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Discovering solutions of economic load dispatch problem by war strategy optimization algorithm

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ABSTRACT

This paper suggested two methods, called war strategy optimization algorithm (WSO) and tunicate swarm algorithm (TSA), to find solutions for economic load dispatch problem (ELD). Various test systems with complex restrictions and discontinuous objective functions are used to assess the efficacy and resilience of the applied methods. The test cases are ranked from the simplest to the most complicated ones, in which the last with load demands are changed from the minimum power to the maximum power of total power of all units. The result comparison indicated that WSO can always reach the best cost for all test systems, but TSA cannot achieve similar values. Namely, WSO can reduced smaller cost than TSA by $ 0.565 and $ 121,325 for the first and second test systems, respectively. In comparison to other previous methods, the results found by WSO are equal to or better than those from others; however, the searchability of WSO is faster. Consequently, WSO is highly effective for handling ELD problem and can be considered for applying different problems in the engineering domain.

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1. INTRODUCTION

Energy resources, particularly power resources, become scarce and valuable because they are frequently and arbitrarily exploited and distributed, which causes massive resource waste and progressively disrupts societal life. In addition, energy consumption and the development of new technologies have always been significant obstacles to economic growth and life security. Therefore, using scarce resources and allocating large-scale power resources are sensibly and effectively crucial. In power systems, economic load dispatch (ELD), is vital. Currently, the best strategy for using power resources is to allocate large-scale power systems' economic load and dispatch them optimally. Thus, developing a practical economic dispatching strategy for a sizable model power system and finding efficient ways to reduce power resource waste is still a burning topic.

Until now, there are many prevalent methods for handling ELD problems, and these methods can be divided into three groups: precise methods, traditional mathematical programming methods, and approximate search methods. In terms of the first group, the foundation of this group is gradients and mathematical ideas, such as the iterative process and gradient approaches. Regarding the second group, techniques for the mathematical programming group relied on condition constraints and the characteristics of mathematical models. Hindi and Ghani [1] have designed an ELD problem as a linear programming one and a conventional method utilizing dual lagrangian function and lagrangian relaxation is suggested for solving the problem. Papageorgiou and Fraga [2], a mixed integer quadratic programming method has been proposed by Papageorgiou *et al.* to solve ELD problem with prohibited operation zones. Abdelaziz *et al.* [3] have introduced a hybrid approach to handle the ELD problems that combine quadratic programming and a Hopfield neural network. The hybrid technique utilized the forward-looking capability to ensure the global optimality of the solution, and the suggested method's validity was confirmed by experimentation. Basically, these techniques perform well when the objective function is linear and convex. However, in real-world engineering applications, the valve-point effect (VPE) [4], [5] and proscribed feasible area (PFA) [6] can cause the objective function to become nonlinear and heterogeneous. Because of this, it is easy to achieve local optimality, and applying the prior mathematical programming may not yield the best solution. Turning the third group, number of methods have been utilized extensively to deal with the optimal ELD problem since they have a strong ability to explore globally and do not have strict restrictions for their objective function. So far, differential evolution (DE) by Noman and Iba [7], particle swarm optimization (PSO) by Selvakumar and Thanushkodi [8], self-organizing hierarchical particle swarm optimization (SOH-PSO) by Chaturvedi *et al.* [9], new particle swarm optimization (NPSO) by Niknam *et al.* [10], opposition-based krill herd algorithm (OKHA) by Bulbul *et al.* [11], improved firefly algorithm (IFA) by Nguyen *et al.* [12], exchange market algorithm (EMA) by Ghorbani and Babaei [13], cuckoo search method (CSM) by Vo, Schegner and Ongsakul [14], one rank cuckoo search method (ORCSM) by Nguyen and Vo [15], krill herd method (KHM) by Mandal *et al.* [16], novel social spider optimization method (ISSM) by Kien *et al.* [17], modified moth swarm algorithm (MSA) by Ha *et al.* [18], hybrid Harris Hawks optimizer (HHHO) by Al-Betar *et al.* [19], chameleon swarm algorithm (CHSA) by Braik *et al.* [20], manta ray foraging optimization algorithm (MRFO) by Zhang *et al.* [21], gradient-based optimizer (GB) by Deb *et al.* [22] and other algorithms with excellent outcomes have been used in economic dispatching, one after the other.

