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Solving Renewable Energy-based Economic Load Dispatch Considering the Multiple Fuel Options of Thermal Power Unit using Sand Cat Swarm Optimization

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Abstract**—** *This study investigates the application of two novel meta-heuristic algorithms, Sand Cat Swarm Optimization (SCSO) and Starfish Optimization Algorithm (SFOA), to address the Renewable Energy-based Economic Load Dispatch (REB-ELD) problem. The primary objective is to minimize the overall fuel expense (OFE) of a 10-Thermal Power Unit (TPU) system by optimizing power allocation for load demands of 2500 MW and 2600 MW, considering renewable energy integration and multiple fuel options. Results demonstrate that SCSO consistently outperformed SFOA, exhibiting superior performance in minimizing objective function evaluations (OFE), achieving faster convergence, and demonstrating greater stability. Specifically, SCSO showed lower OFE value fluctuations across 50 trials and achieved optimal OFE values more rapidly than SFOA for both load demand levels. Furthermore, the average and maximum OFE values obtained by SCSO were lower than those of SFOA, indicating higher efficiency. These findings suggest that SCSO provides a more efficient and effective solution for optimizing power allocation in REB-ELD problems.*

Keywords**—** *Renewable Energy-based Economic Load Dispatch; overall fuel expense; multiple fuel options meta-heuristic algorithm; Sand Cat Swarm Optimization.*

I. INTRODUCTION

The distribution of power generation for optimal cost, known as Economic Load Dispatch (ELD), continues to be a vital function in power system operations [1]. Solving the ELD challenge involves strategically assigning power output to thermal power units (TPUs) to achieve the lowest possible fuel expenditure while meeting load demand and system limitations [2]. Additionally, efficient ELD solutions offer environmental advantages by lessening emissions from fossil fuel power plants [3]. As renewable energy sources like solar and wind become more prevalent, the traditional focus on TPUs has shifted to include Renewable Energy Based-Economic Load Dispatch (REB-ELD) [4-5]. This evolving method integrates conventional and renewable resources to provide both cost-effective and environmentally conscious power delivery.

Recognizing the significance of addressing both ELD and RE-ELD, numerous studies have explored solutions to these challenges. Notably, meta-heuristic algorithms have emerged as the dominant approach. Among the meta-heuristic techniques applied to solve these problems are the search and rescue optimization algorithm (SROA) [6], five phases algorithm (FPA) [7], the improved whale optimization algorithm (IWOA) [8], Performance of turbulent flow of water optimization (TFWO) [9], Ant Lion Optimizer (ALO) [10], Artificial Rabbits Optimization Algorithm (AROA) [11], Modified Krill Herd Algorithm (MKHA) [12], Squirrel Search Optimizer (SSO) [13], Gravitational Search Algorithm (GSA) [14], genetic algorithm (GA) [15], crow search algorithm (CRA)[16], grasshopper optimization algorithm (GOA) [17], Dynamic differential annealed optimization (DDAO) [18], multi-objective Salp Swarm Algorithm (MSSA) [19], Harmony search algorithm (HSA) [20].

In this study, two recently proposed meta-heuristic algorithms, Sand Cat Swarm Optimization (SCSO) [21] and Starfish Optimization Algorithm (SFOA) [22], are used to determine the optimal solution to the Renewable Energy-based Economic Load Dispatch (REB-ELD) problem. Specifically, both SCSO and SFOA will determine the optimal power allocation among all Thermal Power Units (TPUs) in the considered system to minimize the Overall Fuel Expense (OFE). Additionally, the contributions of renewable energy-based power units (RBPUs) and the multiple fuel options of the TPUs are taken into account. Regarding the algorithms used in this study, both SCSO and SFOA are bio-inspired meta-heuristic algorithms, meaning that their development is based on the interaction of particular animals in nature. Particularly, SCSO simulates the living practices of the sand cat, while SFOA mimics certain behaviors of the starfish in the ocean.

