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ENHANCED ECONOMIC DISPATCH OPTIMIZATION USING MOMENTUM IN THE ORCA PREDATION ALGORITHM

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ABSTRACT

The economic dispatch problem aims to minimize total generation costs while maintaining a balanced power allocation in the electrical power system. This paper introduces a new algorithm called the Self-Adaptive Momentum Orca Predation Algorithm (SAMOPA), the first variant of OPA that integrates an adaptive momentum mechanism to solve the economic dispatch problem. This integration enhances the balance between exploration and exploitation, accelerates the convergence process, and reduces the risk of getting stuck in local solutions. SAMOPA was tested on three economic dispatch scenarios with 6, 15, and 40 power plants. In the 6-unit system, SAMOPA achieved the best cost of 15275.9304 dollars with a standard deviation of 2.54E-06, lower than OPA's deviation of 0.0029. SAMOPA's computation time was also faster, at 0.27 seconds compared to OPA's 0.9751 seconds. For the 15-unit system, SAMOPA reduced total generation costs by 0.17 percent compared to OPA. For a 40-unit system, SAMOPA achieves the best cost of 119,369.57 dollars, which is 0.58 percent lower than the best result from OPA. The consistency of SAMOPA's performance is also demonstrated in the Economic Dispatch case with nonlinear valve-point effects and in the CEC 2020 benchmark function, which includes unimodal, hybrid, and composition categories. Statistical validation using the Wilcoxon signed-rank test indicates that SAMOPA exhibits significantly better convergence behavior and solution consistency compared to the comparison method. These results confirm that SAMOPA is an effective and reliable new contribution to solving complex and large-scale economic dispatch problems.

I. INTRODUCTION

Optimization challenges, particularly Economic Dispatch (ED), aim to minimize the operational costs of power plants while ensuring efficient power distribution [1][2]. ED allocates power among generating units while considering operational and technical constraints [3][4]. Due to its non-linear and complex characteristics, ED remains difficult to solve using gradient-based methods, especially in large-scale systems with multiple decision variables. Consequently, metaheuristic algorithms such as Particle Swarm Optimization (PSO) [5][6][7], Bat Algorithm [8], Grey Wolf Optimizer (GWO) [9][10], and Whale Optimization Algorithm (WOA) [11] have emerged as more flexible and efficient alternatives [12]. Table 1 summarizes various algorithm types, their strengths and weaknesses, and their effectiveness across conventional, artificial intelligence (AI)-based, and hybrid approaches to ED problems.

Table 1: Comparison of Recent Approaches for Economic Dispatch.

Approach Type	Representative Methods	Strengths	Weaknesses	Performance Metrics
Conventional [13]	Lambda Iteration, Newton's Method, Interior Point Method, Quadratic Programming	Simple, efficient for small systems, fast implementation	Not effective for large-scale and nonlinear systems	Computational efficiency, solution accuracy
AI-Based [13]	Artificial Neural Networks, Fuzzy, Deep Learning, Reinforcement Learning	Adaptive, capable of handling complex systems, suitable for real-time use	Prone to overfitting, requires large datasets and parameter tuning	Prediction accuracy, generalization ability
Hybrid [13]	PSO+ANN, Fuzzy+Genetic Algorithm, Metaheuristic Hybrid	Combines the strengths of two methods, provides better solutions	Complex implementation and design, more difficult parameter tuning	Computational time, solution quality
Machine Learning -Based [14]	ML-optimized Droop Control	Minimizes generation cost and power loss simultaneously, no central communication needed	Requires model training, sensitive to training data quality	Generation cost, power loss, system stability

Source: Authors, (2026).

Despite substantial advancements in traditional and AI-based optimization methods, these approaches remain limited in accuracy, computational efficiency, and robustness when addressing nonlinear and large-scale challenges. Hybrid AI–physics approaches, which combine machine learning models such as neural networks with classical optimization techniques like PSO or evolutionary algorithms, have gained significant traction in power system applications [15][16][17]. Although effective in handling non-linearity and system complexity, these hybrid methods often demand significant computational resources. To address this gap, this study proposes the Self-Adaptive Momentum Orca Predation Algorithm (SAMOPA), which introduces a new self-adaptive momentum mechanism into the original Orca Predation Algorithm (OPA) framework. This study is the first to combine adaptive momentum strategies, originally proposed by Polyak (1964), to accelerate convergence in gradient-based methods in OPA to solve ED problems [18][19][20]. SAMOPA improves convergence speed, computational efficiency, and solution stability by dynamically adjusting the movement of search agents based on historical progress. Unlike previous OPA variants that improve solution quality through Levy flight or opposition-based learning but incur higher computational costs [21], SAMOPA achieves better cost reduction and faster execution time with minimal additional complexity. Specifically, empirical results show that SAMOPA reduces total generation costs by up to 0.58%, accelerates convergence time by over 70% compared to OPA, and maintains stable performance in ED scenarios with 6, 15, and 40 unit system.

The main contributions of this paper are as follows:

1. Proposal of SAMOPA, a new OPA variant with a self-adaptive momentum update rule tailored to enhance convergence behavior in solving ED problems.
2. Comprehensive benchmarking against six popular algorithms, OPA, PSO, Bat Algorithm, GWO, WOA, and CMA-ES, on ED test cases of increasing complexity.
3. Quantitative validation of improvements in terms of cost reduction, solution robustness, and computational efficiency.
4. Demonstration of SAMOPA's consistent performance in economic dispatch scenarios with nonlinear valve-point effects, as well as on the CEC 2020 benchmark functions covering unimodal, hybrid, and composition categories.
5. Statistical validation through the Wilcoxon signed-rank test confirms that SAMOPA exhibits significantly better convergence behavior and solution consistency compared to the benchmark algorithms.

