Double Teaching Optimization for Short Term Hydro Thermal Scheduling Problem

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Abstracts: This paper presents an efficient and reliable new teaching based optimization algorithm for solving scheduling of hydro-thermal systems with cascaded reservoirs. Unlike the Teaching Learning Based Optimization, the Double Teaching Optimization (DTO) algorithm has two teaching phases i.e. the first teaching phase is identical with conventional TLBO algorithm preserving the inherent basics of it. The second teaching phase is the modified part considering students once again interact with the same teacher, who is the better than average students called double teaching phase. The feasibility of the proposed method is demonstrated in five different cases of two standard test systems consisting of four cascaded hydro and thermal units. The findings of the proposed method are better than the results of other established methods reported in literature in terms of quality of solution and convergence characteristics.

Keywords: Hydrothermal scheduling, cascaded reservoir, differential evolution, double teaching optimization, teaching learning based optimization, prohibited operating zone, valve point loading effect.

1. Introduction

Over the last few decades, we experience energy crisis and ill effects of pollution to save nation, so it is very important to utilize energy in an efficient manner. In order to utilize energy efficiently, cost must be as less as possible and this possesses a requirement to develop scheduling methods that accommodate generation diversity and line flow limitations and concurrently can produce accurate scheduling results. Again the power generation is much lesser as compared to power demand in our country, so the main aim of power system operation is to generate and transmit power to meet the system load demand and losses at minimum fuel cost and minimum environmental pollution. Hence, a mixed of hydrothermal scheduling is necessary. The short range hydrothermal problem has usually as an optimization interval of one day or week. This period is normally subdivided into subintervals for scheduling purposes. Here the load demand, water inflow and discharge of water are known. A set of starting condition that means the reservoirs storage level is being given. The optimal power schedule can be prepared that can minimize the desired objective while meeting the system constraints successfully. In order to solve the scheduling problem of short term hydro-thermal systems, the head of water level is assumed to be constant. The objective of short term hydrothermal scheduling of power system is to determine the optimal hydro and thermal generations in order to meet the load demands over a scheduling horizon of time while

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satisfying the various operational constraints imposed on the hydraulic and thermal power system network. The optimal scheduling of hydrothermal power system is usually more complex than that for all thermal system. It is basically a non-linear problem involving nonlinear objective function and a mixture of linear and non-linear constraints on thermal plants as well as hydroelectric plants [1-2].

Dynamic programming (DP) [3,4] method have been employed in solving most economical hydro thermal generation schedule under the practical constraints. However, this method is suffering from the curse of dimensionality and local optimality. Many stochastic search algorithms like artificial neural network [5],simulated annealing technique [6], a coordinated approach [7], genetic algorithm [8], evolutionary programming (EP) [9], two phase neural network approach [10], fast evolutionary programming [11], fuzzy interactive EP [12], simulated annealing based goal attainment method[13], an efficient real coded GA [14], modified differential evolution (MDE) [15], improved particle swarm optimization (IPSO) [16,18], biogeography based optimization [17], clonal selection algorithm [19], an adaptive artificial bee colony optimization [21], a mixed binary evolutionary particle swarm optimizer [22], teaching learning based optimization (TLBO) [23] and improved DE [24] have applied successfully to solve hydrothermal problems.

The neural network [5,10] based approaches may suffer from excessive numerical iterations. Simulated annealing (SA) [6,12] requires appropriate annealing schedule otherwise achieved solution will be of locally optimal. Genetic algorithm [8,14] is commonly used evolutionary technique and is based on selection, crossover and mutation operation. However it suffered from premature convergence which may lead to a local optimal solution. In differential evolution [15,24] algorithm, it is difficult to properly choose the control parameter. The literature survey of improved particle swarm optimization (IPSO) [16,18,22] reveals that this technique is able to generate high quality solutions with less computational time, but sometimes trapped by local optima. Krill herd algorithm (KHA) [25] technique and symbiotic organisms search (SOS) algorithm [26] have been successfully employed to solve the short-term hydrothermal scheduling (HTS) problem by Roy et.al. and Das et.al, respectively.

Teaching learning based optimization is a derivative free optimization and no control parameters for tuning applied successfully in various large scale problems [20, 23]. This paper proposes modified teaching learning based optimization called as double teaching optimization (DTO) for short term optimal scheduling of generation in a hydro thermal system which involves the allocation of generations among the multi reservoir cascaded hydro plants having prohibited operating zones and thermal units with valve point loading so as to minimize the total fuel cost of thermal plants while satisfying the various constraints imposed on hydraulic and thermal network. To verify the superiority of the proposed approach, two hydrothermal systems have been considered in this study. The first test system consists of a multi-chain cascade of four hydro units and one thermal unit and second test system with same cascaded four hydro units and three thermal units. The results obtained by proposed DTO method are compared with other population based intelligent algorithms and found to be better not only in operating cost but also in convergence property in achieving the optimal solution.

2. Problem Formulation of Short Term Hydro Thermal Scheduling

The objective of the short term scheduling of a multiple hydro-thermal system over a schedule horizon to meet the load demand is to schedule the hydro and thermal plants generation in such a way that minimizes the generation cost without violating any constraints imposed on hydro and thermal plants.

A. Objective function

As the fuel cost of hydropower plants are insignificant in comparison with that of thermal power plants, so the main objective of the HTS is to minimize the fuel cost of thermal units while making use of availability of hydro resource as much as possible. The objective function of HTS problem for thermal units having quadratic cost function is given by

$$\text{Minimize } FC(PT) = \sum_{i=1}^{nt}\sum_{j=1}^{NH} a_i PT_{i,j}^2 + b_i PT_{i,j} + c_i \tag{1}$$

Where nt is the number of thermal generating units and NH is the number of time intervals.

