# Optimal Scheduling of Hydrothermal System Considering Different Environmental Emissions Using NSTLBO Approach

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**Abstract-** In this paper, a simple and reliable approach of non-dominated sorting teaching learning based optimization (NSTLBO) algorithm has been adopted to determine the optimal solution for multi-objective short-term hydrothermal scheduling (STHTS) problem. The problem has been modeled in the form of multi-objective functions which includes fuel cost, transmission loss and environmental emissions such as Nitrogen oxides ($NO_x$), Sulphur oxides ($SO_x$) and Carbon dioxide ($CO_x$) with various constraints of hydrothermal systems. Added to that, the effect of valve-point loading process has also been considered. The introduction of the present NSTLBO algorithm is to decrease the cost of the fuel, transmission losses and different kinds of emissions. By applying this algorithm a set of non-dominated solutions are created. A fuzzy decision making approach has been applied in these solutions in order to identify the best comprise solution among the group of solutions. The practicability of the proposed approach has been demonstrated in a sample test system which consists of four hydro and six thermal units. The experimental finding of this method has been compared with that of well-established techniques in order to validate the performance of the test results. The results confirm that the NSTLBO approach delivers a reliable solution and competitive performance for solving Multi-objective short-term hydrothermal scheduling (MOSTHTS) problem combined with emission constraints.

**Keywords** Hydrothermal System; Emission; Fuel Cost; NSTLBO algorithm.

**Nomenclature**

| | |
|---|---|
| $F_1$ | Total operating cost |
| $F_2$ | $NO_x$ Emission |
| $F_3$ | $SO_x$ Emission |
| $F_4$ | $CO_x$ Emission |
| $F_5$ | Power loss |
| $Q_{hj}^{\min}, Q_{hj}^{\max}$ | Water discharge rate limits of j[th] hydro plant |
| $P_{sit}, P_{hjt}$ | Output of i[th] thermal plant and hydro plant at t[th] instant |
| $N_s$, $N_h$ | Number of thermal and hydro generators |
| $VPL$ | Valve-point loading effect |

| | |
|---|---|
| $a_{si}, b_{si}, c_{si}, d_{si}$ | Cost coefficients |
| $\alpha_{ni}, \beta_{ni}, \gamma_{ni}$ | Emission coefficients of $NO_x$ |
| $\alpha_{si}, \beta_{si}, \gamma_{si}$ | Emission coefficients of $SO_x$ |
| $\alpha_{ci}, \beta_{ci}, \gamma_{ci}$ | Emission coefficients of $CO_x$ |
| $B_{ij}, B_{0i}, B_{00}$ | B-loss coefficients |
| $P_{Lt}$ | Total transmission loss at t$^{th}$ interval |
| $C_{1j} - C_{6j}$ | Hydro power coefficients |
| $V_{Hjt}$ | Storage volume of j$^{th}$ reservoir |
| $Q_{Hjt}$ | Water discharge rate |
| $P_{si}^{\min}, P_{si}^{\max}$ | Minimum and maximum power limit of i$^{th}$ thermal unit |
| $P_{Hj}^{\min}, P_{Hj}^{\max}$ | Minimum and maximum power limit of j$^{th}$ hydro unit |
| $Q_{Hjt}$ | water discharge rate of j$^{th}$ hydro plant at time t |
| $V_{hj}^{\min}, V_{hj}^{\max}$ | Minimum and maximum reservoir volume of j$^{th}$ hydro plant |
| $I_{Hjt}$ | Natural inflow of the j$^{th}$ hydro unit at time t |
| $S_{Hjt}$ | Spillage discharge of the j$^{th}$ hydro unit at time t |
| $\tau_{mj}$ | Water transport delay from reservoir m to j |
| $R_{uj}$ | Number of upstream hydro plants immediately above the j$^{th}$ reservoir |
| $Q_{Hj,p}^{LB}, Q_{Hj,p}^{UB}$ | Lower/upper bounds of the p$^{th}$ prohibited zone of j$^{th}$ hydro unit |
| $n_j$ | Number of prohibited zones of hydro unit j$^{th}$ hydro plant |
| $P_{Dt}$ *and* $P_{Lt}$ | Load demand and power loss at t$^{th}$ instant |
| $UR_i$, $DR_i$ | Up/Down ramp rate limits of i$^{th}$ thermal unit |
| ALO | Ant lion optimization |
| DE | Differential evolution |
| ABC | Artificial bee colony |
| NSTLBO | Non-dominated sorting teaching learning based optimization |
| MOHTS | Multi-objective hydro-thermal scheduling |
| EP | Evolutionary programming |
| TLBO | Teaching learning based optimization |
| PSO | Particle swarm optimization |

## 1. Introduction

In recent years, numerous electric power plants are established in order to meet the ever growing power demand. The optimal generation scheduling of hydrothermal plants are considered to be the interesting subject and perceives much observation in the arena of power engineering. Short-term hydrothermal scheduling (STHTS) is a subject which effectively optimizes the generation scheduling of hydro and thermal plants to meet the load demand. The optimization process has to be well modeled in such a way that it should minimize the total operational cost with the consideration of system operational constraints of thermal and hydro plants are not match with each other. Hence by combining these two types of power plants for the generation purpose will give an economic, feasible solution. Being the running cost of hydropower plants is negligible, the prime objective of the STHTS is to minimize the fuel cost of thermal plants. Moreover, now the researchers are giving more attention to the atmospheric pollution and its harmful effects over the society. So, a well refined hydrothermal scheduling must be developed and it does not only affect the livelihood but also creates the global warming. Since the promulgation of the clean air amendment act, the subject of emission from the power plants occupies the think tank of power engineers [1-3].

