International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 12 (2018) pp. 10939-10947
© Research India Publications. http://www.ripublication.com

An Intelligent Soft Computing Technique for Optimal Power Dispatch of Hydrothermal Systems

Baburao Pasupulati [1*], Ashok Kumar R [2], Asokan K [3]

[1, 2, 3] Department of Electrical Engineering, Annamalai University,
Annamalai Nagar, Tamil Nadu, India.
(Corresponding Author: Pasupulati Baburao[*])

Abstract

The fundamental criteria of STHTS in an electric power system are to optimally regulate the power generation of hydrothermal units while addressing the standard system constraints. The scheduling interval can be a day or even few days. STHTS is a hypothetical non-linear, non-convex and non-smooth stochastic optimization problem. The classical technique may not work well, for this kind of problems. An ITLBO algorithm has been proposed in this paper to encounter such a complicated problem. The algorithm has been built based on three stages of training namely Teaching Phase, Learning Phase and Feedback phase. It is a unique optimization algorithm which does not require any algorithmic tuning parameters which increases the search space in arriving at the optimal solution. The proposed ITLBO algorithm is applied on a four hydro and three thermal test system and simulation results are compared with that of recent experimental results available in the literature.

Keywords: Hydrothermal Scheduling, Water Discharge, Hydro and Thermal Power Generation, Valve-Point Loading Effect, ITLBO.

INTRODUCTION

Short-term hydrothermal scheduling (STHTS) is the process in which the fuel cost of the thermal plant is minimised for the economical operation of hydrothermal systems. It involves hourly scheduling of hydro and thermal power plants in order to meet the prevailing load demand while taking into account the standard system constraints. The constraints of hydrothermal system include power balance, water balance, generation limits, reservoir capacity limits, water release limits and spinning reserve limits. In addition, the impact of valve-point loading on the operating cost of thermal plant is also analysed in this paper. Therefore, STHTS is a large scale, non-convex, non-linear and non-smooth optimization problem [1].

The hydrothermal scheduling process occupies the subject of matter in recent years. However, the problem is yet to be addressed in reaching the global optimal solution. Some of the optimization methods, like Dynamic Programming (DP) [2], Lagrangian Relaxation (LR) [3,7], Mixed-Integer Programming (MIP) [4], Benders Decomposition [5], Newton’s method [6,9], Non-Linear Programming (NLP) [8]. The Dynamic Programming method has been widely used among these techniques. Although the Dynamic Programming is capable of handling the subjects of scheduling problem, it is being suffered from the burden of dimensionality and increasing system size. Hence the method lacks behind large memory storage problem and extended computational time. Because of this reasons, the solutions are ended up with suboptimal solutions for a non-linear problem. Newton’s method has been mathematically viable and efficient in solving non-linear problems. Therefore it has a high regard in evolving solution for the optimization problem. Even though it is based on the constitution of jaccobian matrix, it encounters complication in reaching the solutions for large scale problem. Linear programming is only suitable for the problems, which have linear objective function and constraints. The non-linear programming method, lags from the problem of slow convergence and needs large memory space.

With the advent of evolutionary computation techniques, awareness has been turned towards the application of such techniques in handling the complicated Non-Linear problems. Stochastic search algorithm such as Simulated Annealing (SA) [10], Genetic Algorithm (GA) [11,12], Particle Swarm Optimization (PSO) [13], Improved PSO(IPSO) [14], Evolutionary Programming (EP) [15,16], Differential Evolution (DE) [17], Modified Differential Evolution (MDE) [18], Cuckoo Search Algorithm [19] and Teaching learning based optimization (TLBO) [20] have been suggested for the solution of optimal hydrothermal scheduling problem.

Although many optimization techniques were developed by researchers, the non-linear nature of this problem necessitates the development of an efficient algorithm for the solution of optimal scheduling. A simple methodology of Improved Teaching Learning Based Optimization (ITLBO) algorithm is proposed for solving the optimization problem of STHTS with a view to obtain global optimal solution, best computational effort and high reliability. The suggested technique is devised to minimize the total thermal generation cost of thermal units subjected to power balance, spinning reserve, generation limit, minimum up and down time, water discharge and water storage volume constraints.

The organization of the paper is as follows: Section 2 represents the mathematical formulation of STHTS problem. Section 3 describes the proposed approach and with a short description of the algorithm implemented on the test system. Section 4 depicts the numerical results and discussions. Finally the conclusion has been drawn in section 5.

PROBLEM FORMULATION

A. Problem Formulation

The main objective of STHTS is to ascertain the optimal generation scheduling of hydro and thermal units with a view to minimizing the total operation cost of the thermal plants while satisfying the system constraints. Hydrothermal power plants comprise of several units which has been modeled as an equivalent unit with cost characteristics as shown in Figure. 1.

