IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-8, Aug 2018 E-ISSN: 2347-2693

# A Non-Dominated Sorting TLBO Algorithm for Multi-Objective Short-Term Hydrothermal Self Scheduling of GENCOs in a Competitive Electricity Market

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**Available online at: www.ijcseonline.org**

Accepted: 18/Aug/2018, Published: 31/Aug/2018

***Abstract-*** In competitive electricity market worldwide raises many challenging tasks related to the economic and optimal operation of electric power systems. In deregulated market structure, the generation is being despatched by means of hourly power delivery. The penalty is improved on power producers, if they fail to attain the planned energy delivery. The inadequate hydel resources associated with environmental constraints of thermal plants necessiates a precise scheduling system to satisfy the ever growing power demand. The power generator in a hydrothermal has to manage the conflicting objectives of profit maximization and emission minimization. Normally, the multi-objective optimization problem is tuned for optimising the two or more conflicting objectives subject to some constraints. Short-term hydrothermal scheduling (STHTS) problem deals with more objective functions such as profit maximization and emission minimization. Hence it is necessary to evolve a constructive framework based on intelligent techniques. In this paper, a stochastic multi-objective model is derived for the flexible scheduling of hydrothermal plants with valve-point loading effects. A non-dominated sorting teaching learning based optimization (NSTLBO) algorithm is presented for solving STHTS problem. The proposed algorithm is applied to derive a pair of non-dominated results and then the fuzzy based methodology has been argued to choose the best solution. It is tested on a three thermal and four hydro test system with twenty four hour time period. The results are extracted by means of total profit and emission from the plants. Comparative studies have also been done to validate the viability of the proposed method.

***Keywords-*** Deregulation, Hydrothermal Scheduling, Profit Maximization, Emission Limitations, Non-dominated Sorting TLBO algorithm.

**NOMENCLATURE**

| | |
|---|---|
| PF | Total Profit of GENCOs |
| RV | Total Revenue GENCOs |
| TC | Total fuel cost of GENCOs |
| $P_{sit}$ , $P_{hjt}$ | Thermal and hydro power at hour of t |
| $RP_t$ , $SP_t$ | Reserve power and spot price of hydro power at hour of t |
| $\alpha_i$, $\beta_i$, $\gamma_i$, $n_i$, $\delta_i$ | Emission coefficient of $i^{th}$ generator |
| GENCOs | Generation companies |
| TRANSCOs | Transmission companies |
| DISCOs | Distribution companies |
| ISO | Independent system operator |
| PX | Power exchanger |
| IPP | Independent power producer |
| $P_{s_{it}}$ | Power generation of ith thermal unit for interval |
| $P_{h_{jt}}$ | Power generation of jth hydro for $t^{th}$ interval |
| $Ps_i^{min}$; $Ps_i^{max}$ | Minimum and maximum operating limits of ith thermal unit |
| $Ph_j^{min}$; $Ph_j^{max}$ | Minimum and maximum operating limits of jth hydro plant |
| $P_{loss_t}$ | Transmission loss for $t^{th}$ interval |
| $P_{D_t}$ | Load demand for $t^{th}$ interval |
| $a_i - e_i$ | Fuel cost coefficients of the ith thermal generating units |
| $c_{1j} - c_{6j}$ | Power generation coefficients of jth hydro unit |
| $Q_{hjt}$ | Water discharge of jth hydro plant for interval |
| $Q_{hj}^{min}$; $Q_{hj}^{max}$ | Lower and upper limits of reservoir water discharge of jth hydro plant |
| $V_{hjt}$ | Water storage level of jth hydro reservoir for $t^{th}$ interval |
| $V_{hj}^{min}$; $V_{hj}^{max}$ | Water storage level limits of jth hydro reservoir for $t^{th}$ interval |
| $SR_t$ | Spinning reserve for $t^{th}$ interval |
| DP | Dynamic programming |
| LR | Lagrangian relaxation |
| MIP | Mixed integer programming |
| BD | Benders decomposition |
| NLP | Nonlinear programming |
| LP | Linear programming |

## I. INTRODUCTION

The planning and operation of hydrothermal system is considered to be a complex problem. The STHTS is one of the significant subject in a hydrothermal system and it assign the periodical scheduling of hydro and thermal generators around a pre-planned period [1]. The STHTS is a large scale non-convex, non-linear, Mixed-integer optimization problem. The power generators have the responsibility to meet the load demand at a minimized cost. So the objective of the problem has been designed to minimize the operational cost of the system and the problem is referred as cost based short-term hydrothermal scheduling (CBSTHTS).

Recent years have seen a worldwide pressure towards deregulation and unbundling of service providers by the utilization. The introduction of deregulation and restructuring in Electric power system creates a competitive open market scenario in order to enhance the performance and ideal operation of existing power plants. Generally the generation companies are expected to improve their own profit by minimize the total production cost. In view of this, the Genco's are not necessarily to meet the system demand and reserve generation [2-3]. The UC performed by the Genco's has a distinct objective than that of regular UC and is termed as profit based STHTS which emphasizes the significance of profit.

In regulated power industry, several methods several methods have been proposed for the solution of STHTS. The classical techniques such as Lagrangian relaxation, Mixed-integer programming and Primal dual interior point method are not suitable when the system size increases. Further the computational requirement also increases with the classical methods. The amendment of clean air act 1990 [4], the conventional economic scheduling is not held good for STHTS problems and also the emission problem have to be addressed.

Therefore the researchers have suggested number of evolutionary algorithms in evolving the solution for STHTS problem. An approach based on simulated annealing has been analysed, where in the multi-objective function is transformed in to a single objective function by means of goal attainment algorithm [5, 6]. The major setback of this method is that an assumption has made in the process of decision maker in arriving goals. An improved version of genetic algorithm (GA) [7] by updating the multipliers is tested on STHST problems. Here the multi-objective function was handled by means of e-constraint technique. The method suffers from consuming much time and also obtains a weak pareto optimal solutions.

The hydrothermal scheduling problem were analysed in [8] by adapting self organising hierarchical Particle Swarm Optimization Algorithm. A solution to solve Fixed Head and Variable Head economical hydrothermal scheduling problem has been given in reference [9] using Non-Dominated Sorting Disruption Based Gravitational Search Algorithm. Besides several other methods were used to solve the self scheduling problem, including Mixed Integer Programming (MIP) [10], Lagrangian Relaxation-Evolutionary Programming (LR-EP) [11].

All evolutionary and swarm intelligence based optimization algorithm needs to have control components like population size, sequence of iterations, etc. The exact tuning of their algorithmic parameter decides the performance of the algorithm. The erroneous tuning of algorithmic parameters either burdens the computational effort or attains a local optimal solution. The methodological revolution in the energy market imposes the need for renewed formulation.

In this article, a unique framework based on Non-Dominated Teaching Learning Based Optimization (NSTLBO) algorithm has been proposed for solving optimal scheduling of hydrothermal plants. This algorithm need not depend upon any tuning parameters like other algorithms. It has been modelled to solve multi-objective STHTS problem in the day-ahead energy markets.