The fuel cost function of each thermal generating unit considering the valve point effects is expressed as the sum of quadratic and sinusoidal function. Thus the fuel cost function with valve point effects can be expressed as

$$\text{Minimize } FC(PT) = \sum_{i=1}^{nt}\sum_{j=1}^{NH} a_i PT_{i,j}^2 + b_i PT_{i,j} + c_i + \left| d_i \times \sin\left(e_i \times \left(PT_{\min i} - PT_{i,j}\right)\right)\right| \tag{2}$$

B. Equality Constraints

(i) power balance constraints

The total active power generation must balance the predicted power demand and the transmission loss at each time interval over the scheduling horizon and it may be mathematically expressed as

$$\sum_{i=1}^{nh} PH_{i,j} + \sum_{i=1}^{nt} PT_{i,j} = PD_j + PL_{i,j} \tag{3}$$

Where the hydro electric generation is a function of water discharge rate and storage volume, which can be expressed as follows:

$$PH_{i,j} = C_{1,i} \times V_{i,j}^2 + C_{2,i} \times Q_{i,j}^2 + C_{3,i} \times V_{i,j} \times Q_{i,j} + C_{4,i} \times V_{i,j} + C_{5,i} \times Q_{i,j} + C_{6,i} \tag{4}$$

(ii) Initial and final reservoir storage constraints: Initial and final reservoir volumes are generally set by the midterm scheduling process. This equality constraint implies that the total quantity of available water is fully utilized. This equality constraint is mathematically expressed as follows:

$$V_{i,1} = V_i^{begin}; V_{i,25} = V_i^{end} \tag{5}$$

(iii) Reservoir flow balance: In this constraint, water transportation delay between reservoirs is considered. The flow balance equation relates the water storage volume during previous interval with the current storage, net inflow, discharge and spillage. This may mathematically be expressed as follows:

$$V_{i(j+1)} = V_{ij} + \sum_{u=1}^{R_u}\left[Q_{u(j-\tau)} + s_{u(j-\tau)}\right] - Q_{i(j+1)} - s_{i(j+1)} + I_{i(j+1)} \text{ for } \boldsymbol{j} = 1,2,\ldots,NH \tag{6}$$

C. Inequality constraints

(i) Power generation constraints: Active power generation of each hydro and thermal power plant in each hour is bounded between its upper and lower limits as given below:

$$PH_{\min i} \le PH_{i,j} \le PH_{\max i}, \tag{7}$$

$$PT_{\min i} \le PT_{i,j} \le PT_{\max i}, \text{ Where } i = 1,2,...,..nh, \text{ and } j = 1,2,...,...NH \tag{8}$$

(ii) Reservoir water storage constraints: The water storage capacity of each hydro power plant reservoir at each hour must be within its minimum and maximum limits as given below:

$$V_{\min i} \le V_{i,j} \le V_{\max i}, \text{ Where } i = 1,2,...,...nh, \text{ and } j = 1,2,...,...NH \tag{9}$$

(iii) Water discharge constraints: The water discharge limit of each hydro power plant reservoir at each hour must be within its minimum and maximum limits as given below:

$$Q_{\min i} \le Q_{i,j} \le Q_{\max i} \tag{10}$$

3. Double Teaching Optimization (DTO) Algorithm

This algorithm mainly emphasizes the importance of teacher on the students to increase the mean results of whole class room. Learning phase of TLBO algorithm allows the student–student interaction through group discussion, mutual interaction etc which does not show much improvement in cost rather it unnecessary increases the computational time. In DTO algorithm the learning phase is being neglected and modified. The students once again are allowed to interact with teacher only as the teacher is considered as best among all students, most respected and knowledgeable person in the society and they always motivate the students to attain their goal and this is accomplished by increasing the number of interactions. There are two teaching phases in the proposed algorithm. So, the teacher–student interaction is better than the student-student interaction as the teacher is a scholar better than the average students and ensuring the transformation of quality education in second phase of teaching in a class room i.e. learner phase is neglected. This Double Teaching Optimization (DTO) is also called as double teaching phases based method. The DTO algorithm has certain control parameters i.e. mutation rate, population size and maximum iteration number.

A. First teaching phase:

Here, the students improve their knowledge with the help of teacher and the teacher tries his best to enhance the average results of class room. The teacher always improves the average grade of the class to some extent. If the new average grade of the j^{th} subject at k^{th} iteration is μ_{newj}^{k}, the difference between the existing mean μ_j^k and new mean of the j^{th} subject at the k^{th} iteration may be formulated as [20, 23] given below.

$$\mu_{diffj}^{k} = (rand - 0.5) \times \left(\mu_{newj}^{k} - t_f \mu_j^k\right) \tag{11}$$

where t_f is the teaching factor which is evaluated randomly by the following equation:

$$t_f = round(1 + rand(0,1)) \tag{12}$$

The grade of the j^{th} subject of the i^{th} student at $(k+1)^{th}$ iteration is updated by

$$x_{ij}^{k+1} = x_{ij}^{k} + \mu_{diffj}^{k} \tag{13}$$

B. Second teaching phase:

The teacher is considered as best student (N_p+1) member can improve the knowledge of other students more quickly through interactions with each other. $f(X_{teacher}) = f(x(Np+1,:))$ is the overall grade point of the teacher as best among all students. The best solution in each iteration is updated and considered as teacher. So, in second teaching phase the average grade point of all students is better than the average grade point of learners phase as the teacher updates his knowledge if he finds some talented students during interaction and shares his knowledge among the other students inside the class.

