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Full Length Article

Exploring the Orca Predation Algorithm for Economic Dispatch Optimization in Power Systems

Vivi Aida Fitria [a,b], Arif Nur Afandi [a,*], Aripriharta [a]

[a] Department of Electrical Engineering and Informatics, Universitas Negeri Malang, Indonesia
[b] Informatics, Institut Teknologi dan Bisnis Asia Malang, Indonesia

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ABSTRACT

The Economic Dispatch problem is essential for minimizing generation costs while satisfying power demand in electrical systems. This research looks into the Orca Predation Algorithm, an optimization method based on biology that can solve the Economic Dispatch problem for systems with 6, 13, or 15 producing units. The idea behind Orca Predation Algorithm came from the way orcas hunt for food. It solves problems that other optimization methods and bio-inspired algorithms have, like too much population diversity and too early convergence. This research shows that Orca Predation Algorithm consistently does better than other bio-inspired algorithms like Particle Swarm Optimization, Whale Optimization Algorithm, Grey Wolf Optimizer, the Bat Algorithm, Genetic Algorithm and Ant Colony Optimization in terms of minimum cost, average cost, and solution stability. The sensitivity analysis of the parameters regulating the exploration-exploitation balance in Orca Predation Algorithm demonstrated substantial performance enhancements. By changing these parameters, the best prices came in at $15,275.93 for the 6-unit system, $17,932.49 for the 13-unit system, and $32,256.97 for the 15-unit system. These prices are lower than those in the previous parameter setting. Although Orca Predation Algorithm demonstrates greater performance, it necessitates extended computing time, which future research could mitigate by exploring parallelization or hybrid methodologies. This paper shows that Orca Predation Algorithm is a reliable tool for optimizing Economic Dispatch problems. It gives useful information to power system engineers who are looking for effective and scalable optimization methods for modern power systems.

1. Introduction

The economic dispatch (ED) problem is a critical issue in power system operation, with the primary aim of optimally distributing power among generating units to minimize overall generation costs [1]. This is accomplished while satisfying the load demand, with each generating unit subject to minimum and maximum power limits that must be observed [2,3]. The ED problem, being a convex optimization issue, necessitates a rapid and efficient resolution, particularly in extensive systems comprising numerous generating units [4,5]. Conventional optimization methods, including linear programming and quadratic programming, frequently fail to address the increasing complexity of power systems. This complexity originates from causes including system expansion, the incorporation of variable renewable energy sources, and the existence of numerous local optima in extensive power systems. Moreover, traditional methods encounter challenges in delivering effective global optimization, especially in systems necessitating swift flexibility due to variable energy demands and resources [6]. Bio-inspired algorithms have lately garnered interest as viable solutions for addressing complicated optimization issues, including the ED problem [7]. These algorithms are especially beneficial for navigating extensive search areas and circumventing local optima, obstacles frequently encountered by conventional approaches. Researchers have thoroughly investigated a variety of bio-inspired algorithms for economic dispatch optimization, including Particle Swarm Optimization (PSO) [8,9,10], Bat Algorithm [11], Whale Optimization Algorithm (WOA) [12], Grey Wolf Optimization (GWO) [13], Genetic Algorithm (GA) [14] and Ant Colony Optimization (ACO) [15]. Many of these algorithms frequently encounter premature convergence as a result of insufficient population variety, which in turn limits their ability to fully explore the entire solution space.

Yuxin Jiang developed the Orca Predation Algorithm (OPA) in 2022, a unique bio-inspired optimization technique that demonstrates significant potential in addressing challenges of previous algorithms [16]. The

* Corresponding Author: Department of Electrical Engineering and Informatics, Universitas Negeri Malang, Jl. Semarang 5 Malang 65145 Jawa Timur Indonesia
E-mail address: an.afandi@um.ac.id (A.N. Afandi).

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predatory tactics of orcas inspire OPA, which strikes a balance between exploration and exploitation to maintain population diversity and prevent early convergence. However, the application of OPA to the ED problems has not been studied, and this research aims to evaluate its performance in comparison to other bio-inspired algorithms such as PSO, Bat Algorithm, WOA, GWO, GA and ACO. The originality of this research lies in adapting OPA to the specific restrictions of the ED problem, which emphasizes the optimal distribution of generating units while minimizing costs. OPA is implemented for its capacity to address intricate optimization challenges and derive efficient solutions via adaptive pursuit and assault phases. This study entails the meticulous adjustment of the parameters (p1 and p2) of OPA to enhance its efficacy in addressing ED problems. Parameter p_1 governs the individual's subsequent phase, either driving or encircling, while p_2 adjusts the strength of the attack. A sensitivity study of these parameters is performed to assess their influence on solution quality and computational efficiency, ensuring that the method can accommodate many circumstances with little modification.

