

Optimal Generation Scheduling of Pumped Storage Hydrothermal System with Solar and Wind Energy Sources

A Thesis

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Submitted by

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September 2021

Dedicated to

My Respected Father

Shri. Prakash Chandra Singh Patwal

and

Respected Mother

Smt. Malini Patwal

CERTIFICATE

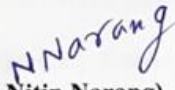
Certified that the thesis entitled, "**Optimal Generation Scheduling of Pumped Storage Hydrothermal System with Solar and Wind Energy Sources**", which is being submitted by **Rituraj Singh Patwal** in fulfillment of the requirements for the award of the degree of **Doctor of Philosophy**, to the Department of Electrical & Instrumentation Engineering, Thapar Institute of Engineering & Technology, Patiala, is a bonafide record of the candidate's own work carried out by him under my supervision and guidance.

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LIST OF ABBREVIATIONS

BPSO	Binary Particle Swarm Optimization
CSA	Colonial Search Algorithm
CSO	Crisscross Search Operators
CSPSO	Crisscross Search Particle Swarm Optimization
DE	Differential Evolution
DP	Dynamic Programming
EP	Evolutionary Programming
ESS	Energy Storage System
FSOC	Final State of Charge
GA	Genetic Algorithm
GSA	Gravitational Search Algorithm
GSO	Glow worm Search Optimization
GWO-MS	Grey Wolf Optimization Technique with Mutation Strategies
HTS	Hydrothermal System
HTGS	Hydrothermal Generation Scheduling
IES	Integrated Energy System
INSOC	Initial State of Charge
IQPSO	Improved Quantum behaved Particle Swarm Optimization
ISAPSO	Improved Self Adaptive Particle Swarm Optimization
LR	Lagrange Relaxation
MB-PSO	Modified Binary Particle Swarm Optimization
MCS-PSO	Modified Crisscross Search Particle Swarm Optimization
MDE	Modified Differential Algorithm
MOABC	Multi-objective Artificial Bee Colony
MO-BC	Multi-objective Bee Colony
MOCA	Multi-objective Cultural Algorithm
MODE	Multi-objective DE
MOEA	Multi-objective Evolutionary Algorithms
MO-HTGS	Multi-objective Hydrothermal Generation Scheduling
MOOP	Multi-objective Optimization problem
MO-RHO	Multi-objective Receding Horizon Optimization
NSGA-II	Non-dominated Sorting GA-II
NSGSA	Non-dominated Sorting GSA

LIST OF ABBREVIATIONS (Continued)

NSPSO-CM	Non-dominated Sorting Particle Swarm Optimization with Chaotic Mutation
NSPSO	Non-dominated Sorting Particle Swarm Optimization
ODEMO	Orthogonal Design DE Multi-objective
PESA	Pareto Envelope Search Algorithm
PPO	Predator Prey Optimization
POT	Proposed Optimization Technique
PSHTS	Pumped Storage Hydrothermal System
PSO	Particle Swarm Optimization
PSU	Pumped Storage Unit
QADEVT	Quadratic Approximation based DE with Valuable Trade-off
RES	Renewable Energy Sources
SA	Simulated Annealing
SCA	Sine Cosine Algorithm
SPEA	Strength Pareto Evolutionary Algorithm
SPV	Solar Photovoltaic Unit
SWT	Surrogate Worth Trade-off
TVAC	Time Varying Acceleration Coefficient
WES	Wind Energy Source

NOMENCLATURE

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

Indices	Description
g	Index for the thermal unit
i	Index for particle
j	Index for the hydro unit
k	Index for objectives
l	Index for pumped storage unit
m	Index for wind unit
s	Index for SPV unit
t	Index for time
it	Index for iteration
Inputs	Description
a_g, b_g, c_g, d_g, e_g	Cost coefficients of g^{th} thermal unit
$\alpha_g, \beta_g, \gamma_g, \eta_g$ and δ_g	The emission coefficients of g^{th} thermal unit
b	The battery bank efficiency
b_1, b_2 and b_3	The battery cost coefficients
$C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}, C_{6j}$	Hydro power coefficients for the j^{th} unit
Cf_1 and Cf_2	Final values for cognitive and social learning acceleration coefficients
Ci_1 and Ci_2	Initial values for cognitive and social learning acceleration coefficients
C_{rm}, C_{pm} and dc	Penalty factors for overestimated, under estimated and direct wind powers
it_{max}	Maximum number of iteration
$L_{1l}, L_{2l}, L_{3l}, L_{4l}, L_{5l}, L_{6l}$	Coefficient of power generation form pump units
nh	Total number of hydrounits
np	Total number of pumped storage units
nt	Total number of thermal units
nw	Total number of wind units

NOMENCLATURE (Continued)

PD_t and PL_t	Power demand and power loss in t^{th} sub-interval
$PH_j^{\max}$ and $PH_j^{\min}$	Maximum and minimum power limits for hydro units (MW)
PR_s	The rated power generation from SPV (MW)
$PS_l^{\max}$	Rated power of l^{th} pumped storage unit (MW)
SH_m and SC_m	The shape factor constant and scaling factor constant for m^{th} wind units
Tr and Ta	Reference and ambient temperature in ($^{\circ}C$)
UC_s	Per unit cost of PV power (\$/KWh)
V	Battery bank potential in volts
$V_j^{\max}$ and $V_j^{\min}$	Upper and lower limit of reservoir volume of j^{th} hydro unit
V_j^{in} and V_j^{end}	Initial and end reservoir volume of the j^{th} hydro unit
Wr_m	Rated wind power for the m^{th} wind unit (MW)
$\omega_{\max}$ and $\omega_{\min}$	The maximum and minimum inertia weight
η_g and η_p	Round trip efficiency during generation and pumping mode
Δ	Time in an hour for which battery has been operated (h)
Variables	Description
CB_t	Battery state of charge at t^{th} hour (Ah)
C_1 and C_2	Cognitive and social acceleration coefficients
HS_i^d and HS_h^d	Moderate solution from i^{th} and h^{th} particle in d^{th} dimension
$OF_k^{\max}$ and $OF_k^{\min}$	Maximum and minimum value of the k^{th} objective
PB_t	Battery power in t^{th} sub interval (MW)
$PH_{j,t}$	Hydropower generation of j^{th} unit in t^{th} sub-interval (MW)
$PS_{l,t}$	Pumped storage power of the l^{th} unit in t^{th} sub-interval (MW)
$PS_{l,t}^p$ and $PS_{l,t}^g$	Generating and pumping power of l^{th} pump storage unit in t^{th} sub-interval
$PT_{g,t}$	Thermal power generation of g^{th} unit in t^{th} sub-interval (MW)
$q_{j,t}$ and $V_{j,t}$	Reservoir discharge (m^3/h) and volume (m^3)
$qa_{l,t+1}$	Pumped water discharge from the lower reservoir in $(t+1)^{th}$ sub-interval
r_a	Exterior penalty factor

NOMENCLATURE (Continued)

$U_{l,t}^g$ and $U_{l,t}^p$	Binary random decision variables for l^{th} pumped storage unit in t^{th} sub-interval
VS_i^{d1}	Moderate solution from i^{th} particle in d^{th} dimension for vertical crossover
$V_i'^d$	The particle velocity for the successive iteration
$WS_{m,t}$	Schedule wind power for the m^{th} wind unit in t^{th} sub-interval (MW)
$X_d^{\max}$ and $X_d^{\min}$	Maximum and minimum limit of the particle in dimension d
Functions	Description
CO, CU and DC	Overestimation, underestimation and direct cost from wind power (
ecb_T	An error computed between initial state of charge and generated charge
ep_t	The error computed for dependent thermal unit power (MW)
epb_t	An error computed for battery power (MW)
$eph_{j,t}$	An error computed for j^{th} unit hydropower in t^{th} sub-interval (MW)
$eps_{l,t}$	An error computed for l^{th} pumped storage unit power in t^{th} sub-interval (MW)
epu_t	An error computed in case of violation of desired utility power (MW)
$ev_{j,t}$	Reservoir volume error for j^{th} hydro unit in t^{th} sub-interval (m^3)
evf_j	An error computed between desired volume and final volume (m^3)
ets_t	An error computed between desired solar share and power demand (MW)
Fc	Cardinal priority ranking.
OF_1	Total power generation cost from the power generating units (\$)
OF_2	Total emission produced from the thermal units (lb)
PSC	The total cost from the pumped storage unit (\$)
PT_t^{dep}	Dependent thermal unit power in t^{th} sub-interval (MW)
PU_t	The utility power at t^{th} hour (MW)

NOMENCLATURE (Continued)

SC	The total cost from the solar photovoltaic units (\$)
Sd	The satisfaction level of one objective with respect to others
S_s	The solar power generated from the s^{th} solar units (MW)
TC	Total cost from the thermal unit (\$)
TS_t	The total generated solar power from the solar units in t^{th} hour (MW)
v_1	Intermediate wind velocity parameter (m/sec.)
$v_{in,m}$	Cut in velocity for the m^{th} wind unit (m/sec.)
$v_{out,m}$	Cut out velocity for the m^{th} wind unit (m/sec.)
$v_{r,m}$	Rated velocity for the m^{th} wind unit (m/sec.)
$Wav_{m,t}$	Available wind power for the m^{th} wind unit in t^{th} sub-interval (MW)
WC	The total cost from the wind units (\$)
μd	A unified objective function for multi-objective problem
$\mu(OE_k)$	Membership function value for the k^{th} objective function

ABSTRACT

Electricity has been playing an important role in the people living standards and the development of various economic sectors like agriculture, industry, commerce, etc. In the past decade, thermal, oil, gas, and nuclear plants, have been the primary sources of energy generation. The emissions produced by the thermal plants have been one of the main reasons of *renewable energy sources (RESs)* in the power systems energy generation. From the past decade, large hydropower plants have been constructed to fulfil the power demand with reducing cost and emissions. The outcome of this development is the alteration of the river's natural flow, degradation of water bodies, and pristine conditions. The *pumped-storage unit (PSU)* is one of the small hydroelectric units with fast response during demand variations and cost minimization of energy generation. The integration of RESs with *pumped storage hydrothermal system (PSHTS)* becomes vital with respect to the present energy scenario of the country.

The importance lies in the acknowledgment of the RESs, which are abundantly available in the country. There are several RESs, such as wind, solar, hydro, etc. have been integrated with the conventional power plants to reduce the emission pollutants and the power generation cost. However, the power generation of RESs are uncertain due to weather conditions. One of the most sustainable ways to mitigate variations in the generation and demand has been the incorporation of the *energy storage systems (ESS)*. The ESS may improve power management and facilitates a robust energy balance within the *integrated energy system (IES)*. The larger involvement of RESs into the existing power system creates a challenge for optimum generation schedule. The optimal generation schedule of an IES is a nonlinear, mixed-variable, constrained optimization problem. The various conventional search techniques have been applied to resolve the optimal generation scheduling problem with number of presumptions to make optimization problem more tractable and simple. In order to overcome the limitations of conventional search techniques, researchers have

proposed global optimization techniques, which do not require any derivative information. The conventional methods are more exploitative in nature and global search techniques are explorative. Therefore, a space for an optimization technique exists that maintains a fine balance between exploration and exploitation phase to reduce the convergence speed of finding the optimum solution.

In *multi-objective optimization problems (MOOP)*, the objective functions are conflicting in nature and multi-objective optimization techniques are applied to find most satisfying non-dominated solution in the presence of trade-offs between two or more conflicting objectives. The MOOP solution methodologies have been categorized in two ways: the method employed to obtain Pareto optimal solutions, the ways and means to interact with *decision maker (DM)* and the information available to the DM. The classical and multi-objective global optimization techniques have been implemented to get a trade-off solution to the interactive MOOP. The multi-objective global optimization algorithms have the ability to search and obtain the set of Pareto optimal solutions in a single run. Further, decision-making is one of the vital aspects of MOOP. Among the decision-making methodologies, the interactive methods are recognized to achieve most satisfactory results because few non-dominated solutions have to be evaluated.

In this work, an optimization technique is proposed combining modified crisscross search particle swarm optimization (MCS-PSO) technique and modified binary PSO (MB-PSO) technique. The proposed optimization technique (POT) has been applied to solve economic, emission and multi-objective scheduling problems for standard hydrothermal system (HTS), PSHTS, and IES. Further, the results have been compared with state-of-art optimization techniques. For MOOP, fuzzy based surrogate worth trade-off (SWT) method has been applied to club different objectives and cardinal priority ranking method is used to select the best non-dominated solution. The brief discussion regarding each chapter of the thesis has been presented.

In chapter 1, the requisite background review of hydro, thermal, pumped storage units and RES have been presented. The significant contributions of several researchers related to optimum generation scheduling of HTS, PSHTS, IES have been reviewed. In Chapter 2, the crisscross search PSO (CSPSO) and improved binary PSO (IBPSO) technique have been implemented for the economic, emission, and the multi-objective generation scheduling problem of the PSHTS. Numerical analysis has been conducted on two test systems (PSHTS-I, and PSHTS-II) with two cases under each test system. The results reveal that the implemented technique is superior as compared to other state-of-art techniques. Further, the impact of the PSU has been analysed in terms cost and emission pollutant. In order to check the statistical performance of the implemented technique, two-sample student t-test has been applied and the performance of the CSPSO-IBPSO technique found satisfactory.

In the successive chapter, an optimization technique has been proposed for resolving the economic, emission and multi-objective PSHTS scheduling problems. The proposed optimization technique (POT) combines MCS-PSO, and MB-PSO for continuous and binary decision variables. Two test systems (HTS-I, and PSHTS-III) have been undertaken and results reveal that the POT is superior as compared to other state-of-art techniques. To check the statistical performance of the POT, two-sample student t-test has been applied and the performance of the POT found satisfactory. In addition, parameter sensitivity has been implemented by perturbing each parameter successively. It has been concluded that the parameter perturbation has very little effect on the result obtained from the POT.

In the ensuing chapter, the PSHTS problem formulation has been extended to the IES scheduling problem considering uncertainties of RESs. The economic, emission and multi-objective scheduling problem of IES has been addressed, in which cost, and emission has been optimized. The POT has been applied to search the optimal results. Two test systems (IES-I, and IES-II) with two cases under each test system have been undertaken to examine the effectiveness of POT. Further, the impact of RES and its uncertainties on the optimum

generation schedule and its impact on cost, and emission have been analysed. It is verified from results that the POT has a significant impact on the economic, emission and multi-objective scheduling of the IES. In the succeeding chapter, the multi-objective generation scheduling problem of IES incorporating RES has been resolved by implementing the POT-surrogate worth trade-off approach. Four different test systems (HTS-I, PSHTS-III, IES-I, and IES-II) have been undertaken to examine the effectiveness of POT-SWT approach. It has been concluded that the SWT approach achieves better non-dominated solutions as compared to its counterparts. Finally, the main conclusions and contributions of the thesis have been presented and suggestions for the future research in this field have been specified.

CHAPTER-1

INTRODUCTION

1.1 Overview

In the current scenario, the power system has become a large complex network comprising, generation, transmission, and distribution of electrical power. Among the power generating units, the thermal power plant has been the major source. However, thermal plants are inefficient to endure the increased power demand and preserve the environmental balance. The hydropower plants have been an attractive alternative for meeting the power demand, without increasing the fuel cost and pollutants emission. Therefore, to provide energy to the consumers at minimum cost and to restraint the environmental degradation, the hydroelectric plants have been integrated with the thermal plants, forming a hydrothermal system (HTS). The optimal hydrothermal generation scheduling (HTGS) has been a significant step in the sustainable operation of the power system (**Brannud et al., 1986;Nguyen et al., 2014**). The problems with hydroelectric plants such as large dams' construction, alteration of natural flow regimes, and uncertainty in the water availability would be more obvious in cascaded hydroelectric plants (**Rawshan et al., 2019**). Alternatively, with increase in population the electricity demand has been continuously rising and cannot be met by hydrothermal plants. Further, the effective utilisation of water resources for irrigation and drinking purpose as well as conservation of fuel reserves have encouraged researchers towards incorporation of pumped storage unit into the HTS. Therefore, to mitigate the limitations of HTS up to some extent pumped storage units (PSU) have been installed. The PSUs have been used since the early 20th century to maintain the stability of the power system by optimally utilizing the available water in the upper and lower reservoirs. The PSUs can store the water in the reservoir, thereby controlling the uncertainty problem with the hydroelectric units. This

procedure has been performed by utilizing the PSUs' ability to pump water back into the upper reservoir in light-load and producing energy to supply the peak-load (**Nezhad et al., 2014**). The main function of PSUs in the electric power systems has been to store inexpensive electric energy available during off-peak load intervals as a potential energy. This has been done by pumping water from the lower reservoir of a PSU into its upper reservoir. The stored potential energy has been used to generate electric energy during peak load intervals. The effective operation of a PSU over a scheduled interval can reduce the power generation cost in a power system (**Fadil and Urazel, 2014**). The power generating system consisting of hydrothermal units and the PSUs forms the pumped storage hydrothermal system (PSHTS).

Globally, the power system structure has been shifting towards renewable energy resources (RES). Various countries have been working towards the utilization of the RESs in coordination with hydrothermal plants to change the current power system structure into a sustainable energy system (**Basu, 2020**). With the growing energy requirement and environmental crisis, the development and application of RESs have become a matter of great urgency (**Vallejos et al., 2015**). The sustainable global energy system can be achieved by the effective integration of the RESs within the power system. The solar photovoltaic (SPV) units have been one of the promising RESs that own the abundant storage to satisfy global energy consumption (**Nge et al., 2019; Shilaja and Ravi, 2017**). Meanwhile, the non-polluting source and low running costs endow solar energy with huge practical applications. The SPV unit has been a limitless source of energy, which generates clean, cheap, and abundant electricity from a photovoltaic cell with zero operating cost. The other merits associated with SPV units like, economical with greater efficiency, long life span, and lower emission have forced researchers towards its utilization in power generation. The drawback of not producing electrical energy in the rainy and cloudy season has forced the researchers to consider other important RESs in coordination with SPV units (**Wanga et al., 2017; Jie et al., 2019**). Among other RESs, wind energy source (WES) has been one of the fastest-growing RESs.

The level of wind power production of a wind turbine depends on the wind speed, which in turn depends on some complex factors such as weather conditions or the pressure gradient. The WES needs less cost for electricity generation and produces zero-emission pollutants **(Samal and Tripathy, 2019; Khaloie et al., 2020)**. The integration of intermittent weather-driven power sources has resulted in larger uncertainties that need to be reduced **(Keihan et al., 2020)**. The energy storage system (ESS) allows storing the surplus electricity generated from the RESs. During the day, the solar units generate electricity and the ESS like battery storage system will ensure that surplus energy used to charge the battery. In the evening time of low solar power generation, the battery system can discharge the stored electricity **(Javed et al., 2020)**.

The optimal generation scheduling problem becomes more complicated by incorporating various power generating units. The variability and intermittency of RES create challenges to be overcome in the generation scheduling problem **(Basu, 2020)**. This intermittent nature may have negative effects on the entire grid. The optimal solutions are hard to obtain for the high dimension, non-differentiable, and multi-modal generation scheduling problems. Researchers have conducted extensive studies towards developing effective optimization techniques to find the optimal generation scheduling of the power generating units. In the previously established work, researchers have implemented classical optimization techniques such as Lagrangian relaxation (LR) **(Salam et al., 1998)**, dynamic programming (DP) **(Chang et al., 1990)**, and other deterministic methods for resolving the optimal scheduling problems. The classical methods are dependent on certain assumptions or initial positions and hence the possibility of stagnancy occurs in local optima. The drawbacks in the classical approach have been mitigated by the global optimization techniques such as evolutionary programming (EP) **(Basu, 2004)**, differential evolution (DE) **(Price and Storm, 1997)**, genetic algorithm (GA) **(Abido, 2003)**, improved GA **(Kumar et al., 2007)** particle swarm optimization (PSO) **(Chaturvedi et al., 2009; Safari and Shayeghi, 2011)** and

simulated annealing (SA) (**Wong and Wong, 1994**). The global search techniques have emerged as effective optimization techniques for generation scheduling problems due to random search ability. The global search technique has been resulting in lower accuracy and increases the computational time for high dimension multi-modal optimization problems. Further, the drawbacks of classical and global search techniques have been overcome by developing hybrid optimization techniques (**Fadil and Urazel, 2014; Li et al., 2019; Narang et al., 2014**). These techniques have been based on the integration of two or more optimization techniques and maintain a fine balance between exploration and exploitation phase. The hybrid optimization technique has ability to jumps out of local optimal solution effectively, which improves the convergence (**Sinha et al., 2003; Awasthi et al., 2017**).

Generally, the real-world search and optimization problems involve multi-objectives (MO) that are contradicting in nature. The multi-objective optimization problems (MOOP) have been studied broadly by various researcher (**Abido, 2003; Marler and Arora, 2004; Xu et al., 2010; Qu et al., 2016; Elattar, 2018**). The MOOP solution methods have been categories in two ways: the information available to the decision maker and the method employed to obtain Pareto optimal solutions. The classical and MO global optimization methods have been implemented to get a trade-off solution to the problems. The classical methods transformed the MOOP to single-objective by providing the preference for each objective using the priori, posteriori or an interactive method. Various classical methods (**Basu, 2005; Singh et al., 2007; Xu et al., 2012; Singh et al., 2018**) have been reported in the literature like weighted method, the ϵ -constraint method, the goal programming method, surrogate worth trade-off method (SWT) etc. There are few drawbacks in classical methods such as selection of the appropriate weights, price penalty factors etc. Further, these methods fails to provide information for DM since only one solution can be obtained in a single run (**Zhang et al., 2017**).

Alternatively, the MO global optimization algorithms have ability to search and obtain

the set of Pareto optimal solutions in one run. These algorithms have been able to resolve the non-convex optimization problems without pairing different objectives. The MO global optimization algorithms, like dynamic artificial bee multi-colony algorithm (**Xiang and Zhou, 2015**), MODE (**Zhang et al., 2013**), MOGA (**Shirazi et al., 2014**), self-adaptive MO teaching–learning-based optimization method (**Yu et al., 2015**), etc., have been implemented for obtaining the Pareto front of the MOOP. The convergence, population diversity, robustness and flexibility have been the merits of MO global techniques over classical methods. However, these techniques sometimes suffer the time-consuming computation process and have been relatively less efficient (**Shukla and Deb, 2007; Lu et al., 2012**).

In the current scenario, with the rapid development of power system network, the complementary coupling of different power generating units has been deepening. Under this environment, the optimal power output from each unit to reduce the power generation cost and emission pollutants, have become an urgent problem to be resolved. The integration of conventional and RES raises practical issues of the optimal generation scheduling in the power system network. In this chapter, the detailed literature review and discussion about optimal generation scheduling problem and multi-objective scheduling problem of power system network has been described in the further section. In the following section, the conventional, global and hybrid optimization techniques have been discussed in detail for generation scheduling problems. The multi-objective optimization techniques have been reviewed in the detail. Further, the scope, objective of the thesis work, and the outline of the thesis has been presented.

1.2 Optimal Generation Scheduling

A modern power system consists of various power generating units connected at the different load centres through the transmission networks. The increase in the power demand due to the globalization, and industrialization has risen the power generation from different generating units. The thermal power plants have fulfilled the major portion of the power demand, which

causes an increase in fuel cost as well as emission pollutants in the environment. Therefore, various RESs such as hydro units, PSUs, SPV units, WES units, etc., have been incorporated with thermal plants to reduce emission and power generation cost (**Yuan et al., 2020**). These power generation units have been utilized in the integrated mode to reduce the cost and emission pollutants while satisfying all the operational constraints. The Optimum generation scheduling of the power generating units in the power system operation has been of the great importance (**Bahramara et al., 2016**).

1.2.1 Hydrothermal Generation Scheduling

The fossil fuel-based power generation plants have been the primary sources of energy generation. As time elapsed, the focus towards power generation from other energy sources increased due to rapid depletion in the fuel-based reserves. Furthermore, the environmental changes and global warming from the pollutant emissions have been deteriorating the ecological conditions. It has been anticipated that if the existing conditions on fuel reserves discovery and consumption progress, the reserves will end by the year 2038 (**Ehsani et al., 2009**). Several attempts have been made to meet the increased power demand at a minimum cost and at reduced emission pollutants (**Basu, 2020; Li and Guo, 2020**). One such attempt is utilizing the water energy sources to produce electricity by hydroelectric plants. Hence, hydropower plants have been integrated with thermal units to provide energy at optimal cost and restraint the environmental degradation. Fundamentally, the HTS have been the major resources of power generation and their integrated operation supports the optimal utilisation of the available energy resources.

The optimal hydrothermal generation scheduling problem has been the vital subject of intensive research work for several decades. The researchers implemented various conventional and global optimization techniques to solve the HTGS problem. Some of the conventional optimization methods are decomposition techniques (**Habibollahzadeh and Bubenko, 1986**), DP approach (**Chang et al., 1990**), mixed integer programming (**Nilsson**

and Sjelvgren, 1996), LR method (**Salam et al., 1998**), gradient method (**Farhat and El-hawary, 2009**), etc. **Chang et al. (1990)** have presented differential DP based on an effective multiplier method for resolving the hydroelectric generation scheduling problem. **Nilsson and Sjelvgren (1996)** have presented a mixed-integer programming approach for short term planning of hydroelectric model. **Petcharaks and Ongsakul (2007)** have proposed a hybrid enhanced LR and quadratic programming based technique for hydrothermal scheduling. However, the traditional methods are time consuming and reflect difficulties in handling constraints. Further, these methods make a number of assumptions to simplify the optimization problem, which may lead to a suboptimal solution.

In order to overcome limitations of local search techniques, the global search techniques have been explored. The global search techniques has a number of distinctive advantages like global search ability, robust and reliable performance, little information requirement, ease of implementation, no requirement of differentiable and continuous objective function. Various global search techniques such as GA (**Orero and Irving, 1998**), DE (**Lakshminarasimman and Subramanian, 2007**), EP (**Hota et al. (1999)**), SA (**Zhang et al., 2018**), PSO (**Mandal and Chakraborty, 2011**), etc. have been applied to resolve optimal HTGS problems. **Mandal and Chakraborty (2008)** have presented DE based optimization algorithm to solve economic HTGS problem with cascaded reservoirs. **Yu et al.(2007)** have employed PSO technique to resolve short-term HTGS problem. **Swain et al. (2011)** have developed an optimization technique based on clonal selection algorithm for the optimal short-term hydrothermal scheduling. The artificial immune system approach has been implemented for optimal scheduling of fixed head HTS (**Basu, 2011**). **Bhattacharjee et al. (2014)** have presented the real coded chemical reaction technique to resolve the HTGS scheduling problem. **Roy et al. (2018)** have implemented krill herd algorithm to resolve the HTGS problem. **Dasgupta et al. (2020)** implemented a novel sine cosine algorithm to minimize the power generation cost, emission and multi-objective for HTGS problem.

However, the drawback with global optimization techniques such as poor convergence rate, exploitation and exploration imbalance, loss of population diversity, etc., needs to be mitigated with development of improved or hybrid version of global optimization techniques. **Cau and Kye (2002)** have proposed an EP approach combining the merits of DP and EP for resolving the optimal HTGS problem. **Sinha et al., (2003)** have implemented a fast EP technique with mutation strategies for obtaining the optimal solution of a short-term HTGS problem. **Chao-Lung (2007)** has implemented improved GA equipped with an improved evolutionary direction operator and a migration operation for solving HTGS problem. **Sasikal and Ramaswamy (2010)** have presented an optimal gamma based algorithm for fixed-head hydrothermal problems using GA. **Hota et al. (2009)** have presented improved PSO technique to resolve the optimal power generation to short-term HTGS problem. **Wang et al. (2012)¹** have applied an improved self-adaptive PSO with a strategy to handle the various constraints for resolving the HTGS problem. **Mahor and Rangnekar (2012)** have proposed a novel self-adaptive inertia weight PSO technique to obtain the optimal generation schedule of cascaded hydroelectric system. **Basu (2014)** presented an improved DE to resolve the optimal HTGS problem. **Zhang et al. (2015)** have proposed a modified chaotic DE methodology for obtaining the optimal solution of HTGS problem. **Gouthamkumar et al. (2015)** have proposed a disruption based gravitational search algorithm to obtain the optimum solution for HTGS problems. **Kaur and Narang (2019)** have implemented a hybrid grey wolf optimization with mutation strategies to resolve the HTGS problem. **Wu et al. (2019)** have presented a couple-based PSO to resolve the short-term hydrothermal scheduling problem incorporating three improvements aimed to overcome the problem of premature convergence.

1.2.2 Pumped Storage Hydrothermal Scheduling

Due to the construction of large hydropower plants, many rivers have been exploited around the world, and have lost their pristine conditions. Therefore, governments of many countries are providing subsidies to promote the development of small hydropower plants (**Zhou et al.,**

2019). The utilization of hydro-energy sources benefits at the cost of environmental loss due to the degradation of water bodies in the ecosystem. The drawbacks have been mitigated up to some extent by installing the PSUs. The pumped-storage hydroelectric plant is getting vast attention all over the world mainly due to the strong development of non-dispatch renewable energies (**Javed et al., 2020**). The PSU provides fast response during demand variations and reduces the cost of energy generation from thermal units.

In the past decades, the optimal scheduling of PSHTS has been vital and researchers have extensively focused towards resolving the optimization problem of PSHTS. **Lee and Chen (1992)** have presented multi-pass DP for HTGS problem including pumped storage unit and battery storage systems. **Tang and Huang (1992)** have developed an algorithm by decomposing the PSHTS into hydro sub-problem and thermal sub-problem by implementing LR method. Further, the former part of problem has been resolved using mixed coordination and later part has been solved analytically. **Mohan et al. (1993)** have presented new problem formulation for PSHTS scheduling by incorporating generator security constraint on water storage level for operating the pumped storage hydro unit. The algorithm implemented for the optimal schedule consist combination of participation factor method and the linear programming method. **Fadil and Yasar (2000)** have resolved pumped storage hydroelectric unit scheduling problem by utilising the pseudo spot price of electricity algorithm. In this work, bus voltage magnitude and transmission line maximum capability constraints have been neglected. **Dieu and Ongsaku (2008)** have developed enhanced merit order and an augmented Lagrange Hopfield network approach for resolving PSHTS scheduling problem. **Parilla and Garcia (2006)** have implemented an optimization technique based on mixed linear integer programming for solving the large-scale PSHTS scheduling. **Perez-Díaz et al. (2016)** have assessed the contribution of a pumped-storage hydropower unit by reducing the system scheduling cost with implementation of hydrothermal weekly unit commitment model.

The EP techniques have been presented to resolve the pumped storage HTGS problem

(Khandualo et al., 2013). Nehzad et al. (2014) demonstrated the PSHTS scheduling problem by implementing the lexicographic optimization technique. **Fadil and Urazel (2014)** have also implemented a modified sub-gradient algorithm to resolve the power dispatch problem for a pumped-storage hydraulic unit and obtain the optimal schedule. Similarly, the pumped storage hydroelectric system has been proposed and the GA along with Pareto optimality concept has been implemented for the system techno-economic optimization **(Ma et al., 2015)**. **Petrakopoulou et al. (2016)** have presented the simulation, optimization, and evaluation of pumped storage hydropower plant with stand-alone solar-wind energy system for off-grid operation. **Simab et al. (2018)** have employed normal boundary intersection method for the MO-HTGS problem incorporating PSUs. Further, the VIKOR decisionmaker has been utilised to obtain the most compromised solution among the Pareto optimal solutions obtained by the normal boundary intersection method.

1.2.3 Integrated Energy System Generation Scheduling

In past decade, fossil fuel-based plants such as the thermal, oil, and gas have been the primary sources of power generation. The environment degrades due to emitted gaseous pollutants from fuel-based energy generating plants influencing the social life **(Koochi-Fayegh and Rosen, 2020; Luo et al., 2020)**. The rapid increment in the electric power demand, environmental hazards caused by thermal units, and depletion in fuel reserves have thrust the researchers in the direction of RESs across the world **(Li et al., 2019; Seulki and Jiyong, 2017)**. The RESs such as hydro units, PSUs, SPV, and WES have contributed significantly to overcome the drawbacks of fossil fuel-based power plants. With the growing energy requirement and environmental crisis, the development and application of RESs have become a matter of great urgency **(Vahedipour-Dahraie et al., 2018)**. From the Indian point of view, at present, the contribution of RESs has been 15.3% of the total installed capacity. In this contribution, the SPV and WESs are more and more being incorporated into the power generation system **(Mehta and Singh, 2014; Banerjee et al., 2016; Reddy, 2017)**. The merits

of the RESs incorporated power system are the environment friendliness, promoting national energy security and minimum power generation cost. The variability and intermittency of solar and wind power sources stimulate significant challenges to be overcome in the generation scheduling problem. This intermittency may have unfavourable effects on the power system network (**Jadhav et al., 2013; Agahei et al., 2013**). Consequently, it is extremely important to include the ESS to balance the mismatch between production and consumption. The ESS safeguards that the surplus energy to be utilized in charging the battery or exporting to the grid and lightens the fluctuations in the generation and the supply (**Jingrui et al., 2012**). To overcome the limitations of hydrothermal plants and RESs, the IES has been formed to satisfy the power demand during each sub-interval. The IES improves system reliability, reduces emission, increases life span, and efficiency. Various IES such as thermal-solar photovoltaic plants (**Khan et al., 2015**), thermal units incorporating wind power (**Zhu et al., 2014**), hydrothermal with wind power (**Banerjee et al., 2016**), hydrothermal with solar and wind (**Zhang et al., 2017**), etc. have been explored by the power system.

The need of the hour is to explore the IES such that the power demand and the intermittency issues with RESs are balanced. The generation scheduling problem of the IES has been one of the practical issues (**Biswas et al., 2018; Paliwal et al., 2019**). **Zhang et al. (2017)** have implemented gradient descent based multi-objective cultural DE to resolve the short-term hydrothermal multi-objective scheduling problem with consideration of integrated intermittent energy sources. **Basu (2020)** has presented the chaotic fast convergence EP technique for resolving the HTGS incorporating a pumped storage unit and considering the uncertainty and outage of the solar units. **Das et al. (2018)** have obtained the short-term optimal scheduling of the hydrothermal and wind-photovoltaic system based on the point estimate approach. In another attempt, the optimal generation scheduling of a hybrid energy system has been resolved by implementing GA and two-point estimate approach (**Reddy, 2017**). **Kaur and Narang (2019)** have resolved the generation scheduling problem of a

coordinated power system by implementing the grey wolf optimization technique with mutation strategies. **Somma et al. (2018)** have provided a stochastic model for optimal generation scheduling of RESs considering economic and environmental impacts. **Zhang et al. (2018)** have solved an integrated hydrothermal-wind scheduling problem including large electric vehicles by using a dual population mechanism. **Wang et al. (2018)** have implemented multi-objective cuckoo search algorithm to resolve the proposed complementary coordinated operation model of interconnected power systems with hydrothermal-wind-photovoltaic plants.

1.2.4 Multi-Objective Generation Scheduling

The sustainable development and improved society quality can be achieved with less impact of power generation on the environment. In the present scenario of globalization and industrialization, the global concern is to minimize pollutant emissions from the thermal plants. Therefore, it is important to minimize the operating cost and emission pollutants simultaneously. Various methodologies have been developed to reduce the environmental pollution (**Talaq et al., 1994**). These include post combustion cleaning equipment installation, moving towards low emission fuels, auxiliary fuel burners, and dispatching with emission considerations. Due to increased capital outlay and installation of new equipment, the first three options have been considered as long term for reducing the emissions. Hence, latter option has been preferred, in which power generation scheduling is done to minimize the emission pollutant. Due to conflicting nature of power generation cost and emission objectives, the generation scheduling problem becomes multi-objective optimization problem. The MOOP are the optimization problems in which the aim is to either maximize or minimize different objective functions. The MO problem is solved to obtain Pareto optimal solutions and, eventually, to achieve an utmost preferred solution. In the MOOP, none of the trade-off solution has been optimal with respect to all the objectives. Hence, number of non-dominated optimal solutions has been existed.

In the past decade, the MOOP have been resolved by implementing the MO classical and global optimization techniques. The classical methods involve preference based and no preference based categories of obtaining the optimal solution. The preference-based categories have been further subcategories as, priori, posteriori and interactive methods. The preference based classical methods are weighted sum, ϵ -constraint method, fuzzy interactive method, goal attainment method, surrogate worth trade-off method etc. **Nanda et al. (1988)** have presented MO-HTGS problem as a multiple, conflicting objective problem and has been resolved using goal-programming techniques. **Chang et al. (1995)** have converted the MO HTGS problem to a scalar objective problem by linear combination of different objectives as a weighted sum. **Singh et al. (2006)** have proposed a solution methodology for determining best objective weights to solve multi-objective thermal power dispatch problem. The weights have been calculated by conventional statistical measures characterizing the correlation coefficients matrix evolution. **Xu et al. (2012)** have proposed ϵ -domination and orthogonal design method based DE technique to resolve the multi-objective power dispatch problems. **Basu (2004)** has presented an interactive fuzzy satisfying method based on EP technique for short-term multi-objective hydrothermal scheduling. **Mandal and Chakraborty (2009) and (2011)** has employed price penalty factor approach for scalarizing the MO generation scheduling problem by implementing DE and PSO.

Alternatively, the MO global optimization techniques such as multi-objective artificial bee colony algorithm (**Zhou et al., 2016**), MODE algorithm (**Qu et al. 2016**), etc. have been implemented to solve MOOP. These techniques simultaneously obtain set of Pareto optimal solution in a single run. Alternatively, the MO global techniques have been less susceptible to the continuity of the Pareto front as compared to classical methods. **Lu et al. (2011)** have developed quadratic approximation based DE with valuable trade off approach to obtain the Pareto optimal solution for multi-objective hydrothermal scheduling problem. **Qu et al. (2016)** have presented a MODE algorithm for optimal economic emission scheduling with

integration of WES. **Zhang et al. (2012)** have developed a new multi-objective cultural algorithm based on PSO to carry through the evolution of population space. **Zhou et al. (2016)** have presented a multi-objective artificial bee colony algorithm for short-term multi-objective scheduling of HTS. A MO hydrothermal wind system scheduling considering the uncertainty of wind power has been solved by applying an enhanced multi-objective bee colony optimization algorithm (**Zhou et al., 2016**). **Dubey et al. (2016)** have developed a MO scheduling of the hydro-thermal-wind system by employing the composite ranking index approach. **Forough et al. (2017)** have presented multi-objective receding horizon optimization technique for optimal scheduling of hybrid renewable energy systems. The economic and emission scheduling of the HTS with integrated RESs has been resolved by implementing a gradient descent based multi-objective cultural DE (**Zhang et al., 2017**). **Zhang et al. (2018)** have proposed Pareto dominance based an adaptive second mutation based multi-objective DE technique for optimal scheduling of hydrothermal system.

1.3 Optimization Techniques

Optimization is the process of obtaining the optimal solutions in the search space for maximizing or minimizing the objective function. The procedure for resolving the optimization problem begins by choosing the decision variables and formulating the objective functions while satisfying equality and inequality constraints. The main aim of formulating the objective function is to obtain the optimal set of decision variables that will achieve the optimum solution while satisfying the constraints (**Deb, 2004**). The objective function for a non-convex, constrained optimization problem has been formulated as:

$$\begin{aligned}
 & \text{Minimize } f(x) \\
 & \text{Subject to : } \left. \begin{aligned} h_i(x) &\leq 0 \\ g_i(x) &= 0 \\ x_i^L &\leq x_i \leq x_i^U \end{aligned} \right\} i = 1, n
 \end{aligned} \tag{1.1}$$

where $f(x)$ represents the objective function value; x represents the decision variables; n is the number of decision variables; $h_i(x)$ and $g_i(x)$ are inequality and equality constraint, respectively; x_i^L and x_i^U represents the upper and lower bound of the decision variables, respectively.

The optimization techniques have been classified as conventional and global search optimization techniques based on the single path search and random search characteristics. The conventional techniques implemented to resolve the optimization problem make a number of simplifying assumptions in order to make the optimization problem more tractable. However, the linearization of objective function causes non-optimal solutions resulting in enormous revenue loss in the course of time (**Sinha et al., 2003**). Alternatively, the global search methods use heuristic optimization techniques and include randomness in moving from one solution to the next. The brief discussion regarding conventional and global search optimization techniques have been presented in following sub-sections.

1.3.1 Conventional Optimization Techniques

The conventional search methods have been diversified into the gradient and direct search methods. The gradient-based techniques require information about first-order and higher-order derivatives of objective functions, whereas the direct search method uses the objective function and the constraints to guide the search strategy (**Sen and Kothari, 1998**). The presence of the objective function gradient information makes the gradient method more efficient. The optimization problem becomes more tractable and simple with the number of streamlined conventions. Sometimes these conventions may lead to the wrong global optimum solution by the feature of simplifications (**Werner and Verstege, 1999**). The direct search techniques perform the search by explorative and pattern moves. One of the main disadvantages of the direct search method is that when the search space is large, the convergence speed is slow. For the same reason, it can be implemented to a different problem

without a change in the search technique. On the contrary, the gradient search quickly converges to a near-optimal solution, but inefficient in non-differentiable problems (**Beheshti and Shamsuddin, 2014**). The traditional methods such as gradient-based technique (**Kler et al., 2019**), LR technique (**Kovacki et al., 2018**), and DP (**Wood and Wollenberg, 2007**), were being implemented to solve the optimization problems. The gradient-based techniques have been widely used for solving different optimization problems due to their capability of finding an optimum solution with a reduced number of function evaluations (**Kler et al., 2019**). The LR idea is to divide the optimization problem into smaller isolated sub-problems. The division executed either by relaxing common constraints or by splitting variables and relaxing their equality binding (**Kovacki et al., 2018**). Dynamic programming is a computational method for optimizing sequential decision processes. This has been achieved by decomposing the given problem into different sub-problems and then leading to an optimal solution (**Wood and Wollenberg, 2007**). The obtained solution may converge to the local optimal solution for the multi-modal problems thereby developing the dimensionality curse and stagnancy problem in the traditional optimization techniques (**Yu et al., 2007**). In the past decade, the demerits associated with traditional search methods have been mitigated by developing global optimization techniques. The global optimization techniques have aroused researchers' interest due to their flexibility and robustness in achieving the global optimal solution (**Kitayama et al., 2011**).

1.3.2 Global Optimization Techniques

The optimization problems having non-linear, non-convex curves and non-differential properties need global optimization techniques to search the optimal solution. Since, the conventional optimization methods are not capable of tackling these issues (**Gouthamkumar et al., 2015**). The global optimization techniques are population based search techniques, have global search capability, and are ease to implement (**Jingrui et al., 2012**). The global optimization techniques have been classified as swarm based intelligence, biological-based,

physics-based etc. The swarm-based algorithms are inspired by the behaviour of social insects, like bees, ants, moths, and wasps, as well as from few other animal societies. The swarm based intelligence techniques use the collective intelligence of multiple interacting particles of a swarm along with their self-organization behaviour. Researchers have developed various algorithms such as PSO (**Clerc and Kennedy, 2002**), firefly algorithm(**Yang, 2010**), cuckoo search algorithm (**Nguyen et al., 2014**), ant colony optimization(**Dorigo et al., 1996**), etc., which are inspired by the collective behaviour of social insects and other animal societies. These optimization algorithms are among the widely used techniques due to their information-sharing ability, self-organization, and self-learning capability during the iterative process.

Particle swarm optimization technique is one of the most used swarm-intelligence based search techniques. **Kennedy and Eberhart (1995)** have introduced the PSO technique. The attractive features of PSO are its simple concept, easy implementation, fast computation, and robust search ability (**Sun and Lu, 2010; Rana et al., 2011**). However, the wrong choice of algorithm parameters may result in divergent particle trajectories, and it causes trapping into local minimum solutions. Further, for high-dimensional optimization problems, the PSO technique suffers from premature convergence resulting in a low optimization precision (**Gao and Xu, 2011; Liang and Kang, 2016**). **Kennedy and Mendes (2002)** proposed local topological structure PSO to avoid stagnancy problems and enhance the search capability. **Liang and Sugantham (2005)** suggested dynamic multi-swarm PSO in which the population has been divided into different small swarms and then these swarms have been reorganized frequently to interchange the information among the swarms. **Mendes et al. (2004)** developed the fully informed PSO algorithm, which uses the information of a complete neighbourhood to lead the particles for obtaining the best solution. An adaptive fuzzy PSO has been presented to regulate the parameters in PSO established on fuzzy inferences (**Juang et al., 2011**). Numerous memetic algorithms have been presented, which hybridized PSO with a local

search and global search techniques (**Liu et al., 2007; Petalas et al., 2007; Schutze et al., 2007**). The centripetal accelerated PSO has been developed based on newton's laws of motion to accelerate the learning procedure and convergence rate of optimization problems (**Beheshti and Shamsuddin, 2014**).

Another classification of global search technique is biological inspired algorithms, which are subset of the nature-inspired algorithms. These algorithms have been inspired by biological activities like evolution and physical features. The biologically inspired algorithms such as GA (**Gill et al., 2003**), DE (**Price and Storn, 1997**), flower pollination algorithm (**Yang, 2012**), invasive weed optimization (**Mehrabian and Lucas, 2006**), etc. have been extensively applied by researchers. The GA has been presented by John Holland in 1975 and implemented optimization strategies by simulating the evolution theory through natural selections (**Holland, 1975**). The implementation process consists of individual selection, crossover, and mutation strategies to form the next generation particles (**Gill et al., 2003**). The DE optimization method has been similar to other evolutionary algorithms. Firstly, particles generation has been randomly initialized and the next generations developed through evolution operators (**Price and Storn, 1997**). DE is very effective for resolving optimization problems that predominantly involve non-smooth objective functions, as it does not require derivative information.

Few algorithms have been developed by imitating the certain natural laws, which are based on physics or chemistry, such as electrical charges, gravity, river systems, etc. The simulated annealing (**Pavlyukevich, 2007**), harmony search (**Askarzadeh, 2017**), gravitational search algorithm (GSA) (**Rashedi et al., 2009**) are few algorithms which are based on physics and chemistry based laws. **Wong and Wong (1994)** have employed a SA technique, in which, current solution randomly reformed with the probability decrease as the computation proceeds. The sufficiency of SA has been judged by searching a large-scale system and obtaining an optimal or near-optimal solution. Another optimization algorithm

named ‘GSA’ has been based on the Newtonian law of gravity (**Rashedi et al., 2013**). In GSA technique, position of the mass corresponds to a solution to the problem, and its gravitational and inertial masses are determined using a fitness function. The researchers have developed few new algorithms which are not bio-inspired or physics/chemistry-based, such as artificial cooperative search (**Civicioglu, 2013**)¹, social-emotional optimization (**Xu et al., 2010**), backtracking search optimization (**Civicioglu, 2013**)², etc. It is sometimes difficult to put some algorithms in these three categories, because these algorithms have been developed by using various characteristics from different sources, such as social, emotional, etc.

The global optimization techniques have been originally developed for continuous-valued spaces, however many practical problems can be defined in terms of discrete valued decision variables (**Engelbrecht, 2005**). Hence, it has been needed to develop discrete version of global optimization techniques. The researchers have developed continuous and discrete versions of GA, PSO, GSA etc. to search in the real and binary search spaces, respectively. **Kennedy and Eberhart (1997)** introduced discrete binary PSO (BPSO) in which each particle symbolizes its position in binary values 0 or 1. The particle velocity has defined the probability that the particle changes its state to one. The PSO and BPSO techniques have simple structures and are easy to implement to solve mix-modal optimization problems. However, BPSO technique has certain drawbacks while solving high dimensional multi-modal problems such as stagnancy in local optima and slow convergence speed (**Liang et al., 2006; Kennedy and Mendes, 2002; Tasgetiren and Liang, 2007**). Therefore, several variants of BPSO have been developed to overcome these problems. Different topologies *i.e.*, improved parameter selection, hybridization with other techniques have been utilized to improve the performance of the optimization techniques. Various improved BPSO algorithms have been presented to address the shortcomings of BPSO technique. **Pampara et al. (2005)** proposed an angle modulation PSO to generate a bit string solution to convert high dimensional problem to the small dimension problem. **Sadri and Suen (2006)** presented a

genetic BPSO methodology by making the swarm population dynamic with a non-fix size of the swarm. **Lee et al. (2008)** proposed a modified BPSO by adopting the mutation operator concept and genotype-phenotype representation of GA. Similarly, **Nezamabadi-pour et al. (2008)** presented new BPSO (NBPSO) technique to overcome the drawbacks of the BPSO. Two different methods have been suggested to mitigate the stagnation problem in NBPSO. The guaranteed convergence BPSO method enhances the performance of NBPSO and improved new BPSO method uses a mutation operator to prevent the stagnancy problem. **Chen et al. (2011)** developed the essential BPSO for the binary search space in which PSO has been broken down to its essential components.

The researchers have developed various global optimization techniques to overcome the limitations of the conventional optimization techniques, and to search global optimal solution with least computational efforts. However, these techniques also have few shortcomings such as loss in population diversity, particle stagnancy in local optima, imbalance in exploration and exploitation of the search space and slow convergence speed for multi-dimension problems (**Shehab et al., 2017**). The population-based search algorithms may provide satisfactory results, however no global search algorithm can provide superior performance than others for all the optimizing problems according to no free lunch (NFL) theorem (**Wolpert and Macready, 1997**). In other words, an algorithm may solve some problems better and some problems worse than other algorithms. Therefore, in order to improve the quality of solutions, various hybrid approaches have been developed by integrating global and conventional techniques or by associating global optimization techniques in a meaningful manner.

1.3.3 Hybrid Optimization Techniques

Optimization problems in the modern day power system are very challenging to resolve because of its design intricacy, widespread geographical dispersal and other irregular factors. Most of the optimization problems consist of non-convex and non-linear characteristics along

with prevailing inequality and equality constraints and different types of decision variables **(Beheshti and Shamsuddin, 2014)**. The complexity in the current power systems structure makes it more difficult for the conventional and global optimization techniques to search optimal generation schedule. Therefore, it is essential to apply most effective optimization techniques with simplified formulation and implementation to solve the practical optimization problem. The decisive aim of any optimization technique is to attain a global best solution, while satisfying operational constraints for a specified scheduling interval. The NFL theory for optimization states that the constant evolution of the optimization technique is vital, since no search technique is proficient for every optimization problem **(Wolpert and Macready, 1997)**. Generally, hybrid optimization techniques consist two or more techniques that operate collectively and balance exploration and exploitation capability in order to make a productive collaboration with their integration. Overall, the implementation of hybrid methods on the optimization problem can yield some improvements in terms of search ability and computational time **(Thangraj et al., 2011; Kumar et al., 2017)**. **Chaturvedi et al. (2009)** have extended this approach by employing the advantage of PSO in time varying acceleration coefficient (TVAC) and proposed a technique named as TVAC-PSO. The TVAC strategy strikes a proper balance between the cognitive and the social component during the initial and the latter part of the search. **Ivatloo et al. (2013)** presented TVAC-PSO algorithm to resolve the combined heat and power economic dispatch problems. In the implemented technique, authors have adaptively varied the acceleration coefficients of PSO to improve the solution quality. **Chaturvedi et al. (2009)** have resolved the non-convex economic dispatch problem using parameter automation strategy employing TVAC to avoid premature convergence. **Beigvand et al. (2017)** proposed hybrid TVAC based gravitational search and PSO algorithm to resolve the large scale non-convex, non-linear and complex combined heat and power dispatch problems. The implemented algorithm is based on laws of gravitation and swarm behaviours. **Liu et al. (2005)** have applied the Cauchy distribution mutation strategy on

global best and mean best positions obtained by quantum-behaved PSO (QPSO). Similarly, **Coelho (2010)** has presented QPSO technique with the Gaussian mutation operator in which random numbers have been generated using a Gaussian distribution for updating the particle's position. **Wang et al. (2012)**² presented a novel effective differential real coded quantum inspired evolutionary algorithm for resolving complex HTGS problems. **Fang et al. (2014)** have presented a hybrid real-coded GA and artificial fish swarm algorithm (RCGA-AFSA) for resolving the hydrothermal scheduling problem. The hybrid RCGA-AFSA takes advantages of their global and local search ability for the optimal solution. **Duman et al. (2015)** have proposed a modified hybrid PSO and GSA based on the fuzzy logic by controlling the ability to search the global optimum solution and increase the performance of the hybrid technique. **Naderi et al. (2017)** have investigated economic dispatch problem considering emission, transmission losses and generation cost by proposing a fuzzy based hybrid PSO-DE algorithm. Similarly, **Srivastava and Singh (2015)** have developed hybrid multi-swarm PSO technique to resolve the reactive power dispatch problem. In this technique, PSO has been implemented as the search technique for each sub swarm and DE has been utilised to improve the particles personal best. **Sivasubramani and Swarup (2011)** have proposed hybrid technique combining DE and sequential quadratic programming for resolving hydrothermal scheduling problem with non-linear fuel cost function. Further, an adaptive mutation PSO technique has been developed with dynamic non-linear inertia weight to reduce the premature convergence problem of PSO technique (**Liang and Kang, 2016**). **Jordehi (2015)** has proposed enhanced leader PSO, based on a successive mutation strategy applied to swarm leader to solve the complex optimization problems.

