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Performance of Osprey Optimization Algorithm for Solving Economic Load Dispatch Problem

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Abstract: The osprey optimization algorithm (OOA) is a new metaheuristic motivated by the strategy of hunting fish in seas. In this study, the OOA is applied to solve one of the main items in a power system called economic load dispatch (ELD). The ELD has two types. The first type takes into consideration the minimization of the cost of fuel consumption, this type is called ELD. The second type takes into consideration the cost of fuel consumption and the cost of emission, this type is called combined emission and economic dispatch (CEED). The performance of the OOA is compared against several techniques to evaluate its reliability. These methods include elephant herding optimization (EHO), the rime-ice algorithm (RIME), the tunicate swarm algorithm (TSA), and the slime mould algorithm (SMA) for the same case study. Also, the OOA is compared with other techniques in the literature, such as an artificial bee colony (ABO), the sine cosine algorithm (SCA), the moth search algorithm (MSA), the chimp optimization algorithm (ChOA), and monarch butterfly optimization (MBO). Power mismatch is the main item used in the evaluation of the OOA with all of these methods. There are six cases used in this work: 6 units for the ELD problem at three different loads, and 6 units for the CEED problem at three different loads. Evaluation of the techniques was performed for 30 various runs based on measuring the standard deviation, minimum fitness function, and maximum mean values. The superiority of the OOA is achieved according to the obtained results for the ELD and CEED compared to all competitor algorithms.

Keywords: osprey optimization algorithm; economic load dispatch; power system

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1. Introduction

An important optimization issue for a power system's efficient and trouble-free operation is the economic load dispatch (ELD). The net electricity demand is rising alarmingly quickly. As a result, the cost of fuel for producing electricity is also rising. Therefore, to ensure power systems operate reliably, it is necessary to lower operational costs. By maximizing the thermal units' ability to produce energy, the ELD issue aims to lower the system's running costs while also enhancing the system's dependability. The combined economic emission dispatch (CEED) problem is a result of the tendency in recent years to consider cost and pollution while planning and operating power systems [1,2]. As a result, ELD and CEED are intricate power system optimization problems with nonlinear fitness functions, equality requirements, and inequality constraints. Because the ELD problem is not linear, standard techniques are only partially effective in addressing it. Different metaheuristic methods have been suggested by researchers to address such issues. The benefits of metaheuristic algorithms have confirmed the effectiveness of other approaches in dealing with complex optimization problems [3–5].

To determine the real and reactive power of the electrical generation system, the linear programming approach was utilized; however, such methods have a significant calculation time and are occasionally unable to offer a global solution for huge data sets [6]. The pattern search approach was suggested as a way to find the best solution to the ELD problem, and the impacts of valve loading were considered. To validate the findings, the suggested algorithm was evaluated on a variety of test data and compared to existing optimization methods [7]. Transmission losses, dynamic operation limitations, and restricted operating zones were all employed in conjunction with the ELD problem in the PSO approaches [8]. The ELD issue, which comprises a DC load flow and network security limitations, was solved using quadratic programming [9].

Numerous metaheuristic (MH) methods have been developed to address the ELD issue in the same setting. These MH techniques may be broadly divided into four sorts of algorithms: evolutionary, swarm-based, physical-based, and human-based. All of these types simulate swarm activity or other natural phenomena to find the best solution.

Recently, many optimization algorithms, such as the white shark optimizer [10], the search and rescue optimization algorithm (SAR) [11], the greedy sine-cosine nonhierarchical gray wolf optimizer (G-SCNHGWO) [12], the efficient chameleon swarm algorithm (CSA) [13], the memetic sine cosine algorithm [14], the hybrid Harris hawks optimizer (HHO) [15], the oppositional pigeon-inspired optimizer (OPIO) algorithm [16], the modified krill herd algorithm [17], the modified differential evolution algorithm [18], artificial eco system-based optimization [19], turbulent flow of water optimization (TFWO) [20], particle swarm optimization (PSO) [21], evolution strategy (ES) [22], teaching learning based optimization (TLBO) [23], the modified symbiotic organisms search algorithm (MSOS) [24], civilized swarm optimization (CSO) [25], the ant lion optimization algorithm (ALO) [26], the efficient distributed auction optimization algorithm (DAOA) [27], the hybrid grey wolf optimizer (HGWO) [28], the improved genetic algorithm (IGA) [29], the improved firefly algorithm (IFA) [30], biogeography-based optimization (BBO) [31], the heat transfer search (HTS) algorithm [32], adaptive charged system search (ACSS) [33], the evolutionary simplex adaptive Hooke–Jeeves algorithm (ESAHJ) [34], the enhanced moth-flame optimizer (EMFO) [35], multi-strategy ensemble biogeography-based optimization (MSEBBO) [36], several new hybrid algorithms [37], a fully decentralized approach (DA) [38], the exchange market algorithm (EMA) [39], bacterial foraging optimization (BFO) [40], the artificial cooperative search algorithm (ACS) [41], a new firefly algorithm (FA) via a non-homogeneous population [42], a modified chaotic artificial bee colony (MABC) [43], a distributed auction based algorithm (AA) [44], the one rank cuckoo search algorithm (ORCSA) [45], and the modified crow search algorithm (MCSA) [46] have been employed to find the optimal solution for the ELD problem. The description of each work is presented in Table 1.

According to the no free lunch (NFL) formula [47–51], different metaheuristics perform and behave differently when tackling diverse classes of problems. One cutting-edge metaheuristic approach to solving the ELD problem is the osprey optimization algorithm (OOA) [52]. The OOA method is simple to implement due to its straightforward formula, few parameters, and fundamental idea.

Table 1. Literature survey for each method.