The presentation of this article can be summarized as follows.

1. Section 2 elaborates the mathematical formulation of STHST problem. It has been modelled as a multi-objective problem by taking in to allow profit and emission as Bi-objective.
2. Section 3 proposes the solution methodology and it includes overview of Teaching-Learning-Based Optimization (TLBO), Non-dominated Sorting TLBO (NSTLBO) algorithm, and Fuzzy decision maker to find the best solutions.
3. Section 4 presents the Implementation of NSTLBO algorithm for STHTS problem under regulated and deregulated environment.
4. Section 5 explains the numerical example, and Section 6 accommodates the conclusions.

## II. PROBLEM FORMULATION

The multi-objective STHTS problem has been modelled with a view to maximize the profit and to minimize the emission level of Gencos. It also establish the optimal scheduling of hydrothermal system by satisfactory the system constraints.

The proposed method for solving STHTS problem consisting of two objective functions, which can be mentioned as $f(x)$ and $g(x)$ where

$f(x)$ - Profit maximization function

$g(x)$ - Emission minimization function

Where, f(x) and g(x) are the objective functions of STHTSS problem and mathematical model can be expressed as

### II.1. Profit maximization function

 

The profit of the concern is termed as the difference between revenue received from the sale of power with market price and total operating cost of the generation companies.

$$\mathrm{Profit}(i,j,t) = \mathrm{Revenue}(i,j,t) - \mathrm{Total\ cost}(i,j,k) \quad (1)$$

$$\mathrm{Maximize\ PF} = \mathrm{RV} - \mathrm{TC} \quad (2)$$

$$\mathrm{RV} = \sum_{t=1}^{T}\sum_{i=1}^{N} P_{sit}SP_tX_{sit} + \sum_{t=1}^{T}\sum_{j=1}^{m} P_{hjt}SP_tX_{sit} + \sum_{t=1}^{T}\sum_{i=1}^{N} R_{sit}RP_tX_{sit} \quad (3)$$

$$\mathrm{TC} = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{si}(P_{sit})X_{sit} + \sum_{t=1}^{T}\sum_{i=1}^{N} F_{si}(R_{sit})X_{sit} + \sum_{i=1}^{N}\sum_{t=1}^{T} STX_{sit} \quad (4)$$

***Mathematical model of thermal plant***

The total operational cost of a thermal plant is highly depends on its fuel cost. Moreover in real time, the value manipulates steam parring the turbine through a group of nozzle. The impact of their valve-point loading makes the fuel cost function as a non-convex curve which has been included in the problem. So the fuel cost equation of a thermal plant for the scheduling period can be formulated as

$$F_i(P_{it}) = a_iP_{sit}^2 + b_iP_{sit} + c_i + d_i\ \mathrm{Sin}\{e_i(P_{sit}^{min} - P_{sit})\} \quad (5)$$

***Mathematical model of hydro plant***

The prime component of hydel power plant includes water discharge and reserve storage volume. The mathematical model of a hydro power plant can be formulated as

$$P_{ht} = C_{1j}V_{hj}^2 + C_{2j}Q_{hj}^2 + C_{3j}V_{hj}Q_{hj} + C_{4j}V_{hj} + C_{5j}Q_{hj} + C_{6j} \quad (6)$$

**II.2. Modelling of emission**

Carbon and gaseous emission from the thermal power plant are treated as a second objective function. The emissions from this power plant are formulated by adding the quadratic and exponential function of thermal output.

$$\mathrm{TE} = \sum_{t=1}^{T}\sum_{i=1}^{N} \alpha_i + \beta_iP_{sit} + \gamma_iP_{sit}^2 + n_i\exp(\delta_iP_{sit}) \quad (7)$$

**II.3. System and unit constraints**

**1. Power balance constraints**

It is a power generation constraint that orients the total power generation of the hydro and thermal plant should be less than or equal to system demand for the planned scheduling interval at time 't'.

$$\sum_{i=1}^{N} P_{sit} + \sum_{j=1}^{M} P_{hjt} - P_{D_t} \le 0 \quad (8)$$

**2. Thermal generation limits**

The thermal limit of the power generator is marked by its lower and higher limits respectively.

$$P_{si}^{min} \le P_{sit} \le P_{si}^{max} \quad (9)$$

**3. Hydro generation limits**

A hydel plant must be reported in a well defined upper and lower limit.

$$P_{hj}^{min} \le P_{hjt} \le P_{hj}^{max} \quad (10)$$

**4. Spinning reserve constraints**

The sum of the reserve power of scheduled thermal units during the planning period augurs to be less than or equal to total spinning reserve of the generating units and is written as in equation (11).

$$\sum_{i=1}^{N} P_{sit}X_{sit} \le SR_t \quad (11)$$

$$0 \le R_{sit} \le (P_{sit}^{max} - P_{sit}^{min})$$

$$R_{sit} + P_{sit} \le P_{sit}^{max}$$

**5. Water discharge constraints**

The discharge of water to the turbine should be within the predefined maximum ($Q_{hj}^{max}$) and minimum ($Q_{hj}^{min}$) operating limits.

$$Q_{hj}^{min} \le Q_{hjt} \le Q_{hj}^{max} \quad (12)$$

**6. Storage volume constraints**

The storage of water in the reservoir must be enough to meet the maximum ($V_{hj}^{max}$) and minimum ($V_{hj}^{min}$) limits.

$$V_{hj}^{max} \le V_{hjt} \le V_{hj}^{max} \quad (13)$$

## III. SOLUTION METHODOLOGY

**III.1 Overview of TLBO algorithm**

An exceptional optimization technique namely Teaching-Learning-Based Optimization algorithm (TLBO), which has been recently introduced in the references [15-25]. It works around the philosophy of the effect of a teacher on the result of learners in the school and consequently learning by interaction between class members, which helps to improve their grades. The method works on the principle of the process of teaching and learning.

The heuristic technique outplays the classical mathematical methods, but its quality of the observation is more sensitive to the algorithmic parameters like population size and iterations. The main drawbacks of their kind of algorithm are the existence of different parameter that has to be neatly tuned to attain the expected performance.

The heuristic technique outplays the classical mathematical methods, but its quality of the observation is more sensitive to the algorithmic parameters like population size and iterations. The main drawbacks of their kind of algorithm are the existence of different parameter that has to be neatly tuned to attain the expected performance.

Presently, Teaching Learning Based Optimization (TLBO) algorithm has been introduced. It is an activity based algorithm that functions on the effect of teaching capacity of a teacher on the result of learners in a class.

It is dominant evolutionary algorithm that involves a population of students, where each and every student has been recognised as a potential solution to an optimization problem.

The searching process includes initialization of a class, teacher phase, learner phase and terminating point. The TLBO algorithm is simple and easy to implent in power system optimization problems. TLBO is a specific, parameter less algorithm and does not require the tuning of any algorithmic parameters. It has the capacity of finding the global optimal solution for a non-convex, non-linear with less computational effort and high reliability.