This research applies a novel population-based algorithm which is called war strategy optimization algorithm (WSO) by Ayyarao *et al.* [23] to reach the best solutions for ELD problem. Besides, PFAs from thermal power plants (TPs) are considered to form more dificult tasks for WSO. In addition, solutions for different load levels from minimum to maximum load demands is investigated. The outcomes from WSO are contrasted with those of tunicate swarm algorithm (TSA) by Kaur *et al.* [24] and other previous algorithms. The study's contributions can be summed up as follows:

- Reach the best solutions for ELD with PFA and other constraints by successfully implementing a revolutionary meta-heuristic algorithm created in early 2022 and TSA.
- Use specific numbers to show how WSO is superior to previous algorithms. In addition, the WSO algorithm performs better than TSA regarding the number of high-quality and best-found solutions.
- Provide solution data for operators and managers in power systems for test systems with load demand changing from minimum to maximum levels of total generated power of all units.

The remainder of the paper is organized as follows, apart from the introduction: section 2 presents the problem model; section 3 introduces the applied method; section 4 shows and discusses the results of the applied method; and section 5 presents the conclusions.

2. PROBLEM MODEL

2.1. The key objective

The cost of purchasing fossil fuels, such as coal and oil, to generate electricity is the main cost of TPs. Generally, the more power a TP produces, the greater its fuel costs. Therefore, the objective of TP is to reduce the fuel cost as low as possible by allocating power generation appropriately. The fuel cost function is formed as follows [25]:

$$FC = \sum_{g=1}^{N_O} \delta_g + \gamma_g P_g + \beta_g P_g^2 \tag{1}$$

Where N_O the quantity of TPs; the weight constants for the fuel cost of TP are δ_g, γ_g, and β_g; and P_g is the generated power by the gth TP.

2.2. The considered restrictions

- Restriction on power balance

The restriction represents the power balance between the consuming and the generating sides. It is given by (2),

$$\sum_{g=1}^{N_o} P_g = PD + TP_{loss} \tag{2}$$

where PD and TP_{loss} stand for power demand and power loss, respectively.

– Restriction on power generation

The generated power by each TP must be lied within its boundaries as shown in (3).

$$P_{g,min} \le P_g \le P_{g,max} \tag{3}$$

Where $P_{g,min}$ and $P_{g,max}$ stand for the smallest and highest limitations of the gth TP.

– Restriction on PFA

The power generation of each TP in the system must strictly impose the constraints:

$$P_g \in \begin{cases} P_{g,min} \le P_g \le P_{g,1}^{l} \\ P_{g,m-1}^{u} \le P_g \le TP_{g,m}^{l}; m = 2, \dots, q \\ P_{g,q}^{u} \le P_g \le P_{g,max} \end{cases} \tag{4}$$

where q is the number of PFAs of the gth TP.

3. THE METHOD

WSO, a revolutionary meta-heuristic algorithm, was introduced by Ayyarao *et al.* [23]. The algorithm was inspired by the strategy of army troop movement to attack or defend the opposing army. In the battle, every soldier continuously modifies his position based on the positions of the King and the commander. To simulate an optimization process, every soldier moves dynamically toward the optimal position. At the beginning of the war, each soldier had a rank and a weight. Soldier's weight is changed depending on how well a soldier performs in terms of assaulting force or fitness level. Attack and defense strategies are two common military strategies that are implemented through the process of upgrading soldier positions or solutions. To develop new solutions, two approaches will be described:

– The attack strategy

The strategy is called exploitation phase. In this phase, the position of soldier is updated by (5).

$$X_i^{new} = X_i + 2 \times \mathcal{E} \times (X^K - X^C) + rand \times \left(W_i \times X^K - X_i\right) \tag{5}$$

In (5), X_i and X_i^{new} are the new and old positions of the ith soldier; $X^K$and X^C the position of the king and commander; $\mathcal{E}$ is random number; W$_i$ is the weight and is computed by (6).

$$W_\text{i} = W_\text{i} \times \left(1 - \frac{E_i}{Highest\_iter}\right)^{\alpha} \tag{6}$$

Where, Highest_iter is the highest iteration; E_i is the rank of the soldier, and it is given by (7).

$$X_i^{new} = X_i \times (F_{new} \ge F_{old}) + X_i \times (F_{new} < F_{old}) \tag{7}$$

Where, F_{new} is the new fitness of X_i^{new}; $F_{old}$is the fitness of X_i.

