

Jellyfish search algorithm for economic load dispatch under the considerations of prohibited operation zones, load demand variations, and renewable energy sources

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ABSTRACT

This paper suggests a modified version of the former economic load dispatch (MELD) problem with the integration of wind power plant (WPP) and solar power plants (SPP) into thermal units (TUs). The target of the whole study is to cut the total producing electricity cost (TPEC) as much as possible. Three meta-heuristic algorithms, including particle swarm optimization (PSO), jellyfish search (JS) and salp swarm algorithm (SSA), are applied to solve the MELD. The real performance of these optimization tools is tested on the first system with six thermal units considering prohibited zones, and the second system with the combination of the first system and one solar, and two WPPs. In addition, the variation of load demand in 24 hours per day is also taken into account in the second system. JS is proved to be the most effective method for dealing with MELD. Furthermore, JS can also reach lower or the same TPEC as other previous algorithms. Hence, JS is a recommended to be a strong computing method for dealing with the MELD problem.

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1. INTRODUCTION

The economic load dispatch (ELD) problem is one of the most considered problems in power system operation. The determination of the optimal solution to ELD not only reduces the total producing electricity cost but also mitigates the environmental damage [1]. Most of the early studies only focused on solving ELD with fixed load demand. In addition, the thermal power plant is the only generating source. Recently, the former ELD problem has been modified to different versions under the name of the modified economic load dispatch problem (MELD), where renewable energy sources and load demand variation are evaluated [2]. Cutting the total producing electricity cost (TPEC) of thermal power plants is mostly considered while solving ELD problems. Besides, wind and solar energies have contributions to significant reduction of TPEC. These sources can partly support thermal sources to serve load demand at peak times [3], [4]. While environmental problems are on high alert, the use of renewable energy sources (RES) is attracted more attentions than ever. By fully aware of the current trend, this study presents a solution of using RES by solving MELD considering the presence of both wind and solar energies.

Currently, meta-heuristic algorithms are acknowledged to be the most effective computing methods to cope with a wide range of optimization problems. ELD and MELD are not exception because they are both classified the optimization problems. There were a lot of researches solving ELD by applying meta-heuristic methods such as hybrid grey wolf optimizer (HGWO) [5], distributed roust optimization (DRO) [6], particle swarm optimization and its improved versions [7]–[9], evolutionary algorithm (EA) [10], tunicate swarm optimizer (TSO) [11], marine predator optimization algorithm (MPOA) [12], k-mean cluster and elbow technique (KMC-ET) [13], a selection of Hyper-heuristic [14], equilibrium optimizer algorithm (EOA) [15], modified social spider optimization (MSSO) [16], ameliorated dragonfly algorithm (ADA) [17], improved jaya algorithm [18], marine predator algorithm [19], modified equilibrium algorithms (MEA) [20], coyote optimization algorithm (COA) [21], harmonic search algorithm (HSA) [22], hybrid swarm intelligence-based HSA (HIS-HAS) [23], squirrel search optimizer (SSO) [24], and improved firefly algorithm (IFA) [25]. The studies have applied different algorithms, such as original and improved versions of metaheuristic algorithms. However, some of these studies have imorged the comparisons between improved and original versions. Other studies have not coped with the shortcoming, but they have neglected the fair comparison criteria such as settings of iterations and population. On the other hand, almost all previous studies only focused on thermal power plants rather than the integration of renewable energies to ther conventional power source.

In this study, we implement particle swarm optimization (PSO) [26], jellyfish search algorithm (JS) [27], and salp swarm optimization (SSA) [28] to search the optimal solutions of ELD and MELD problems. In ELD problem, the constraint about prohibited operation zone (POZ) of thermal power plants is taken into account to investigate the outstanding performance of applied methods. In MELD problem, two wind and one solar power plants are integrated with the first power system. Alongside with that, the variation of load demand over 24 hours is also taken into account. Finally, the study focuses on reaching the smallest values of TPEC as the main objective function. The main contributions of the entire study can be summarized,

- Apply successfully a novel meta-heuristic algorithm, named jellyfish search algorithm (JS) to determine the optimal solutions for both original and modified version of ELD problem.
- Prove the effectiveness of JS over two remaining methods, including PSO and SSA and other methods from previous studies.
- The variation of load demand within a day and the presence of both solar and wind power are successfully implemented.

