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Research Article

Solving the optimal power generation for the thermal generating unit problem, considering the multiple fuel constraints and the presence of renewable energy-based generators using the Pied kingfisher optimizer

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Abstract

This research presents the application of a recently proposed meta-heuristic algorithm, Pied kingfisher optimization (PKO), to solve the optimal power generation for thermal generating unit (OPG-TGU) problem. The main objective of the entire research is to achieve the optimal value of the entire electricity production cost (EEPC) for the ten-multiple-fuel generator power systems serving a load demand of 2500 MW. Besides, a 200 MW wind-based generator and a 100 MW photovoltaic-based generator are also integrated into the given power system as a direct solution to partly lower EEPC values and reduce the generating burden on all generators in the system. The results obtained by PKO are compared with those of another meta-heuristic algorithm, Frilled Lizard Optimization (FLO), for performance evaluation. The results clearly indicate that PKO completely outperforms FLO in terms of convergence speed, the ability to reach the best solution, and especially the ability to avoid local optima. In particular, PKO is more effective than FLO at 2.95% in terms of the minimum EEPC (Min.EEPC), 7.04% in the mean EEPC (Mean.EEPC), and 12.59% in the maximum EEPC. Besides these competitive results, PKO also offers surprising stability throughout the process of addressing the given problem, achieving an STD value of only 0.0055, while FLO achieves 9.7894. Therefore, PKO is recognized as an effective and robust search method, highly recommended for dealing with such OPG-TGU problems.

Keywords: *Optimal power generation for thermal generating unit; entire electricity production cost; multiple fuel option constraint, photovoltaic based generator; wind based generator; Pied kingfisher optimization.*

Introduction

The optimal power generation for thermal generating unit (OPG-TGU) problem is one of the most concerned and important optimization challenges in power system optimization operation. It involves determining the optimal active and/or reactive power outputs among working thermal generating units to cut total fuel cost while supplying enough power and meeting all various operational constraints, including power balance, generation limits, and transmission line losses. As power networks become increasingly

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complicated with the integration of renewable power sources, electric vehicles, and distributed generators, solving the OPG-TGU problem efficiently has become more significant than ever [1, 2, 3].

Classical mathematical programming methods: the lambda iteration-based algorithm and the gradient factor-based approach, are limited in solving the non-linear and non-convex fuel cost function of practical OPG-TGU problems. To overcome these limitations, numerous metaheuristic algorithms have been developed and applied so far. The turbulent flow of water optimization [4] and the modified Krill Herd algorithm [5] demonstrated competitive performance on constrained OPG-TGU problems. The problem was solved to reach superior accuracy [6], while the Growth Optimizer was tested on OPG-TGU problems to reach good results [7]. The memetic sine-cosine algorithm could enhance exploitation in the OPG-TGU problem [8], and the improved Mayfly optimization algorithm solved the OPG-TGU with renewable power sources [9]. OPG-TGU problem with economic load dispatch and economic emission load dispatch was solved in [10].

The growing penetration of renewable power sources (particularly solar photovoltaic (PV) and wind turbines) introduced new research studies in power system operation. Uncertainty in wind speed and wind generation necessitates robust dispatch strategies [11]. Studies on renewable energy penetration have tested economic, technical and stable impacts on power system operation [12]. Optimal integration of distributed generators (DGs) in distribution networks has been shown to OPG-TGU significant technical, economic, and environmental benefits [13]. For hybrid systems with hydropower plants, thermal units, solar PV systems, and variable-speed pumped storage hydro, an economic objective was considered in [14]. The Pied Kingfisher Optimizer was further applied to determine the optimal PV penetration level in distribution networks [15-16]. The presence of electric vehicles (EVs) makes the OPG-TGU problems more complex [16]. Enhancement of EV charging stations was explored for distribution power grids [17], especially where FACTS devices and renewable energy sources are employed to reduce fuel cost, energy loss, and investment costs was studied in [18]. A data-driven coordinated dispatch framework for source-grid-load-storage systems was introduced in [19]. Green economic load dispatch with one more objective function of emission was solved by using metaheuristic algorithms [20] and an enhanced manta ray foraging algorithm [21]. Soft open point components were applied to support the loss reduction [22]. The Dandelion optimizer was applied to solve OPG-TGU [23]. The Greylag Goose Optimization algorithm was applied to solve global optimization and engineering problems [24]. Minimizing total electricity fuel cost for large-scale electric systems with solar and wind sources was obtained by using the Elk Herd Optimizer [25]. Integrated wind turbines with HVDC power transmission lines were analyzed in [26-27]. Both HVDC and energy storage system were used [28]. Photovoltaic inverters was applied [29], and the impact of stealthy false data injection attacks on power flow was mathematically verified in [30]. The EV battery technologies provided a good view for the battery market in power grids [31]. Sand Cat Swarm Optimization (SCSO) was used for global optimal solution finding, which was reported in [32]. Deep reinforcement learning and MPPT control were analyzed to support PV-integrated dispatch systems [33].

