zhang *et al.*, 2018). Patwal and Narang (2020a) have implemented modified crisscross PSO with surrogate worth trade-off for solving MO-HTGS problem. Dasgupta *et al.* (2022) employed sine cosine algorithm to determine the solution of MO-HTGS problem.

**1.2.5 Multi-Objective Combined Heat and Power Generation Scheduling**

The MO-CHPGS problem aims to determine the optimal power generation scheduling of power and CHP units and heat generation scheduling of CHP and heat units to achieve minimum operating cost and pollutant emission simultaneously while meeting all the imposed constraints. The bound operation of power and heat in CHP units and the conflicting nature of the two objectives introduce complexity to the MO-CHPGS problem. Over the past few years, many researchers have contributed to solving the MO-CHPGS problem. Niknam *et al.* (2012) used the fuzzy-based weighted normalized membership approach to convert SOP from the MO-CHPGS problem and applied an enhanced firefly algorithm to get non-dominated solutions. Motevasel *et al.* (2013) applied fuzzy satisfying method for simulating the trade-off between the two objectives of MO-CHPGS problem and achieved the best satisfying solution using modified bacterial foraging optimization.

A stochastic model for the MO-CHPGS problem has been formulated and an improved MOPSO technique has been implemented to achieve minimum fuel cost and emissions simultaneously by Wang and Singh (2008) and Piperagkas *et al.* (2011). Basu (2013) presented NSGA-II for solving the MO-CHPGS problem. Bracco *et al.* (2013) presented a mixed-integer linear programming model for MO-CHPGS of power distributed generation systems in an urban area. Shi *et al.* (2013) applied fuzzy decision-making to attain the best-compromised solution to the MO-CHPGS problem and solved it through the MO line-up competition algorithm. Rong *et al.* (2014) presented a merging algorithm for building the exact Pareto front of the MO-CHPGS problem. Ahmadi *et al.* (2015) presented normal boundary intersection method for solving the MO-CHPGS problem and applied ‘technique for order preference by similarity to ideal solution’ decision-making method for searching for the Pareto optimal solution. Shaabani *et al.* (2017) implemented TVAC-PSO to MO-CHPGS problem. Elattar (2019) presented a modified shuffle frog leaping algorithm for the solution of the MO-CHPGS problem. Li *et al.* (2018) addressed the problem of MO-CHPGS by utilizing a  $\theta$  dominance-based evolutionary algorithm for finding

multiple Pareto-optimal solutions and fuzzy c-means with grey relation projection technique for separating the Pareto-optimal solutions into different clusters and obtaining the best non-dominated solutions. Sun *et al.* (2020) put forward an indicator & crowding distance-based evolutionary algorithm and Alomoush (2021) utilized Bernstein-search DE approach to deal with the MO-CHPGS problem to obtain an optimal schedule.

### 1.2.6 Multi-Objective Coordinated Power System Generation Scheduling

The multi-objective generation scheduling of CPS has gained much attention for meeting power demand with the least cost and emission. In such an attempt, Azizipanah-Abarghooee *et al.* (2015) developed and solved the stochastic MOGS problem with consideration of CHP, wind and PV units by hybrid MCSA-DE technique. Qu *et al.* (2016) implemented summation-based MO evolutionary algorithm to optimize the MO dispatch problem with consideration of stochastic wind power. A MOGS model of hybrid renewable energy systems, including solar units, wind units, battery bank and diesel generator system is presented by Forough and Roshandel (2017) and optimal schedule of hybrid renewable energy system is attained by mixed-integer convex programming technique. Elattar (2018) implemented modified HSA for the MOGS of microgrid considering solar and wind power cost functions. Zhang *et al.* (2017) proposed gradient decent based MO cultural DE technique for solving the short-term MOGS of HT system with wind and photovoltaic units. Further, Zhang *et al.* (2018) formulated and solved the MOGS problem by combining HT and wind with large-scale electric vehicles using improved MO-PSO. Basu (2019a) has solved the integrated power system's multi-area MO dynamic dispatch problem, including HT and wind units using NSGA-II. Gul *et al.* (2019) presented the MOGS model incorporating HT units with solar and wind units and implemented non-linear programming to solve it. Lokeshgupta and Sivasubramani (2022) solved the MOGS problem of integrated the renewable energy resources with demand-side management using NSGA-II and Monte Carlo simulation techniques. Patwal and Narang (2020a) solved the MOGS problem of integrated energy system involving pumped storage HT units with wind, solar and battery units and modified crisscross PSO and

improved binary PSO technique have been used to search for the optimal generation schedule of integrated energy system.

### 1.3 OPTIMIZATION TECHNIQUES

The optimization techniques search the best possible and feasible solution to an optimization problem with respect to an objective function while satisfying all the constraints. Based on the number of objectives, the optimization problems are generally classified into two categories: single-objective and multi-objective optimization problems. The single-objective problem (SOP) has a single objective function whereas the multi-objective problem (MOP) has more than one conflicting objective functions to be minimized or maximized, simultaneously (Erol and Eksin, 2006).

Mathematically, the SOP is stated as (Deb, 2001):

$$\text{Minimize/maximize: } f(X) \tag{1.1}$$

$$X = [x_1 + x_2 + \dots + x_d] \quad (d \in D) \tag{1.2}$$

Subjected to:

$$\text{Inequality constraints: } g_i(X) \leq 0 \quad (i \in I) \tag{1.3}$$

$$\text{Equality constraints: } h_j(X) = 0 \quad (j \in E) \tag{1.4}$$

$$\text{Bound on variables: } x_d^{\min} < x_d < x_d^{\max} \quad (d \in D) \tag{1.5}$$

Mathematically, the MOP is stated as:

$$\text{Minimize/maximize: } f(X) = [f_1(X) + f_2(X) + \dots + f_m(X)]^T \tag{1.6}$$

Subjected to inequality constraints (Eq. (1.3)), equality constraints (Eq. (1.4)) and bounds on decision variables (Eq. (1.5)).

where  $f(X)$  is the objective function;  $X$  is the decision vector;  $I$ ,  $E$  and  $D$  represent the number of inequality constraints, equality constraints and decision variables, respectively;  $x_d^{\min}$  and  $x_d^{\max}$  are the lower and upper bounds on the decision variables;  $m$  is the total number of objective functions.

Over the past few decades, many optimization techniques have been developed and implemented to find the optimal solution of different optimization problems. Generally, the optimization techniques are categorized as conventional and global search techniques. Further, the conventional techniques are classified as direct search and gradient-based techniques. The direct search techniques do not require derivative information; however, these techniques are slow and need many functions evaluation for convergence. The gradient-based techniques use the derivative of objective function or constraints to guide the search process. These gradient-based techniques quickly converge to an optimal solution for differentiable objective functions and constraints. Thus, gradient-based techniques are ineffective for problems with a non-differentiable or discontinuous objective function or constraints whereas direct search methods are the preferred techniques when the objective function is non-linear and non-differentiable (Storn, 1997). The LR (Guan *et al.*, 1995) (Sashirekha *et al.*, 2013), DP (Dias *et al.*, 2013) (Facci *et al.*, 2014), direct solution (Rao, 2006), MIP (Aghaei *et al.*, 2013) (Kim and Edgar, 2014), matrix modelling (Liu *et al.*, 2013) and BD (Rubiales *et al.*, 2013) are some of the conventional techniques have been explored to solve various optimization problems. The conventional techniques may not attain an appropriate solution for solving multi-dimensional optimization problems since the search space increases exponentially with the size of the problem (Rashedi *et al.*, 2009).

Over the last two decades, an increasing interest in global search optimization methodologies has been seen because of the limitations of conventional optimization techniques, such as local optima stagnation and the necessity to derivate the search space. Since the global search strategies are stochastic, they prevent local solution stagnation and allow the whole search space to be examined. Also, the global search techniques do not depend on the mathematical model of the optimization problem (Yin *et al.*, 2020). The global search approaches incorporate rules to mimic natural phenomena like evolutionary process, physics-based and animal or swarm-based. The global search approaches are considered a good choice to optimize complex and challenging real optimization problems. The global search algorithms can be classified into evolutionary,

physics-based and swarm-based algorithms. The evolutionary algorithms are influenced by the concepts of natural evolution like artificial immune systems (Farmer *et al.*, 1986), GA (Holland, 1992), DE (Storn, 1997), EP (Yao *et al.*, 1999), evolution strategies (Beyer and Schwefel, 2002) and biogeography-based optimization (Simon, 2008). In the physics-based algorithms, the search particles communicate and move all over the search space according to physical laws like gravitational force, electromagnetic force, inertia force, *etc.* Among the physics-based algorithms, SA (Kirkpatrick *et al.*, 1983), particle collision algorithm (Sacco and Cassiano, 2005), big-bang big-crunch (Erol and Eksin, 2006), central force optimization (Formato, 2007), GSA (Rashedi *et al.*, 2009) and charged system search (Kaveh and Talatahari, 2010) have been acknowledged as prevalent algorithms. Few more physics-based algorithms which have been implemented in different optimization problems are artificial chemical reaction optimization (Alatas, 2011), galaxy-based search algorithm (Shah-Hosseini, 2011), black hole (Hatamlou, 2012), ray optimization (Kaveh and Khayatazad, 2012) and gases brownian motion optimization (Abdechiri *et al.*, 2013). The swarm-based algorithms are influenced by the social behavior of animals or birds. The swarm-based techniques consist of PSO (Kennedy and Eberhart, 1995), ant colony optimization (Dorigo *et al.*, 1996), ABC (Karaboga and Basturk, 2007), GSO (He *et al.*, 2009), bacterial foraging algorithm (Das *et al.*, 2009), BA (Yang, 2010), fruit fly optimization (Pan, 2012), dynamic virtual bats algorithm (Topal and Altun, 2014), moth-flame optimization (Mirjalili, 2015) and crow search algorithm (Askarzadeh, 2016). The swarm-based algorithms have a few distinct advantages over other types, including enhanced exploration capabilities and flexibility when dealing with non-convex problems. GWO and CSA are the two popular algorithms amongst the swarm-based algorithms which have superior exploration and exploitation capabilities, respectively, as compared to many other global search techniques. The detailed discussion on GWO and CSA techniques is presented below.

### **1.3.1 Grey Wolf Optimizer**

The grey wolves are the members of the Canidae family and are regarded as the top predators.

They mostly live in a pack and have a rigorous social dominance hierarchy with alpha, beta, delta and omega wolves. The first level of hierarchy is alpha which is the leader or dominant and decision maker for the pack. Beta is the second position in the grey wolf hierarchy. The beta wolves assist alphas in making decisions or participating in other pack activities. Third and fourth position in the hierarchy is delta and omega, respectively. Delta wolves must surrender to the alpha and beta wolves, but they dominate the omega wolves. The grey wolf with the lowest ranking is omega which must surrender to all the other dominant wolves (Muro *et al.*, 2011). Another interesting social behaviour of grey wolves is the group hunting.

Mirjalili *et al.* (2014) developed the swarm-based algorithm called grey wolf optimizer (GWO), inspired by the leadership hierarchy and hunting mechanism of grey wolves in nature. The researchers have implemented GWO in various research areas in power systems engineering because of its many advantages like simplicity, flexibility, robustness, easy implementation, and fewer control parameters. GWO possesses strong exploitation ability. Guha *et al.* (2016a) solved the load frequency control problem in an interconnected power system network using the GWO technique. GWO is implemented for the CHP economic dispatch, environmental-economic dispatch and dynamic economic dispatch problems by Jayakumar *et al.* (2016). Wong *et al.* (2014), Kamboj *et al.* (2016) and Pradhan *et al.* (2016) have applied GWO for the solution to the economic ELD problem. GWO is used by Lal *et al.* (2016) to interconnected HT power systems for automatic generation control for obtaining optimal gains of the fuzzy-based proportional, integral and derivative controllers. Reactive-power control of an isolated wind-diesel hybrid power system using GWO is presented by Behera *et al.* (2016). Shakarami and Davoudkhani (2016) proposed a wide-area power system stabilizer design based on a GWO algorithm considering the time delay.

The GWO has shown superior exploitation strength as compared to other heuristic algorithms (Gupta and Deep, 2019), however, it also faces the drawback of trapping into local optima and slow convergence rate, when implemented to complex multi-modal problems (Long *et al.*, 2018b). The GWO algorithm still has a flaw in its position-updated equation, which is good

at exploitation but poor for exploration. Thus, a variety of improved/modified versions of GWO like fuzzy hierarchical operator-based GWO (Rodríguez *et al.*, 2017), improved modified GWO (Heidari and Pahlavani, 2017), chaotic GWO (Kohli and Arora, 2018), random walk GWO (Gupta and Deep, 2019) and inspired GWO (Long *et al.*, 2018b) have been developed to overcome the drawbacks and to enhance the performance of GWO algorithm. Long *et al.* (2018a) presented exploration-enhanced GWO to solve high-dimensional optimization problems by introducing a random individual in the population for guiding the search of new candidate individuals and thus enhancing the exploration of GWO algorithm. Singh and Dhillon (2019) proposed ameliorated GWO for solving the optimization problem. Zhao *et al.* (2020) presented improved GWO in which a hybrid covariance matrix adaptation-evolution strategy is adopted for overcoming the inadequacies of GWO algorithm to easily fall into local minima while dealing with complex multi-modal problems. Hosseini-hemati *et al.* (2022) proposed society-based GWO algorithm for solving the large-scale CHPGS problem considering the valve-point loading effect, transmission losses and prohibited zones of power units.

### **1.3.2 Cuckoo Search Algorithm**

Cuckoos are the unique birds well-known for their melodious sounds and unique breeding practices such as brood parasitism. The cuckoo species practise obligatory brood parasitism by incubating their eggs in the nests of other birds. Yang and Deb (2009) developed a swarm-based cuckoo search algorithm (CSA) which is influenced by the breeding behavior of cuckoo birds and characteristics of Levy flights of some birds and fruit flies. CSA has several advantages as compared to other heuristic algorithms. CSA has fast convergence, lesser control parameters and the convergence rate is insensitive to the control parameters. The effectiveness of CSA over GA and PSO has been validated using benchmark functions and CSA outperformed GA and PSO (Yang and Deb, 2009).

CSA is considered more generic and robust for solving different optimization problems and has undergone remarkable developments in the power and energy sector. CSA has been

successfully implemented for optimal distributed generation allocation to improve voltage profile and reduce the power loss of the distribution network (Moravej and Akhlaghi, 2013). Basu and Chowdhury (2013) and Vo *et al.* (2013) implemented CSA for the non-convex ELD problem. Ahmed and Salam (2014) proposed a maximum power point tracking for PV systems using CSA. Abdelaziz and Ali (2015) implemented CSA for controlling the load frequency of a non-linear interconnected power system.

CSA lacks good convergence property nearby global optimum for solving complex, multi-peak and multi-modal problems. Therefore, several CSA variants have been developed to enhance performance, accelerate convergence speed and avoid conventional CSA's local optima. Walton *et al.* (2011) developed MCSA which includes the accumulation of information exchange between the eggs or the best solutions for improving the searchability of CSA. Nguyen and Vo (2015b) presented one rank CSA to solve the ELD problem. In one rank CSA, the original CSA has been modified by merging new solutions produced by levy flight and replacing a fraction of egg together and later evaluating and ranking the solutions. MCSA with self-adaptive parameter method has been developed by Li and Yin (2015) in which mutation rules are introduced for balancing exploration and exploitation of the algorithm and self-adaptive parameter setting is used to enhance the population's diversity. To enhance the search ability of CSA, Nguyen and Vo (2015a) and Nguyen *et al.* (2018) suggested MCSA and effectively adaptive selective CSA, respectively, for solving the HTGS problem. There are some more variants of CSA proposed by the researchers for solving different optimization problems which include adaptive CSA (Mareli and Twala, 2018), improved discrete CSA (Bibiks *et al.*, 2018), improved CSA (Murali *et al.*, 2018), discrete CSA (Majumder *et al.*, 2018), dynamic feedback CSA (Cheng *et al.*, 2018).

### 1.3.3 Performance Enhancement Methods

The global solution accuracy and convergence rate of global search algorithms are significantly affected by parameter-tuning, exploration, and exploitation strategies. Thus, there is a need to maintain a good balance between exploration and exploitation of algorithm in order to obtain

satisfactory performance. For enhancing the performance of global search techniques in terms of exploitation capability without compromising exploration capability, enhancing global searchability and avoiding the local optima, various strategies or performance enhancement methods like mutation strategies, quantum theory and chaos theory have been implemented to the existing global search techniques (Yin *et al.*, 2020).

The mutation strategies (MS) play an essential role in the existing global search techniques by avoiding the loss of diversity in the population and enhancing the exploration of a greater region of search space. Mutation strategies help in avoiding stagnation of search in local optima and promote variability in the population. The researchers have attempted the integration of mutation operators with different global search techniques. Liu *et al.* (2005) have used a Cauchy distribution mutation operator to improve the global and mean best positions achieved by QPSO technique. Wang *et al.* (2007) implemented Cauchy mutation on the best particle obtained by opposition-based mutation operator. Chakraborty *et al.* (2012) proposed the HSA with a modified differential mutation operator for solving the dynamic ELD problem. The DE algorithm is integrated with different mutation operators such as intersect mutation operator (Zhou *et al.*, 2013), directional mutation operator (Zhang and Yuen, 2015) and hybrid mutation operator (Yi *et al.*, 2015) to improve the searchability. Patwal *et al.* (2018) have proposed the TVAC-PSO based mutation strategies algorithm for optimum generation scheduling of a pumped storage HTGS system incorporating solar units.

In recent years, researchers have paid much attention to quantum theory because of its successful applications in different research areas. Numerous studies influenced by quantum theory have been carried out to improve the efficiency, convergence speed and search process of existing optimization techniques, such as quantum-based whale optimization algorithm (Agrawal *et al.*, 2020), quantum-inspired HSA (Layeb, 2013), QPSO (Xin-gang *et al.*, 2020) and quantum-GWO (Vijay and Nanda, 2019). To overcome the premature convergence and enhance the searchability of CSA, Cheung (2017) developed a quantum-based cuckoo search algorithm

(QCSA) in which the quantum theory and traditional CSA are integrated. The QCSA technique has been explored extensively to solve complex optimization problems due to its excellent searchability. The QCSA overcomes the drawback of CSA by utilizing quantum theory for non-homogeneous up-gradation of the positions and to enhance searchability. Even though the QCSA technique can explore the search space competently, it is still lacking in exploiting promising search areas (Cheng *et al.*, 2018). For improving the exploitation of QCSA, it can be hybridized with other optimization techniques.

One of the recent advances in the application of non-linear dynamics is chaos theory which has been widely used in the field of optimization for the self-adaptive parameter settings. In terms of both local optima avoidance and convergence speed, chaotic maps are one of the most effective strategies for improving the performance of existing algorithms. The researchers have combined chaotic maps with different optimization techniques because of their dynamic behavior for tuning the algorithm parameters and, thus, for dynamically improving the search space exploration. Yuan *et al.* (2008) proposed a chaotic hybrid DE for solving HT generation scheduling problem in which chaos theory is used to attain self-adaptive parameter settings in DE. Sun *et al.* (2009) proposed chaotic PSO for improving the search ability and overcoming the problem of premature convergence. Lu *et al.* (2010) obtained the parameter setting of DE by presenting an adaptive chaotic DE approach and implemented it to the HTGS problem. Gandomi *et al.* (2013) introduced chaotic maps into the firefly algorithm to increase the global searchability and solution quality. Hossein *et al.* (2013) introduced chaos accelerated PSO to enhance the solution quality and global searchability. Lewis (2014) proposed chaotic-biography-based optimization in which chaotic maps are utilised to enhance the performance of biography-based optimization algorithm. Wang and Zhong (2015) proposed CSA with chaotic maps and implemented the proposed algorithm on standard benchmark functions to test its performance. Zhang *et al.* (2015) proposed modified chaotic DE for solving the HTGS problem. Huang *et al.* (2016) proposed chaos enhanced CSA in which five modifications of original CSA have been presented by using five chaotic map

sequences (logistic, tent, Gauss, sinusoidal and circle) for initializing of host nests, changing step size of levy flight and resetting the location of host nests. Singh and Dhillon (2017) proposed chaotic DE and Powell's pattern search algorithm for solving the MO-ELD problem. Boushaki *et al.* (2018) presented quantum chaotic CSA for data clustering in which quantum theory has been used for extending the search capabilities using non-homogeneous update and the chaotic map is utilized for replacing randomness at the initial stage for improving the convergence speed. Kohli and Arora (2018b) introduced the chaos theory into GWO to accelerate convergence speed of constrained optimization problems.

### **1.3.4 Hybrid Optimization Techniques**

Despite excellent ability of global search techniques, these techniques cannot always assure the optimum global solution for complex optimization problems (Elattar, 2019). However, global search approaches may result in a suboptimal or nearly globally optimal solution rather than the global optimum and face slow convergence towards optimal solution. Consequently, the researchers recommend integrating two or more potent techniques to avoid local optima and to enhance the global searchability of the existing techniques for achieving the optimal solution of complex multi-dimensional optimization problems.

A few hybrid approaches have been presented by researchers that integrate the benefits of various independent algorithms into a single framework to yield better results in different research fields. Mohanty *et al.* (2014) suggested hybrid PSO with harmonic search algorithm to minimize the frequency deviation in hybrid distributed generation system. Garg (2016) proposed hybrid PSO-GA for solving the nonlinear constrained optimization problems. Sen and Mathur (2016) developed hybrid ACO-ABC with HSA for solving the ELD problem. Kansal *et al.* (2016) presented a hybrid approach for optimal placement of multiple distribution generations in distribution networks. Lopez-garcia *et al.* (2016) combined GA with cross entropy method for solving continuous optimization functions. Srivastava *et al.* (2016) presented hybrid PSO-GSA technique for optimal over-current relay coordination. Zade *et al.* (2017) presented hybrid CSA

with box complex method for providing a good convergence rate. Puspaningrum and Sarno (2017) proposed hybrid CSA-HSA for the cost estimation problem. Xin-gang *et al.* (2020) proposed DE with crossover quantum-based PSO algorithm to find the solution of MO-ELD problem. Hassan *et al.* (2020) integrated binary PSO and shuffled frog leap algorithms for solving an optimal power flow on radial distribution system. Lin *et al.* (2022) hybridized CSA with DE technique and Taieb *et al.* (2022) suggested CSA with PSO to solve the optimization problems. Yang *et al.* (2022) suggested CSA with DE mutation to solve generation scheduling problem. Kumar *et al.* (2022) proposed sequence-based hybrid technique for islanding detection for microgrid with renewable energy sources.

A few hybrid versions of GWO have been developed by the researchers to overcome the drawbacks of GWO technique like slow convergence speed while solving multi-modal problems, and trapping into local optima (Long *et al.*, 2018a). Zhu *et al.* (2015) integrated GWO with DE to improve the limitations of GWO to jump out of stagnation using DE's strong searchability. Guha *et al.* (2016b) proposed a quasi-oppositional GWO algorithm (QOGWO) for solving load frequency control of large-scale power systems. In QOGWO, the QOBL is combined with GWO for accelerating the convergence speed of conventional GWO. Gaidhane and Nigam (2018) proposed a hybrid GWO-ABC algorithm for solving the complex systems by promoting the exploration ability and retaining the exploitation ability of GWO technique. Teng *et al.* (2019) proposed a hybrid GWO-PSO algorithm in which a chaotic tent map sequence is used to initialize the positions to increase the population diversity. Long *et al.* (2020) proposed hybrid GWO-CSA technique parameter extraction of PV models. Khadanga *et al.* (2022) suggested modified GWO-CSA for designing the load frequency controller of integrated power system.

### 1.3.5 Multi-Objective Optimization Techniques

The most of real-world problems involving multiples conflicting optimization objectives with constraints are represented as a MO optimization problem. Researchers have converted the MOP into a SOP using different methods like min-max (Basu 2004), (Motevasel *et al.* 2013), goal-

attainment method (Basu 2005), weighting method (Singh *et al.* 2006), price penalty factor (Mandal and Chakraborty 2009) and  $\varepsilon$ -constraint technique (Basu 2011), (Xu *et al.* 2012) to solve different optimization problems. The SOP methods can obtain the compromised solution with less complexity; however, choosing the appropriate weights or price penalty factors is complex and challenging (Deb 2001).

The MO optimization problem, unlike, SOP has a set of optimal solutions called Pareto fronts. The researchers have implemented various MO optimization techniques for solving the MO problems. Pradhan and Panda (2012) proposed cat swarm optimization for finding the non-dominated solutions of MO problem using Pareto dominance concept. Sheng *et al.* (2012) suggested improved strength Pareto evolutionary algorithm-II for solving MO problems. The MOGSA technique has been suggested by Hemmatian *et al.* (2014) for minimising the cost and weights of hybrid laminate composites. Velazquez *et al.* (2015) proposed MODE algorithm for finding the optimal solution of MO problem. Hancer *et al.* (2015) proposed MOABC algorithm for feature selection in classification problems. Huo *et al.* (2015) recommended MO technique *i.e.*, elite-guided MOABC to solve the MO optimization problems. Lin *et al.* (2015) MO teaching-learning-based optimization algorithm for reducing carbon emissions and operation time in turning operations. Mirjalili *et al.*, (2016) proposed MO-GWO for solving the multi-criterion optimization problems. Xu *et al.* (2018) proposed decomposition-based MO evolutionary algorithms for dynamic MO optimization problems. Bhamidi and Shanmugavelu (2019) suggested MO-HSA for dynamic optimal power flow with demand side management. Evangeline and Rathika (2022) proposed MO horse herd optimization algorithm for solving the optimal power flow problem.

#### **1.4 SCOPE OF THE WORK**

The power demand on a global scale is rising quickly as a result of population growth and the advancement of science and technology. Electric power workers have always been focused on fulfilling the growing power demand and reducing the fuel cost as well as pollution emissions throughout the electricity generation process. In recent years, many industries and end-users have

become more interested in CHP units, which can generate both power and heat energy. This is primarily due to their ability to deliver both electric power and useful heat from a single source with better energy conversion efficiency of up to 90%, reliable energy supply and lower greenhouse gas emissions. The utilization of CHP units can lead to a significant saving in fossil fuels and reduce pollutant emissions as compared to conventional thermal units. Another essential feature of CHP units is their ability to change their output level quickly. Hence, CHP units have a relatively short start-up and shut-down time. Nowadays, a lot of attention is directed to using renewable energy sources like hydro, solar, wind *etc.*, to fulfil increasing power demand and to deal with environmental issues. The use of CHP and hydro units are believed to be the key to integrating renewable energy sources. The hydro power generation does not require any fuel costs. The research intends to search for the optimum generation schedule for coordinated CHP units with the thermal, heat, hydro and renewable energy sources. The generation scheduling problem of coordinated power system by combining different energy sources forms a complex, multi-dimensional, non-linear, non-convex, and multi-modal optimization problem.

The complex and multi-modal optimization problems are challenging to solve using conventional optimization techniques. The conventional techniques have a single-point search strategy as compared to global search techniques with multi-point search strategies. Despite global search techniques having many advantages compared to conventional search techniques, these techniques are comparatively inefficient in the exploitation of search areas compared to conventional search techniques. Hence, there is a need for a hybrid optimization technique in which two or more techniques are integrated in a meaningful manner to achieve the global best solution with a reasonable convergence rate to solve the CPSGS problem.

## **1.5 OBJECTIVES OF THE RESEARCH**

The objectives of the research work are to formulate and solve the generation scheduling problem:

- a) For coordinated CHP with hydro unit system using heuristic optimization technique.
- b) For coordinated CHP with renewable energy source using heuristic optimization technique.

c) For coordinated power system as multi-objective optimization problem using heuristic optimization technique.

## **1.6 OUTLINE OF THE THESIS**

In this research work, the single objective and multi-objective framework of CPSGS problem has been formulated using CHP, thermal, heat and hydro units. The CPSGS problem is a non-convex, highly constrained, multi-dimensional and complex optimization problem. In order to solve the CHPGS problem, three hybrid optimization techniques, *i.e.*, GWO-MS, QCSA-MS and CTM-QCSA-GWO techniques, have been proposed. In CTM-QCSA-GWO technique, QCSA and GWO are integrated. Further, CTM has been implemented to integrated QCSA-GWO for self-adaptive parameter settings of QCSA-GWO technique. The CTM accelerates convergence and aids in avoiding local optimal solutions. The QCSA-MS and CTM-QCSA-GWO techniques have been implemented to solve the MO-CPSGS problem. The cardinal priority ranking (CPR) method has been implemented for searching for the optimal non-dominated solution to the MO-HTGS and MO-CPSGS problems. The thesis work is organized into seven chapters. A brief description of all the chapters is as under:

In Chapter-1, the significant contributions of researchers in the field of generation scheduling problems have been reviewed. The background and implementation of mathematical, global search and hybrid optimization techniques for solving the optimization problems have been discussed. The multi-objective optimization techniques have also been reviewed to solve the multi-objective generation scheduling problems.

In Chapter-2, the CPSGS problem has been formulated by incorporating hydro, thermal, CHP and heat units. For solving the CPSGS problem, a heuristic optimization technique-I, *i.e.*, GWO-MS, is proposed. In POT-I, the GWO has been utilised for exploring the search space and the solution obtained by GWO is further enhanced by three mutation strategies, *i.e.*, Cauchy, Gaussian and opposition-based. The POT-I exhibits excellent exploration and exploitation capability. The performance of the POT-I is validated by implementing it to four test systems

including HTGS and small, medium and large sized CPSGS problems. The results obtained by POT-I for HTGS problem have been compared with published results and found satisfactory. The results obtained by POT-I for CPSGS problem are better than GWO. The two statistical tests, *i.e.*, *t* test and Mann-Whitey test, have been applied to investigate the statistical performance of the POT-I.

In Chapter-3, a heuristic optimization technique-II, namely, QCSA-MS has been proposed to solve the CPSGS problem. In POT-II, the QCSA technique is integrated with three mutation strategies, *i.e.*, Cauchy, Gaussian and opposition- based. The POT-II has an excellent exploration quality of QCSA and good exploitation feature of MS, which makes it a well-balanced and proficient approach for solving a multi-dimensional and complex CPSGS problem. The POT-II outperforms the QCSA technique in terms of outcomes, convergence characteristics, and distribution diversity. The POT-II achieved significant economic cost while dealing with complex joint constraints of CPSGS problem as compared to optimal cost obtained by QCSA, GWO and POT-I and other established methods.

In Chapter-4, a heuristic optimization technique-III, *i.e.*, a chaotic tent map (CTM) based quantum cuckoo search algorithm (QCSA) with grey wolf optimizer (GWO) (CTM-QCSA-GWO) has been proposed for finding an optimal solution to the CPSGS problem. The POT-III shows the outstanding exploration capability of QCSA and the superior exploitation nature of GWO. The CTM strategy has been applied to QCSA-GWO used to tune the algorithm parameters, speeding up convergence, avoiding local optimal solutions and improving the solution quality. For exhibiting the pertinence and effectiveness of the POT-III, it has been implemented to one HTGS and two CPSGS problems and the results are compared with published results. The results obtained by POT-III are also compared with the results obtained by the GWO, QCSA, POT-I and POT-II and found satisfactory.

In Chapter-5, the CHP-PV generation scheduling (GS) problem is formulated. In CHP-PV generation scheduling problem, thermal, CHP and heat units are incorporated with renewable

energy units, *i.e.*, PV units. The CHPGS and CHP-PV-GS problems are solved using POT-II and III. The incorporation of PV units with thermal, CHP and heat units significantly saves the fuel cost. The results obtained by POT-III are better than results obtained of GWO, QCSA, QCSA-GWO and POT-II.

In Chapter-6, the MO-CPSGS problem has been formulated in which the fuel cost and pollutant emission have been minimised simultaneously. The MO-HTGS and MO-CPSGS problems have been solved using POT-II and III. The cardinal priority ranking method has been utilized for searching the most satisfying non-dominated solution. The results attained by POT-II and III compared with established results and found satisfactory. The POT-III outperforms the POT-II.

Finally, in Chapter-7, the conclusions, contributions, and future scope of the research work has been presented. In this research work, the CPSGS problem considering thermal, CHP, heat and hydro units has been formulated as single-objective as well as MO problem. The CHPGS problem considering renewable energy source, *i.e.*, PV units, has also been formulated and solved separately. Three hybrid optimization techniques have been proposed for solving the HTGS, CHPGS, CPSGS, MO-CPSGS and CHP-PV-GS problems. The effectiveness of the POTs has been validated by using small, medium, and large-sized test systems. The results obtained by the POTs have been compared with the reported results and found satisfactory.

## CHAPTER 2

# OPTIMUM GENERATION SCHEDULING OF COORDINATED POWER SYSTEM USING GREY WOLF OPTIMIZER WITH MUTATION STRATEGIES

### 2.1 INTRODUCTION

The optimum power generation is considered as one of the most challenging and demanding issues in the power systems, because of unexpectedly increase in power demand and fossil fuel prices. The power system researchers are extensively working to achieve the optimum generation scheduling of coordinated power system (CPS) considering its advantages in terms of economic, environmental and reliability requirement. In this chapter, coordinated power system generation scheduling (CPSGS) problem having thermal, combined heat and power (CHP), heat and hydro units has been formulated. Since, the CPSGS problem is a hard constraint, non-convex, non-linear, discontinue, multi-modal and complex optimization problem hence there is a need for an effective hybrid optimization technique.

The main contributions of this chapter are summarized as:

- In a maiden attempt, a CPSGS problem has been formulated. The optimum generation scheduling of CPS involves various complex challenges *i.e.*, (i) effect of valve point on thermal units (ii) mutual dependency of the power and heat generation of CHP units (iii) time delay between upstream and low stream reservoirs for water flow and (iv) subject to satisfaction of complex constraints of thermal, CHP, heat and hydro units.
- In order to solve the CPSGS problem, a hybrid optimization technique-I, namely, grey wolf optimizer (GWO) with mutation strategies (GWO-MS) has been proposed. In the proposed optimization technique (POT)-I, the GWO technique and mutation strategies are integrated. The solution obtained by GWO is further enhanced by three mutation strategies, *i.e.*, Cauchy, Gaussian and Opposition-based. The POT-I exhibits excellent exploration and

exploitation capability as compared to other state of art algorithms.

The remainder of the chapter is organized as follows: The description of the CPS is presented in section 2.2. Section 2.3 presents the problem formulation of CPSGS. Section 2.4 emphasizes on optimization techniques and POT-I, *i.e.*, GWO-MS. The implementation of the POT-I for the CPSGS problem has been presented in section 2.5. Test systems and results are discussed in section 2.6 and conclusions are presented in section 2.7.

## 2.2 DESCRIPTION OF COORDINATED POWER SYSTEM

In this chapter, the CPS is associated with conventional thermal, CHP, heat and hydro units. The power demand is fulfilled by thermal, hydro and CHP units, and heat demand is satisfied by the heat and CHP units. The schematic of the CPS is shown in Fig. 2.1. The decision variables for CPSGS problem consist of power generation of thermal units ( $PT$ ), water discharge rate ( $q$ ), heat production of heat units ( $H$ ), heat and power generation from CHP units ( $HC$  and  $PC$ ). The set of decision variables is represented by an array  $X$  and is given as:

$$X = \left( \begin{array}{cccccccccccc} PT_{1,I} & \dots & PT_{N^{TH},I}, & PC_{1,I} & \dots & PC_{N^{CHP},I}, & HC_{1,I} & \dots & HC_{N^{CHP},I}, & H_{1,I} & \dots & H_{N^H,I}, & q_{1,I} & \dots & q_{N^{HY},I} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ PT_{1,T} & \dots & PT_{N^{TH},T}, & PC_{1,T} & \dots & PC_{N^{CHP},T}, & HC_{1,T} & \dots & HC_{N^{CHP},T}, & H_{1,T} & \dots & H_{N^H,T}, & q_{1,T} & \dots & q_{N^{HY},T} \end{array} \right) \quad (2.1)$$

← Power generation of thermal units
← Power generation of CHP units
← Heat generation of CHP units
← Heat generation of heat units
← Water discharge rate of hydro units

Decision variables of CPSGS problem

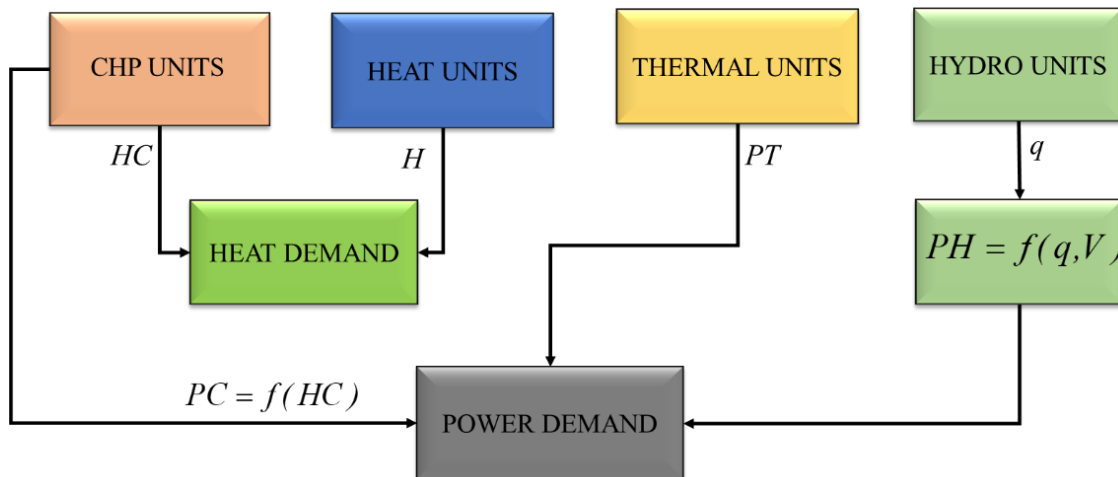


Figure 2.1 Schematic of coordinated power system

For a scheduling interval  $T$  with sub-interval of one-hour, the total number of decision variables are  $T \times (N^{TH} + N^{HY} + N^H + N^{CHP} + N^{CHP})$ .  $N^{TH}$ ,  $N^{HY}$ ,  $N^H$  and  $N^{CHP}$  are the total number of thermal, hydro, heat and CHP units, respectively.  $V$  is the reservoir volume of hydro units.

### 2.3 MATHEMATICAL MODELLING OF GENERATING UNITS

The mathematical model of thermal, CHP, heat and hydro generating units and problem formulation are discussed in the following sub-sections:

**2.3.1 Thermal Units:** The fuel cost function of the thermal units is expressed as a convex quadratic function. For a realistic cost function, the valve point loading effect is also included as a sinusoidal term and is expressed as (Narang *et al.*, 2014):

$$C_{it}(PT_{it}) = a_i(PT_{it})^2 + b_i(PT_{it}) + c_i + \left| d_i \times \sin \left\{ e_i \times (PT_i^{\min} - PT_{it}) \right\} \right| \quad (i \in N^{TH}; t \in T) \quad (\$/h) \quad (2.2)$$

where  $PT_{it}$  represents the power generation of  $i^{th}$  thermal unit at  $t^{th}$  sub-interval;  $a_i$ ,  $b_i$ ,  $c_i$ ,  $d_i$ ,  $e_i$  signify the cost coefficients of  $i^{th}$  thermal unit;  $N^{TH}$  represents the total number of thermal units;  $T$  is the scheduling time period.

The power generation of each thermal unit during each sub-interval should be within its capacity limits and is given as:

$$PT_i^{\min} \leq PT_{it} \leq PT_i^{\max} \quad (i \in N^{TH}; t \in T) \quad (2.3)$$

where  $PT_i^{\min}$ ,  $PT_i^{\max}$  are the power output limits of the  $i^{th}$  thermal unit.

**2.3.2 CHP Units:** The CHP unit is a cogeneration unit that generates power and heat simultaneously; hence it contributes to meet the requirement of power and heat demand. In the CHP unit, there is an interdependency of heat and power on each other. Thus, heat and power of CHP unit must lie in between the feasible operating region (FOR) to obtain the optimum generation schedule of CHP unit. The typical FOR of a CHP unit is shown in Fig. 2.2. The cost function of the CHP units ( $\$/h$ ) is given as (Nagendra, 2006):

$$C_{2j}(PC_{jt}, HC_{jt}) = \varepsilon_j(PC_{jt})^2 + \varphi_j PC_{jt} + \eta_j + \mu_j(HC_{jt})^2 + \delta_j HC_{jt} + \zeta_j PC_{jt} HC_{jt} \quad (j \in N^{CHP}; t \in T) \quad (2.4)$$

where  $PC_{jt}$  and  $HC_{jt}$  represent the power and heat generation of  $j^{th}$  CHP unit at  $t^{th}$  sub-interval;

$\varepsilon_j, \varphi_j, \eta_j, \mu_j, \delta_j, \zeta_j$  are the cost coefficients of  $j^{th}$  CHP unit;  $N^{CHP}$  represents the total number of CHP units.

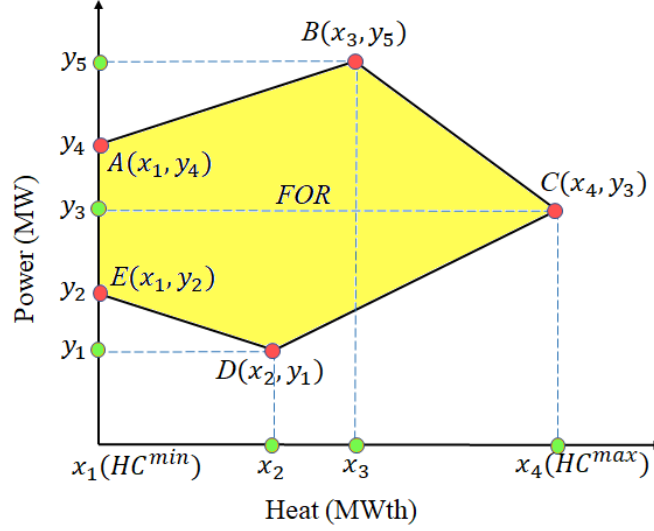


Figure 2.2 Heat-power feasible operation region of CHP unit (Basu, 2015)

The power and heat generation of each CHP unit should be within its capacity limits and is given as:

$$PC_j^{\min}(HC_j) \leq PC_{jt} \leq PC_j^{\max}(HC_j) \quad (j \in N^{CHP}; t \in T) \quad (2.5)$$

$$HC_j^{\min}(PC_j) \leq HC_{jt} \leq HC_j^{\max}(PC_j) \quad (j \in N^{CHP}; t \in T) \quad (2.6)$$

where  $PC_j^{\min}, PC_j^{\max}$  are the power output limits of  $j^{th}$  CHP unit;  $HC_j^{\min}, HC_j^{\max}$  are the heat output limits of  $j^{th}$  CHP unit.

**2.3.3 Heat Units:** The fuel cost function of the heat unit is expressed as convex quadratic function and is given as (Nagendra, 2006):

$$C_{3k}(H_{kt}) = \alpha_k(H_{kt})^2 + \beta_k H_{kt} + \gamma_k \quad (k \in N^H; t \in T) \quad (\$/h) \quad (2.7)$$

where  $H_{kt}$  represents the heat generation of  $k^{th}$  heat unit at  $t^{th}$  sub-interval;  $\alpha_k, \beta_k, \gamma_k$  are the cost coefficients of  $k^{th}$  heat unit;  $N^H$  represents the total number of heat units.

During each sub-interval, the heat generation from heat only unit should be within its production limits and is given as:

$$H_k^{\min} \leq H_{kt} \leq H_k^{\max} \quad (k \in N^H; t \in T) \quad (2.8)$$

where  $H_k^{\min}, H_k^{\max}$  are the heat output limits of the  $k^{th}$  heat unit.

**2.3.4 Hydro Units:** The operating cost of hydro power generation is negligible. The water discharge rate of the hydro units at each sub-interval should be within its set limit and is given as (Patwal *et al.*, 2018):

$$q_l^{\min} \leq q_{lt} \leq q_l^{\max} \quad (l \in N^{HY}; t \in T) \quad (2.9)$$

where  $q_{lt}$  is the water discharge rate of  $l^{th}$  hydro unit at  $t^{th}$  sub-interval;  $q_l^{\min}$  and  $q_l^{\max}$  are the capacity limits of  $l^{th}$  hydro unit;  $N^{HY}$  represents the total number of hydro units.

The multi-chain hydraulic system network of hydro units is shown in Fig. 2.3. In the multi-chain hydro model, the reservoir volume of each hydro unit updates due to reservoir inflow, water discharge rate, spillage, upper reservoir unit's discharge rate and spillage. The updated volume of the reservoir is given as:

$$V_{lt} = V_{lt-1} + \sum_{t=1}^T \left( IN_{lt} - q_{lt} - SP_{lt} + \sum_{m=1}^{UP_l} (q_{mt-\tau_{ml}} + SP_{mt-\tau_{ml}}) \right) \quad (l \in N^{HY}; t \in T) \quad (2.10)$$

where  $V_{lt}$  is the reservoir volume of  $l^{th}$  hydro unit at  $t^{th}$  sub-interval;  $IN_{lt}$  and  $SP_{lt}$  are the inflow and spillage rate of  $l^{th}$  hydro unit at  $t^{th}$  sub-interval.  $\tau_{ml}$  is the water transportation delay from  $m^{th}$  to  $l^{th}$  hydro unit.  $UP_l$  is the number of upstream reservoirs from  $l^{th}$  hydro unit.

The hydro power generation is a function of water discharge rate and reservoir volume and is given as (Patwal *et al.*, 2018):

$$PH_{lt} = C_{1l}(V_{lt})^2 + C_{2l}(q_{lt})^2 + C_{3l}V_{lt}q_{lt} + C_{4l}V_{lt} + C_{5l}q_{lt} + C_{6l} \quad (l \in N^{HY}; t \in T) \quad (2.11)$$

where  $PH_{lt}$  is the hydro power output of  $l^{th}$  hydro unit at  $t^{th}$  sub-interval;  $C_{1l}, C_{2l}, C_{3l}, C_{4l}, C_{5l}, C_{6l}$  are the coefficients of power generation  $l^{th}$  hydro unit.

The maximum and minimum limits of power generation and reservoir volume of hydro units should not be violated in any sub-interval as given below (Narang *et al.* 2014):

$$PH_l^{\min} \leq PH_{lt} \leq PH_l^{\max} \quad (l \in N^{HY}; t \in T) \quad (2.12)$$

$$V_l^{\min} \leq V_{lt} \leq V_l^{\max} \quad (l \in N^{HY}; t \in T) \quad (2.13)$$

where  $PH_l^{\min}, PH_l^{\max}$  are the power output limits of  $l^{th}$  hydro unit;  $V_l^{\min}, V_l^{\max}$  are the reservoir volume limits of  $l^{th}$  hydro unit.

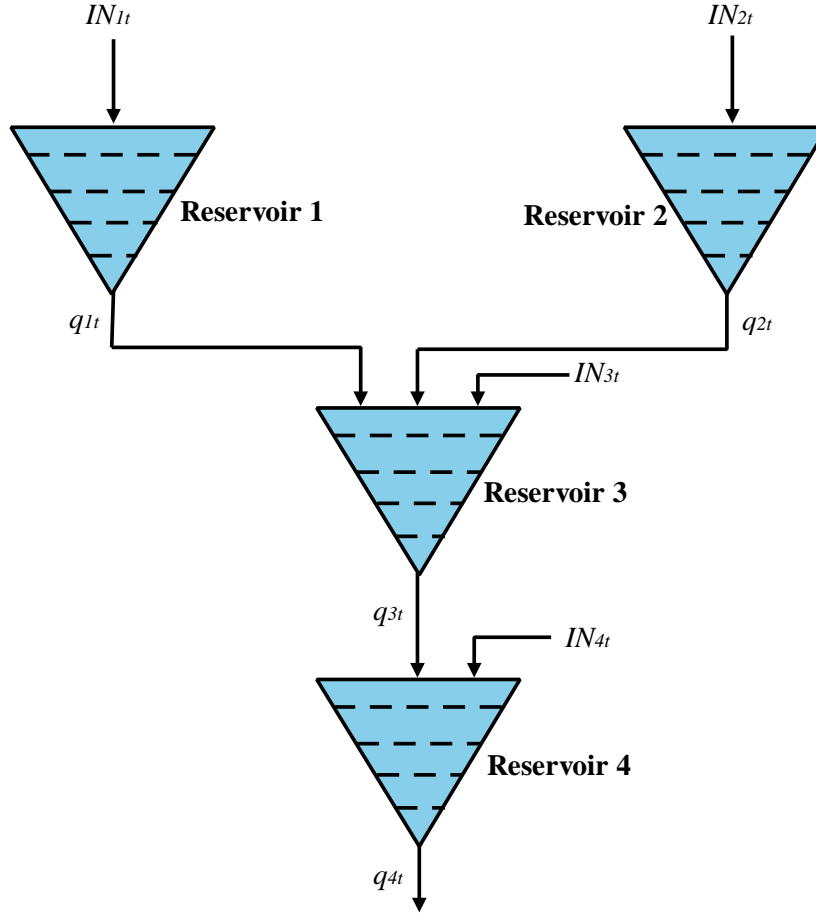


Figure 2.3 Multi-chain hydraulic system network of hydro units

## 2.4 PROBLEM FORMULATION

Four types of generating units (thermal, CHP, heat and hydro) have been considered for CPSGS problem, therefore, the total cost of scheduling problem includes the fuel cost of thermal, heat and CHP units. The fuel cost of hydro units is almost negligible, so it has not been considered. The main objective of the CPSGS problem is to achieve the minimum cost of power and heat generation by assigning optimum generation among the generating units by satisfying the various constraints related to thermal, CHP, heat and hydro units. The total fuel cost is expressed as:

$$\text{Minimize } F_1 = \sum_{t=1}^T \left[ \sum_{i=1}^{N^{TH}} C_{1i}(PT_{it}) + \sum_{j=1}^{N^{CHP}} C_{2j}(PC_{jt}, HC_{jt}) + \sum_{k=1}^{N^H} C_{3k}(H_{kt}) \right] \quad (2.14)$$

Subjected to the satisfaction of various operational constraints.

### 2.4.1 Constraints

The CPSGS problem is subjected to the number of constraints like bounds on decision variables, equality and inequality which are discussed below:

**2.4.1.1 Bounds on Decision Variable:** The generation scheduling problem is subjected to bounds on the decision variables *i.e.*, power generation of thermal and CHP units, heat production of CHP and heat units and water discharge rate of hydro units. All the decision variables should lie within their respective minimum and maximum capacity limits. These bounds on generating units are given by Eqs. (2.3), (2.5), (2.6), (2.8) and (2.9). Further, the CHP unit should operate within the FOR as shown in Fig. 2.2.

**2.4.1.2 Equality Constraints:** The CPSGS is subjected to three equality constraints *i.e.*, power and heat balance of CPS and final volume constraint of hydro units, which are discussed below:

**(i) Power Balance Constraint:** The coordinated power generation of thermal, CHP and hydro units should meet the power demand and transmission losses at each sub-interval and is given as:

$$\sum_{i=1}^{N^{TH}} (PT_{it}) + \sum_{j=1}^{N^{CHP}} (PC_{jt}) + \sum_{l=1}^{N^{HY}} (PH_{lt}) = PD_t + PL_t \quad (t \in T) \quad (2.15)$$

where  $PD_t$  and  $PL_t$  represent the power demand and transmission loss at  $t^{th}$  sub-interval.

The transmission loss is computed by using Kron's formula and is expressed as:

$$PL_t = \sum_{m=1}^{N^{TH}+N^{CHP}+N^{HY}} \sum_{n=1}^{N^{TH}+N^{CHP}+N^{HY}} P_{mt} B_{mn} P_{nt} + \sum_{m=1}^{N^{TH}+N^{CHP}+N^{HY}} B_{om} P_{mt} + B_{oo} \quad (t \in T) \quad (2.16)$$

where  $B_{mn}$ ,  $B_{om}$ ,  $B_{oo}$  are the loss coefficients;  $P_{mt}$  is the power generation of  $m^{th}$  power unit at  $t^{th}$  sub-interval.

**(ii) Heat Balance Constraint:** The heat generation of CHP and heat units should satisfy heat demand ( $HD_t$ ) at each sub-interval and is expressed as (Narang *et al.* 2017):

$$\sum_{j=1}^{N^{CHP}} (HC_{jt}) + \sum_{k=1}^{N^H} (H_{kt}) = HD_t \quad (t \in T) \quad (2.17)$$

**(iii) Final Volume Constraint:** At the end of the scheduling interval, each hydro unit should satisfy the final reservoir volume constraint and is given as:

$$V_l^{fin} = V_l^{ini} + \sum_{t=1}^T \left( IN_{lt} - q_{lt} - SP_{lt} + \sum_{m=1}^{UP_l} (q_{mt-\tau_{ml}} + SP_{mt-\tau_{ml}}) \right) \quad (l \in N^{HY})$$

(2.18)

where  $V_l^{fin}, V_l^{ini}$  are the final and initial reservoir volume of  $l^{th}$  hydro unit, respectively.

**2.4.1.3 Inequality Constraints:** The CPS problem is subjected to two inequality constraints. The reservoir volume and hydro power generation of hydro units should be within the respective capacity limits in each sub-interval, which are given by Eqs. (2.12) and (2.13), respectively.

## 2.4.2 Constraint Handling

The undertaken system is subjected to three equality constraints, two inequality constraints, bounds on decision variables ( $PT, q, H, HC, PC$ ) and FOR of the CHP unit. The initial values of decision variables are randomly generated within their corresponding limits as given below:

$$X_{dt} = X_d^{min} + (X_d^{max} - X_d^{min}) \times rand \quad (d \in N^D; t \in T) \quad (2.19)$$

where  $X_{dt}$  represents the  $d^{th}$  decision variable at  $t^{th}$  sub-interval;  $X_d^{min}, X_d^{max}$  are the bounds on  $d^{th}$  decision variable;  $rand$  is the uniformly distributed random number between 0 and 1;  $N^D$  is the total number of decision variables.

**2.4.2.1 Feasible Decision Variables:** During the search process, the decision variables may violate its bounds. The violation has been treated by fixing the decision variables to its respective bound and is given as:

$$X_{dt} = \begin{cases} X_d^{max}; & X_{dt} > X_d^{max} \\ X_d^{min}; & X_{dt} < X_d^{min} \\ X_{dt}; & X_d^{min} \leq X_{dt} \leq X_d^{max} \end{cases} \quad (d \in N^D; t \in T) \quad (2.20)$$

**2.4.2.2 FOR Constraint Handling:** The heat output of the CHP units is generated using Eq. (2.19).

The limits of power generation of the CHP units are fixed by the slope equation of the straight-line AB, BC, CD and DE (Fig. 2.2). The power output of CHP unit is randomly generated by using minimum (Eq. (2.21)) and maximum (Eq. (2.22)) limits of CHP unit as given in Eq. (2.23):

$$PC_j^{\min} = \begin{cases} \frac{y_2 - y_1}{x_1 - x_2} \times (HC_{jt} - x_2) + y_1; \text{if } (HC_{jt} \leq x_2) \\ \frac{y_3 - y_1}{x_4 - x_2} \times (HC_{jt} - x_2) + y_1; \text{if } (x_2 < HC_{jt} \leq x_4) \end{cases} \quad (2.21)$$

$$PC_j^{\max} = \begin{cases} \frac{y_5 - y_4}{x_3 - x_1} \times (HC_{jt} - x_1) + y_4; \text{if } (x_1 < HC_{jt} \leq x_3) \\ \frac{y_5 - y_3}{x_3 - x_4} \times (HC_{jt} - x_4) + y_3; \text{if } (x_3 < HC_{jt} \leq x_4) \end{cases} \quad (2.22)$$

$$PC_{jt} = PC_j^{\min} + (PC_j^{\max} - PC_j^{\min}) \times rand \quad (j \in N^{CHP}; t \in T) \quad (2.23)$$

**2.4.2.3 Equality Constraints Handling:** For satisfying the power and heat balance equality constraint, one thermal and one heat unit are randomly chosen as a dependent unit. The power generation of the dependent thermal unit ( $PT_t^{dep}$ ) at  $t^{th}$  sub-interval is computed as:

$$PT_t^{dep} = PD_t + \sum_{\substack{m=1 \\ m \neq dep}}^{N^{TH} + N^{CHP} + N^{HY}} \sum_{\substack{n=1 \\ n \neq dep}}^{N^{TH} + N^{CHP} + N^{HY}} P_{mt} B_{nm} P_{nt} + \sum_{\substack{m=1 \\ m \neq dep}}^{N^{TH} + N^{CHP} + N^{HY}} Bo_{mt} P_{mt} + Boo - \sum_{\substack{m=1 \\ m \neq dep}}^{N^{TH} + N^{CHP} + N^{HY}} P_{mt} \quad (t \in T) \quad (2.24)$$

Eq. (2.24) represents the quadratic expression of dependent power generation and its solution provides the dependent unit's power generation.

In a similar manner, the heat generation of the dependent heat unit ( $H_t^{dep}$ ) at  $t^{th}$  sub-interval is computed as given below:

$$H_t^{dep} = HD_t - \sum_{\substack{k=1 \\ k \neq dep}}^{N^H} (H_{kt}) - \sum_{j=1}^{N^{CHP}} (HC_{jt}) \quad (t \in T) \quad (2.25)$$

If the dependent power and heat unit's generation violates the bounds, then a violation error is computed individually for power and heat output and is computed as:

$$EP_t^{DEP} = \begin{cases} (PT_t^{dep} - PT_{dep}^{\min})^2; PT_t^{dep} < PT_{dep}^{\min} \\ (PT_t^{dep} - PT_{dep}^{\max})^2; PT_t^{dep} > PT_{dep}^{\max} \\ 0 & ; PT_{dep}^{\min} \leq PT_t^{dep} \leq PT_{dep}^{\max} \end{cases} \quad (t \in T) \quad (2.26)$$

$$EH_t^{DEP} = \begin{cases} (H_t^{dep} - H_{dep}^{\min})^2; H_t^{dep} < H_{dep}^{\min} \\ (H_t^{dep} - H_{dep}^{\max})^2; H_t^{dep} > H_{dep}^{\max} \\ 0 & ; H_{dep}^{\min} \leq H_t^{dep} \leq H_{dep}^{\max} \end{cases} \quad (t \in T) \quad (2.27)$$

In order to satisfy the final reservoir volume constraint, a mismatch is computed between actual end reservoir volume and the desired value and is computed as:

$$EV_l^{FI} = \begin{cases} (V_l^{fin} - V_l^T)^2; V_l^{fin} \neq V_l^T \\ 0 & ; V_l^{fin} = V_l^T \end{cases} \quad (l \in N^{HY}) \quad (2.28)$$

where  $EP_t^{DEP}$  and  $EH_t^{DEP}$  are the errors computed for dependent power and heat unit, respectively;

$EV_l^{FI}$  is the error computed for final reservoir volume constraint of  $l^{th}$  hydro units.

**2.4.2.4 Inequality Constraints Handling:** The reservoir volume and hydro power should be within the specified limits at each sub-interval. In case of any violation of limits, an error is computed corresponding to the inequality constraints and is given as:

$$EVO_{lt} = \begin{cases} (V_{lt} - V_{lt}^{\min})^2; V_{lt} < V_{lt}^{\min} \\ (V_{lt} - V_{lt}^{\max})^2; V_{lt} > V_{lt}^{\max} \\ 0 & ; V_{lt}^{\min} \leq V_{lt} \leq V_{lt}^{\max} \end{cases} \quad (l \in N^{HY}; t \in T) \quad (2.29)$$

$$EPH_{lt} = \begin{cases} (PH_{lt} - PH_{lt}^{\min})^2; PH_{lt} < PH_{lt}^{\min} \\ (PH_{lt} - PH_{lt}^{\max})^2; PH_{lt} > PH_{lt}^{\max} \\ 0 & ; PH_{lt}^{\min} \leq PH_{lt} \leq PH_{lt}^{\max} \end{cases} \quad (l \in N^{HY}; t \in T) \quad (2.30)$$

where  $EVO_{lt}$  and  $EPH_{lt}$  are the errors computed for violation of inequality constraints, *i.e.*, reservoir volume and hydro power of  $l^{th}$  hydro unit at  $t^{th}$  sub-interval, respectively.

The computed errors are used to formulate the objective function of CPSGS problem.