Narang et al. (2014) have developed a solution methodology by hybridizing predator prey optimization (PPO) technique and Powell pattern search for resolving MO-HTGS problem. **Nazari-Heris et al. (2017)** have proposed real coded GA with an improved Muhlenbein mutation for resolving HTGS problem. **Nguyen et al. (2018)** have developed an

effective adaptive selective cuckoo search algorithm for solving HTGS problems with available reservoir volume constraints and transmission network constraints. **Zhang et al. (2017)** presented a small population based parallel DE methodology to resolve the HTGS problem considering power flow constraints. **Nazari-Heris et al. (2018)** employed an improved harmony search algorithm on the non-convex HTGS problem. Similarly, crisscross search optimization (CSO) technique has been one such optimization technique developed to explore and exploit the search space efficiently (**Meng et al., 2014; Meng et al., 2016¹**). The crisscross search algorithm has been developed for numeric optimization, which has proved a superiority over some popular heuristic algorithms, like PSO (**Gaing, 2003**), extreme learning machine based GA (**Yang et al., 2013**), for high-dimensional multimodal problems. **Meng et al. (2015)²** have implemented the crisscross search PSO (CSPSO) technique to search the optimum generation schedule of combined heat and power dispatch problem.

The mentioned improved or hybrid versions in the above literature have been effective in achieving higher quality solutions. However, the balance of exploration and exploitation is a big challenge. Moreover, when challenged with large-scale power system generation scheduling problem, which is having number of local optimal solutions, the optimization techniques are easy to fall into the stagnancy and exhibits slow convergence speed. Therefore, it is still an issue for meta-heuristic algorithms to overcome the premature convergence and further improve the solution quality for high dimensional generation scheduling problems.

1.4 Multi-Objective Optimization Techniques

The real-world optimization problems have been multi-objective in nature with contradicting objectives. The unique solution does not prevail for multi-objective optimization problems, however set of non-dominated solutions exist in the search space. These solutions have been known as Pareto-optimal solutions, where the improvement in one objective can be achieved only at the expense of other objectives. For MOOP, the results obtained for single objective

can be irrational with respect to the other objectives. Hence, a rational solution approach is required to examine Pareto-optimal solutions and to search the best non-dominated solution.

The general MOOP can be represented as follows (**Deb and Goel, 2001**):

$$\begin{aligned}
 &\text{Minimize } F(x) = [F_1(x), F_2(x), F_3(x), F_4(x), \dots, F_n(x)]^T \\
 &\text{Subject to: } h_i(x) \leq 0 \quad ; \quad i = 1, n \\
 &\quad \quad \quad g_k(x) = 0 \quad ; \quad k = 1, p
 \end{aligned} \tag{1.2}$$

Different MO optimization methods have been developed to determine the non-dominated solution for MOOP. The methods implemented to solve MOOP consist of the generation of the Pareto optimal solutions and interaction with the decision-maker. In the past years, various classical methods have been implemented to resolve MOOP, *i.e.*, weighting method, non-inferior set estimation method, ε -constraint method, goal attainment method, and so on. The MOOP problem has been converted to single objective by implementing weighted sum approach (**Dhillon et al., 1993; Chang et al., 1995**). In weighted sum method, the non-inferior or Pareto optimal solutions have been obtained by varying the weights. However, this approach requires multiple runs to obtain the desired Pareto optimal solutions and cannot be used to obtain Pareto optimal solution for the non-convex Pareto front. This drawback has been mitigated by implementing ε -constraint method for MOOP (**Yokoyama et al., 1988**). The ε -constraint method has been based on priori articulation of preference and considering the other objective as a constraint with some permissible limit. The preference is then altered to obtain the Pareto optimal set. This method is time-consuming and obtains weak non-dominated solutions. The classical methods requires multiple runs to obtain the non-dominated solution, cannot be implement for a non-convex Pareto front, time-consuming and weak non-dominated solutions have been achieved.

In the past years, the MO global optimization techniques have been utilized to resolve the MOOP (**Coello, 1999; Veldhuizen and Lamont, 2000**). The global optimization techniques seem suitable to solve MOOP because these techniques deal simultaneously with a

set of possible solutions in a single run of the algorithm. Additionally, MO techniques are less vulnerable to the shape or continuity of the Pareto front, whereas these two problems have been a concern in traditional MO methods. The strength Pareto evolutionary algorithm (SPEA) (**Abido, 2003**), non-dominating sorting GA (NSGA-II) (**Robert et al., 2004**), MO evolutionary algorithm (MOEA) (**Veldhuizen and Lamont, 2000; De et al., 2002; Abido, 2006**), fuzzy clustering-based PSO (**Agarwal et al., 2008**) etc., constitute the revolutionary MO optimization approaches which have been applied to resolve the MO scheduling problems.

The NSGA encompasses advanced concepts like elitism, fast non-dominated sorting approach and diversity maintenance along the Pareto-optimal front. The drawback with NSGA approach has been in maintaining lateral diversity and obtaining Pareto-optimal with high uniformity (**Jayadevi et al., 2011**). **Villalobos-Arias et al. (2012)** have proposed a methodology to spread the solutions generated by the MOEA. The approach depends on the use of stripes that have been applied in objective function space. In another work, MODE and NSGA-II has been developed for the economic emission scheduling of the hydrothermal power system (**Basu, 2011; Basu, 2003**). **Yang et al. (2009)** have introduced a new Pareto-optimal solution-searching algorithm for finding the optimal solution from the multi-objective PSO technique. In MOPSO algorithm, finding the global optimal particle of the swarm from a set of non-dominated solutions is an important problem. Similarly, the MODE deals with simple low dimensional problem with a fast convergence rate. However, when applied on complicated problems with multiple local optimal fronts, the technique suffers premature convergence because of the decreasing population diversity (**Lu et al., 2011**). The time consumption and the population search diversity have been severe problems resulting in premature convergence. Therefore, further efforts needed to preserve the diversity of the Pareto optimal solutions.

Wang and Yang (2010) have proposed a new ranking scheme based on equilibrium strategy of selection for MOOP. This approach increases the selective pressure when the number of objectives is very large. **Chiang (2007)** has proposed an approach based on the improved GA, multiplier updating and the constraint technique, to resolve the optimal economic emission dispatch problem. **Qin et al. (2010)** have developed the DE with adaptive Cauchy mutation to obtain the optimal trade-offs for MO-HTGS problem. The combined economic emission hydrothermal scheduling has been obtained by implementing an improved quantum-behaved PSO (**Sun and Lu, 2010**). **Tripathi et al. (2007)** have presented a novel PSO approach to MOOP, called time variant MOPSO (TV-MOPSO). The TV-MOPSO technique has been made adaptive in nature by allowing inertia weight and acceleration coefficients to change with iterations. **Agrawal et al. (2008)** have proposed a fuzzy clustering-based PSO algorithm has to resolve the highly constrained economic/environmental dispatch problem. In MO optimization approach, for large the number of objectives of MOOP, Pareto dominance-based ranking procedures become ineffective in sorting quality of solutions. **Pierro et al. (2007)** investigated the potential of using preference order-based approach as an optimality criterion in the ranking stage of MO optimization technique. **Xiang and Zhou (2015)** have developed a dynamic artificial bee multi-colony technique with a fuzzy membership function to resolve the MOOP. **Li et al. (2019)** have solved a MO-HTGS problem with RES by implementing the multi-objective hybrid grey wolf optimization algorithm.

The decision-making is one of the vital aspects of the MOOP. The best non-dominated solution needs to be selected by the DM. In the MOOP, the contradicting objective has been accomplished by the liberal decision-maker, which iteratively examines the existing data, updates the preferences, and thereby chooses the quality solution. The DM has imprecise or fuzzy goals for each of the objective function and fuzzy goals have been quantified by defining their corresponding membership values. The DM then specifies the reference

membership values for each of the objective function and the corresponding optimal Pareto optimal solution can be obtained. Further, the DM reference membership value has been updated through the interactive method by considering the present values of the membership function. **(Basu, 2004)**. **Tapia and Murtagh (1991)** have presented a fuzzy set methodology for solving a decision-making problem involving MO. **Srinivasan et al. (1994)** have proposed a fuzzy MO optimization technique for the economic /emission dispatch problem. However, the obtained solutions have been suboptimal and the systematic framework to obtain the Pareto-optimal front has been missing from the technique. **Huang et al. (1997)** have implemented a fuzzy satisfaction-maximizing decision methodology to resolve the MO economic/emission problem. **Dhillon et al. (2002)** have implemented a fuzzy decision methodology to decide the generation schedule of a long-term hydrothermal MOOP.

The Surrogate worth trade-off (SWT) method has been another decision making approach implemented to obtain the best solution among the set of Pareto optimal solutions in the MOOP **(Dhillon and Kothari, 2000; Singh et al., 2017)**. Within the decision-making category, the SWT method belongs to progressive posteriori articulation of preferences. The progressive DM analyse the obtained non-dominated solutions and update the preferences and selection to achieve the best compromised solution of the contradicting objectives. **Dhillon and Kothari (2000)** have presented a SWT method to provide the interface between the DM preferences and the non-dominated solutions.

1.5 Scope of Work

The electric power systems involve various types of generating units (*i.e.*, thermal, hydro, pumped storage, wind, solar), which have been connected to different load centres through the transmission network. The hydrothermal power generation units have been an important part of the power system structure to satisfy the power demand. The large proportions, high interconnections, and high nonlinearities characterize of electric power systems networks have increased system complexity. The utility planner faces a great challenge to satisfy the

consumer demand and handle the uncertainties of renewable energy sources during the entire scheduling interval. The challenge for optimal power system operation has been to supply economical power with lower emission to maintain the environmental ethics. Over the years, the researchers achieved major breakthroughs to solve generation scheduling problems in the power system. However, with the technology advancement in the field of power system and more exposure to RESs creates new challenges. Hence, there is a need to relook the power system optimization problem with the presence of renewable energy sources under diverse environment.

The focus of this research work is on resolving the economic, emission and multi-objective scheduling problem of the IES with different power generating units. Since, scheduling is a complex optimization problem and it is further challenging due to various other constraints imposed by RES in the IES. In addition to this, restrictions imposed due to clean air act amendments, the utility planner is bound to generate the required power with minimum pollutant emission. Due to which, the single objective scheduling problem has been transformed as a MOOP. From optimization point of view there is a need of a multi-objective hybrid optimization technique, which will able to achieve the Pareto optimal solutions for the MOOP problem.

1.6 Objectives of the Work

The following objectives of the research work have been set as:

- To propose an optimization technique for solving pumped storage hydrothermal generation scheduling problem.
- To propose an optimization technique to obtain optimal generation scheduling for pumped storage hydrothermal system with solar and wind energy sources.
- To search Pareto optimal solution for multi-objective generation scheduling problem.

1.7 Outline of the Thesis

In this thesis, the economic, emission and multi-objective scheduling problem of PSHTS, and IES considering RESs has been formulated. An optimization technique has been proposed to resolve the optimal generation scheduling problem of the PSHTS and IES. The proposed optimization technique combines modified crisscross search PSO (MCS-PSO) technique and modified binary PSO (MB-PSO) technique for resolving the formulated generation scheduling problem. For MOOP, the fuzzy based SWT method has been applied as an interface between non-dominated solution and the decision maker to select the best non-dominated solution. This thesis presents the impact of PSU in the PSHTS as well as the effect of underestimation and overestimation power from RESs in terms of cost and emission.

The significant contribution from researchers related to PSHTS, and IES scheduling problem have been reviewed briefly in the present chapter. Further, an overview of various conventional and global optimization techniques for different generation scheduling problems has been presented. This chapter addresses the review of different multi-objective optimization techniques for power system applications. The scope and objectives of the thesis have been highlighted, and has been presented in further chapters.

Chapter 2 presents the economic, emission, and the multi-objective scheduling problem formulation for the PSHTS. The generation scheduling problem has been resolved by implementing the crisscross search PSO and improved binary PSO (IBPSO) techniques. In the implemented optimization technique, the CSPSO has been used to deal with the continuous decision variables and improved BPSO technique has been applied to deal with binary decision variable. The fuzzy min-max method is implemented to obtain the best-satisfied non-dominated solution for the MOOP. In order to satisfy the various operational constraints of the scheduling problem, the exterior penalty factor method is applied. The superiority of the implemented technique has been verified by conducting a numerical analysis on two PSHTS with two cases under each test system. The impact PSU has been analysed in terms cost and emission reduction. The robustness of the implemented technique

has been verified by the two-sample student t-test, and the performance of the implemented technique found satisfactory.

In Chapter 3, an optimization technique combining MCS-PSO, and MB-PSO has been proposed for resolving the economic, emission and multi-objective PSHTS scheduling problem. In the proposed optimization technique (POT) the best performing particle obtained from CSPSO is further improved by pattern search direction for continuous decision variables. Since, the pattern search direction is based on conjugate search method, which helps to further exploit the promising search areas. Further, the MB-PSO technique has been implemented to update the position of the binary decision variables by considering the previous experience, and the modified sigmoid function helps to mitigate the local optima stagnancy problem. The cardinal priority ranking method has been implemented for the MOOP to achieve the best-compromised solution. Two test systems have been undertaken to verify the effectiveness of the POT technique as compared to other state-of-art techniques. To check the robustness of the POT, a two-sample student t-test and parameter sensitivity analysis has been performed. The test result reveal that the performance of the POT is found satisfactory, and the result obtained from the POT undergo small variation from the parameter perturbation.

The intent of Chapter 4 is to formulate the generation scheduling problem for the IES considering uncertainties of RESs. The IES consist pumped storage unit, hydro and thermal units, and RESs with battery units. The overestimated and underestimated power is considered to analyse the RESs uncertainties effect on cost and emission. The Weibull probability and lognormal probability density function has been utilised to handle the RESs uncertainties. The POT combining MCS-PSO and MB-PSO techniques have been applied to search the optimal solution. The best non-dominated solution for the multi-objective scheduling problem has been obtained by implementing the fuzzy based cardinal priority ranking method. To examine the effectiveness of POT and the impact of RESs on the optimum generation schedule, two

test systems with two cases under each test system have been undertaken. It has been examined from results that the POT achieves the better optimal schedule for the IES generation scheduling problem as compared to well-established techniques. Further, the impact of RES, and its uncertainties on the cost, and emission has been analysed. To check the statistical performance of the POT a parametric two-sample student t-test is performed.

In Chapter 5, a fuzzy based SWT approach has been implemented for obtaining the best-satisfied non-dominated solution for the multi-objective scheduling problem. In the multi-objective framework, a fuzzy membership approach unifies the different objectives owing to contradicting nature of the objectives. The cardinal priority ranking decides the best-satisfied non-dominated solutions. The POT has been implemented to generate the non-dominated solution and fuzzy based SWT method has been implemented as an interface between non-dominated solutions and the decision maker. To verify the effectiveness of the POT-SWT approach and the impact of RES in the IES scheduling problem, four IES test system has been undertaken. The multi-objective result reveals that the presence of RESs and energy storage has a significant impact on fuel cost and pollutant emission. The performance of the POT-SWT approach has been compared with the reported results in the literature as well as with the multi-objective results achieved from the fuzzy based min-max approach.

Finally, the last chapter summarizes the vital conclusions and contributions of the research carried out. Further, few suggestions for the future research scope in this field have been stated.

CHAPTER-2

PUMPED STORAGE HYDROTHERMAL GENERATION SCHEDULING

2.1 Introduction

The rise in the industrialisation and globalization leads to an exponential increase in the power demands. Until now, the thermal plants have been the vital part of the power system in fulfilling the power demands. However, the thermal plants increases the power generation cost and produce emission pollutants. Alternatively, the reduction in the fossil fuel reserve worsened the power generation conditions. The excessive consumption of fossil fuel leads to economic as well as environmental challenges. The environment degrades due to emitted gaseous pollutants from fuel-based energy generating plants, thereby influencing the society life quality. Therefore, the issues caused by fossil fuel resource have led to a consideration of clean energy sources such as hydropower, pumped storage power, solar power, etc. Apart from thermal units, the hydroelectric units have played a major role in, effective operation and efficient planning of the power system. The optimum utilization of different energy sources such as coal, river water, etc. has been the motivation behind the integrated hydrothermal system (**Basu, 2010**). The idea of integration is to utilize all the energy sources and to reduce the power generation cost. The hydroelectric units have mitigated the problem of emission pollutants up to a certain extent.

Apart from the hydroelectric units installed on the dams, run of river hydro energy sources are another type of clean energy source. The power generation from run-of-river hydro units is limited and does not improve the water management (**Nezhad et al., 2014**). This problem would be more evident in the cascaded hydro-units. Therefore, the pumped storage units (PSUs) are installed to optimally utilise the water available through cascaded

hydro unit reservoirs. Alternatively, the PSUs ability, to pump water back to upper reservoir during off peak load and generate power during the peak load, has been utilized to reduce the cost of power generation via thermal units **(Seulki and Jiyong, 2017; Wang et al., 2017)**. The researchers have displayed a profound interest in the PSUs for providing cost-effective energy to the consumer and eco-friendly power generation, **(Perez-Diaz and Jim, 2016; Fadil and Urazel, 2014; Ma et al., 2015)**. The energy system consisting of thermal, hydroelectric and PSUs forms pumped storage hydrothermal system (PSHTS). The optimal power generation scheduling of PSHTS has been the focused research areas among the researchers. The optimal scheduling of the pumped-storage hydraulic unit power dispatch problem has been resolved by developing a modified sub-gradient algorithm **(Perez-Diaz and Jim, 2016)**. The generation and pumping scheduling problem of PSHTS has been resolved by implementing an evolutionary programming technique **(Khandualo et al., 2013)**. In another work, the PSHTS scheduling problem has been formulated and resolved by implementing lexicographic optimization methodology **(Nezhad et al., 2014)**. **Ma et al. (2015)** have implemented genetic algorithm, along with Pareto optimality concept, for the techno-economic optimization of the PSHTS.

The researchers have optimized the performance of the PSHTS by using various optimization techniques, which can be categorize as conventional and global search techniques. Most of the practical system functions are non-differential and discontinue in nature. The conventional search techniques require the derivatives of the functions/constraints, which is not easy to compute for large-scale complex system. Hence, it is not possible to apply conventional optimization techniques to solve practical optimization problems. However, the better exploration capability and flexibility to handle non-convex problems are the advantages associated with the global search techniques. Therefore, the global search techniques is being implemented to solve the optimization problems **(Clerc and**

Kennedy, 2002; Basu, 2004; Kumar and Mohan, 2011; Dubey et al., 2016).

The particle swarm optimization (PSO) technique has been recognized as one of the most favourable population-based optimization technique due to its simple concept, easy implementation, fast convergence, and robust search ability (**Clerc and Kennedy, 2002**). Despite several advantages of PSO, the convergence characteristic of the PSO has been sensitive to its parameter and it suffers from the premature convergence (**Kennedy and Eberhart, 1995**). In order to enhance the global search ability of the PSO and mitigate the premature convergence problem, researchers have attempted to develop some improved or hybrid versions *i.e.*, time-varying acceleration coefficients (TVAC-PSO) (**Chaturvedi et al., 2009; Ratnaweera et al., 2004**), self-organizing hierarchal PSO (SOHPSO) (**Mandal and Chakraborty, 2012**). Recently, the crisscross search optimization (CSO) algorithm has been developed by the Confucian doctrine of gold mean and the crossover operation in GA (**Meng et al., 2014**). **Meng et al. (2016)¹** reported an acceleration of the global convergence of the PSO by utilising crisscross search PSO (CSPSO).

The researchers have tested the CSPSO technique on numerous benchmark functions and found that CSPSO outperforms the conventional PSO and its variants in terms of convergence speed and global search ability. The complex optimization problems have been resolved by exploring various applications of CSO technique. A large-scale dynamic economic dispatch problem considering valve point loading effect has been resolved by implementing CSO technique (**Meng et al., 2015**)¹. A large-scale non-convex economic load dispatch with multiple fuel types and valve-point effects has been solved by applying CSO technique (**Meng et al., 2016**)². The CSO technique has been implemented to search the optimum generation schedule of large-scale combined heat and power dispatch problem (**Meng et al., 2015**)². The optimal distributed generators allocation problem has been resolved by implementing integrated CSO and Monte Carlo simulation (**Peng et al., 2015**).

Few real-time optimization problems consist of binary decision variables *i.e.*, feature selection and dimensionality reduction (**Beretaa and Burczynski, 2007; Zeng et al., 2009; Avishek and Maiti, 2010**), data mining (**Srinivasa et al., 2007**), unit commitment (**Yuan et al., 2009**), etc. In order to search the optimum solution, the researchers have applied binary version of optimization techniques *i.e.*, binary PSO technique (BPSO) (**Kennedy and Eberhart, 1997**), binary genetic algorithm (**Garcia-Martinez et al., 2006**), binary gravitational search algorithm (**Rashedi et al., 2010**), binary grey wolf optimization and PSO (**Al-Tashi et al., 2019**), etc. The BPSO technique has been extensively employed to solve optimization problems due to its simple structure and easy implementation. However, BPSO technique suffers from disadvantages such as easily get trapped in local optima and slow convergence rate for high-dimensional multimodal optimization problems. Recently, few improved versions of the BPSO technique, *i.e.*, enhanced BPSO with mutation probability (**Vieira et al., 2013**), memetic BPSO (**Beheshti et al., 2015**) has been proposed and tested on complex optimization problems and their performance found satisfactory.

The optimal PSHTS generation scheduling has been performed to minimize the total power generation cost by optimal allocation of power generation to PSU and hydrothermal units. Apart from power generation, thermal units produce pollutant emission such as, sulphur dioxide, nitrogen oxide, dust particles etc. during the operation. Now, the researchers are focused towards environmental problems due to global warming and increased pollutants emission. Therefore, emission has become an important objective along with the power generation cost during the optimal scheduling problems. The PSHTS generation scheduling problem can be recognized as multi-objective optimization problem (MOOP) due to cost and pollutant emission as the contradicting objectives. The multi-objective hydrothermal scheduling problem has been undertaken by several researchers (**Yuan et al., 2015; Qu et al., 2016; Zhang et al., 2017**). Different techniques such as weighted method (**Diakoulaki et al.,**

1995), fuzzy satisfying method (**Dhillon et al., 2001; Dhillon et al., 2002; Basu, 2004**), goal attainment method (**Basu, 2005**), DE (**Mandal and Chakraborty, 2009**), improved DE (**Essiet et al., 2019**), and quantum PSO (**Lu et al., 2010**) have been implemented to resolve the MOOP. The non-dominated sorting algorithm-II has been implemented to resolve the economic/environmental dispatch problem of hydrothermal system (**Basu, 2011**). The hybrid multi-objective cultural algorithm has been developed to resolve the short-term economic-environmental hydrothermal generation scheduling problem (**Lu et al., 2011**). In the MOOP the conflicting objectives creates fuzziness in the decision-making. The approach of fuzzy decision-making has been attempted by researchers to deal with the vagueness inherited in the constraints and the goals. **Tapia and Murtagh (1991)** have introduced an interactive fuzzy programming method for solving a decision-making problem involving multiple objectives. **Dhillon et al. (2001)** presented a fuzzy decision methodology to decide the generation schedule of a long-term hydrothermal problem. **Dhillon et al. (2002)** have applied a weighting method to simulate the trade-off relation between the conflicting objectives and fuzzy decision-making methodology to decide the generation schedule of a short-range fixed head hydrothermal problem. An interactive fuzzy satisfying method along with evolutionary programming technique has been presented to short-term multi-objective scheduling of HTS (**Basu, 2004**). **Niknam et al. (2010)** have implemented fuzzy adaptive modified PSO to resolve the non-convex economic dispatch problem. Similarly, **Moeini et al. (2011)** have presented a fuzzy rule based model for hydropower reservoir operation to achieve the ideal or target storage level. **Ahmadi et al. (2015)** have utilized the fuzzy satisfying method for selecting the most preferred solution among the Pareto optimal solutions obtained from multi-objective hydrothermal scheduling problem.

In this research work, the CSPSO and improved BPSO techniques have been implemented to resolve the optimum economic, emission and multi-objective generation

schedule of the PSHTS. The CSPSO technique has been implemented on continuous decision variables (Hydrothermal units). The main motivation of choosing CSPSO is its dual search mechanism *i.e.*, horizontal and vertical crossover operation. The crossover operation reproduces a new set of the population at each generation and only moderate solutions survive, which helps to maintain the best position. The horizontal and vertical crossover forms the chain reaction, which exhibits distinct advantages in solution quality as well as convergence rate, especially for high dimensional multimodal problems. For binary decision variables (Pumped storage units), improved BPSO technique has been implemented. The PSHTS scheduling problem is recognized as multi-objective scheduling problem due to power generation cost and pollutant emission as two contradicting objectives. The fuzzy membership functions have been computed corresponding to multiple objectives and max-min operator is implemented to obtain the best-compromised non-dominated solution. The effectiveness of the implemented optimization techniques have been validated through two pumped storage hydrothermal test system with two different cases. The results have been compared with the state of the art algorithms and with existing PSO, TVAC-PSO and CSPSO techniques. Finally, the impact of PSU has been analysed on the economic, emission and MO generation scheduling of the HTS.

2.2 Mathematical Modelling of Generating Units

The mathematical formulation of the PSHTS has been discussed in this section. The main objective of PSHTS economic, emission and multi-objective generation scheduling is to minimize the total generation cost and emission, while satisfying all operational constraint related to PSHTS. The thermal power generation, reservoir discharge rate and binary decision variables for the operation of PSU are the decision variables.

2.2.1 Thermal Unit

The thermal unit operating cost may be represented by quadratic function; however, the ripple

curve complexity arises due to valve point loading effect, which creates non-linearity and discontinuity in the curve. The valve point loading effect has been represented as sinusoidal part in the cost function. The total power generation cost from the thermal unit (TC) has been given as **(Lakshminarasimman and Subramanian, 2006)**:

$$TC = \sum_{t=1}^T \sum_{g=1}^{nt} \left[a_g + b_g \times PT_{g,t} + c_g \times PT_{g,t}^2 + \left| d_g \times \sin \left\{ e_g \times (PT_g^{\min} - PT_{g,t}) \right\} \right| \right] \quad (2.1)$$

The rapidly increasing environment pollution has led the researchers to give more attention to minimize the pollutants emission produced by thermal plants. The pollutant emission (OF₂) has been described by a quadratic and exponential function **(Narang et al., 2014)**, which has been presented by Eq. (2.2):

$$OF_2 = \sum_{t=1}^T \sum_{g=1}^{nt} \left[\gamma_g + \beta_g \times PT_{g,t} + \alpha_g \times PT_{g,t}^2 + \eta_g \times \exp \left\{ \delta_g \times (PT_{g,t}) \right\} \right] \quad (2.2)$$

where a_g , b_g , c_g , d_g , e_g are the cost coefficients of the g^{th} thermal unit; $\alpha_g, \beta_g, \gamma_g, \eta_g$ and δ_g are the emission coefficient of the g^{th} thermal unit; $PT_g^{\min}$ and $PT_{g,t}$ are the minimum power limit and generated thermal power, respectively, for the g^{th} thermal unit at t^{th} sub-interval; T is the time interval in hour; nt represents the total number of thermal units.

2.2.2 Pumped Storage Hydroelectric Unit

In the multi-chain hydroelectric model, the power generation is a function of water discharge rate and reservoir volume. The lower reservoir volume in the multi-chain model depends on the upper reservoir discharge and water inflow. The reservoir water storage at the end of t^{th} sub-interval has been computed from the volume dynamics of the reservoir network **(Nezhad et al., 2014)**.

The volume dynamics of multi-chain network is given as:

$$V_{j,(t+1)} = V_{j,t} + I_{j,t} - q_{j,t} - S_{j,t} + \sum_{n=1}^{Ru} (q_{n,t-d} + S_{n,t-d}) \quad (j \in nh, \quad t \in T) \quad (2.3)$$

where $V_{j,(t+1)}$ is the j^{th} unit reservoir volume in $(t+1)^{th}$ sub-interval; $V_{j,t}$ represent the j^{th} unit water volume in t^{th} sub-interval; $I_{j,t}$ is the j^{th} unit reservoir inflow in t^{th} sub-interval; $q_{j,t}$ is the j^{th} unit reservoir discharge in t^{th} sub-interval; $S_{j,t}$ is the j^{th} unit spillage in t^{th} sub-interval; $S_{n,t-d}$ is the j^{th} unit spillage in t^{th} sub-interval; $q_{n,t-d}$ is the water discharge from n^{th} upstream in $(t-d)^{th}$ sub-interval with transport delay of d ; Ru represents the number of upstream reservoir; 'n' is the index for upstream reservoir.

In this model, the PSU has been installed between the hydro units 1 and 3, acting as the upper and lower reservoir for the PSU, respectively, as represented in Figure 2.1. With the changing nature of the load, the PSU works either in generating or pumping mode. The switching status of the PSUs is binary in nature that decides the mode of operation. The presence of the PSU affects the volume dynamics of the reservoirs.

The volume dynamics for upper and lower reservoir during generating mode of the PSU is similar to Eq. (2.3). When the PSU works in pumping mode, the volume of the upper reservoir is presented as:

$$V_{l,(t+1)} = V_{l,t} + I_{l,t} - q_{l,t} + qa_{l,t} - S_{l,t} + \sum_{n=1}^{Ru} (q_{n,t-d} + S_{n,t-d}) \quad (l \in np, \quad t \in T) \quad (2.4)$$

where $V_{l,(t+1)}$ is the upper reservoir volume of the l^{th} PSU in the $(t+1)^{th}$ sub-interval; $V_{l,t}$ upper reservoir volume of the l^{th} PSU in the t^{th} sub-interval; $q_{l,t}$ represents the water discharge from the l^{th} PSU in the t^{th} sub-interval; $qa_{l,t}$ is the water discharge from lower reservoir of the l^{th} PSU in t^{th} sub-interval.

Similarly, the lower reservoir volume has been updated by subtracting the lower reservoir water discharge from Eq. (2.3).

The power generation from hydroelectric unit and PSU has been represented as:

$$PH_{j,t} = C_{1j} \times V_{j,t}^2 + C_{2j} \times q_{j,t}^2 + C_{3j} \times V_{j,t} \times q_{j,t} + C_{4j} \times V_{j,t} + C_{5j} \times q_{j,t} + C_{6j} \quad (j \in nh, \quad t \in T) \quad (2.5)$$

$$PS_{l,t} = L_{1l} \times V_{l,t}^2 + L_{2l} \times q_{l,t}^2 + L_{3l} \times V_{l,t} \times q_{l,t} + L_{4l} \times V_{l,t} + L_{5l} \times q_{l,t} + L_{6l} \quad (l \in np, t \in T) \quad (2.6)$$

The cost associated with PSU (PSC) is given as (Nezhad et al., 2014):

$$PSC = \sum_{t=1}^T \left(K_1 + \sum_{l=1}^{np} K_2 (PS_{l,t}^g + PS_{l,t}^p) \right) \quad (2.7)$$

where $C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}, C_{6j}$ are the power coefficients for the j^{th} hydro unit; $L_{1l}, L_{2l}, L_{3l}, L_{4l}, L_{5l}, L_{6l}$ represents the power coefficients for the l^{th} PSU; K_1 and K_2 are the cost coefficients of PSU power; $PH_{j,t}$ and $PS_{l,t}$ represent the power for the j^{th} hydro and l^{th} PSU in t^{th} sub-interval; np is the number of pumped storage units; $PS_{l,t}^g$ and $PS_{l,t}^p$ are the l^{th} PSU power in t^{th} sub-interval for generating and pumping mode, respectively.

2.3 Problem Formulation

The optimal scheduling problem of PSHTS has been formulated as a multi-objective problem, which is concerned with the attempt to minimize simultaneously the total cost of power generation and pollutant emission from the thermal units. The total cost (OF₁) of power generation incorporates the power generation cost from the thermal units and pumped storage units and is represented as:

$$OF_1 = TC + PSC \quad (2.8)$$

Mathematically, the multi-objective scheduling problem is stated as:

Minimize [OF₁, OF₂]

subject to the realization of bounds on the decision variables, equality constraints and inequality constraints.

The PSHTS has been subjected to following set of constraints:

(i) Limits on decision variables:

The decision variables should be restricted within the defined limits. For hydro and thermal units, decision variables are reservoir discharge rate and thermal power generation.

Discharge limits imposed on the hydro units are given as:

$$q_j^{\min} \leq q_{j,t} \leq q_j^{\max} \quad (j \in nh, t \in T) \quad (2.9)$$

Power limits imposed on the thermal units are represented as:

$$PT_g^{\min} \leq PT_{g,t} \leq PT_g^{\max} \quad (g \in nt, t \in T) \quad (2.10)$$

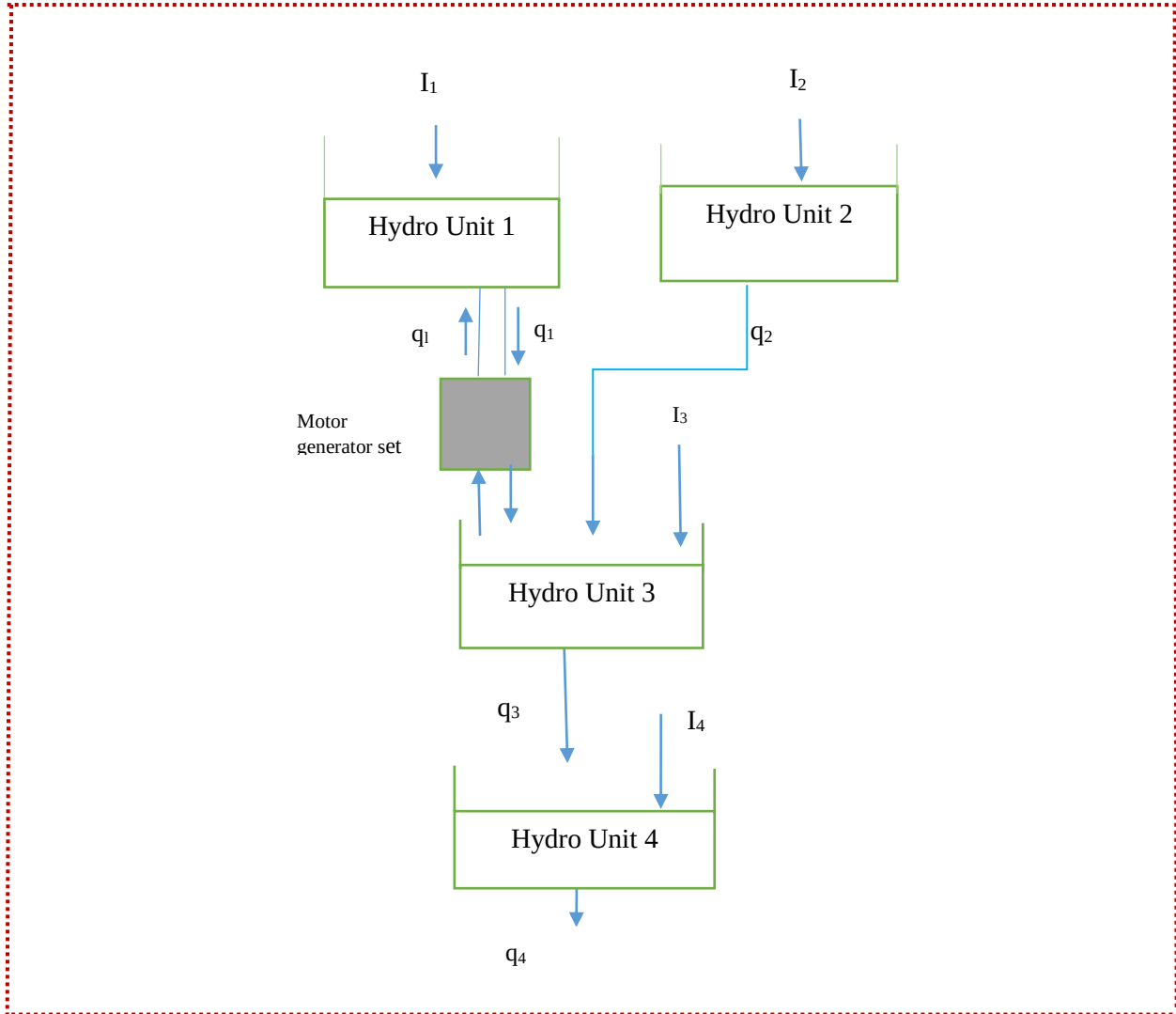


Figure 2.1: Diagrammatic representation of the multi-chain PSHTS model.

The PSU will work either in generating mode or in pumping mode and its operation is controlled by binary decision variables. The restriction on the working of a PSU is enforced as:

$$U_{l,t}^g + U_{l,t}^p \leq 1 \quad (l \in np, t \in T) \quad (2.11)$$

Additional restriction on the PSU is a requirement of minimum changeover time between generating mode to pumping mode and vice-versa and is given as **(Nezhad et al., 2014)**:

$$U_{l,t}^g + U_{l,t-tc}^p \leq 1 \quad (l \in np, t \in T) \quad (2.12)$$

$$U_{l,t}^p + U_{l,t-tc}^g \leq 1 \quad (l \in np, t \in T) \quad (2.13)$$

where $q_j^{\min}$ and $q_j^{\max}$ are the minimum and maximum limit of the water discharge of the j^{th} hydro unit; $PT_g^{\min}$ and $PT_g^{\max}$ are the minimum and maximum power limit of the g^{th} thermal unit; $U_{l,t}^g$ and $U_{l,t}^p$ is the binary status of l^{th} PSU at t^{th} sub-interval in the generating and pumping mode; tc is the changeover period between operating modes; $(l, t-tc)$ represent the l^{th} PSU at $(t-tc)^{th}$ sub-interval.

(ii) Equality constraints:

The equality constraint associated with the final volume of the reservoir is given as:

$$V_j^{\text{end}} = V_j^{\text{in}} + \sum_{t=1}^T I_{j,t} - \sum_{t=1}^T q_{j,t} - \sum_{t=1}^T S_{j,t} + \sum_{t=1}^T \sum_{n=1}^{Ru} (q_{n,t-d} + S_{n,t-d}) \quad (j \in nh) \quad (2.14)$$

The power balance constraint is given as:

$$\sum_{g=1}^{nt} PT_{g,t} + \sum_{j=1}^{nh} PH_{j,t} + \sum_{l=1}^{np} \eta_g \times PS_{l,t}^g = PD_t + \sum_{l=1}^{np} \eta_p \times PS_{l,t}^p + PL_t \quad (2.15)$$

where V_j^{end} and V_j^{in} are the end and initial reservoir volume of the j^{th} hydro unit; PD_t and PL_t represent the power demand and power loss in t^{th} sub-interval; η_g and η_p are the PSU efficiency during generating and pumping mode.

(iii) Inequality constraints:

Inequality constraints associated with the power and reservoir volume of hydro units are given as:

$$PH_j^{\min} \leq PH_{j,t} \leq PH_j^{\max} \quad (j \in nh, t \in T) \quad (2.16)$$

$$V_j^{\min} \leq V_{j,t} \leq V_j^{\max} \quad (j \in nh, t \in T) \quad (2.17)$$

Pumped storage hydropower inequality constraint is represented as:

$$0 \leq PS_{l,t}^g \leq U_{l,t}^g \times PS_l^{\max} \quad (l \in np, t \in T) \quad (2.18)$$

$$0 \leq PS_{l,t}^p \leq U_{l,t}^p \times PS_l^{\max} \quad (l \in np, t \in T) \quad (2.19)$$

where $PH_j^{\min}$ and $PH_j^{\max}$ are the minimum and maximum power limit of the j^{th} hydro unit; $PS_l^{\max}$ is the maximum limit of power from the l^{th} PSU; $v_j^{\min}$ and $v_j^{\max}$ represent the minimum and maximum limit of the reservoir volume of the j^{th} hydro unit.

2.3.1 Constraint Handling

During the search process, if the decision variables violate the bounds, then these are set to their corresponding limit and to satisfy the equality and inequality constraints, the exterior penalty method is used. The error has been computed for any violation of equality and inequality constraints and collective error has been incorporated in the objective function.

For the hydro reservoir final volume equality constraint given by Eq. (2.14), if there is mismatch between desired volume and final volume, then an error is computed as:

$$evf_j = \begin{cases} (V_j^{\text{end}} - V_j^T)^2; & V_j^T \neq V_j^{\text{end}} \\ 0 & ; \quad V_j^T = V_j^{\text{end}} \end{cases} \quad (j \in nh) \quad (2.20)$$

To satisfy power balance equality constraint given by Eq. (2.15), in each sub-interval, any one thermal unit has been randomly taken as the dependent unit during each sub-interval, and the power generation by dependent thermal unit is computed as:

$$PT_t^{\text{dep}} = PD_t + \sum_{l=1}^{np} (\eta_{p,l} \times PS_{l,t}^p) + PL_t - \sum_{\substack{g=1 \\ g \neq \text{dep}}}^{nt} PT_{g,t} - \sum_{j=1}^{nh} PH_{j,t} - \sum_{l=1}^{np} (\eta_{g,l} \times PS_{l,t}^g) \quad (t \in T) \quad (2.21)$$

If the dependent unit power generation violates its defined limit in any sub-interval, then an error is computed as:

$$ep_t = \begin{cases} (PT_t^{\text{dep}} - PT^{\min})^2; & PT_t^{\text{dep}} < PT^{\min} \\ (PT_t^{\text{dep}} - PT^{\max})^2; & PT_t^{\text{dep}} > PT^{\max} \\ 0 & ; \quad PT^{\min} \leq PT_t^{\text{dep}} \leq PT^{\max} \end{cases} \quad (t \in T) \quad (2.22)$$

where evf_j and ep_t are the final volume error of the j^{th} hydro unit and dependent unit power error in t^{th} sub-interval; PT_t^{dep} is the power obtained from the dependent unit in t^{th} sub-interval.

In order to satisfy all the inequality constraints, which have been given by Eq. (2.16) to (2.19), the respective error has been computed on violation of defined limits as:

$$eph_{j,t} = \begin{cases} (PH_j^{\max} - PH_{j,t})^2 ; & PH_{j,t} > PH_j^{\max} \\ (PH_{j,t} - PH_j^{\min})^2 ; & PH_{j,t} < PH_j^{\min} \\ 0 & ; \quad PH_j^{\min} \leq PH_{j,t} \leq PH_j^{\max} \end{cases} \quad (j \in nh, t \in T) \quad (2.23)$$

$$ev_{j,t} = \begin{cases} (V_j^{\max} - V_{j,t})^2 ; & V_{j,t} > V_j^{\max} \\ (V_{j,t} - V_j^{\min})^2 ; & V_{j,t} < V_j^{\min} \\ 0 & ; \quad V_j^{\min} \leq V_{j,t} \leq V_j^{\max} \end{cases} \quad (j \in nh, t \in T) \quad (2.24)$$

$$eps_{l,t} = \begin{cases} (PS_l^{\max} - PS_{l,t})^2 ; & PS_{l,t} \geq PS_l^{\max} \\ (PS_{l,t} - PS_l^{\min})^2 ; & PS_{l,t} \leq PS_l^{\min} \\ 0 & ; \quad PS_l^{\min} \leq PS_{l,t} \leq PS_l^{\max} \end{cases} \quad (l \in np, t \in T) \quad (2.25)$$

where $eph_{j,t}$ and $eps_{l,t}$ represent the power error of the j^{th} hydro unit and l^{th} PSU in t^{th} sub-interval; $ev_{j,t}$ is the error of the reservoir volume of the j^{th} hydro unit in t^{th} sub-interval.

The PSU may work either in generating or pumping mode and it requires a certain change over time between these two modes. A binary decision variable controls the generating mode of the PSU while, pumping mode operation has been regulated to satisfy the Eq. (2.11-2.13).

2.3.2 Objective Function Formulation

The cost and emission are the conflicting objectives, which creates fuzziness to select the best-compromised solution. Bellman and Zadeh (1970) have treated the objective function, and the constraints systematically and defined the fuzzy membership function to deal with the MOOP. The membership function $\mu(OF_k)$ is computed by considering the lower and upper bound of each of the objective functions and is given as:

$$\mu(OF_k) = \begin{cases} 1 & ; \text{ if } OF_k \leq OF_k^{\min} \\ \frac{OF_k^{\max} - OF_k}{OF_k^{\max} - OF_k^{\min}} & ; \text{ if } OF_k^{\min} \leq OF_k \leq OF_k^{\max} \\ 0 & ; \text{ if } OF_k \geq OF_k^{\max} \end{cases} \quad (k \in Nob) \quad (2.26)$$

where $\mu(OF_k)$ is the membership function for k^{th} objective function; $OF_k^{\max}$ and $OF_k^{\min}$ are the maximum and minimum objective function values, respectively; and *Nob* is the number of the objectives.

The higher membership function value indicates the more satisfaction level of the decision maker. In this work, cardinal priority ranking method has been implemented to obtain the non-dominated solutions. The combined effect of multiple objectives by means of their membership function values is obtained in the MOOP. The decision for the best compromised solution is taken by implementing the max-min operator to the membership functions. The maximum value of the cardinal priority ranking represents the desired solution. The cardinal priority ranking or overall objective function (μ_d) is represented as:

$$\mu_d = \{ \max(\min(\mu(OF_1) - f_{er}, \mu(OF_2) - f_{er})) \} \quad (2.27)$$

$$\text{where } f_{er} = r_a \times \left(\sum_{t=1}^T ep_t + \sum_{j=1}^{nh} evf_j + \sum_{j=1}^{nh} \sum_{t=1}^T ev_{j,t} + \sum_{j=1}^{nh} \sum_{t=1}^T eph_{j,t} + \sum_{l=1}^{np} \sum_{t=1}^T eps_{l,t} \right); r_a \text{ is the}$$

exterior penalty factor.

The exterior penalty method as given in Eq. (2.27) has been used to achieve feasible solution.

2.4 Particle Swarm Optimization Technique

The particle swarm optimization (PSO) technique is a population based optimization technique in which the population of particles propagate through the search space to search optimal solutions. The velocity of each particle is updated by Eq. (2.28), which is directed by local and global best particle positions.

$$V_i^d = \omega \times V_i^d + C_1 \times \text{rand}() \times (Plb_i^d - P_i^d) + C_2 \times \text{rand}() \times (PB^d - P_i^d) \quad (i \in N, d \in D) \quad (2.28)$$

The inertia weight (ω) has been updated with the iteration exponentially as:

$$\omega = (\omega_{\max} - \omega_{\min}) \times \exp^{(-b \times it)} + \omega_{\min} \quad (2.29)$$

The time varying inertia weight in Eq. (2.28) helps PSO technique to obtain a good solution at a faster rate. However, its ability to achieve an optimum solution is weak due to the loss of population diversity.

The particle position represented by Eq. (2.30) is modified based on the velocity evaluated from Eq. (2.28):

$$P_i^d = P_i^d + V_i^d \quad (2.30)$$

where V_i^d represent the updated particle velocity in d^{th} dimension; V_i^d is the particle velocity in d^{th} dimension; C_1 and C_2 are the acceleration coefficients; $P_{lb_i}^d$ is the particle local best position in d^{th} dimension; P_i^d represent the particle position; PB^d is the best position in d^{th} dimension; P_i^d represent the updated particle position; $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum limit of inertia weight.

The main strategy in the population-based optimization techniques is to encourage the particles to wander through the search space during the exploration phase, without being trapped around the local optima. In the exploitation stage, the convergence towards the global optima is being stimulated. This has been obtained by involving the time varying acceleration (TVAC) in Eq. (2.28) in such a way that the social component (C_2) dominates as compared to cognitive component (C_1) during the search.

The acceleration coefficients C_1 and C_2 are updated as **(Hadji et al., 2015)**:

$$C_1 = (Cf_1 - Ci_1) \times \left(\frac{it}{it_{\max}} \right) + Ci_1 \quad (2.31)$$

$$C_2 = (Cf_2 - Ci_2) \times \left(\frac{it}{it_{\max}} \right) + Ci_2 \quad (2.32)$$

where C_f and C_i are the final and initial value of the acceleration coefficients; it and it_{max} represent the current and maximum iteration.

The velocity and position of each particle in TVAC-PSO is updated based on the Eq. (2.28) and (2.30). However, still the TVAC-PSO exhibits slow convergence speed and suffer from the premature convergence problem while addressing high dimensional or multimodal problems. The researchers have invested lot of efforts to overcome the limitations of the PSO technique and its various versions. In one of such efforts, the improved PSO (IPSO) technique has been presented **(Meng et al., 2016)¹**.

In the IPSO technique, the individual particle solutions are replaced by local best values and the velocity is updated by using the average value of local best particles (lb) and global best particle (PB^d). The search direction has been established and carried out as:

$$V_i'^d = \omega \times V_i^d + C_1 \times \text{rand}^d \times (lb^d - Plb_i^d) + C_2 \times \text{rand}^d \times (PB^d - Plb_i^d) \quad (i \in N, d \in D) \quad (2.33)$$

In IPSO technique, the updated position does not directly move into the next generation. If the objective function value of the updated position is better than the parent particle, then only the updated particle replaces the parent particle position or else it will be vanished and is given in Eq. (2.34).

$$Plb_i^d = \begin{cases} Plb_i^d + V_i^d & ; \mu_d(Plb_i^d + V_i^d) > \mu_d(Plb_i^d) \\ Plb_i^d & ; \text{otherwise} \end{cases} \quad (i \in N, d \in D) \quad (2.34)$$

2.5 Improved Binary Particle Swarm Optimization Technique

The global optimal solution for the binary decision variables is searched by a BPSO technique **(Kennedy and Eberhart, 1997)**.

Initially, a binary value has been assigned to each dimension of a particle with a 0.5 probability and is represented as follows:

$$U_i^d = \begin{cases} 1, & \text{if } \text{rand}() > 0.5 \\ 0, & \text{otherwise} \end{cases} \quad (d \in D_b) \quad (i \in N) \quad (2.35)$$

The velocity of the particle is updated by using Eq. (2.32) of improved PSO and then sigmoid function has been used to scale the position between 0 and 1 and is given as:

$$\text{sig}(V_i^d) = \frac{1}{1 + e^{-V_i^d}} \quad (i \in N, d \in D_b) \quad (2.36)$$

The local best position of the binary decision variable is updated as:

$$U_i^d = \begin{cases} 1, & \text{if rand()} > \text{sig}(V_i^d) \\ 0, & \text{otherwise} \end{cases} \quad (i \in N, d \in D_b) \quad (2.37)$$

where U_i^d represent the binary value of i^{th} in d^{th} dimension; $\text{sig}(V_i^d)$ represent the sigmoidal function value for i^{th} particle in d^{th} dimension.

In this manner, local best position has been updated by the improved BPSO search technique for binary decision variables.

2.6 Crisscross Search Particle Swarm Optimization Technique

The CSPSO algorithm differs from the classical PSO algorithm in a way that the individual particles solution is directly represented by the particles local best position. Therefore, the CSPSO algorithm always maintains a population of best particles position, which is updated by the IPSO search as well as the crisscross search operator (CSO) from generation to generation. In this work, the improved version of PSO (**Meng et al., 2016**)¹ has been undertaken instead of classical PSO to realize the better performance of the particles position. In the CSPSO technique, the local best solutions obtained from the IPSO have been further refined by CSO by applying horizontal and vertical crossover operators.

The CSO acts as a powerful agent, which has an ability to search the global best solution with accelerated convergence characteristics without distorting the population diversity. The CSO consists of two crossover operators, namely, horizontal crossover and vertical crossover. The moderate solutions obtained from the crossover operation are the offspring reproduced from a parent population (**Meng et al., 2016**)¹. The combination of

horizontal and vertical crossover acts as a gift to crisscross search and enable to improve the performance in terms of convergence speed and accuracy. The horizontal and vertical crossover operation has been elaborated in the following sub-sections:

Horizontal Crossover

The arithmetic crossover operation has been implemented in the horizontal crossover search to generate the moderate solution from all the dimensions between two different individuals in the population. The i^{th} parent particle(Plb_i^d), and the h^{th} parent particle (Plb_h^d) have been chosen to carry out the horizontal crossover operation at the d^{th} dimension.

The generation of moderate solutions by two individuals has been expressed as follows:

$$HS_i^d = \text{rand}() \times Plb_i^d + (1 - \text{rand}()) \times Plb_h^d + E^d \times (Plb_i^d - Plb_h^d) \quad (i \in N, h \in N, d \in D) \quad (2.38)$$

$$HS_h^d = \text{rand}() \times Plb_h^d + (1 - \text{rand}()) \times Plb_i^d + E^d \times (Plb_h^d - Plb_i^d) \quad (i \in N, h \in N, d \in D) \quad (2.39)$$

where HS represent the moderate solutions obtained from horizontal crossover operation; E^d represents the uniform distributed expansion coefficient; i and h represent different particle groups.

It is evident from Eq. (2.38) and (2.39), the moderate solutions have two objects with an effective impact on the search process. In the first object, a similarity appears with the arithmetic crossover in the real value crossover of genetic algorithm. This realizes that within the range of two parent individuals, the reproduced offspring has been randomly positioned. The expansion coefficient in the second object has been used to mitigate the pale spot in search space and boost up the global search ability. The competition among the individuals is the key to the improved search quality, even after the generation of moderate solutions they need to compete with the individual in the parent population. In order to enter the next generation, the moderate solution needs to outperform the particle parent population, and the updated dominant solution acts as the parent population of vertical crossover.

Vertical Crossover

The vertical crossover operation offers to mitigate stagnancy for a multimodal problem. It has been instigated on the individuals by performing an arithmetic crossover operation between two different dimensions. The individuals obtained from horizontal crossover for d_1^{th} and d_2^{th} dimensions have been used to carry out the vertical crossover. The individual offspring for d_1^{th} dimension is updated as follows:

$$VS_i^{d_1} = \text{rand}() \times \text{Plb}_i^{d_1} + (1 - \text{rand}()) \times \text{Plb}_i^{d_2} \quad (i \in N, d_1 \in D, d_2 \in D) \quad (2.40)$$

where VS represent the moderate solutions obtained from vertical crossover operation.