Year	Reference	Description
2003	[21]	The EED problem was solved using the PSO method while taking into account generator limitations such as ramp rate limits and prohibited operation zones.
2005	[29]	Power economic dispatch problems were solved using an IGA, and it was tested using three different scenarios: one that considered valve-point effects, one that considered various fuels, and one that addressed both valve-point effects and numerous fuels.
2008	[40]	Non-convex ED problems with a variety of restrictions may be solved with ease by the Nelder-Mead hybrid technique. Simulations of several standard test systems with variable numbers of generating units were run.
2009	[25]	A series of multi-minima economic dispatch problems were used to evaluate the performance of CSO.
2010	[31]	Convex and non-convex ELD problems facing thermal plants were solved using a BBO method. This approach was applied to four different test systems, both small and big, requiring differing degrees of complexity.
2013	[36]	For resolving ELD problems, the authors suggested a MSEBBO. The no free lunch theorem is used by the MEEBBO to enhance the three elements of BBO to maintain a good balance between exploration and exploitation. Additionally, a powerful repair method is suggested to address the various ELD problem constraints.
2014	[43]	The standard IEEE 30 bus with six generators, fourteen generators, and forty thermal generating units was subjected to the modified artificial bee colony approach for non-convex CEED problems.
2014	[44]	The non-convex ELD problem was solved using a distributed auction-based method and had many constraints, including the valve-point loading effect, numerous fuel alternatives, and restricted operating zones.
2015	[23]	To solve EPLD problems while considering transmission losses, the TLBO method was used. This method explores the solution space for the global optimal point.
2015	[38]	The non-convex formulation of the ED problem can be solved very efficiently using a DA method, and transmission losses can be precisely taken into consideration in a fully decentralized way. Three case studies were examined.
2015	[45]	ELD issues were solved with the ORCSA method. Additionally, complete testing on several systems with various restrictions and thermal unit characteristics was presented.
2016	[24]	Five systems—13-unit, 40-unit, 80-unit, 160-unit, and 320-unit systems—with various features, constraints, and dimensions were used to evaluate the performance of the MSOS.
2016	[28]	Using a HGWO, four economic dispatch problems with 6, 15, 40, and 80 generators were tested.
2016	[39]	The EMA is a reliable and effective technique for locating the global optimization's best solution for ELD situations. Additionally, four test systems in four distinct dimensions—3, 6, 15, and 40 units—with both convex and non-convex cost functions—were used to develop it.
2018	[27]	The most effective approach for the ELD problem was discovered using the DAOA.
2018	[33]	Using an ACSS method, a variety of economic dispatch cases formed of 6-, 13-, 15-, 40-, 160-, and 640-unit generating systems were studied as benchmarks for small- and large-scale problems.
2018	[35]	The non-convex ELD problem with valve-point effects and emissions was solved using the EMFO method on three typical test systems comprising 6, 40, and a large-scale 80 generating units with non-convex fuel cost functions.
2018	[46]	The non-convex ELD problem was solved using the MCSA and applied to five well-known test systems.
2019	[41]	The ACS technique, based on a co-evolutionary technique, was offered as a potential solution to the challenging ELD problem.
2020	[26]	Problems involving the optimal ELD were handled using the ALO. The results of applying the ALO algorithm to all three cases revealed that it has greater potential than other techniques for the solution, stability, and convergence velocity.

Table 1. *Cont.*

Year	Reference	Description
2020	[32]	The HT method was used to resolve the complex ELD problem with the integration of wind generation.
2021	[13]	The ELD problem was resolved based on CSA's effective operation with a six-unit system.
2021	[20]	To solve ELD and CEED issues, the authors created a TFWO method.
2021	[34]	On five generating systems with valve-point effects, the ESAHJ performance was evaluated. The test findings for the suggested approach showed high convergence features and low generation costs, making them extremely effective and encouraging.
2021	[42]	ELD problems were solved with the FA. A 15-unit ELD problem with many considerations for each generator was solved using ten benchmark functions, and a 13-unit non-convex system with a valve-point loading effect was solved.
2022	[11]	The SAR was used by the authors to get at the optimum approach for the CEED and ELD. The outcomes demonstrated that the SAR was the optimum option for ELD, integrated pollution control, and economic dispatch.
2022	[12]	To solve ELD problems, the authors proposed a GSCGWO. The power generators in these four power systems total 10, 15, 40, and 140, with various valuation times.
2022	[16]	The ELD problem of small-scale (13-unit, 40-unit), medium-scale (140-unit, 160-unit), and large-scale (320-unit, 640-unit) test systems was solved using the OPIO algorithm.
2022	[17]	The authors solved an ELD issue with the MKH method. In comparison to other metaheuristics, the MKH was found to perform rather well, and tweaking parameters in the MKH was also fairly simple.
2023	[14]	The ELD problem was solved by a memetic sine cosine algorithm that was applied to six real-world cases: 3, 6, 13, 13, 15, and 40 units of generator.
2023	[15]	ELD problems were solved using HHO methods in six generation units.
2023	[18]	The global minimum and other instances of the ELD were obtained by solving a series of test functions using the modified differential evolution method.

The main points of contribution and objectives in this paper are illustrated as follows:

- To discuss two network studies: ELD with various load demands and CEED with various load demands.
- A new metaheuristic technique called osprey optimization algorithm (OOA) is applied to solve the ELD and CEED problems.
- The proposed OOA method is compared with the rime-ice algorithm (RIME), the tunicate swarm algorithm (TSA), the slime mould algorithm (SMA), and elephant herding optimization (EHO) for the same case study.

The paper is organized as follows: the CEED and ELD issues are deliberated in section two. The OOA method is discussed in section three. The discussion of the results is presented in section four. The conclusions and areas for future work are depicted in section five.

2. Economic Load Dispatch Problem

One of the problems with the operation of power systems is ELD. The primary challenge in solving the ELD issue is reducing fuel consumption expenses to maximize the economic advantage for power plants. The primary variable in the ELD issue defines the vector for distributing resources so that each unit produces the most power. Following is a discussion of CEED and ELD analysis with losses.

2.1. ELD

The mathematical equations of ELD with losses can be labeled as follows. To run n generators, the consumption fuel cost will be pinpointed as follows:

$$\mathrm{Min}(\mathrm{F}) = \mathrm{F}_1(\mathrm{P}_1) + \ldots \mathrm{F}_\mathrm{n}(\mathrm{P}_\mathrm{n}) \tag{1}$$

where F stands for the net fuel cost, F_1 for the cost of fuel in the first generator, and F_n for the cost of fuel in the nth generator. The following methods will be used to obtain a function of consumption fuel cost in quadratic form:

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

where a, b, and c stand for the fuel cost's weight constants. Additionally, using Equations (3) and (5), the generator constraints for each unit can be varied from zero up to 500 MW.

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

where P_D denotes the total demand of the network and P_L denotes 6 transmission losses of the network which can be calculated as follows:

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

where B_{ij} refers to the loss factor, P_i refers to the generated power at the *ith* generator, and P_j refers to the generated power at the jth generator.

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

2.2. CEED

Progress on the ELD issue can be achieved by considering the reduction of emission costs alongside the production cost, which is defined as the CEED. The factor of emission can be mathematically calculated by:

$$\mathrm{Min}(E) = \sum_{k=1}^{n} E_i(P_i) = \sum_{k=1}^{n} \alpha_k P_k^2 + \beta_k P_k + \gamma_k \tag{6}$$

The CEED objective function is calculated according to the following equation:

$$\text{objective function} = \mathrm{Min}\left(\sum_{k=1}^{n} E_i(P_i) + h_e \sum_{k=1}^{n} F_i(P_i)\right) \tag{7}$$

where refers to the penalty factor for the price as given in Equation (8):

$$h_e = \frac{F_i(P_{imax})}{E_i(P_{imax})} \tag{8}$$

The generator constraints in each unit are accounted for by Equations (3) and (5).

3. Osprey Optimization Algorithm

In this section, the recent osprey optimization algorithm (OOA) is presented, and then the mathematical modeling is presented [52].

3.1. Inspiration of OOA

The osprey, often referred to as the fish, river, and sea hawk, is a nocturnal fish-eating bird of prey with a wide geographic range. A clever natural behavior that can serve as the foundation for creating a new optimization algorithm is the osprey approach of catching fish and carrying them to an advantageous location to consume them. To build the suggested OOA method, which is covered in the following section, these intelligent osprey behaviors were mathematically modeled.

3.2. Mathematical Modelling

The procedure of updating the positions of ospreys in the two phases of exploration and exploitation based on the simulation of natural osprey behavior is presented [52] after the startup of the OOA is detailed in this subsection.