### III.2 Non-dominated sorting TLBO algorithm

This article presents an exceptional methodology for producing the pareto optimal solutions for the multi-objective optimization problems namely (NSTLBO). The NSTLBO algorithm is an refurbished version of the TLBO algorithm [12]. The NSTLBO algorithm is an exclusive method for analysing multi-objective optimization problem and preserves the assorted set of solution.

It is very similar to a TLBO algorithm with teacher phase and a learner phase. On the other way with a view to manage the multiple objective effectively and efficiently. The NSTLBO algorithm is equipped with non-dominated sorting approach and crowding distance computation mechanism. [15] The teacher phase and learner phase confirms a better exploitation of the search space while non-dominated sorting approach assures that the selection process in the search space is consistently moves on the way of best solution and the population is rushed towards the pareto front in each iteration process.

The crowding distance assignment terminology ensures the choice of a teacher from the wide region of the search space. Hence the probability of premature convergence of the algorithm at local optima is averted.

In the NSTLBO algorithm, the updation of learners is done based on the teacher phase and learner phase of the TLBO algorithm. It is a simple matter in deciding the best solution in case of single objective optimization problem. But in multiple conflicting objectives, identifying the best solution from the set of solution is not easy job.

In this algorithm, the process of finding the best solution is done by comparing the rank of which is assigned to the solution based on the non-dominated idea and the crowding distance value.

***Initialization***

The algorithm is initialized by a matrix of N rows and D columns with some arbitrarily generated values in the search space. In this case, the value of N indicates the population size of the ‘class’. The value D gives the total number of subjects offered which is equal to the dimensionality of the problem considered. The algorithm is framed to run for ‘g’ number of iterations. The following equation is used to assign the values of $j^{th}$ parameter of the $i^{th}$ vector in the initial stage of iteration.

$$x^1_{(i,j)} = x^{min}_j + rand_{(i,j)} \times (x^{max}_j - x^{min}_j) \qquad (14)$$

Where $rand_{(i,j)}$ denotes a uniformly distributed random variable within the limit (0,1). The components of the $i^{th}$ vector for the generation ‘g’ is shown by

$$X^g_i = \left\lfloor x^g_{(i,1)}, x^g_{(i,2)}, \dots, x^g_{(i,j)}, \dots, x^g_{(i,D)} \right\rfloor \qquad (15)$$

The column vector is formed by the objective values at a particular generation. Two objective functions occupies the similar row vector in this kind of bi-objective problem. The bi-objective (a and b) can be formulated as

$$\begin{bmatrix} Y_{a^g_i} \\ \hline Y_{b^g_i} \end{bmatrix} = \begin{bmatrix} fa(X^g_{(i)}) \\ fb(X^g_{(i)}) \end{bmatrix} \qquad (16)$$

Where i = 1,2,...,N; j = 1,2,...,D; g = 1,2,...,G

***Teacher phase***

The mean vector which consists of the mean learners in the class for each subject is calculated. So the mean vector $\mu$ is shown as

$$M^g = \begin{bmatrix} mean([x^g_{(1,1)}, \dots, x^g_{(i,1)}, \dots, x^g_{(N,1)} \\ mean([x^g_{(1,j)}, \dots, x^g_{(i,j)}, \dots, x^g_{(N,j)} \\ mean([x^g_{(1,D)}, \dots, x^g_{(i,D)}, \dots, x^g_{(N,D)} \end{bmatrix}^T \qquad (17)$$

$$\text{Then } M^g = \left\lfloor m^g_1, m^g_2, \dots, m^g_j, \dots, m^g_D \right\rfloor \qquad (18)$$

The best vector with less objective function value is considered as the teacher for this iteration.

The algorithm progress well by moving the mean of the learners in the direction of the teacher. The current mean and competent mean vector are added to the present population of learners in order to form a advanced set of improved learners.

$$Xnew^g_{(i)} = X^g_{(i)} + rand^g \times (X^g_{Teacher} - T_F M^g) \qquad (19)$$

Hence $T_F$ is the teaching factor in the process of iteration which may be either 1 or 2.

The more skilful learners in the matrix $X_{new}$ displace the sub standard learners in matrix S using the non-dominated sorting algorithm.

***Learner phase***

This phase is dedicated to interaction of learners among themselves. The practice of mutual interaction results in the improvement of the expertise of the learner. Each learner collaborates randomly with other learners and hence expedite the sharing of knowledge. A particular learner ( $X^g_{(i)}$), and the other learner ( $X^g_{(r)}$) has been randomly chosen ( $i \neq r$ ). Finally the $i^{th}$ vector of the matrix $X_{new}$ in the learner phase seems

$$Xnew^g_{(i)} = \begin{cases} X^g_{(i)} + rand^g_{(i)} \times \left(X^g_{(i)} - X^g_{(r)}\right) & if(Y^g_i < Y^g_r) \\ X^g_{(i)} + rand^g_{(i)} \times \left(X^g_{(r)} - X^g_{(i)}\right) & otherwise \end{cases} \qquad (20)$$

In multi-objective optimization problem, there is a possibility of multiple $X_{new}$ matrices in the learner phase. So in case of a bi-objective problem the performance of learner phase may have formulation as.

 

