# Skill optimization algorithm for solving optimal power flow problem

**Chiem Trong Hien[1], Minh Phuc Duong[2], Ly Huu Pham[2]**
[1]Faculty of Electrical and Electronic Technology, Ho Chi Minh City University of Industry and Trade, Ho Chi Minh City, Vietnam
[2]Power System Optimization Research Group, Faculty of Electrical and Electronics Engineering, Ton DucThang University, Ho Chi Minh City, Vietnam

**Article Info**

***Article history:***

Received Nov 18, 2022
Revised Jul 14, 2023
Accepted Aug 2, 2023

***Keywords:***

Optimal power flow
Particle swarm optimization
Skill optimization algorithm
Thermal units
Total fuel cost

**ABSTRACT**

This research presents the implementation of a modern meta-heuristic algorithm called the skill optimization algorithm (SOA) to solve the optimal power flow problem (OPF). An IEEE 30-bus transmission system is selected to test the real performance of SOA. The main objective function of the study is to minimize the total fuel cost (TFC) of all thermal units. To clarify the high performance of SOA, a classical meta-heuristic named particle swarm optimization (PSO) is also applied for comparison. All results reached by SOA are compared with those of PSO on different criteria. Particularly, SOA has reached smaller cost than PSO by $1.04, equivalent to 0.13% of PSO's TFC. Furthermore, SOA has reached a more stable performance by finding better average and maximum TFC over fifty runs. The evaluation of these criteria indicates that SOA completely outperforms PSO. Besides, the optimal solution reached by SOA satisfies all considered constraints with zero violation of the dependent variables. Therefore, SOA is highly suggested to handle the OPF problem.



***Corresponding Author:***

Ly Huu Pham
Power System Optimization Research Group, Faculty of Electrical and Electronics Engineering
Ton DucThang University
Ho Chi Minh City, Vietnam
Email: phamhuuly@tdtu.edu.vn

## 1. INTRODUCTION

Solving the optimal power flow problem (OPF) is a top concern in power system. According to Daqaq *et al.* [1], OPF problem is classified as a large-scale, non-convex, and complicated optimization problem. Therefore, the determination of an optimal solution to OPF that obtains the best value of the objective function and satisfies all related constraints is a huge challenge. In solving OPF problems, the typical objective functions, including minimizing total fuel cost by thermal units, minimizing total power loss in the transmission process, and minimizing total emissions, are commonly considered. Besides, the constraints in this problem, such as the operational limits of the generator, the power balance between the generating side and the receiving side, and the safety constraints, must be satisfied.

An optimal solution to such an OPF problem often includes control and dependent variables. Normally, the control variables include the active power generated by thermal units excluding the one connected with the slack node, the voltage magnitudes at all thermal units, the reactive power of shunt capacitors, and the transformer tap [2]. The dependent variables are the active power generated by the thermal unit at the slack node, the voltage magnitude at load nodes, and the reactive power output of all thermal units. These control variables are fully selected by the optimization methods, while these dependent variables are found by using Mathpower.

Many researchers have conducted their research on the topic by fully acknowledging the importance of solving OPF problems. However, choosing the proper computing method to unfold the OPF problems accompanied by a series of complicated constraints on a large scale is also a tough question. Luckily, meta-heuristic algorithms have recently demonstrated themselves to be highly affordable and the most trusted computing method to deal with optimization problems, including OPF problems. For instant, different meta-heuristic algorithms have been applied to solve the OPF problems such as backtracking search algorithm (BSA) [1], genetic algorithm (GA) [2], Harris Hawks optimization (HHO) [3], [4], grey wolf optimizer algorithm (GWOA) [5], AMTPG-Jaya algorithm [6], differential evolution (DE) [7], [8], effective Cuckoo search algorithm (ECSA) [9], particle swarm optimization (PSO) [10], Gorilla troops algorithm (GTA) [11], modified coyote optimization algorithm (MCSA) [12], black hole optimization (BHO) [13], the hybrid method of Cuckoo search algorithm (MCOA) and sunflower optimization (SFO) [14], improved multi-objective multi-verse algorithm (IMOMVA) [15], firefly krill herd algorithm (FHHA) [16], improved moth-flame optimization (IMFO) [17], antlion optimization (ALO) and its improved version [18], [19], marine predator algorithm (MPA) [20], social spider algorithm (SSA) [21], slime mould algorithm (SMA) [22], whale optimization algorithm (WOA) [23], and golden ratio optimization (GRO) [24]. The effectiveness of meta-heuristic algorithms has shown a huge leap forward when compared with conventional computing methods, such as the Newton-Raphson technique [25], in terms of time response, robustness, and precision degree of the final results. Technically, the OPF problems can be solved by placing different types of flexible alternating current transmission system devices (FACTS). Through experiments, the proper placement of a particular type of FACTS device, such as unified power flow controllers (UPFC) [26] or static synchronous series compensators (SSSC) [27], has brought many positive effects to power system operation, including improving the utilization of the current transmission system, increasing the reliability and availability of the grid, and enhancing the overall power quality. Recently, renewable energy sources such as wind and solar energy have also been evaluated while solving the optimal power flow problems as implemented in [28]–[32].