As $f(X_{teacher}) < f(X_i) = f(x(i,:))$ and $i = 1,2,...Np$

Mathematically, the second teaching phase may be expressed as

$$x_{ij}^{k+1} = x_{ij}^{k} + \left(rand \times mutation.rate \times \mu_{diffj}^{k}\right) \tag{14}$$

$$\mu_{diffj}^{k} = x_{teacher,j} - t_f \mu_j^k \tag{15}$$

Where, x_{ij}^{k+1} , x_{ij}^{k} are grade point of j^{th} subject of the i^{th} student at the k^{th} and $(k+1)^{th}$ iterations; $f(X_i)$ is overall grade point of i^{th} student. The total number of subjects offered to each student is d. where X_i is expressed as

$$X_i = [x_{i.1},\ x_{i.2},\ .,\ .,\ x_{i.j},\ .,\ .,\ x_{i.d}] \tag{16}$$

As the teacher is equated the best student inside the class and the teacher's knowledge is always better than the average performance of students, the student-student interaction is replaced by teacher student interactions same as teaching phase. Therefore, the learning phase is replaced by the teaching phase once again to retain the better performance of each student student. The inherent randomness called mutation-rate incorporated in the second phase as teaching phase of algorithm makes it better than the conventional TLBO algorithm. The DTO algorithm is having excellent exploration and exploitation abilities to provide optimal solution.

4 . DTO Algorithm

The DTO algorithm may briefly be described with the following steps:

Step 1: Generate a random population (Pop) according to the number of students in the class and number of subjects offered. It may mathematically be expressed as

$$Pop = \begin{bmatrix} x_{1,1} & . & . & x_{1,j} & . & . & x_{1,d} \\ . & . & . & . & . & . & . \\ x_{i,1} & . & . & x_{i,j} & . & . & x_{i,d} \\ . & . & . & . & . & . & . \\ x_{Np,1} & . & . & x_{Np,j} & . & . & x_{Np,d} \end{bmatrix}. \tag{17}$$

Where $x_{i,j}$ is the initial grade of the j^{th} subject of the i^{th} student.

Step 2: Evaluate the average grade of each subject offered in the class. The mean grade of the j^{th} subject is given by

$$\mu_j = mean(x_{1,j}, x_{2,j}, \ldots, x_{i,j}, \ldots, x_{Np,j}) \tag{18}$$

Step 3: Based on the overall grade point (objective value) sort the students (population) from best to worst. The best solution is considered as teacher and is given by :

$$X_{teacher} = X \mid f(x) = \min \tag{19}$$

Step 4: Improve the grade point of each subject (control variables) of each of the individual student using equation (13).

Step 5: In second teaching phase, each student can improve the grade point of each subject through the mutual interaction with teacher. The best solution is considered as teacher in each iteration. Improvement of grade point of each subject of every student may be depicted as follows:

As $f(X_{teacher}) < f(X_i) = f(x(i,:))$ and $i = 1,2,\ldots Np$

$$
\begin{aligned}
&for\ \ k = 1 : Iter\max\\
&\quad for\ \ i = 1 : Np\\
&\qquad for\ \ j = 1 : d\\
&\qquad \mu_{diffj}^{k} = (rand - 0.5) \times \left(x^{k}{}_{teacherj} - t_f\, \mu_j^k\right)\\
&\qquad x_{ij}^{k+1} = x_{ij}^{k} + \left(rand \times mutation.rate \times \mu_{diffj}^{k}\right)\\
&\qquad end\\
&\quad end\\
&end
\end{aligned}
$$

In the hydrothermal scheduling the equality constraints correspond to the initial and final reservoir storage volumes as well as the load balance constraints are not satisfied most of the optimization algorithms. Therefore, modifications are incorporated in the beginning of the initialization in order to generate an initial feasible solution for the hydrothermal problem.

5. Implementation of DTO For Short Term Hydro Thermal Scheduling

Step 1: All the dependent variables of the HTS problem like water discharge rate of all plants for all the time intervals are randomly selected between their operating limits. To satisfy the initial and final reservoir storage constraints, the water discharge rate of all the hydro plant in the dependent interval is evaluated using

$$Q_{i,d} = V_{i,1} - V_{i,25} - \sum_{j \neq d}^{NH} Q_{i,j} + \sum_{j=1}^{NH} I_{i,j} - S_{i,j} + \sum_{u=1}^{R_u} \sum_{j=1}^{NH} Q_{u(j-\tau)} \tag{20}$$

The above step is repeated until the element representing the dependent variable satisfies the constraints.

Step 2: The water discharge is evaluated using equation (20), then, the volume of each reservoir is computed using equation (6). After this, the generation schedule of all hydro plants over 24 intervals is calculated using equation (4).

Step 3: The thermal power is calculated using the equality constraint as given in equation (7). To satisfy the load balance constraints including transmission losses, a dependent element $PT(d, j)$ is randomly selected and the dependent thermal generation is evaluated by solving the following equation as

$$B_{dd} PT^2(d, j) + \left(2 \sum_{i=1}^{nh+nt-1} B_{d,i} .PT(i, j) - 1 \right) PT(d, j) + \left(P_D(j) + \sum_{i=1}^{nh+nt-1} \sum_{k=1}^{nh+nt-1} PT(i, j) B_{i,k} PT(k, j) - \sum_{i=1}^{nt} PH(i, j) - \sum_{\substack{i=1 \\ i \neq d}}^{nt} PT(i, j) \right) = 0 \quad (21)$$

The above step is repeated until the element representing the dependent thermal generation does not violate the constraints. Where, Pg= [PT PH].

Step 4: Compute the objective function using equation (1).

Step 5: Calculate the mean grade of all the subjects offered to the students of the class.

Step 6: Identify the best solution (Teacher).

Step 7: Modify all the independent variables (discharge rate of all hydro units at all time interval) based on the teacher knowledge using equation (14) and (15).

Step 8: The water discharge, volume of reservoir and power generation is checked for minimum and maximum limits. If discharge, volume of reservoir and power generations are less than the minimum level it is made equal to minimum value and if the discharge of water, volume of reservoir and power generation is greater than the maximum level it is made equal to maximum level.