The main novelties and contributions of this study are summarized as follows:

- Successful application of two novel meta-heuristic algorithms to solve the Renewable Energy-based Economic Load Dispatch (REB-ELD) problem, considering both Renewable Energy-based Power Units (RBPUs) and the multiple fuel options for each Thermal Power Unit (TPU).
- Determination of the superior algorithm, which exhibits a faster convergence speed and greater stability when addressing the REB-ELD problem, through the use of specific comparison criteria.
- The inclusion of RBPUs provides a practical reference for integrating clean energy sources into the traditional economic

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load dispatch problem, an approach that is increasingly encouraged.

1. Problem description

1.1. The main objective function

The main objective function of the study is to reduce the overall fuel expense (OFE) of all thermal power units (TPUs) in the considered system, as described below:

$$Reducing\ OFE = \sum_{i=1}^{N_{TPUs}} \varepsilon_{1i} TP_i^2 + \varepsilon_{2i} TP_i + \varepsilon_{3i} \quad (1)$$
$$with\ i = 1, \ldots, N_{TPUs}$$

Where OFE is the overall fuel expense of all TPUs in the considered power system; ε_{1i}, ε_{2i}, and ε_{3i} are fuel coefficient of the TPU *i*; TP_i is the power supplied of the TPU *i*; and N_{TPU} is the quantity of the TPUs in the power system.

1.2. The involved constraints

- *The power balance constraint:*

The balance between generated power and load demand, inclusive of losses, is achieved by the subsequent constraint:

$$\sum_{i=1}^{N_{TPU}} TP_i + \sum_{k=1}^{N_{RBPU}} RP_k = P_D + P_{Loss} \quad (2)$$

Where, $\sum_{i=1}^{N_{TPU}} TP_i$ is total amount of power supplied from all the TPUs in the considered system; $\sum_{k=1}^{N_{RPU}} RP_k$ is the total amount of power supplied by all the renewable-based power units (RBPUs) in the system with k = 1, 2, …, N_{RBPU} with N_{RBPU} is the quantity of RBPUs in the systems; P_D and P_{Loss} are the amount of power required by load and the losses.

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

$$P_{Loss} = \sum_{i=1}^{N_{TPU}} \sum_{j=1, i\neq j}^{N_{TPU}} TP_i \gamma_{ij} TP_j + \sum_{i=1}^{N_{TGU}} \gamma_{0i} TP_i + \gamma_{00} \quad (3)$$

Where, γ_{ij}, γ_{0i}, and γ_{00} are, respectively the loss coefficients.

- *The operational constraint of TPUs*

Each TPU's power output is limited by this constraint, which specifies its allowed minimum and maximum values:

$$TP_i^{min} \leq TP_i \leq TP_i^{max} \quad (4)$$

Where, TP_i^{min} and TP_i^{max} are the minimum and maximum power generated by TPU *i*; TP_i is the power generated by the TPU *i*.

- *The multiple fuel option constraint*

As mentioned earlier, this research will evaluate the multiple fuel constraint of each TPU and the mathematical expression of the constraint is given below:

$$OFE = \begin{cases} \varepsilon_{1i}^1 + \varepsilon_{2i}^1 TP_i + \varepsilon_{3i}^1 TP_i^2; & if\ TP_i^{min} \leq TP_i \leq PTG_n^{max} \\ \varepsilon_{1i}^2 + \varepsilon_{2i}^2 TP_i + \varepsilon_{3i}^2 TP_i^2; & if\ TP_i^{min,2} \leq TP_i \leq PTG_n^{max} \\ \ldots & \\ \varepsilon_{1i}^q + \varepsilon_{2i}^q TP_i + \varepsilon_{3i}^q TP_i^2; & if\ TP_i^{min,q} \leq TP_i \leq TP_i^{ma} \end{cases} \quad (5)$$