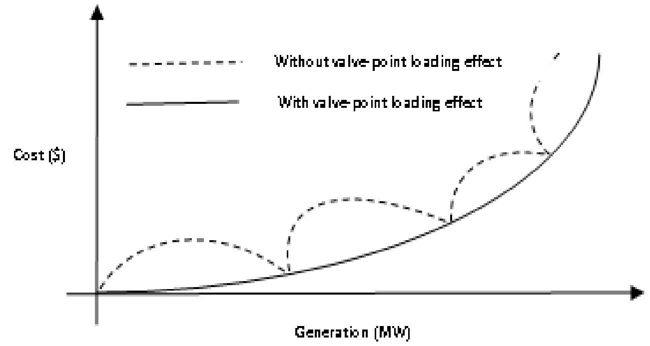

Figure. 1. Cost characteristics of generating unit

$$F_i(P_{it}) = a_i P_{sit}^2 + b_i P_{sit} + c_i \qquad (1)$$

Practically, thermal power plants may have multiple steam admitting values. In order to have a perfect model, it is essential to include the effect of valve-point effect on the fuel cost parameter.

$$F_i(P_{it}) = \begin{Bmatrix} a_i P_{sit}^2 + b_i P_{sit} + c_i \\ + \left| d_i \ \times \mathrm{Sin}\left[e_i \times \left(P_{sit}^{min} - P_{sit} \right) \right] \right| \end{Bmatrix} \qquad (2)$$

From equation (2), the fuel cost of thermal units is found to be non-smooth characteristics of the generated power.

The objective of STHTS is to minimise the total fuel cost (TC) of the thermal plants and it is modelled by the following equation.

$$\min TC = \sum_{t=1}^{T} \sum_{i=1}^{N} \begin{matrix} a_i P_{sit}^2 + b_i P_{sit} + \\ c_i + \left| d_i \ \times \mathrm{Sin}\left[e_i \times \left(P_{sit}^{min} - P_{sit} \right) \right] \right| \end{matrix} \qquad (3)$$

B. System and Unit Constraints

The primary system and unit constraints of STHTS problem includes power balance, thermal generation limits, hydro generation limits, spinning reserve, water balance and water storage volume. It can be mathematically expressed as

a. Power balance constraints

$$\sum_{i=1}^{N} P_{sit} + \sum_{j=1}^{M} P_{hjt} - P_{D_t} - P_{Loss_t} = 0 \qquad (4)$$

The output of hydro power plant mainly depends upon the water discharge and volume of the reservoir. Hence it can be expressed as a quadratic equation.

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

b. Thermal generation limits

$$P_{si}^{min} \le P_{sit} \le P_{si}^{max} \qquad (6)$$

c. Hydro generation limits

$$P_{hj}^{min} \le P_{hjt} \le P_{hj}^{max} \qquad (7)$$

d. Spinning reserve constraints

$$\sum_{i=1}^{N} P_{sit} X_{sit} \le SR_t \qquad (8)$$

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

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

e. Water discharge constraints

$$Q_{hj}^{min} \le Q_{hjt} \le Q_{hj}^{max} \qquad (9)$$

f. Storage volume constraints

$$V_{hj}^{max} \le V_{hjt} \le V_{hj}^{max} \qquad (10)$$

SOLUTION METHODOLOGY

A. TLBO Algorithm

The TLBO algorithm is an optimization technique based on the teaching learning process, introduced by Rao et al. [20-23] which does not require any algorithmic parameters. The algorithm has been organised on the basis of impact of guidance of a teacher on the learners in a class room. The productivity of individuals is weighed by the way of results or grades. The teacher is usually treated as a highly qualified and learned person who imparts his or her expertise to the learners in that class. Moreover, there is a chance for learners to educate from interaction among themselves, which also helps in improving their results.

The algorithm prescribes two basic methods of learning, by the direction of teacher (recognised as teacher phase) and by exchanging the knowledge with other learners (recognised as learner phase). It is a population based optimization algorithm where a group of learners has been considered as a population and certain subjects imparted to the learners are equivalent to the design variables in the optimization problem. The outcome of the learner is assigned to the fitness value of the problem. The finest solution in the absolute population has been graded as the teacher.

a. Teacher Phase

This aspect is the basic component of the algorithm, where in the students enriches their expertise from the guidance of the teacher who is the most intelligent person in the class room environment and whose responsibility is to activate the students to reach their objective. During this course, the teacher makes an attempt to enhance the subject mean performance of the learner based on their capacity.

At the instant of iteration G, let the quantity of subjects is D, the count of learners (population size, k = 1,2,...NP) is NP, then $\text{mean}_{j,g}$ indicates the mean outcome of learners in that subject “j” (j =1,2,...D).

