DOI: https://doi.org/10.62985/j.huit_ojs.vol26.no1E.336

OPTIMAL SOLUTION DETERMINATION TO POWER FLOW PROBLEM OF TRANSMISSION POWER GRIDS CONSIDERING RENEWABLE POWER SOURCES

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Received: 20 May 2025; Revised: 19 June 2025; Accepted: 30 July 2025

ABSTRACT

This study presents the implementation of two metaheuristic methods, Coot Optimization Algorithm (COOT) and Marine Predators Algorithm (MPA), to determine optimal results for a modified Optimal Power Flow (OPF) problem that includes wind power plants (WPPs). The study evaluates COOT and MPA across various versions of the OPF problem, including a basic OPF scenario that does not consider any renewable energy sources and a modified OPF scenario that includes the impact of WPPs. To assess the effectiveness of the two methods, the IEEE 30-node system and its modified versions are utilized. In the case without WPPs, COOT results in lower costs compared to MPA and other methods. In other cases, COOT method also demonstrates better cost savings than MPA. Consequently, COOT is regarded as a powerful and innovative metaheuristic for addressing the OPF problem, particularly in the context of increasing the use of renewable energy in power systems.

Keywords: Coot optimization algorithm, marine predators algorithm, modified optimal power flow, wind power plants, fuel cost.

1. INTRODUCTION

To deliver electricity, a power system integrates various elements, such as power plants, loads, transformers, and transmission/distribution networks [1]. Generators and transformers facilitate power production and transmission, while power networks deliver power to end-users [2]. Maintaining the stable operation of these elements is crucial to the overall efficiency and reliability of the whole system, and solving the optimal power flow (OPF) problem is an important step to achieving that goal.

In OPF problem, the objective functions such as fuel cost, polluted emission or voltage profile are implemented on test systems, in which power plants at generators buses can be thermal, hydro, wind and solar power plants [3]. The key mission of OPF is to find the operation parameters of devices in the power system [4]. They are considered optimal values, which are called control and dependent variables that can be found by methods. In reality, the OPF problem presents an important challenge in the realm of electric power networks due to its non-convex and non-linear nature. Addressing this problem is essential for optimizing electrical systems, and it opens the door for the development of innovative, powerful, and robust algorithms. This is a reason that we apply two methods to resolve OPF problems considering the presence of renewable energy resources and four different test cases..

2. LITERATURE REVIEW

For finding the results to OPF problem, conventional methods such as Gaussidel/Newton-Graphson and metaheuristic algorithms like Tabu Search and simulated annealing (SAA/TSA) [1], wasp optimization algorithm (WOA) [5], improved cuckoo search [6], and Jellyfish search algorithm (JSA) [7], red-tailed hawk optimization algorithm (RT-HOA) [8], Dingo Optimizer (DO) [9], skill optimization algorithm (SOA) [10], elephant herd optimization algorithm (EHOA) [11], adaptive grasshopper optimization algorithm (AGOA) [12], modified artificial hummingbird algorithm (MAHA) [13], the Coot Optimization Algorithm (COOT) [14-15], and multi-objective biogeography-based optimization algorithm (MOBBO) [16] are suggested. The key mission of method is to find correct parameters to minimize production costs and energy losses for system. Among methods, the (SAA/TSA) conducted in 2002 was one of the earliest investigations into OPF. Additionally, the study implemented a Genetic Algorithm (GA), a Tabu Search Algorithm (TSA), and a Simulated Annealing Algorithm (SAA) to explore potential solutions. The research presented in study [9] made significant advancements by optimizing the installation of STATCOM and UPFC, which contributed to a reduction in current levels on transmission lines. A study [10] introduced a study presented a modern meta-heuristic algorithm known as the skill optimization algorithm (SOA), which effectively addresses the optimal power flow problem in the EEE 30-bus transmission system. This innovative approach has the potential to enhance efficiency and improve system performance. Meanwhile, another study [12] highlighted the benefits of using AGOA to help optimize the installation of FACTS in the transmission power network. In [16], authors effectively tackled a multi-objective function by implementing a multi-objective biogeography-based optimization algorithm (MOBBO). In general, these studies have effectively utilized a range of methods to transmission power systems, taking into account both technical and economic aspects. Clearly, meta-heuristic algorithms mentioned above have proven their capability in solving these non-linear and non-convex optimization problems compared to the old-fashioned computing methods; however, while the scale of the optimization grows along with the increase of the complexity involved constraints, the original meta-heuristic algorithms must be improved to maintain their searching performance, which can be seen in [13] and [16]. However, the modern OPF witnesses many connections to other devices such as renewable energy sources, FACTS devices, battery energy storage systems (BESS), etc. Therefore, the OPF problem with the integration of these mentioned devices into the power grid will increase in the complexity when solving it. As a result, the problem should be explored in more detail, and it will be an opportunity for researchers to study.

