Optimal renewable-integrated economic load dispatch for a large-scale power system using One-to-One Optimization Algorithm

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Abstract. *This study presents the application of a new meta-heuristic algorithm called the One-to-One optimization algorithm (OOBO) for solving the renewable-integrated economic load dispatch problem (RI-ELD) with consideration of both wind and solar power plants. The whole study focuses on minimizing the overall expenditure of fuel (OEF) for all thermal electric power plants (TEPPs). The considered power system consists of twenty TEPPs with different working limits. OOBO is applied to solve the given problem in three cases of load demand level, including 2500, 2600, and 2700 MW. The results achieved by OOBO in the three cases are compared with other meta-heuristic algorithms called Coati optimization algorithm (COA) in the four aspects, such as Best OEF (Bst. OEF), Average OEF (Aver. OEF), Maximum OEF (Max. OEF). OOBO not only outperforms COA in all comparison aspects but also provides faster convergence speed to the optimal values of OEF at all three cases of load demand. Moreover, OOBO shows its surprising stability over COA regardless of the increase in load demand in Cases 2 and 3. By observing these results, OOBO deserved the highly effective search tool for solving the large-scale and highly complex RI-ELD problem.*

Keywords: Economic load dispatch, Renewable energy, Thermal electric power plants, Coati optimization algorithm, One-to-One optimization algorithm, Load demand.

1. Introduction

Solving the economic load dispatch problem (ELD) is one of the first priorities in operating the power system [1]. The process of solving the ELD is to optimize the allocation of power generation for each thermal electric power plant (TEPP) to meet the load demand with a minimum overall expenditure of fuel (OEF) and fulfill the involved constraints [2]. In the past, TEPP was the unique generating source while solving the ELD problem. However, the working process of these TEPPs has eliminated a large amount of toxic emissions that strongly destroy both human health and the environment. In these circumstances, the integration of different renewable generating sources (RGSs), such as wind and solar, has become an affordable solution to benefit both the environmental and economic aspects. The consideration of RGSs in solving the ELD problem is called the renewable integrated–economic load dispatch problem (RI-ELD).

Deriving from the ELD, RI-ELD is considered a large-scale and highly complicated optimization problem, especially in the power system with many TEPPs accompanied by different non-linear constraints. In such a scale, applying the former approaches, such as Gauss-Siedel [3] and Jacobian [4], is impractical to find a complete optimal solution. Luckily, different smart computing methods were developed in the past two decades. These methods could be divided into two groups, including human brain-based methods and heuristic methods. One of the most well-known representations of the first group is artificial neural networks (ANNs). Soon, there were many other methods derived from the principle of ANNs, such as artificial neural network (ANN)-balancing composite motion optimization (BCMO) [5], which proved to be more effective than other common optimization algorithms. On the other hand, heuristic methods are also developed based on natural phenomena, physics laws, animal living practices, wildlife, etc. Soon, heuristic methods rapidly evolved and are often known as meta-heuristic algorithms. These methods have witnessed an enormous leap forward in terms of effectiveness while solving large-scale and highly complicated optimization problems in both engineering and economics, and RI-ELD is one of them. A considerable number of researches implemented a different meta-heuristic method to successfully solve the ELD and RI-ELD problem, such as the multi-objective multi-verse optimization (MOMVO) [6], Firework algorithm (FWA) [7], Adaptive cuckoo search algorithm (ACSA) [8], Grasshopper optimization algorithm (GOA) [9], one rank cuckoo search algorithm (ORCSA) [10], chaotic teaching–learning-based optimization with Lévy flight (CTLBO) [11], adaptive simulated annealing (ASA) [12], Modified harmony search algorithm (MHSA) [13], Whale optimization algorithm (WOA) [14], tunicate Swarm Optimizer (TSO) [15], interior search algorithm (ISA) [16], differentia evolution immunized ant colony optimization (DEIANT) [17], JAYA algorithm (YA) [18], moth-flame optimization algorithm (MFO) [19], Real-Coded Elitism Genetic Algorithm (RCEGA) [20], slime mould algorithm (SMA) [21], equilibrium optimizer (EO) [22], Turbulent Flow of Water Optimization (TFWO) [23], firefly algorithm (FA) [24], Chaotic whale optimization algorithm (CWOA) [25].

