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Optimal allocation of power output to the generating units for minimizing the entire fuel cost of the whole power system, considering the prohibited operating zones, using the Starfish optimization algorithm

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Abstract

This study presents the implementation of a recently proposed meta-heuristic algorithm, the Starfish Optimization Algorithm (SFOA), to solve the thermal unit optimization operation (TUOO) problem. The main task of the entire study is to reach the minimum value of the entire fuel cost of all the generating units (GUs) in the given power system with a load demand of 2650 MW. In an effort to mitigate the negative environmental impacts of s and reduce the burden on all TGs, a 100MW solar-powered generator (SPG) and a 150MW wind- powered generator (WPG) have been added to the system. SFOA is applied to determine the optimal allocation of all GUs, taking into account prohibited operating zones (POZs). To verify the actual performance of SFOA, HO is also implemented to solve the given problem using the same initial parameters in terms of population size and maximum number of iterations, which are selected optimally through different settings. The results clearly indicate that SFOA not only achieves the lowest entire fuel cost (LEFC) of the main objective functions but also outperforms HO across the remaining comparison criteria, such as the average entire fuel cost (AEFC), maximum entire fuel cost (MEFC), and especially standard deviation (STD). Based on the achievements and results mentioned, SFOA is strongly recommended for solving the TUOO problem.

Keywords: *Thermal unit optimization operation problem, generating units, prohibited operating zones, solar-power generator, wind-powered generator; Starfish optimization algorithm.*

1. Introduction

Thermal unit optimization operation (TUOO) problem is one of the most important and challenging optimization problems in power system operation. The primary objective of TUOO is to optimize the total power demand among available generating units in a manner that minimizes the total fuel cost while satisfying a set of operational equality and inequality constraints [1,2]. Renewable energy sources and emission constraints are also considered in the TUOO problems [3,4].

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Linear programming and gradient-based algorithms were very effective in solving TUOO problems [2,3], but they are very old. Valve-point effects and prohibited operating zones were challenging issues for the problems [5,6]. Metaheuristic algorithms can solve the complex problems with real-world TUOO formulations [7,8]. Over the past two decades, nature-inspired and swarm intelligence algorithms have been proposed for TUOO. Early contributions include the Stochastic Shaking Algorithm [8], the osprey optimization algorithm [9], cuckoo search optimization [10], Jaya Algorithm [11], and the Dandelion Optimiser [12]. The memetic sine cosine algorithm [7] and the turbulent flow of water optimization [5] each demonstrate competitive performance on standard TUOO benchmarks. More recent developments include the Five Phases Algorithm [15], which offers improved exploration-exploitation balance and robustness against premature convergence. The Jaya Algorithm has also been successfully applied to TUOO in renewable-integrated systems [11], while the Dandelion Optimizer demonstrated promising results for hybrid power plant dispatch [12].

The integration of solar photovoltaic and wind power into TUOO problems represents a growing research frontier [13,14]. The Five Phases Algorithm [15] was also an effective algorithm for the problem. The Greylag Goose Optimisation algorithm [16], the Elk Herd Optimiser (EHO) [17], and the Sharpbelly Fish Optimisation Algorithm [18] were also applied for the optimization problems. EHO [17] mimicked the seasonal movement and social hierarchy of elk herds and outperformed several established algorithms on both unimodal and multimodal test functions. The application of the Sharpbelly Fish Optimization Algorithm [18] leveraged the schooling dynamics of fish for complex engineering problems. The Equilibrium Optimizer [19], inspired by principles of mass-balance physics, demonstrated strong global search capability across diverse engineering benchmarks. The Group Leader Optimisation technique [20] was applied to TUOO with competitive results. The novel Green TUOO formulation addressed carbon-aware dispatch through a dedicated metaheuristic framework [21].

