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The superiority of feasible solutions-moth flame optimizer using valve point loading

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A R T I C L E I N F O

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Superiority of feasible solutions-moth flame optimizer (SF-MFO)
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A B S T R A C T

The optimal power flow (OPF) problem deals with large-scale, nonlinear, and non-convex optimization challenges, often accompanied by stringent constraints. Apart from the primary operational objectives of an energy system, ensuring load bus voltages remain within acceptable ranges is essential for providing high-quality consumer services. The Moth-Flame Optimizer (MFO) method is inspired by the unique night flight characteristics of moths. Moths, much like butterflies, undergo two distinct life stages: larval and mature. They have evolved the ability to navigate at night using a technique called transverse orientation. This article presents a methodology for determining the optimal energy transmission system configuration by integrating power producers. The MFO, Grey Wolf Optimizer (GWO), Success-history-based Parameter Adaptation Technique of Differential Evolution - Superiority of Feasible Solutions (SHADE-SF), and Superiority of Feasible Solutions-Moth Flame Optimizer (SF-MFO) algorithms are applied to address the OPF problem with two objective functions: (1) reducing energy production costs and (2) minimizing power losses. The efficiency of MFO, SF-MFO, SHADE-SF, and GWO for the OPF challenge is evaluated using IEEE 30-feeder and IEEE 57-feeder systems. Based on the collected data, SF-MFO demonstrated the best performance across all simulated instances. For instance, the electricity production costs generated by SF-MFO are $845.521/hr and $25,908.325/hr for the IEEE 30-feeder and IEEE 57-feeder systems, respectively. This represents a cost savings of 0.37 % and 0.36 % per hour, respectively, compared to the lowest values obtained by other comparative methods.

1. Introduction

The inability to store energy in power lines necessitates constant adjustments in power plant output to meet electricity demand, a process known as power plant dispatch. It is assumed that a complex power system network should operate with the lowest resource consumption to provide the highest level of security and dependability possible, a challenge known as the Optimal Power Flow (OPF) issue. OPF is gaining increasing importance in addressing power system problems. To ensure that all changeable variables, such as transformer tap ratios, shunt achievement, reactive energy output of alternators, and static reactive energy compensators, comply with

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a set of physical and operational criteria, it is necessary to configure all changeable variables.

The OPF problem is typically treated separately from Economic Dispatch (ED) even though they pertain to similar systems, thus providing no optimum solution or benefit. Therefore, proposing a new formula to concurrently solve ED and OPF problems could be an interesting research scope. This would require the integration of all possible practical constraints on acting and responding elements in the power structure, including restricted ramp rates and forbidden generation functional areas. This complexity would necessitate the use of an optimizer to solve. Moth Flame Optimizer (MFO), Grey Wolf Optimizer (GWO), Success History-based parameter of Differential Evolution -the Superiority of Feasible Solutions (SHADE-SF), Superiority of Feasible Solutions-Moth Flame Optimizer (SF-MFO) can be utilized to resolve such maximization disputes, facing the more complex and realistic environment variables of OPF in the system with fast convergence and high accuracy. It may come as a surprise that among them, Genetic Algorithm (GA) [1], Ant Colony Optimization (ACO) [2], and Particle Swarm Optimization (PSO) [3] are widely recognized experts in various sectors, not simply computer science. Additionally, comparable optimization methodologies have been effectively used in a broad variety of fields of study, supported by a vast body of theoretical research.

A typical aspect of meta-heuristics is that discovery and growth are the two stages of the hunt strategy [4–8]. This phase is all about scouting out as many potential areas as possible in the search space. Below are a few other metaheuristic methods that are suggested for solitary and multiple scheme OPF solutions [9–25] as in Fig. 1, including:

Physics-based meta-heuristics dominate the landscape of optimization approaches. These optimization algorithms are typically inspired and modeled after actual physical principles. Below in Fig. 2 are some of the most popular algorithms [26–35] in this category:

In this context, it is essential to emphasize the real-world challenges faced in power system planning and operation, such as the need to minimize transmission losses, generation costs, and ensure system security. By framing the discussion around these challenges, we can effectively demonstrate the relevance of the research to readers beyond the immediate domain of optimization algorithms. Moreover, by showcasing the breadth of suggested [36–39] approaches and their motivation from natural hunting and seeking behaviors, establish a context for understanding the emergence of nature-inspired algorithms [40–43] as attractive alternatives for solving complex optimization problems. This context sets the stage for introducing the specific contributions of research, namely the implementation of new algorithms like SF-MFO and SHADE-SF to address these challenges. Furthermore, by highlighting the integration of SF-MFO into OPF and SF issues, emphasize the potential for improving solution quality to these critical challenges in power system operation. This integration not only underscores the novelty of the proposed approach but also underscores its practical relevance in addressing real-world problems.

2. Formulations of OPF problem

When using OPF, the primary goal should be to find the best settings for all controlling tolerances to reduce a given intention purpose while also gratifying all unity also difference criteria. Here's a short summary of the foundation for defining the OPF dispute:

$$\text{Lowest } f = (x, u)$$

$$s.t._{h(x,u)\leq 0}^{g(x,u)=0} \tag{1}$$

As long as the intention purpose is f=(x,u), and the constraint events is g(x, u)=0. If it's less than or equal to 0, it's the restraint of asperity X is name of vulnerable variable vector, also u being the name of the variable that can change. To make this study better, we want to cut down on total distribution dropping, F1 [44], as well as potential changes for energy feeders, F2.

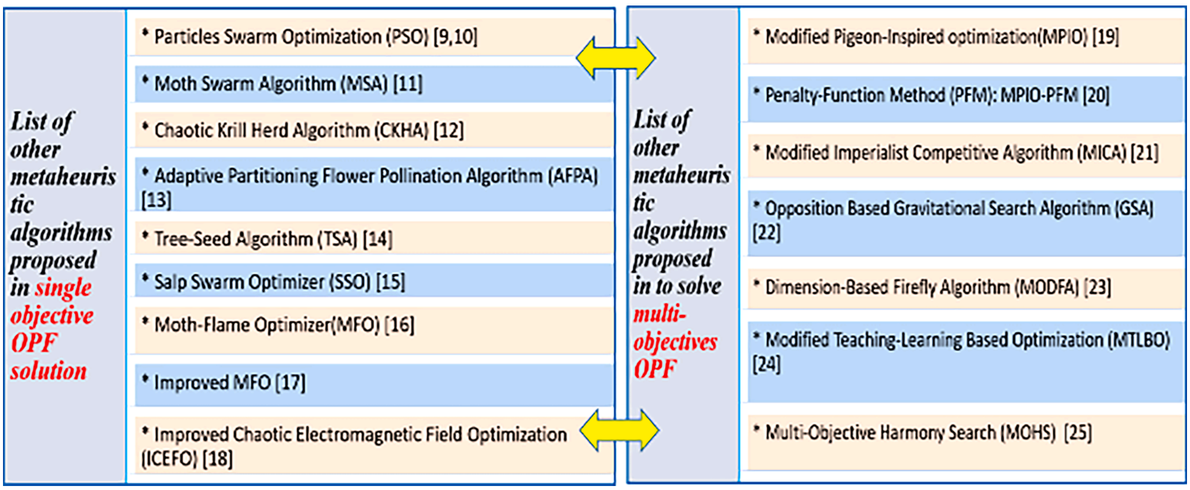

Fig. 1. Solitary and multiple scheme OPF solutions.