– The defense strategy

The strategy is called exploration phase. In this phase, the position of soldier is updated by (8):

$$X_i^{new} = X_i + 2 \times \mathcal{E} \times (X^K - X_{rand}) + rand \times W_i\left(X^C - X_i\right) \tag{8}$$

4. RESULTS AND DISCUSSIONS

In this part, we solved the ELD problem using two different meta-heuristic techniques: WSO [23] and the TSA [24]. Subsection 4.1 reported and discussed the results of the first system with six TPs for PD of 1263 MW, subsection 4.2 applied two methods to solve the ELD with fifteen TPs for PD of 2650 MW, and subsection 4.3 showed solution data for test system 2 with different load demands based on total generating power of TPs.

A personal computer with 8 GB random memory and 2.2 GHz central processing unit is used for all relevant work. On the other hand, all code and simulations are performed using MATLAB software version R2018a.

4.1. Discussion on the first test system

The power system used in this part comprises six TPs, and the information on the system is derived from [8]. The mission of the system is to provide sufficient power to meet the 1,263 MW load demand. Firstly, we applied WSO and TSA to find the optimal power output for the system by considering different constraints such as power balance, PFA, and power loss in branches. The population size (PZ), highest iterations (Highest_iter) and number of trial runs are set to 30, 60, and 100 for two methods, respectively.

Based on 100 independent runs, Figure 1 displays the outcomes of the two methods. In the figure, the costs of WSO are represented by the blue line and those of TSA by the black line. With more optimal values reached than TSA, WSO exhibits the best performance in the figure. The best convergence of WSO and TSA methods among 100 trial runs is shown in Figure 2. As the figure shows, WSO only uses 12 iterations to reach the best cost, while TSA cannot achieve this value from the first iteration to the end one.

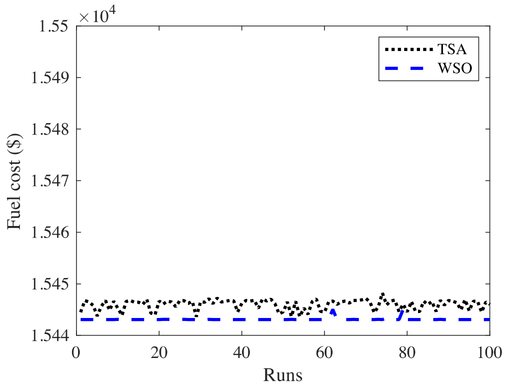

Figure 1. The results given by the TSA and WSO methods with 50 independent runs for system 1

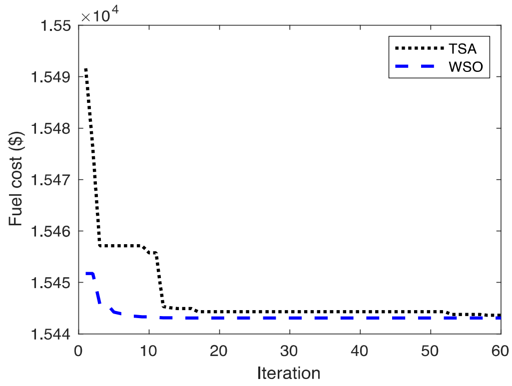

Figure 2. The best convergence feature of TSA and WSO methods for system 1

The results from WSO and TSA methods such as the minimum FC (Min.FC), mean FC (Mean.FC), maximum FC (Max.FC) and standard deviation (Std) are collected and presented in Figure 3. In the figure, we can see three costs of WSO are $15443.075, $ 15443.126, and $ 15445.07, respectively. These values are lower than TSA's by $ 0.565, $ 2.863, and $ 3.142. Even the mean cost of WSO is equal to the best cost of TSA. Regarding STD, the number of WSO is 0.281 while that of TSA is 1.026. Therefore, the WSO method can obtain better results than TSA.