Basically, these studies tried to reach a better total cost than previous studies or existing methods, which were also implemented in the same work. However, approximately all the studies ignored the predetermined limits of the operation parameters. The shortcomings seem simple, but they are significant to the power system's operation. In fact, all electric components have a limit of operation parameter that must be satisfied all the time when power systems are working. So, the paper shows the limits in detail, and then all the proposed parameters are compared to the range. Two algorithms are applied to unfold the given problem, including one classical meta-heuristic method (PSO) [9] and one modern meta-heuristic called the skill optimization algorithm (SOA) [33]. PSO is a very old metaheuristic algorithm, while SOA was recently proposed by Givi and Hubalovska [33]. The main inspiration for designing SOA comes from the process of improving skills in human life. According to the authors, SOA proved its high performance over other up-to-date meta-heuristic algorithms through various test functions. The IEEE 30-bus configuration system is employed to test the real performance of two applied algorithms. The important implications of the whole research are as follows:

- Successfully apply a new meta-heuristic algorithm, the SOA, to minimize the TFC value of all TUs while solving the OPF problem.
- Present and prove the superiority of SOA over PSO by using different criteria such as minimum fuel cost value, average fuel cost value, maximum fuel cost value, and standard deviation. Moreover, the minimum convergences and the fifty cost values are also given to support the claims.
- Diversify and present a good reference regarding the application of novel meta-heuristic algorithms to deal with the high-complex optimization engineering problems that specifically needed to be solved in the power system.

Other sections are organized by: section 2 presents the problem descriptions. Section 3 shows an overview of the applied methods. Section 4 displays the analysis results. Finally, section 5 reveals the conclusions.

## 2. PROBLEM DESCRIPTION

### 2.1. The objective function

The mathematical expression of the considered objective function is presented as (1):

$$\text{Minimize } TFC = \sum_{n=1}^{N_{TU}} \alpha_n + \beta_n P_{TUn} + \gamma_n (P_{TUn})^2 \quad (1)$$

Where $TFC$ stands for the total fuel cost value of the six thermal units in the system; $P_{TUn}$ is the among active power produced by thermal unit $n$; $N_{TU}$ is the quantities of thermal units; and $\alpha_n$, $\beta_n$ and $\gamma_n$ are, respectively, fuel utilizing coefficients belonging to thermal unit $n$.

### 2.2. The related constraints

The operational constraints of generators: the constraints are about the active, reactive power supply and the voltage index generated by generators. The expressions of these constraints are as (2)-(4):

$$P_{TU}^{min} \leq P_{TUn} \leq P_{TU}^{max} \tag{2}$$

$$Q_{TU}^{min} \leq Q_{TUn} \leq Q_{TU}^{max} \tag{3}$$

$$U_{TU}^{min} \leq U_{TUn} \leq U_{TU}^{max} \tag{4}$$

In (2)-(4), $P_{TU}^{min}$ and $P_{TU}^{max}$ stand for the lowest and highest limits of active power output supplied by thermal units; $Q_{TU}^{min}$ and $Q_{TU}^{max}$ stand for the lowest and highest limits of reactive power output supplied by thermal units; $U_{TU}^{min}$ and $U_{TU}^{max}$ are the lowest and highest limits of voltage index belonging to thermal units; $P_{TUn}$, $Q_{TUn}$, and $V_{TUn}$ are, respectively, the active, reactive power output and voltage magnitude generated by thermal unit *n*.

