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Orca Predation Algorithm as an Innovative Solution for IEEE 30 Bus

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A B S T R A C T

The effective operation of the IEEE 30 Bus power system requires economic dispatch optimization to minimize production costs, align energy supply with demand, and ensure system stability. This economic dispatch problem is complex due to its non-linear characteristics, interdependence between generators, and the need to combine cost minimization with power loss reduction. Conventional optimization techniques often struggle to find global solutions, easily get stuck in local optima, and require significant computational time. This study introduces the Orca Predation Algorithm (OPA) as a new approach to address these challenges. Inspired by the hunting behavior of orcas, OPA balances exploration and exploitation through two distinct phases: pursuit and attack. Evaluated on the IEEE 30-Bus system using power loss computation with coefficient B, the algorithm ensures that generator output power allocation meets demand at the lowest cost. OPA's performance is comprehensively compared with Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and Bat Algorithm. The results consistently show that OPA achieves the lowest total cost of $772,754 while maintaining superior system stability and effectively minimizing power losses among the evaluated algorithms. These findings highlight the significant potential of OPA to enhance energy management and advance power system optimization.

INTRODUCTION

Population growth and technological advancements have contributed to a substantial increase in global electricity consumption, including in Indonesia [1]. Data on electricity sales in Indonesia from 2013 to 2024 indicate a consistent upward trend across various sectors, with the residential, commercial, and industrial sectors being the largest contributors. In 2024, electricity sales reached 303.4 TWh, reflecting a 5.1% increase compared to the previous year [2]. This rising demand presents significant challenges in ensuring the efficient and optimal management of the power system [3]. Managing electricity systems involves complex technical and economic considerations. One of the key challenges is maintaining the balance between electricity supply and demand, which is formulated as the Economic Dispatch (ED) problem. The ED problem is a core component of power system operations, involving the determination of optimal power output for each generating unit to meet the load demand at the lowest possible operational cost, while satisfying all technical constraints of the units [4] [5]. Consequently, numerous optimization algorithms have been developed and applied over recent decades to effectively solve the ED problem.

Many traditional optimization methods, like gradient-based techniques, often struggle with issues like getting stuck in local optima and taking a long time to compute, especially in large systems [6]. These drawbacks have driven the development of more efficient and robust algorithms to meet the requirements of modern energy systems. Recently, numerous metaheuristic algorithms have been explored for solving the economic dispatch (ED) problem, including Particle Swarm Optimization (PSO) [7][8][9], Grey Wolf Optimizer (GWO) [10][11], Whale Optimization Algorithm (WOA) [12][13], and the Bat Algorithm [14][15]. PSO is known for its rapid convergence but frequently suffers from premature convergence to local optima [16]. GWO and WOA offer a balance between exploration and exploitation; however, they still encounter challenges in consistently reaching the global optimum [17]. The Bat Algorithm is notable for its computational speed, but often falls short in producing high-quality solutions [18]. Although many studies have proposed improvements to these algorithms, challenges remain in developing a method that consistently minimizes generation cost, maintains system stability, and effectively reduces power losses.

Therefore, this study proposes the Orca Predation Algorithm (OPA) as a novel approach to optimize the Economic Dispatch (ED) problem in the IEEE 30-Bus test system. Inspired by the hunting behavior of orcas, OPA consists of two main phases, the pursuit phase and the attack phase, which are designed to balance exploration and exploitation in the search for optimal solutions [19]. In the pursuit phase, the algorithm intensifies the search around promising areas, while in the attack phase, it promotes

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diversification to avoid premature convergence to local optima. Previous studies have demonstrated that OPA can produce more optimal and stable solutions for solving ED problems [20]. The novelty of this study lies in the application of OPA to the ED problem with a comprehensive objective, minimizing generation cost while simultaneously reducing transmission power losses. This work is expected to contribute to the development of more effective and practical optimization methods to address the increasing demands of modern power systems.

The paper organizes the subsequent sections as follows: Section 2 details the study approach. The document is divided into two sections. The first section describes the economic dispatch problem, including the system constraints, the objective function, and the data that were used in the case study. The subsequent subsection in section 2 outlines the proposed Orca Predation Algorithm (OPA), detailing the phases, implementation, and pseudocode. Section 3 presents the simulation results, comparative analysis, and discussion regarding the efficiency and reliability of the proposed algorithm. Section 4 ultimately summarizes this study by summarizing the key findings, contributions, and potential research directions.