In addition to the introduction, other sections of the study are organized: Section 2 describes the main objective function and all involved constraints. Section 3 introduces the applied method. Section 4 presents the results and discussion obtained by the applied methods in different case studies. Finally, the conclusions are revealed in section 5.

2. METHOD

2.1. Objective function

The study considers the generation cost from thermal power plants due to the high fuel cost from the plants, especially for hours with high generation, while generation from renewable energies power plants is the base supply. The fuel cost for each Megawatt (MW) is different for different power generation values. Normally, each MW of high-power generation cost more fuel than that of low power generation. However, it is very difficult to determine the most suitable power generation for the lowest cost of one MW. So, the use of metaheuristic algorithms for finding the generation is key task of the study, and the duty of the applied metaheuristic algorithms is to reach the following objective function,

$$\text{Cutting TPEC} = \sum_{n=1}^{N_T} \delta_n + \gamma_n TG_n + \beta_n TG_n^2 \quad (1)$$

where N_T is the number of thermal power plants; δ_n , γ_n , and β_n are coefficient of thermal power plant; and TG_n is the power output produced by the nth thermal power plant.

2.2. Constraints

Power balance constraint: Total generation by thermal, wind and solar power plants is supplied to demand of load over operation time. On the other hand, a small part of the transmission power through transmission lines with resistance and reactance is losted. These power plants must compensate the loss so that load demand is fully supplied. Hence, the total generation (generation from wind, solar and thermal power plants), the loss on transmission lines and the load demand must exactly like the (2),

$$\sum_{n=1}^{N_T} TG_n + PW + PSr - (PRD + PL) = 0 \quad (2)$$

where PW and PSr are the power outputs of wind and solar power plants; PRD and PL are demand and loss. Generation and prohibited operation zone limits: Power output of each thermal power plant must satisfy the constraints,

$$TG_{n,min} \leq TG_n \leq TG_{n,max} \quad (3)$$

$$TG_n \in \begin{cases} TG_{n,min} \leq TG_n \leq TG_{n1}^l \\ TG_{nk-1}^u \leq TG_n \leq TG_{nk}^l; k = 2, \dots, z \\ TG_{nz}^u \leq TG_n \leq TG_{n,max} \end{cases} \quad (4)$$

In (3) and (4), $TG_{n,min}$ and $TG_{n,max}$ are the lower and upper limits of thermal power plant n . z is the number of prohibited operation zones belonging to the thermal power plant i . The illustration of prohibited operation zones is given in Figure 1.

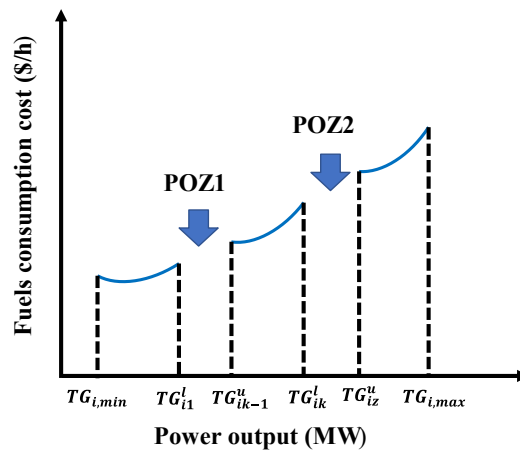


Figure 1. The illustration of prohibited zone operation (POZ)

Generation constraints of solar power plants (SPPs): All SPPs must satisfy the general and individual constraints [21],

$$\sum_q^{NSL} PSr \leq 80\% \times PRD \quad (5)$$

$$PSr_q^{min} \leq |PSr_q| \leq PSr_q^{max} \quad (6)$$

where $\sum_q^{NSL} PSr$ is the total power output generated by solar power plant; PSr_q is power produced by solar power plant q ; PSr_q^{min} and PSr_q^{max} are the minimum and maximum power output supplied by solar power plant z .