In a hydrothermal system, the thermal units happened to be the sources for $CO_x$, $SO_x$, $NO_x$ which causes environmental pollutions [4]. Hence emission must also be considered while deriving the solution for the optimal operation of hydrothermal power system. When the emission products are included in the objective function, STHTS problem will become as multi-objective short-term hydrothermal scheduling problem (MOSTHTS). The MOSTHTS problem is difficult to solve, because of varying production cost, transmission losses, load forecasting error, and inaccuracies present in the information received from different sources [5]. Therefore it is inevitable to explore the possibility of a newer technique for the solution of STHTS problem.

The significance of generation scheduling problem in the hydrothermal integrated system is rightly accepted. Hence variety of classical methods has been proposed to solve the STHTS problem. The methods are Lambda-Gamma Iteration Method (LGM) [6], an Effective Conventional Method (ECM) based on Multiplier Theory [7], Dynamic Programming (DP) [8], Lagrange Relaxation (LR) Method [9], Decomposition and Coordination Method [10], Non-Linear Programming Method (NLP) [11], Progressive Optimality Algorithm [12], Fuzzy Decision Making (FDM) Approach [13, 14]. Lagrangian Relaxation method offers acceptable solution but mostly it suffers from convergence problem particularly when the problem is non-convex [15]. Even though DP and LR methods are popular in solving this kind of problem, the computational and dimensionality of the DP method increases rapidly for large scale system, which is not a preferable one. Normally, these classical methods may not work skillfully in evolving solution for STHTS problems [16].

Apart from the above methods, hydrothermal problem has been assessed by intelligent computational algorithms which produce non-dominated solution [17-21]. It includes Real Coded Genetic algorithm [17], Integrated Predator-Prey Optimization and Powell Search Method [18], Particle Swarm Optimisation [19], Artificial Bee Colony Algorithm [20], Differential Evolution [21]. These approaches always use the weighing parameter in this respective objective function and could not able to establish a true Pareto Optimal Front.

Besides all, other techniques such as Non-Dominated Sorting Genetic Algorithm-II [22, 23], Strength Pareto Evolutionary algorithm [24], Multi-Objective Particle Swarm optimisation [25], Multi-Objective Differential Evolution [26], Non-Dominated Sorting Disruption Based Gravitational Search Algorithm [27], Ant Lion Optimization Technique [28], MO Fuzzy Optimization model [29] and Lexicographic Optimization Technique [30] have been developed to overcome the hurdles of weighing parameter and to make a trade-off between the conflicting objectives.

All evolutionary and swarm intelligence based optimization algorithm needs to have control components like population size, a 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. From the literature reviews, it is understand that the applicability of NSTLBO has not yet been tested for the solution of MOSTHTS problem.

In this assignment, a distinct framework based on non-dominated sorting teaching learning based optimization (NSTLBO) algorithm has been proposed. The algorithm depends upon one or two tuning parameters, whereas the other algorithms have numerous control parameters. It has been modeled to solve the multi-objective STHTS problem in the day-ahead energy markets. The approach effectively allocates the expected total power generation among hydrothermal plants so as to minimise the expected production cost, $NO_x$ emission, $SO_x$ emission, $CO_x$ emission and losses of thermal plants while taking in to account of the constraints such as demand, availability of water constraints in hydro plants, the hydro and thermal power generation output limits over a scheduled time horizon. A numerical example with four hydro and six thermal units are considered to illustrate the performance of the NSTLBO approach and the simulation results are compared with other available methods.

## 2. Formulation of MOSTHTS Problem with Different Environmental Emissions

### *2.1. Multi-objective functions*

The emission constrained STHTS problem is modeled as a multi-objective optimization problem to perform the optimal power dispatch of hydrothermal plants. It is planned to minimize the five of the components mentioned in the objective functions.

$$Min\{F_1, F_2, F_3, F_4, F_5\}$$

Where, $F_1$ - Fuel cost of thermal plant; $F_2$ - $NO_x$ Emission function; $F_3$ - $SO_x$ Emission function; $F_4$ - $CO_x$ Emission function; $F_5$ - Transmission loss

Subject to operating constraints of hydro and thermal system.

The objective functions, like fuel cost with valve-point loading effect, different emissions such as $NO_x$, $SO_x$, $CO_x$, and power losses. The optimization is done with equality and inequality constraints of hydro and thermal plants.