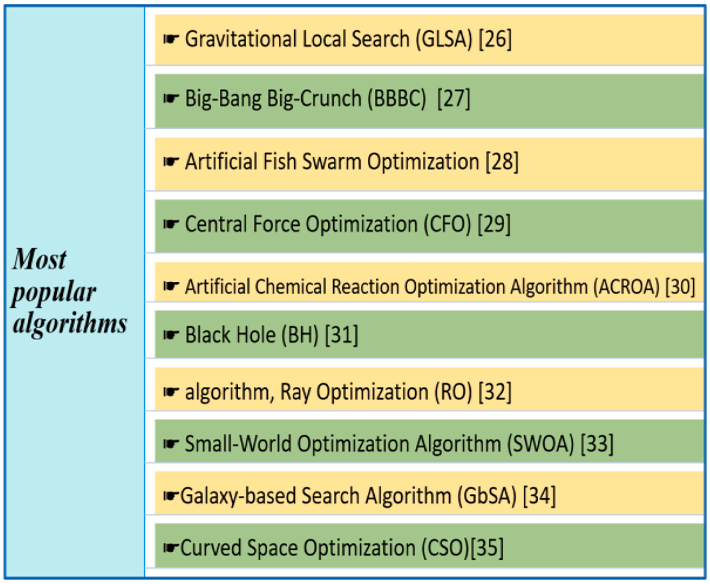

Fig. 2. Popular algorithms.

$$F_1 = P_{loss}(x,u) = \sum_{L=1}^{Nl} P_{loss} \tag{2}$$

$$F_2 = VD(x,u) = \sum_{i=1}^{Nd} \left| V_i - V_i^{sp} \right| \tag{3}$$

N_l stands for the total number of transmitting lines connect to each other, Vi is the potential for energy feeder-i, V_i^{sp} is the stated measure of typically value to 0.95 p.u, and Nd is the energy feeder count. The equality constraint equations are the following:

$$P_{Gi} - P_{Di} = V_i \sum_{j_{eN_i}} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) \tag{4}$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{j_e N_i} V_j \left(B_{ij} \cos\theta_{ij} - G_{ij} \sin\theta_{ij} \right) \tag{5}$$

It can also be said that inequality limitations can be imposed and expressed in regard to operational restrictions, that shown in the example below:

2.1. Generator constraints

In the realm of power generation, there exist various constraints dictating the generation and distribution of both real and reactive energy. These constraints not only encompass the fundamental principles governing their production but also extend to the potentials set for generation feeders. The boundaries defining the maximum and minimum values of real power production are crucial in this regard:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad \mathrm{i} = 1, \ldots..\mathrm{N_G} \tag{6}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le P_{Gi}^{\max} \qquad \mathrm{i} = 1, \ldots\ldots..\mathrm{N_G} \tag{7}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad \mathrm{i} = 1, \ldots.., \mathrm{N_G} \tag{8}$$

here N_G indicates quantity of alternators.

Transformer tap frameworks are constrained by the following maximum and minimum restricts:

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad \mathrm{i} = 1, \ldots\ldots.\mathrm{N_T} \tag{9}$$

here N_T denotes transformers no.

The following constraints apply to reactive compensators (Shunt VARs):

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\min} \qquad \mathrm{i} = 1, \ldots\ldots.\mathrm{N_c} \tag{10}$$

Where NC represents the quantity of parallel compensators.

2.2. ED problem

The ED problem's fundamental purpose is to reduce cost. On the other hand, F_r is the overall fuel cost whereas $F_i(P_{Gi})$ [45] is the price of running producing element i:

$$\min(F_r) = \min \sum_{i=1}^{N} F_i(P_{Gi}). \tag{11}$$

To show the generator's cost curve, quadratic functions are used. F(PG) in (RM/hr) can be written as:

$$F(P_{Gi}) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + C_i P_{Gi} \tag{12}$$

Where N is the quantity of alternators; ai, bi, and ci are the i-th alternators price factor; and P_G is the vector of generators' actual energy outputs.

A number of valves are used by the power plant to regulate the achievement energy of every alternator. The phenomenon known as valve point loading occurs when the steam inlet valve of a turbine is in the open position, causing the cost curve to climb as seen in Fig. 3. A sinusoidal event is included in the quadratic price event to an explanation for this impact on the commercial energy delivery issue. The formula is as follows:

$$\begin{aligned} F_T &= \left(\sum_{j=1}^{n} F_i(P_{Gi})\right) \\ &= \left(\sum_{j=1}^{n} a_i P_{Gi}^2 + c_i + \left|e_i \times \sin\left(f_i \times \left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right|\right) \end{aligned} \tag{13}$$

here e_i and fi denotes the coefficients of i_{th} alternator for valve point loading.

The price event in Eq. (13) is constrained by the following:

a. **Generation Limitations:** To ensure reliable functioning, each generator's true power output is limited by the following maximum and minimum restricts:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \qquad \mathrm{i} = 1, \ldots.., \mathrm{N} \tag{14}$$

Here i_s the product energy of alternator I and are the generator i's lowest and maximum output power limits, respectively.

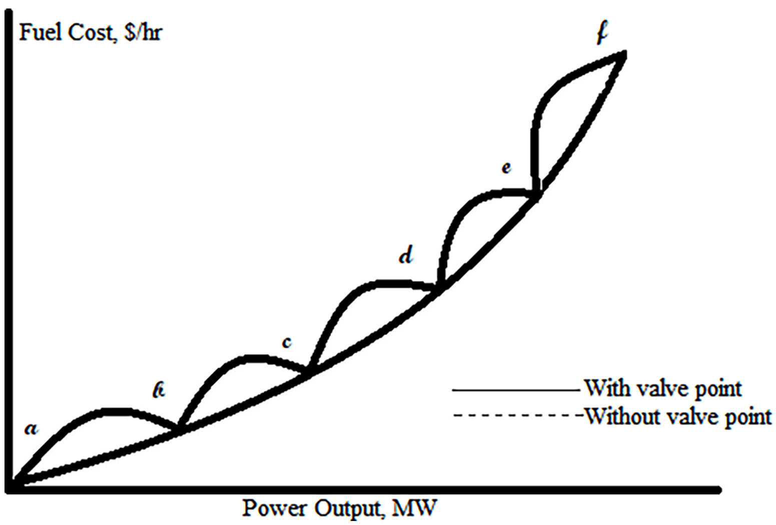

Fig. 3. Propellent price arc for valve point loading [46].

b. **Energy Balanced:** The entire quantity of energy production is equal to the aggregate energy application P_D, and aggregate energy dropping P_{loss}. As a result, the combine product energy is indicated in the following equation:

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_{loss} = 0 \tag{15}$$

Where P_D is energy application and P_{loss} is distribution dropping in the structure.

2.3. Dropping reduction

The next purpose of OPF is to reduce overall actual energy dropping [47] in the distribution structure:

$$F_{Loss} = \sum_{i=j}^{nl} \sum_{j \neq i}^{nl} G_{ij} \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j) \right] \tag{16}$$

Here Vi as well as Vj denote the potentials at the distributing and accepting ends of feeders i and j, subsequently. The conductance of distribution system i-j is denoted by Gij, while the quantity of transmission cables in the electrical power grid structure is indicated by nl.

3. GWO, MFO, SHADE-SF and SF-MFO for OPF explication

3.1. Moth-flame optimizer implementation

The MFO algorithm was developed, in part, to emulate the unique night navigation abilities of moths. In their natural environment, moths share similarities with the butterfly tribe, undergoing two major life stages: larvae and adults. Moths utilize a navigation strategy known as transverse direction, allowing them to fly at night using moonlight as a reference point. They employ a technique called crossing directions for navigation, whereby they maintain a constant angle relative to the moon to travel in a straight path. However, despite their proficiency in transverse direction, moths often exhibit a behavior known as circling lights, wherein they spiral around artificial light sources. Essentially, they are deceived by artificial light, initially attempting to maintain a consistent angle relative to the light source to fly in a straight line. Nevertheless, their attempt to maintain a similar angle with respect to the light source, which is much closer compared to the moon, results in a fatal spiral flight path. This behavior is illustrated in Fig. 4.

The integration of MFO in solving the proposed OPF and SF concurrently is depicted in the flowchart in Fig. 5. The program will be developed in MATLAB. The variables under optimization are referred to as Moths, and the objective function is generated from Eqs. (2), (3), and (13). The update of situation of Moths in relation to flame is treated as the main process of MFO. This procedure is performed until maximal repetition count has been reached.

The SF-MFO program for OPF optimization was developed following the steps outlined below:

i. Define the number of Moths (search agents) and set the maximum iteration.
ii. Gather function details, including lower and upper limits, variable dimensions, and function evaluation criteria.

