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Electric fish optimization for economic load dispatch problem

Ekonomik yük dağitim problemi için elektrik baliği optimizasyonu

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Abstract

The Economic Load Dispatch (ELD) problem is an essential aspect of power system planning and operational scheduling. Different techniques and algorithms have been recommended to solve it, aiming to minimize the cost of power generation with satisfying the load requirements. In this paper, a new algorithm called Electric Fish Optimization (EFO) is used to solve the ELD problem by considering the line losses, ramp rate limits, maximum and minimum capacities of the generators and prohibited operating zones (POZ). The algorithm has been utilized in test systems consisting of 6 and 15 units and its outcomes have been compared to those from previous research studies. The proposed algorithm has been shown to achieve minimum cost, indicating its superiority and effectiveness in addressing power system planning challenges. It is evident that the presented algorithm offers a valuable solution for optimizing ELD problems.

Keywords: Economic load dispatch, Electric fish optimization, Power systems

Öz

Ekonomik Yük Dağıtımı (EYD) problemi, güç sistemi ve güç sisteminin işletimi planlamasında çok önemli bir alandır. Bu problem çözmek için yük talebini karşılarken elektrik üretim maliyetini en aza indirmeyi amaçlayan farklı teknikler ve algoritmalar önerilmiştir. Bu çalışmada, hat kayıpları, rampa hız limitleri, jeneratörlerin maksimum ve minimum kapasiteleri ile yasak çalışma bölgeleri dikkate alınarak EYD problemini çözmek için Elektrik Balığı Optimizasyonu (EBO) adı verilen yeni bir algoritma kullanılmıştır. Algoritma 6 ve 15 birimden oluşan test sistemlerinde uygulanmıştır ve sonuçları daha önce yapılan araştırmalarla karşılaştırılmıştır. Önerilen algoritmanın, güç sistemi planlama zorluklarını ele almadaki üstünlüğünü ve etkinliğini gösteren minimum maliyete ulaştığı gösterilmiştir. Önerilen algoritmanın EYD problemlerini optimize etmek için değerli bir çözüm sunduğu sonucuna varılmıştır.

Anahtar kelimeler: Ekonomik yük dağıtımı, Elektrik balığı optimizasyonu, Güç sistemleri

1 Introduction

Energy is an indispensable source of human life. From primitive times to the present day, the diversity, production and consumption of energy resources have followed an increasing development in parallel with the increasing needs of human beings. Especially after the industrial revolution, the demand for energy increased even more. In addition, while energy was abundant and cheap before the 1973s, energy prices rose rapidly due to the oil crisis in the 1973s [1].

Today, with the developing technology, energy is the most fundamental factor of economic and social development and has become the most important factor guiding the world economy and policies. Due to the ever-increasing energy need, maintaining the balance between energy production and consumption and the import of energy resources by many countries are the most important problems in this regard. The most important goals in the energy policies of societies created according to these problems can be listed as follows:

- Obtaining uninterrupted, timely, cheap and clean energy,
- Using the generated energy economically,
- Bringing energy to more people [2].

In line with these goals, power systems have become quite complex, and the operations of these power systems need to be planned and operated in the most appropriate way. Thermal power plants have a large share in energy production. The process of achieving the most efficient and cost-effective operation of thermal power units to meet power demands, through careful planning and enhancing system reliability, is referred to as ELD. In other words, ELD is the generation of the energy demanded by the system at minimum cost considering certain operational and system constraints [3, 4]. Therefore, the ELD problem is an optimization problem that includes various equations and inequalities such as production capacity ranges of units, cost functions and POZ. In general, classical methods were used to figure out these problems in the past. These generally require continuously and linearly increasing cost functions. However, the ELD problem is not continuous. In addition,

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the desired full performance could not be achieved in these methods due to the increase in calculation time as the system grows [5-7]. For these reasons, nowadays, heuristic methods and nature-inspired algorithms are more preferred in solving these problems. A selection of relevant studies on this topic in the existing literature includes the following:

Tosun et al. have employed a simulation algorithm to minimize the hourly energy consumption of the load supplied by three thermal power plants [8]. Basu has utilized the differential evolution algorithm to address the economic environmental dispatch problem across three distinct test systems, each comprising 6, 10, and 40 generation units [9]. Yang et al. have applied the firefly algorithm to solve the ELD problem in four different test systems. This study has encompassed numerous non-linear aspects, including valve point effects, ramp rate constraints and POZ considerations [10]. L. Slimani and T. Bouktir have employed the artificial bee colony algorithm in their research to address the emission-controlled economic dispatch problem. The algorithm has been applied on two systems: the IEEE 30-bus with 6 generator test system and the 59-bus power system in Algeria [11]. Kumar et al. have implemented an enhanced particle swarm optimization algorithm on three distinct power systems, resulting in lower cost values compared to traditional particle swarm optimization methods and their derivatives [12]. Sulaiman et al. have used cuckoo search algorithm to address the combined economic load-emission dispatch problem on a six-unit power system, where transmission line losses have been neglected, and forty-unit power system, where the valve point effect has been included [13]. Abdelaziz et al. have converted the problem into a single objective function by incorporating a modified price penalty factor to simultaneously minimize both fuel cost and emission levels. They then applied the flower pollination algorithm to solve this transformed problem [14]. Pradhan et al. have implemented grey wolf optimization to tackle the ELD problem across a test system featuring 10, 40, 80, and 140 units. The problem has been enriched with nonlinear components, encompassing ramp rate constraints, valve point effects and POZ considerations [15]. Trivedi et al. have implemented interior search algorithm on a microgrid consisting of distribution generator, solar and wind units for minimizing both fuel cost and emission [16]. Jadoun et al. have employed the fireworks algorithm to address the dynamic ELD problem in a hybrid system comprising solar, thermal generators and wind [17]. Srivastava and Das have introduced a novel human intelligence-based metaheuristic optimization technique for tackling the ELD problem [18]. Das et al. have used dragonfly algorithm for the ELD problem in four varied test systems and obtained the lowest cost value as a result of comparison with many heuristic algorithms in all systems [19]. Deb et al. have applied turbulent water flow optimization for both economic and environmental load distribution on a test system with valve effect and conduction losses and demonstrated through numerical examples that the optimization has successful [20].

This article investigates the ELD problem on test systems comprising 6 units with a load demand of 1263 MW and 15 units with a load demand of 2630 MW. The problem has been enriched with operation constraints for the system, encompassing minimum and maximum production limits for generators, ramp rate limits, POZ constraints and power balance considerations. The EFO, which has been introduced to the new literature in 2019, has been used to address the problem. The success and effectiveness of the algorithm have been proven with the study results.

2 Formulation of economic load dispatch problem

The goal of the ELD problem is to reduce fuel costs while considering a range of both equality and inequality constraints. These encompass ramp rate limits, power balance, generation capacity limits and POZ considerations.

2.1 Objective function

The computation of the objective function for the ELD problem is described in Equation 1.

$$Minimize\ FC = \sum_{x=1}^{g} FC_x(P_x) \tag{1}$$

The total fuel cost ($/h), represented as FC, is determined by the number of generators (g) in the power system, as well as the output power of each generator P_X (MW) and their respective fuel costs FC_X. The primary goal of this function is to minimize FC.

Equation 2 depicts the calculation of fuel cost for each individual generator.

$$FC_x(P_x) = \sum_{x=1}^{g} a_x P_x^2 + b_x P_x + c_x \tag{2}$$

Where a_X, b_X, c_X represent the cost coefficients of the x-th generator.

2.2 Constraints on generator operations

2.2.1 Minimum and maximum generating limits

In a power system, each generator comes with its own minimum and maximum power output constraints. These restrictions are integral to the ELD problem, ensuring that each generator's power output falls within its designated range, as demonstrated in Equation 3 [21, 22].

$$P_{x,min} \leq P_x \leq P_{x,max} \tag{3}$$

Where $P_{x,min}$ and $P_{x,max}$ represent the minimum and maximum power output of the x-th generator, respectively.