The remainder of this paper is structured as follows: Section 2 outlines the research methodology, including the ED problem formulation, the SAMOPA algorithm, and the experimental setup. Section 3 presents the results and comparative analysis, while Section 4 concludes the study and suggests directions for future research.

II. MATERIALS AND METHODS

II.1 SELF ADAPTIVE MOMENTUM ORCA PREDATION ALGORITHM

The original OPA, developed by, is a metaheuristic inspired by the hunting strategies of orca whales, consisting of a chase phase and an assault phase. The algorithm updates the orca's position based on probabilistic rules; however, it is prone to excessive oscillation and premature convergence, especially during early iterations or near the global optimum [22][23]. To address these limitations, SAMOPA introduces a momentum-based enhancement in the chase phase, enabling the search agent to retain directional information from previous iterations. This adjustment improves search stability and promotes more focused exploration [24]. The computational speed of the solution at iteration is defined as equations (1) and (2):

$$v_{chase\ 1,i}^{t} = m * a\left(dx_{best}^{t} - F(bM^{t} + cx_{i}^{t})\right) \tag{1}$$

and

$$v_{chase\ 2,i}^{t} = m * (ex_{best}^{t} - x_{i}^{t}) \tag{2}$$

Let t denote the number of cycles, $v_{chase\,1,i}^{t}$ represent the chasing speed, M signify the average position of the orca group, x_i^t indicate the position of the orca, the orca with the highest fitness value is marked as x_{best}^t, while $a, b,$ and d are random variables within the interval [0,1]. Additionally, e is a random variable within the interval [0,2] and F equals 2. The dynamic modification of m, a momentum component, ensures a balance between exploration and exploitation [25]. Equation (3) articulates this modification:

$$m = m_0 \cdot (1 - \alpha \cdot t) \tag{3}$$

where m_0 represents the initial momentum, valued at 1. The initial momentum value should guarantee optimal exploration in the early phases. α denotes the momentum decay rate of 0.05. The momentum parameter $m_0 = 1$ is employed to augment the algorithm's exploration capacity during the initial phase by leveraging the agent's historical movement data. The decay rate $\alpha = 0.05$ progressively diminishes this influence over time, so facilitating a seamless shift from the exploration to the exploitation phase. This adaptive modification maintains solution diversity in the initial phase and enhances convergence in the final phase. Various combinations of α $(0.01, 0.03, 0.05, \text{and } 0.1)$ and m_0 $(0.5, 1.0, \text{and } 1.5)$ have been evaluated on multiple small-scale economic dispatch problems, with the chosen combination yielding the highest consistent convergence rate and solution quality. This methodology aligns with the DEMON strategy proposed by [26], which demonstrated that progressive momentum decay enhances outcomes by stabilizing parameter updates in the later phase while maintaining flexibility in the initial phase. Adding adaptive momentum to SAMOPA speeds up the search for the best solution, avoids local stagnation, and keeps exploration stable over many iterations. This leads to more accurate and effective solutions, especially for big optimization problems like Economic Dispatch.