3. THE COMPUTING METHOD

The jellyfish search algorithm (JS) is a meta-heuristic algorithm proposed in 2021 [27]. The algorithm has two methods to generate new solutions. The first method uses only one model, but the second method uses two models based on comparison conditions. These methods are expressed in (7) and (8),

$$X_k^{new} = X_k + 0.1 \times Rnd(UB_k - LB_k) \text{ with } k = 1 \dots N_{pop} \quad (7)$$

$$X_k^{new} = \begin{cases} X_k + Rnd \times DF, & \text{if } Rand \leq (1 - SE) \\ LB_k + 0.1 \times Rnd \times (UB_k - LB_k), & \text{otherwise} \end{cases} \quad (8)$$

where, X_k^{new} and X_k are the old and new solution k ; Rnd is the random value in the interval of 0 and 1; UB_k and LB_k are the upper and lower boundaries of solution k ; DF is a step size and determined by:

$$DF = \begin{cases} X_q - X_k & \text{if } F_q < F_k \\ X_k - X_q & \text{if } F_k < F_q \end{cases} \tag{9}$$

where X_q and F_q are a randomly chosen solution and its fitness function; and F_k is fitness function solution k .

Note that, the determination of which method will be applied is dependent on the select factor (SE). If the SE is equal or greater than 0.5, Method 1 will be selected, otherwise Method 2 will be executed. The factor SE is a function of randomization factor, maximum iteration and current iteration obtained by,

$$SE = 1 - \left(M \times \frac{1}{M^{Max}} \right) \times (2 \times rand - 1) \tag{10}$$

4. RESULTS AND DISCUSSIONS

In this section, we apply three meta-heuristic algorithms including particle swarm optimization (PSO) [26], jellyfish search algorithm (JS) [27] and salp swarm algorithm (SSA) [28] to determine the optimal results of for two systems. This work is conducted on a personal computer with a 2.2 GHz central processing unit alongside 8GB of random memory access. Coding and simulation are implemented using MATLAB software version R2018a.

4.1. The conventional ELD with fixed load demand

In this subsection, the power system, including six thermal power plants with prohibited operation zones, must fulfill a fixed load demand of 1263 MW. All data of thermal power plants and boundaries of prohibited operation zones are cited from [22]. Three applied meta-heuristic methods are applied to reach the minimum TPEC while satisfying the load demand and all related constraints of the conventional ELD problem. The initial parameters of these methods regarding population size, the maximum number of iterations, and the number of independent runs are 10, 50, and 100, respectively.

Figure 2 presents the detail and summary of 100 runs by implementing three applied algorithms. The curves in Figure 2(a) describes the results of PSO, while the blue and black ones illustrate the costs of SSA and JS. PSO is the most unstable method, while JS proves itself to be the most reliable method among the three applied ones. Figure 2(b) shows four comparison criteria, including the minimum cost (Min.cost), mean cost (Mean.cost), maximum cost (Max.cost), and standard of deviation (std). The summary of fifty costs indicates that JS has smaller minimum, mean and maximum costs, and more stability than PSO and SSA excluding the same minimum cost as SSA. As a result, JS is the highest performance method.