The balance constraints: total power supplied by the generating side in both active and reactive power must equal the total power consumed by other electric components. The equations for the constraints are shown in (5) and (6).

$$\sum_{n}^{N_{TU}} P_{TUn} + P_L - P_{RS} = 0 \tag{5}$$

$$\sum_{n}^{N_{TU}} Q_{TUn} + Q_{SCm} + Q_L - Q_{RS} = 0 \tag{6}$$

with

$$Q_{SC}^{min} \leq Q_{SCm} \leq Q_{SC}^{max} \; with \; m = 1, \ldots, N_{SC} \tag{7}$$

Where $P_L$ and $Q_L$ are active and reactive power loss; $P_{RS}$ and $Q_{RS}$ are active and reactive consumed by receiving side; $Q_{SC}^{min}$ and $Q_{SC}^{max}$ are the minimum and maximum reactive power of shunt capacitors; and $Q_{SCm}$ is the reactive power injected by shunt capacitor *m*, $N_{SC}$ is the num quantities of existing capacitors in the considered power transmission configuration.

The safety constraints: the constraints are the boundaries of voltage indexes at load nodes and the apparent power circulating on the transmission lines.

$$U_{LD}^{min} \leq U_{LDh} \leq U_{LD}^{max} \text{ with } h = 1, \ldots, N_H \tag{8}$$

$$S_{BNg} \leq S_{BN}^{max} \text{ with } g = 1, \ldots, N_G \tag{9}$$

Where $U_{LD}^{min}$ and $U_{LD}^{max}$ are the minimum and maximum limits of voltage index at load nodes; $S_{BN}^{max}$ is the maximum apparent power sent through the transmission line *g*; $U_{LDh}$ and $S_{BNg}$ are the voltage index at load node *h* and the apparent power in the transmission line *g*; and $N_H$ and $N_G$ represent, respectively the number of load nodes and the transmission line.

## 3. THE APPLIED METHOD

The newly solution update mechanism of two methods is different. This is one of the most important features that greatly affect the overall performance of a particular meta-heuristic method. The process of updating the new solutions of two applied methods is briefly presented as follows:

### 3.1. Particle swarm optimization

New solutions of PSO are updated as (10) and (11):

$$Ve_i^{new} = Ve_i + E_1 \times \gamma_1 \times (X_{Best,i} - X_i) + E_2 \times \gamma_2 \times (X_{Gbest} - X_i) \tag{10}$$

$$X_i^{new} = X_i + Ve_i^{new} \tag{11}$$

In (10) and (11), $Ve_i^{new}$ and $X_i^{new}$ are new velocities and positions belonging to particle $i$. $Ve_i$ and $X_i$ are the present velocities and positions belonging to particle $i$. $E_1$ and $E_2$ are accelerating ratios. $\gamma_1$ and $\gamma_2$ are the random value between 0 and 1. $X_{Best,i}$ and $X_{Gbest}$ are, respectively, the best so far position belonging to particle $i$ and the best position in population.

### 3.2. Skill optimization algorithm

The whole update process of SOA for new solutions consists of the expert acquisition phase and the self-improving phase. The two phases update mechanism provides SOA a better balance between the exploration and exploitation capability for the searching process. The mathematical models for each phase will be described:

The experts acquisition phase: new solutions is updated by:

$$X_m^{new1} = X_m + RN \times (X_E - SF \times X_m) \quad (12)$$

In (12) $X_m^{new1}$ and $X_m$ are the new position and the current position of the individual $m$; $RN$ is the random value between 0 and 1; $X_E$ is the position of expert individual; and $SF$ is randomly selected beween 1 and 2.

The self-improving phase: the update process in this phase is implemented by:

$$X_m^{new2} = \begin{cases} X_m + \frac{1-2\omega}{It} \times X_m, \text{if } \omega < 0.5 \\ X_m + \frac{lb_m + \omega(ub_m - lb_m)}{It}, \text{otherwise} \end{cases} \quad (13)$$

Where $\omega$ is the random value; $It$ is the value of current iteration; and $lb_m$ and $ub_m$ are the minumum and the maximum boundaries of individual $m$.

## 4. RESULTS AND DISCUSSION

In part of the study, PSO [10] and SOA [33] are employed to resolve the OPF problem in the IEEE 30-bus configuration network. The network has 6 thermal units connected with nodes 1, 2, 5, 8, 11, and 13, 41 branches, four transformers, 24 loads, and nine capacitors. The single-line description of this system is shown in Figure 1. For a moderate comparison of the real performance of the two computing methods, each method is run for 50 cost values. Besides, the population and the highest iteration number of such methods are 50 and 100 for PSO, while the values of SOA are 25 and 100, respectively. The entire study is executed on a computer with the following configuration: CPU with 2.3 GHz and RAM with 8 GB. The entire coding and related simulations are executed on MATLAB software version 2018a.