In this research, a recently proposed meta-heuristic algorithm called Pied kingfisher optimization (PKO) [34] will be applied to solve the optimal power generation for thermal generating unit problem (OPG-TGU) for a ten-fuel generator power system serving a load demand of 2500 MW. In the entire process of solving the given problem, the multiple-fuel option constraint of the generators will be considered. Furthermore, a 200 MW wind-based generator (WBG) and a 100 MW photovoltaic-based generator (PVBG) are integrated into the system to reduce the generating burden on the existing generator partially.

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The main novelties and the contribution of the research are as follows:

- Successfully applying Pied kingfisher optimization (PKO) to optimize the power output of all the generators in the given system for the best value of the entire electricity production cost in solving the OPG-TGU problem.
- Proving the superiority of PKO in dealing with the given problem throughout various comparisons with other method.
- Successfully considering the presence of WBG and PVBG is the entire process of solving the given problem.
- Offering a typical framework of applying a modern meta-heuristic algorithm with high efficiency and stability performance in solving such a given problem.

1. Problem description

1.1.Objective Function

The primary goal of this study is to minimize the entire electricity production cost (EEPC) of all multiple fuel generators (MGs) in the system. The objective function is formulated as follows:

$$\text{Minimize EEPC} = \sum_{t=1}^{N_{MGs}} \left(c_{1t} P_{MG,t}^2 + c_{2t} P_{MG,t} + c_{3t}\right) \quad (1)$$

$$with\ t = 1, \dots, N_{MGs}$$

Where, EEPC is the entire electricity production cost of all MGs in the considered power system; c_{1t}, c_{2t}, and c_{3t} are the fuel usage coefficients of the MG t; $P_{MG,t}$ is the active power output of MG t; and N_{MGs} is the total number of MGs in the system.

1.2. Problem Constraints

- ***Power Balance Constraint:***

The total power generated by all units must cover both the load demand and the system transmission losses:

$$\sum_{t=1}^{N_{MGs}} P_{MG,t} + \sum_{r=1}^{N_{PVBGs}} P_{PVBG,r} + \sum_{z=1}^{N_{WBGs}} P_{WBG,r} = AP_{LD} + AP_{Loss} \quad (2)$$

Where, $\sum_{t=1}^{N_{MG}} P_{MG,t}$ is the total power generated by all active MGs; $\sum_{r=1}^{N_{PVBGs}} P_{PVBGr}$ is the total power supplied by PVBGs connected with the given system with $r = 1,2, \dots, N_{PVBGs}$, and N_{PVBGs} is the number of PVBGs; $\sum_{z=1}^{N_{WBGs}} P_{WBG,z}$ is the total power supplied by WBGs connected with the given system with $z = 1,2, \dots, N_{WBGs}$ and N_{WBGs} is the number of WBGs; AP_{LD} and AP_{Loss} represent the active power demand of the load and the transmission loss, respectively.

The transmission loss in Eq. (2) is calculated using the following model:

$$AP_{Loss} = \sum_{t=1}^{N_{MGs}} \sum_{\substack{v=1 \\ v \neq t}}^{N_{MGs}} P_{MG,t} \times \beta_{tv} \times P_{MG,v} + \sum_{t=1}^{N_{MGs}} \beta_{0t} \times P_{MG,t} + \beta_{00} \quad (3)$$

Where β_{tv}, β_{0t}, and β_{00} are the loss coefficients.

- ***Generation Limits of MGs***

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The power output of each MG must stay within its technical lower and upper bounds:

$$P_{MG,t}^{\mathrm{lo}} \leq P_{MG,t} \leq P_{MG,t}^{\mathrm{up}} \tag{4}$$

Where $P_{MG,t}^{\mathrm{lo}}$ and $P_{MG,t}^{\mathrm{up}}$ are the low and up power limits of MG t.