In order to ensure that the reproduced offspring located within the bounded region, the vertical crossover needs to perform the normalization operation on the parent individuals and the reverse normalization is also performed after the completion. In order to ensure the limited population participation in the vertical crossover operation, crossover probability (ρ_v) is used. As in the horizontal crossover, only the better performing newly generated moderate solutions allow to enter the next generation.

The flow chart of the developed optimization technique has been shown in Figure 2.2.

2.7 Implementation

The multi-objective generation scheduling of PSHTS is a nonlinear, non-convex and mixed variable optimization problem. For the continuous decision variable, the CSPSO technique is explored. The improved BPSO technique is implemented to deal with PSUs binary decision variables.

The flowchart of the implementation is depicted in Figure 2.3. The elaborated steps to resolve the scheduling problem are given as follows:

Step 1. Initialization: The scheduling problem of the PSHTS consist a set of continuous as well as binary decision variables. This set is represented as an array ‘X’ with a dimension (

$N_g \times T$) includes the reservoir discharge rate, thermal power generation, on-off status of a PSU. The array is represented as:

$$X = \begin{bmatrix} q_{11} & q_{21} & \dots & q_{nh1} & , & PT_{11} & PT_{21} & \dots & PT_{nt1} & , & U_{11} & U_{21} & \dots & U_{np1} \\ q_{12} & q_{22} & \dots & q_{nh2} & , & PT_{12} & PT_{22} & \dots & PT_{nt2} & , & U_{12} & U_{22} & \dots & U_{np2} \\ . & . & . & . & , & . & . & . & . & , & . & . & . & . \\ . & . & . & . & , & . & . & . & . & , & . & . & . & . \\ . & . & . & . & , & . & . & . & . & , & . & . & . & . \\ q_{1T} & q_{2T} & \dots & q_{nhT} & , & PT_{1T} & PT_{2T} & \dots & PT_{ntT} & , & U_{1T} & U_{2T} & \dots & U_{npT} \\ \xleftarrow{\text{Hydro unit}} & \xleftarrow{\text{Thermal unit}} & \xleftarrow{\text{Pumped storage}} \\ \text{decision var iable} & \text{decision var iable} & \text{decision var iable} \end{bmatrix}$$

The initial status of binary decision variables (switching status for PSU) has been randomly generated by Eq. (2.35). The continuous decision variables (thermal power and water discharge rate) have been randomly generated as:

$$X_i^d = X^{d \min} + (X^{d \max} - X^{d \min}) \times \text{rand}() \quad (i \in N, d \in D) \quad (2.41)$$

where $X^{d \min}$ and $X^{d \max}$ are the minimum and maximum limit of decision variable.

Step 2. Multiple Objectives Evaluation: After initialization, total cost and emission objectives have been computed as given by Eq. (2.8), and (2.2), respectively. The minimum value of the objective function is obtained by giving full weightage to one of the objectives and neglecting others and owing to the conflicting nature of objectives; other objective will have a maximum value.

Step 3. Membership Function Evaluation: The membership function for cost and emission is computed by Eq. (2.26) and a cardinal priority ranking is computed given by Eq. (2.27). The maximum value of the cardinal priority ranking provides the most acceptable non-dominated solution.

Step 4. Up gradation of continuous decision variable: The particles velocity and the local best position of continuous type decision variables is updated by IPSO technique using Eq. (2.33) and (2.34). The moderate solutions from horizontal crossover operator are obtained for each pair of individuals according to Eq. (2.38) and (2.39). The objective function has been evaluated individually for each moderate solution and competes with parent population to enter the next generation. The updated values act as a parent population for the vertical crossover. The moderate solutions are generated using vertical crossover operation after normalization according to Eq. (2.40) and compete with the parent local best solution to enter the next generation.

Step 5. Up gradation of binary decision variable: The velocity of binary decision variables is updated using Eq. (2.33). The updated velocity is utilized to update the local best position of binary decision variables using the sigmoid function given by Eq. (2.36) and (2.37).

Step 6. Termination criterion: The maximum number of iterations has been set as termination criteria. The optimization technique is executed a number of times to set the maximum number of iterations in order to achieve a global best solution with minimum computational burden.

The steps 2, 3 and 4 repeated until the termination criterion occurs.

2.8 Test Systems and Results

The CSPSO approach has been applied to resolve the economic, emission and multi-objective generation scheduling problem of the PSHTS. The effectiveness of the optimization technique and the impact of PSU on the total cost and pollutant emission have been demonstrated by undertaking two PSHTS. Both test systems have two different cases. The case-I consists of thermal, and multi-chain hydro units, whereas for case-II, the PSU has been incorporated with the HTS of case-I.

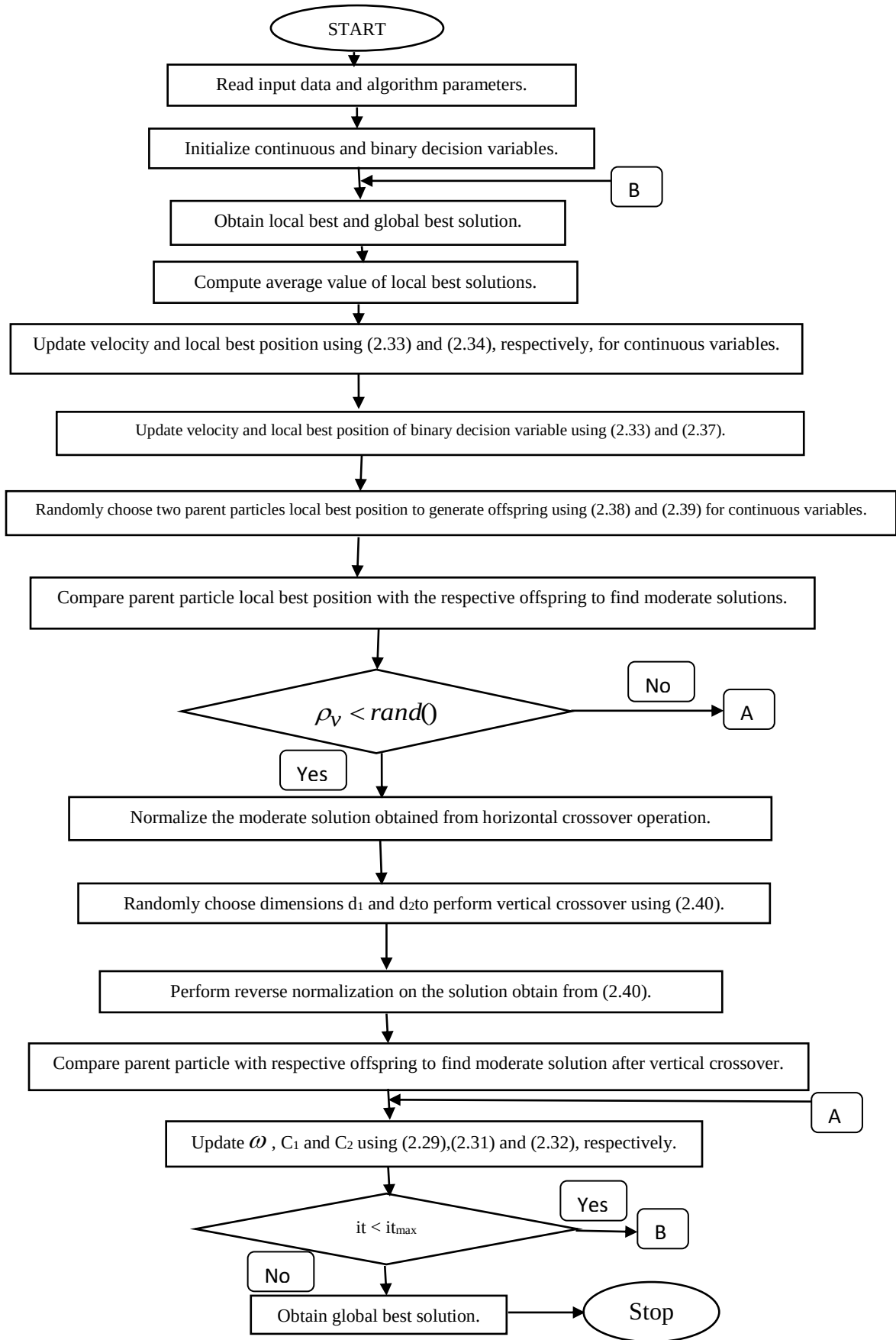


Figure 2.2: Flowchart of the implemented optimization technique

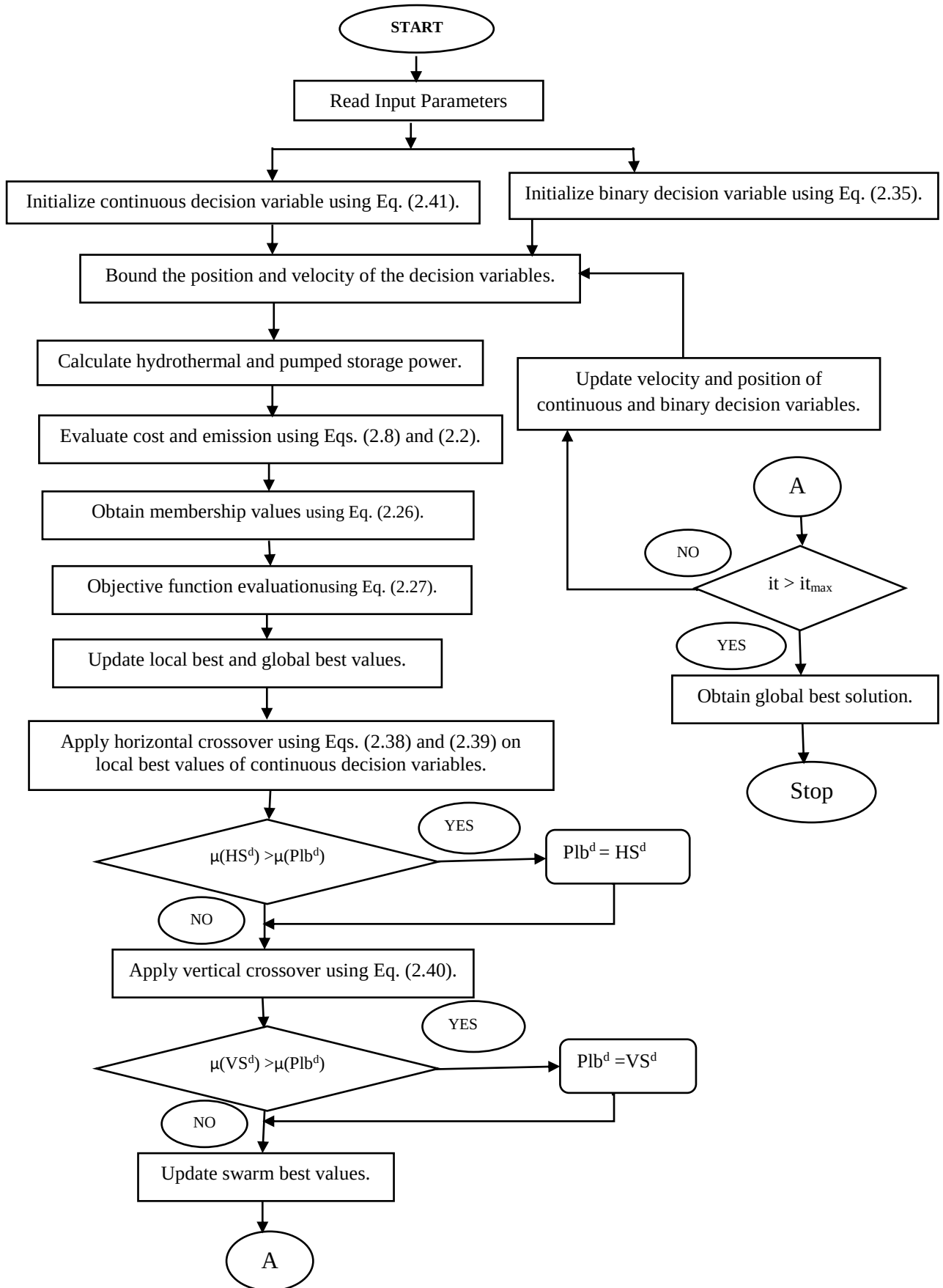


Figure 2.3: System implementation of CSPSO-BPSO technique

For both the test systems, the multi-chain hydro unit structure has been undertaken. The hydro unit structure consists of four units. The hydro unit 1 and 2 act as upper reservoirs for unit 3, and hydro unit 3 operates as an upper reservoir for hydro unit 4. The hydro unit structure has been depicted in Figure 2.1, which illustrates a PSU along with a multi-chain hydro model. The PSU consists of a hydro unit 1 as an upper reservoir and the hydro unit 3 acts as lower reservoir. The PSHTS-I is the standard hydrothermal test system, having three thermal and four multi-chain hydro units, and generating unit characteristics have been referred from **(Basu, 2004)**. Similarly, the PSHTS-II is the standard hydrothermal system, consisting ten thermal and four multi-chain hydro units, and coefficients have been referred from **(Bhattacharjee et al., 2014)**. The details regarding the PSU coefficients have been provided in Appendix B. For all the test systems, the scheduling interval is 24 hr with 1 hr sub-interval.

2.8.1 Parameter Setting

The CSPSO technique has been implemented using the FORTRAN 90 compiler and program is run on personal computer with Intel core-5 processor, 4 GB of RAM at 2.40 GHz. In order to analyse the effect of random population, 30 independent trials are made. Further, in this work, improved PSO and TVAC-PSO techniques are also applied to compare the performance of the CSPSO technique. In order to set the best parameters of CSPSO, the initial and final values of acceleration constants have been varied from 0.5 to 3.0 with a step size of 0.05. The inertia weight is varied from $\omega_{\max}$ to $\omega_{\min}$ exponentially with respect to iteration. The value of $\omega_{\max}$ is varied from 1.5 to 1.0, while $\omega_{\min}$ is varied from 1.0 to 0.5 in a systematic manner. The maximum and minimum value of velocity ($V_{\max}$, $V_{\min}$) for improved BPSO has been referred from **(Beheshti et al., 2015)**. The value of vertical crossover probability (ρ_v) is varied from 0.2 to 0.8 and most appropriate value is set after few

executions. Further, the perturbation on these values is also tried, however, no significant improvement has been found. To find the appropriate size of population, a simulation study has been carried out and it is observed that population size of 100 is adequate to attain a global optimal solution. Higher population size is not preferred as it increases the simulation time. The same procedure is adopted to set the parameters of PSO and TVAC-PSO techniques. The numerical values of these parameters are given in Table 2.1.

Table 2.1: Optimization techniques parameter range for optimum schedule.

Parameters	PSO	TVAC-PSO	CSPSO
Acceleration constants (C_1 and C_2)	2.05 and 2.05	0.5 to 2.5	1.0 to 3.0
b	0.001	0.001	0.001
Inertia Weight (ω)	0.4 to 0.9	0.4 to 0.9	0.3 to 0.9
Crossover probability (ρ)	NA	NA	0.2 to 0.8
E	NA	NA	-1.0 to 1.0
Iteration	2000	2000	2000

2.8.2 Pumped Storage Hydrothermal Test System (PSHTS)-I

To validate the search capability of CSPSO technique, the standard hydrothermal system has been undertaken and the obtained results are compared with the state of the art algorithms as presented in Table 2.2. The minimum cost and pollutant emission obtained by CSPSO technique are 41,080.0 \$ and 15,706.0 lb during economic and emission scheduling, respectively. For economic scheduling, the CSPSO technique is able to reduce the cost reported for EP (**Basu, 2004**), DE (**Lakshminarasimman and Subramanian, 2006**), MDE (**Lakshminarasimman and Subramanian, 2008**), IQPSO (**Sun and Lu, 2010**), PPO (**Narang et al., 2012**), CSA (**Das et al., 2018**), GWO-MS (**Kaur and Narang, 2019**), SCA (**Dasgupta et al., 2020**) and TVAC-PSO by 3983 \$, 2420 \$, 1531 \$, 1280 \$, 962 \$, 1360 \$, 421 \$, 391 \$ and 1748 \$, respectively.

Due to conflicting objectives, the maximum value obtained by CSPSO technique for emission is 28,169 lb. In case of emission scheduling, the pollutant emission reported for EP (**Basu, 2004**), DE (**Lakshminarasimman and Subramanian, 2006**), MDE (**Lakshminarasimman**

and Subramanian, 2008), IQPSO (Sun and Lu, 2010), PPO (Narang et al., 2012), and TVAC-PSO technique has been reduced by 848 lb, 2551 lb, 24 lb, 2061 lb, 22 lb, 1074 lb respectively, after implementing the CSPSO technique. Due to conflicting objectives, the maximum value obtained by CSPSO technique for cost is 51,476 \$.

Table 2.2: Economic, emission and multi-objective results comparison for PSHTS-I, case-I.

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	CPU time (Sec.)
EP (Basu, 2004)	45,063	--	--	16,554	47,906	0.343	26,324	0.148	0.148	4582
DE (Mandal and Chakraborty, 2009)	43,500	21,092	51,449	18,257	44,914	0.631	19,615	0.686	0.631	74.96
MDE (Lakshminarasimman and Subramanian, 2008)	42,611	--	--	15,730	43,198	0.796	20,385	0.625	0.625	--
PPO (Narang et al., 2012)	42,042	--	--	15,728	44,111	0.708	17,473	0.858	0.708	31.62
IQPSO (Sun and Lu, 2010)	42,359	31,298	45,271	17,767	44,259	0.694	18,229	0.797	0.694	--
ε -ODEMO (Ke et al., 2012)	--	--	--	--	44,672	0.654	16,653	0.924	0.654	--
NSGA-II (Ke et al., 2012)	--	--	--	--	46,050	0.521	17,083	0.889	0.521	--
SPEA-II (Ke et al., 2012)	--	--	--	--	45,534	0.571	16,974	0.898	0.571	--
PESA-II (Ke et al., 2012)	--	--	--	--	45,431	0.581	16,838	0.910	0.581	--
MO-BC (Zhou et al., 2014)	--	--	--	--	43,972	0.721	16,132	0.965	0.721	--
MOCA-PSO (Zhang et al., 2012)	42,009	16,842	44,962	16,242	43,873	0.731	16,222	0.958	0.731	--
CSA (Das et al., 2018)	42,440	--	--	--	--	--	--	--	--	--
NSGSA (Tian et al., 2014)	--	--	--	--	44,519	0.669	16,574	0.930	0.669	--
NSPSO (Tian et al., 2014)	--	--	--	--	44,638	0.657	16,694	0.920	0.657	--
NSPSO-CM (Tian et al., 2014)	--	--	--	--	44,248	0.695	16,651	0.924	0.695	--
PSO (Narang et al., 2014)	43,251	24,042	46,046	16,720	44,330	0.687	19,589	0.688	0.687	44.52
GWO-MS (Kaur and Narang, 2019)	41,501	--	--	--	--	--	--	--	--	--
SCA (Dasgupta et al., 2020)	41,471	--	--	--	--	--	--	--	--	--
TVAC-PSO	42,828	26,986	48,722	16,780	44,838	0.638	17,875	0.825	0.638	31.28
CSPSO	41,080	28,169	51,476	15,706	43,440	0.773	16,915	0.903	0.773	20.60

DE: Differential evolution; MDE: Modified differential evolution; PPO: Predator prey optimization; QOGSO: Quasi-oppositional group search optimization; SPEA-II: Strength Pareto evolutionary algorithm-II; PESA-II: Pareto envelope-based selection algorithm-II; MO-BC: multi-objective bee colony; NSGSA: Non-dominated sorting gravitational search algorithm; NSPSO: Non-dominated sorting PSO; NSPSO CM: NSPSO with chaotic mutation; GWO-MS: Grey wolf optimization with mutation strategies; SCA: Sine cosine algorithm.

For multi objective scheduling, the cost and emission obtained by CSPSO technique are 43,440.0 \$ and 16,915.7 lb. In order to compare the multi objective results, cardinal priority ranking is computed. It is evident from Table 2.2, that cardinal priority ranking

achieved by CSPSO technique is 0.773, which is highest as compared to other techniques. Hence, it is concluded that CSPSO technique is able to search the most satisfied non-dominated solution. The average CPU time is also computed and clearly indicates that the time taken by the implemented approach is less in comparison to other state of art algorithms. The average computational (CPU) time required by the CSPSO technique to search the optimum generation schedule has been 20.60 sec. The multi-objective hydrothermal generation schedule obtained from CSPSO technique for PSHTS-I, case-I has been presented in Table 2.3. The hourly discharge rate of hydro units has been represented in the Table 2.4.

Table 2.3: Multi-objective hydrothermal generation schedule for PSHTS-I, case-I.

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)							
		PT_1		PT_2		PT_3		PH_1		PH_2		PH_3		PH_4	
		PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500
t	PD														
1	750	110.5714		208.8391		139.2687		76.32816		55.41347		30.05748		129.5217	
2	780	148.819		209.718		141.0421		76.26119		50.8275		27.62492		125.7072	
3	700	119.4349		159.6196		138.2487		78.62121		54.75257		27.73517		121.5878	
4	650	108.6746		125.0323		140.3788		67.25399		55.3969		37.36577		115.8977	
5	670	110.8452		128.007		139.5703		71.96832		56.19309		30.48264		132.9334	
6	800	126.2735		129.0736		224.1071		73.0182		56.99729		39.18139		151.3489	
7	950	175.00		213.5344		139.5453		78.31016		65.41376		45.19914		232.9972	
8	1010	172.7025		208.6976		207.6428		75.92478		56.41656		45.94497		242.6708	
9	1090	175.00		275.8735		216.2969		77.48758		60.24031		38.5103		246.5914	
10	1080	172.5619		284.4905		220.4292		78.84804		58.37529		38.25896		227.0361	
11	1100	175.00		210.6653		226.6169		92.847		71.04073		41.14586		282.6843	
12	1150	175.00		282.8526		229.578		82.95145		72.56204		39.80132		267.2546	
13	1110	175.00		211.1874		229.8416		77.87086		81.74655		42.43718		291.9164	
14	1030	118.7161		210.6965		219.0315		87.81046		68.05552		34.12194		291.568	
15	1010	173.9859		210.7922		140.1739		83.09915		70.98332		41.59002		289.3754	
16	1060	149.0806		210.3998		214.6455		89.30269		75.20959		39.20835		282.1535	
17	1050	175.00		217.5384		157.0232		89.49187		74.98464		45.05921		290.9027	
18	1120	175.00		210.4025		228.7523		79.0109		82.21552		47.67986		296.9389	
19	1070	174.9908		261.2325		139.8098		65.43629		78.22192		52.48059		297.8282	
20	1050	175.00		214.1731		144.2581		79.72661		79.92903		53.99648		302.9166	
21	910	134.5498		127.4686		139.8123		79.06343		73.90276		56.07536		299.1277	
22	860	105.5581		129.628		139.2619		70.48832		64.88295		54.42296		295.7578	
23	850	105.5674		125.7768		136.2205		59.97398		74.70661		57.69693		290.0579	
24	800	77.59035		123.0495		126.9		65.30902		68.39577		54.66617		284.0892	

**** PT_L and PT_U are the lower and upper limit of thermal power**

**** PH_L and PH_U are the lower and upper limit of hydro power**

For case-II of the PSHTS-I, the presence of PSU has been considered and its effect on power generation cost and emission have been analysed. The results are summarized in Table 2.5 for the case-II of the PSHTS-I. The minimum operating cost obtained for PSHTS-I, case-II is 39,489.23 \$ obtained by the CSPSO optimization technique. For economic scheduling, the minimum cost has been reduced by 5043.77 \$, and 2619.98 \$, when compared with the minimum cost obtained by the PSO and TVAC-PSO techniques, respectively. The similar pattern has been observed in case of emission scheduling, where the emission obtained by the CSPSO technique is reduced by 3282 lb and 1723 lb, when compared with PSO and TVAC-PSO techniques. It is evident from Table 2.5, that cardinal priority ranking achieved by CSPSO technique is 0.89, which is higher as compared to PSO and TVAC-PSO techniques.

Table 2.4: Reservoir discharge rate obtained for PSHTS-I, case-I

Sub-interval (h)	Reservoir Discharge (m ³ /h)							
	q ₁		q ₂		q ₃		q ₄	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	5	15	6	15	10	30	6	20
1	8.103993		6.8346		22.1165		6.0395	
2	8.050694		6.00		21.6369		6.00	
3	8.455888		6.3465		20.9441		6.00	
4	6.746744		6.2266		18.6562		6.0094	
5	7.464964		6.2082		20.0243		6.1638	
6	7.649373		6.2690		17.8016		6.5758	
7	8.526424		7.6596		15.7460		12.9808	
8	8.085023		6.2526		15.4510		13.4816	
9	8.255737		6.7061		17.9110		13.2602	
10	8.358655		6.2458		17.8571		10.9129	
11	11.10546		8.0920		16.7752		16.6953	
12	8.965563		8.3781		17.2130		14.8235	
13	8.019026		10.3527		16.8939		17.8173	
14	9.599337		7.7272		19.3218		17.7564	
15	8.689228		8.1315		17.5047		17.5610	
16	9.769315		8.9459		18.5639		16.5478	
17	9.842984		9.1111		16.9214		17.8004	
18	8.070438		11.3024		16.3599		18.5508	
19	6.2285		10.9350		14.5510		18.8876	
20	8.221663		12.1146		14.1638		19.9250	
21	8.155617		10.8572		11.6248		19.7883	
22	6.908808		8.9316		16.2235		19.8421	
23	5.572482		11.7530		15.0717		19.8513	
24	6.154088		10.6176		16.9364		19.9424	

****q_L and q_U are the lower and upper limit of water discharge**

The case-I and case-II, are having same standard hydrothermal system except that case-II has additional PSU placed between the reservoir-1 and 3. Hence, it is worthwhile to compare the results of these cases. After comparing the results, it has been observed that the inclusion of PSU with the standard HTGS system decreased the cost and emission by 1591 \$ and 3458 \$, respectively, with respect to the results of PSHTS-I, case-I obtained by CSPSO technique. For multi-objective scheduling, cost and emission obtained by CSPSO technique are 40,327 \$ and 13,674 lb, respectively, which is less than by 3113 \$ of cost and 3241 lb of emission as compared to PSHTS-I, case-I.

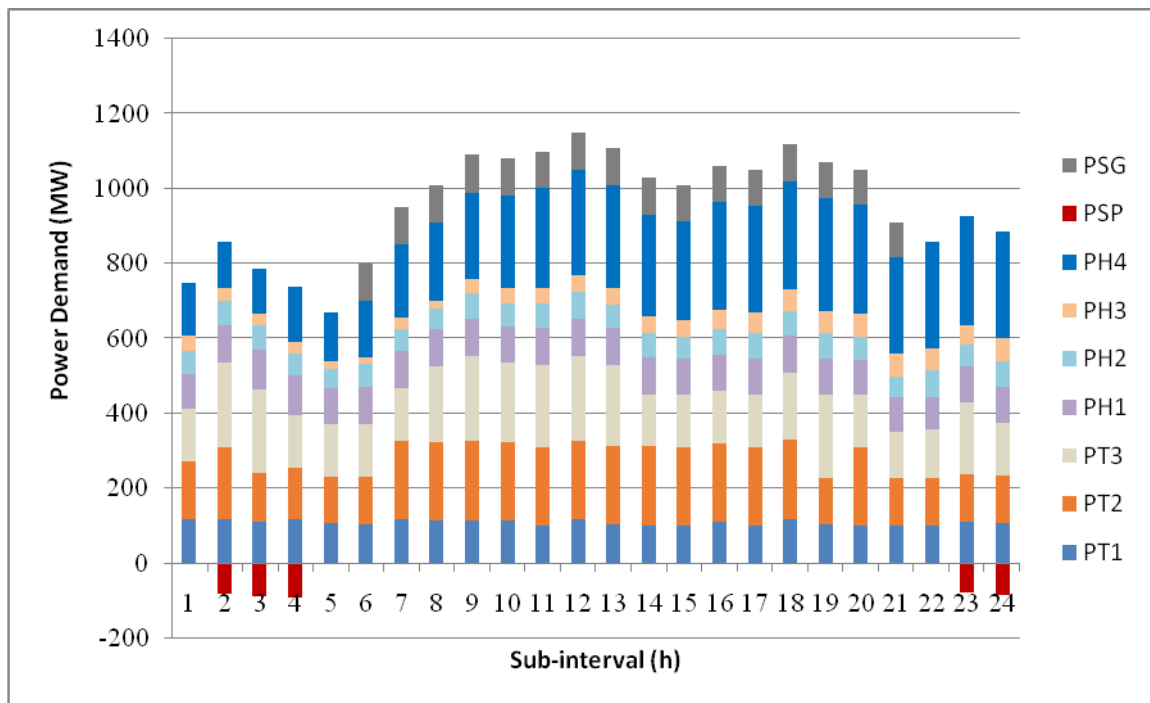


Figure 2.4: Multi-objective hydrothermal generation schedule for PSHTS-I, case-II.

Table 2.5: Economic, emission and multi-objective results comparison for PSHTS-I, case-II.

Technique	Economic		Emission		Multi-objective					CPU time (Sec.)
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	
PSO	46,853	21,277	49,289	15,530	47,924	0.295	16,864	0.644	0.295	35.31
TVAC-PSO	44,709	19,898	47,988	13,971	45,912	0.463	15,162	0.775	0.463	25.22
CSPSO	39,489	25,211	51,460	12,248	40,327	0.930	13,674	0.890	0.890	21.12

Table 2.6: Multi-objective pumped storage hydrothermal generation schedule for PSHTS-I, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT_1		PT_2		PT_3		PH_1		PH_2		PH_3		PH_4		PS^p		PS^g	
		PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U	PS_L	PS_U	PS_L	PS_U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	100	0	100
1	750	119.877		152.672		139.937		94.174		60.155		40.663		142.522		0.000		0.000	
2	780	118.819		191.570		225.168		101.286		64.077		34.325		125.006		80.250		0.000	
3	700	113.353		126.915		226.103		103.277		66.564		29.870		120.707		86.790		0.000	
4	650	119.604		137.656		139.646		104.039		59.636		32.212		147.317		90.110		0.000	
5	670	106.796		124.954		139.942		96.475		52.459		19.957		129.417		0.000		0.000	
6	800	106.313		125.504		139.962		99.387		61.409		19.148		148.889		0.000		99.387	
7	950	118.220		209.735		139.783		99.025		60.434		28.158		195.622		0.000		99.025	
8	1010	115.303		209.682		201.724		98.320		57.125		20.057		209.469		0.000		98.320	
9	1090	116.278		209.765		227.439		99.916		67.945		36.999		231.742		0.000		99.916	
10	1080	114.632		209.809		211.692		97.935		59.163		42.166		246.666		0.000		97.935	
11	1100	103.088		208.632		217.517		98.650		65.262		40.941		267.260		0.000		98.650	
12	1150	117.433		210.071		227.137		98.410		72.130		43.564		282.845		0.000		98.410	
13	1110	103.830		209.828		215.662		99.562		61.139		45.582		274.835		0.000		99.562	
14	1030	102.760		209.525		139.242		98.630		65.143		44.696		271.374		0.000		98.630	
15	1010	102.687		207.772		140.220		94.822		60.449		45.382		263.845		0.000		94.822	
16	1060	111.106		209.648		139.745		96.679		69.550		51.894		284.699		0.000		96.679	
17	1050	102.825		208.290		139.510		96.244		67.869		56.266		282.752		0.000		96.244	
18	1120	119.975		209.763		179.579		98.743		66.872		57.145		289.181		0.000		98.743	
19	1070	104.782		124.946		221.138		94.790		68.092		58.623		302.841		0.000		94.790	
20	1050	100.841		208.839		140.335		93.228		63.206		60.736		289.588		0.000		93.228	
21	910	102.570		125.247		124.677		90.880		55.709		61.129		258.908		0.000		90.880	
22	860	102.250		124.799		131.503		86.646		69.664		60.407		284.732		0.000		0.000	
23	850	111.066		125.971		193.835		95.461		59.340		50.737		291.117		77.527		0.000	
24	800	109.677		125.674		140.109		97.118		69.042		58.647		284.390		84.657		0.000	
Total thermal power generation cost= 38731.339 \$																			
Total pumped storage power generation cost= 1596.443 \$																			

After comparison, it is evident that inclusion of the PSU is able to reduce the cost and emission significantly. The Table 2.6 represents the multi-objective power generation scheduling for the PSHTS obtained with the CPSO technique. The graphical representation

of multi-objective power generation schedule shown in Figure 2.4 clearly shows the low load sub-intervals where PSU operates in pumping mode and high load sub-intervals to make PSU operate in generating mode. The effective operation of PSUs has been presented through the bar chart. The hourly discharge rate of hydro units has been presented in Table 2.7.

Table 2.7: Reservoir discharge rate obtained for PSHTS-I, case-II.

Sub-interval (h)	Reservoir (Discharge ($\times 10^4$ m ³ /h))							
	q ₁		q ₂		q ₃		q ₄	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	5	15	6	15	10	30	6	30
1	12.7206		7.6575		20.122		7.1102	
2	13.1784		8.3604		19.0367		6.0234	
3	12.4995		8.7835		18.0550		6.0132	
4	12.1981		7.4348		16.0505		8.9591	
5	10.6156		6.1982		19.7652		6.3277	
6	11.3723		7.6056		20.3733		6.9791	
7	11.4374		7.6027		18.6901		10.2527	
8	11.3878		7.0866		20.3468		11.0957	
9	11.9221		9.0371		16.5048		12.5987	
10	11.4261		7.3482		15.1484		13.4750	
11	11.5826		8.2867		16.3204		15.3899	
12	11.6254		9.7923		16.2161		16.8929	
13	12.0211		7.7475		16.3538		15.8311	
14	11.7380		8.3615		17.3907		15.4610	
15	10.7881		7.4221		17.9229		14.4432	
16	11.3036		9.1124		16.0609		16.9484	
17	11.3562		9.0357		14.2488		16.7478	
18	12.5521		9.2499		14.7909		17.6170	
19	11.8170		9.9040		14.7687		20.00	
20	12.1273		9.0592		14.0076		18.2664	
21	12.1280		7.5515		15.2748		14.4702	
22	11.2146		10.4129		16.6421		18.0763	
23	11.8151		8.3824		19.1258		19.9999	
24	11.2216		10.8202		14.2287		19.9991	

2.8.3 Pumped Storage Hydrothermal Test system (PSHTS)-II

For PSHTS-II case-I, Table 2.8 presents the results for economic, emission and multi-objective generation scheduling. The minimum cost and the pollutant emission obtained by the CSPSO technique are 1,65,299 \$ and 45,231 lb during economic and emission scheduling, respectively. For economic scheduling, the CSPSO technique is able to reduce the minimum cost by 5277 \$, 12039 \$, 5665 \$, 24051 \$, 2411 \$, 5212 \$, 3972 \$, 7816 \$, and 4477 \$,

respectively, when compared with minimum cost obtained by IDE (Basu, 2014), MDE (Zhang et al., 2012), DE (Mandal and Chakraborty, 2008), SPSO (Zhang et al., 2012), SPPSO (Zhang et al., 2012), GSO (Basu, 2016), PSO-GSA (Narang, 2016), PSO and TVAC-PSO techniques. In case of emission scheduling, the pollutant emission obtained by implementing CSPSO technique has been reduced by 2792 lb and 1474 lb, respectively, when compared with pollutant emission obtained by PSO and TVAC-PSO techniques. Due to conflicting objectives, the maximum value obtained by CSPSO technique for cost and emission are 1,76,258 \$ and 59,495 lb during emission and economic scheduling, respectively. To the best of our knowledge, the multi-objective scheduling results for PSHTS-II, case-I have not been published with the state of art techniques. Therefore, the results obtained by CSPSO technique are compared with well-established PSO and TVAC-PSO techniques.

Table 2.8: Economic, emission and multi-objective results comparison for PSHTS-II, case-I.

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	CPU time (Sec.)
IDE (Basu, 2014)	1,70,576	--	--	--	--	--	--	--	--	--
MDE (Zhang et al., 2012)	1,77,338	--	--	--	--	--	--	--	--	--
DE (Mandal and Chakraborty, 2008)	1,70,964	--	--	--	--	--	--	--	--	--
SPSO (Zhang et al., 2012)	1,89,350	--	--	--	--	--	--	--	--	--
SPPSO (Zhang et al., 2012)	1,67,710	--	--	--	--	--	--	--	--	--
MCDE (Zhang et al., 2015)	1,65,331	--	--	--	--	--	--	--	--	--
GSO (Basu, 2016)	1,70,511	--	--	--	--	--	--	--	--	--
GSA (Narang, 2016)	1,79,457	--	--	--	--	--	--	--	--	--
QOGSO (Basu, 2016)	1,70,293	--	--	--	--	--	--	--	--	--
PSO-GSA (Narang, 2016)	1,69,271	--	--	--	--	--	--	--	--	--
PPO (Narang, 2016)	1,75,160	--	--	--	--	--	--	--	--	--
PSO	1,73,115	56,165	1,76,965	48,023	1,74,885	0.125	50,754	0.612	0.125	44.51
TVAC-PSO	1,69,776	55,897	1,73,468	46,705	1,71,430	0.440	48,712	0.755	0.440	37.64
CSPSO	1,65,299	59,495	1,76,258	45,231	1,67,206	0.826	46,686	0.898	0.826	33.21

IDE: Improved differential evolution; MDE: Modified differential evolution; SPSO: Sequential particle swarm optimization; GSO: Glowworm swarm optimization; GSA: Gravitational search algorithm; PPO: Predator prey optimization; QOGSO: Quasi-oppositional group search optimization; MCDE: Modified chaotic differential evolution.

For multi objective scheduling, the cost and emission obtained by CSPSO technique are 1,67,206 \$ and 46,686 lb. The cardinal priority ranking achieved by CSPSO technique is 0.826, which is highest as compared to the PSO and TVAC-PSO techniques. The average computational time required by the CSPSO technique to search the optimum generation schedule is 33.21 sec. It has been summarized that the CSPSO technique is able to obtain the optimal solution with the competitive execution time. The multi-objective thermal power generation schedule obtained from CSPSO technique for PSHTS-II, case-I has been presented in Table 2.9. The multi-objective hydroelectric units power generation schedule obtained from CSPSO technique for PSHTS-II, case-I has been presented in Table 2.10. The hourly discharge rate of hydroelectric units has been represented in the Table 2.11.

Table 2.9: Multi-objective thermal power generation schedule for PSHTS-II, case-I.

Sub-interval (h)	Power Demand (MW)	Thermal Plant Power (MW)																			
		PT_1		PT_2		PT_3		PT_4		PT_5		PT_6		PT_7		PT_8		PT_9		PT_{10}	
		PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PT_L	PT_U
t	PD	50	455	50	450	20	130	20	130	25	470	40	460	45	465	35	300	25	160	25	180
1	1750	230.574		202.235		96.017		120.000		175.000		139.662		163.113		36.283		160.000		144.525	
2	1780	230.176		269.913		97.445		119.408		175.000		139.576		165.000		36.231		124.837		138.324	
3	1700	227.619		271.913		94.761		120.000		173.618		136.607		159.525		35.905		98.123		127.127	
4	1650	228.574		272.053		95.390		118.024		124.459		108.026		108.981		36.260		157.083		128.479	
5	1670	227.475		217.514		94.167		75.802		175.000		101.990		164.943		35.740		156.383		138.044	
6	1800	229.807		273.660		95.977		117.979		175.000		140.000		165.000		36.225		102.875		149.719	
7	1950	271.543		273.987		96.480		120.000		175.000		140.000		163.855		36.019		158.405		150.000	
8	2010	296.995		273.956		95.312		119.985		175.000		139.985		165.000		36.358		160.000		148.368	
9	2090	311.572		274.562		96.739		120.000		175.000		140.000		165.000		36.260		160.000		148.154	
10	2080	315.991		274.502		98.493		118.139		175.000		140.000		165.000		36.305		160.000		148.719	
11	2100	310.022		274.825		99.180		119.872		175.000		140.000		165.000		36.156		160.000		150.000	
12	2150	317.474		274.747		98.115		120.000		175.000		140.000		165.000		36.001		160.000		149.564	
13	2110	308.065		274.556		95.556		120.000		175.000		140.000		165.000		36.260		160.000		148.123	
14	2030	249.581		274.824		97.734		120.000		175.000		140.000		165.000		36.153		160.000		150.000	
15	2010	227.699		274.569		97.719		120.000		175.000		140.000		165.000		35.864		156.638		149.694	
16	2060	271.197		274.605		95.190		119.906		175.000		140.000		165.000		36.123		156.878		147.711	
17	2050	230.785		273.458		99.362		120.000		175.000		140.000		165.000		36.260		160.000		146.605	
18	2120	291.535		274.277		95.406		119.742		175.000		140.000		165.000		35.617		160.000		148.263	
19	2070	229.965		274.504		97.191		120.000		175.000		140.000		165.000		36.260		159.811		149.993	
20	2050	229.456		273.043		94.872		119.990		175.000		140.000		165.000		35.740		158.133		135.920	
21	1910	225.650		197.716		93.229		120.000		175.000		140.000		165.000		35.576		156.274		124.457	
22	1860	228.761		201.782		95.595		119.506		175.000		138.471		165.000		35.812		98.389		136.999	
23	1850	230.038		199.651		96.153		120.000		175.000		140.000		133.039		35.946		99.972		124.992	
24	1800	224.562		198.683		92.519		119.920		175.000		133.003		155.295		35.926		97.870		125.165	

In the PSHTS-II, case-II, the presence of PSU has been considered and the results are summarized in Table 2.12, for the economic, emission and multi-objective scheduling of PSHTS-II, case-II. The minimum operating cost obtained for PSHTS-II, case-II is 1,63,343 \$ obtained by the CSPSO technique. For economic scheduling, the cost obtained by PSO, and TVAC-PSO technique is being reduced by 7000 \$, and 2992 \$, respectively, after implementing a CSPSO technique. In the emission scheduling, the similar pattern has been observed, where the CSPSO technique is able to reduce the emission by 3086 lb and 789 lb when compared to the emission obtained by the PSO and TVAC-PSO techniques.

Table 2.10: Multi-objective hydroelectric power schedule for PSHTS-II, case-I

Sub-interval (h)	Hydroelectric Power (MW)							
	PH_1		PH_2		PH_3		PH_4	
	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U
	0	500	0	500	0	500	0	500
1	69.401		51.193		32.082		129.915	
2	63.805		52.868		38.572		128.846	
3	65.152		52.714		15.622		121.314	
4	71.236		54.781		30.757		115.897	
5	69.446		55.547		27.659		130.290	
6	70.048		55.736		43.674		144.300	
7	70.927		60.076		39.554		193.898	
8	75.710		61.623		32.855		228.854	
9	83.892		74.295		38.887		265.640	
10	75.492		63.942		41.771		266.647	
11	78.154		63.861		42.221		285.295	
12	91.987		82.627		43.459		296.026	
13	91.708		76.326		39.368		280.037	
14	81.037		64.247		41.833		274.271	
15	89.546		65.856		41.954		270.463	
16	100.759		75.656		33.866		268.110	
17	83.047		81.671		48.906		289.906	
18	93.424		78.054		45.389		298.293	
19	89.265		83.492		50.187		299.331	
20	89.467		79.376		54.752		299.252	
21	59.396		71.414		55.620		290.670	
22	57.699		54.426		59.205		293.354	
23	75.547		70.224		59.283		290.155	
24	78.232		55.137		26.043		282.646	

It is evident from Table 2.12, that cardinal priority ranking achieved by CSPSO technique is 0.89, which is higher as compared to PSO and TVAC-PSO techniques. After comparing the results for case-I and II, respectively, it has been observed that the inclusion of PSU with the

standard hydrothermal system decreased the cost and the emission by 1956 \$ and 6697 lb, respectively, with respect to the results of PSHTS-II, case-I obtained by the CSPSO technique.

Table 2.11: Reservoir discharge rate obtained for PSHTS-II, case-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)							
	q₁		q₂		q₃		q₄	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	5	15	6	15	10	30	6	20
1	7.030069		6.158188		21.76966		6.070998	
2	6.208988		6.254818		19.56795		6.257052	
3	6.338516		6.00013		22.97792		6.000003	
4	7.1476		6.073427		19.80464		6.033042	
5	6.929367		6.042102		20.05721		6.00	
6	7.011892		6.000046		15.61709		6.188913	
7	7.106296		6.658926		17.06432		9.138219	
8	7.751237		6.876721		18.57283		11.56337	
9	9.029593		9.046861		16.47916		14.7702	
10	7.591863		7.164297		15.28859		14.80159	
11	7.875971		7.003161		15.3598		16.99993	
12	10.22657		10.5786		15.36042		18.4479	
13	10.13178		9.449453		17.23591		16.30771	
14	8.207626		7.230993		16.84322		15.66249	
15	9.545282		7.350345		17.56699		15.21177	
16	12.09326		9.084539		19.69101		14.90511	
17	8.514455		10.73025		15.21058		17.58486	
18	10.42809		10.53051		17.32613		19.12257	
19	9.722283		13.16723		15.72227		19.62867	
20	9.941631		12.99411		14.04161		19.600	
21	5.535776		11.08671		14.99127		18.82477	
22	5.315735		7.485733		12.158		19.66206	
23	7.48985		11.07848		15.14321		19.89627	
24	7.826249		7.954389		23.61548		19.67978	

Table 2.12: Economic, emission and multi-objective results comparison for PSHTS-II, case-II

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	CPU time (Sec.)
PSO	1,70,343	46,331	1,76,784	41,620	1,75,274	0.089	42,781	0.668	0.089	48.96
TVAC-PSO	1,66,335	48,429	1,73,415	39,323	1,69,092	0.561	40,725	0.828	0.561	39.33
CSPSO	1,63,343	51,345	1,76,443	38,534	1,64,784	0.890	39,687	0.910	0.890	35.20

For multi-objective scheduling, cost and emission obtained by CSPSO technique are 1,64,784 \$ and 39,687 lb, respectively, which is less than by 2422 \$ of cost and 6999 lb of emission as compared to PSHTS-II, case-I. Hence, it is summarized that inclusion of the PSU is able to reduce the cost and emission significantly. The Tables 2.13 and 2.15 represent the thermal and hydroelectric power generation, respectively for multi-objective generation scheduling obtained by the CSPSO technique.

Table 2.13: Multi-objective thermal power generation schedule of PSHTS-II, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Plant Power (MW)																			
		PT ₁		PT ₂		PT ₃		PT ₄		PT ₅		PT ₆		PT ₇		PT ₈		PT ₉		PT ₁₀	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PT _L	PT _U
		50	455	50	450	20	130	20	130	25	470	40	460	45	465	35	300	25	160	25	180
1	1750	226.53		219.70		97.34		110.04		137.57		132.22		164.05		35.83		160.00		150.00	
2	1780	228.75		238.28		98.10		120.00		175.00		140.00		165.00		36.56		160.00		150.00	
3	1700	229.22		209.13		95.52		107.87		174.99		140.00		164.94		36.27		160.00		149.08	
4	1650	229.09		203.73		99.95		120.00		175.00		94.96		165.00		36.21		160.00		146.16	
5	1670	224.25		200.32		95.12		120.00		175.00		116.56		145.60		35.82		100.04		137.62	
6	1800	226.90		198.81		95.45		120.00		158.73		136.85		162.41		35.28		126.16		128.94	
7	1950	227.45		209.69		97.07		120.00		175.00		140.00		164.87		35.52		138.30		150.00	
8	2010	229.17		267.23		95.75		120.00		175.00		140.00		165.00		36.07		160.00		150.00	
9	2090	237.27		274.71		99.88		120.00		175.00		140.00		165.00		37.00		160.00		149.82	
10	2080	231.48		264.49		99.28		120.00		175.00		140.00		165.00		36.21		160.00		149.71	
11	2100	227.48		260.63		97.69		120.00		175.00		140.00		165.00		36.32		160.00		150.00	
12	2150	231.33		271.53		99.89		120.00		175.00		140.00		165.00		36.56		160.00		150.00	
13	2110	228.80		265.68		95.06		120.00		175.00		140.00		165.00		36.37		160.00		150.00	
14	2030	212.85		199.52		95.39		120.00		175.00		140.00		161.65		35.57		160.00		149.25	
15	2010	228.94		211.77		97.14		120.00		175.00		128.79		163.87		37.00		130.81		148.25	
16	2060	228.67		211.56		99.06		120.00		175.00		140.00		165.00		36.90		158.59		145.34	
17	2050	216.69		197.86		97.28		120.00		175.00		140.00		165.00		35.82		159.62		144.74	
18	2120	225.18		264.70		93.71		120.00		175.00		140.00		165.00		36.18		160.00		150.00	
19	2070	222.44		199.80		97.80		120.00		175.00		140.00		165.00		36.91		160.00		146.62	
20	2050	222.54		200.05		98.37		120.00		175.00		140.00		161.34		35.75		142.68		143.53	
21	1910	157.29		199.67		95.48		120.00		175.00		138.60		106.37		36.17		141.23		144.32	
22	1860	200.85		199.10		95.58		120.00		175.00		140.00		163.86		35.69		127.53		140.65	
23	1850	219.27		199.57		96.24		120.00		175.00		133.09		163.68		36.15		158.60		147.21	
24	1800	205.40		208.35		94.52		120.00		175.00		140.00		165.00		35.24		135.04		140.15	
Total thermal power generation cost= 163187.8 \$																					
Total pumped storage power generation cost= 1596.311 \$																					

The working of PSU has been observed from the Tables 2.6 and 2.15 and it is found that PSU works in the pumping mode during 2nd, 3rd, 4th, 23rd and 24th sub-intervals for light load periods. During the 1st, 5th and 22nd sub-intervals, the PSU does not operate in any mode due to minimum change over time. For remaining sub-intervals, the PSU operates in generating

mode due to higher load demands and generation is close to its maximum power capacity. The multi-objective power generation schedule represented by Figure 2.5 clearly shown the operating pattern of PSU during off peak and peak hours. During off-peak sub-intervals the PSU operates in pumping mode and in high load sub-intervals the PSU operate in generating mode. The effective operation of PSUs has been presented through the bar chart.

The hourly discharge rate of hydro units has been presented in Table 2.14. The convergence characteristics of PSO, TVAC-PSO and CSPSO techniques for PSHTS-II, case-I have been presented in Figures 2.6 and 2.7, respectively, for economic and emission generation scheduling. The Pareto front for case-I is shown in Figure 2.8 and it is self-evident that CSPSO is able to generate well-dispersed front as compared to PSO and TVAC-PSO techniques. It is evident from these figures, that CSPSO technique is better in terms of solution quality and convergence rate.

Table 2.14: Reservoir discharge rate obtained for PSHTS-II, case-II

Sub-interval (h)	Reservoir Discharge ($\times 10^4 \text{ m}^3/\text{h}$)							
	q_1		q_2		q_3		q_4	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	5	15	6	15	10	30	6	20
1	12.3227		6.00		19.35015		6.000014	
2	14.65913		6.00		20.36643		9.827662	
3	10.16318		8.127565		15.23335		6.00	
4	8.977335		8.955302		17.586		6.00	
5	11.81061		9.476198		19.31419		6.003324	
6	12.71886		6.857433		21.01899		6.002429	
7	10.95074		6.402151		19.28473		13.07327	
8	9.623519		6.00		20.23387		12.38111	
9	11.78107		7.369053		16.98841		13.52943	
10	13.21434		8.084085		16.75268		12.48534	
11	11.97822		10.0155		10.00		13.2944	
12	12.11106		8.547312		15.42791		17.78168	
13	11.54666		7.603882		16.26513		15.23411	
14	12.57902		6.00		16.62185		16.22833	
15	10.80162		10.2871		17.94227		13.96706	
16	13.15748		7.035952		12.33771		14.60484	
17	10.71051		10.3138		16.94136		17.22995	
18	12.76821		7.41479		13.63876		15.90612	
19	11.73459		9.992247		16.20338		17.92126	
20	12.84732		9.33707		15.45683		19.99785	
21	12.51226		14.29777		19.03374		17.88027	
22	12.48306		7.835989		17.45788		15.28148	
23	14.71695		9.663616		21.36201		19.99916	
24	7.775526		10.2096		14.2787		17.28388	

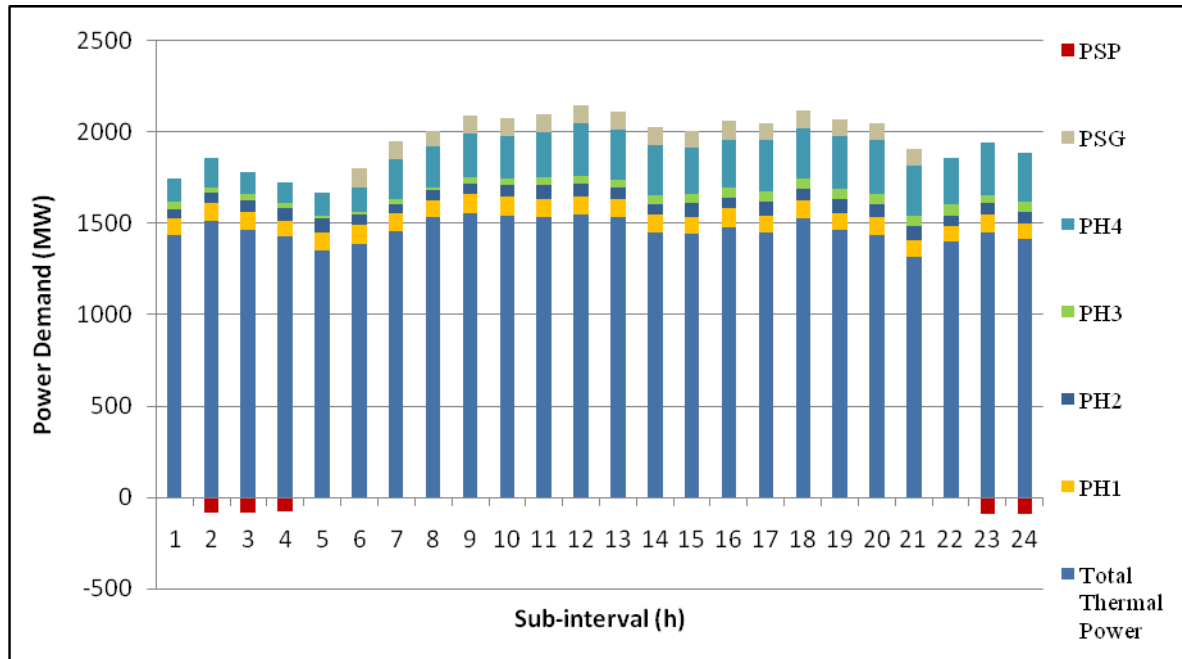


Figure 2.5: Multi-objective power generation for PSHTS-II, case-II.

