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Solving Economic Load Dispatch problem with Multiple Fuels using Teaching Learning based Optimization and Salp Swarm Algorithm

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Abstract

This paper bestows the implementation of bio-inspired algorithms like Teaching-learning Based Optimization (TLBO) and Salp Swarm Algorithm (SSA) for the solution of Economic Load Dispatch (ELD) problem with multiple set of fuels. To obtain the optimal solution, the proposed algorithms are validated on test system consists of ten thermal units with four different load demands. Results have been obtained using SSA and TLBO and they are compared with the results of recently published methods. The study has been done without valve-point effect as well as with valve-point effect for four different load demands. Both the mentioned algorithms are described and presented in this paper. The optimization which has been done taking total fuel cost as the fitness function. The results are simulated for both the cases and analyzed and then presented in this paper. The results reveal the effectiveness and applicability of the proposed algorithms to ELD problem.

Keywords: Salp Swarm Algorithm, Teaching-learning Based Optimization, Valve-point effect, Economic load dispatch, multiple fuels, and Valve-point effect.

1. Introduction

In the present scenario the electric power demand is growing due to the advances in both industrial and public sector. The major source for this electric power is mainly thermal plants and they are expected to satisfy the load demand. For any thermal plant in general the generation cost will be proportional to the fuel cost. So, in order to provide lower generation cost proper load sharing of generating units are required. For this purpose, Economic Load Dispatch (ELD) problem is considered to obtain optimal allocation of generation by all the generating units that minimize the total fuel cost, while satisfying equality constraint and a set of inequality constraints. Usually, the ELD problem is complex due to the design and operation constraints of the generating units such as transmission network losses, valve-point effects, prohibited operating zones and multiple fuel options. In conventional ELD problem, the cost function is approximated by a single quadratic function and the valve-point effects are ignored.

Usually Lambda Iteration method [1] is used to solve the ELD problem for the proper allocation of thermal units with minimum fuel cost. But it is difficult to obtain proper allocation of generating units for large system. To overcome this problem researchers are trying new methods similar to Evolutionary Programming Techniques [2], Genetic Algorithm (GA) [3] and Particle Swarm Optimization (PSO) [4]. In practical power systems, an ELD problem is non-convex due to the valve-point effect, so the application of the classical methods is restricted. In order to solve ELD problem with valve-point effect improved differential evolution (IDE) [5], Tournament-based harmony search (THS) [6] and Oppositional based grey wolf optimization (OGWO) [7] algorithms are used.

Present operating conditions of many thermal units, the generation cost functions for thermal plants be segmented as piecewise quadratic functions. The reasons for this partitioning of the cost curves are many thermal units supplied with multiple fuels like coal, oil and natural gas. Hence, there is a dilemma for some generating units to determining which fuel is most economical to burn. A single unit poses the problem of at least two cost curves for a single unit, these curves are not parallel. Intersecting curves implies that it may be more efficient to burn oil for some MW outputs and natural gas for others. Additionally, varying heat contents of natural gas from multiple suppliers could result in cost curves which are not parallel when compared to each other.

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The notion of multiple cost curves is not limited to applications with multiple fuels. To solve this problem, many methods have been proposed such as hierarchical economic dispatch [8], Hopfield neural network (HNN) [9-10] and PSO [11] without considering the valve-point effect.

A non-convex ELD problem considering the multiple fuels with valve-point effect is more realistic. In recent years, many researchers put effort to solve the realistic ELD problem by applying various search techniques. Biogeography-based optimization (BBO) [12], Improved PSO [13], Improved Random Drift PSO [14], hybrid algorithm consisting of distributed sobol PSO, tabu search algorithm (DSPSO-TSA) [15], backtracking search algorithm (BSA) [16], Lighting Flash algorithm (LFA) [17], new adaptive PSO (NAPSO) [18] and multiple algorithms [19] consisting of modified shuffled frog leaping algorithm (MSFLA), global-best harmony search algorithm (GHS), hybrid algorithm such as SFLA-GHS and shuffled differential evolution (SDE) are committed to the solve ELD problem with valve-point loading and multiple fuel options.

In this paper, implementation and application of some nature inspired algorithms like Teaching-Learning Based Optimization (TLBO) [20] and Salp Swarm algorithm (SSA) [21] for a constrained ELD problem. They are applied on a ten unit thermal system with multiple fuel quadratic cost function as first case and including valve-point effect as second case to test the efficiency of the suggested algorithms.

2. PROBLEM FORMULATION

2.1. *ELD problem formulation*

In order to minimize the cost of operation, Economic Load Dispatch (ELD) is the process of optimal allocation of available generation units to satisfy the required load demand. In general, the generation cost function represented as a second order function, as shown in Eqn. (1).

$$F_k(P_{Gk}) = a_k P_{Gk}^2 + b_k P_{Gk} + c_k \qquad (1)$$

Where a_k , b_k and c_k are coefficients of generator k.

The objective function is minimizing to generation cost as shown in Eqn. (2).

$$F = \min f = \sum_{k=1}^{n} F_k(P_{Gk}) \qquad (\$/h) \qquad (2)$$

Where F_k denotes total generation cost for the generator unit k, which is defined in Eqn. (1).

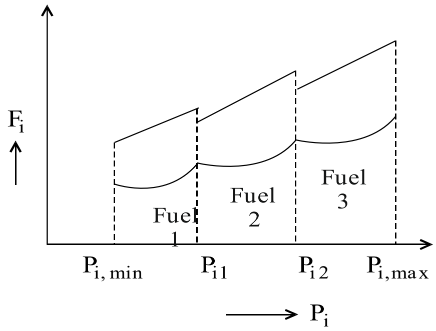

Figure 1. Incremental cost function with multiple fuels

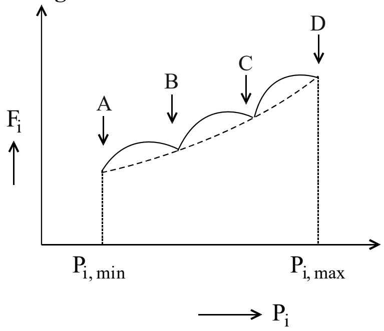

Figure 2. Fuel cost function with valve-point effect.