METHODS

Economic Dispatch

Economic dispatch is an optimization procedure that identifies the appropriate allocation of load among generators to minimize overall production costs while satisfying power demand and adhering to the operational constraints of each generator [21]. The primary problem in economic dispatch is to guarantee that each generator provides sufficient electricity to satisfy demand while minimizing costs and power losses. Equation 1 articulates the quadratic cost function for each generator.

$$F_i = a_i + b_i P_i + c_i P_i^2 \tag{1}$$

F_i represents the total cost for the i-th generator, P_i denotes the power output of that generator, a_i is the fixed cost component, b_i is linear coefficients, and c_i is a quadratic coefficient that indicates the variation in cost as output power escalates. The aim of this optimization is to reduce the overall cost function. Equation 2 shows that the generator's power output determines the total generation cost.

$$F_{Total} = \sum_{i=1}^{6} (a_i + b_i P_i + c_i P_i^2) \tag{2}$$

subject to the constraint that the cumulative power output of all generators must satisfy the power demands, while also considering the power losses in the system as outlined in Equation 3.

$$\sum_{i=1}^{6} P_i = P_D + P_{Loss} \tag{3}$$

where P_D represents the overall power demand (in this instance, 283.4 MW), and P_{Loss} denotes the power loss occurring within the system. Loss of power P_{Loss} is computed via B-coefficients, which characterize the interaction between the generator and the power distribution within the power grid. The formula for power loss can be generally expressed as Equation 4.

$$P_{Loss} = \sum_{i=1}^{6} \sum_{j=1}^{6} P_i B_{ij} P_j \sum_{i=1}^{6} B_0 P_i + B_{00} \tag{4}$$

where B_{ij} denotes the B-coefficients that quantify the influence of the power generated by generator i on the power loss attributed to generator j. B_0 is a vector that directly represents the impact of each generator's power loss. B_{00} is a constant that quantifies the supplementary power loss occurring outside of the generator contact [22]. These coefficients are crucial for considering physical elements that influence power flow in the network, including transmission line resistance.

This study utilizes data from the IEEE 30 Bus system. The system has 30 buses and 6 power-producing units, each of which must function within a certain power limit [23]. The power limitations for each generator are as follows:

1. Generator 1: 50 MW – 200 MW
2. Generator 2: 20 MW – 80 MW
3. Generator 3: 15 MW – 50 MW
4. Generator 4: 10 MW – 35 MW
5. Generator 5: 10 MW – 30 MW
6. Generator 6: 12 MW – 40 MW

The following is the specific cost coefficient of production for each generator:

$a_i = [0, 0, 0, 0, 0, 0]$
$b_i = [2, 1.75, 1, 3.25, 3, 3]$
$c_i = [0.00375, 0.0175, 0.0625, 0.00834, 0.025, 0.025]$

The power loss computation employs B-coefficients, B_0 and B_{00}, which delineate the power losses inside the system. The coefficient matrix B, vector B_0, and constant B_{00} are delineated as follows:

$$B = \begin{bmatrix} 0.000218 & 0.000103 & 0.000009 & -0.00010 & 0.000002 & 0.000027 \\ 0.000103 & 0.000181 & 0.000004 & -0.000015 & 0.000002 & 0.000030 \\ 0.000009 & 0.000004 & 0.000417 & -0.000131 & -0.000513 & -0.000107 \\ -0.00010 & -0.000015 & -0.000131 & 0.000221 & 0.000243 & -0.000000 \\ 0.000002 & 0.000002 & -0.000153 & 0.000094 & 0.000243 & -0.000000 \\ 0.00027 & 0.000030 & -0.000107 & 0.000050 & -0.000000 & 0.000358 \end{bmatrix}$$

$$B_0 = [-0.000003 \quad 0.000021 \quad -0.000056 \quad 0.000034 \quad 0.000015 \quad 0.000078]$$