2.2.2 Ramp rate limits

The ramp rate constraint holds significance within the ELD problem, guaranteeing that a generator's power output does not exceed a specified rate of change, thus maintaining system stability and preventing sudden fluctuations in power generation. It is defined as presented in Equation 4 [21].

$$P_x - P_x^0 \leq UPR_x \quad and\ P_x^0 - P_x \leq DWR_x \tag{4}$$

Where P_x^0 is output power of x-th generator in the previous time, UPR_x and DWR_x indicate the up-ramp and down-ramp limits of the x-th generator, respectively.

Based on Equations 3 and 4, it is possible to derive limitations for P_X as shown in Equation 5 [21].

$$\max\left(P_{x,min},\ P_x^0 - DWR_x\right) \le P_x \le \min\left(P_{x,max},\ P_x^0 + UPR_x\right) \quad (5)$$

2.2.3 Prohibited operating zones limits

While solving the ELD problem, one important consideration is the POZ. These zones represent operating conditions in which the generator cannot operate due to technical or safety reasons.

In practical applications, it is essential to ensure that the output power of a generating unit does not fall within POZ. The limitations for P_X in terms of these operating zones are shown in Equation 6 [21].

$$\begin{cases} P_{x,min} \le P_x \le P_{x,1}^{LW} \\ P_{x,h-1}^{UP} \le P_x \le P_{x,h}^{LW} \quad h = 2, \dots, poz_x \\ P_{x,poz_x}^{UP} \le P_x \le P_{x,max} \end{cases} \quad (6)$$

Where poz_x indicate the number of POZ for the x-th generator, P(x,h)LW and P(x,h)UP represent the lower and upper limits of the h-th POZ for the x-th generator, respectively.

2.3 Power balance

The constraint of power balance is given in Equation 7 [21, 23].

$$\sum_{x=1}^{g} P_x = P_{DM} + P_{LS} \quad (7)$$

As can be seen in Equation 7, the total power generated by the generators must meet the total demand (P_{DM}) and the loss (P_{LS}) on the line.

The estimation of PLS, which is dependent on the actual output power of the generators, is often found by Kron's loss equation. This equation is formulated as shown in Equation 8.

$$P_{LS} = \sum_{x=1}^{g}\sum_{y=1}^{g} P_x B_{xy} P_y + \sum_{x=1}^{g} B_{x0} P_x + B_{00} \quad (8)$$

3 Electric fish algorithm

EFO is a new intuitive algorithm founded on the collective intelligence of electric fish and their distinctive characteristics. This algorithm was introduced to the literature by Yılmaz and Şen in 2019 [24].

The electric fish species that inspired the algorithm have a special electrical organ in their bodies containing disc-like electrical cells (electrocytes) and they produce an electric field thanks to the electrical signals produced by these organs. There are two main parameters that characterize the generated electrical signals and are involved in the algorithm's mechanism. The first factor is frequency, which exhibits an inverse relationship with the time gap between two successive electrical signals. The second factor is the amplitude parameter, which is correlated with the size of the fish [24, 25].

The working mechanism of EFO, like many nature-inspired algorithms, is based on finding the best quality food source. Within an infinite search space, it is assumed that there exists a single food source considered to be the optimal choice. Electric fish are individuals of the optimization algorithm and carry location information within the search space. After the initialization phase, electric fish move through the search space in search of the optimal source. As they move closer to the best source, the frequency of the signal generated by the fish increases and the search space narrows. This state of the electric fish is called active electrolocation mode. Electric fish located at a considerable distance from the best source allow the recognition of distances and the recognition of relationships with other fish. This state of electric fish is called passive electrolocation mode. As mentioned before, the algorithm uses the term frequency as a reference for distance-related operations. Another important feature of the algorithm is that individuals with higher quality sources generate signals with higher amplitude [24, 25].

3.1 Steps of electric fish optimization

3.1.1 General steps

Similar to other nature-inspired algorithms, individuals make up the population in the algorithm. A total of N individuals are initially and randomly placed within the search space [24, 25]:

$$x_{ik} = x_{lowerk} + \varphi(x_{upperk} - x_{lowerk}) \quad (9)$$

where N is the the population size. i depicts the number of the individual (i= 1,2.. N) and k represents dimension of the search space (k=1, 2.. d). x_{ik} is the location information of the ith individual. x_{lowerk} and x_{upperk} correspond to minimum and maximum boundaries for dimension, respectively. φ is a random value ranging from 0 to 1 [24, 25].