It has been assumed that the teacher is an intelligent and experienced man on the subject, then the teacher is designated as the best learner in the total population. Let $X_{\text{total-kbest},G}$ be the result of the finest learner of the entire subjects and who is identified as the teacher with regard to that sequence. The difference obtained from the result of the teacher and the mean result of the learners in every subject is furnished by the equation.

$$\text{Difference}_{\text{mean}_{j,G}} = \text{rand}\left(X_{j,\text{kbest},G} - T_F \text{Mean}_{j,G}\right) \quad (11)$$

Where X_{total} derives the best learner in the subject j, rand is a random in the magnitude (0, 1) and T_F will be the teaching factor which identifies the average to be qualified. The condition of T_F is randomly resolved by the equation.

$$T_F = \text{round}(1 + \text{rand}(0,1)) \quad (12)$$

The solution of the above equation can be modified by the following equation.

$$X_{j,k,G}^{\text{new}} = X_{j,k,G} + \text{Difference\_mean}_{j,G} \quad (13)$$

It is noticed that the values of random number (rand) and teaching factor T_F influence the performance of TLBO algorithm. However, the values of (rand) and T_F are generated arbitrally in the algorithm and these parameters are not used as input to the algorithm. Hence the tuning of (rand) and T_F is not mandatory in the TLBO algorithm.

b. Learner Phase

A student can also learn by interacting with other members in the domain. So the process of learning from the counterparts of their class is known as learner phase. It is another part of the algorithm, wherein the learners enrich their intelligence by exchanging ideas among them. Then every student arbitrarily selects another student for interaction and acquires new ideas from him if that student has better knowledge than him. The learning process has been expressed by the following equation (14) & (15).

Two learners $X_{j,p,G}$,$X_{j,Q,G}$ are randomly selected, such that

$$X_{j,P,G}^{\text{new}} = X_{j,p,G} + \text{rand}\left(X_{j,p,G} - X_{j,Q,G}\right) \text{ If}\left(X_{j,P,G}\right) < f(X_{j,Q,G}) \quad (14)$$

$$X_{j,P,G}^{\text{new}} = X_{j,p,G} + \text{rand}(X_{j,Q,G} - X_{j,P,G})\text{iff}\left(X_{j,Q,G}\right) < f(X_{j,P,G}) \quad (15)$$

$X_{j,P,G}^{\text{new}}$ is considered if it explores the best result.

B. Improved TLBO Algorithm

In the fundamental TLBO algorithm, the teacher educates the learners and attempts to increase the mean result of the class. In this practice of teaching learning, the activities of teacher are scattered and students admits lesser reciprocation which will scale down the capacity of learning. Besides, if the class has a larger group of inferior students, then the teacher has to pay more attention in increasing their output. Despite this exercise, there may not be any progress in the results. When this kind of exercise is applied on the optimization algorithm, it requires a numerous assessments to have optimum solution and yields imperfect converging point. In order to overcome this problem, the fundamental TLBO algorithm is enhanced by introducing the feedback phase. In this, a poorly performing student is randomly selected in the feedback phase and is made to discuss with the teacher directly. This phase thus decreases the search area, leads to a fine search and improves the speed and accuracy of the search [24-26].This phase is expressed by Eqs. (16) and (17).

Two learners $X_{j,R,G}, X_{j,S,G}$ are randomly selected, such that $X_{j,R,G} \neq X_{j,S,G}$

$$X_{j,R,G}^{\text{new}} = X_{j,R,G} + \text{rand}\left(X_{j,\text{kbest},G} - X_{j,S,G}\right)\text{iff}\left(X_{j,R,G}\right) < f\left(X_{j,S,G}\right) \quad (16)$$

$$X_{j,R,G}^{\text{new}} = X_{j,R,G} + \text{rand}(X_{j,\text{kbest},G} - X_{j,R,G})\text{if f}\left(X_{j,S,G}\right) < f(X_{j,R,G}) \quad (17)$$

$X_{j,R,G}^{\text{new}}$ is accepted if it gives the superior result.

SOLUTION OF STHTS PROBLEM USING ITLBO ALGORITHM

The technical steps of the proposed algorithm are as follows

A. Evaluation and selection of STHTS Variables

Step 1: Read the data of hydrothermal system.

Step 2: Initialize the proposed ITLBO algorithmic parameters such as population size NP, maximum number of generation G, number of design variables D, limits of design variables (L, U), scaling factor F, probability of the crossover rate CR.

Step 3: Randomly initialize the population of all dependent variables like water discharge rate and thermal plant generation outputs.

$$Q(j,t) = \text{rand}(Qj^{\min} - Qj^{\max}) \quad (18)$$

$$P(i,t) = \text{rand}(Pi^{\min} - Pi^{\max}) \quad (19)$$

Step 4: Determine water discharge rate for the last interval of time while satisfying the initial and final reservoir constraints using the following equation.

$$Q_{j,T} = V_j^{\text{begin}} - V_j^{\text{end}} - \sum_{j=1}^{T-1} Q_{j,t} + \sum_{j=1}^{T} I_{j,t} + \sum_{k=1}^{Ru_i} \sum_{j=1}^{T}\left(Q_{kj-Td_{k,i}}\right) \quad (20)$$

Step 5: Check the water discharge for its minimum and maximum limits. If it is less than the minimum limits it is made equal to its minimum value and if it is greater than maximum limit it is made equal to maximum limit.