3.2.1. Initialization

The suggested OOA is a population-based strategy that, using a repetition-based method, can find a workable solution based on the search power of its population members in the problem-solving space. Based on its location in the search space, each osprey calculates the values of the problem variables as a member of the OOA population. As a result, each osprey represents a potential solution to the issue, represented numerically by a vector. The OOA population, which is made up of all ospreys, can be described using a matrix per Equation (9). Using Equation (10), the location of ospreys in the search space is initialized at random at the start of the OOA implementation. To be specific, the factors mentioned in Equations (2) and (6) are represented by $x_{i,j}$ as defined in Equation (10).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \therefore & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m}, \tag{9}$$

$$x_{i,j} = lb_j + r_{i,j}\cdot\left(ub_j - lb_j\right), i = 1,2,\ldots,N, j = 1,2,\ldots,m, \tag{10}$$

where X represents the population matrix of the locations of the ospreys, X_i represents the jth osprey (a candidate solution), $x_{i,j}$ represents its jth dimension (problem variable), N represents the number of ospreys, m represents the number of problem variables, $r_{i,j}$ represents random numbers in the range $[0,1]$, lb_j, and ub_j represent the lower bound and upper bound.

The objective function defined in Equations (3) and (7) can be assessed since each osprey is a potential solution to the problem that corresponds to that particular osprey. According to Equation (11), a vector can be used to represent the evaluated values for the problem's objective function.

$$\mathrm{F} = \begin{bmatrix} \mathrm{F}_1 \\ \vdots \\ \mathrm{F}_\mathrm{i} \\ \vdots \\ \mathrm{F}_\mathrm{N} \end{bmatrix}_{\mathrm{N}\times 1} = \begin{bmatrix} \mathrm{F}(\mathrm{X}_1) \\ \vdots \\ \mathrm{F}(\mathrm{X}_\mathrm{i}) \\ \vdots \\ \mathrm{F}(\mathrm{X}_\mathrm{N}) \end{bmatrix}_{\mathrm{N}\times 1}, \tag{11}$$

where F_i is the calculated objective function value for the ith osprey and F is the vector of the objective function values.

The primary criteria for assessing the quality of potential solutions are the values evaluated for the objective function. The best candidate solution (i.e., the best member) corresponds to the best value found for the objective function, and the worst candidate solution (i.e., the worst member) corresponds to the worst value obtained for the objective function. The best candidate solution must be modified in each iteration since the location of the ospreys in the search space is updated on each iteration.

3.2.2. Phase 1: Identification of Positions and Hunting of Fish (Exploration)

Ospreys are powerful hunters with great eyesight that allows them to locate fish underwater. They locate the fish, attack it, and chase the fish by diving under the surface.

The first stage of the OOA's population update was modeled using a simulation of ospreys' actual natural behavior. The position of the osprey in the search space changed significantly as a result of modeling the osprey attack on fish, increasing the exploration capacity of the OOA in locating the ideal location and eluding the local optima.

The placements of other ospreys in the search space that have a higher objective function value were regarded as undersea fishes for each osprey in the OOA design. Using Equation (12), the set of fish for each osprey was determined as:

$$\mathrm{FP_i} = \{\mathrm{X_k} \mid \mathrm{k} \in \{1,2,\ldots,\mathrm{N}\} \wedge \mathrm{F_k} < \mathrm{F_i}\} \cup \{\mathrm{X_{best}}\} \tag{12}$$

where $\mathrm{FP_i}$ is the fish position set for the *i*th osprey and $\mathrm{X_{best}}$ is the best osprey solution.

One of these fish is randomly located by the osprey, which then strikes it. Using Equation (13), a new position for the matching osprey was determined based on the simulation of the osprey's movement towards the fish. According to Equation (14), the osprey will move to this new position if it enhances the value of the objective function.

$$\begin{gathered}\mathrm{x_{i,j}^{P1}} = \mathrm{x_{i,j}} + \mathrm{r_{i,j}}\cdot(\mathrm{SF_{i,j}} - \mathrm{I_{i,j}}\cdot\mathrm{x_{i,j}}),\\ \mathrm{x_{i,j}^{P1}} = \begin{cases}\mathrm{x_{i,j}^{P1}}, \mathrm{lb_j} \le \mathrm{x_{i,j}^{P1}} \le \mathrm{ub_j};\\ \mathrm{lb_j}, \mathrm{x_{i,j}^{P1}} < \mathrm{lb_j};\\ \mathrm{ub_j}, \mathrm{x_{i,j}^{P1}} > \mathrm{ub_j}.\end{cases}\end{gathered} \tag{13}$$

$$\mathrm{X_i} = \begin{cases}\mathrm{X_i^{P1}}, \mathrm{F_i^{P1}} < \mathrm{F_i};\\ \mathrm{X_i}, \mathrm{else},\end{cases} \tag{14}$$

where X_i^{P1} is the *i*th osprey new position based on the first phase of OOA, $x_{i,j}^{P1}$ is its *j*th dimension, F_i^{P1} is its fitness function, SF_i is the fish selected for *i*th osprey, $SF_{i,j}$ is the *j*th dimension, $r_{i,j}$ are random numbers in the interval $[0,1]$, and $I_{i,j}$ are random numbers from the set $\{1,2\}$.

3.2.3. Phase 2: Carrying the Fish to the Suitable Location Position (Exploitation)

The osprey carries a fish it has caught to a good location where it will consume it. Based on a simulation of this real behavior, the second stage of updating the population in the OOA was modeled. The osprey's position in the search space was created by small changes caused by modeling the carrying of the fish to the proper position, which increased the OOA's exploitation power in the local search and caused convergence towards better solutions close to the discovered solutions. In the OOA design, a new random position was initially determined for each member of the population as a "suitable position for eating fish" using Equation (15). This simulated the natural behavior of ospreys.

Then, per Equation (16), it replaced the former location of the related element if the value of the objective function was enhanced in this new position.

$$\begin{gathered}\mathrm{x_{i,j}^{P2}} = \mathrm{x_{i,j}} + \frac{\mathrm{lb_j} + \mathrm{r}\cdot(\mathrm{ub_j} - \mathrm{lb_j})}{\mathrm{t}}, \mathrm{i} = 1,2,\ldots,\mathrm{N}, \mathrm{j} = 1,2,\ldots,\mathrm{m}, \mathrm{t} = 1,2,\ldots,\mathrm{T},\\ \mathrm{x_{i,j}^{P2}} = \begin{cases}\mathrm{x_{i,j}^{P2}}, \mathrm{lb_j} \le \mathrm{x_{i,j}^{P2}} \le \mathrm{ub_j};\\ \mathrm{lb_j}, \mathrm{x_{i,j}^{P2}} < \mathrm{lb_j};\\ \mathrm{ub_j}, \mathrm{x_{i,j}^{P2}} > \mathrm{ub_j},\end{cases}\end{gathered} \tag{15}$$

$$\mathrm{X_i} = \begin{cases}\mathrm{X_i^{P2}}, \mathrm{F_i^{P2}} < \mathrm{F_i};\\ \mathrm{X_i}, \mathrm{else},\end{cases} \tag{16}$$

where X_i^{P2} is the *i*th osprey new position based on the second phase of the OOA, $x_{i,j}^{P2}$ is the *j*th dimension, F_i^{P2} is its fitness function, $r_{i,j}$ are random numbers in the interval $[0,1]$, t is the iteration counter of the method, and T is the total number of iterations.