Step 9: Go to step 2 until the current iteration reaches the predefined maximum iteration number.

6. Simulation Results.

To solve HTS problem the program is written in MATLAB code and is tested on 2.0 GHz core duo processor with 1 GB RAM. Here, 50 independent runs and the best results are presented in the simulation results. The control parameter of DTO algorithm: population size (NP), mutation rate and the maximum iteration number (Itermax) are set to the values 30, 0.05, 500 respectively. These values are obtained after testing and evaluating different parameter combination. To check the effectiveness, the proposed algorithm is implemented on two hydro thermal systems. The system-I consists of four hydro units and a number of thermal units represented by an equivalent thermal plant. The system-II consists of four cascaded thermal units and three thermal units. The scheduling period of 24 hour, with one hour time interval is considered for simulation study. The hydraulic sub-system is characterized by the following:

a) A multichain cascade flow network , with all of the plants in one stream;
b) River transport delay between successive reservoirs;
c) Variable head hydro plants;
d) Variable natural inflow rates into each reservoir;
e) Prohibited operating regions of water discharge rates;
f) Variable load demand over scheduling period.

A. Test System-I:

The data of the test system-I considered here are the same as in [8] and the additional data with valve point loading effect and with prohibited discharge zones (PDZ) of turbines are also same as in Ref [11]. The fuel cost function of the equivalent thermal unit with valve point loading (VPL) is

$$FC(PT) = \sum_{j=1}^{NH} 0.002PT_j^2 + 19.2PT_j + 5000 + \left|700 \times \sin\left(0.085 \times \left(PT_{\min} - PT_j\right)\right)\right| \quad (22)$$

The lower and upper operation limits of this unit are 500 and 2500 MW, respectively. The spillage rate for the hydraulic system-I is not taken into account (simplicity) and further, the electric loss from the hydro plant to the load is neglected. The lower and upper operation limits of hydraulic system are 0 and 500 MW, respectively.

The studied problem may be classified into three categories depending on the type of their fuel cost functions and constraints.

Table 1. Optimal parameter setting

No of population	Cost ($ / day)	Elapsed time (Sec)	
10	917047.57	228.001586	Itermax=1000, Mutation rate=0.1
20	917088.01	416.152436	
30	916996.55	596.399059	
40	916998.97	765.596313	
50	917075.85	1017.857353	
No of iteration	Cost ($ / day)	Elapsed time (Sec)	Population size Np=30, Mutation rate = 0.1
100	917169.92	115.18778	
200	917169.92	232.833243	
500	916998.81	350.371785	
800	917169.92	466.618372	
1000	917075.85	596.399059	
Mutation rate	Cost ($ / day)	Elapsed time (Sec)	Itermax=500, Population size Np=30,
0.05	916926.48	351.931416	
0.1	916998.81	350.371785	
0.15	917095.04	354.555185	
0.2	917298.1	358.357667	
Bold front indicates minimum function value			

There are three different cases of the test system-I by considering the quadratic cost without prohibited discharge zones as case-1; quadratic cost with prohibited discharge zones as case-2 and valve point loading with prohibited discharge zones are considered as case-3. The various control parameters like mutation rate, population size, maximum iteration number have been tested and finally the optimal setting of parameters are provided in Table 1.

A.1 Case 1 (HTS problems with quadratic cost functions):

In this case, the cost functions of the thermal units of the hydrothermal system are considered to be quadratic and there is no prohibited discharge zone of the reservoirs of the hydro plants. The valve point loading of thermal units are also neglected. The Figure 1 shows the cost variation of best hydro thermal schedule of the proposed DTO method when executed 50 times with different random initial solutions. The optimal hourly water discharge of hydro plants obtained by the proposed DTO algorithm is represented in Fig. 2. The proposed DTO approach takes execution time of 351.9314 sec. to obtain the best hydro thermal scheduling. The best results obtained by the proposed algorithm are compared with the reported results by other methods, namely genetic algorithm (GA) [8], classical evolutionary programming (CEP) [11], fast evolutionary programming (FEP) [11], improved fast evolutionary programming (IFEP) [11], binary coded genetic algorithm (BCGA) [14], real coded genetic algorithm (RCGA) [14], modified differential evolution (MDE) [15], improved PSO (IPSO) [16], teaching learning based optimization (TLBO) [23], improved differential evolution (IDE) [24] and Symbiotic organisms search (SOS) [26] and presented in Table 2. It can be found that the DTO produces better execution time, minimum cost, average cost and worst cost than those obtained by the other existing techniques. The hourly power generations of hydro plants obtained by the proposed method in this case are shown in Figure 3.

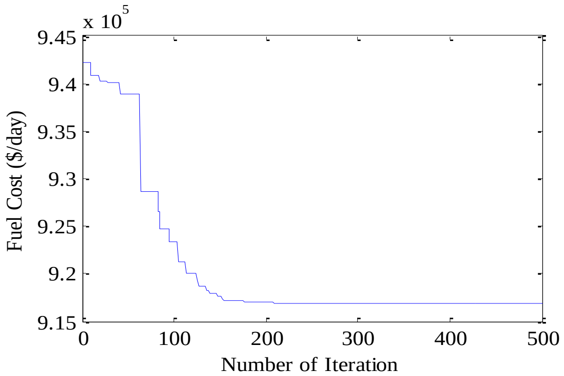

Figure 1. Convergence characteristics of DTO algorithm case-1 of test system-I.