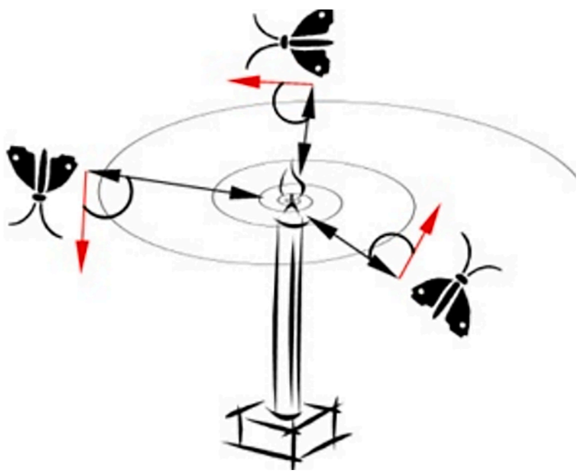

Fig. 4. MFO concept [48].

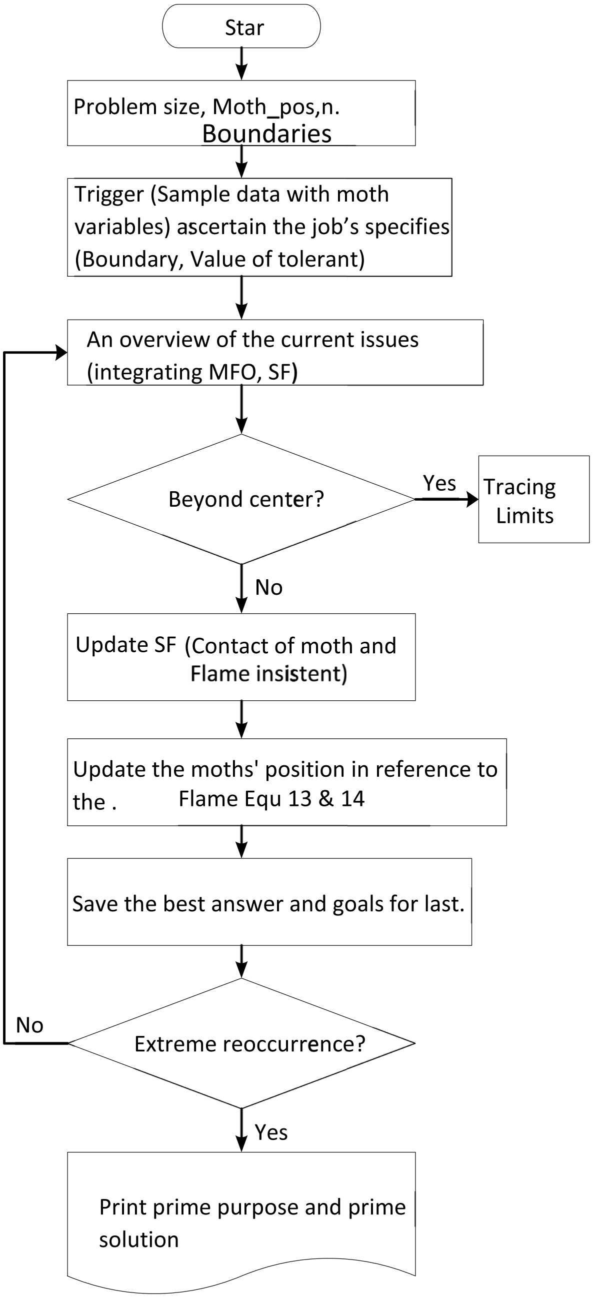

Fig. 5. SF-MFO Flow Chart.

iii. Initialization.
iv. Map control variables from each Moth into the load flow data.
v. Evaluation process: Obtain transmission loss, generation cost, emission control, and voltage deviation from load flow calculations using MATPOWER.
vi. Store the fitness (best result) and variables.
vii. Update positions (variables) using the specified equation.
viii. If not out of limit, proceed to the maximum iteration.

3.2. Grey wolf optimizer (GWO)

Canis lupus, commonly known as the grey wolf [49], is a member of the Canidae family, which also includes foxes and coyotes.

Within this family, the grey wolf holds the apex position, signifying its status as the top predator. Grey wolves are known for their social nature and tendency to form packs. These packs usually consist of between 5 and 12 wolves, although pack sizes can vary. As shown in Fig. 6, the social hierarchy within wolf packs is highly structured and rigid.

In the grey wolf hierarchy, alpha wolves, both male and female, hold supreme leadership roles, making collective decisions for the pack. Alpha status is maintained democratically, with the alpha recognized by the pack through submissive gestures during meetings. The alpha's role is not necessarily based on physical prowess, but rather on their ability to maintain control over the pack. Betas, the second-ranking wolves, assist the alpha in governing and enforcing pack rules, while also serving as potential successors to the alpha position. Omegas, the lowest-ranking wolves, often serve as scapegoats but play a crucial role in maintaining pack harmony. Alongside their social structure, grey wolves exhibit fascinating collective hunting behaviors, involving coordinated pursuit, encirclement, and eventual attack of prey.

3.3. Success history-based parameter adaptation of differential evolution (SHADE)

The SHADE [51,52] technique stands as a cornerstone within the framework of MFO, a metaheuristic algorithm inspired by nature. Drawing inspiration from the mesmerizing behavior of moths as they navigate towards light sources, MFO incorporates this technique to bolster its efficiency and effectiveness. Operating dynamically, this adaptation technique adjusts parameters based on the success history of prior iterations. By striking a balance between exploration and exploitation, it empowers the algorithm to swiftly converge and yield high-quality feasible solutions. Through this adaptive mechanism, MFO demonstrates an exceptional capacity to traverse complex search spaces, offering superior solutions to optimization quandaries. This technique is often expressed mathematically through equations, capturing the evolution of parameters across successive iterations, ensuring a robust and adaptive optimization process. With its innovative approach, MFO emerges as a potent optimization tool capable of tackling a myriad of real-world challenges with remarkable efficiency. It signifies significant progress towards attaining superior solutions in optimization endeavors.

3.4. Superiority of feasible solutions -moth flame optimization (SF-MFO)

In SF-MFO, the comparison is made between a pair of solutions. Solution *xi* is considered superior to solution *xj* when:

xi is feasible but *xj* is infeasible.

Both *xi* and *xj* are feasible, but *xi* yields a smaller objective value (in a minimization problem) than *xj* does.

Both *xi* and *xj* are infeasible, but *xi* results in a smaller overall constraint violation, i.e., $(xi) < (xj)$ as per Eq. (15).

Therefore, feasible individuals are always considered better than the infeasible individuals in this technique. Two feasible solutions are compared based solely on their objective function values, while two infeasible solutions are compared based only on their overall constraint violations. Comparing infeasible solutions based on overall constraint violations aims to push them towards the feasible region, while comparing two feasible solutions based on objective value facilitates overall solution quality improvement.

4. Results and discussion

The static penalty function technique often surpasses the boundaries of these variables, sometimes without the programmer's awareness. A well-implemented SF strategy offers the added advantage of yielding optimal results while enabling operation near the limits. In Table 1 generators is demonstrated:

The IEEE 30-feeder electric network serves as our example, with Fig. 7 illustrating the updated single-line diagram of its feeder lines. This system comprises four thermal generators, situated at buses 1, 2, and 8, along with two wind turbines on feeders 5 and 11.

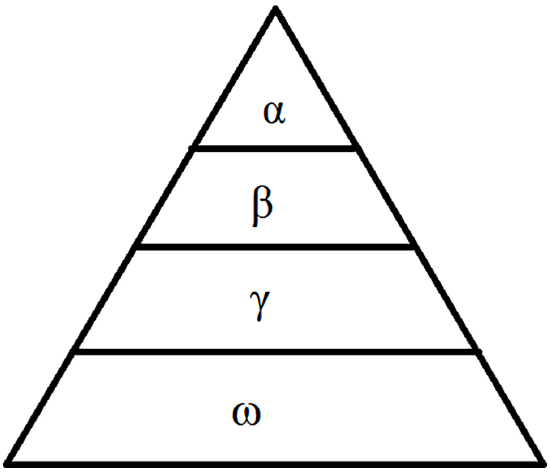

Fig. 6. The grey wolf gets less powerful from the top down [50].

