IJSES

International Journal of Scientific Engineering and Science
Volume 9, Issue 4, pp. 44-49, 2025. ISSN (Online): 2456-7361

Solving A Large-Scale Green Energy-Economic Load Dispatch Problem Using Frilled Lizard Optimization and Greylag Goose Optimization

Quach Minh Thu[1*], Ta Minh Cuong[2]
[1]Admission and Training Department, Ly Tu Trong College, Ho Chi Minh city, Vietnam
[2]Faculty of electrical & electronics engineering, Ly Tu Trong College, Ho Chi Minh city, Vietnam
Email: thuquachminhlytc@gmail.com; taminhcuong@gmail.com
*Corresponding Author: thuquachminhlytc@gmail.com

Abstract– *This study investigates the application of two meta-heuristic algorithms, Frilled Lizard Optimization (FLO) and Greylag Goose Optimization (GGO), to solve the Green Energy-based Economic Load Dispatch (GE-ELD) problem. The primary objective is to optimize power output allocation across all Thermal Power Generators (TPGs) within a large-scale power system, incorporating renewable energy generation, to minimize the total fuel consumption (TFC) of the TPGs. FLO and GGO were employed to determine the optimal power output distribution. The performance of these algorithms was rigorously evaluated and compared using four key criteria: Minimum TFC, Mean TFC, Maximum TFC, and Standard Deviation (STD). The results consistently demonstrate a clear and significant superiority of GGO over FLO. GGO exhibited a notably faster convergence rate, reaching optimal solutions within fewer iterations, indicating a more efficient search mechanism. Furthermore, GGO displayed superior solution stability, evidenced by a significantly lower standard deviation, suggesting a more consistent performance across multiple runs. Quantitatively, GGO achieved a 0.0132% reduction in Minimum TFC, indicating a better ability to find the absolute best solution. The 0.0280% reduction in Mean TFC and the 0.0407% reduction in Maximum TFC highlight GGO's consistent ability to generate lower average and worst-case fuel consumption. Most significantly, the 26.81% reduction in STD compared to FLO indicates a substantial improvement in solution consistency and reliability. These findings conclusively indicate that GGO is a robust and highly effective search method for addressing complex GE-ELD optimization challenges, demonstrating a clear advantage in convergence speed, solution stability, and overall performance.*

Keywords— *Economic Load Dispatch; total fuel consumption; power loss, thermal power generators; wind power generators; meta-heuristic algorithms; Frilled Lizard Optimization; Greylag Goose Optimization.*

I. INTRODUCTION

A fundamental task in running a power grid is figuring out how to allocate electricity production across all the thermal power generators (TPGs) in the given system, known as the Economic Load Dispatch (ELD) [1]. The main objective of solving the ELD problem is to reduce the total fuel consumption of all the TPGs as much as possible while ensuring electricity demand and adhering to operational limits [2]. Historically, this was solely done with traditional TPGs. However, the pollution they generate poses significant health and environmental risks. To address this, integrating renewable energy sources (RES) like solar and wind has become essential, offering both financial and environmental benefits. The challenge becomes the Green Energy-Economic Load Dispatch (GE-ELD) when renewables are included.