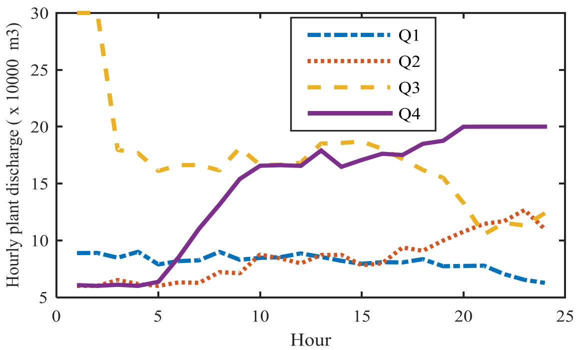

Figure 2. Hourly plants discharge (x 10^4 m^3) for case 1 of Test system-I

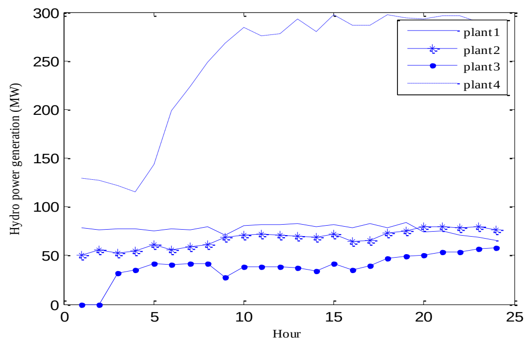

Figure 3. Hourly hydro plant power generations of DTO algorithm.

A.2 Case 2. (HTS problem with quadratic cost functions and prohibited discharge zones):

Here, the prohibited operating zones of reservoirs of hydro plants have been considered to check the feasibility of the proposed approach. The optimal hourly water discharge of hydro units of system-I obtained by the proposed DTO algorithm are given in Fig. 5. The fuel cost obtained by DTO method is compared to other methods and presented in Table 3. It is found that the DTO method provides cheapest generation schedule in comparison to IPSO [16] and TLBO [23] methods and more than SOS [26] method. The cost convergence characteristic obtained by DTO method is shown in Figure 4.

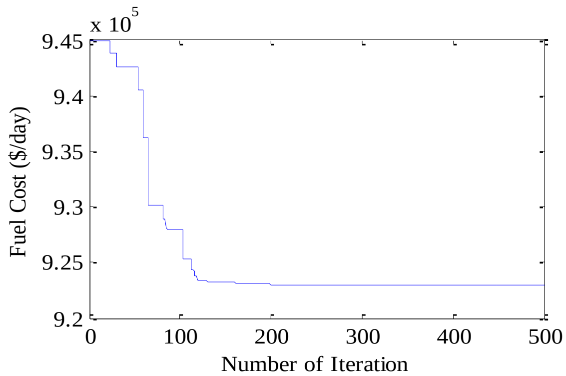

Figure 4. Convergence characteristics of DTO algorithm case-2 of test system-I

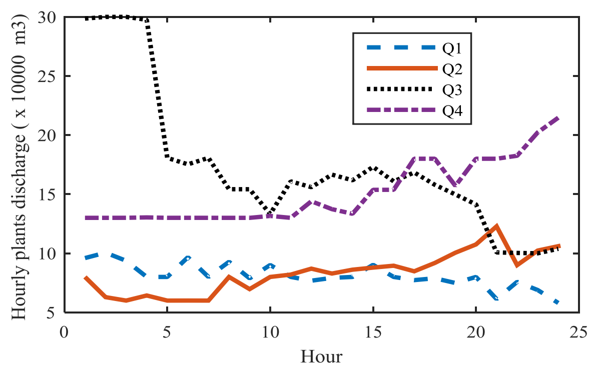

Figure 5. Hourly plants discharge (x 10^4 m^3) for case 2 of Test system-I

Table 2. Comparison of optimal costs for test system-I with quadratic cost and no prohibited discharge zone (case 1)

Method	Best fuel cost ($)	Average fuel cost ($/day)	Worst fuel cost ($/day)	CPU time (sec)
GA[8]	932734	936969	939734	-
EP[11]	930267.92	930897.44	931396.81	-
CEP[11]	930166.25	930373.23	930927.01	-
IFEP[11]	930129.82	930290.13	930881.92	1033.2
BCGA[14]	926922.71	927815.35	929451.09	-
RCGA[14]	925940.03	926120.26	926538.81	-
MDE[15]	922555.44	-	-	-
IPSO [16]	922553.49	-	-	-
TLBO [23]	922373.39	922462.24	922873.81	374.918
IDE[24]	917237.7	917250.1	917277.8	366.0781
SOS[26]	922332.17	922338.2	922482.2	6.21
DTO	916926.48	916962.37	916998.76	351.932

Table 3. Comparison of optimal costs for test system-I case-2 with quadratic cost and with PDZ

Method	Minimum cost ($/day)
IPSO [16]	923443.17
TLBO [23]	923041.91
SOS[26]	922844.7835
DTO	923010.56

A.3 Case 3.(HTS problem considering valve point effect and prohibited discharge zone):

In this case, the valve point loading of thermal units and prohibited operating zones of hydro units are taken in to consideration to verify the robustness of proposed approach. The optimal hourly water discharges of reservoirs obtained by the proposed DTO algorithm are furnished in Fig. 6. The obtained fuel cost in this case is compared to that of IFEP [11], DE [15], IPSO [16], TLBO [23] and IDE [24] methods and reported in Table 4. From this Table 4, one can see the superiority of the proposed DTO method over other reported techniques. The cost convergence characteristic and the trajectories of hourly reservoirs volumes of hydro plants by DTO algorithm are shown in Figures 7 and 8, respectively.