Where ε_{1i}^1, ε_{2i}^1 and ε_{3i}^1 are the fuel coefficient of the TPU *i* while operating with fuel option 1, TP_i^{min} and $TP_n^{max,1}$ are the minimum and maximum power supplied by TPU *i* while operating with the fuel option 1. ε_{1i}^2, ε_{2i}^2 and ε_{3i}^2 are the fuel coefficient of the TPU *i* while operating with fuel option 2, $TP_i^{min,2}$ and $TP_i^{max,2}$ are the minimum and maximum power supplied by TPU *i* while operating with the fuel option 2. ε_{1i}^q, ε_{2i}^q and ε_{3i}^q are the fuel coefficient of the TPU *i* while operating with fuel option *q*, $TP_i^{min,q}$ and TP_i^{max} are the minimum and maximum power supplied by TPU *i* while operating with the fuel option *q*, with *q* is the number of fuel options.

- *The operational constraints of the RBPU*

Similar to the TPU as mentioned earlier, the power supplied by RPU must vary within their design capabilities as follows:

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

Where, RP_k^{min} and RP_k^{max} are the minimum and maximum power supplied by the RBPU k.

II. Applied algorithms

In this section, the mathematical model of the update process for the new solution featured by the two mentioned algorithms will be shortly given in the next two subsections below:

2.1 The Sand Cat Swarm Optimization

The update process of SCSO is based on the variation of the sand cat while hunting for the prey in nature. The simulation of the variation of the sand cat is modeled by the following mathematical expression:

$$X_n^{new} = \begin{cases} \left(X_{Best,n} - rnd \times X_n\right) \times \varphi, & if\ rf\ \leq 1 \\ X_{GBest} - X_{rnd} \times cos(\delta) \times \varphi, & otherwise \end{cases} \quad (7)$$

with

$$X_{rnd} = rnd \times \left(X_{Best,n} - X_t\right) \quad (8)$$

$$\varphi = rg \times rnd \quad (9)$$

$$rg = 2 - \left(\frac{4 \times CI}{CI + HI}\right) \quad (10)$$

Where X_n^{new} and X_n are the new and the current position of the individual *n* with *n* = 1, 2, …, *PS* and *PS* is the population size; rnd is the random value between zero and one; $X_{Best,n}$ is the best-so-far position of the individual n; φ is the navigating factor. X_{GBest} is the best position among the population; δ is the phase angle of the individual n while heading to the prey; rf is the reference factor determined between $[-2rg, 2rg]$ with rg regulating coefficient; CI and HI are the current and the highest index of iteration.

2.2 Starfish Optimization Algorithm

Unlike the SCSO the update process for the new solutions is executed based on two methods as shown below:

- Method 1

This method is conducted based on the dimensions number of the considered problem as follows:

$$X_n^{new} = \begin{cases} \begin{cases} X_n + af_1 \times \left(X_{Best,n} - X_n\right) \times cos(\tau), & if\ rnd\ : \\ X_n - af_1 \times \left(X_{Best,n} - X_n\right) \times sin(\tau), & if\ rnd\ : \end{cases} \\ E_n \times X_n + af_2 \times (X_{rnd,1} - X_n) + af_3 \times (X_{rnd,2} - \end{cases} \quad (11)$$

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Where af_1, af_2, and af_3 are the amplifying factors; τ is the approach angle of the individual n to its prey; D is the number of dimensions of the considered problem; E_n is the energy boost featured by each individual n in the population; $X_{rnd,1}$ and $X_{rnd,2}$ are the two random individuals selected from the population.

- Method 2

The update for the new solutions of this method is executed using the following models:

$$X_n^{new} = \begin{cases} X_n + rnd \times dt_1 + rnd \times dt_2, & \text{if } n \neq PS \\ exp\left(-HI \times \dfrac{PS}{HI}\right) \times X_n, & \text{if } n = PS \end{cases} \quad (12)$$

With dt_1 and dt_2 are the distance between the two random individuals to the individual with the best position in the population.