Step 6: Compute the reservoir water storage volume of j^{th} hydro plant for t^{th} time interval using equation.

$$V_{hj0} - V_{hjT} = \sum_{t=1}^{T} \sum_{l=1}^{R_{uj}} Q_{hl(t-t1j)} - \sum_{t=1}^{T} I_{hjt}, j \in N_h \quad (21)$$

Step 7: Check for the operating limits of water storage volume.

$$V_{j,t} = V_j^{\min} \qquad \text{if } V_{j,t} < V_j^{\min} \quad (22)$$

$$V_{j,t} = V_j^{\max} \qquad \text{if } V_{j,t} > V_j^{\max} \quad (23)$$

Step 8: Estimate the hydro power generation of jth hydro plant for tth time interval using equation (5).

Step 9: Check it for its minimum and maximum limits.

$$\mathrm{Ph}_{j,t} = \mathrm{Ph}_j \min \qquad \text{if } \mathrm{Ph}_{j,t} < \mathrm{Ph}_j^{\min} \qquad (24)$$

$$\mathrm{Ph}_{j,t} = \mathrm{Ph}_j^{\max} \qquad \text{if } \mathrm{Ph}_{j,t} > \mathrm{Ph}_j^{\max} \qquad (25)$$

Step 10: The thermal generation of plant can be estimated using equation (26) by subtracting hydro generation from the power demand by neglecting transmission losses.

$$\sum_{i=1}^{N} P_{sit} + \sum_{j=1}^{M} P_{hjt} - P_{D_t} - P_{Loss_t} = 0 \qquad (26)$$

Step 11: Check the inequality constraints of thermal power, if it is less than minimum limits it is made equal to its minimum value and if it is greater than maximum limit it is made equal to maximum limit.

B. Implementation of ITLBO algorithm

Step 12: Generates initial population of ith Student

$$P = \left[P_{s1}, P_{s2}, \dots, P_{si}, \dots, P_{sN_s}, Q_{h1}, Q_{h2}, \dots, Q_{hj}, \dots, Q_{hN_h}\right]^T \qquad (27)$$

Where

$$P_{si1} = [P_{si1}, P_{si2}, \dots, P_{sit}, \dots, P_{siT}] \qquad (28)$$

$$Q_{hj1} = [Q_{hj1}, Q_{hj2}, \dots, Q_{hjt}, \dots, Q_{hjT}] \qquad (29)$$

Step 13: Determine the mean of the population which will give the mean marks of all subjects of the students.

Step 14: Identify the best solution that acts as the best teacher for that cycle and the mean result of the learners has been obtained.

Step 15: The learners' knowledge is updated with the help of teacher using equation (13).

Step 16: The learners' knowledge is updated through the knowledge of some other learners using equation (14) and (15).

Step 17: The learners' knowledge is updated through the feedback phase using equation (16) and (17).

Step 18: Evaluate the objective function (minimum thermal fuel cost) with these updated values in feedback phase.

Step 19: Save the new solution if it gives the better value of objective function.

Step 20: Stop if maximum number of generation is reached, else go to step 12.

SIMULATION RESULTS

The proposed ITLBO algorithm is applied on a standard IEEE test system in order to evaluate its performance in solving the short-term hydrothermal scheduling problem with valve-point loading effect. The numerical results were used to assess the performance of the proposed methods with that of the similar algorithms. The prescribed algorithm has been experimented in matlab 14.0 platform on i3 processor, 2.40 GHz and 4 GB RAM system. The solution has been evolved in terms of individual plants of hydro and thermal power generation by considering valve-point loading effect.

A. Test system

In this test system consists of four hydro plants and three thermal units. The model diagram of multi-chain hydraulic system network is shown in Figure. 2.

The characteristic of the hydel power plant is described by considering the reservoir storage limits, plant discharge limits, generation limits and the initial and final station of reservoir. The corresponding data is shown in Table A1. Table A2 and Table A3 provide power generation coefficients of hydro generation units and thermal plants. Hour-by-hour load demand of power system is provided in Table A4.