Additionally, there are four tap-switching transformers located on branches 11, 12, 15, and 36. Each node in the network has a voltage reading between 0.95 and 1.061 p.u., while tap transformer settings range between 0.9 and 1.1 p.u. The control variables are in Annex A1. To evaluate the effectiveness of employing SF-MFO to address the OPF problem, we compare it with other methods like SHADE-SF, GWO, and MFO, taking into account practical constraints.

We conducted 8000 Monte Carlo simulations to determine Weibull fits and wind frequency distributions. Furthermore, the thermal generator at bus 13 was replaced with a solar PV unit, as mentioned earlier. Utilizing these simulations, we obtained frequency distributions and lognormal fittings of solar irradiance. By simulating the operation of each component, we were able to ascertain the cost of electricity generation.

4.1. In IEEE 30-feeder structure

Case 1: Reduction of production prices

Table 2 presents the statistical findings for the various optimization methods employed in Case 1 of the IEEE 30 buses study. The table includes the minimum, maximum, average, and standard deviation of the cost per hour ($) obtained from each method: MFO, GWO, SF-MFO, and SHADE-SF. It is evident that there are slight variations in the results obtained by each method, with differences in the minimum, maximum, average, and standard deviation values. For instance, the SF-MFO method yielded a minimum cost of $845.521/h, while the GWO method produced a slightly higher minimum cost of $847.762/h. However, the average costs are relatively close across all methods, ranging from $851.654/h to $852.761/h, indicating comparable performance in terms of average cost. The standard deviations provide insights into the variability of the results, with values ranging from 0.87654 to 1.87653, suggesting varying degrees of consistency in the optimization outcomes.

Regarding convergence curve in Fig. 8, they illustrate the optimization process's progress over iterations. Each curve depicts how the objective function value changes with successive iterations of the optimization algorithm. A steep decline in SF-MFO indicates rapid convergence towards the optimal solution, while a plateau or fluctuating pattern in GWO is slower convergence or convergence to a suboptimal solution.

The boxplot for the IEEE 30 buses study visualizes the distribution of cost values obtained from different optimization methods. It provides a graphical representation of the statistical findings presented in Table 2, allowing for easy comparison of the cost distributions between methods. The boxplot in Fig. 9 shows the range of costs, including outliers, as well as the median and interquartile range for SF-MFO method, offering insights into the variability and central tendency of the optimization results.

Table 2 provides statistical findings for various optimization methods utilized in Case 1, focusing on minimum, maximum, average, and standard deviation of cost per hour ($/h). Notably, the results showcase relatively close values across methods, indicating comparable performance in terms of cost optimization. However, slight variations are evident, with MFO and SF-MFO exhibiting marginally lower minimum and maximum costs compared to GWO and SHADE-SF. The average cost per hour is fairly consistent among all methods, with standard deviations reflecting minimal dispersion from the mean cost. These findings suggest that while computational complexity may differ among the methods, they generally converge towards similar cost optimization outcomes, albeit with subtle differences in efficiency and reliability.

Lastly, voltage stability in Fig. 10 refers to the ability of the power system to maintain stable voltage levels under various operating conditions. In the IEEE 30 buses study, voltage stability is an important consideration, as deviations from desired voltage levels can lead to system instability and potential equipment damage. Analyzing voltage stability involves assessing voltage profiles at different buses in the network and ensuring that they remain within acceptable limits 0.95 to 1.05 p.u. Evaluating voltage stability allows for the identification of potential issues and the implementation of corrective measures to maintain system reliability and performance.

Case 2 Reduction of Gross Transmission Drop

The Table 3 presents the minimum, maximum, average value, and standard deviation of delivery dropping (in MW) for each method: MFO, GWO, SF-MFO, and SHADE-SF. It is evident from the table that there are variations in the delivery dropping values across different methods. For instance, the MFO method yielded a minimum delivery dropping of 2.0723 MW, while the GWO method resulted in a slightly lower minimum value of 2.06785 MW. However, the average delivery dropping values are relatively close across all methods, ranging from 2.0245 MW to 2.1549 MW, indicating comparable performance in minimizing delivery dropping on average. The standard deviations provide insights into the variability of the delivery dropping results, with values ranging from 0.34567 to 0.87565 MW, suggesting varying degrees of consistency in the optimization outcomes.

Regarding convergence curve in Fig. 11, they depict the optimization process's progress over iterations, illustrating how the objective function value changes with successive iterations of the optimization algorithm. A steep decline SF-MFO in the curve

Table 1
Thermal generators characteristics.

Items	G1	G2	G8
No.of bus	1	2	8
P_{min} [MW]	20	30	10
P_{max} [MW]	80	75	35

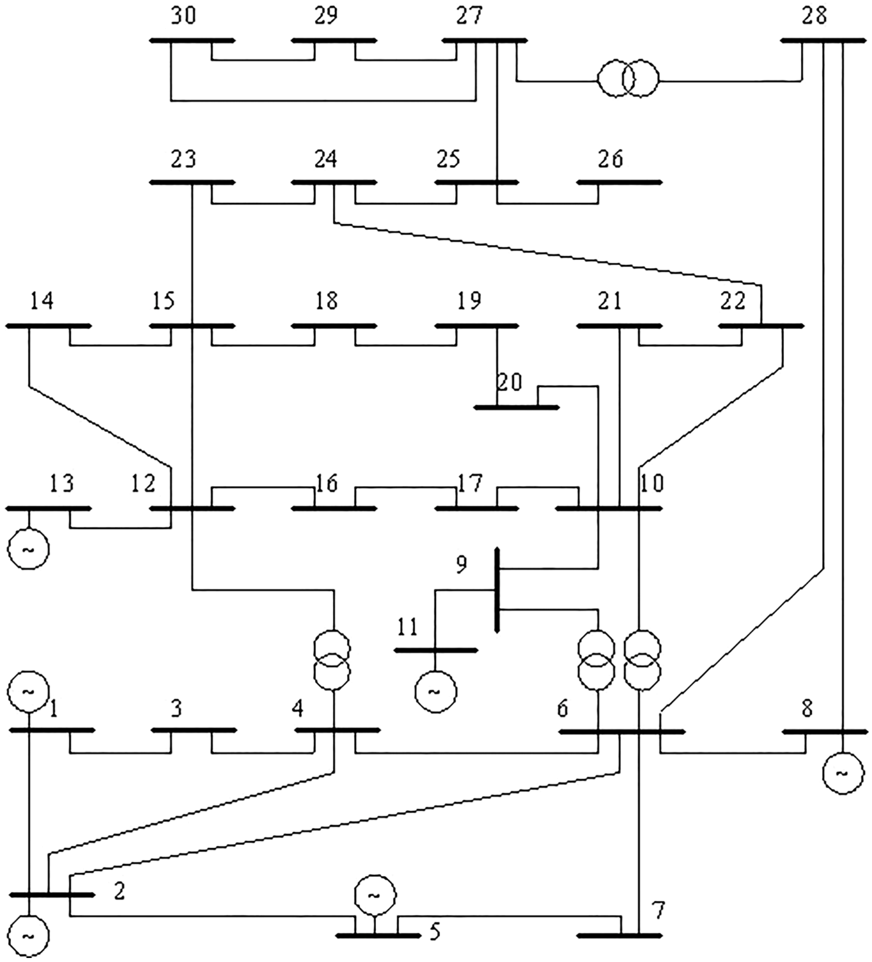

Fig. 7. IEEE 30 bus system adopted [53].

Table 2
The statistical findings for the various methods used in Case 1.

Innovation	Minimum($/h)	Maximum($/h)	Average($/h)	Standard Deviation
MFO	846.654	853.783	850.678	0.87654
GWO	847.762	856.709	852.761	1.87653
SF-MFO	845.521	854.672	851.654	1.65435
SHADE-SF	845.897	855.567	851.597	1.56894

indicates rapid convergence towards the optimal solution, while a plateau or fluctuating SHADE or SHADE-SF or GWO pattern suggests slower convergence or convergence to a suboptimal solution.