GE-ELD presents a complex, large-scale optimization puzzle, particularly in systems with numerous TPGss and intricate non-linear constraints. Older computational methods, such as Gauss-Siedel [3] and Jacobian [4], struggle with this scale of complexity. Fortunately, the last couple of decades have seen the emergence of advanced computational techniques. These methods generally fall into two categories: those that mimic brain functions, such as Artificial Neural Networks (ANNs), and those inspired by natural processes. Nature-inspired techniques, often referred to as meta-heuristic algorithms, have proven exceptionally effective in solving complex problems like GE-ELD. A wide range of meta-heuristic algorithms have been successfully applied to ELD and GE-ELD, including approaches like the multi-objective multi-verse optimization (MOMVO) [5], Rain Optimization Algorithm (ROA) [6], Adaptive cuckoo search algorithm (ACSA) [7], Grasshopper optimization algorithm (GROA) [8], one rank cuckoo search algorithm (ORCSA) [9], adaptive simulated annealing (ASA) [10], Niching Penalized Chimp Optimization [11], Slime Mould algorithm (SMA) [12], chaotic teaching–learning-based optimization with Lévy flight (CTLBO) [13], interior search algorithm (ISA)[14], JAYA algorithm [15], turbulent flow of water optimization (TFWO)[16]. Modified moth swarm algorithm (MMSA) [17], search and rescue optimization algorithm (SARO) [18], astute black widow optimization (ABWO) [19], ameliorated dragonfly algorithm (ADA) [20], Krill Herd Algorithm (MKHA) [21], Firework algorithm (FWA) [22], artificial bee colony algorithm (ABCA) [23], memetic sine cosine algorithm (MSCA) [24], multiswarm statistical particle swarm optimization (MSPSO) [25], Dragonfly algorithm (DA) [26], Chameleon Swarm Algorithm (CSA) [27], Stochastic Shaking Algorithm (SSA) [28], Growth Optimizer Algorithm (GOA) [29], and split-compete optimization (SCO) [30].

In this study, two novel meta-heuristic algorithms, including the Frilled Lizard Optimization (FLO) [31] and Greylag Goose Optimization (GGO) [32], are applied to determine the optimal allocation of power output to all the TPGs besides the

International Journal of Scientific Engineering and Science
Volume 9, Issue 4, pp. 44-49, 2025. ISSN (Online): 2456-7361

renewable-based generators in the power system for total fuel consumption minimization. About FLO, this is a novel metaheuristic inspired by the hunting behavior of frilled lizards. It utilizes a sit-and-wait strategy, modeled in two phases: exploration (attack towards prey) and exploitation (retreat to a tree). FLO demonstrated superior performance in benchmark and real-world engineering problems compared to other algorithms. Regarding GGO, this is also a new swarm-based method inspired by the "V" formation flight of Greylag Geese, using this formation to improve search efficiency by reducing resistance. The algorithm is extensively tested in the developing phase conducted by the author and results in superior optimization performance.

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

- Two novel meta-heuristic algorithms were successfully applied to solve the GE-ELD for the main objective function of minimizing the total fuel consumption by all the TPGs in the given system.
- Successfully integrating the presence of both wind and photovoltaic power generators besides the existing TPGs in the given power system, along with the consideration of power loss.
- Provide a detailed analysis of the performance of the two applied algorithms and indicate the better one based on particular criteria.
- Offer a general framework for solving the large-scale green energy–economic load dispatch using novel searching tools, which are meta-heuristic algorithms.

II. Problem description

A. Objective function

The main goal of this research is to lower the total fuel consumption (TFC) of all the TPGs in the given power system. The fuel cost model for all TPGs is detailed as follows:

$$Minimize\ TFC = \sum_{n=1}^{N_{TPGs}} a_n + b_n P_{TPG,n} + c_n P_{TPG,n}^2 \quad (1)$$

Where TFC is the total fuel consumption of all the TPGs in the given system; a_n, b_n, and c_n are the fuel coefficient corresponding to the TPG n; $P_{TPG,n}$ is the amount of power generated by the TPG n; and N_{TPGs} is the quantity of TPGs in the given system.

B. The involved constraints

- The power balance constraints: This constraint is imposed to ensure the balance between the total amount of power supplied by all existing generating sources and the amount consumed by load plus the amount of loss:

$$\sum_{n=1}^{N_{TPG}} P_{TPG,n} + P_{WPG} + P_{SPG} - P_D - P_{Loss} = 0 \quad (2)$$

Where $\sum_{n=1}^{N_{TPG}} P_{TPG,n}$ is the total amount of power output generated by all the TPGs in the given power system; P_{WPG} and P_{SPG} are the amount of power supplied by the WPG and SPG ; P_{LD} and P_{Loss} are the power required by load and the amount of power loss. The power loss in Equation (2) is determined using the following expression:

$$P_{Loss} = \sum_{n=1}^{N_{TPG}} \sum_{m=1,n\neq m}^{N_{TPG}} P_{TPG,n} B_{nm} PG_{TPG,m} + \sum_{n=1}^{N_{TPG}} B_{0n} PG_{TPG,n} + B_{00} \quad (3)$$

Where, B_{nm}, B_{0n}, and B_{00} are the loss coefficients.