After each iteration of the calculation of location information, the individuals' amplitude and frequency values are updated. In this update, the individuals that are considered to be closer to the source are kept in active mode, i.e. high frequency -narrow range, while the other individuals are kept in passive electrolocation mode, i.e. low frequency-wide range. If the maximum value of the frequency value f_{max} and the minimum value f_{min} are shown, since the frequency value of each individual is related to the source, the frequency value of each individual is related to its fitness value [24, 25]:

$$fitness_i^j = f_{min} + \left(\frac{fitness_{worst}^j - fitness_i^j}{fitness_{worst}^j - fitness_{best}^j}\right)(f_{max} - f_{min}) \quad (10)$$

where $fitness_i^j$ is the fitness value of the ith individual at iteration j. $fitness_{worst}^j$ and $fitness_{best}^j$ are respectively calculated worst and best fitness values at the relevant iteration j. The f_{min} and f_{max} values are also the maximum and values of the fitness value and these values are fixed between 0 and 1, respectively.

The amplitude of the electric fish provides information about its active range and probability of detection and this value (A_i^j) is calculated in relation to the previous amplitude of the individual as follows [24, 25]:

$$A_i^j = \propto A_i^{j-1} + (1-\propto)f_i^j \tag{11}$$

Where ∝ varies between 0-1. The initial amplitude value of the individual is considered equal to the frequency value of that individual.

3.1.2 Active electrolocation steps

In active electrolocation, only one parameter is allowed to change in the range of movement with respect to the presence of neighbours so that fish do not move away from promising spots. This parameter is the individual's activity trajectory and the individual's active distance estimate can be determined using Equation 12 [24, 25].

$$r_i = (X_{upperk} - X_{lowerk})A_i \tag{12}$$

To discover neighbouring individuals in the search range, it is essential to calculate the distance between the ith individual and its neighbouring individual (mth), This value is calculated with the help of the following equation and should be equal to the smaller of the active distance of the individual [24, 25].

$$d_{im} = \|x_i - x_m\| = \sqrt{\sum_{k=1}^{d}(x_{ik} - x_{mk})^2} \tag{13}$$

If there is at least one neighbouring individual within the active area, Equation 14 is employed, otherwise Equation 15 is applied [24, 25].

$$x_{ik}^{cand} = x_{ik} + \omega(x_{mk} - x_{ik}) \tag{14}$$

$$x_{ik}^{cand} = x_{ik} + \omega r_i \tag{15}$$

Where x_{ik}^{cand} states candidate location of the ith individual and w is a random value ranging between -1 and 1.

3.1.3 Passive electrolocation steps

Passive electrolocating individuals (Np) fulfil the global search task within the algorithm. Individuals in passive mode select active electrolocating individuals (N_A) based on their probability of detection and change their locations. The probability of the mth individual (mth ϵ N_A) performing active electrolocation being detected by the ith individual performing passive electrolocation is calculated as follows:

$$p_m = \frac{A_m / d_{im}}{\sum_{k\epsilon N_A} A_k / d_{ik}} \tag{16}$$

After selecting M individuals with the help of the above equation, the calculation of a reference point (xrk) for them is carried out with Equation 17, and finding new positions is carried out with Equation 18.

$$x_{rk} = \frac{\sum_{m=1}^{M} A_m x_{mk}}{\sum_{m=1}^{M} A_m} \tag{17}$$

$$x_{ik}^{new} = x_{ik} + w(x_{rk} - x_{ik}) \tag{18}$$

Although it is not a very common situation, individuals with high frequencies are capable of engaging in passive electrolocation. To prevent it, Equation 19 is used to determine which parameter values of individuals will change.

$$x_{ik}^{cand} = \begin{Bmatrix} x_{ik}^{new} & rand_k(0,1) > f_i \\ x_{ik} & else \end{Bmatrix} \tag{19}$$

In passive electrolocation, finally, a parameter of an individual is changed using Equation 20. The reason for doing this is to increase the possibility of a characteristic of the individual changing.