Table 2.15: Multi-objective hydroelectric and pumped storage power schedule for PSHTS-II, case-II

Sub-interval(h)	Hydroelectric Power (MW)								Pumped Storage Power(MW)			
<i>t</i>	<i>PH</i> ₁		<i>PH</i> ₂		<i>PH</i> ₃		<i>PH</i> ₄		<i>PS</i> ^g		<i>PS</i> ^p	
	<i>PH</i> _L	<i>PH</i> _U	<i>PH</i> _L	<i>PH</i> _U	<i>PH</i> _L	<i>PH</i> _U	<i>PH</i> _L	<i>PH</i> _U	<i>PS</i> _L	<i>PS</i> _U	<i>PS</i> _L	<i>PH</i> _U
	0	500	0	500	0	500	0	500	0	100	0	100
1	93.398		50.164		44.093		129.027		0.000		0.000	
2	103.860		51.296		27.496		168.277		0.000		82.605	
3	93.306		65.683		39.612		117.948		0.000		83.360	
4	87.297		70.385		27.353		112.007		0.000		77.173	
5	102.338		72.218		20.060		124.973		0.000		0.000	
6	104.780		56.976		11.226		137.674		99.780		0.000	
7	97.354		53.662		22.457		221.255		97.354		0.000	
8	90.431		51.397		19.764		219.749		90.431		0.000	
9	100.402		61.003		34.051		236.448		99.402		0.000	
10	104.446		65.921		34.896		234.096		99.446		0.000	
11	100.646		75.648		44.394		247.534		99.646		0.000	
12	100.594		67.687		44.549		288.248		99.594		0.000	
13	98.396		62.334		45.493		269.458		98.396		0.000	
14	101.794		53.233		47.504		278.422		99.794		0.000	
15	95.187		77.873		45.444		254.749		95.187		0.000	
16	102.470		60.207		56.280		261.441		99.470		0.000	
17	93.593		76.553		51.821		282.401		93.593		0.000	
18	99.277		59.953		59.111		272.597		99.277		0.000	
19	94.513		72.249		56.968		288.170		94.513		0.000	
20	94.660		68.175		59.842		293.377		94.660		0.000	
21	91.263		81.971		52.111		279.157		91.263		0.000	
22	88.871		57.206		58.057		257.565		0.000		0.000	
23	100.000		65.840		39.213		286.300		0.000		90.166	
24	77.860		66.768		58.601		267.341		0.000		89.283	

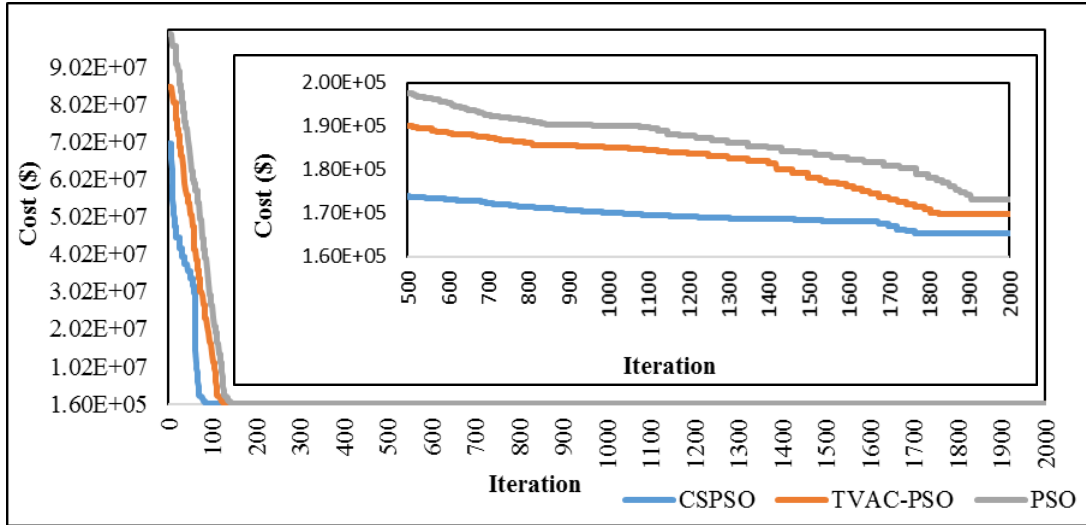


Figure 2.6: Cost convergence characteristics of techniques for PSHTS-II, case-I

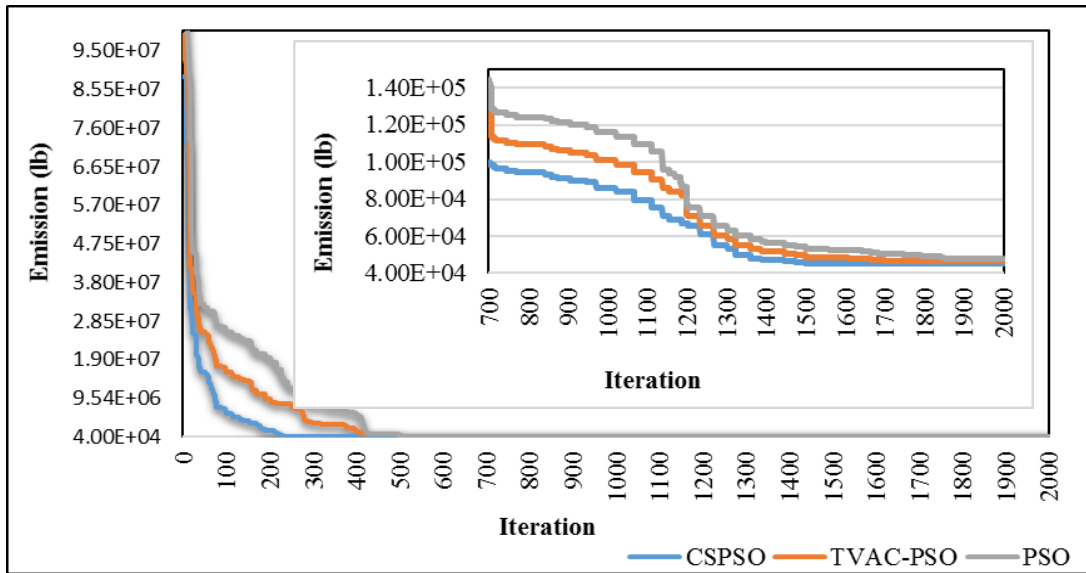


Figure 2.7: Emission convergence characteristics of techniques for PSHTS-II, case-I

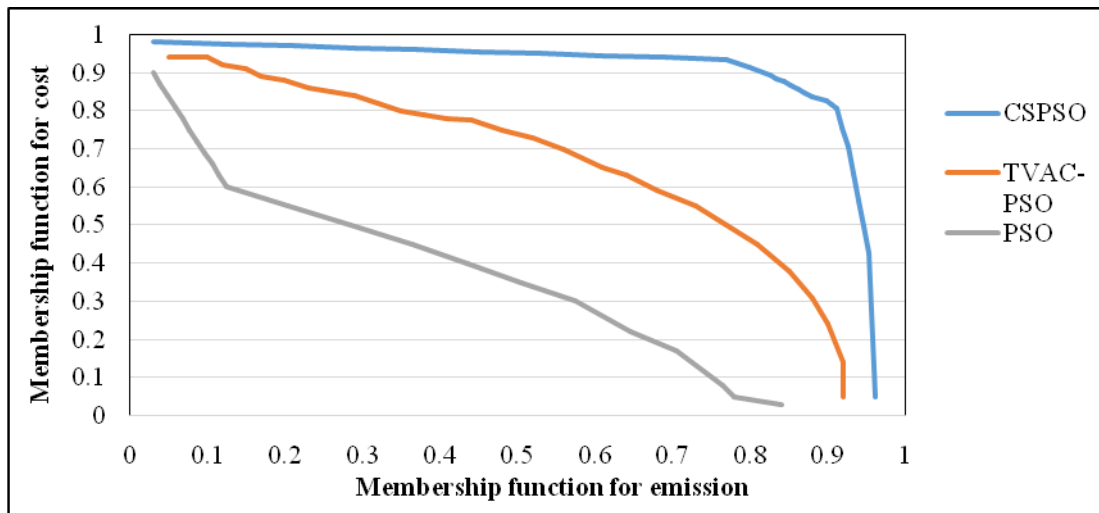


Figure 2.8: Pareto front for PSHTS-II, case-I

2.8.4 Statistical Analysis

The robustness of the statistical results obtained by CSPSO technique is investigated by applying a two-sample student's t-test. The PSHTS-II, case-I has been undertaken and results are compared with PSO and TVAC-PSO techniques. In order to conduct the test an assumption has been undertaken; the populations have equal variances at the significance level of $\alpha = 5\%$. The t-test results have been tabulated in Table 2.16 for economic scheduling. It is evident from the Table 2.16 that the tabulated values of statistics are greater than the critical values for different techniques. The average value of the cost function, variance as well as the tabulated values for CSPSO technique is superior and the results are statistically significant than the PSO and TVAC-PSO techniques at the 5% level of significance.

Table 2.16: Two sample t-test results obtained for PSHTS-II, case-I

	PSO	TVAC-PSO	CSPSO
Average Cost (\$)	1,75,085	1,71,645	1,67,380
Variance	9,515.17	4,362.61	1,211.35
Observations	30	30	30
Pooled variance	5,348.90	2,786.98	
Hypothesized mean difference	0	0	
Degree of freedom	58	58	
t stat	840.70	931.26	
P(T ≤ t) one tail	0	0	
t critical one-tail	1.67	1.67	

2.9 Conclusions

In the contemporary work, a CSPSO and improved BPSO techniques have been implemented for economic, emission and multi-objective generation scheduling of the PSHTS. Two pumped storage hydrothermal test systems have been undertaken and for each test system, the impact of PSU has been investigated on economic, emission and multi-objective generation scheduling problem. The problem consists of binary and continuous decision variables. For binary decision variables, improved BPSO has been implemented and the CSPSO has been implemented for continuous decision variables for PSHTS. In the CSPSO technique, local

best solution has been updated by IPSO and then CSO is applied for further enhancement. The CSO consists horizontal and vertical crossover operators to generate the new moderate solutions from the parent solutions and helps to improve the exploration and exploitation capability of the improved PSO technique.

It has been observed from the obtained results, the CSPSO technique is able to achieve better results as compared to other state of art techniques *i.e.*, EP, DE, MDE, QPSO, GWO, GWO-MS, GSA, DGSA, and SCA for PSHTS-I, case-I. The cost and emission obtained by CSPSO technique is at least reduced by 391 \$ and 22 lb, as compared with the techniques reported in the literature. In case of multi objective scheduling, the cardinal priority ranking achieved by CSPSO is 0.773, which is higher than the well established techniques. Similarly, the economic, emission and multi-objective generation schedule results have been improved for PSHTS-II by the CSPSO technique. It has been observed, that the inclusion of the PSU is able to decrease the cost and emission by 1591 \$ and 3458 lb, for PSHTS-I, case-II obtained from the CSPSO technique. Alternatively, for the multi-objective generation scheduling the cost and emission have been reduced by 3113 \$ and 3241 lb, respectively. Similar pattern has been observed during the economic, emission and multi-objective generation scheduling of PSHTS-II, case-II. The robustness of CSPSO technique investigated by applying a two-sample student's t-test and found promising.

CHAPTER-3

MULTI-OBJECTIVE GENERATION SCHEDULING OF PUMPED STORAGE HYDROTHERMAL SYSTEM

3.1 Introduction

The hydrothermal systems are the vital power generation resources and their integrated operation helps in optimum utilisation of the energy sources (**Fang et al., 2014; Bhattacharjee et al., 2014**). The vast expansion of hydrothermal plants is inadequate to compensate for the increasing power demand and depleting environmental conditions. Therefore, small hydroelectric unit like, pumped storage unit (PSU), may be installed (**Magaju et al., 2019; Kuriqi et al., 2020**) at hydro generation plant. The PSU provides fast response during demand variations and reduces the cost of energy generation from the thermal units. The PSU can work either in generating mode or in motoring mode based on availability of reservoir level. The optimal generation scheduling problem of pumped storage hydrothermal system (PSHTS) is visualized as multi-objective optimization problem (MOOP) in case of minimization of cost and emission objectives simultaneously.

Optimization techniques are classified as local and global search techniques. The local search techniques follow single path search, presume multiple assumptions and are less effective in finding optimal solution for high dimensional problems (**Salam et al., 1998; Li et al., 2009**). Alternatively, the global search techniques have been developed to overcome the limitations of conventional search techniques (**Basu, 2011; Mandal et al., 2008; Lakshminarasimman and Subramanian, 2008; Kennedy and Eberhart, 1995**). Among the global search techniques, particle swarm optimization (PSO) has been the extensively used owing to simple execution, and effective search ability (**Clerc and Kennedy, 2002; Park et al., 2005**). In spite of the several advantages, the PSO suffers from the premature

convergence, which has been mitigated by developing few improved or hybrid versions of PSO (**Ratanweera et al., 2004; Chaturvedi et al., 2008**).

In one of such attempt, **Meng et al. (2014)** developed crisscross search optimization (CSO) technique to explore and exploit the search space proficiently. The CSO adopts a duo search mechanism including horizontal crossover and vertical crossover, which reproduce a population of moderation solutions at each generation by performing different crossover operations. Such competitive mechanism makes the crisscross search always maintain a population in the best position in order to accelerate the convergence speed. The introduction of crisscross search PSO (CSPSO) technique was an attempt to improve the performance of PSO and maintain the balance between exploration and exploitation of the search space to maintain population diversity (**Meng et al., 2016**)¹. The CSPSO algorithm accelerates the search process toward converging to the global optimum by incorporating a CSO inspired by the crossover operation in genetic algorithms. However, intermittently the optimal solution struck into local optimal for multimodal optimization problems.

According to ‘no free lunch’ theorem, the continuous evolution of search techniques motivates the researchers in the development of optimization techniques (**Wolpert and Macready, 1997**). The global search techniques are reasonably incompetent in fine-tuning the technique thereby the search capability is enriched by incorporating a property of local search techniques. **Noman and Iba (2008)** developed a crossover based adaptive local search operator for improving the performance of differential evolution (DE) technique. **Piotrowski (2013)** proposed memetic DE algorithm with global and local search based mutation operators to resolve optimization problems. **Arab and Alfi (2015)** proposed a memetic algorithm with an adaptive gradient descent to improve accuracy and convergence speed. **Mo et al. (2009)** proposed a conjugate direction PSO to improve the searching ability of PSO. **Bao et al. (2013)** examines the behaviour of memetic algorithm based on PSO and pattern search approach. **Wu et al. (2014)** have incorporated local search techniques with a superior solution

guided PSO to improve the search capability.

In the real world, various optimization problems set are discrete in nature or inhibit different types of decision variables. The researchers have applied discrete version of global optimization techniques to optimize these optimization problems. The binary PSO (BPSO) technique has been extensively applied by various researchers due to its excellent search ability (**Vieira et al., 2013; Beheshti et al., 2015**). However, BPSO technique suffers from disadvantages such as easily get trapped in local optima and slow convergence rate for high-dimensional multimodal optimization problems. These problems occur because of the poor exploration in PSO and due to the sigmoid function used in BPSO algorithm (**Beheshti et al., 2015**). Recently, few improved versions of the BPSO technique, *i.e.*, enhanced BPSO with mutation probability (**Vieira et al., 2013**), memetic BPSO (**Beheshti et al., 2015**) have been proposed and tested on complex optimization problems and their performance found satisfactory.

In real-life problems, the objectives are contradicting in nature and the decision-maker is encountered with multiple goals. The multiple objectives levels of attainment are to be expressed in the form of performance criteria and the problem is formulated as a MOOP. The aim in the MOOP is to maximise or minimise multiple objective functions simultaneously. In the MOOP the contradicting objectives creates fuzziness in the decision-making. The growing research on the fuzzy set based application of power system suggest its importance in resolving power system optimization problems (**Dhillon et al., 2002; Jahromi et al., 2012; Norouzi et al., 2014; Feng et al., 2017; Mari et al., 2019; kaur et al., 2020**). An interactive fuzzy programming approach has been presented for resolving a decision-making problem involving multiple objectives (**Tapia and Murtagh, 1991**). The long-term hydrothermal generation scheduling problem has been resolved by implementing a fuzzy decision methodology (**Dhillon et al., 2001**). **Norouzi et al. (2014)** implemented fuzzy satisfying method to obtain most preferred solution in multi-objective hydrothermal scheduling problem.

Kaur et al. (2020) implemented fuzzy satisfying function to resolve the conflict between multiple objectives.

In this work, economic, emission and multi-objective scheduling problems of the PSHTS have been undertaken. The pumped storage hydrothermal generation scheduling problem comprises mixed decision variables. The decision variables for hydrothermal are continuous in nature and the PSU is controlled by the binary decision variables. In this chapter, a modified CSPSO (MCS-PSO) technique has been proposed to deal with continuous decision variables and modified BPSO (MB-PSO) has been implemented for binary decision variables. In MCS-PSO technique, the best performing particle of CSO is further improved by pattern search direction. Since, the pattern search direction is based on conjugate search method, which helps to further exploit the promising search areas. In MB-PSO technique, the particles position updates by considering the experience of its previous position. Further, the modified sigmoid function in MB-PSO technique helps to mitigate the stagnancy problem. For multi-objective scheduling problem, the fuzzy decision methodology has been implemented as selection criteria to achieve the best compromised solution.

3.2 Pumped Storage Hydrothermal Mathematical Modelling

The foremost objectives of generation scheduling are to minimize the power generation cost and pollutant emission with the satisfaction of all the operational constraints. The decision variables in the aforementioned system are continuous and binary in nature. The continuous decision variables are the power and water discharge and the switching status of the PSU is represented by binary decision variable. The total cost obtained from power generation consist the cost inherited by all power generating units. The power-generating cost and emission production from the thermal generators trails a non-linear relationship with the power output and presented by Eq. (2.1) and (2.2) of Section 2.2.1 in Chapter 2.

The connection structure of PSHTS in this work is described in Figure 3.1. In this model, the PSU has a separate upper reservoir (a lake) and hydro unit 3rd acting as the lower

reservoir. The PSU inherits the dual-mode (generating and pumping) operation as per the load requirement. The switching status of the PSUs is binary in nature that decides the mode of operation. The presence of the separate upper reservoir for PSU affects the volume dynamics of the hydro unit reservoirs.

The volume dynamics for pumped storage hydroelectric units during generating mode of the PSU is same as presented in Eq. (2.3) of Sub-section 2.2.2 in Chapter 2. During the pumping mode of PSU, the upper reservoir volume ($V_{l,(t+1)}$) considering the pumped water discharge from the lower reservoir ($qa_{l,t+1}$), has been presented as:

$$V_{l,(t+1)} = V_{l,t} + I_{l,t+1} + qa_{l,t+1} - S_{l,t+1} + \sum_{n=1}^{Ru} (q_{n,t-d} + S_{n,t-d}) \quad (l \in np, \quad t \in T) \quad (3.1)$$

$$qa_{l,t+1} \leq \min(V_{l,t}, V_l^{\max} - V_{l,t}, qa_l^{\max}) \quad (3.2)$$

where $qa_l^{\max}$ is maximum water discharge from the lower reservoir of the l^{th} PSU; $V_l^{\max}$ is maximum water discharge from the lower reservoir of the l^{th} PSU.

The amount of water pumped has been limited due to the available water in the lower reservoir, the vacant storage in the upper reservoir, and the penstock capacity. The power generated by the pumped storage hydroelectric unit has been a quadratic function of water discharge, and reservoir volume as presented by Eq. (2.5) and (2.6) of Sub-section 2.2.2 in Chapter 2.

3.3 Multi-objective Problem Formulation

The multi-objective scheduling problem aims to minimize the total cost of power generation and emission simultaneously subjected to different constraints. The thermal power generation, reservoir discharge rate are continuous nature decision variables and PSU operation is controlled by binary decision variables. Mathematically, the MOOP has been stated in Eq. (2.9) in Section 2.3 of Chapter 2. The system is bounded by various equality and inequality constraints. The inequality constraints constitute power limits, discharge rates and restriction

on PSU working modes. The equality constraints include power demand balance in each sub-interval and final reservoir volume of hydro units. The inequality and equality constraints represented from Eq. (2.10) to (2.20) in Section 2.3 of Chapter 2. For constraint handling an exterior penalty method is applied, in which a function is penalized for each constraint violation. In the search process, the boundary limits may violate by the decision variables. In such cases, the decision variables are set to their upper or lower limits suitably. The variable elimination method is implemented to handle the power balance equality constraint. The thermal generating unit is undertaken as dependent unit to satisfy the equality constraint during each sub-interval. The dependent unit is selected arbitrarily and remaining thermal units acts as independent variables.

The constraint handling and error computation for equality and inequality constraints have been discussed in Sub-section 2.3.1 of Chapter 2.

The cost and pollutant emissions are the conflicting objectives, which creates fuzziness to select the best-compromised solution. The multi-objective function has been treated systematically in terms of fuzzy membership function corresponding to each objective to deal with the MOOP. The membership function is computed by considering the lower and upper bound of each of the objective functions as represented by Eq. (2.27) in Sub-section 2.3.2 of Chapter 2. The best-compromised solution is decided by implementing max-min operator of the membership functions. Mathematically, the unified objective function (μ_d) is presented as Eq. (2.28), in Sub-section 2.3.2 of Chapter 2. The high value of μ_d represents more satisfied non-dominated solution.

3.4 Proposed Optimization Technique

The proposed optimization technique (POT) combining MCS-PSO and MB-PSO has been implemented to resolve the PSHTS scheduling problem consisting continuous and binary decision variables. The MCS-PSO technique with adaptive strategy has been incorporated to update the continuous decision variables. The binary decision variables have been updated by

a MB-PSO technique. The improved PSO (IPSO) and CSO techniques embedded in the MCS-PSO technique have been discussed in Section 2.4 and 2.6 of Chapter 2. The local optimal stagnancy problem exists with CPSO technique for high dimensional problem. Therefore, MCS-PSO technique is being developed to train the non-performing particles to explore the search space and improve the convergence process. This search strategy is significant in terms of the exploration and exploitation phase of the continuous decision variables for multi-modal problems.

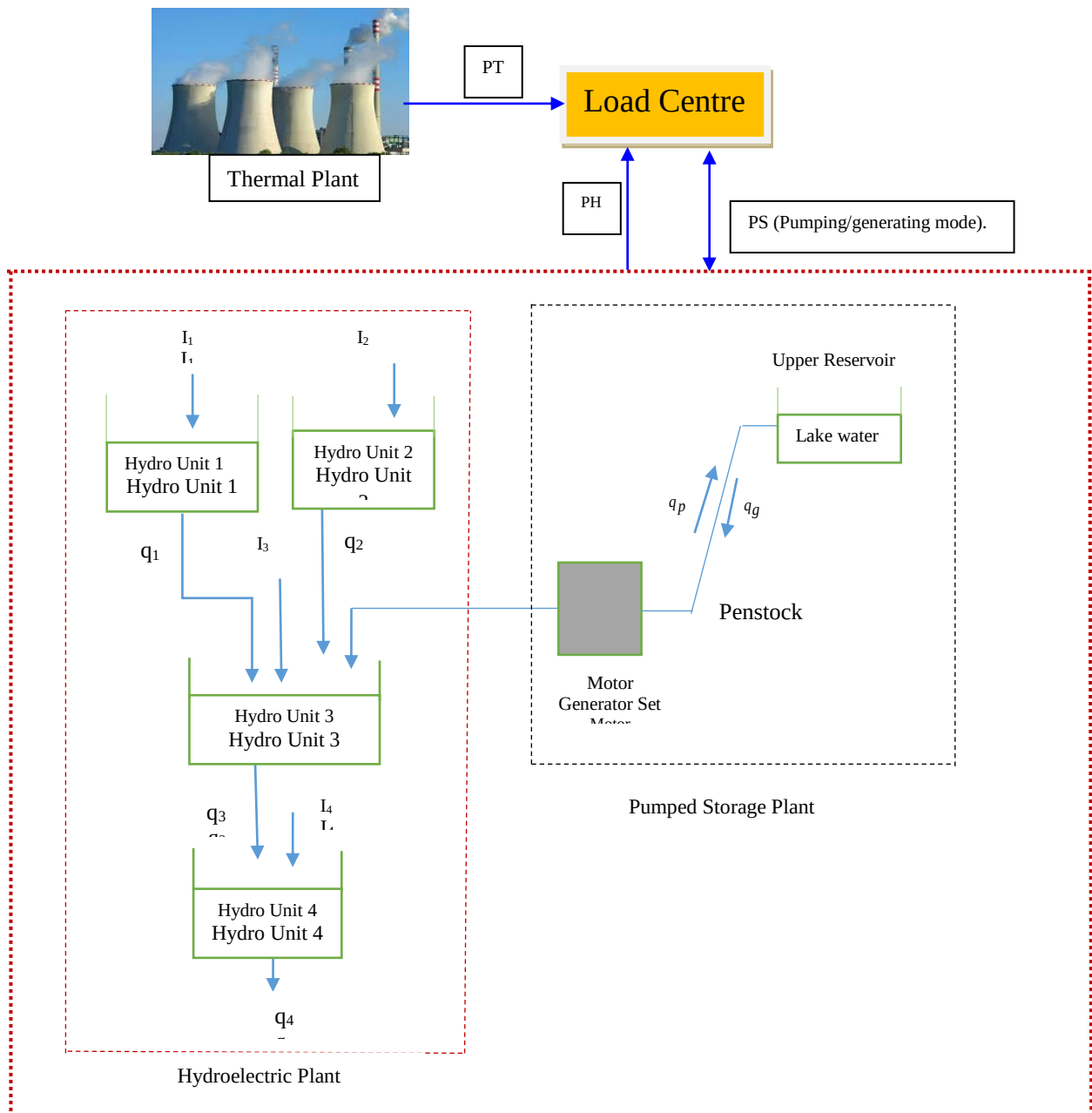


Figure 3.1: Configuration of the pumped storage hydrothermal system.

3.4.1 Modified Crisscross PSO Technique

The crisscross search PSO algorithm is a swarm based search algorithm, which is proposed by **Meng et al. (2014)**. The CSPSO algorithm comprises an IPSO and the crisscross search operators. In IPSO algorithm, the velocity of local best particles updates in the direction of mean value of the local best positions and global best position. Further, the crossover operators have been applied in an adaptive manner to maintain a fine balance between diversity and computational efforts. During the search process, if the solution does not converge up to a satisfactory level for a set number of iterations, then crossover operators are executed. Mathematically, it is represented as:

$$\left. \begin{array}{l} \text{if } (it > it_{min}) \text{ then} \\ \theta = ((of(it - it_{min}) - of(it)) / of(it - it_{min})) \\ \text{if } (\theta < \alpha) \text{ then} \\ \text{implement Modified CSO} \\ \text{endif} \\ \text{endif} \end{array} \right\} \quad (3.3)$$

where it represent the iteration number; $of(it)$ represent the objective function value at it^{th} iteration; $of(it - it_{min})$ is the objective function value at $(it - it_{min})$ iteration; α is the maximum fraction of change in the objective function between $(it - it_{min})$ and (it) iteration.

The details regarding crossover operators have been presented in Section 2.4.2 of Chapter 2.

In the MCS-PSO technique, after the successful implementation of vertical crossover operator, the decision variable updates in the direction of pattern search to improve the exploitation process. The pattern search direction has been computed as:

$$PS_i = (Plb_i - Plb_i^{old}) \quad (i \in N) \quad (3.4)$$

where Plb_i is the particle local best position; PS_i is the particles search direction.

The decision variable (Plb_i) updates along with the search direction as:

$$Plb_i = Plb_i + \lambda_i \times PS_i \quad (i \in N) \quad (3.5)$$

where λ_i is the step size and is randomly generated as:

$$\lambda_i = \lambda_i^{\min} + (\lambda_i^{\max} - \lambda_i^{\min}) \times \text{rand}() \quad (i \in N) \quad (3.6)$$

where $\lambda_i^{\min}$ and $\lambda_i^{\max}$ are the minimum and maximum step size limit.

If the moderate solution obtain from the updated decision variable outperforms its parent variable, then only it is upgraded. The flowchart of the system implementation using the proposed technique has been presented in Figure 3.2.

3.4.2 Modified Binary PSO Technique

In classical BPSO, a large value of the velocity indicates that the current particle's position has been ineffective to exploit the search space. Likewise, a small absolute value of the velocity shows that the particle's current position is ineffective to explore the search space. The exploration capability of PSO is poor and particles get easily trapped into local optima. This poor exploration of PSO affects the BPSO convergence rate because of the presence of the PSO velocity equation given as Eq. (2.29) in Section 2.4 of Chapter 2. Hence, the improved BPSO is implemented which employs the improved PSO velocity equation to make particles jump local optima and performing a global search over the entire search space. In the improved BPSO algorithm, the velocity of particles has been updated using Eq. (2.34) in Chapter 2. However, in the improved BPSO technique, the next position modifies without considering the particle position in the previous iteration as presented by Eq. (2.38) in Section 2.5 of Chapter 2. Therefore, a MB-PSO has been undertaken to mitigate the demerits of PSO and improved BPSO. The MB-PSO has been implemented to update the position of the binary random decision variable. The modification in updating the particle position also depends on the previous position.

The particle position has been computed by the sigmoid function represented by Eq. (3.7) as follows:

$$U_i^d = \begin{cases} \text{exchange}(U_i^d), & \text{if } \text{rand}() < \text{sig}(V_i^d) \\ U_i^d, & \text{otherwise} \end{cases} \quad (i \in N, d \in D_b) \quad (3.7)$$

where $U_i^{d'}$ is the updated binary decision value i^{th} particle with d^{th} dimension; U_i^d is the binary decision value of the i^{th} particle with d^{th} dimension.

The sigmoid function in improved BPSO presented by Eq. (2.37) in Section 2.5 of Chapter 2, has been modified to mitigate the local stagnancy problem, and given as:

$$\text{sig}(V_i^{d'}) = 2 \times \left| \frac{1}{1 + e^{-V_i^{d'}}} - 0.5 \right| \quad (i \in N, d \in D_b) \quad (3.8)$$

where $V_i^{d'}$ is the i^{th} particle velocity of d^{th} dimension for next iteration.

The pseudocode for the proposed technique has been illustrated in Figure 3.3.

3.5 Test Systems and Results

The proposed optimization technique (MCS-PSO with MB-PSO) has been implemented on two different test systems. For both the test systems, the multi-chain hydro unit structure has been undertaken. The hydro unit structure consists of four units. The hydro unit 1 and 2 act as upper reservoirs for unit 3, and hydro unit 3 operates as an upper reservoir for hydro unit 4. The hydro unit structure has been depicted in Figure 3.1, which illustrates a PSU along with a multi-chain hydro model. The PSU consists of a separate upper reservoir (a still water lake nearby the hydro units), and the hydro unit 3 acts as a lower reservoir. The first test system (HTS-I) is the standard hydrothermal system, having three thermal and four multi-chain hydro units. The second test system (PSHTS-III) consist one PSU, three thermal and four multi-chain hydro units and has two different cases. In case-I, effect of PSU has not been undertaken. In case-II, PSU unit has been added between a separate upper reservoir and 3rd hydro unit. The details regarding the pumped-storage hydroelectric system coefficients have been provided in the Appendix B. For both the test systems, the scheduling interval is of 24 hr with 1 hr sub-interval.

3.5.1 Parameter Settings

The POT, CSPSO, TVAC-PSO and PSO technique have been applied individually using the

compiler (FORTRAN 90) on a personal computer with 4 GB of RAM at 2.40 GHz intel core-5 processor. The optimization techniques have undergone a number of trials with different parameter values.

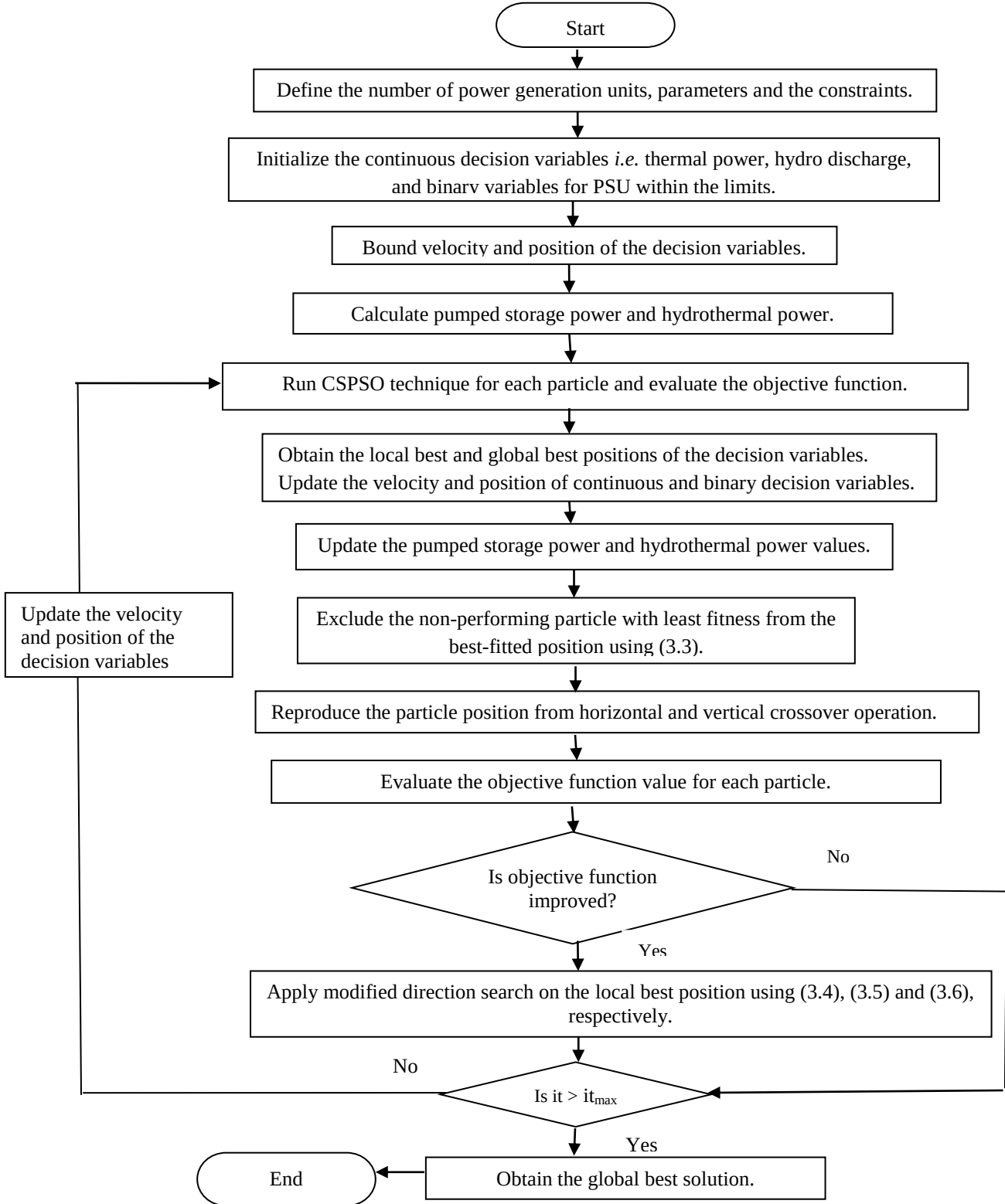


Figure 3.2: Solution methodology using the proposed optimization technique.

```

Start
Read input parameters.
it = 0
  For i =1, N
    For d=1, D
      Randomly generate decision variables i.e. thermal power, water discharge, and binary values for PSU within the
      boundary limits.
      Evaluate the objective function and obtain local best and global best particles position.
      Update particle velocity and position for continuous decision variables.
      Update velocity and position of binary decision variables.
    End do
  End do
  Implement the condition to apply modified CSO using Eq. (3.7).
For i =1, N
  For d=1, D
    Implement horizontal crossover operator as per given equation.
    
$$HS_i^d = r^d \times Plb_i^d + (1 - r^d) \times Plb_h^d + E^d \times (Plb_i^d - Plb_h^d) \quad (i \in N, h \in N, d \in D)$$

    
$$HS_h^d = r^d \times Plb_h^d + (1 - r^d) \times Plb_i^d + E^d \times (Plb_h^d - Plb_i^d) \quad (i \in N, h \in N, d \in D)$$

  End do
For d=1, D
  Apply vertical crossover approach as per given equation.
  
$$VS_i^{d_1} = r^d \times Plb_i^{d_1} + (1 - r^d) \times Plb_i^{d_2} \quad (i \in N, d_1 \in D, d_2 \in D)$$

End do
  Set step size (hh)for tuning  $\lambda_i$ .
For i = count
  Apply modified direction search on local best positions using (3.8), (3.9) and (3.10).
  Count=count+1
  hh = hh/2
End do
  Apply MB-PSO using (3.7) and (3.8).
  Update local best and global bet positions
End do
  it = it+1
  Until (it<itmax)
End

```

Figure 3.3: Pseudo code of the proposed optimization technique

A population size of 50 with 2000 iterations is used, and 30 independent trials are run for all the test systems. The method opted to find the best parameter of the POT, CSPSO, TVAC-PSO and PSO technique is same as described in Sub-section 2.8.1 of Chapter 2. The best parameters are being obtained after varying the parameters independently within the range, as given in Table 3.1. A simulation study has been carried out to find the optimal size of population. The value of parameter ‘ α ’ is varied between 0.03 and 0.05 in a systematic

manner with a step size of 0.01. The value of 'hh' parameter is varied from 0.001 to 0.01 in a systematic manner for tuning the step size ' λ_i '.

Table 3.1: Proposed technique best parameter range for optimum schedule

Parameters	HTS-I	PSHTS-III
Step size (hh)	0.005 to 0.008	0.005 to 0.008
it_{min}	200 to 250	200 to 250
Crossover probability (ρ)	0.8	0.8
Inertia Weight (ω)	0.4 to 0.9	0.4 to 0.9
Acceleration constants (C_1 and C_2)	0.5 to 2.5	0.5 to 2.5
α	0.03	0.03
Expansion coefficient (E)	-1.5 to 1.5	-1.5 to 1.5
b	0.001	0.001

3.5.2 Hydrothermal Test System (HTS)-I

The standard hydrothermal test system has been undertaken to validate the search capability of the MCS-PSO technique. The solution obtained with the MCS-PSO technique has been compared with the state of art techniques, as presented in table 3.2. For economic scheduling, the minimum cost obtained by the MCS-PSO technique is 41,180 \$ and the corresponding maximum emission is 23,942 lb due to the conflicting nature of cost and pollutant emission objectives. Similarly, for emission schedule, the minimum emission obtained by the MCS-PSO technique is 15,679 lb and the corresponding undesirable cost is 49,011 \$.

For the multi-objective generation scheduling problem, the cost and emission obtained by the MCS-PSO technique are 43,966 \$ and 17,140 lb, respectively. The multi-objective results have been compared by computing the cardinal priority ranking based on minimum and undesirable values of the objective. The higher value of the cardinal priority ranking represents the best non-dominated solution. The cardinal priority rank obtained by the MCS-PSO approach using max-min operator is 0.644, which is highest as compared to its counterparts *i.e.*, NSGA-II, SPEA-II, PESA-II, ε -ODEMO, MO-BC etc. Hence, it is summarized that the MCS-PSO approach is able to achieve a most satisfying Pareto-optimal solution with respect to both the objectives.

Table 3.2: Economic, emission and multi-objective results comparison for HTS-I

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	CPU time (Sec.)
EP (Basu, 2004)	45,063	--	--	16,554	47,906	0.141	26,324	0.288	0.141	4582
DE (Mandal and Chakraborty, 2009)	43,500	21,092	51,449	18,257	44,914	0.523	19,615	0.523	0.517	74.96
MDE (Lakshminarasimman and Subramanian, 2008)	42,611	--	--	15,730	43,198	0.742	20,385	0.430	0.430	--
PPO (Narang et al., 2012)	42,042	--	--	15,728	44,111	0.625	17,473	0.782	0.625	31.62
IQPSO (Sun and Lu, 2010)	42,359	31,298	45,271	17,767	44,259	0.606	18,229	0.691	0.606	--
ε -ODEMO (Ke et al., 2012)	--	--	--	--	44,672	0.554	16,653	0.882	0.554	--
NSGA-II (Ke et al., 2012)	--	--	--	--	46,050	0.378	17,083	0.830	0.378	--
SPEA-II (Ke et al., 2012)	--	--	--	--	45,534	0.444	16,974	0.843	0.444	--
PESA-II (Ke et al., 2012)	--	--	--	--	45,431	0.457	16,838	0.859	0.457	--
MO-BC (Zhou et al., 2014)	--	--	--	--	43,972	0.643	16,132	0.945	0.643	--
CSA (Das et al., 2018)	42,440	--	--	--	--	--	--	--	--	--
NSGSA (Tian et al., 2014)	--	--	--	--	44,519	0.573	16,574	0.891	0.573	--
NSPSO (Tian et al., 2014)	--	--	--	--	44,638	0.558	16,694	0.877	0.558	--
NSPSO-CM (Tian et al., 2014)	--	--	--	--	44,248	0.608	16,651	0.882	0.608	--
PSO (Narang et al., 2014)	43,251	24,042	46,046	16,720	44,330	0.597	19,589	0.526	0.526	44.52
GWO-MS (Kaur and Narang, 2019)	41,501	--	--	--	--	--	--	--	--	--
SCA (Dasgupta et al., 2020)	41,471	--	--	--	--	--	--	--	--	--
TVAC-PSO	42,828	26,986	48,722	16,780	44,838	0.532	17,875	0.734	0.532	31.28
MCS-PSO	41,180	23,942	49,011	15,679	43,966	0.644	17,140	0.823	0.644	22.60

SPEA-II: Strength Pareto evolutionary algorithm-II; PESA-II: Pareto envelope-based selection algorithm-II; MO-BC: multi-objective bee colony; NSGSA: Non-dominated sorting gravitational search algorithm; NSPSO: Non-dominated sorting PSO; NSPSO CM: NSPSO with chaotic mutation; GWO-MS: Grey wolf optimization with mutation strategies; SCA: Sine cosine algorithm; PPO: Predator prey optimization.

It has been observed from Table 3.2 that the MCS-PSO technique achieves the better results for economic, emission and multi-objective scheduling of HTS-I as compared to other state of art algorithms. The computational time achieved using MCS-PSO technique has been

reduced in comparison with other state of art techniques. The optimal multi-objective power generation schedule for the hydrothermal system obtained with the MCS-PSO technique has been represented in Table 3.3. The hourly discharge rate of hydro units is presented in Table 3.4. It is summarized that the proposed MCS-PSO technique for HTS-I is able to obtain the optimal solution with the competitive execution time.

Table 3.3: Multi-objective hydrothermal power generation schedule obtained for HTS-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)							
		PT_1		PT_2		PT_3		PH_1		PH_2		PH_3		PH_4	
		PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500
1	750	168.378		140.283		147.805		70.090		55.54313		38.872		129.026	
2	780	124.752		210.387		150.447		74.579		56.38443		35.715		127.734	
3	700	122.062		143.492		139.344		84.439		52.5152		36.674		121.472	
4	650	107.986		125.060		140.538		64.731		57.36467		35.795		118.523	
5	670	112.088		126.117		141.328		63.092		56.33817		41.922		129.112	
6	800	173.531		142.080		152.262		80.060		55.88216		40.566		155.617	
7	950	174.871		220.040		207.751		68.298		56.41016		29.770		192.858	
8	1010	142.342		222.382		223.606		76.119		61.48568		44.859		239.203	
9	1090	174.964		297.315		200.539		77.348		59.147		43.057		237.625	
10	1080	174.967		280.445		217.873		78.017		59.339		38.281		231.075	
11	1100	174.961		206.925		225.544		90.183		69.565		40.420		292.398	
12	1150	174.963		291.434		218.261		81.906		69.074		38.511		275.847	
13	1110	174.962		202.301		240.348		93.878		75.172		38.151		285.185	
14	1030	170.755		212.207		154.948		87.151		75.058		39.584		290.294	
15	1010	174.961		209.420		138.654		82.263		77.406		39.699		287.594	
16	1060	174.443		209.196		186.822		89.454		71.676		41.756		286.650	
17	1050	108.837		209.123		221.523		85.811		81.286		49.015		294.402	
18	1120	174.960		210.978		225.513		87.453		75.473		51.314		294.307	
19	1070	154.959		197.444		219.722		64.916		80.503		52.457		299.995	
20	1050	114.641		210.650		219.315		83.650		69.755		51.971		300.015	
21	910	151.484		124.817		138.959		67.643		72.761		56.517		297.815	
22	860	103.921		125.573		138.916		71.618		78.705		54.351		286.913	
23	850	103.571		127.836		137.611		61.224		73.424		58.388		287.943	
24	800	46.449		122.725		138.172		79.289		71.284		58.077		284.001	

3.5.3 Pumped Storage Hydrothermal Test System (PSHTS)-III

The PSHTS-III considers two cases to validate the effectiveness of the pumped storage unit with the hydrothermal system. To the best of author's knowledge, PSHTS-III, case-II has not been applied with the same connection structure of the PSHTS. Therefore, state of the art algorithms PSO, TVAC-PSO and CSPSO has been implemented for the comparison purpose as presented in Table 3.5. For case-I the minimum cost and minimum emission obtained by the POT are 65,820 \$ and 55,603 lb, respectively. The corresponding undesirable values of

pollutant emission and cost are 84,458 lb and 70,664 \$, respectively. Similarly, for case-II, the minimum cost and minimum emission obtained by the POT are 64,225 \$ and 54,699 lb, respectively and corresponding undesirable values are 89,587 lb and 70,716 \$, respectively.

Table 3.4: Hourly reservoir discharge rate for HTS-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4 \text{ m}^3/\text{h}$)							
	q_1		q_2		q_3		q_4	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	5	15	6	15	10	30	6	20
1	7.130		6.856		20.494		6.00	
2	7.737		6.883		20.262		6.161	
3	9.492		6.079		19.345		6.00	
4	6.395		6.584		19.305		6.238	
5	6.190		6.308		17.825		6.00	
6	8.759		6.184		18.055		7.130	
7	6.897		6.279		20.239		9.430	
8	8.004		7.020		16.129		13.2054	
9	8.119		6.566		16.502		12.578	
10	8.112		6.410		17.777		11.452	
11	10.211		7.868		16.996		17.895	
12	8.617		7.7710		17.507		15.756	
13	10.952		8.874		17.930		16.946	
14	9.419		8.839		17.712		17.594	
15	8.509		9.296		18.086		17.269	
16	9.733		8.306		17.757		17.095	
17	9.085		10.505		15.426		18.175	
18	9.424		9.742		15.144		18.234	
19	6.151		11.538		15.035		19.261	
20	8.837		9.320		16.110		19.559	
21	6.523		10.078		12.031		19.997	
22	7.0186		12.075		16.493		18.838	
23	5.697		11.261		13.879		19.903	
24	7.978		11.346		14.891		19.981	

The results show the credibility of the POT to search the optimal solution repeatedly in both the cases. For case-I, the minimum cost obtained from the MCS-PSO is reduced by 2761 \$, 2458 \$, and 1527 \$, in comparison to minimum cost obtained by PSO, TVAC-PSO and CSPSO technique, respectively. Similarly, for case-II, the POT is able to reduce the minimum cost by 2663 \$, 2327 \$ and 1529 \$ as compared to minimum cost obtained from PSO, TVAC-PSO and CSPSO technique, respectively. For the emission scheduling, the minimum emission obtained from the POT for case-I is reduced by 6836 \$, 5940 \$, and 4816 lb, in comparison to

minimum emission obtained by the PSO, TVAC-PSO and CSPSO techniques, respectively. Similarly, for case-II the minimum emission obtained from the POT has been reduced in comparison to the results obtained by the state of art techniques.

Table 3.5: Economic, emission and multi-objective results comparison for PSHTS-III

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	CPU time (Sec.)
Case-I										
PSO	68,581	71,733	72,769	62,439	71,027	0.416	66,036	0.613	0.416	34.40
TVAC-PSO	68,278	72,353	70,563	61,543	69,455	0.485	64,916	0.688	0.485	32.10
CSPSO	67,347	72,806	70,098	60,419	68,695	0.509	64,098	0.703	0.510	25.80
MCS-PSO	65,820	84,458	70,664	55,603	68,092	0.531	63,769	0.717	0.531	21.20
Case-II										
PSO	66,888	72,049	71,822	61,520	69,918	0.386	65,279	0.643	0.386	35.20
TVAC-PSO	66,552	74,765	71,384	60,271	68,978	0.498	64,576	0.703	0.498	34.10
CSPSO	65,754	76,010	71,205	59,173	68,420	0.511	63,837	0.723	0.511	27.60
Proposed	64,225	89,587	70,716	54,699	67,149	0.549	62,828	0.767	0.549	22.80

For multi-objective generation scheduling of case-I, the cost obtained by the MCS-PSO technique is reduced by 2935 \$, 1363 \$ and 603 \$, whereas the emission has been reduced by 2267 lb, 1147 lb, and 329 lb, respectively, as compared to the cost and emission obtained from PSO, TVAC-PSO and CSPSO techniques. Similarly, for case-II of PSHTS-III the multi-objective cost and emission obtained from the POT has been reduced in comparison to the results obtained by the state of art techniques. The cardinal priority ranking obtained from the proposed technique for the case-I and II of PSHTS-III is 0.531 and 0.549, respectively, which is better in comparison to the cardinal priority ranking achieved by PSO, TVAC-PSO and CSPSO techniques. The mean computational time computed during the multi-objective scheduling of PSHTS-III using the proposed technique indicate that the proposed technique is able to maintain a fine balance between exploration and exploitation capability.

The optimal multi-objective generation schedule of the thermal power, hydroelectric power and pumped storage power obtained by the proposed technique for case-I and II has

been presented in Tables 3.6 and 3.7, respectively, and the reservoir discharge rate is described in Tables 3.8 and 3.9, respectively. Further, the convergence behaviour of cost and emission from PSO, TVAC-PSO, CSPSO, and the proposed technique for case-II has been presented in Figures 3.6 and 3.7, respectively. It is established from these figures, that the proposed technique is able to search optimal solution with less number of iterations as compared to PSO, TVAC-PSO and CSPSO techniques. The Pareto front for case-II is shown in Figure 3.8 and it is self-evident that proposed technique is able to generate well-dispersed front as compared to PSO, TVAC-PSO and CSPSO techniques.

Table 3.6: Multi-objective hydrothermal power generation schedule for PSHTS-III, case-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydro Power (MW)							
<i>t</i>	<i>PD</i>	<i>PT₁</i>		<i>PT₂</i>		<i>PT₃</i>		<i>PH₁</i>		<i>PH₂</i>		<i>PH₃</i>		<i>PH₄</i>	
		<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>
		20	175	40	350	50	500	0	500	0	500	0	500	0	500
1	750	72.097		232.318		268.617		35.750		24.553		39.926		76.738	
2	780	73.858		223.728		305.834		38.622		28.355		33.254		76.349	
3	700	76.250		245.825		225.713		22.686		31.268		23.929		74.328	
4	650	24.082		202.014		288.027		11.545		31.843		21.794		70.695	
5	670	33.392		212.446		262.707		38.289		32.909		12.758		77.499	
6	800	100.703		286.474		289.920		10.632		30.259		7.489		74.523	
7	950	104.827		297.643		408.962		20.364		31.835		12.795		73.574	
8	1010	163.327		292.585		425.093		20.475		29.933		7.813		70.775	
9	1090	164.854		342.599		478.668		9.855		25.146		0.349		68.530	
10	1080	153.663		284.442		484.402		39.950		26.941		21.613		68.988	
11	1100	140.029		341.558		458.176		40.091		18.343		32.841		68.962	
12	1150	169.155		342.078		488.038		18.465		22.960		39.729		69.574	
13	1110	173.020		345.886		472.649		6.980		5.483		33.733		72.250	
14	1030	145.573		344.829		380.645		31.809		12.210		43.124		71.810	
15	1010	154.407		335.708		360.194		29.992		13.471		46.290		69.938	
16	1060	104.282		348.422		457.144		29.211		6.770		47.881		66.290	
17	1050	169.799		283.308		477.691		5.072		0.000		45.106		69.025	
18	1120	165.708		348.129		468.828		18.914		22.189		29.657		66.575	
19	1070	155.000		348.720		436.473		12.055		20.364		29.780		67.608	
20	1050	155.000		305.096		444.597		19.369		20.242		41.238		64.457	
21	910	135.619		300.761		325.379		3.964		19.933		54.246		70.098	
22	860	137.862		294.076		267.976		9.982		25.046		52.294		72.764	
23	850	60.004		286.865		336.135		32.159		12.615		46.841		75.382	
24	800	59.912		235.118		317.558		52.334		11.784		43.197		80.096	
Total thermal power generation cost = 68,092 \$															
Total thermal emission generation = 63,769 lb															

The working of PSU has been observed from the Tables 3.7 and it is found that PSU works in the pumping mode during 4th, 5th, 6th and 24th sub-intervals due to light load periods.