By fully acknowledging the enormous benefits of using meta-heuristic algorithms for solving different optimization problems in previous studies, we decided to apply to novel meta-heuristic algorithms, including coati optimization algorithms (COA) [26] and One-to-One Based Optimizer (OOBO) [27] to determine the optimal solution of to the RI-ELD problem with the consideration of wind power plant (WP) and solar power plant (SP). COA is a nature-inspired optimization problem proposed based on the hunting practices of the coati, while OOBO is built based on the mechanism of exchanging knowledge in a population.

The motivation for selecting COA and OOBO is decided based on different evaluations, as follows:

1. COA and OOBO are the new meta-heuristic algorithms proposed in 2023. These algorithms are the subsequent development of the meta-heuristic algorithms family to solve complex and nonlinear optimization problems.

2. COA and OOBO have been tested by a wide range of benchmark functions, including the optimal design problems in practice. The results from the tests have demonstrated their high effectiveness over the previous meta-heuristic methods such as the Marine predator algorithm (MPA), Tunicate swarm algorithm (TSA), Whale optimization algorithm (WOA), Particle swarm optimization (PSO), Genetic algorithm (GA), etc. [26, 27].

3. Besides their effectiveness in terms of finding the more promising solution in various tests, the update mechanism for the new solution of COA and OOBO has significantly

reduced time response, as investigated in [26], and computer resources, which are often represented by the number of population and maximum iteration for reaching the best fitness values [27].

The novelties and the critical contributions of the whole study are as follows:

- Apply two novel optimization algorithms for solving the most crucial problem in the power system, which is the RI-ELD problem.

- Determine the most affordable method, which is OOBO, for dealing with the RI-ELD problem by using different comparison aspects.

- Both wind and solar power plants are successfully employed in the process of finding the best solution to the RI-ELD problem.

- Proposed a template for integrating different renewable energy sources in power system operation to mitigate the environmental problems that are on high alert today.

2. Problem Formulation

2.1. Objective function

This study aims to minimize the overall expense of fuel (OEF) of all the thermal electric power plants (TEPPs). The OEF of each TEPP in the considered power system is described as follows:

$$\begin{aligned}\text{Minimize OEF} = \sum_{j=1}^{N_{\text{TEPP}}} & \sigma_j + \tau_j PG_{\text{TEPP,j}} \\ & + \varphi_j PG^2_{\text{TEPP,j}}\end{aligned} \tag{1}$$

where OEF is the overall expense of fuel of all the TEPPs; σ_j, τ_j, and φ_j are the fuel utilizing factors of TEPP j; $PG_{\text{TEPP,j}}$ is the power output generated by the TEPP j; and N_{TEPP} is the number of TEPP in the considered power system.

2.2. Constraints

The power balance constraints between the generating end and the receiving end: This constraint infers that total power produced by all types of generating sources at the generating side must equal the total power required by load demand plus the loss in transmission lines:

$$\sum_{j=1}^{N_{\text{TEPP}}} PG_{\text{TEPP,j}} + PG_{\text{WP}} + PG_{\text{SP}} = P_{\text{LP}} + P_{\text{LS}} \tag{2}$$

where $\sum_{j=1}^{N_{\text{TEPP}}} PG_{\text{TEPP,j}}$ is the overall power output generated by all TEPPs in the system; PG_{WP} and PG_{SP} are, respectively, the power generated by WP and SP connected with the power system; P_{LP} and P_{LP} are, respectively, the power consumed by the load and the power loss in the transmission line.

The power loss in Equation 2 is determined using the following expression:

$$\begin{aligned}P_{\text{LS}} = & \sum_{j=1}^{N_{\text{TEPP}}} \sum_{k=1,k\neq j}^{N_{\text{TEPP}}} P_{\text{TEPP,j}} B_{j,k} PG_{\text{TEPP,k}} \\ & + \sum_{j=1}^{N_{\text{TEPP}}} B_{0j} PG_{\text{TEPP,j}} + B_{00}\end{aligned} \tag{3}$$

where $B_{j,k}$, B_{0j}, and $B_0 0$ are the loss factors.