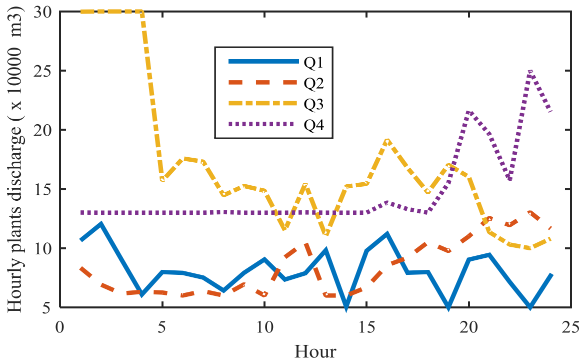

Figure 6. Hourly plants discharge (x 10^4 m^3) case-3 of Test system-I

Table 4. Comparison of optimal costs for test system-I case-3 [VPL & PDZ]

Method	Best fuel cost ($)	Verified Best fuel cost ($)	Average fuel cost ($/day)	Worst fuel cost ($/day)	CPU time Sec
IFEP[11]	933949.25	933949.25	938508.87	942593.02	1450.9
DE [15]	935617.76	935617.76	-	-	
IPSO [16]	925978.84	925978.84	-	-	31.11
TLBO [23]	924550.78 Without VPL	930761.58	924702.43	925149.06	362.54
IDE [24]	923016.29	927814.96	923036.28	923152.06	547.07
DTO	925701.195	925701.195	925765.14	925792.88	330.65

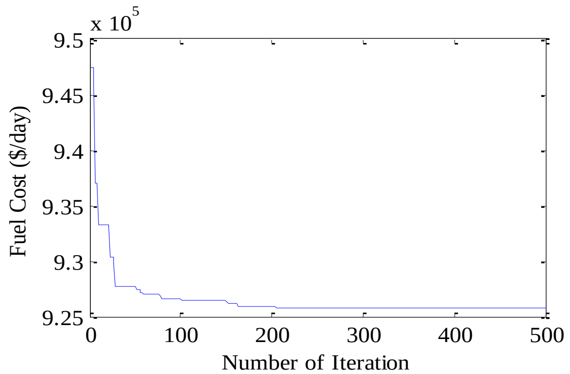

Figure 7. Convergence characteristics of DTO algorithm case-3 of test system-I

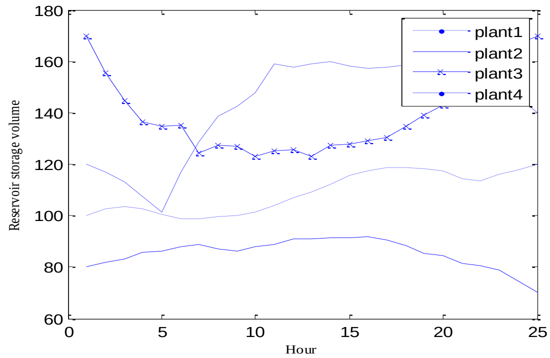

Figure 8. Hydro reservoir storage volumes of DTO algorithm.

B. Test system-II

The test system-II is the modified version of test system-I that comprises four hydro plants coupled hydraulically and three thermal plants. This system does not have the prohibited discharge zones. The data of the test system-II is adopted from reference [12].

B.1 Case-1: Quadratic cost function with valve point loading effect and without transmission losses

The total fuel cost FC as a function of power output of the thermal plant [12] is represented as

$$FC = \sum_{i=1}^{nt}\sum_{j=1}^{NH} c_i PT_{i,j}^2 + b_i PT_{i,j} + a_i + \left| d_i \times \sin\left(e_i \times \left(PT_{\min,i} - PT_{i,j}\right)\right)\right| \qquad (23)$$

Table 5. Optimal hourly discharges(x 10^4 m^3) ,hydro generation, thermal generation of test system-II (case-1)

Hour	Q1	Q2	Q3	Q4	PH1	PH2	PH3	PH4	PT1	PT2	PT3	PD
1	11.2108	7.8670	18.1967	7.8825	90.4679	61.2921	48.5182	151.4142	43.8801	124.9079	229.5196	750
2	6.3735	6.0000	30.0000	6.0000	64.1417	50.2403	0	123.9959	20.0000	292.1027	229.5195	780
3	13.6333	6.0000	17.1328	6.0158	95.1161	51.9231	44.0620	120.0206	34.4507	124.9079	229.5196	700
4	5.1769	6.0000	16.4231	6.0000	53.5039	53.5339	45.8871	113.9411	28.7062	124.9081	229.5197	650
5	12.4808	6.0000	19.3367	6.0000	90.6404	54.5678	37.4559	125.6499	97.0185	124.9078	139.7597	670
6	5.2826	6.0311	6.0311	6.0142	53.1743	55.2828	39.4547	146.2711	66.4809	209.8165	229.5197	800
7	6.5667	7.1837	15.3990	7.5040	63.6472	62.6183	50.0203	174.0177	160.3615	209.8158	229.5193	950
8	6.1697	6.1903	17.6108	13.1740	61.4742	56.2400	43.1700	242.4549	167.3260	209.8155	229.5194	1010
9	5.1040	6.0000	15.8076	10.9546	53.8204	55.8615	47.1154	225.7945	93.4055	294.7235	319.2792	1090
10	5.1293	6.3039	17.4038	19.0088	55.0543	59.3489	41.9059	297.6735	96.9226	209.8157	319.2792	1080
11	7.4942	6.1499	21.9732	13.3410	74.7182	59.5446	17.1839	252.7513	171.5589	294.7234	229.5195	1000
12	5.7156	6.3444	19.5387	17.7217	61.2730	61.6824	27.1018	290.7043	95.2361	294.7231	319.2794	1150