This work offers a thorough comparison of OPA with other prevalent biology-inspired optimization methods, emphasizing its benefits regarding solution stability and convergence speed. By comparing OPA to other methods already used, this study aims to show how reliable and effective it is as a strong optimization tool for solving economic dispatch problems in power systems. This work seeks to provide significant insights into the relevance and efficacy of OPA in treating ED issues while tackling critical concerns such as preserving solution diversity and reducing computational expenses. This study's results will offer practical direction for power system engineers in applying OPA to real-world ED scenarios, hence enhancing the development of efficient optimization solutions for contemporary power systems.

2. Related Work

2.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a global optimization technique developed by Kennedy and Eberhart in 1995 [17]. PSO was inspired by the behavior of avian flocks and schools of fish [18]. Each particle PSO possesses a variable velocity that navigates the search space based on its prior performance [19]. The particles have a propensity to migrate towards more advantageous search regions throughout the search process. Throughout the search process [20]. PSO has been employed in numerous intricate optimization challenges, including the resolution of economic dispatch issues. The findings demonstrate that PSO is proficient in circumventing local minima and achieving convergence to the global optimum, a crucial aspect for economic dispatch problems characterized by intricate and non-linear objective functions alongside various restrictions [21]. Nonetheless, PSO may occasionally encounter premature convergence or sluggish convergence rates, particularly if the parameters are inadequately calibrated. This may impact the precision and dependability of the derived solutions [22]. To enhance the efficacy of PSO in economic dispatch problems, certain research integrate it with alternative optimization methodologies, such as Ant Colony Optimization (ACO), to augment its performance and convergence rate. This hybrid methodology can yield superior answers, yet introduces complication to its execution [23].

2.2. Bat Algorithm

The Bat algorithm is a bio-inspired metaheuristic algorithm introduced by Xin-She Yang in 2010 [24]. Bats' foraging behavior, which involves locating prey and evading obstacles, serves as the basis for the Bat algorithm [25]. The fundamental principle underlying the development of the Bat algorithm is echolocation, which enables bats to identify food sources and obstacles while estimating their distances [26]. The second hypothesis posits that bats can modify their flying patterns in response to experience and environmental feedback, facilitating the exploration of the solution space [27]. The third aspect pertains to the parameters utilized in the Bat algorithm, specifically the loudness and emission rate of the bat's pulse, which serve to equilibrate exploration and exploitation throughout the search process [28]. Prior studies have employed the Bat algorithm to address economic dispatch issues. Included are works that present the application of Ant Lion Optimization (ALOA) and Bat Algorithm (BA) to address economic dispatch issues in power systems. This study evaluated the efficacy of both algorithms on a small-scale three-generator system and a large-scale six-generator system, utilizing the IEEE-30 bus reliability test system. Nonetheless, the results indicate that ALOA exhibits a superior convergence rate compared to the Bat Algorithm (BA) [29].

2.3. Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) draws its optimization technique from the hunting strategies of whales in the ocean [30]. Specifically, it mimics the behavior of whales when they locate their prey, creating a bubble trap that constricts the prey's movement [31]. Upon ensnaring its prey, the whale will promptly consume it. This algorithm provides an effective method for identifying optimal solutions within intricate search spaces by integrating exploration and exploitation phases [32]. The WOA algorithm uses three main methods to find the best solution: first, it copies the way whales circle their prey, moving their positions based on the best solution found; second, it copies the way whales search for food, moving around randomly and exploring the solution space; and third, the bubble net attack mechanism copies the way whales hunt together, working together to completely surround and catch their prey [33]. Prior studies have demonstrated the efficacy of the WOA algorithm in addressing economic dispatch issues. The study demonstrated that WOA can yield optimal or near-optimal solutions by taking into account fuel expenses and pollutants. Superior convergence characteristics set it apart from traditional methods such as PSO [29]. However, if not adequately designed, WOA, akin to other metaheuristics, has sluggish convergence, limited precision, and a propensity to become trapped in local optima [34].