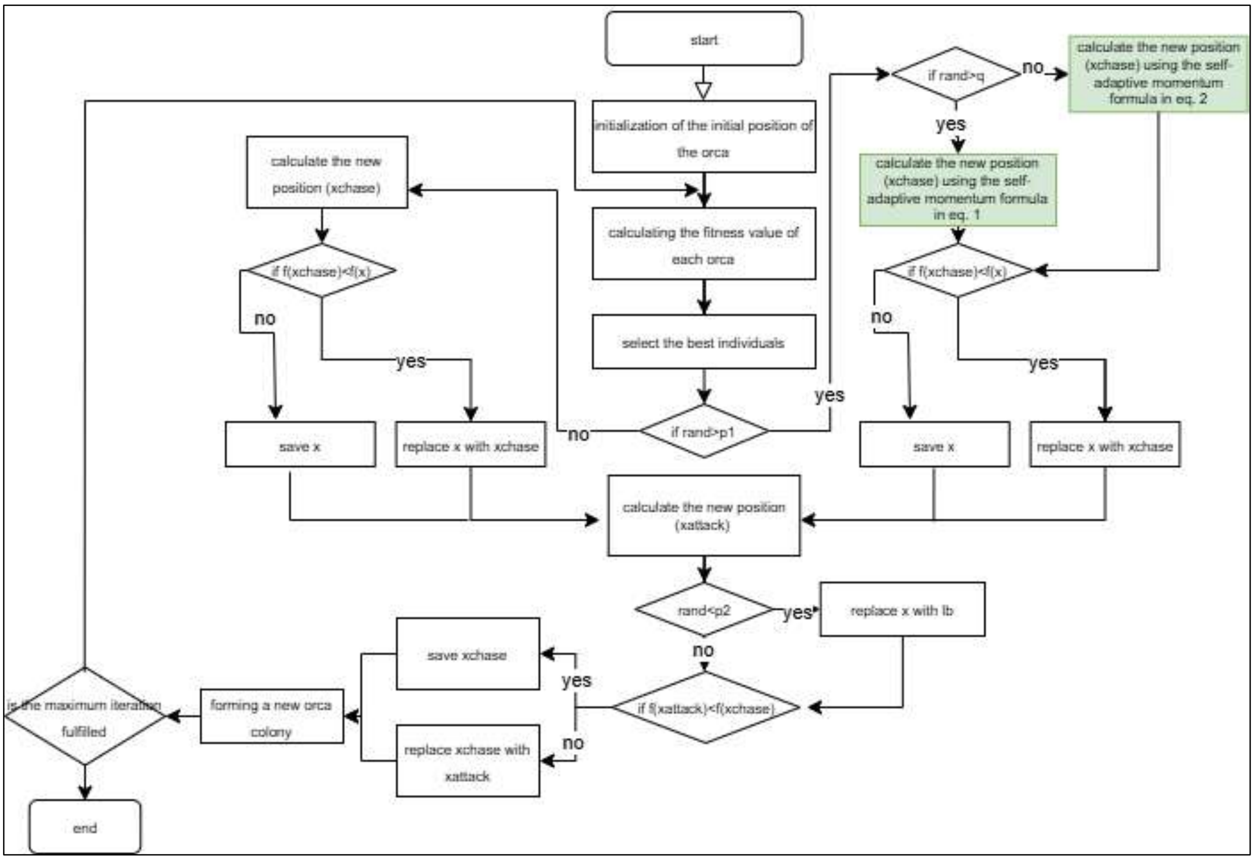

Figure 1: Flowchart of SAMOPA.
Source: Authors, (2026).

The flowchart of SAMOPA in Figure 1 begins with the initialization of the initial position of the orca using a uniform distribution, followed by the calculation of fitness values to determine the best individuals. Based on random values compared to a certain threshold, the system will choose whether to pursue a pursuit strategy or an attack strategy. If the pursuit strategy is chosen, adaptive momentum is used to maintain the direction of change from the previous iteration, making exploration more stable and focused. After evaluation, the new position is saved if it is better than the previous one. If the termination criteria have not been met, the process continues with the formation of a new colony, and iterations continue until the optimal solution is achieved. The combination of these two strategies allows the modified algorithm to achieve more efficient and effective optimization results.

II.2 ECONOMIC DISPATCH PROBLEM FORMULATION

ED is a fundamental optimization problem in power systems that aims to allocate generation output among multiple units in a cost-efficient manner [27]. It is typically formulated as a mathematical model that characterizes the relationship between each unit’s power output and its associated operating cost. The total generation cost is commonly modeled as a quadratic function, as defined in Equation (4):

$$F_{Total} = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i) \tag{4}$$

In this equation, F_{Total} signifies the total operational cost in currency units per hour, while P_i indicates the output power of the i-th power plant in megawatts (MW). Parameters a_i, b_i, c_i represent the operational cost coefficients for each plant, whereas N denotes the total number of plants involved [13]. The primary challenge in ED is to minimize overall operational costs while adhering to diverse technological and operational restrictions. To ensure physical feasibility, the ED problem must comply with two main types of constraints: equality and inequality constraints. The power balance constraint, presented in Equation (5), ensures that the total generated power meets the system demand:

$$P_D = \sum_{i=1}^{n} P_i \tag{5}$$

where P_D is the overall power demand in megawatts (MW) [28]. In this study, the power balance is enforced using a repair-based approach, where the power output of the first unit is adjusted according to Equation (6):

$$P_1 = P_D - \sum_{i=2}^{n} P_i \tag{6}$$

Should the altered value of P_1 be above the unit's operational threshold, the cost function incurs significant penalties, rendering the solution unviable [29]. Furthermore, each generating unit must function within its minimal ($P_{i,min}$) and maximum ($P_{i,max}$) capacity constraints, as in equation 7.

$$P_{i,min} \leq P_i \leq P_{i,max} \text{ for } i = 1, 2, \dots, N \tag{7}$$

These restrictions ensure the safety and reliability of system operations. Accordingly, the ED task is to determine an optimal generation schedule that minimizes total operational cost while meeting load requirements and respecting technical constraints. The constraint-handling mechanism, particularly the power balance adjustment, is essential for preserving the feasibility and stability of candidate solutions throughout the optimization process [30].

II.3 EXPERIMENTAL SETUP

This study investigates the ED problem across systems comprising 6, 15, and 40 generating units. Each unit is characterized by minimum ($P_{i,min}$) and maximum ($P_{i,max}$) power generation limits. For instance, the total load demand is set to 1263 MW for the 6-unit case, 2630 MW for the 15-unit case, and 10500 MW for the 40-unit case. The operational cost coefficients (a_i, b_i, c_i) are drawn from a well-established dataset that accurately reflects real-world plant characteristics, as presented by [31]. These simulations enforce both unit-level generation constraints and the global power balance condition as defined in Equation (7). To evaluate the generalization capability of SAMOPA across various optimization landscapes, the CEC 2020 benchmark functions are employed. These functions span four categories: unimodal, basic, hybrid, and composition. Comparative assessments are conducted against the original OPA, as well as other well-known metaheuristic algorithms, including PSO [32][33], GWO [34][35], WOA [36][37], the Bat Algorithm [38][39], and CMA-ES [40][41]. This study employed the Wilcoxon Signed-Rank Test, a non-parametric statistical method, to compare the performance of SAMOPA with other algorithms by assessing the median difference between two matched data sets. Each algorithm underwent testing across 30 independent iterations for each problem, and the convergent outcomes (global minimum) of the two algorithms were juxtaposed.