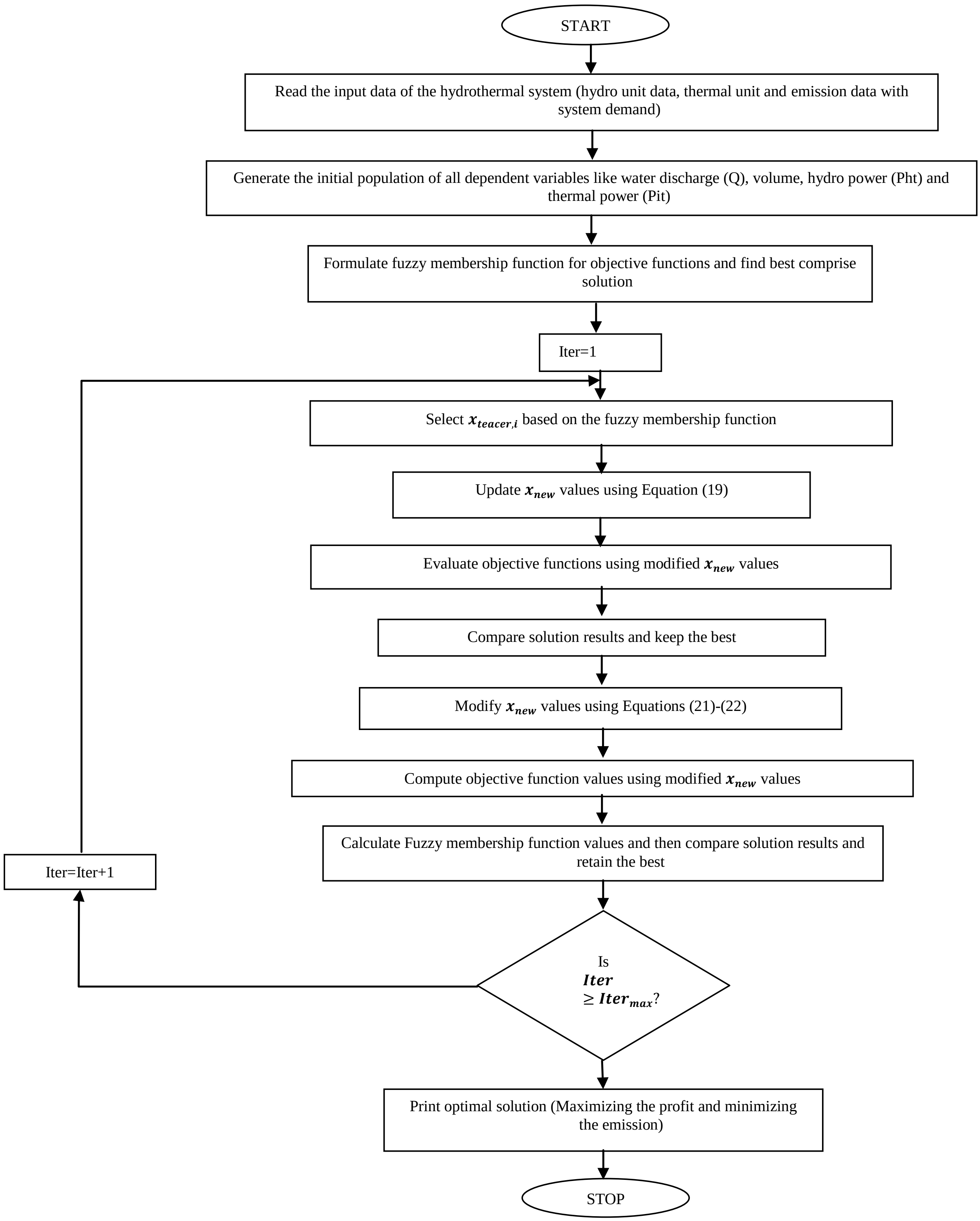


Fig. 1. Flow chart for proposed method to solve multi objective STHTSS problem generation

 

$$\mathrm{Xnew}_{(i)}^{g} = \begin{cases} X_{(i)}^{g} + \mathrm{rand}_{(i)}^{g} \times \left(X_{(i)}^{g} - X_{(r)}^{g}\right) & \mathrm{if}(Ya_{i}^{g} < Ya_{r}^{g}) \\ X_{(i)}^{g} + \mathrm{rand}_{(i)}^{g} \times \left(X_{(r)}^{g} - X_{(i)}^{g}\right) & \mathrm{otherwise} \end{cases} \quad (21)$$

$$\mathrm{Xnew}_{(i)}^{g} = \begin{cases} X_{(i)}^{g} + \mathrm{rand}_{(i)}^{g} \times \left(X_{(i)}^{g} - X_{(r)}^{g}\right) & \mathrm{if}(Yb_{i}^{g} < Yb_{r}^{g}) \\ X_{(i)}^{g} + \mathrm{rand}_{(i)}^{g} \times \left(X_{(r)}^{g} - X_{(i)}^{g}\right) & \mathrm{otherwise} \end{cases} \quad (22)$$

Finally, the X matrix and the $X_{new}$ matrices are processed together in the NDSA, which gives the 'N' best learners for the ensuring iteration. The algorithm will be terminated after 'G' number of iteration is over Fig. 1.

### *III.3 Fuzzy membership function*

The prime objective of the system engineer is to carry out the conflicting parameters by satisfying the constraints of the system. In most of the cases the results, constraints and outcomes of the suggested mechanism are not derived precisely. Much of this error is not accessible. It may be due to vague, erroneous or fuzzy information. By looking on the imperfect manner of the decision maker's behaviour, it is understood that the decision maker may substitute fuzzy or erroneous goals for each objective function. The fuzzy sets are governed by equations called membership function. These functions are assigned by the values ranging from 0 to 1. By considering the minimum and maximum standards of objective function combined with rate of change of membership function, the decision maker must identify the membership function $\mu(j_i)$ in a constructive manner.

It is considered that $\mu(j_g)$ happened to be a linear decreasing and continuous function and is formulated as

$$\mu(j_g) = \begin{cases} 1 & j_g \le j_g^{min} \\ \frac{j_g^{max} - j_g}{j_g^{max} - j_g^{min}} & j_g^{min} \le j_g \le j_g^{max} \\ 0 & j_g \le j_g^{max} \end{cases} \quad (g = 1,2, \ldots, Nob) \quad (23)$$

where $j_g^{min}$ and $j_g^{max}$ are the minimum and maximum values of objective function where in the solution is to be landed.

$N_{ob}$ denotes the number of objective function in the problem.

Normalized membership values $\mu^k$ for each non-dominated solution is calculated by the following equation.

$$\mu^k = \frac{\sum_{i=1}^{Nobj} \mu_i^k}{\sum_{k=1}^{M_{nds}} \sum_{i=1}^{Nobj} \mu_i^k} \quad (24)$$

Where, $M_{nds}$ is the number of non-dominated solutions. Choose the best comprise solution that is having the greatest value of $\mu^k$.

## IV. SIMULATION RESULTS

The simulation were carried out by programming the MATLAB 14.0 software on a computer with i3 processor, Intel (R), Core i3 supported by 4 GB RAM with 2.4 GHZ clock speed. The proposed NSTLBO algorithm has been executed with number of iterations and then the best solution is presented. It is worth mention to note then this algorithm is not having any parameter to be tuned to have global optimal solution.

In this analysis, the parameters like water discharge, water storage volume, revenue fuel cost, profit and emission are considered.

The proposed algorithm was subjected to the training process with a population size of 40 and the iteration was approximately 250. The proposed hydrothermal system comprises of multi-chain cascade of four hydro plants and three thermal plants with twelve hours scheduling period. The model diagram of the cascaded multi-chain hydro system is shown in Fig. 2. The forecasted load demand, reserve demand and forecasted market price of the system is adapted from the reference [13, 14] and is given in Table 1.

The unit cost coefficients, emission coefficients and operating limits of three thermal units are considered from the same reference which is given in Table 2 & 3. The coefficients of hydraulic system, the inflows to the reservoir and limits of the reservoir are considered from reference [11] and is given in Table 4 to 6. The analysis of test system has been divided into two cases, according to the mode power generation and constraints.

