Comparison Investigation into Power System Optimization and Constraint-Based Generator Load Scheduling Using Metaheuristic Algorithms

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ABSTRACT

In this paper, a novel flower pollination algorithm (FPA) is implemented to solve the problem of combined economic emission dispatch (CEED) in the power system. The FPA is a new metaheuristic optimization technique, which takes a biological approach to flower pollination. The FPA mimics the characteristics of flower pollination according to the survival of the fittest concept. CEED represents a combination of the emission and economic dispatch functions, formulated into a single function using the penalty factor. In this paper, the effect of valve point loading in the power system network is considered to obtain minimum fuel cost, minimum emissions, and optimum power generation. The performance of the proposed algorithm is evaluated using two test systems, namely 10 and 14 generating units by contemplating the valve point loading effect as well as transmission loss. The results of the 10 and 14 system units are compared with a learning-based optimization technique to demonstrate the effectiveness of the FPA. The findings reveal that the proposed FPA gives better performance than other algorithms with minimum fuel cost and emissions.

Keywords: Valve Point Loading Effect, Economic Dispatch, Emission Dispatch, Combined Economic Emission Dispatch, Flower Pollination Algorithm, Teaching Learning-Based Optimization Algorithm

1. INTRODUCTION

Nowadays, the electrical energy market is becoming increasingly combative. For sustainability in the present era, optimal power generation is required to minimize the cost of fuel and emission dispatch. The foremost objective of economic load dispatch (ELD) is to reduce the overall generation expenses while addressing equality and inequality constraints. Under the existing conditions, power engineers face the major problem of generator rescheduling. In recent decades, numerous techniques have been implemented to decipher the problem of economic load dispatch. Fossil fuel usage in electrical energy generation results in the release of harmful gases like carbon dioxide (CO_2), nitrogen oxides, and sulfur oxide which affect both the living and non-living in many ways. It also affects climate change and causes damage to materials and visibility. Hence, reducing atmospheric pollution presents a major challenge for the electrical energy industry. Previously, the main purpose of economical dispatch has been confined to minimizing the overall cost of the power generation network while rescheduling the already committed outputs.

Nevertheless, achieving optimal economic load dispatch does not lead to minimum emissions and the ability to meet the environmental regulations enforced in recent decades; emission control has become one of the operational objectives. This has resulted in the revelation of a new model to address the economic emission dispatch (EED) problem [1–3]. Many researchers have addressed the EED issue and attempted to establish a single objective function by linearly combining the other EED objectives. To determine the exchange between environmental cost and fuel cost, the weights must be varied. Some researchers have carried out simultaneous optimization of multiple objectives to address the EED problem using evolutionary algorithms [4, 5].

Dieu *et al.* implemented a hybrid Hopfield neural network to solve the non-convex cost function based

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on optimal power dispatch [6]. Later, the economic dispatch problem was solved using augmented Lagrange Hopfield networks on prohibited operating zones. These techniques are designed based upon the piecewise quadratic cost function and linear quadratic programming [7]. Wang and Singh proposed a model to solve the problem of the environmental economic emission dispatch effect by employing an improved particle swarm optimization technique which is both deterministic and stochastic [8]. Pourakbari-Kasmaei and Rashidi-Nejad implemented a state-of-the-art effortless hybrid method (EHM) to provide an economical dispatch solution for the power network [9]. Pandian and Thanushkodi designed a futuristic technique to solve the power system dispatch problem based upon the cubic cost function and considering transmission loss using multiagent-based hybrid particles for swarm optimization [10]. This method also resolves the randomness issue, with a unique solution for the variable tuning problems present in traditional power system optimization. Lohokare *et al.* implemented a novel aBBOmDE method to resolve the economic dispatch problem using both convex and non-convex cost functions [11]. A novel reinforcement learning technique has also been implemented for solving power system dispatch problems [12].

Alternatively, another approach is available to handle both emission and fuel cost contemporaneously as participating objectives. In the last decade, with the evolution of multi-objective search techniques, many researchers are exhibiting interest in this approach. To solve the EED problem, metaheuristic methods are employed, specifically the flower pollination algorithm (FPA) and teaching learning-based optimization (TLBO) [13].