The null hypothesis (H_0) posits that there is no substantial disparity between the median answers produced by the two algorithms. If the P-value derived from this test is less than 0.05, the null hypothesis is rejected, signifying a substantial difference between the algorithms being tested. The symbols +, -, and = denote the superiority, inferiority, or equivalence of an algorithm, contingent upon a comparison of the ranks of the generated solutions. The parameter configurations of all algorithms in this study were uniformly established to guarantee equitable comparison and dependable replication. The population size was established at 30 for all scenarios, with a maximum of 40 iterations for the 6- and 15-generators cases and 100 iterations for the 40-generators case to ensure sufficient exploration of the broader search space. The parameter settings for each algorithm are modified based on corroborated prior research, including OPA as per Jiang et al.[22], PSO and GWO as outlined by Pokala and Lalitha [42], Bat incorporating enhancements from Meng et al. [43], WOA adhering to the revised version by Chakraborty et al. [44], and CMA-ES reflecting the original configuration by Hansen and Ostermeier [45]. All algorithms were implemented using Python 3.11.12 and run using Google Colab with uniform hardware conditions.

This consistent computing environment ensures that computational time comparisons between methods are fair and reliable. The SAMOPA implementation in Python, along with the entire experimental setup, is available upon request to support transparency and replication in future research. The proposed algorithm, SAMOPA, follows the OPA guidelines for all main settings, except for two key settings: p_1 (the chance of the pursuit phase) and p_2 (the chance of resetting in the attack phase), which are set using a grid search method. This process is carried out on three ED test cases with 6, 15, and 40 generators to find the best combination of settings that results in the lowest cost. The test findings indicate distinct ideal parameter combinations for each scenario: p_1 = 0.9 and p_2 = 0.01 for 6 units, p_1 = 0.9 and p_2 = 0.06 for 15 units, and p_1 = 0.6 and p_2 = 0.04 for 40 generators. The simulation exercise employed fundamental assumptions to streamline the calculation model and enhance the emphasis on the algorithm's performance evaluation. The power load is presumed constant throughout the optimization process, excluding transmission losses and ramp rate constraints. All producing units are presumed to be continuously operational and steady throughout the simulation time.

In the traditional scenario, the generation cost function is presumed to be quadratic and continuous, adhering to the standard economic dispatch model. In the supplementary scenario involving the valve-point impact, the cost function is rendered non-linear and non-convex, accurately representing the actual situations in steam turbines. Physical limitations on the minimum and maximum power of each unit are explicitly considered, and the system power equilibrium is preserved by a repair-based method, by adjusting the power at the initial unit to ensure that total generation meets load demand. All simulations were conducted in 30 independent iterations for each scenario (6, 15, and 40 units) to verify statistical validity.

III. RESULT AND DISCUSSION

III.1 PERFORMANCE OF ECONOMIC DISPATCH PROBLEMS

The performance assessment of SAMOPA in ED with 6, 15 and 40 generators is presented in Table 2.

Table 2: Performance Comparison of the Algorithm on ED Problems.

Algorithm	Units	Best Cost	Mean Cost	Std Dev	Time (s)
SAMOPA	6	**15275.9304**	**15275.9304**	**2.54E-06**	**0.2677**
OPA	6	15275.9306	15275.9327	0.0029	0.9751
PSO	6	15275.9335	15276.7886	2.2008	0.0605
GWO	6	15276.0137	15281.362	10.2684	0.1454
WOA	6	15276.8222	15286.5137	7.5818	0.0388
Bat	6	15283.5699	15306.6403	28.319	0.1179
CMAES	6	15278.6060	15293.0752	10.5748	0.0326
SAMOPA	15	**32256.879**	**32257.767**	**0.646**	**0.266**
OPA	15	32257.415	32258.047	0.606	0.378
PSO	15	32258.844	32369.053	97.605	0.109
GWO	15	32262.852	32417.236	234.646	0.209
WOA	15	32296.006	32452.31	82.416	0.043
Bat	15	32480.021	32733.632	88.709	0.123
CMAES	15	32296.413	32369.321	260.947	0.023
SAMOPA	**40**	**119369.5713**	**120062.3182**	**513.0342**	**0.9378**
OPA	40	120066.9802	121098.2238	742.494	1.4413
PSO	40	122699.5808	133251.8863	5827.9833	0.2936
GWO	40	126436.5593	131538.108	3331.3004	0.872
WOA	40	124377.5908	130962.0752	3550.0292	0.0955
Bat	40	132030.8897	9333342303	2494404695	0.1958
CMAES	40	147602.7932	9333343234.481	3331.3004	0.0577

Source: Authors, (2026).