Table A1 Reservoir Storage Capacity Limits, Plant Discharge Limits, Plant Generation Limits And Reservoir Initial And End Conditions of Four Hydro Plants And Three Thermal Plants

Plant	$V_{hj,min}$	$V_{hj,max}$	$V_{hj,initial}$	$V_{hj,end}$	$Q_{hj,min}$	$Q_{hj,max}$	$Q_{hj,initial}$	$Q_{hj,end}$
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	25	0	500

Table A2 Power Generation Coefficients for Hydro Plants of Four Hydro Plants and Three Thermal Plants

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 A3 Power Generation Coefficients for Thermal Plants of Four Hydro Plants and Three Thermal Plants

Plant	a_i	b_i	c_i	d_i	e_i	$P_{si,min}$	$P_{si,max}$
1	0.0012	2.45	100	160	0.038	20	175
2	0.0010	2.32	120	180	0.037	40	300
3	0.0015	2.10	150	200	0.035	50	500

Table A4 Load Demands Hydrothermal System Consisting of Four Hydro Plants and Three Thermal Plants

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

Table 1 Simulation Results for STHTS Problem with Valve-Point Loading Effect

Hour(h)	**Hydro Power Gen. (MW)**				**Total Hydro Power Gen. (MW)**	**Thermal Power Gen. (MW)**			**Total Thermal Power Gen. (MW)**	**Power Demand (MW)**
	Ph 1	**Ph 2**	**Ph 3**	**Ph 4**		**Ps 1**	**Ps 2**	**Ps 3**		
1	80.6029	48.8209	49.5679	196.0775	375.0692	0	180.9584	193.9724	374.9308	750
2	84.9812	64.7832	8.74130	121.4874	279.9930	0	256.0042	244.0028	500.0070	780
3	88.0306	73.6649	34.8156	107.9399	304.4509	0	193.3292	202.2199	395.5491	700
4	63.9788	53.7400	48.2077	131.1682	297.0946	0	167.7431	185.1622	352.9054	650
5	85.2782	69.0341	49.5267	201.3830	405.2219	0	114.8669	149.9112	264.7781	670
6	69.3507	71.9312	29.4099	114.9470	285.6388	0	264.6167	249.7445	514.3612	800
7	49.2793	41.3463	17.2386	171.2905	279.1547	163.0596	260.6714	247.1143	670.8453	950
8	53.1382	72.5986	52.6833	193.9123	372.3324	152.0004	247.4001	238.2671	637.6676	1010
9	72.2731	44.5552	47.5635	223.9454	388.3373	173.3319	272.9984	255.3323	701.6627	1090
10	54.0079	44.4421	53.8308	251.4321	403.7130	164.8735	262.8482	248.5654	676.2870	1080
11	71.7147	44.1282	54.4479	230.4271	400.7179	172.5384	272.0463	254.6975	699.2821	1100
12	78.3142	61.2104	57.8402	196.9564	394.3212	175.0000	300.0000	280.6788	755.6788	1150
13	81.2938	37.3048	57.1879	228.9992	404.7857	174.5144	274.4197	256.2802	705.2143	1110
14	54.0996	39.3635	58.7309	213.0480	365.2420	161.0304	258.2365	245.4910	664.7580	1030
15	73.5568	52.0439	59.6800	228.6014	413.8822	138.1503	230.7805	227.1870	596.1178	1010
16	58.9615	71.9992	41.4446	254.5693	426.9745	150.4530	245.5435	237.0290	633.0255	1060
17	91.1722	38.9118	56.7052	219.2151	406.0044	154.1096	249.9316	239.9544	643.9956	1050
18	96.4832	72.2318	56.5483	212.7243	437.9875	166.7819	265.1384	250.0922	682.0123	1120
19	59.2423	35.6000	28.2090	203.5228	326.5741	175.0000	297.0553	271.3706	743.4259	1070
20	68.5559	46.4474	59.9270	151.0993	326.0296	175.0000	285.3822	263.5882	723.9704	1050
21	107.6454	36.6465	0	204.4030	348.6950	126.5461	216.8553	271.9036	561.3050	910
22	61.7847	53.6606	59.5503	209.7353	384.7308	97.8675	182.4408	194.9609	475.2692	860
23	82.6178	51.9851	27.5734	273.7175	435.8938	77.4799	157.9758	178.6505	414.1062	850
24	98.5540	46.5119	0	188.7344	333.8004	0	0	466.1996	466.1996	800
Total Fuel Cost									43,317.00	

Table 2 optimal hydro discharge ($\times 10^4 m^3$), reservoir storage volume ($\times 10^4 m^3$) of hydrothermal system