Hour	Q1	Q2	Q3	Q4	PH1	PH2	PH3	PH4	PT1	PT2	PT3	PD
13	10.6577	6.7435	16.9611	19.0010	94.0865	65.0537	37.2966	296.3646	92.9556	294.7234	229.5195	1110
14	12.5499	8.5325	21.3488	19.4397	101.0440	76.7794	15.0616	297.0336	100.7461	209.8157	229.5194	1030
15	10.0597	6.0000	16.3432	16.7164	91.2957	61.1145	37.9048	283.0508	102.1509	294.7235	139.7597	1010
16	9.6824	10.4006	17.9833	19.4547	89.3868	87.0521	34.0868	302.5830	107.5556	209.8159	229.5198	1060
17	8.0957	8.1594	12.3838	19.5051	79.9000	74.2816	47.8143	300.3157	108.3527	209.8161	229.5196	1050
18	11.7338	13.6978	27.9055	19.4099	97.9147	94.6101	0	301.6931	101.5391	294.7234	229.5195	1120
19	6.6402	6.0131	13.3825	18.9552	68.7791	56.7542	45.9461	296.1575	167.8816	294.7224	139.7592	1070
20	5.9697	12.8958	10.2863	19.9588	63.3104	89.9132	48.6703	300.2831	108.4873	209.8162	229.5196	1050
21	11.4877	14.8515	11.3119	19.7616	95.7895	90.9157	52.5113	291.2514	25.1040	124.9084	229.5196	910
22	5.0875	14.2051	10.6923	19.1882	55.3913	85.9300	52.7244	297.0014	99.4333	40.0000	229.5196	860
23	5.4881	9.7507	11.1700	19.7684	59.3174	69.2198	56.2438	293.8147	20.0000	121.8848	229.5196	850
24	7.2102	14.6796	10.8653	19.9512	73.7442	80.4227	57.4621	284.1367	34.7147	40.0000	229.5196	800
Total Cost of thermal generation ($/day)					40727.733							
Elapsed time (Sec)				558.5361 seconds.								

Table 6. Comparison of optimal costs for test system-II with valve point loading (VPL) and without transmission losses (case 1)

Method	Best fuel cost ($/day)	Average fuel cost ($/day)	Worst fuel cost ($/day)	CPU time (sec)
Fuzzy EP[12]	45063	936969	939734	-
DE [15]	44526.1	-	-	-
MDE [15]	42611.14	-	-	-
PSO [18]	42474	-	-	-
IPSO [19]	44321.236	-	-	-
CSA[19]	42440.574	-	-	-
TLBO [23]	42385.88	42407.23	42441.36	527.359
KHA[25]	41926	41998.58	42174.35	-
DTO	40727.733	40788.221	40819.91	558.436

In this case study the number of decision variable is 168 (4×24 + 3×24) representing the discharges of four hydro reservoirs and generation of three thermal plants over the entire scheduling horizon. The optimal hourly discharges obtained by proposed DTO method, generated powers from hydro and thermal plants over the entire scheduling period are provided in Table 5. The optimal cost obtained from the proposed DTO based approach have also been compared with that of EP [12], DE [15], MDE [15], PSO [18], CSA [19], TLBO [23] and KHA[25]and details are given in Table 6. From the result, it is quite evident that the proposed DTO based algorithm provides better solution for the cascaded hydro reservoirs with multiple thermal power plants.

B.2 Case 2 : Quadratic cost function with valve-point loading with transmission losses

The transmission losses also have been considered for the test system-II. The losses are computed using the loss coefficients and is given by

$$PL = \sum_{j=1}^{NH} \sum_{i=1}^{nt+nh} \sum_{k=1}^{nt+nh} PT(i, j) B_{i,k} PT(k, j) + \sum_{j=1}^{NH} \sum_{i=1}^{nt+nh} B_{0,i} PT(i, j) + B_{00} \tag{24}$$

Where B_{ij} , B_{0i} , B_{00} are the loss formula coefficients and are given in [15]. In this case study the number of decision variables is also 168 representing the discharge of four hydro reservoir and generations of three thermal plants over the entire scheduling period. The optimal hourly discharges, hourly generated powers from hydro and thermal plants and transmission losses over the entire scheduling period obtained by the proposed method are provided in Table 7. The optimal cost obtained from the proposed DTO based approach have also been compared with that of MDE [15] and IDE [24] and details are furnished in Table 8. From the Table 8, it is clear that the dispatch result obtained by the proposed DTO satisfies all kinds of constraints of HTS problem while reducing the total fuel cost effectively and efficiently.

Table 7. Optimal hourly discharges (x 10^4 m^3), hydro generation, thermal generation and transmission losses of test system-II (case-2)

Time	Q1	Q2	Q3	Q4	PH1	PH2	PH3	PH4	PT1	PT2	PT3	PL	PD
1	9.2157	6.0179	22.1487	6.5358	82.3952	50.2813	29.866	135.6441	103.5467	124.908	229.5196	6.1608	750
2	7.602	6.0000	24.2115	6.0000	73.1627	51.286	10.3722	125.2484	91.7423	294.7237	139.7598	6.295	780
3	6.7677	6.0000	24.2589	6.0019	67.5925	52.9244	4.9623	121.1391	104.7201	124.9079	229.5196	5.766	700
4	7.3498	6.0000	16.7835	6.0000	71.6794	54.4909	41.9648	115.2915	21.3704	209.8159	139.7598	4.3725	650
5	5.7963	6.0359	21.2628	6.0193	59.9607	55.7383	21.0246	130.7137	53.6367	124.908	229.5196	5.5016	670
6	7.4687	6.2519	17.1063	6.2845	72.4273	57.6625	38.9919	149.4209	134.2167	124.9079	229.5196	7.1467	800
7	9.3087	6.4096	19.5355	8.3738	83.1158	58.5776	27.7337	189.5835	166.6832	294.7237	139.7598	10.1773	950
8	9.6753	6.2507	16.5256	14.8044	84.745	57.8206	38.3651	261.6549	142.0795	209.8158	229.5196	14.0006	1010
9	10.1201	9.0696	17.7565	18.3142	86.7973	75.0047	33.9765	292.3191	94.4414	294.7236	229.5196	16.7822	1090
10	9.8204	8.0003	17.8777	18.6066	85.8105	69.3673	33.201	292.8001	91.2477	294.7237	229.5195	16.6699	1080

