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Research article

Performance of the Walrus Optimizer for solving an economic load dispatch problem

Mokhtar Said[1], Essam H. Houssein[2], Eman Abdullah Aldakheel[3,*], Doaa Sami Khafaga[3], and Alaa A. K. Ismaeel[4,5]

[1] Electrical Engineering Department, Faculty of Engineering, Fayoum University, Fayoum 43518, Egypt
[2] Faculty of Computers and Information, Minia University, Minia 61519, Egypt
[3] Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
[4] Faculty of Computer Studies (FCS), Arab Open University (AOU), Muscat 130, Oman
[5] Faculty of Science, Minia University, Minia 61519, Egypt

* **Correspondence:** Email: eaaldakheel@pnu.edu.sa.

Abstract: A new metaheuristic called the Walrus Optimizer (WO) is inspired by the ways in which walruses move, roost, feed, spawn, gather, and flee in response to important cues (safety and danger signals). In this work, the WO was used to address the economic load dispatch (ELD) issue, which is one of the essential parts of a power system. One type of ELD was designed to reduce fuel consumption expenses. A variety of methodologies were used to compare the WO's performance in order to determine its reliability. These methods included rime-ice algorithm (RIME), moth search algorithm (MSA), the snow ablation algorithm (SAO), and chimp optimization algorithm (ChOA) for the identical case study. We employed six scenarios: Six generators operating at two loads of 700 and 1000 MW each were employed in the first two cases for the ELD problem. For the ELD problem, the second two scenarios involved ten generators operating at two loads of 2000 MW and 1000 MW. Twenty generators operating at a 3000 MW load were the five cases for the ELD issue. Thirty generators operating at a 5000 MW load were the six cases for the ELD issue. The power mismatch factor was the main cause of ELD problems. The ideal value of this component should be close to zero. Using the WO approach, the ideal power mismatch values of 4.1922E−13 and 4.5119E−13 were found for six generator units at demand loads of 700 MW and 1000 MW, respectively. Using metrics for the minimum, mean, maximum, and standard deviation of fitness function, the procedures were evaluated over thirty separate runs. The WO outperformed all other algorithms, as seen by the results generated for the six ELD case studies.

Keywords: Walrus optimizer; economic load dispatch; power system
Mathematics Subject Classification: 68R99

1. Introduction

In power systems, economic load dispatch, or ELD, the aim is to distribute power extracted from producing units as economically as possible while meeting operational demands, maintaining supply-demand equilibrium, and figuring out how to cut down on emissions and power generation costs to help address global warming. There is a lack of coal despite an increase in the need for electricity [1,2]. It is important to note that the fuel consumption curve has a wavy shape due to the valve-point effects. The economic load dispatch problem is therefore a large-scale, highly nonlinear, and constrained optimization problem. Considerable cost reductions can be obtained by optimizing the unit output schedule. With fuel prices rising daily, maximizing the output power from each producing unit is necessary to reduce total fuel expenditures. Mathematical and metaheuristic optimization techniques can be used to achieve this [3].

The linear programming approach was used to determine the electrical producing system's actual and reactive power; however, these methods require a large amount of calculation time and often cannot provide a global answer for large data sets. A number of optimization strategies have been created in this application or another problem with the aim of improving the efficacy of solving the ELD issue [4–8]. The outline search method was proposed as a way to find the best solution for the ELD problem, taking into consideration the impacts of valve loading. A range of test data were employed to evaluate the strategy and compare it to existing optimization techniques in order to bolster the findings [9]. This method was applied to four distinct ELD test systems, ranging in size from small too big and with different degrees of complexity, utilizing the BBO (biogeography-based optimization) method [10]. By solving them using the modified differential evolution approach, several test cases of the ELD were discovered [11]. The authors used the search and rescue optimization technique (SAR) to determine the best strategy for the ELD. According to the study findings, the SAR was the best course of action in every instance of ELD [12].

Six generation units employed the Harris Hawks optimizer technique [13] to address ELD concerns, and the heat transfer search algorithm [14] was utilized to explain the difficult ELD problem after wind energy was added. To address ELD problems, the authors suggested using a multi-strategy ensemble BBO (MSEBBO). The no free lunch theory is used by the MEEBBO to support the three BBO pillars. To comply with the many ELD problem restrictions, a robust repair procedure is also advised [15]. Six real-world generator examples had the ELD problem resolved using the memetic sine-cosine approach [16]. However, as a remedy for ELD problems, the greedy sine-cosine nonhierarchical grey wolf optimizer (G-SCNHGWO) was presented by the authors. In total, there are 40, 15, 10, and 140 power generators in these four power systems, and each has a distinct valuation time [17]. The ant lion optimization algorithm (ALO) was used to fix problems with the ideal ELD. Applying the ALO method to all three circumstances yielded superior results than alternative solutions for the problem, convergence velocity, and stability [18]. The ED problem can be resolved very well using a fully decentralized approach (DA) technique that appropriately accounts for transmission losses in a fully decentralized way. We examined three case studies [19].

In ELD circumstances, the exchange market algorithm (EMA) is a dependable and effective way to identify the best choice for worldwide optimization. Furthermore, it was created utilizing four test systems with convex and non-convex cost functions in four distinct dimensional units [20]. The non-convex ELD problem was solved using the modified crow search algorithm (MCSA), and the results were applied to five popular test systems [21]. In contrast, four ELD with generator counts of 15, 6, 80, and 40 were examined using the hybrid grey wolf optimizer (HGWO) [22]. The modified symbiotic organisms search algorithm (MSOS) was tested on five systems with varying features, restrictions, and dimensions [23]. To address the non-convex ELD issue with valve-point effects and emissions, the enhanced moth-flame optimizer (EMFO) technique was applied to three sample test systems with 6, 40, and a large-scale 80 producing units that had non-convex fuel cost functions [24]. The method of using the one rank cuckoo search algorithm (ORCSA) to solve ELD problems proved effective [25]. By employing the adaptive charged system search (ACSS) technique for both large- and small -scale issue [26]. The artificial cooperative search algorithm (ACS) was introduced with the complicated ELD problem [27]. To extract the best solution for the ELD problem, the efficient distributed auction optimization algorithm (DAOA) was applied [28]. The ELD problems were resolved by a new firefly algorithm (FA) [29].

The authors solved an ELD problem using modified krill herd algorithm (MKH). When compared to other metaheuristics, the MKH was found to function fairly well, and adjusting its settings was not too difficult [30]. The ELD problem was solved using the oppositional pigeon-inspired optimizer (OPIO) algorithm [31]. On five valve-point affected generating systems, the evolutionary simplex adaptive Hooke-Jeeves algorithm's (ESAHJ) performance was evaluated. The suggested technique's test results showed good convergence properties and low generating costs, which made them incredibly appealing and successful [32]. Teaching-learning-based optimization (TLBO) was applied to address ELD problems while accounting for gearbox losses. This method explores the solution space around the global optimum point [33]. The traditional IEEE 30 bus was tested for non-convex CEED concerns [34]. With a number of restrictions, the hybrid Nelder-Mead approach can manage non-convex ED problems with ease. Several traditional test systems were simulated, each with a variable number of generating units [35]. The non-convex ELD problem, which has many limitations such as the valve-point loading impact, a broad range of fuel alternatives, and restricted operating zones, was addressed using the distributed auction-based technique [36]. To solve the ELD and CEED issues, the writers created the turbulent flow of water optimization (TFWO) method [37]. Intelligent optimization techniques known as metaheuristic algorithms guide the search process by employing exploitation and exploration. The development of increasingly metaheuristic algorithms has been spurred by the growing complexity of real-world optimization problems. The actions of walruses, which decide to migrate, roost, breed, gather, feed, and flee in response to critical cues (danger signals and safety signals), served as the model for the Walrus Optimizer (WO) [38].

The following illustrations show the primary goals and contributions of this work:

- The ELD issue is covered in four network studies, one for each of the following generator unit counts: thirty, twenty, ten, and six generators.
- The Walrus Optimizer (WO), a novel metaheuristic technique, is used to resolve the ELD case study.
- For the case studies of six units, ten units, twenty and thirty units, the suggested WO method

is assessed using chimp optimization algorithm (ChOA), moth search algorithm (MSA), snow ablation optimization (SAO), and the rime-ice algorithm (RIME).

- Based on the convergence and robustness statistics, all algorithms are evaluated over thirty runs.
- The disparity in power between the unit's generated power and the load demand determines how well the WO and all other methods are evaluated.

The following is the manuscript's order: In Section 2, the ELD analysis is discussed. Section 3 provides clarification on the WO technique. Section 4 provides an explanation of the findings. Section five provides a description of the conclusions and future work.

2. Analysis of ELD problem

ELD is one of the issues with power systems' functionality. The main obstacle is fixing the ELD problem and maximizing the financial benefit for power plants is reducing fuel consumption expenses. The resource distribution vector in the ELD issue that maximizes extracted power is defined by the primary variable. Below is an explanation of ELD analysis.

The mathematical analysis for ELD can be described using the following notations. The following phrase will be used to compute the cost of fuel used to run n generators:

$$\mathrm{Min(F)} = \mathrm{F_1(P_1)} + \cdots \mathrm{F_n(P_n)}. \tag{1}$$

F is the net cost, $\mathrm{F_n}$ is the cost of the nth generator, and $\mathrm{F_1}$ is the cost of the first generator. The following techniques will be used to obtain the petrol cost function in quadratic equation:

$$\mathrm{Min(F)} = \sum_{k=1}^{n} \mathrm{F_i(P_i)} = \sum_{k=1}^{n} \mathrm{a_k P_k^2 + b_k P_k + c_k}, \tag{2}$$

where the weight constants are a, b, and c. Moreover, Eqs (3) and (5) can be used to modify the generator limits.

$$\sum_{k=1}^{n} P_k - P_D - P_L = 0. \tag{3}$$

If $\mathrm{P_L}$ represents the losses of networks, which are calculated as follows, and $\mathrm{P_D}$ is the demand networks.