Microgrids and distributed generation introduce additional layers of stochasticity and intermittency that classical TUOO solvers are ill-equipped to handle [13,23]. In this context, improved mayfly optimization [13] and enhanced emperor penguin optimization [14] have been proposed for combined economic emission dispatch in renewable-integrated microgrids, achieving notable reductions in both fuel cost and pollutant emissions. Similarly, improved fireworks algorithms have been applied to dynamic TUOO with renewable sources [23], while the novel Green TUOO formulation addressed carbon-aware dispatch through a dedicated metaheuristic framework [21]. Parallel to the evolution of TUOO methods, a new generation of general-purpose metaheuristic algorithms has emerged, providing fresh optimization engines for power system problems. The Equilibrium Optimizer [19], grounded in principles of mass-balance physics, demonstrated strong global search capability across diverse engineering benchmarks. The Greylag Goose Optimisation algorithm [16], inspired by the collective migratory behaviour of geese, achieved state-of-the-art performance on several continuous optimization problems. The Elk Herd Optimizer (EHO) [17], which mimics the seasonal movement and social hierarchy of elk herds, has been shown to outperform several established algorithms on both unimodal and multimodal test functions. Other notable additions to the metaheuristic landscape include the Sharpbelly Fish Optimization Algorithm [18], leveraging the schooling dynamics of fish for complex engineering problems, and the Group Leader Optimization technique [20] applied to TUOO with competitive results. Extensive numerical experiments on typical TUOO power systems confirm the effectiveness and competitiveness of a proposed algorithm compared to other new algorithms reported in the recent literature [21-22]. The benefit of power systems with renewable energies was significant [23].

The application of EHO to large-scale power systems incorporating solar and wind generation was recently explored, significant improvements in total generation cost compared to conventional and competing optimization methods [26]. A further study applying the Skill Optimization Algorithm to hybrid system operation cost minimization also confirmed the advantages of modern metaheuristics in multi-source dispatch scenarios [30]. Moreover, the One-to-One Optimization Algorithm has been introduced for optimal renewable-integrated economic load dispatch in large-scale systems, providing a simple yet effective search mechanism [34]. These contributions collectively highlight the importance of algorithm diversity and adaptability when dealing with real-world power system constraints. The scope of power system studies can expand to energy management, grid resilience, and emerging technologies. Deep reinforcement learning was investigated as an adaptive control method for maximum power point tracking (MPPT) under fast-changing irradiance conditions [24]. The power system with High-voltage direct current (HVDC) transmission [25] and renewable energies [26] integrated was shown to be very effective. The stability and control frameworks for VSC-based HVDC systems were presented in the study [27]. The efficiency cannot be improved without using algorithms [28]. Battery energy storage systems (BESS) in enhancing the stability and effectiveness of the HVDC grid has also been analyzed [29], leading to a significant reduction of the cost [30]. A mitigation system has been proposed to secure grid-connected photovoltaic inverters against cyber threats [31]. An electric vehicle charging station was installed in the distribution power grid, leading to huge challenges to the grids [32-33]. Additionally, false data injection attacks on power transmission lines have been mathematically analyzed [35], and a comprehensive market overview of electric vehicle batteries has been provided to inform future grid-storage strategies [33]. All the parameters of installed electric components could be optimised by using metaheuristic algorithms [34], including the optimisation problem in transmission power networks [35].

By understanding the significant advantages of meta-heuristic algorithms in solving TUOO problems, this research will apply a recently proposed meta-heuristic algorithm, the Starfish optimization algorithm (SFOA) [36], to optimize the allocation of generating units (GUs) in a 15-GU power system to minimize the total fuel cost of those GUs. Besides the prohibited operating zones (POZs) of all the GUs, they are also considered in the entire process of solving the given problem. Furthermore, 100MW solar-powered and 150MW wind-powered generators are also integrated into the given power system as an initial effort to mitigate environmental negative effects caused by the operation of GUs and reduce the burden of feeding a large existing load demand.