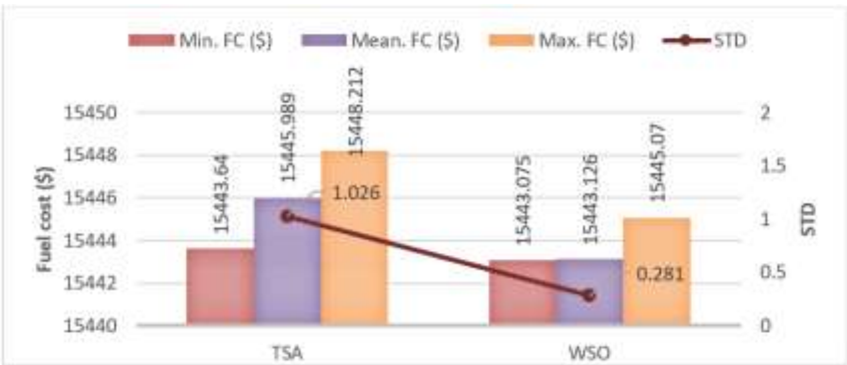

Figure 3. The results obtained by WSO and TSA for system 1

For demonstrating the perfomance of WSO, its results are compared to previous methods as given in Table 1. The first column indicates WSO is outstanding to DE [7], GA [7], PSO [7], PSO [8], LRS-MPSO [8], GA [8], LRS-PSO [8], SOH-PSO [9], PSO [10], FPSO [10], and NPSO [10] with respect to Min. FC while OKHA [11], IFA [12] and EMA [13] can reach the same value as WSO of $ 5443.075. In addition, WSO method's worst and average solutions are comparable to or superior to those of other methods as shown in the second and third columns.

The PZ and highest iteration are set to 30 and 60 for WSO but these values are 20 and 50 for algorithms in [8], 30 and 125 for algorithm in [9], 90 and 100 for PSO [10], 60 and 100 for FPSO [10], and 30 and 100 for NPSO [10]. Therefore, WSO has used 1800 updated solutions, while those from alternative techniques ranged from 1,000 to 10,000 solutions. Consequently, we can say that the suggested method can discover better outcomes than most methods to the system with power balance constraint, PFA, and power loss in branches.

Table 1. The comparison of WSO and other methods for system 1

Method	Min. FC ($)	Mean. FC ($)	Max. FC ($)	PZ	Highest_iter
DE [7]	15449.7660	15449.7770	15449.8740	36	100
GA [7]	15459.0000	15469.0000	15524.0000	NR	NR
PSO [7]	15450.0000	15454.0000	15492.0000	NR	NR
PSO [8]	15450.0000	15454.0000	15492.0000	20	50
LRS-MPSO [8]	15450.0000	15450.5000	15452.0000	20	50
GA [8]	15459.0000	15469.0000	15524.0000	20	50
LRS-PSO [8]	15450.0000	15454.0000	15455.0000	20	50
MPSO [8]	15450.0000	15452.0000	15454.0000	20	50
SOH-PSO [9]	15446.0200	15497.3500	15609.6400	30	125
PSO [10]	15450.0000	15454.0000	15492.0000	90	100
FPSO [10]	15445.2440	15448.0520	15451.6300	60	100
NPSO [10]	15443.7656	15443.7657	15443.7657	30	100
OKHA [11]	15443.0750	15443.9160	15443.3270	NR	100
IFA [12]	15443.075	15443.1270	15443.5389	10	30
EMA [13]	15443.0749	15443.0750	NR	NR	NR
WSO	15443.075	15443.126	15445.07	30	60

4.2. Discussion on the second test system

This section evaluates the optimal solution and the search stability of the suggested methods (TSA and WSO) using the second system, which consists of 15 thermal units and considers both simple powers balancing constraints and PFAs. Readers can view the system's data in paper [17]. Firstly, we set PZ of 50, highest_iter of 100 and 100 trial runs are for TSA and WSO to collect the results for comparison. Figure 4 shows a considerable discrepancy between WSO and TSA when all solutions from WSO are below those from TSA. In Figure 5, WSO needs 40 iterations to obtain the best cost, while TSA is unable to achieve the optimal cost from the first to the last iteration. The costs from the best run found by TSA and WSO are given in Figure 6. The figure indicates that WSO can reach better results than TSA. Therefore, the results of WSO are chosen to compare with those from other methods as listed in Table 2.