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j, \tag{4}$$

where the power extracted at the ith generator is indicated by P_i, the power extracted at the jth generator by $\mathrm{P_j}$, and the factor of loss is indicated by $\mathrm{B_{ij}}$.

$$P_k^{min} \le P_k \le P_k^{max}. \tag{5}$$

3. Walrus optimizer

The Walrus Optimizer (WO) mathematical framework will be addressed in this section [38].

3.1. Initialization

Equation (6) shows how a set of randomly generated candidate keys (X) serves as the starting point for the optimization process.

$$X = LB + \text{rand}\ (UB - LB), \quad (6)$$

where LB and UB represent the lower and upper bounds of the problem parameters, and rand is a uniform random vector in the range of 0 to 1.

The term "walrus" refers to the agents that perform the optimization process. They change their positions continuously during iterations.

$$\mathrm{X} = \begin{bmatrix} X_{1,1} X_{1,2} \cdots X_{1,d} \\ X_{2,1} X_{2,2} \cdots X_{2,d} \\ \vdots\vdots\vdots \\ \vdots\vdots\vdots \\ X_{n,1} X_{n,2} \cdots X_{n,d} \end{bmatrix}_{n\times d}, \quad (7)$$

where n is the size of population and d is the variables dimension.

The matched fitness values of each search agent are retained as follows:

$$\mathrm{F} = \begin{bmatrix} (f_{1,1} f_{1,2} \cdots f_{1,d}) \\ (f_{2,1} f_{2,2} \cdots f_{2,d}) \\ \vdots\vdots\vdots \\ \vdots\vdots\vdots \\ (f_{n,1} f_{n,2} \cdots f_{nd}) \end{bmatrix}_{n\times d}. \quad (8)$$

90% and 10% of the overall walrus population is made up of adult and juvenile populations, respectively. In adult walruses, the male to female ratio is 1:1.

3.2. Safety and danger signals

Foraging and roosting need walruses to be highly watchful. As protectors, a walrus or two will patrol the area, sounding warning signals as soon as they notice any unexpected activity. The meaning of the danger and safety signals in WO is as follows:

$$Danger\ signal = A * R, \quad (9)$$

$$\alpha = 1 - t/T, \quad (10)$$

$$A = 2 \times \alpha, \quad (11)$$

$$R = 2 \times r_1 - 1, \quad (12)$$

where α decreases from 1 to 0 with the number of iterations t, T is the maximum iteration, and A and R are danger factors.

The safety signal in WO that correlates to the danger signal is defined as follows:

$$Safety\ signal = r_2, \quad (13)$$

where, r_2 and r_1 are random values that fall between $(0,1)$.

3.3. Migration

When risks become too large, walrus herds will relocate to areas more conducive to population survival. In this phase, the position of the walrus is updated as follows:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + \text{migratin step}, \tag{14}$$

$$migration\ step = (X_m^t - X_n^t) \cdot \beta \cdot r_3^2, \tag{15}$$

$$\beta = 1 - \frac{1}{1+\exp\left(-\frac{t-\frac{T}{2}}{T}\times 10\right)}, \tag{16}$$

where $X_{i,j}^{t}$ represents the i th walrus's current location on the j thension, and $X_{i,j}^{t+1}$ represents its new position. The step size of the walrus movement is called migration_step, two vigilantes are randomly selected from the population so that their positions match X_m^t and X_n^t, the control factor for migration steps is called β, it evolves iteratively as a smooth curve, and r_3 is a random value between 0 and 1.

3.4. Reproduction

Walrus herds usually do not migrate, instead, they reproduce in currents when danger factors are minimal. The position update of female walruses indicates that the lead walrus (X_{best}^t) and the male walrus ($\text{Male}_{i,j}^t$) impact the female walrus during reproduction. As the iteration progresses, the female walrus starts to rely more on the leader and less on her mate.

$$\text{Female}_{i,j}^{t+1} = \text{Female}_{i,j}^{t} + \alpha \cdot \left(\text{Male}_{i,j}^{t} - \text{Female}_{i,j}^{t}\right) + (1-\alpha) \cdot \left(X_{\text{best}}^{t} - \text{Female}_{i,j}^{t}\right), \tag{17}$$

where $\text{Male}_{i,j}^t$ and $\text{Female}_{i,j}^t$ are the positions of the i th male and female walruses on the j th dimension, and $\text{Female}_{i,j}^{t+1}$ is the new position for the i th female walrus on the j th dimension.

Then, juvenile walruses are often hunted by polar bears and killer whales close to the population's edge. Because of this, young walruses have to get used to their new location in order to avoid predators.

$$\text{Juvenile}_{i,j}^{t+1} = \left(O - \text{Juvenile}_{i,j}^{t}\right) \cdot P, \tag{18}$$

$$O = X_{\text{best}}^{t} + \text{Juvenile}_{i,j}^{t} \cdot LF, \tag{19}$$

where O is the reference safety position, $\text{Juvenile}_{i,j}^{t+1}$ is the new position for the i th juvenile walrus on the j th dimension, and P is the juvenile walrus's distress coefficient, a random number between 0 and 1. Based on the Lévy distribution, LF is a vector of random values that represent Lévy movement.

$$\text{Levy}\ (a) = 0.05 \times \frac{x}{|y|^{\frac{1}{a}}}, \tag{20}$$

where y and x are two normally distributed parameters, $x\ \text{N}(0, \sigma_x^2), y\ \text{N}(0,\ \sigma_y^2)$.

$$\sigma_x = \left[\frac{\Gamma(1+\alpha)\sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{1+\alpha}{2}\right)\alpha 2^{\frac{(\alpha-1)}{2}}}\right]^{\frac{1}{\alpha}}, \sigma_y = 1, \alpha = 1.5, \tag{21}$$

where, σ_y and σ_x are the standard deviations, $\Gamma(x) = (x+1)!$.

When walruses dive for food, they are also a target for natural predators, and when their companions alert them to danger, the animals will leave the area where they are now active. The late WO iteration demonstrates this behavior, and some population disturbance helps walruses in their quest for global exploration.

$$\sigma_x = \left[\frac{\Gamma(1+\alpha)\sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{1+\alpha}{2}\right)\alpha 2^{\frac{(\alpha-1)}{2}}}\right]^{\frac{1}{\alpha}}, \sigma_y = 1, \alpha = 1.5, \tag{22}$$

where the distance between the best and current walrus is shown by the symbol $\left|X_{best}^t - X_{i,j}^t\right|$, and$r_4$ is a random value between 1 and 0.

Furthermore, walruses can cooperate to move and forage dependent on the whereabouts of other walruses in the group as part of their social gathering behavior. Walruses have the ability to help the entire herd find regions of the sea with more food by exchanging location data.

$$X_{i,j}^{t+1} = (X_1 + X_2)/2, \tag{23}$$

$$\begin{cases} X_1 = X_{\text{best}}^t - a_1 \times b_1 \times \left|X_{\text{best}}^t - X_{i,j}^t\right| \\ X_2 = X_{\text{second}}^t - a_2 \times b_2 \times \left|X_{\text{second}}^t - X_{i,j}^t\right|' \end{cases} \tag{24}$$

$$a = \beta \times r_5 - \beta, \tag{25}$$

$$b = \tan(\theta) \tag{26}$$

where $a \; and \; b$ are the gathering coefficients, X_1 and X_2 are two weights influencing the walrus's gathering behaviour, and X_{second}^t reflects the position of the second walrus in the current iteration. $\left|X_{\text{second}}^t - X_{i,j}^t\right|$ indicates the distance between the current walrus and the second walrus. Whereas the values of θ range from 0 to π, the random integer r_5 is between 0 and 1.

3.5. WO flow chart

The flowchart of WO is described in detail in Figure 1.

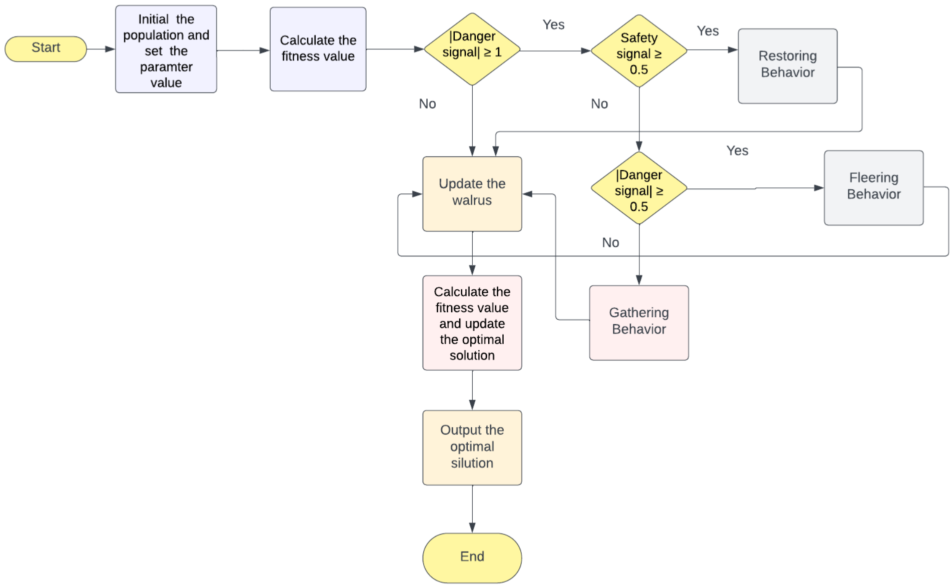

Figure 1. Flow chart of WO algorithm.

4. Results of ELD cases

The ELD receives a donation of the WO performance. The moth search algorithm (MSA) [39], the snow ablation optimization (SAO) [40], the chimp optimization algorithm (ChOA) [41], and the rime-ice algorithm (RIME) [42] were used to evaluate the suggested WO method. The ELD issue was used in the following case studies:

- Six generators operating at two distinct loads (1000 and 700 MW) comprise the first case study.
- There are 10 generators in the second case study with two different loads (1000 and 2000 MW).
- The five-case study has 20 generators operating at 3000 MW loads.
- The six-case study included 30 generators operating at 5000 MW loads.