### 2.4.3 Objective Function Formulation

The objective function is formed by converting the constraint generation scheduling problem into an unconstrained problem by using exterior penalty functions (Yeniay, 2005). The mathematical formulation of the objective function is given as:

$$f(X_d) = F_1 + r \times \left( \sum_{t=1}^T EP_t^{DEP} + \sum_{t=1}^T EH_t^{DEP} + \sum_{l=1}^{N^{HY}} EV_l^{FI} + \sum_{t=1}^T \sum_{l=1}^{N^{HY}} EVO_{lt} + \sum_{t=1}^T \sum_{l=1}^{N^{HY}} EPH_{lt} \right) \quad (2.31)$$

where  $r$  is the exterior penalty factor parameter.

## 2.5 OPTIMIZATION TECHNIQUES

In this section, the mathematical modelling of GWO, mutation strategies and proposed algorithm-I have been discussed in detail.

### 2.5.1 Grey Wolf Optimizer

The grey wolves come under the category of top predators, who like to live and hunt in a group. They follow a unique and strict social ruling hierarchy. The first best solution is designated as alpha ( $\alpha$ ). Consequently, the second and third best solutions are considered as beta ( $\beta$ ) and delta ( $\delta$ ), respectively and all the remaining solutions are presumed as omega ( $\omega$ ). The  $\alpha$ ,  $\beta$  and  $\delta$  surely participates in the hunt process and  $\omega$  may follow them. In GWO algorithm, wolves focus to reach and attack the prey by covering the shortest distance or path. The grey wolves follow few steps as follows (Muro *et al.*, 2011):

**(i) Tracking and chasing the quarry:** The grey wolves encircle the quarry during the hunting process. The grey wolves update their positions by encircling the quarry positions. The encircling behavior by grey wolves is mathematically modelled as (Mirjalili *et al.*, 2014):

$$Z = |B \times X_p - X_{GW}| \quad (2.32)$$

$$X_{GW}^{it+1} = X_p - A \times Z \quad (it \in it^{max}) \quad (2.33)$$

where  $Z$  shows the encircling strategy of grey wolves;  $X_p$  and  $X_{GW}$  represent the position of prey and grey wolf, respectively;  $it$  represents the iteration count;  $it^{max}$  is the maximum number of iterations.

The  $A$  and  $B$  are the coefficient vectors which are reckoned as:

$$A = 2 \times z \times R_1 - z \quad (2.34)$$

$$B = 2 \times R_2 \quad (2.35)$$

$$z = 2 - \frac{2 \times it}{it^{max}} \quad (it \in it^{max}) \quad (2.36)$$

where  $z$  is a control parameter of the GWO algorithm;  $R_1$  and  $R_2$  are uniformly distributed random numbers, whose value lies between 0 and 1.

**(ii) Hunting of quarry:** The alpha as a leader guides the hunting process and it is followed by beta and delta. The remaining wolves update their positions with respect to the leader (alpha), beta and delta. The distance from alpha, beta and delta to each of the remaining wolf are computed as:

$$Z_\alpha = |B_1 \times X_\alpha - X_{GW}| \quad (2.37a)$$

$$Z_\beta = |B_2 \times X_\beta - X_{GW}| \quad (2.37b)$$

$$Z_\delta = |B_3 \times X_\delta - X_{GW}| \quad (2.37c)$$

The mathematical formulation of the up-gradation process of the wolf position is expressed as:

$$X_1 = X_\alpha - A_1 \times Z_\alpha \quad (2.38a)$$

$$X_2 = X_\beta - A_2 \times Z_\beta \quad (2.38b)$$

$$X_3 = X_\delta - A_3 \times Z_\delta \quad (2.38c)$$

$$X_{GW}^{it+1} = \frac{X_1 + X_2 + X_3}{3} \quad (it \in it^{max}) \quad (2.39)$$

where  $X_\alpha$ ,  $X_\beta$  and  $X_\delta$  are the positions of the three best representatives *i.e.*, alpha, beta and delta wolves, respectively;  $X_1$ ,  $X_2$  and  $X_3$  are the positions of prey with respect to alpha, beta and delta. The coefficients  $A_1$ ,  $A_2$ ,  $A_3$  and  $B_1$ ,  $B_2$ ,  $B_3$  are calculated using Eq. (2.34) and (2.35), respectively.

**(iii) Conducting attack:** It is obvious that when the quarry stops, grey wolves will kill the quarry and hunting process is completed. Grey wolves attack the quarry when  $|A| < 1$  and diverge from quarry when  $|A| > 1$  and start searching for new prey. During the hunting process, the value of  $z$  (Eq. 2.36) gradually goes towards zero and grey wolves move towards the quarry as the iteration approaches maximum set iteration.

### 2.5.2 Mutation Strategies

Three mutation strategies, *i.e.*, Cauchy, Gaussian, and opposition-based mutation have been explored to upgrade the solution quality. The Cauchy mutation operator provides the longer jumps and creates a higher possibility to avoid the local optima. The updated positions using Cauchy mutation are expressed as (Jordehi, 2015):

$$X_{1d} = X_d + (X_d^{\max} - X_d^{\min}) \times cau(0, s) \quad (d \in N^D) \quad (2.40)$$

$$cau(0, s) = \frac{1}{3.14 \times (R_1 - s)^2} \quad (2.41)$$

where  $X_{1d}$  represents the updated positions;  $X_d^{\max}$  and  $X_d^{\min}$  are the upper and lower bounds of decision variable  $d$ ; and  $s$  is control parameter of the Cauchy distribution.

The control parameter  $s$  should linearly decrease with iteration and is given as (Jordehi, 2015):

$$s = s - \frac{1}{it^{\max}} \quad (2.42)$$

The Gaussian mutation strategy generates the new positions by employing the gaussian distribution based random number that follows the normal distribution on the current positions. Thus, it aims to strengthen the population diversity, enhance exploration and speed up the convergence rate. As iterations progresses, the mutation rate decreases linearly, thereby helping in maintaining a balance between exploration and exploitation capabilities. The implementation of ‘Gaussian mutation’ strategy to update the positions is expressed as (Jordehi, 2015):

$$X_{2d} = X_d + (X_d^{\max} - X_d^{\min}) \times gau(0, h) \quad (d \in N^D) \quad (2.43)$$

$$gau(0, h) = \frac{1}{\sqrt{6.28}} \times \exp\left(-\frac{R_1^2}{2 \times h^2}\right) \quad (2.44)$$

where  $X_{2d}$  is the updated position by Gaussian mutation;  $gau(0, h)$  is the random number based on the Gaussian distribution;  $h$  is the standard deviation of the Gaussian distribution.

In the up-gradation process, the broad range search is needed during the initial stage and the search should intensify in the mid and last stages hence, the standard deviation is gradually shortening as:

$$h = h - \frac{1}{it^{\max}} \quad (2.45)$$

In the opposition-based mutation strategy, the second set of solutions is generated to incorporate high-quality solutions. The positions are updated using the opposition-based mutation which is given as follows (Jordehi, 2015):

$$X_{3d} = (X_d^{\max} + X_d^{\min}) - X_d \quad (d \in N^D) \quad (2.46)$$

where  $X_{3d}$  is the updated positions by opposition-based mutation strategy.

### 2.5.3 Proposed Heuristic Optimization Technique-I

In the GWO technique, each wolf position is updated with the guidance of three best-performing wolves. The algorithm parameters are adaptive to maintain the balance between exploration and exploitation capability of the GWO technique. However, the entire search process of GWO depends on the performance of leading wolves. Hence, the GWO technique lacks in diversity and performance of GWO technique is not satisfactory on high dimension multi-model problems (Long *et al.*, 2018b). In this work, mutation strategies have been undertaken to improve the diversity and quality of the solution. Three mutation strategies, namely, Cauchy, Gaussian, and opposition-based have been undertaken. The reasons to consider these three mutation strategies are summarized as:

- The variance of a Cauchy mutation is infinity, which will be helpful for the wolves to explore the search area effectively.
- The Gaussian mutation has a finite variance; hence the position of the newly generated wolf is nearby to its current position. This strategy is helpful to avoid any possible stagnation of the leading wolves.

- The opposition-based mutation operator is used to enhance the grey wolf's diversity.

These three mutation strategies have been applied to the solution obtained by the GWO technique to generate moderate solutions. The moderate solutions are compared with the parent solution to update the solution at each iteration. The flowchart for the implementation of POT-I to CPSGS problem is shown in Fig. 2.4.

## 2.6 IMPLEMENTATION OF THE POT-I TO CPSGS PROBLEM

In this section, the implementation of the POT-I to solve the CPSGS problem has been discussed. The elaborated steps are given as:

**Step 1:** Read the input data, *i.e.*, cost coefficients, power and heat demand, maximum and minimum limits of decision variables, etc.

**Step 2:** Initialize the position of wolves as decision variables. For CPSGS problem, the decision variable matrix is given by Eq. (2.1). The decision variables are randomly initialized for thermal, heat and hydro units as given in Eq. (2.19). For the CHP unit, the heat is randomly generated between the specified bounds using Eq. (2.19), and power is randomly generated within the FOR corresponding to the generated heat.

**Step 3:** The objective function (Eq. 2.31) is evaluated for the randomly generated wolves.

**Step 4:** The alpha, beta and delta wolves have been designated on the basis of objective function evaluation.

**Step 5:** The position of the grey wolves is updated to search the optimum location of the quarry, as represented by Eqs. (2.37)- (2.39).

**Step 6:** The moderate solutions are generated using Cauchy, Gaussian and opposition-based mutation strategies using Eqs. (2.40), (2.43) and (2.46), respectively, corresponding to the solution obtained from the GWO technique at each iteration.

**Step 7:** For each moderate solution, the objective function is evaluated (Eq. 2.31).

**Step 8:** Based on objective function evaluation, the best solution is selected among existing best

solution obtained by GWO and moderate solutions obtained by three mutation strategies, for the next iteration.

**Step 9:** The steps 4-8 are repeated until a termination criterion is met. The maximum number of iterations has been undertaken as a termination criterion.

**Step 10:** The global best position represents the optimum generation schedule of the CPS.

**Step 11:** Stop

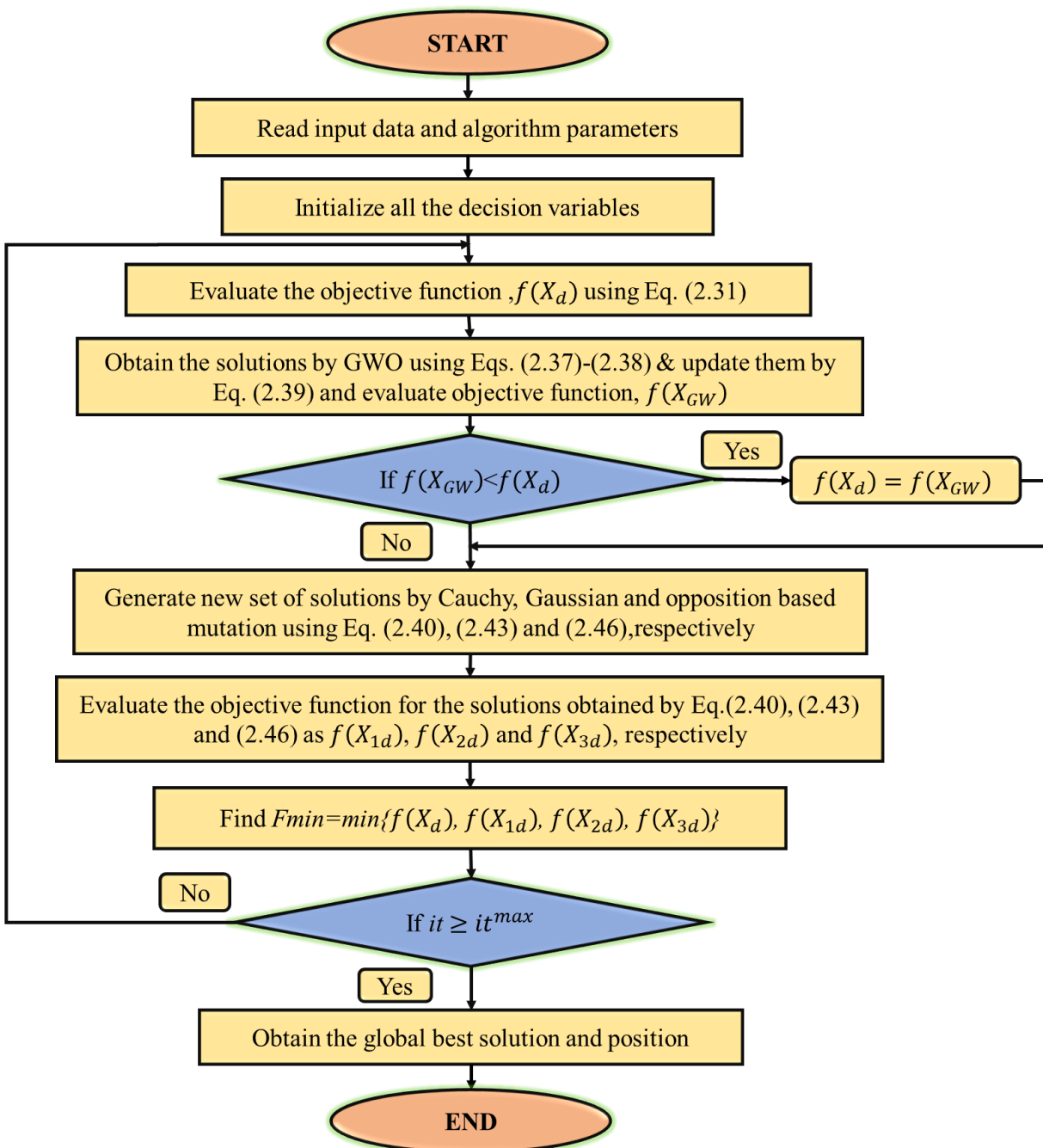


Figure 2.4 Flowchart for implementation of POT-I to CPSGS problem

## 2.7 TEST SYSTEMS, RESULTS AND DISCUSSION

The POT-I and GWO are implemented to solve four test systems to validate their performance. The first test system (TS) is a standard HTGS problem. The TS-II, III and IV are small, medium and large sized CPSGS problems. For all the test systems, the scheduling interval is 24 hrs with 1 hr sub-interval. Hence, the number of decision variables for TS-I, II, III, and IV are 168, 432, 696 and 936, respectively. The details regarding the test systems have been given in following sub-section.

### 2.7.1 Test Systems

For TS-I, HTGS problem has been considered having 3 thermal and 4 hydro units. Multi-chain cascaded model of hydro units is shown in Fig. 2.2. For TS-I, two cases have been considered. In TS-I (case-I), transmission losses of thermal units have been neglected while, in TS-I (case-II), transmission losses of thermal units have been considered. The input data of the TS-I has been referred from Ref. (Basu, 2004). The cost coefficients and capacity limits of thermal units are given in Table A.1.1 of Appendix-A. The input data of hydro units is same for all the test systems. The hydro power generation coefficients, capacity limits of hydro power output and capacity limits of water discharge rate of hydro units for TS-I-IV are given in Table A.2.1 of Appendix-A. The capacity limits of reservoir storage volume, initial and terminal reservoir storage volume limits of hydro units TS-I-IV are given in Table A.2.2 of Appendix-A. Reservoir inflow of hydro units for TS-I is given in Table 2.2.3 of Appendix-A. The power demand for TS-I is given in Table A.5.1 of Appendix-A. The transmission loss coefficients for TS-I (case-II) has been referred from Ref. (Lakshminarasimman and Subramanian, 2008) and are given in Section A.1 of Appendix-A.

The TS-II, III and IV are small, medium and large sized CPSGS problems. The TS-II has total 18 generating units (11 thermal units, 2 CHP units, 1 heat only unit and 4 hydro units). TS-III has total 29 generating units (19 thermal units, 4 CHP units, 2 heat units and 4 hydro units). TS-IV has total 39 generating units (29 thermal units, 4 CHP units, 2 heat units and 4 hydro units).

The input data for hydro, thermal, CHP and heat units for TS-II, III and IV have been referred from Refs. (Basu, 2004), (Basu, 2008) and (Elaiw *et al.*, 2013), respectively. The cost coefficients and power output capacity limits of thermal units of TS-II-IV are given in Tables A.1.2-A.1.4, respectively, of Appendix-A. The cost coefficients of CHP and heat units of TS-II are given in Table A.3.1 and A.3.2, respectively, of Appendix-A. The cost coefficients of CHP and heat units of TS-III and IV are given in Table A.3.3 and A.3.4 of Appendix-A. The FOR of the CHP units of TS-II-IV have been shown in Fig. A.1.1 and A.1.2 of Appendix-A. The power and heat demand for TS-II-IV are given in Tables. A.5.1 and A.5.2, respectively.

### **2.7.2 Algorithm Parameter Settings**

In this work, the FORTRAN 90 compiler has been used for the implementation of the POT-I. The program has been executed on a laptop having a core-i5 processor and 8 GB of RAM at 1.80 GHz. In order to set the algorithm parameters, the maximum and minimum value of each algorithm parameter has been set and parameter values are perturbed with a certain step size. This process continues for all the algorithm parameters, consecutively and the best parameter set has been selected. The population size of 50, 50, 60 and 60 have been set for TS-I and II, III and IV, respectively to achieve the best solution. The control parameter  $z$  of the GWO is initially set to 0.25 and varied by using equation Eq. (2.36). The control parameters  $s$  and  $h$  for Cauchy distribution and Gaussian mutation strategy are initially set to 1.5 and 1.6 and varied by using Eqs. (2.42) and (2.45), respectively. The maximum number of iterations for TS-I, II, III and IV has been set to 5000, 5000, 8000 and 10000, respectively.

### **2.7.3 Simulation Results and Discussion**

The detailed discussion on the results obtained by the POT-I for all the test systems is discussed below:

**2.7.3.1 Test System-I:** For effective validation of the POT-I and GWO technique, these have been applied to solve the typical HTGS problem. The GWO and POT-I have been executed 30 times

and minimum, average, maximum cost and standard deviation have been reported in Table 2.1. The results obtained by POT-I for TS-I (case-I) have been compared with the other state of the art optimization techniques are given in Table 2.1. For TS-I (case-I), the minimum fuel cost obtained by the POT-I and GWO technique is 41,501 \$ and 41,700 \$, respectively. The minimum cost obtained by the POT-I is less than GWO, particle swarm optimization (PSO) (Mandal and Chakraborty, 2011), clonal selection algorithm (Swain *et al.*, 2011), real coded genetic algorithm (RCGA) (Fang *et al.*, 2014), modified differential evolution (MDE) (Lakshminarasimman and Subramanian, 2006) and time varying acceleration coefficient (TVAC)-PSO (Patwal *et al.*, 2018) by 0.48%, 2.29%, 2.21%, 3.23%, 2.60% and 3.34%, respectively. The POT-I attained 0.85%, 2.03%, 1.29% and 0.11% lesser optimal cost than modified hybrid DE (MHDE) (Lakshminarasimman and Subramanian, 2008), quantum PSO (QPSO) (Sun and Lu, 2010), predator prey optimization (PPO) (Narang *et al.*, 2012) and mixed integer linear programming (MILP) (Ahmadi, Kaymanesh, *et al.*, 2015), respectively. It is illustrated from the Table 2.1 that the POT-I has a better success rate as compared to the other optimization techniques results.

**Table 2.1** Comparison of cost for TS-I (case-I)

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
PSO (Mandal and Chakraborty, 2011)	42,474	---	---	---	123.52
Clonal selection algorithm (Swain <i>et al.</i> , 2011)	42,440	---	---	---	109.12
RCGA (Fang <i>et al.</i> , 2014)	42,886	43,261	43,032	---	30.00
MDE (Lakshminarasimman and Subramanian, 2006)	42,611	---	---	---	125.00
TVAC-PSO (Patwal <i>et al.</i> , 2018)	42,936	43,687	43,252	---	21.33
MHDE (Lakshminarasimman and Subramanian, 2008)	41,856	---	---	---	31.00
QPSO (Sun and Lu, 2010)	42,359	---	---	---	---
PPO (Narang <i>et al.</i> , 2012)	42,042	42,099	42,078	---	30.71
MILP (Ahmadi, Kaymanesh, <i>et al.</i> , 2015)	41,549	---	---	---	---
GWO	41,700	42,035	41,901.4	79.7	14.28
POT-I	41,501	41,750	41,600.8	58.8	15.49

In order to check the computational competency of the optimization techniques, CPU time should be compared. It is obvious from the Table 2.1 that the POT-I requires marginal higher

computation time per iteration as compared to GWO technique; however, the POT-I outperforms the GWO in terms of minimum, maximum, average cost and standard deviation. The optimum thermal and hydro power generation is given in Table 2.2 for TS-I, case-I and it is evident that the total power generation satisfies the power demand at each sub interval. The water discharge rate and reservoir volume are shown in Figs. 2.5 and 2.6, respectively. It is illustrated from figures that the water discharge rate and reservoir volume are within its specified limits for each sub interval. Further, final volume constraint is fulfilled at the end of the scheduling interval. The convergence characteristics of the POT-I and GWO are displayed in Fig. 2.7, which shows that the POT-I exhibit superior performance than GWO.

**Table 2.2** Optimum power generation attained by POT-I for TS-I (case-I)

t (hr)	PD (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	102.5	124.9	229.5	93.7	59.2	0.0	140.2	750
2	780	102.6	40.0	319.3	74.0	60.1	16.4	167.6	780
3	700	102.7	124.9	139.8	84.4	56.3	46.9	145.0	700
4	650	20.0	125.0	229.5	54.7	63.6	43.2	114.0	650
5	670	102.0	124.8	139.7	73.3	60.7	33.2	136.1	670
6	800	101.8	124.2	229.3	55.9	67.6	8.3	212.8	800
7	950	96.0	209.3	229.3	76.2	70.6	37.4	231.2	950
8	1010	95.4	124.5	408.8	70.7	49.5	27.9	233.3	1010
9	1090	116.2	209.9	319.4	90.6	57.0	41.5	255.5	1090
10	1080	101.0	279.4	319.3	76.1	66.4	30.4	207.4	1080
11	1100	102.5	124.1	408.9	71.9	59.9	43.8	289.0	1100
12	1150	101.9	209.7	408.7	87.7	67.7	21.0	253.3	1150
13	1110	102.8	210.1	319.9	85.3	63.7	47.9	280.4	1110
14	1030	97.8	123.5	318.8	92.8	64.2	40.7	292.1	1030
15	1010	101.8	124.8	319.2	74.7	68.1	36.4	284.9	1010
16	1060	102.7	124.9	319.2	86.1	75.4	49.6	302.2	1060
17	1050	102.5	124.9	318.7	81.4	75.3	52.8	294.4	1050
18	1120	102.5	209.8	319.2	77.8	70.2	53.6	286.9	1120
19	1070	20.2	210.3	409.3	56.3	58.6	56.2	259.2	1070
20	1050	103.8	215.5	229.6	86.0	59.6	57.2	298.3	1050
21	910	20.0	209.8	229.5	68.6	69.5	58.5	254.1	910
22	860	90.0	121.7	228.7	68.6	54.5	59.2	237.3	860
23	850	20.1	124.8	229.5	64.5	65.9	58.8	286.5	850
24	800	97.6	122.7	139.5	68.2	59.4	39.2	273.3	800

In the POT-I, three mutation strategies have been simultaneously integrated with GWO technique. To study the effect of individual mutation strategy with GWO technique, a comparison among these has been carried out. The convergence characteristics have been presented in Fig. 2.8 for case-I. It is evident from Fig. 2.8 that the individual mutation strategy is able to improve the

convergence pattern as compared to GWO, however, the POT-I performs better as compared to individual mutation strategy integrated with GWO technique.

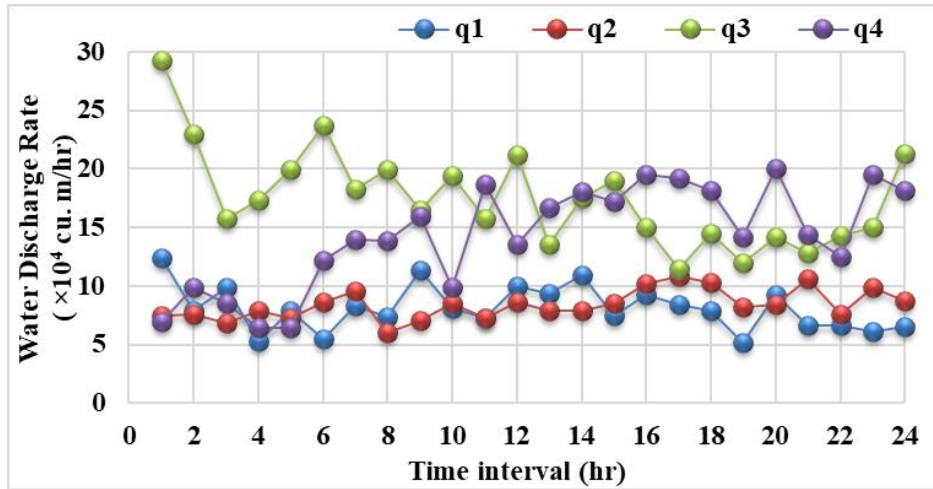


Figure 2.5 Water discharge rate of hydro units attained by POT-I for TS-I (case-I)

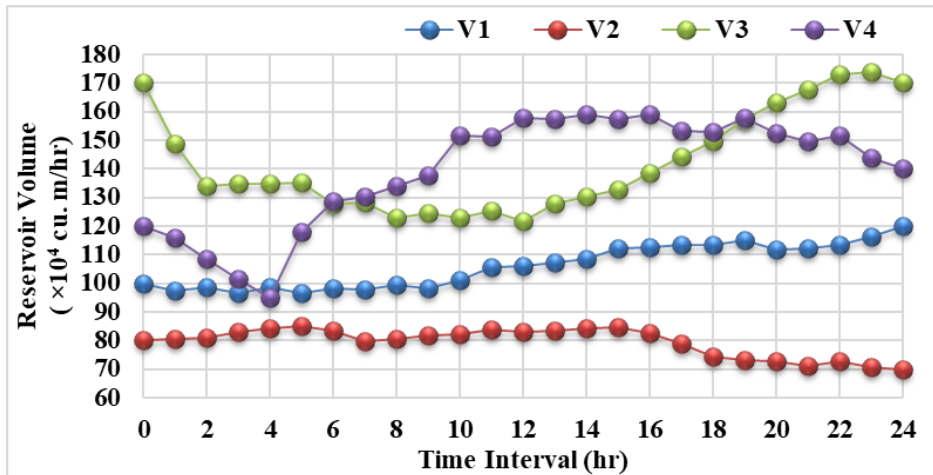


Figure 2.6 Reservoir volume of hydro units attained by POT-I for TS-I (case-I)

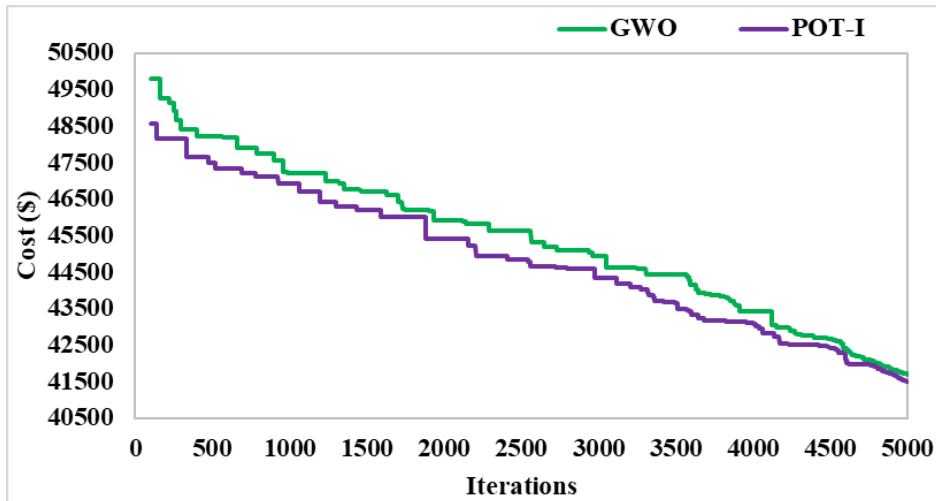
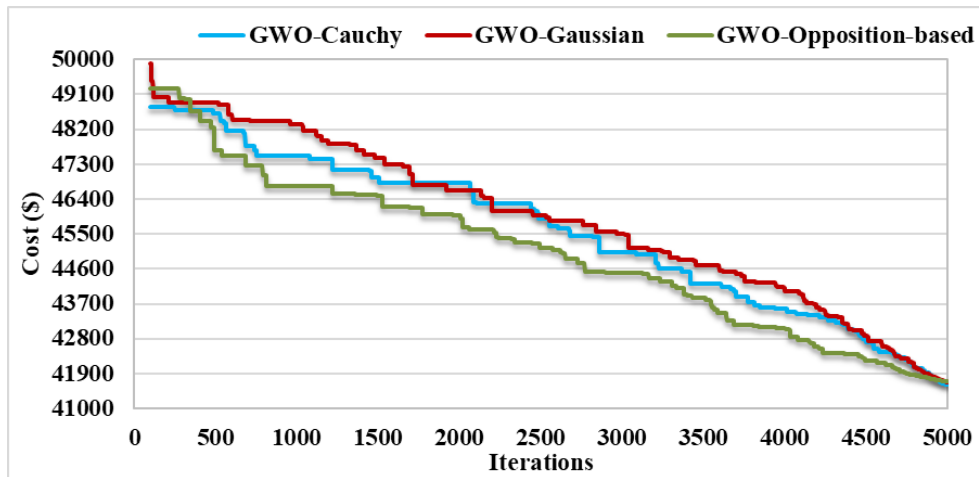


Figure 2.7 Convergence characteristics of cost attained by POT-I for TS-I (case-I)



**Figure 2.8** Convergence characteristics of mutation strategies for TS-I (case-I)

For TS-I (case-II), the minimum cost attained by GWO and POT-I is 42,708 \$ and 42,473 \$, respectively. The minimum, maximum, average cost, standard deviation and average CPU time reported for state of art techniques, *i.e.*, RCGA (Fang *et al.*, 2014), MDE (Lakshminarasimman and Subramanian, 2006), hybrid DE (HDE) (Lakshminarasimman and Subramanian, 2008), MHDE (Lakshminarasimman and Subramanian, 2008), quantum-inspired evolutionary algorithm (QEA) (Wang *et al.*, 2012), small population based PSO (SPPSO) (Zhang *et al.*, 2012), real-coded QEA (RQEA) (Wang *et al.*, 2012) are compared with GWO and POT-I's results and presented in Table 2.3. It is evident from Table 2.3 that the POT-I is able to search the global best and high-quality solution at most of the executions. However, the CPU time required by the POT-I is marginally higher as compared to the GWO technique.

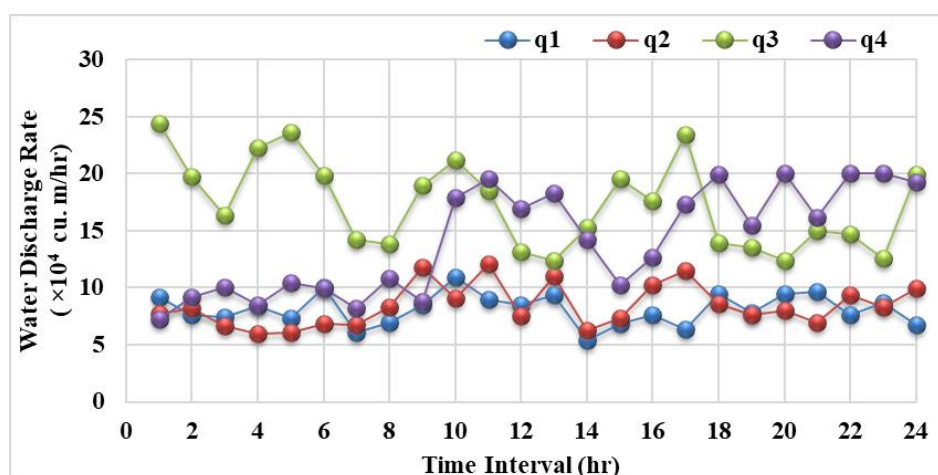
**Table 2.3** Comparison of cost for TS-I (case-II)

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
RCGA (Fang <i>et al.</i> , 2014)	43,465	43,717	43,643	---	32.00
MDE (Lakshminarasimman and Subramanian, 2006)	43,435	---	---	---	---
HDE (Lakshminarasimman and Subramanian, 2008)	43,656	---	---	---	68.00
MHDE (Lakshminarasimman and Subramanian, 2008)	42,679	---	---	---	40.00
QEA (Wang <i>et al.</i> , 2012)	44,686	---	---	---	19.00
SPPSO (Zhang <i>et al.</i> , 2012)	42,740	44,346	43,622	---	32.70
RQEA (Wang <i>et al.</i> , 2012)	42,715	---	---	---	21.00
GWO	42,708	42,994	42,854	81.6	15.38
POT-I	42,473	42,686	42,549	52.5	16.45

The optimal generation of thermal and hydro units and transmission losses for a time interval of 24 hours has been presented in Table 2.4. It can be observed from Table 2.4 that total power generation satisfies the power demand and losses in each sub interval. The water discharge rate and reservoir volume are presented in Figs. 2.9 and 2.10, respectively, and satisfy all the constraints. The comparison of convergence characteristics of the POT-I and GWO are shown in Fig. 2.11 which clearly shows the effectiveness of the POT-I to get the optimal solution as compared to GWO technique.

**Table 2.4** Optimum power generation attained by POT-I for TS-I (case-II) (continued)

t (hr)	PD (MW)	PL (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
			PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	6.5	101.6	124.8	229.4	82.1	60.5	14.6	143.5	756.5
2	780	7.2	102.1	124.8	227.1	73.4	63.2	36.6	160.0	787.2
3	700	6.4	102.5	40.0	229.4	72.3	54.7	47.0	160.6	706.4
4	650	5.3	102.3	40.0	228.1	78.1	52.1	20.4	134.3	655.3
5	670	6.8	102.5	40.0	229.4	70.9	53.4	9.6	171.0	676.8
6	800	7.8	102.3	124.7	229.4	84.9	59.0	31.0	176.4	807.8
7	950	9.9	102.6	207.2	319.2	60.8	58.4	48.1	163.7	959.9
8	1010	11.9	102.6	209.8	319.2	68.2	67.3	49.8	205.1	1021.9
9	1090	12.8	100.6	294.5	319.2	78.7	81.1	35.1	193.7	1102.8
10	1080	16.8	102.4	209.4	319.1	90.7	68.9	21.8	284.6	1096.8
11	1100	17.3	102.0	209.5	319.2	82.7	80.0	34.3	289.6	1117.3
12	1150	17.5	102.3	199.7	407.6	80.4	58.7	50.1	268.7	1167.5
13	1110	16.5	20.1	295.1	319.3	85.6	74.3	53.0	279.1	1126.5
14	1030	14.5	101.0	209.4	319.0	58.4	49.9	53.0	253.7	1044.5
15	1010	13.4	102.1	124.4	408.9	70.8	58.1	41.2	217.9	1023.4
16	1060	14.3	102.5	208.7	319.0	77.2	72.7	48.2	245.9	1074.3
17	1050	16.2	101.2	293.0	229.2	67.1	74.7	17.5	283.5	1066.2
18	1120	17.6	104.3	216.3	319.3	88.8	59.6	53.6	295.8	1137.6
19	1070	15.4	101.8	209.7	319.0	78.7	53.8	54.8	267.5	1085.4
20	1050	17.6	103.7	55.6	409.0	88.6	55.8	57.1	297.7	1067.6
21	910	13.4	95.7	124.8	228.6	89.0	50.6	56.8	277.8	923.4
22	860	14.3	24.1	211.6	140.6	76.6	64.2	58.1	299.0	874.3
23	850	13.7	103.5	126.1	140.3	83.2	58.6	59.8	292.1	863.7
24	800	12.8	89.1	124.5	137.6	70.5	65.7	45.2	280.1	812.8



**Figure 2.9** Water discharge rate of hydro units attained by POT-I for TS-I (case-II)

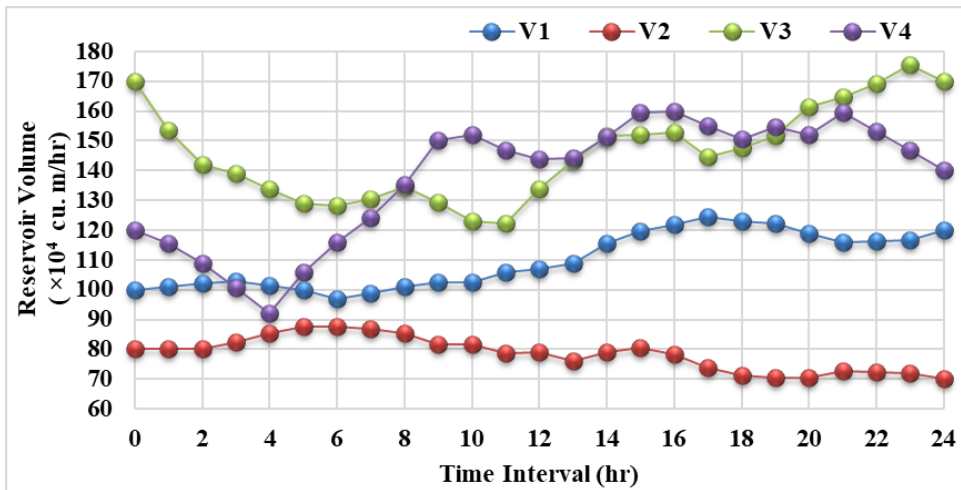


Figure 2.10 Reservoir volume of hydro units attained by POT-I for TS-I (case-II)

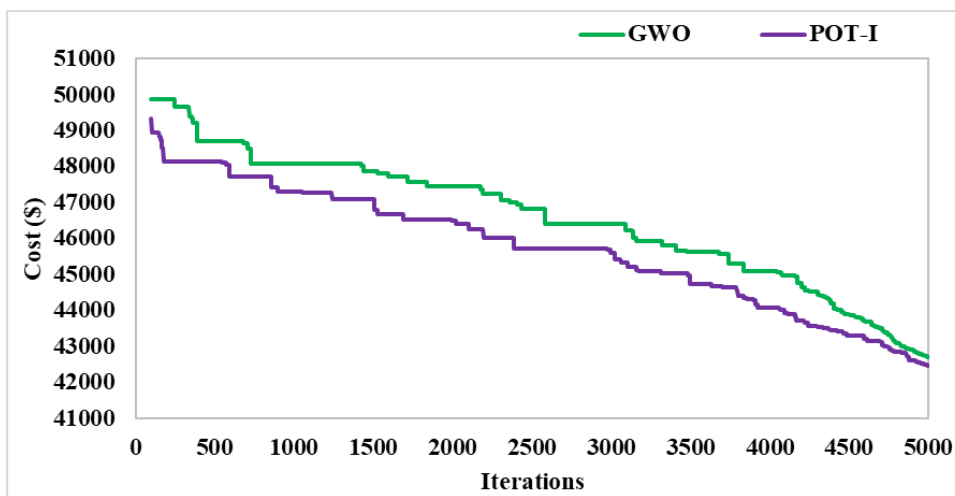


Figure 2.11 Convergence characteristics of cost attained by POT-I for TS-I (case-II)

**2.7.3.2 Test System-II and III:** The TS-II and III are CPSs, consisting of thermal, CHP, heat and hydro units. The results obtained by the POT-I and GWO for TS-II and III are shown in Tables 2.5 and 2.6, respectively. The minimum operating cost attained by the GWO and POT-I for TS-II is 26,08,065\$ and 25,62,644\$, respectively. For TS-III, the minimum cost obtained by GWO and POT-I is 58,28,034\$ and 57,38,132\$, respectively. Hence, it is evident from the obtained result that POT-I improved the results as compared to GWO by 1.74% and 1.54% for TS-II and III. For statistical measures, the average and maximum cost, standard deviation and average CPU time have also been computed. The optimum power generation of thermal, CHP, hydro units is tabulated in Tables 2.7(a)-(b) and heat production of heat and CHP units are tabulated in Table 2.8 for TS-II. The water discharge rate and reservoir volume of hydro units for TS-II are shown in

Figs. 2.12 and 2.13, respectively. It is illustrated from tables and figures that obtained optimum generation schedule satisfy all the constraints. For TS-III, the optimum generation schedule is of thermal, CHP and hydro units is presented in Tables 2.9 (a)-(c). Table 2.10 gives the optimum heat generation schedule of heat and CHP units. Optimum water discharge rate and reservoir volume for TS-III are presented in Figs. 2.14 and 2.15, respectively. It is further established that optimum results are feasible. It is also illustrated from Figs. 2.16 and 2.17, that the POT-I has better convergence than GWO for both the test systems. Hence, it is summarized that the POT-I produces high-quality results repeatedly.

**Table 2.5** Comparison of cost for TS-II

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	26,08,065	27,12,549	26,65,273	33,080	34.06
POT-I	25,62,644	26,35,849	25,97,527	22,762	35.60

**Table 2.6** Comparison of cost for TS-III

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	58,28,034	59,35,955	58,89,836	29,825	59.36
POT-I	57,38,132	58,28,034	57,90,307	24,470	61.90

**Table 2.7(a)** Optimum power generation attained by POT-I for TS-II

t (hr)	PD (MW)	Power (MW) (Thermal Units)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>	PT <sub>11</sub>
1	1786	33.1	53.6	102.5	215.2	228.5	95.7	273.6	72.8	72.5	44.3	23.0
2	1890	52.6	87.2	78.6	223.5	139.7	269.3	177.3	62.0	79.6	53.0	27.2
3	1958	24.2	90.6	164.7	214.1	135.0	162.3	175.6	82.1	45.5	76.7	46.2
4	2056	85.1	201.5	116.4	182.9	174.9	108.4	213.6	112.8	94.9	53.0	37.1
5	2150	143.9	206.8	238.1	168.7	150.3	113.5	152.3	76.7	45.1	50.1	12.6
6	2428	104.3	102.9	355.1	317.9	306.0	94.5	83.5	123.9	51.9	64.0	10.7
7	2652	125.1	156.9	357.5	261.6	211.8	162.4	65.0	131.1	84.4	65.5	28.3
8	2786	149.0	202.1	416.1	317.9	147.2	120.6	177.8	108.3	86.7	38.9	43.0
9	3014	113.7	253.2	465.9	300.1	259.2	312.4	69.4	108.4	112.7	31.0	14.1
10	3102	124.8	243.1	459.7	332.6	279.3	229.5	240.8	77.1	55.5	58.7	38.8
11	3206	159.3	182.4	320.0	402.3	373.5	294.0	228.9	97.7	88.6	33.7	26.8
12	3300	115.4	183.7	455.5	400.9	305.2	259.2	224.2	130.7	83.2	72.0	16.2
13	3182	97.3	128.0	380.7	323.0	377.7	316.4	258.0	160.0	80.9	60.9	41.5
14	2954	172.5	208.2	408.8	325.3	262.1	220.9	149.1	121.0	29.0	35.9	25.9
15	2795	107.7	124.9	451.2	421.8	306.2	138.5	95.6	106.3	53.6	39.7	19.4
16	2614	146.6	181.1	247.1	292.6	154.2	188.6	167.7	59.7	20.0	54.7	15.9
17	2530	95.5	55.1	222.3	286.6	242.1	169.4	270.1	148.6	100.6	66.6	21.5
18	2748	108.7	72.1	306.1	228.8	295.5	173.7	247.4	116.0	123.6	43.4	18.7
19	2846	116.7	191.5	275.3	379.6	209.5	212.5	172.8	90.3	42.5	69.0	29.8
20	3022	150.3	238.9	488.1	307.1	321.8	152.2	269.7	63.7	82.3	47.1	29.9
21	2834	118.9	101.6	472.0	400.2	159.9	303.3	187.4	108.7	75.1	30.4	18.8
22	2488	91.5	130.0	298.9	332.3	159.4	275.9	122.8	130.9	36.8	73.2	48.9
23	2182	129.7	170.6	256.6	281.3	238.5	77.0	142.0	91.4	116.3	29.6	39.5
24	1984	66.5	110.7	338.9	224.1	148.1	143.1	83.1	84.7	30.0	66.3	26.0

**Table 2.7(b)** Optimum power generation attained by POT-I for TS-II

t (hr)	PD (MW)	Power (MW) (CHP Units)		Power (MW) (Hydro Units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	1786	132.1	103.8	56.5	55.3	57.8	161.4
2	1890	121.1	83.9	81.3	65.2	57.2	211.2
3	1958	127.0	88.2	55.5	64.9	50.3	125.5
4	2056	100.6	110.5	86.4	60.5	55.4	117.7
5	2150	100.7	68.7	69.4	52.8	52.6	198.0
6	2428	155.8	85.8	80.4	67.2	53.2	150.4
7	2652	157.6	73.2	61.6	63.5	58.1	156.4
8	2786	213.8	53.9	70.8	66.3	45.1	193.1
9	3014	158.8	83.6	69.4	79.1	34.1	144.4
10	3102	177.8	63.4	76.4	67.9	31.9	152.9
11	3206	176.4	75.6	93.5	60.2	56.4	215.4
12	3300	103.4	120.1	76.9	62.6	56.4	212.1
13	3182	117.7	109.7	63.2	48.6	53.8	164.8
14	2954	196.6	119.2	100.9	60.0	48.6	218.9
15	2795	229.8	55.7	66.8	56.5	38.0	234.0
16	2614	216.7	120.9	95.3	53.6	60.1	205.0
17	2530	155.5	108.5	78.0	51.6	60.6	233.2
18	2748	133.7	95.0	77.1	57.9	60.1	215.4
19	2846	108.0	83.4	82.7	71.3	61.9	249.7
20	3022	192.3	97.7	94.8	73.4	35.2	232.0
21	2834	172.4	79.4	73.9	49.9	36.6	236.6
22	2488	115.2	53.6	69.0	62.4	49.3	249.5
23	2182	191.9	45.9	97.5	65.2	30.3	222.6
24	1984	135.7	94.2	90.4	57.1	28.0	263.8

**Table 2.8** Optimum heat generation attained by POT-I for TS-II

t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)	t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
1	390	28.8	6.7	354.5	13	470	20.5	4.5	445.0
2	400	87.3	63.8	248.8	14	460	159.0	62.8	238.2
3	410	6.2	28.7	375.1	15	450	69.5	39.6	340.9
4	420	85.7	24.4	309.9	16	450	140.2	26.3	283.5
5	440	72.4	52.7	314.9	17	420	96.8	17.0	306.2
6	450	71.0	30.9	348.2	18	435	99.0	42.8	293.2
7	450	36.0	34.3	379.7	19	445	113.9	95.6	235.5
8	455	60.3	52.7	342.0	20	450	152.0	98.8	199.1
9	460	83.1	102.3	274.6	21	445	26.7	9.6	408.7
10	460	89.7	66.1	304.2	22	435	60.9	46.2	327.9
11	470	151.0	68.9	250.1	23	400	164.7	74.8	160.4
12	480	101.8	61.7	316.5	24	400	130.1	41.1	228.8

**Table 2.9 (a)** Optimum power generation attained by POT-I for TS-III

t (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>
1	2822	45.5	114.4	123.2	151.2	226.2	161.1	90.6	115.0	46.3	29.6
2	3000	28.6	50.6	235.2	191.4	178.9	112.1	180.7	125.1	46.7	52.5
3	3216	67.6	155.8	297.8	163.8	177.7	139.1	106.5	78.9	72.3	67.3
4	3462	87.7	177.0	277.0	242.0	196.1	265.7	192.6	95.6	44.6	22.8
5	3630	54.8	112.5	323.1	237.7	217.4	127.6	151.4	132.0	92.9	46.4
6	4056	129.1	291.3	442.6	231.3	283.5	282.4	130.4	104.9	90.7	73.0
7	4354	143.5	200.6	469.2	329.4	297.8	335.3	196.9	112.2	110.1	35.8
8	4562	173.9	255.5	409.8	362.0	299.9	186.6	185.1	158.7	106.2	44.9
9	4938	155.2	240.1	446.6	468.0	399.6	243.2	266.4	109.2	126.3	33.4

**Table 2.9 (a)** Optimum power generation attained by POT-I for TS-III (continued)

t (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>
10	5124	161.4	272.9	429.4	463.8	368.7	288.6	273.2	152.3	113.5	26.8
11	5312	150.8	276.0	444.0	441.4	396.5	335.5	283.9	114.9	123.1	56.8
12	5450	165.1	284.4	461.8	457.6	398.2	311.1	260.1	143.0	107.5	66.0
13	5254	160.2	218.6	438.0	455.3	382.7	328.0	241.4	157.0	126.7	72.5
14	4878	147.2	256.8	471.9	391.9	409.7	324.2	255.0	133.6	78.8	43.2
15	4571	156.1	235.3	403.2	456.6	237.1	214.5	219.1	112.7	103.4	49.2
16	4168	116.7	273.6	450.9	285.8	290.4	214.9	138.3	137.8	53.3	27.3
17	4010	132.4	196.8	448.3	375.2	355.2	294.9	123.9	114.4	39.9	36.6
18	4376	50.0	285.0	483.2	375.3	230.7	295.5	228.4	69.2	35.0	65.8
19	4622	139.4	274.2	305.4	385.2	312.7	268.8	202.6	93.6	96.3	75.9
20	4994	175.0	266.1	464.6	365.7	369.9	280.8	238.3	127.9	111.4	22.1
21	4758	136.6	174.5	417.5	458.7	303.5	305.7	249.0	131.6	81.0	65.1
22	4116	108.6	233.1	417.9	303.4	182.1	155.1	196.5	150.0	78.7	53.2
23	3514	69.1	112.0	247.1	152.9	191.8	252.2	111.2	114.7	36.7	54.6
24	3168	40.3	47.2	233.8	184.5	265.8	128.5	118.9	103.6	60.3	61.9

**Table 2.9 (b)** Optimum power generation attained by POT-I for TS-III

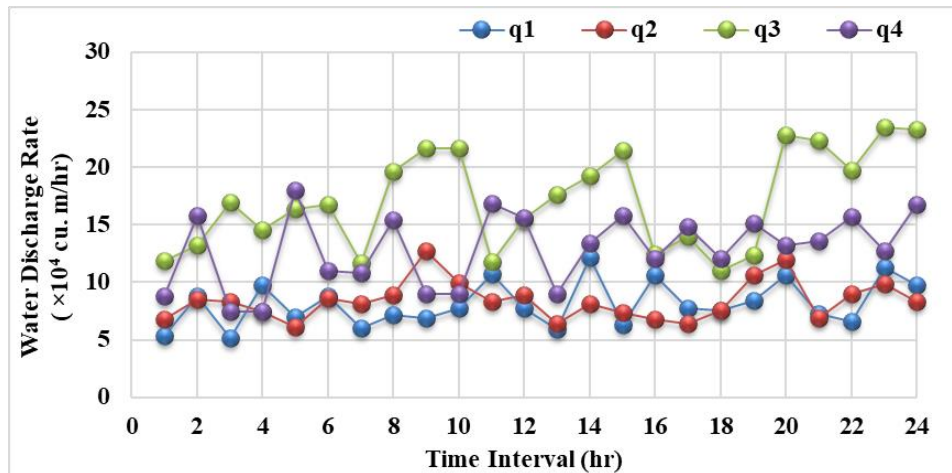
t (hr)	PD (MW)	Power (MW) (Thermal Units)								
		PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
1	2822	48.0	195.4	174.3	110.8	60.6	131.5	56.6	73.8	35.9
2	3000	33.7	213.3	213.6	176.6	92.1	96.4	82.1	37.0	36.6
3	3216	30.7	314.2	151.6	242.3	99.9	118.0	61.9	66.2	45.0
4	3462	34.8	312.7	154.9	160.8	147.4	104.0	85.1	53.4	18.5
5	3630	46.8	210.0	149.8	238.9	182.8	132.8	75.0	60.9	42.4
6	4056	43.2	218.2	324.6	139.2	142.7	140.5	37.0	28.8	34.3
7	4354	51.4	224.2	170.7	284.5	157.5	144.8	113.6	25.5	36.6
8	4562	28.4	336.0	334.6	247.9	258.9	87.8	93.9	29.8	50.3
9	4938	37.7	441.3	260.7	286.3	180.4	157.9	81.8	70.3	14.5
10	5124	44.4	388.4	368.6	252.7	209.0	72.9	114.1	68.8	23.5
11	5312	43.5	383.3	392.4	316.6	208.5	93.8	117.9	62.9	18.3
12	5450	24.4	428.6	439.7	313.6	195.3	155.3	114.0	52.1	42.8
13	5254	44.8	404.1	438.3	229.2	225.9	131.0	127.5	68.5	41.8
14	4878	29.7	347.5	370.0	283.8	185.0	113.4	80.1	26.0	42.6
15	4571	32.6	381.1	315.9	245.0	142.1	124.7	56.8	29.5	31.7
16	4168	42.7	191.9	380.1	148.2	151.1	85.3	80.2	64.5	34.0
17	4010	34.5	186.7	141.4	158.8	103.8	142.6	93.9	47.3	32.6
18	4376	33.8	346.7	330.5	149.6	237.4	110.9	127.8	32.1	23.2
19	4622	19.4	281.3	449.2	263.9	275.6	152.7	49.1	49.2	27.3
20	4994	30.1	404.6	386.2	292.2	217.9	114.9	96.9	32.0	42.0
21	4758	22.4	392.5	282.7	284.8	231.2	105.4	88.3	58.3	28.0
22	4116	37.8	266.4	290.9	237.8	140.0	143.0	86.6	36.8	36.1
23	3514	22.1	347.3	301.4	146.9	149.5	101.1	107.7	31.7	41.4
24	3168	23.6	235.0	390.5	120.5	88.7	117.1	68.3	36.4	17.9

**Table 2.9 (c)** Optimum power generation attained by POT-I for TS-III

t (hr)	PD (MW)	Power (MW) (CHP Units)				Power (MW) (Hydro Units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	2822	208.4	105.1	83.1	51.9	62.1	74.2	35.2	211.9
2	3000	222.4	57.4	152.9	56.8	72.4	62.9	46.1	145.8
3	3216	162.3	66.7	142.4	47.6	67.9	54.8	31.7	185.9
4	3462	101.0	64.4	230.7	52.2	76.2	55.5	39.6	169.7
5	3630	229.8	118.7	197.0	82.9	69.7	54.7	52.1	189.6
6	4056	172.5	106.1	213.1	75.4	62.8	68.4	27.8	162.2
7	4354	218.1	101.5	194.4	73.4	63.5	59.5	40.0	164.0

**Table 2.9 (c)** Optimum power generation attained by POT-I for TS-III (continued)

t (hr)	PD (MW)	Power (MW) (CHP Units)				Power (MW) (Hydro Units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
8	4562	194.3	93.4	195.0	93.5	79.4	59.8	47.0	149.0
9	4938	217.1	98.7	147.8	113.4	88.6	54.5	45.8	153.3
10	5124	201.3	102.0	177.0	97.6	88.4	73.9	50.8	240.0
11	5312	207.0	92.9	209.3	112.4	92.4	70.3	18.6	249.1
12	5450	215.1	90.5	213.9	111.7	75.5	74.2	32.5	216.1
13	5254	201.0	113.8	139.2	74.6	93.5	46.3	49.4	244.6
14	4878	90.3	111.1	176.5	88.4	77.8	55.4	55.1	233.1
15	4571	215.8	69.3	224.8	101.1	77.9	63.1	56.8	215.6
16	4168	195.0	116.7	179.6	108.8	58.9	61.2	51.4	229.5
17	4010	169.4	112.3	181.6	63.7	86.1	58.0	48.4	231.3
18	4376	145.8	110.9	152.3	86.7	64.5	53.6	57.7	194.8
19	4622	223.9	66.3	120.4	54.5	90.9	58.6	58.9	226.7
20	4994	209.4	96.3	205.9	62.9	83.8	67.9	34.6	194.6
21	4758	113.0	64.1	223.0	101.7	82.3	48.2	48.4	260.3
22	4116	237.1	111.4	119.9	122.1	64.9	51.6	39.7	215.2
23	3514	183.1	115.9	132.9	106.8	95.7	71.0	58.5	158.6
24	3168	164.3	52.6	159.9	42.6	97.0	51.4	56.5	200.7



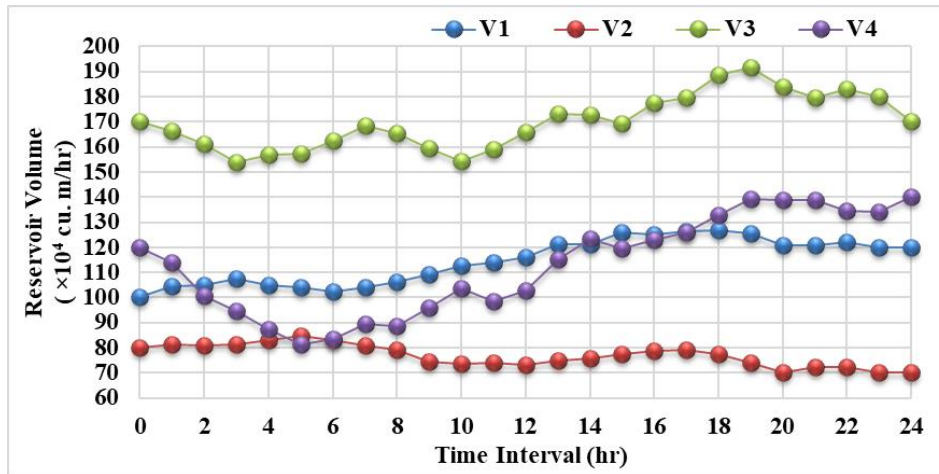
**Figure 2.12** Water discharge rate of hydro units attained by POT-I for TS-II

**Table 2.10** Optimal heat generation attained by POT-I for TS-III

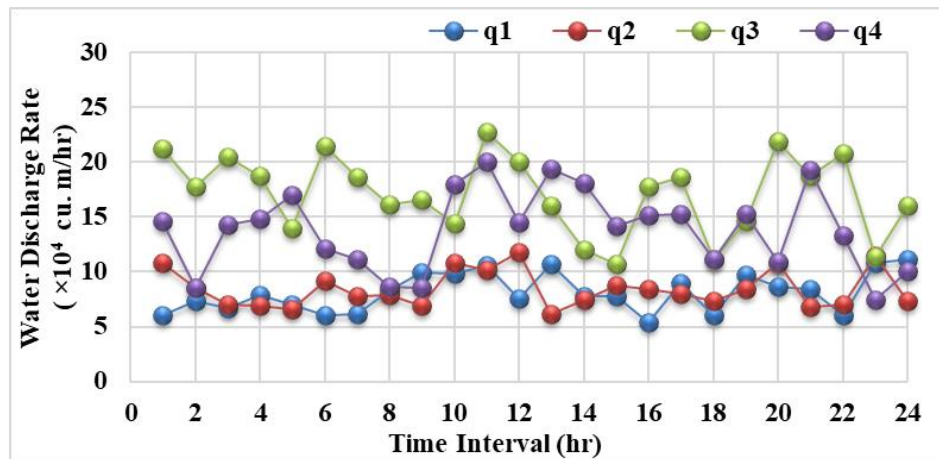
t (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth) (Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
1	780	69.8	123.0	92.6	27.7	215.5	251.3
2	800	30.1	51.2	84.6	63.0	59.9	511.2
3	820	93.6	49.6	81.5	14.3	208.8	372.2
4	840	93.2	56.9	72.1	19.2	111.6	487.0
5	880	65.4	41.8	73.5	29.6	54.7	614.9
6	900	79.2	84.0	157.0	11.6	20.4	547.8
7	900	102.3	67.0	156.1	62.7	105.1	406.7
8	910	151.6	26.1	131.4	83.1	252.2	265.6
9	920	158.0	38.0	53.1	99.8	80.3	490.7
10	920	157.9	72.5	18.7	76.4	39.1	555.4
11	940	151.9	67.7	174.9	134.2	15.4	395.9
12	960	167.7	117.9	166.7	133.2	123.4	251.1
13	940	152.7	49.1	131.9	85.4	215.4	305.5
14	920	91.7	52.0	85.0	102.2	106.7	482.4
15	900	59.9	59.5	84.4	102.7	178.8	414.7
16	900	27.3	62.2	57.3	94.0	115.4	543.7

**Table 2.10** Optimal heat generation attained by POT-I for TS-III (continued)

t (hr)	HD (MWth)	Heat (MWth) (CHP Units)				Heat (MWth) (Heat Units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
17	840	93.7	55.3	123.9	79.1	99.8	388.2
18	870	22.8	128.6	105.1	109.3	84.1	420.1
19	890	73.8	65.7	66.5	61.3	126.3	496.3
20	900	141.6	118.1	160.3	31.1	151.0	298.0
21	890	89.0	49.7	124.0	121.3	112.8	393.2
22	870	53.9	87.7	117.9	32.2	45.2	533.1
23	800	146.3	59.6	45.4	1.2	173.4	374.0
24	800	104.0	10.7	88.3	52.0	7.5	537.4



**Figure 2.13** Reservoir volume of hydro units attained by POT-I for TS-II



**Figure 2.14** Water discharge rate of hydro units attained by POT-I for TS-III

**2.7.3.3 Test System-IV:** It is evident from the results of TS-I, II and III, that the performance of the POT-I is superior as compared to GWO in terms of quality of the solution. However, most of the optimization techniques suffer from “curse of dimensionality” for large scale complex optimization problem. Hence, to further authenticate the performance of the POT-I, a large size test system has been undertaken, having 936 decision variables. The statistical results obtained by

the POT-I and GWO are given in Table 2.11. The minimum cost obtained by GWO and POT-I is 87,60,859 \$ and 86,41,610 \$, respectively, and the standard deviation indicates that the POT-I results are more precise as compared to GWO technique.