- ***Multi-Fuel Constraints of MGs***

For units capable of operating on multiple fuel types, the cost characteristics are represented by a piece-wise quadratic cost function:

$$EEPC_t = \begin{cases} c_{1t}^1 + c_{2t}^1 P_{MG,t} + c_{3t}^1 P_{MG,t}^2; & if\ P_{MG,t}^{lo} \leq P_{MG,t} \leq P_{MG,t}^{up,1} \\ c_{1t}^2 + c_{2t}^2 P_{MG,t} + c_{3t}^2 P_{MG,t}^2; & if\ P_t^{lo,2} \leq P_{MG,t} \leq P_{MG,t}^{up,2} \\ \dots & \\ c_{1t}^z + c_{2t}^z P_{MG,t} + c_{2t}^z P_{MG,t}^2; & if\ P_{MG,t}^{lo,z} \leq P_{MG,t} \leq P_{MG,t}^{up} \end{cases} \tag{5}$$

Where, c_{1t}^1, c_{2t}^1, and c_{3t}^1 are the cost function parameters of MG t while operating with fuel option 1; $P_{MG,t}^{\mathrm{lo}}$ and $P_{MG,t,1}^{\mathrm{up}}$ are the low and up power limits of MG t while operating with fuel option 1; c_{1t}^2, c_{2t}^2, and c_{3t}^2 are the cost function parameters of MG t while operating with fuel option 2; $P_{MG,t,2}^{\mathrm{lo}}$ and $P_{MG,t,2}^{\mathrm{up}}$ are the low and up power limits of MG t while operating with fuel option 2; c_{1t}^z, c_{2t}^z, and c_{3t}^z are the cost function parameters of MG t while operating with fuel option z; $P_{MG,t,q}^{\mathrm{lo}}$ and $P_{MG,t}^{\mathrm{up}}$ are the low and up power limits of MG t while operating with fuel option z, where z is the total number of fuel options.

- ***Generation Limits of PVBG and WBG***

Similar to all the MGs above, the amout of power output supplied by the PVBGs and WBGs are restricted by their designed capacity limits:

$$PVBG_r^{lo} \leq P_{PVBG,r} \leq PVBG_r^{up} \tag{6}$$

$$WBG_z^{lo} \leq P_{WBG,z} \leq WBG_z^{up} \tag{7}$$

Where $PVBG_r^{lo}$ and $PVBG_r^{up}$ are the lower and the upper boundaries of the PVBG r; WBG_z^{lo} and WBG_z^{up} are the lower and the upper boundaries of the WBG z;

1. Pied kingfisher optimizer.

In this section, the update process for the new solution to the Pied kingfisher optimizer (PKO) [34] will be described. In particular, PKO executes two phases of updating for its new solution to complete the optimization process. The description of each phase will be given in the next two subsections as follows:

1.1. Phase 1

During the first phase, each candidate solution in the current population is updated as follows:

$$SO_r^{udt1} = \begin{cases} SO_r + \varepsilon \times G_p \times (SO_m - SO_r), & if\ r_{nd} < 0.8 \\ SO_r + p_h \times \sigma \times f_{ctrl} \times (SO_s - SO_{Gbest}), & otherwise \end{cases} \tag{8}$$

Where, SO_r^{udt1} is the updated solution r in the first phase; SO_r the current solution r in the population; ε is the position factor; G_p is the position gain; SO_m is the neighborhood selected solution; p_h is the hunting probability factor; f_{ctrl} is the control factor adjusting the searching process; σ is the dependent factor; SO_s is a randomly selected solution in the initial population; SO_{Gbest} is the global best solution at the current iteration; r_{nd} is a uniformly distributed random number in the range of [0,1].

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1.1. Phase 2

In the second phase, candidate solutions are refined using the following update rules:

$$SO_r^{udt1} = \begin{cases} SO_m + \sigma \times f_{ctrl} \times (SO_r - SO_m), & if\ rd\ > 1 - Ad_r \\ SO_r, & otherwise \end{cases} \tag{9}$$

Where the advantage Ad_r corresponds to the solution r and is calculated as:

$$Ad_r = Ad^{\mathrm{up}} - \left(Ad^{\mathrm{up}} - Ad^{\mathrm{lo}}\right) \times \frac{it}{it^{\mathrm{up}}} \tag{10}$$

Where, Ad^{up} and Ad^{lo} are the up and low boundaries of the advantage, respectively; it and it^{up} represent the current iteration and the up iteration limit; r_{nd} is a uniformly distributed random number in the range of $[0,1]$.