4.1. Results of six generators

In order to test the ELD issue, a case study with six generators operating at two loads is donated. A variety of techniques were used, including the WO, RIME, SAO, MSA, and ChOA algorithms. Thirty different runs were used to assess each competing strategy's efficacy. The mean, maximum, minimum, and standard deviation values were documented as statistical information for each load using these runs, as shown in Table 1. Using this data, the WO determines the optimal standard deviation and the best objective function. For ELD, the WO algorithm is therefore the most accurate and reliable. Table 2 displays the ideal fuel cost for each situation. Table 3, which was developed using the best objective function among all approaches, displays the ideal power provided by each unit for a load requirement of 700 MW. Table 4 which was generated on the best objective function across all techniques, displays the optimal power provided by each unit to recover load requirement of 1000 MW. The robustness curve determines the fitness function value for each run based on the results of all techniques recorded over the course of the 30 runs.

Table 1. Statistical data of all methods in ($/h) for six generators.

Load (MW)	Algorithm	Minimum	SD	Mean	Maximum
700	WO	8400.997136	196.5147708	8662.170541	9139.212021
	SAO	8465.975761	197.2010827	8753.891609	9155.235854
	ChOA	39475.15105	1415165.954	1594567.940	4960872.827
	MSA	8427.541921	163.3349358	8716.009085	9032.640980
	RIME	154035.3045	78735556.03	64584338.77	348563546.7
1000	WO	12120.25084	131.2152977	12270.39366	12615.36259
	SAO	12141.46728	128.4638379	12318.57722	12643.00452
	ChOA	35568.69974	859586.3590	789710.3604	3975199.582
	MSA	12196.59431	89.66107262	12335.59750	12552.83025
	RIME	2696415.881	84144505.04	76815454.04	279959787.1

Table 2. The optimal fuel usage costs ($/h) for six generators.

Method	700 MW	1000 MW
WO	8400.996922	12120.24203
SAO	8465.925401	12136.61857
ChOA	8995.251114	12330.14858
MSA	9794.135519	14034.62198
RIME	8648.886480	12206.03121

Table 3. The best distribution of power (MW) among six generators for a demand of 700 MW.

WO	SAO	ChOA	MSA	RIME
281.8419643	259.8161060	100	56.03971489	186.8762755
50.50407930	54.58630261	52.35878389	69.97467027	62.88659606
192.6399883	159.3362502	257.1559643	72.80852851	279.7127278
50.02267017	58.20871339	50	103.0726077	51.47179647
78.64437068	94.60440179	200	103.7752893	70.08507476
58.16395368	85.58268340	56.51473367	305.2492779	62.78030728

Table 4. The best distribution of power (MW) among six generators for a demand of 1000 MW.

WO	SAO	ChOA	MSA	RIME
418.8719894	374.5651735	500	54.48410890	462.2467195
118.4807842	173.0458359	176.9449449	79.19002879	142.3428705
207.6997509	210.9436951	116.0761643	124.3800484	226.2392259
87.95314532	77.57138608	86.42470161	155.7910172	50.00204391
139.8294433	132.5356769	62.15523186	246.3641047	50
50.59678231	55.14492812	79.69065610	365.0459344	91.25167800

The robustness curve properties for each case on the system with six units are displayed in Figures 2 and 3. Based on the recorded outcomes from each of the top 30 runs that yield the best fitness function, the convergence curve describes the quickest approach that meets the goal function. The characteristics of the convergence curve for the system with six units at each load level are shown in Figures 4 and 5. Using the convergence and robustness properties as a guide, the WO finds the optimal global solution. Tables 5 and 6 clarify the estimated sharing power from all units over the thirty runs for six units based on the WO method.

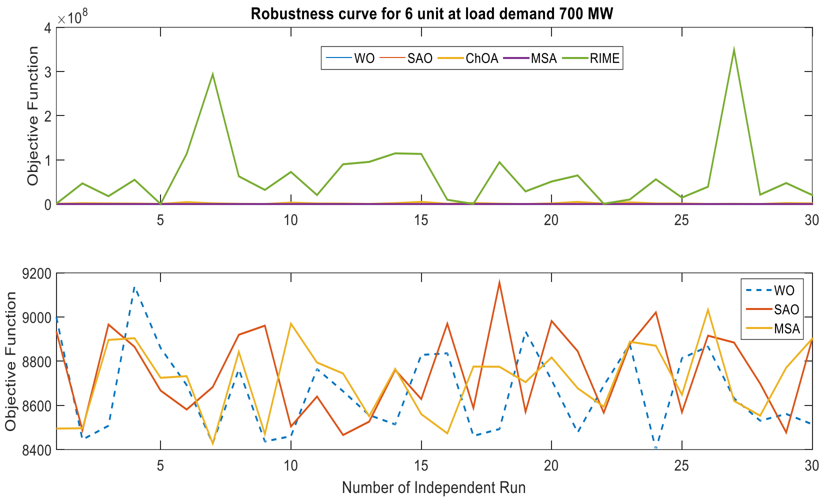

Figure 2. Six generators' robustness curves at a 700 MW load.

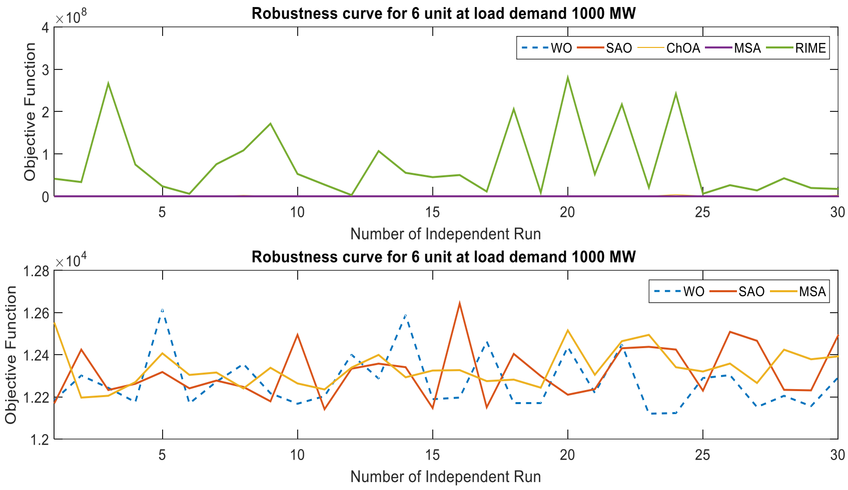

Figure 3. Six generators' robustness curves at a 1000 MW load.

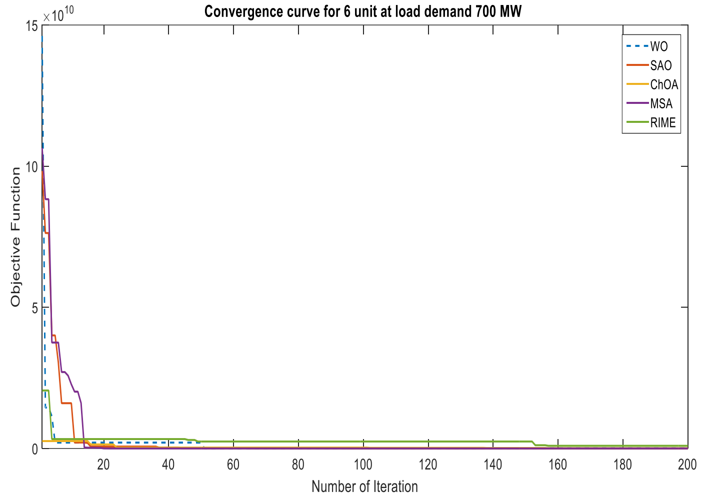

Figure 4. Six generators' convergence curves at a 700 MW load.

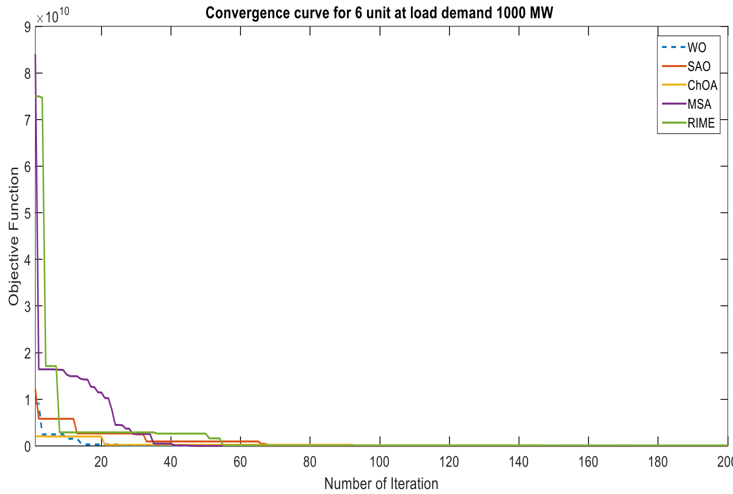

Figure 5. Six generators' convergence curves at a 1000 MW load.

Table 5. The estimated sharing power from all units over the thirty runs for six units based on the WO method at 700 MW.

Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
102.4803134	98.90858263	146.5974124	57.05988267	199.9998093	109.9802472
252.0493973	88.14888891	144.6226086	86.19141850	78.69709537	61.97854274
217.1549197	98.80989745	143.4855378	75.38821598	116.6628773	60.83235654
100	200	80	58.07392804	199.7337076	76.81948039
127.1120581	52.58933520	178.9286417	100.8793515	178.6835637	76.58050636
171.2244733	193.7244687	134.8106730	52.13909507	99.90726427	60.85348710
303.3576528	89.67226612	110.0581270	80.08162413	61.72363427	66.07303450
152.3377111	135.9783145	146.2957426	132.4204045	57.71403532	88.13135753

Continued on next page

Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
272.1414685	127.9969590	127.5023324	75.40811217	50	58.06615553
242.3004371	76.5465688	155.8124437	50.43508027	129.8969541	57.36082528
158.0997819	68.39168686	136.5241416	120.3722600	171.8359666	58.78901335
188.1262448	115.8998675	113.4359860	87.19074785	118.9889349	89.14564073
198.5167438	105.0685979	240.4188648	54.73838761	50.89307970	63.11961272
207.4749216	121.7413134	149.1441977	77.26002026	103.6364154	52.96163304
124.0668650	90.92339930	249.1107843	54.05206681	90.69455487	105.4528787
158.8493266	150.8833468	80	85.19020735	183.8349391	54.90617341
245.2819280	83.65885527	149.1188361	52.40031462	107.4175349	74.22420733
250.5707815	132.2436871	107.0744415	93.33921683	75.77756745	52.51220603
100.2306225	75.89233881	261.0982595	126.1334462	79.42216520	71.86777543
154.0799986	59.35882146	187.5369360	106.2150155	134.8700152	71.79567099
237.8466632	91.53005291	159.3975559	56.00072280	80.97575690	86.27944518
177.6241311	65.73269041	294.1448464	55.61023583	67.27121818	53.70427278
140.7040655	123.5236114	97.96158459	85.70199318	196.2508439	69.98467789
281.8419643	50.50407930	192.6399883	50.02267017	78.64437068	58.16395368
138.2306531	92.01201083	137.1201323	99.63543302	185.3094505	61.83791201
120.1891075	165.0697700	176.0335154	149.5190604	50.95775454	51.47374498
162.7158423	131.8547034	166.5554811	90.71884640	103.3414511	57.59958377
239.5906960	147.6249374	99.59586416	71.95502938	90.85440986	62.14291823
222.4746072	96.56678798	114.6609715	78.22236349	114.0120391	86.46675339
217.8622484	95.40899320	147.2814524	82.06577941	95.45064912	74.16733930

Table 6. The estimated sharing power from all units over the thirty runs for six units based on the WO method at 1000 MW.

Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
341.3981624	140.9413161	198.2286577	110.6886852	140.6813018	92.81221650
284.1819988	143.7225151	210.2178285	97.30437360	179.8132314	111.1492323
309.7621619	117.0385621	246.3548164	107.4187872	152.8137221	92.46722036
344.2115321	131.0580592	211.3389364	100.1877574	148.0912579	89.99270845
266.5532907	173.4169070	186.7969442	139.8422806	190.8918946	68.91202388
366.1897574	115.5512483	219.4230681	95.09084517	122.7059296	105.5195606
476.9243509	54.21667175	187.2306249	68.02355672	125.2463485	111.6764112
336.5581280	138.7634309	221.5640531	104.2301337	142.8800824	80.87432334
311.6684933	157.2394350	220.4660037	113.0076546	128.1239647	94.57957665
357.4839710	152.4713473	230.4426551	62.25645741	125.7710309	96.01873016
326.8077345	149.1901841	235.2728939	73.89699066	135.9788826	103.9965005
375.4374685	197.9903023	97.54151456	54.84573108	179.6313230	119.6729541
310.5525430	200	228.4033442	131.5740260	64.71385590	89.25542297
198.3478713	121.0773544	296.9073980	100.1264281	200	112.5644537
364.5289296	116.8251593	215.8054688	61.26854929	184.5750177	82.22239739
343.2550109	138.7541221	183.5203179	113.6092577	158.6660371	87.11194786
231.2846259	171.2273378	299.9999969	65.36650287	181.4682842	78.30160867

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Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
334.0385473	140.8650324	217.1734714	105.0756383	144.9430579	82.81971939
344.0653060	138.7780745	208.6015833	107.2240187	139.1283197	86.88806222
493.0435454	169.1438687	82.45797790	131.6592578	52.40150981	93.07448376
347.6552919	123.7009673	290.5128504	73.74211351	95.65015628	93.71152034
500	182.2766504	80	149.9880007	59.31734212	50
418.8719894	118.4807842	207.6997509	87.95314532	139.8294433	50.59678231
415.2861783	160.6555421	218.3004690	81.13067886	93.20998978	54.21886616
315.4930839	187.8881017	236.6649001	107.9465190	59.40055137	117.2313561
346.2844095	159.9314812	139.6791036	126.9515242	136.3862798	115.5694083
435.8349834	146.8766561	186.0508011	69.62593103	102.9392750	81.32075210
382.4916920	182.5880896	174.2718067	50	140.8667595	93.75208220
366.9104058	126.1658610	248.4103510	63.15425596	139.9832928	80.01889125
308.1807194	122.1205565	298.0516559	50.56191778	155.8335116	91.75587284

4.2. Results of ten generators

In order to test the ELD issue, a case study with ten generators operating at two loads is donated. A variety of techniques were used, including the WO, RIME, SAO, MSA, and ChOA algorithms. Thirty different runs were used to assess each competing strategy's efficacy. The mean, maximum, minimum, and standard deviation values were documented as statistical information for each load using these runs, as shown in Table 7. Using this data, the WO determines the optimal standard deviation and the best objective function. For ELD, the WO algorithm is therefore the most accurate and reliable. Table 8 displays the ideal fuel cost for each situation. Table 9, which was developed using the best objective function among all approaches, displays the ideal power provided by each unit for a load requirement of 1000 MW. Table 10, which was generated on the best objective function across all techniques, displays the optimal power provided by each unit to recover load requirement of 2000 MW.

Table 7. Statistics data of all methods in ($/h) for ten generators.

Load (MW)	Algorithm	Minimum	SD	Mean	Maximum
1000	WO	99172455.07	22083746.37	125028621.9	204189415.1
	SAO	91025531.85	47461035.30	135774959.0	278926971.6
	ChOA	96169315.81	9092193.300	110754717.8	134377790.8
	MSA	90206604.16	23733842.24	119742282.7	171657419.9
	RIME	96981916.42	77022779.49	187450044.4	394817673.1
2000	WO	475068075.3	40792448.60	533415296.7	617012683.9
	SAO	459517895.5	43408269.26	575882737.8	635659941.4
	ChOA	432244579.1	39158317.85	501777836.9	583106906.4
	MSA	472373206.1	40398057.93	592236498.7	639339146.9
	RIME	465555201.9	71077574.92	576425864.7	777638652.5

Table 8. The optimal fuel usage costs ($/h) for ten generators.

Method	1000 MW	2000 MW
WO	99172455.07	475068075.2
SAO	88057595.74	459419310.3
ChOA	94849826.08	416417404.5
MSA	71535847.32	349536183.6
RIME	94886247.04	459186431.8

Table 9. The best distribution of power (MW) among ten generators for a demand of 1000 MW.

WO	SAO	ChOA	MSA	RIME
189.9585506	162.2053566	154.3329761	12.33748823	174.1680447
137.8622921	135.2619336	135	44.01184975	135
105.6144183	137.8238444	73	66.25826943	115.6444194
60.46282183	125.1864930	97.81644810	68.77385114	128.2000558
120.3049668	79.00989904	198.1933143	117.8098698	153.3188340
148.0244135	82.28033061	140.7465156	126.1331838	117.8700572
38.22264078	91.22832092	79.42576608	135.0403635	25.56604190
105.1471066	91.97426679	96.67066137	143.4200038	68.71055217
49.81657885	77.85222711	26.78146665	146.6648195	80
54.62738077	26.43244080	10	150.0006410	12.19912388

Table 10. The best distribution of power (MW) among ten generators for a demand of 2000 MW.

WO	SAO	ChOA	MSA	RIME
412.2313307	416.1371402	395.8661795	26.65588505	418.1936554
354.1194035	317.6418237	269.9925437	45.93059863	322.4049869
297.3361751	330.0870262	340	119.9951250	332.5336200
299.4981562	290.3535755	300	124.2309670	277.6069160
209.7173057	224.5346635	243	159.9953976	220.4361023
159.9999989	160	111.8960325	242.9999999	129.0094100
81.48722139	120.7940973	130	256.3870356	128.5908911
112.9551673	99.61729215	120	299.9996923	103.1062452
68.12411680	42.42283454	80	302.2501288	70.52565350
47.17968826	40.10417154	47.55800085	465.4640164	39.03613209

The robustness curve determines the fitness function value for each run based on the results of all techniques recorded over the course of the 30 runs. The robustness curve properties for each case on the system with ten units are displayed in Figures 6 and 7. Based on the recorded outcomes from each of the top 30 runs that yield the best fitness function, the convergence curve describes the quickest approach that meets the goal function. The characteristics of the convergence curve for the system with ten units at each load level are shown in Figures 8 and 9. Using the convergence and robustness properties as a guide, the WO finds the optimal global solution. Tables 11 and 12 clarify the estimated sharing power from all units over the thirty runs for ten units based on the WO method.

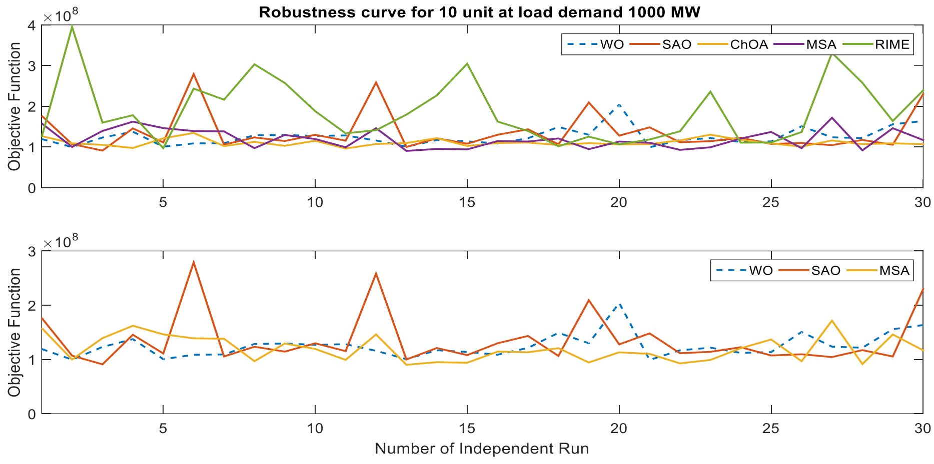

Figure 6. Ten generators' robustness curves at a 1000 MW load.