2.2. *ELD problem with multiple fuels*

Practically the generating units are supplied with multiple fuels like oil, gas and coal. In general fuel cost represent as single quadratic function even though supplied with multiple fuels. But it's not accurate longer than, hence the fuel cost function with multiple fuels should be represented as several piecewise quadratic functions as shown in Fig. 1 reflecting the effects of fuel changes and the generator must identify the most economic fuel to burn. Practically the fuel cost function should be expressed as shown in Eqn. (3).

2.3. *ELD problem with valve-point effect*

In practical power system cost function is non-convex, because of multi-valve steam turbines in generating units. Due to the valve-point effect cost function contains higher order non-linearity as shown in Fig. 2. Hence to simulate the valve-point effect added sinusoidal terms to the second order cost functions as follows Eqn. (4).

Where e_{ck} and f_{ck} are constants of the unit-k due to discontinuities of generating unit.

2.4. *ELD problem with multiple fuels including valve-point effect*

In practical operation, generating units are supplied with multiple fuels and also including valve-point effect to the cost functions in order to get accurate ELD solution. The generation cost function with multiple fuels (3) should be combined with valve-point effect (4), and can be practically expressed as Eqn. (5).

$$F = F_C(P_{Gk}) = \begin{cases} a_{k1}P_{Gk}^2 + b_{k1}P_{Gk} + c_{k1} & P_{Gk}^{min} \le P_{Gk} \le P_{Gk1} \\ a_{k2}P_{Gk}^2 + b_{k2}P_{Gk} + c_{k2} & P_{Gk1} \le P_{Gk} \le P_{Gk2} \\ . & \\ ..a_{kn}P_{Gk}^2 + b_{kn}P_{Gk} + c_{kn} & P_{Gk(n-1)} \le P_{Gk} \le P_{Gk}^{max} \end{cases} \quad (\$/h) \tag{3}$$

$$F_2 = F_C(P_G) = \sum_{k=1}^{N_G} (a_k P_{Gk}^2 + b_k P_{Gk} + c_k) + \left| e_{ck} \times \sin(f_{ck} \times (P_{Gk}^{min} - P_{Gk})) \right| \quad (\$/h) \tag{4}$$

$$F = F_C(P_{Gk}) = \begin{cases} a_{k1}P_{Gk}^2 + b_{k1}P_{Gk} + c_{k1} + \left| e_{ck1} \times \sin(f_{ck1} \times (P_{Gk}^{min} - P_{Gk})) \right| & P_{Gk}^{min} \le P_{Gk} \le P_{Gk1} \\ a_{k2}P_{Gk}^2 + b_{k2}P_{Gk} + c_{k2} + \left| e_{ck2} \times \sin(f_{ck2} \times (P_{Gk}^{min} - P_{Gk})) \right| & P_{Gk1} \le P_{Gk} \le P_{Gk2} \\ . & \\ a_{kn}P_{Gk}^2 + b_{kn}P_{Gk} + c_{kn} + \left| e_{ckn} \times \sin(f_{ckn} \times (P_{G}^{min} - P_{Gk})) \right| & P_{Gk(n-1)} \le P_{Gk} \le P_{Gk}^{max} \end{cases} \tag{5}$$

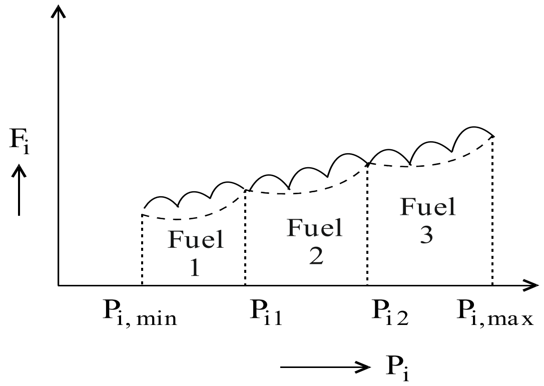

Figure 3. Fuel cost function with multiple fuels including valve-point effect.

Complication of the practical ELD problem is due to the involvement of valve-point effect and multiple fuels to the fuel cost function which is graphically shown in Fig.3.

2.4.1. Equality constraint

Total generation of any power system must meet the required load demand and losses occur in the transmission lines, as shown in Eqn. (6).

$$\sum_{k=1}^{N_G} P_{Gk} = P_D + P_L \tag{6}$$

Where P_L denotes power losses and P_D denotes the power demand. The power loss can be computed using B-coefficient method expressed as a second order function shown in Eqn. (7).

$$P_L = \sum_{j=1}^{n}\sum_{k=1}^{n} P_{Gj}B_{jk}P_{Gk} + \sum_{j=1}^{n} B_{0j}P_{Gj} + B_{00} \quad (MW) \tag{7}$$

2.4.2. Power limit constraint

Any generator output can be varied between minimum and maximum power limits as follows Eqn. (8).

$$P_{Gk}^{min} \le P_{Gk} \le P_{Gk}^{max} \tag{8}$$

3.TLBO ALGORITHM

Based on the influence of a teacher on learners, Ravipudi Venkata Rao proposed Teaching-Learning based optimization technique (TLBO) [20]. This method works on the effect of teacher on the learners in a class, and consequently, learning by interaction between learners which helps in their grades. In this algorithm a number of solutions which is considered as the population or a group of students in a class. Learners' different subjects are represented as design parameters in TLBO, and the learners' grades is similar to the ''fitness''. The best solution in, TLBO is similar to teacher because teacher is the most learned person in the society. TLBO divided into two parts, among the first part is ''teacher phase'' and the second part is ''learner phase''. The learners learning from teachers means ''teacher phase'' and the learners learning through the interaction between learners in a class means ''learner phase''. Now, implementation of TLBO is described below.

3.1. Initialization

The population **X** is randomly initialized which is bounded by matrix of N **(no. of learners)** rows and **D (no.of subjects)** columns. The j^{th} parameter of the i^{th} learner is assigned values randomly using the Eqn. (9).

$$X_{i,j}^0 = X_j^{min} + rand * (X_j^{max} - X_j^{min}) \tag{9}$$

Where rand represents a random variable within the range (0, 1), X_j^{min} and X_j^{max} represents the minimum and maximum value for j^{th} parameter.