$$x_{ik}^{cand} = x_{lowerk} + w(x_{upperk} - x_{lowerk}) \tag{20}$$

For the repositioning of the kth dimension parameter of the ith individual in case it goes beyond the limits of the search space, the following equation is used.

$$x_{ik}^{cand} = \begin{cases} x_{lowerk} & x_{ik}^{cand} < x_{lowerk} \\ x_{ik}^{cand} & x_{upperk} > x_{ik}^{cand} > x_{lowerk} \\ x_{upperk} & x_{ik}^{cand} > x_{upperk} \end{cases} \tag{21}$$

4 Simulation studies and results

In this research, the efficiency of the recommended EFO is evaluated by applying it to both 6-unit test system with 1263 MW load demand and 15-unit test system with 2630 MW load demand in comparison to established optimization techniques commonly used to address the ELD problem. The data for the 6-unit and 15-unit test systems, encompassing details regarding cost coefficients, minimum and maximum generation limits, POZ for generating units, ramp rate constraints and loss coefficients have been sourced from the study [21].

4.1 The results for 6-unit test system

The ELD problem is executed on a 6-unit test system, accounting for factors such as line losses, ramp rate limits, maximum and minimum generating limits and POZ limits. The EFO algorithm has been executed 30 independent runs for the 6-unit system. The proposed approach has been implemented with a maximum of 400 iterations and a population size of 200. The total cost of this operation amounted to $15446.64 and the line losses are determined to be 12.6301 MW.

The optimal generation scheduling and the data of minimum/maximum generating values and POZ of each generator, transmission loss, total cost, total power generation for 6-unit system are presented in Table 1.

Table 1. The outcomes for optimal generation scheduling with the data of minimum/maximum generating values and POZ of each generator for 6-unit system

Unit	Generation (MW)	$P_{x,min}$ (MW)	$P_{x,max}$ (MW)	POZ (MW)
1	437.9359	100	500	[210,240], [350,380]
2	176.6343	50	200	[90,110], [140,160]
3	261.6775	80	300	[150,170], [210,240]
4	136.3328	50	150	[80,90], [110,120]
5	167.9562	50	200	[90,110], [140,150]
6	95.0934	50	120	[75,85], [100,105]

Loss (MW): 12.6301, Cost ($): 15446.64, Total power generation (MW): 1275.6301

As shown in Table 1, the output of the generators remains within the limits of maximum and minimum values, avoiding falling in the POZ. It is observed that the system also meets the ramp rate limits. The data of initial generation (at t=0), up and down ramp limits of each generator for the 6-unit system in the study [21] clearly shows that the units are generating power by providing ramp rate limits. Furthermore, it is noteworthy that the system also satisfies the power balance constraint. The total power generation (1275.6301 MW) meets the total demand (1263 MW) and the loss on the line (12.6301 MW).

The convergence curves of decision variables with iterations for the EFO algorithm and 6-unit system is given in Figure 1.

Upon examining the convergence curves of decision variables for EFO algorithm and 6-unit system in Figure 1, it can be seen that a majority of the generators achieve optimal generating power without reaching the maximum iteration number, indicating the fast convergence of the proposed algorithm.

The convergence curve of objective function with iterations for the EFO algorithm and 6-unit system is given in Figure 2.

The fuel cost convergence curve for the EFO algorithm and 6-unit system presented in Figure 2 shows that the EFO algorithm achieves the lowest objective function in fewer iterations, highlighting the efficiency of this proposed method.

The statistical results for 6-unit system including the best, the worst, the median, the mean cost and the standard deviation of the proposed algorithm and various algorithms documented in the literature have been given in Table 2.