- *The the operational constraints of TPGs:* This constraint is applied to ensure that the power supplied by all the TPGs in the given system can only change within their physical limits as designed:

$$P_{TPG,n}^{Min} \le P_{TPG,n} \le P_{TPG,n}^{Max} \quad (4)$$

Where $P_{TPG,n}^{Min}$ and $P_{TPG,n}^{Max}$ are the minimum and maximum power output supplied by the TPG *j* in its physical design, $P_{TPG,n}$ is power output supplied by TPG *n*.

- *The operational constraint of WPG and SPG*: This constraint means that the amount of power supplied by both WPG and SPG must be varied within their design capability as follows:

$$P_{WPG}^{Min} \le P_{WPG} \le P_{WPG}^{Max} \quad (5)$$

$$P_{SPG}^{Min} \le P_{SPG} \le P_{SPG}^{Max} \quad (6)$$

Where $\mathrm{PG}_{\mathrm{WP}}^{\mathrm{lw}}$ and PG_{WP}^{hg} are the lowest and the highest power generated by WPG, PG_{SP}^{lw} and PG_{SP}^{hg} are the lowest and the highest power generated by SPG, PG_{WP} and PG_{SP} are, respectively, the power generated by the WPG and SPG.

C. The Greylag Goose Optimization

As previously mentioned, Greylag Goose Optimization (GGO) is a population-based meta-heuristic algorithm that shares common characteristics with other algorithms. The distinguishing feature of GGO lies in its unique solution update method. This method comprises two distinct phases, the mathematical models of which are detailed in the subsequent subsections:

a. Phase 1

In this phase, all the solutions are updated using the following mathematical model:

$$X_i^{new} = \begin{cases} w_4 \times |X_B - X_i| \times e^{b\cos(2\pi l)} + [2lw_1 \times (rn_3 + \\ X_B - AF \times |BF \times X_B - X_i|, \\ w_1 \times X_{R1} + z \times w_2 \times (X_{R2} - X_{R3}) + (1 - HI \times PS \end{cases} \quad (7)$$

With

$$AF = 2k \times rn_1 - k \quad (8)$$

$$BF = 2 \times rn_2 \quad (9)$$

In the Equations 7 – 9, X_i^{new} and X_i arethe new and the current solution with *i* = 1, 2, …, *PS*; X_B is the best solution in the whole population; w_1, w_2, w_3, w_4 are the secondary control parameters set up initially; rn, rn_1, rn_2, rn_3, rn_4, and l are the random values between zero and one; ; *HI* is the highest index of iteration; AF and BF the multiflying factors; X_{R1}, X_{R2}, and X_{R1} are the random solutions picked up from the initial

International Journal of Scientific Engineering and Science
Volume 9, Issue 4, pp. 44-49, 2025. ISSN (Online): 2456-7361

population; k is the random value that linearly varies between 2 and 0 according to the authors

b. Phase 2

In this exploitation phase, all the solutions are updated by applying the following model:

$$X_i^{new} = \begin{cases} \left(\sum_{i=1}^{3} X_{Ti}\right)^3, \text{if } rn = 0 \\ X_i + X_{SR} \times (1 + HI \times PS) \times w_4 \times (X_i - X_{Neib}) \end{cases} \quad (10)$$

Where

$$X_{T1} = AF_1 \times |BF_1 \times X_{S1} - X_i|;\ X_{T2}\ AF_2 \times |BF_2 \times X_{S2} - X_i|;\ X_{T3} = AF_3 \times |BF_3 \times X_{S3} - X_i| \quad (11)$$

And

$$X_{SR} = [X_{S1};\ X_{S2};\ X_{S3}] \quad (12)$$

In Equations 10 – 12, X_{T1}, X_{T2}, and X_{T3} are the guiding solutions; X_{S1}, X_{S2}, and X_{S3} are the top three best solutions in the population; X_{SR} is randomly picked from the top three best solutions; X_{Neib} is is the neighborhood solution, which is acknowledged to be close to the best solution.