3.2. Teacher Phase

The mean result of each subject of the learners in the class at generation **p** is given as Eqn. (10).

$$M^p = [m_1^p, m_2^p, m_3^p, ..., m_j^p, ...m_D^p] \tag{10}$$

The minimum objective function of learner is represented as the 'Teacher' (X_T). The teacher tries to improve the grades of other learners (X_L) by updating the mean result (M^p) of the classroom towards X_T position. New position of student is given by Eqn. (11).

$$Xnew_L^p = X_L^p + rand(X_T^p - TF * M^p) \quad (11)$$

Here the valve of TF (teaching factor) either 1 or 2, it is evaluated using Eqn. (12).

$$TF = round[1 + rand(0,1)\{2-1\}] \quad (12)$$

Where TF valve is randomly decided by the algorithm using above Equation.

If $Xnew_L^p$ is found to be lesser than X_L^p in generation p, than it interchanges on X_L^p otherwise it remains X_L^p.

3.3. Learner Phase

In this phase, the learners increase their knowledge with help of other learners. Therefore, each learner learns new knowledge if the other learners have more knowledge than him/her. For a learner X_L^p, randomly select other learner X_{randL}^p as $L \neq randL$. New position of each learner is given by Eqn. (13) and Eqn. (14).

$$Xnew_L^p = X_L^p + rand * (X_L^p - X_{randL}^p) \text{ if } f(X_L^p) < f(X_{randL}^p) \quad (13)$$

$$Xnew_L^p = X_L^p + rand * (X_{randL}^p - X_L^p) \text{ if } f(X_L^p) > f(X_{randL}^p) \quad (14)$$

When MAXIT (maximum iteration) is completed, and then the TLBO algorithm is stop, otherwise 'Teacher Phase' repeated. The flowchart of TLBO algorithm shown in Fig. 4.

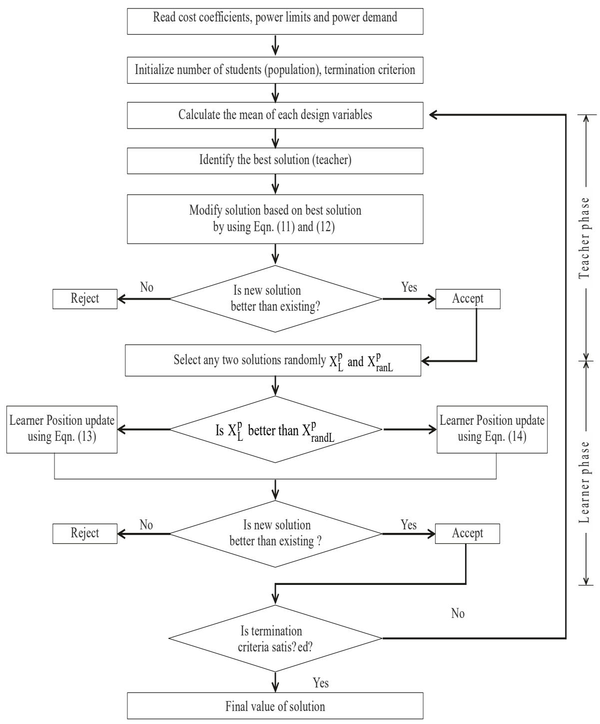

Figure 4. Flowchart of TLBO algorithm

Execution of TLBO algorithm for ELD

The steps for solving ELD problem using TLBO algorithm as follows:

Step 1: Read cost coefficients of generators, minimum/maximum power limits and load demand.

Step 2: Set time count t=1 and repeat the next steps up to maximum iterations.

Step 3: Start "teacher phase", teacher is selected to minimize the cost.

Step 4: In teacher phase new generator matrix is formed using Eqn. (10) and Eqn. (11).

Step 5: Start "learner phase", generation is upgraded by collaboration with different learners.

Step 6: Random learner is selected for an individual learner to interact each other using Eqn. (13) and Eqn. (14).

Step 7: The process is terminated when maximum iteration reached. Otherwise repeat from teacher phase.

4. SALP SWARM ALGORITHM

4.1 Inspiration

Salp Swarm Algorithm (SSA) [21] is a novel optimization algorithm for solving optimization problem. The main inspiration of SSA is the swarming behaviour of salps when navigating and foraging in oceans. Salps belong to the family of Salpidae and have transparent barrel-shaped body. Their tissues are highly similar to jelly fishes. Salps move similar to jelly fish, in which the water is pumped through body as propulsion to move forward. In deep oceans, salps often form a swarm called salp chain. This is done for achieving better locomotion using rapid coordinated changes and foraging.

4.2. Proposed mathematical model for moving salp chains

The population is first divided to two groups: leader and followers. The leader is the salp at the front of the chain, whereas the rest of salps are considered as followers. As the name of these salps implies, the leader guides swarm and the followers follow each other (and leader directly or indirectly). To update the position of the leader the following Eqn. (15) is proposed.

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) & c_3 \geq 0.5 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) & c_3 < 0.5 \end{cases} \quad (15)$$

Where x_j^1 shows the position of the first salp (leader), F_j is the position of the food source, c_1, c_2 and c_3 are random numbers. Equation (15) shows that the leader only updates its position with respect to the food source. The coefficient C_1 is the most important parameter in SSA it defined using Eqn. (16).

$$c_1 = 2e^{-(\frac{4l}{L})^2} \quad (16)$$

Where l is the current iteration and L is the maximum number of iterations.

The parameter C_2 and C_3 are random numbers uniformly generated in the interval of [0, 1]. In fact, they dictate if the next position in *j*th dimension should be towards positive infinity or negative infinity as well as the step size. To update the position of the followers, the following Eqn. (17) is utilized (Newton's law of motion):

$$x_j^i = \frac{1}{2}at^2 + v_0 t \tag{17}$$

Where $i \geq 2$, x_j^i shows the position of *i*th follower salp in *j*th dimension, t is time, V_0 is the initial speed, and $a = \frac{v_{final}}{v_0}$ where $v = \frac{x - x_0}{t}$.