$$B_{00} = 0.0000014 \quad [24]$$

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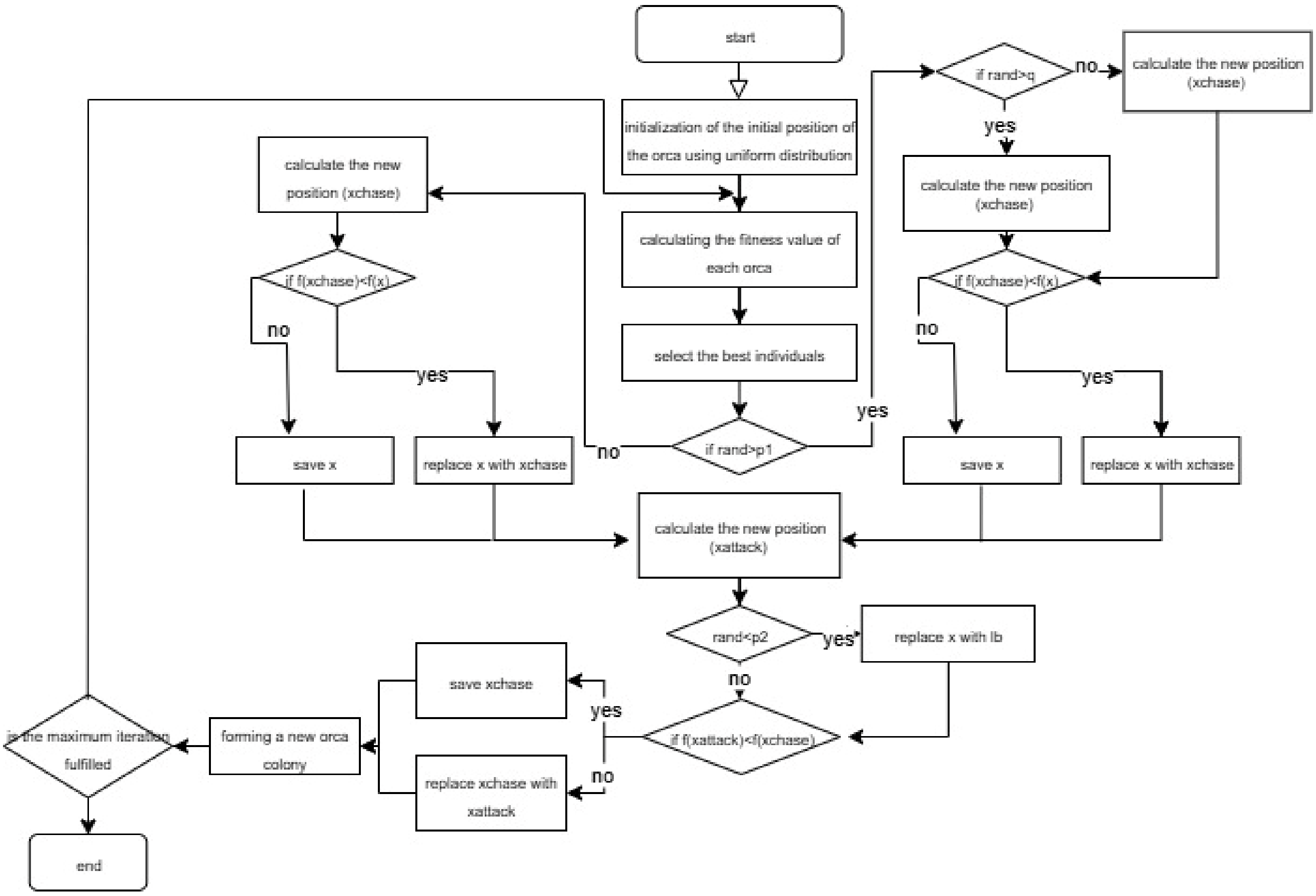

Figure 1. Flowchart of OPA

Orca Predation Algorithm

This research employs the Orca Predation Algorithm (OPA) as an optimization technique to address the power allocation issue in the IEEE 30 Bus system. OPA is a metaheuristic algorithm that emulates the hunting behavior of orcas through two primary phases, the pursuit phase and the attack phase, to identify the ideal solution [19]. It aims to reduce the cost of power generation while minimizing power loss.