III. Results

In this section, FLO and GGO are applied to optimize the allocation of power output to the 20-TPG power system with a load demand of 2500 MW for the main objective function of minimizing the TFC. Wind and solar power generators with rated power of 120MW and 60MW are also integrated with the given power system. FLO and GGO are set by the same initial control parameters regarding population size (*PS*) and Highest index of iteration (*HI*). These parameters for the two applied algorithms are set by 50 and 200, respectively. Besides, each applied algorithm is executed for 50 independent runs to find the best solution before making any comparisons.

All the works and related simulations for the study are conducted in a computer with 2.6 GHz of the central processing unit (CPU) clock speed and 16GB of Random accessing memory (RAM). MATLAB software version R2019a has been selected as the main foundation for implementing two applied algorithms.

Figure 1 presents the TFC values achieved by FLO and GGO after 50 independent runs. The TFC values in the figure indicate that GGO offers a better capability in reaching the optimal value of the main objective functions, and the method also provides better stability throughout all the independent runs due to its TFC values being less fluctuating than those obtained by FLO.

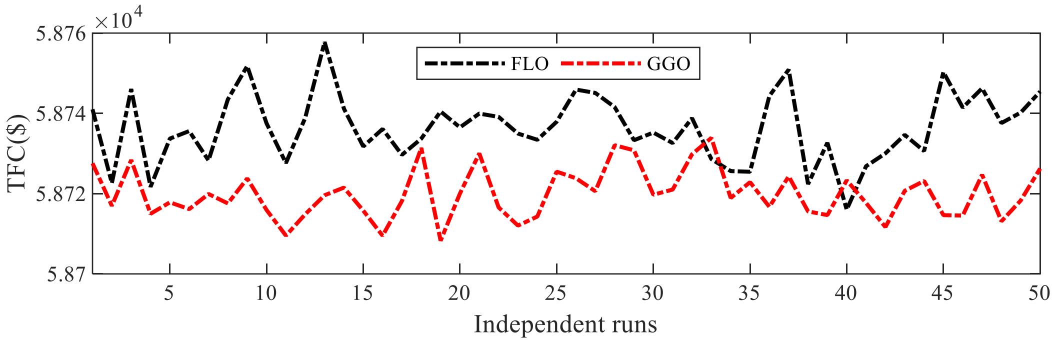

Figure 1. The values of TFC achieved after 50 independent runs of the two applied algorithms