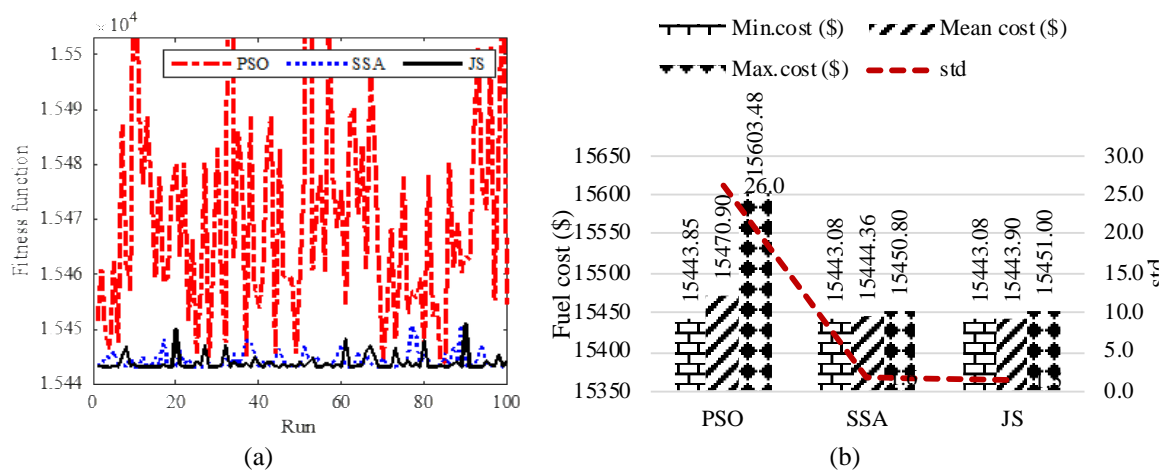


Figure 2. Results obtained by applied methods for 100 runs: (a) the fitness function of 100 implemented runs and (b) summary of minimum fuel, maximum fuel cost, mean fuel cost and standard deviation from 100 implemented runs

The search processes of three applied algorithms are summarized in Figure 3. Figures 3(a)-3(c), respectively, show the best, mean and worst convergence processes of 100 trial runs. JS provides the fastest response capability in all comparisons. Specifically, this method only requires over 35 iterations to reach the optimal value for the best convergence. SSA needs approximately 40 iterations to reach the same solution as JS, while PSO cannot achieve the optimal result for the best run. In terms of the mean and the worst convergences, JS is still the fastest method while PSO is the lowest one.

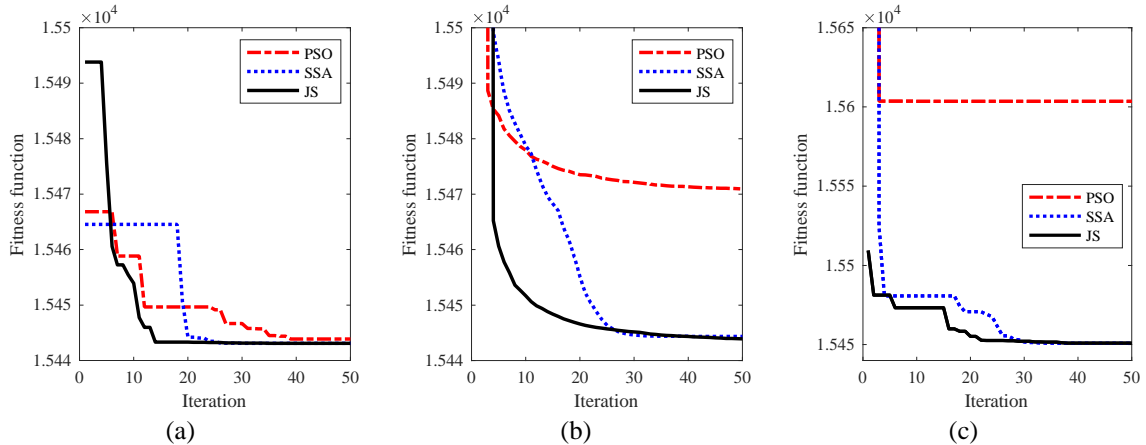


Figure 3. The convergences characteristics: (a) the best run, (b) the mean run, and (c) the worst run

To see the effectiveness of JS, the results of JS are compared with other methods from previous studies as described in Table 1. The minimum cost comparison indicate that JS can reach the same cost as IFA [25] and smaller cost than HSA [22]. HIS and SSO reported smaller cost than others; however, the methods have used slightly different loss coefficients as reported in the original method [22]. As using the same coefficients as [23], [24], JS can reach a little bit smaller than HSA and HIS as seeing the results with the * in the table. So, JS is really effective as compared to previous methods.