#### *2.1.1. Minimization of fuel cost of thermal units*

The valve-point loading effect is defined by assigning a sinusoidal term in the quadratic cost function and are mathematically presented as [28],

$$f_{it}(P_{sit}) = \left\{ \begin{array}{l} a_{si} + b_{si}P_{sit} + c_{si}P_{sit}^2 + \\ \left| d_{si} \times Sin\left[ e_{si} \times \left( P_{si}^{\min} - P_{sit} \right) \right] \right| \end{array} \right\} \tag{1}$$

Where $f_{it}$ – Fuel cost of $i^{th}$ thermal plant at $t^{th}$ interval
$P_{sit}$ – Power generation of $i^{th}$ thermal plant at $t^{th}$ interval

From equation (1), the fuel cost function of the thermal units is found to be a non-smooth function of generated power. The objective is to minimize the total fuel cost of all thermal plants and is given by

$$F_1 = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_S} \left[ f_{it}\left(P_{sit}\right) \right] \right\} \tag{2}$$

#### *2.1.2. Minimization of $NO_x$, $SO_x$ and $CO_x$ emissions*

The $NO_x$, $SO_x$ and $CO_x$ are declared as functions and are included in the following quadratic equation.

$$F_2 = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_S} \left[ \alpha_{ni}P_{sit}^2 + \beta_{ni}P_{sit} + \gamma_{ni} \right] \right\} (Kg/h) \tag{3}$$

Where $\alpha_{ni}, \beta_{ni}, \gamma_{ni}$ - Emission coefficients of **$NO_x$**

$$F_3 = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_S} \left[ \alpha_{si}P_{sit}^2 + \beta_{si}P_{sit} + \gamma_{si} \right] \right\} (Kg/h) \tag{4}$$

Where $\alpha_{si}, \beta_{si}, \gamma_{si}$ - Emission coefficients of $SO_x$

$$F_4 = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_s} \left[ \alpha_{ci} P_{sit}^2 + \beta_{ci} P_{sit} + \gamma_{ci} \right] \right\} (Kg/h) \tag{5}$$

Where $\alpha_{ci}, \beta_{ci}, \gamma_{ci}$ - Emission coefficients of $CO_x$

*2.1.3. Minimization of power loss*

If the total number of units is $N_T = N_s + N_H$ and $P_{i1}$ represents the respective thermal and hydro generation, then the total transmission loss $P_{Lt}$ at $t^{th}$ interval can be calculated using B-loss coefficients.

$$F_5 = P_{Lt} = \sum_{i=1}^{T} \sum_{j=1}^{N_T} P_{it} B_{ij} P_{jt} + \sum_{i=1}^{N_T} B_{0i} P_{it} + B_{00} \tag{6}$$

*2.2. Equality and Inequality constraints of SHTS problem*

*(i) Power balance constraint*

$$\sum_{i=1}^{N_s} P_{sit} + \sum_{j=1}^{N_H} P_{Hjt} = P_{Dt} + P_{Lt} \tag{7}$$

The generation output $j^{th}$ hydro plant can be defined in terms of coefficients of hydropower as mentioned below. The storage volume of the $j^{th}$ reservoir is $V_{Hjt}$ and water discharge rate is $Q_{Hjt}$.

$$P_{Hjt} = C_{1j} \times V_{Hjt}^2 + C_{2j} \times Q_{Hjt}^2 + C_{3j} \times V_{Hjt} \times Q_{Hjt} + C_{4j} \times V_{Hjt} + C_{5j} \times Q_{Hjt} + C_{6j} \tag{8}$$

*(ii) Operating limits of hydro and thermal generating units*

$$P_{si}^{\min} \le P_{sit} \le P_{si}^{\max} \tag{9}$$

$$P_{Hj}^{\min} \le P_{Hjt} \le P_{Hj}^{\max} \tag{10}$$

*(iii) Time period coupling constraints of thermal units*

$$P_{sit} - P_{si(t-1)} \le UR_i \tag{11}$$

$$P_{si(t-1)} - P_{sit} \le DR_i \tag{12}$$

*(iv) Dynamic water balance equality constraints*

$$V_{Hjt} = V_{Hj,t-1} + I_{Hjt} - Q_{Hjt} - S_{Hjt} + \sum_{m=1}^{R_{uj}} \left( Q_{Hm,t-\tau_{mj}} + S_{Hm,t-\tau_{mj}} \right) \tag{13}$$

In $t^{th}$ time, the usual inflow from river to storage reservoir is $I_{Hjt}$ and spillage discharge outflow of the $j^{th}$ hydro plant is noted by $S_{Hjt}$.

*(v) Reservoir storage volume limit*

$$V_{Hj}^{\min} \le V_{Hjt} \le V_{Hj}^{\max} \tag{14}$$

*(vi) Water discharge rate limit*

$$Q_{Hj}^{\min} \le Q_{Hjt} \le Q_{Hj}^{\max} \tag{15}$$

## 3. Solution Methodology

*3.1. Overview of TLBO algorithm*

A unique optimization technique namely Teaching-Learning-Based Optimization algorithm (TLBO), which has been recently introduced in the reference [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 an interaction between class members, which helps to improve their grades. The method works on the principle of the process of teaching and learning.

Normally heuristic technique performs well over the classical mathematical models, but the quality of solutions is mostly dependent on the tuning of algorithmic parameters such as Variation operators (Mutation and recombination) and Selection operators (Parent Selection and Survivor selection). On the other side, the TLBO algorithm has been modeled with less number of parameters (two parameters) and the tuning effort is minimum when compared to other algorithms. It is a process based algorithm that operates on the effect of guidance of a teacher on the result of learners in a class. It is a dominant evolutionary algorithm that involves a population of students, where each and every student has been recognized as a potential solution to an optimization problem. It has the capacity of finding the global optimal solution for non-convex, non-linear problems with less computational effort and high reliability.

*3.2. Non-dominated sorting TLBO algorithm*

This algorithm presents an exceptional methodology for producing the Pareto optimal solutions for the multi-objective optimization problems namely (NSTLBO). The NSTLBO algorithm is a refurbished version of the TLBO algorithm [12]. The NSTLBO algorithm is an exclusive method for analyzing the 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 managing the multiple objectives 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 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 updating 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 a single objective optimization problem. But in multiple conflicting objectives, identifying the best solution from the set of solution is not an 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.