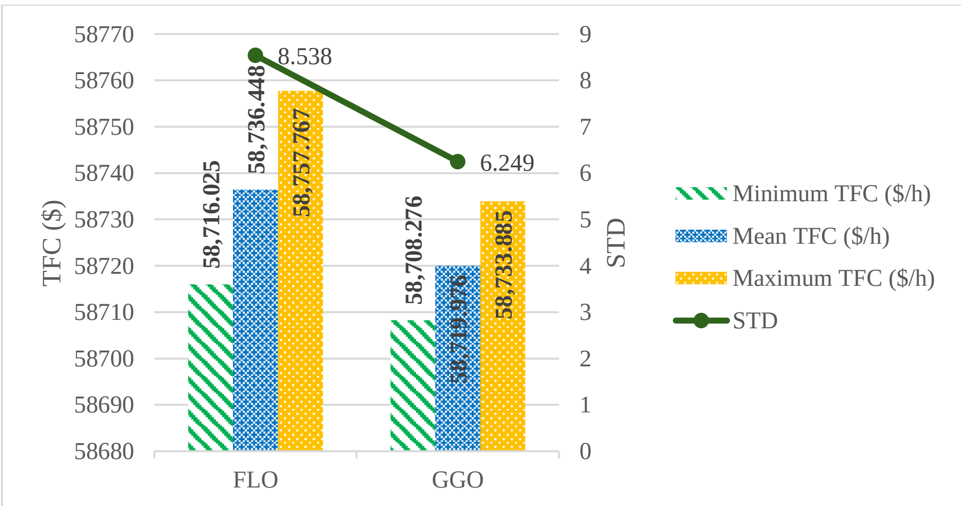

Figure 2. The summary of the results achieved by the two algorithm on different criteria

Volume 9, Issue 4, pp. 44-49, 2025.

ISSN (Online): 2456-7361

Figure 2 presents a comparative analysis of FLO and GGO across four key performance indicators: Minimum Total Flow Cost (TFC), Mean TFC, Maximum TFC, and Standard Deviation (STD). The numerical data clearly demonstrates the superior performance of GGO over FLO in all evaluated metrics. Specifically, GGO achieved the following results: Minimum TFC of $58,708.276, Mean TFC of $58,719.976, Maximum TFC of $58,733.885, and an STD of 6.249. In contrast, FLO exhibited the following performance: Minimum TFC of $58,716.025, Mean TFC of $58,736.448, Maximum TFC of $58,757.767, and an STD of 8.538. Quantitatively, GGO demonstrated improvements over FLO as follows: a 0.0132% reduction in Minimum TFC, a 0.0280% reduction in Mean TFC, a 0.0407% reduction in Maximum TFC, and a 26.81% reduction in STD. These results consistently indicate a significant performance enhancement by GGO compared to FLO.

Figure 3 illustrates the convergence behavior of the two algorithms, FLO and GGO, corresponding to the Minimum, Mean, and Maximum Total Flow Cost (TFC) values presented in Figure 2. Specifically, subfigure (a) depicts the convergence curves for the minimum TFC achieved by each algorithm during their optimal runs. Subfigures (b) and (c) display the convergence trends for the mean and maximum TFC values, respectively.

As shown in subfigure (a), GGO exhibits both a superior ability to achieve the optimal objective function value and a faster convergence rate compared to FLO. Furthermore, subfigures (b) and (c) reinforce GGO's superiority. GGO consistently converges to its optimal values within fewer than 50 iterations, a performance FLO fails to replicate in terms of both convergence speed and final solution quality.

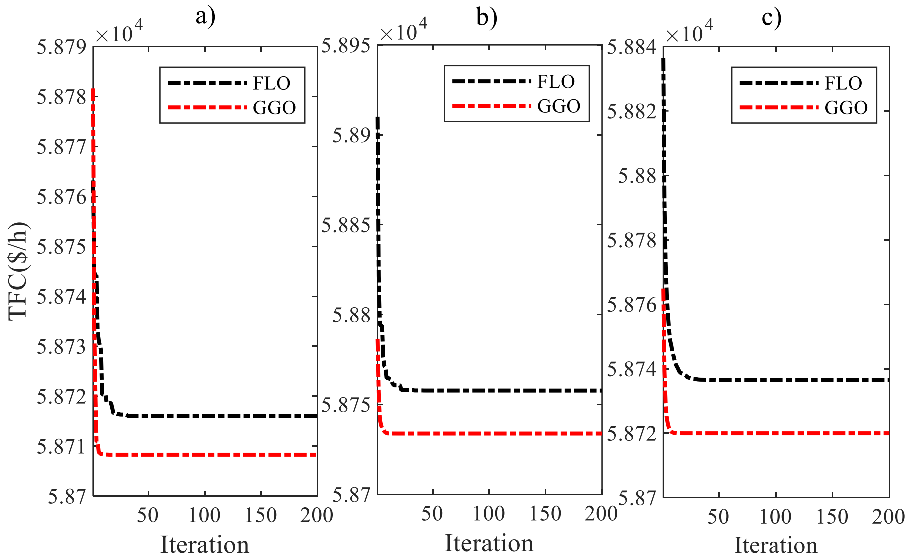

Figure 3. The minimum, mean, and maximum convergences achieved the two algorithms.