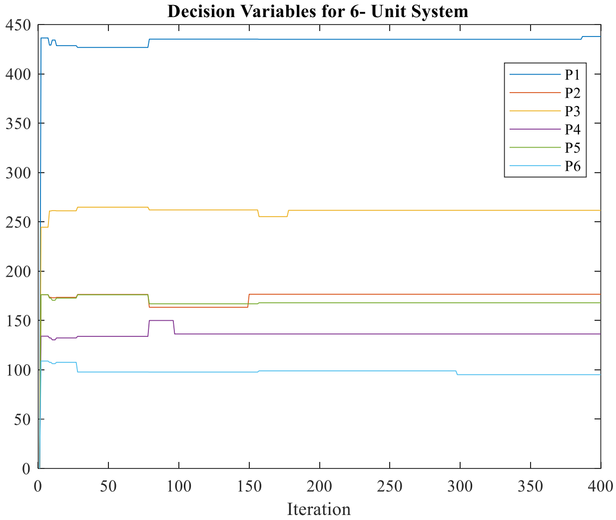

Figure 1. Convergence curves of decision variables for EFO algorithm and 6-unit system

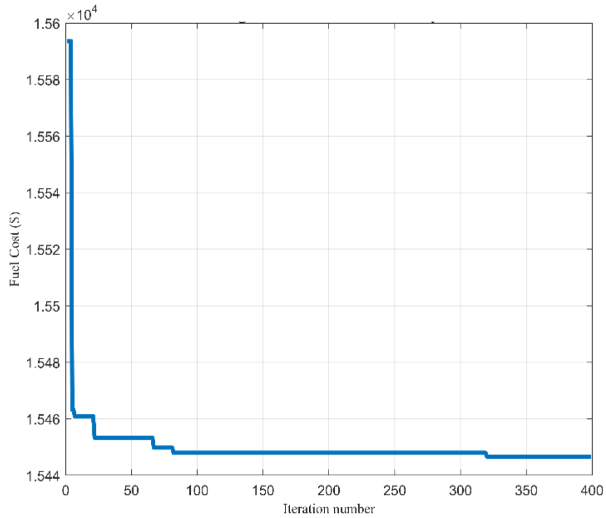

Figure 2. Convergence curve of fuel cost for EFO algorithm and 6-unit system

According to the results presented in Table 2, the EFO algorithm recommended in this study achieves a best cost compared to various methods in the literature with the exception of SOH-PSO and Jaya when solving the ELD problem on the 6-unit test system. Although there is very little difference in the best value with the SOH-PSO and Jaya algorithms, the worst and the mean cost give better results than these algorithms. The mean cost obtained by the EFO algorithm also gives the best result compared to all other algorithms.

4.2 The results for 15-unit test system

The ELD problem is executed on a 15-unit test system, accounting for factors such as line losses, ramp rate limits, maximum and minimum generating limits and POZ limits. The EFO algorithm has been executed 30 independent runs for the 15-unit system. The proposed approach has been implemented with a maximum of 1000 iterations and a population size of 500.

Table 2. Statistical results for 6-unit system

Algorithm	Best	Worst	Median	Mean	Standard Deviation
EFO	15446.64	15450.82	15447.91	15448.08	1.07
GA [26]	15459	15524	NIA	15469	NIA
CBA [27]	15450.24	15518.66	NIA	15454.76	2.965
NPSO-LRS [28]	15450	15454	NIA	15452	NIA
PSO [26]	15450	15492	NIA	15454	NIA
MABC [29]	15449.90	15449.90	NIA	15449.90	6.04E–08
MSSA [30]	15449.90	15453.55	NIA	15449.94	0.3647
ST-IRDPSO [31]	15449.89	NIA	NIA	15450.70	1.416
DEa [32]	15449.77	15449.87	NIA	15449.78	NIA
DEb [33]	15449.58	15449.65	NIA	15449.62	NIA
MCSA [34]	15449.17	15449.39	NIA	15449.24	0.2681
HHS [35]	15449.00	15453.00	NIA	15450.00	NIA
SOH-PSO [36]	15446.02	15609.64	NIA	15497.35	NIA
GAAPI [37]	15449.78	15449.85	NIA	15449.81	NIA
DE [32]	15449.766	15449.777	NIA	15449.874	NIA
Jaya [38]	15446.5675	15573.5151	NIA	15489.7034	13.3122
SA [39]	15461.1	15545.5	NIA	15488.98	28.3678
TS [39]	15454.89	15498.05	NIA	15472.56	13.7195
SSGA [40]	15447	15470	NIA	15450	7.458
FA [41]	15450.509	15458.4427	NIA	15452.531	2.048
CMFA [41]	15449.8994	15449.8994	NIA	15449.8994	8.96E-06
MTS [39]	15450.06	15453.64	NIA	15451.17	NIA

The total cost of this operation amounted to $32692.30 and the line losses are determined to be 29.0475 MW.