Because the time in optimization is iteration, the discrepancy between iterations is equal to 1 and considering $V_0 = 0$, this equation can be expressed as follows:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{18}$$

Where $i \geq 2$ and x_j^i shows the position of *i*th follower salp in *j*th dimension.

When maximum iteration is reached, and then the SSA algorithm is stop, otherwise from leader section algorithm repeated. The flowchart of SSA algorithm shown in Fig. 5.

5. NUMERICAL RESULTS

To prove the efficacy and superiority of present approaches, a ten unit system is considered with multiple fuels in first case and valve-point effects are considered along with multiple fuels in second case. The input data available in reference [19]. In this ELD problem, generators are supplied with three types of fuels, namely 1, 2 and 3. The total ten units are categorized into three subsystems, where the 1st subsystem consists of four thermal units and remaining two subsystems consists of three thermal units. Among the ten thermal units unit-1 supplied with only two types fuels (1 and 2), unit-9 is a different, even though fuel 2 is available but uneconomical to burn and when fuels 1 and 3 are not available then fuel 2 can be utilized instantly.

The parameters require to implementing the TLBO and SSA algorithms are as follows. The population (no.of students in class or no. of salps) and maximum iteration (termination criteria) are set as 40 and 1500. To reduce the statistical errors, test system repeated 50 times and all simulations are developed in MATLAB 2014a.

5.1. ELD problem with multiple fuels

ELD problem with multiple fuels is considered as first case. This case, the 10-unit system data, such as fuel types and its cost coefficients are taken from Ref. [11]. Initially load demand considered as 2400 MW and later with increment of 100 MW, load demand increases upto 2700 MW. The best results of the proposed TLBO and SSA algorithms are shown in Tables 1-4 for different load demands of 2400 MW to 2700 MW respectively. The comparisons of results after 50 trials for the ten unit system with multiple fuels are given in Table 5. Furthermore, the average and maximum values obtained by proposed algorithms are equal to minimum value, which proves the robustness of the proposed algorithms. But the time require for TLBO is more compared with SSA algorithm.

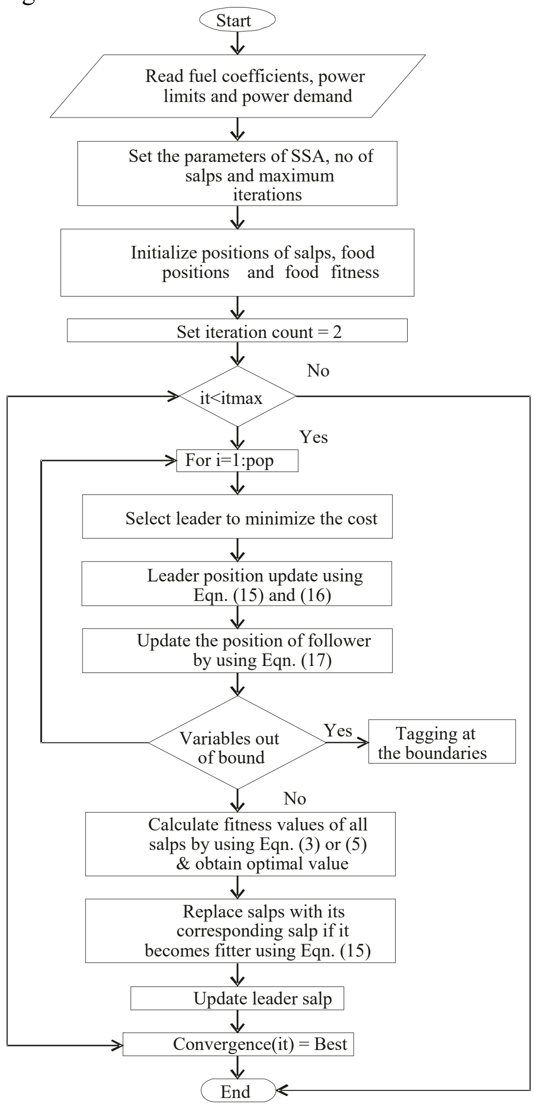

Fig. 5. Flowchart of SSA algorithm

For this ten unit test system, the optimal solution attained from the methods informed in the literature namely, hierarchical economic dispatch [8], HNN [9-10], PSO [11] and the proposed algorithms are listed in Table 1-4 for a demand of 2400 MW to 2700 MW respectively. From the results it can be concluded that the proposed methods obtain optimal results as compare with other methods informed in the literature. The convergence characteristics of the suggested algorithms are shown in Fig. 6-9 for different load demands.

Table 1: Simulation and Comparisons results of proposed algorithms with demand = 2400 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	1	193.2	1	192.7	1	189.1	1	189.7	1	189.7405	1	189.7406
P_2(MW)	1	204.1	1	203.8	1	202.0	1	202.3	1	202.3427	1	202.3427
P_3(MW)	1	259.1	1	259.1	1	254.0	1	253.9	1	253.8953	1	253.8952
P_4(MW)	3	234.3	2	195.1	3	233.0	3	233.0	3	233.0456	3	233.0456
P_5(MW)	1	249.0	1	248.7	1	241.7	1	241.8	1	241.8297	1	241.8296
P_6(MW)	3	195.5	3	234.2	3	233.0	3	233.0	3	233.0456	3	233.0456
P_7(MW)	1	260.1	1	260.3	1	254.1	1	253.3	1	253.2750	1	253.2750
P_8(MW)	3	234.3	3	234.2	3	232.9	3	233.0	3	233.0456	3	233.0455
P_9(MW)	1	325.3	1	324.7	1	320.0	1	320.4	1	320.3832	1	320.3831
P_{10}(MW)	1	246.3	1	246.8	1	240.3	1	239.4	1	239.3969	1	239.3970
PT(MW)	2401.2		2399.8		2400.0		2400		2400		2400	
FC($/h)	488.500		487.87		481.700		481.723		481.7226		481.7226	
Time(sec)	-----		-----		-----		-----		9.1955		4.6413	