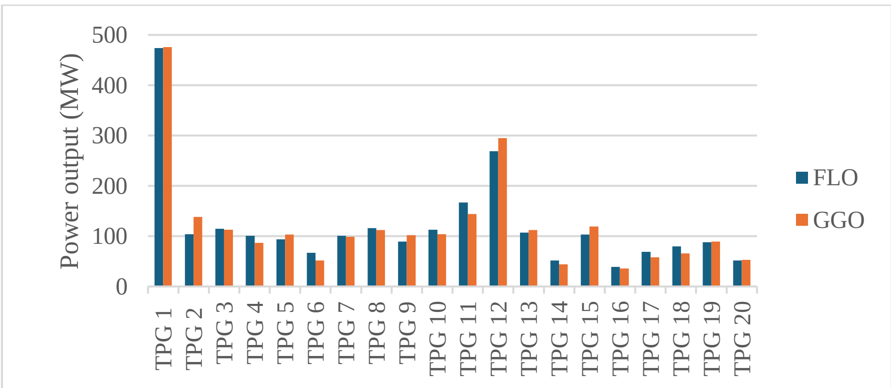

Figure 4. The correspondence between the power output supplied by each TPG achieved by FLO and GGO

Figure 4 illustrates the power output of each Thermal Power Generator (TPG) in the system, as determined by FLO and GGO. The data reveals that GGO yielded higher power output values for TPGs 2, 5, 12, 15, and 19. Conversely, the remaining TPGs exhibited lower power output values when optimized by GGO compared to FLO. Consequently, the reduced power output in these TPGs contributed to the lower Total Flow Cost (TFC) observed previously.

Figure 5 illustrates the fuel cost (FC) associated with the power output of each TPG, as presented in Figure 4. Additionally, the difference in fuel cost (Diff_Cost) between FLO and GGO for each TPG is depicted. The Diff_Cost,

International Journal of Scientific Engineering and Science
Volume 9, Issue 4, pp. 44-49, 2025. ISSN (Online): 2456-7361

represented by the yellow bars, is calculated by subtracting the FC obtained by GGO from the FC obtained by FLO. The downward-pointing yellow bars indicate that FLO resulted in a lower fuel cost for that specific TPG compared to GGO. Conversely, the upward-pointing yellow bars signify that GGO achieved a more economical fuel cost for that TPG.

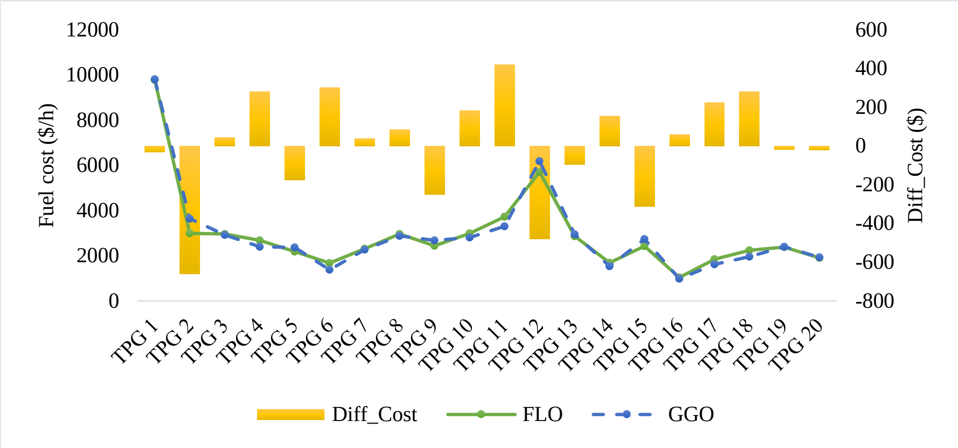

Figure 5. The illustration of fuel cost of each TPG in the system achieved by FLO and GGO