Whereas, during the 8th, 10th, 12th, and 13th sub-intervals, the PSU operates in the generating due to peak load periods satisfying the minimum change over period constraints.

Table 3.7: Multi-objective pumped storage hydrothermal power generation schedule for PSHTS-III, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydro Power (MW)								Pumped Storage Power (MW)			
<i>t</i>	<i>PD</i>	<i>PT₁</i>		<i>PT₂</i>		<i>PT₃</i>		<i>PH₁</i>		<i>PH₂</i>		<i>PH₃</i>		<i>PH₄</i>		<i>PS^g</i>		<i>PS^p</i>	
		<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PS_L</i>	<i>PS_U</i>	<i>PS_L</i>	<i>PS_U</i>
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	100.314		211.089		280.743		8.674		26.117		45.617		77.447		0.000		0.000	
2	780	85.415		201.977		317.594		28.307		28.798		42.572		75.338		0.000		0.000	
3	700	102.177		186.844		221.967		42.759		31.222		42.311		72.721		0.000		0.000	
4	650	117.394		212.811		318.158		23.444		33.777		37.921		68.974		0.000		162.480	
5	670	90.420		206.894		398.098		15.580		33.535		26.259		78.734		0.000		179.520	
6	800	108.982		295.518		414.044		29.130		32.421		15.081		79.945		0.000		215.120	
7	950	75.000		345.606		367.640		27.636		31.631		24.126		78.361		0.000		0.000	
8	1010	145.000		344.049		228.578		36.721		27.679		33.507		76.554		117.912		0.000	
9	1090	175.000		349.489		407.519		19.221		23.652		34.777		80.342		0.000		0.000	
10	1080	75.000		321.038		413.434		33.566		24.591		42.920		81.355		88.097		0.000	
11	1100	175.000		333.922		408.019		42.144		20.045		41.988		78.883		0.000		0.000	
12	1150	105.000		342.221		456.499		24.727		24.126		40.558		76.868		80.000		0.000	
13	1110	175.000		291.123		427.724		6.723		4.300		32.631		72.498		100.000		0.000	
14	1030	75.000		341.155		458.372		29.802		27.372		26.205		72.094		0.000		0.000	
15	1010	139.060		331.477		408.854		6.146		24.953		28.001		71.508		0.000		0.000	
16	1060	75.000		348.133		498.679		23.960		9.246		33.081		71.901		0.000		0.000	
17	1050	148.765		296.416		472.915		16.141		12.956		28.274		74.534		0.000		0.000	
18	1120	75.000		315.949		498.882		18.286		21.861		28.096		66.607		95.319		0.000	
19	1070	121.632		294.607		401.776		5.031		17.737		42.516		69.471		117.228		0.000	
20	1050	119.559		344.661		466.249		5.031		19.311		29.225		65.964		0.000		0.000	
21	910	75.000		342.708		312.062		51.364		18.956		41.198		68.713		0.000		0.000	
22	860	125.208		268.112		231.829		15.180		21.771		45.010		71.405		81.486		0.000	
23	850	75.000		343.554		258.815		27.069		19.108		49.040		77.414		0.000		0.000	
24	800	75.000		310.556		385.839		37.571		11.814		43.265		79.940		0.000		143.984	
Total thermal power generation cost= 66,027 \$																			
Total pumped storage power generation cost= 1121 \$																			

In order to analyse the impact of the pumped storage unit, a comparison is carried out between case-I and II. The impact of PSU in the PSHTS-III is quite evident from Table 3.5, which shows that for economic, emission and multi-objective scheduling the cost and emission in case-II is less than case-I for each of the applied technique. The optimal power generation obtained by the proposed technique in case-I and II are reported in Tables 3.6 and 3.7. It is evident from these tables, for multi-objective scheduling the total thermal power generation for case-I is 19,102.50 MW, and for case-II is 18,868.10 MW. Hence, it is summarized that

the inclusion of a PSU has reduced the thermal power generation by 234.40 MW in case-II. Due to this, the cost of thermal power generation is decreased from 68,092 \$ to 66,027 \$ in case-II as compared to case-I. However, the additional cost of 1121 \$ is incorporated due to the PSU. Similarly, the emission produced from the thermal plants in case-I is 63,769 lb, which is reduced to 62,828 lb in case-II with the presence of PSU. The total reduction of 941 lb is obtained in the pollutant emission.

Table 3.8: Hourly reservoir discharge rate for PSHTS-III, case-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)							
	q ₁		q ₂		q ₃		q ₄	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	0	15	0	30	10	30	13	25
1	8.516409		22.39763		18.5917		22.13809	
2	9.449666		18.49986		20.20438		23.96008	
3	4.789068		19.75619		19.02619		25.00	
4	1.99932		16.22366		18.14728		23.4627	
5	8.78171		15.87623		20.84112		24.72073	
6	1.659698		26.50379		25.59128		22.02427	
7	3.575428		21.80073		23.73074		23.47947	
8	3.356507		20.89803		26.13188		25.00	
9	8.55E-01		13.2353		30.00		25.00	
10	7.438048		18.15138		24.05441		23.52672	
11	7.33578		10.45918		21.18207		25.00	
12	2.195617		16.39004		18.3103		25.00	
13	0.00		5.32871		30.00		25.00	
14	5.21425		8.035224		20.12344		24.56148	
15	4.999203		8.692862		25.763		25.00	
16	5.03474		5.691072		19.30253		25.00	
17	0.00		2.749914		17.28537		25.00	
18	2.859835		14.09776		10.00		23.48794	
19	1.491188		13.93098		10.00365		25.00	
20	3.137869		13.07089		14.26371		25.00	
21	0.00		23.86755		30.00		25.00	
22	1.21995		20.0239		30.00		25.00	
23	6.563938		30.00		30.00		25.00	
24	15.00		29.98326		30.00		25.00	

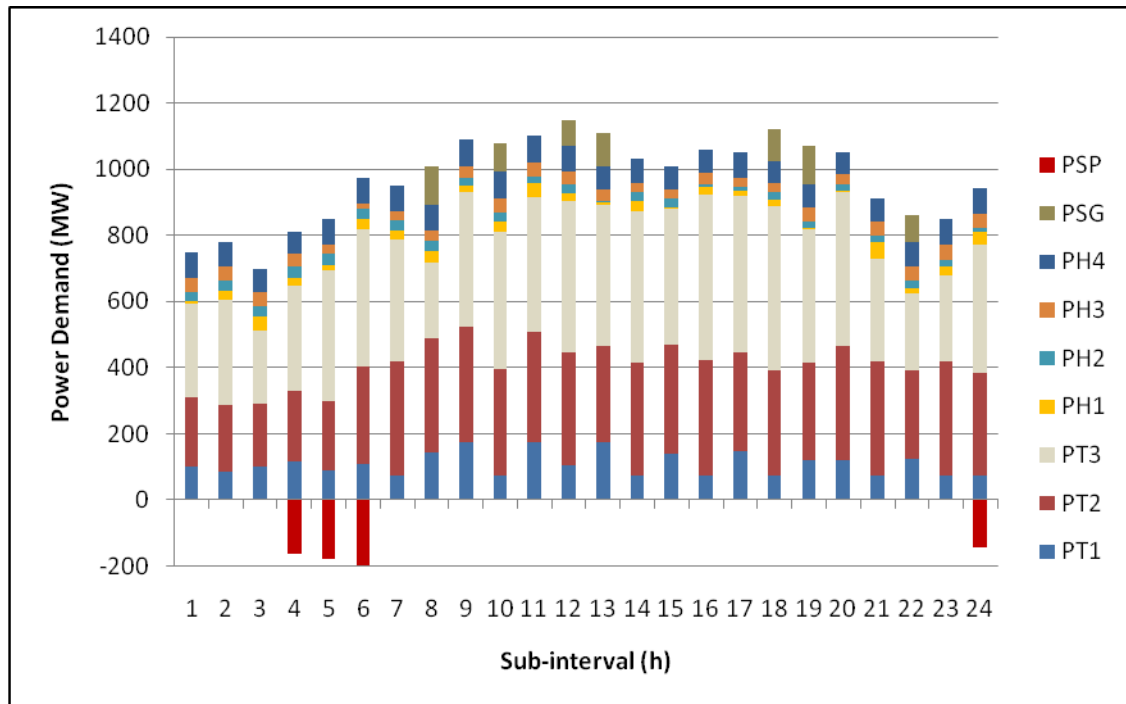


Figure 3.4: Multi-objective power generation schedule for PSHTS-III, case-II

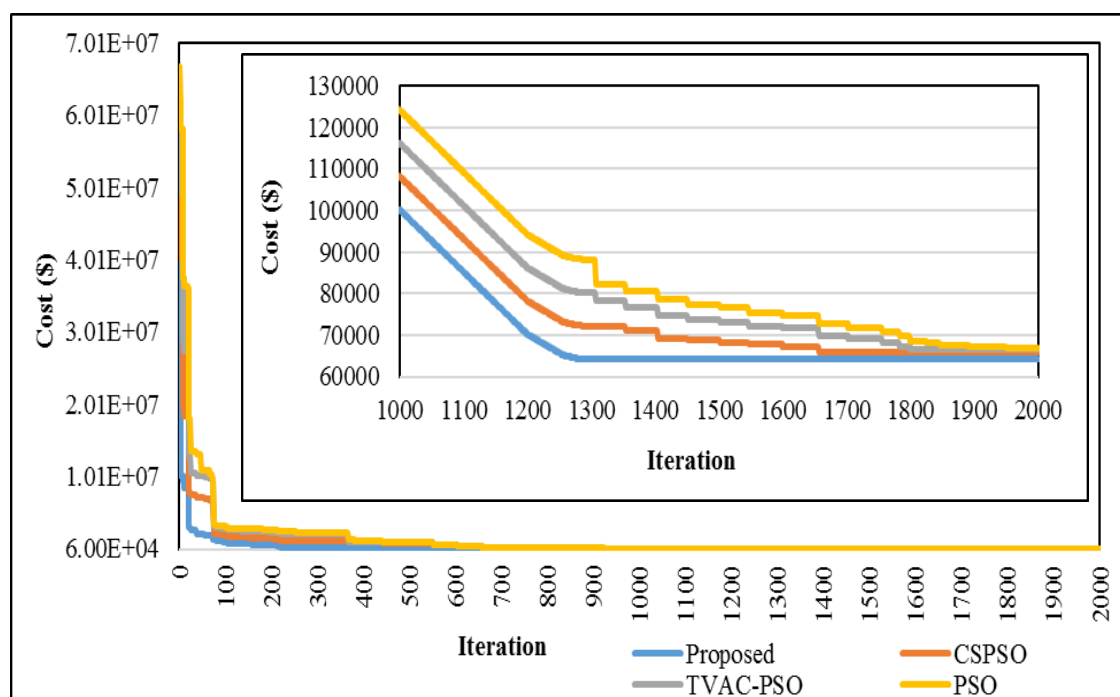
Table 3.9: Hourly reservoir discharge rate for PSHTS-III, case-II

Sub-interval (h)	Reservoir Discharge ($\times 10^4 \text{ m}^3/\text{h}$)									
	q_1		q_2		q_3		q_4		q_5	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	0	15	0	30	10	30	13	25	10	30
1	2.422474		20.88242		26.88665		23.69687		25.46262	
2	6.738595		19.66882		27.41002		25.00		17.96821	
3	9.965998		18.03794		21.85348		25.00		25.22044	
4	4.52274		20.27675		23.10005		25.00		17.75226	
5	3.544298		22.4436		27.79705		25.00		16.4831	
6	5.583423		22.95746		27.03955		25.00		22.13844	
7	5.070239		17.24346		20.0509		25.00		20.93427	
8	7.253107		13.28764		21.03758		22.95489		18.54711	
9	2.810488		11.77214		17.6085		25.00		25.47039	
10	5.864962		11.41261		25.92255		25.00		29.66985	
11	7.919547		10.280187		18.54444		25.00		22.24764	
12	3.549295		11.72151		25.73944		25.00		30.00	
13	0.00		4.616252		30.00		25.00		17.56172	
14	4.831626		22.69902		10.00		22.33227		19.54535	
15	0.00		17.35896		30.00		25.00		23.79919	
16	3.675083		6.455438		18.58594		25.00		23.04239	
17	2.102324		7.9871		13.01518		25.00		15.72022	
18	2.634171		19.71191		10.00		24.53424		20.66675	
19	0.00		15.68613		17.51668		25.00		22.14122	
20	0.00		16.55482		10.00		25.00		22.13866	
21	12.18897		12.78415		30.00		25.00		22.59572	
22	2.542514		23.78747		30.00		25.00		29.00	
23	5.583745		26.47803		30.00		25.00		22.27015	
24	8.66272		29.00		29.00		24.00		18.89816	

Table 3.10: Two sample t-test for PSHTS-III, case II

Technique	PSO	TVAC-PSO	CSPSO	Proposed
Average Cost (\$)	70,168	69,288	68,718	67,321
Variance	9,311.45	7,638.31	5,419.29	1,119.17
Observations	30	30	30	30
Pooled variance	5,215.81	4,378.74	3,269.23	
Hypothesized mean difference	0	0	0	
Degree of freedom	58	58	58	
t stat	152.96	115.14	94.63	
P(T ≤ t) one tail	0	0	0	
t critical one-tail	1.67	1.67	1.67	

In order to investigate the statistical significance of the results obtained by the proposed technique with respect to PSO, TVAC-PSO and CSPSO technique results, a student t-test has been conducted for PSHTS-III, case-II. The test has been conducted at the significance level of 5%, and the populations have equal variances. The tabulated t-test results have been presented in Table 3.10, and it is evident from the statistical values of t and p that the proposed technique is statistically significant as compared to other established techniques.

**Figure 3.5:** Convergence characteristics of cost for PSHTS-III, case-II

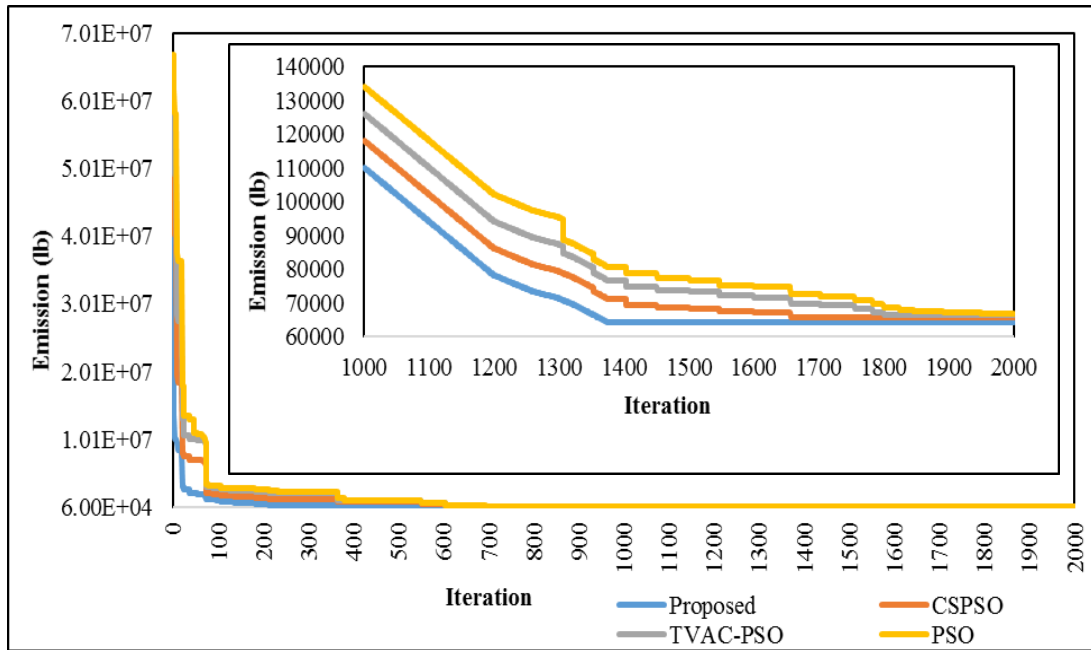


Figure 3.6: Convergence characteristics of emission for PSHTS-III, case-II

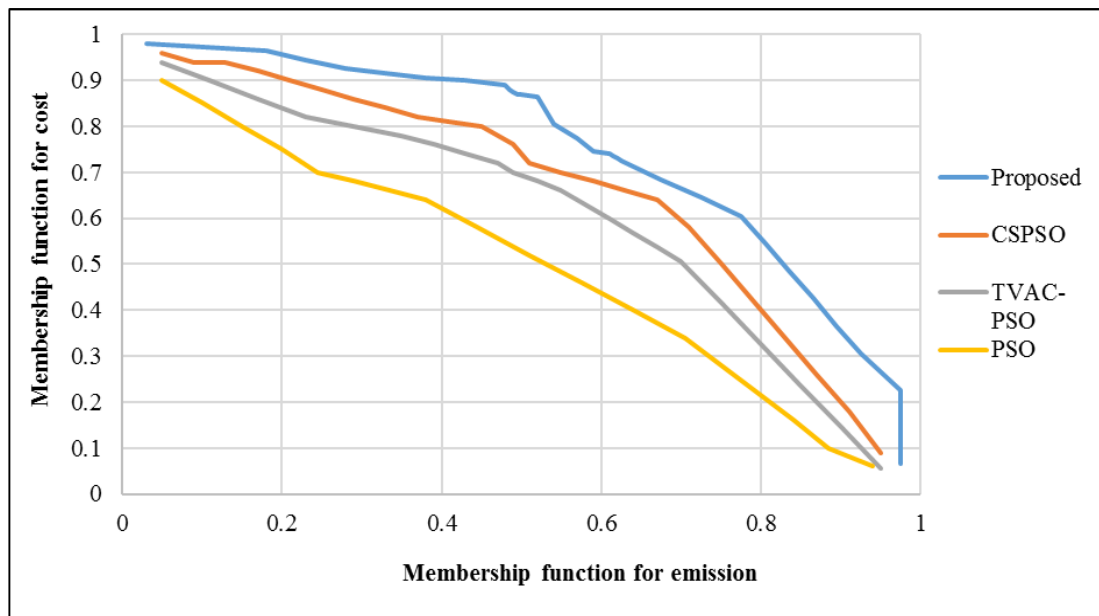


Figure 3.7: Pareto front characteristics of techniques for PSHTS-III, case-II

3.5.4 Parameter Sensitivity analysis

For economic scheduling of HTS-I, the parameter sensitivity analysis has been done by perturbing each parameter successively by $\pm 5\%$ of the best set values. After perturbing the parameters, thirty trials have been undertaken to find the minimum, average, and maximum values of the objective function. The results of parameter perturbation have been presented in Table 3.11, and sensitivity analysis has been described in Figure 3.8. The maximum value of

the minimum cost achieved by the positive perturbation of the C2 parameter is 41,326 \$ and attained a variation by 0.57% from the minimum cost.

Similarly, by negative perturbation of the C2 parameter, the maximum average cost has been varied by 0.67% in comparison with the minimum average cost. The extreme value of the maximum cost achieved by negative perturbation of the ρ parameter is 41,780 \$ and indicates a variation of 0.63% from the lowest maximum cost. Hence, it has been concluded that the parameter perturbation has very little effect on the result obtained from the proposed optimization technique. Another significant contribution of this research work is to propose a MCS-PSO and MB-PSO technique and its implementation in an adaptive manner to maintain a fine balance between exploration and exploitation phase.

Table 3.11: Results obtained after parameter perturbation for HTS-I

Best parameter + Δ	Min. Cost (\$)	Avg. Cost (\$)	Max. Cost (\$)	Best parameter - Δ	Min. Cost (\$)	Avg. Cost (\$)	Max. Cost (\$)
C1	41,301	41,441	41,745	C1	41,281	41,422	41,759
C2	41,326	41,468	41,774	C2	41,311	41,480	41,759
ρ	41,226	41,391	41,780	ρ	41,234	41,405	41,732
α	41,229	41,423	41,777	α	41,239	41,431	41,727
ω	41,257	41,411	41,779	ω	41,248	41,407	41,736
E	41,227	41,419	41,715	E	41,249	41,436	41,755
hh	41,248	41,418	41,755	hh	41,243	41,417	41,765

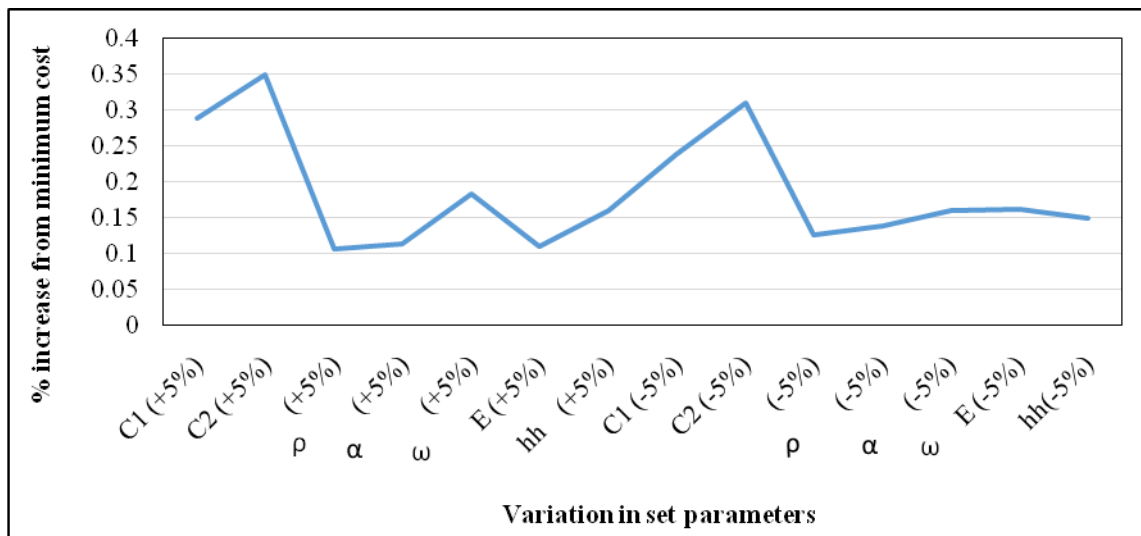


Figure 3.8: Parameter sensitivity analysis for HTS-I

3.6 Conclusions

In this work, the MCS-PSO and MB-PSO technique has been implemented for resolving the economic, emission and multi-objective generation scheduling problem of PSHTS. The undertaken PSHTS system consists thermal units, hydroelectric units and a PSU. The proposed optimization technique incorporates a MCS-PSO technique to update the continuous decision variables, while MB-PSO has been implemented to update the binary random decision variables. In the MCS-PSO technique, the local best solutions obtained from the vertical crossover operator are further refined in the direction of pattern search. This process enhances the exploitation process and improves the search capability of the POT. In order to reduce the computational efforts, the crossover operators of the MCS-PSO technique has been applied in an adaptive manner. Further, the MB-PSO technique has been implement to obtain the optimal binary decision variables by implementing modified sigmoid function.

The performance of the POT has been evaluated by implementing the two test systems. The comparative analysis of the results for HTS-I shows that the MCS-PSO technique has obtained a better quality of solution than other state of art techniques such as EP, DE, CSA, MDE, GWO-MS, IQPSO, PPO, PSO, SCA and TVAC-PSO. The mean computational time of obtained multi-objective results from the POT is less in comparison with the PSO, TVAC-PSO and CSPSO techniques. The impact of the pumped storage hydro unit has been analysed by undertaking two cases of PSHTS-III. The results of the PSHTS-III illustrate that the inclusion of a pumped storage unit facilitates to shave the peak load, which reduces the overall cost and emission significantly. The presence of a pumped storage unit has reduced the total thermal power generated in case-II by 234 MW in comparison with case-I for PSHTS-III. Hence, the thermal power generation cost and emission have been reduced by 3.03% and 1.47%, respectively. The cardinal priority ranking achieved by implementing POT is higher in comparison to the other established techniques for HTS-I and PSHTS-III.

CHAPTER-4

MULTI-OBJECTIVE SCHEDULING OF INTEGRATED ENERGY SYSTEM

4.1 Introduction

In the power generation scenario, the major portion of energy has been produced from fossil fuels. The power generation from fossil fuel energy resource leads to fuel reserve crisis, increased pollutants emission, and global warming. The rapid increment in the electric power demand, environmental hazards caused by thermal units and depletion in fuel reserves has thrust the researchers to explore the renewable energy sources (RESs). The developed countries are extensively working to develop a sustainable energy system in order to decrease the power generation cost from thermal plants and improve environment sustainability (**Luo et al., 2020; Koohi-Fayegh et al., 2020**). The RESs such as pumped storage units (PSU), solar photovoltaic (SPV) and wind energy sources (WES) have significantly contributed in overcoming the drawbacks of fossil fuel-based power plants. The advantages of RESs regarding the environment and economy issues have made their inroads into the energy system structure (**Seulki et al., 2017; Wang et al., 2017**). The PSUs have been installed with the hydrothermal plants to optimally utilize the available water resources and mitigate the water limitation problems. These units are gaining focus throughout the world because of their energy storage characteristics. The PSUs store electric energy during off-peak periods by pumping water from the lower reservoir to the upper reservoir. The stored energy has been utilized to generate energy during the peak load period (**Khandualo et al., 2013**).

The WES and SPV are gaining attention for meeting power demand at reduced cost and zero-emission. **Zhang et al. (2017)** have presented the short-term hydrothermal economic emission scheduling while considering integrated intermittent energy sources. In another

attempt, **Basu (2020)** has presented the hydrothermal generation scheduling incorporating a pumped storage unit and considering the uncertainty and outage of the solar units. **Das et al.(2018)** have obtained the short-term optimal scheduling of the hydrothermal and wind-photovoltaic system based on the point estimate approach. The presence of SPV unit aids in lower manufacturing costs and allowing the SPV to occupy the higher percent of power generation in the near future. The major drawback of using independent RESs is that unavailability of power for all duration of the day. This can be overcome by utilising SPV and WES together, such that if any one source fails other will help in meeting the power demand. Further, RESs need high initial cost and less reliable in fulfilling the high power demand (**Reddy, 2017**). Therefore, an integrated energy system (IES) incorporating RESs and pumped storage hydrothermal system (PSHTS) is reliable to meet the increased power demand at reduced cost and emission.

The incorporation of WES and SPV in the IES creates significant challenges such as intermittency and non-uniformity between generation-supply limits in the optimal scheduling problem due to their uncertainty and variability(**Panda and Tripathy, 2014; Javadi et al., 2017**). Generally the wind and SPV farms are own by the independent system operator and generations from these RESs are uncertain, sometimes the power output may be more than the scheduled power leading to underestimation of the available amount. On contrary, overestimation is the scenario when the generated power is less than the scheduled power (**Biswas et al., 2017**). The uncertainty challenges can be trounced upon by feasible solutions such as demand management through load shifting, incorporating energy storage systems (ESS) which lightens the fluctuations in the generation and the supply, national grids interconnection, etc. (**Park and Lappas, 2017**). Amid all these possible methods, ESS has been projected as the most favourable solution. The presence of ESS improves the power demand management in the grid considering the RESs. The energy storage units match the power demand to power generation, thereby expediting a smooth, and healthy energy balance

within the power system network (**Reddy et al., 2017**).

A growing body of literature from the past suggests that the generation scheduling of IES is one of the practical issues and it is important to obtain the generation scheduling of large-scale IES (**Biswas et al., 2018**). **Hemmati (2018)** has presented the optimal scheduling of an integrated energy system incorporating an energy storage system to smooth out the fluctuations of RESs. The generation scheduling problem of a coordinated power system has been resolved using the hybrid optimization technique (**Kaur and Narang, 2019**). **Somma et al. (2018)** have proposed a stochastic model for optimal generation scheduling of distributed energy sources in the presence of RESs. Similarly, an integrated hydrothermal-wind scheduling problem with large electric vehicles has been resolved using a dual population mechanism (**Zhang et al., 2018**). Hydrothermal-wind-photovoltaic scheduling has been proposed to mitigate the power limitation issue in the RESs by the maximum capitalization of the RESs power generation and curtailing the thermal output instability (**Wang et al., 2018**). Further, to analyse the impact of renewable power sources an interconnected power plant considering hydrothermal wind photovoltaic units has been proposed (**Das et al., 2018**). The multi-objective scheduling problem of the IES is one of the vital scheduling problems, which aims to obtain compromised non-dominated solution for the power generation cost and pollutant emission, simultaneously. **Forough and Roshandel (2017)** have presented multi-objective optimization technique for optimal scheduling of renewable energy systems comprising solar PV, wind units, battery banks, and diesel generator systems. **Qu et al. (2016)** have reported a multi-objective DE algorithm for optimal economic emission scheduling of hydrothermal system integrating wind energy sources.

In this research work, the economic, emission and multi-objective scheduling problem of IES has been resolved to curb the economic/environmental problems. The IES comprise the hydrothermal units, pumped storage units, WES and SPV with a battery bank system. The PSU and battery bank acts as a large energy storage system. The SPV and WES have been

utilized to overcome the intermittency problems like, uncertain weather conditions and inadequate RES power to charge battery units. The uncertain power from wind and solar has been handled utilising the Weibull and lognormal probability density function and has been expressed in the Appendix A. The inadequacy of power generation from RES leads to increased burden on thermal plants, thereby increasing the power generation cost and emission. The impact of renewable energy sources has been analysed in terms of cost and emission. Further, a proposed optimization technique (POT) combining MCS-PSO and MB-PSO techniques as described in section 3.4 of Chapter 3 is applied for resolving the economic, emission and multi-objective scheduling problem of IES. The MCS-PSO technique is being utilized to obtain non-performing solutions and update the non-performing particles to explore the search space and improve the convergence process. This search strategy is significant in terms of the exploration and exploitation phase of the continuous decision variables. The MB-PSO technique updates the position of binary decision variables using the previous particle position and reduces the stagnancy problem in the original BPSO. The fuzzy based cardinal priority ranking method has been implemented to select the best non-dominated solution of the multi-objective scheduling problem.

4.2 System Description and Modelling

The IES comprises thermal, hydro, WES, SPV, pumped storage units and the battery bank and is presented in Figure 4.1. The hydro and thermal unit are the conventional energy sources and the SPV and WES are part of RESs. The battery bank acts as an energy storage device. It can charge/discharge from/to the utility along with SPV and WES. The PSU can act as an energy storage facility and it works in the pumping mode during the off-peak intervals and generating mode during peak intervals. The economic, emission and multi-objective generation scheduling problem of PSHTS along with SPV, WES and battery banks are bound with various equality and inequality constraints. For IES, thermal, hydro and pumped storage unit's model have been referred from Chapter 3. The modelling and description of wind, solar

and battery bank system are presented in following sub-sections.

4.2.1 Wind Model

The wind power cost has been computed by considering the direct cost component, and the wind uncertainty cost components. The uncertainty components incorporate reserve cost and penalty cost due to intermittency in the wind power generation. The uncertainty in the wind velocity causes intermittency in power generation from the wind energy system. The cost incurred due to intermittency includes overestimation (CO) and underestimation (CU), while direct (DC) cost represents the normal operating cost. The wind power overestimation occurs if the scheduled power is more than the available power, and if the scheduled power is less than the available power then the wind power underestimation occurs.

The total cost function for the wind energy system is represented as:

$$WC = \sum_{t=1}^T \sum_{m=1}^{nw} (CO_{m,t} + CU_{m,t} + DC_{m,t}) \quad (4.1)$$

A condition occurs when available wind power (W_{av}) from the WES units is less than the schedule value (W_s). The system operative needs to have reserve in such scenario to deliver continuous supply to the customers. The reserve units power generating cost to meet overestimated amount is called as reserve cost (**Basu et al., 2020**).

Reserve cost for the m^{th} wind energy unit has been represented as:

$$\begin{aligned} CO_{m,t} (W_{s,m,t} - W_{av,m,t}) &= C_{r_m} \times (W_{s,m,t} - W_{av,m,t}) \\ &= C_{r_m} \times \int_0^{W_{s,m,t}} (W_{s,m,t} - W) \times f_W(W) dW \end{aligned} \quad (4.2)$$

The equivalent cost computational formula of wind power in terms of overestimation for m^{th} wind unit at t^{th} sub-interval can be calculated as:

$$CO_{m,t} = C_{r_m} \times \left\{ \begin{aligned} &W_{s,m,t} \times \left[1 - \exp\left(-\left(\frac{v_{in,m}}{SC_m}\right)^{SH_m}\right) + \exp\left(-\left(\frac{v_{out,m}}{SC_m}\right)^{SH_m}\right) \right] \\ &+ \left(\frac{W_{r_m} \times v_{in,m}}{v_{r,m} - v_{in,m}} + W_{s,m,t} \right) \times \left[\exp\left(-\left(\frac{v_{in,m}}{SC_m}\right)^{SH_m}\right) - \exp\left(-\left(\frac{v_1}{SC_m}\right)^{SH_m}\right) \right] \\ &+ \frac{W_{r_m} \times SC_m}{v_{r,m} - v_{in,m}} \times \left\{ \Gamma\left[1 + \frac{1}{SH_m}, \left(\frac{v_1}{SC_m}\right)^{SH_m}\right] - \Gamma\left[1 + \frac{1}{SH_m}, \left(\frac{v_{in,m}}{SC_m}\right)^{SH_m}\right] \right\} \end{aligned} \right\} \quad (4.3)$$

The v_1 variable in the Eq. (4.3) is the intermediate parameter of wind velocity and represented as:

$$v_1 = v_{in,m} + Ws_{m,t} \times \left(\frac{v_{r,m} - v_{in,m}}{W_{r_m}} \right) \quad (4.4)$$

On contrary to the overestimation case, there may be condition in the network when actual power delivered by the wind farm is higher than the estimated value. The renewable source output is underestimated in such case. The surplus power will be wasted if not possible to utilize by reducing power output from conventional power plants (Biswas et al., 2017).

$$\begin{aligned} CU_{m,t} (W_{av,m,t} - Ws_{m,t}) &= Cp_m \times (W_{av,m,t} - Ws_{m,t}) \\ &= Cp_m \times \int_{Ws_{m,t}}^{W_{r_m}} (W - Ws_{m,t}) \times f_W(W) dW \end{aligned} \quad (4.5)$$

The equivalent cost computational formula of wind power in terms of underestimation can be calculated as:

$$CU_{m,t} = Cp_m \times \left\{ \begin{aligned} & (W_{r_m} - Ws_{m,t}) \times \left[\exp \left(- \left(\frac{v_{r,m}}{SC_m} \right)^{SH_m} \right) - \exp \left(- \left(\frac{v_{out,m}}{SC_m} \right)^{SH_m} \right) \right] \\ & + \left(\frac{W_{r_m} \times v_{in,m}}{v_{r,m} - v_{in,m}} + Ws_{m,t} \right) \times \left[\exp \left(- \left(\frac{v_{r,m}}{SC_m} \right)^{SH_m} \right) - \exp \left(- \left(\frac{v_1}{SC_m} \right)^{SH_m} \right) \right] \\ & + \frac{W_{r_m} \times SC_m}{v_{r,m} - v_{in,m}} \times \left\{ \Gamma \left[1 + \frac{1}{SH_m}, \left(\frac{v_1}{SC_m} \right)^{SH_m} \right] - \Gamma \left[1 + \frac{1}{SH_m}, \left(\frac{v_{r,m}}{SC_m} \right)^{SH_m} \right] \right\} \end{aligned} \right\} \quad (4.6)$$

where $Ws_{m,t}$ is the wind power of the m^{th} unit in t^{th} sub-interval; v_r is the rated wind velocity; v_{in} and v_{out} are the cut in and cut out wind velocity; SH_m and SC_m are shape and scale factor for the m^{th} wind unit; Cr_m and Cp_m are the penalty factor for over and under estimated wind power of the m^{th} wind unit

The direct cost from wind power has been represented as:

$$DC_{m,t} = d_c \times W_{m,t} \quad (4.7)$$

where d_c is the direct cost coefficient of the m^{th} wind unit.

4.2.2 Solar Photovoltaic Model

The solar power cost has been computed by considering the direct cost and uncertainty cost of

the SPV units. The uncertainty cost incorporates reserve cost, and penalty cost due to the intermittency in the solar power generation. The uncertainty in the solar radiation causes the intermittency in power generation from the SPV units.

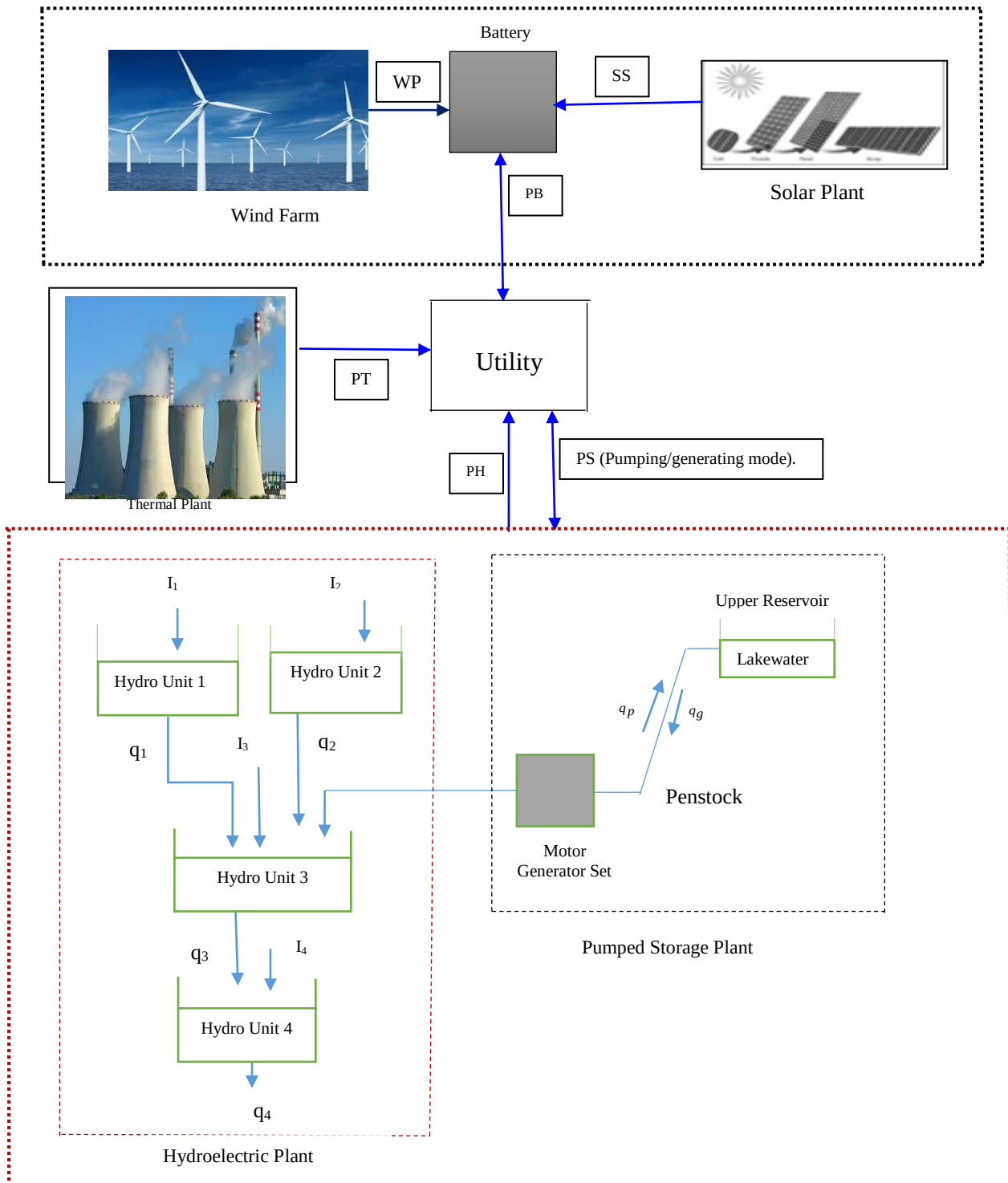


Figure 4.1: Diagrammatic description of the IES.

The cost incurred during intermittency includes the overestimation (CO) and underestimation

(CU), while direct cost (DC) represents the normal operating cost obtained for SPV unit. The total cost of the SPV unit (SC) is represented as:

$$SC = \sum_{t=1}^T \sum_{s=1}^{ns} (CO_{s,t} + CU_{s,t} + DC_{s,t}) \quad (4.8)$$

The solar power (S_s) is computed as:

$$S_s = S_{r_s} \times \{1 + (Tr - Ta) \times \alpha t\} \times \frac{IL}{1000} \quad (s \in ns) \quad (4.9)$$

where S_{r_s} is the rated solar power from each cell; Tr and Ta are the reference and ambient temperature variables, respectively; IL is the solar insolation at any sub-interval; αt is the temperature coefficient for the s^{th} solar unit.

The total solar power generation from the SPV units (TS) is given as:

$$TS_t = \sum_{s=1}^{ns} S_s = \sum_{s=1}^{ns} S_{r_s} \times \{1 + (Tr - Ta) \times \alpha t\} \times \frac{IL}{1000} \quad (s \in ns) \quad (4.10)$$

The SPV units also have intermittent and uncertain outputs. An overestimation condition occurs when available solar power (Sav) from the SPV units is less than the schedule value (Ss). The reserve power generating units are required during overestimation scenario to supply continuous power to the customers. The reserve cost for the s^{th} solar energy unit is represented as **(Biswas et al., 2017)**:

$$\begin{aligned} CO_{s,t} (S_{s,t} - Sav_{s,t}) &= Cr_s \times (S_{s,t} - Sav_{s,t}) \\ &= Cr_s \times \int_0^{S_{s,t}} (S_{s,t} - S) \times f_S(S) dS \end{aligned} \quad (4.11)$$

where Cr_s is the reserve cost factor for overestimated solar power of the s^{th} SPV unit.

On contrary to the overestimation case, there may be condition in the network when available power delivered by the SPV units is higher than the schedule value. The renewable source power output has been underestimated in such case. The surplus power will be wasted if it is not utilize by reducing power output from conventional power plants.

The underestimation penalty cost for the s^{th} solar photovoltaic unit is represented as:

$$\begin{aligned}
CU_{s,t} (S_{av,s,t} - S_{s,t}) &= C_{p_s} \times (S_{av,s,t} - S_{s,t}) \\
&= C_{p_s} \times \int_{S_{s,t}}^{S_{r_s}} (S - S_{s,t}) \times f_s(S) dS
\end{aligned} \tag{4.12}$$

where C_{p_s} is the penalty factor for underestimated solar power of the s^{th} SPV unit.

The SPV direct cost is based on the solar power share and expressed as (**Khan et al., 2015**):

$$DC = \sum_{t=1}^T \sum_{s=1}^{ns} UC_s \times S_{s,t} \tag{4.13}$$

where UC_s is per unit cost of solar power generated from s^{th} solar unit in t^{th} sub-interval; ns is the number of solar units and T is the total sub-interval.

4.2.3 Battery Bank System

The power generation cost from battery bank system *i.e.* ‘BC’ is a quadratic function and is represented as:

$$BC = \sum_{t=1}^T \left[b_1 + b_2 \times |PB_t| + b_3 \times PB_t^2 \right] \tag{4.14}$$

where b_1 , b_2 and b_3 are the cost coefficients, respectively; PB is the battery power during charging/discharging.

In the utility, the power exchange is bidirectional in nature. The utility power depends on total power generated from WES and SPV units as well as, the battery charging or discharging power. The aim of the system operator is to maintain the utility power positive such that the burden on thermal power generating units reduces.

The utility power (PU) is presented as:

$$PU_t = TS_t + \sum_{m=1}^{nw} W_{m,t} - \left(\frac{((CB_t - CB_{t-1}) \times V)}{B \times \Delta} \right) \quad (t \in T) \tag{4.15}$$

where CB is the battery charge; V is the battery bank potential; B is the battery bank efficiency and Δ is time in an hour for which battery is operated.

4.3 Multi-objective Problem Formulation

The IES consists a set of continuous, and binary decision variables. The decision variables set

comprises thermal power (PT), reservoir discharge rate (q), wind power (W), battery charge (CB) and the operating mode of the pump storage unit (U) for a scheduling period of T sub-intervals. Among the decision variable set, operating mode of PSU are binary in nature, whereas other decision variables are continuous type. The decision variable set is represented as an array 'Z'.

$$Z = \left[\begin{array}{c|c} \begin{array}{c} \xleftarrow{\text{Continuous Decision Variables}} \\ PT_{11}PT_{21}.....PT_{nt1}, q_{11} q_{21}.....q_{nh1}, W_{11} W_{21}..... W_{nw1}, CB_{11}CB_{21}.....CB_{nb1} \\ PT_{12}PT_{22}.....PT_{nt2}, q_{12} q_{22}.....q_{nh2}, W_{12} W_{22}..... W_{nw2}, CB_{12}CB_{23}.....CB_{nb2} \\ PT_{13}PT_{23}.....PT_{nt3}, q_{13} q_{23}.....q_{nh3}, W_{13} W_{23}..... W_{nw3}, CB_{13}CB_{23}.....CB_{nb3} \\ \vdots \\ PT_{1T}PT_{2T}.....PT_{ntT}, q_{1T} q_{2T}.....q_{nhT}, W_{1T} W_{2T}..... W_{nwT}, CB_{1T}CB_{2T}.....CB_{nbT} \\ \xleftarrow{\text{Thermal unit}} \quad \xleftarrow{\text{Hydro unit}} \quad \xleftarrow{\text{Wind Unit}} \quad \xleftarrow{\text{Battery Bank}} \end{array} & \begin{array}{c} \xleftarrow{\text{Binary Decision Variable}} \\ U_{11}U_{21}U_{31}.....U_{np1} \\ U_{12}U_{22}U_{32}.....U_{np2} \\ U_{13}U_{23}U_{33}.....U_{np3} \\ \vdots \\ U_{1T}U_{2T}U_{3T}.....U_{npT} \\ \xleftarrow{\text{Pump storage Unit}} \end{array} \end{array} \right]$$

The total cost of power generation (OF₁) includes thermal power cost, pumped storage power cost, wind power cost, solar power cost and the battery charging/discharging cost.

Mathematically, the total cost function is presented as:

$$OF_1 = TC + PSC + WC + SC + BC \quad (4.16)$$

The emission generated from the thermal units (OF₂) is represented as Eq. (2.2) in Sub-section 2.2.1 of Chapter 2.

The problem undertaken is multi-objective in nature as the cost and emission are the contradicting objectives, which needs to be minimized, simultaneously. The multi-objective optimization problem stated as Eq. (2.9) of Chapter 2 aims at minimizing the total cost of power generation and emission pollutants subjected to the satisfaction of the inequality and equality constraints.

The IES is bounded by various equality and inequality constraints. The inequality constraints constitute power limits, discharge rates and restriction on PSU working modes. For hydro and thermal units in the IES, decision variables are reservoir discharge rate and thermal

power generation, respectively. The discharge and power limits imposed on hydrothermal units are represented by Eq. (2.10) and (2.11) of Chapter 2.

The wind power, and battery charge limit constraints are given as:

$$W_m^{\min} \leq W_{m,t} \leq W_m^{\max} \quad (m \in nw, t \in T) \quad \left. \vphantom{W_m^{\min} \leq W_{m,t} \leq W_m^{\max}} \right\} \quad (4.17)$$

$$CB^{\min} \leq CB_t \leq CB^{\max} \quad (t \in T) \quad (4.18)$$

The equality constraints include power demand balance in each sub-interval, final reservoir volume of each hydro unit and initial and final state of battery charge.

The power balance equality constraint for IES is given as:

$$\sum_{g=1}^{nt} PT_{g,t} + \sum_{j=1}^{nh} PH_{j,t} + \sum_{l=1}^{np} (\eta_{g,l} \times PS_{l,t}^g) + PU_t = PD_t + \sum_{l=1}^{np} (\eta_{p,l} \times PS_{l,t}^p) + PL_t \quad (t \in T) \quad (4.19)$$

The equality constraint associated with the final volume of the reservoir is given as Eq. (2.15) in Sub-section 2.3 of Chapter 2.

The equality constraint of battery charge is represented as:

$$\left. \begin{array}{ll} CB_t|_{t=0} = \text{INSOC} \times Q_b & \text{Initial state of charge} \\ CB_t|_{t=T} = \text{FSOC} \times Q_b & \text{Final state of charge} \end{array} \right\} \quad (4.20)$$

The following inequality constraints are associated with IES

a) Power and reservoir volume of the pumped storage hydro units are restricted within upper and lower limits and are given by Eq. (2.17) to (2.20) in Sub-section 2.3 of Chapter 2.

b) The pumped storage unit works either in generating mode or in pumping mode, the restriction on the working of a PSU is represented by Eq. (2.12) to (2.14) in Chapter 2.

c) The utility power and battery power limitations are expressed as:

$$\left. \begin{array}{ll} PU_t \leq PU^{\max} & \text{The utility power} \\ PB_t \leq PB^{\max} & \text{The battery power} \end{array} \right\} \quad (4.21)$$

d) A limit is imposed on maximum solar share to satisfy the power demand and is given as:

$$TS_t \leq x \times PD_t \quad (t \in T) \quad (4.22)$$

where x is the fraction of total power demand to be shared by SPV unit during any sub-interval.

4.3.2 Constraints Handling

In the search process, the boundary limits may violate by the decision variables. In this, the decision variables are set to their corresponding upper or lower limits suitably. In order to satisfy the equality and inequality constraints, an exterior penalty method is applied, in which a function is penalized for each constraint violation. The error has been computed for any violation of constraint and collective error has been incorporated in the objective function. To satisfy the power balance equality constraint, the variable elimination method is implemented in which, a thermal generating unit is randomly chosen as dependent unit. The power generation required by dependent thermal unit is computed as:

$$PT_t^{\text{dep}} = PD_t + \sum_{l=1}^{np} (\eta_{p,l} \times PS_{l,t}^p) + PL_t - \sum_{\substack{g=1 \\ g \neq \text{dep}}}^{nt} PT_{g,t} - \sum_{j=1}^{nh} PH_{j,t} - \sum_{l=1}^{np} (\eta_{g,l} \times PS_{l,t}^g) - PU_t \quad (t \in T) \quad (4.23)$$

If computed power generation of dependent thermal unit violates its power generation limits in any sub-interval, then error is computed using Eq. (2.23) of Sub-section 2.3.1 in Chapter 2.

For hydro reservoir final volume equality constraint, if there is a mismatch between desired volume and final volume, then an error is computed using Eq. (2.21) of Sub-section 2.3.1 of Chapter 2.

An error has been computed for final charge of battery units between desired charge and generated charge as:

$$ecb_T = \begin{cases} (CB_T - \text{FSOC} \times Q_b)^2 & ; CB_T > \text{FSOC} \times Q_b \\ 0 & ; CB_T \leq \text{FSOC} \times Q_b \end{cases} \quad (4.24)$$

In order to satisfy all the inequality constraints for pumped storage hydro units, the respective error has been computed on violation of defined limits as per Eq. (2.24) to (2.26) in Sub-section 2.3.1 of Chapter 2.

For an inequality constraint given from Eq. (4.21) to (4.22), respective error has been

computed on violation of the boundary limits as:

$$epu_t = \begin{cases} (PU_t - PU^{\max})^2; & PU_t > PU^{\max} \\ 0 & ; PU_t \leq PU^{\max} \end{cases} \quad (t \in T) \quad (4.25)$$

$$epb_t = \begin{cases} (PB_t - PB^{\max})^2; & PB_t > PB^{\max} \\ 0 & ; PB_t \leq PB^{\max} \end{cases} \quad (t \in T) \quad (4.26)$$

$$ets_t = \begin{cases} (TS_t - x \times PD_t)^2; & TS_t > x \times PD_t \\ 0 & ; TS_t \leq x \times PD_t \end{cases} \quad (t \in T) \quad (4.27)$$

where epb_t represent final battery charge error; epu_t represent the utility power error; epb_t is the error due to battery power; epu_t represent the error due to solar share.

4.3.3 Objective Function Formulation

The main concern is to obtain the best-compromised solution for the contradicting objectives while satisfying the inequality and equality constraints. Considering the imprecise nature of the decision-maker's judgment, it is natural to presume that the decision maker may have fuzzy or imprecise goals for each objective function. The fuzziness in obtaining the best non-dominated solution for the multi-objective problem is created by the conflicting objectives.

Bellman and Zadeh(1970) have treated the objective function and constraints systematically and defined the fuzzy membership function to deal with the MOOP.