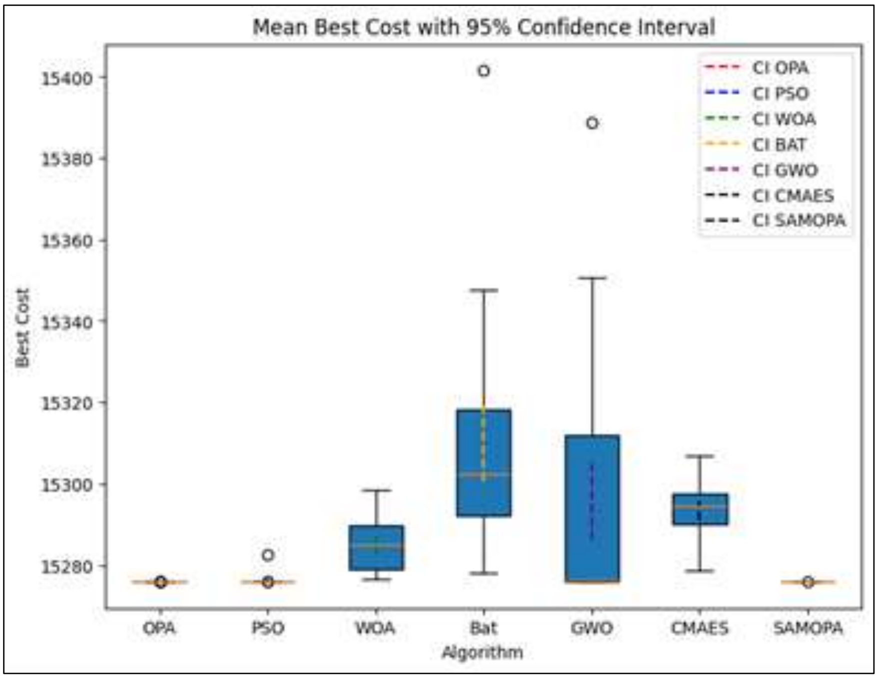

Figure 2: Mean plot with a 95% confidence interval for the algorithms compared across 6 generators.

Source: Authors, (2026).

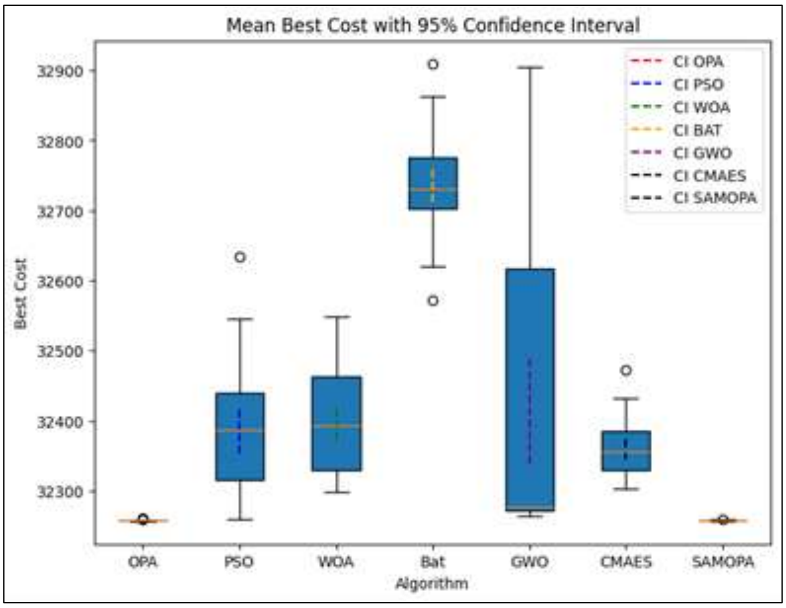

Figure 3: Mean plot with a 95% confidence interval for the algorithms compared across 15 generators.
Source: Authors, (2026).

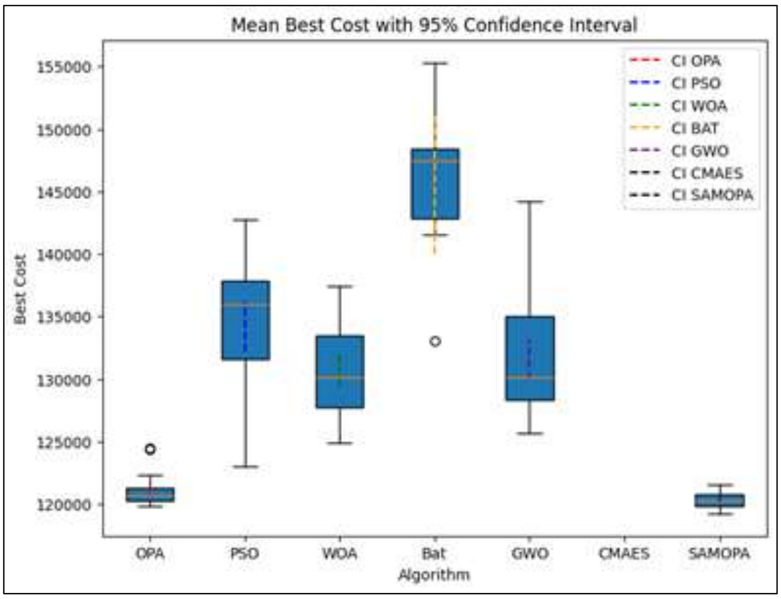

Figure 4: Mean plot with a 95% confidence interval for the algorithms compared across 40 generators.
Source: Authors, (2026).

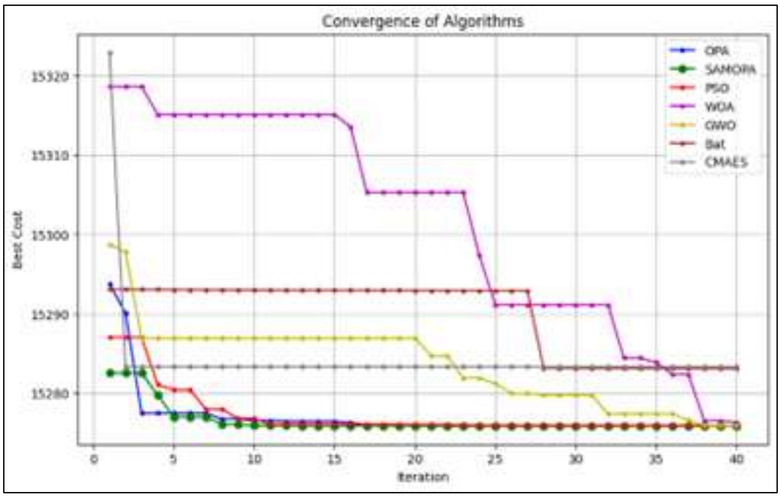

Figure 5: Convergence Curve Comparison of SAMOPA on 6 generators.
Source: Authors, (2026).