2.4. Grey Wolf Optimization

The predatory behavior of wolves in their natural habitat serves as the basis for the Grey Wolf Optimizer (GWO) algorithm. The gray wolf is regarded as an apex predator, characterized by a pronounced social dominance structure. The foremost leaders are designated as alpha, the second tier as beta, the third tier as delta, and the final tier as omega [35]. The GWO algorithm is characterized by three primary phases: first, the wolves encircle the prey according to the positions of the alpha, beta, and delta wolves; second, the wolves adjust their positions by adhering to the alpha, beta, and delta wolves, emulating the actions of tracking, pursuing, and nearing the prey; and third, the wolves launch an attack [36]. The GWO algorithm does a much better job of solving the economic dispatch problem than other meta-heuristic approaches like Biogeography-based Optimization (BBO), Lambda Iteration (LI), Hopfield model approaches (HM), Cuckoo Search (CS), Firefly algorithms, Artificial Bee Colony (ABC), Neural Networks trained by Artificial Bee Colony (ABCNN), Quadratic Programming (QP), and General Algebraic Modeling System (GAMS) [37]. Despite GWO demonstrating superior efficiency relative to other metaheuristic algorithms, it remains computationally demanding for extensive systems or when confronted with intricate limitations [38].

2.5. Genetic Algorithm

The Genetic Algorithm (GA) is an evolutionary computer technique developed by John Holland in the 1970s. Genetic algorithms use selection, crossover, and mutation, along with other ideas from natural selection and genetics, to come up with new solutions and make the ones we already have better. In a genetic algorithm, each solution, referred to as a 'chromosome,' undergoes iterative evolution to enhance its quality according to a designated fitness function [39]. GA have been extensively utilized for diverse complex optimization challenges, including ED issues, owing to their capacity to manage non-linear and non-convex objective functions [14]. Previous research has shown that genetic algorithms are very good at solving economic dispatch problems by finding the best balance between exploring and exploiting in the search space. Research has shown that genetic algorithms can get optimal or near-optimal solutions for extensive power systems, encompassing fuel cost reduction and emission limitations [40]. Nonetheless, genetic algorithms face issues including premature convergence and sensitivity to parameter configurations, such as population size and mutation rate, which can influence their efficacy and dependability. Recent advancements aim to amalgamate GA with other optimization methodologies, such as PSO, to enhance convergence velocity and solution efficacy [41].

2.6. Ant Colony Optimization

Marco Dorigo developed Ant Colony Optimization (ACO), a nature-inspired metaheuristic, in the early 1990s, based on the foraging behavior of ants. In ACO, artificial ants emulate the foraging and pheromone trail-following behaviors of actual ants, enabling them to identify the optimal route between a food source and their colony. Each ant looks at the pheromone trail and heuristic data to figure out what the best solution might be. The pheromone trail is changed over and over to reinforce the best options [42]. Numerous optimization challenges, including economic dispatch issues, have effectively utilized ACO due to its capacity to adjust to dynamic and intricate search environments. Research indicates that ACO excels in emergency department circumstances by effectively balancing exploration and exploitation, particularly in small to medium-sized power systems [15]. Efforts to integrate ACO with other algorithms, including GA and WOA, have demonstrated potential enhancements in efficiency and accuracy. Nonetheless, these hybrid methodologies frequently elevate computational complexity, rendering ACO less advantageous for extensive ED challenges that necessitate high precision and rapid convergence [6].

3. Research Method

3.1. Economic Dispatch Problem

The economic dispatch problem is a crucial concern in power systems, to optimize the distribution of power generation among different power plants to satisfy the demand at the most cost-effective rate [43]. The aim is to reduce the overall generation cost while complying with the operational limits of each facility. The generating cost function is typically expressed as a second-order polynomial of the power output (1) :

$$F_T = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i\right) \quad (1)$$

where F_T denotes the total generation cost in \$/hour, $F(P_i)$ signifies the generation cost of the i-th plant, P_i represents the power output of the i-th plant in MW, and $a_i,\ b_i,\ c_i$ are cost coefficients derived from the operational characteristics and fuel type of the plant. The generator limits characterize the inequality conditions in the ED problem formularization.

$P_{i,min} \le P_i \le P_{i,max}$ for $i = 1,\ 2,\ \ldots,\ n$

The ideal power flow in the power system is impacted by the transmission line losses. These losses can be expressed quantitatively as (2)

Table 1
Dataset of 6 unit system

Variable	Range	Unit
$P_{i,min}$	50-100	MW
$P_{i,max}$	120-500	MW
a	0.007-0.0095	-
b	7-12	-
c	190-240	-

Table 2
Dataset of 13 unit system

Variable	Range	Unit
$P_{i,min}$	0-60	MW
$P_{i,max}$	120-680	MW
a	0.00028 -0.00324	-
b	7.74-8.6	-
c	126-550	-