2. The simulation results

In this section, the Pied Kingfisher Optimizer (PKO) [34] will be applied to determine the optimal power output of the 10-MG power systems to minimize EEPC, considering the MGs' multiple fuel options. Moreover, a 200MW WBG and a 100MW PVBG are initially integrated into the system to partly reduce the generating burden to all the existing MGs in the given power system. The system is supposed to serve a load demand of 2500MW. The optimal results obtained by PKO are evaluated and discussed in terms of their actual performance through different comparisons with Frilled Lizard Optimization (FLO) [35]. The entire performance analysis of the two algorithms is ensured by using the same presets for the population size (*PZ*) and the maximum number of iterations (*MI*). In fact, the presets are established by 20 and 100 throughout the whole optimization process of the two algorithms. Furthermore, each algorithm is executed 50 times to obtain the best solution prior to any comparison.

All the work of the entire research is conducted on a personal computer with the following specifications: a central processing unit (CPU) with a clock speed of 2.26 GHz, and a kit of random-access memory (RAM) with a capacity of 16GB. Moreover, MATLAB 2018a is selected as the main platform for all coding and related simulations.

Figure 1a, 1b, and 1c show the three convergences achieved by the two algorithms in their best runs after 50 trial tests, including the minimum, the mean, and the maximum. The three subfigures show that PKO completely outperforms FLO in terms of convergence speed, the ability to reach better values of the main objective function, and, especially, the capability to escape from local optima, as seen in FLO, which leads to premature convergence in all three subfigures.

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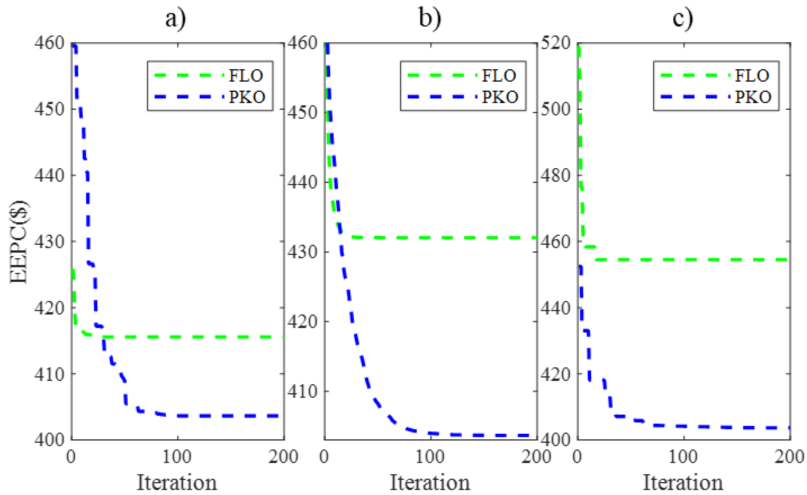

Figure 1. a) The minimum, b) the mean, and c) the maximum convergence achieved by the FLO and PKO for their best runs

Figure 2 offers more detail about how well the PKO compared to FLO in solving the considered problem by using the four different criteria, including the Minimum EEPC (Min.EEPC), Mean EEPC (Mean.EEPC), Maximum EEPC (Max.EEPC), and standard deviation STD. Clearly, PKO has outperformed FLO by achieving lower EEPC values, especially in the first and last criteria, which are Min.EEPC and STD, respectively. In particular, the values obtained by PKO for these terms are 403.654 ($/h) and 0.0055, while those of FLO are 415.572 ($/h) and up to 9.7984. Furthermore, Figure 3 provides the exact measurement of the cost of savings and the corresponding percentage PKO over FLO for the first three criteria, which are mostly focused on real operational situations. The figure indicates that PKO is more effective than FLO 2.95% on the first criterion. And for the last two criteria, the effectiveness of PKO over FLO are 7.04% and 12.59%, respectively.