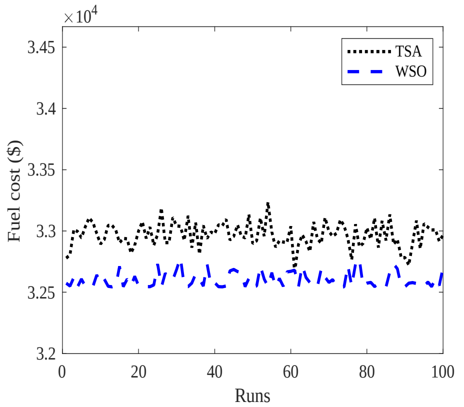

Figure 4. The result given by the TSA and WSO methods with 50 independent runs for system 2

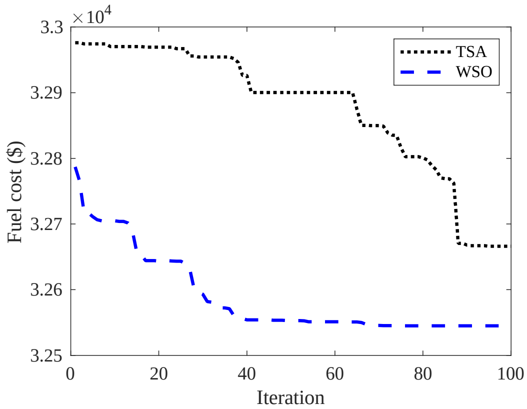

Figure 5. The best convergence feature of TSA and WSO methods for system 2

In terms of Min. Cost, WSO can find the best solution as IFA [12], CSM [14], and ISSM [17] and find a better value than FA [12], KHM-I [16], KHM-II [16], KHM-III [16], KHM-IV [16], and SSM [17] aside from ORCSM [15]. Regarding Mean. Cost and Max. Cost, WSO has nearly the same value as other methods. Regarding searchability, WSO is faster than others because it only uses 5,000 new solutions, corresponding to a one-time solution-producing mechanism, except for ISSM [17], which has 1,500 new solutions.

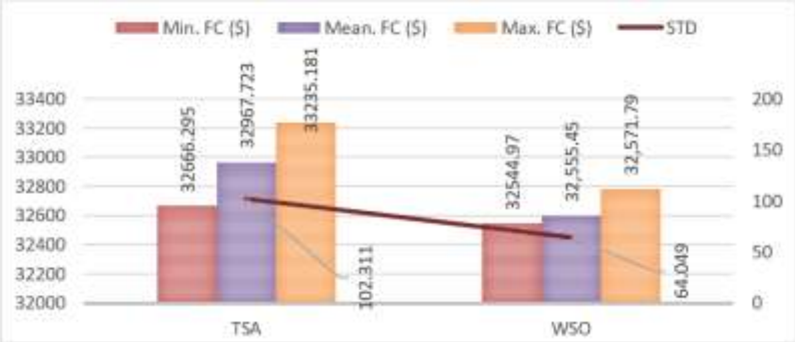

Figure 6. The results obtained by WSO and TSA for system 2

Table 2. The comparison of WSO and other methods for system 2

Method	Min. FC ($)	Mean. FC ($)	Max. FC ($)	PZ	Highest_iter
FA [12]	32,885.84	NR	NR	10	100
IFA [12]	32,544.97	32,545.22	32,545.54	10	100
CSM [14]	32,544.97	32,545.01	32,546.67	10	400
ORCSM [15]	32,542.56	32,543.17	32,546.66	12	500
KHM-I [16]	32,586.75	32,592.04	32,598.02	50	100
KHM-II [16]	32,569.80	32,571.45	32,573.63	50	100
KHM-III [16]	32,564.39	32,566.58	32,567.33	50	100
KHM-IV [16]	32,547.37	32,548.14	32,548.93	50	100
SSM [17]	32,599.07	32,645.30	32,711.26	50	100
ISSM [17]	32,544.97	32,545.45	32,561.79	10	100
WSO	32,544.97	32,555.45	32,571.79	50	100

4.3. Solution data for the second test system

In this section, we continue using WSO to find solution data for system 2 by adjusting the load demand from 960 MW to 3,542 MW with a step size of 1 MW, where 960 MW and 3,542 MW are the system's smallest and biggest total generation power. The results obtained by WSO are given in Figure 7. In the figure, the black line presents the minimum costs, while solutions are displayed in different line bars.