Table 1. The comparison of JS and other method

Method	Min.cost (\$/h)	Mean.cost (\$/h)	Max.cost (\$/h)	std	N_{pop}	Iterations
HSA [22]	15449	15450	15453	-	-	-
HIS-HAS [23]	15442.8423	15446.7142	-	1.8275	30	200
SSO [24]	15442.4	15442.6	-	0.0352	20	100
IFA [25]	15443.075	15443.12	15443.52	-	55	30
JS	15443.075	15443.90	15451.00	1.5	10	50
JS	15442.378*	15442.705*	15444.505*	0.87	10	50

Note that * mean JS is run by using the same system data as [23], [24]

4.2. The MELD with load demand variation

In this section, JS is reapplied to determine the optimal results of the MELD problem. In the second system, six thermal units in System 1 are integrated to two wind power plants (WPP) and one solar power plant. The system is optimally scheduled over 24 hours with different load values. All data of wind and solar plants are taken from [29] and [30], respectively.

Figure 4 shows results obtained by the three applied algorithms for the system. Figure 4(a) presents the results obtained by the three applied methods after 100 independent runs. Throughout 100 runs, JS can reach more optimal results than both SSA and PSO. In addition, Figure 4(b) indicates that JS is the most effective method while PSO is the worst one. The effectiveness of PSO, SSA and JS is clearly shown in Figure 4(b). In the figure, four comparison criteria, including Min.cost, mean cost, Max.cost, and std are given. It is easy to acknowledge that, JS reaches much better results than two others. Specifically, the Min.cost and std values given by JS are 269814.1 (\$) and 7.5, while those of SSA and PSO are (\$269843.7 and 21.3) and (\$269951 and 120.4). The comparisons reveal that JS has advantages over SSA and PSO in terms of strong search process and high stability. So, JS should be used for the MELD problem on behalf of PSO and SSA.

Figure 5 reports the generation of all thermal power plants and renewable energy plants in addition to hourly cost from six thermal units. The generation height of plants indicates that thermal units 1 and 6 are, respectively, the most effective and ineffective since unit 1 account for the highest generation but unit 6 just produce a small power. At hours with high load demand, cost is much higher than others, but the cost is much dependent on wind and solar power plants.