This study explores the application of Coot Optimization Algorithm (COOT) to enhance OPF problem on transmission power network of 30 nodes, aiming to improve system efficiency and reliability. COOT is firmly grounded in the social behavior and foraging techniques of coots and waterfowl renowned for their dynamic social interactions and effective group dynamics [15]. COOT has demonstrated its effectiveness in the strategic placement of wind generators within distribution systems [14], and the stratergy of reducing emissions and power loss [15]. In addition to COOT, Marine predators algorithm (MPA) [17] is applied to implement on the same test system for comparison. The novelty of the study is as follows:

1) Two methods are used to identify optimal parameter settings to minimize cost and reduce losses while enhancing voltage levels.
2) The result of COOT and methods are compared to determine which method is more effective in identifying optimal location for WPPs.

After running COOT and MPA for the IEEE 30-bus transmission power grid for four cases to minimize the total fuel cost of thermal power plants. The four cases are comprised of installing no WPPs, one WPP, two WPPs and three WPPs. The contribution of the study are as follows:

1) The study achieves lower electricity generation costs compared to previous studies.
2) COOT can identify the optimal solutions for OPF to reduce electricity generation costs and enhance voltage stability.
3) COOT can reach better solutions for the problem.

3. PROBLEM DESCRIPTION

In this section, a structured approach provides a comprehensive framework for optimizing the integration of wind power in transmission networks while minimizing operational costs.

3.1. Objective function

In OPF problem, objective functions can include the fuel cost in (\$), the power losses in (kW), the voltage deviations in (p.u), the voltage stability in (p.u), and the emissions in (ton/hr). However, this study only minimize the fuel cost (FC) of thermal power plants in a transmission network, considering the integration of wind power. The objective function is defined as: [15].

$$FC = \sum_{\mathrm{i}=1}^{N_{TPs}} (\theta_{1\mathrm{i}} + \theta_{2\mathrm{i}}.P_i + \theta_{3\mathrm{i}}.P_i^{\,2})(\$/\mathrm{h}) \tag{1}$$

where, θ_{1i}, θ_{2i}, $\theta_{3i}$are the fuel cost parameters of the *ith* thermal power plant; P_i is the active power of the *ith* thermal power plant; and $N_{TPs}$is the number of thermal power plants.

3.2. Constraints of OPF problem

The OPF problem is subject to equality and inequality constraints to ensure feasible and secure operation of the power system as follows:

3.2.1. Equality constraint

At each node, the active and reactive power are presented as follows:

$$P_m + PW_m - PL_m = V_m \sum_{n=1}^{N_{No}} V_n.\begin{bmatrix} C_{mn}.cos(\varphi_{mn}) \\ +S_{mn}.sin(\varphi_{mn}) \end{bmatrix} \tag{2}$$

$$Q_m + QW_m + Qcap_m - QL_m = V_m \sum_{n=1}^{N_{No}} V_n.\begin{bmatrix} C_{mn}.cos(\varphi_{mn}) \\ -S_{mn}.sin(\varphi_{mn}) \end{bmatrix} \tag{3}$$

where, P_m and Q_m denote the active and reactive power of thermal power plant installed at node *m*; PW_m and QW_m are the active and reactive power of the wind power plant at node m; PL_m and QL_m denote the active and reactive power of load at bus *m*; C_{mn} and $S_{mn}$are the conductance and susceptance of the line *mn*; $Qcap_m$ denotes the reactive power compensators connected at node *m;* $\varphi_{mn} = \varphi_m - \varphi_n$where φ_m and φ_n denote voltage phase angels at bus m and bus *n;* and $N_{No}$is the number of buses.

3.2.2. Inequality constraints

The OPF problem also considers inequality constraints representing the operating limits of various components:

Wind Power Plant Generation Limits:

$$PW_w^l \le PW_w \le PW_w^u; w = 1, \dots, N_{WP} \tag{4}$$

$$QW_w^l \le QW_w \le QW_w^u; ; w = 1, \dots, N_{WP} \tag{5}$$

Thermal Power Plant Generation Limits:

$$P_i^l \le P_i \le P_i^u; \ \mathrm{i} = 1, \dots, N_{TPs} \tag{6}$$

$$Q_i^l \le Q_i \le Q_i^u ; \mathrm{i} = 1, \dots, N_{TPs} \tag{7}$$

Reactive Power Compensator Limits:

$$Qcap_c^l \le Qcap_c \le Qcap_c^u ; c = 1, \dots, N_{Cap} \tag{8}$$

Voltage Limits:

$$V_{lo}^l \le U_{lo,d} \le V_{lo}^u; \ d = 1, \dots, N_{NLs} \tag{9}$$

$$V_i^l \le V_i \le V_i^u; \ i = 1, \dots, N_{TPs} \tag{10}$$

Transformer Tap Changer Limits:

$$T^l \leq T_p \leq T^u \; ; \; p = 1,\dots,N_{Ts} \tag{11}$$

Transmission Branch Apparent Power Limits:

$$AS_f \leq AS_f^u \; ; \; f = 1,\dots,N_{Bs} \tag{12}$$

where, PW_w^l and PW_w^u are the wind power plant's lower and upper active power generation limits of the wind power plant *w*; QW_w^l and QW_w^u are the wind power plant's lower and upper reactive power generation limits of the wind power plant *w*; $Qcap_c^l$ and $Qcap_c^u$ are the capacitor's lower and upper reactive power generation limits of the capacitor c; V_{lo}^l and V_{lo}^u are the loads' lower and upper voltage limits; $U_{lo,d}$ is the *dth* load's voltage; V_i^l and V_i^u are the *ith* thermal power plant's lower and upper voltage limits; V_i is the *ith* thermal power plant's working voltage; P_i^l and P_i^u are the *ith* thermal power plant's lower and upper active power generation limits; Q_i^l and Q_i^u are the *ith* thermal power plant's lower and upper reactive power generation limits; P_i and Q_i are the *ith* thermal power plant's active and reactive power generations; T^l and T^u are the transformer's lower and upper tap changers; T_p is the *pth* transformer's tap changer; AS_f and AS_f^u are the *fth* branch working and upper apparent power; and $N_{WP}, N_{Cap}, N_{Ts}, N_{Bs}$ and N_{NLs} are the number of wind power plants, capacitors, transformers, branches, and load buses.

4. METHODS

In this section, COOT and MPA are introduced to solve the problem in the study; however, COOT is the primary method, and MPA is applied to compare with COOT to prove the performance of COOT. As a result, the structure of COOT is presented in detail, while that of MPA is presented briefly.

4.1. Introduction of COOT

COOT is a metaheuristic algorithm that utilizes concepts of population dynamics and randomness. It is a mathematical model that mimics the behavior of a water bird species known as Coots while they search for food. Coots typically gather in groups, moving collectively to find food. Depending on the amount of food they discover, the Coots are classified into two groups: a member group and a leader group. To enhance the effectiveness of COOT, it is important to start with a randomly generated initial solution set. This foundational set can then be refined and improved through the application of two specific techniques. The initial solutions are created based on their upper bound and a lower bound, $Bound^{up}$ and $Bound^{low}$, in which, a solution is refered to the *cth* Coot in the population (S_P). After that, these solutions are ranked by determing the fitness to find the set of low quality (N_l) called $LCoot_a$ and the set of high quality (N_h) called $HCoot_b$. Next, two group of $HCoot_b$ and $LCoot_a$ are updated as follows:

4.1.1. Updating solutions of the low-quality group

In the group, each COOT or each solution is updated following three conditions as shown in Eqs. (13-15) by:

$$LCoot_a^{new} = LCoot_a + FR_1.(Coot_r - LCoot_a) \tag{13}$$

$$LCoot_a^{new} = FR_2.(LCoot_a + LCoot_{a'}) \tag{14}$$

$$LCoot_a^{new} = HCoot_r + FR_3.(HCoot_r - LCoot_a) \tag{15}$$

where, $LCoot_{a'}$ is a coot closest to $LCoot_a$; $Coot_r$ is radom solution among population; and $HCoot_r$ is a random solution in the high-quality group; and FR_1, FR_2, and FR_3 are random scaling factors obtained by:

$$FR_1 = rdv_{0\div 1} \times \frac{HNIter - INter}{HNIter} \tag{16}$$

$$FR_2 = 0.5 \tag{17}$$

$$FR_3 = 2.rdv_{0\div 1}.\cos(2.\pi.rdv_{-1\div 1}) \tag{18}$$

where, $rdv_{0\div1}$ is random value within [0,1] and $rdv_{-1\div1}$ is a random value within [-1,1]; and $INter$ and $HNIter$ are the current and highest iterations.

4.1.2. Updating solutions of the high-quality solution group

In this group, two stratergies are used for updating new solutions as shown in Eqs. (19) and (20) by comparing Rand within [0,1] and 0.5. If Rand is less than 0.5, Eq. (19) is used. Otherwise, Eq. (20) is choosen.

$$HCoot_b^{new} = Coot_{best} + FR_4.(Coot_{best} - HCoot_b) \quad (19)$$

$$HCoot_b^{new} = -Coot_{best} + FR_4.(Coot_{best} - HCoot_b) \quad (20)$$

where, $Coot_{best}$ denotes the best solution in the high-quality group; and FR_4 is random parameter obtained by:

$$FR_4 = \frac{2.HNIter - INter}{HNIter}.rdv_{0\div1}.\cos(2.\pi.rdv_{0\div1}) \quad (21)$$

4.1.3. The flow diagram of the COOT algorithm

The flow diagram of the COOT algorithm for applying the problem is given in Figure 1.