2. PROBLEM FORMULATION

In this article, the load dispatch problem of the power network can be solved by optimum generation allocation while addressing equality and inequality constraints and the generator power balance of the network. The cost of generation can be minimized through simplified quadratic cost functions, subject to various network constraints. The following constraints and objective functions are considered for resolving the ELD optimization problem.

2.1 Basic economic load dispatch objective function

1) Consider the electrical power system network N has a number of generation units.

2) Each and every unit is loaded with P_i MW so that it satisfies both load demand P_D MW and transmission loss P_L MW.

3) Let $F_i(P_i)$ be the fuel input output of the i^{th} unit cost function. The units are selected to minimize the total fuel cost F [14].

$$F = \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

2.2 Real power balancing constraint

The equality constraint must be satisfied to balance the power. The total power generated must be sufficient to satisfy demand and compensate line loss in the system [15].

$$\sum_{i=1}^{N} P_i - (P_D + P_L) = 0 \tag{2}$$

where P_D is the load demand and P_L is the transmission line loss.

Here, the transmission loss is considered to achieve economic load dispatch. The B-coefficient method (mostly used in the power industry) is used to calculate transmission loss. The power network line loss formula is expressed as follows [16].

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} P_i B_{0i} + B_{00} \tag{3}$$

where B_{ij}, B_{0i}, and B_{00} are constants called loss coefficients. In this study, the B-coefficient method is used as the generator capacity constraint. The power output of every generation unit should lie between the minimum and maximum permitted power. The following equation shows the inequality constraint.

$$P_{i,\min} \le P_i \le P_{i,\max} \qquad \text{for } i = 1, 2, \ldots, N \tag{4}$$

2.3 Fuel cost function without the valve point effect

The heat rate curve is also called the input and output curve of the thermal plant, represented in Btu/hr. Multiplying the fuel cost with the heat rate curve gives the cost curve. Opening the inlet valves of the steam turbine increases the output of fossil fuel power plants. The loss incurred by throttling is reduced when the gates are fully open, while increasing when gates are slightly open. This indicates that the incremental heat rate characteristically rises discontinuously.

However, for the purpose of dispatch, the fuel cost function can be approximated as a quadratic function of the active power outputs in the generating unit [17].

$$F_i\left(P_i\right) = a_i p_i^2 + b_i p_i + c_i \tag{5}$$

where a_i, b_i, and c_i are the fuel cost coefficients of the i^{th} generating unit.

2.4 Fuel cost function with the valve point effect

Valve point loading is required to obtain an accurate fuel cost curve for each generating unit. Therefore, the sinusoidal function is associated with the quadratic function, as given in Eq. (6). The cost function of the steam-generating units and valve point loadings are represented in [18].

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin\left(f_i\left(P_i^{min} - P_i\right)\right)\right| \tag{6}$$

where e_i and f_i are coefficients of the generation unit with the valve point loading effect.

2.5 Emission objective

Eq. (7) represents the emission function developed by combining SO_x and NO_x. The total pollutants of emission are represented by the combined quadratic and exponential functions as [19]

$$F_E(P) = \sum_{j=1}^{N}\left(\alpha_j + \beta_j P_j + \gamma_j P_j^2\right) + \xi_j \exp\left(\lambda_j P_j\right) \tag{7}$$

where F_E represents the total emissions, α_j, β_j, γ_j, ξ_j, and λ_j are the j^{th} generator emission coefficients.

3. APPLYING THE FLOWER POLLINATION ALGORITHM TO THE ECONOMIC EMISSION DISPATCH (EED) PROBLEM

Yang *et al.* [13] proposed the FPA inspired by the pollination of flowering plants. The FPA has certain advantages such as robustness and providing a better quality solution compared to other methods. It consists of one main parameter p (switch probability) to facilitate easy and rapid implementation of the algorithm to achieve the optimum solution. The intrinsic property of the FPA algorithm is its ability to find a space solution with high accuracy and precision. Therefore, the FPA can be used along with DE to address the problem of emission dispatch. The main reason for implementing this technique is that it has numerous advantages compared to other similar algorithms.