The working limit of TEPPs: This constraint means that the power generated by each TEPP in the system can vary within its working limits between the lowest and highest boundaries of generation. Any violation of these limits will cause the unstable status of the whole system:

$$\mathrm{PG}^{\mathrm{lw}}_{\mathrm{TEPP,j}} \le \mathrm{PG}_{\mathrm{TEPP,j}} \le \mathrm{PG}^{\mathrm{hg}}_{\mathrm{TEPP,j}} \tag{4}$$

where $\mathrm{PG}^{\mathrm{lw}}_{\mathrm{TEPP,j}}$ and $\mathrm{PG}^{\mathrm{hg}}_{\mathrm{TEPP,j}}$ are the lowest and highest values of power generated by TEPP j, $\mathrm{PG}_{\mathrm{TEPP,j}}$ is power produced by TEPP j.

The working limit of WP and SP: Similar to TEPPs, both WPs and SPs only generate power within the lowest and the highest range as follows:

$$PG^{lw}_{GW} \le PG_{GW} \le PG^{hg}_{GW} \tag{5}$$

$$PG^{lw}_{SW} \le PG_{SW} \le PG^{hg}_{SW} \tag{6}$$

where PG_{GW}^{lw} and PG_{GW}^{hg} are the lowest and the highest power generated by WP, PG_{SW}^{lw} and # are the lowest and the highest power generated by SP, PG_{GW} and PG_{SW} are, respectively, the power generated by the WP and SP.

3. Solution Methodology

3.1. The Coati optimization algorithm

The Coati optimization algorithm (COA) is the nature-inspired optimization algorithm based on the hunting practices of the coati species in wildlife. The update process for new solutions of COA is completed in two phases as follows:

• **Phase 1**: The new solutions are produced using the following expressions:

$$C_i^{new,p1} = \begin{cases} C_i + mf_1 \times (Pt + mf_2 + C_i) & \text{if} \quad i < 0.5N_p \\ C_i + mf_1 \times (Pg + mf_2 + C_i) & \text{if} \quad Ft_{Pg} < Ft_{C_i}, i > 0.5N_p \\ C_i + mf_1 \times (C_i - Pg) & \text{if} \quad \text{otherwise} \end{cases} \tag{7}$$

where $C_i^{new,p1}$ is the new position of the coati i in population in phase 1; C_i is the current position of the coati I in the search space; mf_1 and mf_2 are the magnifying factors, and their values are between 0 and 1 for mf_1 and between 1 and 2 for mf_2. Pt and Pg are, respectively, the positions of the prey on the tree and on the ground; and N_P is the population number.

• **Phase 2**:: The new solutions in Phase 1 are continuously updated in Phase 2 as follows:

$$C_i^{new,p2} = C_i + (1 - 2mf_1) \times \left(Bnd_i^{lw} + mf_1 \times Bnd_i^{hg} - Bnd_i^{lw}\right) \text{ with } \mathrm{i} = 1, 2, ...\mathrm{N_p} \tag{8}$$

where $C_i^{new,p2}$ is the new position of the coat i in Phase 2; Bnd_i^{lw} and Bnd_i^{hg} are the lowest and highest boundaries of the new position in the search space.

3.2. The One-to-One Based Optimizer

Unlike COA, the One-to-One Based optimization algorithm (OOBO) is proposed based on the utilization of the diversification in the population. The advanced characteristic of this implementation is to avoid the reliance on only one individual throughout the updated process. In short, the updated model of the algorithm for new solutions is presented as follows:

$$O_i^{new} = \begin{cases} O_i + Rd \times (O_k - af \times O_i) & \mathrm{if Ft_k < Ft_i} \\ O_i + Rd \times (O_i - O_k) & \text{otherwise} \end{cases} \tag{9}$$

with

$$O_k = [O_{k1}, O_{k2}, ...O_{kN}] \quad \text{with N = N\_p} \tag{10}$$

and

$$af = round\,(1 + Rd) \tag{11}$$

where O_i^{new} is the new solution i of the population; O_i is the current solution; Rd is the random value between 0 and 1; O_k is the random solution picked up from the navigating group; af is the amplifying factor; Ft_k and Ft_i are, respectively, the fitness value of the navigating solution and the considered solution.

