IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 29 December 2023, accepted 8 January 2024, date of publication 23 January 2024, date of current version 6 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3357489

RESEARCH ARTICLE

Performance of Snow Ablation Optimization for Solving Optimum Allocation of Generator Units

ALAA A. K. ISMAEEL[1,2], (Member, IEEE), ESSAM H. HOUSSEIN[3], (Member, IEEE), DOAA SAMI KHAFAGA[4], EMAN ABDULLAH ALDAKHEE[4], AHMED S. ABDELRAZEK[5], AND MOKHTAR SAID[5]

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

Corresponding author: Doaa Sami Khafaga (dskhafga@pnu.edu.sa)

This work was supported by Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia, through the Princess Nourah bint Abdulrahman University Researchers Supporting Project under Grant (PNURSP2024R409).

ABSTRACT The snow ablation optimization (SAO) is a new metaheuristic motivated by the melting and sublimation properties of snow. In this work, the economic load dispatch (ELD) problem, one of the key components of a power system, is solved using the SAO. There is one kind of ELD, that is focused on minimizing fuel usage costs. Assessing the reliability of the SAO, its performance is compared against some techniques. For the same case study, these techniques include the grey wolf optimization (GWO), the tunicate swarm algorithm (TSA), the monarch butterfly optimization (MBO), and the rime-ice algorithm (RIME). There are six cases used in this work: the first two cases are 6 generators at two loads 700 MW and 1000 MW for the ELD problem. The second two cases are 10 generators at two loads 1000 MW and 2000 MW for the ELD problem. The third two cases are 20 generators at two loads 2000 MW and 3000 MW for the ELD problem. The methods were assessed across 30 different runs using metrics for the maximum, mean, minimum objective function, and standard deviation. The primary component of ELD issues is the power mismatch element. This factor's optimal value must approach zero. The optimal power mismatch values of 3.336E-13 and 1.57E-10 are obtained using the SAO method for six generator units at demand loads of 1000 MW and 700 MW, respectively. The optimal power mismatch values of 6.83E-6 and 1.65E-7 are obtained by the SAO method for ten generator units at demand loads of 1000 and 2000 MW, respectively. The optimal power mismatch values of 1.82E-4 and 7.91E-5 are obtained using the SAO method for 20 generator units at demand loads of 2000 and 3000 MW, respectively. The results produced for the six ELD case studies show that the SAO surpasses all competing algorithms, proving its superiority.

INDEX TERMS Snow ablation optimization, economic load dispatch.

I. INTRODUCTION

The goal of economic load dispatch (ELD) in power systems is to allocate power output from producing units as efficiently as possible while satisfying operational requirements, preserving supply-demand balance [1], and determining the best way to lower the power generation cost and minimize emissions so that the problem of global warming is also reduced. Coal is few, while demand for electrical power is rising [2]. It is significant to observe that the valve-point effects provide a wavy pattern on the fuel consumption curve. As a result, the economic load dispatch problem is a massive, very nonlinear,

The associate editor coordinating the review of this manuscript and approving it for publication was Amin Mahmoudi.

and restricted optimization problem. The unit output schedule can be optimized to achieve significant cost savings. The best output power from each producing unit must be reached to lower overall fuel expenditures, as fuel prices are rising every day. This may be done by using mathematical and metaheuristic optimization approaches [3], [4], [5], [6], [7], [8], [9].

The actual and reactive power of the electrical generating system was determined using the linear programming methodology; however, such techniques have a significant computation time and are occasionally unable to produce a global solution for enormous data sets. To increase the effectiveness of addressing the ELD issue, several optimization techniques have been developed for this application or another problem [10], [11], [12], [13]. The effects of valve loading were taken into account, and the outline search technique was offered as a means to identify the optimum ELD problem solution. To support the results, a variety of test data were used to assess the approach, and it was compared to current optimization methods [14]. Using a biogeography-based optimization (BBO) technique, four separate ELD test systems, both large and small, with varying levels of complexity, were subjected to this method [15]. By applying the modified differential evolution technique to solve several test cases of the ELD were discovered [16]. The search and rescue optimization technique (SAR) was employed by the authors to ascertain the optimal approach for the ELD. The research results indicated that the SAR was the optimum option for all cases of ELD [17].

The Harris Hawks optimizer technique was used in six generation units to address ELD issues [18], while with the incorporation of wind energy, the challenging ELD problem was described using the heat transfer search algorithm [19]. The authors proposed a multi-strategy ensemble BBO (MSEBBO) to solve ELD issues. The MEEBBO uses the no-free lunch theorem to strengthen the three components of BBO. A strong repair technique is also recommended to meet the different ELD issue restrictions [20]. A memetic sine-cosine method was used to solve the ELD issue for six practical cases: 40, 15, 13, 6, and 3 units of generator [21], while the authors suggested the greedy sine-cosine nonhierarchical gray wolf optimizer (G-SCNHGWO) as a solution to ELD issues. These four power systems have a total of 140, 40, 15, and 10 power generators, each with a different valuation time [22]. Using the ant lion optimization algorithm (ALO), issues with the ideal ELD were resolved. The ALO algorithm offers better possibilities than other strategies for the problem, convergence velocity, and stability, according to the findings of applying it to all three scenarios [23]. A fully decentralized approach (DA) technique may be used to solve the ED problem extremely effectively while accurately accounting for transmission losses in a fully decentralized manner. Three case studies were looked at [24].

The exchange market algorithm (EMA) is a reliable and efficient method for identifying the optimal option for global optimization in ELD scenarios. Additionally, it was developed using four test systems in four different dimensions-3, 6, 15, and 40 units-with both convex and non-convex cost functions [25]. The modified crow search algorithm (MCSA) was used to resolve the non-convex ELD issue and apply the results to five well-known test systems [26], while four economic dispatch issues with generator counts of 6, 15, 40, and 80 were examined using the hybrid grey wolf optimizer (HGWO) [27]. To assess the performance of the modified symbiotic organisms, search algorithm (MSOS), five systems 13-unit, 40-unit, 80-unit, 160-unit, and 320-unit systems—with varying features, limitations, and dimensions were employed [28]. the enhanced moth-flame optimizer (EMFO) approach was used to address the non-convex ELD issue with valve-point effects and emissions on three representative test systems with 6, 40, and a large-scale 80 generating units that had non-convex fuel cost functions [29].

The one-rank cuckoo search algorithm (ORCSA) approach was successful in resolving ELD difficulties. Complete testing on some systems with different constraints and thermal unit characteristics was also provided [30]. As benchmarks for small- and large-scale problems, a range of economic dispatch instances made up of 6, 13, 15, 40, 160, and 640-unit generating systems were examined using the adaptive charged system search (ACSS) approach [31]. The complex ELD issue was presented using the artificial cooperative search algorithm (ACS), which is based on a co-evolutionary technique [32]. the efficient distributed auction optimization algorithm (DAOA)was used to determine the ELD problem's best solution [33]. A new firefly algorithm (FA) via a non-homogeneous population provided a solution to the ELD issues. Using 10 benchmark functions, a 15-unit ELD issue with several considerations for each generator was solved, as well as a 13-unit non-convex system with a valve-point loading impact [34].

The authors used the modified krill herd algorithm (MKH) to resolve an ELD problem. The MKH was found to perform pretty well compared to other metaheuristics, and changing its settings was also not too difficult [35]. the oppositional pigeon-inspired optimizer (OPIO) algorithm was used to find a solution to the ELD problem for small test systems (13 units, 40 units), medium (140 units, 160 units), and big (320 units, 640 units) [36]. The performance of the evolutionary simplex adaptive Hooke–Jeeves algorithm (ESAHJ) was assessed on five valve-point affected generating systems. The test results for the proposed technique demonstrated good convergence characteristics and cheap generating costs, making them very effective and enticing [37]. The teaching learning-based optimization (TLBO) approach was used to handle ELD issues while taking transmission losses into account. This approach investigates the global optimum point's solution space [38]. For non-convex CEED issues, the conventional IEEE 30 bus with its six generators, fourteen generators, and forty heat-generating units was put to the test [39]. The Nelder-Mead hybrid method can easily handle non-convex ED problems with a variety of limitations. Many conventional test systems with different numbers of generating units were simulated [40]. The distributed auction-based technique was used to address the non-convex ELD issue, which has a lot of restrictions including the valve-point loading impact, a wide range of fuel options, and constrained operating zones [41]. The authors developed a turbulent flow of water optimization (TFWO) approach to address the ELD and CEED problems [42]. The SAO is based on the melting and sublimation properties of snow. Snow's sublimation and melting characteristics served as the model for the SAO. The SAO algorithm's dual-population mechanism, exploration stage, exploitation stage, and initialization stage will all be covered in the analysis of the SAO method [43].

The main items of objectives and contributions in this work are illustrated as follows:

- The ELD issue is discussed for three network studies based on the number of generator units such as 6 units, 10 units, and 20 units.
- A new metaheuristic method called snow ablation optimization (SAO) is performed to solve the case study of ELD.
- The proposed SAO algorithm is evaluated with the grey wolf optimization (GWO), the tunicate swarm algorithm (TSA), the monarch butterfly optimization (MBO), and the rime-ice algorithm (RIME) for the cases study of 6 units, 10 units, and 20 units.
- The evaluation of all techniques is implemented for 30 runs based on computing the convergence and robustness curves.
- The minimum, standard deviation, maximum, and mean fitness function values over 30 runs are used for the statistical data of all employed algorithms.
- The evaluation of SAO and all methods are realized according to the mismatch of power between the unit's power generated and the load demand.
- The suggested SOA algorithm is also compared to other literature techniques including the sine cosine algorithm, elephant herding optimization, Artificial Bee Colony, slime mold algorithm, Earth Worm Algorithm, and Chimp Optimization Algorithm

The manuscript is ordered as follows: the analysis of the ELD problem is considered in section two. The SAO method is clarified in section three. The results discussion is offered in section four. The future work and conclusions are described in section five.

II. ANALYSIS OF THE ELD PROBLEM

ELD is one of the issues with how power systems operate. Reducing fuel consumption costs is the main obstacle to resolving the ELD issue and optimizing the financial benefit for power plants. In the ELD problem, the main variable defines the resource distribution vector that maximizes power output per unit. An explanation of ELD analysis with losses is given below.

The following descriptions can be applied to the ELD mathematical equations with losses. The cost of fuel usage for running n generators will be determined as follows:

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

where F represents the net fuel cost, F_n is the fuel cost in the nth generator, and F_1 the fuel cost in the first generator. The gasoline cost function will be obtained in quadratic form using the following methods:

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

where a, b, and c are the weight constants of the fuel cost. Furthermore, the generator limitations for every unit can be adjusted from zero to 500 MW by utilizing Equations (3) and (5).

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

where P_D stands for the network's total demand and P_L for the network's six transmission losses, which are computed as follows:

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

where P_i denotes the power generated at the ith generator, P_j is the power generated at the jth generator, and B_{ij} stands for the loss factor.