The optimal generation scheduling and the data of minimum/maximum generating values and POZ of each generator, transmission loss, total cost, total power generation for 15-unit system are presented in Table 3.

As shown in Table 3, the output of the generators remains within the limits of maximum and minimum values, avoiding falling in the POZ. It is observed that the system also meets the ramp rate limits. The data of initial generation (at t=0), up and down ramp limits of each generator for the 15-unit system in the study [21] clearly shows that the units are generating power by providing ramp rate limits. Furthermore, it is noteworthy that the system also satisfies the power balance constraint. The total power generation (2659.0475 MW) meets the total demand (2630 MW) and the loss on the line (29.0475 MW).

The statistical results for 15-unit system including the best, the worst, the median, the mean cost and the standard deviation of the proposed algorithm and various algorithms documented in the literature have been given in Table 4.

According to the results presented in Table 4, the EFO algorithm recommended in this study achieves a best cost compared to various methods in the literature when solving the ELD problem on the 15-unit test system.

Table 3. The outcomes for optimal generation scheduling with the data of minimum/maximum generating values and POZ of each generator for 15-unit system

Unit	Generation (MW)	$P_{x,min}$ (MW)	$P_{x,max}$ (MW)	POZ (MW)
1	455	10.1	671	
2	379.9613	10.2	574	[185 255], [305 335], [420 450]
3	130	8.8	374	
4	130	8.8	374	
5	169.9064	10.4	461	[180 200], [305 335], [390 420]
6	459.9839	10.1	630	[230 255], [365 395], [430 455]
7	429.9594	9.8	548	
8	75.4553	11.2	227	
9	58.6954	11.2	173	
10	155.1383	10.7	175	
11	79.9726	10.2	186	
12	79.9749	9.9	230	[30 40], [55 65]
13	25	13.1	225	
14	15	12.1	309	
15	15	12.4	323	

Loss (MW): 29.0475, Cost ($): 32692.30, Total power generation (MW): 2659.0475 MW

Table 4. Statistical results for 15-unit system

Algorithm	Best	Worst	Median	Mean	Standard Deviation
EFO	32692.30	33041.86	32982.51	32967.23	60.32
EO [42]	32701.18	32701.51	NIA	32701.31	NIA
ABC [43]	32787.836	NIA	NIA	32791.5366	NIA
TLBO [44]	32697.22	32697.22	NIA	32697.22	0
MPSO-GA [45]	32702	32755.19	NIA	32701.31	NIA
EO-SCA [46]	32700.51	32701.05	NIA	32702.74	NIA
PSOSIF [47]	32706.88	32709.92	NIA	32707.79	3.04
GAAPI [37]	32732.95	32756.01	NIA	32735.06	NIA
FA [48]	32704.45	33175.00	NIA	32856.10	NIA
EPSO [49]	32704.83	32762.01	NIA	32725.37	NIA
IAEDP [50]	32698.20	32823.78	NIA	32750.22	29.2989
EMA [51]	32704.45	32704.45	NIA	32704.45	NIA
GABC [52]	32706.66	32706.81	NIA	32706.69	0.035838
CCSO [53]	32706.64	32706.64	NIA	32706.64	0.0007
CSO [53]	32709.36	32722.55	NIA	32712.49	4.56
BF-NM [54]	32784.5024	NIA	NIA	32976.81	85.77
DSPSO-TS [55]	32715.06	32730.39	NIA	32724.63	8.4
TS [55]	32917.87	33245.54	NIA	33066.76	66.82
Jaya [38]	32712.6458	32822.9993	NIA	32743.4613	47.0256

The convergence curves of decision variables with iterations for the EFO algorithm and 15-unit system is given in Figure 3.