*3.2.1. 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.

$$X^{1}_{(i,j)} = X^{\min}_{j} + rand_{(i,j)} \times \left( X^{\max}_{j} - X^{\min}_{j} \right) \tag{16}$$

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

$$X^{g}_{i} = \left[ X^{g}_{(i,1)}, X^{g}_{(i,2)}, \ldots, X^{g}_{(i,j)}, \ldots, X^{g}_{(i,D)} \right] \tag{17}$$

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

$$\begin{bmatrix} Y_{a^{g}_{i}} \\ \hline Y_{b^{g}_{i}} \end{bmatrix} = \begin{bmatrix} f_a\left( X^{g}_{(i)} \right) \\ f_b\left( X^{g}_{(i)} \right) \end{bmatrix} \tag{18}$$

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

*3.2.2. 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

$$M^{g} = \begin{bmatrix} mean([X^{g}_{(1,1)}, \ldots, X^{g}_{(i,1)}, \ldots, X^{g}_{(N,1)}) \\ mean([X^{g}_{(1,j)}, \ldots, X^{g}_{(i,j)}, \ldots, X^{g}_{(N,j)}) \\ mean([X^{g}_{(1,D)}, \ldots, X^{g}_{(i,D)}, \ldots, X^{g}_{(N,D)}) \end{bmatrix}^{T} \tag{19}$$

then $M^{g} = \left[ m^{g}_{1}, m^{g}_{2}, \ldots, m^{g}_{j}, \ldots, m^{g}_{D} \right]$ (20)

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 an advanced set of improved learners.

$$X_{new^{g}_{(i)}} = X^{g}_{(i)} + rand^{g} \times \left( X^{g}_{Teacher} - T_F M^{g} \right) \tag{21}$$

Hence $T_F$ is the teaching factor in the process of iteration which may be either 1 or 2. The more skillful learners in the matrix $X_{new}$ displace the substandard learners in matrix S using the non-dominated sorting algorithm.

*3.2.3. Learner phase*

This phase is dedicated to an 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 expedites the sharing of knowledge. A particular learner $\left( X^{g}_{(i)} \right)$, and the other learner $\left( X^{g}_{(r)} \right)$ has been randomly chosen ($i \neq r$). Finally the $i^{th}$ vector of the matrix $X_{new}$ in the learner phase seems

$$X_{new^{g}_{(i)}} = \begin{Bmatrix} X^{g}_{(i)} + rand^{g}_{(i)} \times \left( X^{g}_{(i)} - X^{g}_{(r)} \right) if \left( Y^{g}_{i} \prec Y^{g}_{r} \right) \\ X^{g}_{(i)} + rand^{g}_{(i)} \times \left( X^{g}_{(r)} - X^{g}_{(i)} \right) otherwise \end{Bmatrix} \tag{22}$$