Table 3
Dataset of 15 unit system

Variable	Range	Unit
$P_{i,min}$	20-150	MW
$P_{i,max}$	55-470	MW
a	0.000183-0.00513	-
b	8.8-13.1	-
c	173-671	-

$$P_{Loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \quad (2)$$

In this context, P_{Loss} denotes the total transmission loss in megawatts (MW), while B_{ij}, B_{0i}, and B_{00} are coefficients contingent upon the system setup and network topology. The B coefficients need to be established for a changeable system demand. The prerequisites for electrical equality in ED are shown in (3). [44]

$$P_D = \sum_{i=1}^{n} P_i - P_{Loss} \quad (3)$$

where *PD* is the total system demand measured in megawatts (MW). This study used a data set comprising three test scenarios: 6 units system with a total load demand of 1263 MW, 13 units system with a total load demand of 1800 MW, and 15 units system with a total load demand of 2630 MW. The Tables 1, 2 and 3 displays the data sets used in this study from Hardiansyah's research as well as those from Zakian and Keveh. [45,46]:

3.2. Orca Predation Algorrithm

The Orca Predation Algorithm (OPA) was initially proposed by [16]. The OPA is a bio-inspired metaheuristic optimization method that emulates the hunting behavior of orcas. The purpose is to imitate the hunting strategies of orcas, known for their advanced and highly coordinated hunting techniques, to address complex optimization problems. The algorithm consists of two distinct stages: driving and encircling. In the first step of OPA, important parameters are set, such as the number of populations (N), dimensions (D), maximum iterations, selection probability p_1, p_2, lower bound (lb), and upper bound (ub) of the design variables. The orca group's initial position is randomly created within the specified limits $[lb, ub]$. The objective function determines the second phase of fitness value assessment for each orca. The orca exhibiting the highest fitness value is designated as x_{best}, representing the optimal current solution. The final step involves updating the position

Table 4
Parameters Setting.

Algorithm Name	Parameters	Max_iter
OPA	$a,\ b,\ d\ \epsilon\ [0,1]; e\ \epsilon\ [0,2]; F = 2; q\ =\ 0.9;\ p_1 = 0.4;\ p_2 = 0.05;\ g_1\epsilon[0,2];\ g_2\epsilon[-2.5, 2.5]$ [16]	40
PSO	$c_1\ = 2; c_2\ = 2;\ \omega i\ = 0.9;\ \omega f = 0.2$ [47]	40
Bat-Algorithm	$f_{min}\ =\ 0; f_{min}\ =\ 2; A_0 = [0,2]\ ; r_0\ = [0,1];\ \alpha = 0.9;\ \gamma = 0.9$ [48]	40
WOA	$a\ \epsilon\ [2,0];\ r\ \epsilon\ [0,1];\ b = 1$ [49]	40
GWO	$A\ \epsilon\ [2,0]$ [47]	40
GA	Crossover rate =0.8; Mutation rate =0.1 [47]	40
ACO	$\alpha = 1;\ \beta = 2$; Evaporation rate = 0.2 [50]	40

throughout the pursuit phase. At this juncture, the orca chooses between "driving" or "encircling" its prey based on the selection probability (p_1). This decision dictates whether the orca will prioritize exploration (seeking novel solutions) or exploitation (refining the existing optimal solution). Orcas utilize sonar to modify their location by recalibrating their position in accordance with Equations :

$$v^t_{chase\ 1,i} = a\ \left(dx^t_{best} - F\left(bM^t + cx^t_i\right)\right) \tag{4}$$

$$v^t_{chase\ 2,i} = ex^t_{best} - x^t_i \tag{5}$$

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

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

$$\begin{cases} x^t_{chase\ 1,i} = x^t_i + v^t_{chase\ 1,i}\ if\ rand\ > q \\ x^t_{chase\ 2,i} = x^t_i + v^t_{chase\ 2,i}\ if\ rand\ \leq q \end{cases} \tag{8}$$

where t is the number of cycles, v^t is the chasing speed, M is the average position of the orca group, x^t is the position of the orca, a,b and $d$are random numbers between [0,1], e is a random number between [0,2], F = 2 and q is a number between [0,1]. While the equation when the orca encircles the prey is:

$$x^t_{chase\ 3,i} = x^t_{j1,i} + u\left(x^t_{j2,i} - x^t_{j3,i}\right) \tag{9}$$

$$u = 2(rand - 0.5)\frac{\text{maxiter} - t}{\text{maxiter}} \tag{10}$$

where max *inter* denotes the maximum number of iterations, and $j_1,\ j_2,\ j_3$ represent three distinct orcas selected at random such that $j_1 \neq j_2 \neq j_3$. The position of the i-th whale after selecting the third chase method at time t is denoted as $x^t_{chase\ 3,i}$.