III. RESULTS AND DISCUSSION

3.1 System data and parameter settings

In this section, SCSO and SFOA are applied to solve the Renewable Energy-based Economic Load Dispatch (REB-ELD) problem, with the primary objective of minimizing the Overall Fuel Expense (OFE) as defined in Section 2. The power system under consideration consists of ten Thermal Power Units (TPUs) and a Renewable Energy-based Power Unit (RBPU) with a capacity of 120 MW. SCSO and SFOA are used to optimize the power allocation among the ten TPUs for two load demand levels: 2500 MW and 2600 MW, while considering the multiple fuel options available for each TPU. The performance of the two algorithms is compared using various criteria to determine the superior algorithm. To ensure a fair comparison, SCSO and SFOA employ identical control parameters for population size (*PS*) and maximum number of iterations (*HI*). Specifically, for the 2500 MW load demand, *PS* and *HI* are set to 20 and 100, respectively, while for the 2600 MW load demand, they are set to 30 and 200, respectively. Furthermore, both algorithms are executed for 50 independent trials to obtain their best results before the comparison.

All coding and simulations were performed on a personal computer with the following specifications: a Central Processing Unit (CPU) with a 2.26 GHz clock speed and 16 GB of Random Access Memory (RAM). MATLAB programming language, version 2020a, was used for all computational tasks.

3.2 Simulation results

Figures 1 and 2 present the graphical results obtained by SCSO and SFOA, illustrating various aspects, including the results of 50 independent trials, the minimum convergence, and the maximum convergence, as depicted in subfigures (a), (b), and (c), respectively. Observations of these subfigures reveal that SCSO demonstrates greater stability across its trials, evidenced by the lower fluctuation of OFE values. Furthermore, subfigures (b) and (c) of both Figures 1 and 2 indicate that SCSO achieves not only a faster convergence speed but also superior OFE values for both the minimum and maximum criteria. Consequently, SCSO proves to be more effective than SFOA in addressing the considered problem for both load demand levels.

Figures 3 and 4 present the quantitative results obtained by SCSO and SFOA for two load demand levels. Four criteria are considered: Minimum OFE, Average OFE, Maximum OFE, and Standard Deviation (STD). For the 2500 MW load demand, SCSO achieved the following results: \$437.263 (Minimum OFE), \$473.367 (Average OFE), \$473.567 (Maximum OFE), and 0.077 (STD). In contrast, SFOA yielded \$437.308 (Minimum OFE), \$473.730 (Average OFE), \$747.707 (Maximum OFE), and 0.304 (STD). SCSO demonstrates improvements of \$0.045 in Minimum OFE, \$0.362 in Average OFE, and \$1.140 in Maximum OFE. More significantly, SCSO exhibits approximately four times greater stability than SFOA in the 2500 MW load demand test. In the 2600 MW load demand test, while SCSO still outperforms SFOA across all criteria, the margin of superiority is less pronounced than in the 2500 MW test, particularly for the Maximum OFE.

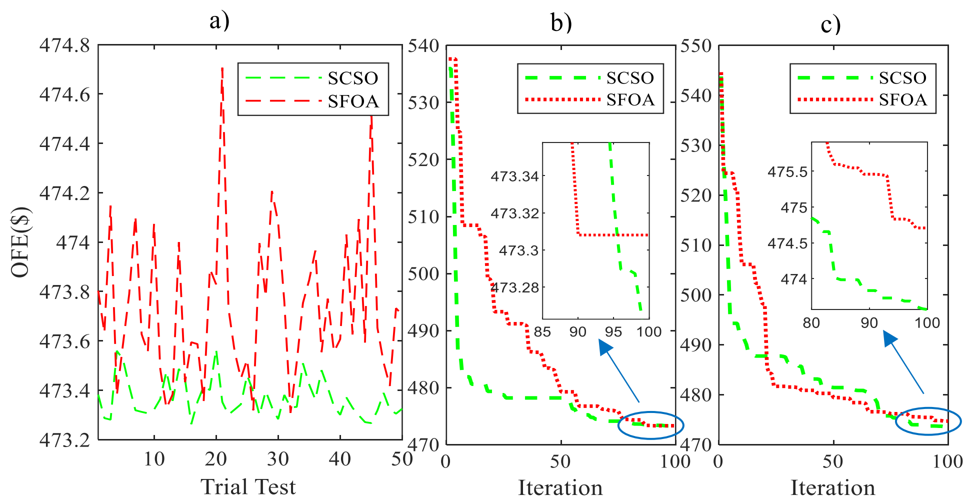

Figure 1. a) The results from 50 trial test, b) the minimum convergences, and c) the maximum convergences obtained by the SCSO and SFOA for 2500MW of load demand