3.3. Repetition Process, Flowchart, and Pseudocode of OOA

The first iteration of the planned OOA was finished by revising all of the ospreys' positions according to the first and second stages. The best candidate solution was then modified based on a comparison of the values of the objective function. The algorithm then moved on to the following iteration with the revised osprey placements, and so forth until the last iteration based on Equations (12)–(16). The best candidate solution saved during the iterations is finally presented as a solution to the problem after the algorithm was fully implemented. The chart in Figure 1 and accompanying pseudocode in Algorithm 1 [52] show the OOA implementation processes.

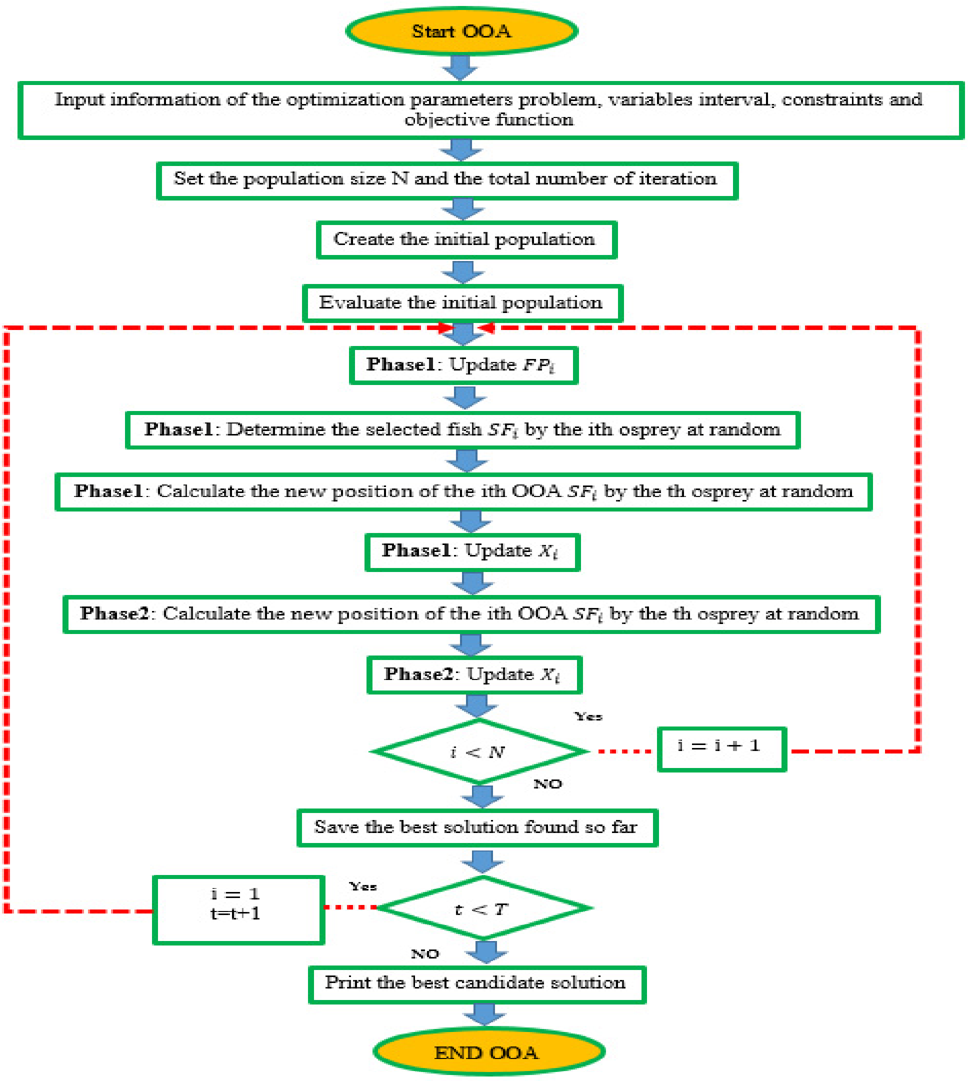

Figure 1. Flow chart of OOA method.

4. Analysis and Discussion of Results

The OOA performance for the two issues of ELD and CEED is presented. The proposed OOA method was compared with the tunicate swarm algorithm (TSA) [53], the RIME [54], the SMA [55] and elephant herding optimization (EHO) [56]. The ELD problem was first applied as a case study for 6 units at three load demand values (700, 1000, and 1200 MW). The CEED problem was applied as a second case study for 6 units at three load demand values (700, 1000, and 1200 MW). The general setting for all techniques is illustrated in Table 2.

Table 2. Parameters setting of each method.

Algorithms	Parameter Setting
General setting	No. of iterations = 1000 Decision parameters = 6 Population size = 30
OOA	ri,j are random numbers in the interval [0, 1], Ii,j are random numbers from the set {1, 2}
RIME	r1, and r3 are random numbers within (−1, 1) r2 is a random number in the range (0, 1)
EHO	alpha = 0.5, beta = 0.1
SMA	Z = 0.03
TSA	Pmin = 1 and Pmax = 4

4.1. Results of ELD Issue

A case study of 6 units at three load demand levels is presented in analysis of the ELD problem. Several algorithms were applied to this problem, such as the OOA, TSA, RIME, SMA, and EHO. Thirty independent runs were applied to measure the performance of all of the competitor methods. Based on these runs, the minimum, standard deviation, mean, and maximum values were recorded as statistical data at each level of load as seen in Table 3. Based on this data, the OOA achieves the best standard deviation and the best objective function. So, the most accurate and reliable algorithm for ELD is the OOA. Table 4 illustrates the best cost of consumption fuel for all cases. Table 5 depicts the best-generated power from each unit at a 700 MW load demand based on the best fitness function for all algorithms. Table 6 shows the best-generated power from each unit at a 1000 MW load demand based on the best fitness function for all algorithms. Table 7 demonstrates the best-generated power from each unit at a 1200 MW load demand based on the best fitness function for all algorithms. Based on the recorded results from all methods among the 30 runs, the robustness curve characterizes the value of the objective function among each run. Figures 2–4 showcase the characteristics of the robustness curve for all levels of the load demand. Based on the recorded results from all of the methods among the best runs out of the 30 that achieve the best fitness function, the convergence curve characterizes the fastest method that reaches the objective function. Figures 5–7 depict the characteristics of the convergence curve for all levels of load demand. Based on the robustness and convergence characteristics, the OOA achieves the optimum global solution.

Table 3. Statistical data for ELD using all algorithms ($ per hour).

Demand (MW)	Algorithm	Min	SD	Mean	Max
700	OOA	8489.71013	5,076,187.167	935,505.3799	27,812,146.81
	RIME	157,119.6598	56,610,134.62	52,654,562.24	190,938,550.9
	EHO	323,503.0771	164,951,021.9	157,742,034.9	830,026,118.4
	SMA	8502.406541	898.1936009	9689.146486	12,698.30255
	TSA	161,424.5504	1.25×10^7	11,045,846.26	43,283,357.63
1000	OOA	12,145.56118	147.1792166	12,328.60609	12,769.69945
	RIME	43,804.62747	45,918,517.41	44,117,668.43	159,925,064.1
	EHO	1,385,818.233	43,729,545	39,739,552.31	160,205,265
	SMA	12,310.85263	3167.418523	13,720.89249	29,123.65877
	TSA	338,416.1136	1.49×10^7	14,797,087.09	70,710,421.98
1200	OOA	14,844.17028	106,377.3814	34,559.66353	597,774.5881
	RIME	647,657.0993	111,021,190.9	76,380,860.23	557,699,468.3
	EHO	66,594,721.86	2,050,678,201	2,246,833,875	8,220,483,497
	SMA	14,960.25669	2462.012063	16,065.99129	27,329.59533
	TSA	1,040,954.65	21,439,850.48	23,898,498.47	65,710,037.14

Table 4. Minimum fuel consumption costs for ELD ($ per hour).