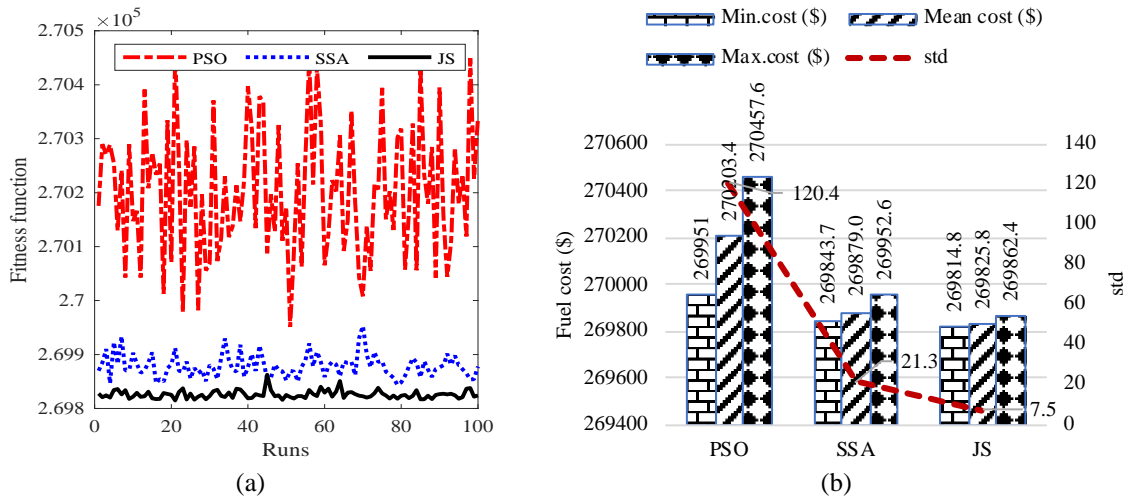


Figure 4. Results obtained by the three applied algorithms (a) the fitness function of 100 runs, and (b) the fuel cost comparison summary from 100 trial runs

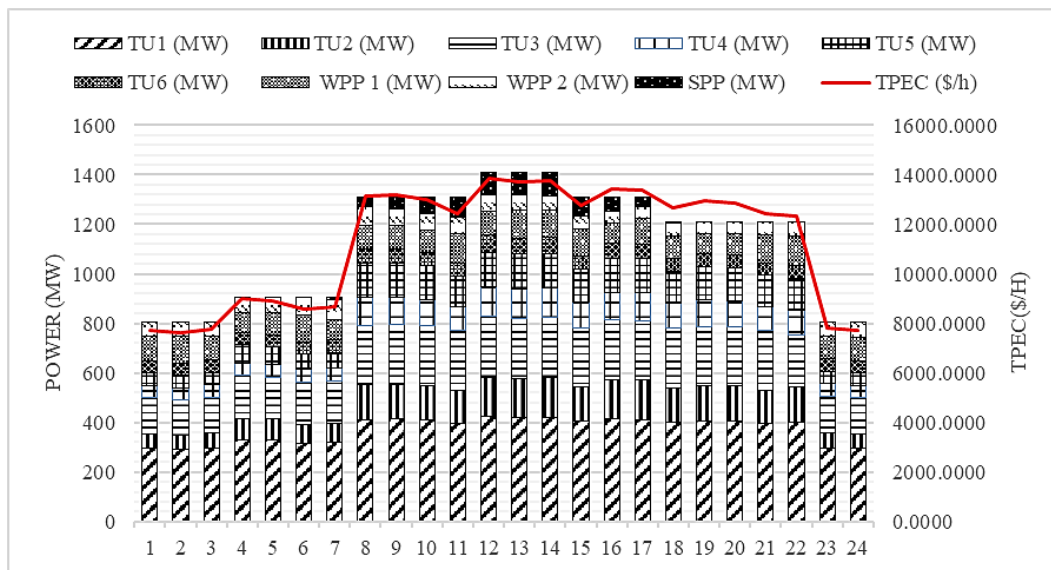


Figure 5. Optimal generation of power plants and hourly cost of all thermal power plants obtained by JS

5. CONCLUSIONS

In this study, three meta-heuristic algorithms, including PSO, SSA and JS, were successfully applied to solve both the original and modified version of the ELD problem with renewable energies and one working day. During the whole process of finding the optimal value of TPEC, different states of load demand are considered, including fixed and varied load demands. Besides, the prohibited operation zones and the presence of wind and solar power plants are also taken into account. JS proved it was the most effective method. Besides, while compared with other previous methods, JS also showed its high performance by reaching the same or better cost but using less population size and iterations. Therefore, JS is considered the most powerful search tool, and it is highly recommended for solving MELD problems. In future work, JS will be modified to improve

their raw performance for dealing with higher-degree complex problems. In addition, the MELD problem should also be expanded by the consideration of large-scale power systems with various generating sources, more complicated constraints such as multiple fuels, ramp-rate and valve point effect constraints.