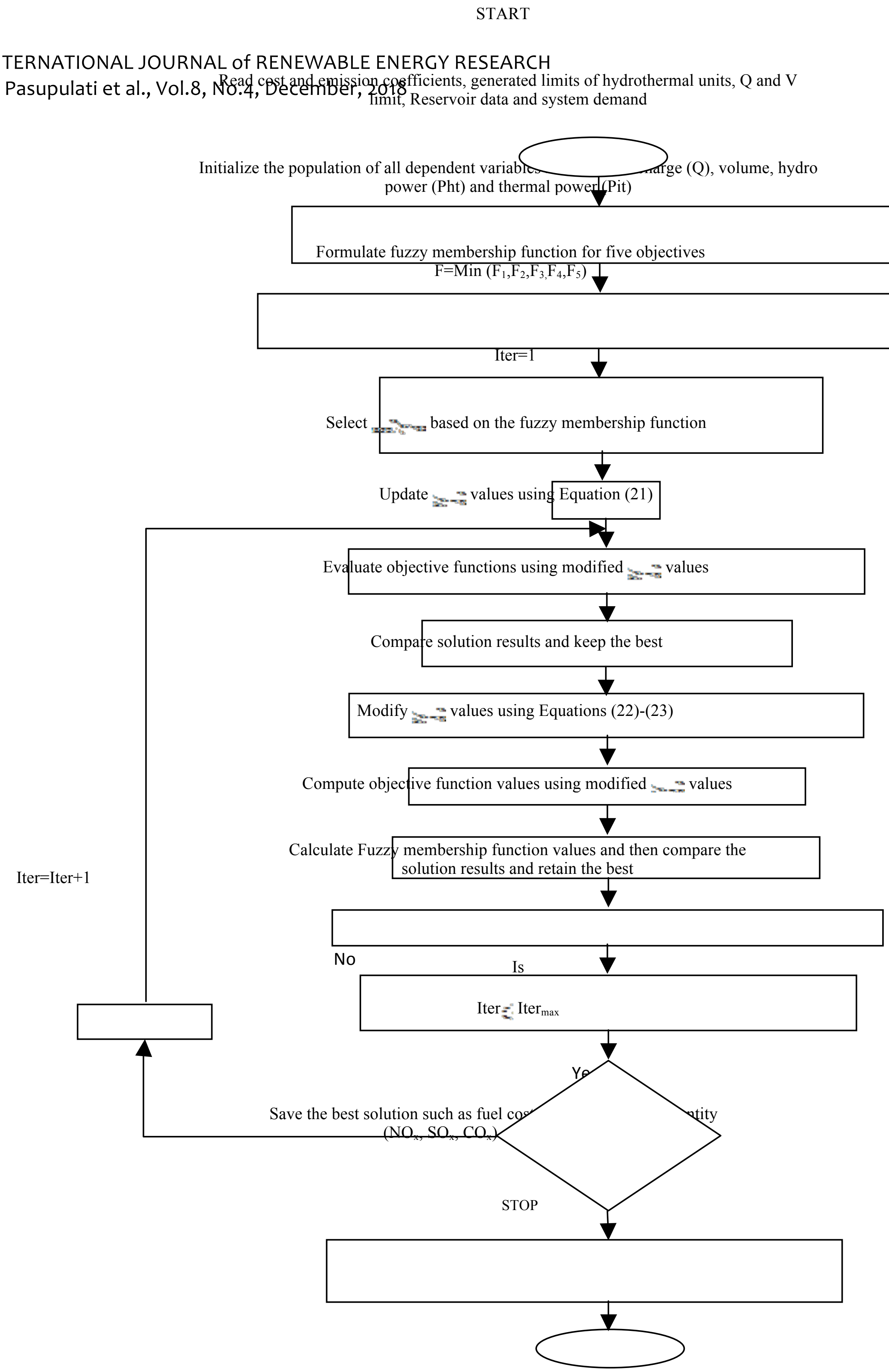


**Fig. 1.** Flow chart for the proposed method

In the 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

$$X_{new_{(i)}^{g}} = \begin{cases} X_{(i)}^{g} + rand_{(i)}^{g} \times \left( X_{(i)}^{g} - X_{(r)}^{g} \right) if \left( Y_{a_i^g} \prec Y_{a_r^g} \right) \\ X_{(i)}^{g} + rand_{(i)}^{g} \times \left( X_{(r)}^{g} - X_{(i)}^{g} \right) otherwise \end{cases} \tag{23}$$

$$X_{new_{(i)}^{g}} = \begin{cases} X_{(i)}^{g} + rand_{(i)}^{g} \times \left( X_{(i)}^{g} - X_{(r)}^{g} \right) if \left( Y_{b_i^g} \prec Y_{b_r^g} \right) \\ X_{(i)}^{g} + rand_{(i)}^{g} \times \left( X_{(r)}^{g} - X_{(i)}^{g} \right) otherwise \end{cases} \tag{24}$$

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

### *3.3. 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 at 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 the 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

$$\mu(j_g) = \begin{cases} 1 & j_g \le j_g^{\min} \\ \dfrac{j_g^{\max} - j_g}{j_g^{\max} - j_g^{\min}} & j_g^{\min} \le j_g \le j_g^{\max} (g = 1,2,\ldots,N_{ob}) \\ 0 & j_g \ge j_g^{\max} \end{cases} \tag{25}$$

Where $j_g^{\min}$ and $j_g^{\max}$ are the minimum and maximum values of objective function wherein 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.

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M_{nds}} \sum_{i=1}^{Nobj} \mu_i^k} \tag{26}$$

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

## 4. Numerical Results

This section, explains the numerical test system and simulation results of various emission constrained STHTS problem. A test system consists of a multi-chain cascade of four hydro units and six thermal units. The described scheduling period is chosen as one day with 24 intervals of 1 hour each. The system data of load demand, hydro unit coefficients, reservoir inflows and reservoir limits has been considered from the reference [30]. The diagrammed representation of the cascaded multi-chain hydro system is shown in Fig. 2. The thermal cost coefficients, different emission coefficients of $NO_x$, $SO_x$ and $CO_x$ are also adopted from the same literature [30]. A simulation has been performed on the test system in order to demonstrate the performance of the proposed algorithm.

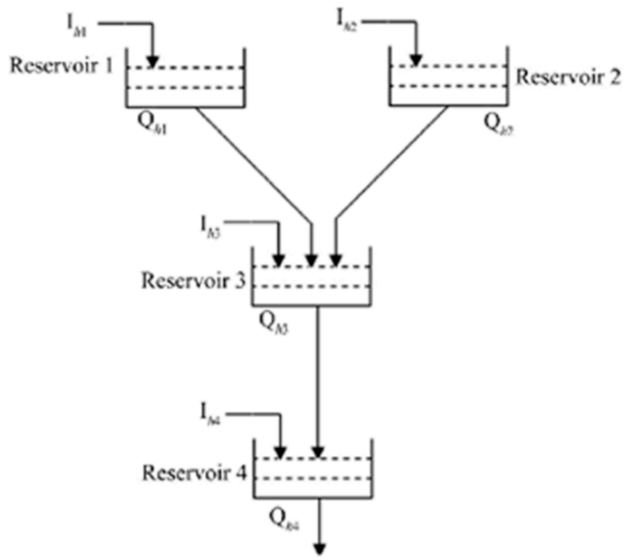


**Fig. 2.** Standard multi-chain four hydro System network [28]

The optimal values of control parameters of the proposed method were entertained by a parameter setting through trial and error method for the present test system. The proposed algorithm has only two control parameter like population size and the maximum number of iteration. The best value of these two parameters is 50 and 200 respectively. These parameter settings are helpful in arriving the global optimal solutions.