Algorithm	700 MW	1000 MW	1200 MW
OOA	8489.71013	12,145.56118	14,844.17028
RIME	8930.126895	12,220.14976	14,929.15938
EHO	9201.247567	13,577.96384	17,159.01262
SMA	8502.406541	12,269.08288	14,890.22354
TSA	8719.411543	12,324.03706	15,043.25053

Table 5. The generated power (MW) from each unit for ELD at 700 MW load demand.

OOA	RIME	EHO	SMA	TSA
288.1936492	100	74.27685394	291.9724948	179.5604411
71.24189189	97.67174678	96.60780328	95.58202252	68.62630472
94.19305375	172.6253448	108.0508678	96.94958415	120.8437852
77.62559738	134.7024241	128.464386	66.84420361	133.2068048
101.6542888	112.6905922	151.8904691	97.50539107	161.4281797
78.76324794	96.46689215	153.8266087	62.48476668	50

Table 6. The generated power (MW) from each unit for ELD at 1000 MW load demand.

OOA	RIME	EHO	SMA	TSA
400.5765793	416.3680247	89.88251423	413.3002088	499.1064857
184.3641601	58.65210153	115.9348269	199.8242953	56.13947257
198.9629992	247.8243991	136.9111861	186.8499139	144.1194586
60.51914068	107.9181452	145.4592182	51.97368989	138.9537992
124.4995504	95.19702846	208.9981201	50.99369441	114.1379038
54.35074684	98.1158557	327.7323289	119.9990952	70.12055135

Table 7. The generated power (MW) from each unit for ELD at 1200 MW load demand.

OOA	RIME	EHO	SMA	TSA
468.1992937	500	76.71759497	415.970695	500
183.9250281	90.28209597	113.5295062	168.0667693	190.1559272
248.0430036	247.1131882	179.1731727	298.2491761	122.6292221
97.982237	123.8746742	181.4297643	104.1223325	128.515068
169.116858	157.7756826	192.5547606	199.9999955	173.3199231
67.2444517	115.9580053	491.0321006	50.06577066	120

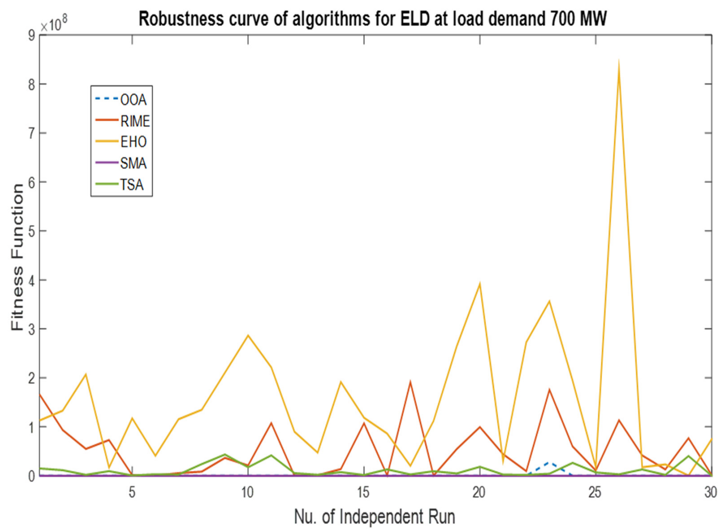

Figure 2. Robustness curves of all methods for ELD at 700 MW load demand.

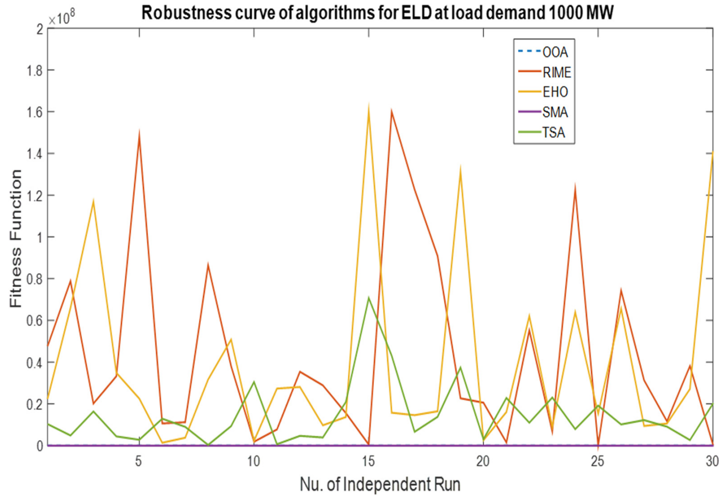

Figure 3. Robustness curves of all methods for ELD at 1000 MW load demand.

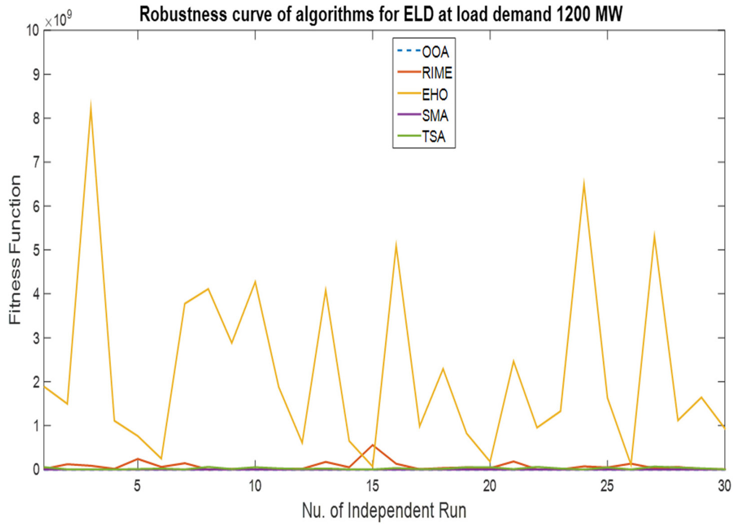

Figure 4. Robustness curves of all methods for ELD at 1200 MW load demand.

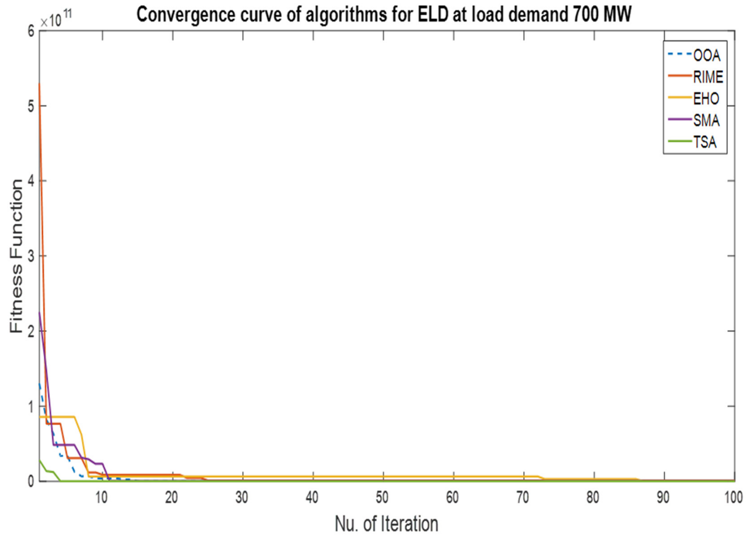

Figure 5. Convergence curves for all methods for ELD at 700 MW load demand.