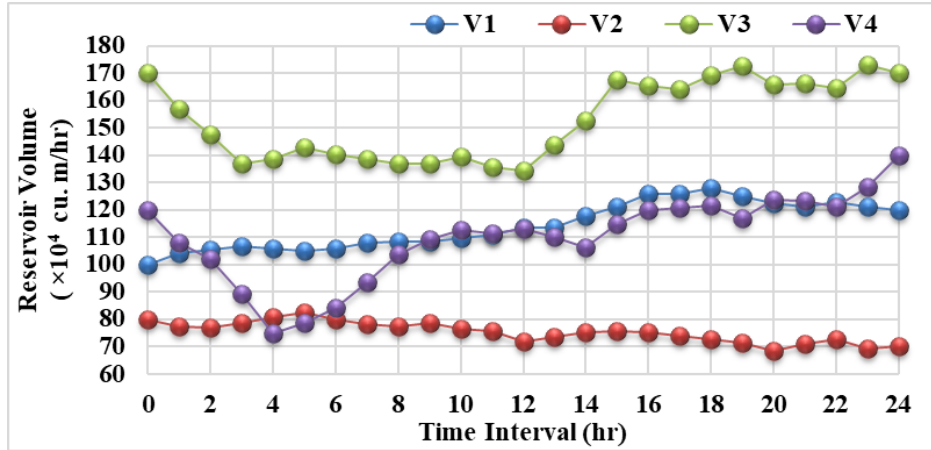


Figure 2.15 Reservoir volume of hydro units attained by POT-I for TS-III

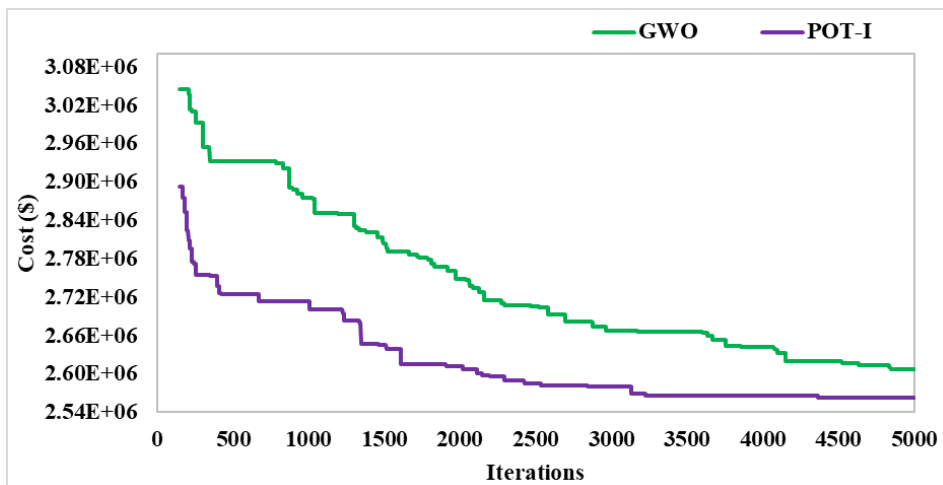


Figure 2.16 Convergence characteristics of cost attained by POT-I for TS-II

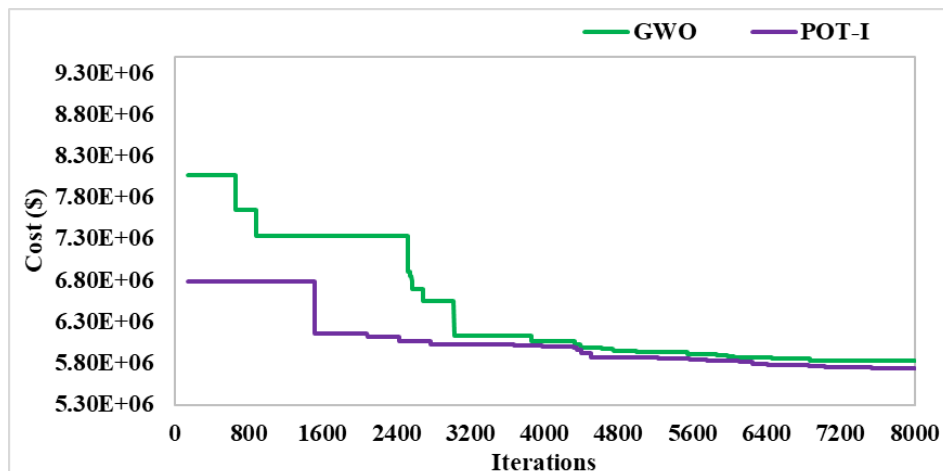


Figure 2.17 Convergence characteristics of cost attained by POT-I for TS-III

The convergence characteristics of the POT-I and GWO for TS-IV are shown in Fig. 2.18. For comparison purpose, the maximum number of iterations has been set to 10,000. However, it is worth observing from Fig. 2.18 that, the POT-I and GWO approximately require 7500 and 9600 iterations, respectively for the convergence. The average CPU time for the actual iterations required by each algorithm has been reported in Table 2.11. Hence, it is concluded that the POT-I is computationally superior as compared to the GWO for large scale optimization problem and able to achieve the global best solution. The optimum generation from thermal, hydro, and CHP units is reported in Tables 2.12 (a)-12(d). The heat production of CHP and heat units are reported in Table 2.13. The optimum water discharge rate and reservoir volume of hydro units are shown in Figs. 2.19 and 2.20, respectively.

**Table 2.11** Comparison of cost for TS-IV

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	87,60,859	88,68,906	88,26,332	31,035	144.34
POT-I	86,41,610	87,17,096	86,74,366	22,712	137.45

**Table 2.12 (a)** Optimum power generation attained by POT-I for TS-IV

t (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>
1	3858	61.8	85.9	101.9	155.4	185.7	151.8	144.5	94.7	53.6	42.0
2	4110	78.7	63.9	106.8	172.0	290.5	166.6	62.6	74.3	55.0	40.0
3	4474	35.5	174.2	163.1	164.4	221.3	174.9	105.5	104.2	79.1	23.6
4	4868	96.4	152.6	270.3	266.5	380.7	277.4	113.6	100.1	42.1	48.3
5	5110	75.9	94.2	198.0	260.0	256.3	178.1	146.8	85.9	122.7	68.9
6	5684	101.5	204.7	311.1	179.0	355.3	217.8	210.4	102.6	109.9	56.7
7	6056	104.8	247.2	286.2	420.8	446.7	222.2	99.0	69.5	112.0	76.4
8	6338	122.0	230.0	432.3	378.8	332.6	203.2	275.2	71.9	75.3	23.0
9	6862	160.0	190.5	497.0	360.9	421.1	165.9	294.6	94.4	118.6	57.5
10	7146	108.9	272.9	437.5	378.4	437.5	318.0	206.4	140.2	90.8	73.4
11	7418	146.8	295.5	495.4	421.5	403.7	296.8	266.8	153.4	91.3	78.3
12	7600	159.3	296.2	486.8	446.5	459.1	275.5	282.6	136.5	95.5	56.4
13	7326	145.9	205.2	496.8	466.7	437.4	226.9	245.6	118.9	127.7	58.4
14	6802	155.6	252.3	496.1	394.3	310.9	213.7	233.8	149.6	99.2	76.9
15	6347	150.8	180.1	491.3	277.9	399.8	248.6	148.3	95.7	74.8	72.7
16	5722	114.8	135.3	487.1	359.5	201.4	262.7	300.0	104.6	51.6	61.9
17	5490	112.3	206.7	73.8	378.7	204.8	302.4	224.7	62.6	68.9	41.3
18	6004	102.1	192.9	269.4	369.6	327.7	324.5	206.4	143.6	105.0	46.0
19	6398	147.6	251.4	418.8	323.7	432.0	232.6	250.4	75.3	108.4	57.5
20	6966	127.9	275.4	459.8	458.0	338.7	294.3	160.0	153.7	122.7	55.1
21	6682	100.6	226.0	498.7	439.4	446.1	198.5	174.0	150.3	110.7	61.6
22	5744	129.9	202.5	402.2	190.1	374.5	294.2	245.3	104.1	54.3	55.5
23	4846	27.7	242.2	94.3	240.7	252.2	126.3	138.5	103.9	38.3	52.0
24	4352	33.5	229.3	93.0	263.8	217.8	101.2	71.9	87.4	70.3	37.3

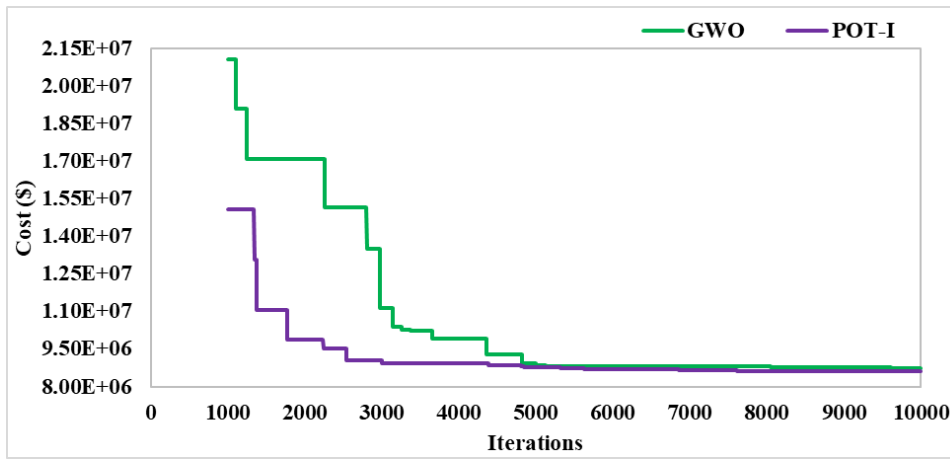


Figure 2.18 Convergence characteristics of cost attained by POT-I for TS-IV

Table 2.12 (b) Optimum power generation attained by POT-I for TS-IV

t (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>	PT <sub>20</sub>
1	3858	43.4	192.9	185.4	118.4	111.7	112.1	27.9	29.6	22.4	216.3
2	4110	28.1	233.8	181.7	100.8	139.4	143.8	78.6	63.2	39.5	281.4
3	4474	53.7	193.1	207.5	117.8	164.0	106.4	59.2	42.2	26.4	409.5
4	4868	47.2	235.6	216.3	182.7	109.2	96.1	50.5	50.5	37.9	313.5
5	5110	46.8	380.7	258.9	257.1	210.5	114.7	115.8	72.7	13.5	175.3
6	5684	40.3	328.9	287.0	215.7	259.6	90.9	68.8	48.6	24.6	387.7
7	6056	18.2	287.6	404.9	243.8	128.2	104.0	79.8	43.3	40.3	244.7
8	6338	29.3	398.1	335.3	296.5	236.1	124.7	84.6	64.7	46.6	284.5
9	6862	33.2	420.7	425.0	329.2	258.8	133.8	111.0	51.7	25.9	379.9
10	7146	45.2	364.8	398.2	296.0	290.4	128.3	101.7	75.7	42.1	422.1
11	7418	25.6	449.9	418.0	328.5	298.9	104.7	98.0	59.6	30.8	404.1
12	7600	39.7	457.8	455.3	271.8	270.1	134.5	98.5	36.6	45.1	443.1
13	7326	27.7	436.1	427.1	305.9	236.9	141.2	65.0	62.6	49.7	430.2
14	6802	44.4	356.0	417.0	291.9	233.7	85.3	117.0	25.7	37.0	419.4
15	6347	43.7	428.1	321.1	120.8	263.9	126.1	79.9	62.5	32.7	396.1
16	5722	40.0	398.4	262.6	183.7	94.9	105.4	63.5	66.5	39.5	354.2
17	5490	40.1	283.3	323.3	306.7	259.2	86.7	25.0	45.1	46.2	290.4
18	6004	42.6	360.8	382.2	287.7	268.7	120.6	45.2	48.8	47.3	186.0
19	6398	39.0	425.3	375.8	324.6	256.0	100.9	75.4	26.2	30.3	212.6
20	6966	26.4	373.2	405.8	311.9	199.3	100.9	93.5	44.3	39.4	436.3
21	6682	31.1	316.0	400.3	290.7	241.7	78.1	61.0	36.6	39.0	297.0
22	5744	47.6	292.5	286.8	254.1	154.0	78.9	65.0	56.4	13.8	235.1
23	4846	32.3	232.8	203.9	293.8	217.5	95.3	79.6	53.9	26.5	372.2
24	4352	15.4	230.2	215.1	84.0	171.5	113.1	73.9	38.3	13.7	178.4

Table 2.12 (c) Optimum power generation attained by POT-I for TS-IV

t (hr)	PD (MW)	Power (MW): (Thermal Units)								
		PT <sub>21</sub>	PT <sub>22</sub>	PT <sub>23</sub>	PT <sub>24</sub>	PT <sub>25</sub>	PT <sub>26</sub>	PT <sub>27</sub>	PT <sub>28</sub>	PT <sub>29</sub>
1	3858	174.2	151.9	104.8	158.5	65.7	59.1	119.3	51.1	37.1
2	4110	167.5	187.7	152.6	96.3	83.5	89.7	62.2	28.1	33.4
3	4474	160.0	209.8	101.5	141.8	131.2	84.4	85.4	36.6	34.3
4	4868	224.9	125.7	79.7	154.0	101.5	56.3	103.5	29.3	29.6
5	5110	319.3	200.7	81.4	89.8	93.0	44.7	102.9	72.8	37.4
6	5684	196.0	213.5	287.2	144.0	125.2	99.1	104.6	45.8	11.5
7	6056	351.6	237.2	274.5	190.2	81.2	68.2	79.7	56.7	25.0
8	6338	404.3	220.6	298.2	205.0	102.5	117.0	91.3	67.0	35.1
9	6862	393.7	284.2	201.7	211.1	92.8	87.8	90.0	75.4	48.4
10	7146	350.9	298.7	237.3	221.4	148.2	108.7	80.2	46.9	17.7
11	7418	392.3	333.6	297.6	144.1	119.4	61.8	100.2	29.6	44.4

Table 2.12 (c) Optimum power generation attained by POT-I for TS-IV (continued)

t (hr)	PD (MW)	Power (MW): Thermal Units								
		PT <sub>21</sub>	PT <sub>22</sub>	PT <sub>23</sub>	PT <sub>24</sub>	PT <sub>25</sub>	PT <sub>26</sub>	PT <sub>27</sub>	PT <sub>28</sub>	PT <sub>29</sub>
12	7600	445.2	290.9	297.0	171.3	119.3	60.3	107.8	30.9	32.7
13	7326	403.7	271.5	272.6	186.8	117.9	76.3	114.2	68.4	38.1
14	6802	329.3	312.3	284.0	208.1	126.3	81.6	83.6	43.1	34.5
15	6347	285.7	302.1	288.2	163.1	148.9	61.0	96.7	23.4	36.6
16	5722	248.7	265.7	231.9	91.0	115.0	64.7	69.3	21.5	26.8
17	5490	367.0	132.0	156.9	90.7	111.0	80.2	100.6	50.5	33.7
18	6004	332.3	269.5	147.0	101.5	107.4	39.5	106.6	44.6	36.8
19	6398	281.1	279.6	226.9	117.1	88.0	98.5	103.1	67.9	15.6
20	6966	320.3	246.3	225.2	130.1	158.1	52.4	91.0	74.7	18.5
21	6682	317.3	298.9	278.4	174.5	135.0	83.8	64.4	67.3	43.1
22	5744	289.3	150.4	231.6	222.8	113.3	68.2	72.4	47.7	43.3
23	4846	319.4	215.4	107.7	104.1	105.5	81.3	56.6	60.5	31.3
24	4352	192.5	147.6	148.9	148.2	106.2	85.0	84.8	63.9	40.2

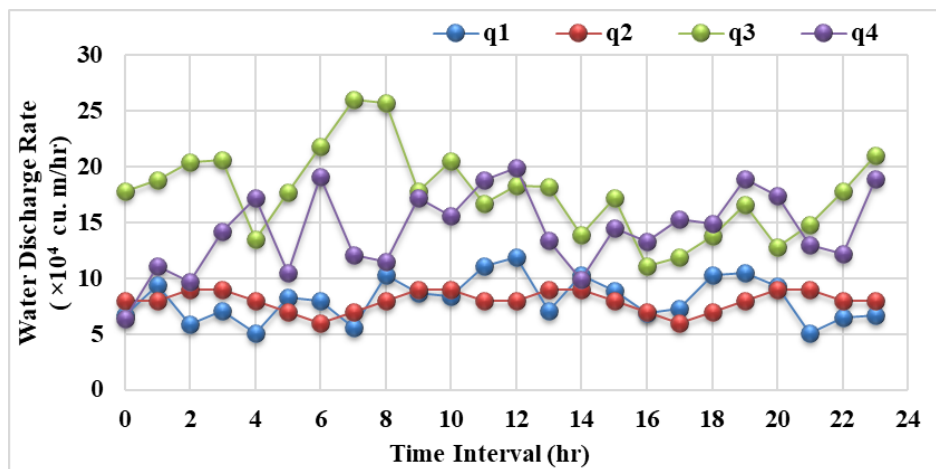


Figure 2.19 Water discharge rate of hydro units attained by POT-I for TS-IV

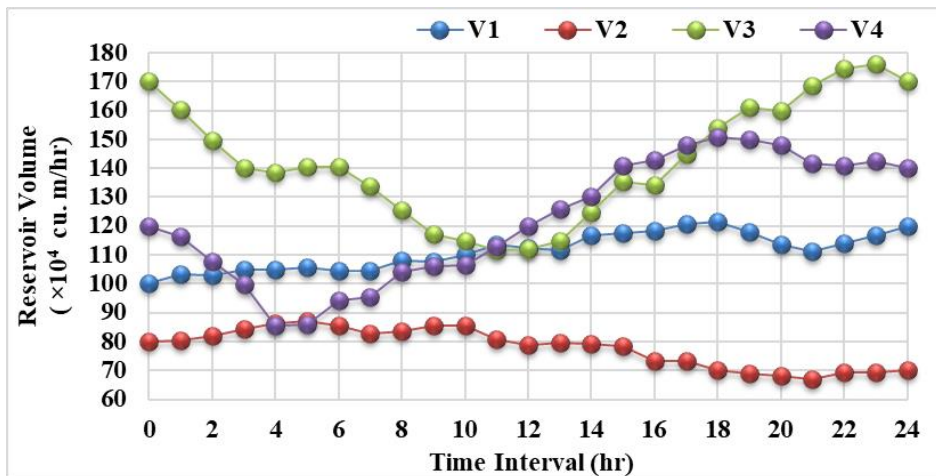


Figure 2.20 Reservoir volume of hydro units attained by POT-I for TS-IV

Table 2.12 (d) Optimum power generation attained by POT-I for TS-IV

t (hr)	PD (MW)	Power (MW) (CHP Units)				Power (MW) (Hydro Units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	3858	127.8	116.1	151.8	92.5	67.1	60.1	49.9	133.7
2	4110	205.5	81.0	108.5	53.2	83.7	53.5	43.3	179.7
3	4474	213.1	46.1	229.0	70.5	61.1	54.6	33.0	156.3

**Table 2.12 (d)** Optimum power generation attained by POT-I for TS-IV (continued)

t (hr)	PD (MW)	Power (MW) (CHP Units)				Power (MW) (Hydro Units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
4	4868	185.1	80.0	178.7	91.4	70.5	59.1	31.6	179.8
5	5110	180.5	68.5	231.3	84.6	54.7	62.9	51.8	201.0
6	5684	91.3	119.5	190.0	107.0	78.4	67.3	44.0	158.9
7	6056	230.6	118.0	156.3	114.6	76.1	69.4	23.2	224.0
8	6338	144.1	49.8	185.2	76.9	59.0	51.8	0.0	185.6
9	6862	152.5	53.1	212.5	103.9	90.0	53.7	0.0	181.3
10	7146	230.9	104.3	172.8	87.0	81.8	69.3	33.6	227.8
11	7418	186.9	110.9	213.9	102.6	80.9	87.1	20.2	224.7
12	7600	210.9	112.8	206.8	111.4	94.7	71.4	36.0	253.8
13	7326	179.8	113.6	210.0	110.0	97.4	55.6	31.6	266.8
14	6802	130.0	70.0	212.5	73.3	72.2	69.6	36.1	225.7
15	6347	95.6	88.2	211.6	119.3	92.5	70.8	50.0	198.5
16	5722	134.5	48.9	161.7	98.2	85.1	79.2	43.1	248.2
17	5490	193.8	115.7	178.1	78.6	71.2	53.3	52.7	241.7
18	6004	149.8	82.1	143.0	112.1	74.5	62.0	55.3	263.0
19	6398	193.3	65.0	131.5	104.0	92.6	54.8	56.9	258.3
20	6966	230.7	111.8	226.5	112.5	92.3	59.1	53.0	286.9
21	6682	159.4	84.0	223.9	76.1	85.8	63.8	58.7	270.0
22	5744	238.0	57.3	184.1	95.7	55.6	46.6	59.1	232.0
23	4846	154.0	80.3	138.0	66.9	67.6	54.3	53.8	225.4
24	4352	179.3	117.1	148.6	111.6	69.5	51.2	40.3	277.9

**Table 2.13** Optimum heat generation attained by POT-I for TS-IV

t (hr)	HD (MWth)	Heat (MWth) (CHP Units)				Heat (MWth) (Heat Units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
1	780	61.7	35.7	82.6	3.5	144.1	452.4
2	800	98.0	1.1	95.1	52.7	316.5	236.6
3	820	45.9	76.9	78.3	59.5	191.4	368.0
4	840	110.5	99.2	110.3	72.3	72.1	375.7
5	880	55.7	42.1	77.6	42.4	83.9	578.3
6	900	99.7	31.1	95.9	21.9	34.7	616.8
7	900	90.1	61.4	78.7	118.1	15.8	535.9
8	910	19.5	48.2	118.2	38.4	391.5	294.2
9	920	111.6	37.3	178.8	43.5	315.8	233.1
10	920	88.7	104.3	155.0	74.9	128.6	368.5
11	940	146.7	134.2	178.2	65.0	19.2	396.7
12	960	161.0	133.1	174.6	131.4	46.6	313.4
13	940	83.2	52.9	176.8	135.2	140.9	350.9
14	920	54.5	74.0	178.6	96.9	61.0	455.1
15	900	91.6	67.0	176.6	47.9	232.9	284.0
16	900	73.4	82.4	85.9	91.5	72.0	494.7
17	840	90.6	59.2	9.5	75.0	340.1	265.5
18	870	84.4	50.6	60.5	62.2	165.8	446.5
19	890	117.8	67.3	89.9	77.7	70.0	467.3
20	900	90.4	72.2	90.6	112.1	250.7	283.9
21	890	88.8	60.0	46.8	105.4	73.0	516.0
22	870	6.9	72.5	54.4	51.6	96.0	588.5
23	800	94.4	26.4	95.7	57.4	120.8	405.3
24	800	79.0	62.7	82.6	48.6	217.0	310.1

## 2.8 STATISTICAL ANALYSIS

The two different statistical tests, *i.e.*, two-sample t-test and Mann-Whitney test have been perfo-

formed to investigate the robustness of the statistical results obtained by the POT-I in comparison with GWO.

**Two-Sample T-Test:** For conducting the t-test, the populations are assumed to have equal variances at the 5% significance level. The results of the test have been tabulated in Tables 2.14-2.15 for TS-I, II, III and IV, respectively. It is observed from tables that the tabulated values of statistics obtained from t-test for GWO are greater than the critical values in both the cases, *i.e.*, one-tailed and two-tailed, for all the test systems. The average value of cost and variance attained by POT-I is also superior and statistically significant at 5% significance value as compared to the GWO technique.

**Table 2.14** Two-sample t-test assuming equal variances for TS-I

	TS-I (Case-I)		TS-I (Case-II)	
	GWO	POT -I	GWO	POT-I
Variance	6348.626	3452.74	6660.92	2761.826
Observations	30	30	30	30
Pooled Variance	4900.683		4711.373	
Hypothesized Mean Difference	0		0	
Degree of freedom (Df)	58		58	
t Stat	16.11971		17.21152	
P(T≤t) one-tail	0		0	
t Critical one-tail	1.671553		1.671553	
P(T≤t) two-tail	0		0	
t Critical two-tail	2.001717		2.001717	

**Table 2.15** Two-sample t-test assuming equal variances for TS-II, III and IV

	TS-II		TS-III		TS-IV	
	GWO	POT-I	GWO	POT-I	GWO	POT-I
Variance	1.09E+09	5.18E+08	8.9E+08	5.99E+08	9.63E+08	5.16E+08
Observations	30	30	30	30	30	30
Pooled Variance	8.06E+08		7.44E+08		7.4E+08	
Hypothesized Mean Difference	0		0		0	
Df	58		58		58	
t Stat	11.240806		14.13051		16.64293	
P(T≤t) one-tail	0		0		0	
t Critical one-tail	1.671553		1.671553		1.671553	
P(T≤t) two-tail	0		0		0	
t Critical two-tail	2.001717		2.001717		2.001717	

**Mann-Whitney Test:** A non-parametric Mann-Whitney U test has also been applied to investigate the significant difference between the POT-I and GWO technique. The test has been performed at a 5% significance level for 20 observations for all the test systems. The test results have been presented in Table 2.16. It is evident from the results that for all the test systems  $p \leq 0.001$ , hence,

Null hypothesis is rejected and results obtained by the POT-I are significantly better and different than GWO technique.

**Table 2.16** Mann-Whitney test for TS-I-IV

	TS-I (Case-I)	TS-I (Case-II)	TS-II	TS-III	TS-IV
p	6.7956e-08	6.7956e-08	9.1474e-08	6.7956e-08	6.7956e-08
h	1	1	1	1	1
zval	5.3965	5.3965	5.3429	5.3965	5.3965
Rank-sum	610	610	608	610	610

## 2.9 CONCLUSIONS

This chapter is concluded in twofold, (i) formulation of CPSGS problem (ii) development and successful implementation of the proposed heuristic optimization technique-I, *i.e.*, GWO-MS, to search optimal generation schedule of CPSGS problem. In this chapter, a CPS model has been formulated by considering thermal, heat, CHP and multi-chain hydro system to meet the growing demands of energy. In order to obtain the optimal generation schedule of the CPS, POT-I based on the integration of GWO with three mutation strategies, *i.e.*, Cauchy, Gaussian and opposition based, have been proposed. The diverse characteristics of Gaussian and Cauchy mutation strategies improve the diversification and intensification capability of the algorithm. Further, the opposition-based mutation strategy has been applied for initial diversification of the wolves. The POT-I has been applied to four test systems. For TS-I, case-I, the minimum fuel cost obtained by the POT-I is 41,501 \$ and is less than PSO, CSA, RCGA, MDE, TVAC-PSO, MHDE, QPSO, PPO, MILP and GWO. The optimum cost attained by the POT-I for TS-I (case-II) is 42,473 \$ which is superior to the other reported results obtained by RCGA, MDE, HDE, MHDE, QEA, SPPSO, RQEA and GWO techniques.

The TS-II, III and IV represent a small, medium and large sized CPSGS problem which is solved by applying GWO and POT-I. The minimum cost obtained by POT-I for test system-II, III and IV are 25,62,644\$, 57,38,132\$ and 86,41,610\$, respectively, which is less by 1.74%, 1.54% and 1.36% as compared to the results obtained by GWO technique. For all the test systems, the GWO and POT-I have been executed thirty times and statistical analysis in terms of minimum,

maximum and average cost has been carried out to verify the robustness of the POT-I. The CPU time is also compared and it has been found that the POT-I is computationally efficient to solve the large size test system. Further, two sample *t*-test and non-parametric Mann-Whitey test have been carried out and it is concluded that the POT-I is significantly better than the GWO technique. The simulation results of small to large size test systems reveal that the POT-I searches global best solution with a high degree of success with the fair computational cost.



## CHAPTER-3

# OPTIMUM GENERATION SCHEDULING OF COORDINATED POWER SYSTEM USING QUANTUM-BASED CUCKOO SEARCH ALGORITHM WITH MUTATION STRATEGIES

### 3.1 INTRODUCTION

According to no free lunch theorem, there is no single optimization technique that can address all optimization problems (Wolpert and Macready, 1997). The optimization algorithms differ in their behaviour and performance when addressing one type of optimization problem versus another. Despite the numerous advantages, global search optimization algorithms have a higher computational complexity and the solution is dependent on algorithm parameters, which might make it difficult to converge to the optimum solution in each attempt. Thus, the research is active in the field of developing new or hybrid or heuristic optimization techniques to solve different types of optimization problems. In this chapter, a heuristic optimization technique-II, *i.e.*, quantum-based cuckoo search algorithm (QCSA) with mutation strategies (MS) is proposed for searching the optimal generation schedule of coordinated power system generation scheduling (CPSGS) problem. The integration of thermal, CHP, heat and hydro units, interconnected constraints and scheduling period of twenty-four hours make the CPSGS problem a very complex constrained, complicated, non-linear and multidimensional optimization problem. Thus, a proficient heuristic optimization technique is needed to solve the CPSGS problem.

The traditional cuckoo search algorithm (CSA) is simple and efficient optimization technique than many other heuristic algorithms but it may easily trap in local optima, especially for complex multimodal problems due to the uniform search behaviour of cuckoos. Additionally, number of iterations required to discover an optimal solution are more because centroids were randomly initialised in the first phase (Boushaki *et al.*, 2018). Thus, Cheung *et al.* (2017) proposed the quantum-based cuckoo search algorithm (QCSA) in which the quantum theory and traditional

CSA are integrated. The QCSA overcomes the drawback of CSA by utilizing quantum theory for non-homogeneous up-gradation of the positions and to enhance the search ability (Cheung *et al.*, 2017). The QCSA technique has been explored extensively to solve complex optimization problems due to its excellent search ability. Even though the QCSA technique can explore the search space efficiently, however it is still lacking in the exploitation of promising search areas (Cheng *et al.*, 2018). For improving the exploitation of QCSA, it can be hybridized with other optimization techniques.

In this chapter, a heuristic optimization technique-II, *i.e.*, quantum-based cuckoo search algorithm with mutation strategies (QCSA-MS) has been proposed for solving the CPSGS problem. Initially, QCSA has been used to explore the search space. Then three mutation strategies, *i.e.*, Cauchy, Gaussian and opposition-based mutation strategies have been integrated with the QCSA technique for increasing the population diversity, avoiding premature convergence and to fulfil the requirement of an algorithm's balanced exploration and exploitation quality. The proposed optimization technique (POT)-II is implemented to the hydro-thermal generation scheduling (HTGS) and CPSGS problems. The optimal cost obtained by POT-II has been compared with the optimal cost obtained by other optimization techniques. The POT-II outperforms several existing states of art optimization techniques. Further, t-test has been evaluated for verifying the robustness of the POT-II in comparison with QCSA.

The chapter is organized as follows: Section 3.2 presents the problem formulation. The optimization techniques, *i.e.*, QCSA, MS and the POT-II are briefly introduced in section 3.3. The step-wise implementation of the POT-II for CPSGS is described in section 3.4. Section 3.5 presents the test systems and numerical results. The conclusions are given in section 3.6.

### **3.2 PROBLEM FORMULATION**

The CPSGS problem includes four different types of generating units (CHP, hydro, thermal and heat). The main objective of the CPSGS problem is the attainment of minimum fuel cost by scheduling the power generation of thermal, hydro and CHP units, heat generation of heat and

CHP units while fulfilling all the constraints in a specific time spell. The power generation of thermal ( $PT_{it}$ ) and CHP units ( $PC_{jt}$ ), heat generation of heat ( $H_{kt}$ ) and CHP units ( $HC_{jt}$ ), water discharge rate of hydro units ( $q_{it}$ ) for the time period  $T$  are the decision variables for CPSGS problem. The mathematical modelling of thermal, CHP, heat and hydro generating units is discussed in section 2.3 of chapter 2. The objective function formulation and the constraints of the CPSGS problem are discussed in the section 2.4 of chapter 2.

### 3.3 OPTIMIZATION TECHNIQUES

In this section, a brief introduction and mathematical modeling of CSA, QCSA, mutation strategies (MS) and the proposed QCSA-MS technique are presented.

#### 3.3.1 Cuckoo Search Algorithm

The cuckoo search algorithm (CSA) is inspired by the identical breeding behaviour of cuckoos (Yang and Deb, 2009). In CSA, the fertilized eggs of cuckoo are laid in the nests of any other randomly chosen host birds and the nest carrying the high quality of eggs will be carried to the next generations. The unfamiliar eggs are discovered by the host bird with a discovery probability  $pd$  ( $0 \leq pd \leq 1$ ). The transition of the cuckoo from the current position ( $X_{it}$ ) to the next position ( $X_{it+1}$ ) is done by Levy flight, which is dependent on current and global best position ( $X_{gb}$ ) and given as (Boushaki *et al.*, 2018):

$$X_{it+1} = X_{it} + rand \times S_{it} \quad (it \in it^{max}) \quad (3.1)$$

where  $X_{it}$  is the current solution;  $rand$  is the uniform distributed random number (0 to 1);  $it^{max}$  is the maximum number of iterations;  $S_{it}$  represents step size of  $it^{th}$  iteration, which is attained as follows:

$$S_{it} = \frac{\alpha \times p}{|q|^{1/\beta}} (X_{it} - X_{gb}) \quad (it \in it^{max}) \quad (3.2)$$

where,  $\alpha > 0$  is a scaling factor;  $X_{gb}$  is the best solution;  $p$  and  $q$  are the normally distributed random numbers with variance  $\sigma_p$  and  $\sigma_q$ , respectively;  $\sigma_p$  is controlled by distribution factor  $\beta$  ( $1 \leq \beta \leq 2$ ) and computed as:

$$\sigma_p = \left[ \frac{(\sin \pi\beta / 2) \times \Gamma(1 + \beta)}{2^{(\beta-1)/2} \times \beta \times \Gamma\left(\frac{1+\beta}{2}\right)} \right]^{\frac{1}{\beta}} ; \quad \sigma_q = 1 \quad (3.3)$$

To replace the nests that the hosts have abandoned, the CS algorithm uses discovery probability  $pd$ . The updation of positions is based on the discovery probability  $pd$  of the host bird to find the unfamiliar eggs in its nest, which is given as (Wang and Zhong 2015):

$$X_{it+1} = \begin{cases} X_{iter} + rand \times (X_x - X_y); & rand > pd \\ 0 & ; else \end{cases} \quad (it \in it^{max}) \quad (3.4)$$

where  $X_x$  and  $X_y$  are the randomly chosen positions from the entire population.

### 3.3.2 Quantum-Based Cuckoo Search Algorithm (QCSA)

**3.3.2.1 Quantum Mechanism:** In the last few decades, the quantum theory (QT) has been considered to provide novel evolutionary computation ideas. The time-subordinate Schrödinger equation in quantum mechanics illustrates how a physical framework's quantum condition evolves with respect to time and space. The following equation serves as a representation of it (Cheung *et al.* 2017):

$$i\hbar \frac{\partial}{\partial t} \psi(\gamma, t) = \left[ \frac{-\hbar^2}{2v} \nabla^2 + V(\gamma, t) \right] \psi(\gamma, t) \quad (3.5)$$

In quantum mechanism, the delta potential is defined by Dirac delta function ( $\delta(\gamma)$ ) and is represented as:

$$V(\gamma) = -\lambda\delta(\gamma) \quad (3.6)$$

where  $i$  is the imaginary unit;  $\hbar$  is the reduced Planck constant;  $\psi(\gamma, t)$  is the wave function of the

quantum system at position  $\gamma$  and time  $t$ ;  $v$  is the mass of particle;  $V(\gamma, t)$  is the potential and  $\nabla^2$  is the Laplacian operator;  $\lambda$  is the intensity of the Dirac delta function.

The wave function  $\psi(\gamma)$  of the nest position is derived from Eqs. (3.5) and (3.6), which represent each cuckoo's quantum behaviour with its quantum state and it is given as:

$$\psi(\gamma) = \frac{1}{\sqrt{L}} \exp\left[-\frac{|\gamma|}{L}\right] \quad (3.7)$$

The probability density function  $|\psi(\gamma)|^2$  of the nest position is given as:

$$|\psi(\gamma)|^2 = \frac{1}{L} \exp\left[-\frac{2|\gamma|}{L}\right] \quad (3.8)$$

If  $\eta = \exp(-2|\gamma|/L)$  and subjected to uniform distribution (0 to 1), then the solution of  $|\gamma|$  is obtained as below:

$$|\gamma| = \frac{L}{2} \ln\left[\frac{1}{\eta}\right] \quad (3.9)$$

**3.3.2.2 Non-Homogeneous Update Laws:** According to QT,  $L$  represents the distance between the current nest position ( $X_{it}$ ) and the mean position ( $\bar{X}$ ) of all nests in the current iteration and is given as:

$$L = 2\delta(\bar{X} - X_{it}) \ln(1/\eta) \quad (3.10)$$

The step size  $S'_{it} = |\gamma|$  using QT can be redefined as follows (Cheung *et al.* 2017):

$$S'_{it} = \delta |(\bar{X} - X_{it})| \ln[1/\eta] \quad (it \in it^{\max}) \quad (3.11)$$

where  $\delta$  is a control parameter, which controls the difference between the current position and the mean position of the nest;  $\eta$  is a uniformly distributed random number.

In QCSA, there are three update rules instead of a single update as compared to CSA. The original update rule of traditional CSA (Eq. (3.1)) is replaced with non-homogeneous search mechanisms using QT to enhance the individual's search ability. The locations are updated by selecting one update rule from the three with the same probability. Standard CSA provides the first update rule (Eq. (3.12(a))), and the QT drives the other two update rules. The second update

equation (Eq. (3.12(b))) is obtained using the step size  $S'_{iter}$  given by QT. The third update law in Eq. (3.12(c)) ensures that there are no significant fluctuations around the global best solution ( $X_{gb}$ ). The two update equations given by quantum theory, *i.e.*, Eq. (3.12 (b)) and Eq. (3.12 (c)), emphasis on making small perturbation in the existing solution in combination with the mean and the best solution to overcome the problem of trapping in the local optima. In the QCSA technique, the up-gradation is performed non-homogeneously by randomly choosing one update rule among the three rules given in Eq. (3.12 (a)-(c)) as given below:

$$X_{it+1} = \begin{cases} X_{it} + \frac{\alpha \times rand \times p}{|q|^{1/\beta}} [X_{it} - X_{gb}]; rand \in (0.67, 1] & 3.12(a) \\ \bar{X} + \delta \ln\left(\frac{1}{\eta}\right) [\bar{X} - X_{it}]; rand \in (0.33, 0.67] & 3.12(b) \\ X_{it} + \delta \exp(\eta) [X_{gb} - X_{it}]; else & 3.12(c) \end{cases} \quad (it \in it^{\max})$$

### 3.3.3 Mutation Strategies

The mutation strategies (MS) play a vital role in the heuristic optimization techniques by exploring the greater region of search space and to exploit the promising search areas. Various mutation operators have diverse characteristics hence the variability in the existing population is achieved by introducing the new individuals into the population, which helps to avoid stagnation of the search in local optima (Andrews, 2006). In this chapter, Cauchy, Gaussian and opposition-based mutation strategies has been used. A brief discussion about these mutation strategies has been presented in the section 2.5.2 of chapter 2.

### 3.3.4 Implementation of POT-II to CPSGS Problem

The QCSA technique has excellent exploration capability, however, still lacks in exploitation. Thus, the best solutions obtained by QCSA are further enhanced by three MS. The three MS, *i.e.*, Cauchy, Gaussian, and opposition-based mutation have been used to improve the solution quality obtained by QCSA technique. At each iteration, three new sets of solutions are obtained by

Cauchy, Gaussian, and opposition-based mutation by using the Eqs. (2.40), (2.43) and (2.46), respectively, of chapter 2. After applying each mutation operator, the objective function is evaluated. The greedy search mechanism is applied among the solutions obtained by the mutation strategies and previous solution to select the better solution. The pseudo-code for the implementation of the POT-II to CPSGS problem is shown in Fig. 3.1.

```

Begin
-Initialize the input parameters, population size ( $N^p$ ), cost coefficients and generation limits of thermal, CHP,
heat and hydro units and control parameters of QCSA, Cauchy and Gaussian mutation
-Initialise the positions  $X_i (i \in N^p)$ 
-Calculate fitness of each position by using Eq. (2.31) (chapter-2) and determine the current best positions and
fitness
while the stop criterion, i.e.,  $it^{max}$  is not met
for ( $i \in N^p$ )
// QCSA
-Select two individual positions  $X_x$  and  $X_y$  randomly from the population
-Abandon the worst positions according to discovery probability  $p_d$  and create new positions using Eq. (3.4)
-Evaluate the fitness for the positions created by Eq. (3.4)
    Update the positions and fitness using greedy search mechanism
-Obtain the positions using Eq. (3.12) based on quantum mechanism and evaluate fitness
    Update the positions and fitness using greedy search mechanism
// Mutation strategies
-Obtain the positions using Eq. (2.40) (chapter-2) using Cauchy mutation strategy and evaluate the fitness
    Update the positions and fitness using greedy search mechanism
-Obtain the positions using Eq. (2.43) (chapter-2) using Gaussian mutation strategy and evaluate the fitness
    Update the positions and fitness using greedy search mechanism
-Obtain the positions using Eq. (2.46) (chapter-2) using opposition-based mutation strategy and evaluate the
fitness
    Update the positions and fitness using greedy search mechanism
end for
end while
-Obtain the global best fitness and position
End
    
```

**Figure 3.1** Pseudo code of the implementation of POT-II to CPSGS problem

### 3.4 TEST SYSTEMS, RESULTS AND DISCUSSION

The performance of the POT-II and QCSA has been demonstrated using three test systems. The scheduling period considered is of 1 day, *i.e.*, 24 sub-intervals per 1 hour each. The first test system (TS) is a standard HTGS problem. The TS-II and III are small and medium sized CPSGS problems. For all the test systems, the scheduling interval is 24 hrs with 1 hr sub-interval. The details regarding the test systems have been given in following sub-section.

### **3.4.1 Test Systems**

Test system (TS)-I is a standard HTGS problem which consists of 3-thermal and 4-hydro units. The TS-I has been solved for two cases: i) neglecting transmission losses and ii) considering transmission losses. Input data for TS-I has been referred from Ref. (Basu, 2004) and given in Table A.1.1, A.2.1-A.2.3 of Appendix-A. The power demand for TS-I is given in Table A.5.1 of Appendix-A. The transmission loss coefficients for TS-I (case-II) has been referred from Ref. (Lakshminarasimman and Subramanian, 2008) and are given in Section A.1 of Appendix-A.

The TS-II is a small sized CPSGS problem which comprises 11-thermal, 2-CHP, 1-heat and 4-hydro units. TS-III is medium sized CPSGS problem which is having 4-hydro, 19-thermal, 4-CHP and 2-heat units. The data for TS-II and TS-III has been taken from (Basu, 2010b), (Basu, 2008) and (Elaiw *et al.*, 2013) for HT, thermal, CHP and heat units, respectively. The details of system coefficients for TS-II-IV are provided in Tables A.1.2-A.1.4, A.2.1-A.2.3 and A.3.1-A.3.4 of Appendix-A. The power and heat demand for TS-II-IV are given in Tables A.5.1 and A.5.2, respectively of Appendix-A. The FOR of the CHP units of TS-II and III have been shown in Fig. A.1.1 and A.1.2 of Appendix-A.

### **3.4.2 Algorithm Parameter Settings**

The codes are implemented in FORTRAN 90 on PC with 1.80 GHz, core-i5 processor, 8GB RAM. The QCSA and POT-II have been implemented to all three test systems and thirty trials have been taken for evaluating the performance of these techniques. The population size is fixed to 50 for all the test systems and the maximum iteration count has been set to 5000, 5000 and 8000 for TS-I, II and III, respectively. For obtaining the best possible results, the control parameters of the POT-II are chosen carefully after multiple trials. The parameters  $\beta$  and  $\delta$  of QCSA are fixed to 1.5 and 1.6 initially and these variables decrease with respect to iterations. The control parameter  $s$  and  $h$  for Cauchy and Gaussian mutation strategies are initially fixed to 1.8 and 1.9 and linearly decreasing with respect to iterations.

### 3.4.3 Simulation Results and Discussion

**3.4.3.1 Test System-I:** The comparison of results obtained by the POT-II with well-established heuristic techniques have been reported in Table 3.1 for TS-I (case-I). For TS-I (case-I), the minimum cost attained by the POT-II is 41,238 \$. The minimum cost obtained by the POT-II is less than particle swarm optimization (PSO) (Mandal and Chakraborty, 2011), CSA (Swain *et al.*, 2011), real coded genetic algorithm (RCGA) (Fang *et al.*, 2014), modified differential evolution (MDE) (Lakshminarasimman and Subramanian, 2006), time varying acceleration coefficient (TVAC-PSO) (Patwal *et al.*, 2018), modified hybrid differential evolution (MHDE) (Lakshminarasimman and Subramanian, 2008), quantum PSO (QPSO) (Sun and Lu, 2010), predator prey optimization (PPO) (Narang *et al.*, 2012) and mixed integer linear programming (MILP) (Ahmadi *et al.*, 2015) by 2.91%, 2.83%, 3.84%, 3.22%, 3.95%, 1.48%, 2.65%, 1.91%, 0.75%, respectively. The POT-II obtained 1.11%, 1.52% and 0.63% lesser cost than grey wolf optimizer (GWO), QCSA and POT-I (GWO-MS). It is illustrated from the results that the POT-II has a better success rate as compared to the other optimization techniques results. The POT-II outperforms the QCSA in terms of minimum, maximum, average cost and standard deviation.

**Table 3.1** Comparison of cost for TS-I (case-I)

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU time (sec)
PSO (Mandal and Chakraborty, 2011)	42,474	---	---	---	123.52
Clonal selection algorithm (Swain <i>et al.</i> , 2011)	42,440	---	---	---	109.12
RCGA (Fang <i>et al.</i> , 2014)	42,886	43,261	43,032	---	30.00
MDE (Lakshminarasimman and Subramanian, 2006)	42,611	---	---	---	125.00
TVAC-PSO (Patwal <i>et al.</i> , 2018)	42,936	43,687	43,252	---	21.33
MHDE (Lakshminarasimman and Subramanian, 2008)	41,856	---	---	---	31.00
QPSO (Sun and Lu, 2010)	42,359	---	---	---	---
PPO (Narang <i>et al.</i> , 2012)	42,042	42,099	42,078	---	30.71
MILP (Ahmadi <i>et al.</i> , 2015)	41,549	---	---	---	---
GWO	41,700	42,035	41,901	79.7	14.28
QCSA	41,875	42,135	42,003	81.9	15.14
POT-I	41,501	41,750	41,601	58.8	15.49
POT-II	41,238	41,401	41,319	51.6	15.55

The optimum thermal and hydro power generation is given in Table 3.2 for TS-I (case-I). It is evident from Table 3.2, that the total power generation satisfies the power demand at each sub interval. The water discharge rate and reservoir volume for TS-I (case-I) are shown in Figs. 3.2 and 3.3, respectively. It is illustrated from figures that the water discharge rate and reservoir volume are within its specified limits for each sub interval. Further, final volume constraint is fulfilled at the end of the scheduling interval. The convergence characteristics of the POT-I and GWO for TS-I (case-I) are displayed in Fig. 3.4, which shows that the POT -II (QCSA-MS) exhibit superior performance than QCSA technique.

**Table 3.2** Optimum power generation attained by POT-II for TS-I (case-I)

t (hr)	PD (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	102.5	209.8	139.6	59.3	61.1	40.5	137.2	750
2	780	21.18	124.9	319.3	66.0	59.9	40.8	147.9	780
3	700	100.8	207.8	139.5	71.2	52.0	0.0	128.8	700
4	650	102.6	124.9	139.8	59.4	53.8	48.8	120.8	650
5	670	102.7	209.9	50.05	92.5	60.1	0.0	154.9	670
6	800	102.6	124.9	229.5	85.7	76.4	13.8	167.0	800
7	950	102.2	124.9	319.2	83.5	55.0	46.3	219.0	950
8	1010	102.2	209.8	319.3	67.5	52.6	36.8	221.7	1010
9	1090	20.0	294.3	319.1	67.3	85.1	41.8	262.4	1090
10	1080	102.7	209.8	319.3	68.5	63.0	40.4	276.3	1080
11	1100	102.6	209.8	319	75.5	64.2	47.8	281.1	1100
12	1150	102.6	294.6	319.2	96.5	62.9	32.5	241.7	1150
13	1110	175	209.8	229.5	102.4	59.6	38.9	294.8	1110
14	1030	102.1	124.8	319.3	75.8	72.0	51.3	284.8	1030
15	1010	102.8	40.14	409	87.3	53.9	23.7	293.2	1010
16	1060	99.47	209.4	319.2	62.0	56.8	49.1	264.0	1060
17	1050	102.7	124.9	409	58.8	53.7	54.7	246.3	1050
18	1120	102.5	294.6	229.5	74.4	74.9	54.8	289.2	1120
19	1070	110.2	132	320.3	91.5	57.2	55.4	303.3	1070
20	1050	102.2	124.8	316.9	86.8	70.0	54.2	295.0	1050
21	910	174.5	40	229.4	79.2	49.7	56.3	280.8	910
22	860	100.4	209.8	50	91.8	77.5	58.4	272.1	860
23	850	101.7	124.9	139.6	70.5	75.8	54.7	282.8	850
24	800	20.0	208.8	139.7	55.4	61.2	55.7	259.2	800

In TS-I (case-II), the minimum cost attained by POT-II is 42,278 \$. The minimum, maximum, average cost, standard deviation and average CPU time is reported for state of art techniques, *i.e.*, RCGA (Fang *et al.*, 2014), MDE (Lakshminarasimman and Subramanian, 2006), hybrid DE (HDE) (Lakshminarasimman and Subramanian, 2008), MHDE (Lakshminarasimman and Subramanian, 2008), quantum-inspired evolutionary algorithm (QEA) (Wang *et al.*, 2012),

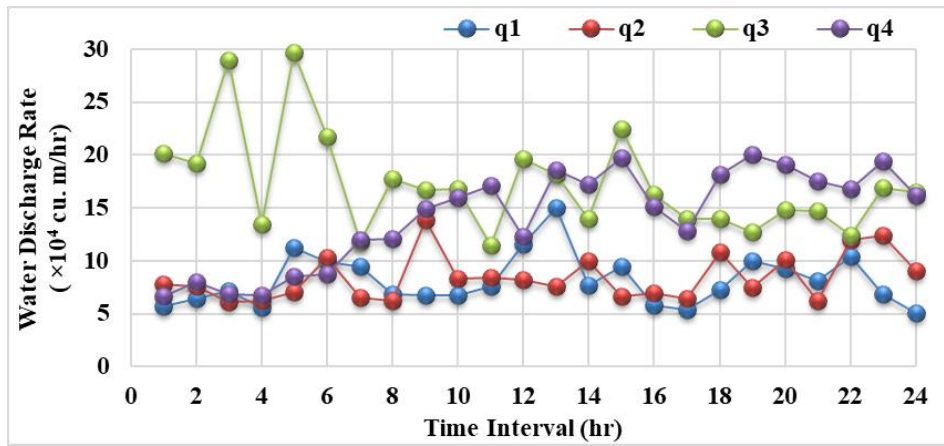


Figure 3.2 Water discharge rate of hydro units attained by POT-II for TS-I (case-I)

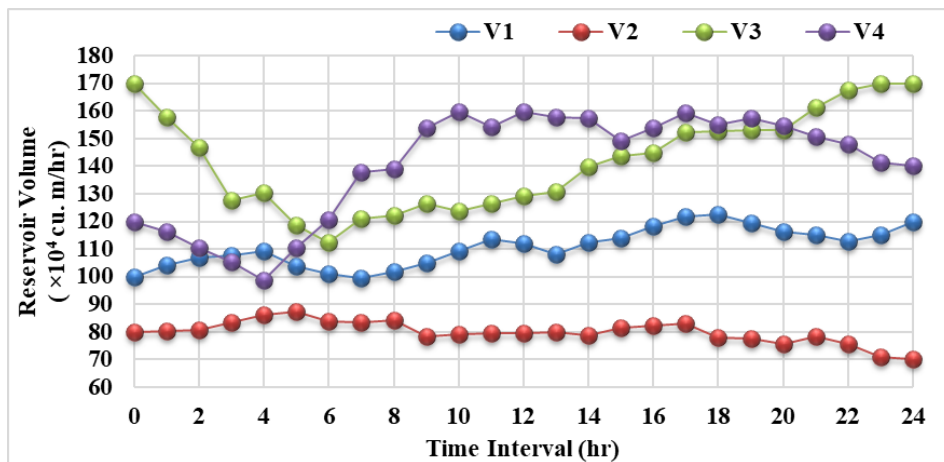


Figure 3.3 Reservoir volume of hydro units attained by POT-II for TS-I (case-I)

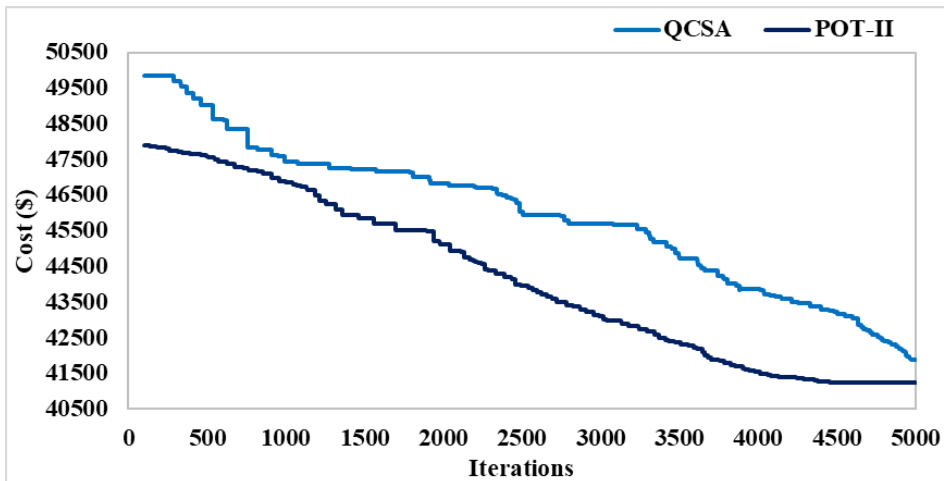


Figure 3.4 Convergence characteristics of cost attained by POT-II for TS-I (case-I)

small population based PSO (SPPSO) (Zhang *et al.*, 2012), real-coded QEA (RQEA) (Wang *et al.*, 2012), GWO (Kaur and Narang, 2019), QCSA, POT -I and POT-II in Table 3.3. It is evident from Table 3.3 that the POT-II searches the global best and high-quality solution at most of the executions. The POT-II attained 1.01%, 1.30% and 0.46% better optimal cost than GWO, QCSA

and POT-I, respectively. However, the CPU time required by the POT-II is marginally higher as compared to the GWO, POT-I and QCSA techniques. The optimal generation of thermal and hydro units and transmission losses for a time interval of 24 hours has been presented in Table 3.4. It can be observed from Table 3.4 that total power generation satisfies the power demand and losses in each sub interval. The water discharge rate and reservoir volume attained by POT-II for TS-I (case-II) are presented in Figs. 3.5 and 3.6, respectively, and satisfy all the constraints. The comparison of convergence characteristics of the POT-II and QCSA is shown in Fig. 3.7 which clearly shows the effectiveness of the POT-II to get the optimal solution as compared to QCSA technique.