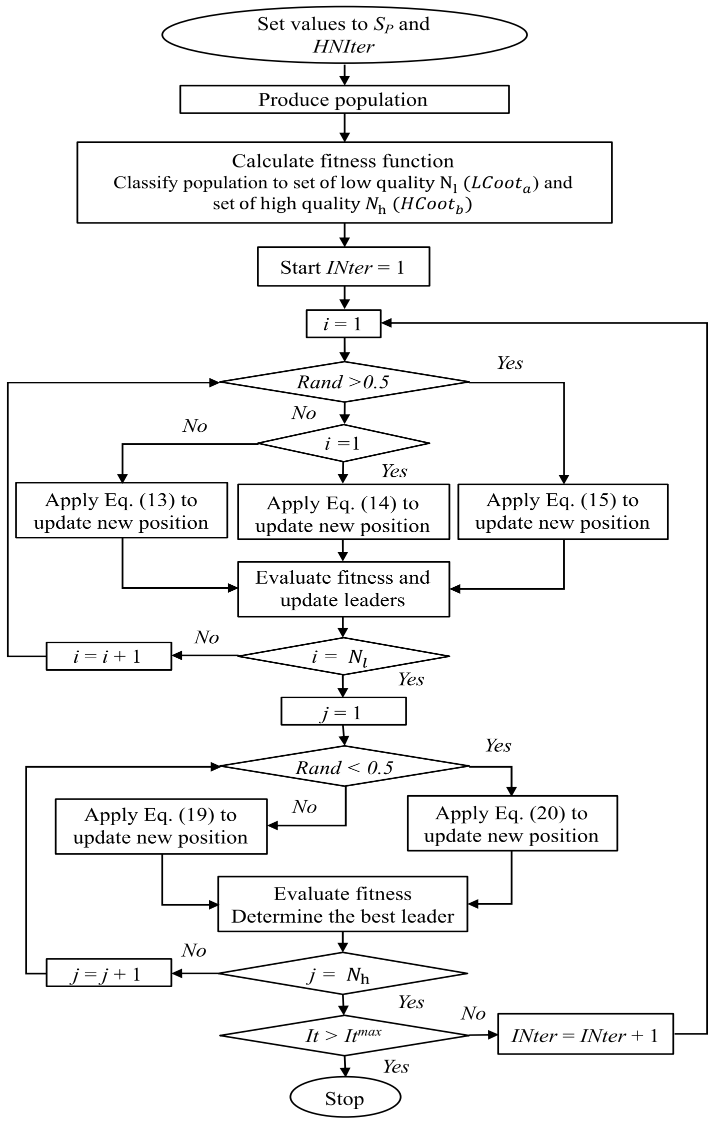


Figure 1. Flow chart for the implementation of COOT algorithm

4.2. Introduction of MPA

MPA has developed two innovative solution generations for each iteration. The first generation incorporates three distinct updating techniques, tailored to the specific phase of the iteration. In contrast, the second generation focuses on applying two techniques consistently across the entire range of iterations.

In the first generation, the application of the three techniques is thoughtfully segmented: the first technique is implemented during the initial third of the maximum iterations, the second technique is utilized in the middle third, and the final technique is reserved for the last third of the iterations

- Stage 1: $INter \leq \frac{1}{3} HNIter$

$$X_s^{new} = X_s + \epsilon \times \theta \times \partial \times (X^* - \partial \times X_s)\ ; \quad s = 1 \ldots S_p \tag{22}$$

- Stage 2: $\frac{1}{3} HNIter < INter < \frac{2}{3} HNIter$

The first half of the population is updated with Eq. (23), and the second half is updated with Eq. (24)

$$X_s^{new} = X_s + \epsilon \times \theta \times \varepsilon \times (X^* - \varepsilon \times X_s)\ ; \quad s = 1 \ldots \frac{S_p}{2} \tag{23}$$

$$X_s^{new} = X^* + \vartheta \times \left(1 - \frac{INter}{HNIter}\right)^{\left(2 \times \frac{INter}{HNIter}\right)} \times \mu \times \left(\mu \times X^* - X_s\right)\ ; \quad s = \frac{S_p}{2} \ldots S_p \tag{24}$$

- Stage 3: $\frac{2}{3} HNIter \leq INter \leq HNIter$

$$X_s^{new} = X^* + \vartheta \times \left(1 - \frac{INter}{HNIter}\right)^{\left(2 \times \frac{INter}{HNIter}\right)} \times \alpha \times \left(\alpha \times X^* - X_s\right)\ ; \quad s = 1 \ldots S_p \tag{25}$$