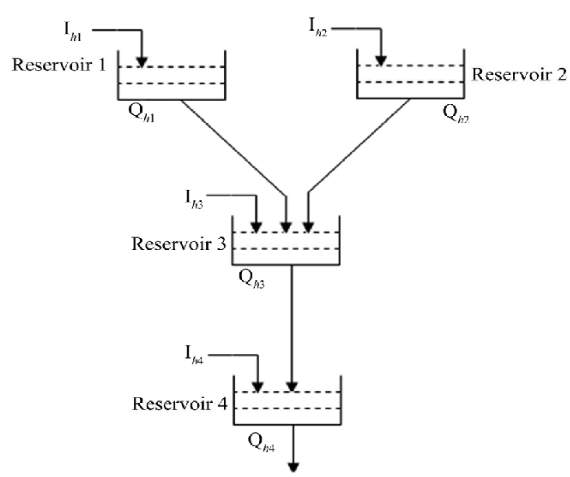


Fig. 2. Standard multi-chain four hydro System network

Table 1. Load demand and market price of four hydro three thermal unit test system

| Hour (h) | Forecasted Demand (MW) | Forecasted Reserve (MW) | Forecasted Market Price ($/MWh) |
|---|---|---|---|
| 1 | 750 | 20 | 10.55 |
| 2 | 780 | 25 | 10.35 |
| 3 | 700 | 40 | 9.00 |
| 4 | 650 | 55 | 9.45 |
| 5 | 670 | 70 | 10.00 |
| 6 | 800 | 95 | 11.25 |
| 7 | 950 | 100 | 11.30 |
| 8 | 1010 | 80 | 10.65 |
| 9 | 1090 | 65 | 10.35 |
| 10 | 1080 | 35 | 11.20 |
| 11 | 1100 | 40 | 10.75 |
| 12 | 1150 | 55 | 10.60 |

Table 2. Cost curve coefficients and operating limits of thermal generators

| Unit | $a_{si}$ ($/h) | $b_{si}$ ($/MWh) | $c_{si}$ ($/$(MW)^2h$) | $e_{si}$ ($/h) | $f_{si}$ (1/MW) | $P_{si}^{min}$ (MW) | $P_{si}^{max}$ (MW) |
|---|---|---|---|---|---|---|---|
| 1 | 100 | 2.45 | 0.0012 | 160 | 0.038 | 20 | 175 |
| 2 | 120 | 2.32 | 0.0010 | 180 | 0.037 | 40 | 300 |
| 3 | 150 | 2.10 | 0.0015 | 200 | 0.035 | 50 | 500 |

Table 3. Emission coefficients of thermal generators

| Unit | $\propto_{si}$(Ib/h) | $\beta_{si}$(Ib/MWh) | $\gamma_{si}$(Ib/(MW)2h) | $\eta_{si}$(Ib/h) | $\delta_{si}$(1/MW) |
|---|---|---|---|---|---|
| 1 | 60 | -1.355 | 0.0105 | 0.4968 | 0.01925 |
| 2 | 45 | -0.600 | 0.0080 | 0.4860 | 0.01694 |
| 3 | 30 | -0.555 | 0.0120 | 0.5035 | 0.01478 |

Table 4. Hydro power generation coefficients

| Plant | $c_{1j}$ | $c_{2j}$ | $c_{3j}$ | $c_{4j}$ | $c_{5j}$ | $c_{6j}$ |
|---|---|---|---|---|---|---|
| 1 | -0.0042 | -0.42 | 0.030 | 0.90 | 10.0 | -50 |
| 2 | -0.0040 | -0.30 | 0.015 | 1.14 | 9.5 | -70 |
| 3 | -0.0016 | -0.30 | 0.014 | 0.55 | 5.5 | -40 |
| 4 | -0.0030 | -0.31 | 0.027 | 1.44 | 14.0 | -90 |

Table 5. Reservoir inflows ($\times 10^4 m^3$)

| Hour (h) | Plant 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | 10 | 8 | 8.1 | 2.8 |
| 2 | 9 | 8 | 8.2 | 2.4 |
| 3 | 8 | 9 | 4 | 1.6 |
| 4 | 7 | 9 | 2 | 0 |
| 5 | 6 | 8 | 3 | 0 |
| 6 | 7 | 7 | 4 | 0 |
| 7 | 8 | 6 | 3 | 0 |
| 8 | 9 | 7 | 2 | 0 |
| 9 | 10 | 8 | 1 | 0 |
| 10 | 11 | 9 | 1 | 0 |
| 11 | 12 | 9 | 1 | 0 |
| 12 | 10 | 8 | 2 | 0 |

Table 6. Reservoir storage capacity limits, plant discharge limits, reservoir end Conditions ($\times 10^4 m^3$) and plant generation limits (mw)

| Plant | $V_{hj}^{min}$ | $V_{hj}^{max}$ | $V_{hj0}$ | $V_{hjT}$ | $Q_{hj}^{min}$ | $Q_{hj}^{max}$ | $P_{hj}^{min}$ | $P_{hj}^{max}$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 80 | 150 | 100 | 120 | 5 | 15 | 0 | 500 |
| 2 | 60 | 120 | 80 | 70 | 6 | 15 | 0 | 500 |
| 3 | 100 | 240 | 170 | 170 | 10 | 30 | 0 | 500 |
| 4 | 70 | 160 | 120 | 140 | 6 | 20 | 0 | 500 |

***Case-A: Multi-Objective STHTSS without Reserve Power Generation***

In this test case, the fuel cost and emission components of thermal units form the quadratic equation by considering valve point loading effect. The total profit, revenue and fuel cost parameter of Case-I are represented by the following equation.

$$\text{Maximize } PF = RV - TC$$

$$\mathbf{RV} = \sum_{t=1}^{T}\sum_{i=1}^{N} \mathbf{P_{sit} SP_t X_{sit}} + \sum_{t=1}^{T}\sum_{i=1}^{N} \mathbf{R_{sit} RP_t X_{sit}} \quad (25)$$

$$\mathrm{TC} = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{si}(P_{sit})X_{sit} + \sum_{i=1}^{N}\sum_{t=1}^{T} STX_{sit} \quad (26)$$

Table 7. Water discharge and water storage volume of proposed four hydro systems

| Hour (h) | Water Discharge ($* 10^4 m^3$) | | | | Volume ($* 10^4 m^3$) | | | |
|---|---|---|---|---|---|---|---|---|
| | Plant1 | Plant2 | Plant3 | Plant4 | Plant1 | Plant2 | Plant3 | Plant4 |
| 1 | 9.2661 | 6.5965 | 16.5344 | 13.7843 | 95.0000 | 73.1240 | 148.1030 | 100.6460 |
| 2 | 10.1344 | 9.1504 | 24.4233 | 7.5658 | 95.7339 | 74.5275 | 139.6686 | 89.6617 |
| 3 | 11.0221 | 11.3187 | 19.4287 | 6.3723 | 94.5995 | 73.3771 | 133.4453 | 90.4959 |
| 4 | 6.7322 | 7.5930 | 12.6037 | 8.2055 | 91.5774 | 71.0584 | 127.2827 | 91.7236 |
| 5 | 10.6081 | 10.3477 | 10.8560 | 16.5056 | 91.8452 | 72.4654 | 133.4099 | 89.5181 |
| 6 | 7.7901 | 11.4980 | 21.5373 | 7.0266 | 87.2371 | 70.1177 | 145.7264 | 89.5469 |
| 7 | 5.0474 | 6.2434 | 23.6008 | 10.3524 | 86.4470 | 65.6197 | 146.2400 | 106.9436 |
| 8 | 5.4013 | 12.8595 | 11.4094 | 11.6203 | 89.3996 | 65.3763 | 143.8403 | 116.0199 |
| 9 | 7.9115 | 7.4039 | 17.7914 | 14.8600 | 92.9983 | 60.0000 | 152.5687 | 117.0033 |
| 10 | 5.3099 | 7.3086 | 10.5845 | 20.0000 | 95.0868 | 60.5961 | 152.3227 | 112.9993 |
| 11 | 7.4438 | 7.0481 | 10.7343 | 16.1023 | 100.7769 | 62.2875 | 154.3829 | 114.5366 |
| 12 | 8.2709 | 9.9661 | 13.9669 | 11.3053 | 105.3331 | 64.2394 | 165.4196 | 122.0351 |