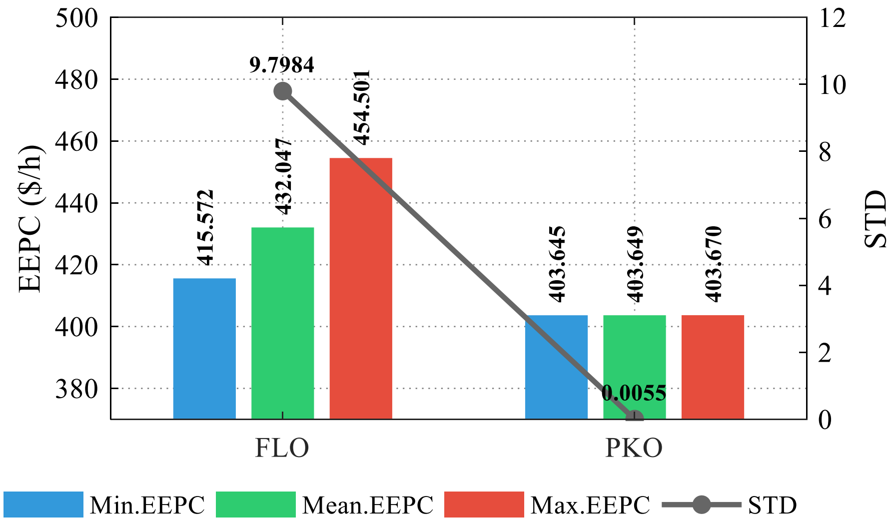

Figure 2. The statistical results after 50 trial runs achieved by FLO and PKO across various criteria.

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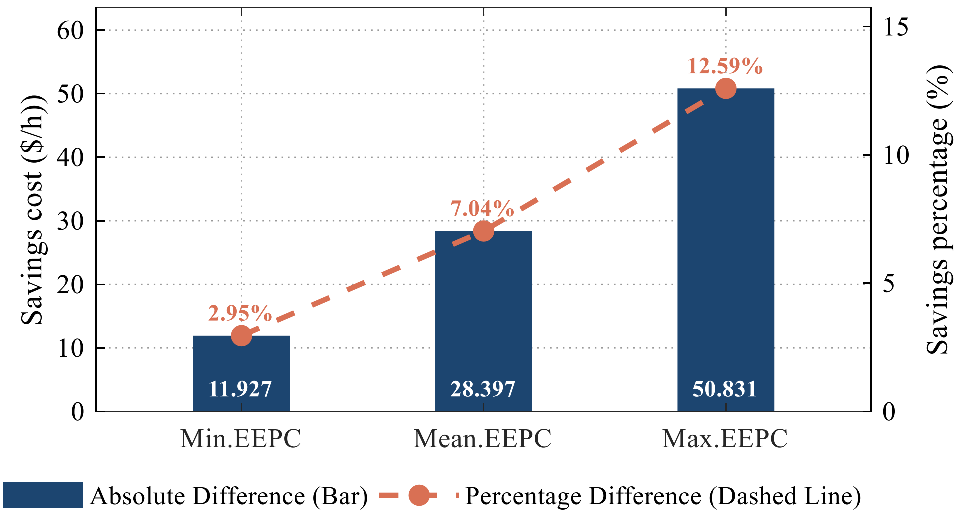

Figure 3. The measurement of the effectiveness of PKO over FLO

Figure 4 shows the optimal power output of each MG in the power system and the corresponding fuel cost (FC). The results in the figure clearly indicate that PKO mostly achieves lower power output than the MGs, except for MGs 4, 6, 8 and 10. The lower power output from MGs leads to smaller FC values, which, in turn, result in a lower EEPC overall. It is noted that the multiple fuel constraints of the MGs, as presented in the section, will increase the fragmented nature of the cost curve of each MG. As a result, the consideration of such constraints will lead to the existence of many local optima in the search space, which requires the applied algorithm to be able to avoid those local optima before reaching the global optimum.