IV. CONCLUSIONS

This study successfully applies two meta-heuristic algorithms, Frilled Lizard Optimization (FLO) and Greylag Goose Optimizatio (GGO), to optimize power output allocation within a 20-TPG system integrated with wind and photovoltaic power generation. The objective was to minimize the total fuel consumption of the TPGs while meeting a 2500 MW load demand, accounting for transmission losses. Both algorithms were employed to determine the optimal power output for each of the 20 TPGs. The performance of the algorithms was evaluated using four key criteria: Minimum TFC, Mean TFC, Maximum TFC, and Standard Deviation (STD). The results demonstrate a clear superiority of GGO over FLO across all criteria, particularly in convergence speed and solution stability. Specifically, GGO exhibited the following improvements over FLO: a 0.0132% reduction in Minimum TFC, a 0.0280% reduction in Mean TFC, a 0.0407% reduction in Maximum TFC, and a 26.81% reduction in STD. These findings suggest that GGO is a robust and effective search method for addressing large-scale and complex optimization problems, such as the Generation Economic Load Dispatch (GE-ELD) problem.

REFERENCES

1. Van Hong, T. P., Ngoc, D. V., & Tuan, K. D. (2021, April). Environmental economic dispatch using stochastic fractal search algorithm. In *2021 International Symposium on Electrical and Electronics Engineering (ISEE)* (pp. 214-219). IEEE.
2. Mustafa, N., & Vennila, H. (2018). A meta-heuristic, moth inspired algorithm for combined economic and environmental power dispatch. International Journal of Enterprise Network Management, 9(1), 47-57.
3. Chen, J. F., Chen, H. C., & Huang, C. L. (1995). The uniqueness of the local minimum for power economic dispatch problems. Electric power systems research, 32(3), 187-193.
4. Farag, A., Al-Baiyat, S., & Cheng, T. C. (1995). Economic load dispatch multiobjective optimization procedures using linear programming techniques. IEEE Transactions on Power systems, 10(2), 731-738.
5. Acharya, S., Ganesan, S., Kumar, D. V., & Subramanian, S. (2023). Optimization of cost and emission for dynamic load dispatch problem with hybrid renewable energy sources. Soft Computing, 1-33.
6. Yousefi, N., Joorabian, M., & Abasi, M. (2024). Solving Combined Economic Emission Dispatch Problem Using the Rain Optimization Algorithm. *Journal of Applied Research in Electrical Engineering*, *3*(1), 19-32.
7. Nguyen, T. T., & Vo, D. N. (2015). The application of one rank cuckoo search algorithm for solving economic load dispatch problems. Applied Soft Computing, 37, 763-773.
8. Nguyen, H. D., Truon, K. H., & Le, N. A. (2023). The application of equilibrium optimizer for solving modern economic load dispatch problem considering renewable energies and multiple-fuel thermal units. International Journal of Renewable Energy Development, 12(3).
9. Pham, L. H., Nguyen, T. T., Vo, D. N., & Tran, C. D. (2016). Adaptive cuckoo search algorithm based method for economic load dispatch with multiple fuel options and valve point effect. Int. J. Hybrid Inf. Technol, 9(1), 41-50.
10. Saxena, N., & Ganguli, S. (2015). Solar and wind power estimation and economic load dispatch using firefly algorithm. Procedia Computer Science, 70, 688-700.
11. Zhang, L., Khishe, M., Mohammadi, M., & Mohammed, A. H. (2022). Environmental economic dispatch optimization using niching penalized chimp algorithm. *Energy*, *261*, 125259.
12. Kamboj, V. K., Kumari, C. L., Bath, S. K., Prashar, D., Rashid, M., Alshamrani, S. S., & AlGhamdi, A. S. (2022). A cost-effective solution for non-convex economic load dispatch problems in power systems using slime mould algorithm. Sustainability, 14(5), 2586.
13. He, X., Rao, Y., & Huang, J. (2016). A novel algorithm for economic load dispatch of power systems. Neurocomputing, 171, 1454-1461.
14. Trivedi, I. N., Jangir, P., Bhoye, M., & Jangir, N. (2018). An economic load dispatch and multiple environmental dispatch problem solution with microgrids using interior search algorithm. Neural Computing and Applications, 30, 2173-2189.
15. Bhoye, M., Pandya, M. H., Valvi, S., Trivedi, I. N., Jangir, P., & Parmar, S. A. (2016, April). An emission constraint economic load dispatch problem solution with microgrid using JAYA algorithm. In 2016 international conference on energy efficient technologies for sustainability (ICEETS) (pp. 497-502). IEEE.
16. 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, 77882-77893.
17. Ha, P. T., Hoang, H. M., Nguyen, T. T., & Nguyen, T. T. (2020). Modified moth swarm algorithm for optimal economic load dispatch problem. TELKOMNIKA (Telecommunication Computing Electronics and Control), 18(4), 2140-2147.
18. Said, M., Houssein, E. H., Deb, S., Ghoniem, R. M., & Elsayed, A. G. (2022). Economic load dispatch problem based on search and rescue optimization algorithm. IEEE Access, 10, 47109-47123.