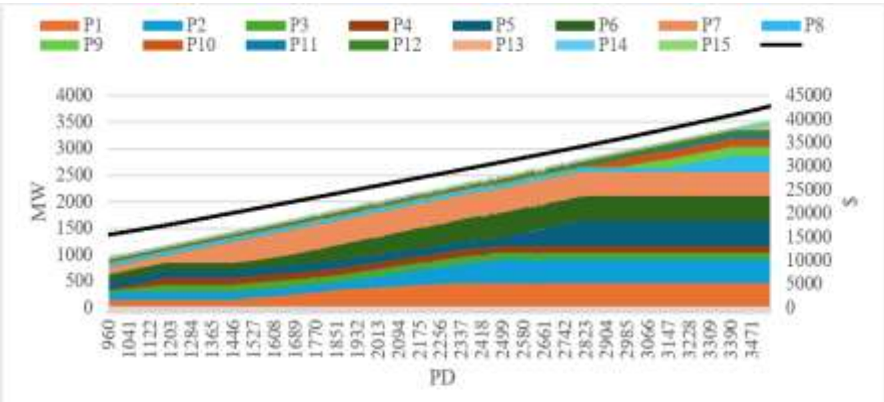

Figure 7. The costs and solutions obtained by WSO for system 2 with various loads

Clearly, with each load value, we can find one cost and generation power of 15 thermal units. Doing this will give operators a map of the complete system's solutions. Data are beneficial because they help operators make decisions quickly when requiring correct power generation from power plants. If the supply side always meets the consumption side, the system will operate efficiently and safely. To demonstrate the performance of this work, we assume that system 2 must supply power for loads in one day, as shown in Figure 8; the fuel cost of the power plant and the power of units can be found easily by searching the solution map mentioned. Therefore, the results and solutions will be presented in Figure 9.