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

III. SNOW ABLATION OPTIMIZATION (SAO)

This section provides the idea behind SAO [43], which is based on the melting and sublimation properties of snow. Following that, this algorithm's mathematical model is shown. In conclusion, we present the SAO pseudo-code and examine its temporal complexity: snow's sublimation and melting characteristics served as the model for the SAO. The SAO algorithm's dual-population mechanism, exploration stage, exploitation stage, and initialization stage will all be covered in the sections that follow [43].

A. INITIALIZATION STAGE

The iteration process in SAO begins with a swarm that is generated at random. The entire swarm is typically represented as a matrix with Dim columns and N rows, where N is the size of the swarm and Dim is the number of dimensions in the solution space, as shown in Equation (6).

$$Z = L + \theta \times (U - L) = \begin{bmatrix} z_{1,1} & z_{1,2} & \cdots & z_{1,Dim-1} & z_{1,Dim} \\ z_{2,1} & z_{2,2} & \cdots & z_{2,Dim-1} & z_{2,Dim} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ z_{N-1,1} & z_{N-1,2} & \cdots & z_{N-1,Dim-1} & z_{N-1,Dim} \\ z_{N,1} & z_{N,2} & \cdots & z_{N,Dim-1} & z_{N,Dim} \end{bmatrix}_{N\times Dim} \tag{6}$$

L and U denote the solution space's lower and upper bounds, respectively, among them. A randomly generated number in [0, 1] is represented by θ.

B. EXPLORATION STAGE

This section provides a detailed description of SAO's exploration approach. Because of the erratic movement, the search agents exhibit a high-decentralized feature when the snow or the liquid water that was once snow turns into steam. Brownian motion is used in this work to model this scenario. Brownian motion is a stochastic process that is widely used to simulate various phenomena such as animal foraging behavior [44], infinitesimal and erratic particle movement [45], etc. For a typical Brownian motion, the step size is determined by the probability density function based on the normal distribution with mean zero and variance one. The following is the corresponding mathematical representation [44]:

$$f_{BM}(x; 0, 1) = \frac{1}{\sqrt{2\pi}} \times exp\left(-\frac{x^2}{2}\right) \tag{7}$$

The following is the formula to determine positions throughout the exploration process:

$$Z_i(t+1) = Elite\,(t) + BM_i(t) \otimes (\theta_1 \times (G(t) - Z_i(t)) + (1-\theta_1) \times (\bar{Z}(t) - Z_i(t))) \tag{8}$$

Among them, the symbol $\otimes$ indicates entry-wise multiplications, θ_1 indicates a number randomly selected from [[0, 1], $Z_i(t)$ identifies the i^{th} individual during the t^{th} iteration, and $BM_i(t)$ indicates a vector including random values based on Gaussian distribution signifying the Brownian motion. Additionally, $\bar{Z}(t)$ indicates the centroid position of the entire swarm, Elite (t) is a randomly chosen member of a group of many elites in the swarm, and $G(t)$ refers to the current best solution. The following lists the associated mathematical expressions [43]:

$$\bar{Z}(t) = \frac{1}{N}\sum_{i=1}^{N} Z_i(t) \tag{9}$$

$$Elite(t) \in [G(t), Z_{second}(t), Z_{third}(t), Z_c(t)] \tag{10}$$

where $Z_{\text{third}}\,(t)$ and $Z_{\text{second}}\,(t)$ denote, respectively, the third and second-best individuals in the current population. The centroid position of those whose fitness values fell inside the top 50% is indicated by $Z_c(t)$. For the sake of simplicity, the leaders in this study are those whose fitness levels fell within the top 50%. Furthermore, $Z_c(t)$ is computed using the mathematical formula found in Equation (11).

$$Z_c(t) = \frac{1}{N_1}\sum_{i=1}^{N_1} Z_i(t) \tag{11}$$

where $Z_i(t)$ denotes the i^{th} best leader and N_1 denotes the number of leaders, or half the size of the entire swarm. As a result, the Elite (t) is chosen at random from a set that includes the centroid location of leaders, the current best solution, the second-best individual, and the third-best individual during each iteration.

C. EXPLOITATION STAGE

This section introduces the exploitative nature of SAO. When the snow melts and becomes liquid water, search agents are urged to take use of high-quality solutions surrounding the current best solution, rather than growing with a highly decentralized feature in the solution area. The degree-day technique [46] is one of the most often used models of snowmelt and is used to depict the melting process. The following is how this strategy is generally presented:

$$M = DDF \times (T - T_1) \tag{12}$$

M stands for the snowmelt rate among them, that is an important parameter to mimic the melting behavior during the exploitation phase. T is the daily average temperature, according to [46] T_1 denotes the basal temperature, which is often set to 0. This leads to:

$$M = DDF \times T \tag{13}$$

where DDF, which varies from 0.35 to 0.6, represents the degree-day factor [47]. The following is the mathematical expression that updates the DDF value in each iteration:

$$DDF = 0.35 + 0.25 \times \frac{e^{\frac{t}{t_{\max}}} - 1}{e - 1} \tag{14}$$

where the termination condition is denoted by $t_{\max}$. The melting rate in SAO is then computed using the subsequent formula:

$$M = \left(0.35 + 0.25 \times \frac{e^{\frac{t}{t_{max}}} - 1}{e - 1}\right) \times T(t),\, T(t) = e^{\frac{-t}{t_{max}}} \tag{15}$$

Next, the position updating equation is shown as follows during the SAO exploitation stage:

$$Z_i(t+1) = M \times G(t) + BM_i(t) \otimes (\theta_2 \times (G(t) - Z_i(t)) + (1-\theta_2) \times (\bar{Z}_i(t) - Z_i(t))) \tag{16}$$

where θ_2 denotes the random integer selected from [−1, 1]., and M is the snowmelt rate. This characteristic makes it easier for people to communicate with one another. During this phase, individuals are more likely to take advantage of promising regions thanks to the cross terms $-\theta_2 \times (G(t) - Z_i(t))$ and $(1-\theta_2) \times (\bar{Z}(t) - Z_i(t))$, which are dependent on the centroid position of the swarm and the current best search agent.

D. DUAL POPULATION MECHANISM

Understanding that there is a trade-off between exploration and exploitation is crucial when using metaheuristic algorithms. As stated in Section III-A, the exploration process can also be carried out by turning some of the liquid water that was formed from the snow into steam. That is, as time goes on, there is a greater chance that people will exhibit erratic movements with a high degree of decentralization. After that, the algorithm starts to progressively explore the

TABLE 1. Techniques parameters situating.

Algorithms	Parameter Setting
General setting	Iterations number = 1000 Size of population = 30
SAO	A number generated at random in [0,1] is represented by $\theta 1$. The random number selected from [−1,1] is indicated by $\theta 2$. The base temperature, or $T1$, is typically set to 0.
RIME	r_3 *and* r_1 *with in* $(-1$ *and* $1)$ r_2 *with in* $(0$ *and* $1)$
MBO	peri indicates the migration period and is set to 1.2 p is set to 5/12
GWO	a decrease linearly from 2 to 0
TSA	P_{min} *and* P_{max} *equal* 1 *and* 4 *respectively*

TABLE 2. Statistical data for 6 generators based on all techniques ($/h).

Load (MW)	Method	Minimum	SD	Mean	Maximum
700	SAO	**8382.727669**	206.1561217	8727.147026	9021.198839
	RIME	**50754.47178**	63861730.36	45116935.91	238818316.5
	MBO	**8674.446349**	33928.26209	40033.77354	120579.4628
	TSA	**219863.0447**	12544977.14	12030685.27	45849466.82
	GWO	**8622.319269**	11427750.13	10171247.74	48628295.93
1000	SAO	**12136.07434**	107.9008060	12332.42292	12591.74905
	RIME	**49234.87133**	45494471.37	36546372.51	145220781.5
	MBO	**13487.29747**	952363656.6	173938783.8	5216372332
	TSA	**513017.4415**	25787851.34	23876720.91	100550789.9
	GWO	**148048.4999**	12648583.39	11320795.73	39692087.16

TABLE 3. Fuel consumption optimum costs for 6 generators ($/h).

Algorithm	700 MW	1000 MW
SAO	**8381.566642**	**12136.06674**
RIME	**8584.553322**	**12366.11251**
MBO	**9867.999120**	**13610.58675**
TSA	**8564.395710**	**12352.53542**
GWO	**8642.455914**	**12152.88082**

TABLE 4. The optimal allocation power (MW) from 6 generators at 700 MW demand.

SAO	RIME	MBO	TSA	GWO
283.9706564	188.5609427	63.39673076	274.5143750	228.4890274
91.51507435	62.69305005	67	55.66328378	187.8982842
148.5370566	188.6938083	76	108.2715919	83.01780354
55.40151926	90.14606030	84	82.13205507	59.76621669
77.11685416	119.3436240	89	71.46526845	79.55895424
54.72064672	63.73841438	331.3759462	120	73.30278090

solution space. The dual-population mechanism in our work is designed to account for this circumstance and sustain both exploration and exploitation. In the initial stage of the iteration, the entire population is randomly split into two equal-sized subpopulations, as shown in Algorithm 1. We refer to these two subpopulations as P_a, and P_b, respectively, and the whole population as P. Furthermore, P, P_a, and P_b sizes are represented by N, N_a, and N_b, respectively. Of them, P_a is dependable to the exploration while P_b is dependable to the exploitation. The size of P_a increases

TABLE 5. The optimal allocation power (MW) from 6 generators at 1000 MW demand.