REFERENCES

- [1] Y. Xiang *et al.*, “Low-carbon economic dispatch of electricity-gas systems,” *Energy*, vol. 226, 2021, doi: 10.1016/j.energy.2021.120267.
- [2] H. Zhang, S. Liang, M. Ou, and M. Wei, “An asynchronous distributed gradient algorithm for economic dispatch over stochastic networks,” *International Journal of Electrical Power and Energy Systems*, vol. 124, 2021, doi: 10.1016/j.ijepes.2020.106240.
- [3] T. G. Hlalele, J. Zhang, R. M. Naidoo, and R. C. Bansal, “Multi-objective economic dispatch with residential demand response programme under renewable obligation,” *Energy*, vol. 218, 2021, doi: 10.1016/j.energy.2020.119473.
- [4] J. Kim and K. K. Kim, “Dynamic programming for scalable just-in-time economic dispatch with non-convex constraints and anytime participation,” *International Journal of Electrical Power and Energy Systems*, vol. 123, 2020, doi: 10.1016/j.ijepes.2020.106217.
- [5] M. A. Al-Betar, M. A. Awadallah, and M. M. Krishan, “A non-convex economic load dispatch problem with valve loading effect using a hybrid grey wolf optimizer,” *Neural Computing and Applications*, vol. 32, no. 16, pp. 12127–12154, 2020, doi: 10.1007/s00521-019-04284-9.
- [6] X. Chang, Y. Xu, H. Sun, and I. Khan, “A distributed robust optimization approach for the economic dispatch of flexible resources,” *International Journal of Electrical Power and Energy Systems*, vol. 124, 2021, doi: 10.1016/j.ijepes.2020.106360.
- [7] N. Chopra, Y. S. Brar, and J. S. Dhillon, “An improved particle swarm optimization using simplex-based deterministic approach for economic-emission power dispatch problem,” *Electrical Engineering*, vol. 103, no. 3, pp. 1347–1365, 2021, doi: 10.1007/s00202-020-01164-7.
- [8] Z. Xin-gang, Z. Ze-qi, X. Yi-min, and M. Jin, “Economic-environmental dispatch of microgrid based on improved quantum particle swarm optimization,” *Energy*, vol. 195, 2020, doi: 10.1016/j.energy.2020.117014.
- [9] L. Ping, J. Sun, and Q. Chen, “Solving power economic dispatch problem with a novel quantum-behaved particle swarm optimization algorithm,” *Mathematical Problems in Engineering*, vol. 2020, 2020, doi: 10.1155/2020/9741595.
- [10] S. Kumar, V. Kumar, N. Katal, S. K. Singh, S. Sharma, and P. Singh, “Multiarea economic dispatch using evolutionary algorithms,” *Mathematical Problems in Engineering*, vol. 2021, 2021, doi: 10.1155/2021/3577087.
- [11] C. T. Hien, P. T. Ha, T. H. Phan-Van, and T. M. Phan, “Multi-period economic load dispatch with wind power using a novel metaheuristic,” *GMSARN International Journal*, vol. 16, no. 2, pp. 165–173, 2022.
- [12] H. S. Hoang, V. B. Nguyen, V. D. Phan, and H. N. Nguyen, “Marine predator optimization algorithm for economic load dispatch target considering solar generators,” *GMSARN International Journal*, vol. 16, no. 1, pp. 11–26, 2022.
- [13] M. Q. Duong, L. H. Lam, B. T. M. Tu, G. Q. Huy, and N. H. Hieu, “A combination of k-mean clustering and elbow technique in mitigating losses of distribution network,” *GMSARN International Journal*, vol. 13, no. 4, pp. 153–158, 2019.
- [14] L. Yang, D. He, and B. Li, “A selection hyper-heuristic algorithm for multiobjective dynamic economic and environmental load dispatch,” *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/4939268.
- [15] M. A. El-Shorbagy and A. A. Mousa, “Constrained multiobjective equilibrium optimizer algorithm for solving combined economic emission dispatch problem,” *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/6672131.
- [16] W. Yang, T. Cheng, Y. Guo, Z. Yang, and W. Feng, “A modified social spider optimization for economic dispatch with valve-point effects,” *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/2865929.