3.3. The discussion of using random factors in the update process of COA and OOBO

Note that the implementation of the magnifying factors plays a significant role and directly affects the quality of the newly updated solution. As a result, the higher the quality of newly updated solutions, the more effective the search process will be. The so-called effective meta-heuristic algorithm must balance the exploration and exploitation phases while solving the optimization problems. Mainly, exploration represents the capability of searching for new solutions in unexplored areas inside the search space, while exploitation aims to refine and enhance current solutions found by the algorithm. However, both exploitation and exploitation must be controlled by an affordable technique because the overuse of one phase between the two will significantly affect the overall performance of a meta-heuristic algorithm.

The popular implementation of improving the balance for the two phases is using the random factors or the amplifier, which could be named under different titles but share the same function. In particular, the exploration phase of the COA and OOBO is controlled by mf_2 and af. In contrast, the exploitation phase of the two applied methods is manipulated by mf_1 and rnd, respectively. The proper use of these factors reduces the possibility that the whole searching process gets trapped in the local optima, resulting in a non-competitive solution compared to other previous methods. Moreover, the optimal selection of the mentioned factors also provides a high capability to scan for optimal solutions while dealing with multi-dimension optimization problems with many local optima and a wide range of complicated constraints that must be satisfied before the legal optimal solution is achieved.

4. Results and Discussion

In this section, COA and OOBO are applied to solve the renewable integrated-economic load dispatch (RI-ELD) with different cases of load demand from 2500, 2600, and 2700 MW. The selected power system consists of twenty TEPPs with different constraints of power generation [9]. The main objective function of the whole study is to minimize the OEF as much as possible. On the other hand, a WP and an SP with a rated power generation of 100 and 50 MW are integrated with the power system in all cases of load demand levels. For a fair evaluation of the real performance of the two applied algorithms, the initial control parameters, such as population number (Np) and maximum iteration index (MImax), are fairly set by 50 and 100, respectively. Moreover, the two applied methods will be operated in 50 trial runs for the best values of the main objective function.

All coding and related simulation for the study is performed in a computer with 2.4 GHz of the central processing unit (CPU) clock speed and 4GB of Random accessing memory (RAM). MATLAB software version R2018a is utilized for the main platform to carry out the implementation of two applied methods.

Figure 1 shows the best convergences of the two applied methods among 50 trial runs. OOBO always reaches the best optimal value at the end of the optimizing process, regardless of the increase in load demand levels from Case 1 to Case 3. In the meantime, all the OEF values reached by COA in the same cases are all the local ones and cannot considered as the optimal value for the considered problem. Figure 2 describes the results achieved by both COA and OOBO after 50 trial runs in three cases of load demand. It is easy to observe that, in three load demands cases, OOBO outperformed COA by reaching a more optimal value of the OEF, while COA cannot provide the same capability. Specifically, all the OEF values achieved by COA in the three cases are extremely far from the optimal one. The observation on the average