The boxplot in Fig. 12 visualizes the distribution of delivery dropping values obtained from different optimization methods. The SF-MFO shows the range of delivery dropping values, including outliers, as well as the median and interquartile range, providing insights into the variability and central tendency of the optimization results.

Voltage deviation in Fig. 13 shows the deviation of voltage levels from 095 to 1.05 p.u in different points in the IEEE 30 buses. Analysing voltage deviation involves assessing voltage profiles at various nodes in the network and identifying areas where voltage levels deviate significantly from desired values. By minimizing voltage deviation, operators can maintain stable voltage levels, prevent equipment damage, and ensure efficient power transmission and distribution.

4.2. System based on the IEEE 57 feeder

Another IEEE structure, especially the IEEE-57 feeder structure as in Fig. 14 has been tested to assess the effectiveness of the SF-MFO. These structures supervise also state tolerance have been set to their lowest and highest possible values, of the MATPOWER

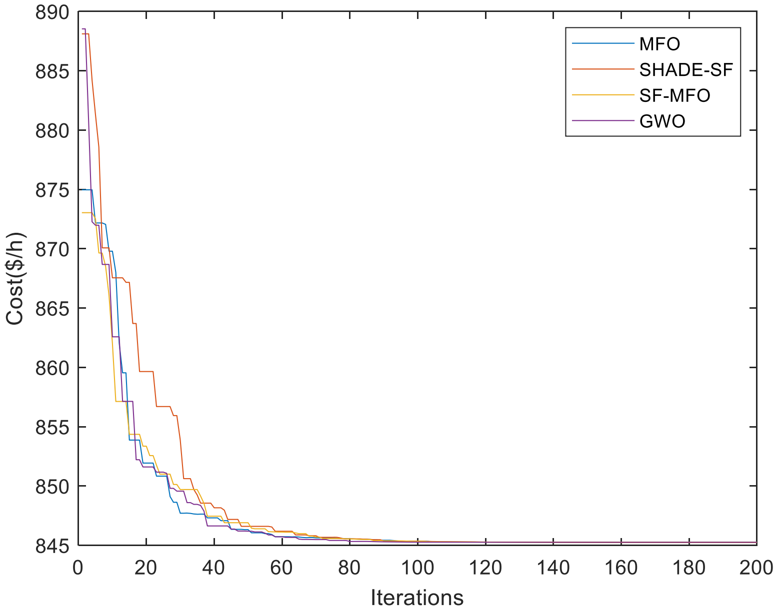

Fig. 8. Convergence curve for case 1.

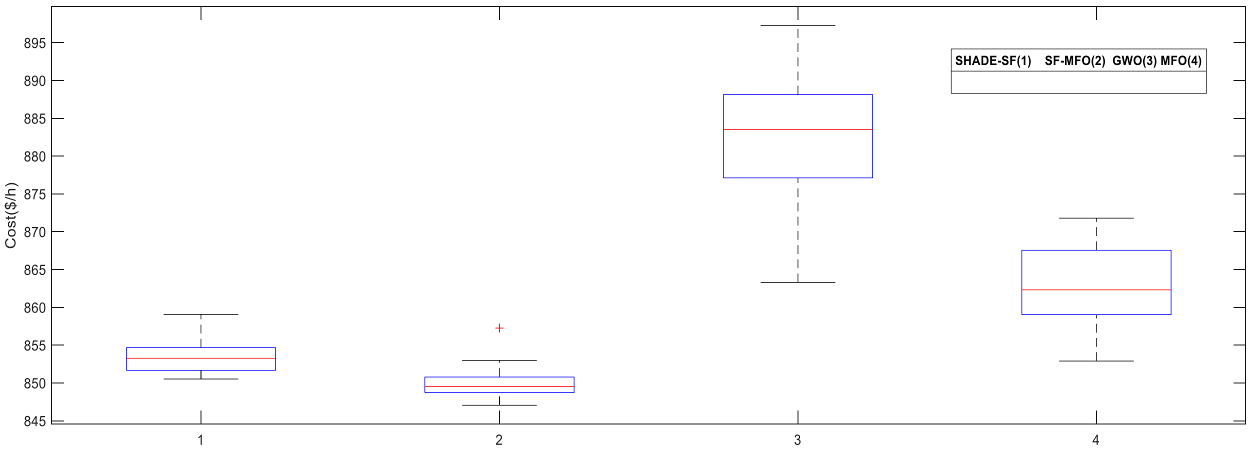

Fig. 9. Boxplot for case 1.

package and control variables are shown in Annex A2.

Case 3: Cost-cutting measures in the Generating Process

Table 4 presents the cost of production results for the IEEE 57 buses obtained using different optimization algorithms. When comparing SF-MFO to other algorithms, it is evident that SF-MFO achieves competitive results. For instance, SF-MFO yields an average cost of production of 25,901.897 MW, which is slightly lower than that of GWO (259,830.456 MW) and SHADE-SF (25,984.873 MW), showcasing its effectiveness in minimizing production costs on average. Additionally, SF-MFO demonstrates lower standard deviation (0.9871 MW) compared to GWO (0.67858 MW) and SHADE-SF (0.8723 MW), indicating more consistent results with less variability.

The convergence curve in Fig. 15 illustrates the optimization process's progress over iterations, showing how the objective function value changes with successive iterations of the optimization algorithm. A steep decline by SF-MFO in the curve indicates rapid convergence towards the optimal solution.

In Fig. 16 shows the range of production cost values, including outliers, as well as the median and interquartile range for each algorithm, providing insights into the variability and central tendency of the optimization results by SF-MFO.

Voltage deviation refers in Fig. 17 from 0.95 to 1.05 p.u. to the deviation of voltage levels from desired values at various nodes in the power system. By minimizing voltage deviation, operators can maintain stable voltage levels, prevent equipment damage, and

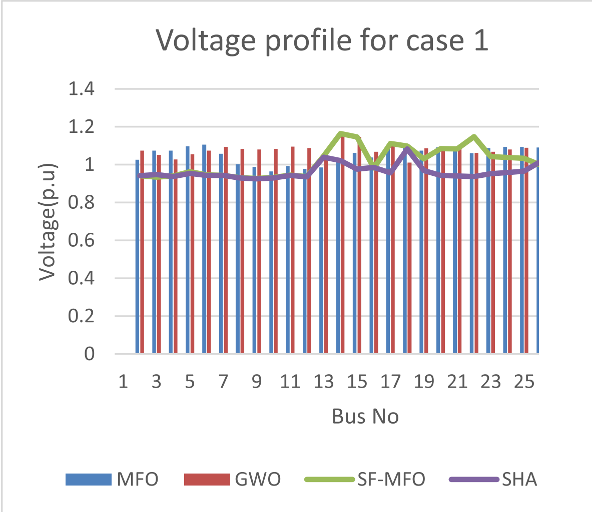

Fig. 10. Voltage Deviation for case 1.

Table 3
Overall delivery dropping minimization.

Innovation	Minimum (MW)	Maximum (MW)	Average value (MW)	Standard Deviation
MFO	2.0723	2.8765	2.1456	0.87565
GWO	2.06785	2.8765	2.1549	0.78098
SF-MFO	1.4023	2.3657	2.0245	0.34591
SHADE-SF	1.4054	2.3256	2.0247	0.34567

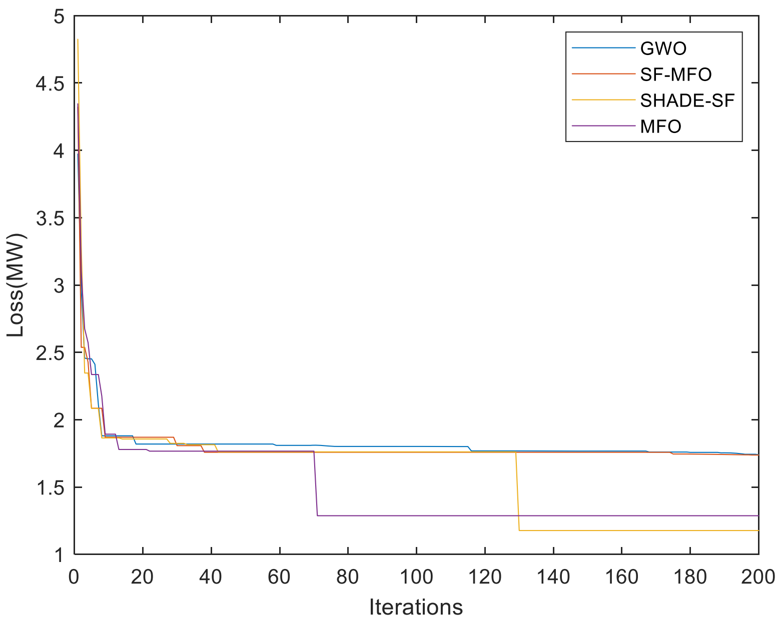

Fig. 11. Convergence Curve for case 2.

ensure efficient power transmission and distribution.