The membership functions represent the degree of membership in certain fuzzy sets using values from 0 to 1. For each of the multiple objectives, minimum and maximum values are obtained by giving full weightage to one objective while neglecting other objective. The membership function $\mu(OF_k)$ is computed by considering the lower, and upper bound of each of the objective functions and is given as:

$$\mu(OF_k) = \begin{cases} 1 & ; \text{if } OF_k \leq OF_k^{\min} \\ \frac{OF_k^{\max} - OF_k}{OF_k^{\max} - OF_k^{\min}} & ; \text{if } OF_k^{\min} \leq OF_k \leq OF_k^{\max} \\ 0 & ; \text{if } OF_k \geq OF_k^{\max} \end{cases} \quad (k \in \text{Nob}) \quad (4.28)$$

Further, the membership functions are used to find the unified effect of all the objectives after

clubbing the multiple objectives. The minimum value of overall membership function indicates the satisfaction level of the objective functions corresponding to a non-dominated solution. The decision for the best non-dominated solution is taken by implementing the max-min operator to the membership functions. The maximum value of the cardinal priority ranking represents the desired solution.

The cardinal priority ranking (overall objective function) is expressed as:

$$\mu_d = \{\max(\min(\mu(\text{OF}_1) - f_{er}, \mu(\text{OF}_2) - f_{er}))\} \quad (4.29)$$

where

$$f_{er} = r_a \times \left(\sum_{t=1}^T \text{ep}_t + \sum_{j=1}^{nh} \text{evf}_j + \sum_{j=1}^{nh} \sum_{t=1}^T \text{ev}_{j,t} + \sum_{j=1}^{nh} \sum_{t=1}^T \text{eph}_{j,t} + \sum_{l=1}^{np} \sum_{t=1}^T \text{eps}_{l,t} + \sum_{t=1}^T \text{epb}_t + \sum_{t=1}^T \text{ecb}_t + \sum_{t=1}^T \text{epu}_t + \sum_{t=1}^T \text{ets}_t \right) \text{ and } r_a \text{ is}$$

the exterior penalty factor.

4.4 Solution Methodology

The economic, emission and multi-objective scheduling problem of IES is a nonlinear, non-convex and mixed variable optimization problem. The POT as discussed in Section 3.4 of Chapter 3 is explored for optimum generation scheduling of IES. The elaborated steps to implement the POT are given as follows:

Step 1: The initial position of binary and continuous decision variables has been generated as an array 'Z' with dimension $(N_g \times T)$.

Step 2: After initialization, the total power generation cost has been computed as given by Eq. (4.8), and the pollutant emission is computed using Eq. (2.2) of Chapter 2.

Step 3: The fuzzy membership value has been computed for each objective function using Eq. (4.28).

Step 4: The cardinal priority ranking is computed using Eq. (4.29), the maximum value of cardinal priority ranking provides most satisfied non-dominated solution.

Step 5: The velocity of a continuous and binary decision variables has been updated by using Eq. (2.34) of Chapter 2.

Step 6: The local best position of continuous and binary decision variables has been updated using Eq. (2.35), and (3.7), respectively, of Chapter 2, and 3.

Step 7: The objective function is evaluated for each moderate solution and competes with parent population to enter the next generation. Finally, global best position is upgraded using the updated local best positions.

Step 8: Check the termination criteria, and if it not satisfied repeat steps 3-7. For POT, the maximum number of iterations has been set as termination criteria.

4.5 Test Systems

In this work, two integrated test systems have been undertaken to analyse the effectiveness of the proposed (MCS-PSO with MB-PSO) approach in comparison with other well-established techniques. Further, the impact of RES on PSHTS has been studied on economic, emission and multi- objective generation scheduling problem of the IES. The IES-I consists four multi-cascade hydro units, three thermal units, one PSU, thirteen SPV units and one battery bank. The IES-II consists of four hydro units, three thermal units, one PSU, two WES units, thirteen SPV units, and one battery bank system. In this work, two different cases have been undertaken for each integrated test system. In the case-I, the uncertainty of RESs have been neglected, and for case-II, the RESs uncertainties have been considered. From these two cases, the impact of uncertainty of RESs has been investigated. The total scheduling interval is of 24 hrs with 1 hr sub-intervals. The details regarding the different power generating units of IES have been presented in Appendix B.

4.6 Parameter Settings

The performance of the optimization techniques is being affected by the parameter values. The optimization techniques have undergone the number of trials with different parameter values. The best parameters are being obtained after varying the parameters independently within the minimum and maximum values, as given in Table 4.1. A population size of 50 has been undertaken and maximum iteration has been set to 2000. Higher population size is not

preferred as it increases the simulation time. In order to achieve the optimal solution, the POT has been performed on IES for 30 independent times. The procedure opted to achieve the best parameter for the proposed, CSPSO, TVAC-PSO and PSO technique is same as described in Sub-section 2.8.1 of Chapter 2.

Table 4.1: Proposed optimization technique best Parameter range for the optimum schedule of IES

Parameters	IES-I	IES-II
Acceleration constants (C_1 and C_2)	1.5 to 2.5	1.5 to 2.5
Step size (hh)	0.001 to 0.005	0.005 to 0.05
Crossover probability (ρ)	0.6	0.6
Inertia Weight (ω)	0.4 to 0.9	0.4 to 0.9
E	-1.0 to 1.0	-1.0 to 1.0
α	0.03	0.03
it_{min}	200 to 250	200 to 250

4.7 Results and Discussion

4.7.1 Integrated Energy System (IES)-I

The economic, emission and multi-objective scheduling results, for cases-I and II, obtained by PSO, CSPSO, TVAC-PSO and the POT have been presented in Table 4.2. For economic scheduling in case-I, the minimum cost obtained by the implementation of the POT is 60,838 \$, which is less than by 1275 \$, 1690 \$ and 2880 \$ as compared to the cost attained by implementing the CSPSO, TVAC-PSO and PSO techniques, respectively. For emission scheduling, the minimum emission obtained by the implementation of the POT is 30,143 lb, which is less than by 1668 lb, 3321 lb and 5397 lb in comparison to the minimum emission, attained by implementing the CSPSO, TVAC-PSO and PSO techniques, respectively. For case-II, the minimum cost and emission obtained by the proposed optimization technique is 68,198 \$ and 30,996 lb, which is minimum as compared to the minimum cost and emission attained by CSPSO, TVAC-PSO and PSO techniques as reported in Table 4.2.

The multi-objective cost and emission for case-I obtained by the POT are 63,613 \$ and 39,335 lb, respectively. Similarly, for case-II, the multi-objective cost and emission obtained by the proposed optimization technique are 73,270 \$ and 36,245 lb, respectively. The multi-

objective results have been reduced in comparison to the well-established, PSO, TVAC-PSO and CSPSO techniques. In order to compare the result of multi-objective problem, the cardinal priority ranking is computed. It is evident from Table 4.2 that maximum value of cardinal priority ranking obtained by POT for cases-I and II are 0.550 and 0.629, respectively, which are higher than rankings achieved from the CSPSO, TVAC-PSO and PSO techniques.

Table 4.2: Economic, emission and multi-objective results and CPU time comparison for IES-I

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	μ (OF_1)	OF_2 (lb)	μ (OF_2)	μ_d	CPU time (Sec.)
Case-I										
PSO	63,718	54,228	71,406	35,540	68,231	0.413	44,361	0.528	0.413	39.10
TVAC-PSO	62,528	52,546	69,701	33,464	66,409	0.459	42,261	0.539	0.459	37.58
CSPSO	62,113	52,277	68,490	31,811	65,123	0.528	40,448	0.578	0.528	30.36
Proposed	60,838	50,569	67,953	30,143	63,613	0.610	39,335	0.550	0.550	28.32
Case-II										
PSO	71,428	45,716	81,570	35,105	77,189	0.432	39,689	0.568	0.432	40.33
TVAC-PSO	70,326	43,299	80,113	33,685	75,210	0.501	37,646	0.588	0.501	38.55
CSPSO	69,349	42,416	81,393	32,233	74,251	0.593	36,225	0.608	0.593	32.35
Proposed	68,198	47,348	81,869	30,996	73,270	0.629	36,245	0.679	0.629	29.51

The multi-objective generation schedule of the thermal, hydro and PSU obtained from the proposed optimization technique for cases-I and II have been presented in Tables 4.3 and 4.5, respectively. The multi-objective schedule power from the solar energy units, battery units and utility for cases-I and II have been presented in Tables 4.4 and 4.6, respectively. The mean computational time for the multi-objective schedule required by the POT is less in comparison to other well-established techniques. The water discharge rate for cases-I and II have been illustrated in Figures 4.2 and 4.3, respectively. In Tables 4.4 and 4.6, the positive and negative values of battery power represent the charging and discharging mode of the battery, respectively.

Table 4.3: Multi-objective power schedule of thermal, hydro, pumped storage units for IES-I, case-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
<i>t</i>	<i>PD</i>	<i>PT₁</i>		<i>PT₂</i>		<i>PT₃</i>		<i>PH₁</i>		<i>PH₂</i>		<i>PH₃</i>		<i>PH₄</i>		<i>PS^g</i>		<i>PS^p</i>	
		<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PS_L</i>	<i>PS_U</i>	<i>PS_L</i>	<i>PS_U</i>
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	175.00		213.307		232.309		26.010		18.644		48.248		77.483		51.505		0.000	
2	780	171.77		208.192		229.432		30.897		16.090		46.633		75.070		0.000		0.000	
3	700	171.81		292.889		253.656		21.502		25.103		39.322		72.530		0.000		180.002	
4	650	174.98		127.208		235.187		4.522		26.384		35.346		68.777		0.000		0.000	
5	670	174.97		249.736		307.349		28.567		26.276		37.057		80.604		0.000		203.102	
6	800	145.50		208.362		138.293		23.046		23.659		43.554		82.718		0.000		0.000	
7	950	170.11		324.315		412.442		26.705		19.850		36.111		83.226		0.000		224.402	
8	1010	166.92		311.861		430.702		5.666		21.018		23.201		76.990		0.000		243.902	
9	1090	173.48		324.998		222.730		61.248		14.866		30.249		79.672		0.000		0.000	
10	1080	174.96		261.684		408.479		38.503		6.192		28.021		78.735		0.000		249.602	
11	1100	174.58		218.972		238.941		6.669		0.000		17.610		81.318		0.000		0.000	
12	1150	173.28		222.919		218.001		46.057		0.000		25.317		78.305		0.000		0.000	
13	1110	174.94		198.150		227.250		10.232		16.232		25.655		80.747		0.000		0.000	
14	1030	133.49		156.595		210.857		8.840		5.224		30.833		77.735		106.828		0.000	
15	1010	163.27		222.962		180.027		6.798		0.000		30.703		79.802		0.000		0.000	
16	1060	172.47		208.360		293.133		6.712		21.195		24.163		82.139		0.000		0.000	
17	1050	133.95		273.352		366.011		12.170		15.994		29.558		77.170		92.370		0.000	
18	1120	174.98		339.190		302.919		14.109		0.000		31.401		71.635		86.770		0.000	
19	1070	166.61		279.780		498.295		8.190		16.465		29.539		68.384		0.000		0.000	
20	1050	157.13		301.972		414.111		45.997		25.167		25.330		63.842		0.000		0.000	
21	910	104.54		252.922		340.298		11.839		25.647		30.188		67.831		56.648		0.000	
22	860	173.14		280.230		318.819		17.220		13.493		28.498		72.494		68.119		0.000	
23	850	122.05		158.527		276.909		51.713		12.626		32.317		76.857		0.000		0.000	
24	800	114.58		192.002		190.567		50.496		11.759		47.366		79.202		66.577		0.000	
Total thermal power cost= 58380.409 \$																			
Pumped storage unit power cost= 1320.66 \$																			

Further, a comparison of the cost, and emission obtained by the POT has been done between IES-I, and PSHTS-III system to analyse the effect of the solar-battery units in the IES. The PSHTS-III system has been discussed in Sub-section 3.5.3 of Chapter 3. The economic, emission and multi-objective results for case-II of PSHTS-III, obtained by the POT, as reported in Table 3.4 of Chapter 3 has been undertaken for comparison with IES-I due to presence of PSU. The compared results are discussed further to present the impact of solar battery units with the PSHTS-III. In case-I, IES-I, the impact of SPV and battery units is able to decrease the cost, and emission by 3387 \$ and 24,556 lb, respectively, as compared to

case-II, PSHTS-III, for economic and emission scheduling obtained by the proposed optimization technique. The multi-objective cost and emission obtained for case-I, IES-I, has been reduced by 3536 \$ and 23,493 lb compared to case-II of PSHTS-III. In case-II of IES-I, the power generation cost has been increased by 3973 \$ and 6121 \$, for economic and multi-objective scheduling, due to reserve and penalty cost for overestimation and underestimation power.

Table 4.4: Multi-objective schedule of solar-battery-utility power for IES-I, case-I

Sub-interval (h)	Solar Share (MW)		Battery Power (MW)		Utility Power (MW)	
t	SS		PB		PU	
	SS _{min}	SS _{max}	PB _{min}	PB _{max}	PU _{min}	PU _{max}
	0	440	0	350	0	450
1	0.000		92.868		-92.868	
2	0.000		-1.909		1.909	
3	0.000		-3.187		3.187	
4	0.000		22.410		-22.410	
5	2.261		33.726		-31.457	
6	61.105		-73.755		134.860	
7	104.930		3.295		101.636	
8	216.697		-0.846		217.543	
9	205.371		22.617		182.754	
10	267.904		-65.117		333.021	
11	403.172		41.263		361.909	
12	413.545		27.433		386.112	
13	365.671		-11.115		376.786	
14	306.031		6.440		299.591	
15	262.193		-64.243		326.436	
16	231.647		-20.173		251.819	
17	139.165		89.743		49.422	
18	77.601		-21.385		98.993	
19	14.399		11.666		2.733	
20	0.000		-16.449		16.449	
21	0.000		-20.080		20.080	
22	0.000		112.021		-112.021	
23	0.000		-118.998		118.998	
24	0.000		-47.445		47.445	
Solar power cost= 798.29 \$ Battery power cost= 3114.00 \$						

However, it has been compensated by large decrement in the emission pollutants. The emission obtained for case-II, IES-I, has been reduced by 23,703 lb and 26,583 lb in comparison with case-II, PSHTS-III, for emission and multi-objective scheduling. The presence of solar battery system reduces the burden on thermal power generation, which is observed by the power generated from the thermal units. The total thermal power generation obtained for cases-I and II, IES-I, are 16,613 MW and 16,213 MW, which is reduced by 2255

MW and 2655 MW in comparison with thermal power generated in case-II, PSHTS-III. Further, the primary reason of high cost in case-II, IES-I, is the reserve and penalty cost imposition to the operator due to overestimation and underestimation of the solar power. The total reserve and penalty cost imposed on the operator for case-II is 6995 \$ and the direct cost is 798.29 \$. However, the evaluation of uncertainty power for the SPV unit in case-II, IES-I has reduced the thermal power generation by 400 MW in comparison with case-I, IES-I, thereby reducing the emission pollutants.

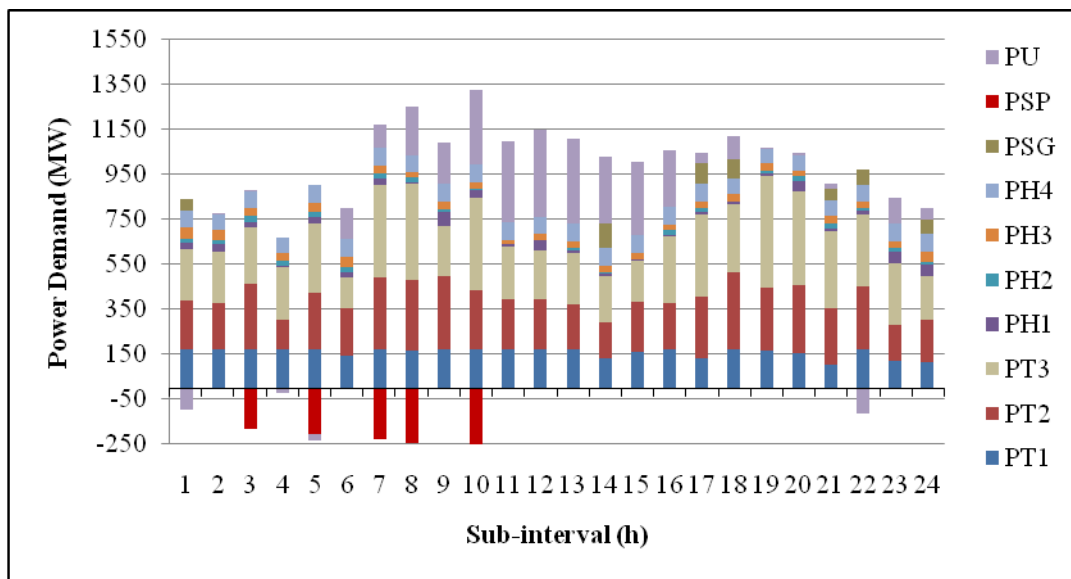


Figure 4.2: Multi-objective power generation schedule for IES-I, case-I

Table 4.5: Reservoir discharge rate for IES-I, case-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4 \text{ m}^3/\text{h}$)									
	q_1		q_2		q_3		q_4		q_5	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	0	15	0	30	10	30	13	25	10	30
1	5.610576		26.51935		29.73005		24.70749		29.99724	
2	6.741845		28.05866		29.28613		24.81179		23.60083	
3	4.162172		22.70203		26.04023		25.00		28.65257	
4	2.67E-01		22.18776		12.50513		25.00		10.600	
5	5.414747		22.23819		29.99948		25.00		10.71815	
6	3.97366		23.91761		23.33828		25.00		14.40647	
7	4.660691		24.50204		25.84643		25.00		10.58403	
8	0.00		14.67395		28.59531		24.43017		23.35309	
9	14.7		24.30835		14.03047		23.88024		24.86993	
10	7.186586		6.797512		18.84564		22.266		22.10623	
11	0.00		1.572674		30.00		24.99922		20.56826	
12	8.562416		1.629121		26.79263		18.76757		17.38358	
13	6.47E-01		10.60798		15.08763		24.84484		14.55421	
14	3.94E-01		5.340561		14.24756		24.98979		29.08466	
15	1.58E-02		0.00		18.77969		22.99767		14.88816	
16	0.00		13.04689		11.93931		25.00		15.31393	
17	1.050514		9.963718		13.56491		25.00		21.06682	
18	1.463518		1.29E-01		13.58443		23.82474		22.00594	

19	3.38E-01	9.447623	12.19299	21.50126	25.99116
20	9.342701	19.77405	10.00	23.86358	29.89562
21	1.329933	18.23836	27.50689	25.00	10.6028
22	2.513392	30.00	30.00	23.73429	16.49367
23	12.69232	30.00	30.00	24.97114	21.54031
24	14.06417	29.99711	24.24193	23.57522	20.35016

Table 4.6: Multi-objective schedule of thermal, hydro and pumped storage power for IES-I, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS ^g		PS ^p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	174.871		209.654		139.699		33.351		23.521		45.409		77.257		57.549		0.000	
2	780	175.000		294.259		317.744		25.647		27.479		54.808		75.779		42.134		0.000	
3	700	174.967		223.407		229.141		2.574		29.016		52.664		73.171		0.000		0.000	
4	650	28.477		124.171		149.039		30.700		32.998		55.573		69.436		0.000		0.000	
5	670	107.630		124.798		140.189		26.132		32.291		51.822		74.000		0.000		130.290	
6	800	104.731		297.511		296.204		29.102		33.542		50.037		77.000		0.000		0.000	
7	950	174.943		210.641		241.074		23.263		34.578		42.176		75.198		0.000		149.772	
8	1010	174.981		295.320		282.223		35.875		27.328		50.363		76.551		0.000		0.000	
9	1090	174.828		252.625		132.648		29.765		26.003		49.769		74.967		0.000		0.000	
10	1080	100.817		207.839		203.867		38.119		28.050		50.370		75.963		0.000		0.000	
11	1100	174.965		300.543		264.303		19.911		14.811		43.487		70.867		0.000		167.814	
12	1150	174.996		329.183		324.448		26.780		27.711		24.305		71.092		0.000		164.416	
13	1110	104.996		296.575		230.438		7.006		27.043		30.630		71.110		0.000		0.000	
14	1030	173.113		295.736		317.118		7.006		24.094		27.752		70.756		0.000		0.000	
15	1010	172.073		305.865		248.603		17.394		26.397		17.056		69.752		0.000		179.579	
16	1060	104.995		293.593		296.869		23.978		22.701		9.415		72.424		0.000		0.000	
17	1050	174.998		297.496		393.669		27.845		24.737		9.246		71.287		0.000		0.000	
18	1120	174.987		296.624		341.349		24.843		20.510		19.476		69.604		99.676		0.000	
19	1070	174.998		343.175		409.914		22.950		19.505		27.374		65.132		0.000		0.000	
20	1050	160.159		247.644		332.995		22.470		16.949		31.467		64.579		88.251		0.000	
21	910	172.722		300.563		411.095		25.431		4.356		33.251		66.244		77.957		0.000	
22	860	170.979		286.772		186.409		27.689		16.766		38.603		69.273		69.708		0.000	
23	850	105.241		294.368		295.886		36.796		18.762		43.011		75.855		0.000		0.000	
24	800	40.788		213.226		215.245		22.625		15.871		43.197		80.235		0.000		0.000	
Total thermal power cost= 55259.73 \$																			
Pumped storage unit power cost= 998.5172 \$																			

4.7.2 Integrated Energy System (IES)-II

For IES-II, wind-solar-battery system has been undertaken with PSHTS-III and two cases have been considered to analyse the effect of RESs uncertainty. The obtained results from the POT for both the cases have been compared with PSO, TVAC-PSO and CSPSO techniques. The economic, emission and multi-objective results along with mean computational time has been presented in Table 4.9. The results show the credibility of the POT to search the optimal

solution repeatedly with fewer computational efforts. The minimum cost obtained by implementing the POT for cases-I and II, IES-II, are 63,515.83 \$ and 83,473.43 \$, respectively. The minimum cost obtained from the implemented POT for case-I has reduced the power generation cost by 6198 \$, 4324 \$ and 2053 \$, as compared to the PSO, TVAC-PSO and CSPSO technique, respectively. Similarly, for case-II, the minimum cost has been reduced by 3646 \$, 2424 \$ and 825 \$ in comparison to the minimum cost obtained from the well-established techniques. The minimum emission obtained by the implementation of the POT for cases-I and II are 24,378 lb and 22,980 lb, respectively which is minimum in comparison to the emission, attained by implementing the CSPSO, TVAC-PSO and PSO techniques.

Table 4.7: Multi-objective power generation schedule of solar-battery units and utility for IES-I, case-II

Sub-interval (h)	Solar Share (MW)		Battery Power (MW)		Utility Power (MW)	
t	SS		PB		PU	
	SS _{min}	SS _{max}	PB _{min}	PB _{max}	PU _{min}	PU _{max}
	0	440	0	350	0	450
1	0.000		11.310		-11.311	
2	0.000		232.852		-232.852	
3	0.000		84.941		-84.941	
4	0.000		-159.606		159.606	
5	2.261		-241.159		243.428	
6	61.105		149.232		-88.127	
7	104.930		-192.969		297.899	
8	216.697		149.338		67.359	
9	205.371		-144.025		349.395	
10	267.904		-107.071		374.975	
11	403.172		24.246		378.926	
12	413.545		37.645		375.900	
13	365.671		23.469		342.202	
14	306.031		191.606		114.425	
15	262.193		-110.245		372.438	
16	231.647		-4.379		236.026	
17	139.165		88.443		50.722	
18	77.601		4.678		72.930	
19	14.399		7.445		6.954	
20	0.000		-85.486		85.486	
21	0.000		181.619		-181.619	
22	0.000		6.200		-6.200	
23	0.000		19.919		-19.919	
24	0.000		-168.813		168.813	
Solar power cost= 798.29 \$						
Solar uncertainty power cost= 6995 \$						
Battery power cost= 9218.00 \$						

The multi-objective cost and emission for case-I obtained by the POT are 73,490 \$ and 34,690 lb, respectively. Similarly, for case-II, the multi-objective cost and emission obtained by the POT are 88,019 \$ and 32,571 lb, respectively. The multi-objective results have been reduced in comparison to the well-established PSO, TVAC-PSO and CSPSO techniques. It is evident from Table 4.9 that the cardinal priority ranking achieved by the proposed optimization technique for cases-I and II are 0.595 and 0.650, respectively, which are higher than rankings achieved from CSPSO, TVAC-PSO and PSO techniques. The mean computational time for the multi-objective scheduling obtained by the proposed optimization technique has been reduced in comparison to its counterparts.

Table 4.8: Reservoir discharge rate for IES-I, case-II

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)									
	q ₁		q ₂		q ₃		q ₄		q ₅	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	0	15	0	30	10	30	13	25	10	30
1	7.746151		23.35155		16.6864		23.30401		24.09859	
2	5.429694		20.57741		26.75942		25.00		26.77828	
3	0.00		15.04343		21.5044		25.00		12.49874	
4	6.179994		20.75108		27.61962		25.00		17.18579	
5	4.936301		15.89854		24.83379		22.07165		25.6127	
6	5.581798		16.34754		19.95401		25.00		11.023	
7	4.010064		19.4495		15.30236		25.00		23.27016	
8	6.957424		11.99095		25.41586		25.00		14.96863	
9	5.202466		11.20692		25.03461		20.92992		18.36702	
10	7.111397		12.61017		24.33831		25.00		25.23174	
11	2.6547		6.629556		23.1306		24.99305		14.83241	
12	3.906244		12.82274		30.00		25.00		26.0737	
13	0.00		13.07782		22.86247		25.00		23.87822	
14	0.00		11.71178		21.86473		25.00		16.35831	
15	2.029698		14.39133		16.84064		25.00		12.77022	
16	3.48713		12.33344		24.00735		25.00		13.65262	
17	4.493757		18.50813		10.00		24.99999		18.00289	
18	3.98062		14.10892		10.53955		25.00		28.3286	
19	3.709294		16.73832		17.44747		25.00		19.60471	
20	3.757976		21.29041		13.62673		25.00		23.49036	
21	4.646103		5.237664		29.99735		25.00		21.27865	
22	5.477193		27.04491		30.00		25.00		25.78984	
23	8.521264		26.21403		30.00		25.00		25.17262	
24	5.021288		28.00329		30.00		25.00		26.62008	

Table 4.9: Economic, emission and multi-objective results comparison for IES-II

Technique	Economic		Emission		Multi-objective					
	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	OF_2 (lb)	OF_1 (\$)	μ (OF_1)	OF_2 (lb)	μ (OF_2)	μ_d	CPU time (Sec.)
Case-I										
PSO	69,713	47,831	83,533	29,167	78,489	0.365	39,918	0.424	0.365	39.21
TVAC- PSO	67,839	51,359	83,884	27,362	76,327	0.471	37,729	0.568	0.471	37.96
CSPSO	65,568	52,045	84,810	25,286	74,785	0.521	35,963	0.601	0.521	33.35
Proposed	63,515	55,817	88,144	24,378	73,490	0.595	34,690	0.672	0.595	31.19
Case-II										
PSO	87,119	53,746	100,096	27,050	93,932	0.475	38,129	0.585	0.475	40.26
TVAC- PSO	85,897	52,263	100,841	25,785	92,368	0.567	35,185	0.645	0.567	38.37
CSPSO	84,298	54,066	99,295	24,025	90,432	0.591	33,488	0.685	0.591	34.57
Proposed	83,473	58,371	96,461	22,980	88,019	0.650	32,571	0.729	0.650	32.68

The multi-objective generation schedule of the thermal, hydro and pumped storage units, for cases-I and II, obtained from the POT has been presented in Tables 4.12 and 4.14, respectively. The SPV units, WES units, battery units and utility's multi-objective power schedule have been presented in Tables 4.13 and 4.15, respectively. In Tables 4.13 and 4.15, respectively, the positive and negative values of battery power represent the charging and discharging mode of the battery. The hourly reservoir discharge rate for cases-I and II has been illustrated in Figures 4.4 and 4.5, respectively. The convergence behaviour of cost obtained from the PSO, TVAC-PSO, CSPSO, and the proposed optimization technique for case-I has been presented in Figure 4.6. Similarly, the emission convergence behaviour obtained by implementing the PSO, TVAC-PSO, CSPSO, and the POT has been presented in Figure 4.7. The Pareto front for case-I is shown in Figure 4.8 and it is established from these figures, that the POT is able to search the optimal solution with a less number of iterations as compared to PSO, TVAC-PSO and CSPSO techniques.

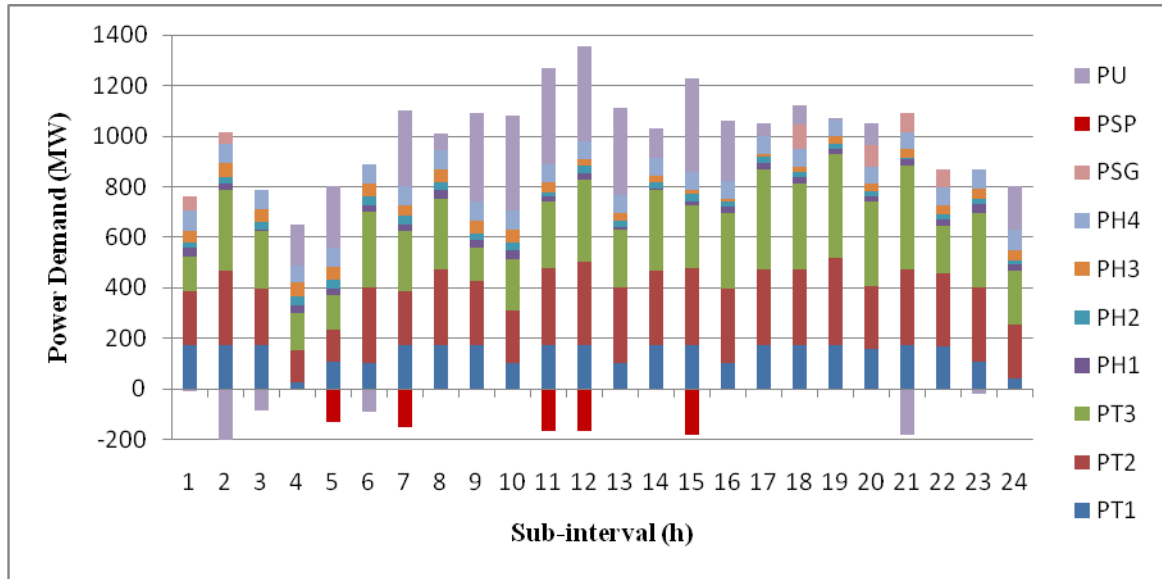


Figure 4.3: Multi-objective power generation schedule for IES-I, case-II

Further, a comparison of cost and emission obtained by the POT has been done between IES-II, and PSHTS-III system to analyse the effect of the wind-solar-battery units in the IES. The economic, emission and multi-objective results for case-II of PSHTS-III system presented in Table 3.4 in Sub-section 3.5.3 of Chapter 3 has been undertaken for comparison due to presence of PSU. In similar pattern with IES-I, for IES-II, case-I and case-II has been compared with case-II of PSHTS-III. The compared results are discussed further to present the impact of wind-solar battery units with PSHTS-III system.

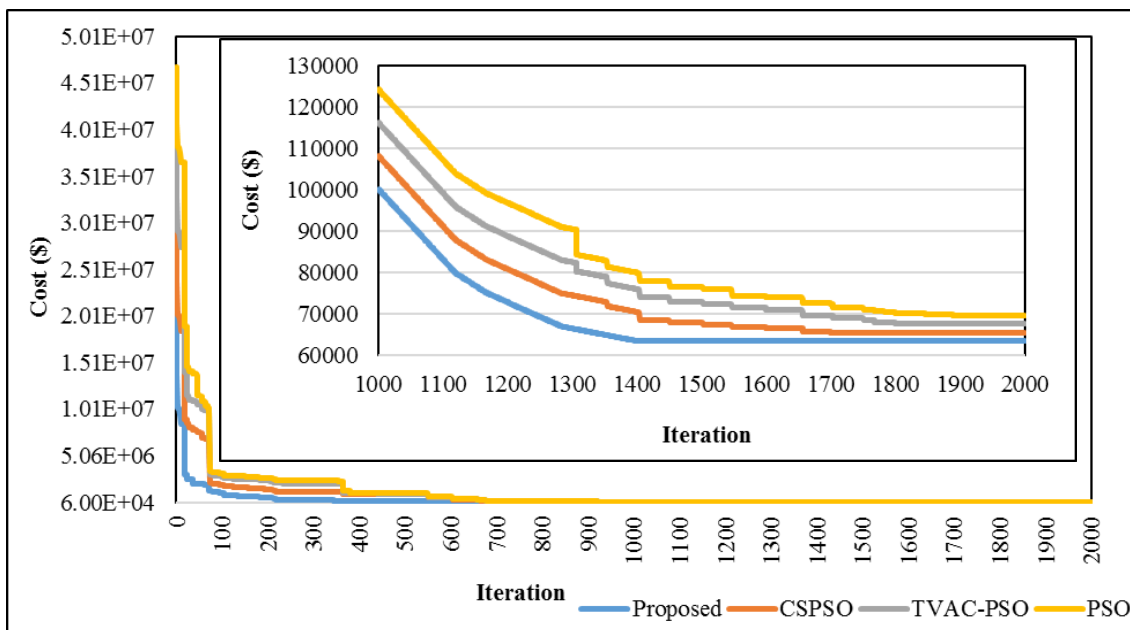


Figure 4.4: Convergence characteristics for cost obtained for IES-II, case-I

Table 4.10: Reservoir discharge rate for IES-II, case-I.

Sub-interval (h)	Reservoir Discharge ($\times 10^4 \text{ m}^3/\text{h}$)									
	q_1		q_2		q_3		q_4		q_5	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	0	15	0	30	10	30	13	25	10	30
1	7.500342		25.41374		19.56791		24.30282		24.5698	
2	5.250603		12.9008		13.26796		17.76809		10.00	
3	5.400363		30.00		25.42038		25.00		24.41232	
4	3.482673		21.82268		30.00		24.91815		22.69939	
5	10.64224		24.57825		24.39307		25.00		30.00	
6	5.500939		25.33982		24.68723		25.00		13.76473	
7	7.92619		18.38603		18.85169		25.00		14.3043	
8	5.531041		10.42351		18.32212		25.00		30.00	
9	0.00		5.436635		22.63104		25.00		19.92508	
10	0.00		14.97471		23.30694		25.00		19.26748	
11	4.690304		11.49674		17.33096		22.41426		26.72502	
12	3.913507		12.61262		30.00		25.00		17.20463	
13	3.856027		14.346		16.113		25.00		12.78971	
14	9.537015		14.97617		23.4994		25.00		30.00	
15	0.00		3.896508		23.78694		17.09933		15.28154	
16	4.46E-01		0.00		19.12508		25.00		30.00	
17	1.560424		11.71349		14.53467		25.00		22.39772	
18	0.00		12.45805		14.22648		25.00		21.79242	
19	8.15E-01		6.741583		13.57114		19.34889		13.88766	
20	0.00		19.53709		10.00		25.00		26.81982	
21	2.458003		8.756811		30.00		25.00		20.20756	
22	6.101859		30.00		30.00		25.00		30.00	
23	10.18261		30.00		30.00		25.00		12.55595	
24	10.32214		30.00		30.00		25.00		30.00	

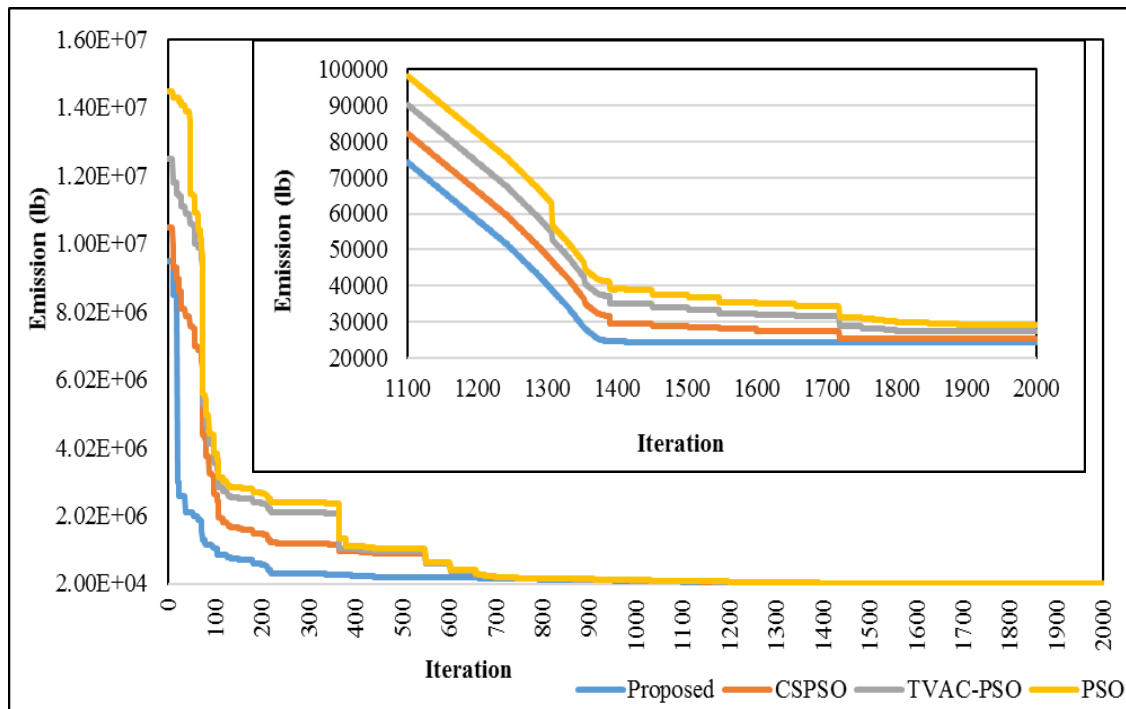
**Figure 4.5:** Convergence characteristics for emission obtained for IES-II, case-I

Table 4.11: Reservoir discharge rate for IES-II, case-II

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)									
	q ₁		q ₂		q ₃		q ₄		q ₅	
	q _{min}	q _{max}	q _{min}	q _{max}	q _{min}	q _{max}	q _{min}	q _{max}	q _{min}	q _{max}
	0	15	0	30	10	30	13	25	10	30
1	8.544195		19.73331		28.85038		22.21289		10.00	
2	5.53841		22.87854		23.18012		25.00		29.21336	
3	4.892568		27.80065		12.8145		25.00		17.37027	
4	4.141741		12.03459		26.57043		25.00		30.00	
5	8.524909		24.08177		12.97216		25.00		13.98277	
6	6.750887		22.04949		16.10277		25.00		30.00	
7	4.687999		11.97944		30.00		25.00		24.31154	
8	3.22E-01		28.90797		23.91484		25.00		10.00	
9	3.472249		17.43076		22.42871		19.48317		10.00	
10	2.795066		11.89575		19.4752		25.00		13.19827	
11	8.42E-01		13.38997		30.00		25.00		23.99644	
12	8.850356		20.56349		26.83985		25.00		19.70683	
13	4.567636		2.367401		22.45078		19.22069		23.79797	
14	3.284631		3.580861		18.45815		25.00		15.47629	
15	5.872131		7.803906		30.00		20.36337		14.36127	
16	1.832741		17.11139		13.84733		25.00		10.00	
17	2.588526		9.604062		10.00		25.00		22.8763	
18	2.750495		6.502343		11.34098		25.00		10.00	
19	0.00		13.90683		10.79262		25.00		10.00	
20	0.00		1.271374		17.89499		25.00		30.00	
21	5.084443		13.0598		30.00		25.00		30.00	
22	1.984871		30.00		30.00		25.00		30.00	
23	8.133297		30.00		30.00		25.00		30.00	
24	9.4664		27.69624		30.00		25.00		30.00	

In case-I, IES-II, the impact of wind-solar-battery units is able to decrease the cost and emission by 710 \$ and 30,421 lb, respectively, as compared to case-II, PSHTS-III, for economic and emission scheduling obtained by the POT. The multi-objective cost has been increased by 5398 \$, however, this increase has been compensated by 29,079 lb of emission reduction as compared to case-II, PSHTS-III. In case-II, IES-II, the power generation cost has been increased by 19,248 \$ and 20,870 \$, for economic and multi-objective scheduling, due to reserve and penalty cost for overestimation and underestimation power. However, it has been compensated by large decrement in the emission pollutants. The emission obtained for case-II, IES-II, has been reduced by 31,719 lb and 30,257 lb in comparison with case-II, PSHTS-III, for emission and multi-objective scheduling. The presence of wind-solar-battery system reduces the burden on thermal power generation, which is observed by the power generated from the thermal units. The total thermal power generation obtained for cases-I and II, IES-II,

are 15,225 MW and 14,748 MW, which is reduced by 3643 MW and 4120 MW in comparison with thermal power generated in case-II, PSHTS-III.

Table 4.12: Multi-objective schedule of thermal, hydro, pumped storage and utility power for IES-II, case-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS _g		PS _p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	175.000		258.799		229.565		32.557		20.599		45.846		77.463		0.000		0.000	
2	780	175.000		209.563		228.381		25.035		24.425		37.468		70.264		0.000		0.000	
3	700	105.000		207.943		200.548		26.255		18.663		46.794		76.415		0.000		0.000	
4	650	174.748		210.979		231.933		18.951		29.624		45.578		72.780		0.000		0.000	
5	670	103.250		209.207		139.589		44.483		26.958		42.477		79.287		0.000		162.480	
6	800	104.915		238.842		362.294		26.981		24.237		37.769		73.250		0.000		179.520	
7	950	105.000		245.730		434.512		36.118		26.667		35.294		73.471		0.000		195.120	
8	1010	105.000		238.707		361.756		27.921		19.380		31.647		76.074		0.000		209.280	
9	1090	170.262		235.801		403.110		4.188		8.744		25.464		75.761		0.000		222.000	
10	1080	153.225		202.754		315.962		5.613		26.129		25.556		75.599		0.000		66.000	
11	1100	105.397		222.219		318.614		29.373		20.807		24.756		72.098		0.000		66.000	
12	1150	106.885		206.164		315.983		26.796		21.337		2.763		70.197		0.000		0.000	
13	1110	100.856		207.629		322.961		25.941		21.610		18.227		68.917		0.000		0.000	
14	1030	106.700		205.878		212.941		46.964		20.092		13.034		67.996		0.000		0.000	
15	1010	114.348		212.019		295.448		5.344		0.416		10.001		59.725		0.000		0.000	
16	1060	98.699		215.080		231.637		7.635		0.000		26.177		70.824		116.000		0.000	
17	1050	112.667		225.790		387.666		13.090		18.820		24.220		65.987		0.000		0.000	
18	1120	109.310		253.194		320.578		5.067		18.678		21.483		65.154		0.000		0.000	
19	1070	164.265		295.980		409.053		9.198		8.356		17.660		62.922		0.000		0.000	
20	1050	169.242		126.563		336.073		4.951		21.951		19.746		64.353		106.341		0.000	
21	910	48.691		192.762		164.125		16.933		14.578		21.278		68.509		91.720		0.000	
22	860	158.284		270.123		349.809		31.692		13.426		24.265		73.443		88.499		0.000	
23	850	169.206		138.541		269.895		43.520		12.558		32.944		77.874		61.111		0.000	
24	800	75.450		132.015		208.648		40.920		11.683		43.197		80.392		68.216		0.000	
Total thermal power cost= 53294.79 \$																			
Pumped storage unit power cost= 1322.63 \$																			

In order to investigate the effect of WES to its fullest capacity, the cost, and emission obtain by the POT for cases-I and II, IES-II, has been compared with IES-I. It has been found that cost is increased by 2677 \$, and 15,275 \$, while emission has been decreased by 5765 lb, and 8016 lb with respect to cases-I and II, IES-I. The primary reason of high cost in case-II,

IES-II is the reserve and penalty cost imposition to the operator for not utilizing the wind power at the fullest extent. The reserve and penalty cost due to overestimation and underestimation power from the wind units affects the total power generation cost and emission. The total reserve and penalty cost obtained from wind energy units has been computed as 6335 \$ and 744 \$, respectively. In addition, the presence of WES in IES-II has reduced the thermal power generation by 1388 MW and 1465 MW in comparison with IES-I, thereby, reducing the emission pollutants.

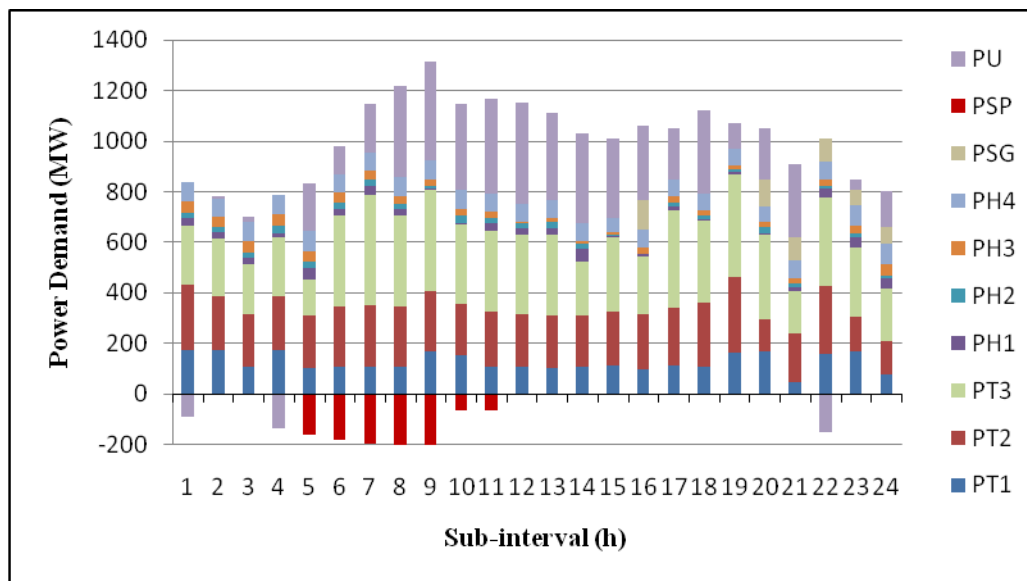


Figure 4.6:Multi-objective power generation schedule for IES-II, case-I

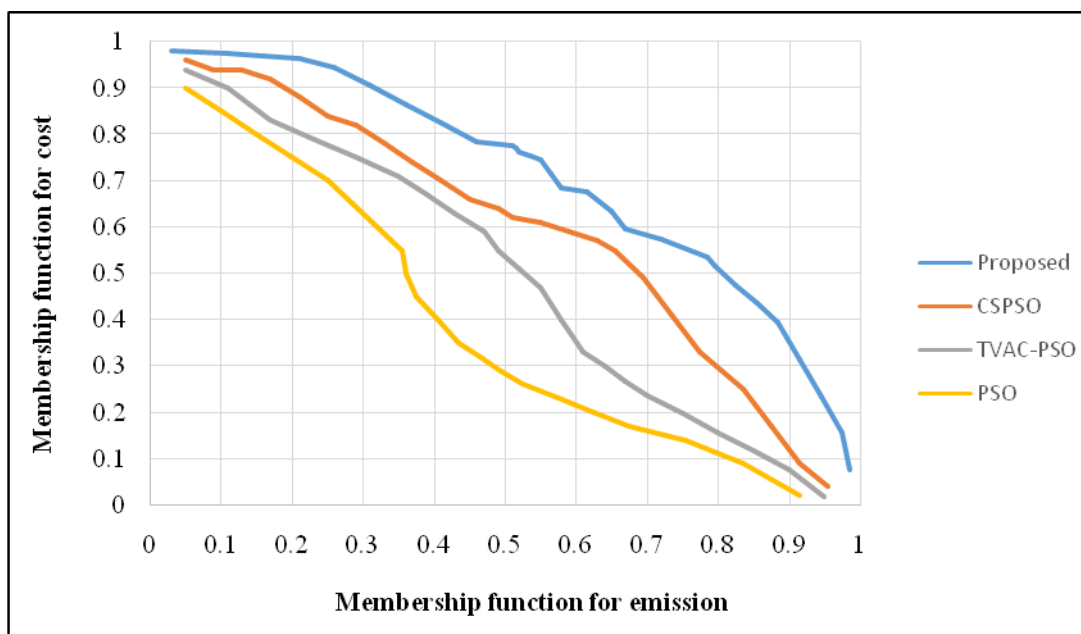


Figure 4.7:Pareto front obtained for IES-II, case-I

Table 4.13: Multi-objective schedule of wind-solar-battery-utility power for IES-II, case-I

Sub-interval (h)	Wind Power (MW)				Solar Share (MW)		Battery Power (MW)		Utility Power (MW)	
t	W ₁		W ₂		SS		PB		PU	
	W _{min}	W _{max}	W _{min}	W _{max}	SS _{min}	SS _{max}	PB _{min}	PB _{max}	PU _{min}	PU _{max}
	0	110	0	110	0	440	0	350	0	400
1	7.507		31.322		0.000		128.659		-89.830	
2	0.129		0.391		0.000		-9.34355		9.864	
3	0.083		0.107		0.000		-18.1929		18.383	
4	1.418		0.642		0.000		136.6544		-134.594	
5	42.252		1.003		2.269		-141.706		187.231	
6	40.147		49.251		61.105		39.27195		111.231	
7	54.487		28.426		104.930		-4.84E-01		188.328	
8	23.446		25.318		216.697		-93.3342		358.795	
9	10.994		21.015		205.371		-151.291		388.670	
10	16.397		68.222		267.904		11.36133		341.162	
11	19.351		21.320		403.172		71.1067		372.737	
12	18.915		23.172		413.545		55.75597		399.876	
13	16.987		61.419		365.671		100.2168		343.860	
14	66.841		35.914		306.031		52.38992		356.395	
15	25.132		33.129		262.193		7.754417		312.699	
16	0.130		29.000		231.647		-33.1708		293.948	
17	4.643		46.810		139.165		-11.1418		201.760	
18	0.000		94.137		77.608		-154.792		326.537	
19	12.112		34.302		14.399		-41.7518		102.565	
20	45.031		58.038		0.000		-97.7119		200.781	
21	52.363		35.849		0.000		-203.193		291.405	
22	61.418		86.684		0.000		297.6421		-149.540	
23	68.920		49.828		0.000		74.39794		44.350	
24	48.225		72.497		0.000		-18.7568		139.479	
Total wind power cost= 10813.09 \$										
Solar power cost= 798.29 \$										
Battery power cost= 7261 \$										

Table 4.14: Optimal schedule of thermal, hydro, and pumped storage power for IES-II, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS _g		PS _p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	102.621		124.904		139.806		35.834		26.367		42.185		76.780		0.000		0.000	
2	780	174.837		211.414		229.823		25.856		26.954		44.863		76.342		0.000		0.000	
3	700	101.200		208.478		137.913		24.002		21.840		35.312		73.744		0.000		0.000	
4	650	105.000		285.462		231.333		21.502		25.262		39.391		70.024		0.000		162.480	
5	670	174.963		209.993		227.846		37.939		30.169		31.421		81.312		0.000		179.520	
6	800	174.997		207.328		137.951		31.675		30.665		33.748		80.408		0.000		195.120	
7	950	164.776		294.689		227.422		24.265		25.147		14.886		74.187		0.000		209.280	
8	1010	103.818		295.910		318.366		5.520		19.104		17.200		75.005		0.000		222.000	
9	1090	105.000		295.114		293.429		21.966		25.636		20.612		66.678		0.000		66.000	
10	1080	105.000		201.743		286.673		19.999		19.974		19.749		66.762		0.000		0.000	
11	1100	88.137		206.192		313.720		11.431		20.503		8.030		69.489		0.000		0.000	
12	1150	104.472		232.797		297.957		47.503		18.888		11.822		68.901		0.000		0.000	
13	1110	96.985		277.494		315.841		29.155		0.000		13.885		65.447		0.000		0.000	
14	1030	103.520		251.159		319.300		22.715		0.000		17.679		67.639		0.000		0.000	
15	1010	141.332		207.460		224.528		33.151		10.614		1.734		68.999		0.000		66.000	
16	1060	122.416		202.133		287.975		14.490		19.597		12.270		73.787		0.000		0.000	
17	1050	107.477		212.230		401.965		17.727		11.578		8.059		72.444		0.000		0.000	

18	1120	174.439	296.607	396.404	18.013	5.542	9.697	68.939	0.000	0.000
19	1070	108.462	293.087	409.403	4.336	15.878	11.915	71.626	0.000	0.000
20	1050	115.371	219.666	417.550	4.336	0.000	25.620	65.563	116.000	0.000
21	910	97.222	207.326	413.910	27.382	21.250	17.580	67.218	106.700	0.000
22	860	103.896	103.670	138.557	13.103	12.496	23.499	70.658	95.600	0.000
23	850	104.788	122.405	134.332	36.644	11.620	32.875	73.730	82.700	0.000
24	800	147.216	125.770	225.216	38.392	16.283	43.190	80.326	68.000	0.000
Total thermal power cost= 49956.46 \$ Pumped storage unit power cost= 1272.32 \$										

Table 4.15:Optimal wind-solar-battery-utility power for optimal scheduling of IES-II, case-II

Sub-interval (h)	Wind Power (MW)				Solar Share (MW)		Battery Power (MW)		Utility Power (MW)	
t	W ₁		W ₂		SS		PB		PU	
	W _{min}	W _{max}	W _{min}	W _{max}	SS _{min}	SS _{max}	PB _{min}	PB _{max}	PU _{min}	PU _{max}
	0	110	0	110	0	440	0	350	0	400
1	5.572		81.965		0.000		-113.967		201.504	
2	39.380		44.468		0.000		93.936		-10.088	
3	13.835		28.495		0.000		-55.180		97.510	
4	19.738		31.457		0.000		16.694		34.501	
5	47.151		68.139		2.269		61.682		55.877	
6	59.622		29.352		61.105		-148.268		298.348	
7	49.882		110.000		104.930		-69.097		333.909	
8	21.562		20.078		216.697		-138.741		397.078	
9	59.940		62.253		205.371		0.000		327.564	
10	40.674		51.521		267.904		0.000		360.099	
11	18.077		39.438		403.172		78.188		382.499	
12	51.578		47.001		413.545		144.464		367.661	
13	36.730		18.399		365.671		109.607		311.193	
14	51.359		38.797		306.031		148.198		247.989	
15	68.876		51.463		262.193		-5.650		388.182	
16	16.920		86.094		231.647		7.330		327.331	
17	22.194		30.747		139.165		-26.414		218.520	
18	17.786		23.539		77.608		-31.426		150.360	
19	28.059		56.558		14.399		-56.279		155.295	
20	0.000		68.700		0.000		-17.193		85.894	
21	33.225		84.933		0.000		166.746		-48.588	
22	65.169		103.081		0.000		-130.271		298.520	
23	33.670		110.000		0.000		-107.236		250.906	
24	74.174		53.807		0.000		72.375		55.605	
Solar power cost= 798.29 \$ Solar uncertainty power cost= 6995 \$ Battery power cost= 6410.092 \$										
Wind power cost= 15508.21 \$ Wind uncertainty power cost= 7079.41 \$										

4.7.3 Statistical Analysis

In order to investigate the statistical significance of the results obtained by the POT, a parametric and non-parametric test has been performed on a pair of techniques for case-I of IES-II. The independent two-sample t-test is a parametric test. This test has been conducted at

the significance level of 5%. The tabulated t-test result for the multi-objective cost has been presented in Table 4.16. In the student t-test, the statistical values obtained are greater than the critical values. The test results suggest that the proposed solution approach is statistically significant in comparison to other techniques.