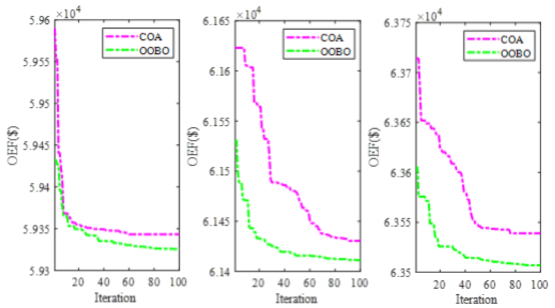

Fig. 1: The best convergences achieved by COA and OOBO among 50 trial runs

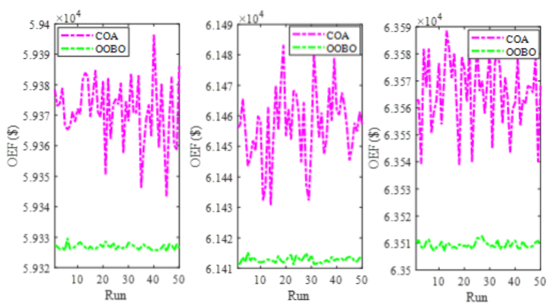

Fig. 2: The results achieved by COA and OOBO after 50 trial runs

convergences and the maximum convergences in Figure 3 and Figure 4 are continuously the superiority of OOBO over COA. Notably, in both Figure 3 and Figure 4, OOBO always results in better values in terms of Mean OEF and Maximum OEF at the end of the optimizing process. Where the values of Mean OEF and Maximum OEF reached by COA are vividly larger than the similar ones found by OOBO. Figure 5 shows the detailed comparison between COA and OOBO in different aspects of the first case where load demand 2500 MW is employed, including Best OEF (Bst.OEF), Average OEF (Aver.OEF), Maximum OEF (Max.OEF), and standard deviation (Std). OOBO outperforms COA in the four mentioned aspects. Particularly, OOBO not only reaches the best value of Bst.OEF, but also given the surprising stability degree. Specifically, the results obtained by OOBO in these aspects are \$59325.4 for the Bst.OEF and 0.907 for Std, while the similar values achieved by COA are \$59343.333 and up to 10.53 for Std. By converting into percentages, OOBO is better than COA 0.05% for the Bst.OEF, 0.09% for the Aver.OEF, 0.12% for the Max.OEF and 89.87% for the Std. Next, the investigation of the performance of the COA and OOBO with the two remaining levels of load demand are described in Figure 6 and Figure 7, respectively. OOBO continuously shows its superiority over COA regardless of the increase of load demand in these two cases from 2600 to 2700 MW. Particularly, for the case of load demand 2600MW, the superiority of OOBO over COA measured in percentages is 0.032% for the Bst.OEF, 0.071% for the Aver. OEF, 0.11% for the Max.OEF, and 91,71 for Std, respectively. While load demand level 2700 MW is employed, the similar percentages of the four comparison aspects are 0.03%, 0.075%, 0.11%, and 91,39%.

Note that, the optimal solutions achieved by COA and OOBO in the three cases of load de-