Case 4: Reduction of overall distribution dropping

It is evident that SF-MFO achieves competitive results in terms of real power loss minimization as in Table 5. For instance, SF-MFO

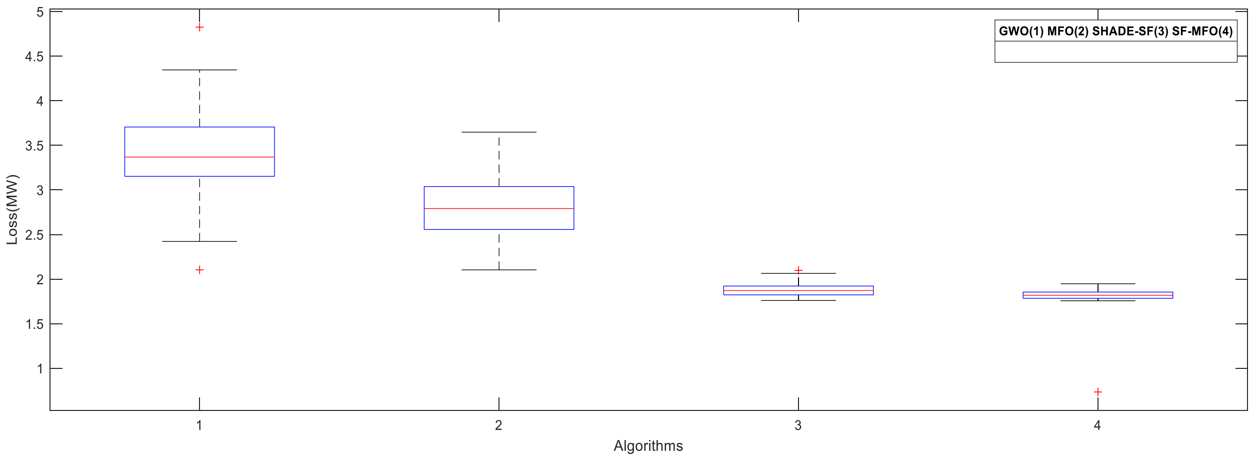

Fig. 12. Boxplot for case 2.

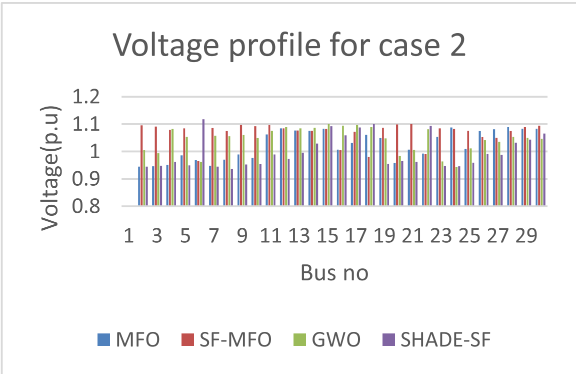

Fig. 13. Voltage deviation for case 2.

yields an average real power loss of 27.654 MW, which is lower than that of GWO (26.876 MW) and SHADE-SF (28.007 MW), indicating its effectiveness in reducing power loss on average. Additionally, SF-MFO demonstrates a moderate standard deviation (1.0023 MW) compared to GWO (0.7864 MW) and SHADE-SF (0.8759 MW), suggesting relatively consistent results with some variability.

The convergence curve in Fig. 18 illustrates the optimization process's progress over iterations, indicating how the objective function value changes with successive iterations of the optimization algorithm.

Fig. 19 highlights the range of real power loss values, including outliers, as well as the median and interquartile range for SF-MFO algorithm, offering insights into the variability and central tendency of the optimization results.

Minimizing voltage deviation is crucial for ensuring the stability and reliability of the power system. Analyzing voltage deviation in Fig. 20 involves evaluating voltage profiles at different points in the network and identifying areas where voltage levels deviate significantly from 1 p.u.

Examining Table 5 it is evident that each algorithm presents varying levels of computational complexity in optimizing real power loss. GWO demonstrates a narrow range of real power loss values, with relatively low standard deviation, indicating a more stable and predictable performance. Conversely, MFO exhibits a wider range of real power loss values but with a lower standard deviation, suggesting potential computational efficiency despite occasional extremes. SF-MFO, while achieving competitive real power loss results, shows the highest standard deviation among the compared algorithms, implying a higher level of variability and potentially greater computational complexity in optimization.

5. Conclusion, limitations and future works

Our study presents SF-MFO as a robust and effective approach for optimizing power flow in electrical grids. Through extensive experimentation, we have demonstrated its ability to efficiently balance power generation, transmission, and distribution, leading to enhanced grid performance and reliability. Additionally, SF-MFO offers a scalable solution that can accommodate various grid configurations and operational constraints, making it highly adaptable to real-world applications. Furthermore, the comparative analysis

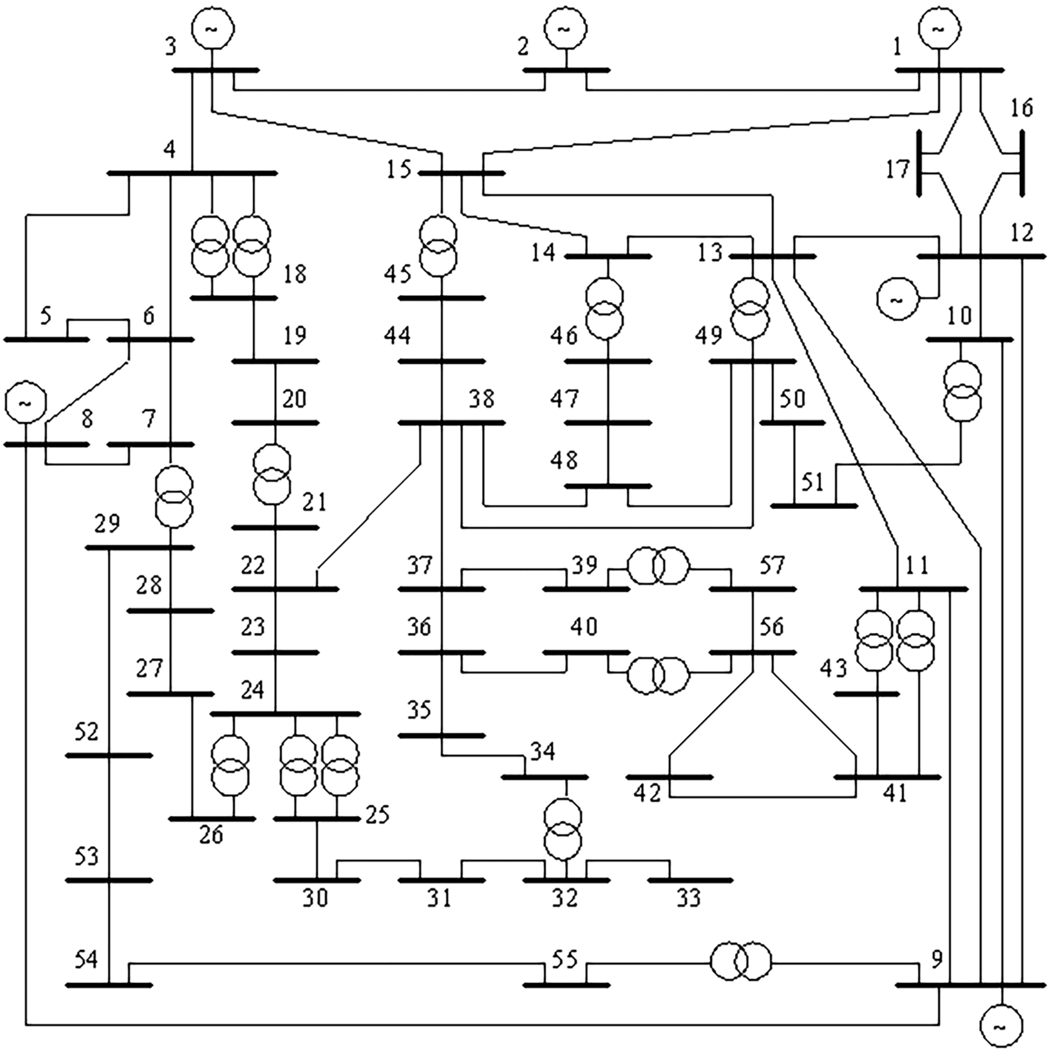

Fig. 14. The IEEE 57 feeder system has been adapted from [53].