SAO	RIME	MBO	TSA	GWO
411.6378804	421.1289227	73	500	386.5595810
149.9604020	136.8855647	120	190.2175803	167.3580317
189.3951100	80.00408067	150	94.11613766	172.9999006
65.56040239	131.1884710	159	73.19660117	101.1928302
138.04100120	179.8868556	200	111.8730319	138.5084774
68.77892844	75.33657988	322.5836124	52.34908180	56.99831529

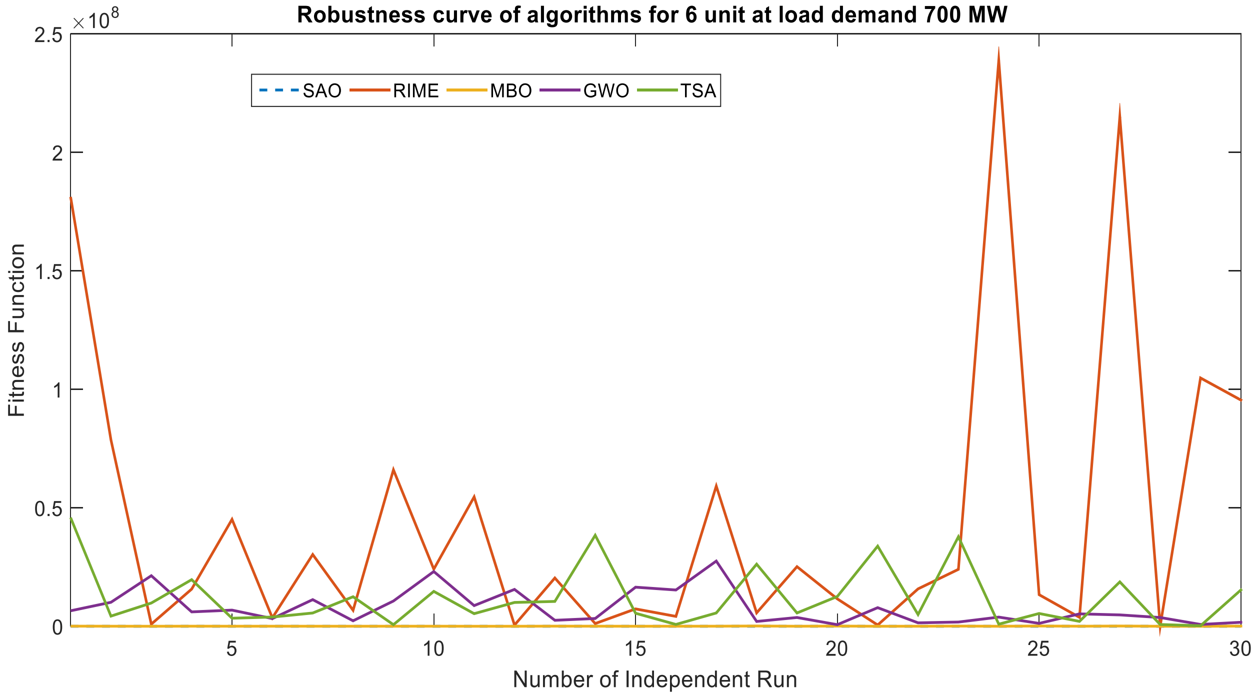

FIGURE 1. Robustness curves of 6 generators at load 700 MW.

TABLE 6. Statistical data for 10 generators based on all techniques ($/h).

Load (MW)	Method	Minimum	SD	Mean	Maximum
1000	SAO	**91476538.31**	58434347.61	141856741.8	299607764.5
	RIME	**102814042.9**	73152719.81	170877907.2	419309767.9
	TSA	**96372268.63**	35949849.45	138366640.8	243144533.6
	GWO	**103412018.6**	23744665.78	135068736.8	193230140.2
2000	SAO	**477169048.2**	35357978.80	572604477.6	623604982.6
	RIME	**498709381.5**	78297821.92	619049388.7	801965397.7
	TSA	**495956050.1**	43768776.45	610577122.9	686002804.2
	GWO	**521673866.1**	33901845.49	588719837.6	649327385.2

with the progressive decrease in P_b size in the following iterations.

In conclusion, the following illustrates the SAO algorithm's whole position updating equation:

$$Z_i(t+1) = \begin{cases} \text{Elite}\,(t) + BM_i(t) \otimes (\theta_1 \times (G(t) - Z_i(t)) \\ +(1-\theta_1) \times \left(\bar{Z}(t) - Z_i(t)\right)\right), & i \in \text{index}_a \\ M \times G(t) + BM_i(t) \otimes (\theta_2 \times (G(t) - Z_i(t)) \\ +(1-\theta_2) \times \left(\bar{Z}(t) - Z_i(t)\right)\right), & i \in \text{index}_b \end{cases} \quad (17)$$

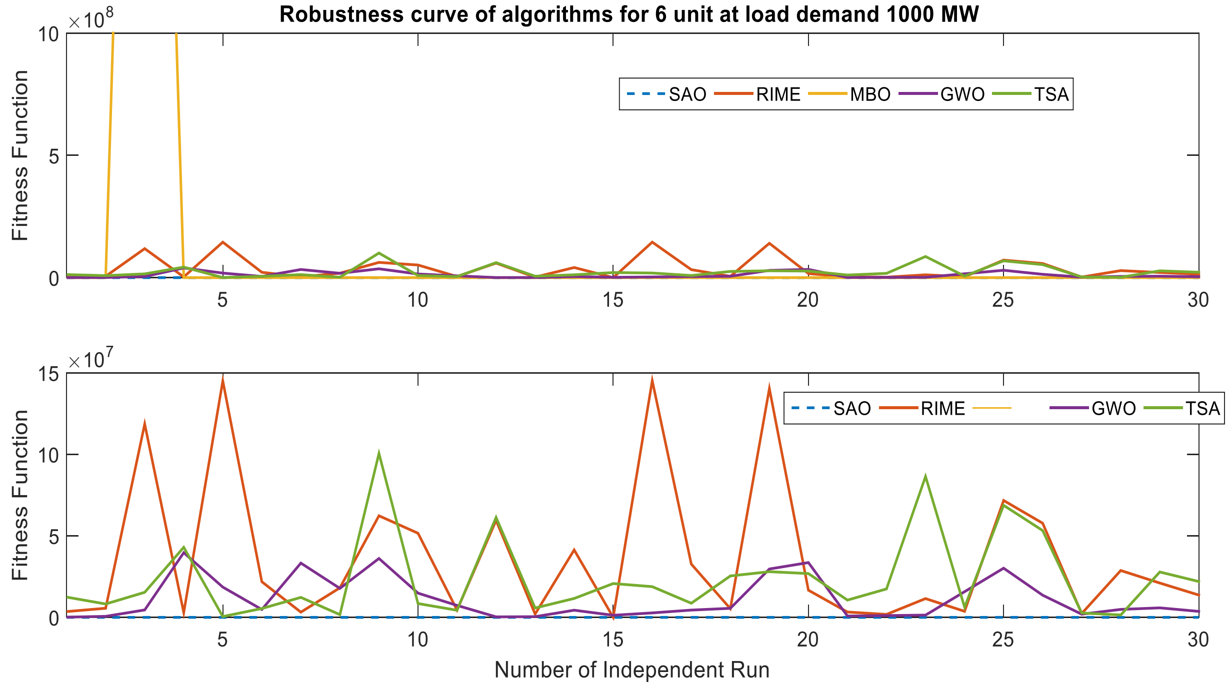

FIGURE 2. Robustness curves of 6 generators at load 1000 MW.

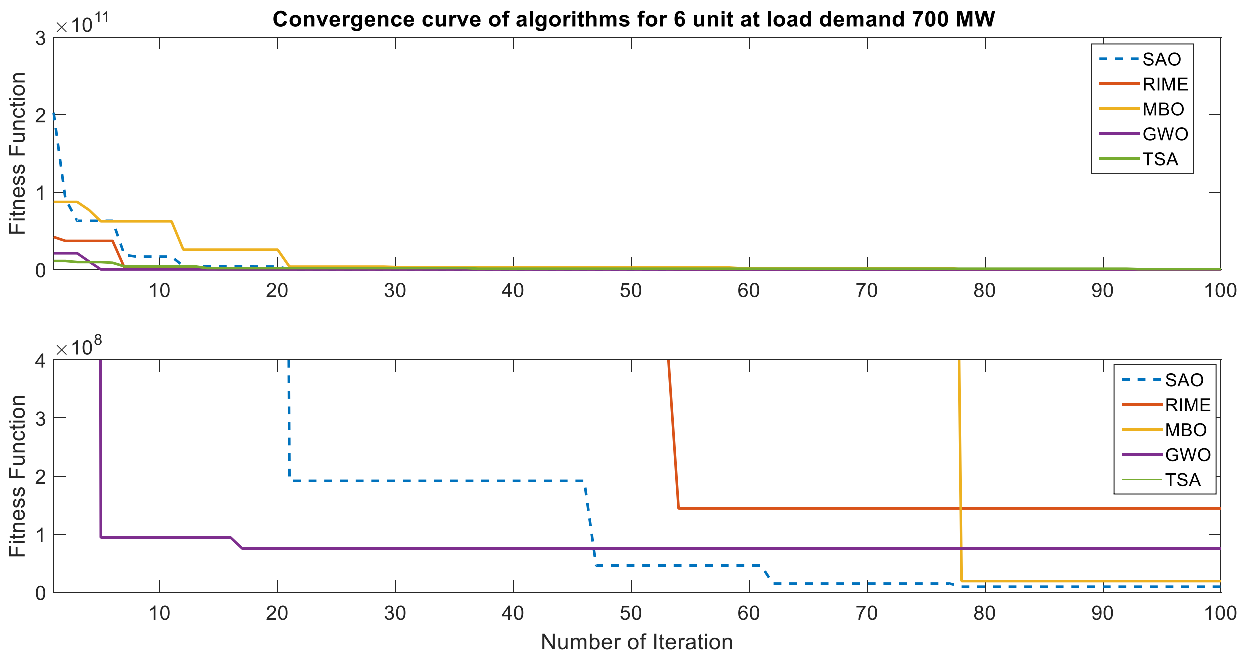

FIGURE 3. Convergence curves of 6 generators at load 700 MW.

In actuality, the entire population is a position matrix, as stated in Equation (6). For this reason, in Equation (17), $index_a$ and $index_b$, respectively, indicate a set of indexes that include the line numbers of the persons in P_a and P_a over the whole position matrix. Algorithm 2 encapsulates the SAO algorithm's whole process.

IV. RESULTS OF NUMERICAL ANALYSIS

The SAO performance is tested for the ELD. The proposed SAO technique was evaluated with the grey wolf optimization (GWO) [48], the tunicate swarm algorithm (TSA) [49], the monarch butterfly optimization (MBO) [50], and the rime-ice algorithm (RIME) [10] using MATLAB 2015Ra established

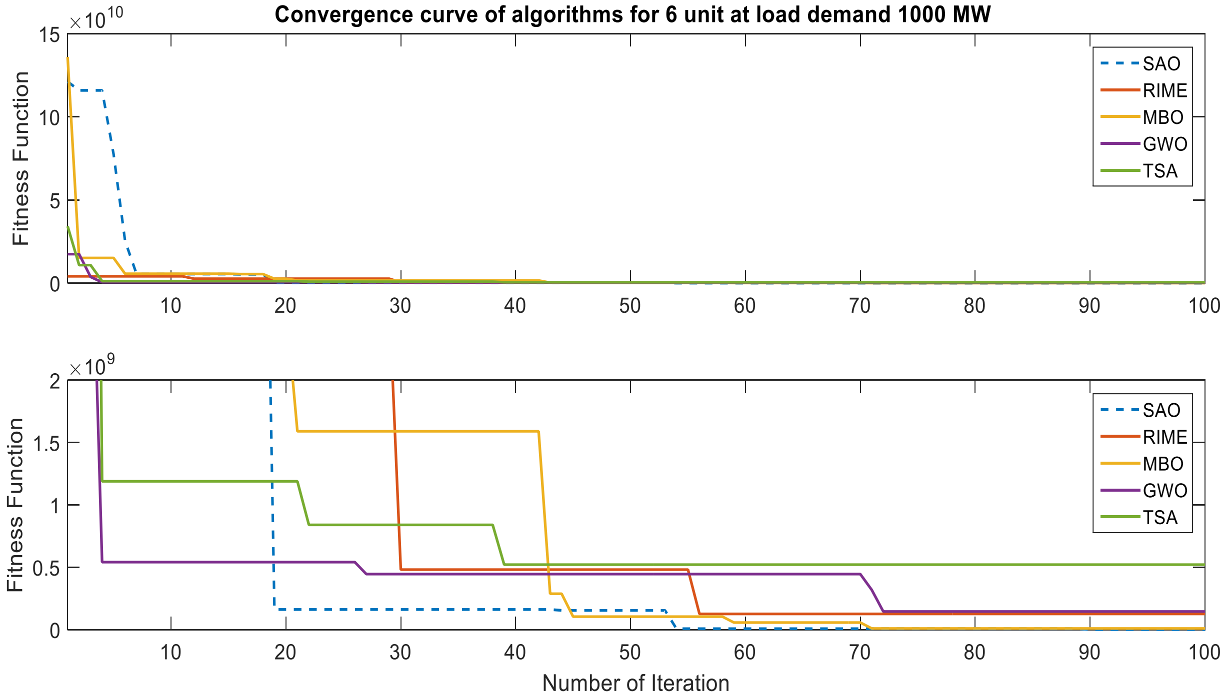

FIGURE 4. Convergence curves of 6 generators at load 1000 MW.