As shown in Fig. 1, implementation of the algorithm first requires the amount of cross and self-pollination to be determined. The next step involves initializing a specified population number (N), with each containing a group of variables, optimized by applying the objective function. This technique consists of a main indexed term such as the flower constancy of every population to determine the strength of the variables as well as minimizing the objective function. Depending on the flower constancy, a good sample can be found among the queued populations [20].

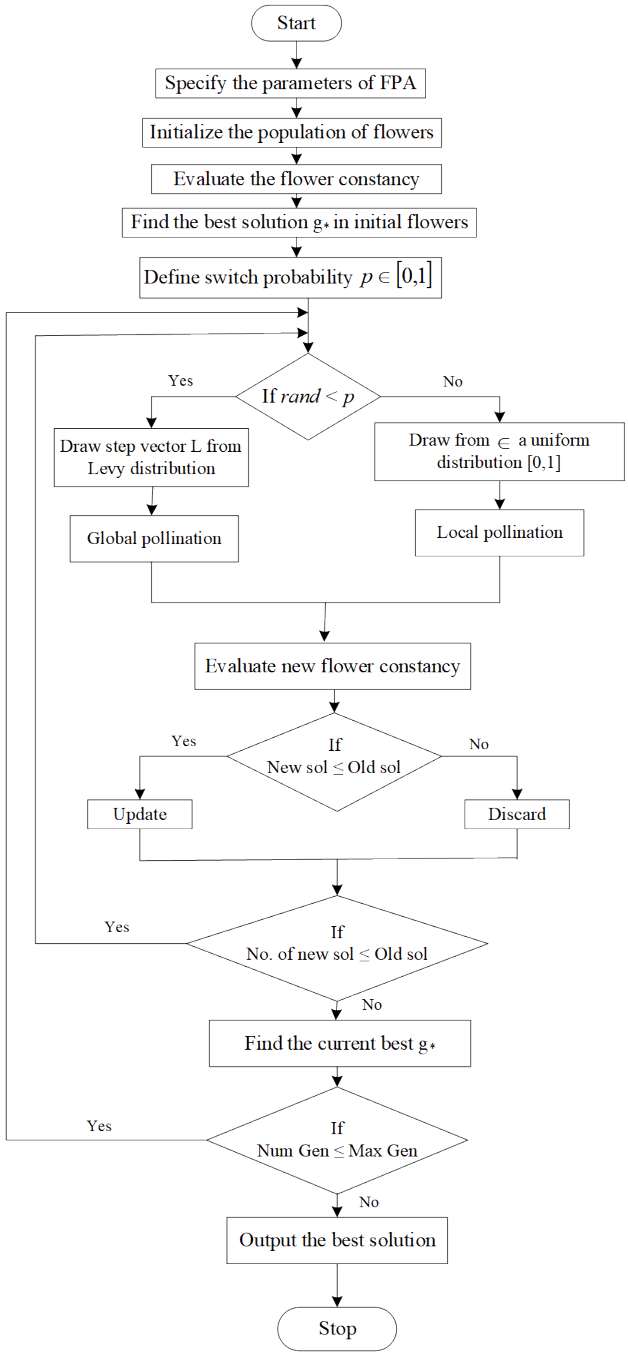

Fig. 1: *Flower pollination algorithm (FPA) flow chart.*

The FPA continues by initiating a new population, depending on whether the random number is greater or less than parameter p, which represents the self- or cross-pollination of flowers. The random numbers range between 0 and 1. In the case of global pollination, the agents pollinating these flowers should move in random step sizes from one flower to another. This moment is a representation of levy flight distribution, as given by Eq. (8) [20].

Table 1: *Simulation results of TLBO for the ten-unit system with the valve point loading effect for different objectives where* $P_D = 2000\,MW$.