Table 4
Cost of production.

Algorithms	Best (MW)	Worst(MW)	Average(MW)	Std Dev
GWO	259,238.456	26,004.782	259,830.456	0.67858
SHADE-SF	25,956.321	26,132.673	25,984.873	0.8723
MFO	25,916.670	26,345.791	26,003.543	0.8934
SF-MFO	**25,908.325**	26,457.876	26,001.897	0.9871

against existing optimization methods showcases the superior performance and convergence speed of SF-MFO, highlighting its potential as a valuable tool for power system engineers and operators. Overall, our research contributes to advancing the field of optimal power flow by introducing a novel optimization technique that addresses the complex challenges faced by modern electrical grids.

5.1. Research limitations

While our study yields promising results, it is important to acknowledge certain limitations. These include the reliance on simplified network models and the assumption of linear behavior for certain components, which may not fully capture the intricacies of real-world power systems. Additionally, the effectiveness of SF-MFO may vary depending on the specific characteristics of the grid and the accuracy of input data.

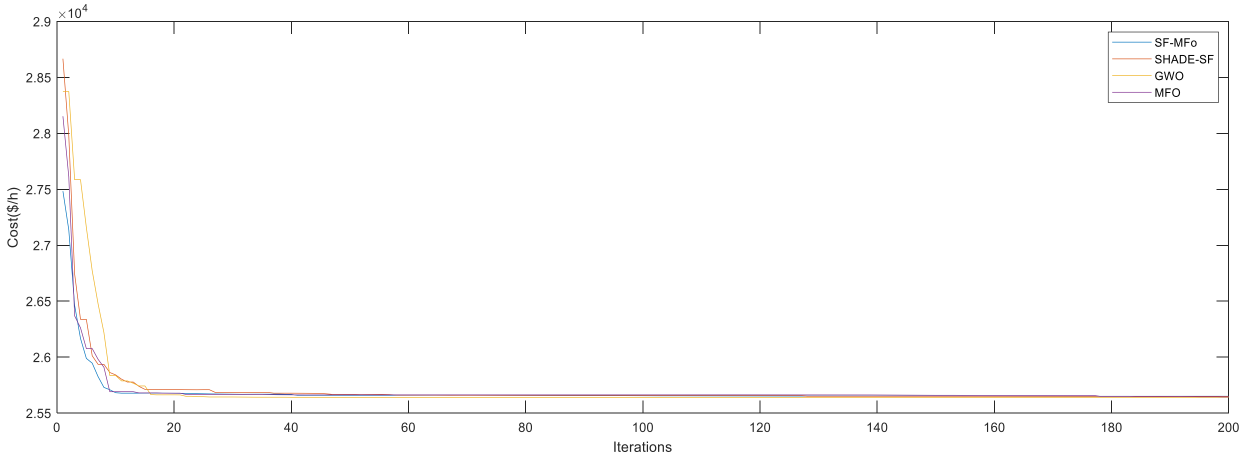

Fig. 15. Convergence Curve for Case 3.

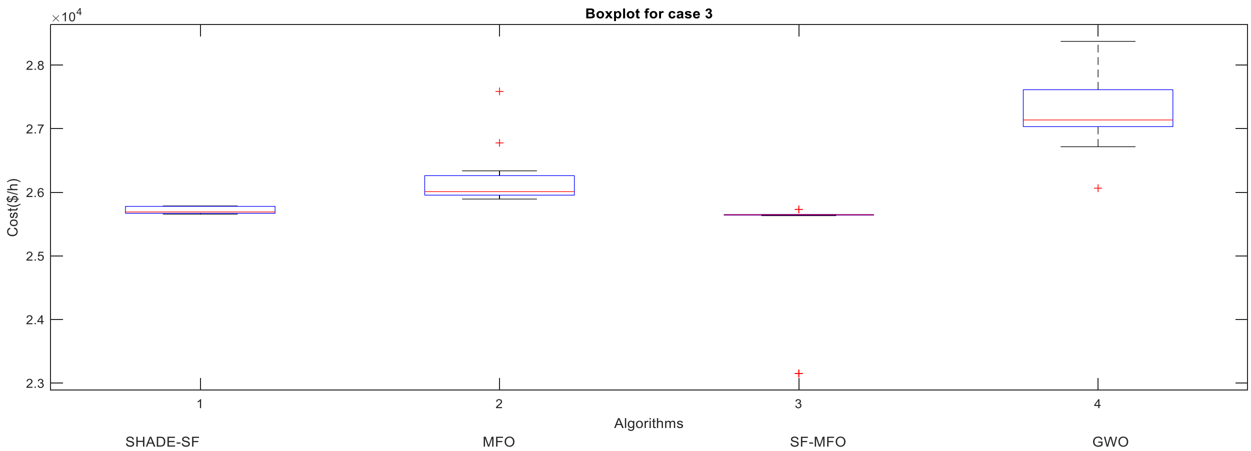

Fig. 16. Boxplot for IEEE 57 buses-case 3.

5.2. Future works

Moving forward, future research endeavors could focus on refining SF-MFO to incorporate more comprehensive network models and non-linear behaviors, thereby improving its accuracy and applicability in diverse power system scenarios. Furthermore, exploring hybrid optimization techniques that combine SF-MFO with FACTS could potentially enhance its performance and scalability. Additionally, efforts should be made to validate SF-MFO using real-world data and to develop user-friendly software implementations for practical deployment in power system management.

Declaration of competing interest

The authors affirm their lack of awareness regarding any financial conflicts of interest that could have impacted the findings presented in the current study. Moreover, they assert that there are no close amicable acquaintances whose influence might have skewed the results of their research. This declaration underscores the authors' commitment to transparency and integrity in their work, aiming to uphold the highest standards of academic rigor. By explicitly addressing potential sources of bias or undue influence, the authors seek to reassure readers about the objectivity and reliability of their study's outcomes. Such proactive disclosure serves to enhance the credibility and trustworthiness of their research within the scholarly community.

Data availability

Data will be made available on request.

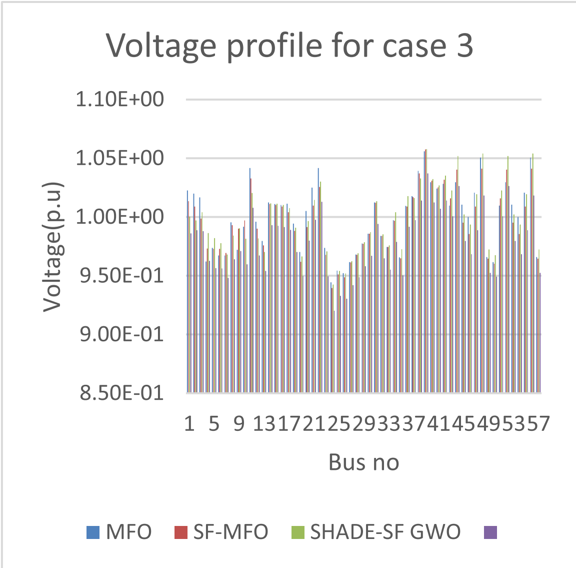

Fig. 17. Voltage Deviation for case 3.