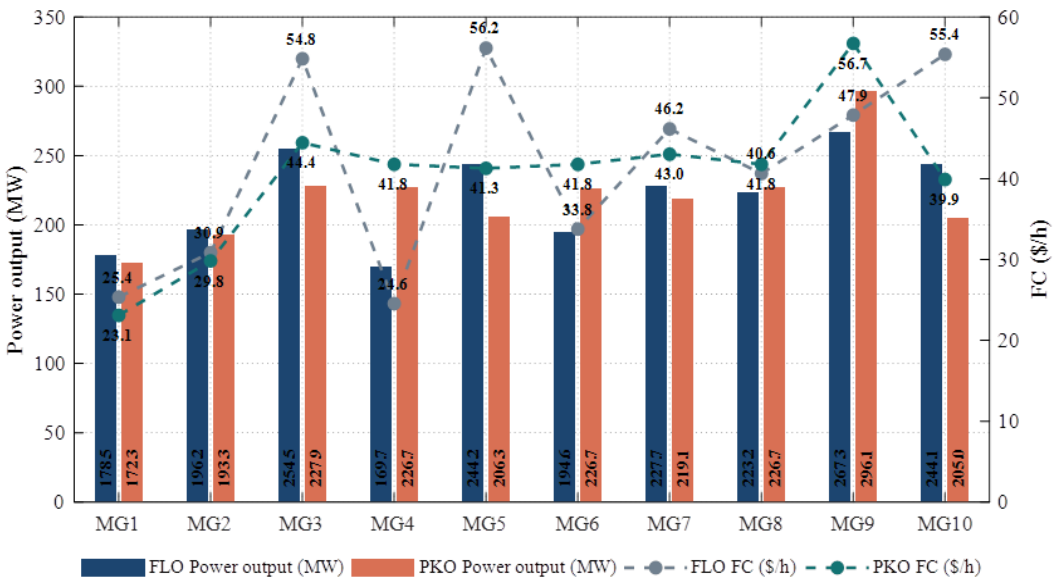

Figure 4. The power output and the fuel cost of the ten multiple fuel generators achieved by FLO and PKO for their best runs

Figure 5 presents the specific measurements of the difference in power output and fuel cost achieved by FLO and PKO. Actually, these measurements are determined by the absolute difference between the power output and the fuel cost, as shown in Figure 4. The positive values of the bars and the FC values stand

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for the savings power output and the savings cost on each MG of PKO compared to FLO. As shown in the figure, the bar values and fuel costs at some MGs are negative, indicating that FLO's power output is better than PKO's; however, the sum of those negative values cannot compete with the sum of the positive values overall. Hence, this illustration once again proves the actual effectiveness of PKO compared to FLO.

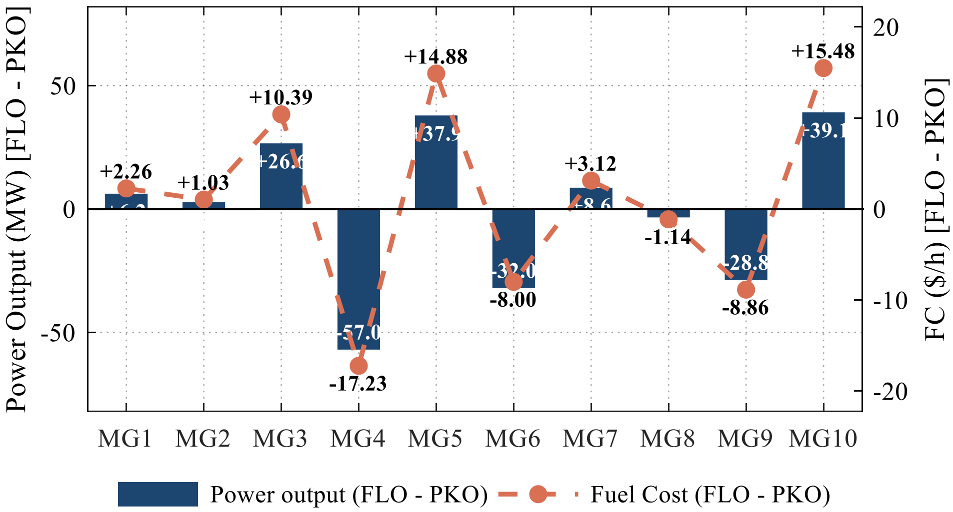

Figure 5. The difference in terms of power output and the fuel cost of the ten MGs of PKO compared to FLO.

3. Conclusions

In this research, a recently proposed meta-heuristic algorithm, Pied kingfisher optimization (PKO), has been successfully applied to solve the optimal power generation problem for thermal generating units (OPG-TGU). Throughout the process, the optimal solution is found to achieve the best values for the total electricity production cost, and the contributions of renewable energy, including the presence of the PVBG and the WBG, are taken into account. Furthermore, the multiple fuel constraints of the generator in the ten-generator power system are also considered. The results obtained by PKO are compared with another recent proposed meta-heuristic, the all Frilled lizard optimization, and clearly demonstrate its superiority in terms of convergence speed, optimal solutions, and the ability to avoid local optima arising from the evaluation of multiple fuel constraints in MGs. Particularly, PKO is more effective than FLO 2.95% on the Minimum EEPC, 7.04% on the Mean EEPC, and 12.59% on the Maximum EEPC. Besides, the PKO also offers surprising stability throughout the process of dealing with the considered problem, with a standard deviation of only 0.0055 after 50 test runs. At the same time, that of FLO is up to 9.7984. Based on the results and the achievement, PKO is recognized as an effective and robust optimization method, which is highly recommended for use to solve the OPG-TGU problem.