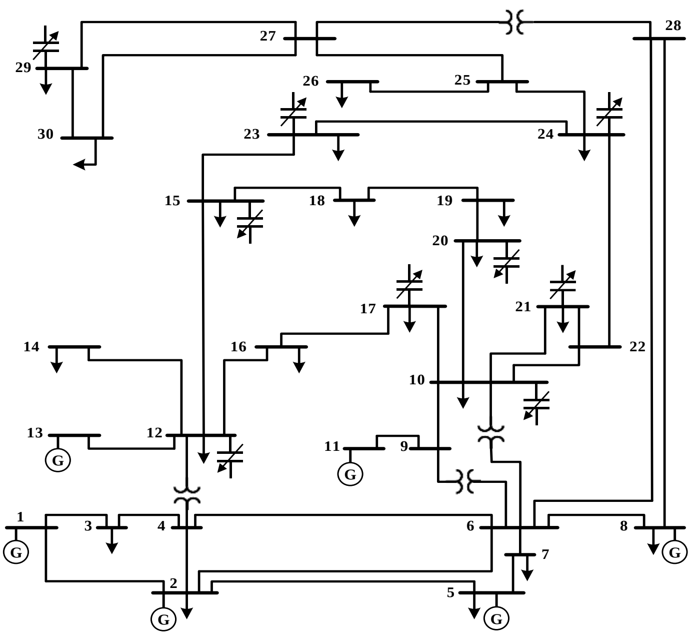
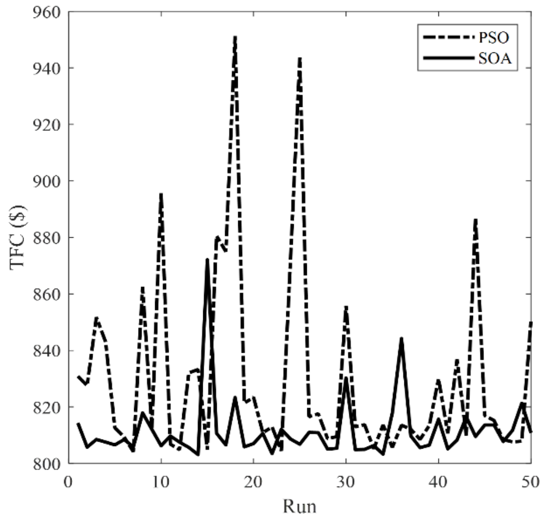



Figure 1. The model of the IEEE 30-bus configuration system

Figure 2 shows the fitness values obtained by two applied methods on 50 cost values obtained by both PSO and SOA. The observation of the 50 cost values indicates that SOA reaches more optimal values than PSO. Moreover, SOA shows lower fluctuations of fitness values than PSO among 50 cost values. This means that SOA can provide a stable performance when applied to the 30-bus transmission power system. The observation of the best convergences given by the two applied methods in Figure 3 indicates that SOA can provide a faster response capability than PSO. Specifically, SOA can obtain the best value after 100 iterations, while PSO cannot do the same. Clearly, the ability to seek the global optimum solution offered by SOA is more productive than PSO.



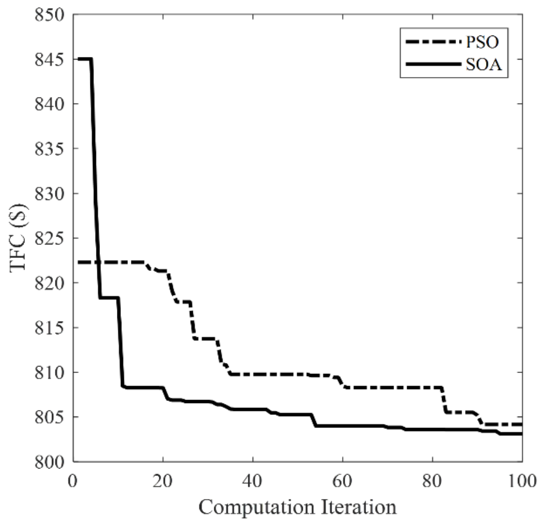




Figure 2. Fifty costs resulted by PSO and SOA

Figure 3. The best convergences given by PSO and SOA

Figure 4 presents the comparison between PSO and SOA in terms of the minimum cost (Min.Cost), the average cost (Aver.Cost), the maximum cost (Max.Cost), and standard deviation (Std). In the Figure 4, the results of SOA are better than those of PSO, in terms of the Min.Cost, the result of PSO is 804.1675 ($/h), but that of SOA is only 803.1437 ($/h). Clearly, the application of SOA has saved approximately $1.04, or 0.13% of TFC, for each hour. Furthermore, Aver.Cost and Max.Cost of SOA are only 811.7451 ($/h) and 872.0927 ($/h), but those of PSO are 830.3455 ($/h) and 951.2637 ($/h). By taking simple calculations, the savings costs and the corresponding percentages for each hour resulted by SOA over PSO on the two criteria are, respectively, $18.6 and 2.24%, and $79.17 and 8.32%. Finally, the Std value given by SOA is only 11.340, while that of PSO is 33.9804. The Std values once again confirm that SOA is more stable than PSO when dealing with the considered problem. Clearly, SOA outperforms PSO in all comparison criteria.