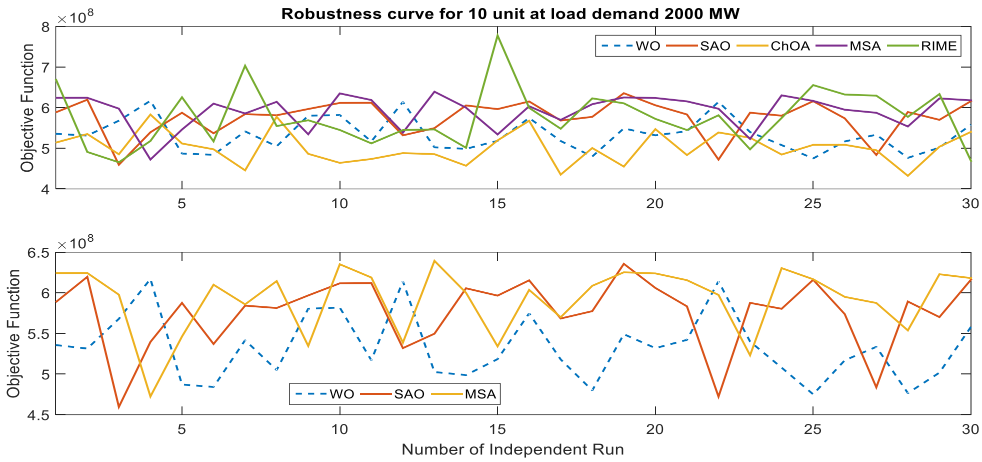

Figure 7. Ten generators' robustness curves at a 2000 MW load.

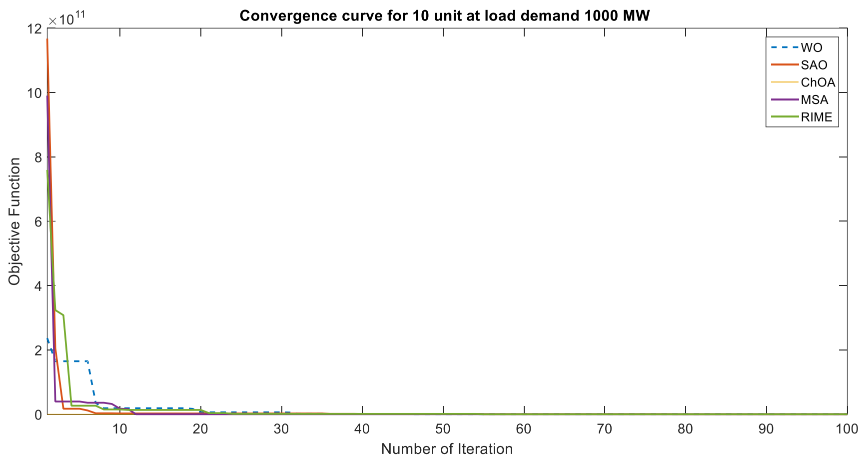

Figure 8. Ten generators' convergence curves at a 1000 MW load.

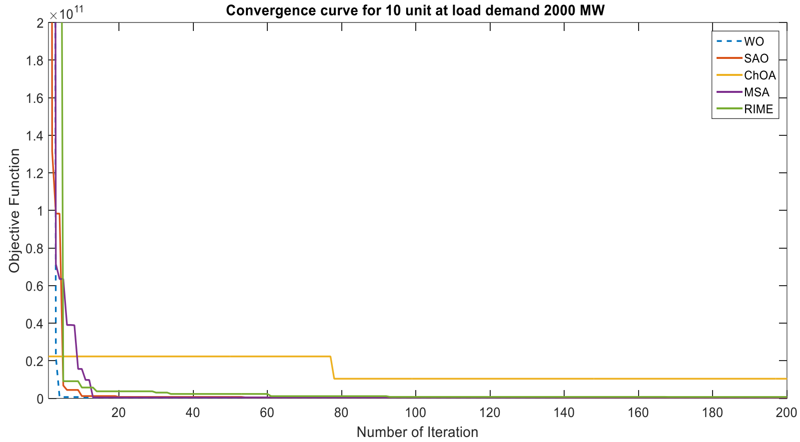

Figure 9. Ten generators' convergence curves at a 2000 MW load.

Table 11. The estimated sharing power from all units over the thirty runs for ten units based on the WO method at 1000 MW.

Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
159.2159925	205.1542627	77.35307172	175.9486537	166.5926449	92.35376392	34.40883372	47.5618075	21.04762987	33.99557635
160.1030938	162.0074058	182.6936501	64.84722692	96.90956346	75.28673255	97.85111033	56.37649123	59.7835778 6	55
231.6370454	172.9971196	124.0327942	138.1810285	120.4438399	76.83609233	43.21498018	54.0797019	27.50471812	22.34660415
297.0510775	138.7638412	111.2012504	107.3178205	77.78582904	104.4015475	46.37748384	58.52670653	20.10876075	50.40279529
154.1313930	135	214.1969545	92.19856823	165.9868429	66.18561734	86.30825998	55.9262042	28.66518161	12.22339933
222.348739	139.4559695	100.8188328	186.7052467	79.14978809	76.18654879	81.03239416	48.48638539	61.25889537	15.88444985
175.4413944	135.0226018	89.64707499	267.772138	73	127.2842840	30.12195729	78.93259336	25.29184388	10.00000005
235.2670748	158.3604452	176.9214304	77.94781019	75.05940957	159.9043481	33.26798728	47.03480229	35.43235191	12.61601629
222.2455874	198.9585264	133.2846076	114.6020956	106.2140985	75.1981615	46.26249066	60.96494526	31.71475946	21.85463807
222.7335791	185.3936952	168.1266204	114.470871	75.5569208 4	64.09124533	87.60568621	47.79453443	24.50415781	20.85087625
241.2563633	168.4369199	172.9156304	60.80558564	78.03386632	57.54671684	20.00685788	103.6024601	77.65784392	28.23306747
188.1525628	194.451753	116.7529253	87.14449367	118.0462450	111.9303454	36.11260949	66.97493347	74.43932201	17.23178485
180.2933015	148.2087336	182.5790718	98.90030204	96.72667057	76.26538453	45.87469691	74.66056189	74.66528952	30.87468895
213.6771494	172.0073669	110.4307990	60	129.064921 9	90.46599244	22.83272537	120	78.14464174	13.00750412
209.5248331	162.3583379	82.39817875	180.7584185	145.714440 9	57	64.38812327	65.54054761	33.0194012	11.37312312
154.9925692	173.6751037	112.0207399	211.3494988	121.3415918	110.25215	24.15834555	58.48033319	22.51364093	23.11060133
236.400897	165.3637865	100.5876852	143.0854971	101.104806 5	98.2583874	28.32240061	74.39012859	22.4737011	41.45500504
290.9903704	180.1161077	111.1939527	89.44872095	124.063247 8	73.6829613	34.3507097	56.23315767	37.14807602	15.51345443
212.5603041	208.9283893	134.4543464	107.6806232	94.95230511	75.58137433	37.10654997	66.16773945	55.13999334	18.44545653
158.2374826	345.6263731	73.16475215	71.45397246	152.2656396	59.85089507	62.8970225	53.76695369	27.49964172	14.07082341
189.9585506	137.8622921	105.6144183	60.46282183	120.3049668	148.0244135	38.22264078	105.147106 6	49.81657885	54.62738077
197.6620039	186.9874661	135.826066	107.5450569	87.00044521	109.816946	71.79764467	65.41337606	34.52665800	14.51310919
235.8701998	138.9810028	129.3330681	69.23232825	223.284818 4	61.04359029	28.61580145	69.1050002 2	23.78682105	32.85745335
181.1324307	184.9282264	153.1808598	108.5734387	114.8465169	66.11002425	85.34879155	63.51312899	37.49681069	15.75990624
233.6393711	139.5236933	84.22606041	60.5875545	115.8070188	158.9289702	79.24832213	76.29601522	29.2076877	34.39384127
322.6035983	140.3409282	131.236310 0	77.0150188	73.28499122	83.94471891	66.87240103	47.1032357	37.75253618	32.45997671

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Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
180.2520248	185.4205927	94.11881173	264.0011458	75.4327111	57	69.84014218	49.4514016	23.85295787	13.07985644
267.5710745	135	93.19580244	153.9877712	78.57795601	60.62471705	62.78212018	59.37321338	79.99944159	20.57353603
150.0500502	280.2883568	99.04657934	92.92107204	94.65560650	140.9116580	29.94288849	74.00109769	27.42179229	25.32489640
150.0440645	284.8799976	73.00000058	223.5071776	74.69581295	62.25644561	46.55371377	47	20.16888136	33.88947346

Table 12. The estimated sharing power from all units over the thirty runs for ten units based on the WO method at 2000 MW.

Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
428.0982723	417.7643835	290.7395516	285.9557676	170.8925859	134.5408063	121.2784259	94.59391201	53.54997275	49.80925878
388.1017765	446.1179611	269.6210476	265.3121883	194.5587579	147.1267506	107.5622969	105.7971318	75.60553088	48.57343027
419.9645588	458.1691315	275.7242539	252.0763891	190.0235745	152.6207006	122.3828213	100.4709633	34.89703043	43.96784911
470	446.72697	339.8623129	299.9806668	82.99905601	159.4956349	29.54956098	119.8265272	52.42093001	44.14627465
450.1496196	335.2756905	304.3891891	294.4576684	229.4492262	114.3338339	95.61309569	103.6951507	75.52527954	39.65895347
372.71844	398.4222273	308.3259975	262.9682916	193.9403648	158.8206066	119.5484443	112.7696192	70.72483215	46.28807342
444.5795722	419.9636507	238.966268	285.881978	224.2082906	125.3142064	97.39351277	82.61953498	76.50259923	54.8422977
384.5500323	413.8709687	265.3486526	299.8081442	231.9730852	154.1573168	104.0949083	76.83479117	70.5213366	47.2983988
406.1802318	459.8603496	333.4903322	242.8711336	231.6858442	151.6981355	85.33452909	92.71106967	20.08637784	24.39942245
467.9679976	428.3309168	296.3827596	299.5874475	101.2616463	143.0174477	129.900161	110.7717226	20.47073827	50.1455135
414.5919729	408.2329251	297.3225483	262.5842117	205.0380753	133.2135416	111.6110689	103.5565033	66.16902266	43.53730963
465.3926078	455.0110264	330.6164285	298.9217218	83.02290621	60.19747039	129.9709871	119.8934767	75.81215309	28.03921375
457.3085445	341.6409802	324.1213944	299.7258376	195.3717413	141.2953509	49.37406341	99.41533932	79.99973381	53.44677173
387.6028351	403.7838295	301.1756945	251.572342	239.1790535	140.31152	110.1653136	108.1416534	67.3268931	36.27017624
394.6879332	423.9236727	289.2115421	252.6339103	224.8741427	143.7732071	90.88320764	109.6978583	73.16231506	43.43877876
468.4662924	427.911449	306.6047926	201.7387548	242.644638	82.16221703	97.3784371	103.4339958	68.53126331	49.5647736
426.6172538	406.7945802	262.0453947	272.5524587	206.1571276	147.4071999	102.6374548	104.2898131	71.50860007	47.1176062
424.884686	343.5060783	314.1299114	297.3862956	240.5331876	104.9658907	82.22764731	117.7593807	63.70287415	52.38247512
382.6193821	450.9885973	293.6944731	300	209.3489807	159.9678292	47.80446207	97.99045294	75.95010153	28.52894728
383.6260834	442.241986	275.3078995	288.3220013	216.4277126	151.5372682	105.4972441	72.70620601	74.21427914	39.5823027
437.9366298	416.0085116	318.8706489	228.2631104	173.905161	154.3336904	109.0310292	105.8461975	61.8623995	39.76218428
469.4466025	459.9999637	340	150.2114857	208.2614235	91.5986107	130	108.3645804	42.01877182	50.79978166
432.8995631	404.4758705	327.7598376	277.7123065	185.4334227	156.4713072	86.30860545	111.6608485	28.68140535	32.71694383
403.5274754	405.6548252	308.1246595	253.4877107	203.2876437	138.3456277	110.4757841	97.90411147	71.85980287	52.96546268
412.2313307	354.1194035	297.3361751	299.4981562	209.7173057	159.9999989	81.48722139	112.9551673	68.1241168	47.17968826
431.268416	396.176757	307.5683835	256.6920566	185.7613956	133.519391	112.4859199	101.1797122	71.54351032	48.91764929
401.5443966	424.3925779	319.1914116	253.0436952	228.9338026	151.2061905	37.82310017	98.1229274	80	50.92031943
371.0873022	382.6125425	338.884372	242.4323102	230.8253159	145.3676986	107.1052479	103.2482867	68.16686284	54.03182796
419.1885618	390.0135451	286.854260	260.6994848	212.2401164	148.6285556	114.4061915	103.2356786	68.8754878 6	41.46820991
376.6740049	459.9832529	313.6472886	263.762858	237.0071809	147.171602	20	110.9244507	67.46366796	49.75691359

4.3. Results of twenty generators

In order to test the ELD issue, a case study with twenty generators operating at 3000 MW load is donated. A variety of techniques were used including the WO, RIME, SAO, MSA, and ChOA algorithms. Thirty different runs were used to assess each competing strategy's efficacy. The mean, maximum, minimum, and standard deviation values were documented as statistical information for each load using these runs, as shown in Table 13. Using this data, the WO determines the optimal standard deviation and the best objective function. For ELD, the WO algorithm is therefore the most accurate and reliable. Table 14 displays the ideal fuel cost. Table 15, which was developed using the best objective function among all approaches, displays the ideal power provided by each unit for a load requirement of 3000 MW. The robustness curve determines the fitness function value for each run based on the results of all techniques recorded over the course of the 30 runs. The robustness curve properties for the system with twenty units is displayed in Figure 10. Based on the recorded outcomes from each of the top 30 runs that yield the best fitness function, the convergence curve describes the quickest approach that meets the goal function. The characteristics of the convergence curve for the system with twenty units is shown in Figure 11. Using the convergence and robustness properties as a guide, the WO finds the optimal global solution.

Table 13. Statistics data of all methods in ($/h) for twenty generators.

Load (MW)	Method	Minimum	SD	Mean	Maximum
3000	WO	464390784.6	80385278.05	601882926.3	781664638.0
	SAO	386134352.9	93352458.10	647520789.4	837732536.6
	ChOA	378479313.7	62470909.71	508890772.8	674400824.9
	MSA	474920850.4	62784168.97	587293620.1	706048241.3
	RIME	492737490	112461311.7	703071978.6	999229765.2

Table 14. The optimal fuel usage costs ($/h) for twenty generators.

Method	3000 MW
WO	464390784.6
SAO	382573772.5
ChOA	377610655.8
MSA	382886269.5
RIME	453827249.1

Table 15. The best distribution of power (MW) among twenty generators for a demand of 3000 MW.

WO	SAO	ChOA	MSA	RIME
395.8114381	151.6528541	189.1359163	27.67575842	289.6249510
135	184.2648197	151.4504418	36.49556758	189.5337518
273.1416448	190.7183576	209.1384204	38.00643724	209.1991579
194.9170343	300	273.7818598	48.00263656	296.5966165
215.7882232	221.9169631	188.7549064	49.00183238	113.8978953
121.2980218	156.1339232	160	69.00346450	160
71.60958816	130	94.57254207	86.99422477	50.97508515
84.48652671	47.29866951	112.7781839	115.0102537	47.02325440
68.96129708	80	20	143.6024661	57.67211139
29.73786810	34.40590622	41.68599962	153.1579086	13.74646693
225.5746355	211.8911419	163.8029810	174.9828705	246.0582500

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WO	SAO	ChOA	MSA	RIME
203.6821211	179.8235087	136.9346654	180.0031293	233.0110822
188.0154112	283.2667993	335.6229908	180.9930170	174.9402437
240.0733159	223.3191179	300	184.0201986	277.3906292
195.9195348	137.2674686	177.1829979	193.0178273	198.0835046
104.0455988	159.8454509	160	205.0149350	156.9012038
72.67502373	119.0941065	64.86963812	212.0163116	78.02459914
76.59300054	114.2839665	112.3046859	253.0011000	118.9234432
64.06909787	64.58733512	65.54825073	319.9601154	40.53005757
38.60061834	10.22996721	42.44420644	330.0399455	47.87158727

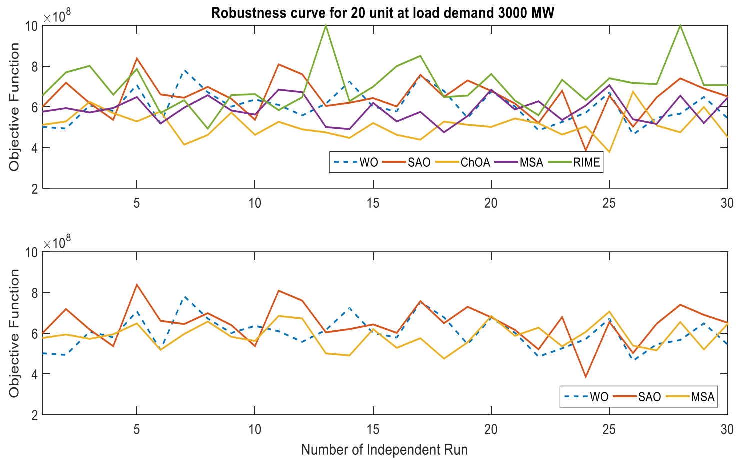

Figure 10. Twenty generators' robustness curves at a 3000 MW load.

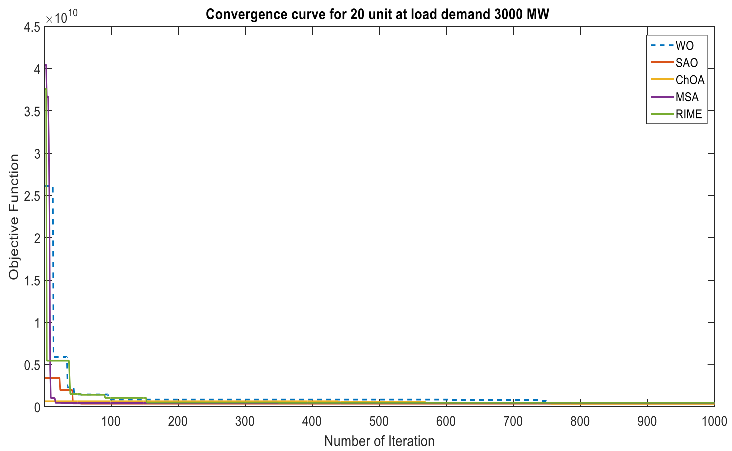

Figure 11. Twenty generators' convergence curves at a 3000 MW load.

4.4. Results of thirty generators

In order to test the ELD issue, a case study with thirty generators operating at 3000 MW load is donated. A variety of techniques were used including the WO, RIME, SAO, MSA, and ChOA algorithms. Thirty different runs were used to assess each competing strategy's efficacy. The mean, maximum, minimum, and standard deviation values were documented as statistical information for each load using these runs, as shown in Table 16. Using this data, the WO determines the optimal standard deviation and the best objective function. For ELD, the WO algorithm is therefore the most accurate and reliable. Table 17 displays the ideal fuel cost. Table 18, which was developed using the best objective function among all approaches, displays the ideal power provided by each unit for a load requirement of 5000 MW. The robustness curve determines the fitness function value for each run based on the results of all techniques recorded over the course of the 30 runs. The robustness curve properties for the system with thirty units is displayed in Figure 12. Based on the recorded outcomes from each of the top 30 runs that yield the best fitness function, the convergence curve describes the quickest approach that meets the goal function. The characteristics of the convergence curve for the system with thirty units is shown in Figure 13. Using the convergence and robustness properties as a guide, the WO finds the optimal global solution.