**Table 3.3** Comparison of cost for TS-I (case-II)

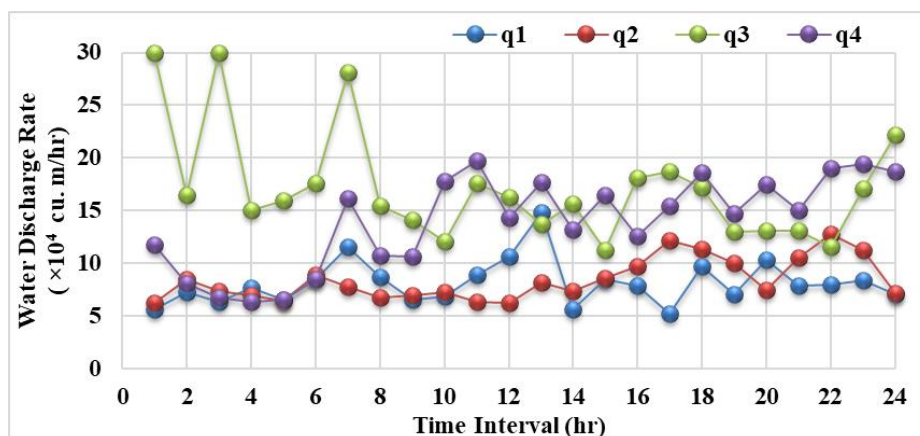
Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU time (sec)
RCGA (Fang <i>et al.</i> , 2014)	43465	43717	43643	---	32.00
MDE (Lakshminarasimman and Subramanian, 2006)	43435	---	---	---	---
HDE (Lakshminarasimman and Subramanian, 2008)	43656	---	---	---	68.00
MHDE (Lakshminarasimman and Subramanian, 2008)	42679	---	---	---	40.00
QEA (Wang <i>et al.</i> , 2012)	44686	---	---	---	19.00
SPPSO (Zhang <i>et al.</i> , 2012)	42740	44346	43622	---	32.70
RQEA (Wang <i>et al.</i> , 2012)	42715	---	---	---	21.00
GWO	42708	42994	42854	81.6	15.38
QCSA	42835	43115	42791	85.1	16.40
POT-I	42473	42686	42549	52.5	16.45
POT-II	42278	42437	42351	48.3	16.57

**Table 3.4** Optimum power generation attained by POT-II for TS-I (case-II)

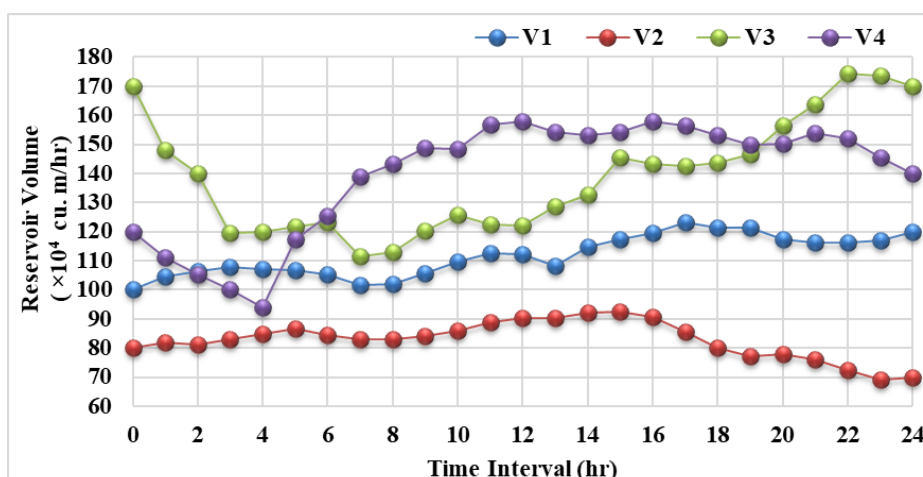
t (hr)	PD (MW)	PL (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
			PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	8.1	106.0	209.9	142.4	58.5	51.6	0.0	189.7	758.1
2	780	6.3	20.5	294.9	142.3	71.4	65.6	47.3	144.3	786.3
3	700	5.9	102.8	125.0	229.6	65.3	60.1	0.0	123.1	705.9
4	650	4.4	102.7	124.9	139.8	74.8	58.2	43.0	111.0	654.4
5	670	5.4	20.0	125.1	229.5	66.1	55.9	41.8	137.0	675.4
6	800	7.3	102.7	209.9	139.8	79.3	70.1	37.6	168.0	807.3
7	950	13.9	104.7	126.1	319.4	92.9	62.3	0.0	258.4	963.9
8	1010	13.1	102.8	125.0	409.0	80.0	55.6	39.6	211.0	1023.1
9	1090	14.5	102.6	209.7	409.0	66.1	58.1	44.7	214.3	1104.5
10	1080	17.3	20.0	209.9	409.1	69.7	60.7	47.8	280.1	1097.3
11	1100	18.8	20.4	210.7	409.1	83.9	55.9	37.4	301.4	1118.8
12	1150	16.2	101.8	294.6	319.2	92.6	56.2	41.3	260.5	1166.2
13	1110	17.8	174.9	40.0	409.0	102.3	68.8	47.9	284.9	1127.8
14	1030	13.6	102.7	294.7	229.5	60.0	64.7	46.5	245.4	1043.6
15	1010	14.6	102.2	209.7	229.4	82.1	72.5	53.0	275.7	1024.6
16	1060	14.2	102.3	209.8	319.3	78.1	77.7	43.7	243.3	1074.2
17	1050	16.0	169.8	124.5	319.3	57.2	85.1	41.2	269.0	1066.0
18	1120	17.4	102.7	209.8	319.3	90.2	78.3	46.5	290.7	1137.4

**Table 3.4** Optimum power generation attained by POT-II for TS-I (case-II) (continued)

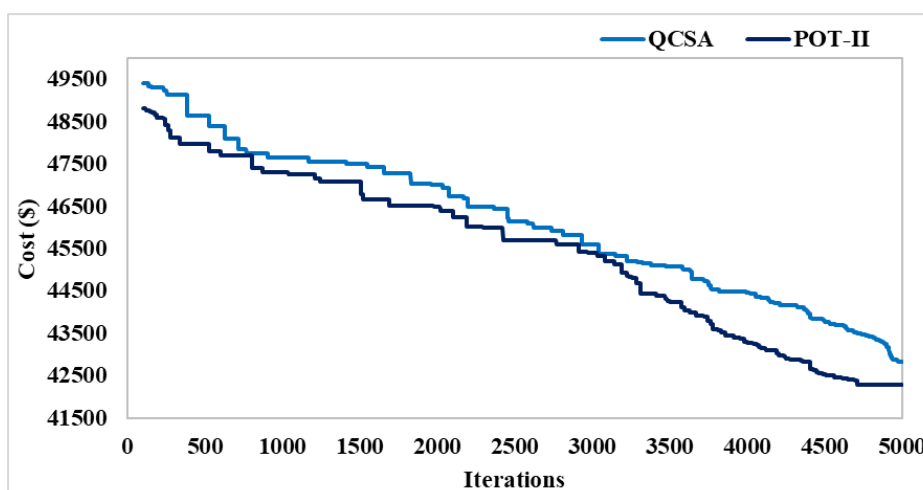
t (hr)	PD (MW)	PL (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
			PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
19	1070	14.9	102.3	209.6	319.2	72.4	70.7	53.7	257.0	1084.9
20	1050	15.2	140.2	209.8	229.5	92.6	57.4	56.1	279.5	1065.2
21	910	12.7	102.0	208.9	139.7	78.3	72.4	57.7	263.6	922.7
22	860	14.1	102.5	124.9	139.8	78.3	77.9	59.0	291.7	874.1
23	850	13.5	20.0	209.7	139.7	81.3	70.2	55.3	287.5	863.5
24	800	13.3	20.0	40.0	319.3	72.2	50.1	34.7	276.9	813.3



**Figure 3.5** Water discharge rate of hydro units attained by POT-II for TS-I (case-II)



**Figure 3.6** Reservoir volume of hydro units attained by POT-II for TS-I (case-II)



**Figure 3.7** Convergence characteristics of cost attained by POT-II for TS-I (case-II)

**3.4.3.2 Test System-II and III:** For TS-II and III, the CPSGS problem has been considered with scheduling period of one day with 24 intervals and solved using QCSA and POT-II. The results obtained by the POT-II and QCSA for TS-II and III are shown in Tables 3.5 and 3.6, respectively. The comparative analysis of the results attained by the QCSA, POT-I and POT-II for TS-II and III is done in terms of minimum, maximum and average value of cost, standard deviation and CPU time acquired in 30 trials. It is evident from Tables 3.5 and 3.6, the minimum, average and maximum cost and standard deviation obtained by POT-II are superior as compared to GWO, QCSA and POT-I results. The minimum operating cost attained by the QCSA and POT-II for TS-II is 26,27,422 \$ and 25,20,514 \$, respectively. The POT-II improves the results as compared to GWO, QCSA and POT-I by 3.36%, 4.07% and 1.64%, respectively. The optimum power generation of thermal, CHP, hydro units is tabulated in Tables 3.7(a)-(b) and heat production of heat units is tabulated in Table 3.8. The optimum water discharge rate and reservoir volume of hydro units for TS-II are shown in Figs. 3.8 and 3.9, respectively. It is illustrated from tables and figures that obtained optimum generation schedule satisfy all the constraints.

**Table 3.5** Comparison of cost for TS-II

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	26,08,065	27,12,549	26,65,273	33,080	34.06
QCSA	26,27,422	27,26,300	26,76,481	29,632	38.67
POT-I	25,62,644	26,35,849	25,97,527	22,762	35.60
POT-II	25,20,514	25,85,514	25,53,597	19,947	39.25

**Table 3.6** Comparison of cost for TS-III

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	58,28,034	59,35,955	58,89,836	29,825	59.36
QCSA	58,50,636	59,45,925	59,01,467	31,071	65.09
POT-I	57,38,132	58,28,034	57,90,307	24,470	61.90
POT-II	57,28,260	57,98,360	57,61,097	21,843	68.25

**Table 3.7(a)** Optimum power generation attained by POT-II for TS-II

t (hr)	PD (MW)	Power (MW) (Thermal Units)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>	PT <sub>11</sub>
1	1786	26.0	232.0	155.6	170.2	164.1	83.8	104.2	141.1	82.0	52.2	28.6
2	1890	30.4	238.6	278.4	155.1	164.5	137.4	226.7	62.9	44.0	58.8	14.3
3	1958	62.6	256.0	274.8	155.2	158.2	120.7	120.3	132.6	75.4	44.5	23.2
4	2056	25.0	293.8	287.5	156.4	148.6	206.8	94.8	138.7	71.0	36.0	41.2
5	2150	43.7	289.5	204.2	151.2	161.4	300.7	66.8	145.9	62.7	40.4	28.7
6	2428	104.5	288.9	395.4	150.5	193.6	242.2	222.9	64.5	37.2	41.9	15.8

**Table 3.7(a)** Optimum power generation attained by POT-II for TS-II (continued)

t (hr)	PD (MW)	Power (MW) (Thermal Units)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>	PT <sub>11</sub>
7	2652	167.8	264.4	443.5	163.5	206.3	286.7	174.9	137.4	74.6	34.1	26.1
8	2786	174.4	299.3	456.7	199.5	230.1	195.4	275.4	80.0	110.5	49.3	41.2
9	3014	153.9	295.1	399.0	268.0	303.9	331.6	263.1	143.4	114.0	58.2	22.4
10	3102	169.2	297.9	449.7	256.1	313.6	335.8	252.0	78.8	101.2	73.9	30.6
11	3206	171.3	298.5	431.8	418.0	231.0	327.3	258.0	111.4	122.7	37.8	48.2
12	3300	171.8	299.0	473.7	392.4	367.0	340.0	247.0	73.2	49.1	58.6	16.6
13	3182	134.8	297.5	457.5	434.6	279.9	279.4	214.2	149.0	54.9	76.3	19.4
14	2954	133.4	264.1	440.5	292.5	232.7	334.5	213.8	125.0	122.1	53.0	41.6
15	2795	158.7	266.9	459.9	270.2	215.9	199.5	203.6	71.0	100.8	65.4	15.5
16	2614	155.2	299.5	388.2	165.0	192.7	235.0	162.5	103.2	59.5	26.4	51.6
17	2530	98.1	284.7	435.6	165.5	222.8	253.1	188.0	80.0	86.9	45.6	16.8
18	2748	127.6	299.1	399.0	181.9	152.3	338.9	193.0	105.1	48.3	72.4	26.4
19	2846	138.6	296.8	366.7	207.7	284.3	323.6	111.4	145.8	94.9	59.1	36.2
20	3022	129.0	299.4	457.9	240.6	312.1	334.3	293.1	150.4	52.9	42.6	39.3
21	2834	166.9	294.0	384.4	174.9	215.8	305.5	173.4	147.2	91.1	37.0	35.6
22	2488	44.4	299.3	335.8	204.5	154.9	266.3	86.4	140.7	126.7	42.0	33.2
23	2182	27.7	265.4	181.7	151.2	254.2	255.8	140.3	104.9	44.6	54.0	37.0
24	1984	54.4	211.4	161.7	174.3	174.9	137.5	87.9	87.3	118.4	25.7	41.3

**Table 3.7(b)** Optimum power generation attained by POT-II for TS-II

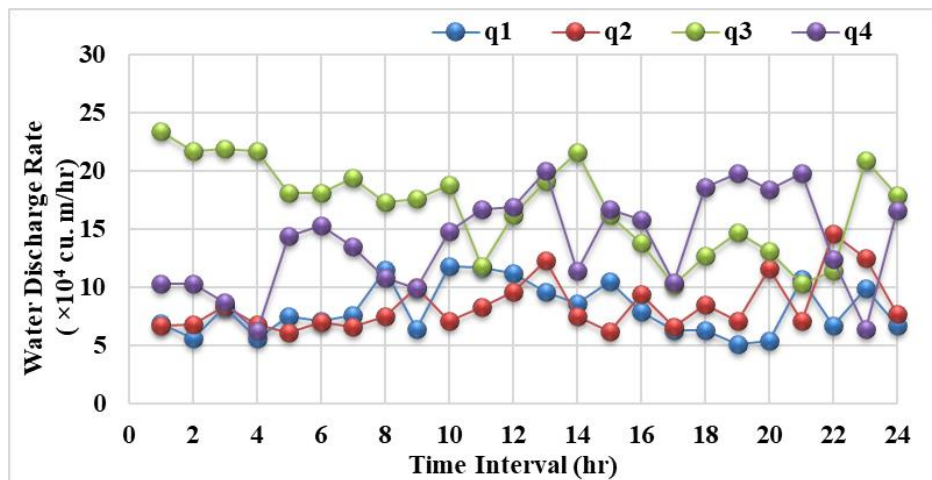
t (hr)	PD (MW)	Power (MW) (CHP Units)		Power (MW) (Hydro Units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	1786	158.5	66.3	68.2	54.8	21.6	176.7
2	1890	102.6	66.5	58.6	55.9	27.0	168.3
3	1958	107.5	118.2	78.8	66.1	20.7	143.3
4	2056	213.1	101.3	59.3	57.4	18.6	106.4
5	2150	200.7	90.2	73.7	53.7	35.9	200.6
6	2428	199.2	90.0	70.6	59.7	35.7	215.5
7	2652	204.1	97.3	74.3	56.9	29.4	210.7
8	2786	207.0	78.8	93.5	62.5	36.8	195.5
9	3014	215.4	76.2	66.0	75.4	34.8	193.7
10	3102	211.1	101.0	95.6	59.9	30.2	245.1
11	3206	203.8	73.7	95.3	67.7	45.8	263.7
12	3300	226.4	109.2	92.9	74.1	43.4	265.5
13	3182	183.5	114.8	86.2	82.5	35.4	282.2
14	2954	216.0	99.6	81.7	60.1	23.5	219.8
15	2795	202.5	108.3	91.7	53.7	47.2	264.2
16	2614	230.6	84.3	77.6	72.1	53.5	257.1
17	2530	221.4	43.0	66.0	55.8	54.2	212.4
18	2748	229.4	95.8	66.7	65.7	57.0	289.5
19	2846	222.7	94.7	55.9	57.4	56.6	293.6
20	3022	102.6	93.4	59.1	77.7	57.7	279.7
21	2834	210.2	114.2	94.1	56.1	56.4	277.3
22	2488	216.3	105.3	69.7	83.6	58.4	220.6
23	2182	210.9	90.9	90.2	75.0	42.1	156.3
24	1984	198.5	72.0	69.9	53.9	52.2	262.7

**Table 3.8** Optimum heat generation attained by POT-II for TS-II

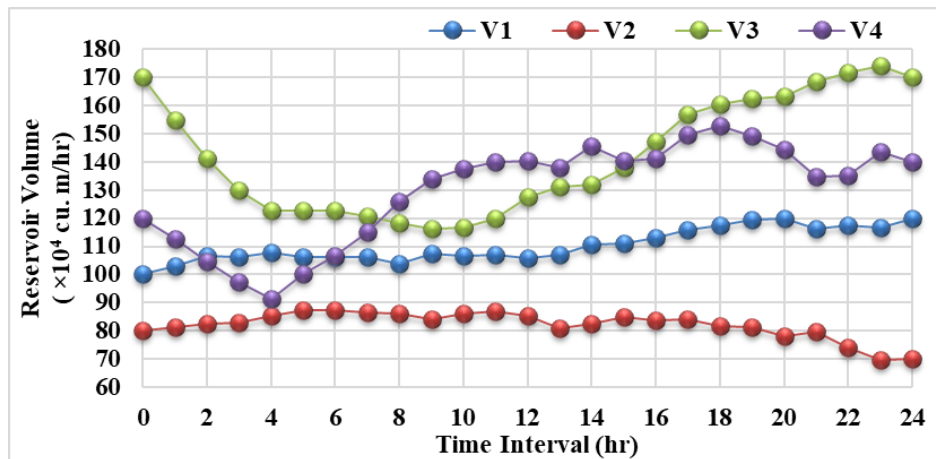
t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)	t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
1	390	88.0	75.5	226.6	13	470	135.5	122.4	212.1
2	400	55.2	58.9	285.9	14	460	70.4	67.5	322.1
3	410	78.2	64.7	267.2	15	450	163.2	94.5	192.3

**Table 3.8** Optimum heat generation attained by POT-II for TS-II (continued)

t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)	t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
4	420	121.3	54.1	244.6	16	450	57.6	26.3	366.1
5	440	54.1	34.6	351.3	17	420	61.2	38.6	320.2
6	450	136.6	117.2	196.2	18	435	46.9	68.4	319.7
7	450	173.0	116.8	160.2	19	445	77.0	96.2	271.7
8	455	172.6	48.8	233.6	20	450	114.5	111.2	224.3
9	460	109.7	94.0	256.3	21	445	164.0	63.2	217.9
10	460	174.1	59.1	226.8	22	435	66.2	130.9	237.9
11	470	172.6	78.5	218.9	23	400	39.6	101.2	259.2
12	480	93.7	121.6	264.6	24	400	168.0	66.0	166.1



**Figure 3.8** Water discharge rate of hydro units attained by POT-II for TS-II



**Figure 3.9** Reservoir volume of hydro units attained by POT-II for TS-II

For TS-III, the minimum cost obtained by QCSA and POT-II is 58,50,636 \$ and 57,28,260 \$, respectively. For TS-III, the minimum cost attained by POT-II is 1.71%, 2.09% and 0.17% lesser than GWO, QCSA and POT-I, respectively. For TS-III, the optimum power generation schedule of thermal, CHP and hydro units is presented in Tables 3.9(a)-(c). Table 3.10 gives the

optimum heat generation schedule of heat and CHP units. Optimum water discharge rate and reservoir volume of hydro units for TS-III are presented in Figs. 3.10 and 3.11, respectively. It is further established that optimum results are feasible. Convergence characteristics of POT-II for TS-II and TS-III are shown in Figs. 3.12 and 3.13, respectively, and it is also illustrated that the POT-II has better convergence than QCSA for both the test systems. Hence, it is summarized that the integration of QCSA technique and MS improves the solution quality and convergence behaviour for complex CPSGS problem.

**Table 3.9(a)** Optimum power generation attained by POT-II for TS-III

t (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>
1	2822	55.0	77.1	148.9	155.2	161.6	110.1	103.0	118.5	67.1	76.1
2	3000	48.4	97.3	184.6	218.7	200.5	135.5	63.0	124.4	72.0	29.2
3	3216	22.8	86.3	268.6	172.6	265.5	180.7	165.2	142.2	99.3	34.6
4	3462	71.4	98.6	260.7	219.6	187.1	182.0	248.8	135.1	74.5	59.1
5	3630	154.3	136.2	220.3	162.1	215.0	298.1	261.5	141.7	100.6	59.6
6	4056	154.7	147.3	317.3	268.1	398.5	276.7	257.1	87.5	77.2	34.2
7	4354	167.2	258.2	375.5	371.1	415.0	174.5	266.6	126.9	65.4	61.4
8	4562	165.1	295.4	284.2	343.6	403.6	335.2	273.1	135.8	71.3	37.6
9	4938	149.0	287.6	454.0	422.7	378.2	280.5	271.1	124.8	117.9	59.9
10	5124	162.6	248.2	439.8	432.3	404.0	296.9	289.5	145.0	103.6	26.2
11	5312	122.1	298.9	480.2	460.0	403.7	337.6	273.9	134.2	123.4	65.9
12	5450	127.0	297.9	437.3	452.3	447.5	315.9	267.6	146.0	87.7	74.7
13	5254	154.2	284.1	456.6	424.1	425.8	334.3	296.6	145.1	49.2	70.4
14	4878	158.1	224.7	437.6	425.0	391.8	251.0	152.8	120.5	20.0	62.7
15	4571	137.5	275.5	369.7	332.1	369.3	269.9	151.4	73.6	69.5	65.8
16	4168	64.1	229.5	475.7	318.6	247.7	209.0	84.4	103.2	89.7	22.2
17	4010	53.2	143.8	384.0	164.7	358.8	132.6	167.5	136.1	69.6	66.8
18	4376	156.3	110.2	396.5	468.2	359.0	151.7	65.2	107.2	81.5	57.8
19	4622	138.3	251.6	448.2	396.3	298.6	115.9	235.4	156.6	95.6	69.8
20	4994	166.0	285.0	426.1	456.9	410.0	309.0	164.6	109.0	126.2	67.1
21	4758	161.3	164.2	464.4	339.9	373.7	331.7	238.6	124.5	102.2	73.8
22	4116	156.1	202.4	408.9	305.5	317.6	250.1	230.4	101.4	81.9	27.9
23	3514	32.0	47.2	224.4	300.0	365.8	178.1	105.1	76.2	33.8	27.7
24	3168	55.0	45.4	130.9	154.8	180.6	253.2	105.4	110.1	63.7	57.7

**Table 3.9(b)** Optimum power generation attained by POT-II for TS-III

t (hr)	PD (MW)	Power (MW) (Thermal Units)								
		PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
1	2822	20.0	208.7	199.5	117.2	65.6	118.8	77.3	50.8	17.4
2	3000	26.3	253.1	174.2	116.9	163.0	97.3	86.3	64.4	31.3
3	3216	13.4	154.6	172.2	186.9	148.4	64.2	74.1	70.3	10.4
4	3462	29.7	208.1	221.2	146.3	174.4	89.9	81.3	75.1	27.5
5	3630	22.5	173.8	290.8	167.7	91.0	73.8	92.8	52.2	42.8
6	4056	25.9	263.1	229.0	168.2	220.6	109.5	86.7	29.8	48.1
7	4354	27.9	257.6	219.9	159.7	197.8	138.3	81.9	60.9	34.7
8	4562	40.4	217.2	420.8	301.3	122.1	105.9	82.9	43.4	17.1
9	4938	33.3	294.8	352.1	336.9	264.7	72.7	74.5	29.4	44.2
10	5124	54.0	450.7	367.0	296.1	213.7	132.2	35.8	52.7	38.0
11	5312	32.8	335.3	441.7	250.2	227.9	109.4	101.8	65.1	38.7

**Table 3.9(b)** Optimum power generation attained by POT-II for TS-III (continued)

t (hr)	PD (MW)	Power (MW) (Thermal Units)								
		PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
12	5450	31.2	421.2	438.9	324.7	262.9	155.7	54.3	60.9	22.8
13	5254	41.3	442.8	435.0	241.4	192.8	158.8	80.4	38.0	22.8
14	4878	29.1	334.4	416.9	297.8	262.1	153.3	91.6	33.9	31.9
15	4571	48.7	366.7	260.9	292.5	169.6	110.8	103.3	66.8	47.3
16	4168	16.4	267.4	219.8	222.0	267.8	127.2	89.2	64.9	26.0
17	4010	42.7	169.1	320.0	317.5	251.1	92.4	104.3	37.9	42.0
18	4376	46.9	269.2	240.4	315.1	184.7	141.2	77.8	57.2	32.9
19	4622	37.6	311.4	379.4	192.5	295.7	91.6	93.3	40.0	32.2
20	4994	34.6	307.2	305.5	285.2	237.6	75.1	74.7	65.3	52.1
21	4758	48.4	243.7	350.2	229.4	199.9	137.1	84.9	31.9	50.5
22	4116	11.1	232.6	250.5	299.1	66.0	89.1	81.0	32.0	24.9
23	3514	27.5	279.4	218.3	292.6	131.3	111.1	91.1	33.3	52.5
24	3168	10.8	150.7	235.4	133.7	245.5	139.0	102.3	48.5	25.9

**Table 3.9(c)** Optimum power generation attained by POT-II for TS-III

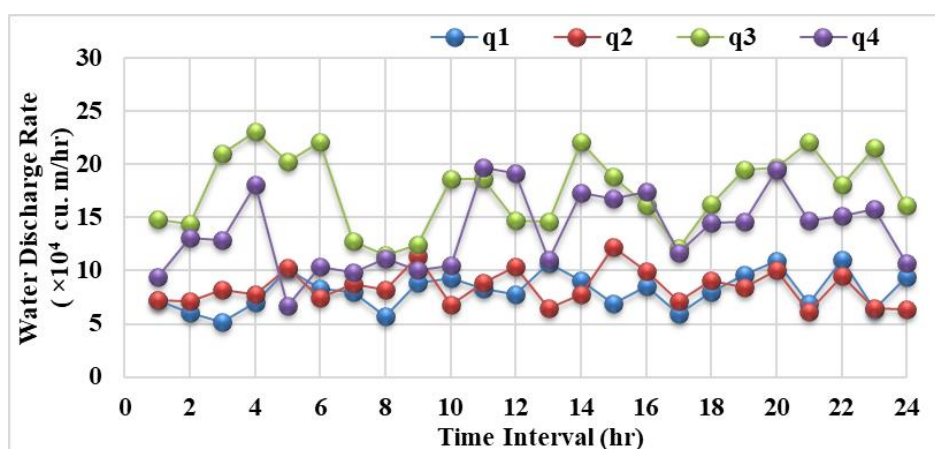
t (hr)	PD (MW)	Power (MW) (CHP units)				Power (MW) (Hydro units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	2822	132.5	82.0	220.7	85.5	70.8	57.7	56.7	168.0
2	3000	119.5	48.1	195.2	82.4	62.1	57.8	55.6	192.9
3	3216	218.9	96.5	192.2	46.0	55.6	64.7	33.0	176.8
4	3462	136.2	108.0	218.1	71.0	70.5	62.7	17.7	187.1
5	3630	210.7	92.9	164.6	108.0	88.2	74.6	31.7	102.4
6	4056	191.3	77.3	163.6	119.9	77.7	58.9	20.9	146.8
7	4354	186.3	56.0	191.3	112.0	76.0	65.3	52.0	154.4
8	4562	215.6	104.8	138.4	50.5	60.2	61.4	54.0	181.1
9	4938	180.3	97.9	97.5	122.3	82.1	73.9	55.3	180.2
10	5124	195.3	121.2	131.2	110.2	85.2	52.2	43.9	196.3
11	5312	151.9	113.3	183.3	109.1	80.7	64.4	43.6	262.7
12	5450	175.2	99.0	216.9	79.3	76.8	70.1	55.3	250.7
13	5254	214.3	94.2	194.7	68.3	94.1	49.2	56.4	189.0
14	4878	220.5	54.4	175.4	113.6	86.1	58.0	31.6	243.3
15	4571	223.8	112.2	169.1	46.9	71.9	76.7	47.5	241.9
16	4168	191.5	69.2	214.7	100.6	83.2	66.1	55.3	242.6
17	4010	232.6	108.8	169.7	72.4	63.3	51.1	58.8	199.4
18	4376	209.2	108.9	194.2	114.4	80.1	59.8	57.8	232.7
19	4622	90.2	118.2	189.8	112.0	89.9	55.4	48.2	238.1
20	4994	214.6	91.7	156.4	101.8	95.8	61.9	46.1	268.5
21	4758	190.8	118.4	221.1	96.7	71.7	41.6	34.5	232.9
22	4116	125.3	86.3	201.1	87.8	95.6	61.1	52.4	237.9
23	3514	115.3	56.6	196.5	121.6	66.9	45.0	37.7	246.8
24	3168	202.9	85.2	136.7	97.3	88.0	45.3	56.2	207.6

**Table 3.10** Optimum heat generation attained by POT-II for TS-III

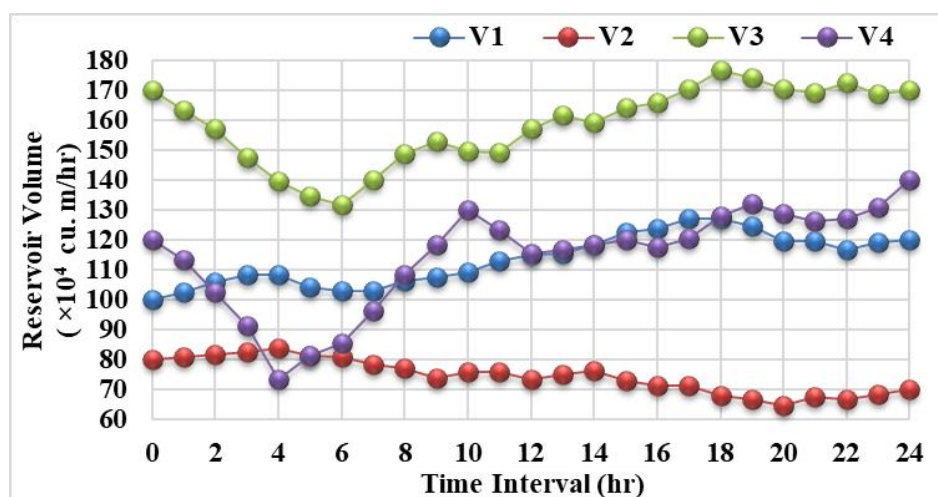
t (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth)(Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
1	780	58.6	34.3	98.9	79.4	42.7	466.0
2	800	76.0	47.9	53.1	74.0	116.4	432.7
3	820	57.3	35.9	148.7	40.7	317.7	219.7
4	840	97.9	59.0	119.0	63.1	137.1	363.9
5	880	169.1	61.3	132.2	2.2	86.0	429.1
6	900	88.1	80.6	145.8	22.8	85.4	477.4
7	900	151.9	88.0	150.3	76.7	146.0	287.1
8	910	76.7	85.5	91.4	39.7	79.6	537.1
9	920	89.5	105.3	62.4	30.7	122.8	509.3
10	920	158.8	32.3	85.3	123.9	87.0	432.7

**Table 3.10** Optimum heat generation attained by POT-II for TS-III (continued)

t (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth) (Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
11	940	124.5	43.8	96.5	133.1	167.6	374.6
12	960	127.2	122.7	143.5	83.1	3.4	480.0
13	940	113.6	97.9	114.5	93.1	59.0	461.9
14	920	146.5	23.3	142.2	128.7	205.0	274.3
15	900	75.4	110.0	70.7	80.3	163.3	400.3
16	900	41.0	96.8	43.2	80.9	191.3	446.8
17	840	48.4	40.1	49.8	18.3	26.9	656.5
18	870	84.2	31.2	53.1	121.5	199.7	380.3
19	890	100.6	33.4	110.9	76.2	148.6	420.4
20	900	170.8	77.8	67.3	96.3	79.2	408.6
21	890	55.1	28.3	142.3	87.0	337.5	239.9
22	870	79.6	76.2	165.7	67.1	221.0	260.5
23	800	18.3	41.5	101.5	62.5	108.9	467.3
24	800	93.5	3.5	64.2	53.2	191.7	393.9



**Figure 3.10** Water discharge rate of hydro units attained by POT-II for TS-III



**Figure 3.11** Reservoir volume of hydro units attained by POT-II for TS-III

### 3.5 STATISTICAL ANALYSIS

Two-sample t-test has been performed to investigate the robustness and significant difference

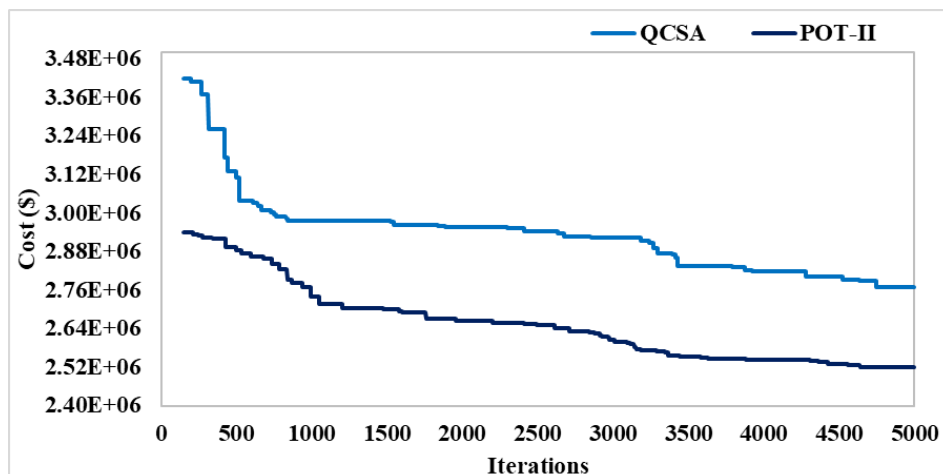
between the POT-II and QCSA technique. Tables 3.11 and 3.12 show the statistical comparison of the QCSA and POT-II for TS-I, II and III. The statistical test has been run for thirty trials. It can be seen from the Tables 3.11 and 3.12 that the standard deviation and mean of fitness function of the POT-II is better as compared to the QCSA technique. The t-test is performed at the 0.05 significance level for all three test systems. The statistical  $p$  value for all the test systems is lesser than the critical value which shows the significant difference between the two techniques.

**Table 3.11** Two-sample t-test assuming equal variances for TS-I

	TS-I (case-I)		TS-I (case-II)	
	QCSA	POT-II	QCSA	POT-II
Variance	6708.317	2663.89	7257.54	2332.823
Observations	30	30	30	30
Pooled Variance	4686.103		4795.182	
Hypothesized Mean Difference	0		0	
Df	58		58	
t Stat	38.71		34.71	
P(T≤t) one-tail	1.96E-43		8.47E-41	
t Critical one-tail	1.67		1.67	
P(T≤t) two-tail	3.92E-43		1.69E-40	
t Critical two-tail	2.001717		2.001717	

**Table 3.12** Two-sample t-test assuming equal variances for TS-II and III

	TS-II		TS-III	
	QCSA	POT-II	QCSA	POT-II
Variance	8.78E+08	3.98E+08	9.65E+08	4.77E+08
Observations	30	30	30	30
Pooled Variance	6.38E+08		7.21E+08	
Hypothesized Mean Difference	0		0	
Df	58		58	
t Stat	18.84		20.24	
P(T≤t) one-tail	1.06E-26		2.84E-28	
t Critical one-tail	1.67		1.67	
P(T≤t) two-tail	2.12E-26		5.68E-28	
t Critical two-tail	2.001717		2.001717	



**Figure 3.12** Convergence characteristics of cost attained by POT-II for TS-II

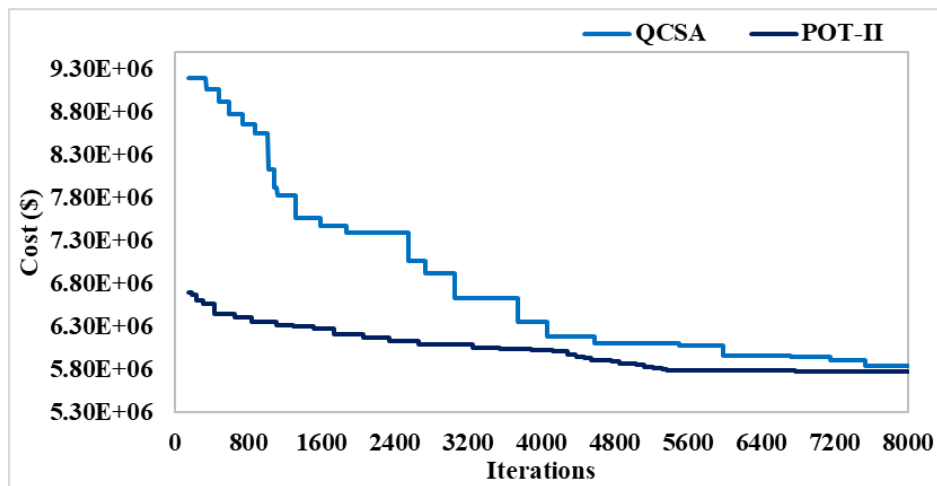


Figure 3.13 Convergence characteristics of cost attained by POT-II for TS-III

### 3.6 CONCLUSIONS

In this chapter, CPSGS problem has been considered for the time horizon of 24 hours. For solving the CPSGS problem, a heuristic optimization technique-II has been proposed which possesses the features of both QCSA and MS. The POT-II has an excellent exploration quality of QCSA and good exploitation feature of MS, which makes it a well-balanced and proficient approach for solving a multidimensional and complex problem of CPSGS. The POT-II and QCSA has been employed on three test systems. The first test system deals with a HTGS problem. The best cost by the POT-II for TS-I (case-I) and TS-I (case II) is 41,238 \$ and 42,278 \$, respectively. For TS-I (case-I), the POT-II saved 1.11%, 0.63% and 1.52% of the fuel cost per day as compared to results of QCSA, GWO and POT-I, respectively. For TS-I (case-II), the POT-II saved 1.01%, 0.46% and 1.30% of the fuel cost per day as compared to results of QCSA, GWO and POT-I, respectively. It also attained the better results as compared to its peers which show its superior performance than many other heuristic techniques. In TS-II, which is CPSGS problem, the optimal cost attained by the POT-II is 25,20,514 \$. For TS-II, the POT-II saved 3.36%, 1.64% and 4.07% of the cost per day as compared to the best cost attained by QCSA, GWO and POT-I techniques, respectively, which shows its superior performance than QCSA, GWO and POT-I techniques. For TS-III, POT-II attained the fuel cost of 57,28,260\$, which is 1.71 %, 0.17% and 2.09% lesser than QCSA, GWO and POT-I techniques, respectively. Hence, the POT-II exhibits a stronger capability

of exploring the search space and finding the global best solution of the CPSGS problem. Moreover, the POT-II achieves better convergence characteristics and distribution diversity than QCSA technique. Further, the robustness of POT-II has been verified by statistical analysis, *i.e.*, two sample *t*-test test which concludes that the POT-II is significantly better than the QCSA technique. Thus, it is established from the results that the POT-II is more capable of accomplishing prominent benefits of economic cost while dealing with complex joint constraints of CPSGS problem as compared to results obtained by QCSA, GWO and POT-I techniques and other established optimization techniques.

## CHAPTER 4

# OPTIMUM GENERATION SCHEDULING OF COORDINATED POWER SYSTEM USING CHAOTIC TENT MAP BASED QUANTUM-CUCKOO SEARCH ALGORITHM WITH GREY WOLF OPTIMIZER

### 4.1 INTRODUCTION

The heuristic optimization techniques are drawing the attention of researchers because of their flexibility, derivative-free nature, and excelling exploration and exploitation capability to determine the optimal solution. Whereas the traditional techniques are efficient for solving differential and linear optimization problems, however not suitable for solving complex, multi-modal, non-convex and non-linear problems like hydro-thermal generation scheduling (HTGS), combined heat and power generation scheduling (CHPGS) and coordinated power system generation scheduling (CPSGS) problems. Heuristic optimization techniques are experience-based techniques that quickly decide on optimal solutions. Altogether the heuristic approaches have some benefits over the other. Still, the heuristic techniques may not assure a global solution for complex and multi-dimensional problems (Rasoulzadeh-Akhijahani and Mohammadi-Ivatloo, 2015). Thus, a novel hybrid optimization technique is essentially required to surmount the conflicting challenges, *i.e.*, convergence rate and quality of the solution.

The cuckoo search algorithm (CSA) is a heuristic approach inspired by the reproductive strategy of the cuckoo bird by laying its eggs in the host nests to increase its population (Yang and Deb, 2009). CSA is more generic, robust and superior in exploration ability as compared to the existing algorithms for many optimization problems (Yang and Deb, 2009). However, CSA has homogeneous search behavior, which may contribute to weak solutions by getting trapped in local optima and leading to early convergence (Cheung *et al.*, 2017). Thus, to improve the performance and increase the search potential of traditional CSA, quantum-inspired non-homogenous CSA

(QCSA) is proposed by Cheung *et al.* (2017). In QCSA, non-homogenous updating laws have been employed, which are further based on quantum theory for enhancing the efficiency, speed and searchability of typical optimization algorithms. Nevertheless, the QCSA focuses on exploring the solution space but still lacks good exploitation (Cheng *et al.*, 2018).

Mirjalili *et al.* (2014) proposed a grey wolf optimizer (GWO), which is motivated by the administrative and chasing nature of grey wolves for prey hunting. GWO possesses strong exploitation ability. Owing to the advantages like simplicity, easy implementation, and fewer algorithm parameters, GWO also confronts some drawbacks. GWO cannot always ensure global search well. Thus, the researchers have proposed a few hybrid/modified GWO techniques to progress the searchability of the algorithm.

For global search techniques, selecting the appropriate control parameters is crucial for achieving the best optimal solution with the least computational effort. One of the recent advances in the application of non-linear dynamics is chaos theory which has been widely used in optimization for the variable value scheme. The researchers have combined chaos theory using chaotic maps with different optimization techniques because of their dynamic behavior for tuning the algorithm parameters and, thus, for dynamically improving the search space exploration. Hence, integrating a chaotic tent map (CTM) sequence with global optimization techniques can improve the technique's performance in terms of search capability and computational efforts.

In this chapter a heuristic optimization technique-III, *i.e.*, chaotic tent map-based quantum-cuckoo search algorithm with grey wolf optimizer (CTM-QCSA-GWO), is proposed for searching the optimum generation schedule of complex and multi-modal coordinated power system generation scheduling (CPSGS) problem. The proposed optimization technique (POT) -III incorporates the QCSA technique with the GWO technique, which has excellent exploration capability of QCSA and superior exploitation capability of the GWO technique. Further, the CTM is applied to get the adaptive value of the parameters of the integrated QCSA-GWO technique, *i.e.*, the scaling factor of Levy flight, discovery probability of the random walk of QCSA and

control parameter of GWO. In contrast, the QCSA has a constant value of these parameters. The CTM enhances the solution quality and accelerates the convergence speed. The performance of the POT-III is extensively investigated on HTGS and CPSGS problems and compared with other techniques. The better results obtained by the POT-III show that it is a promising technique for solving the CPSGS problem.

The chapter is framed as follows: Section 4.2 portrays the problem formulation of CPSGS problem. Section 4.3 centres around the optimization techniques, *i.e.*, QCSA, GWO, CTM and POT-III. In section 4.4, test systems, results and statistical analysis are examined. Finally, section 4.5 presents the conclusions.

## **4.2 PROBLEM FORMULATION**

The CPSGS problem is aimed at minimalizing the overall fuel cost due to fuel consumption of thermal, CHP and heat units by fulfilling all the constraints of hydro, thermal, CHP and heat units simultaneously over a specified period. The mathematical model of generating units is discussed in section 2.3 of chapter-2. The constraints, constraint handling and objective function formulation of the CPSGS problem are discussed in section 2.4 of chapter-2.

## **4.3 OPTIMIZATION TECHNIQUES**

This chapter proposes a heuristic CTM-QCSA-GWO technique (POT-III) to solve the CPSGS problem. In POT-III, initially, QCSA and GWO techniques are integrated. Further, CTM strategy has been applied to hybrid QCSA-GWO technique to reduce the dependency on algorithm parameters and to improve the solution quality and the convergence speed. The mathematical modelling of QCSA is discussed in section 3.3.1 of chapter-3. The GWO technique is discussed in detail in section 2.5.1 of chapter-2. A brief introduction to CTM and the POT-III are presented below:

### 4.3.1 Chaotic Tent Map

Chaos theory deals with the dynamical systems which are extremely sensitive to the initial conditions. The different chaotic maps like tent map, circle map, piecewise map, gauss map, sinusoidal map, etc. show the behavior of a chaotic system. In this work, chaotic tent map is applied to get adaptive values of the algorithm parameters of QCSA, *i.e.*, scaling factor and discovery probability and control parameter of GWO.

**Chaotic Tent Map for Scaling Factor:** The scaling factor  $\alpha$  given in Eq. (3.2) of chapter-3 for updating the step size is fixed throughout, which needs to be adaptive. Thus, the scaling factor is made adaptive by using the chaotic tent map sequence. Eq. (3.2) of chapter-3 is rewritten by replacing  $\alpha$  by CTM sequence ( $c_1$ ) and is given as (Wang and Zhong, 2015):

$$S_{it} = \frac{c_1 \times p}{|q|^{1/\beta}} (X_{it} - X_{gb}) \quad (it \in it^{max}) \quad (4.1)$$

**Chaotic Tent Map for Discovery Probability:** In Eq. (3.4) of chapter-3, the lower value of discovery probability  $pd$  favors the exploration and the higher value is suitable for exploitation. Hence, for a balanced approach between exploration and exploitation capability, Eq. (3.4) of chapter-3 is rewritten by replacing  $pd$  with CTM sequence ( $c_2$ ) to redefine the value of  $pd$  as follows (Wang and Zhong, 2015):

$$X_{it+1} = \begin{cases} X_{it} + rand \times (X_x - X_y); rand > c_2 \\ 0; else \end{cases} \quad (it \in it^{max}) \quad (4.2)$$

where  $c_1$  and  $c_2$  are the chaotic tent map sequences given as follows:

$$c_i = \begin{cases} c_i / 0.7 & ; c_i < 0.7 \\ [10(1 - c_i)] / 3; c_i \geq 0.7 \end{cases} \quad (i \in 2) \quad (4.3)$$

### 4.3.2 Implementation of POT-III To CPSGS Problem

In traditional CSA, the update is achieved homogeneously using Eq. (3.1) of chapter-3, which may

lead to poor outcomes by trapping in local optima. In contrast, QCSA guarantees the non-homogeneity of updates by using two more updates, as given in Eq. (3.12). In Eq. (3.12), CSA gives the first update equation (Eq. 3.12(a), chapter-3) and the quantum mechanism inspires the other two update equations (Eq.3.12(b)-(c), chapter-3). The QCSA overcomes the issue of trapping in local optima by making small perturbations in the existing solution using the average and best solutions. Thus, using a quantum mechanism, QCSA extensively searches the entire search space using long jumps by Levy flight and the non-homogeneous update rules. However, QCSA still results in poor exploitation when dealing with complex problems (Cheng *et al.*, 2018). To overcome the poor exploitation of the QCSA technique, it is integrated with the GWO technique, which has better exploitation quality compared to different heuristic algorithms like PSO, GSA, DE, etc. (Mirjalili *et al.*, 2014).

The QCSA has the drawback of having a constant value of scaling factor and discovery probability, which may stick the solutions in local optima and does not allow the algorithm to explore the search space effectively. Thus, CTM has been used with QCSA-GWO, which gives the variable value of scaling factor and discovery probability parameters instead of the fixed value for strengthening the Levy flight ability of CSA. Hence, CTM improves performance by preventing premature convergence to local optima and enhances the solution quality and convergence speed (Wang and Zhong, 2015).

In the POT-III, the initial search is performed by the QCSA technique and then the GWO technique is applied to exploit the solution obtained by the QCSA technique. Further, the CTM sequence is used to update the scaling factor, the discovery probability of QCSA, and the control parameter of GWO. The pseudo-code of the implementation of the POT-III to the CPSGS problem is shown in Fig. 4.1.

#### **4.4 TEST SYSTEMS, RESULTS AND DISCUSSION**

The POT-III, GWO, QCSA and QCSA-GWO are implemented to resolve three test systems. The

test systems include one HTGS and two CPSGS problems for investigating the performance and search capability with minimal computational efforts of the techniques. The scheduling horizon of 24 hours with 1 hour time interval is considered for all the test systems.

```

Begin
Initialize the generation counter  $it=0$ , maximum number of iterations ( $it^{max}$ ); population size ( $N^P$ )
Initialize the parameters of QCSA ( $\alpha, \beta, \delta$ ), GWO ( $z, A, B$ ) and the values of the chaotic tent map ( $c_1, c_2$ ) randomly
Initialize the populations  $X_i (i \in N^P)$ 
Calculate the fitness of each individual using Eq. (2.31) (chapter-2) and find the current best fitness
while ( $it < it^{max}$ )
//CTM-QCSA-GWO
for  $i:N^P$ 
    Generate tent map sequence  $c_1$  and  $c_2$  for scaling factor  $\alpha$  and discovery probability  $pd$ , respectively, according to Eq. (4.3)
    Generate CTM sequence for control parameter  $z$  of GWO using Eq. (4.3)
    Select two individual positions  $X_x$  and  $X_y$  randomly from the population  $N^P$ 
    Abandon the worst positions according to  $pd$  and create new positions using Eq. (3.4) (chapter-3)
    Evaluate the fitness for the positions obtained by Eq. (3.4)
    Refresh the fitness and obtain the current best fitness and position
    Create the new positions using Eq. (3.12) (chapter-3) based on QCSA and evaluate fitness
    Refresh the fitness and obtain the current best fitness and position

end for
//GWO (transfer the best fitness and positions obtained by QCSA to the GWO)
for  $i:N^P$ 
    Update the positions using Eq. (2.39) (chapter-2) and evaluate the fitness
    Rank the solutions and find the current best fitness and position

end for
 $it=it+1$ 
end while
Obtain the global best fitness and position
    
```

**Figure 4.1** Pseudo code of the implementation of POT-III to CPSGS problem

#### 4.4.1 Test Systems

The test system (TS)-I is a HTGS problem consisting of four hydro and three thermal units. The technical data for TS-I has been taken from Ref. (Basu, 2004) and given in Tables A.1.1 and A.2.1-A.2.3 of Appendix-A. The TS-I has two test cases in which the transmission losses are ignored for case-I and losses have been considered for case-II. The transmission loss coefficients of thermal units are given in Appendix A.1.

For TS-II and III, the CPSGS problem has been examined with a scheduling period of one day with 24 intervals. TS-II and III have total 18 generating units (4 hydro, 11 thermal, 2 CHP and 1 heat unit) and 29 generating units (4 hydro, 19 thermal, 4 CHP and 2 heat units), respectively, and solved by the POT-III, GWO, QCSA and QCSA-GWO techniques. The TS-II and III have

been composed by combining the hydro, thermal, CHP and heat units. The technical data for TS-II and III is referred from Ref. (Basu, 2010b) for hydro-thermal units, Ref. (Basu, 2008) for thermal units and Ref. (Elaiw *et al.*, 2013) for CHP and heat units. The system coefficients for TS-II and III are given in Tables A.1.2, A.1.3, A.2.1-A.2.3 and A.3.1-A3.1.4 of Appendix-A.

#### **4.4.2 Algorithm Parameter Settings**

The POT-III has been implemented using FORTRAN 90 compiler on a workstation with core-i5 processor and 8 GB of RAM at 1.80 GHz. The values of control variables of the QCSA-GWO technique are fixed subsequently executing numeral trials with a population size of 50. For the QCSA-GWO technique, the optimal control parameters  $\alpha$ ,  $\beta$ ,  $\delta$  and  $pd$  are set to 0.02, 1.5, 1.6 and 0.7, respectively, for all three test systems. The parameters  $\beta$  and  $\delta$  linearly decrease with iterations with a step size of 0.5 and 0.6, respectively. Initially, the control parameter  $z$  of GWO has been set to 0.25 and then decreases linearly with iterations. For the POT-III, all the control parameters of the hybrid QCSA-GWO technique are varied according to the CTM sequence given in Eq. (4.3). The maximum iterations for TS-I, II and III have been fixed to 5000, 5000 and 8000, respectively.

An extensive parametric sensitivity analysis has been performed to understand the impact of each individual control parameter and its effect on the performance of POT-III. For TS-I, the control parameters  $\alpha$ ,  $\beta$ ,  $\delta$ ,  $pd$  and  $z$  of the POT-III have been varied by  $\pm 5\%$  considering one variation at a time and the corresponding percentage variation in fuel cost from the optimal cost is shown in Table 4.1. It can be observed from the Table 4.1 that that minimum and maximum and minimum increase in fuel cost as compared to optimal value of fuel cost is about 0.15% and 0.85%, respectively. Results of the sensitivity analysis reveals that POT-III was most sensitive to the  $\beta$ ,  $\delta$  and  $z$  control parameters. Also, the CPU time to achieve convergence is same as time take to achieve the optimal fuel cost. The sensitivity analysis conducted by varying control parameters of POT-III reveals that changes of up to  $\pm 5\%$  in these parameters did not exert a substantial effect on the results. This observation underscores the robustness of the optimization technique to parameter

variations within this range. Despite modest alterations to key parameters, the overall performance metrics, including convergence behaviour, solution quality and stability, remains consistent across the parameter space. These findings suggest that the POT-III exhibits a high level of resilience to small perturbations in the parameter settings. Such robustness is crucial for practical applications, as it indicates that the technique can reliably produce consistent results even in the presence of minor variations in the optimization environment.

**Table 4.1** % Increase in cost with respect to variation in control parameters of POT-III for TS-I

Variation in control Parameter	% increase in cost from optimal value of cost	Variation in control Parameter	% increase in cost from optimal value of cost
+5% $\alpha$	0.15	-5% $\alpha$	0.23
+5% $\beta$	0.76	-5% $\beta$	0.65
+5% $\delta$	0.68	-5% $\delta$	0.54
+5% $pd$	0.35	-5% $pd$	0.26
+5% $z$	0.85	-5% $z$	0.75

### 4.4.3 Simulation Results and Discussion

**4.4.3.1 Test System-I:** The results are evaluated regarding the minimum, average, maximum cost, standard deviation, and average CPU time. For TS-I (case-I), results are distinguished with state art optimization techniques. It is worth noticing from Table 4.2 that the POT-III attained comparatively better minimum, average and maximum cost than the already published results. The POT-III has attributes of GWO and QCSA techniques. Thus, a comparison has been made among these techniques, with the same number of iterations, population size and results have been analysed for 30 trials. The minimum cost obtained by the QCSA-GWO is 41,189 \$, which is 1.22% and 1.64% lesser than the cost obtained by GWO and QCSA, respectively. The minimum cost obtained by the POT-III is 40,873 \$ and it is 0.77% better than the QCSA-GWO technique.

Further, the average cost, worst cost and standard deviation of the results obtained by the POT-III are better than its counterparts. The average CPU time required by the POT-III is slightly higher than GWO, QCSA, POT-I, time varying acceleration coefficient with particle swarm optimization (PSO) and mutation strategies (TVAC-PSO-MS) (Patwal *et al.*, 2018) and improved predator influenced civilized swarm optimization (IPCSO) (Narang, 2017) techniques, which is

reliant on CPU configuration and it can be reduced by using fast computational facilities. The optimum power output of thermal and hydro units is given in Table. 4.3 and the obtained results satisfy inequality and equality constraints. Figs. 4.2 and 4.3 show the optimum water discharge rate and reservoir volume of hydro units. The optimum water discharge rate and reservoir volume of hydro units are within the set limits and the final volume equality constraint is satisfied. Fig. 4.4 shows the convergence characteristics of the POT-III and determines the proficiency of the POT-III to attain better solutions in fewer iterations than GWO, QCSA and QCSA-GWO techniques. Hence, a conclusion can be drawn that the POT-III performs better than other undertaken heuristic optimization techniques while satisfying all the constraints.

**Table 4.2** Comparison of cost for TS-I (case-I)

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
PSO (Mandal and Chakraborty, 2011)	42,474	---	---	---	123.52
PPO (Narang <i>et al.</i> , 2014a)	42,042	42,099	42,078	---	30.71
RCGA (Fang <i>et al.</i> , 2014)	42,886	43,261	43,032	---	30.00
MHDE (Lakshminarasimman and Subramanian, 2008)	41,856	---	---	---	31.00
TVAC-PSO-MS (Patwal <i>et al.</i> , 2018)	41,263	41,374	41,324	---	18.21
CPSO (Wu <i>et al.</i> , 2019)	41,215	41,844	41,683	---	45.50
ERWCA (Haroon and Malik, 2017)	41,223	42,511	---	---	19.20
CSPSO (Patwal and Narang, 2018)	41,080	---	---	---	18.30
RCGA-AFSA (Fang <i>et al.</i> , 2014)	40,913	41,362	41,235	---	21.00
MCDE (Zhang <i>et al.</i> , 2015)	40,945	41,977	41,380	---	50.80
IPCSO (Narang, 2017)	40,881	40,954	40,905	---	12.77
GWO	41,700	42,035	41,901	79.7	14.28
QCSA	41,875	42,135	42,003	81.9	15.14
POT-I	41,501	41,750	41,601	58.8	15.49
POT-II	41,238	41,401	41,319	51.6	15.55
QCSA- GWO	41,189	41,305	41,243	35.5	18.05
POT-III	40,873	40,941	40,904	22.8	18.10

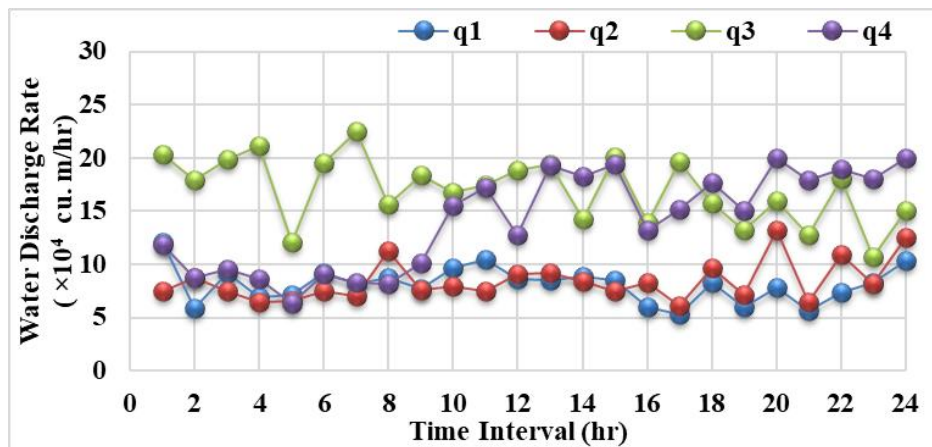
Note: PPO-predator prey optimization; RCGA-real coded genetic algorithm; MHDE-modified hybrid differential evolution; CPSO-couple-based PSO; ERWCA-evaporation rate-based water cycle algorithm; CSPSO-crisscross PSO; RCGA-AFSA- RCGA-artificial fish swarm algorithm; MCDE modified chaotic differential evolution.

**Table 4.3** Optimum power generation attained by POT-III for TS-I (case-I)

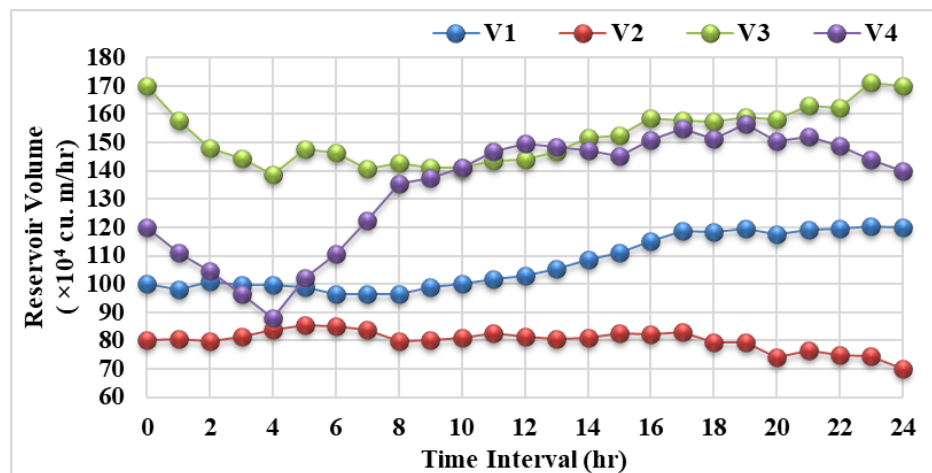
t (hr)	PD (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	102.5	124.8	139.7	92.9	59.4	39.8	190.8	750
2	780	102.6	124.9	229.5	59.7	65.8	45.9	151.7	780
3	700	20.0	209.8	139.7	82.2	59.5	37.3	151.7	700
4	650	102.6	124.9	139.8	68.2	54.5	28.9	131.2	650
5	670	102.6	40.0	229.5	69.1	55.9	53.9	119.0	670
6	800	102.6	124.9	229.5	81.1	61.6	39.4	161.0	800

**Table 4.3** Optimum power generation attained by POT-III for TS-I (case-I) (continued)

t (hr)	PD (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
7	950	102.7	209.8	319.3	75.0	58.4	21.8	163.0	950
8	1010	102.0	209.8	319.3	78.6	77.6	49.8	173.0	1010
9	1090	102.7	294.7	319.3	72.8	59.7	41.7	199.2	1090
10	1080	102.7	209.8	319.3	84.3	62.0	46.9	255.1	1080
11	1100	102.6	209.8	319.3	88.8	60.3	45.6	273.7	1100
12	1150	102.7	209.8	409.0	80.0	69.1	41.3	238.1	1150
13	1110	102.7	209.8	319.3	79.7	68.7	40.1	289.8	1110
14	1030	102.7	124.9	319.3	82.7	64.7	54.3	281.4	1030
15	1010	102.7	209.8	229.5	81.4	60.7	38.8	287.1	1010
16	1060	102.7	209.8	319.3	63.8	64.9	56.3	243.2	1060
17	1050	102.7	209.8	319.3	58.3	51.4	42.8	265.8	1050
18	1120	102.7	209.8	319.3	80.9	70.9	53.8	282.6	1120
19	1070	102.7	207.9	317.1	63.9	56.3	56.7	265.5	1070
20	1050	102.7	209.8	229.5	78.0	80.4	53.7	295.9	1050
21	910	102.7	124.9	229.5	60.4	50.1	57.6	284.7	910
22	860	20.0	124.8	229.5	75.0	73.0	49.5	288.2	860
23	850	20.0	124.8	229.5	81.6	59.6	57.4	277.1	850
24	800	20.0	40.0	229.5	93.2	75.3	57.9	284.1	800

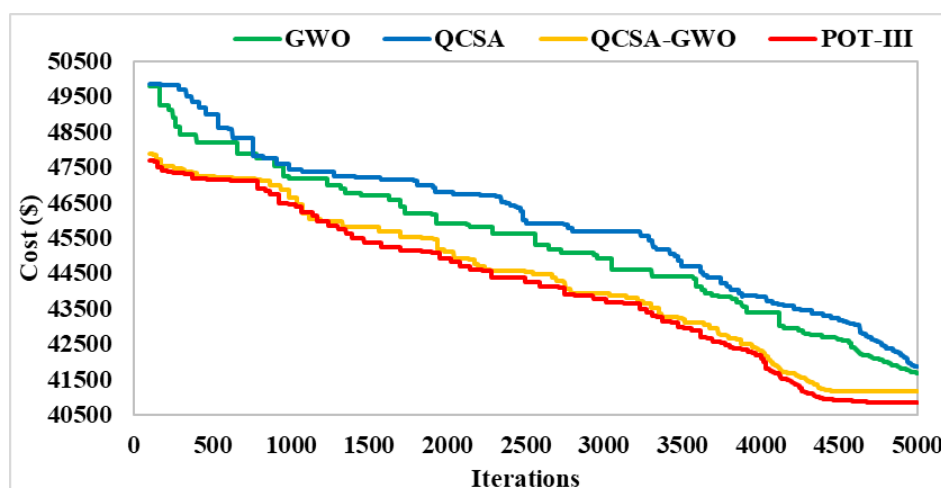


**Figure 4.2** Water discharge rate of hydro units attained by POT-III for TS-I (case-I)



**Figure 4.3** Reservoir volume of hydro units attained by POT-III for TS-I (case-I)

For TS-I (case-II), the optimum cost obtained by POT-III is compared with the results reported by other state of art techniques, as given in Table 4.4. The QCSA-GWO adequately



**Figure 4.4** Convergence characteristics of cost attained by POT-III for TS-I (case-I)

reduces the cost attained by GWO, QCSA, POT-I and POT-II by 1.52%, 1.81%, 0.97% and 0.52%, respectively. Further, POT-III adequately reduced the cost than GWO, QCSA and QCSA-GWO by 2.78%, 3.07% and 1.28%, respectively. The cost obtained by MCDE (Zhang *et al.*, 2015), RCGA-RTVM (Haghran *et al.*, 2015), RCGA-IMM (Nazari-Heris *et al.*, 2017) and IHSA (Nazari-Heris *et al.*, 2018) is less as compared to the POT-III, but the reported decision variables do not satisfy all the constraints, whereas the POT-III yields competitive results while meeting all the constraints. The optimum power generation of thermal and hydro units for a time interval of 24 hours achieves the given power demand and transmission losses, as given in Table 4.5 for TS-I (case-II). The water discharge rate and reservoir volume constraints are satisfied and are given in Figs. 4.5 and 4.6, respectively for TS-I (case-II). Fig. 4.7 shows convergence characteristics of the POT-III and determines the proficiency of the POT-III as compared to GWO, QCSA and QCSA-GWO techniques. The POT-III shows the effectiveness of attaining better results comparatively.