In the second generation, MPA decisively evaluates r and F to determine whether to utilize Eq. (26) or Eq. (27) for updating new solutions. The two equations are clearly defined as follows:

$$X_s^{new} = X_s + \left[X^{min} + \omega \times \left(X^{max} - X^{min}\right)\right] \times \varphi \times \left(1 - \frac{INter}{HNIter}\right)^{\left(2 \times \frac{INter}{HNIter}\right)}\ ; \ if\ r \leq F \tag{26}$$

$$X_s^{new} = X_s + [F \times (1 - r) + r] \times (X_{r4} - X_{r5})\ ; \ if\ r > F \tag{27}$$

where X_{r4} and X_{r5} are random solutions from the current population, and X^* is the best solution; F is fish aggregating device; X^{min} and X^{max} are the minimum and maximum bounds of the *sth* solution; $,\theta, r, \omega$ are randomly selected number within 0 and 1; ∂, μ are Brownian motion based random number; α, ε are Lévy movement based random number; ϵ, ϑ, φ are predetermined number.

5. NUMERICAL RESULTS

5.1. System simulation cases

In this section, we harness the power of COOT and MPA to optimize the placement of wind power plants (WPPs) within the IEEE 30-node transmission power system as shown in Figure 2, with four study cases as follows:

Case 1: Find solutions without WPPs.

Case 2: Find solutions with one WPP.

Case 3: Find solutions with two WPPs.

Case 4: Find solutions with three WPPs.

In order to achieve the objectives in the four cases mentioned, COOT and MPA have been implemented over 50 trial runs. The program has been coded using MATLAB software version 2018b, and it runs on a personal computer equipped with a 2.4 GHz processor and 8 GB of RAM. Data from the test system are cited from the study [6].

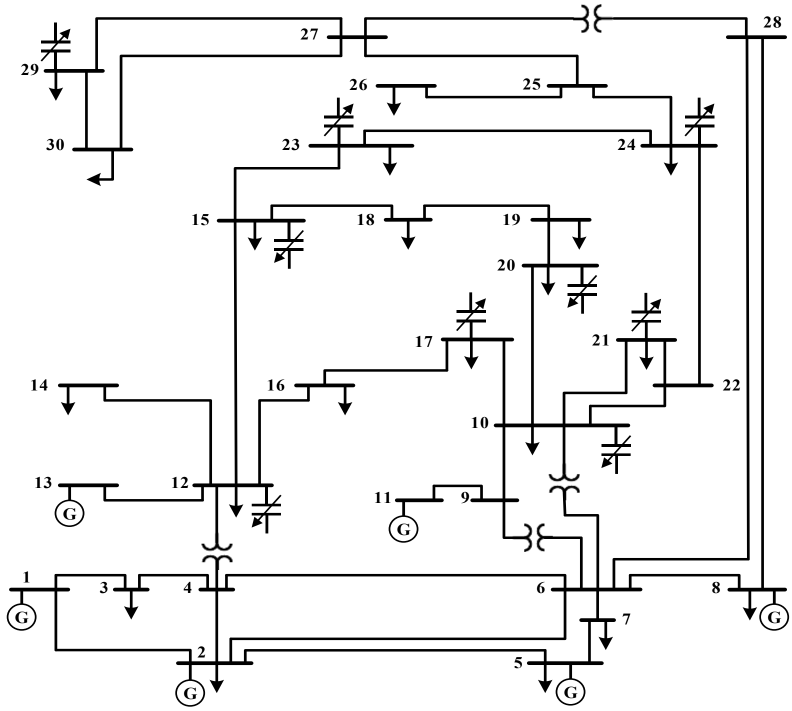


Figure 2. The IEEE 30-bus system [10]

5.2. Obtained results

For applying two methods, two parameters, such as the population size and the iteration number ($HNIter$), are first investigated on Case 1 by citing previous studies. The investigated results are collected and shown in Table 1. In the table, S_p and $HNIter$ are adjusted from 30 to 50. And a number of newly generated solutions (N_{us}) is calculated by multiplying S_P and $HNIter$. With these values of S_p and $HNIter$, the cost of MPA and COOT are different. However, the best costs for MPA and COOT are \$ 799.51 and \$ 799.48, respectively, for the S_p of 50 and the $HNIter$ of 50.

Besides, CPU time of each method per run is shown in the Table 1, where COOT has less CPU time than MPA for three investigations by 2,6 (s), 4.46 (s), and 2.23 (s), respectively.