Table 16. Statistics data of all methods in ($/h) for thirty generators.

Load (MW)	Method	Minimum	SD	Mean	Maximum
5000	WO	982540947.5	91938497.93	1156733522	1336706848
	SAO	908558160.8	143278429.4	1211191850	1513082334
	ChOA	801191500.7	99936778.88	1007797884	1207996618
	RIME	1037852896	159765617.6	1253663161	1617847664

Table 17. The optimal fuel usage costs ($/h) for thirty generators.

Method	3000 MW
WO	982529390
SAO	904975533.8
ChOA	787860293.7
RIME	1012965738

Table 18. The best distribution of power (MW) among twenty generators for a demand of 3000 MW.

WO	SAO	ChOA	RIME
361.7630873	168.0622420	205.4777664	399.2227256
286.4259419	305.2577836	239.8677456	248.9833745
217.4959595	274.3045256	340	181.6597908
201.1152074	259.3996384	208.6892241	277.8493217
179.0307835	242.9886794	118.1445066	183.6734269
119.9338007	103.2976540	160	118.7190545
81.03038860	23.58266429	78.83205900	35.43137407
97.99971207	119.0761287	120	107.3780597
52.00113619	72.59531050	62.56425338	33.81402317
34.57432282	47.68354245	55	49.59621356
306.8486138	187.2472111	175.9067214	393.0652103
338.7023182	252.4448604	261.7622078	302.1274649

Continued on next page

WO	SAO	ChOA	RIME
238.4998547	316.2628216	268.3381195	280.9736853
223.3491903	299.3864879	207.1881123	85.59393119
180.5191017	218.6818710	243	230.2698858
126.9556699	154.6733846	94.46223648	137.8008438
109.8918576	129.9483846	97.66863888	60.35154872
87.51357368	59.94573212	120	120
63.94496690	22.39995053	55.02037904	36.08305683
38.23076929	10	50.45341015	46.60655867
357.4468090	449.0518667	332.6299565	234.7062162
296.4047702	139.3053811	162.8862309	337.5808507
234.5334060	317.9662357	340	274.3350697
219.2973389	299.9910290	300	238.5976231
185.8148553	241.8390582	222.6389246	242.1331374
114.0038275	58.80668289	160	107.6366599
64.37558862	102.8953648	130	68.95720026
92.47625889	47.00006457	80.31172714	68.00115191
53.81758571	21.03713721	80	73.10745947
36.00330252	54.86794885	29.29109226	25.74259255

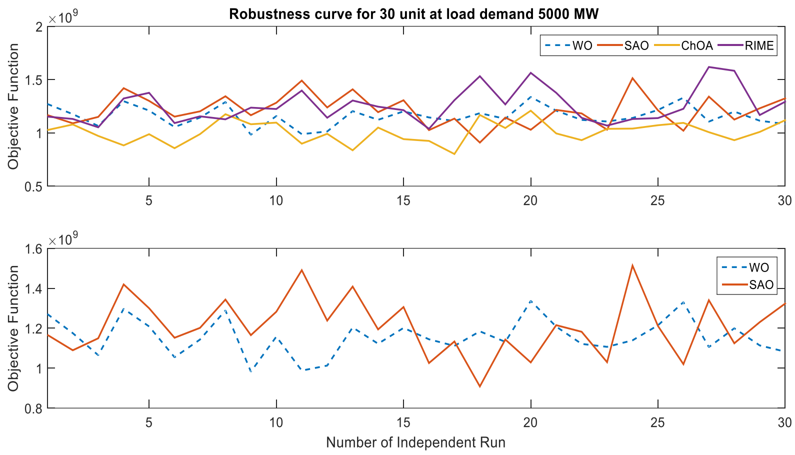

Figure 12. Thirty generators' robustness curves at a 5000 MW load.

4.5. Discussion

The main factor contributing to ELD problems is the power mismatch value, the precise difference between the units of power generated and the entire demand plus transmission losses. The power mismatch value is nearly zero, hence the high-performance methods is employed to get it. Table 19 explains the importance of this component for ELD. In addition to the five methods used in the run, the proposed WO algorithm is contrasted with other methods found in the literature, such as the monarch butterfly optimization (MBO), the grey wolf optimization (GWO), Earth Worm Algorithm (EWA), Elephant herding optimization (EHO), and Sine cosine algorithm (SCA) [9,43,44].

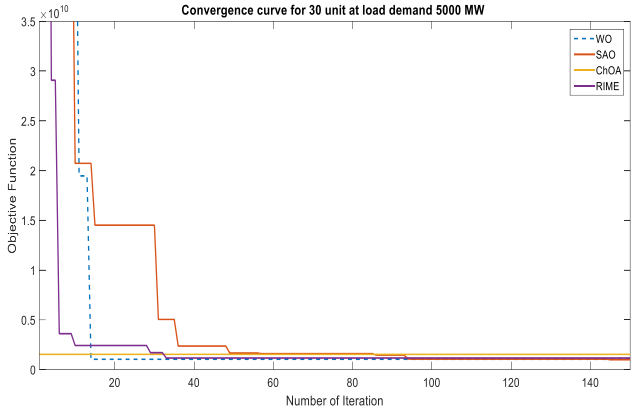

Figure 13. Thirty generators' convergence curves at a 5000 MW load.

Table 19. the power mismatch for all unit generators based on all algorithms.

Case	Technique	700 MW	1000 MW
6 generators	**WO**	**4.1922E−13**	**4.51195E−13**
	SAO	5.03597E−12	4.85414E−10
	ChOA	0.000304799	0.000232386
	MSA	7.850121146	12.80174784
	RIME	0.0000145386	0.000268421
	MBO [44]	8.624894662	10.11850299
	GWO [44]	0.000067	0.0000136
	SCA [43]	0.00076719	0.000182
	EWA [43]	5.71	20.1
	EHO [9]	2.239431602	9.904979361
	SMA [9]	5.61E−9	4.18E−9
20 generators	Technique	3000 MW	
	WO	**9.09495E−13**	
	SAO	0.000356058	
	ChOA	0.00868658	
	MSA	4.47608E−9	
	RIME	0.003891024	
30 generators	Technique	4000 MW	
	WO	**1.15575E−6**	
	SAO	0.000358263	
	ChOA	0.133312071	
	MSA	0.002488716	
	RIME	1.15575E−6	

5. Conclusions

The walrus optimizer (WO), a novel metaheuristic method, mimics how walruses migrate, roost, feed, spawn, gather, and run away in response to crucial cues (safety and danger signals). Moreover, the effectiveness of four distinct algorithms was compared with that of the WO. Economic load dispatch (ELD) is a crucial problem that this work employs the WO to solve. ELD specifically helps to lower the cost of petrol. The fuel cost is the main factor to consider when optimizing the ELD problem. The WO aims to minimize this cost while maximizing the economic value of the power system. The primary variable of ELD issue reflects the unit-specific allocation vector that determines the best outcome for each system. The WO's performance was compared to other algorithms, including the rime-ice algorithm (RIME), moth search algorithm (MSA), snow ablation optimization (SAO), and chimp optimization algorithm (ChOA). Using the WO approach, the ideal power mismatch values of 4.1922E−13 and 4.5119E−13 are found for six generator units at demand loads of 700 MW and 1000 MW, respectively. Using the WO approach, the ideal power mismatch values of 4.5474E−13 and 1.05729E−11 are found for ten generator units at demand loads of 1000 MW and 2000 MW, respectively. Using the WO approach, the ideal power mismatch values of 9.09495E−13 is found for twenty generator units at demand load of 4000 MW. Using the WO approach, the ideal power mismatch values of 1.15575E−6 is found for thirty generator units at demand load of 5000 MW. Ultimately, results verified that the WO was effective in lowering the fuel expenses for every ELD cases when compared to the alternatives. Additional major, practical optimization issues relating to solar energy, ELD of renewable energy sources, and power systems may be resolved in the future using the WO technique.

Use of AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflicts of interest.

References

1. W. K. Hao, Y. P. Li, J. S. Wang, Q. Zhu, Solving economic load dispatch problem of power system based on differential evolution algorithm with different mutation strategies, *IAENG Int. J. Comput. Sci.*, **49** (2022), 156–165.