TABLE 7. Fuel consumption optimum costs for 10 generators ($/h).

Algorithm	1000 MW	2000 MW
SAO	**91408138.73**	**477167397.4**
RIME	**95774255.60**	**495979709.5**
TSA	**95323180.17**	**493139938.1**
GWO	**99997353.4**	**506204174.8**

TABLE 8. The optimal allocation power (MW) from 10 generators at 1000 MW demand.

SAO	RIME	TSA	GWO
150.1248562	160.7928639	150	174.4586993
135.0794828	135	150.2416518	144.6575843
160.8922306	109.9704204	153.5644468	125.5607168
145.0204447	108.4324292	120.4851057	109.6776448
106.4223734	219.7927205	73	96.34011645
59.17198045	57	128.3733879	157.9323651
110.2250583	20	64.03199783	114.7999461
96.52976737	92.87012217	107.3681686	50.40706448
20.01487386	52.92807737	35.37319066	20
25.48445124	54.11982570	26.88315974	17.62904106

on intel core i7 (2.1 GHz) and 8 GB of ram. The ELD problem was applied to several case studies as follows:

- The first case study is 6 generators at two different loads (1000 and 700 MW).
- The second case study is 10 generators at two different loads (1000 and 2000 MW).
- The third case study is 20 generators at two different loads (2000 and 3000 MW).

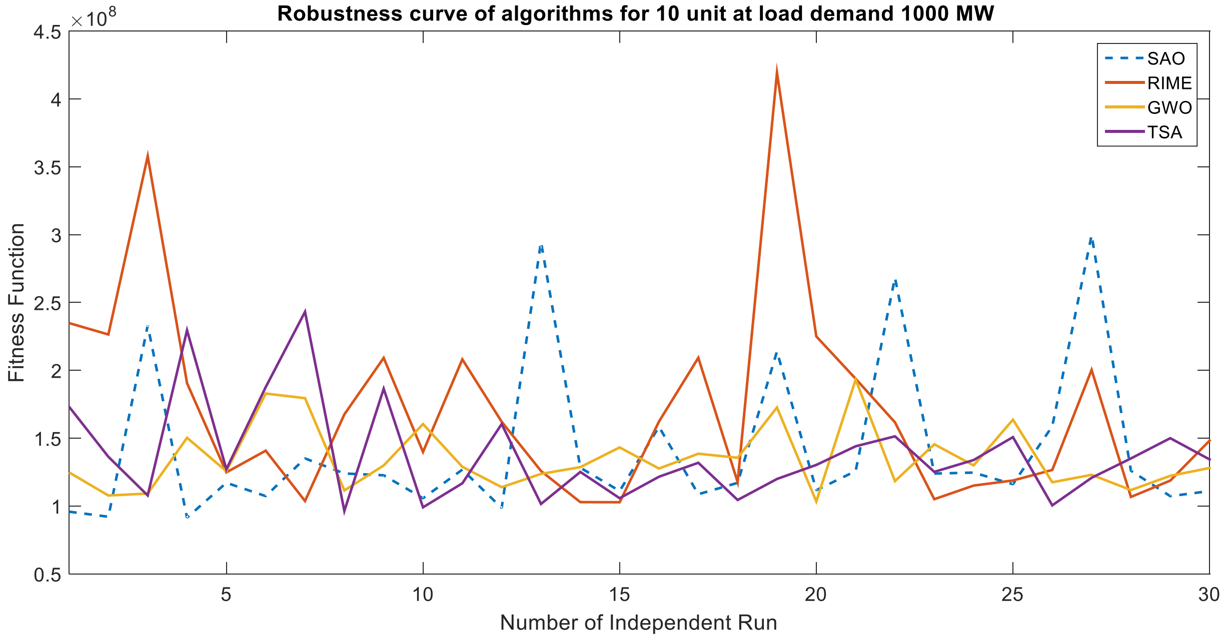

FIGURE 5. Robustness curves of 10 generators at load 1000 MW.

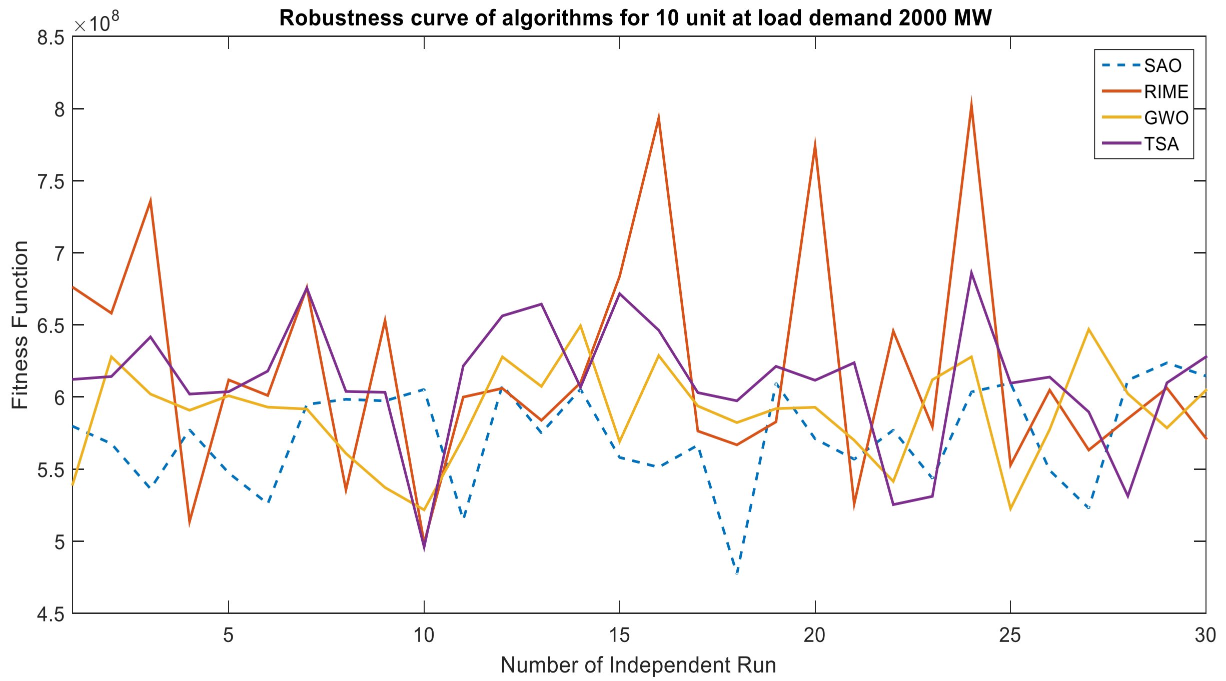

FIGURE 6. Robustness curves of 10 generators at load 2000 MW.

The common parameters for all algorithms are clarified in Table 1.

A. RESULTS OF 6-UNIT GENERATORS

Case research of 6 generators at two loads is applied in testing the ELD issue. Numerous methods were pertained, such as the SAO, TSA, GWO, MBO, and RIME. The effectiveness of every rival approach was evaluated using thirty separate runs. As can be seen in Table 2, these runs were used to record the mean, maximum, minimum, and standard deviation values as statistical data at each load level. The SAO obtains the best objective function and standard deviation based on this data. Thus, the SAO algorithm is the most precise and dependable one for ELD. The optimal fuel cost for each scenario is shown in Table 3. Table 4 shows the optimal power generated by each unit for a load demand of 700 MW, created on the

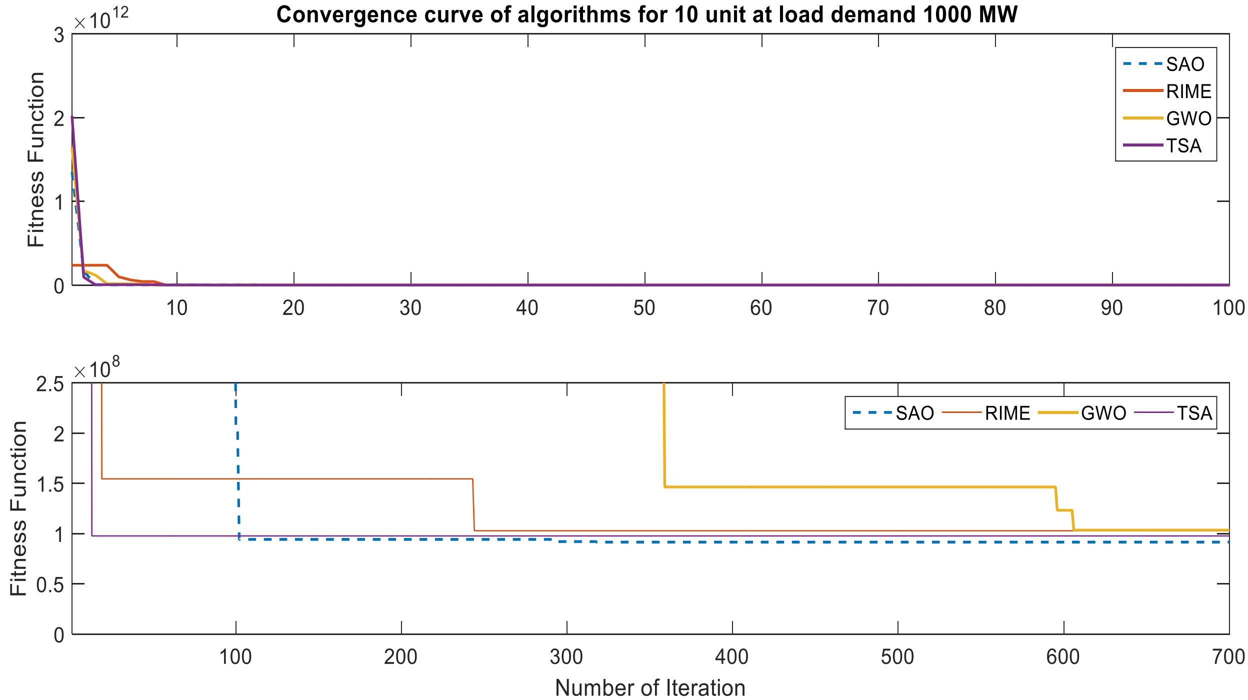

FIGURE 7. Convergence curves of 10 generators at load 1000 MW.