In this procedure, orcas ascertain the location of their prey and modify their position to enhance the efficacy of the solution. The fourth phase involves updating the position during the attack phase. During this phase, orcas enhance their positioning to effectively assault prey. Equations (11)-(13) guide the revision of the position. During the assault, certain orcas may attain the boundaries of the search zone. If they surpass the limit, their position will revert to the lower limit (lb). [16]

$$v^t_{attack\ 1,i} = \frac{\left(x^t_{first} + x^t_{second} + x^t_{third} + x^t_{four}\right)}{4 - x^t_{chase,j}} \tag{11}$$

$$v^t_{attack\ 2,i} = \frac{\left(x^t_{chase,j1} + x^t_{chase,j2} + x^t_{chase,j2}\right)}{3 - x^t_i} \tag{12}$$

$$x^t_{attack,i} = x^t_{chase,i} + g_1\ v^t_{attack\ 1,i} + g_2 v^t_{attack\ 2,i} \tag{13}$$

where $v^t_{attack\ 1,i}$ represents the speed vector of the i-th orca during the hunting phase at time t, $v^t_{attack\ 2,i}$ indicates the speed vector of the i-th orca returning to the cage at time t, $x^t_{first},\ x^t_{second},\ x^t_{third},\ x^t_{four}$ denote the four orcas positioned optimally in succession, $j_1,\ j_2,\ j_3$ signify three randomly selected orcas from a total of N in the pursuit phase, ensuring $j_1 \neq j_2 \neq j_3$. $x^t_{attack,i}$ indicates the position of the i-th orca at time t following the attack phase, g_1 is a random number within the range [0,2] dan g_2 is a random number within the interval [-2.5;2.5]. The fifth step involves the establishment of a new population. Following the assault phase, we establish a new pod of orcas. The orcas' placements are revised according to the outcomes of the pursuit and assault phases. This stage ensures the diversity of the population while maintaining the identified optimal solution. The final step is the loop's termination. The algorithm verifies if the maximum iteration count (max*iter*) has been attained or if the optimal solution has been identified. If the termination condition remains unfulfilled, we repeat the procedure from Step 2.

3.3. Scenarios

This study uses the OPA to optimize the ED issue across three distinct power generation systems: 6, 13, and 15 generating units. The aim of each scenario is to reduce the overall generation cost while satisfying all power demand and operational restrictions. Each scenario assesses OPA's capacity to manage escalating system complexity and scale while benchmarking its performance against other bio-inspired optimization methods, including PSO, Bat Algorithm, WOA, GWO, GA and ACO.

3.2.1. Scenario Setup

Multiple constraints structure ED problem solving around test data: the first constraint mandates that each generating unit has a specified minimum and maximum generation capacity, the second constraint requires the aggregate power output of all units to align with system demand, and the objective is to minimize the total cost function, which is characterized as a quadratic function for each generator.

3.3.2. Parameter Tuning and Sensitivity Analysis

The parameter configurations for all algorithms included in this study were derived from prior research sources to guarantee appropriateness and pertinence. The subsequent Table 4 encapsulates the parameters.

The subsequent experiment aimed to optimize the settings of the OPA algorithm to enhance its performance. The grid search technique fine-tunes the essential parameters p_1 and p_2 of the OPA to optimize the unique characteristics of the ED issue using the OPA algorithm. These two criteria are crucial for balancing the exploration and exploitation stages. The parameter p_1 determines the chance of the orca transitioning into the driving or encircling phase, whereas p_2 governs the attack phase. These parameters control the balance between exploring and exploiting during the optimization process. Making sure they are set up correctly is very important to avoid premature convergence and make sure that the whole solution space is explored. Grid search is conducted by examining multiple combinations of p_1 and p_2 variables. This research grid search process has many key steps: initially, setting the parameter ranges p_1 and p_2, where $p_1 \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ and $p_2 \in \{0.01, 0.03, 0.05, 0.07, 0.1\}$, resulting in a 5×5 grid combination. Afterwards, the OPA algorithm is run 40 times in the ED scenario to test each parameter combination and find the fitness value (generation cost) for each setting. The performance is judged by writing down the lowest