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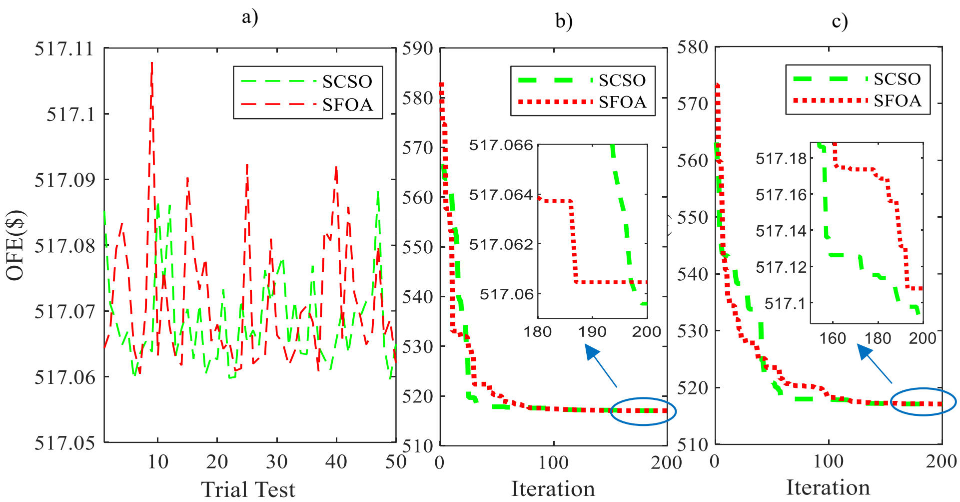

Figure 2. a) The results from 50 trial test, b) the minimum convergences, and c) the maximum convergences obtained by the SCSO and SFOA for 2600MW of load demand

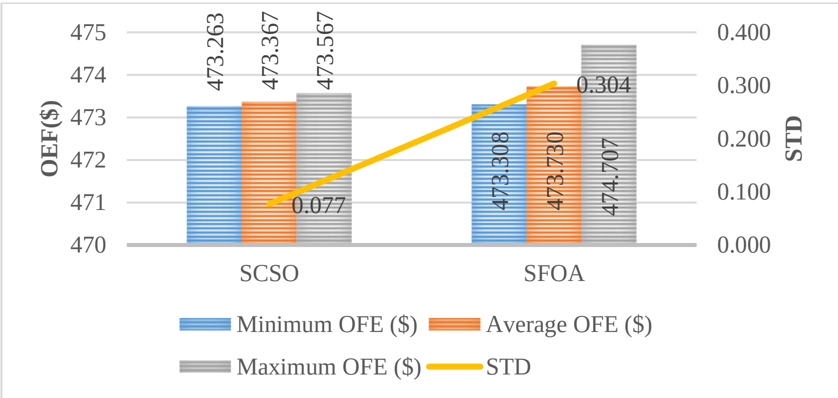

Figure 3. The comparison on different criteria between SCSO and SFOA for 2500 MW of load demand.