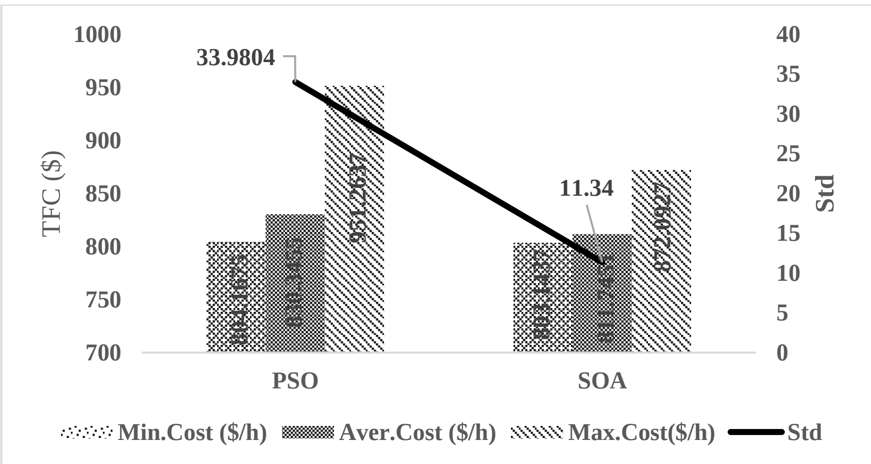



Figure 4. The specific comparison between PSO and SOA on different criteria

Figure 5 depicts the voltage values of each node in the whole system given by the two applied methods. Clearly, the two methods can provide optimal solutions with the allowable voltage for all nodes between 0.95 and 1.1 pu. However, the voltage profile of SOA is better once the fluctuation of voltage is around 1.0 pu, which is the rated value of voltage and an expected operation voltage.

The optimal variables given by the two applied methods are presented in Table 1. In the Table 1, not only optimal variables but also their operation limits are also reported for checking the validation of the proposed solutions. The observation of Table 1 indicated that all the optimal variables found by the two applied methods are located within the initial limits.

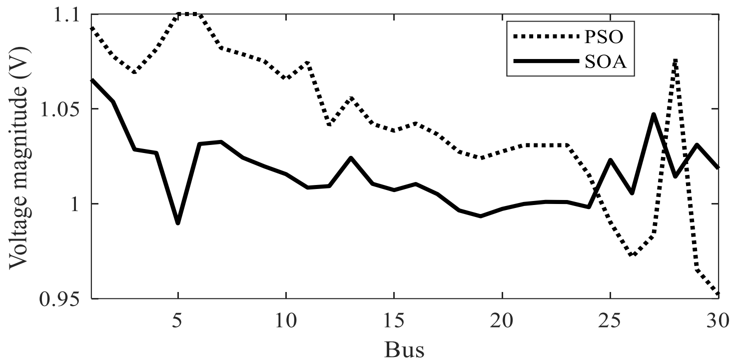



Figure 5. The voltage profile of all nodes in the system achieved by PSO and SOA

Table 1. The limit of control variables and optimal control variable proposed by SOA