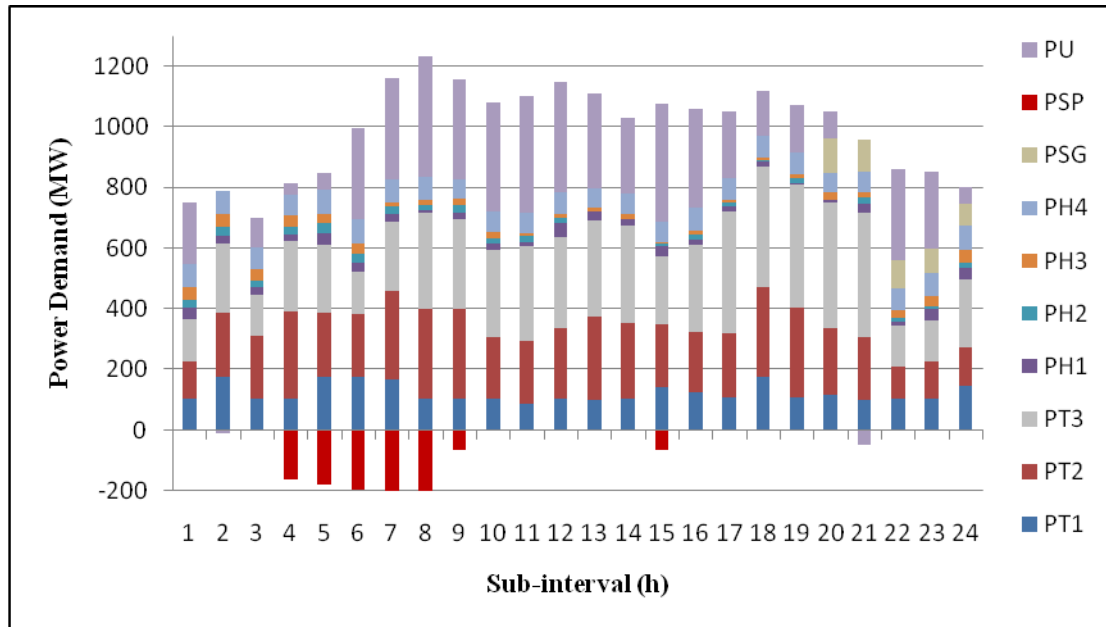


Figure 4.8: Power generation schedule obtained for IES-II, case-II

Table 4.16:Two sample t-test result of multi-objective cost for IES-II, case-I

	PSO	TVAC-PSO	CSPSO	Proposed
Average	78,728	76,708	75,085	73,692
Variance	7852.31	6965.11	5329.45	1095.91
Observations	30	30	30	30
Pooled variance	4473.50	4530.51	3212.68	
Hypothesized mean difference	0	0	0	
Degree of freedom	58	58	58	
t stat	291.62	173.54	94.50	
P(T ≤ t) one tail	0	0	0	
t critical one-tail	1.67	1.67	1.67	

4.8 Conclusions

In this work, economic, emission and multi-objective generation scheduling problem of IES incorporating RESs have been resolved by implementing the POT. The IES consist of PSHTS with WES, SPV and battery units. Two different test systems have been undertaken in this work with two cases under each test system. To validate the effectiveness of the proposed

optimization technique, the obtained results of IES-I and II have been compared with established PSO, TVAC-PSO and CSPSO techniques. For IES-I, case-I, the comparative analysis shows that the minimum cost obtained from POT has been reduced by 1275 \$, 1690 \$ and 2880 \$ as compared to cost incurred from the implemented PSO, TVAC-PSO and CSPSO techniques. Similarly, the minimum emission has been reduced by 1668 lb, 3321 lb and 5397 lb in comparison to the emission attained from the implemented PSO, TVAC-PSO and CSPSO techniques. For multi-objective scheduling of IES-I, case-I, the cardinal priority ranking achieved by the POT is 0.550, which is higher as compared to the ranking achieved by the well-established techniques. The economic, emission and multi-objective results obtained from the POT confirm the superior search ability to obtain the near global best solution. Similar result pattern has been observed for case-II, IES-I and for both cases of IES-II. It is observed from the economic and emission scheduling results of the POT for IES-I, case-I, and PSHTS-III, case-II, that the inclusion of the solar-battery units is able to reduce the cost and emission by 3387 \$ and 24,556 lb, respectively. Similarly, for multi-objective scheduling, cost and emission are reduced by 3536 \$ and 23,493 lb, respectively. The presence of a solar battery system in IES-I, cases-I and II, has reduced the total thermal power generation by 2255 MW and 2655 MW as compared to thermal power generation in case-II, PSHTS-III. Further, the impact of WES is investigated simultaneously in IES-II and results reveal that the total thermal power generation are reduced by 1388 MW and 1465 MW, for cases-I and II, respectively, as compared to IES-I. To validate the robustness of the POT in comparison to PSO, TVAC-PSO and CSPSO, statistical test have been performed and the results were found satisfactory. The reduction in power generation cost and emission encourage the researchers to increase the presence of renewable energy sources in the IES.

CHAPTER-5

SURROGATE WORTH TRADE-OFF METHOD FOR MULTI-OBJECTIVE GENERATION SCHEDULING OF INTEGRATED ENERGY SYSTEM

5.1 Introduction

The excessive consumption of fossil fuel leads to environmental and economic problems. Due to increasing concern over the environmental considerations, society demands electricity at minimum level of emission and thereby pressuring electric utilities to reduce the emission level below certain limit (**Zheng et al., 2020**). It has become a worldwide concern to promote the incorporation of renewable energy sources (RESs) and to facilitate the integration of multiple power generating units in the modern power system (**Wang et al., 2017**). Nonetheless, RESs limitations are still an issue, leading to the emerging concept of an integrated energy system (IES) that is actively constructed in order to make centralized planning and coordinated operation among different power generating units (**Gonzalez-longatt et al., 2011; Wang et al., 2019**). Therefore, the integration of various forms of energy has been growing intensified along the energy generation and consumption sectors (**Nalamati et al., 2018; Farrokhifar et al., 2020**). The IESs have attracted more and more attention by the countries all over the globe (**Mathiesen et al., 2015; Chen et al., 2019**). In the optimal scheduling of IES the economic cost and emission pollutants are two conflicting objectives, therefore the scheduling problem becomes a multi-objective optimization problem (MOOP) (**Mirajalli et al., 2016**).

Generally, the real-world optimization problems are multi-objective in nature with contradicting objectives. Such optimization problems require specific methodology to compute set of decision variables for obtaining set of optimal trade off values. Therefore, a

multiple objective optimization approach should be employed in order to resolve such problems. The unique solution does not prevail for multi-objectives, however set of non-dominated solutions exist in the search space (**Pierro et al., 2007**). These solutions are known as Pareto optimal solutions, which represents various trade-offs between the multi-objectives (**Coello et al., 2007**).

There have been two approaches developed for handling multiple objectives, a priori and a posteriori methods (**Branke et al., 2001**). The former class of optimizers combines the objectives to a single objective with a set of weights that defines the importance of each objective. In contrary, a posterior method maintains the multi-objective formulation, allowing to explore the behaviour of the problems across a range of design parameters and operating conditions compared to a priori approach (**Deb, 2001**). The solution methodology for MOOP consist two main parts; (a) Generating the non-dominated solutions; (b) Interaction with the decision maker. In the last several years, various techniques have been implemented to generate the non-dominated solutions *i.e.*, weighting method, non-inferior set estimation method, ε -constraint method, interactive fuzzy method, goal attainment method and so on (**Abido, 2003**). The major disadvantage with weighting method is that there is no coherent approach of determining the suitable weights. The drawback with ε -constraint method is that it inclined to find weak Pareto optimal solutions and it is time consuming. An extension of fuzzy interactive method to include more objectives is a very qualm fact. Alternatively, the goal attainment method requires higher effort from the decision maker (**Abido, 2003**).

The global optimization techniques such as NSGA-II (**Deb et al., 2002**), SPEA-2 (**Ke et al., 2012**), MOPSO (**Wang and Singh, 2007**), and MODE (**Zhang et al., 2013**), seem suitable to resolve MOOPs as they obtain an entire set of Pareto optimal solution in single run of optimization technique. Moreover, these techniques are less sensitive to the shape and continuity of the Pareto front. However, all these techniques exhibits lack of ability for generating the true Pareto optimal trade-offs between multiple objectives due to their

drawbacks. The NSGA-II suffers from the premature convergence, which is caused by genetic drifting, and preference-searching strategy inherited from genetic algorithm **(Jayadevi et al., 2011)**. In case of SPEA2, its elite solution preservation mechanism is quite time consuming, and it suffers from premature convergence. MOPSO and MODE can deal with simple low-dimensional problem with a fast convergence rate. However, when applied to multi-modal high dimensional problems, MOPSO and MODE may end up with premature convergence because of the poor population diversity caused by their fast convergence rate **(Lu et al., 2011)**.

The decision-making is one of the vital aspects of the MOOP. The decision maker needs to select the best-compromised solution from a set of non-dominated solutions. The weak non-dominated solutions are preferred in results and the set of parameters has been required to provide feasible solution. The Surrogate worth trade-off (SWT) method is an approach implemented to handle the MOOP **(Dhillon et al., 2000; Singh et al., 2017)**. The SWT function is a quality inference tool that acts as an interface between the Pareto-front and the decision maker. The SWT function takes into account the membership representation of objective functions, as an alternative to objective function value. It assigns trade-off values to the available non-inferior solutions at each iteration. The surrogate function assigns preference to the solutions that helps to decide suitable non-dominated solution. The SWT method provides an interface between the decision maker preferences and the mathematical model associated with non-dominated solutions **(Singh et al., 2018)**. In decision-making preferences, the SWT belongs to the posteriori expression of preferences. The contradicting objective has been accomplished by the liberal decision maker, which iteratively examines the existing data, updates the preferences and thereby chooses the quality solution **(Singh et al., 2018)**. The SWT method recognizes that optimization technique is much more concerned with the relative value of change in the multiple objectives, at a given value of each objective function.

Furthermore, for any given set of objective levels attained, it is much easier for the decision makers to assess the relative value of the trade-off between the objectives.

The intent of this chapter is to resolve the multi-objective IES scheduling problem exploiting the fuzzy based surrogate worth trade-off (SWT) method. The proposed optimization technique (POT) as discussed in Chapter 3 has been implemented for optimal operation of IES, considering multi-reservoir PSHTS model with WES, SPV and battery system. In surrogate worth trade-off method, the SWT function acts as an interface between the decision-maker and the Pareto-front. The motivation behind implementing the SWT method has been the progressive expression. The progressive expression iteratively analyses the available data, updates preferences and selects the best non-dominated solution. The information obtain from the membership function of the best solutions of each particle obtain from the proposed optimization technique (MCS-PSO with MB-PSO) is utilised to update the satisfactory SWT function. The POT-SWT approach is applied to four IES for multi-objective scheduling problem and results obtained are compared with state of art techniques. The impact of renewable energy sources has been analysed in terms of cost and emission.

5.2 Multi-Objective Integrated Energy System Scheduling

The IES comprises thermal, hydro, pumped storage, solar and wind units along with battery system. The optimal scheduling of IES requires the mathematical modelling of power generating units incorporated in the IES. The modelling of thermal, hydro and pumped storage unit's model has been referred from Chapter 3, whereas modelling of solar, wind and battery units has been discussed in Chapter 4. The IES consists of a set of continuous and binary decision variables and decision variable set is represented by an array 'Z' in Section 4.3 of Chapter 4. In this chapter, multi-objective generation scheduling problem has been undertaken, in which cost and emission are two contradicting objectives. The total cost of power generation includes thermal power cost, pumped storage power cost, wind power cost, solar power cost and the battery charging/discharging cost. Mathematically, the total cost

function has been given by Eq. (4.16) in Chapter 4. The pollutant emission has been described by a quadratic and exponential function, which is given by Eq. (2.2) of Chapter 2.

The IES is bounded by various equality and inequality constraints. The inequality constraints associated with hydro units are represented by Eq. (2.10), (2.11) and (2.20) of Chapter 2. The pumped storage unit works either in generating mode or in pumping mode, the restriction on the working of a PSU is represented by Eq. (2.12) to (2.14) in Chapter 2, further power and reservoir volume of the pumped storage hydro units are restricted and are given by Eq. (2.17) to (2.20) of Chapter 2. The limit on thermal unit generation is given by Eq. (2.11) of Chapter 2. The inequality constraint on wind unit is given by Eq. (4.17) of Chapter 4. The battery charge limit, utility power and battery power limitations are expressed by Eq. (4.17) and (4.21), respectively in Chapter 4. The equality constraints include power demand balance in each sub-interval, final reservoir volume of each hydro unit, and final battery charge. The power balance and battery charge equality constraint for IES is given by Eq. (4.19) and (4.20) of Chapter 4. The final reservoir volume of each hydro unit is given by Eq. (2.15) of Chapter 2.

5.3 Surrogate Worth Trade-off Method

In decision-making problems, several criteria exist for achieving the best possible non-inferior solution. In this work, the surrogate worth trade-off (SWT) function has been undertaken to act as interface between the decision maker and Pareto-front solutions (**Singh et al., 2018**).

The SWT function represents the objective function in term of membership function (Sd), assigns a compromised value of non-dominated solutions and represented as:

$$Sd = \frac{1}{Nob(Nob - 1)} \left(\sum_{a=1}^{Nob} \sum_{\substack{b=1 \\ b \neq a}}^{Nob} \frac{\mu(OF_a)}{\mu(OF_b)} \right) \quad (5.1)$$

Considering contradicting nature of objectives, the objective functions have been transformed to fuzzy values by considering the minimum and maximum values of the objectives. For the

membership function, a monotonous linear function has been undertaken and has been given as:

$$\mu(OF_k) = \begin{cases} 1 & ; \text{ if } OF_k \leq OF_k^{\min} \\ \frac{OF_k^{\max} - OF_k}{OF_k^{\max} - OF_k^{\min}} & ; \text{ if } OF_k^{\min} \leq OF_k \leq OF_k^{\max} \\ 0 & ; \text{ if } OF_k \geq OF_k^{\max} \end{cases} \quad (k \in \text{Nob}) \quad (5.2)$$

The objectives are conflicting in nature, therefore, a unified objective function has been undertaken by clubbing the all objective functions. Considering the satisfaction level of objectives with respect to each other, the desired membership function value (μ_d) has been defined as:

$$\mu_d = \begin{cases} Fc \times Sd & ; \text{ if } Sd \leq 1 \\ Fc \times Sd^{-1} & ; \text{ if } Sd > 1 \end{cases} \quad (5.3)$$

The 'Fc' in Eq. (5.3) represents the cardinal priority ranking and is computed as:

$$Fc = \min(\mu(OF_1), \mu(OF_2)) \quad (5.4)$$

In Eq. (5.2), the unified membership function specifies the satisfaction level of the objectives. Hence, the higher the value of ' μ_d ' represents the better satisfaction level of the all the objectives. In order to satisfy all operational constraints, the exterior penalty approach is applied. For each constraint violation, the error is computed and cumulative error is included in the unified objective function (OF) and expressed as:

$$OF = \mu_d - r_a \times (f_{er}) \quad (5.5)$$

where r_a is the exterior penalty factor, and f_{er} is the cumulative error.

The computation of cumulative error has been discussed in Sub-section 4.3.2 of Chapter 4.5.4

Implementation of SWT for IES Problem

The multi-objective optimization problem (MOOP) is being formulated considering economy and emission pollutants as conflicting objectives. The solution procedure to solve the MOOP,

involves two main parts: (a) Implementation of the POT to obtain non-dominated optimal solutions (b) Fuzzy set based SWT method has been implemented for interaction with decision maker to find the best non-dominated solution. The MOOP of IES is a mixed variable optimization problem, therefore the POT, which has been discussed in Section 3.5 of Chapter 3 is applied. In the POT, modified binary PSO (MB-PSO) algorithm is applied to deal with binary decision variables, whereas for the continuous decision variables, the modified crisscross search PSO (MCS-PSO) technique has been explored. During the search process, the particle movement do not guarantee to satisfy the constraints. An exterior penalty method is applied for constraint handling, in which for each constraint violation the error function is penalized. The multiple objectives in the MOOP of the IES are organized by assuming that the decision maker has fuzzy goals for each of the objective functions. During the search procedure, the non-dominated solutions have been obtained to develop the Pareto front. The SWT function acts as an interface between decision maker and Pareto-front. The satisfaction level with respect to the conflicting objectives has been computed using Eq. (5.3). The highest value of satisfaction level represents the best non-dominated solution. The flowchart of the proposed solution methodology has been presented in Figure 5.1.

5.5 Test Systems and Results

Four different test systems have been undertaken to solve the MOOP of IES. The standard hydrothermal system (HTS-I) consisting four multi-cascade hydro and three thermal units is the first test system. The second test system is the pumped storage hydrothermal system (PSHTS-III) consisting of an additional PSU in comparison with HTS-I. In the third test system (IES-I), PSHTS-III is being integrated with thirteen solar units and one battery bank system. Finally, last test system (IES-II) comprises the solar, wind and battery bank units integrated with PSHTS-III. In this work, two different cases have been undertaken for each integrated test system. In the case-I, the uncertainty of RESs have been neglected, and for

case-II, the RESs uncertainties have been considered. The total scheduling interval is 24 hrs with 1 hr sub-intervals. The data for the standard hydrothermal system has been undertaken from (Mandal et al., 2008).

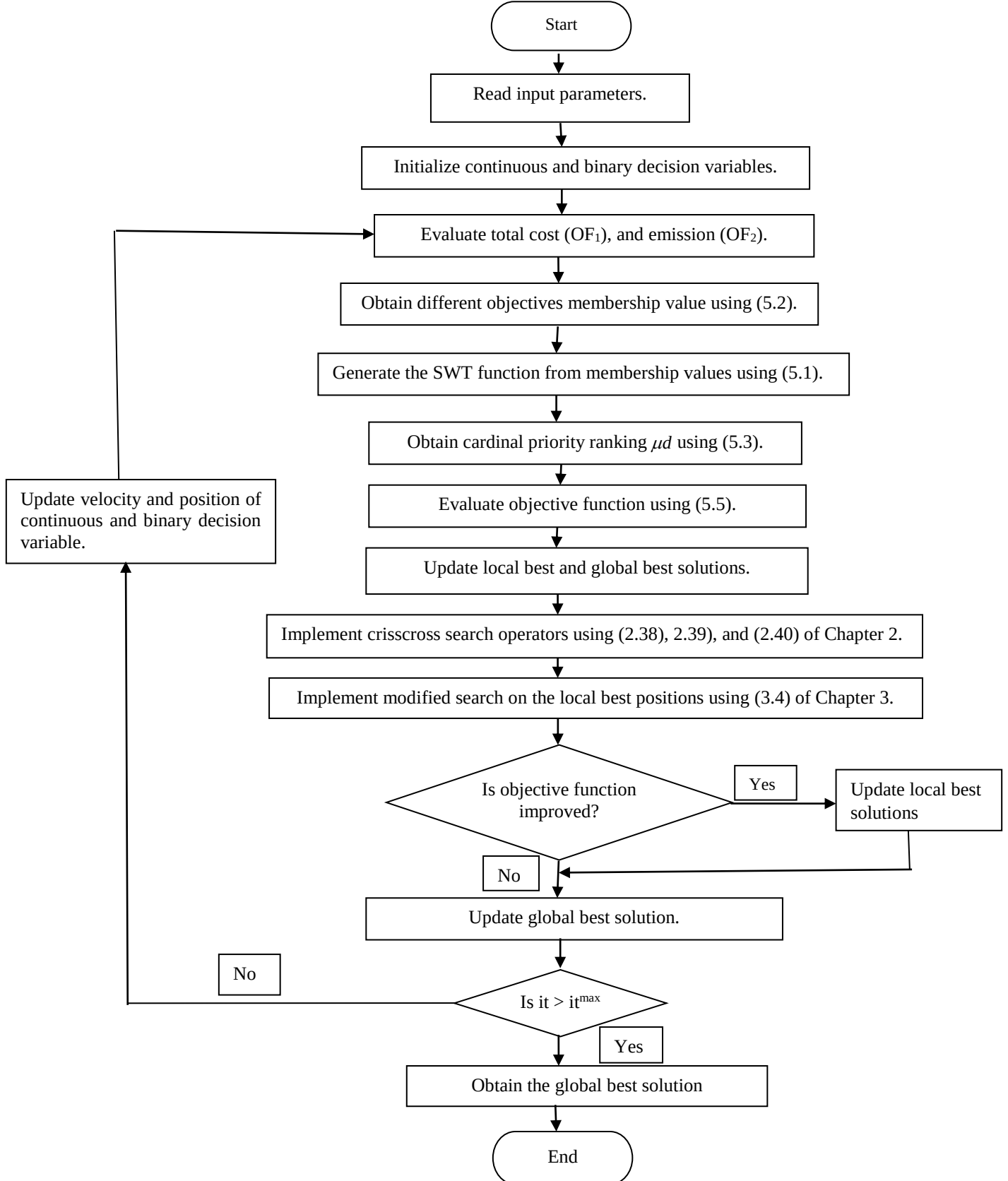


Figure 5.1: Flowchart of POT-SWT approach for MOOP.

The coefficients details regarding the pumped-storage hydroelectric system, WES, SPV and battery bank have been described in Appendix B. The economic, emission and multi-objective generation scheduling of HTS-I, and PSHTS-III have been performed using MCS-PSO and POT as discussed in Chapter 3. Similarly, the economic, emission and multi-objective scheduling of IES-I, and IES-II has been performed using POT in Chapter 4. However, the fuzzy min-max methodology has been implemented to obtain the best non-dominated solution or cardinal priority ranking in both the chapters for multi-objective scheduling.

In this work, for multi-objective point of view, HTS-I has been undertaken to analyse the effectiveness of the MCS-PSO with SWT approach in comparison with other well-established techniques. Similarly, PSHTS-III, IES-I, and IES-II have been undertaken to compare the multi-objective results obtained by using POT with SWT approach (POT-SWT) as compared to PSO-SWT, TVAC-PSO-SWT, and CSPSO-SWT techniques results. Further, the multi-objective results for all the test systems using POT-SWT approach have been compared with multi-objective results obtained by using POT min-max approach and are given in Chapter 3 and 4. Since, the performance of the optimization techniques is being affected by the parameter values. In this work, the parameter values have been varied within a certain range as presented in Tables 3.1 and 4.1 for the undertaken test systems.

5.5.1 Hydrothermal Test System-I

The standard hydrothermal system has been undertaken to validate the effectiveness of the MCS-PSO with SWT approach (MCS-PSO-SWT) for MOOP. The obtained results have been compared with results reported by other state of art algorithms such as DE (**Mandal and Chakraborty, 2009**), IQPSO (**Sun and Lu, 2010**), NSGA-II (**Ke et al., 2012**), SPEA-II (**Ke et al., 2012**), PESA-II (**Ke et al., 2012**), MOCA-PSO (**Zhang et al., 2012**), CSA (**Das et al., 2018**), TLBO (**Roy, 2013**), CABC (**Liao et al., 2013**), NSGSA (**Tian et al., 2014**), NSPSO (**Tian et al., 2014**), NSPSO-CM (**Tian et al., 2014**), etc. For comparison of the results, the overall membership value of the unified objective function has been computed. The higher

value of the cardinal priority ranking represents the best non-dominated solution. The cardinal priority rank obtained by the MCS-PSO-SWT approach is 0.663, which is highest as compared to its counterparts *i.e.*, NSGA-II, SPEA-II, PESA-II, etc. Hence, it is concluded that the MCS-PSO-SWT approach can achieve the most satisfying non-dominated solution with respect to both the objectives. The cost and emission obtained by the MCS-PSO-SWT technique are 43,686 \$ and 16,938 lb, respectively. It is illustrated in Table 5.1 that the proposed MCS-PSO-SWT approach needs nominal computational time to achieve the global best solution. The Table 5.2 and 5.3 represents the reservoir water discharge and hydrothermal power generation schedule obtained by MCS-PSO-SWT approach for MOOP of the IES, respectively.

Table 5.1: Multi-objective results and CPU time comparison for HTS-I

Technique	Multi-objective					
	OF_1 (\$)	$\mu(OF_1)$	OF_2 (lb)	$\mu(OF_2)$	μ_d	CPU time (Sec.)
DE (Mandal and Chakraborty, 2009)	44,914	0.529	19,615	0.523	0.523	74.96
IQPSO (Sun and Lu, 2010)	44,259	0.609	18,229	0.691	0.601	–
ε -ODEMO (Ke et al., 2012)	44,672	0.558	16,653	0.882	0.499	–
NSGA-II (Ke et al., 2012)	46,050	0.389	17,083	0.830	0.285	–
SPEA-II (Ke et al., 2012)	45,534	0.452	16,974	0.843	0.366	–
PESA-II (Ke et al., 2012)	45,431	0.465	16,838	0.859	0.379	–
MO-BC (Zhou et al., 2014)	43,972	0.645	16,132	0.945	0.598	–
MOCA-PSO (Zhang et al., 2012)	43,873	0.657	16,222	0.934	0.617	–
NSGSA (Tian et al., 2014)	44,519	0.577	16,574	0.891	0.521	–
NSPSO (Tian et al., 2014)	44,638	0.563	16,694	0.877	0.505	–
NSPSO-CM (Tian et al., 2014)	44,248	0.611	16,651	0.882	0.568	–
PSO (Narang et al., 2014)	44,330	0.601	19,589	0.526	0.593	44.52
PSO-SWT	44,325	0.609	17,416	0.789	0.586	34.33
TVAC-PSO-SWT	44,088	0.658	17,156	0.801	0.586	33.12
MCS-PSO-SWT	43,686	0.680	16, 938	0.848	0.663	26.13

SPEA-II: Strength Pareto evolutionary algorithm-II; PESA-II: Pareto envelope-based selection algorithm-II; MO-ABC: multi-objective artificial bee colony; NSGSA: Non-dominated sorting gravitational search algorithm; NSPSO: Non-dominated sorting PSO; NSPSO CM: NSPSO with chaotic mutation.

5.5.2 Pumped Storage Hydrothermal Test System-III

The multi-objective scheduling results from case-I and II have been reported in Table 5.4. The effectiveness of the POT-SWT approach has been validated by comparing it with the CSPSO-

SWT, TVAC-PSO-SWT and PSO-SWT techniques. For case-I the compromised cost, and emission obtained by implementing the POT-SWT approach are 66,987 \$, and 63,117 lb, respectively. The cost has been reduced by 4.47%, 3.24%, and 1.55% as compared to cost obtained by implementing PSO-SWT, TVAC-PSO-SWT, and CSPSO-SWT techniques. Similarly, the emission has been reduced by 2.91%, 1.57% and 0.29% as compared to emission obtained by implementing PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT techniques.

Table 5.2: Reservoir discharge rate for HTS-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)							
	q ₁		q ₂		q ₃		q ₄	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	5	15	6	15	10	30	6	20
1	12.1781		7.115063		19.5795		6.567796	
2	12.63592		7.817969		18.49427		6.023489	
3	11.95703		8.241084		17.51258		6.013204	
4	11.65567		6.892357		15.50804		8.416664	
5	10.07314		6.198237		19.22271		6.327748	
6	10.82981		7.063144		19.83085		6.436673	
7	10.89499		7.060203		18.14769		9.71024	
8	10.84536		6.54412		19.80432		10.55329	
9	11.37961		8.494697		15.96231		12.05621	
10	10.88363		6.805701		14.60594		12.93256	
11	11.04011		7.744229		15.77796		14.84746	
12	11.08298		10.334831		15.67362		16.35047	
13	11.47867		8.290088		15.81135		15.28861	
14	11.19554		8.904006		16.84829		15.46101	
15	10.24563		7.964622		18.46541		14.98578	
16	10.76114		9.654906		16.60348		17.49093	
17	10.81372		9.578201		14.79138		17.29034	
18	12.00965		9.79243		15.33343		18.15956	
19	11.81708		10.446516		15.31126		20.00	
20	12.1273		9.601755		14.55017		18.8089	
21	12.12801		8.094089		15.81736		15.01273	
22	10.67214		10.95543		17.18469		18.61886	
23	11.81517		8.924926		19.66836		19.99994	
24	11.22168		11.36276		14.77128		19.99916	

For case-II, PSHTS-III, the compromised cost, and emission obtained by the POT-SWT approach are 66,551 \$ and 61,867 lb, respectively. The cost obtained for case-II by using POT-SWT technique is being reduced by 3.87%, 2.64% and 1.61% as compared to the cost obtained from PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT techniques, respectively. Similarly, the reduction of 4.06%, 2.45% and 1.33%, has been observed in the pollutant

emission compared to emission obtained by using CSPSO-SWT, TVAC-PSO-SWT and PSO-SWT techniques, respectively.

Table 5.3: Multi-objective hydrothermal power generation schedule for HTS-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)							
t	PD	PT_1		PT_2		PT_3		PH_1		PH_2		PH_3		PH_4	
		PT_L	PT_U	PT_L	PT_U	PT_L	PT_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U	PH_L	PH_U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500
1	750	114.8774		157.6723		139.9369		94.17351		60.15452		40.66283		142.5224	
2	780	100.8185		188.5703		165.9183		101.2859		64.07651		34.32462		125.0059	
3	700	70.3534		156.9153		152.313		103.2774		66.56411		29.87007		120.7067	
4	650	69.604		117.6556		119.536		104.0392		59.63584		32.21213		147.3172	
5	670	96.7959		134.9542		139.9421		96.47529		52.45897		19.95687		129.4166	
6	800	106.3131		215.5038		149.3495		99.3874		61.40908		19.1484		148.8887	
7	950	114.2196		212.759		239.7831		99.02452		60.43445		28.15751		195.6218	
8	1010	115.3033		209.6823		210.0444		98.32002		57.12452		60.0566		259.4689	
9	1090	114.2782		219.7654		229.4393		99.91574		69.86067		62.99943		293.7415	
10	1080	104.6324		219.8091		258.6924		99.43546		64.66294		62.16582		270.6014	
11	1100	103.0881		219.6322		265.1671		98.64993		65.26208		60.9408		287.2599	
12	1150	114.4332		219.0714		289.5473		98.40965		72.12972		63.56424		292.8448	
13	1110	114.8301		218.8283		257.2244		99.56155		61.1393		63.58181		294.835	
14	1030	114.3897		209.5247		193.2419		98.63039		65.14336		57.69566		291.3739	
15	1010	102.6868		212.5944		200.2203		94.8224		60.44934		55.38158		283.8452	
16	1060	111.1061		216.3271		219.7447		96.67912		69.54993		61.89448		284.6985	
17	1050	102.8248		204.5341		239.5099		96.24367		67.86919		56.26627		282.7524	
18	1120	114.9751		219.7629		267.5817		98.92778		67.05681		61.32976		289.3662	
19	1070	114.7822		219.9457		210.1382		94.98657		68.28866		58.8195		303.0377	
20	1050	114.8411		219.8391		208.3349		93.28464		63.26279		60.79257		289.6453	
21	910	112.5696		175.2472		155.5572		90.8799		55.70911		61.12888		258.9081	
22	860	102.2503		124.7985		131.5027		86.64552		69.66382		60.40695		284.7322	
23	850	111.0661		125.9707		116.308		95.46098		59.33994		50.73695		291.1173	
24	800	59.6771		105.6739		125.4519		97.11828		69.04164		58.64692		284.3903	

The cardinal priority ranking obtained from the POT-SWT approach for the case-I and II, PSHTS-III, are 0.706 and 0.658, which is higher in comparison to the ranking achieved by CSPSO-SWT, TVAC-PSO-SWT and PSO-SWT techniques. The computational time indorse

that, POT-SWT approach is able to generate a better solution with the least computational burden. The reservoir discharge rate is described in Tables 5.5 and 5.6, respectively. The optimal multi-objective generation schedule of thermal power, hydroelectric power and pumped storage power obtained by the POT-SWT approach for case-I and II has been presented in Tables 5.7 and 5.8, respectively.

5.5.3 Integrated Energy System-I

The multi-objective scheduling results for case-I, and II obtained by PSO-SWT, CSPSO-SWT, TVAC-PSO-SWT, and POT-SWT approach have been presented in Table 5.6. The compromised cost and emission for case-I obtained by the POT-SWT approach are 62,620 \$ and 36,849 lb, respectively. Similarly, for case-II, the compromised cost and emission obtained by the POT-SWT approach are 70,717 \$ and 33,275 lb, respectively. The multi-objective results have been reduced in comparison to the, PSO-SWT, TVAC-PSO-SWT, and CSPSO-SWT techniques. In order to compare the result of multi-objective problem, the cardinal priority ranking is computed. It is evident from Table 5.9 that maximum value of cardinal priority ranking obtained by POT-SWT approach for case-I, and II are 0.576 and 0.668, respectively, which are higher than rankings achieved from CSPSO-SWT, TVAC-PSO-SWT and PSO-SWT techniques.

Table 5.4: Economic, emission and multi-objective results and CPU time comparison for PSHTS-III

Technique	Multi-objective Scheduling					
	OF_1 (\$)	μ (OF_1)	OF_2 (lb)	μ (OF_2)	μ_d	CPU time (Sec.)
Case-I						
PSO-SWT	70,128	0.358	65,015	0.443	0.350	32.35
TVAC-PSO	69,235	0.440	64,125	0.489	0.437	28.66
CSPSO-SWT	68,041	0.490	63,305	0.520	0.489	23.88
POT-SWT	66,987	0.758	63,117	0.708	0.706	21.62
Case-II						
PSO-SWT	68,927	0.435	64,486	0.435	0.435	34.11
TVAC-PSO	68,056	0.462	63,421	0.481	0.461	31.11
CSPSO-SWT	67,641	0.494	62,701	0.493	0.492	26.18
POT-SWT	66,551	0.658	61,867	0.658	0.658	23.90

Table 5.5: Reservoir discharge rate for PSHTS-III, Case-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)							
	q₁		q₂		q₃		q₄	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	0	15	0	30	10	30	13	25
1	3.850		22.609		21.017		22.292	
2	4.685		24.056		17.294		22.852	
3	6.085		23.203		23.381		24.361	
4	2.626		23.048		23.011		23.803	
5	2.234		18.641		24.198		22.374	
6	4.687		22.876		12.646		25.000	
7	11.224		24.418		22.856		24.072	
8	1.847		9.262		30.000		25.000	
9	4.108		1.699		30.000		25.000	
10	4.607		13.306		19.135		25.000	
11	4.749		6.539		25.818		25.000	
12	4.618		16.527		23.600		25.000	
13	0.232		12.880		30.000		25.000	
14	4.615		0.796		10.000		25.000	
15	5.726		19.114		27.070		25.000	
16	0.331		9.069		22.731		25.000	
17	0.855		16.625		10.578		25.000	
18	12.459		9.787		17.948		21.717	
19	0.000		11.611		10.000		25.000	
20	4.771		12.373		11.703		25.000	
21	5.923		9.859		28.863		25.000	
22	0.000		27.314		30.000		25.000	
23	3.427		30.000		30.000		25.000	
24	10.675		30.000		30.000		25.000	

The multi-objective generation schedule of the thermal, hydro and PSU obtained from the POT-SWT technique for cases-I and II have been presented in Tables 5.10 and 5.12, respectively. The multi-objective schedule power from the solar energy units, battery units and utility for cases-I and II have been presented in Tables 5.14 and 5.15, respectively. The mean computational time for the multi-objective schedule required by the POT-SWT technique is less in comparison to CSPSO-SWT, TVAC-PSO-SWT and PSO-SWT techniques. The water discharge rate for case-I and II have been illustrated in Tables 5.11 and 5.13, respectively. In the Tables 5.14 and 5.15, the positive and negative values of the battery power represent the charge and discharge mode of the battery, respectively.

In order to analyse the effectiveness of the POT-SWT approach in comparison to POT with min-max approach, the multi-objective results of Table 4.2 of Chapter 4 and Table 5.9 are compared. For case-I of IES-I the cost, and emission reported in Table 5.9, obtained by implementing POT-SWT approach are being reduced by 993 \$ and 2486 lb, as compared to cost, and emission obtained by implementing POT with min-max approach. Similarly, for case-II of IES-I the cost, and emission results obtained by implementing POT-SWT approach are being reduced by 2553 \$ and 2970 lb in comparison to cost, and emission obtained by implementing POT with min-max approach.

Table5.6: Reservoir discharge rate for PSHTS-III, Case-II

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)									
	q ₁		q ₂		q ₃		q ₄		q ₅	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	0	15	0	30	10	30	13	25	10	30
1	2.422474		20.88242		26.88665		23.69687		25.46262	
2	6.738595		19.66882		27.41002		25.00		17.96821	
3	9.965998		18.03794		21.85348		25.00		25.22044	
4	4.52274		20.27675		23.10005		25.00		17.75226	
5	3.544298		22.4436		27.79705		25.00		16.4831	
6	5.583423		22.95746		27.03955		25.00		22.13844	
7	5.070239		17.24346		20.0509		25.00		20.93427	
8	7.253107		13.28764		21.03758		22.95489		18.54711	
9	2.810488		11.77214		17.6085		25.00		25.47039	
10	5.864962		11.41261		25.92255		25.00		29.66985	
11	7.919547		10.280187		18.54444		25.00		22.24764	
12	3.549295		11.72151		25.73944		25.00		30.00	
13	0.00		4.616252		30.00		25.00		17.56172	
14	4.831626		22.69902		10.00		22.33227		19.54535	
15	0.00		17.35896		30.00		25.00		23.79919	
16	3.675083		6.455438		18.58594		25.00		23.04239	
17	2.102324		7.9871		13.01518		25.00		15.72022	
18	2.634171		19.71191		10.00		24.53424		20.66675	
19	0.00		15.68613		17.51668		25.00		22.14122	
20	0.00		16.55482		10.00		25.00		22.13866	
21	12.18897		12.78415		30.00		25.00		22.59572	
22	2.542514		23.78747		30.00		25.00		29.00	
23	5.583745		26.47803		30.00		25.00		22.27015	
24	8.66272		29.00		29.00		24.00		18.89816	

As seen from Table 4.2 of Chapter 4, the cardinal priority ranking obtained from the POT with min-max approach for the case-I and II, are 0.550 and 0.629, respectively, whereas the cardinal priority ranking obtained from the POT-SWT approach for the case-I, and II are 0.576 and 0.668, respectively. The reported results clearly indicate effectiveness of the POT-

SWT approach as the higher cardinal priority ranking is being achieved by implementing the POT-SWT approach.

Table 5.7:Multi-objective thermal power generation schedule for PSHTS-III, Case-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)							
<i>t</i>	<i>PD</i>	<i>PT₁</i>		<i>PT₂</i>		<i>PT₃</i>		<i>PH₁</i>		<i>PH₂</i>		<i>PH₃</i>		<i>PH₄</i>	
		<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>
		20	175	40	350	50	500	0	500	0	500	0	500	0	500
1	750	67.814		184.120		331.168		19.197		24.342		46.534		76.824	
2	780	103.108		232.063		281.632		23.702		24.610		38.909		75.977	
3	700	75.000		218.383		245.056		29.797		27.334		29.573		74.857	
4	650	84.996		188.642		236.323		15.953		28.099		24.433		71.553	
5	670	84.150		219.115		227.154		14.991		29.942		16.020		78.628	
6	800	54.983		276.942		324.139		26.555		28.367		12.239		76.774	
7	850	173.170		303.066		308.848		49.533		24.196		15.252		75.935	
8	1010	174.996		305.025		420.589		14.190		17.254		2.554		75.393	
9	1090	171.114		332.447		480.657		25.832		0.000		4.973		74.977	
10	1080	174.965		340.256		420.138		28.995		25.723		21.520		68.403	
11	1000	174.997		312.651		478.645		30.489		12.262		23.724		67.232	
12	1150	174.950		347.713		479.559		30.721		27.115		19.991		69.950	
13	1110	174.996		342.328		471.146		8.715		22.277		17.919		72.619	
14	1030	173.525		299.820		432.528		29.969		0.000		24.674		69.484	
15	1010	155.323		287.567		406.713		33.881		25.338		31.252		69.925	
16	1060	174.998		338.887		412.592		8.025		14.736		41.593		69.169	
17	1050	175.000		326.195		416.792		10.670		21.685		27.806		71.852	
18	1120	170.424		300.157		477.995		54.390		13.635		39.731		63.670	
19	1070	169.724		364.019		420.305		4.444		15.562		29.315		66.630	
20	1050	175.000		296.054		435.024		26.275		17.570		34.703		65.375	
21	910	132.124		195.941		416.882		29.717		16.214		51.772		67.350	
22	860	74.999		207.376		433.793		2.736		18.582		48.233		74.281	
23	850	100.999		246.562		351.382		18.490		12.646		43.053		76.868	
24	800	67.329		192.814		362.629		42.183		11.772		43.016		80.258	

Table 5.8:Multi-objective thermal power generation for PSHTS-III, Case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
<i>t</i>	<i>PD</i>	<i>PT₁</i>		<i>PT₂</i>		<i>PT₃</i>		<i>PH₁</i>		<i>PH₂</i>		<i>PH₃</i>		<i>PH₄</i>		<i>PS_g</i>		<i>PS_p</i>	
		<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PT_L</i>	<i>PT_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PH_L</i>	<i>PH_U</i>	<i>PS_L</i>	<i>PS_U</i>	<i>PS_L</i>	<i>PS_U</i>
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	54.314		212.089		325.743		9.674		28.117		44.617		75.447		0.000		0.000	
2	780	79.415		210.977		313.594		29.307		28.798		42.572		75.338		0.000		0.000	
3	700	51.177		236.844		221.967		42.759		32.222		42.311		72.721		0.000		0.000	
4	650	117.394		212.811		318.158		23.444		33.777		37.921		68.974		0.000		162.480	
5	670	91.420		206.894		358.098		15.580		33.535		25.259		78.734		0.000		139.520	
6	800	107.982		275.518		414.044		29.130		32.421		16.081		79.945		0.000		155.120	
7	950	73.000		345.606		367.640		27.636		33.631		24.126		78.361		0.000		0.000	
8	1010	145.000		344.049		228.578		36.721		27.679		35.507		76.554		115.912		0.000	
9	1090	174.000		348.489		407.519		20.221		24.652		34.777		80.342		0.000		0.000	
10	1080	74.000		320.038		413.434		34.566		25.591		42.920		81.355		88.097		0.000	
11	1100	174.000		332.922		408.019		43.144		21.045		41.988		78.883		0.000		0.000	
12	1150	105.000		341.221		456.499		25.727		24.126		40.558		76.868		80		0.000	
13	1110	170.000		290.123		427.724		7.723		4.300		32.631		72.498		105		0.000	
14	1030	170.000		290.155		413.372		30.802		27.372		26.205		72.094		0.000		0.000	
15	1010	139.060		270.477		468.854		7.146		24.953		28.001		71.508		0.000		0.000	
16	1060	91.000		339.133		490.679		24.960		9.246		33.081		71.901		0.000		0.000	

17	1050	148.765	295.416	472.915	17.141	12.956	28.274	74.534	0.000	0.000
18	1120	74.000	314.949	498.882	19.286	22.861	28.096	66.607	95.319	0.000
19	1070	121.632	289.607	403.776	6.031	17.737	42.516	69.471	119.228	0.000
20	1050	119.559	313.661	496.249	6.031	19.311	29.225	65.964	0.000	0.000
21	910	74.000	241.708	412.062	51.364	19.956	41.198	68.713	0.000	0.000
22	860	123.208	207.112	291.829	16.180	21.771	44.010	70.405	85.486	0.000
23	850	167.000	242.554	266.815	28.069	19.108	49.040	77.414	0.000	0.000
24	800	174.000	249.556	305.839	38.571	12.814	43.265	79.940	0.000	103.984

Table 5.9: Multi-objective result comparison for IES-I

Technique	Multi-objective Scheduling					
	OF_1 (\$)	μ (OF_1)	OF_2 (lb)	μ (OF_2)	μ_d	CPU time (Sec.)
Case-I						
PSO-SWT	66,571	0.466	42,125	0.475	0.465	37.24
TVAC-PSO	65,496	0.488	41,068	0.495	0.487	34.24
CSPSO-SWT	64,593	0.513	39,549	0.511	0.510	29.31
POT-SWT	62,620	0.628	36,849	0.578	0.576	28.11
Case-II						
PSO-SWT	77,214	0.523	39,068	0.523	0.523	39.41
TVAC-PSO	75,180	0.575	37,635	0.575	0.575	36.52
CSPSO-SWT	72,989	0.625	36,010	0.625	0.625	32.39
POT-SWT	70,717	0.668	33,275	0.668	0.668	29.53

Table 5.10: Optimal pumped storage hydrothermal power generation for MOOP: IES-I, case-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS _g		PS _p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	164.714		208.049		139.420		25.353		25.351		39.133		77.475		57.679		0.000	
2	780	141.844		289.866		139.402		37.186		29.070		51.174		75.177		0.000		0.000	
3	700	99.700		204.756		227.708		2.415		31.171		49.814		72.558		0.000		0.000	
4	650	173.790		210.786		231.719		12.835		32.909		51.554		66.886		0.000		0.000	
5	670	118.077		130.981		147.310		4.373		34.059		54.821		75.132		45.884		0.000	
6	800	175.000		220.710		145.885		37.260		35.042		49.523		75.882		0.000		0.000	
7	950	175.000		297.493		278.884		42.799		31.221		51.922		74.931		0.000		134.334	
8	1010	174.681		297.102		240.878		35.542		30.306		49.474		75.375		0.000		0.000	
9	1090	175.000		297.531		295.294		10.107		26.402		44.541		75.051		0.000		153.526	
10	1080	103.008		212.076		238.264		21.289		5.456		49.604		71.583		0.000		0.000	
11	1100	174.954		301.271		252.807		38.426		7.038		45.129		70.773		0.000		171.277	
12	1150	174.951		284.271		456.805		37.912		28.612		37.629		73.426		0.000		187.589	
13	1110	103.321		280.542		227.607		33.366		26.733		35.391		68.889		0.000		0.000	
14	1030	140.067		307.584		313.493		29.894		24.628		16.066		68.866		0.000		202.461	
15	1010	98.490		127.144		300.756		19.176		21.264		5.535		69.119		0.000		0.000	
16	1060	171.022		291.148		382.039		12.085		0.000		19.404		66.654		0.000		0.000	
17	1050	161.876		336.920		410.196		22.178		20.151		20.765		63.230		0.000		0.000	
18	1120	133.843		309.453		336.354		19.441		17.010		23.223		67.160		73.408		0.000	
19	1070	149.519		296.972		304.706		27.976		8.416		34.992		69.736		96.813		0.000	
20	1050	129.426		290.876		399.586		29.625		0.000		28.145		65.132		85.231		0.000	
21	910	140.843		207.936		315.339		8.144		11.888		44.886		68.187		76.275		0.000	
22	860	98.614		254.781		324.553		3.244		12.727		45.037		71.574		57.682		0.000	
23	850	102.508		224.796		306.540		41.275		11.853		43.742		77.777		0.000		0.000	
24	800	159.562		211.357		254.181		35.197		15.833		43.149		80.296		0.000		0.000	

Table 5.11: Reservoir discharge rate for IES-I, case-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)									
	q ₁		q ₂		q ₃		q ₄		q ₅	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	0	15	0	30	10	30	13	25	10	30
1	5.43281		14.51363		13.43466		24.46627		23.69853	
2	8.66112		22.46916		26.56035		25.00		17.92342	
3	0.00		15.70852		21.7794		25.00		20.12898	
4	1.91659		23.83231		25.85613		19.52215		15.97162	
5	0.00		17.65064		24.3755		25.00		21.12979	
6	7.288247		19.39873		18.40642		23.72654		14.88835	
7	8.871304		24.57039		23.4838		25.00		18.64092	
8	6.764103		21.82947		30.00		25.00		10.00	
9	8.16E-01		13.99567		17.21911		25.00		25.7076	
10	2.841642		4.079323		20.67792		25.00		24.13943	
11	6.523344		4.429193		24.50838		25.00		21.53466	
12	6.250551		15.69348		20.48743		25.00		22.53762	
13	5.400777		15.94872		20.0076		21.71227		10.00	
314	4.793729		19.04884		26.34572		23.76358		16.90332	
15	2.575132		16.1881		30.00		25.00		13.9098	
16	1.187994		2.912353		13.72691		25.00		10.00	
17	3.36037		15.59188		12.54655		20.43322		22.06436	
18	2.880414		19.19043		11.28411		25		12.1151	
19	4.991217		8.825257		16.91239		22.39571		30.00	
20	5.675955		3.854195		10.00		25.00		23.1799	
21	9.64E-01		7.693226		30.00		25.00		24.94395	
22	0.00		30.00		30.00		25.00		15.11409	
23	9.645177		30.00		30.00		25.00		17.58821	
24	8.506408		28.00375		30.00		25.00		14.33076	

Table 5.12: Multi-objective hydro, pump, solar, battery and utility power schedule for IES-I, case-I

Sub-interval (h)	Utility Power (MW)		Battery Power (MW)		Solar Share (MW)	
t	PU		PB		SS	
	PU _{min}	PU _{max}	PB _{min}	PB _{max}	SS _{min}	SS _{max}
	0	400	0	350	0	440
1	12.825		-12.825		0.000	
2	16.280		-16.280		0.000	
3	11.879		-11.879		0.000	
4	-130.480		130.480		0.000	
5	59.363		-57.094		2.269	
6	60.699		0.406		61.105	
7	132.084		-27.153		104.930	
8	106.641		110.056		216.697	
9	319.600		-114.229		205.371	
10	378.721		-110.817		267.904	
11	380.880		22.292		403.172	
12	243.984		169.562		413.545	
13	334.150		31.521		365.671	
14	331.863		-25.832		306.031	
15	368.518		-106.324		262.193	
16	117.649		113.998		231.647	
17	14.685		124.480		139.165	
18	140.108		-62.500		77.608	
19	80.871		-66.472		14.399	
20	21.978		-21.978		0.000	
21	36.502		-36.502		0.000	
22	-8.211		8.211		0.000	
23	41.508		-41.508		0.000	
24	0.424		-0.424		0.000	

5.5.4 Integrated Energy System-II

For IES-II, the obtained multi-objective results from the POT-SWT approach for both the cases have been compared with PSO-SWT, TVAC-PSO-SWT and CPSO-SWT techniques. The multi-objective results along with mean computational time have been presented in Table 5.16. The results show the credibility of the POT-SWT approach to search the best non-dominated solution with less computational efforts.