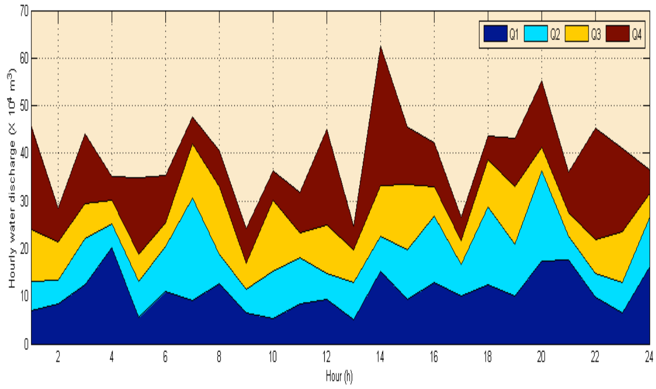


**Fig. 3.** Water discharge rate of four hydro six thermal test system

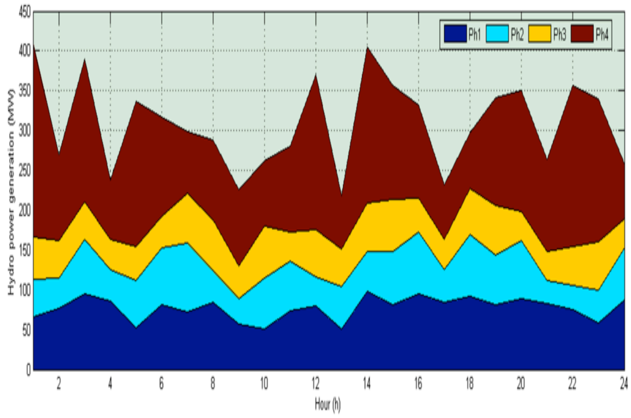


**Fig. 4.** Hydro power generation of four hydro six thermal test system

**Table 1.** Water discharge and hydro power generation of four hydro and six thermal test system

| Hour (h) | Hourly water discharge ($X10^4$ $m^3$) | | | | Hourly hydro power generation (MW) | | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $H_1$ | $H_2$ | $H_3$ | $H_4$ |
| 1 | 6.9000 | 6.3000 | 10.8000 | 21.8000 | 66.2000 | 46.7000 | 53.1000 | 241.8000 |
| 2 | 8.3000 | 5.0000 | 8.1000 | 7.1000 | 76.3000 | 38.5000 | 47.6000 | 107.0000 |
| 3 | 12.5000 | 9.5000 | 7.5000 | 14.7000 | 94.3000 | 68.7000 | 47.4000 | 180.0000 |
| 4 | 20.2000 | 5.0000 | 5.0000 | 5.0000 | 85.2000 | 40.1000 | 38.1000 | 74.4000 |
| 5 | 5.6000 | 7.5000 | 5.7000 | 16.2000 | 52.2000 | 60.0000 | 42.7000 | 181.6000 |
| 6 | 11.1000 | 9.4000 | 5.0000 | 9.9000 | 81.7000 | 71.0000 | 39.9000 | 124.8000 |
| 7 | 9.0000 | 21.7000 | 11.2000 | 5.8000 | 72.7000 | 86.1000 | 61.9000 | 78.4000 |
| 8 | 12.7000 | 6.1000 | 14.2000 | 7.5000 | 84.8000 | 39.0000 | 64.7000 | 99.4000 |
| 9 | 6.4000 | 5.0000 | 5.6000 | 7.2000 | 57.2000 | 31.8000 | 41.7000 | 94.6000 |
| 10 | 5.4000 | 9.9000 | 14.8000 | 6.2000 | 51.3000 | 63.6000 | 65.3000 | 82.1000 |
| 11 | 8.5000 | 9.7000 | 5.0000 | 8.5000 | 74.1000 | 61.8000 | 36.6000 | 108.6000 |
| 12 | 9.3000 | 5.5000 | 10.1000 | 20.2000 | 80.1000 | 36.7000 | 58.6000 | 194.6000 |
| 13 | 5.0000 | 7.9000 | 6.8000 | 5.0000 | 50.9000 | 53.7000 | 46.2000 | 67.8000 |
| 14 | 15.3000 | 7.3000 | 10.6000 | 29.4000 | 98.2000 | 50.3000 | 60.1000 | 196.4000 |
| 15 | 9.3000 | 10.4000 | 13.7000 | 12.2000 | 81.3000 | 67.6000 | 64.9000 | 143.4000 |
| 16 | 12.8000 | 14.1000 | 6.0000 | 9.3000 | 94.5000 | 78.5000 | 42.3000 | 117.5000 |
| 17 | 10.1000 | 6.6000 | 5.0000 | 5.0000 | 84.7000 | 41.4000 | 36.7000 | 68.6000 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 18 | 12.5000 | 16.3000 | 9.9000 | 5.0000 | 92.0000 | 76.8000 | 58.0000 | 70.7000 |
| 19 | 10.1000 | 10.8000 | 12.2000 | 10.1000 | 82.0000 | 61.3000 | 63.2000 | 135.3000 |
| 20 | 17.3000 | 18.9000 | 5.0000 | 14.0000 | 88.5000 | 73.4000 | 36.6000 | 151.8000 |
| 21 | 17.6000 | 5.0000 | 5.0000 | 8.4000 | 83.3000 | 28.5000 | 36.6000 | 115.3000 |
| 22 | 9.7000 | 5.0000 | 7.2000 | 23.3000 | 75.8000 | 30.0000 | 48.0000 | 202.9000 |
| 23 | 6.6000 | 6.4000 | 10.6000 | 17.5000 | 58.4000 | 41.7000 | 60.1000 | 179.0000 |
| 24 | 16.1000 | 10.4000 | 5.0000 | 5.0000 | 87.6000 | 65.8000 | 36.6000 | 67.8000 |