Table 1. The investigated parameters of two applied methods for Case 1

Parameters						
Sp	HNIter	Nus	MPA		COOT	
			Cost ($/h)	Cpu time (s)	Cost ($/h)	Cpu time (s)
30	30	900	800.30	5.4	801.55	2.8
40	40	1600	799.79	10.1	799.88	5.64
50	50	2500	799.51	11.5	799.48	9.27

The best result of MPA and COOT is compared to the modified differential evolution algorithm (MDE) [18], genetic algorithm (GA) [19], GA-fuzzy system approach (GA-FSA) [19], shuffle frog leaping algorithm (SFLA) [20], modified shuffle frog leaping algorithm (MSFLA) [20], and improved social spider optimization algorithm (ISSO) [21], as shown in Table 2.

In the table, COOT's cost is less than MPA and ISSO [21] by \$ 0.03 and \$ 0.28, and others by \$ 2.52 to \$ 3.03, respectively. Regarding N_{us}, MPA and COOT use 2500, which equals GA [19] and GA-FSA [19], is less than SLFA [20], MSLFA [20], and MDE [18], and higher than ISSO [20]. For the best view, the cost and N_{us} of all methods are plotted in Figure 3, in which the cost is presented in blue bars and N_{us} is presented in an orange curve.

Table 2. The result comparisons

Methods	Cost (\$/h)	S_p	$HNIter$	N_{us}
MDE [18]	802.37	18	160	2880
GA [19]	802.38	50	50	2500
GA-FSA [19]	802.00	50	50	2500
SLFA [20]	802.51	20	180	3600
MSLFA [20]	802.28	20	180	3600
ISSO [21]	799.76	20	30	600
MPA	799.51	50	50	2500
COOT	799.48	50	50	2500

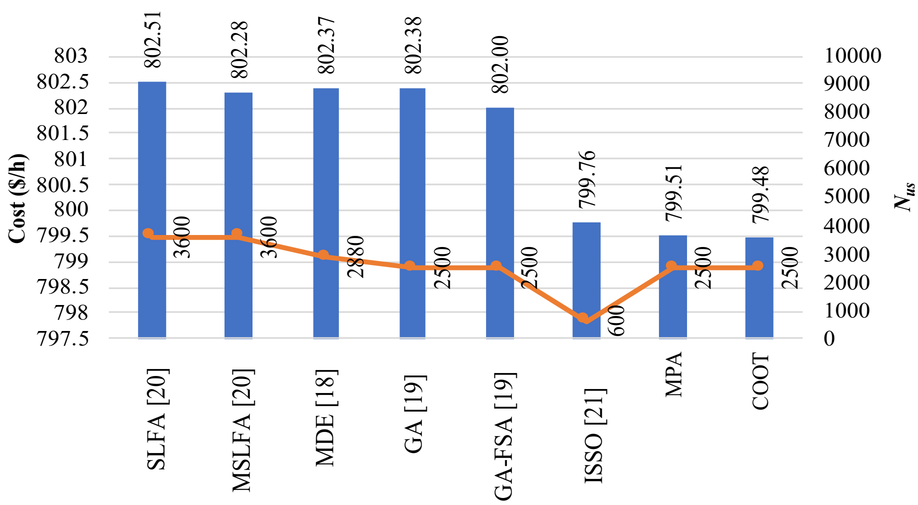


Figure 3. Cost vs N_{us} from MPA, COOT and others

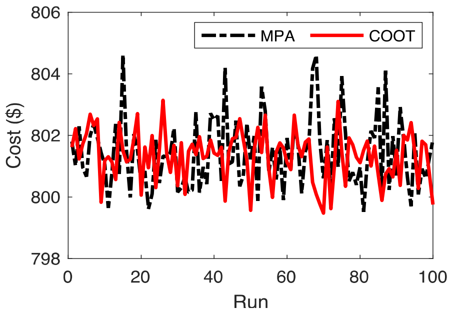
Similar to Case 1, S_p and $HNIter$ are investigated on Cases 2-4 with the presence of WPPs, in which the rated power of a WPP is 10MW. The results of the investigation of the parameters for different cases are shown in Table 3. As seen in Table 3, S_p is 50, but $HNIter$ is different.

Table 3. The investigated parameters of two applied methods for Cases

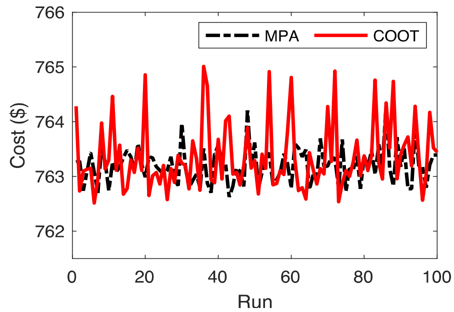
Parameters	Case 2	Case 3	Case 4
S_p	50	50	50
$HNIter$	100	150	200

To show the process of searching for solutions, two methods are run with 100 trial runs. As a result, 100 costs for four cases, which MPA and COOT obtain, are shown in Figure 4. Figure 4a is for Case 1 without WPPs, Figure 4b is for Case 2 with a WPP, Figure 4c is for Case 3 with two WPPs, and Figure 4d is for Case 4 with three WPPs. In four subfigures, the curve in black is for MPA, and the curve in red is for COOT. MPA's curve fluctuates less than COOT's curve. This means that MPA is more stable than COOT. However, COOT can find more optimal solutions than MPA.