Number of units	TLBO algorithm		
	Economic Dispatch	Emission Dispatch	CEED
1	55.0000	54.9998	55.0000
2	80.0000	79.9998	80.0000
3	106.8984	80.9279	85.3015
4	100.6541	82.8710	83.8637
5	81.7543	159.9998	139.5767
6	82.7328	239.9998	159.2863
7	300.0000	295.6908	300.0000
8	340.0000	299.2810	315.4372
9	470.0000	395.1220	431.6587
10	470.0000	392.6056	433.9235
Min. cost ($/h)	111 497.6500	116 430.5135	113 282.4474
Emission (t/h)	4572.3307	3932.4779	4129.0021
Power loss (MW)	87.0897	81.4975	84.0476

Table 2: *Simulation results of the FPA for the ten-unit system with the valve point loading effect for different objectives where* $P_D = 2000\,MW$.

Number of units	TLBO algorithm		
	Economic Dispatch	Emission Dispatch	CEED
1	55.0000	55.0000	55.0000
2	80.0000	80.0000	80.0000
3	106.9383	81.1338	85.2966
4	100.5761	81.3645	83.8629
5	81.5041	160.0000	139.5769
6	83.0204	240.0000	159.2850
7	300.0000	294.4847	300.0000
8	340.0000	297.2678	315.4370
9	470.0000	396.7602	431.6844
10	470.0000	395.5843	433.9048
Min. cost ($/h)	111 497.6301	116 412.4344	113 282.4213
Emission (t/h)	4572.1866	3932.2432	4129.0020
Power loss (MW)	87.0388	81.5952	84.0477

$$L \sim \frac{\lambda \Gamma(\lambda) \sin\left(\dfrac{\pi\lambda}{2}\right)}{\lambda} \cdot \frac{1}{s^{1+\lambda}}, \quad (s \gg s_0 > 0) \tag{8}$$

The newly generated population is given by

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)\left(g_* - x_i^t\right) \tag{9}$$

where x_i^t is the i^{th} generating solution vector and g_* is the local best solution found in the i^{th} generation of the solution, and the parameter function γ is a factor of scaling to decide the step size taken by the agents. $L(\lambda)$ represents the entire levy flight distribution function. Self-pollination occurs among the neighbors of the current population without involving the current minima, so parameter ϵ is chosen to represent the step size from a unique distribution. The expression for self-pollination is mathematically represented in Eq. (10) [20].

$$x_i^{t+1} = x_i^t + \epsilon\left(x_j^t - x_k^t\right) \tag{10}$$

where x_j^t and x_k^t are the flowering characteristics of different flowers in the same population.

The new population has the same flower constancy as previously expressed. If the new population is better than the previous, it is modernized in the previous place or rejected. This generation and comparison process continues up to N counts, and the best among them is declared to be the current global best and the optimum solution.

4. SIMULATION RESULTS AND DISCUSSION

In this paper, the proposed algorithms, FPA, and TLBO are tested on the EED problem with the valve point loading effect and loss. The efficacy and practicality of the proposed methods are demonstrated on 10 generating units and 14-unit systems. The proposed algorithms are implemented using MATLAB 9.5 R2018b running on an Intel® Core™ i5 processor, 2.26 GHz, 8 GB RAM PC. Initially, the fuel cost and emission objectives are advanced individually by taking the weighting factor W as 1 and 0 in the fitness function. The algorithm proposed to address the problem and bi-objectives are treated at the same time as the competing objectives.

4.1 Case study 1: 10-unit test system

In this test system, 10 thermal units with the valve point loading effect are studied. The total load demand is taken as 2000 MW [14]. The simulation results using the proposed methods, TLBO, and FPA with dissimilar objective functions are given in Tables 1 and 2, respectively. For this test system, 20 independent trials are conducted, each containing 300 iterations. Based on the data obtained, the comparisons of the ten thermal units tested by dissimilar methods are presented in Table 3. The convergence characteristics of the TLBO algorithm and FPA for the cost objective, emission objective, and fitness of the ten-unit system are compared in Figs. 2, 3, and 4.