Volume 9, Issue 4, pp. 44-49, 2025. ISSN (Online): 2456-7361

19. Ahmed, I., Rehan, M., Basit, A., & Hong, K. S. (2022). Greenhouse gases emission reduction for electric power generation sector by efficient dispatching of thermal plants integrated with renewable systems. *Scientific Reports*, *12*(1), 12380.
20. Suresh, V., Sreejith, S., Sudabattula, S. K., & Kamboj, V. K. (2019). Demand response-integrated economic dispatch incorporating renewable energy sources using ameliorated dragonfly algorithm. *Electrical Engineering*, *101*, 421-442.
21. 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.
22. Jadoun, V. K., Pandey, V. C., Gupta, N., Niazi, K. R., & Swarnkar, A. (2018). Integration of renewable energy sources in dynamic economic load dispatch problem using an improved fireworks algorithm. *IET renewable power generation*, *12*(9), 1004-1011.
23. Abu-Mouti, F. S., & El-Hawary, M. E. (2012, March). Optimal dynamic economic dispatch including renewable energy source using artificial bee colony algorithm. In *2012 IEEE International Systems Conference SysCon 2012* (pp. 1-6). IEEE.
24. 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.
25. Keswani, R., Verma, H. K., & Sharma, S. K. (2020, October). Dynamic economic load dispatch considering renewable energy sources using multiswarm statistical particle swarm optimization. In *2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON)* (pp. 405-410). IEEE.
26. Das, D., Bhattacharya, A., & Ray, R. N. (2020). Dragonfly algorithm for solving probabilistic economic load dispatch problems. *Neural Computing and Applications*, *32*, 3029-3045.
27. Said, M., El-Rifaie, A. M., Tolba, M. A., Houssein, E. H., & Deb, S. (2021). An efficient chameleon swarm algorithm for economic load dispatch problem. *Mathematics*, *9*(21), 2770.
28. 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).
29. 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.
30. Kusuma, P. D., & Hasibuan, F. C. (2025). A stochastic optimization called split-compete optimization and its utilization on economic load dispatch problem. *Bulletin of Electrical Engineering and Informatics*, *14*(2), 1486-1496.
31. Falahah, I. A., Al-Baik, O., Alomari, S., Bektemyssova, G., Gochhait, S., Leonova, I., ... & Dehghani, M. (2024). Frilled lizard optimization: A novel nature-inspired metaheuristic algorithm for solving optimization problems. *Preprints*, 2024030898.
32. 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.