The main novelies and contributions of the entire research are as follows:

- Successfully applied a recent proposed meta-heuristic algorithm called the Starfish optimization algorithm to solve the TUOO problem.

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- Successfully modeling and considering the prohibited operating zones constraint (POZs) of the GUs in the entire process of solving the given problem.
- Considering the presence of solar-powered and wind-powered systems in supporting the GUs while feeding the huge load demand.
- Demonstrate the effectiveness of SFOA through comparisons with another modern meta-heuristic algorithm on different comparison criteria.

The remainder of this paper is organized as follows. Section 2 formulates the ELD problem mathematically. Section 3 describes the proposed algorithm. Section 4 presents the experimental results and comparative analysis. Section 5 concludes the paper.

2. Problem formulation

The thermal unit optimization operation (TUOO) problem determines the optimal power generation of committed available generating units while minimizing the total fuel cost and satisfying all operational constraints. The main objective is to find the smallest total electricity fuel generation cost of all available units economically while meeting the required system load demand.

2.1. The main objective function

The total fuel cost must be minimum in the TUOO problem. Each fuel cost function of the generating units (GUs) is expressed as:

$$EFC = \sum_{k=1}^{NO_{gs}} (a_k P_{Gk}^2 + b_k P_{Gk} + c_k) \quad (1)$$

where: EFC is the entire fuel cost (\$/h), NO_{gs} is the total number of generating units, P_{Gk} is the generated power of unit k(MW), a_k, b_k, and c_k are the fuel cost coefficients of generator k.

2.2. The related constraint

The objective of the TUOO problem is to minimize the total generation cost but it must satisfy the operational constraints as follows:

- **Power Balance Constraint**: The total generated power must satisfy the system load demand and transmission losses. Therefore, the equality constraint is given by:

$$\sum_{k=1}^{NO_{gs}} P_{Gk} = P_{Load} + P_{Lloss} \quad (2)$$

where P_{Load} is the total system load demand (MW), P_{Lloss} is the total transmission power loss (MW).

- **Generation Limits Constraint**: Each generating unit must operate within its allowable operating range:

$$P_{Gk}^{Lowest} \le P_{Gk} \le P_{Gk}^{Highest}, k = 1,2, \dots, NO_{gs} \quad (3)$$

where P_{Gk}^{Lowest} is the lowest power generation limit of unit k, $P_{Gk}^{Highest}$ is the highest power generation limit of unit k.

- **The prohibited operating zones constraint**: This constraint is applied to avoid the interval power output that might cause the GU to work unstably. The mathematical expression of the constraint is given as follows:

$$P_{Gk} \in \begin{cases} P_{G,k}^{low} \le P_{G,k} \le G_{G,k,1}^{p} \\ P_{G,k,s-1}^{q} \le P_{G,k} \le P_{G,k,s}^{p}\ ; s = 2, \dots, n_s; \forall z \in \Omega \\ P_{G,k,n_s}^{q} \le P_{G,k} \le P_{G,k}^{high} \end{cases} \quad (4)$$

Where, n_s is the number of POZ of the GUs in the system.

3. Starfish Optimization Algorithm (SFOA).

This section formulates the mathematical framework governing the Starfish Optimization Algorithm (SFOA) [36]. While SFOA shares the population-based foundation of conventional swarm intelligence methods, its defining feature lies in a specialized, bifurcated position-updating mechanism designed to enhance convergence reliability:

- **Stage 1: Exploration and Local Search**

In this first stage, the spatial dimensionality (DS) of the search space dictates how candidate positions are modified. The new solutions will be updated using the following model:

$$SP_t^{mod1} = \begin{cases} \begin{cases} SP_t + AF \times (SP_{best} - SP_t) \times cos\omega, & if\ \ rs \le 0.5 \\ SP_t + AF \times (SP_{best} - SP_t) \times sin\omega, & otherwise \end{cases} \\ SF \times SP_t + rs_1 \times (SP_{rg1} - SP_t) + rs_2 \times (SP_{rg2} - SP_t) \end{cases} \quad (5)$$