**Table 2.** Thermal power generation of four hydro six thermal test system

| **Hour (h)** | **Hourly thermal power generation (MW)** | | | | | |
|---|---|---|---|---|---|---|
| | $P_{s1}$ | $P_{s2}$ | $P_{s3}$ | $P_{s4}$ | $P_{s5}$ | $P_{s6}$ |
| 1 | 150.0000 | 306.2000 | 350.0000 | 177.0000 | 309.1000 | 170.0000 |
| 2 | 150.0000 | 332.6000 | 355.9000 | 252.9000 | 355.9000 | 173.3000 |
| 3 | 150.0000 | 307.4000 | 350.0000 | 180.4000 | 311.2000 | 170.0000 |
| 4 | 150.0000 | 322.1000 | 350.0000 | 222.8000 | 337.3000 | 170.0000 |
| 5 | 150.0000 | 322.4000 | 350.0000 | 223.5000 | 337.7000 | 170.0000 |
| 6 | 150.0000 | 329.1000 | 350.0000 | 242.8000 | 349.7000 | 171.0000 |
| 7 | 150.0000 | 336.4000 | 362.5000 | 263.7000 | 362.5000 | 175.7000 |
| 8 | 155.4000 | 343.3000 | 374.8000 | 283.6000 | 374.8000 | 180.2000 |
| 9 | 213.1000 | 373.6000 | 428.6000 | 370.9000 | 428.6000 | 199.9000 |
| 10 | 221.3000 | 378.0000 | 436.2000 | 383.3000 | 436.2000 | 202.7000 |
| 11 | 200.5000 | 367.0000 | 416.9000 | 351.9000 | 416.9000 | 195.6000 |
| 12 | 198.8000 | 366.1000 | 415.3000 | 349.4000 | 415.3000 | 195.0000 |
| 13 | 212.4000 | 373.3000 | 428.0000 | 369.9000 | 428.0000 | 199.7000 |
| 14 | 171.2000 | 351.6000 | 389.5000 | 307.6000 | 389.5000 | 185.6000 |
| 15 | 167.000 | 349.4000 | 385.6000 | 301.1000 | 385.6000 | 184.1000 |
| 16 | 160.2000 | 345.8000 | 379.3000 | 290.9000 | 379.3000 | 181.8000 |
| 17 | 190.9000 | 362.0000 | 407.9000 | 337.4000 | 407.9000 | 192.3000 |
| 18 | 180.3000 | 356.4000 | 398.0000 | 321.2000 | 398.0000 | 188.7000 |
| 19 | 190.9000 | 361.9000 | 407.9000 | 337.3000 | 407.9000 | 192.3000 |
| 20 | 196.9000 | 365.1000 | 413.5000 | 346.4000 | 413.5000 | 194.3000 |
| 21 | 205.7000 | 369.8000 | 421.8000 | 359.8000 | 421.8000 | 197.4000 |
| 22 | 165.2000 | 348.4000 | 383.9000 | 298.4000 | 383.9000 | 183.5000 |
| 23 | 150.000 | 314.8000 | 350.0000 | 201.7000 | 324.3000 | 170.0000 |
| 24 | 159.2000 | 345.3000 | 378.4000 | 289.4000 | 378.4000 | 181.5000 |

The proposed NSTLBO efficiently optimizes the system variables like water discharge, water storage volume, thermal power and transmission loss for the purpose of minimized fuel cost, limited emissions and lower transmission loss. The best optimized hydro water discharge rate and hydropower generation of the proposed test system are given in Table 1. In Fig. 3 it is revealed that each and every hydro plant has varying quantity of water discharge since because of optimized scheduling pattern. The individual power generation data of four hydro plants has been shown in Fig. 4. The tuned thermal power despatches of six thermal units are reported in Table 2. The optimal power generation of the individual thermal plants has been graphically demonstrated in Fig. 5.