| Variable | Range | Value | Variable | Range | Value |
|---|---|---|---|---|---|
| $TU_1$ (MW) | [50, 200] | 181.2924 | $Q_{Ca1}$ (MVar) | [0, 5] | 0.7958 |
| $TU_2$ (MW) | [20, 80] | 46.0928 | $Q_{Ca2}$ (MVar) | [0, 5] | 2.9665 |
| $TU_3$ (MW) | [15, 50] | 21.9865 | $Q_{Ca3}$ (MVar) | [0, 5] | 1.2337 |
| $TU_4$ (MW) | [10, 35] | 18.6298 | $Q_{Ca4}$ (MVar) | [0, 5] | 1.136 |
| $TU_5$ (MW) | [10, 30] | 12.2539 | $Q_{Ca5}$ (MVar) | [0, 5] | 1.4913 |
| $TU_6$ (MW) | [12, 40] | 13.027 | $Q_{Ca6}$ (MVar) | [0, 5] | 2.2836 |
| $V_{TU1}$ (pu) | [0.95, 1.1] | 1.0656 | $Q_{Ca7}$ (MVar) | [0, 5] | 1.047 |
| $V_{TU2}$ (pu) | [0.95, 1.1] | 1.0538 | $Q_{Ca8}$ (MVar) | [0, 5] | 1.8609 |
| $V_{TU3}$ (pu) | [0.95, 1.1] | 1.0286 | $Q_{Ca9}$ (MVar) | [0, 5] | 1.0616 |
| $V_{TU4}$ (pu) | [0.95, 1.1] | 1.0268 | $TT_1$ (pu) | [0.9, 1.1] | 0.9921 |
| $V_{TU5}$ (pu) | [0.95, 1.1] | 0.9897 | $TT_2$ (pu) | [0.9, 1.1] | 0.9315 |
| $V_{TU6}$ (pu) | [0.95, 1.1] | 1.0315 | $TT_3$ (pu) | [0.9, 1.1] | 0.9757 |
| | | | $TT_4$ (pu) | [0.9, 1.1] | 0.9304 |

## 5. CONCLUSION

In this research, a modern SOA was successfully implemented to unfold the OPF problem for the IEEE 30-bus configuration system. The sole objective function of the whole study is to find the best cost of all thermal units. The results obtained by SOA are compared to PSO in different criteria. The evaluation of these criteria indicates that SOA completely outperforms PSO in all compared criteria. Moreover, SOA not only provides a fast response capability but also proves itself to be far more stable than PSO. Therefore, SOA is demonstrated as the high effective search method to deal with the OPF problem. Besides, there are several drawbacks that is needed to be improved for better quality, as follows: i) the scale of the considered problem is relatively small when compared with other theoretical transmission networks, such as the IEEE 57, IEEE 118-bus systems, or an existing transmission network in practice; ii) the study only considers one objective function, minimizing TFC. Other objective functions, such as minimizing the total emissions, minimizing the voltage deviation, and many others, are not evaluated; and iii) the contribution of wind and solar energy is not considered.

By acknowledging all these drawbacks, a future study should be conducted on the larger scale of the OPF problem by using a larger configuration of transmission networks with the consideration of different objective functions and the presence of clean energy.

## REFERENCES

[1] F. Daqaq, M. Ouassaid, and R. Ellaia, "A new meta-heuristic programming for multi-objective optimal power flow," *Electrical*