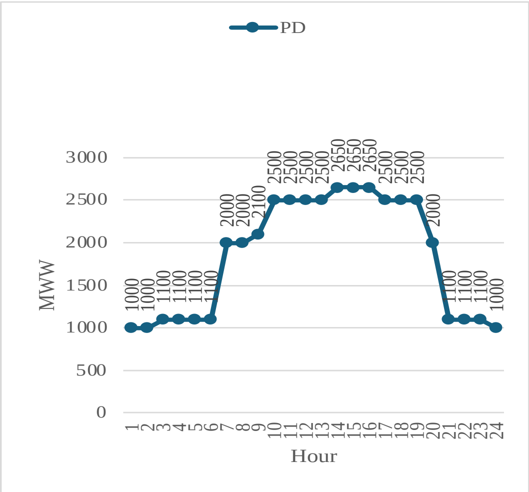

Figure 8. Typical loads in one day for system 2

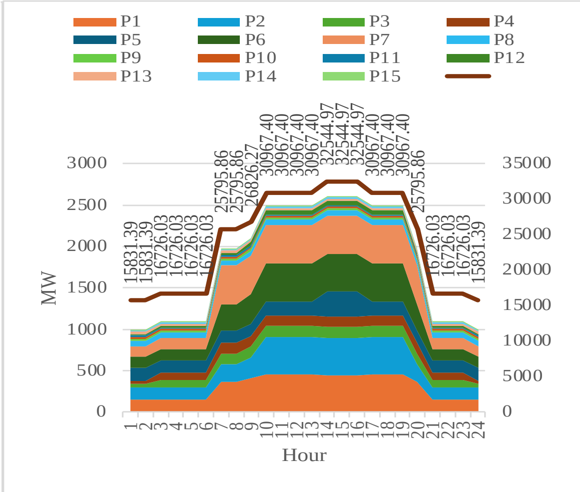

Figure 9. The costs and solutions obtained by WSO in one day for system 2

5. CONCLUSIONS

This study has successfully applied two methods (WSO and TSA) to reach optimal solutions for ELD problem. Three study cases have been investigated with two purposes: a. checking the effectiveness of two applied methods (WSO and TSA) by implementing the first two study cases; b. providing solution data for operators by implementing the last study case. Firstly, as can be seen from the ELD problem solution outcomes of Systems 1 and 2, WSO outperforms TSA. In addition, these results from WSO are also competed to other methods. As a result, WSO can reach the same best cost or better than others, concluding that WSO is an effective search method. Finally, by changing the load from the smallest and highest power of all units of system 2, WSO can find a set of solutions. From the solution set, we will assist operators in deciding on power plants when loads are given. In the coming, further improvements in WSO's performance can be achieved by changing the way it updates itself with new solutions. In addition, the uncertain features of renewable energy sources like solar radiation and wind speed will be considered and examined to demonstrate how energy instability affects the power system's technical and economic concerns.

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REFERENCES

[1] K. S. Hindi and M. R. Ab Ghani, "Dynamic economic dispatch for large scale power systems: a Lagrangian relaxation approach," *International Journal of Electrical Power and Energy Systems*, vol. 13, no. 1, pp. 51–56, Feb. 1991, doi: 10.1016/0142-0615(91)90018-Q.

[2] L. G. Papageorgiou and E. S. Fraga, "A mixed integer quadratic programming formulation for the economic dispatch of generators with prohibited operating zones," *Electric Power Systems Research*, vol. 77, no. 10, pp. 1292–1296, Aug. 2007, doi: 10.1016/j.epsr.2006.09.020.

[3] A. Y. Abdelaziz, M. Z. Kamh, S. F. Mekhamer, and M. A. L. Badr, "A hybrid HNN-QP approach for dynamic economic dispatch problem," *Electric Power Systems Research*, vol. 78, no. 10, pp. 1784–1788, Oct. 2008, doi: 10.1016/j.epsr.2008.03.011.

[4] T. Nguyen Trung, D. Vo Ngoc, B. Dinhhoang, and L. Phamhuu, "Modified cuckoo search algorithm for solving nonconvex economic load dispatch problems," *Advances in Electrical and Electronic Engineering*, vol. 14, no. 3, pp. 236–246, Sep. 2016, doi: 10.15598/aeee.v14i3.1633.

[5] L. H. Pham, T. T. Nguyen, L. D. Pham, and N. H. Nguyen, "Stochastic fractal search based method for economic load dispatch," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 17, no. 5, pp. 2535–2546, Oct. 2019, doi: 10.12928/TELKOMNIKA.v17i5.12539.

[6] H. D. Nguyen and L. H. Pham, "Solutions of economic load dispatch problems for hybrid power plants using Dandelion optimizer," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 5, pp. 2569–2576, Oct. 2023, doi: 10.11591/eei.v12i5.5245.

[7] N. Noman and H. Iba, "Differential evolution for economic load dispatch problems," *Electric Power Systems Research*, vol. 78, no. 8, pp. 1322–1331, Aug. 2008, doi: 10.1016/j.epsr.2007.11.007.

[8] A. I. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 42–51, Feb. 2007, doi: 10.1109/TPWRS.2006.889132.