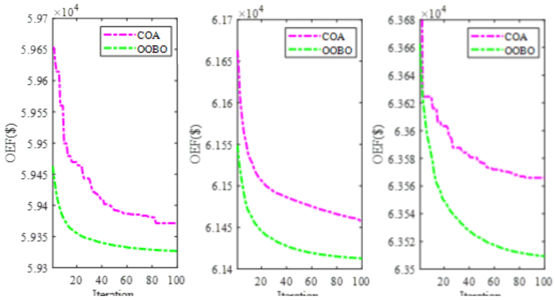

Fig. 3: The average convergences achieved by COA and OOBO among 50 trial runs

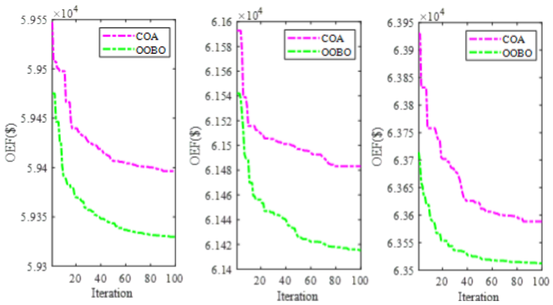

Fig. 4: The maximum convergences achieved by COA and OOBO among 50 trial runs

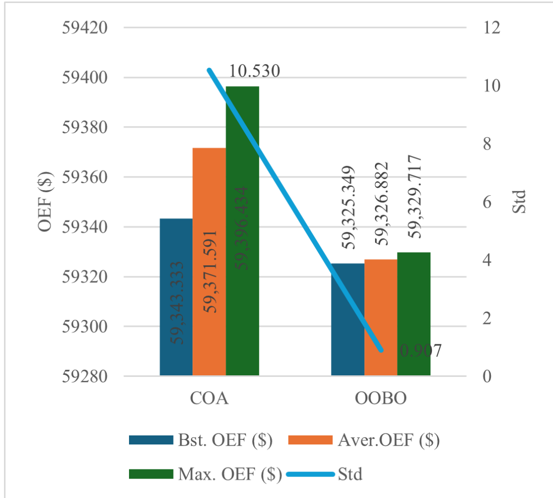

Fig. 5: The comparison between COA and OOBO on different criteria in Case 1

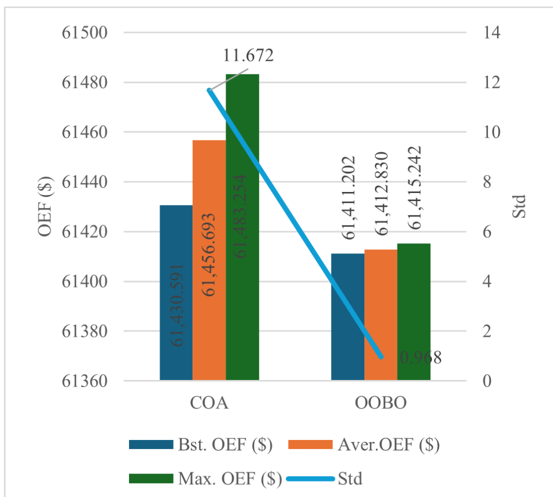

Fig. 6: The comparison between COA and OOBO on different criteria in Case 2

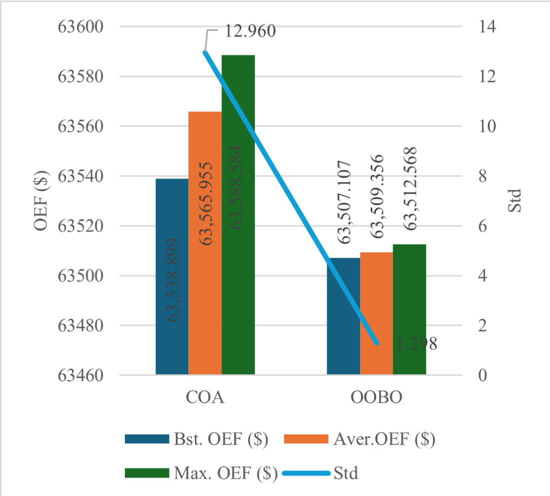

Fig. 7: The comparison between COA and OOBO on different criteria in Case 3

mand levels are reported in the Table A1 of the Appendix.

For a better demonstration of OOBO's performance, the results achieved by the algorithm have been compared to other previous methods, including the Tunicate Swarm algorithm (TSA) [28], the Whale Optimization Algorithm (WOA) [29], and the Marine Predator Algorithm (MPA) [30]. Besides, these algorithms are also tested by various optimization problems by the authors while developing the new OOBO. Note that all the initial parameters for the tested algorithms in terms of population number (Np) and maximum iteration index (MImax) are equally set, similar to OOBO, as mentioned earlier.

Table 1 presents the results obtained by previous algorithms in Case 1 with a load demand of 2500 MW. In the table, the results achieved by OOBO are completely better than others in all criteria, especially in terms of the best value of the considered objective function (Bst. OEF) and time response (TR). Next, Tables 2 and 3 describe the comparison in Cases 2 and 3, while load demand levels are increased to 2600 MW and 2700 MW, respectively. Similar to the first case of load demand, OOBO still maintains its superiority over the previous methods, regardless of load demand increment. Specifically, OOBO is still the only method that offers the capability of finding the best OEF value with a small TR.

Tab. 1: The comparison on different criteria between OOBO and other algorithms in the Case 1.

Method	TSA	WOA	MPA	OOBO
Bst.OFE ($)	59326.99	59358.17	59325.37	59325.35
Aver.OEF ($)	59329.41	59389.33	59328.09	59326.88
Max.OEF ($)	59331.88	59423.87	59333.13	59329.72
Std	1.153	16.049	1.918	0.907
TR	1.392	0.576	0.954	0.175

Tab. 2: The comparison on different criteria between OOBO and other algorithms in the Case 2.

Method	TSA	WOA	MPA	OOBO
Bst.OFE ($)	61412.14	61441.39	61411.21	61411.2
Aver.OEF ($)	61415.4	61479.82	61414.65	61412.83
Max.OEF ($)	61418.32	61531.08	61419.25	61415.24
Std	1.43	19.714	2.109	0.968
TR	1.474	0.648	1.133	0.207

Tab. 3: The comparison on different criteria between OOBO and other algorithms in the Case 2.