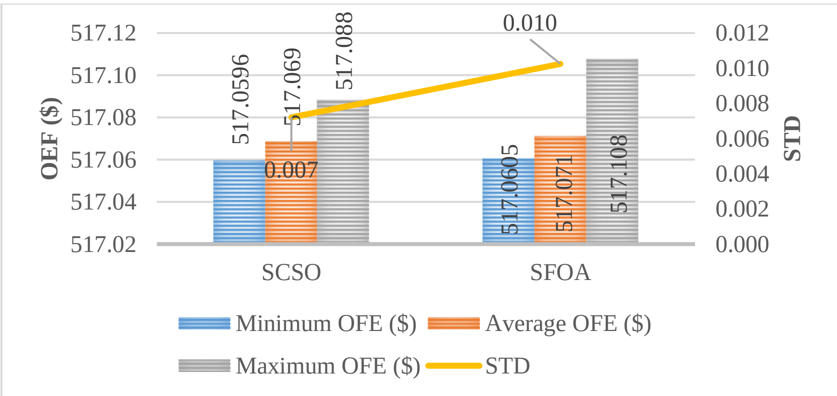

Figure 4. The comparison on different criteria between SCSO and SFOA for 2600 MW of load demand.

Figures 5 and 6 illustrate the power supplied by the 10 TPUs in the system, as allocated by SCSO and SFOA. As shown in Figure 5, the higher power allocation by SCSO to TPUs 1, 3, 5, and 9 resulted in a lower OFE value, as previously presented for the 2500 MW load demand case. However, the power allocations by SCSO and SFOA are nearly identical in Figure 6, leading to a negligible difference in the OFE values achieved by these two algorithms for this particular load demand.

Figures 7 and 8 depict the fuel expense (FE) for each TPU at the two load demand levels, 2500 MW and 2600 MW, as determined by SCSO and SFOA. Minor variations in the FE values are observed in the 2500 MW load demand case, attributed to the differences in power allocation between the two algorithms, as previously discussed. However, the FE values are nearly identical in the 2600 MW load demand case, consistent with the earlier analysis.

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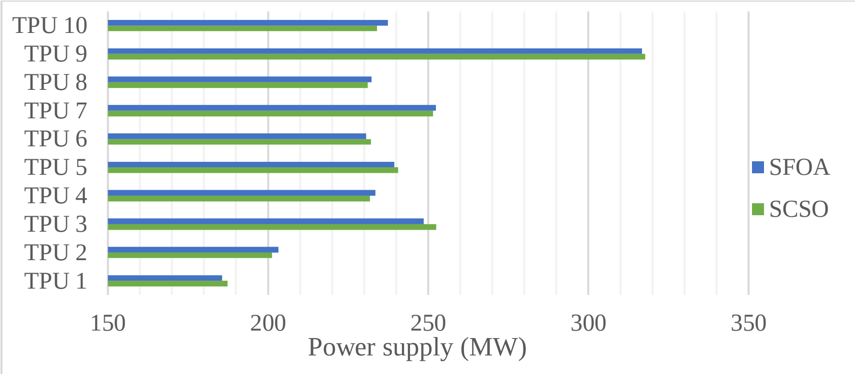

Figure 5. The power supplied by each generators in the system for 2500 MW of load demand

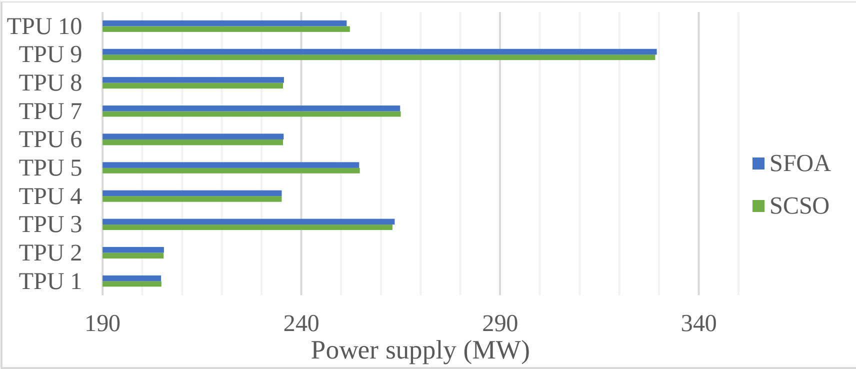

Figure 6. The power supplied by each generators in the system for 2600 MW of load demand.