Table 2: Simulation and Comparisons results of proposed algorithms with demand = 2500 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	206.6	2	206.1	2	206.0	2	206.5	2	206.5190	2	206.5190
P_2(MW)	1	206.5	1	206.3	1	206.3	1	206.5	1	206.4573	1	206.4573
P_3(MW)	1	265.9	1	265.7	1	265.7	1	265.7	1	265.7391	1	265.7392
P_4(MW)	3	236.0	3	235.7	3	235.9	3	236.0	3	235.9531	3	235.9532
P_5(MW)	1	258.2	1	258.2	1	257.9	1	258.0	1	258.0177	1	258.0177
P_6(MW)	3	236.0	3	235.9	3	235.9	3	236.0	3	235.9531	3	235.9531
P_7(MW)	1	269.0	1	269.1	1	269.6	1	268.9	1	268.8635	1	268.8635
P_8(MW)	3	236.0	3	235.9	3	235.9	3	235.9	3	235.9531	3	235.9531
P_9(MW)	1	331.6	1	331.2	1	331.4	1	331.5	1	331.4877	1	331.4877
P_{10}(MW)	1	255.2	1	255.7	1	255.4	1	255.1	1	255.0562	1	255.0561
PT(MW)	2501.1		2499.8		2500.0		2500.0		2500.0		2500.0	
FC($/h)	526.700		526.13		526.2300		526.239		526.2388		526.2388	
Time(sec)	-----		-----		-----		-----		8.7299		4.5864	

Table 3: Simulation and Comparisons results of proposed algorithms with demand = 2600 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	216.4	2	215.3	2	215.8	2	216.5	2	209.7880	2	209.7880
P_2(MW)	1	210.9	1	210.6	1	210.7	1	210.9	1	207.9079	1	207.9079
P_3(MW)	1	278.5	1	278.9	1	279.1	1	278.5	1	269.9146	1	269.9146
P_4(MW)	3	239.1	3	238.9	3	239.1	3	239.1	3	236.9782	3	236.9782
P_5(MW)	1	275.4	1	275.7	1	276.3	1	275.5	1	263.7247	1	263.7247
P_6(MW)	3	239.1	3	239.1	3	239.1	3	239.1	3	236.9782	3	236.9782
P_7(MW)	1	285.6	1	286.2	1	286.0	1	285.7	1	274.3591	1	274.3591
P_8(MW)	3	239.1	3	239.1	3	239.1	3	239.1	3	236.9782	3	236.9782
P_9(MW)	1	343.3	1	343.5	1	342.8	1	343.5	1	402.7945	1	402.7945
P_{10}(MW)	1	271.9	1	272.6	1	271.9	1	272.0	1	260.5767	1	260.5767
PT(MW)	2600.0		2599.8		2600.00		2600.00		2600.00		2600.00	
FC($/h)	574.030		574.26		574.370		574.381		573.7413		573.7413	
Time(sec)	-----		-----		-----		-----		8.9296		4.5722	

Table 4: Simulation and Comparisons results of proposed algorithms with demand = 2700 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	218.4	2	224.5	2	225.7	2	218.3	2	209.7880	2	209.7880
P_2(MW)	1	211.8	1	215.0	1	215.2	1	211.7	1	207.9079	1	207.9079
P_3(MW)	1	281.0	3	291.8	1	291.8	1	280.7	1	269.9146	1	269.9146
P_4(MW)	3	239.7	3	242.2	3	242.3	3	239.6	3	236.9782	3	236.9782
P_5(MW)	1	279.0	1	293.3	1	293.7	1	278.5	1	263.7247	1	263.7247
P_6(MW)	3	239.7	3	242.2	3	242.3	3	239.6	3	236.9782	3	236.9782
P_7(MW)	1	289.0	1	303.1	1	302.8	1	288.6	1	274.3591	1	274.3591
P_8(MW)	3	239.7	3	242.2	3	242.3	3	239.6	3	236.9782	3	236.9782
P_9(MW)	3	429.2	3	355.7	3	355.1	3	428.5	3	402.7945	3	402.7945
P_{10}(MW)	1	275.2	1	289.5	1	288.8	1	274.9	1	260.5767	1	260.5767
PT(MW)	2702.2		2699.7		2700.00		2700.00		2700.00		2700.00	
FC($/h)	625.180		626.12		626.240		623.809		622.8092		622.8092	
Time(sec)	-----		-----		-----		-----		9.1236		4.3085	

Table 5: Statistical comparison of proposed algorithms for 50 trials.

Load (MW)	Cost ($/h)	SDE [19]	SFLA-GHS [19]	TLBO	SSA
2400	Minimum cost	481.7226	481.7226	481.7226	481.7226
	Average cost	481.7226	481.7226	481.7226	481.7226
	Maximum cost	481.7226	481.7226	481.7226	481.7226
2500	Minimum cost	526.2388	526.2388	526.2388	526.2388
	Average cost	526.2388	526.2388	526.2388	526.2388
	Maximum cost	526.2388	526.2388	526.2388	526.2388
2600	Minimum cost	574.3808	574.3808	573.7413	573.7413
	Average cost	574.3808	574.3808	573.7413	573.7413
	Maximum cost	574.3808	574.3808	573.7413	573.7413
2700	Minimum cost	623.8092	623.8092	622.8092	622.8092
	Average cost	623.8092	623.8092	622.8092	622.8092
	Maximum cost	623.8092	623.8092	622.8092	622.8092

From the convergence characteristics the results presented in the tables are ratified. From the graphs observed that TLBO algorithm get convergence with less number of iterations as compare with SSA algorithm, but the amount of time require for (each trial) TLBO algorithm is more as compared with SSA algorithm. For statistical analysis proposed algorithms are repeated 50 times and corresponding convergence curves for 50 trials are presented in Fig. 10 and Fig. 11 for the load demand of 2700 MW.

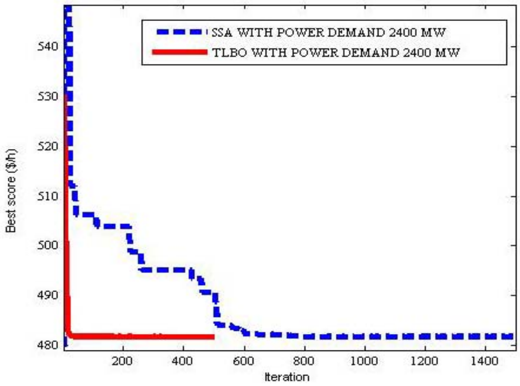

Figure 6. Convergence characteristics of 10 unit system with power demand = 2400 MW for case 1.