The proposed TLBO algorithm and FPA are initiated using different objective functions and tabulated

Table 3: *Comparison of simulation results for the ten-unit system with the valve point loading effect for FPA and TLBO.*

	Cost objective		Emission objective		CEED	
	TLBO	FPA	TLBO	FPA	TLBO	FPA
Cost ($/h)	111 497.6500	111 497.6301	116 430.5135	116 412.4344	113 282.4474	113 282.4213
Emission (t/h)	4572.3307	4572.1866	3932.4779	3932.2432	4129.0021	4129.0020
Power loss (MW)	87.0397	87.0388	81.4975	81.5952	84.0476	84.0477

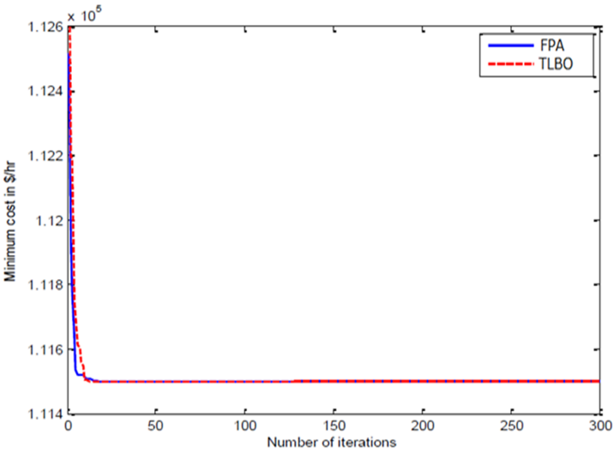

Fig. 2: *Comparison of convergence characteristics for the EED problem in the ten-unit system with the valve point loading effect for the cost objective.*

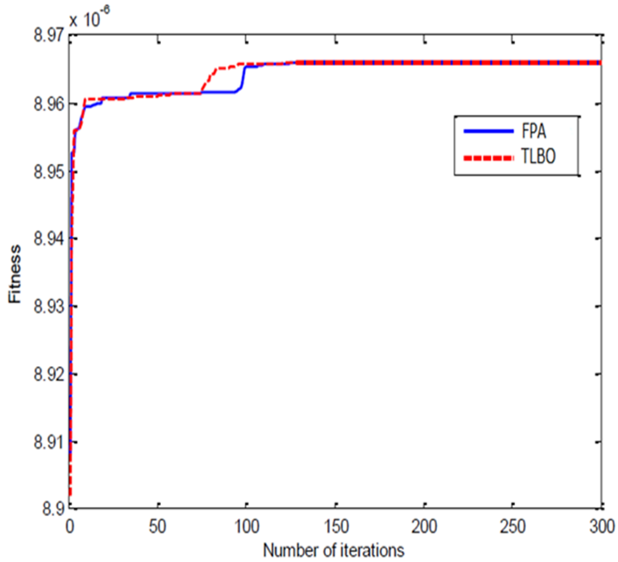

Fig. 3: *Comparison of the convergence characteristics for the EED problem in the ten-unit system with the valve point loading effect for fitness.*

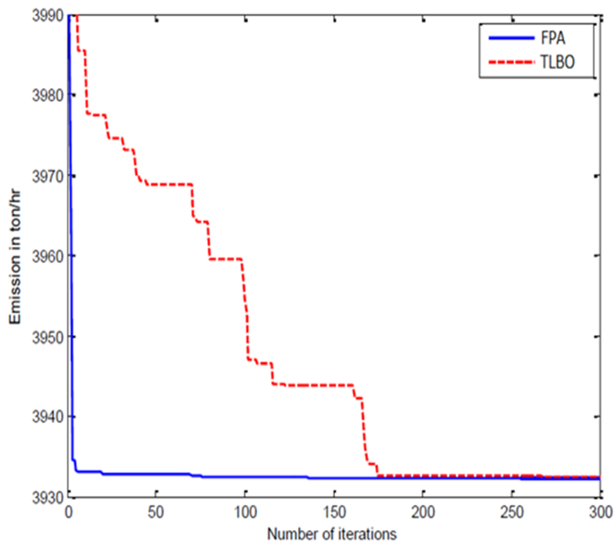

Fig. 4: *Comparison of the convergence characteristics for the EED problem in the ten-unit system with the valve point loading effect for the emissions objective.*

in Tables 1 and 2, respectively. The comparative simulation results for the suggested methods are shown in Table 3. As can be observed from Table 3, in the case of the cost objective, the cost obtained by TLBO is 111 497.6500 $/h with emissions and power loss of 4572.3307 t/h (tons per hour) and 87.0897 MW, respectively. The cost, emissions, and power loss obtained by the FPA are 111 497.6301 $/h, 4572.1866 t/h, and 87.0388 MW, respectively.