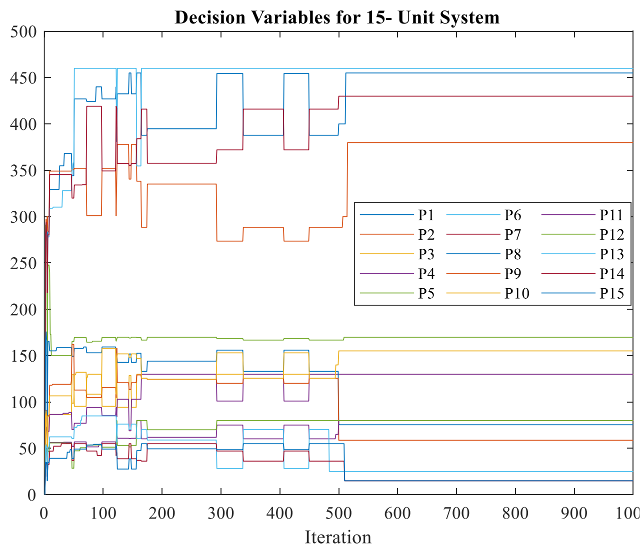

Figure 3. Convergence curves of decision variables for EFO algorithm and 15-unit system

Upon examining the convergence curves of decision variables for EFO algorithm and 15-unit system in Figure 3, it can be seen that a majority of the generators achieve optimal generating power without reaching the maximum iteration number, indicating the fast convergence of the proposed algorithm.

The convergence curve of objective function with iterations for the EFO algorithm and 15-unit system is given in Figure 4.

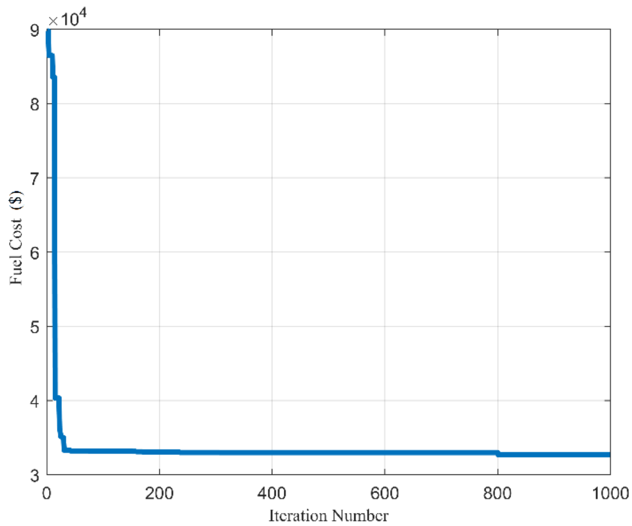

Figure 4. Convergence curve of fuel cost for EFO algorithm and 15-unit system

The fuel cost convergence curve for the EFO algorithm and 15-unit system presented in Figure 4 shows that the EFO algorithm achieves the lowest objective function in fewer iterations, highlighting the efficiency of this proposed method.

5 Conclusion

The ELD problem is crucial in power system planning and operational scheduling. Its primary aim is to minimize power generation costs while meeting load demands. Numerous methods and algorithms have been developed over time to address this challenge. In this article, a new approach called the EFO is recommended for the ELD problem. The algorithm considers various factors such as line losses, POZ limits, ramp rate constraints, generator capacity limits (both maximum and minimum). To verify its efficacy, the EFO algorithm is evaluated on various test systems consisting of both 6-unit and 15-unit configurations.

In conclusion, the EFO algorithm used in this study offers a superior solution to the ELD problem for 6-unit and 15-unit test systems. It generates a generation scheduling with lower cost compared to other techniques and algorithms. The EFO algorithm proves to be efficient and effective in solving the ELD problem, providing a lower cost generation scheduling. The results indicate that the proposed algorithm consistently yields superior solutions compared to established optimization techniques documented in the literature. The convergence curves clearly demonstrate that the EFO exhibits favorable convergence characteristics, converging rapidly and efficiently.

In the future work, the proposed EFO algorithm can be implemented on large test systems such as IEEE 118-bus test system and the proposed approach can be used for solving other optimization problems in the area of power systems.

Conflict of interest

The authors declare that there is no conflict of interest.

Similarity rate (iThenticate): 20%

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