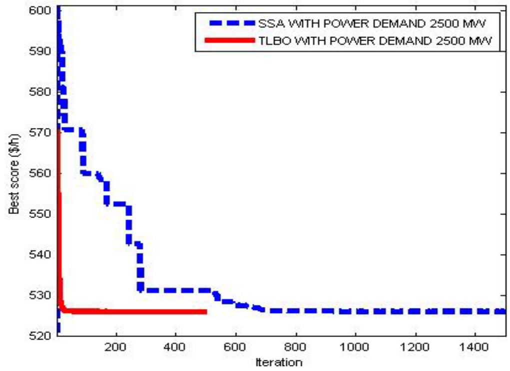

Figure 7. Convergence characteristics of 10 unit system with power demand = 2500 MW for case 1.

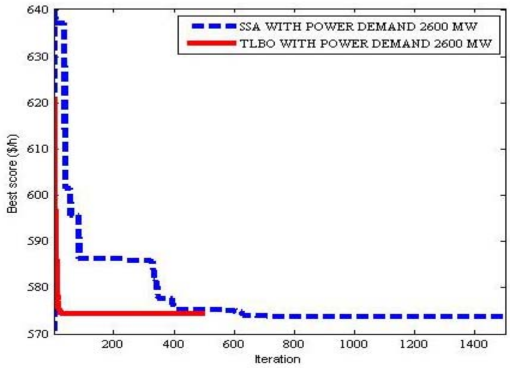

Figure 8. Convergence characteristics of 10 unit system with power demand = 2600 MW for case 1.

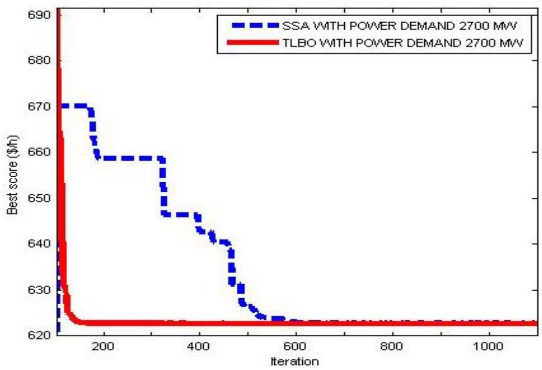

Figure 9. Convergence characteristics of 10 unit system with power demand = 2700 MW for case 1.

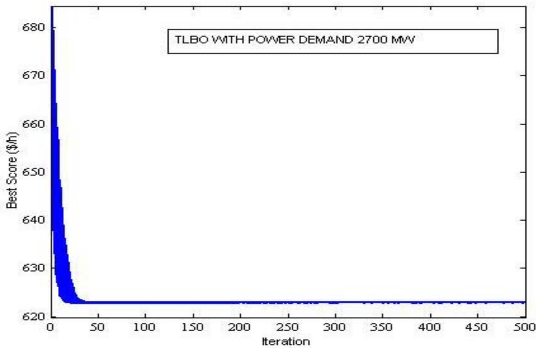

Figure 10. TLBO characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 1.

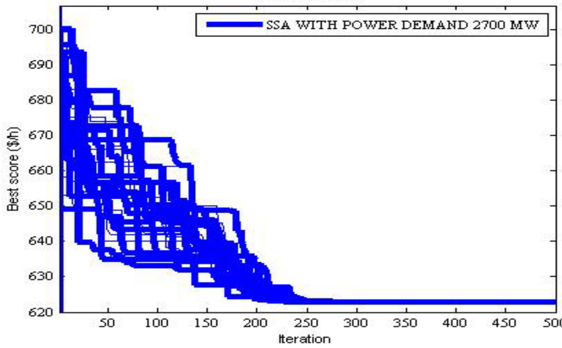

Figure 11. SSA characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 1.

5.2. ELD problem with multiple fuels including Valve-Point effect

ELD problem with multiple fuels including valve-point effect is considered as second case. This case, the 10-unit system data, such as fuel types and its cost coefficients are taken from Ref. [17]. Load demands are consider as similar to previous case like 2400 MW to 2700 MW with increment of 100 MW. The best results of the proposed TLBO and SSA algorithms are shown in Tables 6-9 for different load demands of 2400 MW to 2700 MW respectively. The comparisons of results after 50 trials for the ten unit thermal system with multiple fuels with valve-point effect are given in Table 10. Furthermore, the average and maximum values obtained by proposed algorithms are approximately same as minimum value because due to the effect of valve-point effect.

Table 6: Simulation and Comparisons results of proposed algorithms with demand = 2400 MW.

Unit	SDE [19]		MSFLA[19]		GHS [19]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	1	190.09	1	184.57	1	189.31	1	188.52	1	190.0426	1	189.7406
P_2(MW)	1	202.3	1	204.78	1	202.55	1	203.54	1	201.7834	1	202.3427
P_3(MW)	1	254.44	1	244.36	1	253.43	1	254.44	1	254.1962	1	253.8952
P_4(MW)	3	233.05	3	231.85	3	233.05	3	234.53	3	233.0582	3	233.0456
P_5(MW)	1	240.36	1	254.55	1	243.96	1	239.93	1	240.6335	1	241.8296
P_6(MW)	3	233.05	3	29.29	3	234.13	3	232.78	3	231.2827	3	233.0456
P_7(MW)	1	252.16	1	257.11	1	252.18	1	254.54	1	253.1148	1	253.2750
P_8(MW)	3	233.05	3	234.53	3	233.45	3	231.71	3	232.8416	3	233.0455
P_9(MW)	1	320.39	1	323.16	1	319.28	1	322.05	1	322.6016	1	320.3831
P_{10}(MW)	1	241.06	1	235.79	1	238.63	1	237.3	1	240.4456	1	239.3970
PT(MW)	2400.0		2400.0		2400.0		2400.0		2400.0		2400.0	
FC($/h)	481.7305		482.278		481.75043		481.7754		481.7489		481.6420	
Time(sec)	-----		-----		-----		-----		60.1740		15.5595	

Table 7: Simulation and Comparisons results of proposed algorithms with demand = 2500 MW.