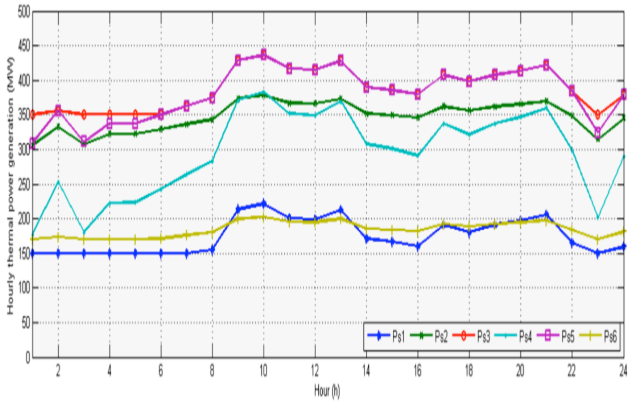


**Fig. 5.** Thermal power dispatch of four hydro six thermal test system

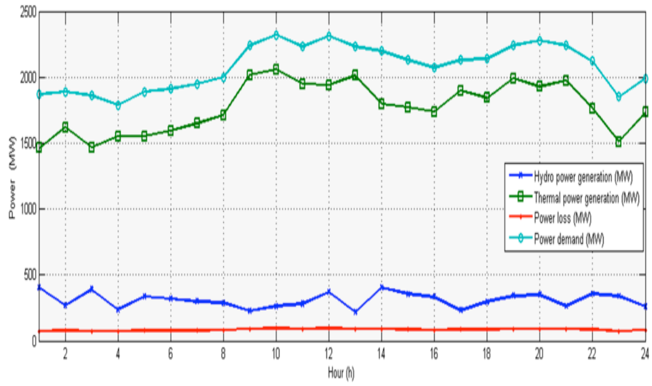


**Fig. 6.** Hydro power generation, thermal power generation, power loss and power demand of proposed test system

**Table 3.** Simulation results of four hydro and six thermal system with different emissions

| Hours (h) | Total Hydro power generation (MW) | Total Thermal power generation (MW) | Total Power loss (MW) | Load demand (MW) | Hours (h) | Total Hydro power generation (MW) | Total Thermal power generation (MW) | Total Power loss (MW) | Load demand (MW) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 407.8000 | 1462.2000 | 75.735 | 1870 | 13 | 218.7000 | 2011.3000 | 90.315 | 2230 |
| 2 | 269.4000 | 1620.6000 | 76.545 | 1890 | 14 | 405.0000 | 1795.0000 | 89.100 | 2200 |
| 3 | 391.1000 | 1468.9000 | 75.330 | 1860 | 15 | 357.2000 | 1772.8000 | 86.265 | 2130 |
| 4 | 237.8000 | 1552.2000 | 72.495 | 1790 | 16 | 332.8000 | 1737.2000 | 83.835 | 2070 |
| 5 | 336.4000 | 1553.6000 | 76.545 | 1890 | 17 | 231.4000 | 1898.6000 | 86.265 | 2130 |
| 6 | 317.4000 | 1592.6000 | 77.355 | 1910 | 18 | 297.5000 | 1842.5000 | 86.670 | 2140 |
| 7 | 299.1000 | 1650.9000 | 78.975 | 1950 | 19 | 341.8000 | 1989.2000 | 90.720 | 2240 |
| 8 | 287.9000 | 1712.1000 | 81.000 | 2000 | 20 | 350.3000 | 1929.7000 | 92.340 | 2280 |
| 9 | 225.4000 | 2014.6000 | 90.720 | 2240 | 21 | 263.8000 | 1976.2000 | 90.720 | 2240 |
| 10 | 262.3000 | 2057.7000 | 93.960 | 2320 | 22 | 356.7000 | 1763.3000 | 85.860 | 2120 |
| 11 | 281.2000 | 1948.8000 | 90.315 | 2230 | 23 | 339.3000 | 1510.7000 | 74.925 | 1850 |
| 12 | 370.0000 | 1940.0000 | 93.555 | 2310 | 24 | 257.8000 | 1732.2000 | 80.595 | 1990 |

| | |
|---|---|
| **Total cost ($)** | **412,440.00** |
| **Total Emission NOx (Kg)** | **47,925.000** |
| **Total Emission SOx (Kg)** | **485,680.00** |
| **Total Emission COx (Kg)** | **1204,500.0** |
| **Power Loss (MW)** | **485,680.00** |

**Table 4.** Comparison of fuel cost, power loss and different emissions proposed with existing methods

| **Methods** | **Fuel cost ($)** | **$NO_x$ Emission (Kg)** | **$SO_x$ Emission (Kg)** | **$CO_x$ Emission (Kg)** | **Power loss (MW)** |
|---|---|---|---|---|---|
| ALO | 417899.4444 | 52661.5986 | 322093.5748 | 1352441.9211 | 20236.0672 |
| DE | 419566.1611 | 52753.8837 | 320631.0452 | 1349639.4655 | 2036.3876 |
| ABC | 419949.1163 | 52737.0713 | 320932.5688 | 1348715.9193 | 2036.3442 |
| **NSTLBO (Proposed)** | **412,440.00** | **47,925.000** | **485,680.00** | **1204,500.000** | **485,680.00** |

A simulation has been performed for the proposed system for the time period of 24 hours and is shown in Table 3. This table clearly establishes the total hydro and thermal power generation, total transmission loss and demand for about 24 hours also the total amount of gaseous emission from the plant has also been reported. In order to show the overall performance of the proposed system a graph has been exhibited in Fig. 6, by considering the generation output of the hydro and thermal plants, the total power demand of the system with the transmission loss. In order to show the reliability and viability of the proposed method a comparison has been made in terms of fuel cost, different emissions and transmission loss with other optimization methods reported in literature and it is displayed in Table 4. From this data it is concluded that the proposed method delivers much better results than the existing algorithms.

## 5. Conclusion

The main focus of the work is to develop an intelligent tool using an NSTLBO algorithm to solve a multi-objective environmental emission constrained STHTS optimization problem. An idea of multi-objective functions of fuel cost, power loss and different environmental emissions such as NOx, SOx and COx are considered with hydrothermal scheduling problem and has been applied with NSTLBO algorithm. The numerical results of the NSTLBO algorithm prove the satisfactory performance of the constrained optimization problem. It deliberately handles the diverse set of solution. A comparison has also been made for proposed with existing benchmark methods. It indicates that the NSTLBO algorithm is better in terms of solution quality as well as computational time. From the contributions, the proposedNSTLBO has the ability to easily solve different types of Multi-objective power system optimization problems.

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