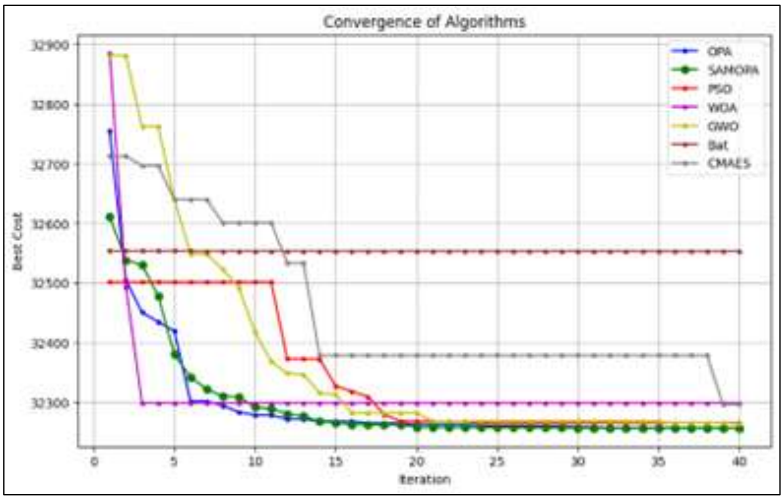

Figure 6: Convergence Curve Comparison of SAMOPA on 15 generators.
Source: Authors, (2026).

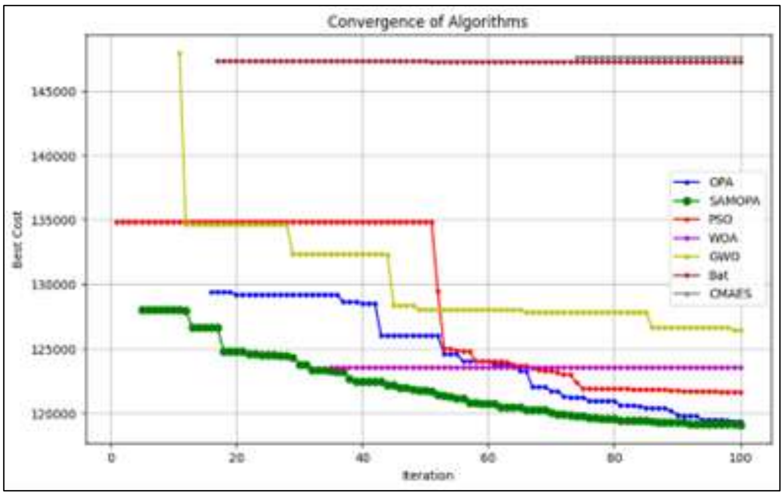

Figure 7: Convergence Curve Comparison of SAMOPA on 40 generators.
Source: Authors, (2026).

Table 2 demonstrates that SAMOPA consistently outperforms other algorithms in economic dispatch scenarios involving 6, 15, and 40 generating units. It achieves the lowest total cost, minimal standard deviation, and competitive computational time, particularly surpassing OPA, PSO, WOA, Bat, GWO, and CMA-ES in terms of solution stability and accuracy. Figures 2–4 further illustrate that SAMOPA consistently yields the lowest mean best cost and the narrowest 95% confidence intervals compared to the benchmark algorithms. The convergence plots in Figures 5–7 reveal that SAMOPA converges more rapidly and maintains greater stability throughout the optimization process. This combination of fast convergence, high accuracy, and robust performance positions SAMOPA as the most reliable method for solving economic dispatch problems across small, medium, and large-scale systems.

III.2 EVALUATION OF NON-CONVEX ED CASES WITH VALVE-POINT EFFECT

To evaluate the robustness of the proposed SAMOPA algorithm under more realistic and complex economic dispatch conditions, further tests were conducted on systems with 6, 15, and 40 generating units incorporating valve-point effects. These effects introduce significant non-linearity and non-convexity into the cost function, closely reflecting practical scenarios in thermal power systems. The performance results for all configurations are presented in Table 3.

Table 3: Performance Comparison of the Algorithm on ED with Valve-Point Effect

Algorithm	Units	Best Cost	Mean Cost	Std Dev	Time (s)
SAMOPA	6	**14326.02**	**14334.26**	**18.41**	0.3788
OPA	6	14326.03	14337.85	21.32	0.5266
PSO	6	14326.09	14389.24	116.65	0.0711
GWO	6	14326.48	14555.78	316.14	0.1427
WOA	6	14354.51	14584.49	142.71	0.0407
Bat	6	14459.1	14885.84	272.8	0.061
CMAES	6	14670.77	-	-	0.0196
SAMOPA	15	**31545.05**	**31644.18**	**72.35**	0.4041
OPA	15	31577.99	31707.11	91.33	0.7249
PSO	15	31826.78	32217.21	265.74	0.1142

Algorithm	Units	Best Cost	Mean Cost	Std Dev	Time (s)
GWO	15	31597.95	32086.14	612.01	0.2621
WOA	15	32144.4	32734.33	266.19	0.0427
Bat	15	32654.2	33252.61	253.83	0.0414
CMAES	15	32598.61	-	612.01	0.0198
SAMOPA	40	116569	118143.2	670.503	1.19
OPA	40	117275.7	119195.6	838.296	1.55
PSO	40	126451.8	9.67E+09	1.8E+09	0.19
GWO	40	-	-	-	-
WOA	40	124307.3	131762	4126.151	0.1
Bat	40	131734.5	-	-	-
CMAES	40	-	-	-	-

Source: Authors, (2026).