The flowchart of the Orca Predation Algorithm (OPA) is illustrated in Figure 1. OPA consists of two primary stages: the driving stage and the encircling stage. At the beginning of the algorithm, several key parameters are initialized, including population size (N), dimensionality (D), maximum number of iterations, selection probabilities (p_1 and p_2), and the lower (lb) and upper (ub) bounds of the decision variables. The initial positions of the orca population are randomly generated within the defined boundaries. The fitness of each orca is then evaluated using the objective function defined in Equation 1, which corresponds to the Economic Dispatch (ED) cost function. The orca with the best fitness value at each iteration is designated as x_{best}, representing the current best solution that yields the minimum total operating cost F_i.

In the subsequent pursuit phase, each orca updates its position using either the driving or encircling strategy, based on a probabilistic decision governed by p_1. If a randomly generated number exceeds p_1, the orca employs the driving strategy; otherwise, it adopts the encircling strategy. This probabilistic mechanism helps balance exploration (searching for new regions in the solution space) and exploitation (refining known good solutions). Within the driving strategy, the position update further depends on the value of a randomly generated number compared to a predefined threshold q, which represents the orca population density condition. If rand > q, the orca's velocity $v^t_{chase\ 1,i}$ is updated using Equation 5, and its position $x^t_{chase\ 1,i}$, it is updated using Equation 8. Conversely, if rand ≤ q, both the velocity and position are updated using Equations 9–10.

$$v^t_{chase\ 1,i} = a\left(dx^t_{best} - F(bM^t + cx^t_i)\right) \tag{5}$$

$$M = \frac{\sum_{i=1}^{N} x^t_i}{N} \tag{6}$$

$$c = 1 - b \tag{7}$$

$$x^t_{chase\ 1,i} = x^t_i + v^t_{chase\ 1,i} \tag{8}$$

$$v^t_{chase\ 2,i} = ex^t_{best} - x^t_i \tag{9}$$

$$x^t_{chase\ 2,i} = x^t_i + v^t_{chase\ 2,i} \tag{10}$$

In the position update mechanism, M represents the average position of the entire orca population. The parameters $a, b,$ and d are random numbers uniformly distributed in the range [0,1], while e is a random number in the range [0,2]. The parameter F is a constant value set to 2, and q is also a random number in the range [0,1]. Meanwhile, in the encircling strategy, the orca position $x^t_{chase\ 3,i}$ is updated according to Equations 11–12.

Table 2. Comparison of Power Output on Each Algorithm

Algorithm	P1	P2	P3	P4	P5	P6
OPA	195.97	45.53	19.69	10	10	12
PSO	181.24	46.89	19.48	13.78	10	12
Bat Algorithm	173.94	42.89	21.62	20.21	10.82	13.92
WOA	199.24	48.89	20.32	14.76	10.13	13.18
GWO	181.76	46.94	19.47	13.67	10	12

$$x^t_{chase\ 3,i} = x^t_{j1,i} + u\left(x^t_{j2,i} - x^t_{j3,i}\right) \quad (11)$$

$$u = 2(rand - 0.5)\frac{\max iter - t}{\max iter} \quad (12)$$

Here, $\max iter$ denotes the maximum number of iterations, j_1, j_2, j_3 are three randomly selected orcas, with the condition $j_1 \neq j_2 \neq j_3$. In this procedure, orcas estimate the prey's position and adjust their own positions to enhance the effectiveness of the solution search process. The orca's position is subsequently updated during the attack phase, where each orca refines its position to effectively target the prey. During this phase, some orcas may exceed the boundaries of the search space. An orca's position is reset to the lower boundary (lb) if it exceeds either the upper or lower bounds. The position update in the attack phase is governed by Equations 13-15 :

$$v^t_{attack\ 1,i} = \frac{\left(x^t_{first} + x^t_{second} + x^t_{third} + x^t_{four}\right)}{4 - x^t_{chase,j}} \quad (13)$$

$$v^t_{attack\ 2,i} = \frac{\left(x^t_{chase,j1} + x^t_{chase,j2} + x^t_{chase,j2}\right)}{3 - x^t_i} \quad (14)$$

$$x^t_{attack,i} = x^t_{chase,i} + g_1\, v^t_{attack\ 1,i} + g_2 v^t_{attack\ 2,i} \quad (15)$$

After completing the attack phase, a new population is generated by updating the orcas' positions based on the outcomes of both the pursuit and attack phases. This step is intended to maintain population diversity while preserving the best solution identified thus far. The algorithm terminates when the maximum number of iterations ($\max iter$) is reached or when a satisfactory optimal solution has been found. If neither termination condition is satisfied, the optimization process resumes from the second phase [19].