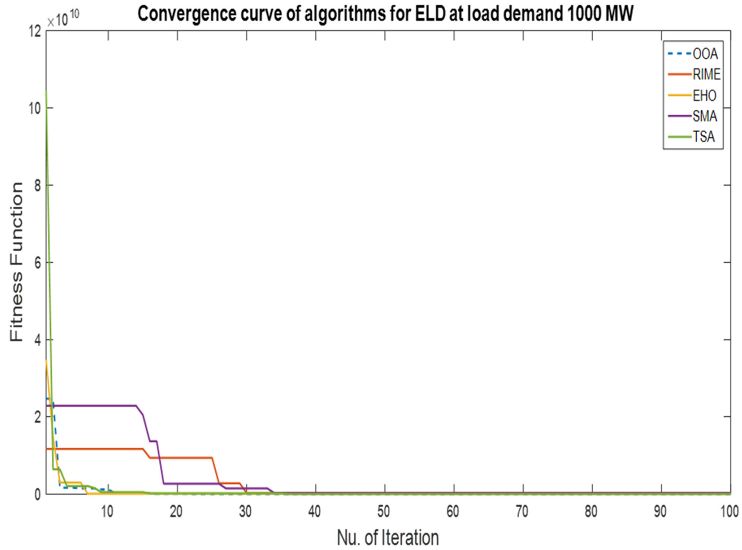

Figure 6. Convergence curves for all methods for ELD at 1000 MW load demand.

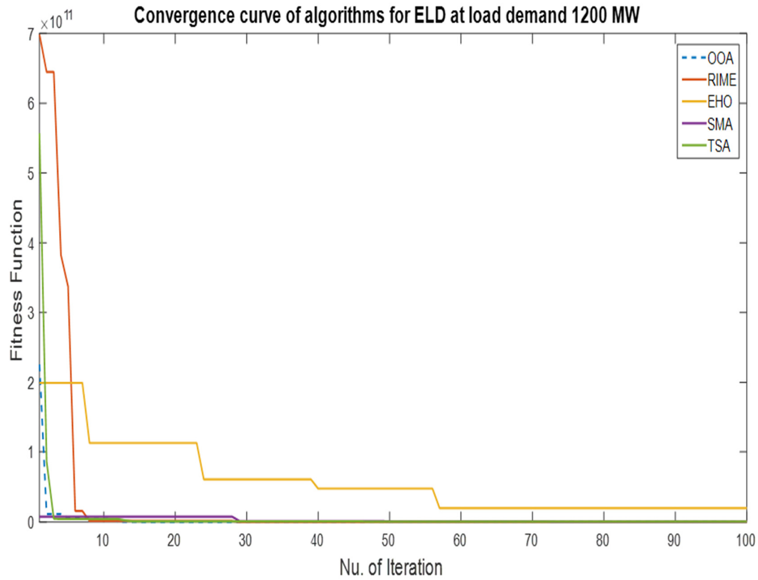

Figure 7. Convergence curves for all methods for ELD at 1200 MW load demand.

4.2. Results of CEED Problem

A case study of 6 units at three load demand levels is presented to analyze the CEED problem. Several algorithms were applied to this problem, such as the OOA, TSA, RIME, SMA, and EHO. Thirty independent runs were applied to measure the performance of all of the competitor methods. Based on these runs, the minimum, standard deviation, mean, and maximum values were recorded as statistical data at each level of load as seen in Table 8. Based on this data, the OOA achieves the best standard deviation and the best objective function. So, the most accurate and reliable algorithm for ELD is the OOA. Table 9 illustrates the best cost of consumption fuel for all cases. Table 10 depicts the best-generated power from each unit at a 700 MW load demand based on the best fitness function for all algorithms. Table 11 shows the best-generated power from each unit at a 1000 MW load demand based on the best fitness function for all algorithms. Table 12 presents the best-generated power from each unit at a 1200 MW load demand based on the best fitness function for all algorithms. Based on the recorded results from all of the methods among the 30 runs, the robustness curve characterizes the value of the objective function among each run. Figures 8–10 depict the characteristics of the robustness curve for all levels of load demand. Based on the recorded results from all of the methods among the best runs from the 30 runs that achieve the best fitness function, the convergence curve characterizes the fastest method that reaches the objective function. Figures 11–13 display the characteristics of the convergence curve for all levels of load demand. Based on the robustness and convergence characteristics, the OOA achieves the optimum global solution.

Table 8. Statistical data for CEED using all algorithms ($ per hour).

Demand (MW)	Algorithm	Min	SD	Mean	Max
700	OOA	13,729.25276	451.5174275	14,516.06635	15,328.15021
	RIME	192,447.3458	208,328,375.9	124,827,189.5	1,026,320,992
	EHO	14,201,636.42	266,068,058.3	245,161,496.9	1,180,743,975
	SMA	13,902.65065	1346.302672	16,232.30745	20,837.35633
	TSA	437,640.1904	14,454,883.71	13,696,680.57	59,328,593.81
1000	OOA	21,615.36632	942.8912121	22,726.61646	24,636.02763
	RIME	1,716,313.573	62,284,621.82	55,672,191.78	295,816,509.5
	EHO	37,048.65857	40,394,801.02	39,978,221.4	128,249,578.6
	SMA	21,825.35037	2359.444736	24,422.15373	32,181.52154
	TSA	1,527,919.533	16,727,355.69	16,432,066.87	71,410,265.4
1200	OOA	27,973.14804	51,923.65941	38,269.17284	313,175.7045
	RIME	867,550.5025	64,850,599.89	64,743,277.09	222,328,197.6
	EHO	48,039,881.34	2,312,392,376	1,919,239,905	8,618,622,585
	SMA	28,405.56152	1902.826273	30,216.01233	36,613.94417
	TSA	231,004.4218	18,455,252.22	22,333,023.46	68,956,768.4

Table 9. Minimum fitness function for CEED ($ per hour).

Algorithm	700 MW		1000 MW		1200 MW	
	Fuel	Emission	Fuel	Emission	Fuel	Emission
OOA	8483.634452	5588.646691	12,161.84094	10,233.44274	14,866.11098	14,612.79425
RIME	8431.695806	5047.42326	12,307.94781	13,121.02468	14,861.21847	15,743.05095
EHO	9206.302521	10,616.02658	13,814.47332	27,920.96174	17,437.93278	50,362.10471
SMA	8507.728643	6105.614158	12,188.25965	9816.166095	14,862.5486	15,868.57055
TSA	8776.708178	7371.129746	12,381.47358	10,375.96202	14,920.81305	18,329.33556

Table 10. The generated power (MW) from each unit for CEED at 700 MW load demand.