For emission dispatch, the cost procured by TLBO is 116 430.5135 $/h with emissions of 3932.4779 t/h and power loss of 81.4975 MW. The cost, emissions, and power loss obtained by FPA are 116 412.4344 $/h, 3932.2432 t/h, and 81.5952 MW, respectively. In the case of combined economic emission dispatch (CEED), the cost obtained by TLBO is 113 282.4474 $/h with emissions and power loss of 4129.0021 t/h and 84.0476 MW, respectively. The cost, emissions, and power loss obtained by FPA are 113 282.4213 $/h, 4129.0020 t/h, and 84.0477 MW, respectively. The results indicate that the FPA offers a better performance in comparison to TLBO.

Fig. 2 presents a comparison of the convergence characteristics of the EED problem of the ten-unit system, including the valve point loading effect in relation to the cost objective at a power demand of 2000 MW. As can be observed in Fig. 3, there are two plots: one for TLBO and the other for the FPA,

Table 4: Simulation results for TLBO in the 14-unit system with the valve point loading effect for different objectives where $P_D = 2500\,MW$.

Number of units	TLBO algorithm		
	Economic Dispatch	Emission Dispatch	CEED
1	419.2794	286.6902	329.5196
2	374.3995	153.5419	224.7998
3	130.0000	130.0000	130.0000
4	130.0000	130.0000	119.9748
5	299.5997	235.1755	249.7331
6	184.8666	460.0000	384.3328
7	234.7331	298.0071	234.7331
8	159.7331	235.8714	259.4662
9	162.0000	162.0000	162.0000
10	153.2968	160.0000	160.0000
11	80.0000	80.0000	80.0000
12	80.0000	80.0000	80.0000
13	85.0000	85.0000	85.0000
14	52.3999	55.0000	53.9391
Min. cost ($/h)	12 542.4661	14 214.6900	12 846.5707
Emission (t/h)	8767.1429	5994.1748	6396.5984
Power loss (MW)	45.3080	51.2861	53.4984

Table 5: Simulation results for FPA in the 14-unit system with the valve point loading effect for different objectives where $P_D = 2500\,MW$.

Number of units	FPA		
	Economic Dispatch	Emission Dispatch	CEED
1	419.2794	286.6830	329.5196
2	374.5743	153.4521	224.7998
3	130.0000	130.0000	126.2424
4	120.1869	130.0000	119.7331
5	299.5997	235.4270	249.7331
6	234.7337	460.0000	384.3327
7	184.8667	297.6711	284.5997
8	159.7332	236.0786	209.5996
9	162.0000	162.0000	162.0000
10	160.0000	160.0000	160.0000
11	80.0000	80.0000	80.0000
12	80.0000	80.0000	80.0000
13	85.0000	85.0000	85.0000
14	55.0000	55.0000	52.3999
Min. cost ($/h)	12 437.7031	14 210.0114	12 816.6164
Emission (t/h)	8716.7541	5994.1740	6373.8274
Power loss (MW)	44.9739	51.3119	47.9600

shown colored red and blue, respectively. The total cost obtained by TLBO is around 112 600 $/h, around 112,500 $/h for the FPA at the first iteration. Finally, the global minimum calculated by TLBO is at the 15th iteration and at the 20th iteration by the FPA.