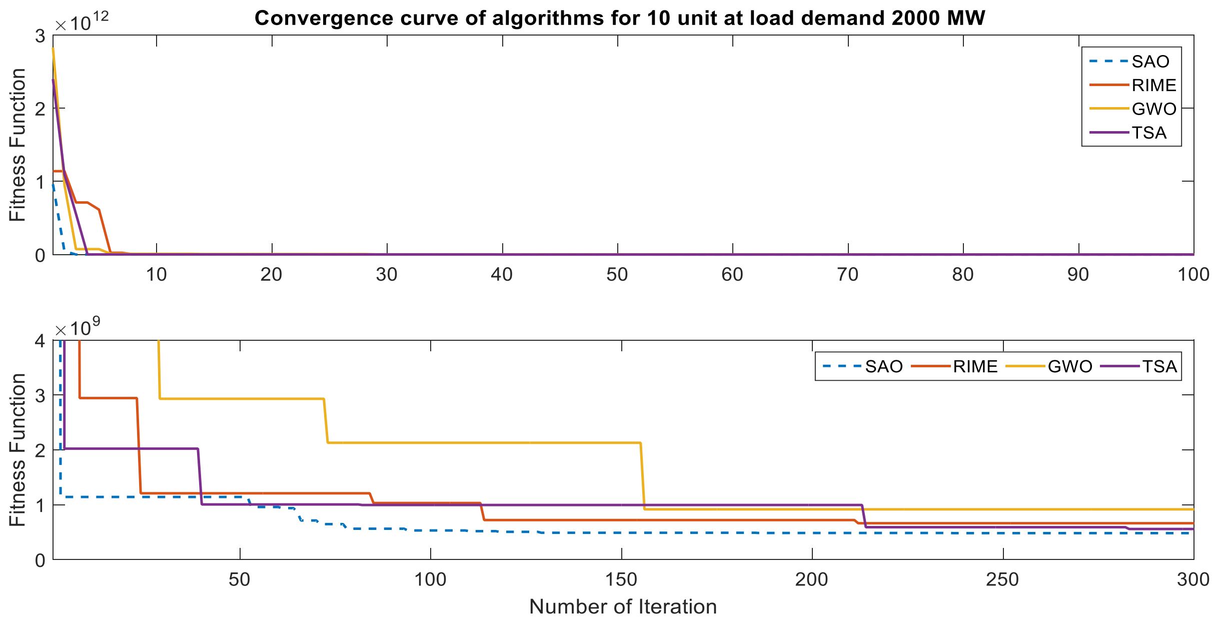

FIGURE 8. Convergence curves of 10 generators at load 2000 MW.

best objective function across all methods. Table 5 shows the optimal power generated by each unit for a load demand of 1000 MW, created on the best objective function across all methods. Based on the recorded outcomes from all techniques throughout the 30 runs, the robustness curve identifies the value of the target function for each run. Figures 1–2 show the properties of the robustness curve for each load for the 6 units' system. Figure 2 contains 2 subgraphs; the low graph is a magnified of the high figure to explain the intersection between plotting. Based on the recorded results from every method among the top 30 runs that yield the best fitness function, the convergence curve describes the quickest method that achieves the objective function. Figures 3–4 display the features of the convergence curve for each load level for the 6 units' system. Figures 3 and 4 contain 2 subgraphs; the low graph is a magnified of the high figure to explain

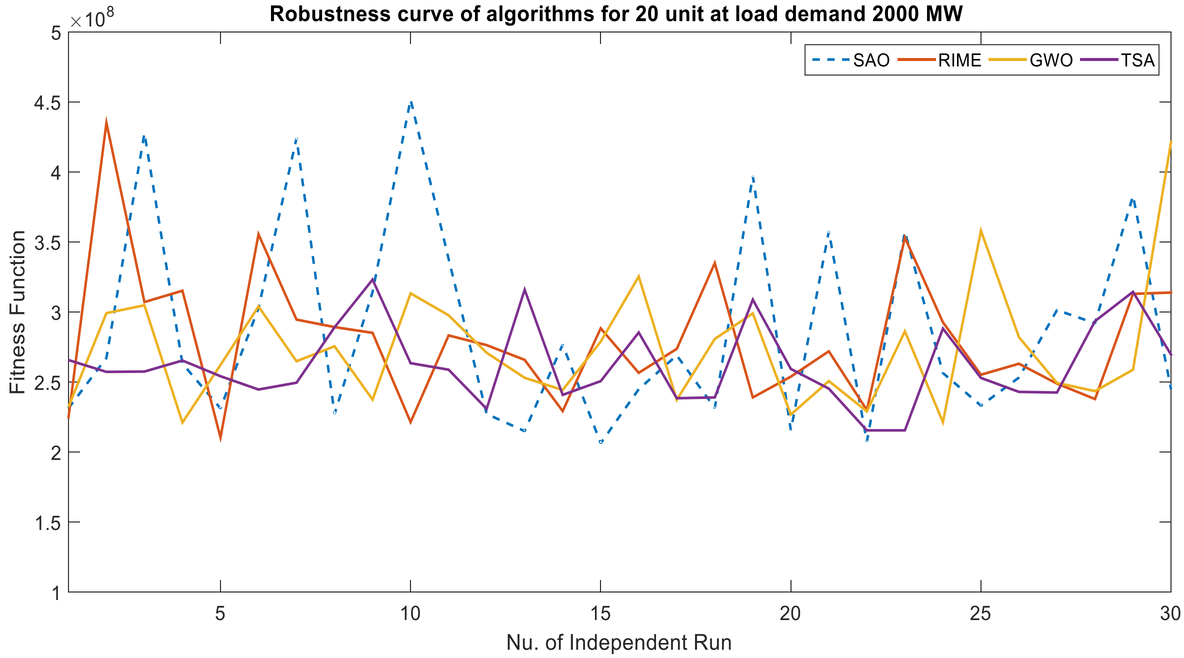

FIGURE 9. Robustness curves of 20 generators at load 2000 MW.

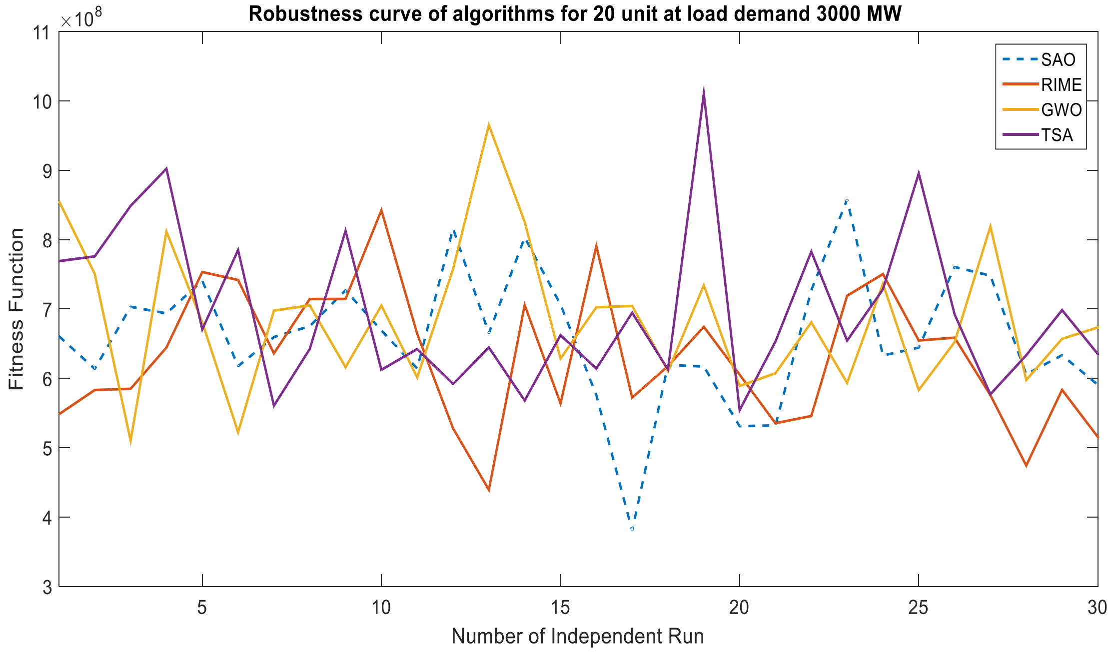

FIGURE 10. Robustness curves of 20 generators at load 3000 MW.

the intersection between plotting. The SAO realizes the best global solution based on the convergence and robustness properties.

B. RESULTS OF 10-UNIT GENERATORS

Case research of 10 generators at two loads is used in the testing of the ELD issue. Numerous methods were pertained, such as the SAO, TSA, GWO, MBO, and RIME. The effectiveness of every rival approach was evaluated using thirty separate runs. As can be seen in Table 6, these runs were used to record the mean, maximum, minimum, and standard deviation values as statistical data at each load level. The SAO obtains the best objective function and standard deviation based on this data. Thus, the SAO algorithm is the most precise and dependable one for ELD. The optimal fuel cost for each scenario is shown in Table 7. Table 8 shows the optimal

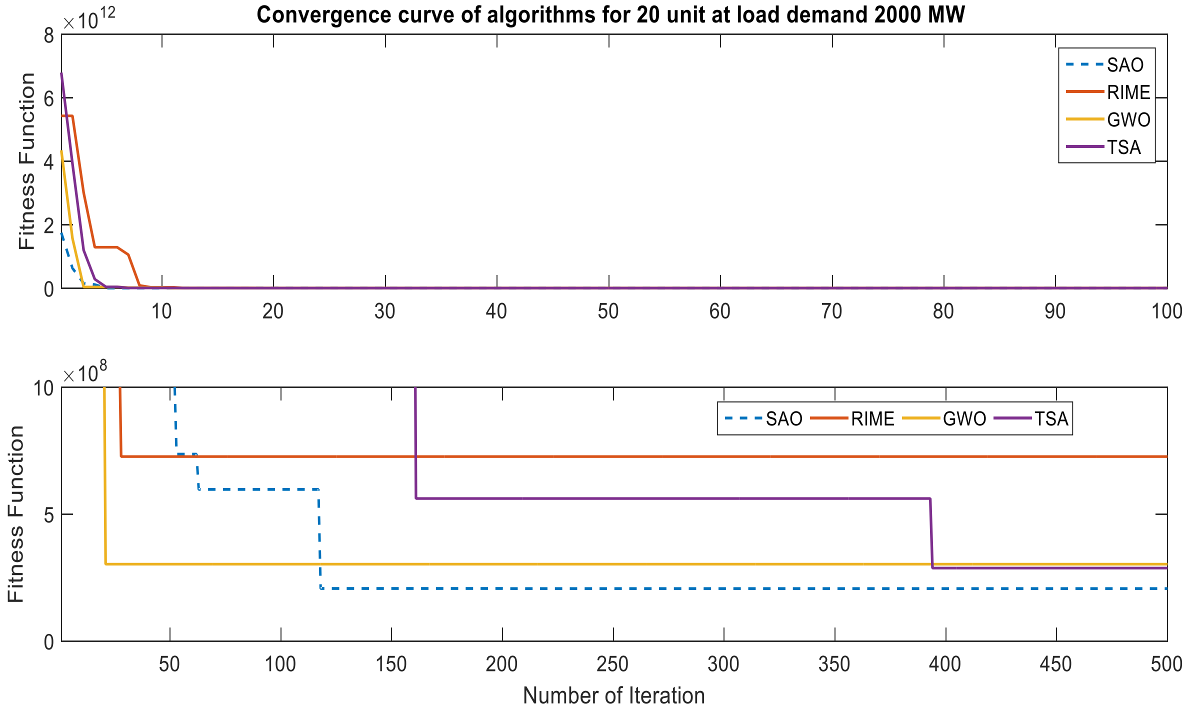

FIGURE 11. Convergence curves of 20 generators at load 2000 MW.