Table 8. Hydro and thermal generation of proposed four hydro and three thermal systems

| Hour (h) | Hydro power generation (MW) | | | | Thermal power generation (MW) | | |
|---|---|---|---|---|---|---|---|
| | Ph1 | Ph2 | Ph3 | Ph4 | Ps1 | Ps2 | Ps3 |
| 1 | 80.6029 | 48.8209 | 49.5679 | 196.0775 | 0 | 180.9585 | 193.9723 |
| 2 | 84.9812 | 64.7832 | 8.7413 | 121.4874 | 0 | 300.0070 | 200.000 |
| 3 | 88.0306 | 73.6649 | 34.8156 | 107.9399 | 0 | 195.5491 | 200.000 |
| 4 | 63.9788 | 53.7400 | 48.2077 | 131.1682 | 0 | 167.7481 | 185.1573 |
| 5 | 85.2782 | 69.0341 | 49.5267 | 201.3830 | 0 | 114.8701 | 149.9079 |
| 6 | 69.3507 | 71.9312 | 29.4099 | 114.9470 | 0 | 314.3612 | 200.000 |
| 7 | 49.2793 | 41.3463 | 17.2386 | 171.2905 | 0 | 400.000 | 200.00 |
| 8 | 53.1382 | 72.5986 | 52.6833 | 193.9123 | 0 | 400.00 | 200.00 |
| 9 | 72.2731 | 44.5552 | 47.5635 | 223.9454 | 198.4791 | 303.1836 | 200.00 |
| 10 | 54.0079 | 44.4421 | 53.8308 | 251.4321 | 0 | 400.00 | 200.00 |
| 11 | 71.7147 | 44.1282 | 54.4479 | 230.4271 | 0 | 400.00 | 200.00 |
| 12 | 78.3142 | 61.2104 | 57.8402 | 196.9564 | 223.0276 | 332.6512 | 200.00 |

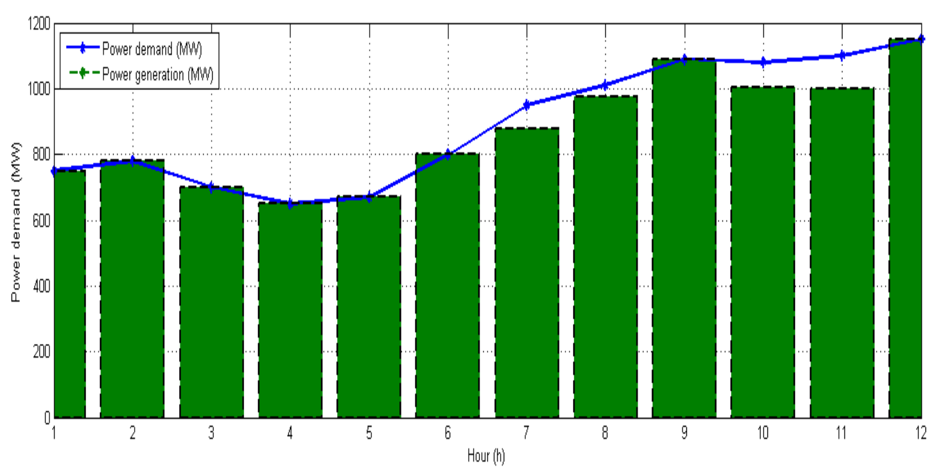


Fig. 3. Comparison of power generation and power demand of the Proposed test system (Case A)

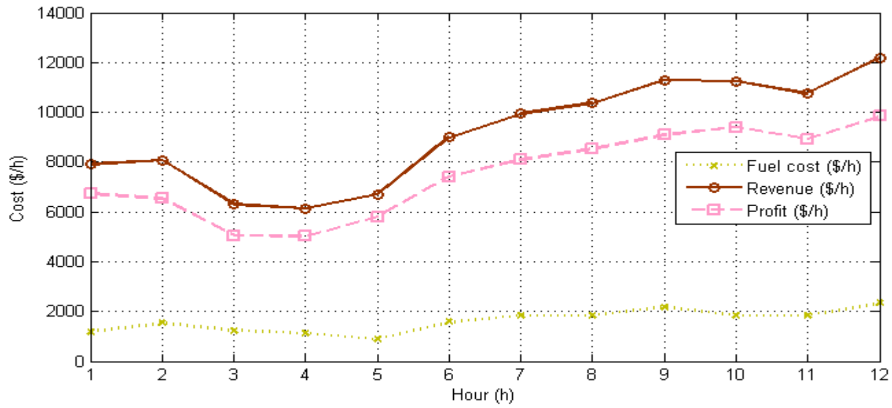


Fig. 4. Revenue, Fuel cost and Profit of the proposed test system (Case A)

Table 9. Simulation results of proposed four hydro and three thermal systems without reserve generation

| Hour (h) | Load demand (MW) | Total power generation (MW) | Revenue ($/h) | Fuel Cost ($/h) | Profit ($/h) | Emission (Tons/h) |
|---|---|---|---|---|---|---|
| 1 | 750 | 750.0000 | 7912.50 | 1186.35 | 6726.15 | 652.01 |
| 2 | 780 | 780.0000 | 8073.00 | 1536.02 | 6536.98 | 1132.51 |
| 3 | 700 | 700.0000 | 6300.00 | 1241.91 | 5058.09 | 716.10 |
| 4 | 650 | 650.0000 | 6142.50 | 1127.57 | 5014.93 | 584.70 |
| 5 | 670 | 670.0000 | 6700.00 | 898.20 | 5801.79 | 366.62 |
| 6 | 800 | 800.0000 | 9000.00 | 1578.14 | 7421.86 | 1216.00 |
| 7 | 950 | 879.1547 | 9934.44 | 1840.72 | 8093.71 | **1248.07** |
| 8 | 1010 | 973.3324 | 10365.99 | 1840.72 | 8525.26 | **1248.07** |
| 9 | 1090 | 1090.0000 | 11281.50 | 2178.85 | 9102.65 | 1317.13 |
| 10 | 1080 | 1003.7129 | 11241.58 | 1840.72 | 9400.85 | **1248.07** |
| 11 | 1100 | 1000.7179 | 10757.71 | 1840.72 | 8916.98 | **1248.07** |
| 12 | 1150 | 1150.0000 | 12190.00 | 2338.51 | 9851.49 | 1591.92 |
| **Total Profit ($)** | | | | **90450.76** | | **12569.30** |