Hour (h)	Water Discharge ($\times 10^4 m^3$)				Reservoir Storage Volume ($\times 10^4 m^3$)			
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3	Plant 4
1	9.26610	6.59650	16.5344	13.7843	95.0000	73.1240	148.103	100.646
2	10.1344	9.15040	24.4233	7.5658	95.7339	74.5275	139.668	89.6617
3	11.0221	11.3187	19.4287	6.3723	94.5995	73.3771	133.445	90.4959
4	6.73220	7.59300	12.6037	8.2055	91.5774	71.0584	127.282	91.7236
5	10.6081	10.3477	10.8560	16.5056	91.8452	72.4654	133.409	89.5181
6	7.79010	11.4980	21.5373	7.0266	87.2371	70.1177	145.726	89.5469
7	5.04740	6.24340	23.6008	10.3524	86.4470	65.6197	146.240	106.943
8	5.40130	12.8595	11.4094	11.6203	89.3990	65.3763	143.840	116.019
9	7.91150	7.40390	17.7914	14.8600	92.9983	60.0000	152.568	117.003
10	5.30990	7.30860	10.5845	20.0000	95.0868	60.5961	152.322	112.999
11	7.44380	7.04810	10.7343	16.1023	100.776	62.2875	154.382	114.536
12	8.27090	9.96610	13.9669	11.3053	105.333	64.2394	165.419	122.035
13	8.68750	6.00300	14.9311	14.7715	107.062	62.2733	166.166	122.139
14	5.00000	6.09270	14.0854	12.6052	109.374	64.2703	169.987	125.159
15	7.24530	7.76660	12.6510	14.5891	116.374	67.1776	174.221	123.138
16	5.42670	11.8860	21.5701	19.0376	120.129	68.4110	183.224	119.283
17	9.78680	6.00000	10.0000	14.6673	124.702	64.5250	174.656	114.212
18	10.86290	12.6867	17.1132	13.844	123.915	65.5250	179.994	114.476
19	5.452600	6.00000	23.6877	12.7731	121.053	60.0000	178.075	114.718
20	6.52230	7.59410	12.2220	7.8821	122.600	61.0000	177.060	114.596
21	14.9383	6.00000	29.9047	11.4237	122.078	61.0000	182.700	128.284
22	5.80520	8.70170	13.1934	12.0878	114.139	62.4059	172.935	126.860
23	8.56930	8.48680	23.5955	19.7641	116.334	61.7042	174.264	131.885
24	11.7652	7.44850	27.9008	9.3852	116.765	62.2174	174.201	135.809

Table 3 Comparison of the Obtained Simulation Results for STHTS Problem with Considering Valve-Point Loading Effect

Methods	Fuel cost ($)
NSGSA-CM	43,207.00
NSPSO-CM	44,248.00
NSGSA	44,519.00
NSPSO	44,638.00
Fuzzy EP [21]	47,906.00
QADEVT [22]	43,395.00
QPSO [23]	44,259.00
DE [24]	44,914.00
QPSO-DM [25]	43,507.00
ITLBO (Proposed)	**43,317.00**

The ITLBO algorithm has been applied on a test system in order to demonstrate the applicability of the proposed method. It involves optimal scheduling of hydrothermal system where in valve-point loading effect of the thermal has been considered. The optimal hydrothermal power generation and water discharge for the twenty four hour time period using the proposed ITLBO method are given in Table 1 and Table 2 respectively. It is also graphically represented in Figure. 3, Figure. 4 and Figure. 5. A comparative study of the proposed method has also been done with other methods found in the literature. And it is shown in the Table 3. It is observed from the table, that the fuel cost of the hydrothermal plant has been minimised by the proposed method.