The results presented in Table 3 indicate that SAMOPA consistently outperformed all comparative algorithms across the 6, 15, and 40 unit ED cases with valve-point effects. It achieved the lowest generation costs, the smallest standard deviations, and competitive computational times, underscoring its robustness and reliability in addressing non-convex ED problems. OPA ranked second, producing results close to SAMOPA but with noticeably longer computation times. PSO, GWO, and WOA demonstrated moderate effectiveness on smaller systems but showed degraded accuracy and consistency as system size increased. In contrast, Bat and CMA-ES failed to generate valid or stable solutions for the 40-unit case. Overall, SAMOPA exhibited superior accuracy, stability, and computational efficiency, confirming its suitability for solving large-scale, non-convex ED problems with realistic system complexities.

III.3 BENCHMARK EVALUATION USING CEC 2020

The CEC 2020 benchmark suite was selected for its ability to capture key characteristics of the ED problem, including non-linearity, multi-modality, and constraint handling. Its complex function landscape, particularly in hybrid and composition categories, closely reflects real-world challenges such as valve-point effects and operational limits in power systems. The performance of SAMOPA on these benchmark functions is summarized in Table 4.

Table 4: Performance Comparison of the SAMOPA Algorithm on CEC 2020 function.

Algorithm		Unimodal Function	Basic Function	Hybrid Function	Composition Function
PSO	**Best**	8.59E+04	1.10E+03	2.33E+03	3.46E+03
	Mean	4.16E+08	1.61E+03	2.33E+03	3.46E+03
	Std	5.59E+08	1.17E+03	3.53E-01	1.52E+00
	Time	1.20E-01	1.30E-01	1.40E-01	2.30E-01
Bat	**Best**	9.30E+09	1.21E+04	2.39E+03	3.53E+03
	Mean	2.12E+10	1.96E+04	2.85E+03	4.85E+03
	Std	6.31E+09	5.14E+03	2.55E+02	9.77E+02
	Time	8.00E-02	9.00E-02	2.30E-01	2.10E-01
WOA	**Best**	5.68E+09	6.64E+03	2.36E+03	3.46E+03
	Mean	1.34E+10	1.96E+04	2.42E+03	3.60E+03
	Std	3.71E+09	4.88E+03	4.60E+01	1.59E+02
	Time	7.00E-02	1.30E-01	1.00E-01	1.60E-01
GWO	**Best**	4.55E+05	1.10E+03	2.33E+03	3.46E+03
	Mean	6.51E+07	1.16E+03	2.33E+03	3.46E+03
	Std	1.09E+08	9.37E+01	1.02E+00	1.85E+00
	Time	3.50E-01	3.90E-01	1.80E-01	2.20E-01
CMA-ES	**Best**	2.06E+08	1.18E+03	2.33E+03	3.46E+03
	Mean	1.32E+09	1.89E+03	2.36E+03	3.49E+03
	Std	2.08E+07	1.19E+02	7.73E-01	2.79E+00
	Time	4.39E-02	7.01E-02	8.47E-02	1.21E-01
OPA	**Best**	1.94E+02	1.10E+03	2.33E+03	3.46E+03
	Mean	2.60E+03	1.10E+03	2.33E+03	3.46E+03
	Std	3.62E+03	2.00E-02	9.00E-02	4.52E-01
	Time	6.50E-01	6.50E-01	6.90E-01	5.30E-01
SAMOPA	**Best**	1.00E+02	1.10E+03	2.33E+03	3.46E+03
	Mean	1.01E+02	1.10E+03	2.33E+03	3.46E+03
	Std	2.19E+00	1.14E-06	5.00E-02	2.43E-01
	Time	4.90E-01	5.40E-01	5.90E-01	7.50E-01

Source: Authors, (2026).

Table 4 presents the benchmark evaluation results on the CEC 2020 test suite, demonstrating that SAMOPA consistently outperforms all comparative algorithms across all function categories—unimodal, basic, hybrid, and composition. It achieved the best objective values, the lowest mean costs, and the smallest standard deviations, reflecting superior accuracy, stability, and convergence reliability. For example, SAMOPA obtained an optimal value of 1.00E+02 in the unimodal function with a mean of 1.01E+02 and a minimal deviation of 2.19E+00, significantly outperforming OPA, PSO, Bat, and WOA. Similarly, in the basic function category, SAMOPA maintained an average of 1.10E+03 with an extremely low variance of 1.14E−06, indicating consistent convergence.

Its performance remained robust in hybrid and composition functions, with variances of just 5.00E−02 and 2.43E−01, whereas other algorithms such as CMA-ES, GWO, and WOA exhibited greater variability. Although SAMOPA incurred slightly higher computation times than some competitors, the trade-off is justified by its consistent optimization quality. These results confirm that the adaptive momentum mechanism significantly enhances the original OPA framework. A series of Wilcoxon signed-rank tests were conducted on four types of benchmark functions, Unimodal, Basic, Hybrid, and Composition, to statistically confirm that the SAMOPA algorithm is better than other algorithms. We conducted the tests in pairs, comparing SAMOPA with six comparative algorithms: OPA, PSO, WOA, Bat, GWO, and CMA-ES. The findings of this statistical test are summarized in Table 5 below.