The dynamic steering factor (SF) is defined as:

$$SF = \left(\frac{K - k}{K}\right) \times cos\omega \quad (6)$$

In Equations (5) and (6), SP_t^{mod1} represents the modified spatial coordinates of the t-th starfish ($t = 1, 2, \dots, PS$) resulting from the first phase, with PS denoting the total population size. SP_t represents the current position vector of the t-th starfish. AF is the amplification factor scaling the step size. SP_{best} is the best-performing solution identified in the current iteration. ω denotes the phase angle defining the angular trajectory toward the optimum. DS represents the dimensional boundary of the optimization problem. SF is the steering modulator balancing exploration scope and exploitation precision. k and K denote the current iteration index and the pre-established maximum iteration limit, respectively. rs_1, rs_2, and rs_3 are stochastic scalars uniformly drawn from the continuous interval [0, 1]. SP_{rg1} and SP_{rg2} are two unique positions selected at random from the active population, serving as reference points for random-walk perturbations.

- **Stage 2: Position Exploitation**

The second phase of SFOA focuses on localized refinement of candidate solutions. The updated position SP_t^{mod2} is formulated as:

$$SP_t^{mod2} = \begin{cases} SP_t + rs_1 \times SD_1 + rs_2 \times SD_2, if\ t \ne PS \\ exp\left(\frac{-k \times PS}{K}\right) \times SP_t, if\ t\ = PS \end{cases}$$

Where, the spatial distance vectors SD_1 and SD_2 characterize the distance between the randomly selected reference individuals and the current best-performing agent.

4. Numerical Results

In this section, SFOA is applied to determine the optimal allocation of power output for a 15-TPP power system serving a load demand of 2653 MW, accounting for the prohibited operating zone constraints for each TPP. Besides, a 100MWp SPP and a 150MWp

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WPP are also integrated into the given power system to reduce the burden on all the TPPs partly. The main objective is to minimize the EFC. The performance of SFOA is further investigated by comparing it with another meta-heuristic algorithm, the Hippopotamus optimization (HO) [37]. The justification of the comparisons between the two algorithms is ensured by using the same settings for population size (*Pz*) and maximum iteration number (I_{max}), after a series of trial-and-error tests with different settings for these terms. The detail of the variation of these two paremeters are shown in Table 1 and Table 2. Besides, both HO and SFOA are executed for 50 test runs to obtain the best solutions before any comparison. All the works are conducted in the on a personal computer with the following specifications: a central processing unit with the maximum clock speed of 2.6GHz, 16GB of random accessing memmory (RAM). Besides, MATLAB programming language version 2018a is selected to be the main plaform for all coding and simulations.

Table 1: The variation of *Pz* with I_{max} is kept unchanged at 100 iteration

Pz	10	20	50	100	150	200
I_{max}	100	100	100	100	100	100
MEFC	29928.16687	29928.12385	29928.12373	29928.12375	29928.12372	29928.12373

Table 2: The variation of I_{max} with *Pz* is kept unchanged at 25 iteration

I_{max}	50	100	150	200	250	300
Pz	25	25	25	25	25	25
MEFC	29928.16008	29928.12385	29928.12373	29928.16517	29928.33385	29928.33385

Figure 1 and Figure 2 presents the lowest EFC (LEFC), average EFC (AEFC), and maximum EFC (MEFC) obtained by SFOA with different settings of *Pz* and I_{max}. Particularly, Figure 1 shown the EFC values with *Pz* varied from 10 to 200 while I_{max} is kept unchanged at 100. On the other hands, Figure 2 show the EFC values with I_{max} varied from 50 to 300 while *Pz* is kept unchanged at 25.