- [17] V. Suresh, S. Sreejith, S. K. Sudabattula, and V. K. Kamboj, “Demand response-integrated economic dispatch incorporating renewable energy sources using ameliorated dragonfly algorithm,” *Electrical Engineering*, vol. 101, no. 2, pp. 421–442, 2019, doi: 10.1007/s00202-019-00792-y.
- [18] C. Chen, D. Zou, and C. Li, “Improved jaya algorithm for economic dispatch considering valve-point effect and multi-fuel options,” *IEEE Access*, vol. 8, pp. 84981–84995, 2020, doi: 10.1109/ACCESS.2020.2992616.
- [19] L. H. Pham, B. H. Dinh, and T. T. Nguyen, “Optimal power flow for an integrated wind-solar-hydro-thermal power system considering uncertainty of wind speed and solar radiation,” *Neural Computing and Applications*, vol. 34, no. 13, pp. 10655–10689, 2022, doi: 10.1007/s00521-022-07000-2.
- [20] M. Q. Duong, T. T. Nguyen, and T. T. Nguyen, “Optimal placement of wind power plants in transmission power networks by applying an effectively proposed metaheuristic algorithm,” *Mathematical Problems in Engineering*, vol. 2021, 2021, doi: 10.1155/2021/1015367.
- [21] V. D. Phan, M. Q. Duong, M. M. Doan, and T. T. Nguyen, “Optimal distributed photovoltaic units placement in radial distribution system considering harmonic, distortion limitation,” *International Journal on Electrical Engineering and Informatics*, vol. 13, no. 2, pp. 354–367, 2021, doi: 10.15676/ijeii.2020.13.2.7.
- [22] M. Fesanghary and M. M. Ardehali, “A novel meta-heuristic optimization methodology for solving various types of economic dispatch problem,” *Energy*, vol. 34, no. 6, pp. 757–766, 2009, doi: 10.1016/j.energy.2009.02.007.
- [23] V. R. Pandi, B. K. Panigrahi, R. C. Bansal, S. Das, and A. Mohapatra, “Economic load dispatch using hybrid swarm intelligence based harmony search algorithm,” *Electric Power Components and Systems*, vol. 39, no. 8, pp. 751–767, 2011, doi: 10.1080/15325008.2010.541411.
- [24] M. Suman, V. P. Sakthivel, and P. D. Sathya, “Squirrel search optimizer: Nature inspired metaheuristic strategy for solving disparate economic dispatch problems,” *International Journal of Intelligent Engineering and Systems*, vol. 13, no. 5, pp. 111–121, 2020, doi: 10.22266/ijies2020.1031.11.
- [25] 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, 2018, doi: 10.1155/2018/7267593.
- [26] N. Bansal, R. Gautam, R. Tiwari, S. Thapa, and A. Singh, “Economic load dispatch using intelligent particle swarm optimization,” pp. 93–105, 2021, doi: 10.1007/978-981-15-8443-5_8.
- [27] J. S. Chou and D. N. Truong, “A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean,” *Applied Mathematics and Computation*, vol. 389, 2021, doi: 10.1016/j.amc.2020.125535.
- [28] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, “Salp swarm algorithm: A bio-inspired optimizer for engineering design problems,” *Advances in Engineering Software*, vol. 114, pp. 163–191, 2017, doi: 10.1016/j.advengsoft.2017.07.002.




- [29] H. Zhang, D. Yue, X. Xie, C. Dou, and F. Sun, "Gradient decent based multi-objective cultural differential evolution for short-term hydrothermal optimal scheduling of economic emission with integrating wind power and photovoltaic power," *Energy*, vol. 122, pp. 748–766, 2017, doi: 10.1016/j.energy.2017.01.083.
- [30] W. A. Augusteen, S. Geetha, and R. Rengaraj, "Economic dispatch incorporation solar energy using particle swarm optimization," *2016 3rd International Conference on Electrical Energy Systems, ICEES 2016*, pp. 67–73, 2016, doi: 10.1109/ICEES.2016.7510618.

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