Reference

1. Naresh, S., Anupalli, I., & Reddy, Y. K. (2026). Electric Vehicle integration in Economic Load Dispatch with Renewable Energy Sources: A Systematic Literature Review. In E3S Web of Conferences (Vol. 692, p. 02001). EDP Sciences.
2. Kusuma, P. D., & Prasasti, A. L. (2024). Stochastic Shaking Algorithm: A New Swarm-Based Metaheuristic and Its Implementation in Economic Load Dispatch Problem. International Journal of Intelligent Engineering & Systems, 17(3).

ISSN (Online): 1595-6709
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3. Wang, X., Chu, S. C., Snášel, V., Shehadeh, H. A., & Pan, J. S. (2023). Five phases algorithm: a novel meta-heuristic algorithm and its application on economic load dispatch problem. Journal of Internet Technology, 24(4), 837–848.
4. Deb, S., Houssein, E. H., Said, M., & Abdelminaam, D. S. (2021). Performance of turbulent flow of water optimization on economic load dispatch problem. IEEE Access, 9, 77882–77891.
5. Kaur, A., Singh, L., & Dhillon, J. S. (2022). Modified Krill Herd Algorithm for constrained economic load dispatch problem. International Journal of Ambient Energy, 43(1), 4332–4342.
6. Ismaeel, A. A., Houssein, E. H., Khafaga, D. S., Aldakheel, E. A., AbdElrazek, A. S., & Said, M. (2023). Performance of osprey optimization algorithm for solving economic load dispatch problem. Mathematics, 11(19), 4107.
7. Shaban, A. E., Ismaeel, A. A., Farhan, A., Said, M., & El-Rifaie, A. M. (2024). Growth Optimizer Algorithm for Economic Load Dispatch Problem: Analysis and Evaluation. Processes, 12(11), 2593.
8. Al-Betar, M. A., Awadallah, M. A., Zitar, R. A., & Assaleh, K. (2023). Economic load dispatch using memetic sine cosine algorithm. Journal of Ambient Intelligence and Humanized Computing, 14(9), 11685–11713.
9. Nagarajan, K., Rajagopalan, A., Angalaeswari, S., Natrayan, L., & Mammo, W. D. (2022). Combined economic emission dispatch of microgrid with the incorporation of renewable energy sources using improved mayfly optimization algorithm. Computational Intelligence and Neuroscience, 2022(1), 6461690.
10. Singh, N., Chakrabarti, T., Chakrabarti, P., Margala, M., Gupta, A., Praveen, S. P., & Unhelkar, B. (2023). Novel heuristic optimization technique to solve economic load dispatch and economic emission load dispatch problems. Electronics, 12(13), 2921.
11. Zhang, Y., Wang, X., Nie, G., He, C., Yang, Y., He, M., & Meng, X. (2026). Robust dispatch of multi-electrolyzer systems for renewable energy hydrogen production under wind forecast uncertainty. Applied Energy, 409, 127483.
12. Harb, A., & Al Ramahi, I. (2026). On the Impacts of Renewable Energy Penetration on the Economic Dispatch and Sustainability of Power Systems. Journal of Sustainability Research, 8(1).
13. Nguyen, B. N., Nguyen, Q. V., Van Nguyen, M., Phung, T. S., & Nguyen, T. T. (2026). Optimal integration of distributed generation in distribution networks using a novel serial hybridization approach: Technical, economic, and environmental impacts. Ain Shams Engineering Journal, 17(7), 104207.
14. Phan, T. M., Le, M. H., Nguyen, T. T., & Duong, M. P. (2025). Economic Objective Optimization for Thermal, Solar Photovoltaic and Variable Speed Pumped Storage Hydro Hybrid Power Systems. International Energy Journal, 25(4).
15. Pham, H. H., Nguyen, T. T., Quan, D. M., & Marco, M. (2026). Optimal Penetration Level of Photovoltaic Units in Distribution Networks Considering Engineering and Economic Performance Using the Pied Kingfisher Optimizer. Electronics, 15(8), 1674.
16. Ba, T., Yang, Z., Chen, L., Chen, G., He, L., Liu, Y., & Xiao, R. (2026). Multi-objective dispatch strategy for vehicle-to-grid enabled electric vehicles in renewable energy microgrids under diverse load scenarios. Journal of Energy Storage, 150, 120219.