Fig. 4 represents the comparative convergence characteristics for the EED problem in the ten-unit system, including the valve point loading effect for the emissions objective at 2000 MW demand. As can be observed in Fig. 5, there are two plots: one for the FPA and the other for TLBO, shown colored blue and red, respectively. The emissions obtained by TLBO are above 3990 t/h, while for the FPA they are also above 3990 t/h at the first iteration. Finally, the global minimum is calculated by TLBO at the 270th iteration and at the 140th iteration by the FPA.

4.2 Case study 2: 14-unit test system

This case study involves a system with 14 thermal units, including the valve point loading effect. The total load demand is taken as 2500 MW [22, 23]. The dispatch results using the proposed TLBO and FPA are presented in Tables 4 and 5, respectively. This test system consists of 20 separate trials, each containing 500 iterations. Comparisons of the 14 thermal unit tests with various objects using different methods are shown in Table 6. The comparative TLBO and FPA convergence characteristics for the cost objective, emissions objective, and fitness of the 14-unit system are presented in Figs. 5, 6, and 7.

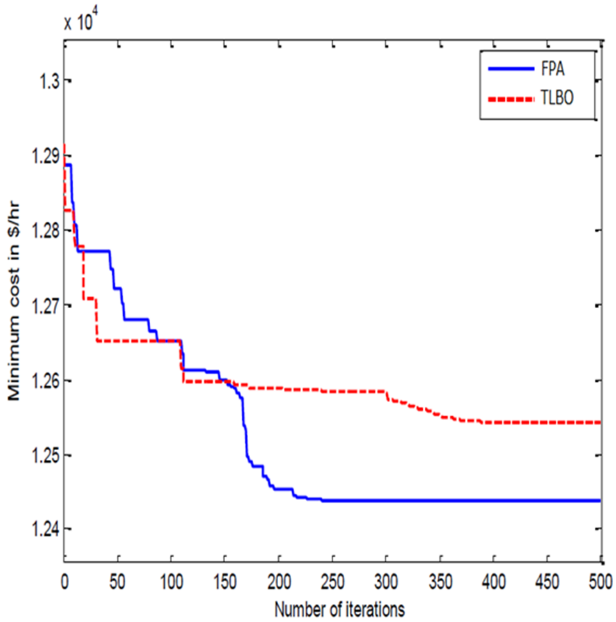

Fig. 5: Comparison of the convergence characteristics for the EED problem in the 14-unit system with the valve point loading effect for the cost objective.

As can be observed from Table 6, in the cost objective case, the total cost obtained by TLBO is 12 542.4661 $/h with emissions and power loss being 8767.1429 t/h and 45.308 MW, respectively. The cost, emissions, and power loss obtained by the FPA

Table 6: *Comparison of simulation results for the 14-unit system with the valve point loading effect for FPA and TLBO.*

	Cost objective		Emission objective		CEED	
	TLBO	FPA	TLBO	FPA	TLBO	FPA
Cost (\$/h)	12 542.4661	12 542.4661	12 542.4661	12 542.4661	12 542.4661	12 542.4661
Emission (t/h)	8767.1429	8716.7541	5994.1748	5994.1740	6396.5984	6373.8274
Power loss (MW)	45.3080	44.9739	51.2861	51.3119	53.4984	47.9600

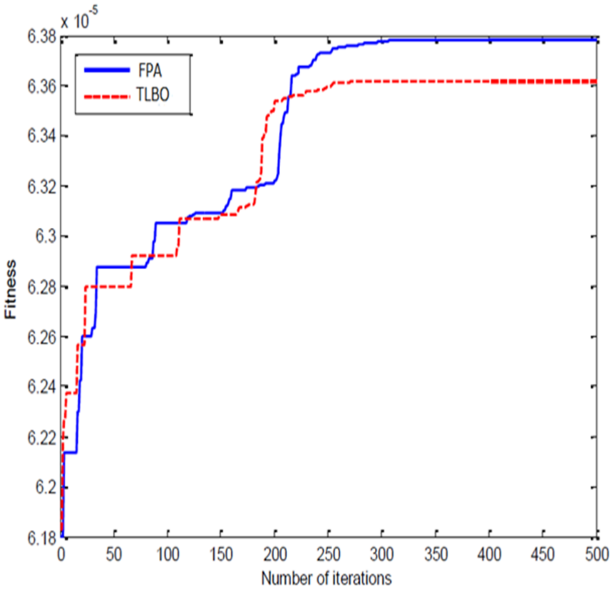

Fig. 6: *Comparison of the convergence characteristics for the EED problem in the 14-unit system with the valve point loading effect for fitness.*