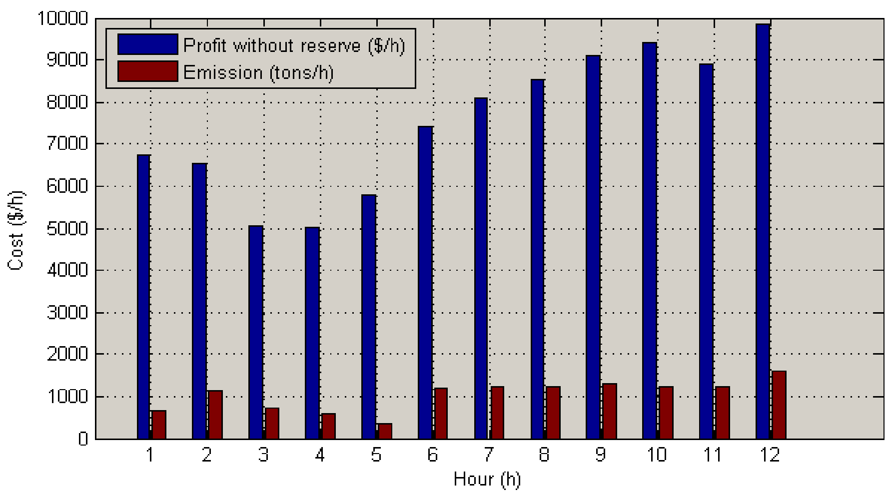


Fig. 5. Comparison of profit and emission level of the Proposed test system (Case A)

 

The proposed NSTLBO algorithm is tested on the sample system not only to maximize the profit of the system but also to minimize the emission at the same time. The best hydro discharge rate and storage volume of the proposed test system are shown in Table 7. The detailed optimal schedules of hydro and thermal power generations are given in Table 8. Fig. 3 elaborates the comparative studies of generated power are load demand of the proposed test system. The hourly revenue, fuel cost and profit are displayed in Fig. 4.

The simulation results test cases are presented in Table 9. This table summarizes the revenue, fuel cost profit and emission without considering the reserve power generation. Finally the profit and emission levels has been compared and graphically represented in Fig. 5.

### *Case-B: Multi-Objective STHTSS with Reserve Power Generation*

In this case, an attempt has been made to achieve more profit by considering the reserve power generation. In the reserve market operation, GENCOs profit can be calculated by energy price in the reserve market and the amount of reserve capacity allocated and hence actually been dispatched. From the literature reviews, it is learnt that the reserve allocation is usually ten percent of the forecasted load demand. In STHTSS problem, satisfying reserve demand is no longer an obligation of reserve generation. Table 10 demonstrates the power generation and reserve allocation of the proposed hydro thermal system in detail and graphically reported in Fig. 6.

Table 10. Hydro and thermal power with reserve generation of proposed four hydro and three thermal systems

| Hours (h) | Hydro power Generation (MW) | | | | Thermal power Generation (MW) | | | Reserve power Generation (MW) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Ph1 | Ph2 | Ph3 | Ph4 | Ps1 | Ps2 | Ps3 | R1 | R2 | R3 |
| 1 | 80.6029 | 48.8209 | 49.5679 | 196.0775 | 0 | 180.9585 | 193.9723 | 0 | 98.9723 | 6.0277 |
| 2 | 84.9812 | 64.7832 | 8.7413 | 121.4874 | 0 | 300.0070 | 200.00 | 0 | 78 | 0 |
| 3 | 88.0306 | 73.6649 | 34.8156 | 107.9399 | 0 | 195.5491 | 200.00 | 0 | 70 | 0 |
| 4 | 63.9788 | 53.7400 | 48.2077 | 131.1682 | 0 | 167.7481 | 185.1573 | 0 | 50.1573 | 14.8427 |
| 5 | 85.2782 | 69.0341 | 49.5267 | 201.3830 | 0 | 114.8701 | 149.9079 | 0 | 16.9097 | 50.0903 |
| 6 | 69.3507 | 71.9312 | 29.4099 | 114.9470 | 0 | 314.3612 | 200.00 | 0 | 80 | 0 |
| 7 | 49.2793 | 41.3463 | 17.2386 | 171.2905 | 0 | 400.00 | 200.00 | 0 | 0 | 0 |
| 8 | 53.1382 | 72.5986 | 52.6833 | 193.9123 | 0 | 400 | 200.00 | 0 | 0 | 0 |
| 9 | 72.2731 | 44.5552 | 47.5635 | 223.9454 | 198.4791 | 303.1836 | 200.00 | 49.5547 | 59.4453 | 0 |
| 10 | 54.0079 | 44.4421 | 53.8308 | 251.4321 | 0 | 400.00 | 200.00 | 0 | 0 | 0 |
| 11 | 71.7147 | 44.1282 | 54.4479 | 230.4271 | 197.4010 | 301.8811 | 200.00 | 50.0028 | 59.9973 | 0 |
| 12 | 78.3142 | 61.2104 | 57.8402 | 196.9564 | 223.0276 | 332.6512 | 200.00 | 52.281 | 62.7191 | 0 |

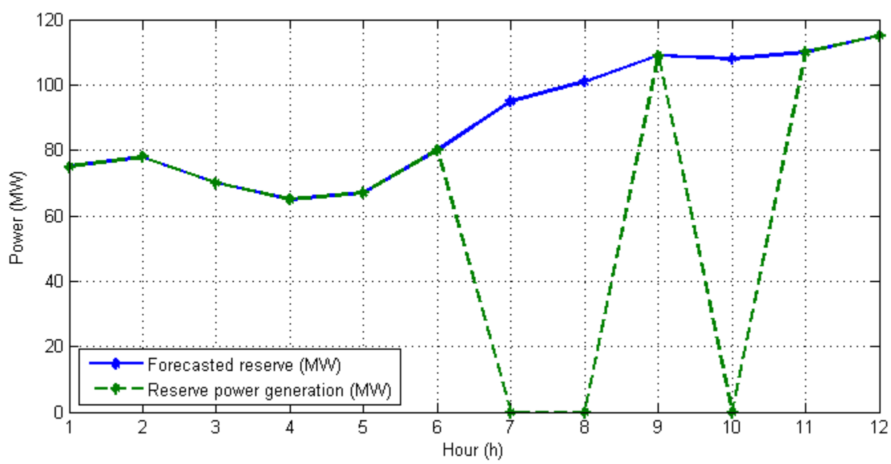


Fig. 6. Comparison of power generation and power demand of the Proposed test system (Case B)

 