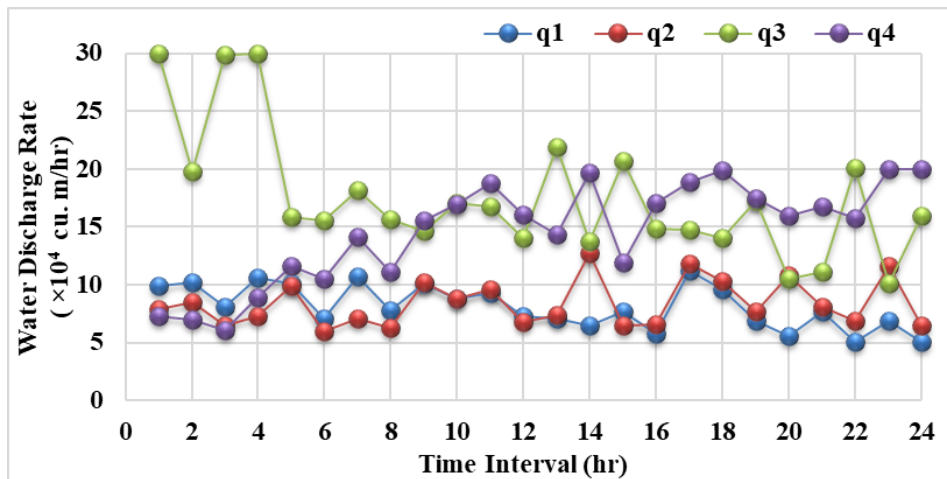
**Table 4.4** Comparison of cost for TS-I (case-II)

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
HDE (Lakshminarasimman and Subramanian, 2008)	43,656	---	---	---	68.00
RCGA (Fang <i>et al.</i> , 2014)	43,465	43,717	43,643	---	32.00
SPPSO (Zhang <i>et al.</i> , 2012)	42,740	44,346	43,622	---	32.70
MHDE (Lakshminarasimman and Subramanian, 2008)	42,679	---	---	---	40.00
MCDE (Zhang <i>et al.</i> , 2015)	41,586*	42,365	42,022	---	100.05
RCGA- RTVM (Haghran <i>et al.</i> , 2015)	40,486*	---	---	---	---
RCGA-IMM (Nazari-Heris <i>et al.</i> , 2017)	40483*	---	---	---	---

**Table 4.4** Comparison of cost for TS-I (case-II) (continued)

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
IHSA (Nazari-Heris <i>et al.</i> , 2018)	39,335*	---	---	---	---
RCGA- AFSA (Fang <i>et al.</i> , 2014)	41,707	41,894	41,832	---	25.00
IPCSO (Narang, 2017)	41,636	41,689	41,712	---	12.52
GWO (Kaur and Narang, 2019)	42,708	42,994	42,854	81.6	15.38
POT-I	42,473	42,686	42,549	52.5	16.45
QCSA	42,835	43,115	42,791	85.1	16.40
POT -II	42,278	42,437	42,351	48.3	16.57
QCSA- GWO	42,059	42,222	42,129	45.5	19.48
POT-III	41,521	41,625	41,573	31.7	20.16

Note: HDE- hybrid DE; RCGA-RTVM- RCGA with random transfer vectors-based mutation; RCGA-IMM- RCGA with improved Mühlenbein mutation;  
 Note:\*constraints are not satisfied



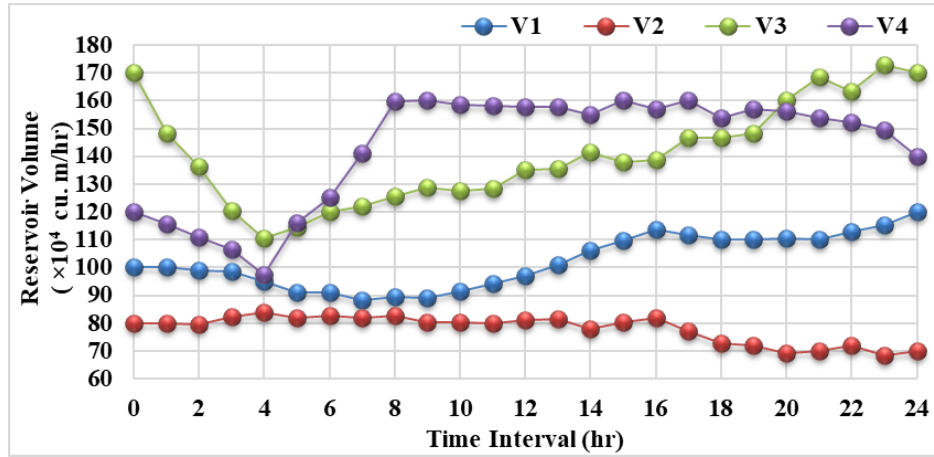
**Figure 4.5** Water discharge rate of hydro units attained by POT-III for TS-I (case-II)

**Table 4.5** Optimum power generation attained by POT -III for TS-I (case-II)

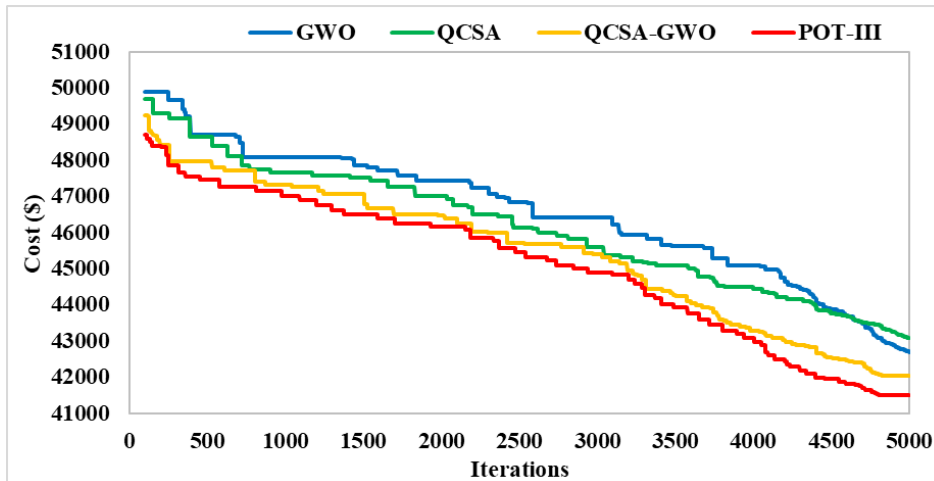
t (hr)	PD (MW)	PL (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
			PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	6.6	25.0	209.9	229.7	85.8	61.5	0.0	144.7	756.6
2	780	6.4	24.8	210.1	229.5	86.4	64.6	34.3	136.8	786.4
3	700	5.7	102.6	124.8	229.5	75.3	53.3	0.0	120.2	705.7
4	650	5.4	102.7	209.8	50.3	86.9	60.2	0.0	145.5	655.4
5	670	7.2	23.3	125.0	140.3	82.7	73.3	39.2	193.3	677.2
6	800	8.4	102.7	125.0	229.5	66.2	50.9	42.0	192.0	808.4
7	950	12.2	102.8	209.8	229.6	84.1	57.4	35.3	243.2	962.2
8	1010	12.4	102.6	294.7	229.4	70.4	52.6	44.0	228.7	1022.4
9	1090	15.6	103.2	295.0	230.4	82.3	73.9	46.9	273.9	1105.6
10	1080	16.2	103.5	294.9	229.6	76.7	66.8	41.1	283.6	1096.2
11	1100	17.2	103.0	294.8	229.6	80.4	70.7	42.2	296.5	1117.2
12	1150	17.3	102.7	294.7	319.3	69.6	55.3	49.8	275.9	1167.3
13	1110	16.3	100.0	294.7	319.2	69.0	59.3	23.1	261.0	1126.3
14	1030	16.6	21.0	294.8	231.4	66.4	81.8	52.0	299.3	1046.6
15	1010	12.9	102.6	294.7	229.5	75.3	52.8	30.6	237.5	1022.9
16	1060	16.0	102.7	294.7	229.5	61.8	54.0	49.9	283.3	1076.0
17	1050	16.4	102.7	209.8	229.6	94.9	78.0	52.3	299.0	1066.4
18	1120	17.4	102.8	296.7	229.6	87.0	69.1	53.2	299.0	1137.4
19	1070	16.2	102.7	294.7	229.6	70.2	55.2	47.9	285.9	1086.2
20	1050	15.5	174.9	294.7	139.7	59.2	68.7	55.2	273.1	1065.5

**Table 4.5** Optimum power generation attained by POT-III for TS-I (case-II) (continued)

t (hr)	PD (MW)	PL (MW)	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
			PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
21	910	13.6	102.7	124.9	229.5	75.4	55.8	57.5	277.9	923.6
22	860	12.8	102.4	124.9	229.3	55.1	50.4	42.6	268.2	872.8
23	850	14.2	102.9	126.0	142.0	70.4	71.3	56.7	294.9	864.2
24	800	12.9	20.4	210.0	139.8	55.8	45.9	56.6	284.4	812.9



**Figure 4.6** Reservoir volume of hydro units attained by POT-III for TS-I (case-II)



**Figure 4.7** Convergence characteristics of cost attained by POT-III for TS-I (case-II)

**4.4.3.2 Test System-II and III:** The results for TS-II and III are presented in terms of minimum, maximum and mean cost, standard deviation and average CPU time acquired in 30 trials in Tables 4.6 and 4.7, respectively. From the given tables, it is noticeable that the QCSA-GWO has outperformed the GWO, QCSA, GWO-MS, and QCSA-MS techniques by 4.84%, 5.55%, 3.16% and 1.54% for TS-II. The POT-III further enhances results of QCSA-GWO by 1.52% for TS-II. Tables 4.8(a)-(b) give the optimum power generation for thermal, hydro, and CHP units. Table 4.9 gives the heat generation of CHP and heat units obtained by the POT-III for TS-II. The total power

generation of thermal, hydro and CHP units and heat generation of CHP and heat units in each sub-interval satisfies the power demand and heat demand. The hydro unit's water discharge rate and reservoir volume by the POT-III for the duration of 24 hours are shown in Figs. 4.8 and 4.9, respectively, in case of TS-II. The water discharge rate and reservoir volume of hydro units is within the respective limits

**Table 4.6** Comparison of cost for TS-II

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	26,08,065	27,12,549	26,65,273	33,080	34.06
QCSA	26,27,422	27,26,300	26,76,481	29,632	38.67
POT-I	25,62,644	26,35,849	25,97,527	22,762	35.60
POT-II	25,20,514	25,85,514	25,53,597	19,947	39.25
QCSA-GWO	24,81,728	25,47,444	25,20,741	19,124	45.09
POT-III	24,43,921	24,80,221	24,60,618	10,890	46.15

**Table 4.7** Comparison of cost for TS-III

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
GWO	58,28,034	59,35,955	58,89,836	29,825	59.36
QCSA	58,50,636	59,45,925	59,01,467	31,071	65.09
POT-I	57,38,132	58,28,034	57,90,307	24,470	61.90
POT-II	57,28,260	57,98,360	57,61,097	21,843	68.25
QCSA-GWO	55,28,841	55,96,741	55,61,904	20,790	75.67
POT-III	54,86,652	55,27,452	55,08,312	12,594	76.53

**Table 4.8(a)** Optimum power generation attained by POT-III for TS-II

t (hr)	PD (MW)	Power (MW) (Thermal Units)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>	PT <sub>11</sub>
1	1786	59.4	243.4	229.8	158.6	152.9	84.8	93.2	112.3	66.9	73.0	17.4
2	1890	121.8	192.3	227.7	159.9	145.5	87.7	70.3	126.2	56.2	64.7	18.1
3	1958	138.8	297.1	193.1	213.5	180.7	96.0	122.8	69.8	52.4	69.7	27.2
4	2056	70.6	299.9	398.4	167.4	162.2	80.7	82.1	103.0	37.7	67.5	40.1
5	2150	133.8	299.4	306.6	194.4	153.5	211.4	101.6	100.7	52.0	20.8	29.8
6	2428	149.4	300.0	418.0	195.0	135.6	220.1	150.9	123.9	56.6	38.0	17.4
7	2652	174.8	299.4	347.2	204.0	266.2	279.8	173.8	94.3	129.7	78.3	42.0
8	2786	174.2	298.0	426.3	167.0	223.1	296.6	204.0	102.4	73.3	64.2	33.0
9	3014	157.0	298.9	458.9	267.1	299.8	335.4	237.8	113.3	52.0	69.7	35.1
10	3102	172.8	296.9	490.1	187.5	327.2	333.2	294.9	96.6	94.1	46.6	42.1
11	3206	170.7	275.7	491.7	234.2	358.7	311.4	282.5	149.0	66.6	59.0	18.4
12	3300	146.3	297.4	458.7	325.1	381.9	317.2	297.6	146.0	101.7	34.1	18.9
13	3182	117.1	297.3	483.7	289.7	356.7	322.3	271.0	109.3	76.7	53.6	25.1
14	2954	169.7	296.0	431.8	206.4	306.1	267.4	176.9	147.3	129.7	27.0	28.6
15	2795	156.9	299.5	312.2	155.2	193.3	331.7	230.5	124.7	119.2	59.9	51.5
16	2614	148.9	290.7	406.0	163.3	202.2	152.6	243.8	61.6	81.5	56.4	17.1
17	2530	101.0	295.9	358.5	173.1	165.7	328.4	96.0	103.0	43.0	68.2	19.0
18	2748	158.4	299.4	364.9	206.9	241.4	277.2	170.6	82.3	84.3	61.5	49.8
19	2846	114.9	290.7	422.6	224.1	288.7	309.5	139.7	121.2	44.1	44.9	17.6
20	3022	157.6	299.9	460.2	249.3	144.6	337.8	253.6	128.9	104.8	38.7	48.6
21	2834	171.5	300.0	427.7	169.4	219.1	297.2	242.0	146.6	57.6	36.1	45.3
22	2488	134.8	298.0	382.9	233.1	162.4	128.5	122.8	112.4	31.2	70.2	18.6
23	2182	169.4	296.8	260.0	172.2	135.1	94.0	111.5	118.1	110.4	42.2	29.1

**Optimum generation scheduling of coordinated power system using CTM-QCSA-GWO**

**Table 4.8(a)** Optimum power generation attained by POT-III for TS-II (continued)

t (hr)	PD (MW)	Power (MW) (Thermal Units)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>	PT <sub>11</sub>
24	1984	125.2	267.4	165.2	165.9	147.0	88.6	109.1	108.4	46.6	65.2	51.8

**Table 4.8(b)** Optimum power generation attained by POT-III for TS-II

t (hr)	Power (MW) (CHP Units)		Power (MW) (Hydro Units)			
	PC1	PC2	PH1	PH2	PH3	PH4
1	180.5	48.7	53.6	51.8	23.8	135.9
2	215.3	76.1	58.5	52.6	15.5	201.5
3	110.2	68.2	55.3	54.4	14.3	194.7
4	220.9	69.1	82.0	58.9	9.9	105.3
5	119.8	91.4	77.2	67.1	20.6	169.7
6	178.5	91.8	64.0	61.7	45.0	182.1
7	203.0	57.9	54.8	55.2	32.5	159.4
8	214.5	110.0	94.3	78.3	45.5	181.2
9	214.3	106.7	96.1	63.3	46.2	162.1
10	214.1	109.1	96.0	86.6	31.4	182.9
11	212.0	110.2	92.2	60.8	34.8	278.1
12	210.6	89.4	91.2	81.5	44.6	257.9
13	213.2	101.9	94.6	70.1	37.9	261.7
14	220.6	89.8	81.8	47.7	53.3	273.8
15	218.1	81.1	61.7	51.0	58.0	290.6
16	213.3	108.7	80.4	60.4	57.0	270.2
17	192.9	114.8	64.8	49.1	59.2	297.4
18	177.6	116.2	67.9	62.8	53.3	273.6
19	198.8	115.6	96.4	72.8	57.3	287.3
20	214.1	111.3	84.5	60.8	47.5	279.6
21	215.9	58.3	59.5	52.4	59.2	276.2
22	190.1	97.7	96.0	64.4	60.6	284.5
23	112.6	97.6	55.6	75.2	44.0	258.3
24	113.1	103.5	62.5	57.9	29.9	276.5

**Table 4.9** Optimum heat generation attained by POT-III for TS-II

t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)	t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
1	390	71.1	23.5	295.4	13	470	178.6	106.8	184.6
2	400	169.5	24.5	206.0	14	460	116.7	42.5	300.8
3	410	93.4	30.0	286.6	15	450	43.0	29.6	377.4
4	420	131.1	22.5	266.4	16	450	175.3	122.0	152.6
5	440	113.4	35.4	291.2	17	420	79.2	99.4	241.4
6	450	135.8	40.4	273.8	18	435	66.2	24.8	344.0
7	450	103.7	88.0	258.3	19	445	101.1	65.8	278.2
8	455	180.0	130.3	144.7	20	450	170.3	133.9	145.9
9	460	179.6	41.7	238.7	21	445	39.9	43.8	361.3
10	460	179.4	133.9	146.7	22	435	162.5	100.3	172.2
11	470	177.4	135.3	157.3	23	400	60.3	122.6	217.1
12	480	175.8	113.3	190.9	24	400	73.6	95.5	231.0

For TS-III, the minimum cost attained by QCSA-GWO is 5.13%, 3.65% 5.50% and 3.48%, lesser than GWO, QCSA, GWO-MS and QCSA-MS techniques, respectively. The POT-III further decreased the cost than the optimal cost attained by QCSA-GWO by 0.76% for TS-III. The results

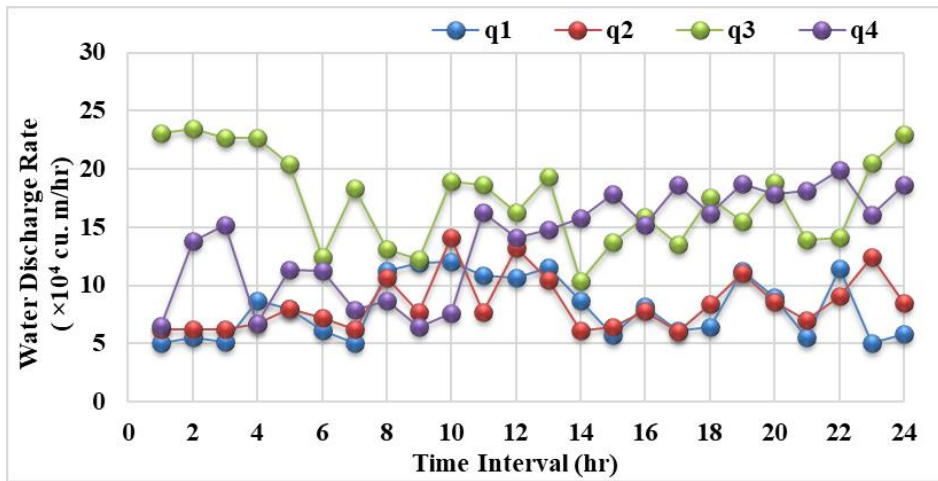


Figure 4.8 Water discharge rate of hydro units attained by POT-III for TS-II

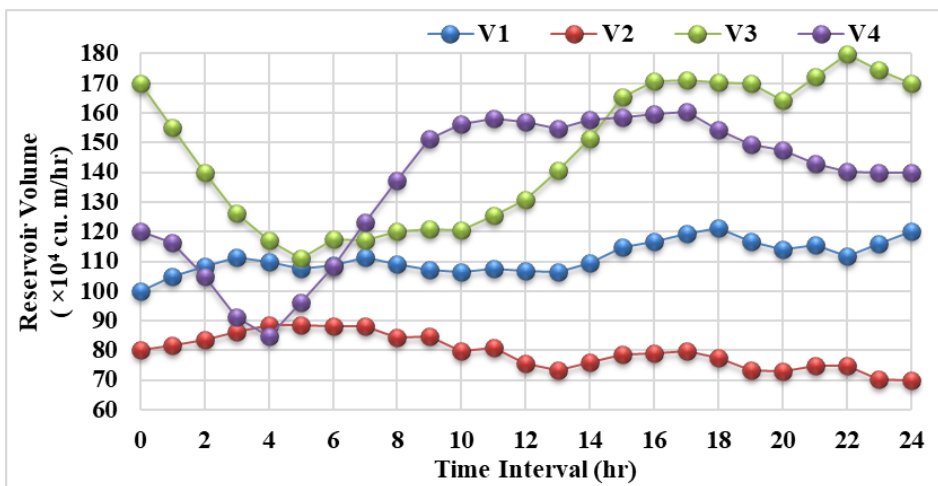


Figure 4.9 Reservoir volume of hydro units attained by POT-III for TS-II

illustrate that the POT-III maintains a good balance amongst exploration and exploitation throughout the search process. Even though the computational time taken by GWO, QCSA, GWO-MS and QCSA-MS is less in contrast to the POT-III, however, the POT-III attained the optimal cost in a smaller number of iterations. For TS-III, the optimal power generation schedule is given in Tables 4.10(a)-(c) and heat generation schedule attained by the POT-III is given in Table 4.11. The optimal water discharge rate and reservoir volume are presented in Figs. 4.10 and 4.11. All the constraints for TS-III are satisfied. The cost convergence performance of POT-III distinguishes it from GWO, QCSA and QCSA-GWO, as depicted in Figs. 4.12 and 4.13 for TS-II and III, individually. These figures illustrate that POT-III converges faster than the GWO, QCSA and QCSA-GWO techniques for searching a globally optimal solution. Therefore, it concludes that the

scheduling problems. POT-III has the ability to search for high-quality optimal results for large-size generation

**Table 4.10(a)** Optimum power generation attained by POT-III for TS-III

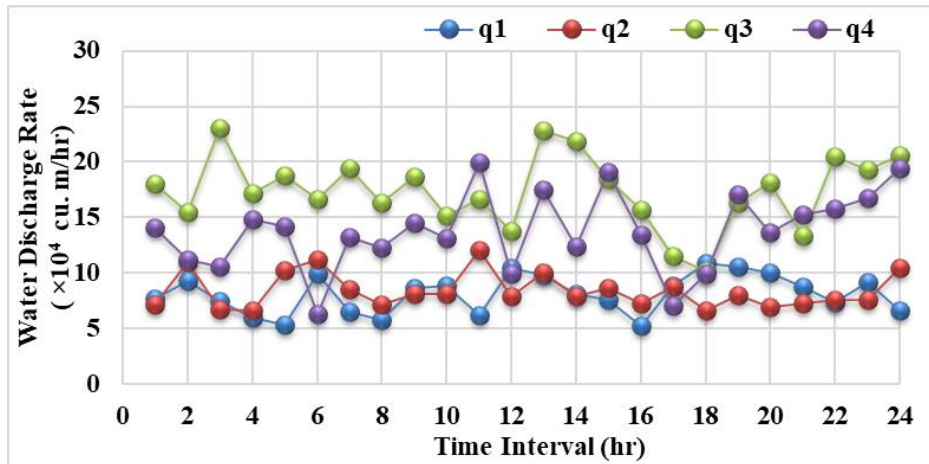
t (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>
1	2822	25.8	101.7	200.4	209.2	241.4	130.1	86.8	79.8	33.0	26.1
2	3000	168.1	89.8	96.0	219.5	201.5	79.8	121.8	110.7	52.7	49.2
3	3216	59.7	40.9	404.5	249.0	223.4	79.9	205.2	85.1	47.1	30.0
4	3462	142.2	60.8	464.6	204.0	221.6	152.9	197.7	106.9	65.0	47.9
5	3630	116.0	114.7	485.8	181.3	285.3	102.2	179.4	88.5	24.3	77.8
6	4056	155.5	176.6	462.2	305.4	200.1	224.7	201.1	154.8	117.6	75.3
7	4354	174.1	297.8	496.3	232.9	238.7	203.6	175.1	130.1	96.5	72.2
8	4562	174.0	292.9	383.8	271.7	388.0	330.9	229.5	127.4	39.8	70.9
9	4938	158.1	276.1	491.2	365.6	348.2	277.3	220.1	95.1	104.8	56.0
10	5124	172.5	293.3	496.4	412.6	406.5	307.6	276.0	128.4	96.6	54.9
11	5312	159.3	256.9	484.0	447.9	415.4	305.5	270.6	146.0	101.9	57.2
12	5450	156.8	280.3	480.2	419.2	447.0	323.7	234.0	148.7	118.7	67.4
13	5254	85.7	275.6	484.9	340.6	414.4	339.7	259.5	149.4	103.7	72.6
14	4878	162.6	262.2	498.2	258.9	333.2	329.6	285.3	153.0	110.6	62.1
15	4571	141.4	211.2	496.2	307.1	208.3	306.6	193.0	105.5	125.2	78.0
16	4168	137.0	279.2	391.4	352.8	231.3	265.6	267.9	94.0	31.7	27.6
17	4010	103.0	160.9	428.5	304.6	176.8	189.9	246.2	115.4	122.2	72.9
18	4376	132.2	270.7	497.3	225.9	252.2	238.9	274.7	149.1	127.8	52.9
19	4622	112.7	297.9	460.5	293.8	309.4	334.2	191.1	90.8	129.9	74.1
20	4994	138.9	268.0	488.1	324.9	381.6	314.1	260.8	155.7	52.0	47.8
21	4758	80.4	269.3	464.5	399.8	405.6	113.9	179.8	119.1	104.7	69.9
22	4116	79.0	284.4	453.6	255.6	171.9	300.6	115.5	138.8	99.7	70.7
23	3514	21.5	57.0	305.0	279.7	232.1	89.0	121.7	100.2	38.7	41.0
24	3168	128.7	245.1	74.5	193.1	192.9	97.5	241.9	87.9	64.3	43.8

**Table 4.10(b)** Optimum power generation attained by POT-III for TS-III

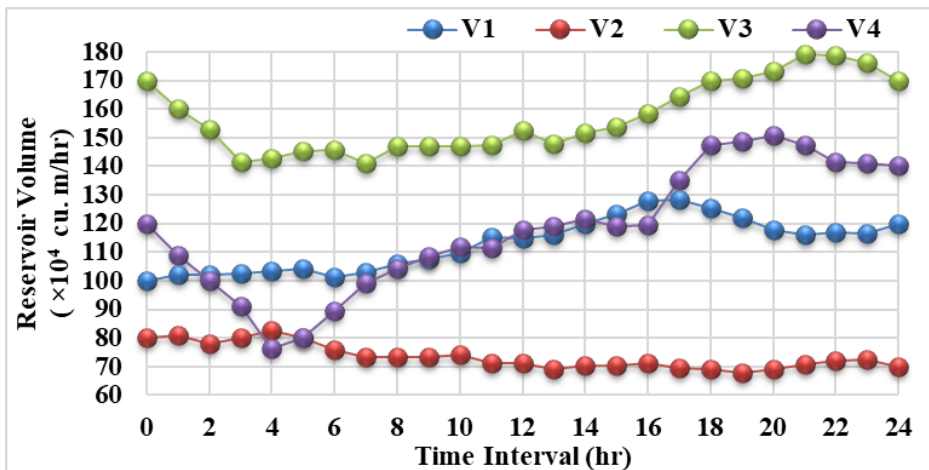
t (hr)	PD (MW)	Power (MW) (Thermal Units)								
		PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
1	2822	12.1	179.1	166.6	77.7	129.7	58.0	81.3	71.1	28.3
2	3000	27.8	213.2	205.6	107.7	97.3	118.3	20.4	43.2	20.2
3	3216	42.5	214.8	166.4	168.7	160.3	60.4	20.9	67.1	14.8
4	3462	29.1	175.6	140.9	302.4	79.5	107.3	83.7	26.6	10.7
5	3630	32.4	187.6	171.4	273.1	184.3	131.7	28.6	58.6	36.1
6	4056	43.1	253.2	173.9	216.9	155.8	126.9	27.1	31.5	46.2
7	4354	45.4	195.6	271.3	309.0	221.2	142.8	124.4	44.8	49.1
8	4562	39.7	171.3	247.9	264.0	210.5	124.7	88.8	51.2	38.8
9	4938	35.3	347.5	317.0	319.8	193.8	124.6	90.4	61.2	38.8
10	5124	40.7	440.5	196.3	315.8	162.3	119.6	127.1	40.7	44.2
11	5312	43.7	272.2	393.9	330.8	226.8	147.0	68.6	70.7	54.2
12	5450	52.7	356.3	446.7	334.8	258.5	152.5	102.1	47.0	37.1
13	5254	51.0	455.7	279.5	337.0	212.2	105.9	123.0	75.1	39.1
14	4878	39.1	382.4	270.3	290.4	268.0	69.5	124.8	62.7	49.1
15	4571	40.4	239.0	242.2	299.0	202.9	151.3	82.5	78.6	39.0
16	4168	24.1	284.0	220.8	199.3	177.7	74.9	110.0	23.0	26.3
17	4010	53.2	176.3	227.4	305.1	187.7	158.6	22.2	23.1	24.9
18	4376	40.0	182.3	199.3	306.2	161.0	133.5	88.6	24.1	21.9
19	4622	44.6	276.9	157.0	337.6	268.0	92.3	61.1	65.8	51.3
20	4994	54.6	333.3	390.8	314.3	262.1	141.6	39.2	64.0	43.8
21	4758	51.0	291.0	377.1	336.2	172.5	126.1	90.0	74.1	38.3
22	4116	21.8	259.3	278.9	222.2	169.8	147.7	40.8	25.8	40.5
23	3514	36.6	260.0	303.4	152.7	288.2	129.0	21.7	24.6	54.0

**Table 4.10(b)** Optimum power generation attained by POT-III for TS-III (continued)

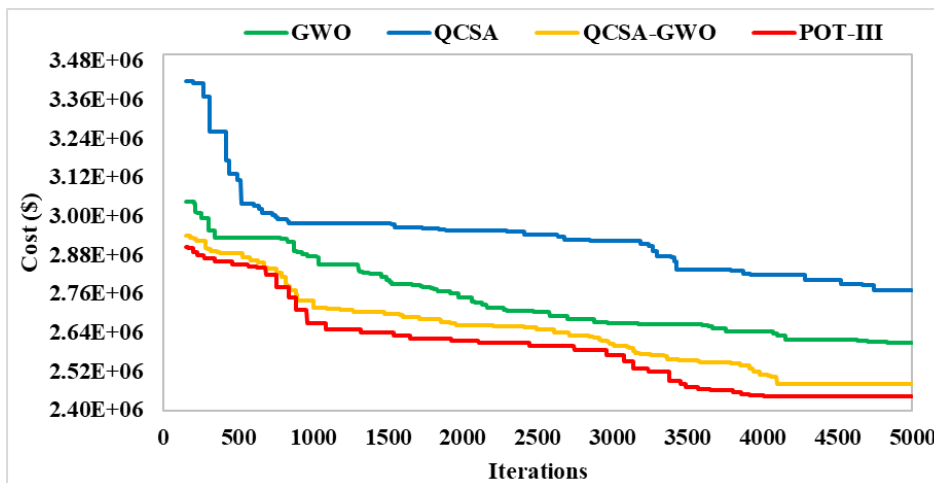
t (hr)	PD (MW)	Power (MW) (Thermal Units)								
		PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
24	3168	33.5	208.6	170.6	87.2	185.6	120.4	55.5	41.6	28.1



**Figure 4.10** Water discharge rate of hydro units attained by POT-III for TS-III



**Figure 4.11** Reservoir volume of hydro units attained by POT-III for TS-III



**Figure 4.12** Convergence characteristics of cost attained by POT-III for TS-II

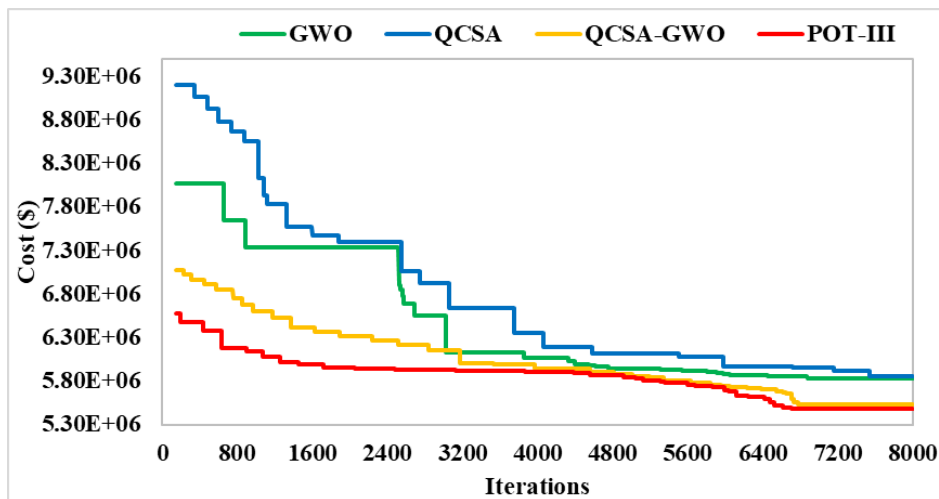


Figure 4.13 Convergence characteristics of cost attained by POT-III for TS-III

Table 4.10(c) Optimum power generation attained by POT-III for TS-III

t (hr)	PD (MW)	Power (MW) (CHP units)				Power (MW) (Hydro units)			
		PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	2822	119.3	53.4	207.7	115.6	73.9	57.3	49.0	207.8
2	3000	223.8	114.3	189.4	46.2	82.9	75.7	53.1	171.9
3	3216	197.2	100.1	214.6	62.6	72.4	54.0	18.9	155.4
4	3462	102.8	113.6	198.8	92.5	61.8	54.7	46.2	172.1
5	3630	163.0	99.1	175.1	88.6	56.2	73.9	41.9	173.0
6	4056	193.9	118.7	164.4	116.2	86.0	75.0	48.6	105.3
7	4354	166.5	45.9	210.8	55.7	65.6	61.1	38.0	189.4
8	4562	197.2	124.6	237.6	107.8	60.1	52.7	49.7	186.5
9	4938	224.0	93.0	205.0	102.3	81.2	58.0	42.7	210.8
10	5124	222.9	120.7	146.3	105.4	82.7	58.7	52.0	203.1
11	5312	221.7	79.4	207.3	113.1	65.0	74.7	49.0	249.1
12	5450	222.2	81.9	210.0	91.7	92.7	55.5	54.9	177.5
13	5254	208.2	114.1	205.1	98.9	89.8	65.3	22.7	245.2
14	4878	149.1	94.3	199.7	50.6	80.4	55.2	29.6	207.0
15	4571	195.8	94.5	225.3	71.3	77.0	59.1	45.7	254.9
16	4168	207.9	54.7	221.7	86.3	57.7	51.7	54.1	215.0
17	4010	208.9	52.0	200.7	88.3	86.1	59.3	57.2	158.5
18	4376	194.0	80.3	222.1	97.1	96.7	46.5	56.3	204.5
19	4622	216.7	66.5	158.9	51.4	94.5	53.9	56.1	274.8
20	4994	169.8	71.7	129.5	107.6	91.2	48.3	52.2	248.0
21	4758	223.9	82.7	153.6	79.7	83.9	51.2	60.6	258.8
22	4116	108.3	64.0	219.4	116.1	74.2	54.5	45.3	257.5
23	3514	175.7	61.3	193.9	71.9	86.2	54.8	49.3	264.9
24	3168	94.4	94.3	175.8	42.2	68.7	67.9	42.4	281.2

Table 4.11 Optimum heat generation attained by POT-III for TS-III

t (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth) (Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
1	780	63.5	81.7	125.7	15.4	160.7	333.0
2	800	71.0	64.7	108.3	44.3	130.2	381.5
3	820	129.8	107.7	179.5	34.4	272.2	96.4
4	840	36.2	104.4	35.9	8.1	85.1	570.4
5	880	0.2	44.8	124.5	95.9	246.6	368.0
6	900	53.8	13.1	72.9	71.3	195.5	493.4
7	900	14.0	26.2	17.4	26.1	202.4	613.9
8	910	25.3	20.4	2.9	110.8	19.1	731.6
9	920	87.1	110.0	128.7	122.4	13.4	458.4
10	920	5.2	2.7	110.8	106.3	181.1	514.0

**Table 4.11** Optimum heat generation attained by POT-III for TS-III (continued)

t (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth) (Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
11	940	75.9	31.5	159.0	135.3	90.6	447.7
12	960	132.0	82.3	176.6	88.7	452.0	28.4
13	940	106.2	116.7	172.8	115.7	397.1	31.5
14	920	51.4	8.6	163.0	57.0	197.9	442.0
15	900	26.6	67.4	67.1	82.1	222.6	434.3
16	900	50.5	1.9	21.7	8.9	250.0	567.0
17	840	13.3	59.5	125.1	17.7	98.1	526.3
18	870	99.0	56.3	3.0	35.4	516.7	159.5
19	890	152.0	2.2	106.7	0.0	500.8	128.3
20	900	151.5	85.5	80.8	83.9	168.7	329.6
21	890	33.4	93.5	145.1	100.7	136.3	381.0
22	870	51.2	94.8	28.9	22.7	426.2	246.2
23	800	146.8	32.8	126.3	36.6	328.8	128.8
24	800	88.5	121.4	10.0	72.7	200.2	307.2

## 4.5 STATISTICAL ANALYSIS

The two-sample t-test is conducted at 0.05 confidence level for TS-I for investigating the robustness of the POT-III. For the t-test, the observations are supposed to have equal variances, and the statistical analysis results are presented in Table 4.12. The t-test results demonstrate that the POT-III is competent to accomplish more noteworthy statistical values than the critical values. The better standard deviations and average value attained with the POT-III demonstrate that it performs better, more stable and statistically significant than GWO, QCSA and QCSA-GWO technique.

**Table 4.12** Two-sample t-test assuming equal variances for TS-I

		Variance	Pooled Variance	t Stat	P(T≤t) one-tail
Case-I	GWO	6385	3454	64.5	5.40E-56
	QCSA	6708	3615	70.8	2.60E-58
	QCS-GWO	1260	891	44.0	1.43E-46
	POT-III	523			
Case-II	GWO	6661	3833	80.1	2.15E-61
	QCSA	7257	4131	84.2	1.18E-62
	QCSA-GWO	2069	1537	54.9	5.30E-52
	POT-III	1004			

## 4.6 CONCLUSIONS

In this chapter, a heuristic optimization technique-III, *i.e.*, ‘CTM-QCSA-GWO’ has been proposed to deal with complex constrained, large-scale, non-convex and multi-modal optimization problem.

complex coordinated power system generation scheduling problem. The POT-III fully utilizes the diversification ability of QCSA to explore a broader range of search space and the exploitation ability of GWO for searching the optimal result by enhanced convergence rate. The CTM has been employed with a hybrid QCSA-GWO technique in order to enhance the solution quality and convergence speed by employing the variable value schema of the control parameters of QCSA-GWO. These tuned parameters control the exploration and the exploitation of the algorithm in a balanced manner. The standard benchmark functions and three test systems of optimum generation scheduling problems verify the performance of the POT-III. The first TS consists of hydro and thermal units and an optimal schedule is searched with due consideration of valve point effect and transmission losses. The second and third test systems are medium size CPS comprising of hydro, thermal, CHP, heat and hydro units. The cost obtained by POT-III for TS-I, case-I and II is 40,873\$ and 41,521\$, respectively, which is comparatively better than its peers. The minimum cost achieved by the POT-III for TS-II and III is 24,43,921\$ and 54,86,652\$, respectively. For TS-II, the least cost obtained by the QCSA-GWO is 4.84%, 3.16%, 5.55% and 1.54% lesser than GWO, POT-I, QCSA and POT-II, respectively. A similar progression is observed from the optimal results of TS-III, in which, QCSA-GWO outperforms the results of GWO, POT-I, QCSA and POT-II by 5.13%, 3.65%, 5.50% and 3.48%, respectively. For TS-II and III, the proposed CTM-QCSA-GWO technique further enhanced the cost than QCSA-GWO by 1.52% and 0.76%, respectively. The results reveal that the application of CTM enhanced the results by tuning the control parameters of QCSA-GWO using the chaotic values, which improves the global exploration and vitality of the algorithm. The convergence characteristics illustrate that the POT-III can sustain a fair evenness between diversification and intensification during the search process. The statistical analysis has been carried out for 30 trials using the two-sample t-test to compare the robustness of the POT-III vs GWO, QCSA and QCSA-GWO techniques. The analytical results show that the POT-III is comparatively superior and robust as compared to the GWO, QCSA and QCSA-GWO techniques. The utilization of two well-known theories, *i.e.*, quantum theory and chaos theory for

extending the capabilities of standard CSA in terms of global search ability, local optima avoidance, convergence speed and employment of the GWO for better exploitation make the POT-III a unique, more efficient, well balanced, and superior technique than conventional hybrid techniques.

## CHAPTER 5

# COORDINATED COMBINED HEAT AND POWER WITH PHOTO-VOLTAIC GENERATION SCHEDULING USING HEURISTIC OPTIMIZATION TECHNIQUES

### 5.1 INTRODUCTION

A significant enervation of conventional fossil fuel energy and rising environmental protection awareness has escalated the curiosity to incorporate combined heat and power (CHP) or cogeneration plants and renewable energy sources into the present power systems. The CHP units decrease the generation cost by 10-40% by retaining partial or all of the heat produced. The CHP units fully utilize the wasted heat and have up to 90% of conversion efficiency (Vasebi, Fesanghary and Bathaee, 2007). Also, CHP units are more advantageous than thermal units in reducing fossil fuelled emissions by about 13-18% (A M Elaiw, Xia and Shehata, 2013). Therefore, less fuel makes CHP units yield the same amount of useful energy. The CHP units have a convincing usage in the urban energy systems by the industry and commercial building. The combined attributes and diverse demand of power and heat of CHP units bring a complex procedure into their scheduling process.

Furthermore, energy-based research is more inclined to use renewable energy sources (RESs) like solar or wind units across the globe due to the exhaustion of fossil fuels and global warming instigated by fossil energy resources. The RESs are not only sustainable but also emission and economical. Although the RESs are abundant sources of clean and cheap energy, their power generation capacity is still less and they have more considerable uncertainties. Thus, the RESs alone cannot fulfil the high-power demand of the consumers. On the other hand, the thermal units accomplish most of the power demand and their existence in the power systems cannot be ignored. In case of solar units, the solar radiations are directly converted into solar energy by using photovoltaic (PV) cells, but the solar radiations are uncertain. Because of the uncertain characteris-

-tics of renewable energy units and load demands, power system operators face numerous issues. Therefore, integrating different energy sources has become necessary and challenging to meet the economic, environmental, and reliable requirements.

In this chapter, CHP-PV generation scheduling (CHP-PV-GS) problem has been formulated in which photovoltaic (PV) units are incorporated with CHP, thermal and heat units. The joint heat-power constraints are modelled in the multi-period CHP generation scheduling (CHPGS) problem. Interdependence of heat and power outputs of CHP units, as well as valve-point effects of thermal units and unpredictable nature of solar units impose non-convexities, nonlinearities, and complexities in CHP-PV-GS problem modelling. The CHP-PV-GS problem is solved by using two proposed optimization techniques (POT). POT-II is quantum based cuckoo search algorithm with mutation strategies (QCSA-MS). POT-III is chaotic tent map-based quantum-cuckoo search algorithm with grey wolf optimizer (CTM-QCSA-GWO). The results obtained by POT-II and III for CHPGS and CHP-PV-GS problem are compared with quantum based cuckoo search algorithm (QCSA), grey wolf optimizer (GWO) and QCSA-GWO techniques. The POT-III outperforms the POT-II. The inclusion of PV units with thermal, CHP and heat units significantly saves the fuel cost and emission.

The remaining chapter is arranged as follows: The mathematical problem formulation of CHP-PV-GS problem is discussed in Section 5.2. Section 5.3 describes the implementation of POT- III TO CHP-PV-GS problem. Section 5.4 reports the numerical results and discussions and finally Section 5.5 concludes the chapter.

## **5.2 COMBINED HEAT AND POWER- PHOTOVOLTAIC GENERATION SCHEDULING PROBLEM FORMULATION**

The CHP-PV-GS mathematical model constitutes of four distinct types of units, *i.e.*, thermal, CHP, heat and PV units. The CHP-PV-GS problem determines the optimum schedule of power and heat generation of generating units so that the overall fuel cost is minimised while satisfying power and

heat demand over a specific period under various constraints. The power demand is fulfilled by thermal, CHP and PV units whilst heat demand is fulfilled by heat and CHP units as shown in Fig. 5.1. The time-period of twenty-four hours with one hour of sub-interval is considered for the CHP-PV-GS problem.

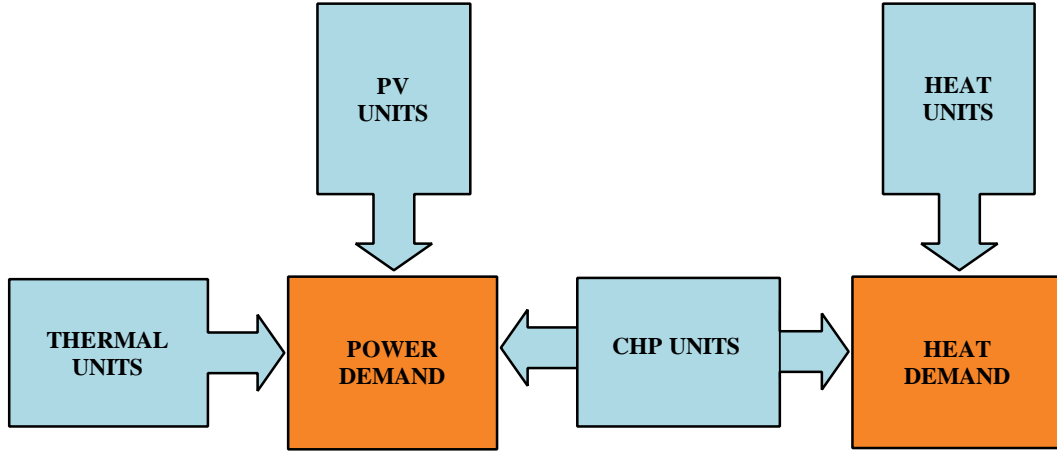


Figure 5.1 Schematic of CHP-PV-GS problem

The mathematical representation of total fuel cost of thermal, CHP, heat and PV units for CHP-PV-GS problem is expressed as follows:

$$\text{Minimize } F_3 = \sum_{t=1}^T \left[ \sum_{i=1}^{N^{TH}} C_{1i}(PT_{it}) + \sum_{j=1}^{N^{CHP}} C_{2j}(PC_{jt}, HC_{jt}) + \sum_{k=1}^{N^H} C_{3k}(H_{kt}) + \sum_{m=1}^{N^{PV}} C_{4m}(PS_{mt}) \right] \quad (5.1)$$

where  $C_{1i}(PT_{it})$ ,  $C_{2j}(PC_{jt}, HC_{jt})$ ,  $C_{3k}(H_{kt})$  and  $C_{4m}(PS_{mt})$  are the fuel cost functions of thermal, CHP, heat and PV units, respectively;  $PT_{it}$  represents the power generation of  $i^{th}$  thermal units at  $t^{th}$  sub-interval;  $PC_{jt}$  is the power generation of  $j^{th}$  CHP units at  $t^{th}$  sub-interval;  $PS_{mt}$  represent the power generation of  $m^{th}$  PV units at  $t^{th}$  sub-interval;  $HC_{jt}$  and  $H_{kt}$  are the heat generation outputs of  $j^{th}$  CHP and  $k^{th}$  heat units, respectively, at  $t^{th}$  sub-interval;  $N^{TH}$ ,  $N^{CHP}$ ,  $N^H$  and  $N^{PV}$  are the total number of thermal, CHP, heat and PV units, respectively;  $T$  represents the scheduling interval.

The fuel cost function of thermal, heat and CHP units considering valve-point effect is given in Eqs. (2.2), (2.4) and (2.6) of chapter-2, respectively. The cost function of PV units is given as below:

$$C_{4m}(PS_{mt}) = \sum_{t=1}^T \sum_{m=1}^{N^{PV}} K_m \times PS_{mt} \times U_{mt} \quad (5.2)$$

where  $K_m$  is the per unit cost of  $m^{th}$  PV unit;  $U_{mt}$  represents the binary variable (0/1) representing the on/off status of  $m^{th}$  PV unit at  $t^{th}$  sub-interval.

The power generation of PV units is a function of ambient temperature and the incident solar radiations and it is expressed as (Patwal and Narang, 2018):

$$PS_{mt} = P_m^{rated} \times \left\{ 1 + (T^{ref} - T^{amb}) \alpha \right\} \times (SR^{in} / 1000) \quad (m \in N^{PV}) \quad (5.3)$$

where  $P_m^{rated}$  is the rated power,  $T^{ref}$  and  $T^{amb}$  are the reference and ambient temperature, respectively;  $\alpha$  is the temperature coefficient;  $SR^{in}$  represents incident solar radiation.

The solar share ( $S^{share}$ ) or the scheduled solar power is given as:

$$S_t^{share} = \sum_{m=1}^{N^{PV}} PS_{mt} \times U_{mt} \quad (m \in N^{PV}; t \in T) \quad (5.4)$$

### 5.2.1 Constraints for CHP-PV-GS Problem

The CHP-PV-GS problem is subjected to constraints like bounds on decision variable, equality and inequality constraints which are discussed below:

**5.2.1.1 Bounds on Decision Variables:** The decision variables for the CHP-PV-GS problem are the power output of CHP units, heat output of CHP and heat units, which must be within their respective capacity limits during each sub-interval as given in Eq. (2.7), (2.8) and (2.5), respectively, of chapter-2.

**5.2.2.2 Equality Constraints:** The equality constraints of CHP-PV-GS problem are the power and heat balance constraints as given below:

**Power Balance Constraint:** The power generation of thermal, CHP and PV units should meet the power demand ( $PD_t$ ) in each sub-interval as expressed below:

$$\sum_{i=1}^{N^{TH}} (PT_{it}) + \sum_{j=1}^{N^{CHP}} (PC_{jt}^{CHP}) + \sum_{m=1}^{N^{PV}} (PS_{mt}) = PD_t \quad (t \in T) \quad (5.5)$$

where  $PD_t$  is power demand at  $t^{th}$  sub-interval.

**Heat Balance Constraint:** The heat generation of CHP and heat units must satisfy the heat demand ( $HD_t$ ) in each sub interval as given in Eq (2.17) of chapter-2.

**5.2.1.3 Inequality Constraint:** The generation limit constraint for solar power generation of PV units is taken into consideration. Based on the upper limit of solar power shared at any sub interval the inequality constraint of PV units is represented as given below (Ahmed *et al.*, 2015):

$$S_t^{share} \leq 0.3 \times PD_t \quad (t \in T) \quad (5.6)$$

## 5.2.2 Constraint Handling for CHP-PV-GS Problem

The initial values of decision variables are randomly generated within their corresponding limits as given in Eq. (2.19) (chapter-2). During the search process, if the decision variables violate the limits, then limits are fixed to their respective bounds using Eq. (2.20) (chapter-2). The equality, inequality and FOR constraints handling of CHP-PV-GS problem are discussed below:

**FOR Constraint Handling:** The CHP units generates both heat and power which is mutually-coupled and constrained by feasible operating region (FOR) of CHP unit as shown in Fig. 2.2 of chapter-2. The heat output of the CHP units is generated using Eq. (2.19) (chapter-2). FOR constraint handling of CHP units is discussed in section 2.4.2.2 of chapter-2.

**Equality Constraint Handling:** For satisfying the power and heat balance constraint, one dependent power and heat unit is randomly chosen. The power generation of dependent power and heat unit is given in Eqs. (2.24) and (2.25) of chapter-2, respectively. On the violation of dependent thermal and heat unit's capacity limits, error is computed individually, as given in Eqs. (2.26) and (2.27) of chapter-2, respectively.

**Inequality Constraint Handling:** The inequality constraint of solar share of PV units should be satisfied. In case of any violation of limits, an error is computed corresponding to the inequality constraints and is given as:

$$ES_t^{Share} = \begin{cases} (S_t^{share} - 0.3 \times PD_t)^2; S_t^{share} > 0.3 \times PD_t \\ 0 & ; S_t^{share} \leq 0.3 \times PD_t \end{cases} \quad (t \in T) \quad (5.7)$$

### 5.2.3 Objective Function Formulation of CHP-PV-GS Problem

The objective function ( $OF_3$ ) to be optimized is formulated by transforming the constrained problem to the unconstrained problem by using a penalty method and is given as (Yeniay, 2005):

$$OF_3 = F_3 + r \times \left( \sum_{t=1}^T EP_t^{DEP} + \sum_{t=1}^T EH_t^{DEP} + \sum_{t=1}^T ES_t^{Share} \right) \quad (5.8)$$

where  $r$  is the exterior penalty factor parameter;  $EP_t^{DEP}$  and  $EH_t^{DEP}$  are the errors computed for dependent power and heat unit, respectively;  $ES_t^{Share}$  is the error computed for solar share of PV units.

## 5.3 IMPLEMENTATION OF POT-III TO CHP-PV-GS PROBLEM

The POT-II and III attained better results as compared to the POT-I for TS-I-III as discussed in chapter-3 and 4. Thus, POT-II and III are implemented to the CHP-PV-GS problem. The detailed discussion about POT-II and III have been done in section 3.3.4 (chapter-3) and section 4.3.2 (chapter-4) already. The steps for the implementation of the POT-III to solve the CHP-PV-GS problem are given below:

**Step 1:** Read the input data, *i.e.*, cost coefficients, power and heat demand, maximum and minimum limits of decision variables, *etc.*

**Step 2:** Initialize the decision variables randomly using Eq. (2.19) (chapter-2). For the CHP unit, the heat is randomly generated between the specified bounds using Eq. (2.19) (chapter-2), and power is randomly generated within the FOR corresponding to the heat generated by CHP units.

**Step 3:** The objective function is evaluated using Eq. (5.8).

**Step 4:** Update the control parameters of QCSA-GWO technique using CTM using Eq. (4.3) of chapter-4.

**Step 5:** Obtain the positions based on QCSA using Eq. (3.12) (chapter-3) and evaluate the objective function.

**Step 6:** Update the positions and objective function using greedy search mechanism.

**Step 7:** Abandon the worst positions according to  $pd$  and create new positions using Eq. (3.4) (chapter-3) and evaluate the objective function.

**Step 8:** Update the positions and objective function obtained in step 7 using greedy search mechanism.

**Step 9:** Pass the updated positions to GWO. Obtain the positions using Eq. (2.39) (chapter-2) and evaluate objective function. Update the positions and objective using greedy search mechanism.

**Step 10:** Update the positions and objective function obtained in step 9 using greedy search mechanism

**Step 11:** The steps 4-10 are repeated until a termination criterion is met. The maximum number of iterations has been undertaken as a termination criterion.

**Step 12:** Obtain the global best positions which represent the optimum generation schedule of the CHP-PV-GS problem.

**Step 13:** Stop

## 5.4 TEST SYSTEMS, RESULTS AND DISCUSSION

The POT-II POT-III, QCSA-GWO, QCSA and GWO have been implemented to solve two test systems, *i.e.*, test system-V and VI, to the validate their performance. The scheduling period for

the TS-V and VI is 24 hours with 1 hour of sub-interval. The details regarding the test systems have been given in following sub-section.

### **5.4.1 Test Systems**

The simulation is carried out by considering two test systems. The TS-V is the CHPGS problem considering total 11 generating units (8 thermal, 2 CHP, 1 heat unit). The TS-VI is the CHP-PV-GS problem having total 24 generating units (8 thermal, 2 CHP, 1 heat and 13 PV units). For TS-V and VI, the cost coefficients and capacity limits of thermal units have been referred from Ref. (Albert and Jeyakumar, 2005) and are given in Table A.1.5 of Appendix-A. The input data for CHP and heat units have been referred from Ref. (Bahmani-firouzi *et al.*, 2013), respectively. The cost coefficients of CHP and heat units for TS-V and VI are given in Tables A.3.1 and A.3.2, respectively, of Appendix-A. The FOR of the CHP units have been shown in Fig. A.1.1 and A.1.2 of Appendix-A. The power and heat demand for are given in Tables A.5.1 and A.5.2, respectively, of Appendix-A. The input data for PV units for TS-VI has been referred from Ref. (Ahmed *et al.*, 2015). The power ratings and per unit rates of PV units are given in Table A.4.1 of Appendix-A. Solar radiation and temperature for PV units given in Table A.4.2 of Appendix-A.

### **5.4.2 Simulation Results and Discussion**

**5.4.2.1 Test System-V:** In TS-V, CHPGS problem has been considered and solved by POT-II, POT-III, GWO, QCSA and GWO-QCSA in order to verify the performance of these techniques. The comparison of the optimal cost attained by these techniques based on minimum, maximum, average cost and standard deviation is given in Table 5.1. The optimal cost attained by the POT-III for TS-V is 12,42,855 \$, which is 4.56%, 3.29%, 0.06% and 0.61% better than QCSA, GWO, QCSA-GWO and POT-II.

The optimum power and heat generation obtained by POT-III is given in Tables 5.2 and 5.3, respectively. The power and heat balance equality constraints are satisfied. The power and

heat generation of CHP units satisfies the FOR constraint. The power generation of thermal and CHP units and heat generation of CHP and heat units lies between the respective capacity limits. The convergence characteristics for TS-V are shown in Fig. 5.2, which shows that the POT-III exhibit superior performance than QCSA, GWO, QCSA-GWO and POT-II. It is evident from the given results that the POT-III outperformed QCSA, GWO, QCSA-GWO and POT-II.