RESULTS AND DISCUSSION

This section provides an in-depth evaluation of the performance of five distinct optimization algorithms applied to the IEEE 30-bus power system. The algorithms under comparison include the Orca Predation Algorithm (OPA), Particle Swarm Optimization (PSO), the Bat Algorithm, Whale Optimization Algorithm (WOA), and Grey Wolf Optimizer (GWO). Table 2 presents a detailed comparison of the power output generated by each algorithm, highlighting their efficiency and effectiveness in maximizing power delivery. Additionally, Table 3 offers comprehensive metrics such as power loss results, the optimal operational cost achieved by each method, the average optimal cost over multiple runs, the standard deviation to assess consistency, and the computational time required for each algorithm to converge.

Table 3 indicates that the Orca Predation Algorithm (OPA) achieves optimal performance at a cost of $ 772.754, establishing itself as the most cost-effective solution among the assessed algorithms. The Grey Wolf Optimizer (GWO) attains an optimal cost of 777.05, closely corresponding with the outcomes of PSO and WOA. Nevertheless, the Bat Algorithm, which achieved the minimal power loss of 8.19 MW, resulted in the highest overall cost of 778.69, signifying that while this algorithm was proficient in minimizing power loss, its total expenditure remained superior to that of the other algorithms. The low mean cost and standard deviation figures for OPA and GWO demonstrate the reliability of these algorithms in achieving the optimal solution over numerous trials. Moreover, regarding calculation time, WOA exhibits exceptional efficiency, with a duration of 0.0358 seconds, making it one of the most time-efficient algorithms; however, it incurs the largest power loss at 10.91 MW. OPA demonstrates superior cost efficiency, although it exhibits the greatest computation duration at 0.6417 seconds.

Table 3. Comparison of Result on Each Comparison

Algorithm	Power Loss	Best Cost	Mean	Std	Computation Time
OPA	9.79	772.754	773.44	0.5916	0.6417
PSO	9.16	777.055	777.25	0.38	0.1659
Bat Algorithm	8.19	778.69	786.12	4.534	0.094
WOA	10.91	777.078	778.369	0.5215	0.0358
GWO	9.21	777.05	777.059	0.0035	0.183

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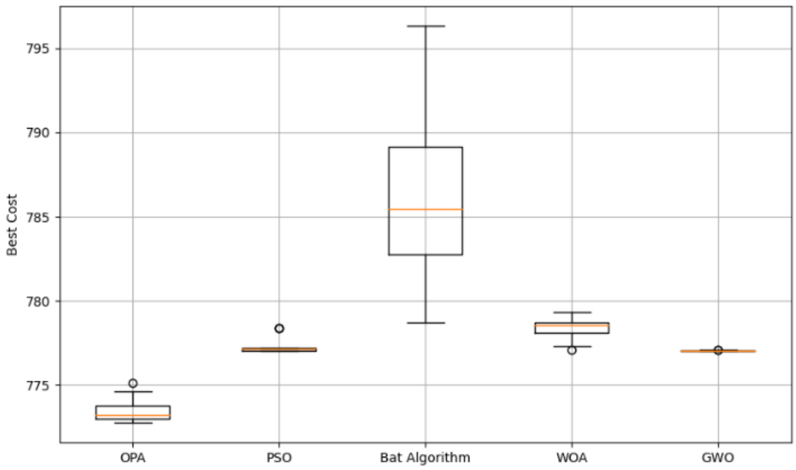

Figure 2. Boxplot comparison of each algorithm

The boxplot in Figure 2 indicates that the Orca Predation Algorithm (OPA) exhibits the most consistent and optimal performance, characterized by the narrowest range of cost values, between 772 and 775, with no notable outliers present. Particle Swarm Optimization (PSO) exhibited satisfactory performance; however, it demonstrated inferior stability compared to OPA, yielding a median of approximately 775, with one notable outlier. The Bat Algorithm exhibited the poorest performance, characterized by significant cost variability and a consistent failure to attain the ideal solution, with a median value of approximately 785. The Whale Optimization Algorithm (WOA) and the Grey Wolf Optimizer (GWO) both performed better than the Bat Algorithm over time; however, they were still outperformed by the Optimized Particle Algorithm (OPA), with WOA exhibiting many outliers that fell outside its range. Overall, OPA demonstrated greater stability and efficacy, making it a more advantageous option for optimizing the IEEE 30 Bus system compared to alternative algorithms.