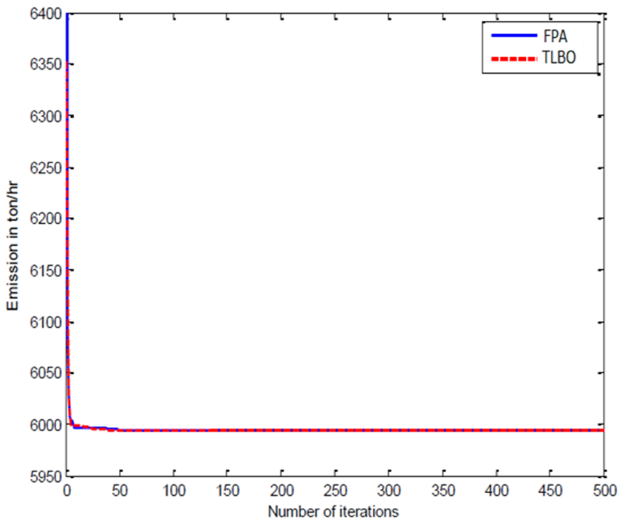

Fig. 7: *Comparison of the convergence characteristics for the EED problem in the 14-unit system with the valve point loading effect for the emissions objective.*

are 12 437.7031 \$/h, 8716.7541 t/h, and 44.9739 MW, respectively. The cost obtained for emission dispatch by TLBO is 14 214.69 \$/h with emissions of 5994.1748 t/h with a power loss of 51.2861 MW. The cost, emissions, and power loss obtained by the FPA are 14 210.0114 \$/h, 5994.1740 t/h, and 51.3119 MW, respectively. In the case of combined economic emission dispatch (CEED), the cost obtained by TLBO is 12 846.5707 \$/h with emissions and power loss of 6396.5984 t/h and 53.4984 MW, respectively. The cost, emissions, and power loss obtained by the FPA are 12 816.6164 \$/h, 6373.8274 t/h, and 47.96 MW, respectively. The results reveal that the FPA offers a better performance in comparison to TLBO.

Fig. 6 presents the comparative convergence characteristics of the EED problem in the 14-unit system, including the valve point loading effect for the cost objective at a load demand of 2500 MW. As can be observed in Fig. 5, there are two plots: one for TLBO and is the other for the FPA, colored red and blue, respectively. The total cost calculated by TLBO is around 12 910 \$/h and around 12 890 \$/h by the FPA at the first iteration. Finally, the global minimum calculated by TLBO is at the 395th iteration and at the 245th iteration by the FPA.

Fig. 7 presents the comparative convergence characteristics of the EED problem in the 14-unit system, including the valve point loading effect for the emissions objective at a load demand of 2500 MW. The emissions calculated by TLBO are above 6350 t/h, and by the FPA above 6400 t/h at the first iteration. Finally, the global minimum calculated by TLBO is at the 25th iteration and at 50th iteration by the FPA. The results reveal that the FPA offers a better performance in comparison to TLBO.

5. CONCLUSION

This paper applies the FPA TLBO optimization methods to the valve point loading effect and combined economic emissions dispatch problem, respectively. This suggested FPA provides the best global solution in systems of 10 and 14 units. The algorithm gives a better optimal solution than that obtained from other different complex algorithms. The results demonstrate that the proposed approach is more efficient for multi-objective optimization. Therefore, it can be concluded that the solution for economic emissions dispatch provided by the FPA is the best compromise among the optimal solutions of the two optimizing techniques. It can help the power system to adjust the level of generation to improve the economy of the utility while causing less damage to the environment. Therefore, the FPA based solution is proposed as being more robust and reliable compared to other techniques and can be recommended for use in resolving other optimization problems encountered in power system networks.

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