**Table 5.1** Comparison of cost for TS-V

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
QCSA	13,02,253	13,04,713	13,03,374	788	20.35
GWO	12,85,212	12,87,277	12,86,256	640	18.10
QCSA-GWO	12,43,583	12,45,273	12,44,267	487	25.40
POT-II	12,50,477	12,52,332	12,51,273	536	22.52
POT-III	12,42,855	12,43,965	12,43,350	334	26.15

**Table 5.2** Optimum power generation attained by POT-III for TS-V

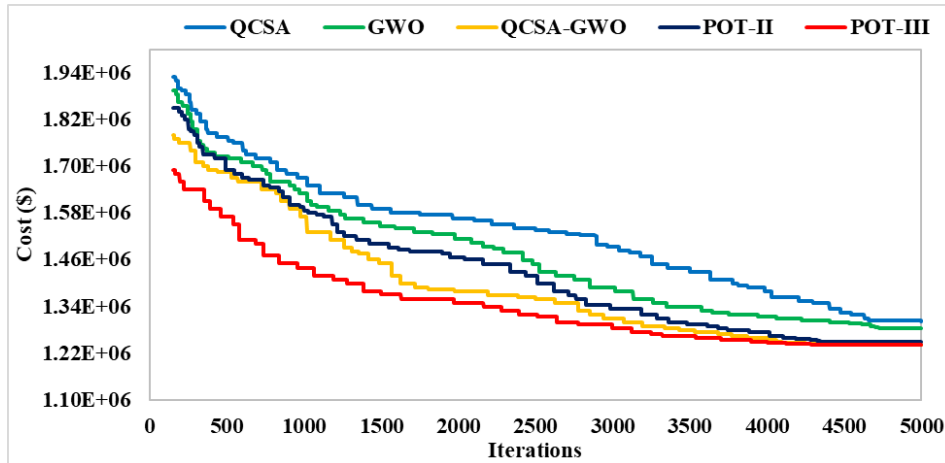
t (hr)	PD (MW)	Power (MW)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PC <sub>1</sub>	PC <sub>2</sub>
1	1036	150.0	135.2	201.4	60.2	122.4	129.6	20.0	55	85.4	76.8
2	1110	150.0	135.1	253.8	60.0	122.4	129.3	20.0	55	137.0	47.4
3	1258	226.2	214.8	264.0	60.0	122.6	129.7	20.1	55	117.7	47.9
4	1406	303.3	294.5	288.2	60.1	122.4	129.9	20.0	55	83.9	48.7
5	1480	303.4	309.6	232.3	62.8	122.3	129.8	20.0	55	134.8	109.9
6	1628	379.3	389.6	163.1	112.8	122.4	129.2	20.0	55	205.4	51.1
7	1702	379.4	396.5	250.2	120.3	122.4	129.6	20.0	55	168.8	59.8
8	1776	457.3	397.0	285.4	170.8	122.7	129.3	20.0	55	98.0	40.6
9	1924	456.6	397.0	288.1	220.6	159.9	129.9	20.0	55	154.5	42.3
10	2072	456.9	396.7	298.9	270.7	159.9	129.8	50.1	55	199.7	54.5
11	2146	454.5	459.0	290.6	300.0	159.9	129.5	52.1	55	197.6	47.8
12	2220	456.8	459.7	331.4	299.1	159.8	129.4	52.0	55	190.6	86.2
13	2072	456.2	396.5	264.9	300.0	159.9	129.8	52.1	55	209.8	47.9
14	1924	455.2	397.8	274.8	250.5	122.5	129.6	22.1	55	162.5	54.0
15	1776	380.5	396.9	274.3	239.9	122.5	129.6	20.0	55	116.1	41.1
16	1554	303.5	316.5	144.5	190.8	122.4	129.1	20.0	55	168.4	103.8
17	1480	225.6	315.0	232.3	181.2	122.1	129.4	20.0	55	121.8	77.6
18	1628	302.8	395.6	189.7	180.8	122.2	129.9	20.0	55	188.1	44.0
19	1776	379.4	397.3	269.3	181.9	159.8	129.6	20.0	55	142.0	41.7
20	2072	457.3	459.0	261.8	231.8	160.0	129.7	20.0	55	192.8	104.5
21	1924	456.8	396.1	275.1	181.0	160.0	129.1	20.1	55	195.9	54.9
22	1628	380.0	394.8	227.5	131.8	122.3	129.4	20.0	55	118.0	49.1
23	1332	303.6	314.4	135.1	81.4	122.5	129.5	20.0	55	99.3	71.1
24	1184	227.1	310.6	74.7	60.0	122.6	129.3	20.0	55	115.5	69.3

**Table 5.3** Optimum heat generation attained by POT-III for TS-V

t (hr)	HD (MWth)	Heat (MWth)			t (hr)	HD (MWth)	Heat (MWth)		
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
1	401	104.5	75.0	221.5	13	474	139.0	75.0	260.1
2	407	110.0	75.0	222.1	14	470	143.2	75.2	251.7
3	417	110.7	74.9	231.4	15	462	112.6	75.0	274.4
4	431	106.1	74.8	250.1	16	443	104.9	74.9	263.2
5	438	124.5	74.9	238.6	17	438	111.4	74.8	251.8

**Table 5.3** Optimum heat generation attained by POT-III for TS-V (continued)

t (hr)	HD (MWth)	Heat (MWth)			t (hr)	HD (MWth)	Heat (MWth)		
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
6	450	104.6	74.9	270.4	18	450	106.1	75.0	269.0
7	455	137.6	75.0	242.4	19	462	124.2	75.1	262.7
8	462	108.8	75.0	278.2	20	474	153.0	85.7	235.3
9	472	139.9	75.0	257.1	21	468	140.5	75.1	252.5
10	474	154.0	79.4	240.6	22	449	110.1	75.1	263.8
11	478	144.5	75.0	258.6	23	430	104.9	75.0	250.1
12	483	146.3	94.3	242.5	24	414	105.0	75.3	233.6



**Figure 5.2** Convergence characteristics of cost attained by POT-III for TS-V

**5.4.2.2 Test System-VI:** The CHP-PV-GS problem is solved by the POT-III, POT-II, QCSA-GWO, QCSA and GWO for verifying the performance of these techniques. The comparison of results of TS-VI attained by POT-III, POT-II, QCSA-GWO, QCSA and GWO are given in Table 5.4 in terms of minimum, maximum, average and standard deviation. The POT-III is having attributes of GWO and QCSA technique, thus, a comparison has been made among these techniques, with the same number of iterations, population size and results have been analyzed for 30 trials. It is worth noticing from Table 5.4 that the POT-III attained comparatively better results than QCSA, GWO, QCSA-GWO and POT-II, respectively. The optimal cost obtained by the POT-III for TS-VI is 11,85,498 \$, which is 9.11%, 3.81%, 1.46% and 2.87%, lesser than the minimum cost obtained by QCSA, GWO, QCSA-GWO and POT-II, respectively. Hence, it is evident from the tables that the POT-III produces precise and optimal results.

The optimum power generation for thermal, CHP and PV units obtained by POT-III is given in Table 5.5, which clearly shows that the power generation of thermal, CHP and solar units

**Table 5.4** Comparison of cost for TS-VI

Technique	Minimum Cost (\$)	Maximum Cost (\$)	Average Cost (\$)	Standard Deviation	Average CPU Time (sec)
QCSA	13,04,374	13,08,674	13,06,276	1332	28.38
GWO	12,32,446	12,36,096	12,34,074	1128	24.12
QCSA-GWO	12,03,060	12,06,270	12,04,399	992	33.40
POT-II	12,20,599	12,24,169	12,22,104	1091	30.56
POT-III	11,85,498	11,86,696	11,88,298	875	34.15

**Table 5.5** Optimum power generation attained by POT-III for TS-VI

t (hr)	PD (MW)	Power (MW)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PC <sub>1</sub>	PC <sub>2</sub>	P <sub>Share</sub>
1	1036	150.3	135.0	158.6	60.3	122.5	129.6	20.0	55.0	118.2	86.4	0.0
2	1110	150.1	135.2	231.8	60.5	122.1	129.9	20.0	55.0	123.6	81.8	0.0
3	1258	150.2	215.4	288.2	60.1	122.3	129.7	20.0	55.0	112.9	104.3	0.0
4	1406	162.8	295.1	314.2	60.1	122.4	129.6	20.0	55.0	186.6	60.2	0.0
5	1480	240.7	310.4	249.3	63.2	122.4	129.5	20.0	55.0	220.7	66.3	2.4
6	1628	193.4	391.2	314.1	112.8	122.6	129.7	20.0	55.0	187.2	58.5	43.3
7	1702	213.5	396.9	337.0	120.7	122.2	129.7	20.0	55.0	152.8	42.1	112.1
8	1776	186.9	397.3	217.6	170.3	122.3	129.7	20.0	55.0	165.2	72.1	239.6
9	1924	173.6	397.5	272.5	220.5	159.9	129.7	20.0	55.0	159.0	100.9	235.2
10	2072	150.1	395.9	223.5	270.9	159.7	129.6	50.0	55.0	200.2	84.7	352.5
11	2146	150.1	459.7	158.5	299.8	160.0	129.8	52.2	55.0	153.6	48.4	479.1
12	2220	150.2	459.9	127.0	299.3	159.8	129.8	52.1	55.0	210.2	76.1	500.7
13	2072	150.2	396.9	159.8	299.6	160.0	129.4	52.1	55.0	172.9	44.9	451.3
14	1924	150.0	396.5	179.6	249.8	122.5	129.4	22.1	55.0	176.8	64.5	377.7
15	1776	150.4	396.4	148.7	240.1	122.5	129.7	20.0	55.0	145.0	44.6	323.6
16	1554	150.2	316.1	134.8	190.5	122.4	129.7	20.0	55.0	93.8	49.9	291.5
17	1480	150.1	316.6	91.8	180.4	122.2	129.7	20.0	55.0	184.4	54.7	175.1
18	1628	150.1	395.8	269.5	180.7	122.6	129.7	20.0	55.0	92.3	116.6	95.8
19	1776	324.4	396.8	305.4	181.7	159.9	129.6	20.0	55.0	125.6	60.4	17.1
20	2072	406.5	458.9	295.9	231.6	160.0	129.6	20.0	55.0	206.3	108.1	0.0
21	1924	407.4	395.9	284.0	181.2	159.9	129.5	20.0	55.0	217.5	73.6	0.0
22	1628	177.3	394.1	338.5	131.6	122.3	129.5	20.0	55.0	155.7	104.1	0.0
23	1332	222.3	314.1	182.2	81.6	122.5	129.4	20.0	55.0	93.9	111.0	0.0
24	1184	150.1	309.5	186.5	60.2	122.5	129.7	20.0	55.0	89.6	60.8	0.0

**Table 5.6** Optimum heat generation attained by POT-III for TS-VI

t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)	t (hr)	HD (MWth)	Heat (MWth) (CHP Units)		Heat (MWth) (Heat Units)
		HC <sub>1</sub>	HC <sub>2</sub>				H <sub>1</sub>		
1	401	104.98	74.851	221.17	13	474	44.9	139.2	75.0
2	407	110.22	75.016	221.76	14	470	64.5	143.4	75.0
3	417	110.9	75.103	230.99	15	462	44.6	112.6	74.9
4	431	106.1	75.04	249.86	16	443	49.9	104.9	74.9
5	438	124.35	74.906	238.75	17	438	54.7	111.6	75.1
6	450	104.54	75.093	270.37	18	450	116.6	106.2	75.1
7	455	137.94	75.018	242.04	19	462	60.4	124.3	75.1
8	462	108.68	75.01	278.31	20	474	108.1	152.6	85.7
9	472	139.97	75.064	256.96	21	468	73.6	140.6	75.1
10	474	153.83	79.284	240.89	22	449	104.1	109.8	74.9
11	478	145.07	75.157	257.78	23	430	111.0	104.9	75.1
12	483	146.1	94.432	242.47	24	414	60.8	104.8	74.9

satisfy the power balance constraint in each sub-interval. Table 5.6 gives the heat generation of

CHP and heat units obtained by the POT-III. Heat generation of CHP and heat units satisfy the heat balance constraint in each sub-interval. All constraints are satisfied. The Convergence characteristics for TS-VI are shown in Fig. 5.3 and it is also illustrated that the POT-III has better convergence than QCSA, GWO, QCSA-GWO and POT-II. Hence, it is summarized that the integration of CTM to QCSA-GWO improves the solution quality and convergence behaviour for complex CHP-PV-GS problem.

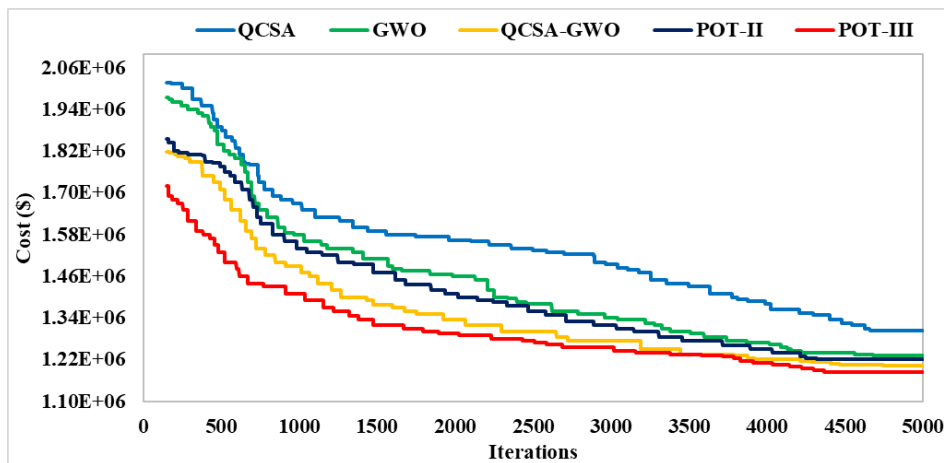


Figure 5.3 Convergence characteristics of cost attained by POT-III for TS-VI

## 5.5 CONCLUSIONS

In this chapter, CHP-PV generation scheduling problem has been formulated for the time horizon of twenty-four hours considering thermal, CHP, heat and PV units. Two test systems have been considered having CHPGS and CHP-PV-GS problems. For both test systems, POT-III, POT-II, QCSA-GWO, GWO and QCSA techniques have been implemented and comparison has been made based on optimal results obtained by these techniques. The optimal cost attained by the POT-III for TS-V is 12,42,855 \$, which is 4.56%, 3.29%, 0.06% and 0.61% better than QCSA, GWO, QCSA-GWO and POT-II. The optimal cost obtained by the POT-III for TS-VI is 11,85,498 \$, which is 9.11%, 3.81%, 1.46% and 2.87%, lesser than the minimum cost obtained by QCSA, GWO, QCSA-GWO and POT-II, respectively. All the constraints are satisfied in both the cases. The comparative convergence characteristics shows that POT-III converges faster than the QCSA,

GWO, QCSA-GWO and POT-II for searching a globally optimal solution and the POT-III is competent in exploring better quality solutions. The incorporation of PV units along with thermal, CHP and heat units save the fuel cost by 4.6%. The incorporation of PV units offers significant cost saving benefits compared to conventional fuel-based thermal and CHP units. Also, the utilization of renewable energy source promotes environmental sustainability as well as economic benefits.



## CHAPTER 6

# MULTI-OBJECTIVE GENERATION SCHEDULING OF COORDINATED POWER SYSTEM USING HEURISTIC OPTIMIZATION TECHNIQUES

### 6.1 INTRODUCTION

Optimizing fuel cost and pollutant emission while satisfying various operational constraints is the main aim of optimum generation scheduling (GS). The fossil-fueled-based power plants predominantly release greenhouse gases into the atmosphere while generating electricity using fossil fuels., which should be limited to protect the environment from harmful contaminants. The usage of low-emission fuel seems a good alternative for reducing emissions. However, it would not be cost-effective because of the high cost and limited supply of low-emission fuel. Consequently, researchers focus on economic emission generation scheduling of power systems. The fuel cost and pollutant emission objectives are of conflicting nature and thus, forms a multi-objective (MO) optimization problem. Hence, multi-objective generation scheduling (MOGS) of coordinated power system (CPS) is one of the foremost challenges. Currently, electric utilities focus on integrating various energy sources to obtain power and heat at the lowest possible price with minimum pollutant emission. The combined heat and power (CHP) plants are recognized as very efficient not only because of the concurrent generation of heat and electricity and saving the generation cost of about 10% to 40% but also by reducing greenhouse gas emissions by 13% to 18% (Li *et al.* 2018). The hydro plants are also extensively preferred due to their competence to fulfill peak load demand, insignificant pollutant emissions, and fuel costs. However, due to hydro resources uncertainty and reliability concerns, it is difficult to rely solely on hydro units to provide all of the electrical energy demand (Ourahou *et al.* 2020). Thus, the hydro plants must coordinate with other reliable energy sources like thermal, CHP and heat units to fulfill the power and heat

demands. An efficient heuristic optimization technique is required to search for the global optimum solution for complex constrained and multi-dimensional MO coordinated power system generation scheduling (CPSGS) problem.

The main contributions of this chapter are summarized as:

- Over the last decade, researchers have individually addressed MO scheduling problems like MO-CHPGS and MO-HTGS. The recent trend is more focused on integrated energy systems. The MO-CPSGS problem, which includes thermal, CHP, heat and hydro units, is formulated for one-day scheduling horizon. The MO-CPSGS problem is a complex, non-convex, multi-dimensional and high constrained MO optimization problem.
- Two heuristic optimization techniques, *i.e.*, proposed optimization techniques (POT)-II and III, are employed for achieving the optimum schedule for the MO-HTGS and MO-CPSGS problem. The POT-II is quantum based cuckoo search algorithm (QCSA) with mutation strategies (MS) (QCSA-MS) and POT-III is chaotic tent map (CTM) based QCSA with grey wolf optimizer (GWO) (CTM-QCSA-GWO).
- The cardinal priority ranking (CPR) method has been implemented for searching for the optimal non-dominated solution to the MO-HTGS and MO-CPSGS problems. For MO-HTGS and MO-CPSGS problems, the results obtained by the POTs are compared with published results and found satisfactory. The POTs outperform several existing states of art optimization algorithms and indicating the superiority of the POTs. Further, POT-III outperforms the POT-II.

The chapter is structured as follows: Problem formulation of MO-CPSGS problem is discussed in Section 6.2. Objective function formulation of MO-CPSGS problem is discussed in section 6.3. In Section 6.4, implementation of POT-II and III to MO-CPSGS problem are briefly reviewed. Section 6.5 presents the test systems, numerical outcomes, and discussion. Section 6.6 suggests the conclusions.

## 6.2 PROBLEM FORMULATION

Four different types of generating units (thermal, CHP, heat and hydro) are taken into account for the MO-CPSGS problem. The primary aim of the MO-CPSGS problem is to schedule the power generation of thermal, CHP and hydro units as well as the heat generation of heat and CHP units while fulfilling all the constraints in a specific period for achieving optimal fuel cost and emission. The decision variables for the MO-CPSGS problem are (i) power output of thermal and CHP units ( $PT, PC$ ), (ii) heat output of heat and CHP units ( $H, HC$ ) and (iii) water discharge rate of hydro units ( $q$ ) as shown in Fig. 6.1. Each decision variable searches for a time period  $T$  of 24 hours with sub-interval of one hour. Therefore, the MO-CPSGS problem has  $[T \times (PT + PC + H + HC + q)]$  decision variables (Kaur and Narang 2019). The objectives and constraints for the MO-CPSGS problem are discussed below:

### 6.2.1 Economic Cost

The total cost to be optimized for the MO-CPSGS problem comprises of fuel cost of thermal, CHP and heat units, whereas the fuel cost of hydro units is inconsiderable. The total cost ( $$/h$ ) to be minimized is given by Eq. (2.14) of chapter-2.

### 6.2.2 Economic Emission

Fossil fuels are mainly used in the process of producing heat and power. Consequently, various pollutants like carbon dioxide ( $CO_2$ ), nitrogen oxides ( $NO_x$ ), *etc.*, are emitted and these harmful emissions need to be reduced. The hydroelectric units do not produce any harmful emissions. Thus, the total emission for the MO-CPSGS problem is emitted by thermal, CHP and heat units in each sub-interval and is given as follows (Sundaram 2020):

$$\text{Minimize } F_2 = \sum_{t=1}^T \left[ \sum_{i=1}^{N^{TH}} E_{1i}(PT_{it}) + \sum_{j=1}^{N^{CHP}} E_{2j}(PC_{jt}, HC_{jt}) + \sum_{k=1}^{N^H} E_{3k}(H_{kt}) \right] \quad (6.1)$$

where  $E_{1i}(PT_{it})$ ,  $E_{2j}(PC_{jt}, HC_{jt})$  and  $E_{3k}(H_{kt})$  are the emission functions of thermal, CHP and heat units, respectively, which are stated below (Sundaram 2020):

$$E_{1i}(PT_{it}) = a_i(PT_{it})^2 + b_i(PT_{it}) + c_i + d_i \exp[e_i(PT_{it})] \quad (i \in N^{TH}; t \in T) \quad (6.2)$$

$$E_{2j}(PC_{jt}, HC_{jt}) = (\varepsilon_j + \phi_j)PC_{jt} \quad (j \in N^{CHP}; t \in T) \quad (6.3)$$

$$E_{3k}(H_{kt}) = (\alpha_k + \beta_k)H_{kt} \quad (k \in N^H; t \in T) \quad (6.4)$$

where  $a_i, b_i, c_i, d_i, e_i$  are the emission coefficients of thermal units;  $\varepsilon_j, \phi_j$  are the emission coefficients of CHP units;  $\alpha_k, \beta_k$  are the emission coefficients of heat units.

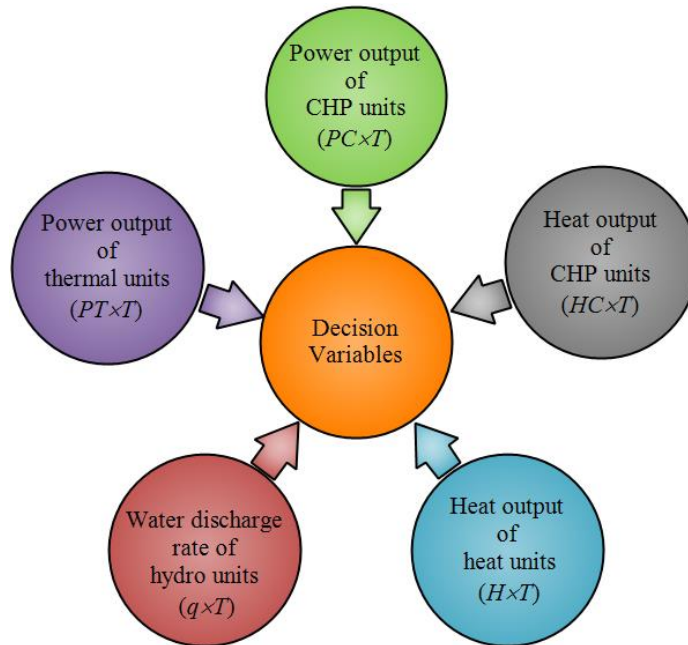


Figure 6.1 Decision variables of MO-CPSGS problem

### 6.2.3 Constraints

The MO-CPSGS problem is subject to a number of constraints like equality, inequality and limits on decision variables, which are discussed below. The constraint handling is discussed in detail in section 2.4.2 of chapter-2.

**6.2.3.1 Limits of Decision Variables:** The power output of thermal ( $PT_{it}$ ) and CHP units ( $PC_{jt}$ ), heat output of heat ( $H_{kt}$ ) and CHP units ( $HC_{jt}$ ), water discharge rate of hydro units ( $q_{it}$ ) for the time period  $T$  are the decision variables for MO-CPSGS problem. Every decision variable needs to be

between its corresponding minimum and maximum values as given in Eqs. (2.3), (2.5) and (2.7-2.9) of chapter-2.

**6.2.3.2 Inequality Constraints:** The maximum and minimum limits of power generation and reservoir volume of hydro units should not be violated in any sub-interval as given in Eqs. (2.12) and (2.13) of chapter-2.

**6.2.3.3 Equality Constraints:** The power and heat balance of the CPS and final reservoir volume of hydro units, are the equality constraints, which are discussed in Eqs. (2.15), (2.17) and (2.18) of chapter-2.

## 6.3 OBJECTIVE FUNCTION FORMULATION

### 6.3.1 Fuzzy Decision Making

In the MOGS problem, two contradictory objectives are minimized simultaneously, *i.e.*, fuel cost and pollutant emissions. Fuzzy decision-making is used to choose the optimal non-dominated solution by computing the membership function ( $\mu(F_d)$ ) for each objective and taking into account the minimum and maximum values of the objectives as given below (Patwal and Narang 2018):

$$\mu(F_d) = \begin{cases} 1 & ; F_d \leq F_d^{\min} \\ \frac{F_d^{\max} - F_d}{F_d^{\max} - F_d^{\min}} & ; F_d^{\min} < F_d < F_d^{\max} \\ 0 & ; F_d \geq F_d^{\max} \end{cases} \quad (d \in N^{OB}) \quad (6.5)$$

The optimal non-dominated solution is obtained by the cardinal priority ranking (CPR) method, using the max-min operator on the membership functions. The CPR  $\mu_d$  is mathematically expressed as (Patwal and Narang 2018):

$$OBJ_2 = \mu_d = \max [\min(\mu(F_1) - \text{error}, \mu(F_2) - \text{error})] \quad (6.6)$$

$$\text{error} = r \times \left( \sum_{t=1}^T EP_t^{DEP} + \sum_{t=1}^T EH_t^{DEP} + \sum_{l=1}^{N^{HY}} EV_l^{FI} + \sum_{l=1}^T \sum_{l=1}^{N^{HY}} EVO_{lt} + \sum_{l=1}^T \sum_{l=1}^{N^{HY}} EPH_{lt} \right) \quad (6.7)$$

## 6.4 IMPLEMENTATION OF PROPOSED OPTIMIZATION TECHNIQUES TO MO-CPSGS PROBLEM

Two heuristic optimization techniques, *i.e.*, POT-II (QCSA-MS) and POT-III (CTM-QCSA-GWO) have been employed for achieving the optimum schedule for the MO-HTGS and MO-CPSGS problems. For, POT-II, the mathematical modelling QCSA and mutation strategies are discussed in detail in section 3.3.1 of chapter-3 and 2.5.2 of chapter-2, respectively. The POT-III is discussed in detail in section 4.4.5 of chapter-4. The implementation of POT-II and III to MO-CPSGS problem is discussed below:

### 6.4.1 Implementation of POT-II to MO-CPSGS Problem

In this section, the solution methodology, and the implementation of POT-II for solving the MO-CPSGS problem are discussed in the following steps:

**Step 1: Initialization:** The decision variables ( $PT_{it}$ ), ( $PC_{jt}$ ), ( $HC_{jt}$ ), ( $H_{kt}$ ) and ( $q_{lt}$ ) are randomly initialized using Eq. (2.19) of chapter-2.

**Step 2: Constraint Handling:** The decision variables may deviate from their boundaries throughout the search phase and equality and inequality constraints may not be satisfied. The details of constraint handling are given in section 2.4.2 of chapter-2.

**Step 3: Membership Function Evaluation:** Initially, the two objectives, *i.e.*, fuel cost (Eq. (2.14) of chapter-2) and emission (Eq. (6.1)), are minimized individually. The minimization of one objective provides the most undesirable solution to another objective, because of the contradictory nature of the two objectives. Then, the membership function  $\mu(F_d)$  for both objectives is individually assessed using Eq. (6.5) and CPR is evaluated using Eq. (6.6).

**Step 4: Optimum Schedule by QCSA:** The QCSA technique updates the decision variables using Eqs. (3.4) and (3.12) of chapter-3 and the best solutions obtained by QCSA are transferred to the

mutation operators for further upgradation.

**Step 5: Optimum Schedule by Mutation Strategies:** Three mutation operators, *i.e.*, Cauchy, Gaussian and opposition-based, are used to generate new solutions using Eqs. (2.37), (2.40) and (2.43), respectively, of chapter-2. The greedy search mechanism is applied to update the positions and fitness.

**Step 6: Termination criterion:** The procedure is repeated from step 4 until predetermined iteration count has been reached.

#### **6.4.2 Implementation of POT-III to MO-CPSGS Problem**

In the POT-III, the search is carried out in two phases. In the first phase, the QCSA technique is used to explore the search area, in which cuckoo birds' positions are updated by one of the three rules as given in Eq. (3.12) of chapter-3. During the search process, positions are updated by either conventional CSA upgradation rule or by applying two other laws, which are derived from QT. Cuckoo birds get a better opportunity to achieve a high-quality solution by following this procedure. Since the GWO technique has better exploitation capability than the QCSA technique, the solutions obtained by QCSA are transferred to the GWO technique for further exploitation in the second phase. In the GWO technique, the upgradation of grey wolves' position is guided by the three best positions of wolves as given by Eqs. (2.34-2.36) of chapter-2. The algorithm parameters of the global optimization technique influence the solution quality and convergence characteristics. Hence in the proposed optimization technique, the algorithm parameters of QCSA and GWO techniques, *i.e.*, scaling factor, distribution factor, and discovery probability of QCSA and control parameter of GWO, are made adaptive by incorporating the CTM. The generalized procedure of the proposed method is given in Fig. 6.2.

For the MO-CPSGS problem, the decision variables are randomly generated within their respective bounds using Eq. (2.19) of chapter-2. For CHP units, heat is initially randomly

generated and power is generated within the feasible operating region. Decision variables are restricted to their respective limits if they breach their bounds throughout the search process. For satisfying the equality, inequality and FOR constraint, the constraint handling procedure is discussed in section 2.4.2 of chapter-2. The CPR approach is used for MO-HTGS and MO-CPSGS problems. Eq. (6.6) gives the final objective function. The highest value of CPR represents the optimal non-dominated solution. The flowchart of the POT-III to solve the MO-CPSGS problem is illustrated in Fig. 6.3.

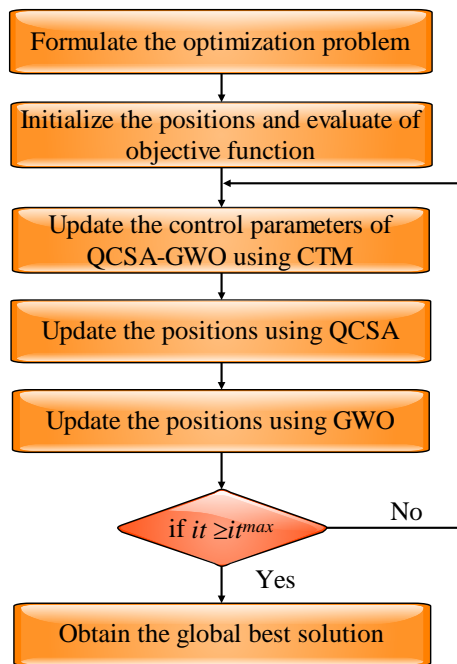


Figure 6.2 Generalized procedure of the POT-III

## 6.5 TEST SYSTEMS, RESULTS AND DISCUSSION

The POT-II, POT-III, QCSA-GWO, QCSA and GWO are examined with three test systems to fully illustrate their viability and efficacy. Each test system (TS) has been resolved for three test cases, *i.e.*, economic GS, emission GS and MOGS. The economic GS optimizes the fuel cost and emission GS optimizes the emission. In MOGS, the fuel cost and emission are simultaneously optimized. The CPR method has been implemented for searching for the optimal non-dominated solution for all the test systems. The scheduling period of twenty-four hours with sub-interval of one hour is considered for all the test systems. The total decision variables for TS-I, II and III are

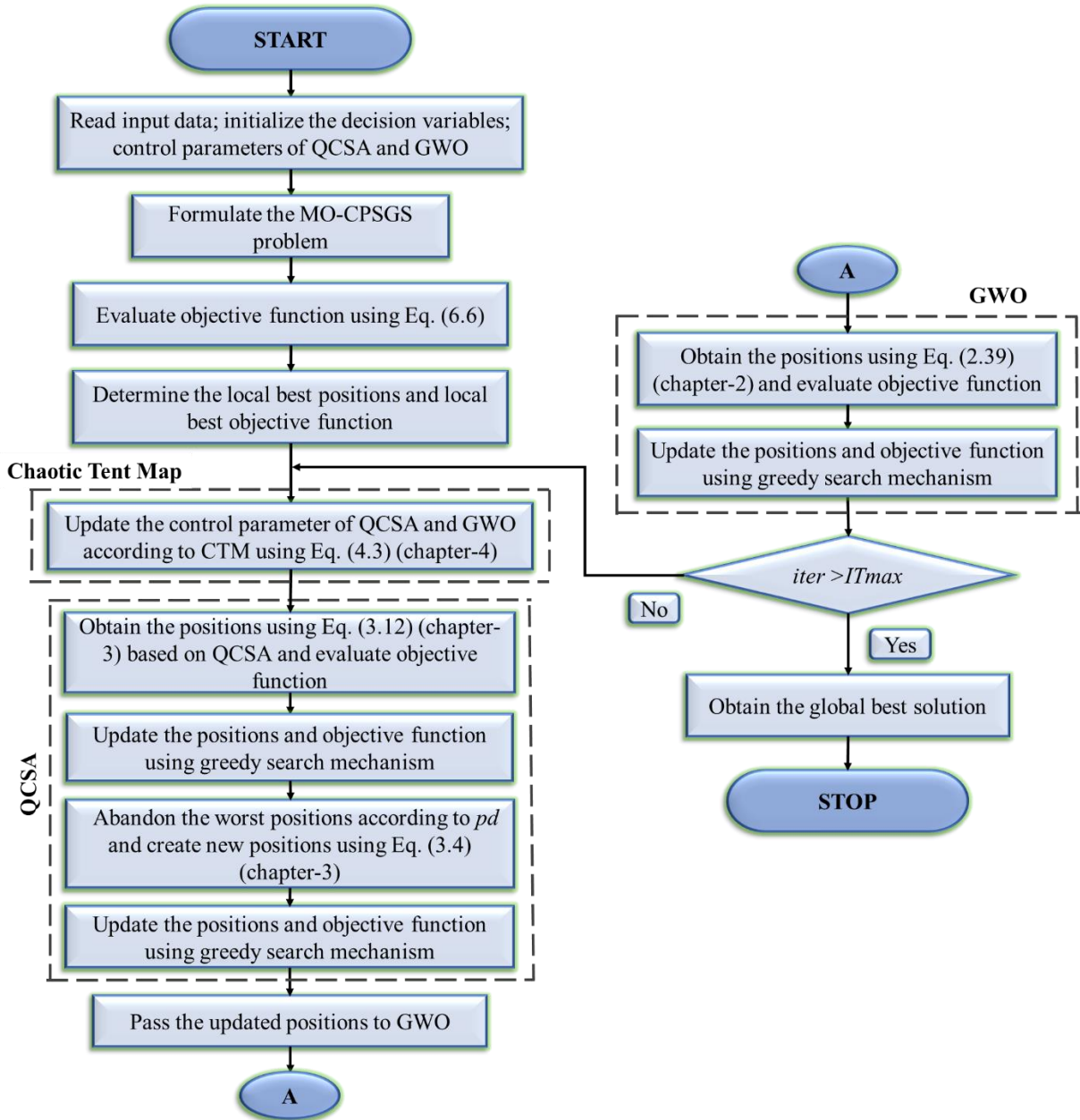


Figure 6.3 Flow chart of the implementation of POT-III to MO-CPSGS problem

(7×24), (18 ×24) and (29×24), respectively. Valve-point loading effect of thermal units has been considered for all the test systems. The technical details of the test systems have been given in following sub-section.

### 6.5.1 Test Systems

For test system (TS)-I, hydro-thermal system is considered, consisting of 3 thermal and 4 hydro units and the technical data is taken from Ref. (Basu 2004). The test system (TS)-I has been solved for three test cases. In TS-I (case-I) is economic GS problem, case-III is emission GS problem and

case-IV is MOGS problem of HT units. The details of the TS-I (case-I) are discussed in section 2.7.1 of chapter-2. The emission coefficients of thermal units for TS-I (case-III-IV) are given in Table A.1.6 of Appendix-A.

The TS-II and III are CPSGS problems. The TS-II has 18 generating units, including 11 thermal, 4 hydro, 2 CHP and 1 heat unit. TS -III has 29 generating units, including 19 thermal, 4 hydro, 4 CHP and 2 heat units. The data for TS-II and III has been taken from (Basu 2010b), (Basu 2008) and (Elaiw *et al.* 2013) for hydro-thermal, CHP and heat units, respectively. The technical details of TS-II and III (case-I) have been discussed in section 2.7.1 under chapter-2. The emission coefficients of thermal, CHP and heat units for TS-II (case-II and III) are given in Tables A.1.7, A.3.5 and A.3.6, respectively of Appendix-A. The emission coefficients of thermal, CHP and heat units for TS-III (case-II and III) are given in Tables A.1.8, A.3.6 and A.3.7, respectively of Appendix-A.

## **6.5.2 Algorithm Parameter Settings**

The selection of the best values of the algorithm parameters for searching for the optimal solution has been made after numerous trials. The population size is 50. The maximum iterations considered for TS-I, II and III are 5000, 5000 and 8000, respectively. The initial values of optimal algorithm parameters for QCSA-GWO and the POT-II and III are given as follows:

POT-II:  $s=1.5$ ;  $h=1.6$

QCSA-GWO:  $\alpha=0.02$ ;  $\beta=1.5$ ;  $\delta=1.6$ ;  $pd=0.7$ ;  $z=0.25$

POT-III:  $\alpha = 0.75$ ;  $\beta = 0.8$ ;  $\delta = 0.65$ ;  $pd = 0.65$ ;  $z=0.35$

For QCSA-GWO, the parameters  $\beta$  and  $\delta$  linearly decrease with iterations with a step size of 0.5 and 0.6, respectively. The control parameter  $z$  of GWO decreases linearly with the course of iterations. For the POT-III, all the algorithm parameters vary according to the CTM sequence given in Eq. (4.3) of chapter-4. The POTs have been implemented using FORTRAN 90 compiler on a workstation with a Core-i5 processor and 8 GB of RAM at 1.80 GHz.

### 6.5.3 Simulation Results and Discussion

The detailed discussion on the results obtained by the POT-II and III for all the test systems is discussed below:

**6.5.3.1 Test System-I:** The optimal solutions attained by the POT-II and III for the MO-HTGS problem have been compared with GWO, QCSA, QCSA-GWO and other existing optimization techniques, as shown in Table 6.1. Table 6.1 compares the outcomes of the POT-II and III with those of well-established heuristic techniques in terms of economic GS, emission GS and MOGS of HT system for TS-I. The minimum cost and emission attained by the POT-II and III for economic GS and emission GS of the HT system are comparatively better than the published results. Further, the results of POT-II and III are also compared and POT-III got better results than POT-II for case-I and II.

**Table 6.1** Comparison of results for TS-I

Technique	Case-I: Economic GS		Case-III: Emission GS		Case-IV: MO-HTGS			
	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	CPR	CPU Time (sec)
DE (Mandal and Chakraborty 2009)	43,500	21,092	51,449	18,257	44,914	19,615	0.493	74.96
PSO (Narang <i>et al.</i> 2014)	43,251	24,042	46,046	16,720	44,330	19,589	0.566	44.52
PSO (Mandal and Chakraborty, 2011)	42,474	28,132	48,263	16,928	43,280	17,899	0.733	132.45
Improved QPSO (Sun and Lu 2010)	42,359	31,298	45,271	17,767	44,259	18,229	0.605	--
PPO (Narang <i>et al.</i> 2014)	42,170	26,177	49,072	15,805	43,146	17,009	0.715	29.31
PSO-PPS (Narang <i>et al.</i> 2014)	42,056	27,532	48,006	15,801	43,005	17,054	0.733	32.31
PPO-PPS (Narang <i>et al.</i> 2014)	41,530	28,757	48,920	15,716	42,836	17,254	0.754	29.19
QADEV (Lu and Sun 2011)	41,762	30,710	45,971	16,654	42,939	17,918	0.741	--
HMOCA (Lu <i>et al.</i> 2011)	41,805	16,841	46,744	15,914	43,593	16,204	0.659	--
ASMODE (Zhang <i>et al.</i> 2018)	41,965	16,718	46,689	15,936	43,960	16,234	0.613	--
PSO-SWT (Patwal and Narang 2020)	43,598	25,635	48,110	16,884	44,259	17,416	0.575	34.33
MCPSO-SWT (Patwal and Narang 2020)	41,180	23,942	49,011	15,679	43,686	16,938	0.647	24.13
QCSA	41,875	30,263	48,704	16,261	43,897	19,338	0.621	17.03
GWO	41,700	26,544	48,881	15,983	42,823	18,393	0.736	16.14
QCSA-GWO	41,189	27,609	48,849	15,712	42,687	17,650	0.772	20.50
POT-II	41,238	26,542	48,893	15,714	42,703	17,671	0.770	18.24
POT-III	40,873	26,071	48,845	15,641	42,357	17,538	0.814	21.15

For TS-I (case-IV), *i.e.*, MO-HTGS problem, the POT-II achieves the lowest cost of 42,703 \$ and emission of 17,671 lb, individually. The optimum cost and emission achieved by the POT-III for case-III are 42,357 \$ and 17,538 lb, respectively. The CPR obtained by the POT-II and III is 0.770 and 0.814, respectively. The CPR obtained by the POT-II is comparatively better than its peers and 23.99% better than the QCSA technique, which shows that the integration of QCSA and MS improves the search process. Further, the results obtained by POT-III are comparatively 65.11%, 43.82%, 11.05%, 34.54%, 13.84%, 11.05%, 7.96%, 9.85%, 23.52%, 32.79%, 41.56%, 25.81%, 31.1%, 10.6% and 5.44% better than that of DE (Mandal and Chakraborty 2009), PSO (Narang *et al.* 2014), PSO (Mandal and Chakraborty, 2011), improved QPSO (Sun and Lu 2010), PPO (Narang *et al.* 2014), PSO-PPS (Narang *et al.* 2014), PPO-PPS (Narang *et al.* 2014), quadratic approximation based DE with valuable trade-off (QADEV) (Lu and Sun 2011), HMOCA (Lu *et al.* 2011), adaptive second mutation based MO-DE (ASMMODE) (Zhang *et al.* 2018), PSO-SWT (Patwal and Narang 2020), MCP-PSO-SWT (Patwal and Narang 2020), QCSA, GWO and QCSA-GWO, individually. Further, the POT-III attained 5.71% better results than the POT-II, which shows the superiority of POT-III over POT-II.

Table 6.2 gives the optimal power generation of thermal units obtained by POT-III for TS-I (case-IV). The thermal and hydro power generation is within the respective bounds of each unit in each sub-interval and satisfies the load balance constraint. The water discharge rate of hydro units attained by POT-III in each sub-interval lies between each unit's minimum and maximum bounds, as shown in Fig. 6.4. The reservoir volume of each hydro unit attained by POT-III also lies within its respective limits in each sub-interval and fulfils the terminal reservoir volume constraint as shown in Fig. 6.5.

The distribution of Pareto optimal schemes attained by the POT-II, III, QCSA-GWO, QCSA and GWO has been shown in Fig. 6.6, which depicts better convergence and diversity distribution of the POT-II and III compared with GWO, QCSA and QCSA-GWO. It can be demonstrated that the POT-II outperforms QCSA and GWO on the Pareto front in terms of

Table 6.2 Optimum power generation attained by POT -III for TS-I (case-IV)

Time (hr)	Power Demand	Power (MW) (Thermal Units)			Power (MW) (Hydro Units)				Total Power
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>	
1	750	175.0	128.4	139.8	93.3	56.8	26.9	129.8	750
2	780	155.8	209.8	139.4	66.6	56.2	26.6	125.7	780
3	700	174.9	124.9	139.8	63.6	60.4	14.7	121.6	700
4	650	108.7	128.0	139.8	62.6	57.0	35.8	118.2	650
5	670	103.0	129.6	139.7	77.3	56.3	30.7	133.3	670
6	800	121.2	125.1	229.5	77.8	54.2	38.5	153.7	800
7	950	108.7	209.8	229.5	80.1	63.7	38.1	220.1	950
8	1010	175.0	209.8	228.0	70.9	54.4	44.8	227.2	1010
9	1090	175.0	219.5	229.5	82.1	63.8	39.6	280.4	1090
10	1080	175.0	232.7	229.5	81.7	56.8	33.6	270.7	1080
11	1100	175.0	209.9	229.5	89.7	65.2	40.4	290.3	1100
12	1150	175.0	275.8	228.8	89.3	65.0	45.2	270.9	1150
13	1110	175.0	209.8	229.2	94.3	77.8	31.9	291.9	1110
14	1030	175.0	210.2	142.4	82.2	76.5	42.9	300.8	1030
15	1010	102.7	209.8	228.6	68.9	71.7	46.1	282.3	1010
16	1060	175.0	209.8	207.7	84.4	69.2	39.9	274.1	1060
17	1050	163.0	209.9	176.3	81.8	73.7	48.5	296.9	1050
18	1120	116.1	291.0	223.6	67.2	80.9	53.7	287.4	1120
19	1070	136.9	209.8	226.1	86.1	77.7	51.5	281.8	1070
20	1050	108.1	209.8	228.1	72.5	73.8	53.3	304.5	1050
21	910	102.7	208.2	139.7	54.3	51.8	57.0	296.3	910
22	860	102.7	124.9	138.6	68.8	72.1	58.4	294.4	860
23	850	102.9	124.9	139.8	54.9	80.0	57.5	290.0	850
24	800	144.5	124.9	50.0	62.3	75.0	58.9	284.4	800

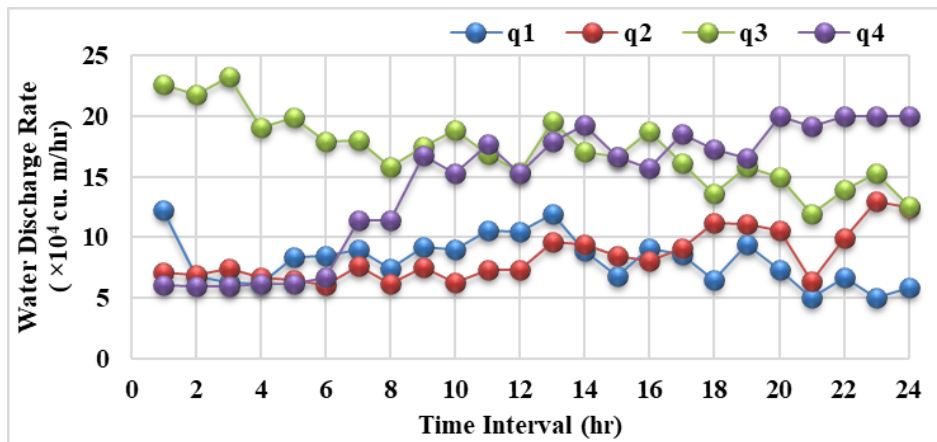


Figure 6.4 Water discharge rate of hydro units attained by POT-III for TS-I (case-IV)

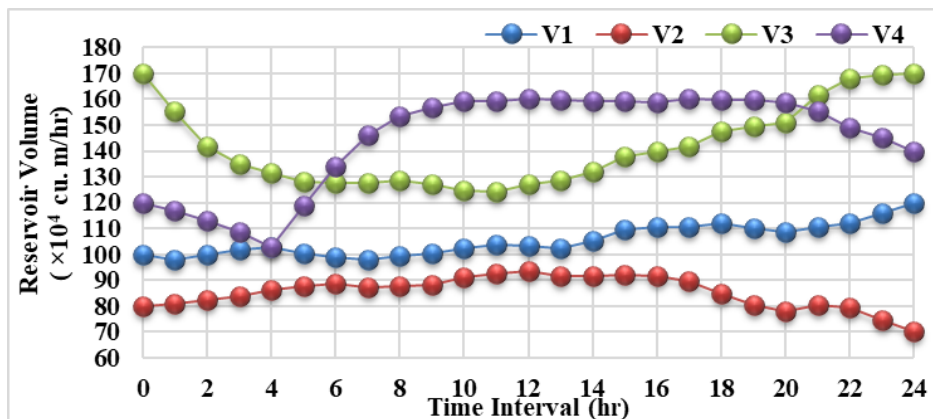


Figure 6.5 Reservoir volume of hydro units attained by POT-III for TS-I (case-IV)

distribution diversity. Additionally, the POT-III attains more even distribution of the non-dominated solutions in comparison with POT-II and the other techniques. It recommends that the POT-III is more capable of lessening the emission level with the same fuel cost or vice versa. The convergence characteristics of the CPR of the POT-II and III are compared with those of QCSA, GWO and QCSA-GWO, as revealed in Fig. 6.7. It can be observed from it that the POT-II has better convergence than QCSA and GWO. It can also be seen that the POT-III converges more quickly than QCSA, GWO, QCSA-GWO and POT-II in smaller number of iterations. The POT-III leads to better solutions for economic, emission and MOGS of HT system as compared to other techniques. Besides, the computational time taken by the POT-III to solve MO-HTGS problem is quite reasonable and better than other techniques. Hence, it is demonstrated that application of the proposed approach-III outcomes in better solution for economic, emission and MOGS of HT system.

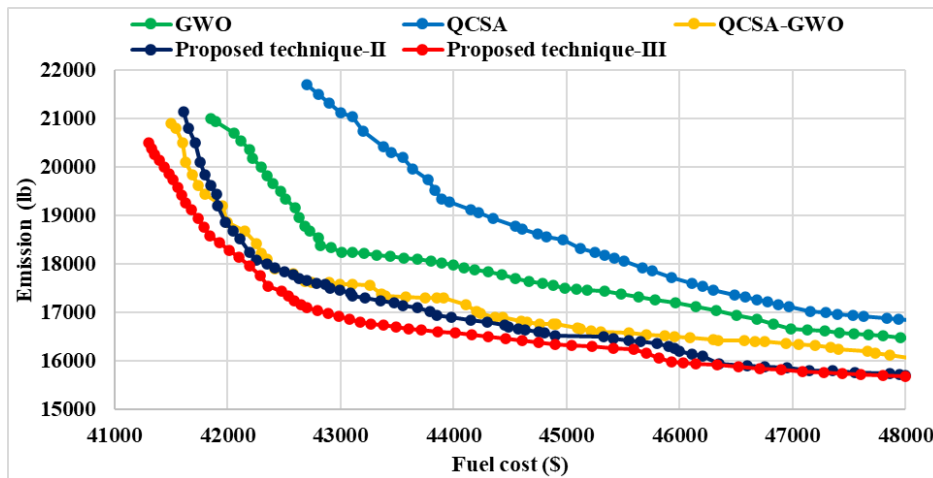


Figure 6.6 Comparison of optimal Pareto front for TS-I (case-IV)

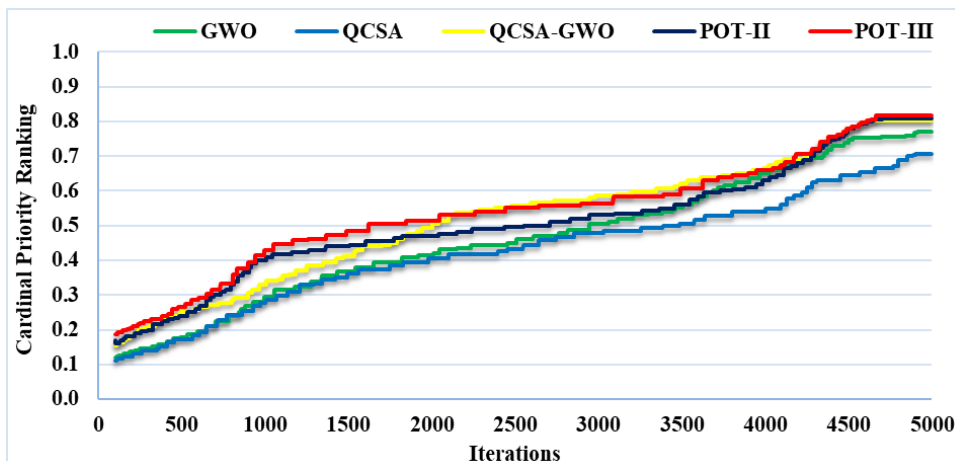


Figure 6.7 Convergence characteristics for TS-I (case-IV)

**6.5.3.2 Test systems-II:** The CPS has been taken for TS-II. The economic GS, emission GS and MO-CPSGS problems have been solved by QCSA, GWO, QCSA-GWO, POT-II and III and comparative analysis of results have been made. Table 6.3 compares the optimal outcomes attained by the POT-II, POT-III, GWO, QCSA and QCSA-GWO for all the test cases for TS-II. POT-II achieved better cost and emission than the QCSA for TS-II (case-I and II). For case-III, the best-compromised cost and emission by the POT-II are 25,39,312 \$ and 2,51,407 lb. The POT-II outperforms QCSA for the MO-CPSGS problem in terms of cost and emission by 4.01% and 5.31%, respectively. The CPR using the POT-II is 0.791, which is 20.03% better than the CPR using QCSA technique.

**Table 6.3** Comparison of results for TS-II

Technique	Case-I: Economic GS		Case-II: Emission GS		Case-III: MO-CPSGS			
	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	CPR	CPU Time (sec)
QCSA	26,27,422	3,00,333	26,80,093	2,62,296	26,45,359	2,65,524	0.659	40.09
GWO	26,08,065	2,74,655	26,51,053	2,58,888	26,25,416	2,60,738	0.596	37.17
QCSA-GWO	24,81,728	2,60,134	25,74,547	2,45,666	24,88,135	2,47,334	0.885	47.23
POT -II	25,20,514	2,72,602	26,10,263	2,50,490	25,39,312	2,51,407	0.791	41.25
POT -III	24,43,921	2,54,554	25,81,944	2,44,568	24,51,015	2,45,140	0.943	49.15

**Table 6.4(a)** Optimum power generation attained by POT-III for TS-II (case-III)

Time (hr)	PD (MW)	Power (MW) (Thermal Units)										
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>	PT <sub>11</sub>
1	1786	34.8	231.3	184.5	166.7	154.0	97.7	75.4	124.9	65.2	32.4	40.8
2	1890	36.3	160.0	330.8	166.0	137.5	159.3	84.4	92.5	107.3	35.6	28.6
3	1958	121.6	271.9	219.9	167.7	163.7	78.2	86.6	151.5	39.7	54.4	44.0
4	2056	148.9	261.2	318.6	209.4	164.0	88.3	120.2	87.7	81.6	59.3	10.5
5	2150	161.4	291.9	346.5	189.1	144.1	125.6	146.7	65.8	41.3	31.8	17.7
6	2428	113.8	295.6	301.2	161.0	174.4	311.2	158.3	110.9	125.6	53.5	29.9
7	2652	155.1	299.9	404.2	192.2	189.5	336.8	203.8	79.0	56.5	56.8	30.0
8	2786	164.7	298.9	418.8	193.9	212.7	226.4	262.4	130.5	121.8	51.1	28.6
9	3014	172.0	284.9	469.1	262.5	240.7	320.0	233.8	139.9	59.3	71.3	30.3
10	3102	174.8	299.0	489.5	220.8	320.6	318.1	203.6	155.0	111.9	45.3	45.0
11	3206	174.4	296.4	461.9	339.9	307.7	318.9	231.7	144.2	101.7	53.0	24.8
12	3300	158.6	299.0	467.9	387.1	316.6	334.2	263.4	133.3	49.6	67.2	49.6
13	3182	171.1	293.5	472.9	277.0	306.9	316.2	233.2	66.9	126.6	65.4	14.9
14	2954	128.1	296.1	428.0	267.6	315.3	163.9	250.9	126.7	100.1	60.9	28.6
15	2795	167.4	283.5	405.5	215.1	240.4	189.3	243.1	119.9	105.7	35.7	12.1
16	2614	96.6	299.1	308.3	225.0	142.2	328.0	215.6	73.1	52.3	26.3	34.8
17	2530	122.1	297.7	301.0	234.6	185.3	191.2	123.9	151.7	99.5	43.6	17.8
18	2748	132.2	296.8	441.7	193.2	221.9	269.1	237.5	107.0	36.9	33.5	24.2
19	2846	162.0	295.5	413.1	208.4	233.6	298.4	184.7	136.4	55.0	53.6	33.7
20	3022	164.5	298.6	415.2	241.8	291.8	269.7	216.3	155.2	121.9	29.3	17.2
21	2834	168.6	281.0	395.1	284.4	221.5	179.7	184.8	130.1	78.4	36.1	48.3
22	2488	128.0	286.4	260.0	190.6	206.2	165.7	172.1	139.1	92.4	24.2	28.5
23	2182	147.4	265.5	277.8	196.1	156.5	86.3	113.2	94.4	92.8	21.9	41.9
24	1984	100.3	293.6	248.4	164.4	143.2	109.8	88.7	97.3	54.6	33.9	19.2

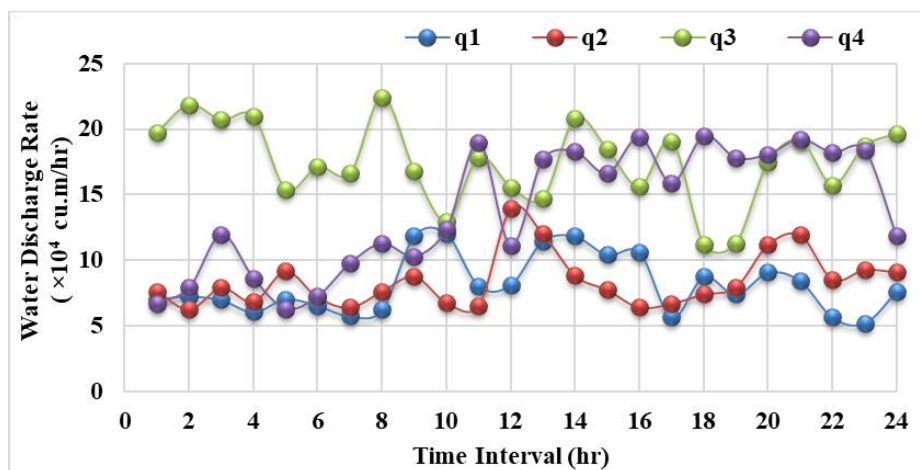
For economic scheduling of CPS for TS-II, the optimal cost attained by the POT-III is 24,43,921 \$, which is 6.98%, 6.29%, 1.52% and 3.04% better than QCSA, GWO, QCSA-GWO and POT-II, respectively. For emission scheduling of CPS for TS-II, the optimal emission attained by the POT-III is 2,44,568 lb which is 6.76%, 5.53%, 0.45% and 2.36% better than QCSA, GWO, QCSA-GWO and POT-II, respectively. In the case of MO-CPSGS, the non-dominated fuel cost and emission acquired by the POT-III are 24,51,016 \$ and 2,45,140 lb, respectively. The CPR attained by the POT-III for TS-II is 0.943, which is 43.1%, 58.22%, 6.55% and 19.21% superior compared to QCSA, GWO, QCSA-GWO and POT-II, respectively. The power and heat generation schedule attained by POT-III for TS-II is given in Table 6.4 and 6.5, respectively, which is within the scope of respective minimum and maximum limits of each generating unit in each sub-interval. Power and heat balance constraint is satisfied in each sub-interval. Figs. 6.8 and 6.9 represent the optimal hourly water discharge rate and reservoir volume of hydro attained by POT-III, respectively. The comparison of convergence characteristics is portrayed in Fig. 6.10, reflecting that the POT-III attains better convergence and solutions in fewer iterations than QCSA, GWO and QCSA-GWO and POT -II. The POT-II and III satisfies all the constraints of economic, emission and MO-CPSGS problems.