Unit	SDE [19]		MSFLA[19]		GHS [19]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	207.29	2	208.32	2	207.30	2	206.22	2	212.1764	2	207.1101
P_2(MW)	1	206.26	1	206.01	1	206.76	1	206.76	1	205.2873	1	203.5421
P_3(MW)	1	265.53	1	266.54	1	265.53	1	265.53	1	265.5651	1	265.3599
P_4(MW)	3	236.01	3	237.08	3	235.60	3	234.26	3	236.6921	3	236.2802
P_5(MW)	1	258.34	1	254.37	1	258.27	1	258.49	1	252.2533	1	254.9352
P_6(MW)	3	236.01	3	236.95	3	235.20	3	235.07	3	235.0916	3	234.5333
P_7(MW)	1	268.75	1	266.49	1	268.75	1	271.17	1	269.9148	1	273.6039
P_8(MW)	3	236.01	3	236.68	3	236.28	3	233.86	3	233.8608	3	239.2363
P_9(MW)	1	332.02	1	328.69	1	332.56	1	334.23	1	331.4671	1	333.1278
P_{10}(MW)	1	253.74	1	258.82	1	253.71	1	254.37	1	257.6916	1	252.2711
PT(MW)	2500.0		2500.0		2500.0		2500.0		2500.0		2500.0	
FC($/h)	526.24266		526.33166		526.26547		526.32577		526.2762		526.1032	
Time(sec)	-----		-----		-----		-----		54.3198		12.8801	

Table 8: Simulation and Comparisons results of proposed algorithms with demand = 2600 MW.

Unit	SDE [19]		MSFLA[19]		GHS [19]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	216.53	2	218.59	2	209.34	2	214.48	2	216.8075	2	212.0521
P_2(MW)	1	210.72	1	203.04	1	207.99	1	212.70	1	210.4631	1	208.4934
P_3(MW)	1	278.64	1	271.58	1	269.62	1	277.63	1	282.6441	1	272.5263
P_4(MW)	3	238.83	3	236.41	3	236.95	3	239.63	3	239.3174	3	236.1458
P_5(MW)	1	276.31	1	276.43	1	265.48	1	275.03	1	276.4376	1	263.5184
P_6(MW)	3	238.96	3	241.92	3	235.87	3	241.25	3	238.4607	3	236.8176
P_7(MW)	1	285.35	1	287.72	1	273.51	1	282.98	1	282.9223	1	277.0237
P_8(MW)	3	238.83	3	240.84	3	237.75	3	239.37	3	238.4305	3	237.2208
P_9(MW)	1	343.09	1	344.19	1	403.32	1	344.19	1	342.0667	1	395.7819
P_{10}(MW)	1	272.70	1	27.22	1	260.11	1	272.69	1	272.4502	1	260.4200
PT(MW)	2600.0		2600.0		2600.00		2600.00		2600.00		2600.00	
FC($/h)	574.3839		574.89446		574.78857		574.4561		573.7620		573.5663	
Time(sec)	-----		-----		-----		-----		54.1888		13.4834	

For this ten unit test system, the optimal solution attained from the methods informed in the literature namely, SDE [19], MSFLA [19], GHS [19], SFLA-GHS [19] and the proposed algorithms are listed in Table 6-8 for a demand of 2400 MW, 2500 MW and 2600 MW respectively. For 2700 MW power demand optimal solution compared with DPSO-TSA [15], BSA [16], NAPSO [18], SFLA-GHS [19] and the proposed algorithms are listed in Table 9. From the results it can be concluded that the suggested methods obtain best results as compare with other methods informed in the literature. The convergence characteristics of the suggested algorithms are shown in Fig. 12-15 for different load demands.

Table 9: Simulation and Comparisons results of proposed algorithms with demand = 2700 MW.

Unit	DPSO-TSA [15]		BSA [16]		NAPSO [18]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	217.55	2	218.57	2	219.06	2	218.59	2	219.7690	2	221.6360
P_2(MW)	1	211.21	1	211.21	1	211.16	1	212.20	1	210.9383	1	209.7312
P_3(MW)	1	279.64	3	279.56	1	279.65	1	279.64	1	278.8449	1	280.6238
P_4(MW)	3	240.04	3	239.50	3	239.41	3	239.90	3	239.1031	3	240.5800
P_5(MW)	1	279.94	1	279.97	1	280.09	1	279.95	1	277.9823	1	276.8772
P_6(MW)	3	239.77	3	241.11	3	239.52	3	239.77	3	237.0181	3	239.2363
P_7(MW)	1	287.73	1	289.79	1	287.73	1	290.09	1	285.2918	1	294.9909
P_8(MW)	3	239.50	3	240.57	3	240.08	3	239.50	3	238.9219	3	239.5051
P_9(MW)	3	428.70	3	426.88	3	428.17	3	427.45	3	439.2320	3	423.6788
P_{10}(MW)	1	275.86	1	272.79	1	275.07	1	272.84	1	272.8986	1	273.1406
PT(MW)	2700.0		2700.0		2700.00		2700.00		2700.00		2700.00	
FC($/h)	623.8375		623.9016		623.62170		623.84065		622.8490		622.7174	
Time(sec)	-----		-----		-----		-----		52.0099		22.8867	

Table 10: Statistical comparison of proposed algorithms for 50 trials.

Load (MW)	Cost ($/h)	TLBO	SSA
2400	Minimum cost	481.7489	481.6420
	Average cost	481.8118	481.9565
	Maximum cost	481.8655	482.1060
2500	Minimum cost	526.2762	526.3032
	Average cost	526.3337	527.9598
	Maximum cost	526.4121	526.5349
2600	Minimum cost	573.7620	573.5663
	Average cost	574.1227	574.2088
	Maximum cost	574.5190	574.7104
2700	Minimum cost	622.8490	622.7174
	Average cost	622.8836	622.9975
	Maximum cost	622.9424	623.1005

From the results conclude that proposed methods produce better results as compared with other methods proposed in the literature. For given different load demands proposed method SSA produce better result as compare with TLBO Method and also the computational time for SSA is less as compared with TLBO method. The convergence characteristics for TLBO and SSA are shown in below figures.