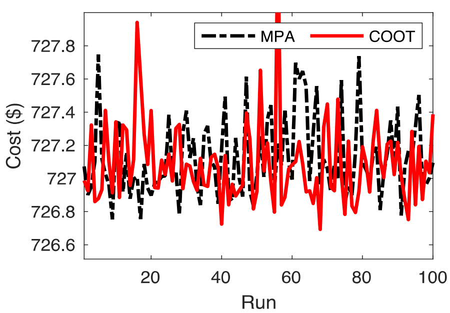
From 100 runs, we select the best run among 100 runs to show the process of searching for the optimal solution from the first iteration to the final iteration, as shown in Figure 5. It can be seen that the curve of COOT in Figures 5a, 5b, and 5d is under the curve of MPA from 20 to the final iterations, except for Figure 5c from 70 to the end. This proves COOT has a faster speed than MPA.



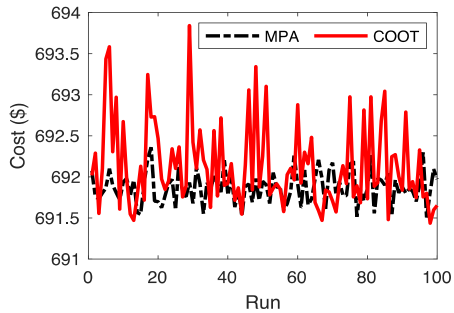
4a. Case1



4b. Case2

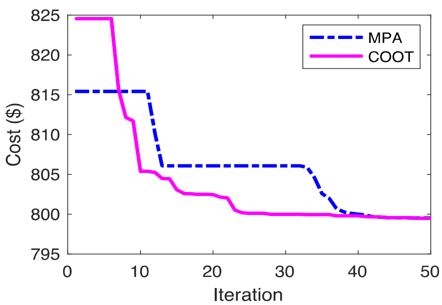


4c. Case3

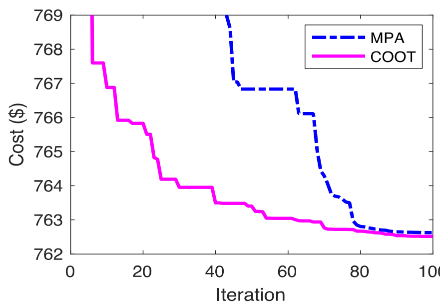


4d. Case4

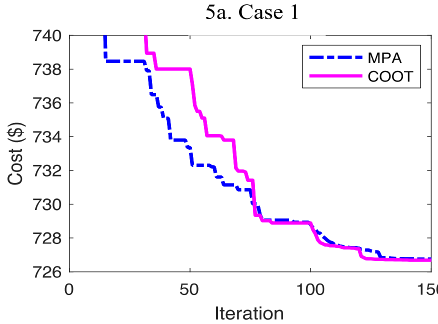
Figure 4. Costs from 100 runs obtained by MPA and COOT