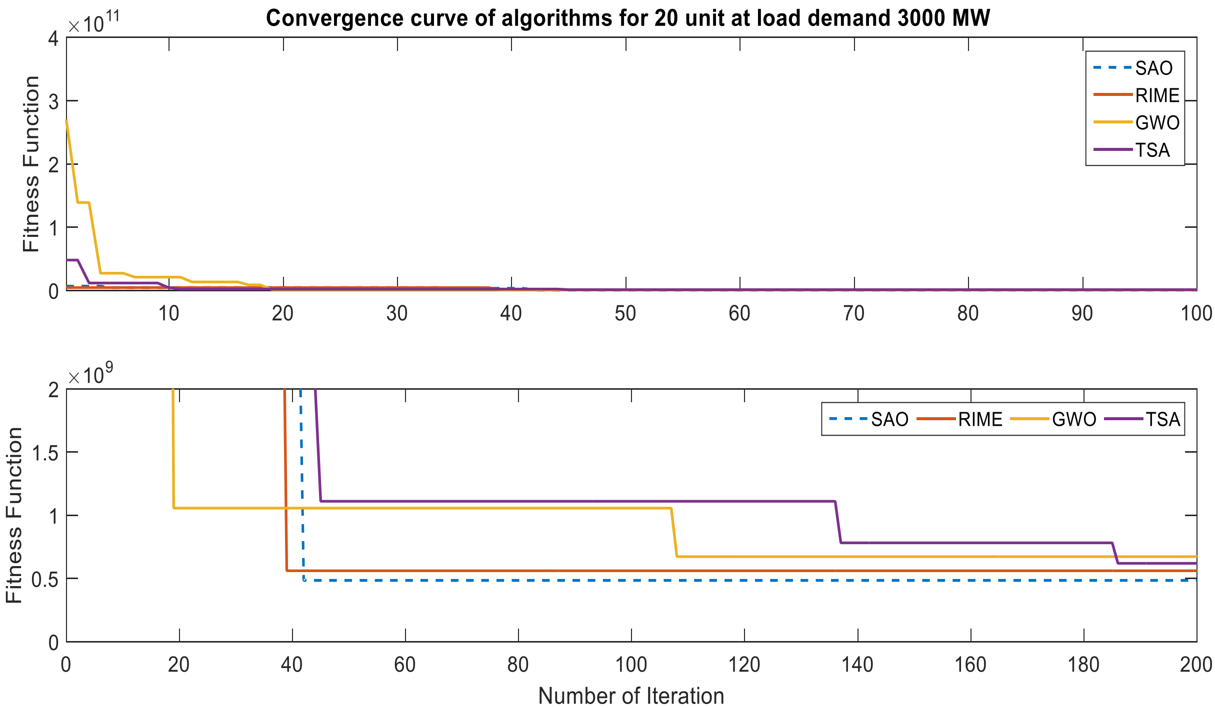

FIGURE 12. Convergence curves of 20 generators at load 3000 MW.

power generated by each unit for a load demand of 700 MW, created on the best objective function across all methods. Table 9 shows the optimal power generated by each unit for a load demand of 1000 MW, created on the best objective function across all methods. Based on the recorded outcomes from all techniques throughout the 30 runs, the robustness curve identifies the value of the target function for each run. Figures 5–6 show the properties of the robustness curve

TABLE 9. The optimal allocation power (MW) from 10 generators at 2000 MW demand.

SAO	RIME	TSA	GWO
421.7444271	406.7144664	388.3530707	470
331.9962798	375.6091023	390.4128598	327.2463921
324.8437439	340	340	340
299.9999995	300	232.1927614	300
241.9771641	197.2058403	228.1910008	206.2300426
159.9998492	87.38506616	137.4819032	57
129.5029286	101.2144177	117.8275913	130
47.04868646	99.23091826	98.18173173	106.2348635
62.33904412	80	72.80401239	80
26.25793238	55	39.13108271	24.9843736

TABLE 10. Statistical data for 20 generators based on all techniques ($/h).

Load (MW)	Method	Minimum	SD	Mean	Maximum
2000	SAO	**206350163.1**	72002912.01	288312190.0	451797905.2
	RIME	**210483640.9**	47793956.09	280648189.3	435127973.2
	TSA	**215533558.1**	28314998.02	262647777.4	323187351.3
	GWO	**221140711.5**	43577338.57	274345925.6	421530487.7
3000	SAO	**380388985.2**	94693458.50	660672742.3	857898161.4
	RIME	**439184820.8**	96610953.20	631164946.7	842339414.2
	TSA	**554112543.3**	112700647.1	697427585.7	1010486886
	GWO	**510171774.2**	101536499.9	685754012.9	965294670

TABLE 11. Fuel consumption optimum costs for 20 generators ($/h).

Algorithm	2000 MW	3000 MW
SAO	**204528254.5**	**379597887.8**
RIME	**209395514.2**	**436398458.1**
TSA	**210709710.1**	**521458574.5**
GWO	**216801551.9**	**492334302.8**

Algorithm 1 Dual-Population Mechanism

1. Initialization: $t = 0$. $N_b = N_a = N$, where N means the size of population and t_{max}
2. while $(t < t_{max})$
3. if $N_a < N$
4. $N_b = N_b - 1$, $N_a = N_a + 1$
5. end
6. $t = t+1$
7. end

for each load for 10 units' system. Based on the recorded results from every method among the top 30 runs that yield the best fitness function, the convergence curve describes the quickest method that achieves the objective function. Figures 7–8 display the features of the convergence curve for each load level for the 10-unit system. Figures 7 and 8 contain 2 subgraphs; the low graph is a magnified of the high

Algorithm 2 SAO Pseudo Code

1. Initialization: $Z.t = 0$. $N_b = N_a$ *and* t_{max}.
2. Evaluation the fitness
3. Record $G(t)$; the current best individual
4. while $(t < t_{max})$
5. Calculate M; the snowmelt rate from Equation (15)
6. Divide the entire population P into P_b and P_a subpopulations at random
7. for each individual do
8. Update each individual's position through Equation (17)
9. end
10. $t = t + 1$
11. Evaluation of the fitness
12. Update $G(t)$
13. end
14. Return $G(t)$

TABLE 12. The optimal allocation power (MW) from 20 generators at 2000 MW demand.

SAO	RIME	TSA	GWO
150.4979409	150	192.9629338	150
166.9118788	150.0466471	170.4411376	135
73.04970211	138.7709097	174.4737479	182.6455009
66.07744376	69.69811274	131.3356197	233.1174361
80.89049187	116.0905954	81.81422840	74.53651841
135.5816331	58.42084911	122.5408877	66.1565480
71.66816524	39.58410420	27.93030915	31.26033211
67.13876542	120	55.60410577	86.7605740
78.96542895	79.99922740	40.98733522	53.16391203
10.08733713	38.50048272	20.22929998	42.46522987
154.2581300	242.5875992	150	167.7469301
180.3591563	137.9460713	151.5361168	210.4598639
128.5270011	105.1261017	150.7771368	87.91754827
62.18161930	187.8933464	61.99015651	155.4209198
227.4665010	73	116.5752264	94.57424847
57.00864126	119.7105746	155.0815497	66.76377315
60.51869134	20	81.56252018	33.06698272
117.8085459	75.69914011	48.66027502	53.19348312
59.49404868	27.28501436	55.24501755	58.14058966
51.50906007	49.64111510	10.25287818	17.60917560

TABLE 13. The optimal allocation power (MW) from 20 generators at 3000 MW demand.

SAO	RIME	TSA	GWO
217.8989538	254.2777498	194.8593026	257.0323604
229.3884389	154.7463353	330.6281393	135.3759895
167.0872394	228.3226657	117.9914913	303.9696309
112.1585480	175.2440360	211.4451964	238.2057905
242.5881500	104.2378414	155.4336745	178.3905035
96.40470877	140.7282178	143.5900903	61.89430417
116.9890823	81.71907749	83.31521860	105.2878221
118.0922344	102.6310999	120	50.89194393
80	66.74773708	38.0537140	66.92045562
54.06438527	53.89392817	41.53431619	11.00276612
150.0357110	364.7435737	337.2748720	361.0734356
135.0172451	144.2190517	228.3354707	255.4231904
255.8586667	219.3117391	258.5109439	196.9619736
299.2954168	264.8400175	178.2131901	235.3570136
242.9949148	241.1338869	243	177.7873041
149.3666235	83.20973686	57	119.1406517
113.2956538	122.1935569	102.9421412	126.8690338
119.7385126	98.02889946	51.76211329	60.30198923
59.39962774	72.74783559	65.71576015	32.32046776
40.32596648	27.02329226	40.39763104	25.79158967

figure to explain the intersection between plotting. The SAO realizes the best global solution based on the convergence and robustness properties.

C. RESULTS OF 20-UNIT GENERATORS

Case research of 20 generators at two loads is applied in testing the ELD issue. Numerous methods were pertained,

TABLE 14. The power mismatch for 6-unit generators based on all algorithms.

Case	Method	700 MW	1000 MW
6 units	SAO	**1.157E-10**	**3.446E-13**
	RIME	4.22E-06	3.69E-06
	MBO	8.624894662	10.11850299
	TSA	2.11E-05	5.01E-05
	GWO	6.70E-05	1.36E-05
	SCA [9]	0.00076719	0.000182
	ABC [14]	8.85E-05	0.000172518
	ChOA [14]	0.000284475	0.000476787
	EWA [9]	5.71	20.1
	EHO [14]	2.239431602	9.904979361
	SMA [14]	5.61E-9	4.18E-9

TABLE 15. The optimal allocation power (MW) extracted from SAO for 6 generators at 700 MW.