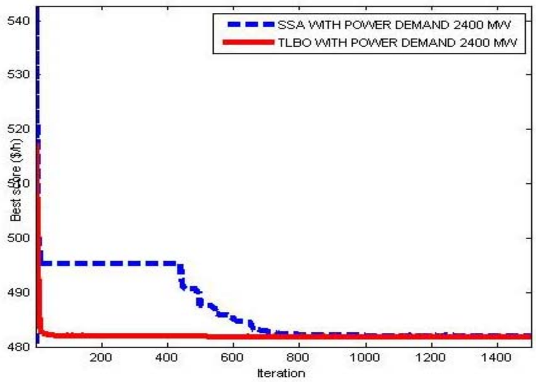

Figure. 12. Convergence characteristics of 10 unit system with power demand = 2400 MW for case 2.

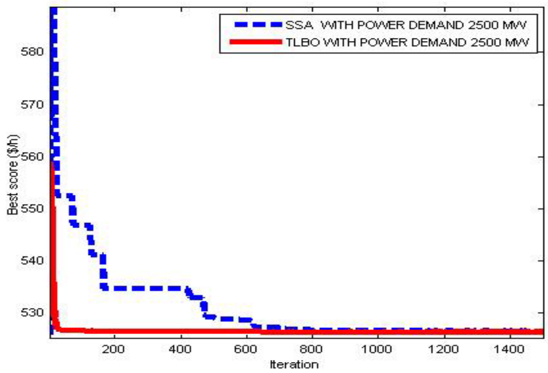

Figure. 13. Convergence characteristics of 10 unit system with power demand = 2500 MW for case 2.

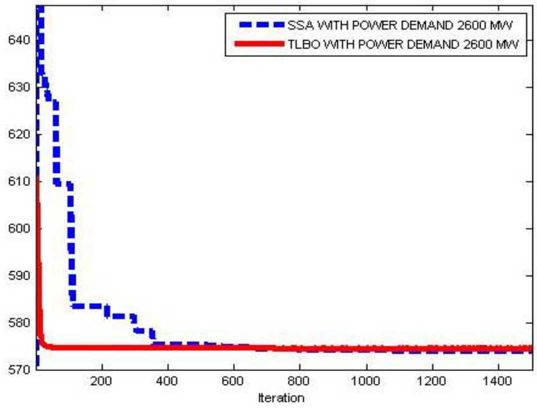

Figure 14. Convergence characteristics of 10 unit system with power demand = 2600 MW for case 2.

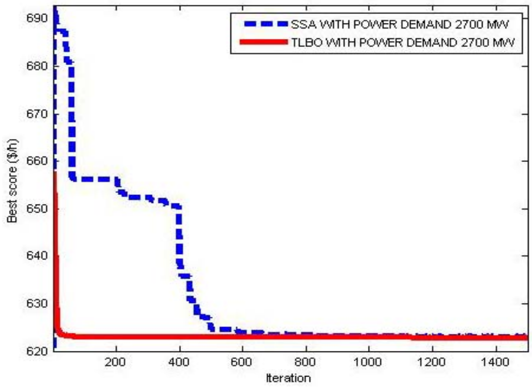

Figure 15. Convergence characteristics of 10 unit system with power demand = 2700 MW for case 2.

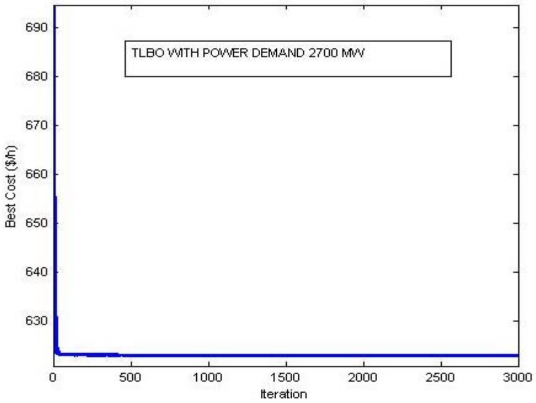

Figure 16. TLBO characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 2.

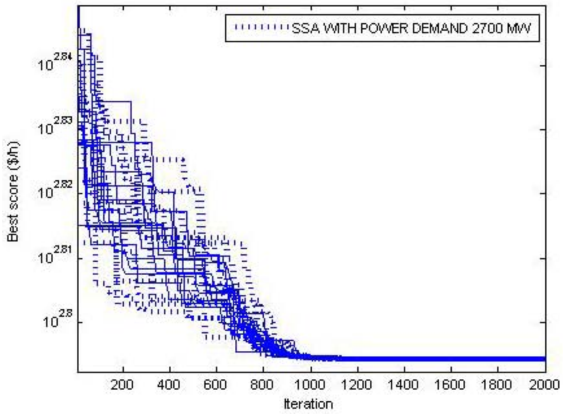

Figure 17. SSA characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 2.

From the convergence characteristics the results presented in the tables are ratified. From the graphs observed that TLBO algorithm get convergence with less number of iterations as compare with SSA algorithm, but the amount of time require for (each trial) TLBO algorithm is more as compared with SSA algorithm. For statistical analysis proposed algorithms are repeated 50 times and corresponding convergence curves for 50 trials are presented in Fig. 16 and Fig. 17 for the load demand of 2700 MW.

6. CONCLUSIONS

In this paper, we attempt to use recently developed Teaching-Learning Based Optimization (TLBO) and Salp Swarm Algorithm (SSA) to solve the realistic Economic Load Dispatch (ELD) problem. In this work, we address the 10-unit system with multiple fuel option as first case and non-convex ELD problem with multiple fuel options as second case. The proposed methods exhibits same result during first case, but for second case SSA method exhibits better result as compare with TLBO method. The suggested algorithms found optimal results for the 10 unit thermal system than the other results found so far in the literature. The results clearly indication that the suggested methods can be used as an effective optimizer providing better results for real power system ELD problems.

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