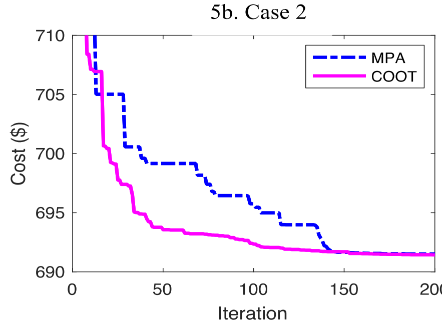
5a. Case 1



5b. Case 2



5c. Case 3



5d. Case 4

Figure 5. Converge features of MPA and COOT

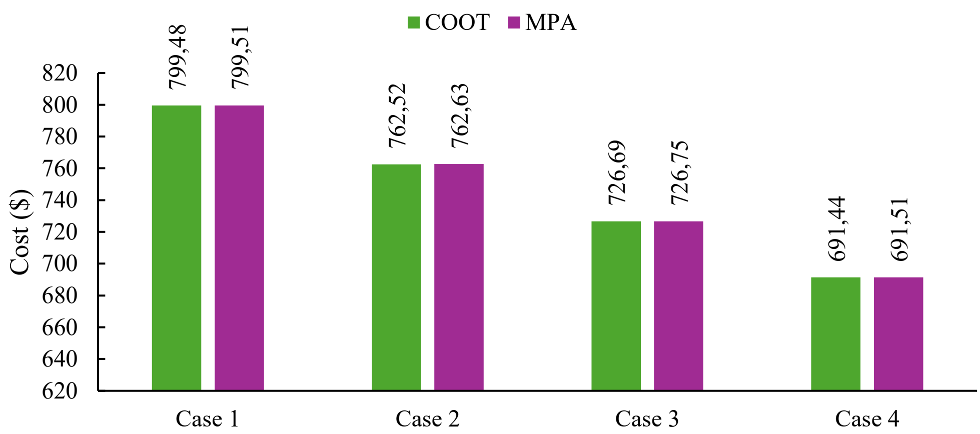


Figure 6. Cost obtained by COOT of four cases

In addition, the best cost from MPA and COOT of the four cases is displayed in Figure 6. The cost of MPA is presented under the purple bar, and that of COOT is presented under the green bar. The cost of COOT is less than MPA by \$ 0.03 for Case 1, \$ 0.11 for Case 2, \$ 0.06 for Case 3, and \$ 0.07, respectively. In the cost comparison of the four cases from COOT, the cost of Case 4 is the smallest, and that of Case 1 is the biggest. From these results, COOT is the most effective method, and more WPPs installed in the system result in a significant cost reduction.

The optimal solution found by COOT is reported in Table 4. In the table, the position for installing the WPP is at node 30 for Case 2, the position for installing WPPs is at nodes 30 and 5 for Case 3, and the position for installing WPPs is at nodes 30, 5, and 19 for Case 4.

Table 4. Optimal solution found by COOT

Parameter	Case 1	Case 2	Case 3	Case 4
P_1 (MW)	176.3617	170.3876	165.0112	161.1747
P_2 (MW)	49.4268	47.2209	46.4666	44.8417
P_3 (MW)	21.3456	20.9464	20.4183	19.8874
P_4(MW)	19.658	17.8226	15.1955	11.8455
P_5(MW)	11.8003	10.9291	10.0005	10.0177
P_6 (MW)	12.0228	12	12.0006	12.0006
V_1(pu)	1.1	1.1	1.1	1.1
V_2 (pu)	1.0829	1.0872	1.0886	1.0865
V_3 (pu)	1.0556	1.0607	1.0652	1.0614
V_4 (pu)	1.0606	1.0692	1.071	1.0684
V_5 (pu)	1.0943	1.1	1.1	1.0912
V_6 (pu)	1.097	1.1	1.1	1.0987
$Qcap_1$ (Mvar)	2.3693	4.995	2.8712	3.7829
$Qcap_2$ (Mvar)	4.0051	4.5411	3.4608	4.9974
$Qcap_3$(Mvar)	4.5121	2.8812	0.5461	4.0351
$Qcap_4$(Mvar)	4.9049	2.979	4.9999	3.3846
$Qcap_5$(Mvar)	2.5472	4.5167	1.7447	3.3542
$Qcap_6$(Mvar)	4.7553	0.1298	4.9969	4.9932
$Qcap_7$(Mvar)	3.1435	3.8271	4.6943	1.8155
$Qcap_8$(Mvar)	3.0098	5	2.8533	4.9308
$Qcap_9$(Mvar)	2.4193	2.3101	2.4214	1.5955
Tp_1 (%)	0.9724	1.0333	1.0276	1.0141
Tp_2 (%)	0.9774	0.906	0.9292	0.938
Tp_3 (%)	0.9982	1.0008	0.9963	0.994
Tp_4 (%)	0.955	0.9769	0.9827	0.9758
Position of WPP 1	-	30	30	30
Position of WPP 2	-	-	5	5
Position of WPP 3	-	-	-	19

6. CONCLUSION

In this paper, we present a constructive approach by successfully implementing COOT and MPA to address Optimal Power Flow problems, both with and without the integration of renewable energy sources, specifically focusing on wind energy. We thoroughly evaluate the performance of these methods by striving to minimize system costs across a variety of case studies. Importantly, our analysis includes scenarios that exclude the influence of wind energy. All case studies are conducted using an IEEE-30 node configuration, along with its modified versions. The findings demonstrate that COOT not only achieves superior results compared to MPA and other algorithms, such as SLFA, MSLFA, MDE, GA, GA-FSA, and ISSO, but also adheres to all constraints related to the OPF problem. This research provides valuable insights into effectively optimizing power flow, highlighting the potential of COOT as a robust solution in this domain.

Acknowledgment: This work belongs to the project grant number B2024-SPK-08 funded by Ministry of Education and Training, and hosted by Ho Chi Minh City University of Technology and Education, Vietnam.

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