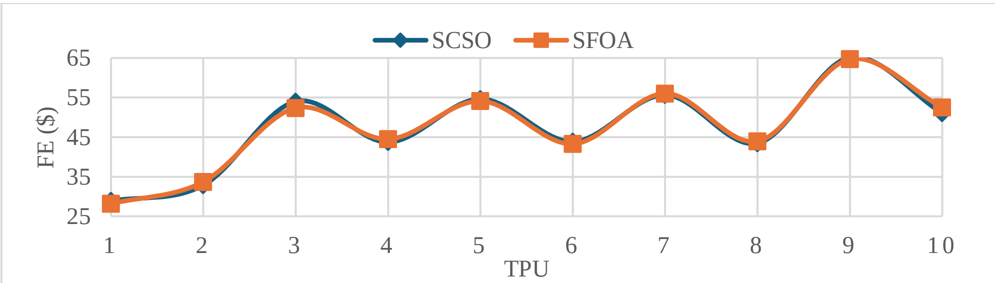

Figure 7. The fuel expenditure for each thermal power unit for 2500 MW of load demand

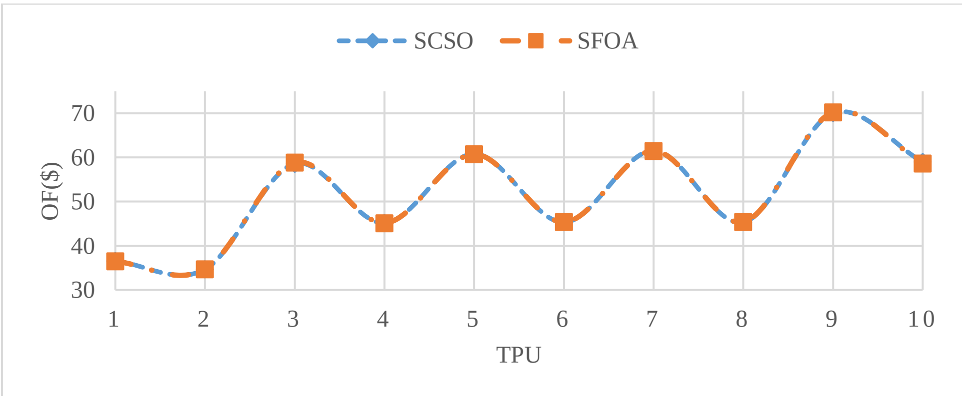

Figure 8. The fuel expenditure for each thermal power unit for 2600 MW of load demand

IV. Conclusion

In this study, two novel meta-heuristic algorithms, Sand Cat Swarm Optimization (SCSO) and Starfish Optimization Algorithm (SFOA), were successfully applied to solve the Renewable Energy-based Economic Load Dispatch (REB-ELD) problem, with the primary objective of minimizing the overall fuel expense for a 10-TPU power system. Furthermore,

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the power allocation of all TPUs was optimized for two load demand levels, 2500 MW and 2600 MW, considering the contribution of a Renewable Energy-based Power Unit (RBPU) and the multiple fuel options available for each TPU. The results obtained by the two algorithms for both load demand levels indicate that SCSO outperforms SFOA across all comparison criteria, including Minimum OFE, Average OFE, Maximum OFE, and Standard Deviation (STD), for the 2500 MW load demand. For the 2600 MW load demand, SCSO maintained its advantages over SFOA; however, the performance difference was less pronounced than in the 2500 MW case. Overall, SCSO exhibited a faster convergence speed to the optimal value of the objective function and greater stability compared to SFOA. Based on these findings, SCSO demonstrates an efficient search methodology and is highly recommended for optimizing the power allocation in REB-ELD problems.