Table 11. Simulation results of proposed four hydro and three thermal systems with reserve generation

| Hour (h) | Load demand (MW) | Total power generation (MW) | Forecasted Reserve (MW) | Total Reserve generation (MW) | Revenue ($/h) | Fuel Cost ($/h) | Profit ($/h) | Emission (Tons/h) |
|---|---|---|---|---|---|---|---|---|
| 1 | 750 | 750.0000 | 75 | 75 | 8703.75 | 1392.30 | 7311.45 | 897.46 |
| 2 | 780 | 780.0000 | 78 | 78 | 8880.30 | 1769.87 | 7110.43 | 1723.99 |
| 3 | 700 | 700.0000 | 70 | 70 | 6930.00 | 1436.59 | 5493.41 | 962.65 |
| 4 | 650 | 650.0000 | 65 | 65 | 6756.75 | 1303.02 | 5453.73 | 782.78 |
| 5 | 670 | 670.0000 | 67 | 67 | 7370.00 | 1071.73 | 6298.27 | 525.06 |
| 6 | 800 | 800.0000 | 80 | 80 | 9900.00 | 1820.44 | 8079.56 | 1908.92 |
| 7 | 950 | 879.1547 | 95 | 0 | 9934.44 | 1840.72 | 8093.71 | **1248.07** |
| 8 | 1010 | 973.3324 | 101 | 0 | 10365.99 | 1840.72 | 8525.26 | **1248.07** |
| 9 | 1090 | 1090.0000 | 109 | 109 | 12409.70 | 2504.31 | 9905.34 | 1943.03 |
| 10 | 1080 | 1003.7129 | 108 | 0 | 11241.58 | 1840.72 | 9400.85 | **1248.07** |
| 11 | 1100 | 1000.7179 | 110 | 110 | 13007.50 | 2500.10 | 10507.40 | 1933.14 |
| 12 | 1150 | 1150.0000 | 115 | 115 | 13409.00 | 2689.04 | 10720.00 | 2443.17 |
| **Total Profit ($)** | | | | | | | **96899.10** | **16864.40** |

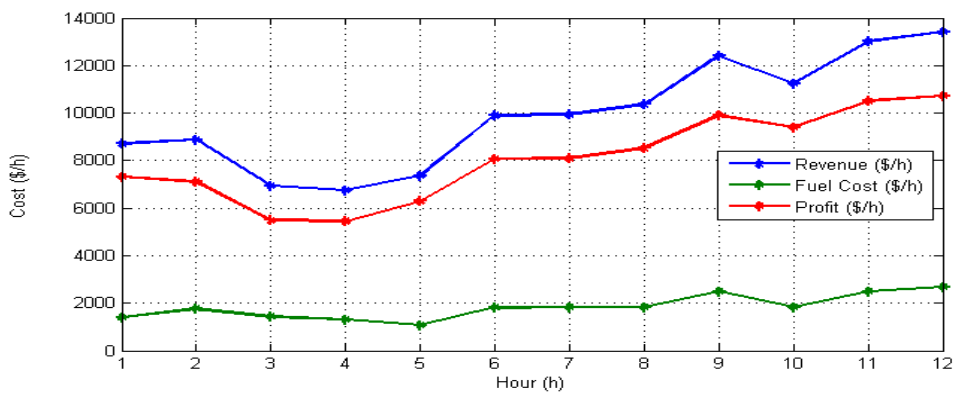


Fig. 7. Revenue, Fuel cost and Profit of the proposed test system (Case B)

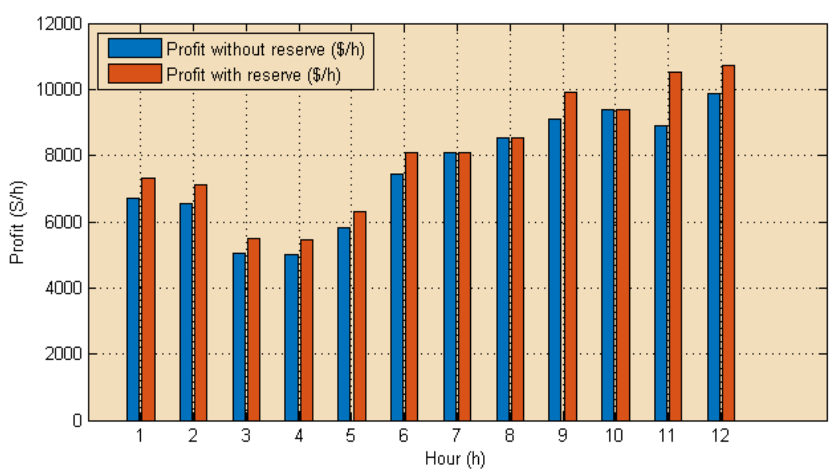


Fig. 8. Comparison of profit of Case A and Case B

 

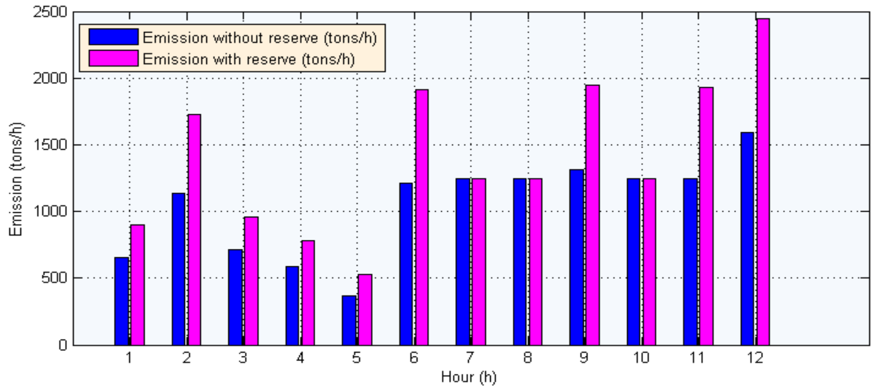


Fig. 9. Comparison of emission level of Case A and Case B

The simulation results of revenue, fuel cost, profit and emission level of GENCOs are represented in Table 11. The best profit of proposed test system is $ 96899.10 and minimum emission is 16864.40 tons. In Fig. 7 the revenue, total cost and profit of the GENCOs are displayed in a hourly schedule of the day-ahead energy market. A comprehensive comparison has been made to analyse the profit of the system with/without power generation which is seen in Fig. 8.

Moreover the emission levels of the system with and without reserve generations are presented in Fig. 9. From the results, it has been noticed that the proposed method significantly improves the profit and minimizes the emission level of the GENCOs with less computational time by considering reserve power generation.

## V. CONCLUSION

This paper projects a practical methodology for analysing the conflicting objectives of hydrothermal power producers in a day-ahead energy market. The approach is based on the multi-objective optimizational for simultaneously optimizing the expected profits and minimizing the total emission level in the presence of standard hydro and thermal constraints. Non-dominated sorting based teaching-learning optimization (NSTLBO) algorithm has been used to solve the multi-objective STHTSS problem.

The proposed NSTLBO algorithm identifies a set of non-dominated solutions which includes revenue, fuel cost, profit and emission level. The fuzzy model has also been employed to find the global best solution among the pareto parameters. The proposed method has been tested on four hydro and three thermal units with 12 hour scheduling period. The simulations has been carried out on the test system in order to evolve the water discharge and water storage volume, hydro and thermal power generation, reserve power allocation, revenue, fuel cost, profit and emission level by considering with/without reserve generation. From the results, it is observed that the proposed approach provides more profit, with minimized emission. Also the proposed approach may not impose any constraints on the number of objective function and its extension to include more objectives is a straightforward process.

## ACKNOWLEDGEMENT

The authors gratefully acknowledge the authorities of Annamalai University for the facilities offered to carry out this work.

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