Time	Q1	Q2	Q3	Q4	PH1	PH2	PH3	PH4	PT1	PT2	PT3	PL	PD
11	10.4358	9.1442	17.6418	18.1664	89.1584	75.869	33.9218	291.1647	102.4811	294.7236	229.5196	16.8382	1100
12	8.214	8.3442	18.3763	17.7913	77.9312	71.172	32.3004	287.2613	174.9267	294.7237	229.5195	17.8349	1150
13	10.0553	9.5758	17.739	17.8875	88.3247	77.0926	36.6128	287.819	108.2754	209.8159	319.2794	17.2199	1110
14	9.7975	9.975	17.3289	18.3433	87.7202	78.5358	39.18	290.5288	106.1996	124.9082	319.2794	16.3518	1030
15	9.4222	9.2877	17.0936	16.7381	86.1957	74.8897	41.5557	279.6553	103.2742	209.8158	229.5196	14.9061	1010
16	7.0585	8.4744	18.8892	16.7408	71.6405	70.1418	36.2791	281.2316	92.3406	294.7237	229.5196	15.8768	1060
17	8.803	8.8136	15.9704	17.7035	83.4145	71.0318	47.2446	288.5629	136.4023	209.8158	229.5196	15.9914	1050
18	8.2978	11.3345	15.0329	19.8362	80.2174	79.6715	50.0613	300.0837	103.3574	294.7237	229.5196	17.6347	1120
19	7.2429	9.9005	14.5534	17.3185	72.9428	71.5518	51.8523	283.0644	172.2444	294.7237	139.7598	16.1392	1070
20	9.5821	12.2195	15.7376	19.999	86.7821	77.9611	50.7169	299.6297	112.1579	209.8158	229.5196	16.5831	1050
21	5.3497	9.6259	11.9966	17.7141	57.3935	66.9752	55.6285	283.1171	21.7066	209.8159	229.5196	14.1564	910
22	5.7392	11.7489	13.3763	19.4128	61.0688	73.8801	57.5599	289.6628	37.5699	124.9079	229.5196	14.169	860
23	6.6117	11.1379	13.079	19.2874	68.5571	69.2698	58.7185	283.7585	28.8281	124.9079	229.5196	13.5595	850
24	5.2657	6.382	13.8719	18.7505	57.4879	45.3111	58.8417	277.1939	20	124.3002	229.5196	12.6544	800
Total Cost of thermal generation ($/day) 40433.56													
Elapsed time (Sec) 560.297 seconds.													

Table 8. Comparison of optimal costs for test system-II with valve point loading (VPL) and transmission losses (case 2)

Method	Best fuel cost ($/day)	Average fuel Cost ($/day)	Worst fuel cost ($/day)	CPU time (sec)	Condition of PH+PT=PD+PL
MDE [15]	43435.41	-	-	-	Satisfied
IDE [24]	40627.92	40708.53	40860.7	627.06	Not satisfied
DTO	40433.56	40481.49	40509.66	560.297	Satisfied

7. Conclusion

This paper proposes a new evolutionary derivative free double teaching optimization (DTO) algorithm successfully implemented to solve convex hydrothermal problems. The results have been compared with those obtained by other heuristic optimization techniques such as differential evolution (DE), modified DE, Improved PSO (IPSO), TLBO, Improved DE (IDE) algorithm, Krill herd Algorithm (KHA) and Symbiotic Organisms Search (SOS) algorithms. It is found that the execution time and total production costs produced by the proposed DTO method over the scheduling horizon is better or close to other existing optimization techniques in almost all cases considered in this study.

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List of symbols

FC total generation cost

PT_j power generation of thermal unit at j time interval.

$PH_{i,j}$ power generation of i^{th} hydro unit at j^{th} time interval.

Pg power generations from both thermal and hydro at each time interval.

PD_j the load demand at the j^{th} time interval

PL_j the transmission loss at the j^{th} time interval.

a_i, b_i , c_i , d_i , e_i the fuel cost coefficients of the i^{th} thermal plant.

$C_{1,i}$, $C_{2,i}$, $C_{3,i}$, $C_{4,i}$, $C_{5,i}$, $C_{6,i}$ the power generation coefficients of i^{th} hydro plant.

$Q_{i,j}$ the water discharge of the i^{th} hydro plants during the j^{th} time interval.

$Q_{\max,i}$ the maximum water discharge rate of the i^{th} hydro plants

$Q_{\min,i}$ the minimum water discharge rate of the i^{th} hydro plants

$V_{i,j}$ the water storage level in the i^{th} hydro reservoir at the beginning of the j^{th} time interval.

$V_{i,1}$, $V_{i,25}$ the volume of the i^{th} reservoir at the beginning of 1^{st} and 25^{th} hour.

$V_{\min,i}$, $V_{\max,i}$ the minimum and maximum water storage level limit of the i^{th} hydro reservoir.

$I_{i,j}$ the natural inflow of the i^{th} reservoir at the j^{th} time interval.

$S_{i,j}$ Spillage discharge rate of the i^{th} reservoir at the j^{th} time interval.

τ Water delay time between reservoir i and its up-stream u at interval j .

R_u Set of upstream units directly above hydro-plant i .

nh number of hydro unit

nt number of thermal unit

NH number of time interval

Np number of population

$X_{i,j}^{k}$, $X_{i,j}^{k+1}$ the grade of the j^{th} subject of the i^{th} student at the k^{th} and $(k+1)^{th}$ iteration

μ_{diffj}^{k} the difference between the mean of the j^{th} control variable at the k^{th} and $(k+1)^{th}$ iteration.

rand random number between [0,1]

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