Table 5
Actual output from the system's six generators

Algorithm	P1	P2	P3	P4	P5	P6
PSO	446.82995889	171.19809142	264.10692378	125.1393930	172.10194858	83.62368431
Bat Algorithm	443.68052541	188.20549581	269.86504536	108.6707606	159.0956169	93.48255591
WOA	105.2252307	172.17792636	278.86546458	130.10435371	173.48050005	83.44119756
GWO	446.56908253	169.21357222	264.21317023	125.86927672	172.14265957	84.99223872
GA	447.5046163	170.79042194	266.01133413	123.22171545	169.17913187	86.29278031
ACO	446.3378674	162.65821351	262.98062072	150.	162.65821351	78.36508487
OPA	446.64128102	171.26899505	264.14790971	125.18833083	172.11574993	83.63773346

Table 6
Economic Dispatch on 6 Generators

Algorithm	Minimum Cost	Mean	Std	Computation Time
PSO	15275.930594364689	15277.54602959566	3.352045776164392	0.05616219043731689
Bat Algorithm	15283.57585596129	15311.85874126833	37.97378990142223	0.11467342376708985
WOA	15276.354615304797	15284.83732050414	7.475160434950923	0.10255167484283448
GWO	15275.988847142546	15296.143454969084	31.57586518826314	0.195526856642503
GA	15276.129209510731	15281.089977499496	3.320602022291739	0.04007517496744792
ACO	15283.094249517922	15294.727679662261	5.124485757627291	0.3876126050949097
OPA	15275.930461640604	15275.933494696532	0.003482677781155	0.5794726530710856

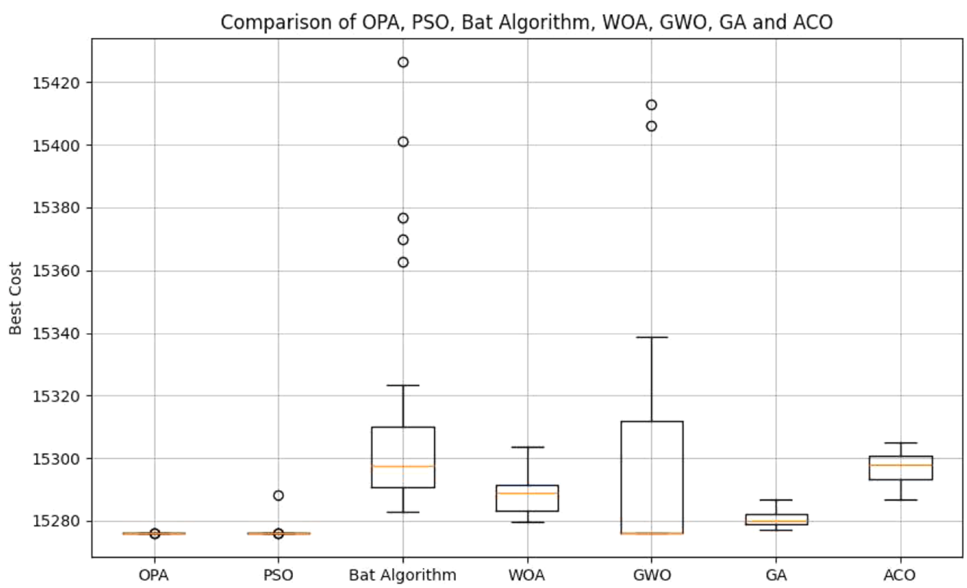

Fig. 1. Box Plot Comparison on 6 Generators

cost that can be reached for each set of parameters. The test is run several times to lessen the effect of stochastic variations in the algorithm. The aim of the grid search is to determine the parameter configurations that yield the optimal balance between convergence rate and solution quality. As part of the tuning process, sensitivity analysis is used to see how changes in p_1 and p_2 affect the optimal cost, how the solution converges, and how stable it is in general. The sensitivity of parameters p_1 and p_2 is illustrated by contour plots, depicting the effect of parameter modification on the optimal cost attained. These contour plots show how stable the OPA algorithm is with different parameter settings. The best parameter setting is shown by the global minimum on the curve. Grid search carefully examines all parameter combinations, guaranteeing that every alternative is evaluated and no solution is overlooked. This research employs the grid search method because of its advantages in parallelization and implementation [51].

3.3.3. *Evaluation Metrics*

In all scenarios, the efficacy of OPA and other comparative algorithms is assessed using several critical metrics: the minimum total generation cost attained by each algorithm, the mean generation cost across multiple tests to evaluate solution consistency, the standard deviation to gauge result variation and algorithm stability, and the average computation time. To compare OPA to current methods and determine how well it can adapt to growing system sizes, this study will use these criteria in all situations.

4. Result and Discussion

Experiments have been carried out to evaluate the performance of the OPA, PSO, Bat Algorithm, WOA and GWO on three well-known test systems: the 6-unit, 13-unit, and 15-unit systems.