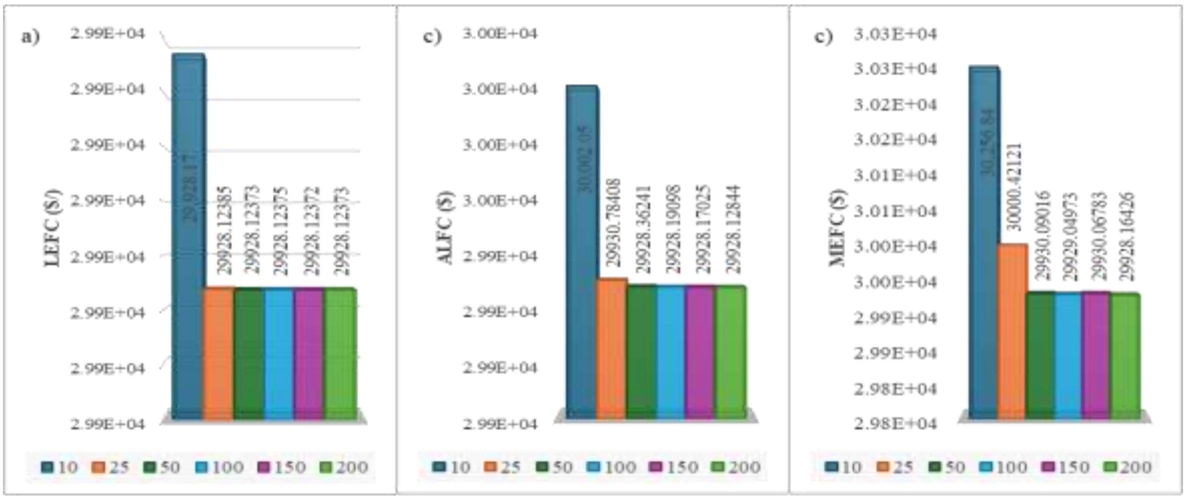

Figure 1. The LEFC, AEFC, and MEFC obtained by SFOA with different settings of the *Pz* while I_{max} is kept unchanged by 100.

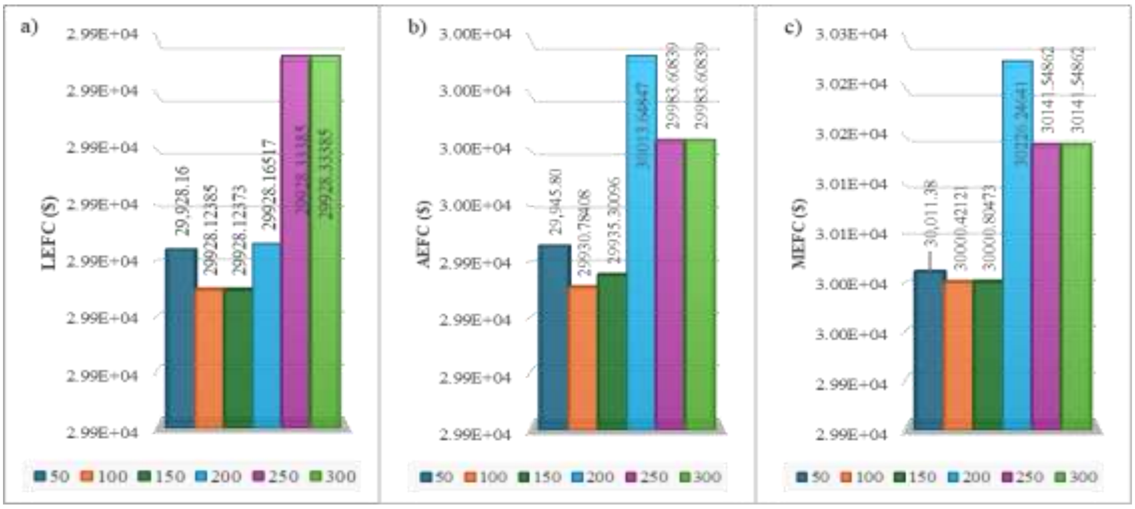

Figure 2. The LEFC, AEFC, and MEFC obtained by SFOA with different settings of I_{max} while the *Pz* is kept unchanged by 25.