Table 5
Real power loss.

Algorithms	Best (MW)	Worst(MW)	Average(MW)	Std Dev
GWO	26.656	27.023	26.876	0.7864
SHADE-SF	27.455	28.125	28.007	0.8759
MFO	27.892	29.989	28.247	0.7698
SF-MFO	26.563	28.564	27.654	1.0023

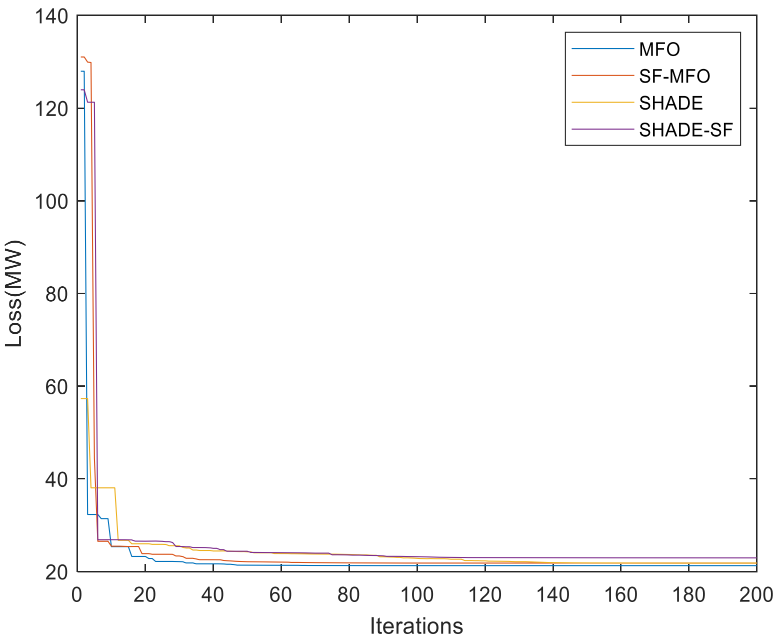

Fig. 18. Convergence curve for case 4.

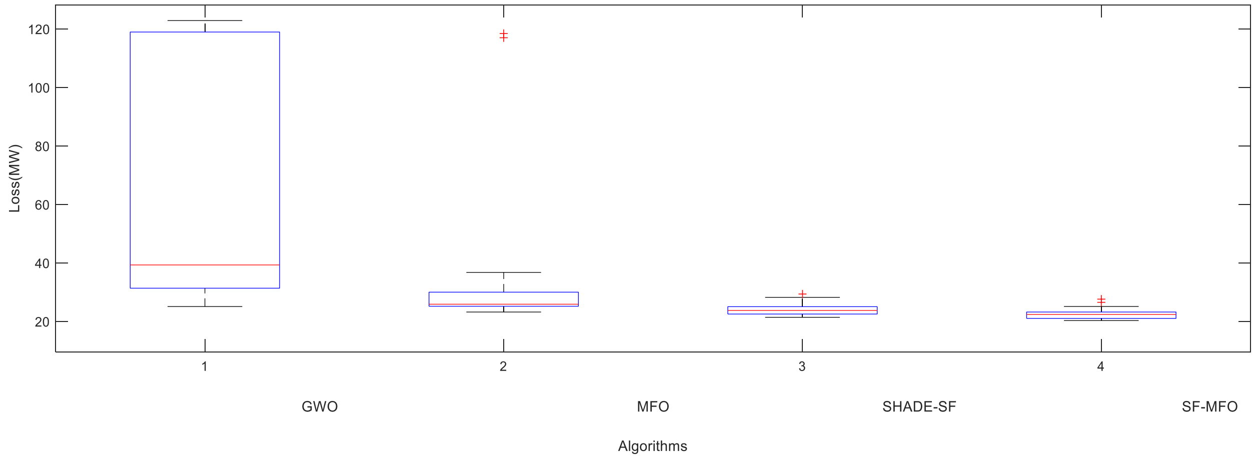

Fig. 19. Boxplot for case 4.

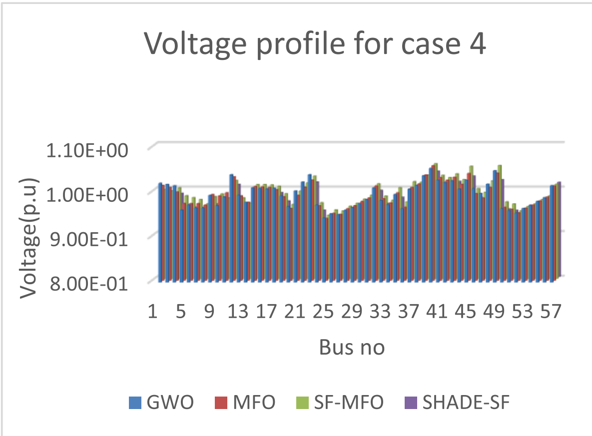

Fig. 20. Voltage deviation for IEEE-57 buses-Case 4.

Appendix. Detail results of different cases 1–4

Annex A1. Control variables for cases 1–2 for IEEE-30 bus - results

Item	SF-MFO	SHADE-SF	GWO	MFO
Pg2(MW)	3,218,564	53.78	31.5	33.9
Pg5(MW)	27.54	26.7	27.78	26.4
Pg8(MW)	44.56	44.65	43.65	43.67
Pg11(MW)	11	12.56	11.56	11.32
Pg13(MW)	31.45	35.87	32.67	32.45
Vg1(p.u)	0.976	0.98	0.97	0.98
Vg2(p.u)	0.98	0.97	0.98	1.01
Vg5(p.u)	1.0	0.98	1.01	1.02
Vg8(p.u)	0.97	0.97	0.98	0.98
Vg11(p.u)	0.98	0.98	0.99	0.99
Vg13(p.u)	1.02	1.02	0.98	1.02
$Q_{TG1}(MVA_{r})$	-1.34	10.56	-23.65	-20.98
$Q_{TG2}(MVA_{r})$	16.75	35.67	31.43	34.34
$Qw_{G4}(MVA_{r})$	14.56	16.56	18.67	18.56
$Q_{TG3}(MVA_{r})$	25.45	23.54	21.34	14.67
$Qw_{G5}(MVA_{r})$	26.45	24.76	42.54	35.45
$Qw_{G6}(MVA_{r})$	32.45	13.76	44.65	33.54
Fuel Valve Cost($/h)	**845.521**	845.897	847.762	846.654

Annex A2. Control variables for case Cases 3–4 for IEEE-57 bus- results

Item	SF-MFO	SHADE-SF	GWO	MFO
Pg2MW)	27.678	53.4	34.5	31.7
Pg3(MW)	94.786	26.6	27.87	28.7
Pg6(MW)	24.782	44.67	43.45	43.45
Pg8(MW)	353.564	11.23	12.65	11.54
Pg9(MW)	183.543	36.45	32.34	32.45
Pg12MW)	203.546	67.45	45.87	46.54
Vg1(p.u)	1.03	0.98	0.97	0.97
Vg2(p.u)	0.98	0.98	0.98	1.01
Vg3(p.u)	1.04	0.98	1.01	1.02
Vg5(p.u)	1.03	0.99	0.98	0.98
Vg8(p.u)	1.02	0.98	0.99	0.99
Vg9(p.u)	1.01	1.02	0.98	1.02
Vg13	0.98	1.01	1.03	1.03
Q_{TG1}(MVA$_{r)}$	85.564	10.87	-25.67	-22.67
Q_{TG2}(MVA$_{r)}$	-14.00	35.56	35.87	34.98
Qw$_{G12}$(MVA$_{r)}$	64.00	16.76	18.78	18.23
Q_{TG3}(MVA$_{r)}$	24.000	25.65	23.78	14.87
Qw$_{G6}$(MVA$_{r)}$	90.34	24.65	43.34	37.34
Qw$_{G8}$(MVA$_{r)}$	8.000	13.56	47.87	34.45
Qw$_{G9}$(MVA$_{r)}$	48.87	55.87	35.34	69.54
Ploss (MW)	**26.563**	27.455	27.65	27.892

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