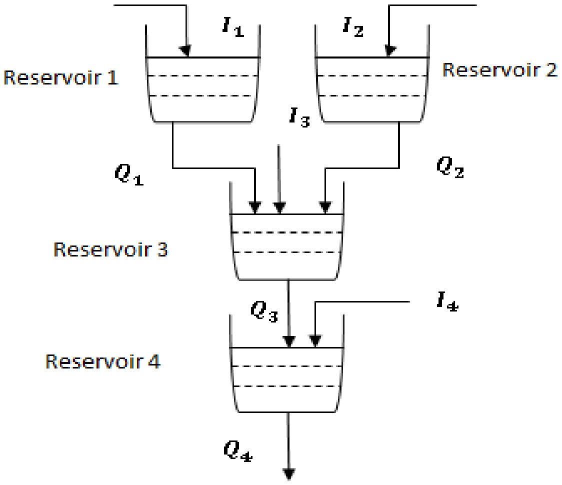

Figure. 2. Multi-chain cascaded hydro system

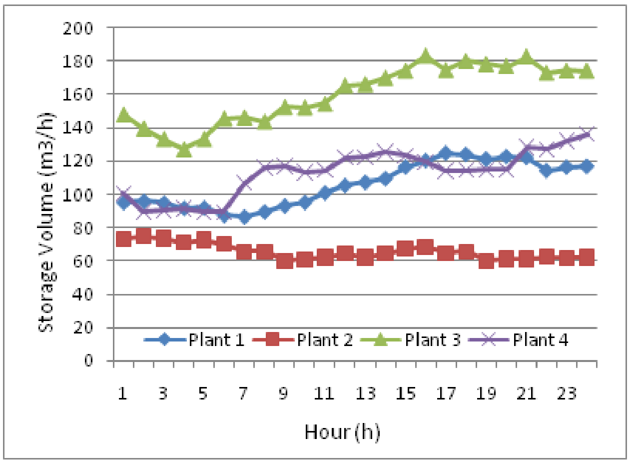

Figure. 3.Reservoir storage volume of the four hydro units

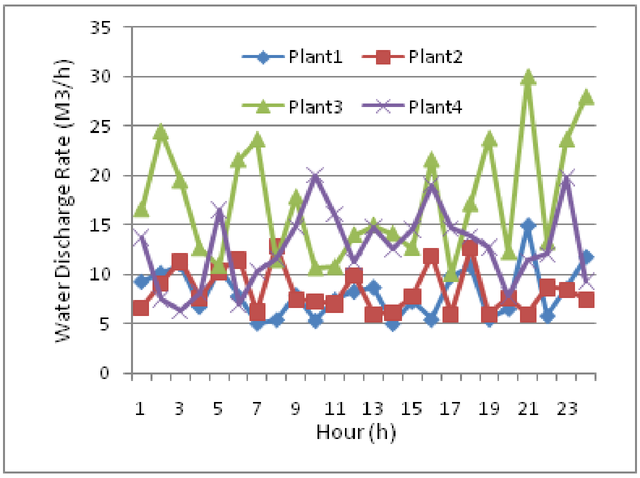

Figure. 4. Water discharge of the four hydro units

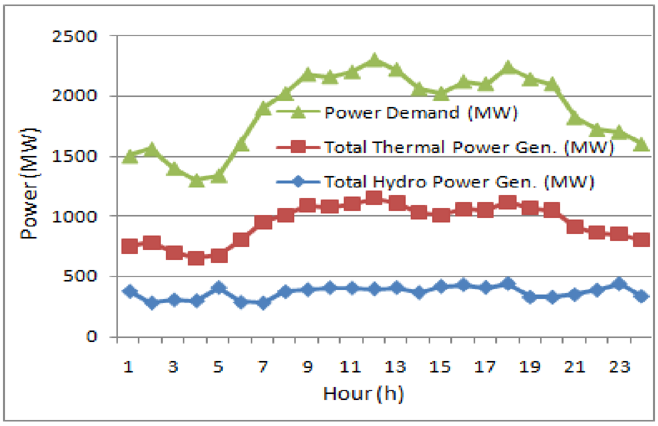

Figure. 5. Power demand, total thermal and hydro power generation

CONCLUSION

The problem of optimal generation scheduling of a hydrothermal power plant has been solved by implementing the Improved Teaching Learning Based Optimization algorithm. This algorithm does not require any tuning parameter like other evolutionary algorithm. The proposed ITLBO algorithm has been successfully applied on a IEEE test system which consists four hydro and three thermal plants. The experimental results have been compared with those obtained by similar algorithm. Reported in the literature, it is observed from the test results and comparisons that the proposed ITLBO algorithm perform well in solving hydrothermal scheduling problems.

APPENDIX

NOMENCLATURE	
TC	Total fuel cost of thermal units
$P_{s_{it}}$	Power generation of ith thermal unit for tth interval
$P_{h_{jt}}$	Power generation of jth hydro for tth 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 tth interval
P_{D_t}	Load demand at tth 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 tth 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

ACKNOWLEDGEMENT

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

REFERENCES

[1] Basu, M. (2016). Quasi-oppositional group search optimization for hydrothermal power system. *International Journal of Electrical Power & Energy Systems*, *81*, 324-335.

[2] Nazari-Heris, M., Mohammadi-Ivatloo, B., & Gharehpetian, G. B. (2017). Short-term scheduling of hydro-based power plants considering application of heuristic algorithms: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *74*, 116-129.

[3] Guan, X., Ni, E., Li, R., & Luh, P. B. (1997). An optimization-based algorithm for scheduling hydrothermal power systems with cascaded reservoirs and discrete hydro constraints. *IEEE Transactions on Power Systems*, *12*(4), 1775-1780.

[4] Mgiuntoli, M. G., & Poli, D. (2011). A novel mixed-integer linear algorithm to generate unit commitment and dispatching scenarios for reliability test grids. *International Review of Electrical Engineering*.

[5] Sifuentes, W. S., & Vargas, A. (2007). Hydrothermal scheduling using benders decomposition: accelerating techniques. *IEEE Transactions on Power Systems*, *22*(3), 1351-1359.

[6] Guangyi, L., Jinlong, Q., Erkeng, Y., & Xiaomin, B. (1988). Convex flow programming and its application to the economic scheduling of hydro-thermal power systems. *Proc Chinese Soc Electr Eng*, *8*, 9-18.

[7] Zaghlool, M. F., & Trutt, F. C. (1988). Efficient methods for optimal scheduling of fixed head hydrothermal power systems. *IEEE transactions on power systems*, *3*(1), 24-30.