4.1. *6-unit system*

The system comprises six thermal units, 26 buses, and 46 transmission lines. The load demand is 1263 megawatts. Table 5 shows the actual power output of each unit based on the five optimization strategies used. This constitutes a crucial component of the optimal ED

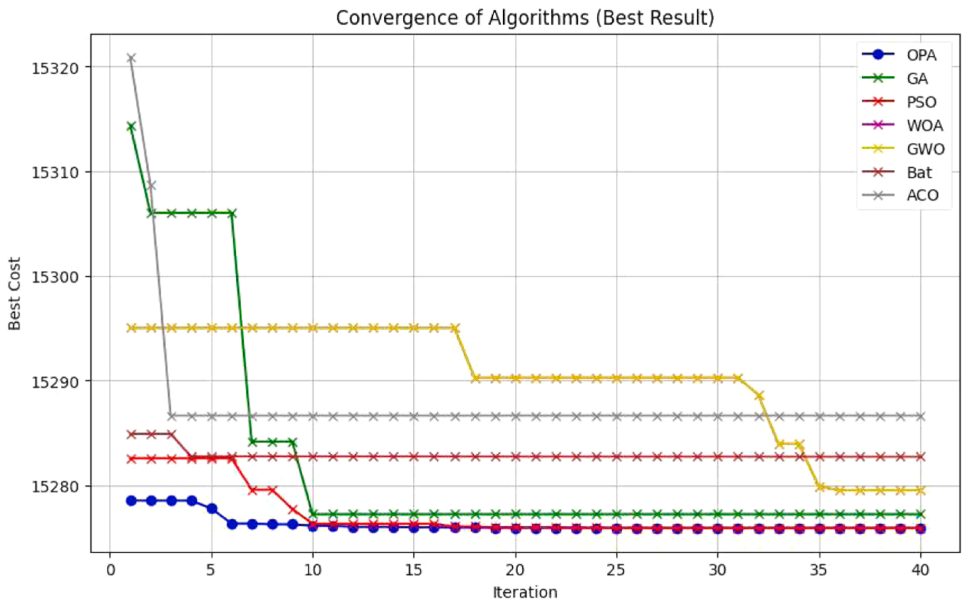

Fig. 2. Convergence curves on 6 Generators

calculation. Table 6 presents the minimum system cost, average cost, standard deviation, and computation time for each method following 30 trials. Fig. 1 depicts the minimum cost associated with each evaluated strategy across 40 iterations.

Table 6, which encompasses six power plants, indicates that OPA exhibits superior performance, with the lowest cost of 15275.9305 and the most stable average cost of 15275.9335 in comparison to GA, PSO, ACO, the Bat Algorithm, WOA, and GWO. Moreover, OPA's minimal standard deviation (0.0035) signifies that its optimization outcomes are highly consistent. This is markedly superior to other, more variable algorithms, such as the Bat Algorithm (37.9738) and GWO (31.5759). GA and PSO exhibited similar performance, with GA achieving a minimal cost of 15276.13 and PSO reaching a nearly identical minimum cost of 15275.9306, along with slightly higher standard deviations of 3.3206 and 3.3520, respectively. Although OPA's computation time is slightly increased at 0.579 seconds, its dependability in producing the ideal solution establishes it as the preeminent approach for the ED problem.

Fig. 1's boxplot demonstrates that OPA exhibits the most constrained cost distribution, lacking outliers and hence confirming its reliability. PSO and GA exhibit similarly tight distributions, albeit with slightly greater variability than OPA. Conversely, ACO exhibits a broader spectrum with a greater number of outliers, signifying less consistent performance. The Bat Algorithm and GWO display the broadest distribution with numerous outliers, indicating their instability, while WOA shows improved performance but remains less stable than OPA, PSO, and GA. The convergence curve in Fig. 2 shows that OPA is clearly better because it reaches stability and the lowest possible cost (about $15,275) in just 10 rounds. PSO demonstrated rapid convergence, with a final outcome nearly identical to OPA. GA demonstrated rapid and consistent convergence, but with a somewhat elevated final cost. ACO necessitates additional iterations to attain stability, resulting in a higher optimal cost compared to OPA, PSO, and GA. The Bat Algorithm and GWO exhibited negligible enhancement across iterations, with optimal costs persisting at elevated levels. Concurrently, WOA exhibited incremental enhancement but plateaued at a suboptimal cost of around 15284. This confirms that OPA is the leading algorithm, producing the most optimal solution and demonstrating efficiency and stability that significantly exceed those of alternative algorithms.