The convergence graph in Figure 3 indicates that the Orca Predation Algorithm (OPA) has superior performance, achieving the lowest cost value of around 773, with rapid convergence in under 10 rounds. Particle Swarm Optimization (PSO) achieved a cost value of approximately $775 after 15 iterations, ranking second; however, it was less efficient than OPA in terms of convergence time. At the same time, both the Grey Wolf Optimizer (GWO) and the Whale Optimization Algorithm (WOA) exhibited rapid early convergence but ceased moving when the costs reached high levels of approximately 778 and 779, respectively. This meant that further research could not proceed. The Bat Algorithm exhibited the poorest performance, maintaining a constant cost exceeding 786 across the iterations, demonstrating its inadequate adaptability in this context. OPA demonstrates superiority in attaining ideal values, as well as in stability and efficiency, rendering it an excellent solution for optimizing the IEEE 30 Bus system.

To further validate the effectiveness of the Orca Predation Algorithm (OPA), we compared the optimal fuel cost obtained in this study with that reported by Mohamed et al. In their work, several algorithms were evaluated for fuel cost minimization, achieving an optimal cost of $786.03/hour [3]. This comparison is significant, as the optimal cost produced by OPA in our study is $772.754/hour, lower than the result reported by Mohamed et al. This finding demonstrates that OPA not only outperforms other metaheuristic algorithms tested in this study but also surpasses previous benchmark results for the economic dispatch problem on the IEEE 30-bus system.

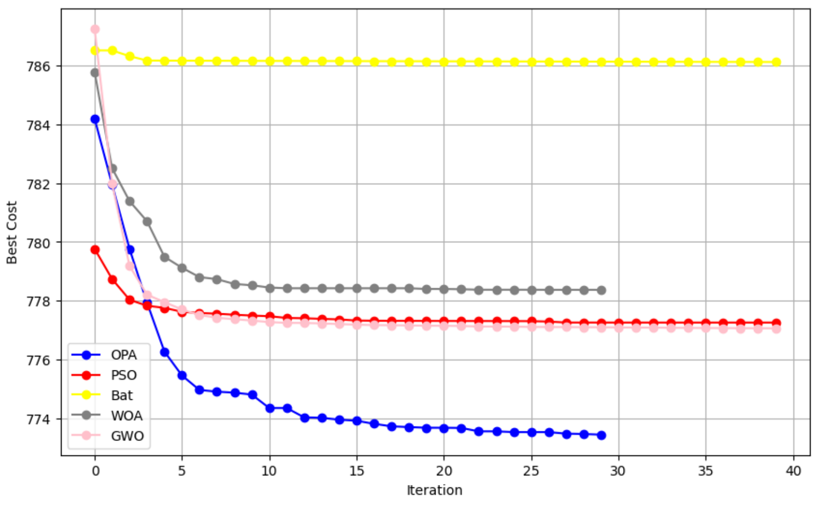

Figure 3. Convergence curves of each algorithm

CONCLUSIONS

This study successfully presented and tested the OPA as a novel approach to addressing the ED problem in the IEEE 30-Bus system, aiming to reduce generation costs, maintain system stability, and minimize power losses. Experimental results consistently demonstrate the superiority of OPA, achieving the lowest total cost of $772,754/hour, along with improved consistency and stability compared to benchmark algorithms. These advantages are particularly valuable for power system operators, as they directly enhance operational efficiency and the reliability of electricity supply. Despite its longer computation time and slightly higher power losses compared to certain algorithms, these limitations highlight promising directions for further research. Future work may focus on developing hybrid variants of OPA to improve computational efficiency and reduce power losses, as well as extending its application to larger and more complex power systems, thereby enhancing its practical relevance in modern energy management.

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