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Based on the results shown in Figures 1 and 2, the optimized *Pz* and I_{max} are 25 and 100, respectively. These optimized parameters are used as the initial parameters for HO to address the given problem, and are compared with the SFOA to provide further performance analysis. Figure 3 shows the EFC values obtained by the two algorithms across 50 test runs, using the optimized settings determined from the statistical results shown in Figures 1 and 2. Figure 3 shows that SFOA is much more stable and efficient, as evidenced by significantly lower fluctuations and lower EFC values across all test runs compared to HO. That means that SFOA is more capable in reaching the best EFC values with lower standard deviation than HO.

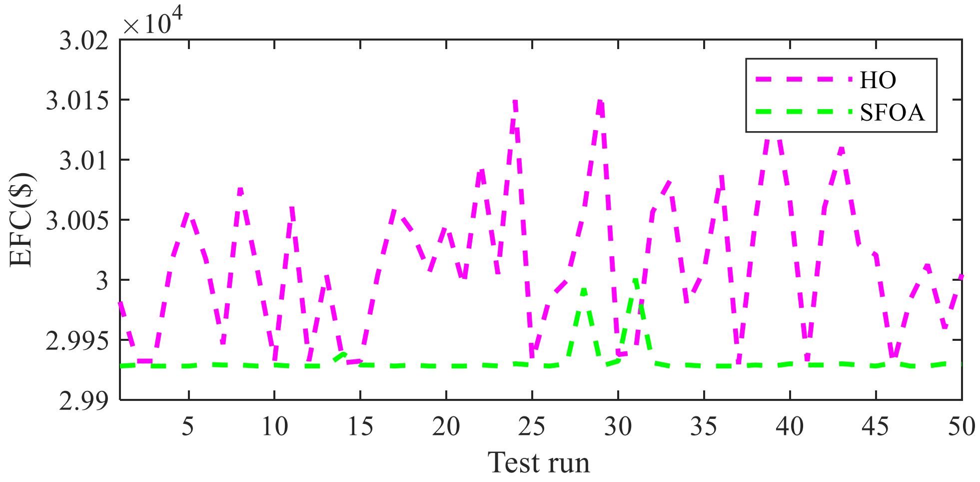

Figure 3. The EFC values obtained by HO and SFOA after 50 test runs.

Figure 4a, 4b, and 4c show the three convergences obtained by HO and SFOA in their best runs. The observation from these three subfigures clearly indicates that SFOA not only converges faster than HO, but also reaches the best values at all three convergences. In particular, for optimal convergence, SFOA requires only around 50 iterations to reach the best EFC values. For the average and the maximum convergences, the number of iterations needed is around 80 and over 50, respectively. In the meantime, HO cannot provide the same capability.

Figure 5 further highlights the superiority of SFOA over HO across various comparison criteria, including LEFC, AEFC, MEFC, and STD. The numerical results indicated that the SFOA demonstrates clear superiority over the HO across all four criteria in addressing the given problem. Particularly, SFOA achieves a lower LEFC of 29,929.090 ($/h) corresponding to 0.0032% reduction in this criterion compared with 29,928.125 ($/h). This economic advantage is further demonstrated across repeated simulations, where SFOA lowers AEFC by 0.2687% to 29,931.812 ($/h), compared to 30,012.456 ($/h), demonstrating its ability to reach better EFC values in this regard. Furthermore, SFOA also achieved the MEFC much lower than HO, with 30,000.955 ($/h) over 30,155.149 ($/h), corresponding to a better percentage of 0.5113%. Most notably, SFOA delivers an exceptional 78.6258% reduction in Standard Deviation (STD), plummeting from 63.344 to 13.539, which is further proof of SFOA's overall stability, reliability, and robustness in dealing with this problem.