REFERENCES

1. Van, T. P., Snášel, V., & Nguyen, T. T. (2020). Antlion optimization algorithm for optimal non-smooth economic load dispatch. Int. J. Electr. Comput. Eng, 10(2), 1187-1199.
2. Dasgupta, Koustav, and Sumit Banerjee. "An analysis of economic load dispatch using different algorithms." 2014 1st International Conference on Non Conventional Energy (ICONCE 2014). IEEE, 2014
3. Wu, L. H., Wang, Y. N., Yuan, X. F., & Zhou, S. W. (2010). Environmental/economic power dispatch problem using multi-objective differential evolution algorithm. Electric power systems research, 80(9), 1171-1181
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. Kherfane, N., Kherfane, R. L., Younes, M., & Khodja, F. (2014). Economic and emission dispatch with renewable energy using HSA. Energy Procedia, 50, 970-979
6. 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.
7. 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.
8. Li, Q., Li, X., Guo, Z., & Du, H. (2022, December). An improved whale optimization algorithm and its application on ELD. In *Frontier Academic Forum of Electrical Engineering* (pp. 1287-1295). Singapore: Springer Nature Singapore.
9. 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.
10. Bhargava, R., Dixit, M., Gupta, I., Prasad, T. N., Muthu, R., & Naidu, R. C. (2022, December). A Bio-inspired Meta-heuristic Optimization approach for Economic Load Dispatch. In *2022 7th International Conference on Environment Friendly Energies and Applications (EFEA)* (pp. 1-6). IEEE.
11. Samal, P., Mohapatra, A., & Samal, S. (2023, May). Application of artificial rabbits optimization algorithm to the economic load dispatch problem. In *2023 4th International Conference for Emerging Technology (INCET)* (pp. 1-5). IEEE.
12. 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.
13. Suman, M., Sakthivel, V. P., & Sathya, P. D. (2020). Squirrel Search Optimizer: Nature Inspired Metaheuristic Strategy for Solving Disparate Economic Dispatch Problems. *International Journal of Intelligent Engineering & Systems*, *13*(5).
14. Kumar, G., Kumar, L., Kar, M. K., & Kumar, S. (2023). Bid-based economic load dispatch in coordination with virtual power plant. In *Soft Computing Applications in Modern Power and Energy Systems: Select Proceedings of EPREC 2022* (pp. 189-202). Singapore: Springer Nature Singapore.
15. Khan, M., Shafi, M. A., & Khosa, M. S. K. (2023). An analysis of stochastic wind power approach for economic load dispatch optimization using genetic algorithm. *Southern Journal of Engineering & Technology*, *1*(02), 36-45.
16. Spea, S. R. (2020). Solving practical economic load dispatch problem using crow search algorithm. *International Journal of Electrical & Computer Engineering (2088-8708)*, *10*(4).
17. Hazra, S., Pal, T., & Roy, P. K. (2021). Renewable energy based economic emission load dispatch using grasshopper optimization algorithm. In *Research Anthology on Clean Energy Management and Solutions* (pp. 869-890). IGI Global.
18. Shafiee, M., Zamani, A. A., & Sajadinia, M. (2023). Using improved DDAO algorithm to solve economic emission load dispatch problem in the presence of wind farms. *International Journal of Industrial Electronics Control and Optimization*, *6*(3), 161-169.
19. Hassan, M. H., Kamel, S., Domínguez-García, J. L., & El-Naggar, M. F. (2022). MSSA-DEED: A multi-objective salp swarm algorithm for solving dynamic economic emission dispatch problems. *Sustainability*, *14*(15), 9785.
20. Sahoo, A. K., Panigrahi, T. K., Paramguru, J., & Hota, A. P. (2021). Dynamic economic dispatch using harmony search algorithm. In *Advances in Machine Learning and Computational Intelligence: Proceedings of ICMLCI 2019* (pp. 425-435). Springer Singapore.
21. Seyyedabbasi, A., & Kiani, F. (2023). Sand Cat swarm optimization: A nature-inspired algorithm to solve global optimization problems. *Engineering with computers*, *39*(4), 2627-2651.
22. Zhong, C., Li, G., Meng, Z. *et al.* Starfish optimization algorithm (SFOA): a bio-inspired metaheuristic algorithm for global optimization compared with 100 optimizers. *Neural Comput & Applic* **37**, 3641–3683 (2025)