Table 5.13: Reservoir discharge rate for IES-I, case-II

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)									
	q ₁		q ₂		q ₃		q ₄		q ₅	
	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U	q _L	q _U
	0	15	0	30	10	30	13	25	10	30
1	2.7303		14.82804		15.72417		20.15451		23.53613	
2	6.118569		17.92308		12.09631		21.31351		30.00	
3	7.757259		23.02299		20.67915		25.00		23.67389	
4	3.661108		22.91732		24.50946		21.23703		23.16666	
5	0.00		14.39782		30.00		25.00		24.91219	
6	2.442658		27.65046		30.00		25.00		18.54168	
7	9.031837		19.87642		30.00		22.46818		17.50733	
8	5.668234		19.31399		24.55722		25.00		30.00	
9	7.825403		12.22853		20.71677		25.00		15.58145	
10	2.264458		14.81567		22.44742		25.00		22.50777	
11	7.236235		15.60536		20.71367		25.00		23.66771	
12	3.469935		9.469069		30.00		25.00		30.00	
13	5.55E-01		8.007589		10.00		25.00		24.26065	
14	1.991986		1.068315		30.00		25.00		23.64961	
15	2.304528		24.27172		23.78445		25.00		21.95117	
16	5.127107		16.86464		15.36982		25.00		21.05728	
17	2.007521		12.4902		10.00		25.00		20.51431	
18	8.220257		1.295206		11.0946		25.00		30.00	
19	2.688311		10.13887		14.6649		25.00		30.00	
20	4.271809		6.455307		15.44726		25.00		14.76691	
21	1.186638		16.94454		30.00		25.00		27.58115	
22	2.150939		30.00		29.03689		25.00		30.00	
23	10.43627		25.88639		30.00		25.00		30.00	
24	6.176301		30.00		30.00		25.00		30.00	

Table 5.14: Multi-objective pumped storage hydrothermal power generation schedule for IES-I, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS _g		PS _p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	174.514		152.472		130.693		14.506		25.583		41.762		75.160		0.000		0.000	
2	780	175.000		290.679		228.994		29.397		30.465		35.158		76.116		0.000		0.000	
3	700	175.000		314.530		268.350		35.546		32.048		41.567		76.724		0.000		162.480	
4	650	175.000		231.783		150.370		20.026		32.744		42.884		72.121		0.000		0.000	
5	670	174.999		211.901		146.581		3.717		31.118		37.903		79.509		0.000		0.000	
6	800	174.929		214.793		157.364		16.653		28.260		38.106		72.865		0.000		0.000	
7	950	175.000		233.517		148.880		43.456		32.150		37.485		70.407		0.000		0.000	
8	1010	174.676		203.212		138.494		31.449		30.555		48.648		71.657		68.000		0.000	
9	1090	174.922		222.167		156.788		40.400		24.366		50.010		74.293		0.000		0.000	
10	1080	175.000		286.674		220.710		17.752		26.565		51.633		76.880		0.000		0.000	
11	1100	174.891		288.828		229.392		40.290		25.248		47.472		79.417		0.000		162.480	
12	1150	174.967		261.983		214.623		24.938		16.419		40.739		79.194		0.000		0.000	
13	1110	174.989		227.329		234.606		10.111		13.302		29.338		77.020		0.000		0.000	
14	1030	174.995		305.065		302.639		17.336		0.000		32.557		75.707		0.000		179.520	
15	1010	174.936		349.482		300.985		18.587		20.385		25.653		73.473		0.000		195.120	
16	1060	174.995		349.294		362.003		30.902		19.972		15.170		76.076		0.000		209.280	
17	1050	174.996		343.171		305.704		16.083		15.337		7.973		68.119		0.000		0.000	
18	1120	175.000		349.432		341.074		41.140		0.000		22.256		70.821		106.70		0.000	
19	1070	174.963		311.021		317.008		17.570		13.286		34.754		70.169		95.600		0.000	
20	1050	174.984		299.895		292.187		23.913		7.832		36.912		64.896		0.000		0.000	
21	910	173.906		290.243		306.570		9.359		24.019		26.636		66.559		0.000		0.000	
22	860	172.311		291.774		302.642		13.635		11.782		23.270		69.880		0.000		0.000	
23	850	174.977		294.630		280.649		43.037		19.960		31.560		74.996		82.700		0.000	
24	800	111.074		209.966		169.015		26.982		11.832		43.218		80.316		68.000		0.000	

The compromised cost and emission obtained by implementing the POT-SWT approach for case-I of IES-II, are 71,568 \$ and 33,873 lb, respectively. Similarly, for case-II, the compromised cost and emission obtained by the POT-SWT approach are 84,224 \$ and 27,346 lb, respectively. The multi-objective results have been reduced in comparison to the PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT techniques. It is evident from Table 5.16 that the cardinal priority ranking achieved by the POT-SWT approach for cases-I and II are 0.619 and 0.729, respectively, which are higher than rankings achieved from CSPSO-SWT, TVAC-PSO-SWT and PSO-SWT techniques. The multi-objective generation schedule of the thermal, hydro and pumped storage units, for cases-I and II, obtained from the POT-SWT approach has been presented in Tables 5.18 and 5.21, respectively. Similarly, the optimal power

generation schedule from the wind, solar, and battery units have been presented in Tables 5.19-5.22, respectively. In Tables 5.19 and 5.22, respectively, the positive and negative values of battery power represent the charging and discharging mode of the battery. The hourly reservoir discharge rate for case-I and II has been illustrated in Tables 5.17 and 5.20, respectively. The total power generated has been depicted in Figure 5.2. Further, the convergence characteristic has been presented in Figure 5.3. It has been observed from the convergence characteristics of cardinal priority ranking that the POT-SWT approach has obtained the best Pareto optimal solutions than the PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT techniques. The Pareto front curve has been described in Figure 5.4, and it is evident from the curve that the POT-SWT approach is able to generate the well-spread front as compared to PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT techniques.

Table 5.15: Multi-objective solar, battery and utility power schedule for IES-I, case-II

Sub-interval (h)	Utility Power (MW)		Battery Power (MW)		Solar Share (MW)	
t	PU		PB		SS	
	PU_{min}	PU_{max}	PB_{min}	PB_{max}	SS_{min}	SS_{max}
	0	400	0	350	0	440
1	135.311		-135.311		0.000	
2	-85.810		85.810		0.000	
3	-81.285		81.285		0.000	
4	-74.927		74.927		0.000	
5	-15.726		17.996		2.269	
6	97.031		-35.926		61.105	
7	209.105		-104.175		104.930	
8	243.310		-26.613		216.696	
9	347.054		-141.683		205.370	
10	224.786		43.119		267.904	
11	376.942		26.230		403.172	
12	337.137		76.408		413.545	
13	343.306		22.365		365.670	
14	301.221		4.809		306.030	
15	241.619		20.575		262.193	
16	240.868		-9.222		231.646	
17	118.617		20.548		139.165	
18	13.577		64.031		77.608	
19	35.630		-21.231		14.399	
20	149.382		-149.382		0.000	
21	12.709		-12.709		0.000	
22	-25.294		25.294		0.000	
23	-152.509		152.509		0.000	
24	79.597		-79.597		0.000	

Table 5.16: Multi-objective results comparison for IES-II

Technique	Multi-objective Scheduling					
	OF_1 (\$)	μ (OF_1)	OF_2 (lb)	μ (OF_2)	μ_d	CPU time (Sec.)
Case-I						
PSO-SWT	74,868	0.352	36,483	0.354	0.352	39.21
TVAC-PSO	74,065	0.419	36,021	0.422	0.418	37.66
CSPSO-SWT	73,435	0.460	35,521	0.460	0.460	33.35
POT-SWT	71,568	0.620	33,873	0.622	0.619	31.19
Case-II						
PSO-SWT	90,198	0.585	33,689	0.585	0.585	40.26
TVAC-PSO	89,095	0.615	32,249	0.615	0.615	38.78
CSPSO-SWT	87,813	0.634	31,451	0.634	0.634	34.57
POT-SWT	84,224	0.729	27,346	0.729	0.729	32.68

Table 5.17: Reservoir discharge rate for IES-II, case-I

Sub-interval (h)	Reservoir Discharge ($\times 10^4$ m ³ /h)									
	q_1		q_2		q_3		q_4		q_5	
	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U	q_L	q_U
	0	15	0	30	10	30	13	25	10	30
1	2.405826		21.38642		27.80007		21.82416		26.58356	
2	11.24652		21.49812		22.90973		25.00		29.7	
3	5.288141		14.54612		20.04801		25.00		18.88162	
4	3.1023		25.20232		18.12469		24.88398		25.83359	
5	7.079431		19.49837		25.42863		25.00		29.32618	
6	6.848522		17.70991		23.82397		25.00		18.85954	
7	3.79966		16.32832		17.54716		25.00		26.39115	
8	7.20E-01		15.9611		20.8573		24.25194		18.59108	
9	7.450403		14.10013		22.96843		21.99162		12.8635	
10	1.746066		10.55677		26.4504		25.00		30.00	
11	3.37379		11.14007		18.06892		25.00		27.15691	
12	3.069228		10.45112		29.99993		25.00		29.49274	
13	5.605776		7.281144		14.46206		24.37416		20.67134	
14	1.898194		6.718934		28.32085		25.00		28.30879	
15	2.25E-01		0.00		21.51915		25.00		19.163	
16	1.21E-01		10.17305		28.54699		20.49988		12.69971	
17	6.00558		11.80239		10.00		25.00		16.15066	
18	2.776232		15.62143		12.0834		25.00		16.6054	
19	5.528039		19.91607		13.12496		25.00		26.27017	
20	3.564911		28.92434		12.07699		25.00		18.21992	
21	8.73E-01		17.8278		29.91998		25.00		22.19003	
22	2.785598		30.00		30.00		25.00		23.70813	
23	10.0618		26.2494		30.00		25.00		26.31166	
24	9.269523		22.69297		30.00		25.00		24.0394	

In order to analyse the effectiveness of the POT-SWT approach in comparison to POT with min-max approach, the multi-objective results reported in the Table 4.7 of Chapter 4, and Table 5.16 are being compared. For case-I the cost, and emission result obtained by using the

POT-SWT technique is being reduced by 1922 \$ and 817 lb, respectively, in comparison with cost, and emission obtained by POT-min-max approach. Similarly, for case-II the cost, and emission result reported in Table 5.16, is being reduced by 3795 \$ and 5225 lb, respectively. It has been observed from Table 4.7 of Chapter 4, the cardinal priority ranking obtained from the POT with min-max approach for the case-I and II, are 0.595 and 0.650, respectively, whereas the cardinal priority ranking obtained from the POT-SWT approach for case-I and II are 0.619 and 0.729, respectively. The reported results clearly indicate effectiveness of the POT-SWT approach as the higher cardinal priority ranking is being achieved by utilising the POT-SWT approach.

Table 5.18: Multi-objective pumped storage hydrothermal power generation schedule for IES-II, case-I

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS _g		PS _p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	175.000		282.388		226.285		13.094		25.427		35.051		76.546		0.000		162.480	
2	780	175.000		295.241		319.090		45.227		27.560		28.919		76.541		0.000		179.520	
3	700	174.985		211.880		224.847		25.617		28.826		17.005		73.948		0.000		195.120	
4	650	174.991		211.864		228.859		17.168		29.833		25.563		70.258		0.000		0.000	
5	670	22.723		165.796		140.347		33.461		32.789		24.345		81.042		0.000		0.000	
6	800	174.970		299.655		230.613		32.637		32.697		13.550		80.001		0.000		209.280	
7	950	173.574		291.046		312.504		21.154		31.627		23.512		77.500		0.000		0.000	
8	1010	174.940		348.430		307.759		8.023		30.834		16.202		73.991		0.000		222.000	
9	1090	111.258		281.584		322.200		38.397		28.331		14.374		73.942		0.000		66.000	
10	1080	174.915		215.778		323.638		14.858		22.513		5.901		75.514		0.000		66.000	
11	1100	169.717		212.995		227.761		23.775		22.994		16.090		71.601		0.000		0.000	
12	1150	101.155		183.850		232.772		23.290		21.211		9.097		69.377		115.91		0.000	
13	1110	103.248		204.568		194.458		34.093		14.222		25.818		68.400		99.395		0.000	
14	1030	104.439		208.750		139.927		16.478		12.954		27.069		69.401		99.935		0.000	
15	1010	95.154		214.532		230.436		7.748		0.000		31.702		65.606		0.000		0.000	
16	1060	107.229		242.916		290.956		7.173		22.160		17.880		67.310		0.000		0.000	
17	1050	93.967		215.976		402.846		34.301		24.479		16.966		65.029		0.000		0.000	
18	1120	103.091		279.007		347.094		19.414		27.573		17.552		66.866		0.000		0.000	
19	1070	93.026		208.876		317.931		30.690		25.650		26.448		64.940		89.390		0.000	
20	1050	173.827		316.776		384.630		21.472		10.879		28.940		66.903		73.690		0.000	
21	910	169.612		296.200		406.772		8.440		22.063		27.436		68.544		0.000		0.000	
22	860	95.565		135.354		311.424		17.213		8.633		25.265		72.346		0.000		0.000	
23	850	105.419		117.755		234.767		42.930		16.451		40.326		76.584		69.940		0.000	
24	800	112.019		213.018		280.970		37.801		22.488		43.191		80.168		0.000		0.000	

Table 5.19: Multi-objective wind-solar-battery-utility power generation schedule for IES-II, case-I

Sub-interval (h)	Wind Power (MW)				Solar Share (MW)		Battery Power (MW)		Utility Power (MW)	
<i>t</i>	<i>W</i> ₁		<i>W</i> ₂		<i>SS</i>		<i>PB</i>		<i>PU</i>	
	<i>W</i> _{min}	<i>W</i> _{max}	<i>W</i> _{min}	<i>W</i> _{max}	<i>SS</i> _{min}	<i>SS</i> _{max}	<i>PB</i> _{min}	<i>PB</i> _{max}	<i>PU</i> _{min}	<i>PU</i> _{max}
	0	110	0	110	0	440	0	350	0	400
1	0.000		0.075		0.00		-78.517		78.592	
2	59.211		102.669		0.00		169.938		-8.057	
3	0.000		46.774		0.00		-91.237		138.012	
4	8.200		6.529		0.00		123.266		-108.537	
5	0.000		0.000		2.269		-167.230		169.499	
6	39.884		13.307		61.105		-30.862		145.158	
7	0.000		69.815		104.930		155.661		19.084	
8	105.334		32.081		216.697		82.289		271.822	
9	9.302		0.226		205.371		-71.015		285.915	
10	0.000		7.698		267.904		-37.280		312.883	
11	7.210		0.000		403.172		55.315		355.068	
12	13.776		0.800		413.545		34.784		393.338	
13	31.729		5.982		365.671		37.582		365.799	
14	19.616		29.954		306.031		4.553		351.047	
15	24.136		5.594		262.193		-72.899		364.822	
16	20.816		0.000		231.647		-51.914		304.377	
17	93.713		0.000		139.165		36.441		196.437	
18	0.000		41.413		77.608		-140.382		259.404	
19	26.856		55.579		14.399		-116.216		213.050	
20	52.623		98.237		0.00		177.978		-27.118	
21	82.605		52.365		0.00		224.037		-89.067	
22	30.268		21.353		0.00		-142.579		194.200	
23	25.592		20.496		0.00		-99.741		145.828	
24	4.400		4.400		0.00		-1.545		10.345	

Table 5.20: Reservoir discharge rate for IES-II, case-II.

Sub-interval (h)	Reservoir Discharge (×10 ⁴ m ³ /h)									
	<i>q</i> ₁		<i>q</i> ₂		<i>q</i> ₃		<i>q</i> ₄		<i>q</i> ₅	
	<i>q</i> _L	<i>q</i> _U	<i>q</i> _L	<i>q</i> _U	<i>q</i> _L	<i>q</i> _U	<i>q</i> _L	<i>q</i> _U	<i>q</i> _L	<i>q</i> _U
	0	15	0	30	10	30	13	25	10	30
1	5.843028		19.00191		27.79553		24.87275		20.14676	
2	6.884793		16.95399		29.9999		21.5915		20.44814	
3	3.192214		23.09999		17.61177		25.00		27.14087	
4	4.669261		20.76262		21.56437		25.00		22.60096	
5	7.741448		20.5323		26.125		25.00		26.42733	
6	5.018743		16.15498		26.01884		25.00		20.29714	
7	6.153422		10.96082		25.30767		22.92582		22.74631	
8	5.020899		18.79248		13.89752		25.00		28.11712	
9	3.906406		17.87288		19.66967		25.00		21.91116	
10	1.830498		12.07286		21.43545		25.00		12.79131	
11	2.787569		3.741896		28.67464		22.6496		26.35332	
12	4.877821		12.55327		21.29933		25.00		17.58102	
13	4.029473		13.52985		20.09234		23.00216		11.61319	
14	0.00		12.05297		22.07332		25.00		26.51137	
15	5.116979		10.30306		21.39128		25.00		27.91342	
16	3.961732		10.27288		21.6411		25.00		26.09064	
17	3.249874		19.21618		10.00		25.00		14.37749	
18	2.781089		11.28632		10.87046		25.00		17.38326	
19	3.419376		12.29425		10.00		25.00		30.00	
20	7.194004		20.63738		20.98186		25.00		21.16365	
21	1.253761		6.424678		30.00		25.00		22.44928	
22	3.004414		29.22781		30.00		25.00		19.70903	
23	7.311483		27.9829		30.00		25.00		21.2454	
24	5.901834		30.00		26.81165		25.00		15.85984	

Table 5.21: Multi-objective pumped storage hydrothermal power generation schedule for IES-II, case-II

Sub-interval (h)	Power Demand (MW)	Thermal Power (MW)						Hydroelectric Power (MW)								Pump Storage Power (MW)			
t	PD	PT ₁		PT ₂		PT ₃		PH ₁		PH ₂		PH ₃		PH ₄		PS _g		PS _p	
		PT _L	PT _U	PT _L	PT _U	PT _L	PT _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PH _L	PH _U	PS _L	PS _U	PS _L	PS _U
		20	175	40	350	50	500	0	500	0	500	0	500	0	500	0	250	0	250
1	750	71.795		224.901		133.758		26.858		26.589		48.266		77.481		57.277		0.00	
2	780	75.000		224.926		137.489		31.331		29.084		48.508		74.080		47.638		0.00	
3	700	75.000		226.356		139.149		17.389		30.971		46.278		74.136		0.00		0.00	
4	650	71.711		222.982		136.610		24.295		32.970		51.910		70.427		0.00		0.00	
5	670	104.860		203.926		139.880		36.068		33.393		53.060		81.160		0.00		0.00	
6	800	174.998		235.781		139.149		26.026		32.334		48.817		83.612		0.00		137.130	
7	950	93.797		138.424		143.215		31.023		25.712		50.566		79.495		0.00		0.00	
8	1010	74.740		302.856		134.754		27.288		34.139		40.343		79.289		0.00		0.00	
9	1090	72.821		301.201		227.421		23.652		32.201		50.417		79.853		0.00		0.00	
10	1080	129.109		189.103		229.916		15.194		25.376		51.688		80.362		0.00		0.00	
11	1100	104.740		236.081		225.185		20.961		5.078		50.997		79.873		0.00		0.00	
12	1150	128.493		216.370		225.367		31.505		26.090		50.969		76.081		0.00		0.00	
13	1110	106.844		288.467		308.751		27.014		26.273		45.224		73.175		0.00		156.118	
14	1030	93.931		303.229		311.488		6.756		23.221		36.115		72.478		0.00		173.667	
15	1010	100.248		222.087		381.603		31.054		19.687		25.927		74.410		0.00		189.775	
16	1060	171.555		300.823		340.049		25.224		19.144		11.818		72.465		0.00		204.444	
17	1050	112.053		201.429		367.300		21.391		24.397		10.162		69.843		0.00		0.00	
18	1120	152.960		258.805		320.195		18.715		17.455		17.322		68.257		89.948		0.00	
19	1070	163.581		234.553		315.215		21.068		17.739		22.852		66.277		96.405		0.00	
20	1050	55.054		207.393		307.154		35.205		19.834		40.380		64.411		83.227		0.00	
21	910	132.768		213.593		313.849		9.268		8.585		29.143		66.079		0.00		0.00	
22	860	110.944		267.955		299.032		16.954		14.209		32.621		69.290		74.016		0.00	
23	850	108.950		209.412		241.161		32.749		16.579		42.489		71.971		67.298		0.00	
24	800	101.958		140.230		231.757		25.987		11.719		46.294		80.204		0.00		0.00	

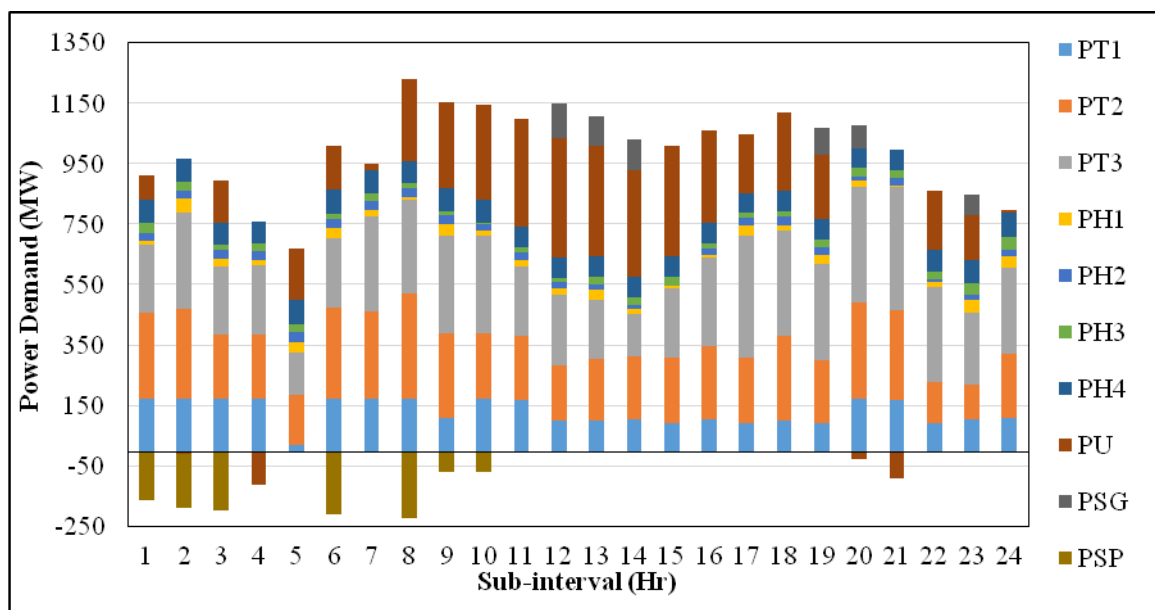
**Figure 5.2:** Multi-objective power obtained by the POT-SWT approach for IES-II, case-II

Table 5.22: Multi-objective wind-solar-battery-utility power generation schedule for IES-II, case-II

Sub-interval (h)	Wind Power (MW)				Solar Share (MW)		Battery Power (MW)		Utility Power (MW)	
t	W_1		W_2		SS		PB		PU	
	W_{min}	W_{max}	W_{min}	W_{max}	SS_{min}	SS_{max}	PB_{min}	PB_{max}	PU_{min}	PU_{max}
	0	110	0	110	0	440	0	350	0	400
1	15.086		103.581		0.00		35.592		83.075	
2	0.000		65.698		0.00		-46.245		111.944	
3	33.334		45.243		0.00		-12.143		90.720	
4	24.415		16.673		0.00		1.992		39.096	
5	0.000		83.895		2.269		68.510		17.653	
6	27.190		95.960		61.105		-12.157		196.412	
7	33.155		64.963		104.930		-184.720		387.768	
8	18.645		102.193		216.697		20.942		316.593	
9	35.117		38.609		205.371		-23.337		302.434	
10	34.268		50.947		267.904		-6.133		359.253	
11	48.569		22.405		403.172		97.060		377.086	
12	20.426		33.939		413.545		72.785		395.126	
13	39.097		29.876		365.671		44.274		390.370	
14	12.423		69.058		306.031		31.064		356.448	
15	31.734		46.958		262.193		-3.874		344.760	
16	36.893		48.863		231.647		-5.963		323.365	
17	20.351		64.701		139.165		-19.208		243.426	
18	61.764		62.229		77.608		25.257		176.343	
19	24.011		51.449		14.399		-42.453		132.311	
20	41.955		86.636		0.00		-108.751		237.342	
21	39.443		57.138		0.00		-40.133		136.715	
22	21.921		56.069		0.00		103.012		-25.021	
23	32.975		76.358		0.00		49.943		59.391	
24	25.769		89.358		0.00		-46.723		161.851	

In order to investigate the statistical significance of the results obtained by the POT-SWT technique, an independent two-sample t-test is has been performed on a pair of techniques for IES-II, case-II. This test has been conducted at the significance level of 5%. The tabulated t-test result for the multi-objective cardinal priority ranking has been presented in Table 5.23. In the t-test, statistical values obtained are greater than the critical values. The test results suggest that the POT-SWT approach is statistically significant compared to other techniques.

Table 5.23: Two-sample t-test result of cardinal priority ranking for IES-II, case-II

	PSO-SWT	TVAC-PSO-SWT	CSPSO-SWT	POT-SWT
Average μ_d	0.578	0.598	0.627	0.722
Variance	2.885×10^{-5}	2.621×10^{-5}	2.381×10^{-5}	1.764×10^{-5}
Observations	30	30	30	30
Pooled variance	2.405×10^{-5}	2.263×10^{-5}	2.149×10^{-5}	--
Hypothesized mean difference	0	0	0	--
Degree of freedom	58	58	58	--
t stat	456.47	491.35	523.83	--
P(T $\leq$ t) one tail	0	0	0	--

t critical one-tail	1.67	1.67	1.67	--
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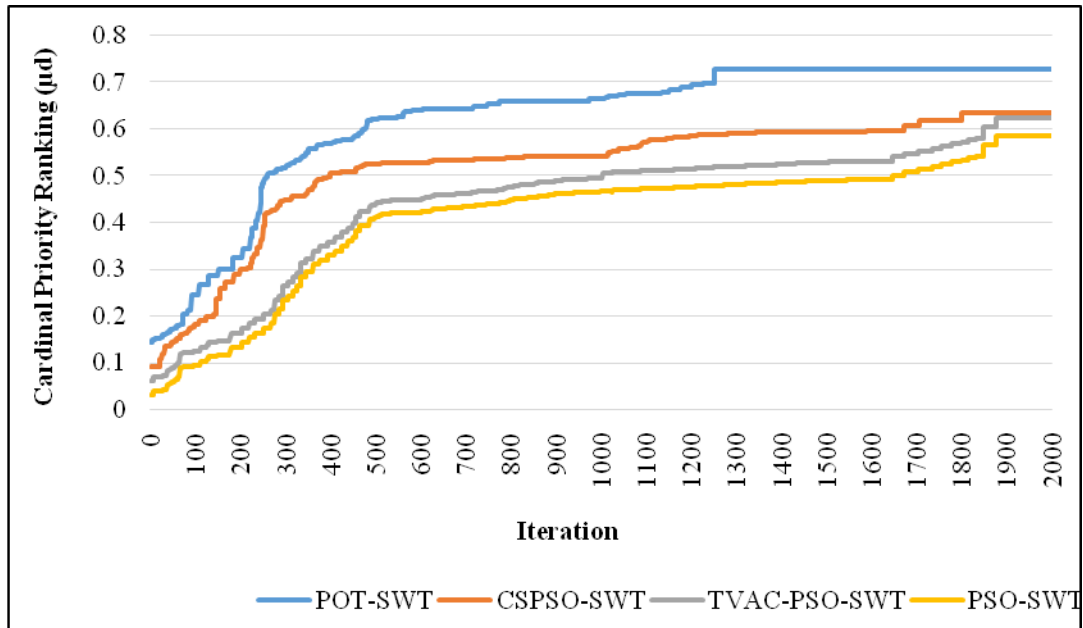


Figure 5.3: Convergence characteristic for cardinal priority ranking obtain for IES-II, case-II.

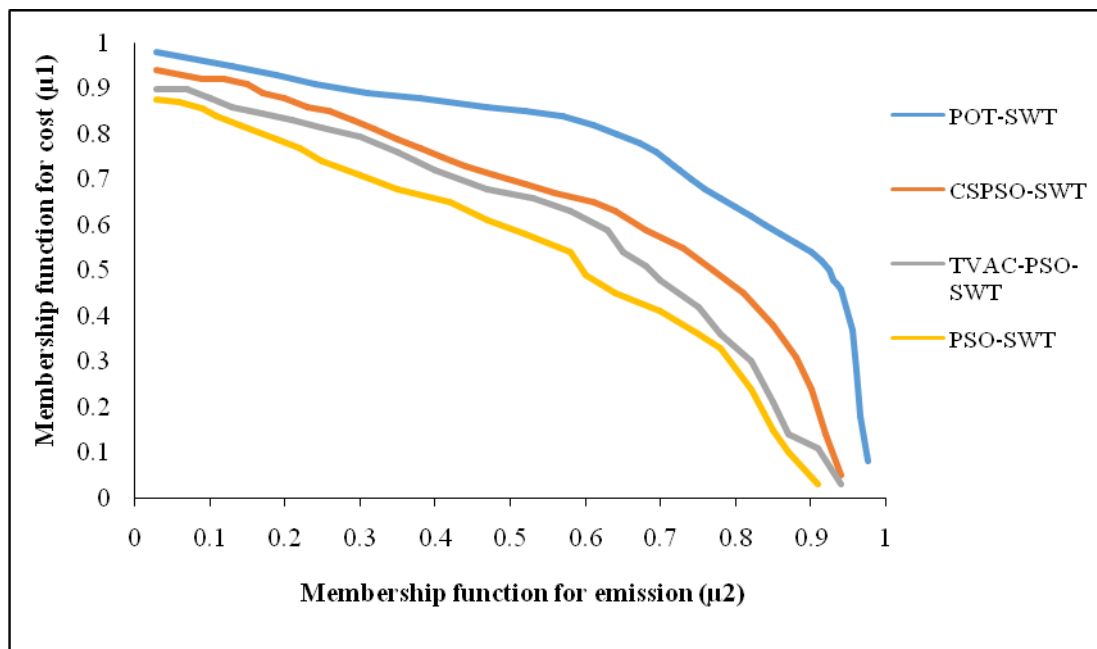


Figure 5.4: Pareto front for IES-II, case-II.

5.6 Conclusions

In this chapter, multi-objective scheduling problems of IES incorporating RES have been resolved. A fuzzy set-based SWT approach has been applied as an interface between decision-makers and generated non-dominated solutions. In order to get the optimal solution POT combining MCS-PSO and MB-PSO is being explored. For the continuous decision variables,

MCS-PSO has shown great potential to maintain the population diversity and reduces stagnancy problem by implementing horizontal and vertical crossover operators. The MB-PSO implemented for the binary decision variables utilising modified sigmoid function. The practical viability of the POT-SWT approach is being illustrated through four different test systems. The obtained results of HTS-I have been compared with other established techniques *i.e.*, DE, PSO, IQPSO, ε -ODEMO, NSGA-II, SPEA-II, PESA-II, MO-BC, MOCA-PSO, CSA, TLBO, CABC, NSGSA, NSPSO, and NSPSO-CM and it has been concluded that POT-SWT approach is able to achieve the best non-dominated solution. For remaining three test systems, the obtained results from the POT-SWT approach are compared with PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT techniques. The obtained results of the POT-SWT approach confirm the superior search ability along with the competence to identify the most satisfying non-dominated solution. To validate the robustness of the POT-SWT approach in comparison to PSO-SWT, TVAC-PSO-SWT and CSPSO-SWT, two-sample student t-test has been performed and the results found satisfactory. Further, in order to analyse the effectiveness of the POT-SWT approach a comparison has been done with POT with min-max approach and it has been summarized that SWT technique is able to provide the best non-dominated solutions.

CHAPTER-6

CONCLUSIONS AND FUTURE SCOPE

6.1 Introduction

In this chapter, the prominent and noteworthy contributions of the thesis have been presented concerning some commendations for future research scope.

6.2 Significant Contributions

The research work presented in this thesis is to propose an optimization technique for resolving the economic, emission, and multi-objective scheduling problem of integrated energy system. A decision-making approach has been implemented to obtain the best-satisfied non-dominated solution.

The following significant contribution results from this research.

1. The pumped storage hydrothermal system (PSHTS) generation scheduling problem has been formulated considering a multi-chain hydro model. The scheduling problem consists of binary and continuous decision variables. A crisscross search PSO (CSPSO) and improved binary PSO (BPSO) techniques have been implemented for resolving the economic, emission and multi-objective generation scheduling problem of the PSHTS. For binary decision variables, improved BPSO has been implemented and the CSPSO has been implemented for the continuous decision variables. In the CSPSO technique, local best solution has been updated by improved PSO and then horizontal and vertical crossover operators are applied for further enhancement. The CSO consist horizontal and vertical crossover operators to generate the new moderate solutions from the parent solutions and helps to improve the exploration and exploitation capability of the improved PSO technique. Two pumped storage hydrothermal test systems with two cases under each test system have been

undertaken. For each test system, the impact of the pumped storage unit has been investigated on the optimum generation schedule. Further, the parametric student t-test has been successfully tested on the HTS-I, and PSHTS-III test systems.

2. An optimization technique has been proposed for optimum generation schedule of the PSHTS. The proposed optimization technique (POT) combines modified crisscross search PSO (MCS-PSO) and modified binary PSO (MB-PSO) techniques to maintain a fine balance between exploration and exploitation search. In the MCS-PSO technique, the local best solutions obtained from the vertical crossover operator are further refined in the direction of pattern search. This process enhances the exploitation process and improves the search capability of the POT. The MB-PSO technique has been implemented for achieving the optimal binary decision variables by implementing modified sigmoid function. The POT exhibits excellent search capability with less computational burden, hence it is able to obtain optimal solution. The parameter sensitivity analysis and a parametric student t-test have been successfully tested on HTS-I, and PSHTS-III test systems.
3. The integrated energy system (IES) generation scheduling problem has been formulated by considering pumped storage unit, hydro and thermal units, and renewable energy sources (RES) with battery units. The uncertainty of the RES considered in terms of overestimation and underestimation power. The probability density functions has been considered to handle the RESs uncertainties. The economic, emission and multi-objective scheduling problems of IES have been resolved by implementing the POT. Two different test systems for IES considered with two cases under each test system.
4. The results obtained from the POT confirm the superior search ability to obtain the global best solution. For multi-objective scheduling problem, the cardinal priority ranking achieved by the POT, and compared with the ranking achieved by the well-

established techniques. The impact of wind, solar and battery units on the cost and emission has been analysed for the IES. The reduction in power generation cost and emission encourage increasing the presence of RES in the IES.

5. The multi-objective scheduling problem of IES incorporating RES has been resolved by implementing the POT with fuzzy based surrogate worth trade-off (SWT) approach. A SWT method has been implemented for achieving the best-satisfied non-dominated solution. In the POT-SWT approach, the SWT act as an interface between decision-makers and generated non-dominated solutions. The SWT exhibits progressive expression that iteratively analyses the available data, updates preferences and selects the best non-dominated solution. The multi-objective results obtained by implementing POT-SWT approach has been compared with results obtained using fuzzy min-max method. The non-dominated solutions obtained by utilising the POT-SWT approach represent the superior quality of SWT method in decision-making problems.

6.3 Future Scope

The scope of future work is always present in any field of research. Some of the possible research directions are listed below:

1. The performance of proposed optimization technique can be enhanced, and implemented to solve hard-constrained optimization problems.
2. The transmission line losses, prohibited operating zones and ramp rate constraints, can be considered in problem formulation of IES.
3. The load power flow analysis and flexibility assessment can also be included as future work.
4. This research work can be extend by considering the uncertainty of generator cost coefficients, emission cost coefficients, load forecasting, load model coefficients, etc.

5. The other renewable energy sources like, biogas, geothermal energy etc. can be incorporate with conventional power generation units to analyse their effect in power generation cost and emission pollutants.
6. This work can be further extended to the concept of deregulation and restructuring with price based dispatch from the PSU.
7. The multi-objective version of proposed optimization technique can be proposed.
8. Novel interactive decision-making methodology can be develop for obtaining the best-satisfied non-dominated solution.

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APPENDIX A

PROBABILITY DENSITY FUNCTIONS

A.1 WEIBULL PROBABILITY DENSITY FUNCTION

The Weibull probability density function (PDF) is utilised for wind speed distribution. Based on this PDF the overestimation and underestimation power cost formulae has been obtained. The probability of wind speed following Weibull PDF with shape factor (SH) and scale factor (SC) is represented by:

$$f_v(v) = \left(\frac{SH}{SC}\right) \times \left(\frac{v}{SC}\right)^{(SH-1)} \times \exp\left(-\left(\frac{v}{SC}\right)^{SH}\right) \quad \text{for } 0 < v < \infty \quad (A.1)$$

Based on the PDF of wind speed, the cumulative density function (CDF) can be obtained:

$$F_v(v) = 1 - \exp\left(-\left(\frac{v}{SC}\right)^{SH}\right) \quad (A.2)$$

When the wind speed is between cut-in and rated speed the PDF of wind power is expressed as:

$$f_W(W) = \left(\frac{SH \times h \times v_{in}}{W_r \times SC}\right) \times \left[\frac{\left(1 + \frac{h \times W}{W_r}\right) \times v_{in}}{SC}\right]^{(SH-1)} \times \exp\left[-\left[\frac{\left(1 + \frac{h \times W}{W_r}\right) \times v_{in}}{SC}\right]^{SH}\right] \quad (A.3)$$

$$\text{where } h = \left(\frac{v_r}{v_{in}} - 1\right).$$

The Eq. (A.3) is being utilized for presenting the continuous probability function. For the discrete probabilities based on wind power output equals '0' or 'W_r', the expressions are presented as follows:

$$P(W = 0) = 1 - \exp\left(-\left(\frac{v_{in}}{SC}\right)^{SH}\right) + \exp\left(-\left(\frac{v_{out}}{SC}\right)^{SH}\right) \quad (A.4)$$

$$P(W = W_r) = \exp\left(-\left(\frac{v_r}{SC}\right)^{SH}\right) - \exp\left(-\left(\frac{v_{out}}{SC}\right)^{SH}\right) \quad (A.5)$$

The CDF of 'W' is derived from integrating Eq. (A.3) to (A.5) as:

$$F_W(W) = \begin{cases} 0 & ; (W < 0) \\ \left(\frac{SH \times h \times v_{in}}{W_r \times SC}\right) \times \left[\frac{\left(1 + \frac{h \times W}{W_r}\right) \times v_{in}}{SC}\right]^{(SH-1)} \times \exp\left\{-\left[\frac{\left(1 + \frac{h \times W}{W_r}\right) \times v_{in}}{SC}\right]^{SH}\right\} & ; (0 \leq W < W_r) \\ 1 & ; (W \geq W_r) \end{cases} \quad (A.6)$$

A.2 LOGNORMAL PROBABILITY DENSITYFUNCTION

The power output from solar photovoltaic unit depends on solar irradiance, which follows the lognormal PDF. The probability of solar insolation (IL) following lognormal PDF with mean and standard deviation is represented by:

$$f_{IL}(IL) = \left(\frac{1}{IL \times \sigma \sqrt{2\pi}}\right) \times \exp\left\{-\frac{(\ln(IL) - \mu)^2}{2\sigma^2}\right\} \quad \text{for } IL > 0 \quad (A.7)$$

where IL is solar insolation; σ and μ represents the standard deviation and mean value.

APPENDIX B

TEST SYSTEMS

B.1 DATA FOR HYDROTHERMAL SYSTEM-I (HTS-I)

Hydrothermal tests system-I consist of 4-hydro and 3-thermal units, having 24-hourscheduling period divided into 24 sub-intervals of 1 hour each. Hydropower generation coefficients are given in Table B.1. The number of upstream reservoir and time delay between upstream and downside reservoir in hydro connection structure is presented in Table B.2. A set of operating characteristics of hydro unit and reservoir inflow are given in Tables B.3 and B.4, respectively. Thermal unit cost coefficients and emission pollutants coefficients for 3-thermal units used in the research work undertaken are given in Tables B.5 and B.6, respectively. Power demand utilised for the research work is presented in Table B.7.

Table B.1: Hydro power generation coefficients for HTS-I

Unit (j)	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C_{5j}	C_{6j}
1	-0.0042	-0.42	0.03	0.9	10	-50
2	-0.004	-0.3	0.015	1.14	9.5	-70
3	-0.0016	-0.3	0.014	0.55	5.5	-40
4	-0.0030	-0.31	0.027	1.44	14	-90

Table B.2: Upstream reservoirs and time delay between upstream and downside reservoir for HTS-I

Unit	1	2	3	4
Ru (upstream reservoir)	0	0	2	1
d (delay time)	2	3	4	0

Table B.3: Reservoir storage limits, initial and final storage limits, reservoir discharge limits and power generation limits for HTS-I

Unit (j)	$V_j^{\min}$	$V_j^{\max}$	V_j^{in}	V_j^{end}	$q_j^{\min}$	$q_j^{\max}$	$PH_j^{\min}$	$PH_j^{\max}$
	$(\times 10^4 \text{ m}^3)$				$(\times 10^4 \text{ m}^3/\text{h})$		(MW)	
1	80	150	100	120	5.0	15.0	0	500
2	60	120	80	70	6.0	15.0	0	500
3	100	240	170	170	10.0	30.0	0	500
4	70	160	120	140	6.0	20.0	0	500

Table B.4: Reservoir inflows ($\times 10^4 \text{ m}^3/\text{h}$) for HTS-I

t (hr)	Reservoir				t (hr)	Reservoir				t (hr)	Reservoir			
	1	2	3	4		1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	9	10	8	1	0	17	9	7	2	0
2	9	8	8.2	2.4	10	11	9	1	0	18	8	6	2	0
3	8	9	4	1.6	11	12	9	1	0	19	7	7	1	0
4	7	9	2	0	12	10	8	2	0	20	6	8	1	0
5	6	8	3	0	13	11	8	4	0	21	7	9	2	0
6	7	7	4	0	14	12	9	3	0	22	8	9	2	0
7	8	6	3	0	15	11	9	3	0	23	9	8	1	0
8	9	7	2	0	16	10	8	2	0	24	10	8	0	0

Table B.5: Cost coefficients and operating limits of thermal units for HTS-I

Unit (g)	a_g (\$/h)	b_g (\$/MWh)	c_g (\$/MW ² h)	d_g (\$/h)	e_g (1/MW)	$PT_g^{\min}$ (MW)	$PT_g^{\max}$ (MW)
1	100	2.45	0.0012	160	0.038	20	175
2	120	2.32	0.001	180	0.037	40	350
3	150	2.1	0.0015	200	0.035	50	500

Table B.6: Emission coefficients of thermal units for HTS-I

Unit (g)	α_g (lb/MW ² h)	β_g (lb/MWh)	γ_g (lb/h)	η_g (lb/h)	δ_g (1/MW)
1	0.0105	-1.355	60	0.4968	0.01925
2	0.008	-0.6	45	0.486	0.01694
3	0.012	-0.555	30	0.5035	0.01478

Table B.7: Power demand for HTS-I

t (hr)	PD_t (MW)	t (hr)	PD_t (MW)	t (hr)	PD_t (MW)
1	750	9	1090	17	1050
2	780	10	1080	18	1120
3	700	11	1100	19	1070
4	650	12	1150	20	1050
5	670	13	1110	21	910
6	800	14	1030	22	860
7	950	15	1010	23	850
8	1010	16	1060	24	800

B.2 DATA FOR PUMPED STORAGE HYDROTHERMAL SYSTEM-I (PSHTS-I)

Two different cases have been undertaken under each Pumped storage hydrothermal system-

I. In case-I the standard hydrothermal system has been undertaken consisting 4-hydro and 3-thermal units, having the 24-hour scheduling period with the sub-interval of 1 hour each. The hydrothermal generation coefficients are given from Table B.1 to B.6. In case-II the standard hydrothermal system has been undertaken along with a pumped storage unit install between hydro unit 1 and 3. The PSHTS-I, case-II consist 4-hydro units, 3-thermal units and 1-PSU,

having the 24-hour scheduling period with the sub-interval of 1-hour each. The pumped storage hydropower generation coefficients and capacity limit for pumped storage unit is given in Table B.8.

Table B.8: The pumped storage hydro power generation coefficients and capacity limit for PSHTS-I

Unit (l)	L_{1l}	L_{2l}	L_{3l}	L_{4l}	L_{5l}	L_{6l}	$PS_l^{\max}$	$PS_l^{\min}$
1 (generating mode)	-0.0042	-0.42	0.03	0.9	10	-50	100	0
1 (pumping mode)	-0.0042	-0.42	0.03	0.9	10	-50	100	0

B.3 DATA FOR PUMPED STORAGE HYDROTHERMAL SYSTEM-II (PSHTS-II)

Two different cases have been undertaken under each Pumped storage hydrothermal system-II. In case-I the standard hydrothermal system has been undertaken consisting 4-hydro and 10-thermal units, having the 24-hour scheduling period with the sub-interval of 1 hour each. The thermal unit's cost and emission generation coefficients are given from Table B.9 to B.10. Power demand utilised for the research work is presented in Table B.11. In case-II the standard hydrothermal system has been undertaken along with a PSU install between hydro unit 1 and 3. The PSHTS-I, case-II consist 4-hydro units, 10-thermal units and 1-PSU.

Table B.9: Cost coefficients of thermal units for PSHTS-II

Unit (g)	a_g (\$/h)	b_g (\$/MWh)	c_g (\$/MW ² h)	d_g (\$/h)	e_g (1/MW)	$PT_g^{\min}$ (MW)	$PT_g^{\max}$ (MW)
1	150	1.89	0.0050	300	0.035	50	455
2	115	2.00	0.0055	200	0.042	50	450
3	40	3.50	0.0060	200	0.042	20	130
4	122	3.15	0.0050	150	0.063	20	130
5	125	3.05	0.0050	150	0.063	25	470
6	120	2.75	0.0070	150	0.063	40	460
7	70	3.45	0.0070	200	0.053	45	465
8	70	3.45	0.0700	150	0.063	35	300
9	130	2.45	0.0050	180	0.043	25	160
10	130	2.45	0.0050	100	0.062	25	180

Table B.10: Emission coefficients of thermal units for PSHTS-II

Unit (g)	α_g (lb/MW ² h)	β_g (lb/MWh)	γ_g (lb/h)	η_g (lb/h)	δ_g (1/MW)
1	0.0105	-1.355	60	0.4968	0.01925
2	0.008	-0.6	45	0.486	0.01694
3	0.012	-0.555	30	0.5035	0.01478

Table B.10: Emission coefficients of thermal units for PSHTS-II (Continued)

4	0.0105	-1.355	60	0.4968	0.01925
5	0.008	-0.6	45	0.486	0.01694
6	0.012	-0.555	30	0.5035	0.01478
7	0.0105	-1.355	60	0.4968	0.01925
8	0.008	-0.6	45	0.486	0.01694
9	0.012	-0.555	30	0.5035	0.01478
10	0.0105	-1.355	60	0.4968	0.01925

Table B.11: Power demand for PSHTS-II

Sub-interval (hr)	Power Demand (MW)	Sub-interval (hr)	Power Demand (MW)
1	1750	13	2110
2	1780	14	2030
3	1700	15	2010
4	1650	16	2060
5	1670	17	2050
6	1800	18	2120
7	1950	19	2070
8	2010	20	2050
9	2090	21	1910
10	2080	22	1860
11	2100	23	1850
12	2150	24	1800

B.4 DATA FOR PUMPED STORAGE HYDROTHERMAL SYSTEM-III (PSHTS-III)

The power generation coefficients for PSHTS-III are given in Tables B.12 and B.13, respectively. A set of operating characteristics of hydro unit and reservoir inflow are given in Table B.14 and B.15, respectively. The Thermal unit cost coefficients, emission coefficients and total power demand data are given in Tables B.5, B.6 and B.7, respectively.

Table B.12: Coefficients of pumped storage hydroelectric units for PSHTS-III.

Unit	C_{1j}	C_{2j}	C_{3j}	C_{4j}	C_{5j}	C_{6j}
1	-0.001	-0.1	0.01	0.40	4.0	-30.0
2	-0.001	-0.1	0.01	0.40	4.0	-30.0
3	-0.001	-0.1	0.01	0.30	3.0	-30.0
4	-0.001	-0.1	0.01	0.45	4.5	-30.0

Table B.13: Pumped storage unit power generation coefficients and power capacity limit for PSHTS-III

Unit (l)	L_{1l}	L_{2l}	L_{3l}	L_{4l}	L_{5l}	L_{6l}	$PS_l^{\max}$ (MW)	$PS_l^{\min}$ (MW)
1 (generating mode)	-0.001	-0.1	0.01	0.70	7.0	-30.0	250	0
1 (pumping mode)	-0.001	-0.1	0.01	0.42	4.2	-30.0	250	0

Table B.14: Volume and discharge limits for the PSHTS-III

Unit	$V_j^{\min}$	$V_j^{\max}$	V_j^{in}	V_j^{end}	$q_j^{\min}$	$q_j^{\max}$	$PH_j^{\min}$	$PH_j^{\max}$
	$(\times 10^4 \text{ m}^3)$				$(\times 10^4 \text{ m}^3/\text{h})$		(MW)	
1	80	150	100	100	0.0	15.0	0	500
2	60	120	80	80	0.0	30.0	0	500
3	50	300	170	170	10.0	30.0	0	500
4	70	160	100	100	13.0	25.0	0	500
Pumped Storage Unit	40	250	100	100	10.0	30.0	--	--

Table B.15: Reservoir inflows ($\times 10^4 \text{ m}^3/\text{h}$) for PSHTS-III

t	Reservoir				t	Reservoir				t	Reservoir			
(hr)	1	2	3	4	(hr)	1	2	3	4	(hr)	1	2	3	4
1	10	28	20	20	9	10	12	1	0	17	0	8	1	0
2	9	28	20	20	10	10	10	1	0	18	0	8	1	0
3	8	29	10	20	11	10	8	1	0	19	0	8	1	0
4	7	25	10	18	12	10	8	1	0	20	0	16	1	0
5	7	22	5	18	13	0	8	1	0	21	0	20	1	18
6	7	20	4	0	14	0	8	1	0	22	0	28	1	20
7	8	16	5	0	15	0	8	1	0	23	0	28	20	20
8	9	14	5	0	16	0	8	1	0	24	0	28	20	20

B.5 DATA FOR INTEGRATED ENERGY SYSTEM (IES)

The IES-I, and II have been considered as a test systems for the research work. Two different cases have been considered under each test system. The IES-I consist of PSHTS-III with solar and battery units, whereas IES-II consist PSHTS-III with wind, solar and battery units. The PSHTS cost, emission and power generation coefficient data for IES-I, and II have been provided in Appendix B.4. The solar unit power rating and per unit cost data for IES-I, and II have been presented in Table B.16. Similarly, the solar radiation and temperature data are given in Table B.17. The battery unit coefficients for IES-I, and II are presented in Table B.18. Wind energy unit coefficients is given in Table B.19. Power demand is presented in Table B.11.

Table B.16: Solar units power rating and per unit cost for IES

Solar Units	Power Rating (MW)	Per Unit Cost (\$/hr)
1	20	0.22
2	25	0.23
3	25	0.23
4	30	0.24
5	30	0.24
6	35	0.25

Table B.16: Solar units power rating and per unit cost for IES(Continued)

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 B.17: Solar radiation and temperature data for IES

t (hr)	T _{amb} (°C)	IL (Watt/m ²)	t (hr)	T _{amb} (°C)	IL (Watt/m ²)
1	30	0	13	37	1013.5
2	29	0	14	37	848.2
3	28	0	15	37	726.7
4	28	0	16	38	654
5	28	5.4	17	38	392.9
6	0	101	18	37	215.1
7	29	253.7	19	35	38.5
8	31	541.2	20	34	0
9	33	530.4	21	34	0
10	34	703.9	22	33	0
11	35	1078	23	0	0
12	36	1125.6	24	32	0

Table B.18: Battery coefficients data for the IES

Battery bank	b1 (\$/h)	b2 (\$/MWh)	b3 (\$/MW ² h)	B	V (kV)	PU ^{max} (MW)	PB ^{max} (MW)	PB ^{min} (MW)	Q _b (kAhr)
1	0.0	3.0	0.005	0.85	2	400	350	0	500

Table B.19: Data for wind energy units for IES-II

Unit	SH	SC	V _{in} (m/sec)	V _{out} (m/sec)	V _r (m/sec)	C _{oe} (\$/MW)	C _{ue} (\$/MW)	dc(\$/MW)
1	1	15	5	30	15	1.0	5.0	7.0
3 2	2	15	5	30	15	1.0	5.0	7.0

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M.E.	Power Systems	Thapar University	7.60	2016
B. Tech.	Electrical Engineering	Dehradun Institute of Technology	71.79	2012
SSC	CBSE	ST. Theresa Senior Secondary School	83.00	2008
HSC	CBSE	ST. Theresa Senior Secondary School	86.20	2006

2. SCI Publications (Related to Ph.D. work)

1. **R.S. Patwal**, N. Narang. “Optimal generation scheduling of pumped storage hydrothermal system with wind energy sources.” Applied Soft Computing Journal, vol. 93(1); pp. 106345, (2020). **IF: 5.472**
2. **R.S. Patwal**, N. Narang. “Multi-objective generation scheduling of integrated energy system using fuzzy based surrogate worth trade-off approach”. Renewable Energy, vol. 156(1); pp. 864–882, (2020). **IF: 6.274**
3. **R.S. Patwal**, N. Narang. “Crisscross PSO algorithm for multi-objective generation scheduling of pumped storage hydrothermal system incorporating solar units”. Energy conversion and Management, vol. 169(1); pp. 238–254, (2018). **IF: 8.208**

3. International Conferences

1. **R. S. Patwal**, **N. Narang**. “Optimal Economic Emission Scheduling of Integrated Energy Systems using Heuristic Optimization Technique”. 2nd International Conference on Power, Energy and Environment: Towards Smart Technology (ICEPE); Year: 2018; Pages: 1-6.
2. **R. S. Patwal**, **N. Narang**. “Heuristic optimization technique for hydrothermal scheduling considering pumped storage unit”. 1st IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES); Year: 2016; Pages: 1-5.