OOA	RIME	EHO	SMA	TSA
269.767936	343.4755772	88.50987751	217.1592473	131.1911477
96.13075673	59.06883111	92.10828089	89.13670916	170.6718075
111.2458027	96.84808663	104.5033046	156.2882148	199.7174815
101.0842946	55.47194818	109.9641282	82.28373091	55.52645172
60.74111401	93.04112837	124.918835	96.78800842	72.68207485
72.43570158	63.01857975	192.5541969	70.63969799	83.47079715

Table 11. The generated power (MW) from each unit for CEED at 1000 MW load demand.

OOA	RIME	EHO	SMA	TSA
365.8570453	346.5147003	87.1819096	357.847752	483.0745935
158.5402394	50	102.8530268	167.9022744	131.8231399
189.5613645	266.824565	102.8581958	202.5030352	101.8290821
110.3792318	85.95375207	134.8791731	50	146.1161231
115.2493189	200	247.0179056	166.607947	59.26627522
84.29429492	77.67398741	350.2591399	79.834013	99.95671992

Table 12. The generated power (MW) from each unit for CEED at 1200 MW load demand.

OOA	RIME	EHO	SMA	TSA
449.6819234	494.9447771	52.0752919	494.283923	461.4678788
147.8653475	143.4837708	100.9132864	142.773607	104.8448432
243.9501883	278.0708989	131.3313064	270.2859306	300
99.5666135	107.0759198	177.0521457	135.9364431	100.5227517
195.2957655	155.8467164	290.5798172	139.9015771	149.014853
99.41554831	54.80297076	481.7029118	50.79427633	120

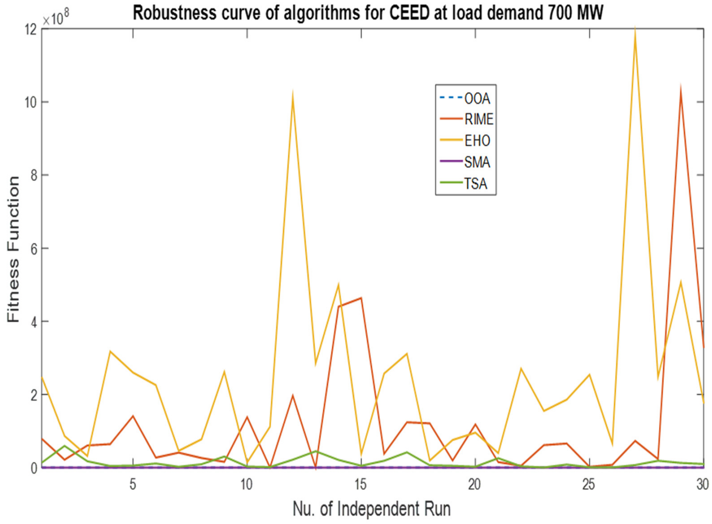

Figure 8. Robustness curves of all methods for CEED at 700 MW load demand.

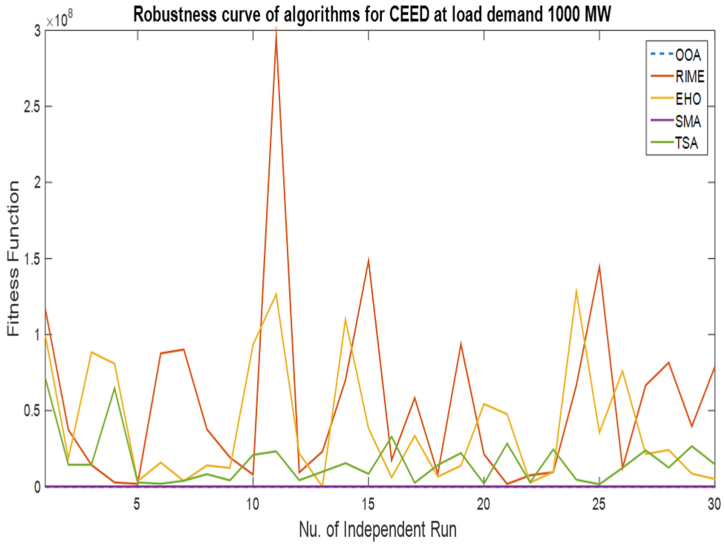

Figure 9. Robustness curves of all methods for CEED at 1000 MW load demand.

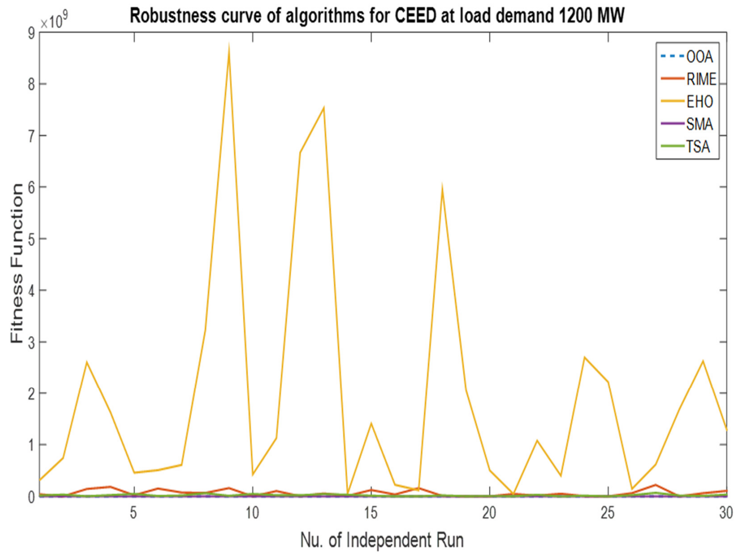

Figure 10. Robustness curves of all methods for CEED at 1200 MW load demand.

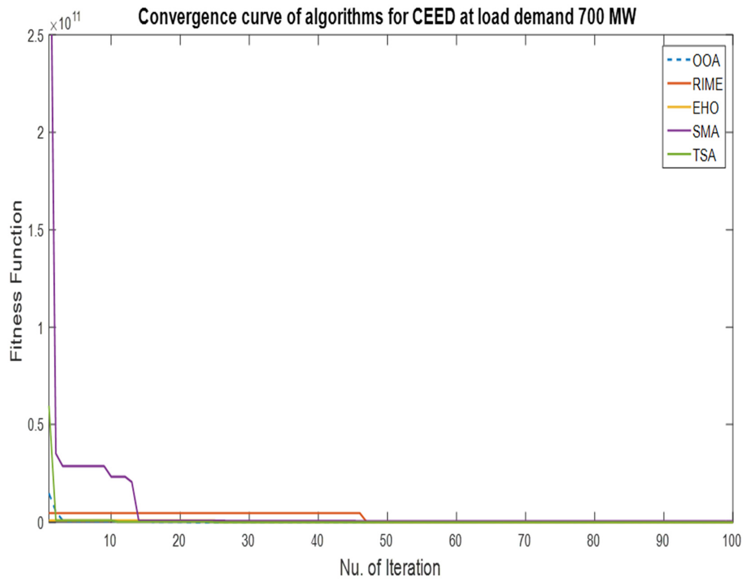

Figure 11. Convergence curves for all methods for CEED at 700 MW load demand.