2. N. Singh, T. Chakrabarti, P. Chakrabarti, M. Margala, A. Gupta, S. P. Praveen, et al., Novel heuristic optimization technique to solve economic load dispatch and economic emission load dispatch problems, *Electronics*, **12** (2023), 2921. https://doi.org/10.3390/electronics12132921
3. G. Abbas, I. A. Khan, N. Ashraf, M. T. Raza, M. Rashad, R. Muzzammel, On employing a constrained nonlinear optimizer to constrained economic dispatch problems, *Sustainability*, **15** (2023), 9924. https://doi.org/10.3390/su15139924
4. D. S. AbdElminaam, E. H. Houssein, M. Said, D. Oliva, A. Nabil, An efficient heap-based optimizer for parameters identification of modified photovoltaic models, *Ain Shams Eng. J.*, **13** (2022), 101728. https://doi.org/10.1016/j.asej.2022.101728
5. A. A. K. Ismaeel, E. H. Houssein, D. Oliva, M. Said, Gradient-based optimizer for parameter extraction in photovoltaic models, *IEEE Access*, **9** (2021), 13403–13416. https://doi.org/10.1109/ACCESS.2021.3052153
6. E. H. Houssein, S. Deb, D. Oliva, H. Rezk, H. Alhumade, M. Said, Performance of gradient-based optimizer on charging station placement problem, *Mathematics*, **9** (2021), 2821. https://doi.org/10.3390/math9212821
7. D. S. Abdelminaam, M. Said, E. H. Houssein, Turbulent flow of water-based optimization using new objective function for parameter extraction of six photovoltaic models, *IEEE Access*, **9** (2021), 35382–35398. https://doi.org/10.1109/ACCESS.2021.3061529
8. M. Said, E. H. Houssein, S. Deb, A. A. Alhussan, R. M. Ghoniem, A novel gradient-based optimizer for solving unit commitment problem, *IEEE Access*, **10** (2022), 18081–18092. https://doi.org/10.1109/ACCESS.2022.3150857
9. A. A. K. Ismaeel, E. H. Houssein, D. S. Khafaga, E. A. Aldakheel, A. S. AbdElrazek, M. Said, Performance of osprey optimization algorithm for solving economic load dispatch problem, *Mathematics*, **11** (2023), 4107. https://doi.org/10.3390/math11194107
10. A. Bhattacharya, P. K. Chattopadhyay, Biogeography-based optimization for different economic load dispatch problems, *IEEE T. Power Syst.*, **25** (2010), 1064–1077. https://doi.org/10.1109/TPWRS.2009.2034525
11. G. L. Andrade, C. Schepke, N. Lucca, J. P. J. Neto, Modified differential evolution algorithm applied to economic load dispatch problems, In: *Computational science and its applications—ICCSA 2023*, 2023. https://doi.org/10.1007/978-3-031-36805-9_2
12. M. Said, E. H. Houssein, S. Deb, R. M. Ghoniem, A. G. Elsayed, Economic load dispatch problem based on search and rescue optimization algorithm, *IEEE Access*, **10** (2022), 47109–47123. https://doi.org/10.1109/ACCESS.2022.3168653
13. M. A. Al-Betar, M. A. Awadallah, S. N. Makhadmeh, I. A. Doush, R. A. Zitar, S. Alshathri, et al., A hybrid Harris Hawks optimizer for economic load dispatch problems, *Alex. Eng. J.*, **64** (2023), 365–389. https://doi.org/10.1016/j.aej.2022.09.010
14. A. Hazra, S. Das, A. Laddha, M. Basu, Economic power generation strategy for wind integrated large power network using heat transfer search algorithm, *J. Inst. Eng. Ser. B*, **101** (2020), 15–21. https://link.springer.com/article/10.1007/s40031-020-00427-y
15. G. Xiong, D. Shi, X. Duan, Multi-strategy ensemble biogeography based optimization for economic dispatch problems. *Appl. Energy*, **111** (2013), 801–811. https://doi.org/10.1016/j.apenergy.2013.04.095

16. M. A. Al-Betar, M. A. Awadallah, R. A. Zitar, K. Assaleh, Economic load dispatch using memetic sine cosine algorithm, *J. Ambient. Intell. Humaniz. Comput.*, **14** (2022), 11685–11713. https://link.springer.com/article/10.1007/s12652-022-03731-1
17. A. S. Alghamdi, Greedy sine-cosine non-hierarchical grey wolf optimizer for solving non-convex economic load dispatch problems, *Energies*, **15** (2022), 3904. https://doi.org/10.3390/en15113904
18. T. P. Van, V. Snasel, T. T. Nguyen, Antlion optimization algorithm for optimal non-smooth economic load dispatch, *Int. J. Elec. Comput. Eng.*, **10** (2020), 1187–1199. http://doi.org/10.11591/ijece.v10i2.pp1187-1199
19. W. T. Elsayed, E. F. El-Saadany, A fully decentralized approach for solving the economic dispatch problem, *IEEE T. Power Syst.*, **30** (2015), 2179–2189. https://doi.org/10.1109/TPWRS.2014.2360369
20. N. Ghorbani, E. Babaei, Exchange market algorithm for economic load dispatch, *Int. J. Elec. Power Energy Syst.*, **75** (2016), 19–27. https://doi.org/10.1016/j.ijepes.2015.08.013
21. F. Mohammadi, H. Abdi, A modified crow search algorithm (MCSA) for solving economic load dispatch problem, *Appl. Soft Comput.*, **71** (2018), 51–65. https://doi.org/10.1016/j.asoc.2018.06.040
22. T. Jayabarathi, T. Raghunathan, B. R. Adarsh, P. N. Suganthan, Economic dispatch using hybrid grey wolf optimizer, *Energy*, **111** (2016), 630–641. https://doi.org/10.1016/j.energy.2016.05.105
23. D. C. Secui, A modified symbiotic organisms search algorithm for large scale economic dispatch problem with valve-point effects, *Energy*, **113** (2016), 366–384. https://doi.org/10.1016/j.energy.2016.07.056
24. A. A. Elsakaan, R. A. El-Sehiemy, S. S. Kaddah, M. I. Elsaid, An enhanced moth-flame optimizer for solving non-smooth economic dispatch problems with emissions, *Energy*, **157** (2018), 1063–1078. https://doi.org/10.1016/j.energy.2018.06.088
25. T. T. Nguyen, D. N. Vo, The application of one rank cuckoo search algorithm for solving economic load dispatch problems, *Appl. Soft Comput.*, **37** (2015), 763–773. https://doi.org/10.1016/j.asoc.2015.09.010
26. P. Zakian, A. Kaveh, Economic dispatch of power systems using an adaptive charged system search algorithm, *Appl. Soft Comput.*, **73** (2018), 607–622. https://doi.org/10.1016/j.asoc.2018.09.008
27. S. H. A. Kaboli, A. K. Alqallaf, Solving non-convex economic load dispatch problem via artificial cooperative search algorithm, *Expert Syst. Appl.*, **128** (2019), 14–27. https://doi.org/10.1016/j.eswa.2019.02.002
28. S. Cui, Y. W, Wang, X. Lin, X. K. Liu, Distributed auction optimization algorithm for the nonconvex economic dispatch problem based on the gossip communication mechanism, *Int. J. Elec. Power Energy Syst.*, **95** (2018), 417–426. https://doi.org/10.1016/j.ijepes.2017.09.012
29. K. Kapelinski, J. P. J. Neto, E. M. dos Santos, Firefly Algorithm with non-homogeneous population: A case study in economic load dispatch problem., *J. Oper. Res. Soc.*, **72** (2021), 519–534. https://doi.org/10.1080/01605682.2019.1700184
30. A. Kaur, L. Singh, J. S. Dhillon, Modified krill herd algorithm for constrained economic load dispatch problem, *Int. J. Ambient Energy*, **43** (2022), 4332–4342. https://doi.org/10.1080/01430750.2021.1888798
31. R. Ramalingam, D. Karunanidy, S. S. Alshamrani, M. Rashid, S. Mathumohan, A. Dumka, Oppositional pigeon-inspired optimizer for solving the non-convex economic load dispatch problem in power systems, *Mathematics*, **10** (2022), 3315. https://doi.org/10.3390/math10183315

32. M. F. Tabassum, M. Saeed, N. A. Chaudhry, J. Ali, M. Farman, S. Akram, Evolutionary simplex adaptive HookeJeeves algorithm for economic load dispatch problem considering valve point loading effects., *Ain Shams Eng. J.*, **12** (2021), 1001–1015. https://doi.org/10.1016/j.asej.2020.04.006
33. S. Banerjee, D. Maity, C. K. Chanda, Teaching learning based optimization for economic load dispatch problem considering valve point loading effect. *Int. J. Elec. Power Energy Syst.*, **73** (2015), 456–464. https://doi.org/10.1016/j.ijepes.2015.05.036
34. H. Shayeghi, A. Ghasemi, A modified artificial bee colony based on chaos theory for solving non-convex emission/economic dispatch., *Energy. Convers. Manag.*, **79** (2014), 344–354. https://doi.org/10.1016/j.enconman.2013.12.028
35. B. K. Panigrahi, V. R. Pandi, Bacterial foraging optimisation: Nelder–Mead hybrid algorithm for economic load dispatch., *IET Gener. Transm. Dis.*, **2** (2008), 556–565. https://doi.org/10.1049/iet-gtd:20070422
36. G. B inetti, A. Davoudi, D. Naso, B. Turchiano, F. L. Lewis, A distributed auction-based algorithm for the nonconvex economic dispatch problem, *IEEE T. Ind. Inform.*, **10** (2014), 1124–1132. https://doi.org/10.1109/TII.2013.2287807
37. S. Deb, E. H. Houssein, M. Said, D. S. Abdelminaam, Performance of turbulent flow of water optimization on economic load dispatch problem, *IEEE Access*, **9** (2021), 77882–77893. https://doi.org/10.1109/ACCESS.2021.3083531
38. **M.** Han, Z. Du, Y. K. Yuan, H. Zhu, Y. Li, Q. Yuan, Walrus optimizer: A novel nature-inspired metaheuristic algorithm., *Expert Syst. Appl.*, **239** (2024), 122413. https://doi.org/10.1016/j.eswa.2023.122413
39. G. G. Wang, Moth search algorithm: A bio-inspired metaheuristic algorithm for global optimization problems, *Memetic Comp.*, **10** (2018), 151–164. https://doi.org/10.1007/s12293-016-0212-3
40. L. Deng, S. Liu, Snow ablation optimization: A novel metaheuristic technique for numerical optimization and engineering design, *Expert Syst. Appl.*, **225** (2023), 120069. https://doi.org/10.1016/j.eswa.2023.120069
41. M. Khishe, M. R. Mosavi, Chimp optimization algorithm, *Expert Syst. Appl.*, **149** (2020), 113338. https://doi.org/10.1016/j.eswa.2020.113338
42. H. Su, D. Zhao, A. A. Heidari, L. Liu, X. Zhang, M. Mafarja, et al., RIME: A physics-based optimization, *Neurocomputing*, **532** (2023), 183–214. https://doi.org/10.1016/j.neucom.2023.02.010
43. M. Said, A. M. El-Rifaie, M. A. Tolba, E. H. Houssein, S. Deb, An efficient chameleon swarm algorithm for economic load dispatch problem, *Mathematics*, **9** (2021), 2770. https://doi.org/10.3390/math9212770
44. A. A. K. Ismaeel, E. H. Houssein, D. S. Khafaga, E. A. Aldakheel, A. S. AbdElrazek, M. Said, Performance of snow ablation optimization for solving optimum allocation of generator units., *IEEE Access*, **12** (2024), 17690–17707. https://doi.org/10.1109/ACCESS.2024.3357489