**Table 6.4(b)** Optimum power generation attained by POT-III for TS-II (case-III)

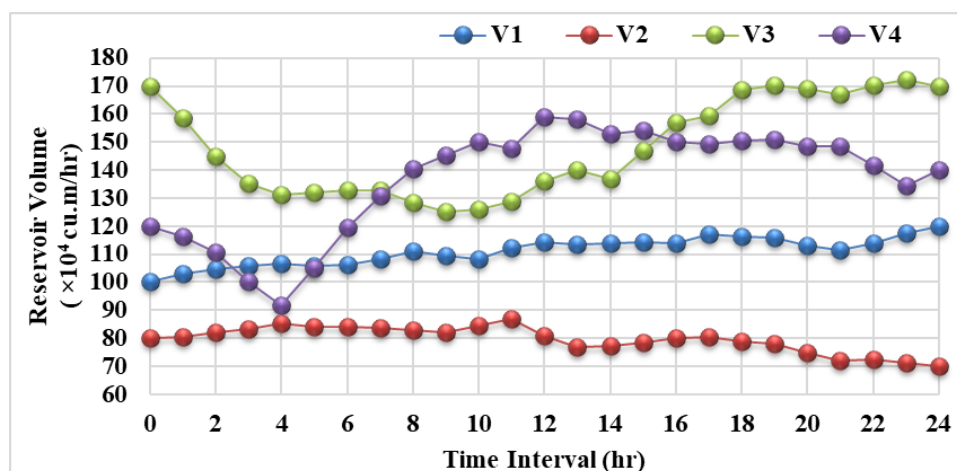
Time (hr)	Power (MW) (Hydro Units)				Power (MW) (CHP Units)	
	PH1	PH2	PH3	PH4	PC <sub>1</sub>	PC <sub>2</sub>
1	69.5	59.9	42.4	137.8	197.6	71.2
2	71.4	52.1	27.4	147.3	188.8	64.7
3	69.6	63.3	29.6	179.5	115.9	100.8
4	62.7	57.9	26.6	135.6	172.4	51.0
5	70.2	71.1	46.7	122.0	177.2	101.0
6	66.3	59.2	42.9	148.1	187.2	88.9
7	60.3	54.0	44.4	188.4	194.4	106.8
8	64.9	61.6	17.0	214.1	205.7	113.1
9	96.6	67.8	41.0	207.6	206.5	110.9
10	96.8	56.8	47.6	234.6	214.4	68.2
11	78.5	56.7	39.2	287.0	198.5	91.6
12	79.4	87.3	47.7	228.0	216.4	114.6
13	96.6	78.7	50.5	288.9	212.1	110.7
14	97.9	64.9	29.8	287.6	182.2	125.3
15	92.3	59.5	43.6	276.7	206.1	99.0
16	93.1	51.8	54.0	292.1	208.1	113.5
17	60.8	54.1	45.3	266.1	231.7	103.5
18	83.7	57.7	57.6	292.9	192.8	69.3
19	74.5	60.5	58.0	282.5	210.9	85.2

**Table 6.4(b)** Optimum power generation attained by POT-III for TS-II (case-III) (continued)

Time (hr)	Power (MW) (Hydro Units)				Power (MW) (CHP Units)	
	PH1	PH2	PH3	PH4	PC <sub>1</sub>	PC <sub>2</sub>
20	85.0	74.2	53.2	282.1	215.4	90.8
21	80.7	74.8	47.4	289.3	215.0	118.8
22	60.3	60.1	57.0	275.2	228.8	113.4
23	56.6	63.0	50.3	268.6	162.8	86.9
24	76.8	61.3	46.3	219.7	147.6	78.7



**Figure 6.8** Water discharge rate of hydro units by POT-III for TS-II (case-III)



**Figure 6.9** Reservoir volume of hydro units by POT-III for TS-II (case-III)

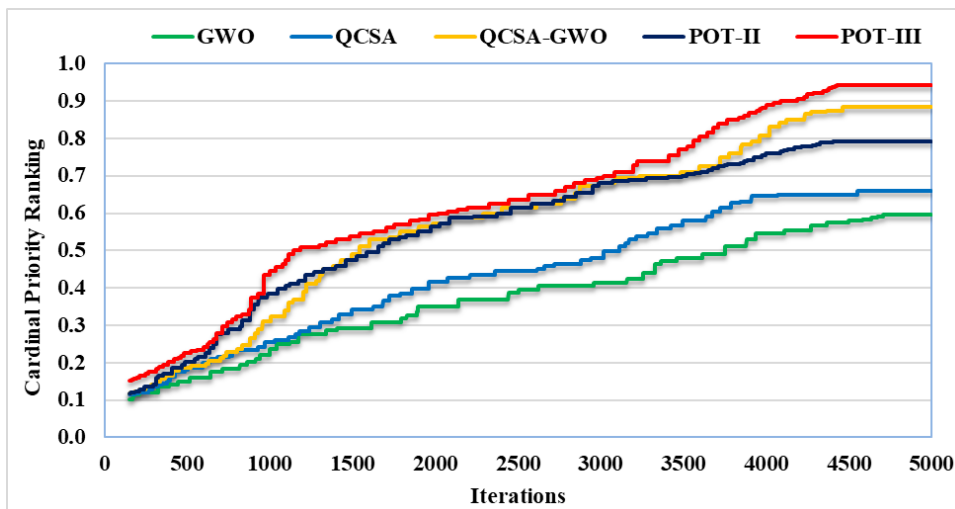
**Table 6.5** Optimum heat generation attained by POT-III for TS-II (case-III)

Time (hr)	Heat Demand (HD) (MWth)	Heat (MWth) (CHP units)		Heat (MWth) (Heat units)	Time (hr)	HD (MWth)	Heat (MWth) (CHP units)		Heat (MWth) (Heat units)
		HC <sub>1</sub>	HC <sub>2</sub>				H <sub>1</sub>	HC <sub>1</sub>	
1	390	136.6	21.2	232.2	13	470	176.9	134.2	158.9
2	400	161.1	13.5	225.4	14	460	158.3	24.5	277.3
3	410	76.3	22.9	310.8	15	450	171.3	77.4	201.2
4	420	149.5	16.7	253.8	16	450	175.4	93.7	180.9
5	440	130.9	123.0	186.1	17	420	52.1	65.5	302.4
6	450	87.6	88.5	273.9	18	435	138.0	53.9	243.0
7	450	48.5	131.6	269.9	19	445	177.1	39.7	228.3
8	455	111.5	93.1	250.4	20	450	143.5	92.8	213.7
9	460	157.0	127.2	175.8	21	445	166.8	91.0	187.1

**Table 6.5** Optimum heat generation attained by POT-III for TS-II (case-III) (continued)

Time (hr)	Heat Demand (HD) (MWth)	Heat (MWth) (CHP units)		Heat (MWth) (Heat units)	Time (hr)	HD (MWth)	Heat (MWth) (CHP units)		Heat (MWth) (Heat units)
		HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>			HC <sub>1</sub>	HC <sub>2</sub>	H <sub>1</sub>
10	460	179.9	51.3	228.8	22	435	31.0	51.3	352.7
11	470	142.8	78.7	248.5	23	400	143.9	35.0	221.0
12	480	159.6	119.5	201.0	24	400	114.9	25.6	259.5

**6.5.3.3 Test System-III:** The TS-III aims to examine the performance of POT-II and III on a medium-scale MO-CPSGS problem by increasing the number of thermal, CHP and heat units and having a total of 696 decision variables. In Table 6.6, the outcomes of the POT-II and III for TS-III (case-I, II and III) are compared to the outcomes of QCSA-GWO, QCSA and GWO techniques. For TS-III (case-I), the economic cost acquired by the POT-II is 57,77,378 \$ and the corresponding emission is 6,92,209 lb. For case-I, the results of the POT-II are 1.25% better than those of the QCSA in terms of minimal cost. For TS-III (case-II), the economic emission obtained by the POT-II is 6,67,886 lb and the corresponding cost is 58,20,651 \$. For TS-III (case-II), the minimum emission obtained by the POT-II is 5.34% lower than QCSA. For case-III, *i.e.*, MO-CPSGS, the economic cost and emission are 57,85,233 \$ and 67,23,34 lb, respectively. For MO-CPSGS problem, the POT-II decreased the cost by 1.6% and the emission by 5.11% compared to the QCSA technique. The higher value of CPR by the POT-II, *i.e.*, 0.817, as compared to QCSA, *i.e.*, 0.712, shows the superiority of the POT-II over the QCSA technique.



**Figure 6.10** Convergence characteristics for TS-II (case-III)

For TS-III (case-I), the POT-III obtained an optimal fuel cost of 54,86,652 \$ and the corresponding emission of 6,15,659 lb. In contrast, the fuel cost is increased to 55,92,994 \$ and emission is decreased to 5,96,290 lb for the emission GS of CPS. The optimum cost attained by the POT-III for economic GS of CPS is 6.22%, 5.86% and 0.76% better than QCSA, GWO and QCSA-GWO, respectively. The minimum emission obtained by the POT-III for emission GS of CPS is 15.49%, 14.64% and 2.12% better than QCSA, GWO, and QCSA-GWO, respectively. For the MO-CPSGS problem, the economic cost and emission are 54,88,676 \$ and 5,96,753 lb, respectively.

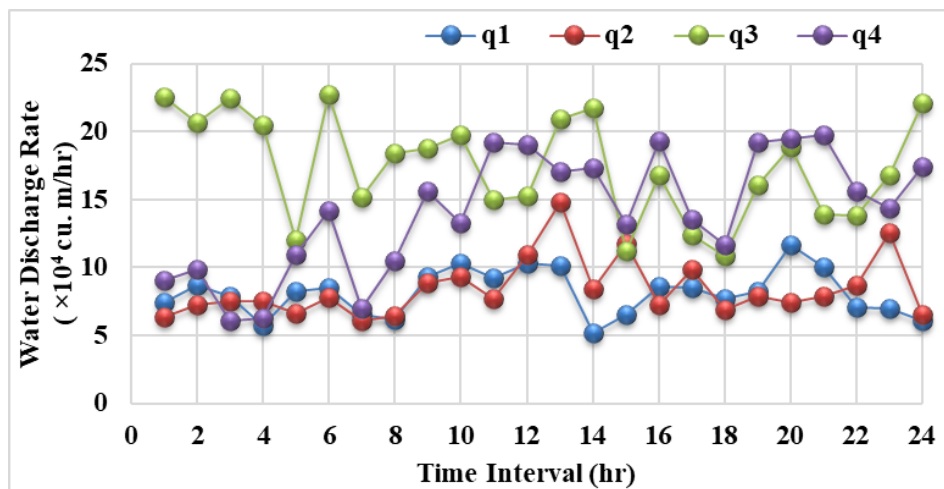
The optimum power and heat generation schedule of the MO-CPSGS problem obtained by the POT-III are given in Tables 6.7 and 6.8, respectively. The power generation of thermal, CHP and hydro units and heat generation of CHP and heat units satisfy the expected power and heat demand in each sub-interval. Each power and heat unit's power and heat output do not violate the limits in each sub-interval. The water discharge rate and reservoir volume of hydro units for the MO-CPSGS problem attained by POT-III is shown in Fig. 6.11 and Fig. 6.12, respectively. The figure and tables show that the POT-III satisfy the predefined constraints. The water discharge rates and reservoir volume of hydro units are within the set limits in each sub-interval. The CPR attained by the POT-III for TS-III is 0.976, which is 37.08%, 39.43%, 11.03% and 14.46% higher than QCSA, GWO, QCSA-GWO and POT-II, respectively, shows the superiority of the POT-III over the other techniques. Fig. 6.13 depicts the convergence characteristics of CPR for MO-CPSGS of TS-III. It could be affirmed from the convergence curve that the POT-III converges quickly and smoothly compared to QCSA and has better search ability. The figures and tables verify that the POT-III attained better results than QCSA, GWO, QCSA-GWO and POT-II and controlled all the constraints. Thus, it concludes that the hybridization of QCSA-GWO and CTM implementation primarily impacts the QCSA and GWO by improving the results. The POT-III has a strong ability to find the optimal global solution to complex multi-dimensional MO-CPSGS problems.

**Table 6.6** Comparison of results for TS-III

Technique	Case-I: Economic GS		Case-II: Emission GS		Case-III: MO-CPSGS			
	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	F <sub>1</sub> (\$)	F <sub>2</sub> (lb)	CPR	CPU Time (sec)
QCSA	58,50,636	7,15,856	59,76,981	7,05,571	58,79,332	7,08,533	0.712	68.25
GWO	58,28,034	7,10,247	59,24,903	6,98,565	58,57,121	6,99,657	0.700	62.56
QCSA-GWO	55,28,841	6,30,609	56,21,917	6,09,195	55,37,388	6,11,777	0.879	76.54
POT-II	57,77,378	6,92,209	58,20,651	6,67,886	57,85,233	6,72,334	0.817	70.04
POT-III	54,86,652	6,15,659	55,92,994	5,96,290	54,88,676	5,96,753	0.976	78.04

**Table 6.7(a)** Optimum power generation attained by POT-III for TS-III (case-III)

Time (hr)	PD (MW)	Power (MW) (Thermal Units)									
		PT <sub>1</sub>	PT <sub>2</sub>	PT <sub>3</sub>	PT <sub>4</sub>	PT <sub>5</sub>	PT <sub>6</sub>	PT <sub>7</sub>	PT <sub>8</sub>	PT <sub>9</sub>	PT <sub>10</sub>
1	2822	71.5	154.5	102.8	184.9	256.2	77.9	114.5	66.4	28.5	39.0
2	3000	23.4	72.9	76.7	324.1	194.1	83.1	201.3	116.8	72.8	67.3
3	3216	140.4	145.8	205.9	185.3	241.6	75.0	100.1	110.4	55.4	36.7
4	3462	101.4	183.7	126.0	283.2	230.7	120.0	218.6	107.7	56.3	22.3
5	3630	28.6	51.8	442.4	259.1	171.9	272.3	109.5	66.2	66.9	36.4
6	4056	147.7	269.6	498.0	269.7	235.7	206.4	192.5	84.5	78.5	38.6
7	4354	169.4	288.7	341.9	277.8	254.9	258.9	175.4	121.2	34.2	67.4
8	4562	168.0	286.1	490.3	288.4	307.6	317.8	229.3	151.5	92.6	44.3
9	4938	163.9	293.3	494.7	274.7	305.1	296.1	283.9	159.4	122.4	56.6
10	5124	170.5	241.7	472.5	330.1	394.5	307.2	253.6	83.1	128.9	45.9
11	5312	171.9	296.6	493.0	387.9	413.1	297.4	220.0	153.3	121.5	79.7
12	5450	147.8	247.7	481.0	411.6	424.3	299.5	264.6	121.4	90.9	62.1
13	5254	170.4	271.1	494.2	336.1	415.3	333.6	280.3	113.7	89.5	39.6
14	4878	148.3	293.1	449.3	382.7	275.2	188.9	274.8	151.0	43.6	48.0
15	4571	174.1	300.0	384.8	204.2	275.7	308.4	197.2	141.2	57.7	37.9
16	4168	86.9	279.7	316.1	229.3	306.0	258.6	89.7	67.0	58.2	60.1
17	4010	169.4	239.2	334.2	212.6	250.4	209.2	196.4	86.2	69.7	35.5
18	4376	125.7	283.5	468.1	247.1	204.1	298.6	161.5	140.5	106.3	46.1
19	4622	147.6	255.2	471.7	306.1	338.4	291.7	241.3	121.9	127.1	63.4
20	4994	163.5	298.7	494.5	413.8	327.1	298.6	241.7	152.1	119.0	57.6
21	4758	168.1	280.0	492.5	214.3	313.8	239.8	279.3	105.9	68.4	68.7
22	4116	146.5	190.0	481.8	318.3	266.3	256.7	190.3	154.6	54.8	21.9
23	3514	138.3	280.4	85.3	221.0	187.5	103.8	192.5	122.9	69.9	60.9
24	3168	20.5	133.8	326.6	222.5	213.9	98.0	94.5	127.5	35.4	25.9



**Figure 6.11** Water discharge rate of hydro units attained by POT-III for TS-III (case-III)

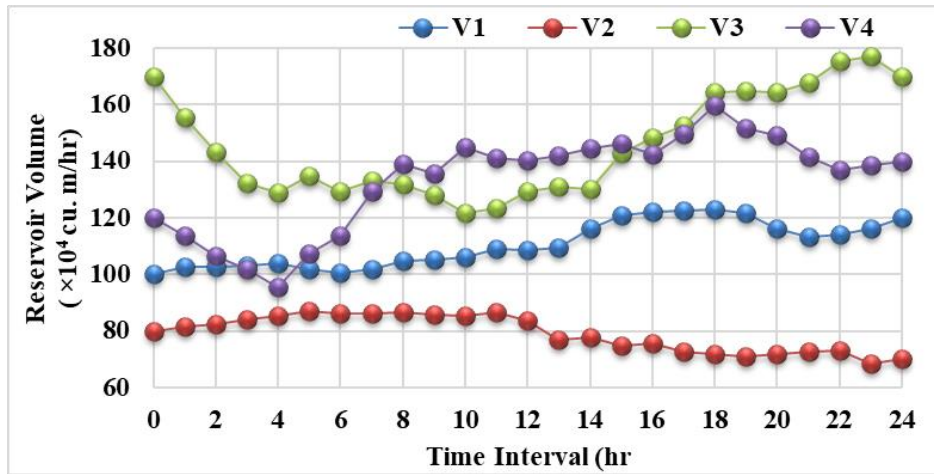


Figure 6.12 Reservoir volume of hydro units attained by POT-III for TS-III (case-III)

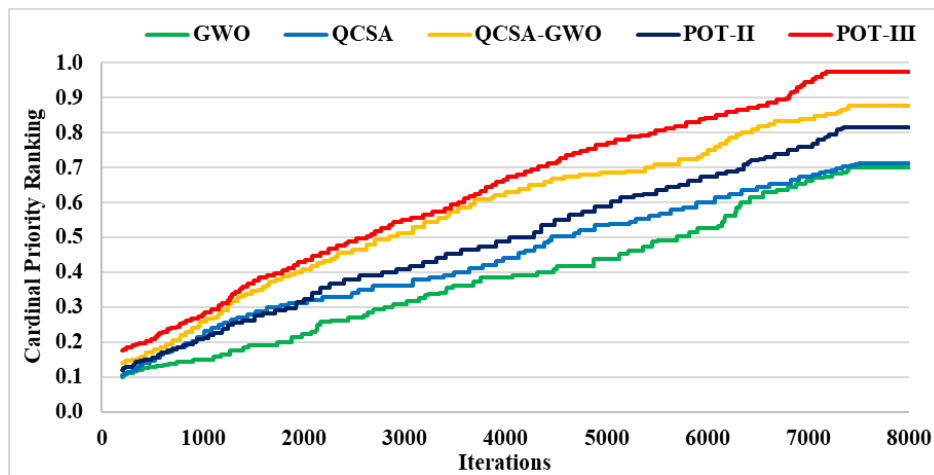


Figure 6.13 Convergence characteristics for TS-III (case-III)

Table 6.7(b) Optimum power generation attained by POT-III for TS-III (case-III)

Time (hr)	Power (MW) (Thermal Units)								
	PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
1	11.1	191.0	218.9	152.3	80.1	110.2	91.1	27.5	46.0
2	13.5	245.2	177.9	179.1	64.3	94.2	78.7	35.3	44.2
3	49.6	223.4	334.8	146.7	169.5	63.7	62.3	32.7	13.5
4	20.3	256.2	259.3	204.1	139.3	133.1	65.9	71.9	49.1
5	47.7	211.6	227.9	182.3	271.5	84.7	83.9	68.8	26.0
6	14.3	214.1	248.7	261.1	198.9	58.0	28.4	53.2	45.8
7	48.6	305.9	410.6	267.0	165.1	120.1	41.2	54.4	51.2
8	53.8	369.5	249.6	269.1	117.1	96.1	26.4	59.2	13.0
9	48.0	361.6	319.2	230.6	266.2	123.1	90.8	54.7	43.7
10	53.0	461.6	343.9	323.6	260.5	102.5	79.3	62.0	40.7
11	53.7	388.7	363.7	285.9	246.8	81.4	107.7	21.2	20.9
12	43.6	389.5	443.3	314.8	247.9	153.9	79.3	49.0	47.1
13	50.7	380.3	355.4	307.4	283.8	95.7	76.9	67.6	46.8
14	54.5	336.1	365.0	280.4	259.6	92.1	121.2	74.2	38.5
15	50.4	315.9	225.3	226.9	254.7	142.1	100.9	54.5	53.1
16	50.9	400.0	267.2	309.2	91.8	134.1	127.3	42.5	17.6
17	17.1	153.8	325.7	188.0	244.9	63.9	51.3	40.4	49.5
18	19.7	407.7	274.8	282.8	119.8	157.7	49.2	57.8	51.0
19	38.6	328.1	338.3	254.8	159.0	76.1	65.5	34.3	38.3
20	47.1	327.0	289.9	269.1	199.2	98.4	104.1	29.4	51.7
21	52.7	230.6	343.2	276.6	246.1	132.7	85.7	55.5	37.0
22	24.3	202.1	213.2	122.1	195.7	131.6	125.0	29.6	14.1

**Table 6.7(b)** Optimum power generation attained by POT-III for TS-III (case-III) (continued)

Time (hr)	Power (MW) (Thermal Units)								
	PT <sub>11</sub>	PT <sub>12</sub>	PT <sub>13</sub>	PT <sub>14</sub>	PT <sub>15</sub>	PT <sub>16</sub>	PT <sub>17</sub>	PT <sub>18</sub>	PT <sub>19</sub>
23	43.5	187.6	248.1	241.1	138.5	89.0	79.7	54.2	51.0
24	20.3	226.6	178.6	169.3	151.3	70.4	30.4	54.0	23.1

**Table 6.7(c)** Optimum power generation attained by POT-III for TS-III (case-III)

Time (hr)	Power (MW) (CHP Units)				Power (MW) (Hydro Units)			
	PC <sub>1</sub>	PC <sub>2</sub>	PC <sub>3</sub>	PC <sub>4</sub>	PH <sub>1</sub>	PH <sub>2</sub>	PH <sub>3</sub>	PH <sub>4</sub>
1	212.5	68.4	107.7	92.4	72.4	52.6	27.4	164.2
2	217.4	79.4	101.0	100.6	80.3	58.6	32.8	165.1
3	235.9	51.6	183.2	81.6	75.4	61.2	18.6	115.8
4	225.4	98.0	105.0	122.3	59.8	62.0	28.1	112.3
5	126.1	92.4	220.6	119.1	77.3	57.1	50.5	177.3
6	172.5	78.8	186.9	101.1	78.5	64.2	15.9	214.4
7	179.9	87.5	222.3	91.4	65.4	52.8	47.4	153.1
8	150.7	121.4	183.0	115.8	63.4	55.8	38.2	204.0
9	178.0	73.3	150.7	107.7	84.4	70.3	35.5	250.2
10	183.8	86.3	202.0	67.8	89.3	72.5	28.5	238.7
11	213.4	104.4	202.9	112.5	84.7	64.2	44.5	280.9
12	215.1	101.2	209.9	110.2	90.1	79.1	46.0	279.2
13	190.2	102.1	201.1	81.5	89.6	86.0	26.8	268.2
14	168.1	111.5	206.8	101.4	56.6	62.7	21.7	272.6
15	218.0	118.1	183.6	109.9	68.5	76.2	52.3	239.3
16	148.0	61.5	191.2	105.1	83.5	54.4	48.9	282.9
17	233.5	111.7	176.9	99.2	83.0	66.9	55.3	246.1
18	188.2	89.9	110.6	66.6	77.5	49.9	56.4	234.9
19	137.7	43.9	152.0	106.8	81.3	55.3	55.3	292.6
20	132.9	69.4	206.6	112.4	98.1	53.0	47.7	291.7
21	168.0	101.2	187.4	120.6	90.0	56.5	58.4	285.0
22	217.2	48.0	141.3	125.4	71.9	61.3	59.9	251.9
23	161.8	70.7	199.8	41.7	71.3	74.3	56.7	242.4
24	108.8	109.9	214.2	98.6	64.5	46.2	34.9	268.4

**Table 6.8** Optimum heat generation attained by POT-III for TS-III (case-III)

Time (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth) (Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
1	780	23.3	62.2	74.5	47.2	355.2	217.6
2	800	99.8	48.1	43.3	12.9	44.0	552.1
3	820	49.9	14.6	152.3	50.4	451.3	101.6
4	840	36.7	29.8	38.3	11.2	356.7	367.2
5	880	118.0	76.7	140.7	88.8	37.3	418.6
6	900	88.0	34.2	128.0	60.2	58.7	531.0
7	900	56.3	31.4	53.4	34.6	165.2	559.1
8	910	79.9	46.5	162.2	68.4	229.4	323.6
9	920	146.6	42.6	120.0	69.0	204.1	337.7
10	920	155.8	57.9	168.8	92.3	110.6	334.5
11	940	179.2	120.7	86.6	108.0	114.6	330.9
12	960	136.6	119.5	165.6	128.2	16.8	393.4
13	940	157.7	74.9	170.2	92.7	116.8	327.7
14	920	63.3	112.9	168.7	110.4	63.7	400.9
15	900	31.6	39.1	36.8	89.3	352.8	350.4
16	900	137.8	44.2	107.6	131.0	271.3	208.2
17	840	34.7	106.6	62.0	44.4	403.2	189.1
18	870	76.5	39.6	96.9	37.5	74.5	544.9
19	890	92.5	36.9	115.0	130.7	90.1	424.7
20	900	101.5	33.3	127.4	129.8	286.7	221.3

**Table 6.8** Optimum heat generation attained by POT-III for TS-III (case-III) (continued)

Time (hr)	HD (MWth)	Heat (MWth) (CHP units)				Heat (MWth) (Heat units)	
		HC <sub>1</sub>	HC <sub>2</sub>	HC <sub>3</sub>	HC <sub>4</sub>	H <sub>1</sub>	H <sub>2</sub>
21	890	146.2	60.6	114.2	58.2	167.3	343.5
22	870	61.4	35.0	87.7	26.1	270.3	389.5
23	800	63.8	29.5	58.1	64.5	316.6	267.5
24	800	50.9	42.0	179.4	109.2	162.4	256.1

## 6.6 CONCLUSIONS

In this chapter, the MO-CPSGS problem has been formulated. Two heuristic optimization techniques, *i.e.*, QCSA-MS and CTM-QCSA-GWO have been implemented to solve the MO-HTGS and MO-CPSGS problems. The performance of the POT-II and III are verified by implementing it on three test systems having three test cases. The CPR method has been utilized for searching the most satisfying non-dominated solution of MOGS problems. The first test system deals with MO-HTGS problem and the best cost and emission attained by the POT-II (case-III) are 42,703 \$ and 17,671 lb. The POT-II simultaneously saved 2.89% of the cost and 7.31% of emissions per day as compared to results of QCSA and it also attained a higher value of CPR, *i.e.*, 0.770, compared to its peers, which shows its superior performance than many other optimization techniques. The best-compromised cost, emission and CPR achieved by the POT-III are 42,703 \$, 17,671 lb and 0.814, respectively, which are better compared to results obtained by many existing methods. The CPR attained by POT-III is 5.71% better than POT-II.

The second and third test systems are medium-sized MO-CPSGS problems. For TS-II (case-III), the CPR attained by POT-III is 0.943, which 43.1%, 58.22%, 6.55% and 19.21% higher than CPR achieved by QCSA, GWO, QCSA-GWO and POT-II, respectively. A similar progression observed from the optimal results of TS-III reveals that the POT-III outperforms the results of QCSA, GWO and QCSA-GWO. Further, POT-III attained better results than POT-II. Moreover, the POT-III achieves better convergence characteristics and distribution diversity than QCSA, GWO, QCSA-GWO and POT-II. The results of hybrid QCSA-GWO reveal that it is superior to its peers. Further, results obtained by CTM-QCSA-GWO indicate that the application of CTM to

hybrid QCSA-GWO enhanced the results by tuning the algorithm parameters of QCSA-GWO using the chaotic values. Thus, it concludes that hybrid QCSA-GWO and POT-III are superior to other existing techniques. It is established from the results that the POTs are more capable of accomplishing excellent outcomes for complex multi-dimensional MO problems.

# CHAPTER 7

## CONCLUSIONS AND FUTURE SCOPE

### 7.1 INTRODUCTION

The significant contributions and the future scope of the research work are presented in this chapter.

### 7.2 CONTRIBUTIONS

The significant contributions of the research work are presented below:

1. The coordinated power system generation scheduling (CPSGS) problem is formulated. In coordinated power system (CPS), thermal, combined heat and power (CHP), heat and hydro units are considered. The CPSGS problem is solved for the scheduling period of twenty-four hours with sub-interval of one-hour. The valve-point loading effect of thermal units, multi-chain hydro units considering time delay between upstream and low stream reservoirs for water flow, mutual dependency of the power and heat generation of CHP units due to feasible operating region of CHP units and multiple constraints increase the complexity of the CPSGS problem and make it a non-convex, multi-modal optimization problem. Thus, in order to solve the CPSGS problem, three heuristic optimization techniques have been proposed.
2. The proposed optimization technique (POT)-I is grey wolf optimizer (GWO) with mutation strategies (GWO-MS) in which GWO is integrated with three mutation strategies, i.e., Cauchy, Gaussian and opposition based. The GWO explores the search space effectively and the solution obtained by GWO is further enhanced by three mutation strategies, Cauchy, Gaussian and opposition-based mutation. The integration of mutation strategies to GWO helps in avoiding stagnation of search in local optima, promote variability in the

3. population and maintaining a balance between the exploration and exploitation of the algorithm. The performance of the POT-I is validated by implementing it to four test systems including HTGS and small, medium and large sized CPSGS problems. The results obtained by POT-I for HTGS and CPSGS problems are compared with existing state of art techniques. The POT-I exhibits superiority over other state of art algorithms. Further, two statistical tests, *i.e.*, *t* test and Mann-Whitey test, have been applied to the test systems which demonstrates the robustness of the POT-I as compared to other state-of-the-art algorithms.
4. The POT-II is quantum based cuckoo search algorithm (QCSA) with mutation strategies (QCSA-MS). In POT-II, the QCSA has been used to explore the search space. Three mutation strategies, *i.e.*, Cauchy, Gaussian and opposition-based mutation strategies have been integrated with the QCSA technique for increasing the population diversity, avoiding premature convergence and to fulfil the requirement of an algorithm's balanced exploration and exploitation quality. The POT-II is implemented to solve HTGS and small and medium sized CPSGS problems. The optimal cost obtained by POT-II has been compared with the optimal cost obtained by other optimization techniques. The POT-II outperforms several existing states of art optimization techniques. Further, t-test has been evaluated for verifying the robustness of the POT-II.
5. The POT-III is chaotic tent map (CTM)-based quantum-cuckoo search algorithm (QCSA) with grey wolf optimizer (GWO) (CTM-QCSA-GWO). The POT-III incorporates the QCSA technique with the GWO technique, which has excellent exploration capability of QCSA and superior exploitation capability of the GWO technique. Further, the CTM is applied to get the adaptive value of the parameters of the hybrid QCSA-GWO technique, *i.e.*, the scaling factor of Levy flight, discovery probability of the random walk of QCSA and control parameter of GWO. In contrast, the QCSA has a constant value of these

parameters. The CTM enhances the solution quality and accelerates the convergence speed. The performance of the POT-III is extensively investigated on HTGS and CPSGS problems and compared with other techniques. The better results obtained by the POT-III show that it is a promising technique for the CPSGS problem.

6. The CHP-photo-voltaic generation scheduling (CHP-PV-GS) problem is formulated considering thermal, CHP, heat and photo-voltaic units. The CHP generation scheduling (CHPGS) and CHP-PV-GS problems are solved by POT-II, III, QCSA, GWO and QCSA-GWO techniques. The comparative analysis of results obtained by POT-II and III for CHPGS and CHP-PV-GS problems shows the superiority of POT-III over other techniques. The fuel cost obtained by POT-II and III for CHP-PV-GS problem is better as that of CHPGS problem, which shows that inclusion of renewable energy source significantly saves the fuel cost involved by thermal and CHP units.
7. The multi-objective (MO)-CPSGS problem is formulated considering the two objectives, *i.e.*, fuel cost and pollutant emission. The cardinal priority ranking method has been implemented for searching for the optimal non-dominated solution to the MO-HTGS and MO-CPSGS problems. The MO-HTGS and MO-CPSGS problems are solved by POT-II and III and the results obtained by the POTs are compared with published results and found satisfactory. The POT-II and III outperform several existing states of art optimization algorithms and indicating the superiority of the POTs. Further, POT-III outperforms the POT-II.
8. This research work emphasizes the practical relevance of its contributions to power utilities. By optimizing generation schedules, the proposed heuristic optimization techniques offer potential benefits such as fuel costs and emissions minimization of coordinated power system. Case studies and comparative evaluations demonstrate the applicability and effectiveness of the POTs in real-world utility environments.

**7.3 FUTURE SCOPE OF WORK**

This section highlights some possible future research directions as given below:

1. The proposed algorithms can be further modified by hybridising it with other potential heuristic algorithms, which may motivate the researchers to adopt the proposed approach for generation scheduling problems.
2. For solving the MO-CPSGS problem, MO optimization technique can be proposed.
3. The potential integration of machine learning techniques, real-time scheduling approaches and consideration of market dynamics and environmental impacts could also contribute to the holistic advancement of the research work.
4. The CPSGS problem can be extended by incorporating wind units and energy storage systems. The consideration of the transmission constraints and uncertainty of renewable energy sources can be studied as future work.
5. The CPSGS problem can consider several uncertainties, such as market clearing prices in the objective function and run-off in hydro units.
6. To improve power supply dependability, future research may examine a more flexible and adaptable power transmission protocol mechanism as well as demand-side response scheduling.

## REFERENCES

- Abdechiri, M., Meybodi, M. R. and Bahrami, H. (2013) ‘Gases brownian motion optimization: An algorithm for optimization (GBMO)’, *Applied Soft Computing Journal*, 13(5), pp. 2932–2946.
- Abdelaziz, A. and Ali, E. (2015) ‘Cuckoo search algorithm based load frequency controller design for nonlinear interconnected power’, *International Journal of Electrical Power and Energy Systems*, 73, pp. 632–643.
- Abdolmohammadi, H. R. and Kazemi, A. (2013) ‘A Benders decomposition approach for a combined heat and power economic dispatch’, *Energy Conversion and Management*, 71, pp. 21–31.
- Aghaei, J., Ahmadi, A., Shayanfar, H. A. and Rabiee, A. (2013) ‘Mixed integer programming of generalized hydro-thermal self-scheduling of generating units’, *Electrical Engineering*, 95(2), pp. 109–125.
- Agrawal, R. K., Kaur, B. and Sharma, S. (2020) ‘Quantum based whale optimization algorithm for wrapper feature selection’, *Applied Soft Computing Journal*, 89, p. 106092.
- Ahmadi, A., Kaymanesh, A., Siano, P., Janghorbani, M., Nezhad, A.E. and Sarno, D. (2015) ‘Evaluating the effectiveness of normal boundary intersection method for short-term environmental/economic hydrothermal self-scheduling’, *Electric Power Systems Research*, 123, pp. 192–204.
- Ahmadi, A., Moghimi, H., Nezhad, A. E., Agelidisa, V. G. and Sharaf, A. M. (2015) ‘Multi-objective economic emission dispatch considering combined heat and power by normal boundary intersection method’, *Electric Power Systems Research*, 129, pp. 32–43.
- Ahmadi, A., Masouleh, M. S., Janghorbani, M., Manjili, N. Y. G., Sharaf, A. M. and Nezhad, A. E. (2015) ‘Short term multi-objective hydrothermal scheduling’, *Electric Power Systems Research*, 121, pp. 357–367.
- Ahmed, J. and Salam, Z. (2014) ‘A maximum power point tracking (MPPT) for PV system using cuckoo Search with partial shading capability’, *Applied Energy*, 119, pp. 118–130.
- Ahmed, N., Ahmed, B., Anzar, M., Sohail, R., Adnan, Z., Guftaar, A. and Sidhu, S. (2015) ‘Combined emission economic dispatch of power system including solar photo voltaic generation’, *Energy Conversion and Management*, 92, pp. 82–91.
- Alatas, B. (2011) ‘ACROA: Artificial chemical reaction optimization algorithm for global optimization’, *Expert Systems With Applications*, 38(10), pp. 13170–13180.
- Albert, T. A. and Jeyakumar, A. E. (2005) ‘A modified hybrid EP – SQP approach for dynamic dispatch with valve-point effect’, *Electrical Power and Energy Systems*, 27, pp. 594–601.
- Alomoush, M. I. (2021) ‘Microgrid dynamic combined power – heat economic-emission dispatch with deferrable loads and price-based energy storage elements and power exchange’, *Sustainable Energy, Grids and Networks*, 26, p. 100479.
- Amjady, N. and Soleymanpour, H. R. (2010) ‘Daily hydrothermal generation scheduling by a new modified adaptive particle swarm optimization technique’, *Electric Power Systems Research*, 80(6), pp. 723–732.
- Andrews, P. S. (2006) ‘An investigation into mutation operators for particle swarm optimization’, *2006 IEEE International Conference on Evolutionary Computation*, pp. 1044–1051.
- Askarzadeh, A. (2016) ‘A novel metaheuristic method for solving constrained engineering

- optimization problems: Crow search algorithm', *Computers and Structures*, 169, pp. 1–12.
- Azizipanah-Abarghooee, R., Niknam, T., Bina, M. A. and Zare, M. (2015) 'Coordination of combined heat and power-thermal-wind-photovoltaic units in economic load dispatch using chance-constrained and jointly distributed random variables methods', *Energy*, 79, pp. 50–67.
- Bahmani-firouzi, B., Farjah, E. and Sei, A. (2013) 'A new algorithm for combined heat and power dynamic economic dispatch considering valve-point effects', *Energy*, 52, pp. 320–332.
- Banerjee, S., Dasgupta, K. and Kumar, C. (2016) 'Short term hydro-wind- thermal scheduling based on particle swarm optimization technique', *International Journal of Electrical Power & Energy Systems*, 81, pp. 275–288.
- Basu, M. (2004) 'An interactive fuzzy satisfying method based on evolutionary programming technique for multiobjective short-term hydrothermal scheduling', *Electric Power Systems Research*, 69, pp. 277–285.
- Basu, M. (2005) 'A simulated annealing-based goal-attainment method for economic emission load dispatch of fixed head hydrothermal power systems', *International Journal of Electrical Power & Energy Systems*, 27(2), pp. 147–153.
- Basu, M. (2006) 'Bi-objective generation scheduling of fixed head hydrothermal power systems through an interactive fuzzy satisfying method and particle swarm optimization', *International Journal of Emerging Electric Power Systems*, 6(1).
- Basu, M. (2008) 'Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II', *International Journal of Electrical Power and Energy Systems*, 30(2), pp. 140–149.
- Basu, M. (2010a) 'Combined heat and power economic dispatch by using differential evolution', *Electric Power Components and Systems*, 38(8), pp. 996–1004.
- Basu, M. (2010b) 'Economic environmental dispatch of hydrothermal power system', *International Journal of Electrical Power and Energy Systems*, 32(6), pp. 711–720.
- Basu, M. (2011a) 'Artificial immune system for fixed head hydrothermal power system', *Energy*, 36(1), pp. 606–612.
- Basu, M. (2011b) 'Bee colony optimization for combined heat and power economic dispatch', *Expert Systems with Applications*, 38(11), pp. 13527–13531.
- Basu, M. (2011c) 'Economic environmental dispatch of fixed head hydrothermal power systems using nondominated sorting genetic algorithm-II', *Applied Soft Computing Journal*, 11(3), pp. 3046–3055.
- Basu, M. (2012) 'Artificial immune system for combined heat and power economic dispatch', *International Journal of Electrical Power and Energy Systems*, 43(1), pp. 1–5.
- Basu, M. (2013) 'Combined heat and power economic emission dispatch using nondominated sorting genetic algorithm-II', *International Journal of Electrical Power and Energy Systems*, 53(1), pp. 135–141.
- Basu, M. (2014) 'Improved differential evolution for short-term hydrothermal scheduling', *International Journal of Electrical Power and Energy Systems*, 58, pp. 91–100.
- Basu, M. (2015) 'Combined heat and power economic dispatch using opposition-based group search optimization', *International Journal of Electrical Power and Energy Systems*, 73, pp. 819–829.
- Basu, M. (2016) 'Group search optimization for combined heat and power economic dispatch',

---

*International Journal of Electrical Power and Energy Systems*, 78, pp. 138–147.

Basu, M. (2019a) ‘Multi-area dynamic economic emission dispatch of hydro-wind-thermal power system’, *Renewable Energy Focus*, 28, pp. 11–35.

Basu, M. (2019) ‘Multi-region dynamic economic dispatch of solar- wind-hydro-thermal power system incorporating pumped hydro energy storage’, *Engineering Applications of Artificial Intelligence*, 86, pp. 182–196.

Basu, M. (2019b) ‘Squirrel search algorithm for multi-region combined heat and power economic dispatch incorporating renewable energy sources’, *Energy*, 182, pp. 296–305.

Basu, M. (2020) ‘Optimal generation scheduling of hydrothermal system with demand side management considering uncertainty and outage of renewable energy sources’, *Renewable Energy*, 146, pp. 530–542.

Basu, M. and Chowdhury, A. (2013) ‘Cuckoo search algorithm for economic dispatch’, *Energy*, 60, pp. 99–108.

Behera, S., Sahoo, C. P., Subudhib, B. and Pati, B. B. (2016) ‘Reactive power control of isolated wind-diesel hybrid power system using grey wolf optimization technique’, *Procedia Computer Science*, 92, pp. 345–354.

Beigvand, S. D., Abdi, H. and Scala, M. L. (2016) ‘Combined heat and power economic dispatch problem using gravitational search algorithm’, *Electric Power Systems Research*, 133, pp. 160–172.

Beyer, H. G. and Schwefel, H. P. (2002) ‘Evolution strategies-A comprehensive introduction’, *Natural Computing*, 1(1), pp. 3–52.

Bhamidi, L. and Shanmugavelu, S. (2019) ‘Multi-objective harmony search algorithm for dynamic optimal power flow with demand side management’, *Electric Power Components and Systems*, 47(8), pp. 721–731.

Bhattacharjee, K., Bhattacharya, A. and Dey, S. H. N. (2014) ‘Oppositional real coded chemical reaction based optimization to solve short-term hydrothermal scheduling problems’, *International Journal of Electrical Power and Energy Systems*, 63, pp. 145–157.

Bibiks, K., Hu, Y. F., Li, J. P., Pillai, P. and Smith, A. (2018) ‘Improved discrete cuckoo search for the resource-constrained project scheduling problem’, *Applied Soft Computing Journal*, 69, pp. 493–503.

Boushaki, S. I., Kamel, N. and Bendjeghaba, O. (2018) ‘A new quantum chaotic cuckoo search algorithm for data clustering’, *Expert Systems with Applications*, 96, pp. 358–372.

Bracco, S., Dentici, G. and Siri, S. (2013) ‘Economic and environmental optimization model for the design and the operation of a combined heat and power distributed generation system in an urban area’, *Energy*, 55, pp. 1014–1024.

Bruno, S., Iurlaro, C., La, S. C. and Marco, M. (2022) ‘Integration of operating reserve constraints in the predictive optimal dispatch of energy and storage resources in small islands’, *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe, IEEEIC / I and CPS Europe 2022*, pp. 1–6.

Bruno, S., Giannoccaro, G., Cosimo, I., La, S. M. and Marco, M. (2022) ‘Predictive Optimal Dispatch for Islanded Distribution Grids considering Operating Reserve Constraints’, *MELECON 2022 - IEEE Mediterranean Electrotechnical Conference, Proceedings. IEEE*, pp. 518–523.

## References

---

- Cavazzini, G., Pavesi, G. and Ardizzon, G. (2018) 'A novel two-swarm based PSO search strategy for optimal short-term hydro-thermal generation scheduling', *Energy Conversion and Management*. Elsevier, 164(February), pp. 460–481.
- Chakraborty, P., Roy, G. G., Panigrahi, B. K., Bansal, R. C. and Mohapatra, A. (2012) 'Dynamic economic dispatch using harmony search algorithm with modified differential mutation operator', *Electrical Engineering*, 94, pp. 197–205.
- Chang, S. C., Chen, C. H., Fong, I. and Luh, P. (1990) 'Hydroelectric generation scheduling with an effective differential dynamic programming algorithm', *IEEE Trans. Power Syst*, 5(3), pp. 737–743.
- Cheng, J., Wang, L., Jiang, Q., Cao, Z. and Xiong, Y. (2018) 'Cuckoo search algorithm with dynamic feedback information', *Future Generation Computer Systems*, 89, pp. 317–334.
- Cheung, N. J., Ding, X. M. and Shen, H. B. (2017) 'A nonhomogeneous cuckoo search algorithm based on quantum mechanism for real parameter optimization', *IEEE Transactions on Cybernetics*, 47(2), pp. 391–402.
- Chiang, C. (2007) 'Optimal economic emission dispatch of hydrothermal power systems', 29, pp. 462–469.
- Das, S., Biswas A., Dasgupta, S. and Ajith, A. (2009) 'Bacterial foraging optimization algorithm: theoretical foundations, analysis, and applications', *Foundations of Computational Intelligence Volume 3. Studies in Computational Intelligence*, 203, pp. 23–55.
- Das, S., Bhattacharya, A. and Chakraborty, A. K. (2018) 'Fixed head short-term hydrothermal scheduling in presence of solar and wind power', *Energy Strategy Reviews*, 22(June), pp. 47–60.
- Das, S., Bhattacharya, A. and Kumar, A. (2018) 'Solution of short-term hydrothermal scheduling using sine cosine algorithm', *Soft Computing*, 22(19), pp. 6409–6427.
- Dasgupta, K., Kumar, P. and Mukherjee, V. (2022) 'Solution of short term integrated hydrothermal-solar-wind scheduling using sine cosine algorithm', *Energy Strategy Reviews*, 40, p. 100824.
- Deb, K. (2001) *Multi-Objective Optimization using Evolutionary Algorithms*. John Wiley & Sons, Ltd.
- Deep, K. and Bansal, J. C. (2009) 'Hybridization of particle swarm optimization with quadratic approximation', *Opsearch*, 46(1), pp. 3–24.
- Dhillon, J. S., Parti, S. C. and Kothari, D. P. (2001) 'Fuzzy decision making in multiobjective long-term scheduling of hydrothermal system', 24, pp. 19–29.
- Dhillon, Jarnail S, Dhillon, J S and Kothari, D. P. (2011) 'Real coded genetic algorithm for stochastic hydrothermal generation scheduling', *Journal of Systems Science and Systems Engineering*, 20(Mar), pp. 87–109.
- Dias, B. H., Tomim, M. A., Marcato, A. L. M., Ramos, T. P., Brandi, R. B. S., Junior, I. C. S. and Filho, J. A. P. F. (2013) 'Parallel computing applied to the stochastic dynamic programming for long term operation planning of hydrothermal power systems', *European Journal of Operational Research*, 229(1), pp. 212–222.
- Dorigo, M., Maniezzo, V. and Coloni, A. (1996) 'Ant system: optimization by a colony of cooperating agents', *IEEE Transactions on systems, Man, and Cybernetics- Part B: Cybernetics*, 26(1), pp. 29–41.

- Dubey, H. M., Pandit, M. and Panigrahi, B. K. (2016) 'Hydro-thermal-wind scheduling employing novel ant lion optimization technique with composite ranking index', *Renewable Energy*, 99, pp. 18–34.
- Ebeed, M., Fateh, S. A., Kamel, S., Nasrat, L., Jurado, F. and Harrison, A. (2023) 'Incorporating photovoltaic inverter capability into stochastic optimal reactive power dispatch through an enhanced artificial gorilla troops optimizer', *IET Renewable Power Generation*, 17(13), pp. 3267–3288.
- Elaiw, A M, Xia, X. and Shehata, A. M. (2013) 'Combined heat and power dynamic economic dispatch with emission limitations using hybrid DE-SQP method', *Abstract and Applied Analysis*, 2013(1), pp. 1-10.
- Elattar, E. E. (2018) 'Modified harmony search algorithm for combined economic emission dispatch of microgrid incorporating renewable sources', *Energy*, 159, pp. 496-507.
- Elattar, E. E. (2019) 'Environmental economic dispatch with heat optimization in the presence of renewable energy based on modified shuffle frog leaping algorithm', *Energy*, 171, pp. 256–269.
- Erol, O. K. and Eksin, I. (2006) 'A new optimization method: big bang-big crunch', *Advances in Engineering Software*, 37(2), pp. 106–111.
- Facci, A. L., Andreassi, L. and Ubertini, S. (2014) 'Optimization of CHCP (combined heat power and cooling) systems operation strategy using dynamic programming', *Energy*, 66, pp. 387–400.
- Fakhar, M. S., Kashif, S. A. R., Saqib, M. A. and Hassan, T. (2015) 'Non cascaded short-term hydro-thermal scheduling using fully-informed particle swarm optimization', *International Journal of Electrical Power and Energy Systems*, 73, pp. 983–990.
- Fang, N., Zhou, J., Zhang, R., Liu, Y. and Zhang, Y. (2014) 'A hybrid of real coded genetic algorithm and artificial fish swarm algorithm for short-term optimal hydrothermal scheduling', *International Journal of Electrical Power and Energy Systems*, 62, pp. 617–629.
- Farhat, I. A. and El-Hawary, M. E. (2009) 'Optimization methods applied for solving the short-term hydrothermal coordination problem', *Electric Power Systems Research*, 79(9), pp. 1308–1320.
- Faridnia, N., Habibi, D., Lachowicz, S. and Kavousifard, A. (2019) 'Optimal scheduling in a microgrid with a tidal generation', *Energy*, 171, pp. 435–443.
- Farmer, J. D., Packard, N. H. and Perelson, A. S. (1986) 'The immune system, adaptation and machine learning', *Physica D: Nonlinear Phenomena*, 2(1–3), pp. 187–204.
- Feng, Z., Niub, W., Zhoua, J., Chengc, C. and Zhanga, Y. (2017) 'Scheduling of short-term hydrothermal energy system by parallel multi-objective differential evolution', *Applied Soft Computing Journal*, 61, pp. 58–71.
- Feng, Z., Niu, W. and Cheng, C. (2017) 'Multi-objective quantum-behaved particle swarm optimization for economic environmental hydrothermal energy system scheduling', *Energy*, 131, pp. 165–178.
- Formato, R. A. (2007) 'Central force optimization: a new metaheuristic with applications in applied electromagnetics', *Progress in Electromagnetics Research*, 77, pp. 425–91.
- Forough, A. B. and Roshandel, R. (2017) 'Multi objective receding horizon optimization for optimal scheduling of hybrid renewable energy system', *Energy & Buildings*. Elsevier B.V., 150, pp. 583–597.

## References

---

- Fu, X., Li, A., Wang, L. and Ji, C. (2011) 'Short-term scheduling of cascade reservoirs using an immune algorithm-based particle swarm optimization', *Computers and Mathematics with Applications*, 62(6), pp. 2463–2471.
- Gaidhane, P. J. and Nigam, M. J. (2018) 'A hybrid grey wolf optimizer and artificial bee colony algorithm for enhancing the performance of complex systems', *Journal of Computational Science*, 27, pp. 284–302.
- Gandomi, A. H., Yang, X. S., Talatahari, S. and Alavi, A. H. (2013) 'Firefly algorithm with chaos', *Communications in Nonlinear Science and Numerical Simulation*, 18(1), pp. 89–98.
- Garg, H. (2016) 'A hybrid PSO-GA algorithm for constrained optimization problems', *Applied Mathematics and Computation*. Elsevier Inc., 274, pp. 292–305.
- Ghorbani, N. (2016) 'Combined heat and power economic dispatch using exchange market algorithm', *International Journal of Electrical Power and Energy Systems*, 82, pp. 58–66.
- Gil, E., Bustos, J. and Rudnick, H. (2003) 'Short-term hydrothermal generation scheduling model using a genetic algorithm', *IEEE Transactions on Power Systems*, 18(4), pp. 1256–1264.
- Glotić, A. and Zamuda, A. (2015) 'Short-term combined economic and emission hydrothermal optimization by surrogate differential evolution', *Applied Energy*, 141, pp. 42–56.
- Guan, X., Zhang, L. and Luh, P. B. (1995) 'Nonlinear approximation method in Lagrangian relaxation-based algorithms for hydrothermal scheduling', *IEEE Transactions on Power Systems*, 10(2), pp. 772–778.
- Guha, D., Roy, P. K. and Banerjee, S. (2016a) 'Load frequency control of interconnected power system using grey wolf optimization', *Swarm and Evolutionary Computation*, 27, pp. 97–115.
- Guha, D., Roy, P. K. and Banerjee, S. (2016b) 'Load frequency control of large scale power system using quasi-oppositional grey wolf optimization algorithm', *Engineering Science and Technology, an International Journal*, 19(4), pp. 1693–1713.
- Gul, E., Kang, C. and Wang, J. (2019) 'Multi-Objective short-term integration of hydrothermal operation with wind and solar power using nonlinear programming', *Energy Procedia*. Elsevier B.V., 158, pp. 6274–6281.
- Gupta, S. and Deep, K. (2019) 'A novel random walk grey wolf optimizer', *Swarm and Evolutionary Computation*, pp. 101–112.
- Habibollahzadeh, H. and Bubenko, J. A. (1986) 'Application of decomposition techniques to short term operation planning of hydrothermal power system', *IEEE Trans. Power Syst*, 1(1), pp. 41–47.
- Hagh, M. T., Teimourzadeh, S., Alipour, M. and Aliasghary, P. (2014) 'Improved group search optimization method for solving CHPED in large scale power systems', *Energy Conversion and Management*, 80, pp. 446–456.
- Haghray, A., Mohammadi-ivatloo, B. and Seyedmonir, S. (2015) 'Real coded genetic algorithm approach with random transfer vectors-based mutation for short-term hydro-thermal scheduling', *IET Generation, Transmission & Distribution*, 9(1), pp. 75–89.
- Hancer, E., Xue, B., Zhang, M., Karaboga, D. and Akay, B. (2015) 'A multi-objective artificial bee colony approach to feature selection using fuzzy mutual information', *2015 IEEE Congress on Evolutionary Computation, CEC 2015 - Proceedings*. IEEE, pp. 2420–2427.
- Haroon, S. S. and Malik, T. N. (2017) 'Evaporation rate-based water cycle algorithm for short-

- term hydrothermal scheduling', *Arabian Journal for Science and Engineering*, 42, pp. 2615–2630.
- Hassan, A. S., Sun, Y. and Wang, Z. (2020) 'Multi-objective for optimal placement and sizing DG units in reducing loss of power and enhancing voltage profile using BPSO-SLFA', *Energy Reports*, pp. 1581–1589.
- Hatamlou, A. (2012) 'Black hole: a new heuristic optimization approach for data clustering', *Information Sciences*, 222, pp. 175–84.
- He, S., Wu, Q. H. and Saunders, J. R. (2009) 'Group search optimizer: An optimization algorithm inspired by animal searching behavior', *IEEE Transactions on Evolutionary Computation*, 13(5), pp. 973–990.
- He, Z., Zhou, J., Sun, N., Jia, B. and Qin, H. (2019) 'Integrated scheduling of hydro, thermal and wind power with spinning reserve', *Energy Procedia*, 158, pp. 6302–6308.
- Heidari, A. A. and Pahlavani, P. (2017) 'An efficient modified grey wolf optimizer with Lévy flight for optimization tasks', *Applied Soft Computing Journal*, 60, pp. 115–134.
- Hemmatian, H., Fereidoon, A. and Assareh, E. (2014) 'Optimization of hybrid laminated composites using the multi-objective gravitational search algorithm (MOGSA)', *Engineering Optimization*, 46(9), pp. 1169–1182.
- Holland, J. H. (1992) 'Genetic algorithms', *Scientific American*, 267(1), pp. 66–73.
- Hosseini, A., Yun, G. J., Yang, X. and Talatahari, S. (2013) 'Chaos-enhanced accelerated particle swarm optimization', *Communications in Nonlinear Science and Numerical Simulation*, 18(2), pp. 327–340.
- Hosseini-hemati, S., Beigvand, S. D., Abdi, H. and Rastgou, A. (2022) 'Society-based grey wolf optimizer for large scale combined heat and power economic dispatch problem considering power losses', *Applied Soft Computing*, 117, p. 108351.
- Hota, P. K., Barisal, A. K. and Chakrabarti, R. (2009) 'An improved PSO technique for short-term optimal hydrothermal scheduling', *Electric Power Systems Research*, 79, pp. 1047–1053.
- Huang, L. Ding, S., Yu, S., Wang, J. and Lu, K. (2016) 'Chaos-enhanced cuckoo search optimization algorithms for global optimization', *Applied Mathematical Modelling*, 40(5–6), pp. 3860–3875.
- Huo, Y. Zhuang, Y., Gu, J. and Ni, S. (2015) 'Elite-guided multi-objective artificial bee colony algorithm', *Applied Soft Computing*, 32, pp. 199–210.
- Ida Evangeline, S. and Rathika, P. (2022) 'Wind farm incorporated optimal power flow solutions through multi-objective horse herd optimization with a novel constraint handling technique', *Expert Systems with Applications*, p. 116544.
- Jap, N. and Dhillon, S. J. S. (2018) 'Multi-objective thermal power load dispatch using chaotic differential evolutionary algorithm and Powell's method', *Soft Computing*, 22(7), pp. 2159–2174.
- Jayabarathi, T., Afshin, Y., Ramesh, V. and Raghunathan, T. (2014) 'Combined heat and power economic dispatch problem using the invasive weed optimization algorithm', *Frontiers in Energy*, 8(1), pp. 25–30.
- Jayakumar, N., Subramanian, S., Ganesan, S., Elanchezhian, E. B. (2016) 'Grey wolf optimization for combined heat and power dispatch with cogeneration systems', *International Journal of Electrical Power and Energy Systems*, 74, pp. 252–264.
- Jordehi, A. R. (2015) 'Enhanced leader PSO (ELPSO): A new PSO variant for solving global

- optimisation problems’, *Applied Soft Computing Journal*, 26, pp. 401–417.
- Kamboj, V. K., Bath, S. K. and Dhillon, J. S. (2016) ‘Solution of non-convex economic load dispatch problem using grey wolf optimizer’, *Neural Computing and Applications*, 27(5), pp. 1301–1316.
- Kansal, S., Kumar, V. and Tyagi, B. (2016) ‘Hybrid approach for optimal placement of multiple DGs of multiple types in distribution networks’, *International Journal of Electrical Power and Energy Systems*, 75, pp. 226–235.
- Karaboga, D. and Basturk, B. (2007) ‘Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems’, *Advances in Soft Computing: Foundations of Fuzzy Logic and Soft Computing*, 4529, pp. 789–798.
- Kaur, A. and Narang, N. (2019) ‘Optimum generation scheduling of coordinated power system using hybrid optimization technique’, *Electrical Engineering*, 101(2), pp. 379–408.
- Kaveh, A. and Khayatazad, M. (2012) ‘A new meta-heuristic method: ray optimization’, *Computers & Structures*, 112, pp. 283–94.
- Kaveh, A. and Talatahari, S. (2010) ‘A novel heuristic optimization method: charged system search’, *Acta Mechanica*, 213(3), pp. 267–89.
- Kennedy, J. and Eberhart, R. (1995) ‘Particle swarm optimization’, *Proceedings, IEEE international conference*, pp. 1942–1948.
- Khadanga, R. K., Kumar, A. and Panda, S. (2022) ‘A modified grey wolf optimization with cuckoo search algorithm for load frequency controller design of hybrid power system’, *Applied Soft Computing*, 124, p. 109011.
- Kim, J. S. and Edgar, T. F. (2014) ‘Optimal scheduling of combined heat and power plants using mixed-integer nonlinear programming’, *Energy*, 77, pp. 675–690.
- Kirkpatrick, S., Gelatt, C. D. and Vecchi, M. P. (1983) ‘Optimization by simulated annealing’, *Science*, 220(4598), pp. 671–80.
- Kohli, M. and Arora, S. (2018) ‘Chaotic grey wolf optimization algorithm for constrained optimization problems’, *Journal of Computational Design and Engineering*, 5(4), pp. 458–472.
- Kumar, A. and Dhillon, J. S. (2022) ‘Environmentally sound short-term hydrothermal generation scheduling using intensified water cycle approach’, *Applied Soft Computing*, 127, p. 109327.
- Kumar, P., Kumar, V. and Tyagi, B. (2022) ‘Sequence-Based Hybrid Technique for Islanding Detection for Microgrid with RES’, *IEEE Transactions on Industry Applications*, 58(1), pp. 185–200.
- Kumar Roy, P., Sur, A. and Pradhan, D. K. (2013) ‘Optimal short-term hydro-thermal scheduling using quasi-oppositional teaching learning based optimization’, *Engineering Applications of Artificial Intelligence*, 26(10), pp. 2516–2524.
- Lakshminarasimman, L. and Subramanian, S. (2006) ‘Short-term scheduling of hydrothermal power system with cascaded reservoirs by using modified differential evolution’, *IEE Proc. Gener. Transm. Distrib.*, 153(6), pp. 693–700.
- Lakshminarasimman, L. and Subramanian, S. (2008) ‘A modified hybrid differential evolution for short-term scheduling of hydrothermal power systems with cascaded reservoirs’, *Energy Conversion and Management*, 49(10), pp. 2513–2521.
- Lal, D. K., Barisal, A. K. and Tripathy, M. (2016) ‘Grey wolf optimizer algorithm based fuzzy

- PID controller for AGC of multi-area power system with TCPS', *Procedia Computer Science*, 92, pp. 99–105.
- Lasemi, M. A., Assili, M. and Hajizadeh, A. (2020) 'Multi-objective hydrothermal generation scheduling and fuel dispatch management considering liquid fuel dispatch network modeling', *Electric Power Systems Research*, 187, p. 106436.
- Layeb, A. (2013) 'A hybrid quantum inspired harmony search algorithm for 0–1 optimization problems', *Journal of Computational and Applied Mathematics*, 253, pp. 14–25.
- Li, C., Zhou, J., Lu, P. and Wang, C. (2015) 'Short-term economic environmental hydrothermal scheduling using improved multi-objective gravitational search algorithm', *Energy Conversion and Management*, 89, pp. 127–136.
- Li, X. and Yin, M. (2015) 'Modified cuckoo search algorithm with self adaptive parameter method', *Information Sciences*, 298, pp. 80–97.
- Li, Y., Wang, J., Zhao, D., Li, G. and Chen C. (2018) 'A two-stage approach for combined heat and power economic emission dispatch: combining multi-objective optimization with integrated decision making', *Energy*, 162, pp. 237–254.
- Liao, X., Zhou, J., Ouyang, S., Zhang, R. and Zhang, Y. (2013) 'An adaptive chaotic artificial bee colony algorithm for short-term hydrothermal generation scheduling', *International Journal of Electrical Power and Energy Systems*, 53(1), pp. 34–42.
- Lin, W., Yu, D. Y., Wang, S., Zhang, C., Zhang, S., Tian, H., Luo, M. and Liu, S. (2015) 'Multi-objective teaching-learning-based optimization algorithm for reducing carbon emissions and operation time in turning operations', *Engineering Optimization*, 47(7), pp. 994–1007.
- Liu, D., Zang, C. and Zeng, P. (2018) 'Research on the optimal dispatch of wind power consumption based on combined heat and power with thermal energy storage', *Energy Procedia*, 152, pp. 978–983.
- Liu, J., Xu, W. and Sun, J. (2005) 'Quantum-behaved particle swarm optimization with mutation operator', *Proceedings of the 17th IEEE Int. Conf. on Tools with Artificial Intelligence*.
- Liu, M., Shi, Y. and Fang, F. (2013) 'Optimal power flow and PGU capacity of CCHP systems using a matrix modeling approach', *Applied Energy*, 102, pp. 794–802.
- Lokeshgupta, B. and Sivasubramani, S. (2022) 'Dynamic economic and emission dispatch with renewable energy integration under uncertainties and demand-side management', *Electrical Engineering*, 104(4), pp. 2237–2248.
- Long, W., Jiao, J., Liang, X., and Tang, M. (2018a) 'An exploration-enhanced grey wolf optimizer to solve high-dimensional numerical optimization', *Engineering Applications of Artificial Intelligence*, 68, pp. 63–80.
- Long, W., Jiao, J., Liang, X., and Tang, M. (2018b) 'Inspired grey wolf optimizer for solving large-scale function optimization problems', *Applied Mathematical Modelling*, 60, pp. 112–126.
- Long, W., Caia, S., Jiaob, J., Xub, M. and Wu, T. (2020) 'A new hybrid algorithm based on grey wolf optimizer and cuckoo search for parameter extraction of solar photovoltaic models', *Energy Conversion and Management*, 203, p. 112243.
- Lopez-garcia, P., Onieva, E., Osaba, E., Masegosa, A. D. and Perallos, A. (2016) 'Regular articles GACE: A meta-heuristic based in the hybridization of genetic algorithms and cross entropy methods for continuous optimization', *Expert Systems With Applications*, 55, pp. 508–519.