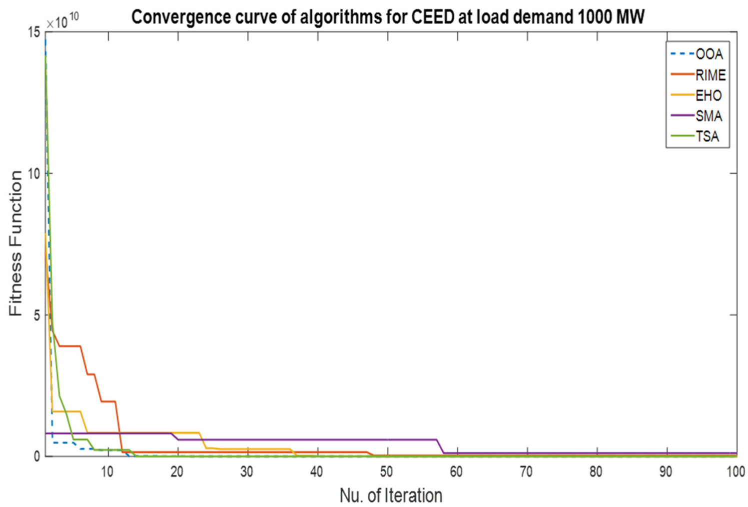

Figure 12. Convergence curves for all methods for CEED at 1000 MW load demand.

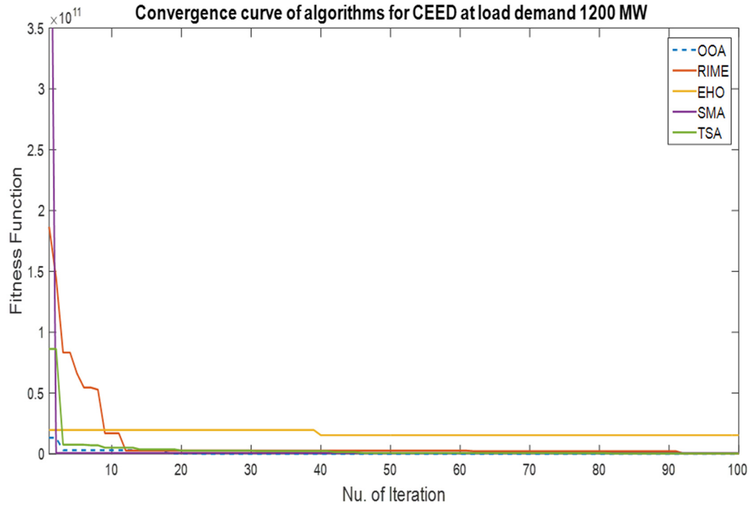

Figure 13. Convergence curves for all methods for CEED at 1200 MW load demand.

4.3. Discussion

The main item in ELD problems is called the value of power mismatch. This is the absolute error between the units' generated power and the summation of the demand and transmission losses. As the value of power mismatch tends towards zero, the method that extracts this value is the highest-performing technique. Table 13 contains the value of this factor for ELD and CEED. Also, the proposed OOA is matched with other techniques from the literature, such as the sine cosine algorithm, monarch butterfly optimization, an artificial bee colony, the moth search algorithm, and the chimp optimization algorithm in addition to the five methods used during the runs. Based on this data, the OOA technique achieves the best power mismatch value in all cases. The Friedman test is a statistical test used to decide the best algorithm for solving a problem. The results of the Friedman rank test are shown in Figure 14. It is observed that OOA obtains the best rank, followed by SMA then RIME, TSA, and EHO.

Table 13. The value of ELD and CEED power mismatch.

Cases	Method	700 MW	1000 MW	1200 MW
ELD	OOA	7.64×10^{-13}	7.50×10^{-13}	4.26×10^{-13}
	RIME	1.48×10^{-5}	3.16×10^{-6}	6.33×10^{-5}
	EHO	2.239431602	9.904979361	20.33855573
	SMA	5.61×10^{-9}	4.18×10^{-9}	7.00×10^{-9}
	TSA	1.53×10^{-5}	3.26×10^{-5}	0.000102591
	SCA [11]	0.00076719	0.000182	0.00154
	MBO [11]	2.338728225	20.33553784	13.5932468
	ABC [11]	8.85×10^{-5}	0.000172518	0.000464669
	MSA [11]	8.164408631	16.26317	22.86726197
	ChOA [11]	0.000284475	0.000476787	1.28×10^{-5}
CEED	OOA	1.10×10^{-13}	1.07×10^{-13}	9.32×10^{-10}
	RIME	1.79×10^{-5}	0.000169392	8.39×10^{-5}
	EHO	2.939436145	11.67444458	23.59139609
	SMA	2.52×10^{-8}	5.57×10^{-9}	2.29×10^{-8}
	TSA	4.23×10^{-5}	0.000150503	2.03×10^{-5}
	SCA [11]	0.000128581	0.001259941	0.00153618
	MBO [11]	2.224948582	18.75789013	19.58822153
	ABC [11]	0.000176679	3.74×10^{-5}	0.000402522
	MSA [11]	7.228241532	12.18295414	23.26274643
	ChOA [11]	0.000284475	0.000476787	6.47×10^{-5}

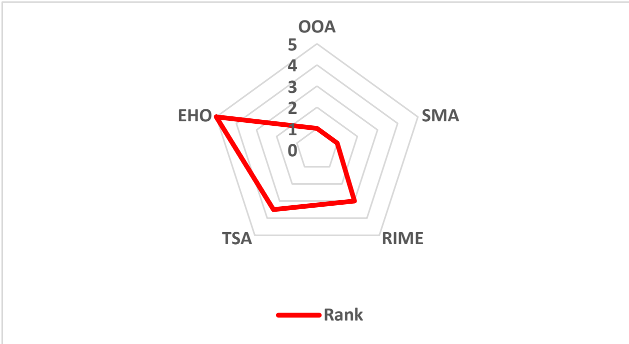

Figure 14. Friedman rank test for all methods.

5. Conclusions

A brand new metaheuristic algorithm called the osprey optimization algorithm (OOA) imitates the way ospreys seek fish in the ocean in nature. To optimize 29 common benchmark functions from the CEC 2017 test suite, the OOA was assessed. Additionally, the effectiveness of the OOA was contrasted with the effectiveness of twelve algorithms. In this study, economic load dispatch (ELD), a crucial issue, is resolved using the OOA. ELD specifically comes in two varieties: (1) the minimization of fuel consumption costs (also known as ELD); and (2) the minimization of fuel consumption costs and emissions costs (also known as Combined Emission and Economic Dispatch, or CEED). The goal of the OOA is to maximize the economic value of the power system while minimizing the cost of fuel use, which is the main concern with optimizing the ELD problem. The primary variable in the ELD problem reflects the unit-specific allocation vector that determines the best output for each system unit. The performance of the OOA was compared to several algorithms, such as the slime mould algorithm (SMA), the rime-ice algorithm (RIME), the tunicate swarm algorithm (TSA), and elephant herding optimization (EHO). Ultimately, the findings supported the OOA's effectiveness in cutting the cost of fuel for ELD and the cost of fuel and emissions for CEED in comparison to the alternatives. Future applications of the OOA method include resolving other large-scale, practical optimization issues related to power systems and photovoltaic energy.

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Conflicts of Interest: The authors declare that there are no conflict of interest.

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