*Engineering*, vol. 103, no. 2, pp. 1217–1237, Apr. 2021, doi: 10.1007/s00202-020-01173-6.
[2] A. Salhi, D. Naimi, and T. Bouktir, “Fuzzy Multi-Objective Optimal Power Flow Using Genetic Algorithms Applied to Algerian Electrical Network,” *Advances in Electrical and Electronic Engineering*, vol. 11, no. 6, Dec. 2013, doi: 10.15598/aeee.v11i6.832.
[3] H. Diab, M. Abdelsalam, and A. Abdelbary, “A Multi-Objective Optimal Power Flow Control of Electrical Transmission Networks Using Intelligent Meta-Heuristic Optimization Techniques,” *Sustainability*, vol. 13, no. 9, p. 4979, Apr. 2021, doi: 10.3390/su13094979.
[4] S. Birogul, “Hybrid Harris Hawk Optimization Based on Differential Evolution (HHODE) Algorithm for Optimal Power Flow Problem,” *IEEE Access*, vol. 7, pp. 184468–184488, 2019, doi: 10.1109/ACCESS.2019.2958279.
[5] H. A. Hassan and M. Zellagui, “Application of Grey Wolf Optimizer Algorithm for Optimal Power Flow of Two-Terminal HVDC Transmission System,” *Advances in Electrical and Electronic Engineering*, vol. 15, no. 5, Jan. 2018, doi: 10.15598/aeee.v15i5.2110.
[6] W. Warid, “Optimal power flow using the AMTPG-Jaya algorithm,” *Applied Soft Computing*, vol. 91, p. 106252, Jun. 2020, doi: 10.1016/j.asoc.2020.106252.
[7] S. S. Reddy and P. R. Bijwe, “Differential evolution-based efficient multi-objective optimal power flow,” *Neural Computing and Applications*, vol. 31, no. S1, pp. 509–522, Jan. 2019, doi: 10.1007/s00521-017-3009-5.
[8] T. M. Dao, M. Q. Tran, L. T. Duong, D. P. N. Do, N. N. Nguyen, and D. N. Vo, “Temperature Dependent Optimal Power Flow Using Combined Particle Swarm Optimization and Differential Evolution Method,” *GMSARN International Journal*, vol. 18, no. 1, pp. 84–105, 2024.
[9] L. H. Pham, B. H. Dinh, and T. T. Nguyen, “Optimal power flow for an integrated wind-solar-hydro-thermal power system considering uncertainty of wind speed and solar radiation,” *Neural Computing and Applications*, vol. 34, no. 13, pp. 10655–10689, Jul. 2022, doi: 10.1007/s00521-022-07000-2.
[10] K. Rojanaworahiran and K. Chayakulkheeree, “Probabilistic optimal power flow considering load and solar power uncertainties using particle swarm optimization,” *GMSARN International Journal*, vol. 15, no. 1, pp. 37–43, 2021.
[11] A. Ginidi, E. Elattar, A. Shaheen, A. Elsayed, R. El-Sehiemy, and H. Dorrah, “Optimal Power Flow Incorporating Thyristor-Controlled Series Capacitors Using the Gorilla Troops Algorithm,” *International Transactions on Electrical Energy Systems*, vol. 2022, pp. 1–23, Aug. 2022, doi: 10.1155/2022/9448199.
[12] Z. Li, Y. Cao, L. V. Dai, X. Yang, and T. T. Nguyen, “Optimal Power Flow for Transmission Power Networks Using a Novel Metaheuristic Algorithm,” *Energies*, vol. 12, no. 22, p. 4310, Nov. 2019, doi: 10.3390/en12224310.
[13] O. S. Velasquez, O. D. M. Giraldo, V. M. G. Arevalo, and L. F. G. Norena, “Optimal Power Flow in Direct-Current Power Grids via Black Hole Optimization,” *Advances in Electrical and Electronic Engineering*, vol. 17, no. 1, Mar. 2019, doi: 10.15598/aeee.v17i1.3069.
[14] T. L. Duong, N. A. Nguyen, and T. T. Nguyen, “A Newly Hybrid Method Based on Cuckoo Search and Sunflower Optimization for Optimal Power Flow Problem,” *Sustainability*, vol. 12, no. 13, p. 5283, Jun. 2020, doi: 10.3390/su12135283.
[15] M. Abdullah, N. Javaid, A. Chand, Z. A. Khan, M. Waqas, and Z. Abbas, “Multi-objective Optimal Power Flow Using Improved Multi-objective Multi-verse Algorithm,” 2019, pp. 1071–1083.
[16] A. Khelifi, B. Bentouati, and S. Chettih, “Optimal Power Flow Problem Solution Based on Hybrid Firefly Krill Herd Method,” *International Journal of Engineering Research in Africa*, vol. 44, pp. 213–228, Aug. 2019, doi: 10.4028/www.scientific.net/JERA.44.213.
[17] M. A. Taher, S. Kamel, F. Jurado, and M. Ebeed, “An improved moth-flame optimization algorithm for solving optimal power flow problem,” *International Transactions on Electrical Energy Systems*, vol. 29, no. 3, p. e2743, Mar. 2019, doi: 10.1002/etep.2743.
[18] S. Tiwari, N. Vaddi, S. B. Metta, and M. Kumar, “Optimal Power Flow Solution with Nature Inspired Antlion Meta-Heuristic Algorithm,” *Journal of Physics: Conference Series*, vol. 1478, no. 1, p. 012035, Apr. 2020, doi: 10.1088/1742-6596/1478/1/012035.
[19] D. Ramavath and M. Sharma, “Optimal Power Flow Using Modified ALO,” in *2020 International Conference on Renewable Energy Integration into Smart Grids: A Multidisciplinary Approach to Technology Modelling and Simulation (ICREISG)*, Feb. 2020, pp. 84–89, doi: 10.1109/ICREISG49226.2020.9174551.
[20] M. Farhat, S. Kamel, A. M. Atallah, and B. Khan, “Developing a Marine Predator Algorithm for Optimal Power Flow Analysis considering Uncertainty of Renewable Energy Sources,” *International Transactions on Electrical Energy Systems*, vol. 2022, pp. 1–16, Jun. 2022, doi: 10.1155/2022/3714475.
[21] T. T. Nguyen, “A high performance social spider optimization algorithm for optimal power flow solution with single objective optimization,” *Energy*, vol. 171, pp. 218–240, Mar. 2019, doi: 10.1016/j.energy.2019.01.021.
[22] S. Khunkitti, A. Siritaratiwat, and S. Premrudeepreechacharn, “Multi-Objective Optimal Power Flow Problems Based on Slime Mould Algorithm,” *Sustainability*, vol. 13, no. 13, p. 7448, Jul. 2021, doi: 10.3390/su13137448.
[23] M. H. Nadimi-Shahraki, S. Taghian, S. Mirjalili, L. Abualigah, M. A. Elaziz, and D. Oliva, “EWOA-OPF: Effective Whale Optimization Algorithm to Solve Optimal Power Flow Problem,” *Electronics*, vol. 10, no. 23, p. 2975, Nov. 2021, doi: 10.3390/electronics10232975.
[24] K. Nusair and F. Alasali, “Optimal Power Flow Management System for a Power Network with Stochastic Renewable Energy Resources Using Golden Ratio Optimization Method,” *Energies*, vol. 13, no. 14, p. 3671, Jul. 2020, doi: 10.3390/en13143671.
[25] M. N. Hawas, R. K. Ibrahim, and A. J. Sultan, “Optimal operation of thermal system based on optimum power flow,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 3, pp. 1204–1210, Jun. 2021, doi: 10.11591/eei.v10i3.1901.
[26] P. G. Burade, “Optimal Location of FACTS Device on Enhancing System Security,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 2, no. 3, Apr. 2012, doi: 10.11591/ijece.v2i3.250.
[27] M. Mbae and N. Nwulu, “Impact of hybrid FACTS devices on the stability of the Kenyan power system,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 1, p. 12, Feb. 2022, doi: 10.11591/ijece.v12i1.pp12-21.
[28] S. Haddi, O. Bouketir, and T. Bouktir, “Improved Optimal Power Flow for a Power System Incorporating Wind Power Generation by Using Grey Wolf Optimizer Algorithm,” *Advances in Electrical and Electronic Engineering*, vol. 16, no. 4, Dec. 2018, doi: 10.15598/aeee.v16i4.2883.
[29] L. C. Kien, T. T. B. Nga, T. M. Phan, and T. T. Nguyen, “Coot Optimization Algorithm for Optimal Placement of Photovoltaic Generators in Distribution Systems Considering Variation of Load and Solar Radiation,” *Mathematical Problems in Engineering*, vol. 2022, pp. 1–17, Apr. 2022, doi: 10.1155/2022/2206570.
[30] M. P. Duong, D. N. Vo, T. T. Nguyen, and D. V. Phan, “Optimal Power Flow in Power System Considering Wind Power Integrated into Grid,” *GMSARN International Journal*, vol. 15, no. 4, pp. 287–300, 2021.
[31] A. H. Shojaei, A. A. Ghadimi, M. R. Miveh, F. Mohammadi, and F. Jurado, “Multi-Objective Optimal Reactive Power Planning