Table 5: Statistical Result using Wilcoxon Signed Rank.

	SAMOPA vs OPA				**SAMOPA vs PSO**			
Problem	**P-value**	**T+**	**T−**	**Winner**	**P-value**	**T+**	**T−**	**Winner**
Unimodal Function	1.86E-09	0	1E+05	+	1.86E-09	0	9E+09	+
Basic Function	1.86E-09	0	0	+	1.86E-09	0	42879	+
Hybrid Function	1.05E-01	2	0	=	3.05E-05	0	20	+
Composition Function	2.89E-01	6	2	=	1.23E-04	2	46	+
	SAMOPA vs WOA				**SAMOPA vs Bat**			
Problem	**P-value**	**T+**	**T−**	**Winner**	**P-value**	**T+**	**T−**	**Winner**
Unimodal Function	1.86E-09	0	4E+11	+	1.86E-09	0	4E+11	+
Basic Function	1.86E-09	0	5E+05	+	1.86E-09	0	5E+05	+
Hybrid Function	1.86E-09	0	2993	+	1.86E-09	0	54564	+
Composition Function	1.86E-09	0	6303	+	1.86E-09	0	36461	+
	SAMOPA vs GWO				**SAMOPA vs CMAES**			
Problem	**P-value**	**T+**	**T−**	**Winner**	**P-value**	**T+**	**T−**	**Winner**
Unimodal Function	1.86E-09	0	2E+09	+	1.86E-09	0	3E+10	+
Basic Function	1.86E-09	0	43	+	1.86E-09	0	26256	+
Hybrid Function	1.86E-09	0	48	+	1.86E-09	0	786	+
Composition Function	1.86E-09	0	87	+	1.86E-09	0	1340	+

Source: Authors, (2026).

Table 5 shows the results of the Wilcoxon Signed-Rank Test, indicating that SAMOPA consistently performs better than other algorithms like OPA, PSO, WOA, Bat, GWO, and CMAES on various test functions, including Unimodal, Basic, Hybrid, and Composition. In nearly all comparisons, minimal P-values (<0.05) signify substantial differences, demonstrating that SAMOPA is superior in producing optimal solutions. The '+' symbol in all comparisons shows that SAMOPA usually does better than other algorithms in terms of solution quality and convergence; however, in the Hybrid and Composition functions, the higher P-values indicate that there is no significant difference between SAMOPA and the other algorithms. SAMOPA consistently outperformed its competitors in most comparisons, showcasing its superiority in efficiency and performance throughout the studied optimization functions. SAMOPA demonstrates strong performance across all test scenarios, including both standard and non-convex economic dispatch problems, validating its capability to consistently achieve global optimal solutions. This success is primarily attributed to the adaptive momentum mechanism, which dynamically balances exploration and exploitation by adjusting momentum over iterations.

Unlike fixed momentum approaches, SAMOPA gradually reduces momentum to encourage broad exploration in early stages and focused exploitation in later phases, enhancing both convergence stability and solution quality, as evidenced in Figures 4–6 and Tables 2–3. Although SAMOPA incurs slightly longer computation times than PSO, WOA, and GWO, it consistently delivers more accurate and stable outcomes while avoiding premature convergence. These findings align with prior studies [18], [46], [47], which highlight the benefits of momentum in stabilizing convergence in metaheuristic frameworks. Compared to the original OPA, SAMOPA significantly improves computational efficiency without compromising accuracy. Nonetheless, the comparatively extended execution time relative to alternative algorithms remains a difficulty for real-time applications, particularly in extensive optimization contexts. To address this constraint, future research may investigate the incorporation of hardware acceleration methods, including GPU-based parallelization, multi-core processing, and distributed computing frameworks.

These methodologies facilitate concurrent assessment of populations, expedite the optimization process, and enhance the scalability of algorithms. Moreover, the deployment of cloud infrastructure can enhance the efficiency and real-time responsiveness of SAMOPA. The adaptive momentum mechanism in SAMOPA can be further enhanced through feedback-driven momentum adjustment techniques or dynamic learning rate adaptation, potentially decreasing computing time while maintaining accuracy. Potential hybridization with other metaheuristic algorithms, such as the incorporation of exploitation operators from Particle Swarm Optimization (PSO) or Differential Evolution (DE), may enhance convergence speed and overall solution quality. Finally, while SAMOPA has demonstrated robust empirical convergence, it lacks a mathematical proof of convergence. Consequently, additional theoretical investigations are required to enhance the mathematical foundation and reliability of this methodology over time.

IV. CONCLUSION

This study has proposed and evaluated the SAMOPA as a solution for ED problems in power systems. Experimental results demonstrate that SAMOPA consistently delivers more accurate and reliable solutions than conventional metaheuristic algorithms, even under complex conditions such as valve-point effects. This performance advantage is primarily attributed to the integration of an adaptive momentum mechanism, which effectively balances exploration and exploitation to accelerate convergence.

SAMOPA's strong results across various benchmark scenarios affirm its suitability for real-world power system optimization tasks. Future research will focus on further improving computational efficiency, strengthening the theoretical foundation of the algorithm, and extending its application to ultra-large-scale systems involving 100 or more generating units to evaluate its scalability in more complex and realistic environments.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Vivi Aida Fitria and Arif Nur Afandi.
Methodology: Vivi Aida Fitria and Arif Nur Afandi.
Software: Vivi Aida Fitria.
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