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17. Fokui, W. S. T., Akupan, R. E., & Wandji, D. K. N. (2025). Enhancement of the utilization of electric vehicle charging stations in a commercial distribution network. Journal of Advanced Engineering and Computation, 9(4), 184–201.
18. Kien, L. C., Nguyen, T. A., Arkhincheev, V., Phan, T. M., & Nguyen, T. T. (2025). Reducing fuel, energy loss, investment, operation, and maintenance costs for transmission power grids with FACTS and renewable energy. Scientific Reports, 15(1), 32988.
19. Qian, J., Wei, M., Wang, P., & He, W. (2026). Data-driven coordinated dispatch of source-grid-load-storage systems with renewable energy resources and storage integration. International Journal of Electrical Power & Energy Systems, 175, 111625.
20. Tang, N. A., & Cuong, N. M. D. (2023). Solving the Green Economic Load Dispatch by Applying the Novel Meta-heuristic Algorithm. Journal of Computing Theories and Applications, 1(2), 129–139.
21. Spea, S. R. (2025). Cost-effective economic dispatch in large-scale power systems using enhanced manta ray foraging optimization. Neural Computing and Applications, 1–38.
22. Tran, H. V., Nguyen, T. T., & Truong, A. V. (2025). War strategy optimization for energy loss and electricity purchase cost minimization in distribution power grids by optimizing location and capacity of clean power sources and soft open point components. International Transactions on Electrical Energy Systems, 2025(1), 5119735.
23. Nguyen, H. D., & Pham, L. H. (2023). Solutions of economic load dispatch problems for hybrid power plants using Dandelion optimizer. Bulletin of Electrical Engineering and Informatics, 12(5), 2569–2576.
24. El-Kenawy, E. S. M., Khodadadi, N., Mirjalili, S., Abdelhamid, A. A., Eid, M. M., & Ibrahim, A. (2024). Greylag goose optimization: nature-inspired optimization algorithm. Expert Systems with Applications, 238, 122147.
25. Nguyen, V. P. U., & Dang, T. N. (2026). Minimizing the overall electricity production cost to the large-scale power system incorporating solar and wind energy sources using Elk Herd Optimizer. Journal of Advanced Engineering and Computation, 10(1), 36–49.
26. Mohammadi, F., Danapour S., N., & Rouzbehi, K. (2024). Integrated Wind Turbines and HVDC Power Transmission Lines. IEEE Transactions on Sustainable Energy, 15(3).
27. Mohammadi, F., Azizi, N., Moradi CheshmehBeigi, H., & Rouzbehi, K. (2024). Stability and Control of VSC-Based HVDC Systems: A Systematic Review. e-Prime – Advances in Electrical Engineering, Electronics and Energy, 8.
28. Azizi, N., Moradi, H., Rouzbehi, K., & Mohammadi, F. (2023). HVDC Grids Stability Enhancement through the Integration of Battery Energy Storage Systems. IET Renewable Power Generation.
29. Mohammadi, F., Bok, R., & Saif, M. (2023). A Proactive Intrusion Detection and Mitigation System for Grid-Connected Photovoltaic Inverters. IEEE Transactions on Industrial Cyber-Physical Systems, 1.
30. Mohammadi, F., & Rashidzadeh, R. (2022). Impact of Stealthy False Data Injection Attacks on Power Flow of Power Transmission Lines—A Mathematical Verification. International Journal of Electrical Power and Energy Systems, 142.
31. Mohammadi, F., & Saif, M. (2023). A Comprehensive Overview of Electric Vehicle Batteries Market. e-Prime – Advances in Electrical Engineering, Electronics and Energy, 3.

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32. Ngoc, N. N. T., Arkhincheev, V., & Hoang, H. M. (2026). Starfish Optimization, Sand Cat Swarm Optimization, Weighted Average and Mirage Search Optimization Algorithms for Finding Global Optimal Solutions. Journal of Advanced Engineering and Computation, 10(1), 50–68.
33. Big-Alabo, A. (2026). Analyses of Deep Reinforcement Learning and Conventional MPPT Control under Fast-Changing Irradiance. Journal of Advanced Engineering and Computation, 10(1), 13–35.
34. Bouaouda, A., Hashim, F. A., Sayouti, Y., & Hussien, A. G. (2024). Pied kingfisher optimizer: a new bio-inspired algorithm for solving numerical optimization and industrial engineering problems. *Neural Computing and Applications*, *36*(25), 15455-15513.
35. Falahah, I., Al-Baik, O., Alomari, S., Bektemyssova, G., Gochhait, S., Leonova, I., ... & Dehghani, M. (2024). Frilled lizard optimization: A novel bio-inspired optimizer for solving engineering applications. *Computers, Materials, & Continua*, *79*(3), 3631.