under Load Demand and Wind Power Generation Uncertainties Using ε-Constraint Method," *Applied Sciences*, vol. 10, no. 8, p. 2859, Apr. 2020, doi: 10.3390/app10082859.
[32] A. Abdollahi, A. Ghadimi, M. Miveh, F. Mohammadi, and F. Jurado, "Optimal Power Flow Incorporating FACTS Devices and Stochastic Wind Power Generation Using Krill Herd Algorithm," *Electronics*, vol. 9, no. 6, p. 1043, Jun. 2020, doi: 10.3390/electronics9061043.
[33] H. Givi and M. Hubalovska, "Skill Optimization Algorithm: A New Human-Based Metaheuristic Technique," *Computers, Materials & Continua*, vol. 74, no. 1, pp. 179–202, 2023, doi: 10.32604/cmc.2023.030379.

## BIOGRAPHIES OF AUTHORS

**Chiem Trong Hien** has completed the M.Sc. degree in electrical engineering from Ho Chi Minh City University of Technology and Education, Ho Chi Minh City, Vietnam. He is currently a Lecturer in the Faculty of Electrical Engineering and Electronics, Ho Chi Minh City University of Food Industry, Ho Chi Minh City, Vietnam. His research interests include applications of modern control methods and intelligent algorithms in motor drives. He can be contacted at email: hienct@hufi.edu.vn.

**Minh Phuc Duong** received the B.E. (2019), M.E. (2022) degrees in electrical engineering from Ton DucThang University, Vietnam. His research interests include optimization algorithms, and distribution and transmission networks. He can be contacted at email: duongminh.nt190296@gmail.com.

**Ly Huu Pham** received the B.E. (2004), M.E. (2009) degrees in electrical engineering from Ho Chi Minh City University of Technology, Vietnam. Now, he is teaching at Ton DucThang University, Ho Chi Minh City. His research interests include optimization algorithms, power system optimization, and renewable energy. He can be contacted at email: phamhuuly@tdtu.edu.vn.