[9] K. T. Chaturvedi, M. Pandit, and L. Srivastava, "Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1079–1087, Aug. 2008, doi: 10.1109/TPWRS.2008.926455.
[10] T. Niknam, H. D. Mojarrad, and H. Z. Meymand, "A new particle swarm optimization for non-convex economic dispatch," *European Transactions on Electrical Power*, vol. 21, no. 1, pp. 656–679, Jan. 2011, doi: 10.1002/etep.468.
[11] S. M. A. Bulbul, M. Pradhan, P. K. Roy, and T. Pal, "Opposition-based krill herd algorithm applied to economic load dispatch problem," *Ain Shams Engineering Journal*, vol. 9, no. 3, pp. 423–440, Sep. 2018, doi: 10.1016/j.asej.2016.02.003.
[12] T. T. Nguyen, N. V. Quynh, and L. Van Dai, "Improved firefly algorithm: A novel method for optimal operation of thermal generating units," *Complexity*, vol. 2018, no. 1, Jan. 2018, doi: 10.1155/2018/7267593.
[13] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *International Journal of Electrical Power and Energy Systems*, vol. 75, pp. 19–27, Feb. 2016, doi: 10.1016/j.ijepes.2015.08.013.
[14] D. N. Vo, P. Schegner, and W. Ongsakul, "Cuckoo search algorithm for non-convex economic dispatch," *IET Generation, Transmission and Distribution*, vol. 7, no. 6, pp. 645–654, Jun. 2013, doi: 10.1049/iet-gtd.2012.0142.
[15] T. T. Nguyen and D. N. Vo, "The application of one rank cuckoo search algorithm for solving economic load dispatch problems," *Applied Soft Computing Journal*, vol. 37, pp. 763–773, Dec. 2015, doi: 10.1016/j.asoc.2015.09.010.
[16] B. Mandal, P. K. Roy, and S. Mandal, "Economic load dispatch using krill herd algorithm," *International Journal of Electrical Power and Energy Systems*, vol. 57, pp. 1–10, May 2014, doi: 10.1016/j.ijepes.2013.11.016.
[17] L. C. Kien, T. T. Nguyen, C. T. Hien, and M. Q. Duong, "A novel social spider optimization algorithm for large-scale economic load dispatch problem," *Energies*, vol. 12, no. 6, p. 1075, Mar. 2019, doi: 10.3390/en12061075.
[18] P. T. Ha, H. M. Hoang, T. T. Nguyen, and T. T. Nguyen, "Modified moth swarm algorithm for optimal economic load dispatch problem," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 18, no. 4, pp. 2140–2147, Aug. 2020, doi: 10.12928/TELKOMNIKA.V18I4.15032.
[19] M. A. Al-Betar *et al.*, "A hybrid Harris Hawks optimizer for economic load dispatch problems," *Alexandria Engineering Journal*, vol. 64, pp. 365–389, Feb. 2023, doi: 10.1016/j.aej.2022.09.010.
[20] M. S. Braik, M. A. Awadallah, M. A. Al-Betar, A. I. Hammouri, and R. A. Zitar, "A non-convex economic load dispatch problem using chameleon swarm algorithm with roulette wheel and Levy flight methods," *Applied Intelligence*, vol. 53, no. 14, pp. 17508–17547, Jul. 2023, doi: 10.1007/s10489-022-04363-w.
[21] X. Y. Zhang, W. K. Hao, J. S. Wang, J. H. Zhu, X. R. Zhao, and Y. Zheng, "Manta ray foraging optimization algorithm with mathematical spiral foraging strategies for solving economic load dispatching problems in power systems," *Alexandria Engineering Journal*, vol. 70, pp. 613–640, May 2023, doi: 10.1016/j.aej.2023.03.017.
[22] S. Deb, D. S. Abdelminaam, M. Said, and E. H. Houssein, "Recent methodology-based gradient-based optimizer for economic load dispatch problem," *IEEE Access*, vol. 9, pp. 44322–44338, 2021, doi: 10.1109/ACCESS.2021.3066329.
[23] T. S. L. V. Ayyarao *et al.*, "War strategy optimization algorithm: a new effective metaheuristic algorithm for global optimization," *IEEE Access*, vol. 10, pp. 25073–25105, 2022, doi: 10.1109/ACCESS.2022.3153493.
[24] S. Kaur, L. K. Awasthi, A. L. Sangal, and G. Dhiman, "Tunicate swarm algorithm: a new bio-inspired based metaheuristic paradigm for global optimization," *Engineering Applications of Artificial Intelligence*, vol. 90, p. 103541, Apr. 2020, doi: 10.1016/j.engappai.2020.103541.
[25] C. D. Tran, T. T. Dao, and V. S. Vo, "Economic load dispatch with multiple fuel options and valve point effect using cuckoo search algorithm with different distributions," *International Journal of Energy Optimization and Engineering*, vol. 9, no. 3, pp. 24–38, Jul. 2021, doi: 10.4018/ijeoe.2020070102.

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