[8] Saha, T. N., & Khaparde, S. A. (1978). An application of a direct method to the optimal scheduling of hydrothermal system. *IEEE Transactions on Power Apparatus and Systems*, (3), 977-983.

[9] Qing, X., Niande, X., Shiying, W., Boming, Z., & Mei, H. (1988). Optimal daily scheduling of cascaded plants using a new algorithm of nonlinear minimum cost network flow. *IEEE transactions on power systems*, *3*(3), 929-935.

[10] Wong, K. P., & Wong, Y. W. (1994). Short-term hydrothermal scheduling part. I. Simulated annealing approach. *IEE Proceedings-Generation, Transmission and Distribution*, *141*(5), 497-501.

[11] Chen, P. H., & Chang, H. C. (1996). Genetic aided scheduling of hydraulically coupled plants in hydro-thermal coordination. *IEEE Transactions on Power Systems*, *11*(2), 975-981.

[12] Zoumas, C. E., Bakirtzis, A. G., Theocharis, J. B., & Petridis, V. (2004). A genetic algorithm solution approach to the hydrothermal coordination problem. *IEEE Transactions on Power Systems*, *19*(3), 1356-1364.

[13] Yuan, X., Wang, L., & Yuan, Y. (2008). Application of enhanced PSO approach to optimal scheduling of hydro system. *Energy Conversion and Management*, *49*(11), 2966-2972.

[14] Hota, P. K., Barisal, A. K., & Chakrabarti, R. (2009). An improved PSO technique for short-term optimal hydrothermal scheduling. *Electric Power Systems Research*, *79*(7), 1047-1053.

[15] Sinha, N., Chakrabarti, R., & Chattopadhyay, P. K. (2003). Fast evolutionary programming techniques for short-term hydrothermal scheduling. *Electric Power Systems Research*, *66*(2), 97-103.

[16] Türkay, B., Mecitoğlu, F., & Baran, S. (2011). Application of a fast evolutionary algorithm to short-term hydro-thermal generation scheduling. *Energy Sources, Part B: Economics, Planning, and Policy*, *6*(4), 395-405.

[17] Mandal, K. K., & Chakraborty, N. (2008). Differential evolution technique-based short-term economic generation scheduling of hydrothermal systems. *Electric Power Systems Research*, *78*(11), 1972-1979.

[18] Lakshminarasimman, L., & Subramanian, S. (2006). Short-term scheduling of hydrothermal power system with cascaded reservoirs by using modified differential evolution. *IEE Proceedings-Generation, Transmission and Distribution*, *153*(6), 693-700.

[19] Chandrasekaran, K., Simon, S. P., & Padhy, N. P. (2014). Cuckoo search algorithm for emission reliable

economic multi-objective dispatch problem. *IETE Journal of Research*, *60*(2), 128-138.

[20] Roy, P. K. (2013). Teaching learning based optimization for short-term hydrothermal scheduling problem considering valve point effect and prohibited discharge constraint. *International Journal of Electrical Power & Energy Systems*, *53*, 10-19.

[21] Rao, R., & Patel, V. (2012). An elitist teaching-learning-based optimization algorithm for solving complex constrained optimization problems. *International Journal of Industrial Engineering Computations*, *3*(4), 535-560.

[22] Rao, R. V., Savsani, V. J., & Balic, J. (2012). Teaching–learning-based optimization algorithm for unconstrained and constrained real-parameter optimization problems. *Engineering Optimization*, *44*(12), 1447-1462.

[23] Rao, R. V., & Patel, V. (2013). An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems. *Scientia Iranica*, *20*(3), 710-720.

[24] Yu, K., Wang, X., & Wang, Z. (2016). An improved teaching-learning-based optimization algorithm for numerical and engineering optimization problems. *Journal of Intelligent Manufacturing*, *27*(4), 831-843.

[25] Satapathy, S., & Naik, A. (2013). Improved teaching learning based optimization for global function optimization. *Decision Science Letters*, *2*(1), 23-34.

[26] Niu, Q., Zhang, H., & Li, K. (2014). An improved TLBO with elite strategy for parameters identification of PEM fuel cell and solar cell models. *International journal of hydrogen energy*, *39*(8), 3837-3854.

[27] Haghrah, A., Mohammadi-ivatloo, B., & Seyedmonir, S. (2014). Real coded genetic algorithm approach with random transfer vectors-based mutation for short-term hydro–thermal scheduling. *IET Generation, Transmission & Distribution*, *9*(1), 75-89.

[28] Das, S., & Bhattacharya, A. (2016). Symbiotic organisms search algorithm for short-term hydrothermal scheduling. *Ain Shams Engineering Journal*.

[29] Nazari-Heris, M., Mohammadi-Ivatloo, B., & Gharehpetian, G. B. (2017). Short-term scheduling of hydro-based power plants considering application of heuristic algorithms: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *74*, 116-129.