Run	Generator power					
1	100.0061486	54.56388631	299.9505249	51.65138075	159.4793474	50.43274908
2	291.5644841	83.36984542	148.938611	70.34882563	55.95793331	60.91392993
3	283.9706564	91.51507435	148.5370566	55.40151926	77.11685416	54.72064672
4	207.6942382	95.81262119	162.1194594	97.36360487	57.54666403	91.74855536
5	170.3339745	106.4741928	84.61659475	106.8771399	162.9385324	82.38057815
6	258.4248869	78.74800914	133.0250562	60.01430485	130.8356218	51.02829651
7	211.3078759	147.2848343	97.30984833	50.26859369	150.3791854	56.0655393
8	1.51E+02	89.23732763	259.179463	104.2547904	50.01170369	60.29876738
9	2.05E+02	73.97407718	164.3694987	70.28004812	94.45326214	104.9446342
10	113.4801884	88.28453078	117.8067361	112.3581735	199.5715439	83.34439043
11	1.67E+02	50	213.9744073	140.4163183	88.40473331	53.96904343
12	110.9671226	55.09401544	297.9058259	147.5624719	52.83355742	50.81927072
13	149.2688389	131.4541626	89.93477858	88.18455273	174.9751055	79.98032572
14	126.7056713	125.5306273	164.770001	87.3176138	138.967616	70.28529278
15	259.3623487	52.7908398	82.11956676	116.3815363	150.9133418	51.18860161
16	260.399308	81.82804825	100.4310293	52.17264465	142.7124911	74.77299958
17	339.9536553	68.09188449	80.00000004	105.4960803	50.00013378	67.19753997
18	217.1641823	102.8470397	140.250415	84.65501863	102.4984953	64.7924967
19	100.9103328	72.30859879	282.4409245	149.0101224	51.08205809	59.15557385
20	164.481678	56.43658615	285.5905918	70.4431106	51.25590404	86.00053994
21	134.0416647	171.1526408	257.1133122	50.05444266	51.23936681	50.0231248
22	181.4534356	70.11452272	171.909802	76.75232896	156.920342	56.33109069
23	100.504145	159.5805331	145.7349573	86.58589276	142.695139	78.71910986
24	130.2969923	165.5390547	92.55250535	134.7522482	134.449326	55.95946128
25	188.9447274	197.8629739	81.69468826	75.44284445	118.6896002	50.02926207
26	139.7845481	65.98401788	80.04949264	146.9313778	193.2757016	89.03021567
27	257.658546	77.55470248	141.2542124	61.7543979	107.624481	66.08160734
28	151.2820351	94.65898443	228.0090339	93.20661582	89.36713238	56.8922577
29	128.8510833	53.9577098	267.0002158	148.9629604	61.86495129	53.91719521
30	104.531898	196.7795238	130.9765552	50.32519427	139.4542386	91.81486307

such as the SAO, TSA, GWO, MBO, and RIME. The effectiveness of every rival approach was evaluated using thirty separate runs. As can be seen in Table 10, these runs were used to record the mean, maximum, minimum, and standard deviation values as statistical data at each load level. The SAO obtains the best objective function and standard deviation based on this data. Thus, the SAO algorithm is the most precise and dependable one for ELD. The optimal fuel cost for each scenario is shown in Table 11. Table 12 shows the optimal power generated by each unit for a load demand

TABLE 16. **The optimal allocation power (MW) extracted from SAO for 6 generators at 1000 MW.**

Run	Generator power					
1	499.4773579	90.75228704	138.762008	112.8737547	103.2858036	76.84630596
2	356.4356487	193.5778648	97.88707178	58.69716543	199.9015447	119.2206778
3	411.6378804	149.960402	189.39511	65.56040239	138.0410012	68.77892844
4	373.0930479	70.22660271	200.2176876	139.1500397	170.5200985	72.15204736
5	496.1396133	199.9461365	88.67698982	135.0270254	50.11912896	51.54900734
6	332.1716845	94.12014468	210.2940285	91.29102188	181.9042213	116.3932557
7	405.1880901	174.878404	203.2317089	95.38714015	58.35272855	85.70782289
8	3.72E+02	124.0930309	191.0118805	107.4601719	169.0436678	61.18843638
9	3.54E+02	158.9648158	150.0034607	85.11866111	180.2048318	96.53545228
10	284.9504405	199.7490056	249.6083907	50.10201654	121.4351133	119.989792
11	4.71E+02	168.8193645	80.62484741	79.92799196	162.2943706	60.5300686
12	499.9948309	50.00567368	250.8988668	108.2491905	50.02033489	62.96416197
13	388.2144998	50.01231057	290.7466252	149.9639781	93.47567555	52.60245216
14	466.8844806	159.7361861	80.47521719	50.17338297	173.5335612	92.75142176
15	476.8392689	193.4282286	152.7209062	58.80657954	58.37418342	81.41697075
16	378.1623346	85.53561622	207.305576	58.51133815	199.9297253	96.2421169
17	446.7204912	179.2250208	99.00559908	127.6714954	50.00139008	119.9990913
18	499.8774293	54.13927156	81.58975357	97.42949127	196.6584269	94.64832048
19	369.1290098	62.28832574	258.7786816	148.6330684	80.54866276	105.5959459
20	493.2318499	74.95653543	87.97169594	50.00000364	199.7107534	118.5884338
21	301.7217487	132.7519436	136.7212423	143.7727734	200	111.7293024
22	495.9119795	191.5486121	135.4714831	68.9464636	78.41431138	50.99109097
23	316.756281	117.6721153	297.5026903	84.94463956	88.88682612	119.9999635
24	383.6208275	189.352549	132.3151144	112.3278455	107.8501076	98.16695156
25	495.6004552	56.8564242	83.70147245	149.4276662	180.9157799	57.53317777
26	458.8898802	97.75051481	109.8633736	106.2785358	130.686253	120
27	199.725272	199.4592964	271.2537415	50.95448641	188.0510293	118.722389
28	335.2457873	193.3907347	125.683745	140.5155595	175.8726052	54.39111118
29	497.0159265	61.91226875	88.49553888	110.9296025	181.3484143	84.17485259
30	479.0850898	101.3696407	103.173352	123.9126602	95.32629696	119.8956443

of 700 MW, created on the best objective function across all methods. Table 13 shows the optimal power generated by each unit for a load demand of 1000 MW, created on the best objective function across all methods. Based on the recorded outcomes from all techniques throughout the 30 runs, the robustness curve identifies the value of the target function for each run. Figures 9–10 show the properties of the robustness curve for each load for 20 units' system. Based on the recorded results from every method among the top 30 runs that yield the best fitness function, the convergence curve describes the quickest method that achieves the objective function. Figures 11–12 display the features of the convergence curve for each load level for the 20-unit system. Figures 11 and 12 contain 2 subgraphs; the low graph is a magnified of the high figure to explain the intersection between plotting. The SAO realizes the best global solution based on the convergence and robustness properties.

D. DISCUSSION

The value of the power mismatch is the primary component in ELD difficulties. the exact discrepancy between the total demand and transmission losses and the units of generated electricity. The high-performance methodology is used to retrieve the power mismatch value because it is almost nil. The value of this factor for ELD is explained in Table 14. Together with the five approaches utilized in the run, the suggested SOA algorithm is also compared to other literature techniques including the sine cosine algorithm, elephant herding optimization, Artificial Bee Colony, slime mould algorithm, Earth Worm Algorithm, and Chimp Optimization Algorithm, as explained in Table 14. The SOA approach consistently delivers the optimal power mismatch value based on this data. The optimal allocation power (MW) from the 6-unit generator at each MW demand extracted from the SAO method is explained in Tables 15-16.

The original Snow Ablation Optimization (SAO) algorithm has demonstrated competitive performance when compared to other cutting-edge algorithms, demonstrating features like fast convergence, simplicity, and dependability, avoiding local optima, and maintaining the equilibrium between exploration and exploitation.

We use Optimum Allocation of Generator Units, which maintains extremely complicated issue landscapes, for the thorough evaluation of the SAO. Subsequently, the SAO's superiority and practicability are thoroughly confirmed through comparison with multiple counterparts. The comparison's findings show that the SAO is a strong and attractive solution for solving the optimal allocation of the generator unit's problem.

In addition to its advantages, the SAO has certain limitations, which are covered below:

• The NFL theorem states that no single optimization approach can handle all optimization problems.

• We do not evaluate the SAO's performance with high Optimum Allocation of Generator Units. The authors conclude that the SAO technique adheres to the same principles as the other metaheuristics methods, even though it outperforms several other well-known and contemporary algorithms.

V. CONCLUSION

A new metaheuristic technique called snow ablation optimization (SAO) imitates the melting and sublimation properties of snow. Furthermore, the SAO's efficacy was compared to that of four different algorithms. This work uses the SAO to solve a critical problem: economic load dispatch (ELD). In particular, ELD contributes to the reduction of fuel costs. The primary concern in optimizing the ELD problem is the cost of fuel use, which the SAO seeks to minimize while maximizing the power system's economic worth. The vector of unit-specific allocation that establishes the optimal result for every system is reflected in the main variable of the ELD problem. The rime-ice algorithm (RIME), grey wolf optimization (GWO), the monarch butterfly optimization (MBO), and the tunicate swarm algorithm (TSA) were among the algorithms with which the SAO's performance was contrasted. The optimum fuel cost values of 12136.06674 and 8381.566642 are achieved using the SAO method for six generator units at demand loads of 1000 MW and 700 MW, respectively. The optimum fuel cost values of 91408138.73 and 477167397.4 are achieved by the SAO method for ten generator units at demand loads of 1000 and 2000 MW, respectively. The optimum fuel cost values of 204528254.5 and 379597887.8 are achieved using the SAO method for 20 generator units at demand loads of 2000 and 3000 MW, respectively. In the end, the results confirmed that, when compared to the alternatives, the SAO was successful in reducing the cost of fuel for all cases of ELD. The SAO approach may be used in the future to solve further significant, real-world optimization problems about solar energy and power system and real world power system cases with thousands of generators and loads.

REFERENCES

[1] W.-K. Hao, Y.-P. Li, J.-S. Wang, and Q. Zhu, "Solving economic load dispatch problem of power system based on differential evolution algorithm with different mutation strategies," *Int. J. Comput. Sci.*, vol. 49, pp. 156–165, May 2022.

[2] N. Singh, T. Chakrabarti, P. Chakrabarti, M. Margala, A. Gupta, S. P. Praveen, S. B. Krishnan, and B. Unhelkar, "Novel heuristic optimization technique to solve economic load dispatch and economic emission load dispatch problems," *Electronics*, vol. 12, no. 13, p. 2921, Jul. 2023, doi: 10.3390/electronics12132921.