Method	TSA	WOA	MPA	OOBO
Bst.OFE ($)	63509.41	63548.73	63507.54	63507.11
Aver.OEF ($)	63511.71	63586.55	63510.83	63509.36
Max.OEF ($)	63514.86	63646.98	63517.44	63512.57
Std	1.248	19.108	2.644	1.298
TR	1.526	0.708	1.6	0.238

5. Conclusions

In this study, both new meta-heuristic algorithms, including COA and OOBO, are successfully applied to solve the RI-ELD problem for the overall expense of fuel minimization considering both wind and solar power plants. Different load demand levels were employed, including 2500, 2600, and 2700 MW, to judge the real performance of the two applied methods. A comparison of the results shows that OOBO is completely superior to OOA in all comparison aspects, regardless of the increase in load demand levels in the three cases. The optimal results achieved by OOBO not only fulfill all the involved constraints but also reach the optimal value of the considered objective function. In the three cases of load demand levels, the results achieved by COA and OOBO are evaluated on the four aspects, including Bst. OEF, Aver. OEF, Max. OEF, and Std. Surprisingly, OOBO always reaches better values in all comparison aspects, although the scale of load demand is expanded in Case 2 and Case 3. For instance, the superiority of OOBO over COA over the four mentioned aspects in Case 1 are, respectively, 0.05% for the Bst. OEF, 0.09% for the Aver. OEF, 0.12% for the Max. OEF and 89.87% for the Std. The similar values in Case 2 are 0.03%, 0.075%, 0.11%, and 91.39%, respectively. Lastly, in Case 3, these percentages are 0.03%, 0.075%, 0.11%, and 91.39v. Moreover, OOBO also proves its superiority when compared to other previous methods, such as TSA, WOA, and MPA, especially in terms of finding the best OEF values with a short time response. Based on this evidence, OOBO deserves a highly effective search method, and we strongly suggest using OOBO to deal with large-scale and highly complex problems such as RI-ELD.

Appendix

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Tab. A1: The optimal solution achieved by COA and OOBO in the three cases of load demand levels.

TEPP no.	Case 1 (2500 MW)		Case 2 (2600 MW)		Case 3 (2700 MW)	
	COA	OOBO	COA	OOBO	COA	OOBO
TEPP 1 (MW)	396.757	395.380	421.027	416.119	419.647	424.266
TEPP 2 (MW)	124.022	147.212	146.201	155.979	164.630	177.049
TEPP 3 (MW)	108.402	115.243	131.315	121.992	125.032	129.143
TEPP 4 (MW)	89.790	96.275	116.248	104.053	114.756	107.049
TEPP 5 (MW)	124.591	102.361	121.288	112.633	103.259	113.375
TEPP 6 (MW)	54.402	66.830	37.953	71.618	71.508	75.346
TEPP7 (MW)	87.710	108.568	107.351	113.509	101.888	113.811
TEPP 8 (MW)	104.986	110.676	113.724	112.001	100.509	118.487
TEPP 9 (MW)	111.528	99.369	106.373	100.674	111.055	107.636
TEPP 10 (MW)	104.652	101.945	106.310	109.082	114.722	110.044
TEPP 11 (MW)	154.992	151.100	148.260	151.894	176.111	158.023
TEPP 12 (MW)	270.868	285.981	289.683	286.114	307.249	292.263
TEPP 13 (MW)	113.708	111.955	108.918	118.829	130.877	117.909
TEPP 14 (MW)	50.086	29.111	43.601	35.466	74.006	35.746
TEPP 15 (MW)	115.950	106.509	121.523	106.096	92.917	111.798
TEPP 16 (MW)	43.461	35.739	35.975	37.080	42.875	38.738
TEPP 17 (MW)	66.734	60.358	62.295	62.511	53.592	67.772
TEPP 18 (MW)	73.073	81.036	68.445	83.137	94.462	91.919
TEPP 19 (MW)	95.435	92.635	97.469	96.166	91.727	100.343
TEPP 20 (MW)	58.853	51.718	66.041	55.048	59.181	59.282

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