## References

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- López-Salgado, C. J., Añó, O. and Ojeda-Esteybar, D. M. (2016) 'Hydrothermal scheduling with variable head hydroelectric plants: Proposed strategies using benders decomposition and outer approximation', *IEEE Power and Energy Conference at Illinois, PECEI 2016*, pp. 7–14.
- Lu, P., Zhou, J., Wang, C., Qiao, Q. and Mo, L. (2015) 'Short-term hydro generation scheduling of Xiluodu and Xiangjiaba cascade hydropower stations using improved binary-real coded bee colony optimization algorithm', *Energy Conversion and Management*, 91, pp. 19–31.
- Lu, S. and Sun, C. (2011) 'Quadratic approximation based differential evolution with valuable trade off approach for bi-objective short-term hydrothermal scheduling', *Expert Systems with Applications*, 38(11), pp. 13950–13960.
- Lu, Y., Zhou, J., Qin, H., Wang, Y. and Zhang, Y. (2010) 'An adaptive chaotic differential evolution for the short-term hydrothermal generation scheduling problem', *Energy Conversion and Management*, 51(7), pp. 1481–1490.
- Lu, Y., Zhou, J., Qin, H., Wang, Y. and Zhang, Y. (2011) 'A hybrid multi-objective cultural algorithm for short-term environmental/economic hydrothermal scheduling', *Energy Conversion and Management*, 52(5), pp. 2121–2134.
- Majumder, A., Laha, D. and Suganthan, P. N. (2018) 'A hybrid cuckoo search algorithm in parallel batch processing machines with unequal job ready times', *Computers and Industrial Engineering*, 124(June), pp. 65–76.
- Mandal, K. K., Basu, M. and Chakraborty, N. (2008) 'Particle swarm optimization technique based short-term hydrothermal scheduling', *Applied Soft Computing Journal*, 8(4), pp. 1392–1399.
- Mandal, K. K. and Chakraborty, N. (2008) 'Differential evolution technique-based short-term economic generation scheduling of hydrothermal systems', *Electric Power Systems Research*, 78(11), pp. 1972–1979.
- Mandal, K. K. and Chakraborty, N. (2009) 'Short-term combined economic emission scheduling of hydrothermal power systems with cascaded reservoirs using differential evolution', *Energy Conversion and Management*, 50, pp. 97–104.
- Mandal, K. K. and Chakraborty, N. (2011) 'Short-term combined economic emission scheduling of hydrothermal systems with cascaded reservoirs using particle swarm optimization technique', *Applied Soft Computing Journal*, 11(1), pp. 1295–1302.
- Mareli, M. and Twala, B. (2018) 'An adaptive Cuckoo search algorithm for optimisation', *Applied Computing and Informatics*, 14(2), pp. 107–115.
- Meng, A., Mei, P., Yin, H., Peng, X. and Guo, Z. (2015) 'Crisscross optimization algorithm for solving combined heat and power economic dispatch problem', *Energy Conversion and Management*, 105, pp. 1303–1317.
- Ming, B., Liu, P., Cheng, L., Zhou, Y. and Wang, X. (2018) 'Optimal daily generation scheduling of large hydro – photovoltaic hybrid power plants', *Energy Conversion and Management*, 171(June), pp. 528–540.
- Mirjalili, S. (2015) 'Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm', *Knowledge-Based Systems*, 89, pp. 228–249.
- Mirjalili, S., Saremia, S., Mirjalili, S. M., Coelho, L. S. (2016) 'Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization', *Expert Systems with Applications*, 47, pp. 106–119.
- Mirjalili, S., Mirjalili, S. M. and Lewis, A. (2014) 'Grey wolf optimizer', *Advances in Engineering*

*Software*, 69, pp. 46–61.

Mohammadi-ivatloo, B., Moradi-dalvand, M. and Rabiee, A. (2013) ‘Combined heat and power economic dispatch problem solution using particle swarm optimization with time varying acceleration coefficients’, *Electric Power Systems Research*, 95, pp. 9–18.

Mohan, H., Pandit, M. and Panigrahi, B. K. (2016) ‘Ant lion optimization for short-term wind integrated hydrothermal power generation scheduling’, *International Journal of Electrical Power and Energy Systems*, 83, pp. 158–174.

Mohanty, S. R., Kishor, N. and Ray, P. K. (2014) ‘Robust H-infinite loop shaping controller based on hybrid PSO and harmonic search for frequency regulation in hybrid distributed generation system’, *International Journal of Electrical Power and Energy Systems*, 60, pp. 302–316.

Moravej, Z. and Akhlaghi, A. (2013) ‘A novel approach based on cuckoo search for DG allocation in distribution network’, *International Journal of Electrical Power and Energy Systems*, 44(1), pp. 672–679.

Motevasel, M., Seifi, A. R. and Niknam, T. (2013) ‘Multi-objective energy management of CHP (combined heat and power)-based micro-grid’, *Energy*, 51, pp. 123–136.

Mu, Y., Li, H. Yu, X., Jia, H., Wang, M., Hou, K., and Wang, Z. (2021) ‘A scenario-based optimal dispatch for joint operation of wind farms and combined heat and power plants considering energy flexibilities in heating networks’, *Electric Power Systems Research*, (July), p. 107683.

Murali, G. B., Deepak, B., Biswal, B., Mohanta, G. B. and Rout, A. (2018) ‘Robotic optimal assembly sequence using improved cuckoo search algorithm’, *Procedia Computer Science*, 133, pp. 323–330.

Muro, C., Escobedo, R., Spector, L. and Coppinger, R. P. (2011) ‘Wolf-pack (*Canis lupus*) hunting strategies emerge from simple rules in computational simulations’, *Behavioural Processes*, 88(3), pp. 192–197.

Murugan, R., Mohan, M. R., Rajan, C. C. A., Sundari, P. D. and Arunachalam, S. (2018) ‘Hybridizing bat algorithm with artificial bee colony for combined heat and power economic dispatch’, *Applied Soft Computing Journal*, 72, pp. 189–217.

Nagendra Rao, P. S. (2006) ‘Combined heat and power economic dispatch: A direct solution’, *Electric Power Components and Systems*, 34(9), pp. 1043–1056.

Naik, A., Chandra, S. and Abraham, A. (2020) ‘Modified Social Group Optimization — a meta-heuristic algorithm to solve short-term hydrothermal scheduling’, *Applied Soft Computing Journal*, 95, p. 106524.

Narang, N. (2017) ‘Short-term hydrothermal generation scheduling using improved predator influenced civilized swarm optimization technique’, *Applied Soft Computing Journal*, 58, pp. 207–224.

Narang, N. (2018) ‘Hydro-thermal generation scheduling using integrated gravitational search algorithm and predator – prey optimization technique’, *Neural Computing and Applications*, 30(2), pp. 519–538.

Narang, N., Dhillon, J. S. and Kothari, D. P. (2012) ‘Multi-objective short-term hydrothermal generation scheduling using predator-prey optimization’, *Electric Power Components and Systems*, 40(15), pp. 1708–1730.

Narang, N., Dhillon, J S and Kothari, D. P. (2012) ‘Multiobjective fixed head hydrothermal scheduling using integrated predator-prey optimization and Powell search method’, *Energy*, 47(1),

pp. 237–252.

Narang, N., Dhillon, J. S. and Kothari, D. P. (2014a) ‘Scheduling short-term hydrothermal generation using predator prey optimization technique’, *Applied Soft Computing Journal*, 21, pp. 298–308.

Narang, N., Dhillon, J. S. and Kothari, D. P. (2014b) ‘Weight pattern evaluation for multiobjective hydrothermal generation scheduling using hybrid search technique’, *International Journal of Electrical Power and Energy Systems*, 62, pp. 665–678.

Narang, N., Sharma, E. and Dhillon, J. S. (2017) ‘Combined heat and power economic dispatch using integrated civilized swarm optimization and Powell’s pattern search method’, *Applied Soft Computing Journal*, 52, pp. 190–202.

Nazari-Heris, M. *et al.* (2018) ‘Improved harmony search algorithm for the solution of non-linear non-convex short-term hydrothermal scheduling’, *Energy*, 151, pp. 226–237.

Nazari-Heris, M., Mohammadi-Ivatloo, B. and Haghrah, A. (2017) ‘Optimal short-term generation scheduling of hydrothermal systems by implementation of real-coded genetic algorithm based on improved Mühlenbein mutation’, *Energy*, 128, pp. 77–85.

Nezhad, A. E., Javadi, M. S. and Rahimi, E. (2014) ‘Applying augmented e-constraint approach and lexicographic optimization to solve multi-objective hydrothermal generation scheduling considering the impacts of pumped-storage units’, *International Journal of Electrical Power and Energy Systems*, 55, pp. 195–204.

Nguyen, T. T. and Vo, D. N. (2015a) ‘Modified cuckoo search algorithm for short-term hydrothermal scheduling’, *International Journal of Electrical Power and Energy Systems*, 65, pp. 271–281.

Nguyen, T. T. and Vo, D. N. (2015b) ‘The application of one rank cuckoo search algorithm for solving economic load dispatch problems’, *Applied Soft Computing Journal*, 37, pp. 763–773.

Nguyen, T. T. and Vo, D. N. (2017) ‘Modified cuckoo search algorithm for multiobjective short-term hydrothermal scheduling’, *Swarm and Evolutionary Computation*, 37(February), pp. 73–89.

Nguyen, T. T., Vo, D. N. and Dinh, B. H. (2016) ‘Cuckoo search algorithm for combined heat and power economic dispatch’, *International Journal of Electrical Power and Energy Systems*, 81, pp. 204–214.

Nguyen, T. T., Vo, D. N. and Dinh, B. H. (2018) ‘An effectively adaptive selective cuckoo search algorithm for solving three complicated short-term hydrothermal scheduling problems’, *Energy*, 155, pp. 930–956.

Nguyen, T. T., Vo, D. N. and Truong, A. V. (2014) ‘Cuckoo search algorithm for short-term hydrothermal scheduling’, *Applied Energy*, 132, pp. 276–287.

Niknam, T., Azizipanah-Abarghooee, R., Roosta, A. and Amiri, B. (2012) ‘A new multi-objective reserve constrained combined heat and power dynamic economic emission dispatch’, *Energy*, 42(1), pp. 530–545.

Nilsson, O. and Sjelvgren, D. (1996) ‘Mixed-Integer programming applied to short-term planning of a hydro-thermal system’, *IEEE Transactions on Power Systems*, 11(1), pp. 281–286.

Ojeda-Esteybar, D. M., Lopez-Salgado, C. J., Pringles, R., Ano, O. and Rubio-Barros, R. G. (2020) ‘Co-optimization in the operation of hydroelectric and solar generation in the province of San Juan: Methodology’, *2020 IEEE PES Transmission and Distribution Conference and Exhibition - Latin America, T and D LA 2020*.

- Oliveira, G. G. and Soares, S. (1995) 'A second-order network flow algorithm for hydrothermal scheduling', *IEEE Trans. Power Syst*, 10(3), pp. 1635–1641.
- Ourahou, M., Ayir, W., Hassouni, B. E. and Haddi, A. (2020) 'Review on smart grid control and reliability in presence of renewable energies : Challenges and prospects', *Mathematics and Computers in Simulation*, 167, pp. 19–31.
- Pan, W. (2012) 'A new fruit fly optimization algorithm : taking the financial distress model as an example', *Knowledge-Based Systems*, 26, pp. 69–74.
- Patwal, R. S. and Narang, N. (2018) 'Crisscross PSO algorithm for multi-objective generation scheduling of pumped storage hydrothermal system incorporating solar units', *Energy Conversion and Management*, 169(May), pp. 238–254.
- Patwal, R. S. and Narang, N. (2020a) 'Multi-objective generation scheduling of integrated energy system using fuzzy based surrogate worth trade-off approach', *Renewable Energy*, 156, pp. 864–882.
- Patwal, R. S. and Narang, N. (2020b) 'Optimal generation scheduling of pumped storage hydrothermal system with wind energy sources', *Applied Soft Computing Journal*, 93, p. 106345.
- Patwal, R. S., Narang, N. and Garg, H. (2018) 'A novel TVAC-PSO based mutation strategies algorithm for generation scheduling of pumped storage hydrothermal system incorporating solar units', *Energy*, 142, pp. 822–837.
- Pereira, S., Ferreira, P., Ismael, A. and Vaz, F. (2012) 'Short-term scheduling model for a wind-hydro-thermal electricity system', *Proceedings Of Ecos 2012 - The 25th International Conference On Efficiency, Cost, Optimization, Simulation And Environmental Impact Of Energy Systems June 26-29, 2012, Perugia, Italy*, pp. 1–11.
- Pinto, R. J., Borges, C. L. T. and Maceira, M. E. P. (2013) 'An efficient parallel algorithm for large scale hydrothermal system operation planning', *IEEE Transactions on Power Systems*. IEEE, 28(4), pp. 4888–4896.
- Piperagkas, G. S., Anastasiadis, A. G. and Hatziargyriou, N. D. (2011) 'Stochastic PSO-based heat and power dispatch under environmental constraints incorporating CHP and wind power units', *Electric Power Systems Research*, 81(1), pp. 209–218.
- Pradhan, M., Roy, P. K. and Pal, T. (2016) 'Grey wolf optimization applied to economic load dispatch problems', *International Journal of Electrical Power and Energy Systems*, 83, pp. 325–334.
- Pradhan, P. M. and Panda, G. (2012) 'Solving multiobjective problems using cat swarm optimization', *Expert Systems with Applications*, 39(3), pp. 2956–2964.
- Puspaningrum, A. and Sarno, R. (2017) 'A hybrid cuckoo optimization and harmony search algorithm for software cost estimation', *Procedia Computer Science*, 124, pp. 461–469.
- Qin, H., Zhou, J., Lu, Y., Wang, Y. and Zhang, Y. (2010) 'Multi-objective differential evolution with adaptive Cauchy mutation for short-term multi-objective optimal hydro-thermal scheduling', *Energy Conversion and Management*, 51(4), pp. 788–794.
- Qu, B. Y., Liang, J. J., Zhu, Y. S., Wang, Z. Y. and Suganthan, P. N. (2016) 'Economic emission dispatch problems with stochastic wind power using summation based multi-objective evolutionary algorithm', *Information Sciences*, 351, pp. 48–66.
- Rajpurohit, B. S., Singh, S. N. and Erlich, I. (2008) 'Wind power in electricity markets: key issues and challenges', *International Journal of Energy Technology and Policy*, 6(3), pp. 196–211.

## References

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- Ramesh, V., Jayabarathi, T., Shrivastava, N. and Baska, A. (2009) 'A novel selective particle swarm optimization approach for combined heat and power economic dispatch', *Electric Power Components and Systems*, 37(11), pp. 1231–1240.
- Rashedi, E., Nezamabadi-pour, H. and Saryazdi, S. (2009) 'GSA: A gravitational search algorithm', *Information Sciences*, 179(13), pp. 2232–2248.
- Rasoulzadeh-Akhijahani, A. and Mohammadi-Ivatloo, B. (2015) 'Short-term hydrothermal generation scheduling by a modified dynamic neighborhood learning based particle swarm optimization', *International Journal of Electrical Power and Energy Systems*, 67, pp. 350–367.
- Rodríguez, L., Castillo, O., Soria, J., Melin, P., Valdez, F., Gonzalez, C. I., Martinez, G. E. and Soto, J. (2017) 'A fuzzy hierarchical operator in the grey wolf optimizer algorithm', *Applied Soft Computing Journal*, 57, pp. 315–328.
- Rong, A., Figueira, J. R. and Lahdelma, R. (2014) 'An efficient algorithm for bi-objective combined heat and power production planning under the emission trading scheme', *Energy Conversion and Management*, 88, pp. 525–534.
- Rong, A. and Lahdelma, R. (2007) 'An efficient envelope-based branch and bound algorithm for non-convex combined heat and power production planning', *European Journal of Operational Research*, 183(1), pp. 412–431.
- Rooijers, F. J. and van Amerongen, R. A. M. (1994) 'Static economic dispatch for co-generation systems', *IEEE Transactions on Power Systems*, 9(3), pp. 1392–1398.
- Roy, P. K. (2013) 'Teaching learning based optimization for short-term hydrothermal scheduling problem considering valve point effect and prohibited discharge constraint', *International Journal of Electrical Power and Energy Systems*, 53, pp. 10–19.
- Roy, P. K. (2014) 'Hybrid chemical reaction optimization approach for combined economic emission short-term hydrothermal scheduling', *Electric Power Components and Systems*, 42(15), pp. 1647–1660.
- Roy, P. K., Paul, C. and Sultana, S. (2014) 'Oppositional teaching learning based optimization approach for combined heat and power dispatch', *International Journal of Electrical Power and Energy Systems*, 57, pp. 392–403.
- Roy, P. K., Pradhan, M. and Paul, T. (2018) 'Krill herd algorithm applied to short-term hydrothermal scheduling problem', *Ain Shams Engineering Journal*, 9(1), pp. 31–43.
- Rubiales, A. J., Lotito, P. A. and Parente, L. A. (2013) 'Stabilization of the generalized benders decomposition applied to short-term hydrothermal coordination problem', *IEEE Latin America Transactions*, 11(5), pp. 1212–1224.
- Sacco, W. F. and Cassiano, R. E. (2005) 'A new stochastic optimization algorithm based on a particle collision metaheuristic', *World congress of structural and multidisciplinary optimization*.
- Santos, T. N., Diniz, A. L. and Borges, C. L. T. (2017) 'A new nested benders decomposition strategy for parallel processing applied to the hydrothermal scheduling problem', *IEEE Transactions on Smart Grid*, 8(3), pp. 1504–1512.
- Saremi, S., Mirjalili, S. and Lewis, A. (2014) 'Biogeography-based optimisation with chaos', *Neural Computing and Applications*, 25, pp. 1077–1097.
- Sashirekha, A., Pasupuleti, J., Moin, N. H. and Tan, C. S. (2013) 'Combined heat and power (CHP) economic dispatch solved using Lagrangian relaxation with surrogate subgradient multiplier updates', *International Journal of Electrical Power and Energy Systems*, 44(1), pp. 421–430.

- Selvakumar, A. I. (2013) 'Civilized swarm optimization for multiobjective short-term hydrothermal scheduling', *International Journal of Electrical Power and Energy Systems*, 51, pp. 178–189.
- Sen, T. and Mathur, H. D. (2016) 'Electrical Power and Energy Systems A new approach to solve Economic Dispatch problem using a Hybrid ACO – ABC – HS optimization algorithm', *International Journal of Electrical Power and Energy Systems*, 78, pp. 735–744.
- Shaabani, Y., Seifi, A. R. and Kouhanjani, M. J. (2017) 'Stochastic Multi-objective optimization of combined heat and power economic/emission dispatch', *Energy*, 141, pp. 1892–1904.
- Shah-Hosseini, H. (2011) 'Principal components analysis by the galaxy-based search algorithm: a novel metaheuristic for continuous optimization', *International Journal of Computational Science and Engineering*, 6, pp. 132–40.
- Shaheen, M., Ullah, Z., Hasaniien, H. M., Tostado-Véliz, M., Ji, H., Qais, M. A., Alghuwainem, S. and Jurado, F. (2023) 'Enhanced transient search optimization algorithm-based optimal reactive power dispatch including electric vehicles', *Energy*, 277, p. 127711.
- Shakarami, M. R. and Davoudkhani, I. F. (2016) 'Wide-area power system stabilizer design based on grey wolf optimization algorithm considering the time delay', *Electric Power Systems Research*, 133, pp. 149–159.
- Sheng, W., Liu, Y., Meng, X., and Zhang, T. (2012) 'An improved strength pareto evolutionary algorithm 2 with application to the optimization of distributed generations', *Computers and Mathematics with Applications*, 64(5), pp. 944–955.
- Shi, B., Yan, L. X. and Wu, W. (2013) 'Multi-objective optimization for combined heat and power economic dispatch with power transmission loss and emission reduction', *Energy*, 56, pp. 135–143.
- Simon, D. (2008) 'Biogeography-based optimization', *IEEE Transactions on Evolutionary Computation*, 12(6), pp. 702–713.
- Singh, B. and Singh, S. N. (2009) 'Wind Power Interconnection into the Power System: A Review of Grid Code Requirements', *Electricity Journal*, 22(5), pp. 54–63.
- Singh, D. and Dhillon, J. S. (2019) 'Ameliorated grey wolf optimization for economic load dispatch', *Energy*, 169, pp. 398–419.
- Singh, L., Dhillon, J. S. and Chauhan, R. C. (2006) 'Evaluation of Best Weight Pattern for Multiple Criteria Load Dispatch', *Electric Power Components and Systems*, 34, pp. 21–35.
- Sinha, N., Chakrabarti, R. and Chattopadhyay, P. K. (2003) 'Fast evolutionary programming techniques for short-term hydrothermal scheduling', *Electric Power Systems Research*, 66, pp. 97–103.
- Sivasubramani, S. and Swarup, K. S. (2011) 'Hybrid DE-SQP algorithm for non-convex short term hydrothermal scheduling problem', *Energy Conversion and Management*, 52(1), pp. 757–761.
- Srivastava, A., Tripathi, J. M., Mohanty, S. R. and Panda, B. (2016) 'Optimal over-current relay coordination with distributed generation using hybrid particle swarm optimization-gravitational search algorithm', *Electric Power Components and Systems*, 44(5), pp. 506–517.
- Storn, R. (1997) 'Differential evolution – A simple and efficient heuristic for global optimization over continuous spaces', *Journal of Global Optimization*, 11, pp. 341–359.

- Sun, C. and Lu, S. (2010) ‘Short-term combined economic emission hydrothermal scheduling using improved quantum-behaved particle swarm optimization’, *Expert Systems With Applications*, 37(6), pp. 4232–4241.
- Sun, J., Deng, J. and Li, Y. (2020) ‘Indicator & crowding distance-based evolutionary algorithm for combined heat and power economic emission dispatch’, *Applied Soft Computing Journal*, 90, p. 106158.
- Sun, Y., Qi, G., Wang, Z., Van, W. B. J. and Hamam, Y. (2009) ‘Chaotic particle swarm optimization’, *2009 World Summit on Genetic and Evolutionary Computation, 2009 GEC Summit - Proceedings of the 1st ACM/SIGEVO Summit on Genetic and Evolutionary Computation, GEC’09*, pp. 505–510.
- Sundaram, A. (2020) ‘Multiobjective multi-verse optimization algorithm to solve combined economic , heat and power emission dispatch problems’, *Applied Soft Computing Journal*, 91, p. 106195.
- Taieb, A., Salhi, H. and Chaari, A. (2022) ‘Adaptive TS fuzzy MPC based on Particle Swarm Optimization-Cuckoo Search algorithm’, *ISA Transactions*, 131, pp. 598–609.
- Teng, Z., Lv, J. and Guo, L. (2019) ‘An improved hybrid grey wolf optimization algorithm’, *Soft Computing*, 23(15), pp. 6617–6631.
- Thirumal, K., Sakthivel, V. P. and Sathya, P. D. (2023) ‘Solution for short-term generation scheduling of cascaded hydrothermal system with turbulent water flow optimization’, *Expert Systems with Applications*, 213(PA), p. 118967.
- Tian, H., Yuan, X., Ji, B. and Chen, Z. (2014) ‘Multi-objective optimization of short-term hydrothermal scheduling using non-dominated sorting gravitational search algorithm with chaotic mutation’, *Energy Conversion and Management*, 81, pp. 504–519.
- Tian, H. *et al.* (2015) ‘An improved gravitational search algorithm for solving short-term economic/environmental hydrothermal scheduling’, *Soft Computing*, 19(10), pp. 2783–2797.
- Topal, A. O. and Altun, O. (2014) ‘Dynamic virtual bats algorithm (DVBA) for global numerical optimization’, *Proceedings - 2014 International Conference on Intelligent Networking and Collaborative Systems, IEEE INCoS 2014*, pp. 320–327.
- Vasebi, A., Fesanghary, M. and Bathaee, S. M. T. (2007) ‘Combined heat and power economic dispatch by harmony search algorithm’, *International Journal of Electrical Power and Energy Systems*, 29(10), pp. 713–719.
- Velazquez, J. M. O., Coello, C. A. and Arias-Moñtano, A. (2015) ‘Multi-objective compact differential evolution’, *IEEE SSCI 2014 - 2014 IEEE Symposium Series on Computational Intelligence - SDE 2014: 2014 IEEE Symposium on Differential Evolution, Proceedings*.
- Vijay, R. K. and Nanda, S. J. (2019) ‘A quantum grey wolf optimizer based declustering model for analysis of earthquake catalogs in an ergodic framework’, *Journal of Computational Science*, 36, p. 101019.
- Vo, D. N., Schegner, P. and Ongsakul, W. (2013) ‘Cuckoo search algorithm for non-convex economic dispatch’, *IET Generation, Transmission & Distribution*, 7(6), pp. 645–654.
- Walton, S., Hassan, O., Morgan, K. and Brown, M. R (2011) ‘Modified cuckoo search : A new gradient free optimisation algorithm’, *Chaos, Solitons and Fractals*, 44(9), pp. 710–718.
- Wang, H., Liu, Y., Zeng, S., Li, H., and Li, C. (2007) ‘Opposition-based particle swarm algorithm with cauchy mutation’, *EEE Congress on Evolutionary Computation*, (1), pp. 4750–4756.

- Wang, L. and Singh, C. (2008) ‘Stochastic combined heat and power dispatch based on multi-objective particle swarm optimization’, *International Journal of Electrical Power and Energy Systems*, 30(3), pp. 226–234.
- Wang, L. and Zhong, Y. (2015) ‘Cuckoo search algorithm with chaotic maps’, *Mathematical Problems in Engineering*, 1, pp. 1–14.
- Wang, Y., Zhou, J., Mo, L., Zhang, R. and Zhang, Y. (2012) ‘Short-term hydrothermal generation scheduling using differential real-coded quantum-inspired evolutionary algorithm’, *Energy*, 44(1), pp. 657–671.
- Wolpert, D. H. and Macready, W. G. (1997) ‘No free lunch theorems for optimization’, *IEEE Transactions on Evolutionary Computation*, 1(1), pp. 67–82.
- Wong, K. P. and Wong, Y. W. (1994) ‘Short-term hydrothermal scheduling Part I: simulated annealing’, *IEE Proc. Gener. Transm. Distrib.*, 141(5), p. 497.
- Wong, L. I., Sulaiman, M. H., Mohamed, M. R. and Hong, M.S. (2014) ‘Grey wolf optimizer for solving economic dispatch problems’, *IEEE International Conference Power & Energy (PECON)*, pp. 150–154.
- Wu, Y., Ho, C. and Wang, D. (2000) ‘A diploid genetic approach to short-term scheduling of hydro-thermal system’, *IEEE Trans. Power Syst*, 15(4), pp. 1268–1274.
- Wu, Yuqiang, Wu, Yonggang and Liu, X. (2019) ‘Couple-based particle swarm optimization for short-term hydrothermal scheduling’, *Applied Soft Computing Journal*, 74, pp. 440–450.
- Xin-gang, Z. Ji, L., Jin, Z., and Yin, Z. (2020) ‘An improved quantum particle swarm optimization algorithm for environmental economic dispatch’, *Expert Systems With Applications*, p. 113370.
- Xu, K., Zhou, J., Zhang, Y. and Gu, R. (2012) ‘Differential evolution based on  $\epsilon$ -domination and orthogonal design method for power environmentally-friendly dispatch’, 39, pp. 3956–3963.
- Yang, J. S. and Chen, N. (1989) ‘Short term hydrothermal coordination using multi-pass dynamic programming’, *IEEE Trans. Power Syst*, 4(August), pp. 1050–1056.
- Yang, Q., Liu, P., Zhang, J. and Dong, N. (2022) ‘Combined heat and power economic dispatch using an adaptive cuckoo search with differential evolution mutation’, *Applied Energy*, 307(October 2021), p. 118057.
- Yang, X. S. (2010) ‘A new metaheuristic bat-inspired algorithm’, *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*, 284, pp. 65–74.
- Yang, X. S. and Deb, S. (2009) ‘Cuckoo search via Levy flights’, *World Congress on Nature and Biologically Inspired Computing (NABIC 2009) - Proceedings, IEEE publications, USA*, pp. 210–214.
- Yao, X., Liu, Y. and Lin, G. (1999) ‘Evolutionary Programming Made Faster’, *IEEE Transactions on Evolutionary Computation*, 3(2), pp. 82–102.
- Yazdani, A., Jayabarathi, T. Ramesh, V. and Raghunathan, T. (2013) ‘Combined heat and power economic dispatch problem using firefly algorithm’, *Frontiers in Energy*, 7(2), pp. 133–139.
- Yeniay, O. (2005) ‘Penalty function methods for constrained optimization with genetic algorithms’, *Mathematical and Computational Applications*, 10(1), pp. 45–56.
- Yi, W. Gao, L., Li, X. and Zhou, Y. (2015) ‘A new differential evolution algorithm with a hybrid mutation operator and self-adapting control parameters for global optimization problems’, *Applied Intelligence*, 42(4), pp. 642–660.

## References

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- Yin, S. and Wong, W. (2001) 'Hybrid simulated annealing / genetic algorithm approach to short-term hydro-thermal scheduling with multiple thermal plants', *Electrical Power and Energy Systems*, 23, pp. 565–575.
- Yuan, X. Cao, B., Yang, B. and Yuan, Y. (2008) 'Hydrothermal scheduling using chaotic hybrid differential evolution', *Energy Conversion and Management*, 49(12), pp. 3627–3633.
- Yuan, X., Ji, B., Chen, Z. and Chen, Z. (2014) 'A novel approach for economic dispatch of hydrothermal system via gravitational search algorithm', *Applied Mathematics and Computation*, 247, pp. 535–546.
- Zade, A., Patel, N. and Padhiyar, N. (2017) 'Effective constrained handling by hybridized cuckoo search algorithm with box complex method', *IFAC-PapersOnLine*, 50(2), pp. 209–214.
- Zhang, H. Zhou, J., Zhang, Y., Lu, Y. and Wang, Y. (2013) 'Culture belief based multi-objective hybrid differential evolutionary algorithm in short term hydrothermal scheduling', *Energy Conversion and Management*, 65, pp. 173–184.
- Zhang, H. Yue, D., Xie, X., Hu, S. and Weng, S. (2018) 'Pareto-dominance based adaptive multi-objective optimization for hydrothermal coordinated scheduling with environmental emission', *Applied Soft Computing Journal*, 69, pp. 270–287.
- Zhang, H., Yue, D. and Xie, X. (2017) 'Gradient decent based multi-objective cultural differential evolution for short-term hydrothermal optimal scheduling of economic emission with integrating wind power and photovoltaic power', *Energy*, 122, pp. 748–766.
- Zhang, J., Lin, S. and Qiu, W. (2015) 'A modified chaotic differential evolution algorithm for short-term optimal hydrothermal scheduling', *International Journal of Electrical Power and Energy Systems*, 65, pp. 159–168.
- Zhang, J., Wang, J. and Yue, C. (2012) 'Small population-based particle swarm optimization for short-term hydrothermal scheduling', *IEEE Trans. Power Syst*, 27(1), pp. 142–152.
- Zhang, Q., Xie, J. U. N. and Pan, X. (2021) 'A short-term optimal scheduling model for wind-solar-hydro-thermal complementary generation system considering dynamic frequency response', *IEEE Access*, 9, pp. 142768–142781.
- Zhang, R., Zhou, J. and Wang, Y. (2012) 'Multi-objective optimization of hydrothermal energy system considering economic and environmental aspects', *International Journal of Electrical Power and Energy Systems*, 42(1), pp. 384–395.
- Zhang, X. and Yuen, S. Y. (2015) 'A directional mutation operator for differential evolution algorithms', *Applied Soft Computing Journal*, 30, pp. 529–548.
- Zhang, Y. Le, J., Liao, X., Zheng, F., Liu, K. and An, X. (2018) 'Multi-objective hydro-thermal-wind coordination scheduling integrated with large-scale electric vehicles using IMOPSO', *Renewable Energy*, 128, pp. 91–107.
- Zhao, Y., Li, W. and Liu, A. (2020) 'Improved grey wolf optimization based on the two-stage search of hybrid CMA-ES', *Soft Computing*, 24, pp. 1097–1115.
- Zhou, J., Liao, X., Ouyang, S., Zhang, R. and Zhang, Y. (2014) 'Multi-objective artificial bee colony algorithm for short-term scheduling of hydrothermal system', *International Journal of Electrical Power and Energy Systems*, 55, pp. 542–553.
- Zhou, S. *et al.* (2020) 'Combined heat and power system intelligent economic dispatch : A deep reinforcement learning approach', *Electrical Power and Energy Systems*, 120(March), p. 106016.

- Zhou, Y., Li, X. and Gao, L. (2013) 'A Differential evolution algorithm with intersect mutation operator', *Applied Soft Computing*, 13, pp. 390–401. Available at: 14.
- Zhu, A., Xu, C., Li, Z., Wu, J and Liu, Z. (2015) 'Hybridizing grey wolf optimization with differential evolution for global optimization and test scheduling for 3D stacked SoC', *Journal of Systems Engineering and Electronics*, 26(2), pp. 317–328.
- Zou, D., Li, S., Kong, X., Ouyang, H. and Li, Z. (2019) 'Solving the combined heat and power economic dispatch problems by an improved genetic algorithm and a new constraint handling strategy', *Applied Energy*, 237, pp. 646–670.
- Zugno, M., Morales, J. M. and Madsen, H. (2016) 'Commitment and dispatch of heat and power units via affinely adjustable robust optimization', *Computers and Operations Research*, 75, pp. 191–201.



# APPENDIX-A

## TEST SYSTEMS

### A.1 INPUT DATA OF THERMAL UNITS

The test system (TS)-I has 3 thermal and 4 hydro units. The input data of the thermal units for TS-I has been referred from Ref. (Basu, 2004). The cost coefficients and power output capacity limits of thermal units for TS-I, II, III and IV are given in Table A.1.1, A.1.2, A.1.3 and A.1.4, respectively. The cost coefficients and power output capacity limits of thermal units for TS-V-VI are given in Table A.1.5. The emission coefficients of thermal units for TS-I and II (case-III and IV) are given in Table A.1.6 and Table A.1.7, respectively.

**Table A.1.1** Cost coefficients and power output capacity limits of thermal units for TS-I (case-I-IV)

Thermal Units ( $i$ )	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$PT_i^{\min}$	$PT_i^{\max}$
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 A.1.2** Cost coefficients and power output capacity limits of thermal units for TS-II

Thermal Units ( $i$ )	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$PT_i^{\min}$	$PT_i^{\max}$
1	0.0037	2.00	10	18	0.037	20	175
2	0.0175	1.75	10	16	0.038	40	300
3	0.0625	1.00	20	14	0.040	50	500
4	0.1524	38.5397	786.7988	450	0.041	150	470
5	0.1058	46.1591	451.3251	600	0.036	135	470
6	0.0280	40.3965	1049.9977	320	0.028	73	340
7	0.0354	38.3055	1243.5311	260	0.052	60	300
8	0.0179	38.2704	1356.6592	310	0.048	57	160
9	0.0121	36.5104	1450.7045	300	0.086	20	130
10	0.1090	39.5804	1455.6056	270	0.094	20	80
11	0.1295	40.5407	1469.4026	380	0.094	10	55

**Table A.1.3** Cost coefficients and power output capacity limits of thermal units for TS-III

Thermal Units ( $i$ )	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$PT_i^{\min}$	$PT_i^{\max}$
1	0.0037	2.00	10	18	0.037	20	175
2	0.0175	1.75	10	16	0.038	40	300
3	0.0625	1.00	20	14	0.040	50	500
4	0.1524	38.5397	786.7988	450	0.041	150	470
5	0.1058	46.1591	451.3251	600	0.036	135	470
6	0.0280	40.3965	1049.9977	320	0.028	73	340
7	0.0354	38.3055	1243.5311	260	0.052	60	300
8	0.0179	38.2704	1356.6592	310	0.048	57	160
9	0.0121	36.5104	1450.7045	300	0.086	20	130
10	0.1090	39.5804	1455.6056	270	0.094	20	80

**Appendix-A**

**Table A.1.3** Cost coefficients and power output capacity limits of thermal units for TS-III (continued)

Thermal Units ( <i>i</i> )	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$PT_i^{\min}$	$PT_i^{\max}$
11	0.1295	40.5407	1469.4026	380	0.094	10	55
12	0.1524	38.5397	786.7988	450	0.041	150	470
13	0.1058	46.1591	451.3251	600	0.036	135	470
14	0.0280	40.3965	1049.9977	320	0.028	73	340
15	0.0354	38.3055	1243.5311	260	0.052	60	300
16	0.0179	38.2704	1356.6592	310	0.048	57	160
17	0.0121	36.5104	1450.7045	300	0.086	20	130
18	0.1090	39.5804	1455.6056	270	0.094	20	80
19	0.1295	40.5407	1469.4026	380	0.094	10	55

**Table A.1.4** Cost coefficients and power output capacity limits of thermal units for TS-IV

Thermal Units ( <i>i</i> )	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$PT_i^{\min}$	$PT_i^{\max}$
1	0.0037	2.00	10	18	0.037	20	175
2	0.0175	1.75	10	16	0.038	40	300
3	0.0625	1.00	20	14	0.040	50	500
4	0.1524	38.5397	786.7988	450	0.041	150	470
5	0.1058	46.1591	451.3251	600	0.036	135	470
6	0.0280	40.3965	1049.9977	320	0.028	73	340
7	0.0354	38.3055	1243.5311	260	0.052	60	300
8	0.0179	38.2704	1356.6592	310	0.048	57	160
9	0.0121	36.5104	1450.7045	300	0.086	20	130
10	0.1090	39.5804	1455.6056	270	0.094	20	80
11	0.1295	40.5407	1469.4026	380	0.094	10	55
12	0.1524	38.5397	786.7988	450	0.041	150	470
13	0.1058	46.1591	451.3251	600	0.036	135	470
14	0.0280	40.3965	1049.9977	320	0.028	73	340
15	0.0354	38.3055	1243.5311	260	0.052	60	300
16	0.0179	38.2704	1356.6592	310	0.048	57	160
17	0.0121	36.5104	1450.7045	300	0.086	20	130
18	0.1090	39.5804	1455.6056	270	0.094	20	80
19	0.1295	40.5407	1469.4026	380	0.094	10	55
20	0.1524	38.5397	786.7988	450	0.041	150	470
21	0.1058	46.1591	451.3251	600	0.036	135	470
22	0.0280	40.3965	1049.9977	320	0.028	73	340
23	0.0354	38.3055	1243.5311	260	0.052	60	300
24	0.0211	36.3278	1658.5696	280	0.063	73	243
25	0.0179	38.2704	1356.6592	310	0.048	57	160
26	0.0121	36.5104	1450.7045	300	0.086	20	130
27	0.0121	36.5104	1450.7045	300	0.082	47	120
28	0.1090	39.5804	1455.6056	270	0.094	20	80
29	0.1295	40.5407	1469.4026	380	0.094	10	55

**Table A.1.5** Cost coefficients and power output capacity limits of thermal units: TS-V-VI

Thermal units ( <i>i</i> )	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$PT_i^{\min}$	$PT_i^{\max}$
1	0.00043	21.6	958.2	450	0.041	150	470
2	0.00063	21.05	1313.6	600	0.036	135	460
3	0.00039	20.81	604.97	320	0.028	73	340
4	0.00070	23.9	471.6	260	0.052	60	300
5	0.00056	17.87	601.75	310	0.048	57	160
6	0.00211	16.51	502.7	300	0.086	20	130
7	0.10908	19.58	455.6	270	0.098	20	80
8	0.00951	22.54	692.4	380	0.0943	55	55

**Table A.1.6** Emission coefficients of thermal units for TS-I (case-III-IV)

Thermal Units ( <i>i</i> )	$a1_i$	$b1_i$	$c1_i$	$d1_i$	$e1_i$
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 A.1.7** Emission coefficients of thermal units for TS-II (case-II-III)

Thermal Units ( <i>i</i> )	Emission Coefficients				
	$a1_i$	$b1_i$	$c1_i$	$d1_i$	$e1_i$
1	0.0105	-1.355	60	0.4968	0.01925
2	0.0080	-0.6	45	0.486	0.01694
3	0.0120	-0.555	30	0.5035	0.01478
4	0.0312	-2.4444	103.3908	0.5035	0.0207
5	0.0312	-2.4444	103.3908	0.5035	0.0207
6	0.0509	-4.0695	300.391	0.4968	0.0202
7	0.0509	-4.0695	300.391	0.4968	0.0202
8	0.0344	-3.8132	320.0006	0.4972	0.02
9	0.0465	-3.9023	330.0056	0.5163	0.0214
10	0.0465	-3.9524	350.0056	0.5475	0.0234
11	0.0470	-3.9864	360.0012	0.5475	0.0234

**Table A.1.8** Emission coefficients of thermal units for TS-III (case-II-III)

Thermal Units ( <i>i</i> )	Emission Coefficients				
	$a1_i$	$b1_i$	$c1_i$	$d1_i$	$e1_i$
1	0.0105	-1.355	60	0.4968	0.01925
2	0.0080	-0.6	45	0.486	0.01694
3	0.0120	-0.555	30	0.5035	0.01478
4	0.0312	-2.4444	103.3908	0.5035	0.0207
5	0.0312	-2.4444	103.3908	0.5035	0.0207
6	0.0509	-4.0695	300.391	0.4968	0.0202
7	0.0509	-4.0695	300.391	0.4968	0.0202
8	0.0344	-3.8132	320.0006	0.4972	0.02
9	0.0465	-3.9023	330.0056	0.5163	0.0214
10	0.0465	-3.9524	350.0056	0.5475	0.0234
11	0.0470	-3.9864	360.0012	0.5475	0.0234
12	0.0312	-2.4444	103.3908	0.5035	0.0207
13	0.0312	-2.4444	103.3908	0.5035	0.0207
14	0.0509	-4.0695	300.391	0.4968	0.0202
15	0.0509	-4.0695	300.391	0.4968	0.0202
16	0.0344	-3.8132	320.0006	0.4972	0.02
17	0.0465	-3.9023	330.0056	0.5163	0.0214
18	0.0465	-3.9524	350.0056	0.5475	0.0234
19	0.0470	-3.9864	360.0012	0.5475	0.0234

The transmission loss coefficients of thermal units for TS-I (case-II) has been referred from Ref.

(Lakshminarasimman and Subramanian, 2008) and are given below:

#### Transmission loss coefficients of thermal units: TS-I (case-II)

$$Bo = [-0.75 \quad -0.06 \quad 0.70 \quad -0.03 \quad 0.27 \quad -0.77 \quad -0.01] \times 10^{-6} \text{ MW}$$

$$Boo = 0.55 \text{ MW}$$

$$B = \begin{bmatrix} 0.34 & 0.13 & 0.09 & -0.01 & -0.08 & -0.01 & -0.02 \\ 0.13 & 0.14 & 0.10 & 0.01 & -0.05 & -0.02 & 0.01 \\ 0.09 & 0.10 & 0.31 & 0.00 & -0.11 & -0.07 & -0.05 \\ -0.01 & 0.01 & 0.00 & 0.24 & -0.08 & -0.04 & -0.07 \\ -0.08 & -0.05 & -0.11 & -0.08 & 0.192 & 0.27 & -0.02 \\ -0.01 & -0.02 & -0.07 & -0.04 & 0.27 & 0.32 & 0.00 \\ -0.02 & -0.01 & -0.05 & -0.07 & -0.02 & 0.00 & 1.35 \end{bmatrix} \times 10^{-4} \text{MW}^{-1}$$

## A.2 INPUT DATA OF HYDRO UNITS

The input data of hydro units for TS-I-IV has been referred from Ref. (Basu, 2004). The power generation coefficients, power output capacity limits and water discharge rate of hydro units for TS-I-IV are given in Table A.2.1. The capacity limits of reservoir storage volume, initial and terminal reservoir storage volume limits of hydro units TS-I-IV are given in Table A.2.2 The reservoir inflow of hydro units for TS-I-IV is given in Table A.2.3

**Table A.2.1** Power generation coefficients, power output capacity limits and water discharge rate of hydro units for TS-I-IV

Hydro Units ( $l$ )	$C_{1l}$	$C_{2l}$	$C_{3l}$	$C_{4l}$	$C_{5l}$	$C_{6l}$	$PH_l^{\min}$	$PH_l^{\max}$	$q_l^{\min}$	$q_l^{\max}$
1	-0.0042	-0.42	0.03	0.9	10	-50	0	500	5	15
2	-0.004	-0.3	0.015	1.14	9.5	-70	0	500	6	15
3	-0.0016	-0.3	0.014	0.55	5.5	-40	0	500	10	30
4	-0.003	-0.31	0.027	1.44	14	-90	0	500	6	20

**Table A.2.2** Reservoir storage volume limits, initial and terminal reservoir storage volume limits of hydro units for TS-I-IV

Hydro Units ( $l$ )	$V_l^{\min}$	$V_l^{\max}$	$V_l^{ini}$	$V_l^{final}$	$UP_l$	$\tau_{ml}$
1	80	150	100	120	0	2
2	60	120	80	70	0	3
3	100	240	170	170	2	4
4	70	160	120	140	1	0

Note:  $UP_l$  is the number of upstream reservoirs from  $l^{th}$  hydro unit;  $\tau_{ml}$  is the water transportation delay from  $m^{th}$  to  $l^{th}$  hydro unit ( $m \in UP_l$ ).

**Table A.2.3** Reservoir inflow of hydro units for TS-I-IV

Sub-interval ( $t$ )	Reservoir Inflow				Sub-interval ( $t$ )	Reservoir Inflow			
	1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	13	11	8	4	0
2	9	8	8.2	2.4	14	12	9	3	0
3	8	9	4	1.6	15	11	9	3	0
4	7	9	2	0	16	10	8	2	0
5	6	8	3	0	17	9	7	2	0
6	7	7	4	0	18	8	6	2	0

**Table A.2.3** Reservoir inflow of hydro units for TS-I-IV (continued)

Sub-interval ( $t$ )	Reservoir Inflow				Sub-interval ( $t$ )	Reservoir Inflow			
	1	2	3	4		1	2	3	4
7	8	6	3	0	19	7	7	1	0
8	9	7	2	0	20	6	8	1	0
9	10	8	1	0	21	7	9	2	0
10	11	9	1	0	22	8	9	2	0
11	12	9	1	0	23	9	8	1	0
12	10	8	2	0	24	10	8	0	0

### A.3 INPUT DATA OF CHP AND HEAT UNITS

The cost coefficients of CHP and heat units for TS-II, V and VI are given in Tables A.3.1 and A.3.2, respectively. Cost coefficients of CHP and heat units TS-III and IV are given in Table A.3.3 and A.3.4. The FOR of the CHP units have been shown in Fig. A.1.1 and A.1.2 of Appendix-A.

**Table A.3.1** Cost coefficients of CHP units for TS-II, V and VI

CHP Units ( $j$ )	$\varepsilon_j$	$\varphi_j$	$\eta_j$	$\mu_j$	$\delta_j$	$\zeta_j$	$HC_j^{\min}$	$HC_j^{\max}$
1	0.0345	14.5	2650	0.030	4.2	0.031	104.8	180
2	0.0435	36	1250	0.027	0.6	0.011	15.9	135.6

**Table A.3.2** Cost coefficients of heat unit for TS-II, V and VI

Heat Units ( $k$ )	$\alpha_k$	$\beta_k$	$\gamma_k$	$H_k^{\min}$	$H_k^{\max}$
1	0.038	2.0109	950	0	2695.2

**Table A.3.3** Cost coefficients of CHP units for TS-III and IV

CHP Units ( $j$ )	$\varepsilon_j$	$\varphi_j$	$\eta_j$	$\mu_j$	$\delta_j$	$\zeta_j$	$HC_j^{\min}$	$HC_j^{\max}$
1	0.0345	14.5	2650	0.030	4.2	0.031	104.8	180
2	0.0435	36	1250	0.027	0.6	0.011	15.9	135.6
3	0.0345	14.5	2650	0.030	4.2	0.031	104.8	180
4	0.0435	36	1250	0.027	0.6	0.011	15.9	135.6

**Table A.3.4** Cost coefficients of heat unit for TS-III and IV

Heat Units ( $k$ )	$\alpha_k$	$\beta_k$	$\gamma_k$	$H_k^{\min}$	$H_k^{\max}$
1	0.038	2.0109	950	0	2695.2
2	0.038	2.0109	950	0	2695.2

**Table A.3.5** Emission coefficients of CHP units for TS-II (case-II-III)

CHP Units ( $j$ )	$\varepsilon 1_j$	$\varphi 1_j$
1	0.00015	0.00150
2	0.00015	0.00150

## Appendix-A

**Table A.3.6** Emission coefficients of heat unit for TS-II (case-II-III)

Heat Units (k)	$\alpha 1_k$	$\beta 1_k$
1	0.0008	0.0010

**Table A.3.7** Emission coefficients of CHP units for TS-III (case-II-III)

CHP Units (j)	$\epsilon 1_j$	$\phi 1_j$
1	0.00015	0.00150
2	0.00015	0.00150
3	0.00015	0.00150
4	0.00015	0.00150

**Table A.3.8** Emission coefficients of heat unit for TS-III (case-II-III)

Heat Units (k)	$\alpha 1_k$	$\beta 1_k$
1	0.0008	0.0010
2	0.0008	0.0010

## A.4 INPUT DATA OF PHOTOVOLTAIC UNITS

The input data for PV units for TS-VI has been referred from Ref. (Ahmed *et al.*, 2015). The power ratings and per unit rates of PV units are given in Table A.4.1 of Appendix-A. Solar radiation and temperature for PV units given in Table A.4.2 of Appendix-A.

**Table A.4.1** Power ratings and per unit rates of PV units for TS-VI

PV units (m)	$P_m^{rated}$	Unit rate (\$/KWh)
1	20	0.22
2	25	0.23
3	25	0.23
4	30	0.24
5	30	0.24
6	35	0.25
7	35	0.26
8	40	0.27
9	40	0.27
10	40	0.275
11	40	0.28
12	40	0.28
13	40	0.28

**Table A.4.2** Solar radiation and temperature for PV units for TS-VI

Sub-interval (t)	Global solar radiation (W/m <sup>2</sup> )	Temperature (°C)	Sub-interval (t)	Global solar radiation (W/m <sup>2</sup> )	Temperature (°C)
1	0	30	13	1013.5	37
2	0	29	14	848.2	37
3	0	28	15	726.7	37
4	0	28	16	654	38
5	5.4	28	17	392.9	38
6	101	0	18	215.1	37
7	253.7	29	19	38.5	35

**Table A.4.2** Solar radiation and temperature for PV units for TS-VI (continued)

Sub-interval (t)	Global solar radiation (W/m <sup>2</sup> )	Temperature (°C)	Sub-interval (t)	Global solar radiation (W/m <sup>2</sup> )	Temperature (°C)
8	541.2	31	20	0	34
9	530.4	33	21	0	34
10	793.9	34	22	0	33
11	1078	35	23	0	32
12	1125.6	36	24	0	0

## A.5 POWER AND HEAT DEMAND FOR TEST SYSTEMS

The power demand and heat demand for all the test systems is given in Tables A.5.1 and A.5.2, respectively.

**Table A.5.1** Power demand for TS-I-VI

Sub-interval (t)	Power Demand (PD)					Sub-interval (t)	Power Demand (PD)				
	TS-I	TS-II	TS-III	TS-IV	TS-V-VI		TS-I	TS-II	TS-III	TS-IV	TS-V-VI
1	750	1786	2822	3858	1036	13	1110	3182	5254	7326	2072
2	780	1890	3000	4110	1110	14	1030	2954	4878	6802	1924
3	700	1958	3216	4474	1258	15	1010	2795	4571	6347	1776
4	650	2056	3462	4868	1406	16	1060	2614	4168	5722	1554
5	670	2150	3630	5110	1480	17	1050	2530	4010	5490	1480
6	800	2428	4056	5684	1628	18	1120	2748	4376	6004	1628
7	950	2652	4354	6056	1702	19	1070	2846	4622	6398	1776
8	1010	2786	4562	6338	1776	20	1050	3022	4994	6966	2072
9	1090	3014	4938	6862	1924	21	910	2834	4758	6682	1924
10	1080	3102	5124	7146	2072	22	860	2488	4116	5744	1628
11	1100	3206	5312	7418	2146	23	850	2182	3514	4846	1332
12	1150	3300	5450	7600	2220	24	800	1984	3168	4352	1184

**Table A.5.2** Heat demand for TS-II-VI

Sub-interval (t)	Heat Demand (HD)					Sub-interval (t)	Heat Demand (HD)				
	TS-II	TS-III	TS-IV	TS-V	TS-VI		TS-II	TS-III	TS-IV	TS-V	TS-VI
1	390	780	780	401	401	13	470	940	940	474	474
2	400	800	800	407	407	14	460	920	920	470	470
3	410	820	820	417	417	15	450	900	900	462	462
4	420	840	840	431	431	16	450	900	900	443	443
5	440	880	880	438	438	17	420	840	840	438	438
6	450	900	900	450	450	18	435	870	870	450	450
7	450	900	900	455	455	19	445	890	890	462	462
8	455	910	910	462	462	20	450	900	900	474	474
9	460	920	920	472	472	21	445	890	890	468	468
10	460	920	920	474	474	22	435	870	870	449	449
11	470	940	940	478	478	23	400	800	800	430	430
12	480	960	960	483	483	24	400	800	800	414	414

**FOR of CHP units:** The feasible operating region (FOR) of CHP units for TS-II-VI are given below:

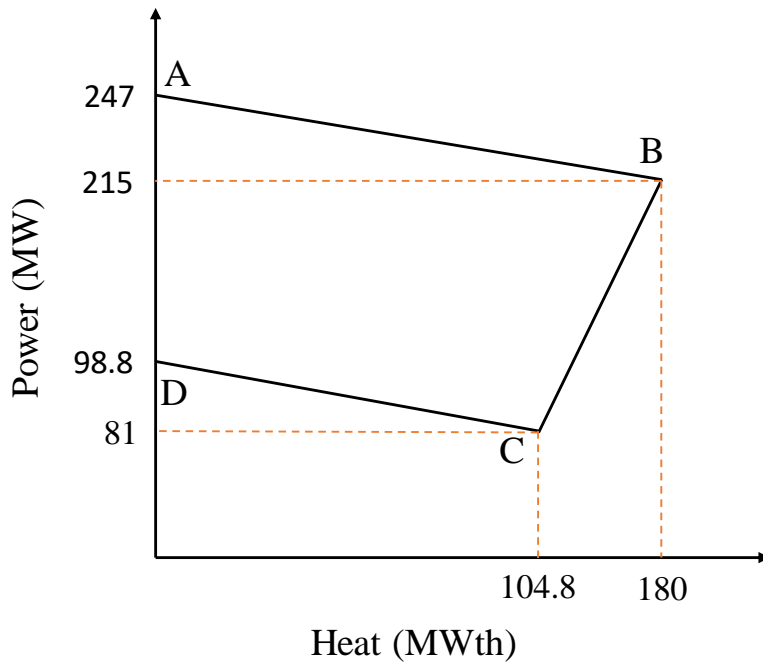


Figure A.1.1 FOR of CHP units-1 and 3 for TS-II-VI

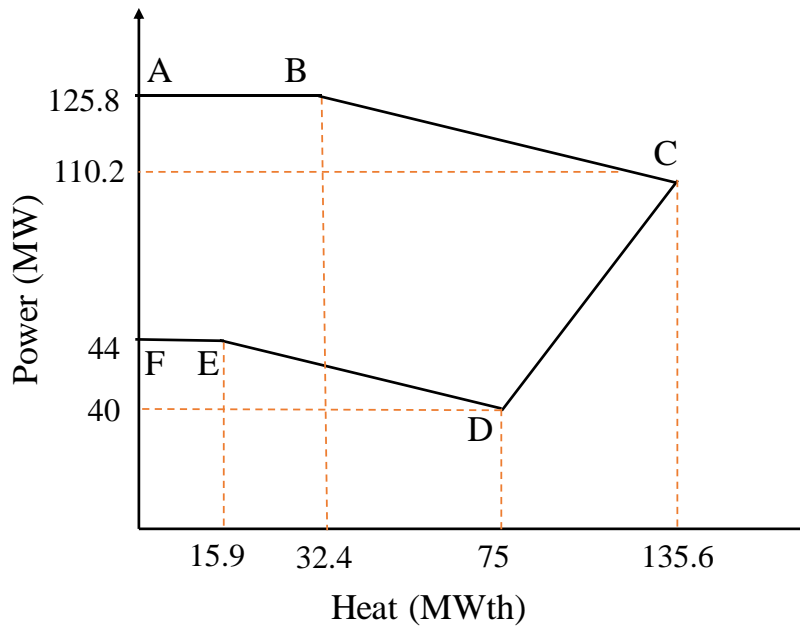


Figure A.1.2 FOR of CHP units-2 and 4 for TS-II-VI

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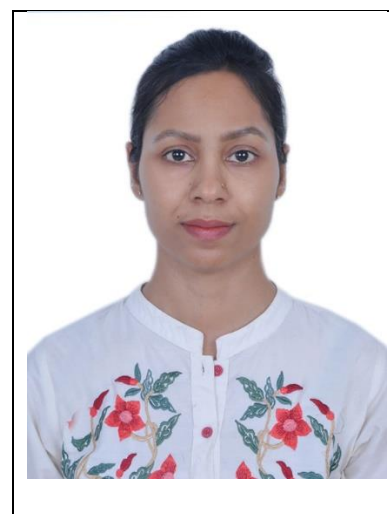
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M.E.	Power Systems and Electric Drives	Thapar Institute of Engineering and Technology, Patiala	60%	2011
B. Tech	Electrical and Electronics Engineering	Punjab Technical University, Jalandhar	64.5%	2008
Diploma	Information Technology	Punjab State Board of Technical Education, Chandigarh	64.6%	2005
Class 10 <sup>th</sup>	Science (CBSE)	Dhilwan International Public School, Dhilwan, Kapurthala, Punjab	61.5%	2002

### **SCI Publications:**

[1] Kaur A and Narang N (2019) Optimum generation scheduling of coordinated power system using hybrid optimization technique. *Electrical Engineering*, 101, 379-408.

[2] Kaur A and Narang N (2023) Economic emission generation scheduling of interconnected energy system using hybrid optimization technique. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, 47, 103-124.

[3] Kaur A and Narang N (2024) Multi-objective generation scheduling of integrated energy system using hybrid optimization technique. *Neural Computing and Applications*, 36, 1215-1236.