[3] Y. Feng, S. Deb, G.-G. Wang, and A. H. Alavi, "Monarch butterfly optimization: A comprehensive review," *Expert Syst. Appl.*, vol. 168, Apr. 2021, Art. no. 114418.

[4] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," *Future Gener. Comput. Syst.*, vol. 111, pp. 300–323, Oct. 2020.

[5] Y. Feng and G.-G. Wang, "A binary moth search algorithm based on self-learning for multidimensional knapsack problems," *Future Gener. Comput. Syst.*, vol. 126, pp. 48–64, Jan. 2022.

[6] Y. Yang, H. Chen, A. A. Heidari, and A. H. Gandomi, "Hunger games search: Visions, conception, implementation, deep analysis, perspectives, and towards performance shifts," *Expert Syst. Appl.*, vol. 177, Sep. 2021, Art. no. 114864.

[7] I. Ahmadianfar, A. A. Heidari, A. H. Gandomi, X. Chu, and H. Chen, "RUN beyond the metaphor: An efficient optimization algorithm based on Runge Kutta method," *Expert Syst. Appl.*, vol. 181, Nov. 2021, Art. no. 115079.

[8] A. A. Heidari, S. Mirhalili, H. Faris, I. Aljarah, M. Mafarj, and H. Chen, "Harris Hawks optimization: Algorithm and application," *Future Gener. Comput. Syst.*, vol. 97, Aug. 2019, pp. 849–872.

[9] M. Said, A. M. El-Rifaie, M. A. Tolba, E. H. Houssein, and S. Deb, "An efficient chameleon swarm algorithm for economic load dispatch problem," *Mathematics*, vol. 9, no. 21, p. 2770, Nov. 2021.

[10] H. Su, D. Zhao, A. A. Heidari, L. Liu, X. Zhang, M. Mafarja, and H. Chen, "RIME: A physics-based optimization," *Neurocomputing*, vol. 532, pp. 183–214, May 2023.

[11] E. H. Houssein, S. Deb, D. Oliva, H. Rezk, H. Alhumade, and M. Said, "Performance of gradient-based optimizer on charging station placement problem," *Mathematics*, vol. 9, no. 21, p. 2821, Nov. 2021.

[12] D. S. Abdelminaam, M. Said, and E. H. Houssein, "Turbulent flow of water-based optimization using new objective function for parameter extraction of six photovoltaic models," *IEEE Access*, vol. 9, pp. 35382–35398, 2021.

[13] M. Said, E. H. Houssein, S. Deb, A. A. Alhussan, and R. M. Ghoniem, "A novel gradient based optimizer for solving unit commitment problem," *IEEE Access*, vol. 10, pp. 18081–18092, 2022.

[14] A. A. K. Ismaeel, E. H. Houssein, D. S. Khafaga, E. A. Aldakheel, A. S. AbdElrazek, and M. Said, "Performance of osprey optimization algorithm for solving economic load dispatch problem," *Mathematics*, vol. 11, no. 19, p. 4107, Sep. 2023, doi: 10.3390/math11194107.

[15] A. Bhattacharya and P. K. Chattopadhyay, "Biogeography-based optimization for different economic load dispatch problems," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1064–1077, May 2010.

[16] G. L. Andrade, C. Schepke, N. Lucca, and J. P. J. Neto, "Modified differential evolution algorithm applied to economic load dispatch problems," in *Computational Science and its Applications* (Lecture Notes in Computer Science), vol. 13956. Cham, Switzerland: Springer, 2023.

[17] M. Said, E. H. Houssein, S. Deb, R. M. Ghoniem, and A. G. Elsayed, "Economic load dispatch problem based on search and rescue optimization algorithm," *IEEE Access*, vol. 10, pp. 47109–47123, 2022.

[18] M. A. Al-Betar, M. A. Awadallah, S. N. Makhadmeh, I. A. Doush, R. A. Zitar, S. Alshathri, and M. A. Elaziz, "A hybrid Harris Hawks optimizer for economic load dispatch problems," *Alexandria Eng. J.*, vol. 64, pp. 365–389, Feb. 2023.

[19] A. Hazra, S. Das, A. Laddha, and M. Basu, "Economic power generation strategy for wind integrated large power network using heat transfer search algorithm," *J. Inst. Eng., B*, vol. 101, no. 1, pp. 15–21, Feb. 2020.

[20] G. Xiong, D. Shi, and X. Duan, "Multi-strategy ensemble biogeography based optimization for economic dispatch problems," *Appl. Energy*, vol. 111, pp. 801–811, Aug. 2013.

[21] M. A. Al-Betar, M. A. Awadallah, R. A. Zitar, and K. Assaleh, "Economic load dispatch using memetic sine cosine algorithm," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 9, pp. 11685–11713, Sep. 2023.

[22] A. S. Alghamdi, "Greedy sine-cosine non-hierarchical grey wolf optimizer for solving non-convex economic load dispatch problems," *Energies*, vol. 15, no. 11, p. 3904, May 2022.

[23] T. P. Van, V. Snasel, and T. T. Nguyen, "Antlion optimization algorithm for optimal non-smooth economic load dispatch," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 2, p. 1187, Apr. 2020.
[24] W. T. Elsayed and E. F. El-Saadany, "A fully decentralized approach for solving the economic dispatch problem," *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 2179–2189, Jul. 2015.
[25] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 19–27, Feb. 2016.
[26] F. Mohammadi and H. Abdi, "A modified crow search algorithm (MCSA) for solving economic load dispatch problem," *Appl. Soft Comput.*, vol. 71, pp. 51–65, Oct. 2018.
[27] T. Jayabarathi, T. Raghunathan, B. R. Adarsh, and P. N. Suganthan, "Economic dispatch using hybrid grey wolf optimizer," *Energy*, vol. 111, pp. 630–641, Sep. 2016.
[28] D. C. Secui, "A modified symbiotic organisms search algorithm for large scale economic dispatch problem with valve-point effects," *Energy*, vol. 113, pp. 366–384, Oct. 2016.
[29] A. A. Elsakaan, R. A. El-Sehiemy, S. S. Kaddah, and M. I. Elsaid, "An enhanced moth-flame optimizer for solving non-smooth economic dispatch problems with emissions," *Energy*, vol. 157, pp. 1063–1078, Aug. 2018.
[30] T. T. Nguyen and D. N. Vo, "The application of one rank cuckoo search algorithm for solving economic load dispatch problems," *Appl. Soft Comput.*, vol. 37, pp. 763–773, Dec. 2015.
[31] P. Zakian and A. Kaveh, "Economic dispatch of power systems using an adaptive charged system search algorithm," *Appl. Soft Comput.*, vol. 73, pp. 607–622, Dec. 2018.
[32] S. H. A. Kaboli and A. K. Alqallaf, "Solving non-convex economic load dispatch problem via artificial cooperative search algorithm," *Expert Syst. Appl.*, vol. 128, pp. 14–27, Aug. 2019.
[33] S. Cui, Y.-W. Wang, X. Lin, and X.-K. Liu, "Distributed auction optimization algorithm for the nonconvex economic dispatch problem based on the gossip communication mechanism," *Int. J. Electr. Power Energy Syst.*, vol. 95, pp. 417–426, Feb. 2018.
[34] K. Kapelinski, J. P. J. Neto, and E. M. dos Santos, "Firefly algorithm with non-homogeneous population: A case study in economic load dispatch problem," *J. Oper. Res. Soc.*, vol. 72, no. 3, pp. 519–534, Mar. 2021.
[35] A. Kaur, L. Singh, and J. S. Dhillon, "Modified Krill Herd Algorithm for constrained economic load dispatch problem," *Int. J. Ambient Energy*, vol. 43, no. 1, pp. 4332–4342, Dec. 2022.
[36] R. Ramalingam, D. Karunanidy, S. S. Alshamrani, M. Rashid, S. Mathumohan, and A. Dumka, "Oppositional pigeon-inspired optimizer for solving the non-convex economic load dispatch problem in power systems," *Mathematics*, vol. 10, no. 18, p. 3315, Sep. 2022.
[37] M. F. Tabassum, M. Saeed, N. A. Chaudhry, J. Ali, M. Farman, and S. Akram, "Evolutionary simplex adaptive Hooke-Jeeves algorithm for economic load dispatch problem considering valve point loading effects," *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 1001–1015, Mar. 2021.
[38] S. Banerjee, D. Maity, and C. K. Chanda, "Teaching learning based optimization for economic load dispatch problem considering valve point loading effect," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 456–464, Dec. 2015.
[39] H. Shayeghi and A. Ghasemi, "A modified artificial bee colony based on chaos theory for solving non-convex emission/economic dispatch," *Energy Convers. Manage.*, vol. 79, pp. 344–354, Mar. 2014.
[40] B. K. Panigrahi and V. R. Pandi, "Bacterial foraging optimisation: Nelder–Mead hybrid algorithm for economic load dispatch," *IET Gener., Transmiss. Distrib.*, vol. 2, no. 4, p. 556, 2008.
[41] G. Binetti, A. Davoudi, D. Naso, B. Turchiano, and F. L. Lewis, "A distributed auction-based algorithm for the nonconvex economic dispatch problem," *IEEE Trans. Ind. Informat.*, vol. 10, no. 2, pp. 1124–1132, May 2014.
[42] S. Deb, E. H. Houssein, M. Said, and D. S. Abdelminaam, "Performance of turbulent flow of water optimization on economic load dispatch problem," *IEEE Access*, vol. 9, pp. 77882–77893, 2021.
[43] M. Dehghani and P. Trojovský, "Osprey optimization algorithm: A new bio-inspired Metaheuristic algorithm for solving engineering optimization problems," *Frontiers Mech. Eng.*, vol. 8, Jan. 2023, Art. no. 1126450.
[44] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm," *Knowl.-Based Syst.*, vol. 191, Mar. 2020, Art. no. 105190.
[45] M. Abdel-Basset, L. Abdel-Fatah, and A. K. Sangaiah, "Metaheuristic algorithms: A comprehensive review," in *Computational Intelligence for Multimedia Big Data on the Cloud With Engineering Applications*. 2018, pp. 185–231.
[46] G. Zhou, M. Cui, J. Wan, and S. Zhang, "A review on snowmelt models: Progress and prospect," *Sustainability*, vol. 13, no. 20, p. 11485, Oct. 2021.
[47] J. Martinec and A. Rango, "Parameter values for snowmelt runoff modelling," *J. Hydrol.*, vol. 84, nos. 3–4, pp. 197–219, May 1986.
[48] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014.
[49] S. Kaur, L. K. Awasthi, A. L. Sangal, and G. Dhiman, "Tunicate swarm algorithm: A new bio-inspired based Metaheuristic paradigm for global optimization," *Eng. Appl. Artif. Intell.*, vol. 90, Apr. 2020, Art. no. 103541.
[50] G.-G. Wang, S. Deb, and Z. Cui, "Monarch butterfly optimization," *Neural Comput. Appl.*, vol. 31, no. 7, pp. 1995–2014, 2019.