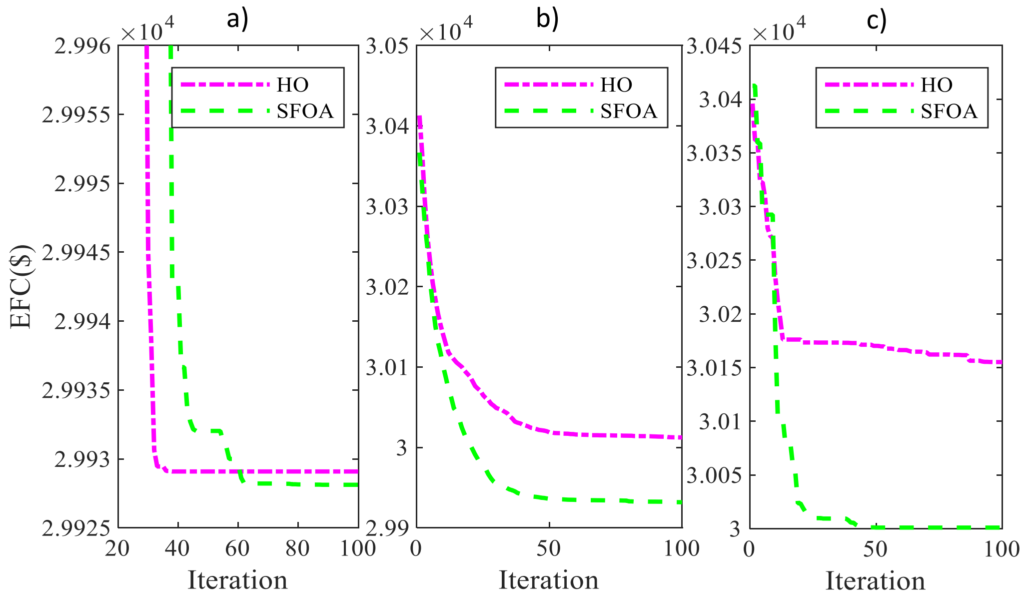

Figure 4. The minimum, average, and maximum convergences obtained by HO and SFOA for their best runs.

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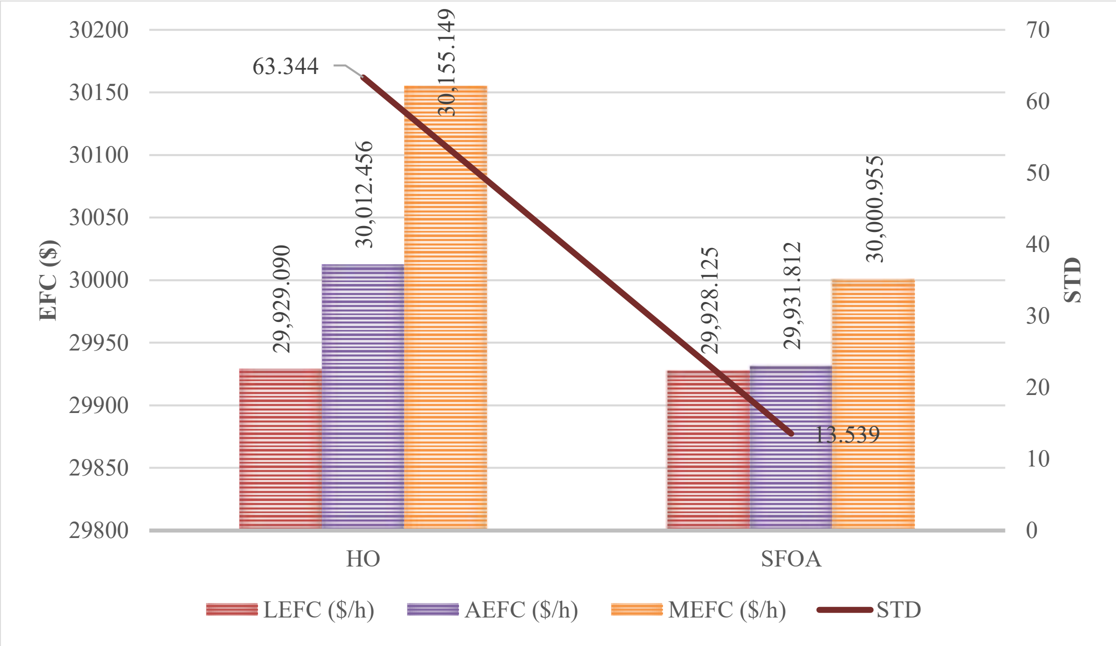

Figure 5. The statictical results of HO and SFOA on different criteria while dealing with the given problem.

Figure 6 presents the optimized power outputs and the corresponding fuel costs (FC) for each TP in the given power system. At first glance, the power outputs of all the TPs achieved by the two algorithms are mostly identical, except for TP1, TP2, and TP6. By comparing the results in previous figures, the differences among those three TPs, especially in TP2, have resulted in lower EFC values overall obtained by SFOA compared to HO.

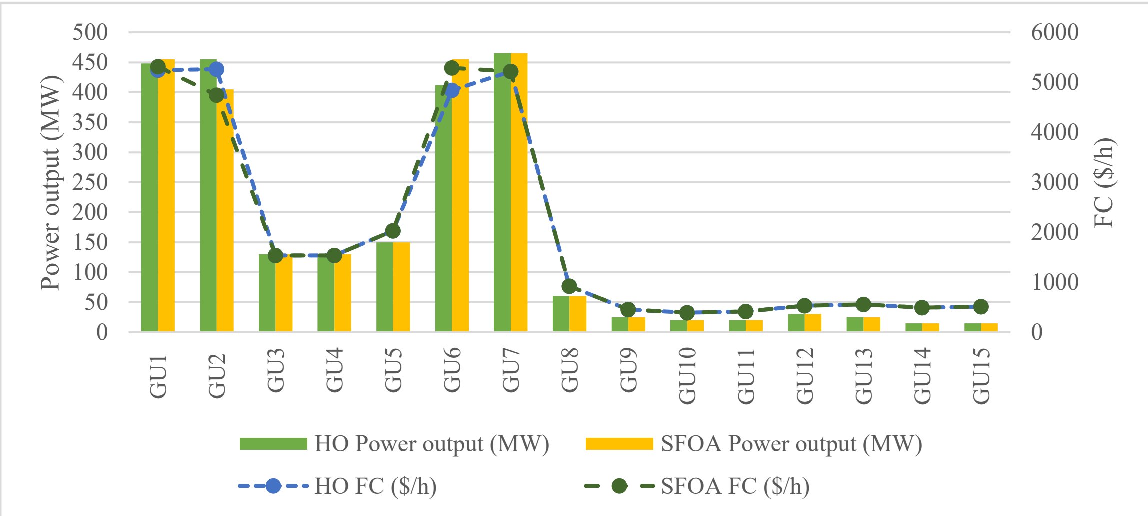

Figure 6. The optimized power output and the corresponding FC values achieved by the HO and SFOA

5. Conclusion

In this research, SFOA is successfully applied to determine the optimal allocation of all TPPs, along with the SPP and WPP, in the given power system to achieve the lowest EFC values. The SFOA's capability to deal with the given problem is further evaluated through a comparison with HO, another meta-heuristic algorithm. The results clearly indicate that SFOA not only delivers surprising search performance, achieving better EFC values across a series of comparisons, but also demonstrates faster convergence and greater stability throughout the optimization process, as shown by the lower STD values. Based on the achieved results and comparisons as presented in the previous section. SFOA used the high-capability search tool, which is strongly recommended for solving the problem of optimizing the allocation of TPPs in the power system, considering the prohibited operating zones of the TPPs.

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