The experimental results for the OPA algorithm utilize the identical parameter values p_1 and p_2 as those in Yuxin's study. The forthcoming discussion will present the results of the sensitivity graph for parameters p_1 and p_2 following the adjustment of certain parameters.

The experimental results from the sensitivity graph of parameters p_1 and p_2 for 6 system units using the OPA algorithm show that the best cost changes a lot depending on the combinations of parametersp_1 and p_2, especially when the values are low. In the lower left quadrant of the graph, particularly within the range of p_1 from 0.1 to 0.4 and p_2 from 0.01 to 0.08, a notable alteration in the optimal cost is observed. Conversely, when p_1 approaches 0.9, the fluctuation in the optimal cost diminishes, as evidenced by the more uniform coloration of the graph. This indicates that elevated levels of p_1 (approaching 1) and diminished p_2 yield stability in the outcomes, albeit with minimal variation in the optimal cost. Furthermore, experimental outcomes with the p1 and p2 parameter values from Yuxin's study yielded an optimal cost of 15275.930461640604. Further optimization yielded a superior cost of 15275.930398908155, using parameter values $p_1 = 0.9$ and $p_2 = 0.01$. The sensitivity graph indicates that parameter adjustment substantially influences the optimization outcomes. The combination of elevated p_1 (0.9) and diminished p_2 (0.01) demonstrated superior optimality compared to the parameter values employed in Yuxin's article. This

Table 7
Actual output from the system's 13 generators

Algorithm	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
PSO	782	86	223	72	85	75	108	89	76	42	41	58	57
Bat Algorithm	510	288	175	72	93	70	97	103	165	60	40	57	64
WOA	658	228	225	101	114	108	99	97	92	40	39	55	56
GWO	499	257	253	100	101	101	101	99	101	40	40	55	55
GA	505	194	247	136	102	104	87	96	89	51	50	59	73
ACO	528	264	306	120	60	60	105	60	60	60	60	60	55
OPA	505	255	254	97	98	99	100	98	98	40	40	55	55

Table 8
Economic Dispatch on 13 Generators

Algorithm	Minimum Cost	Mean	Std	Computation Time
PSO	17981.852673781043	18010.25471739617	12.105198962784101	0.0828967014948527
Bat Algorithm	17972.28367998929	18006.380485156496	18.17393100098788	0.11570893923441569
WOA	17935.78738096655	17975.3459921142	15.979580254725192	0.06328445275624593
GWO	17932.597705266875	17932.841638157162	0.19262156142012746	0.1848301410675049
GA	17963.61906345404	17981.56961907532	9.25872245439762	0.05540952682495117
ACO	17978.631481258828	17998.38803106319	9.697338387501473	0.8677584489186605
OPA	17932.495398652336	17932.556635945206	0.058578778625625744	1.039674949645996

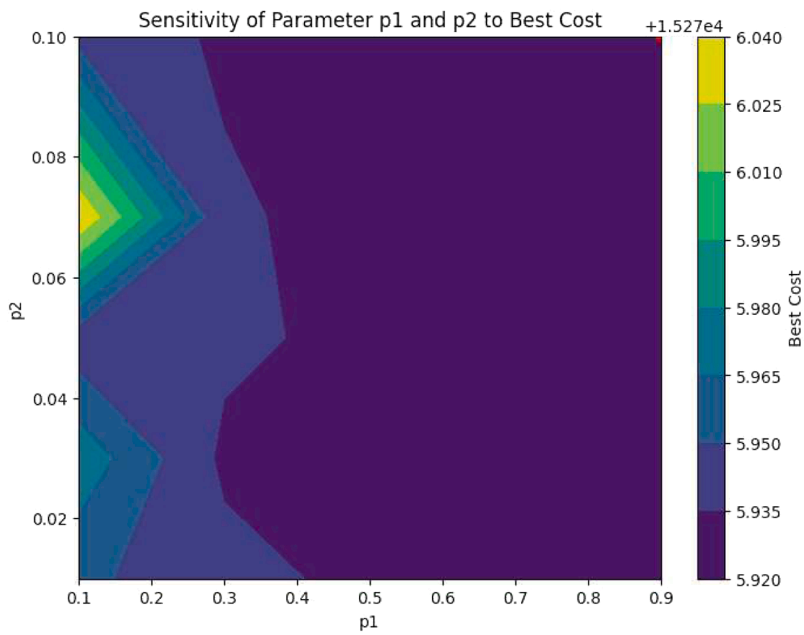

Fig. 3. Parameter Sensitivity Graph on 6 System Units

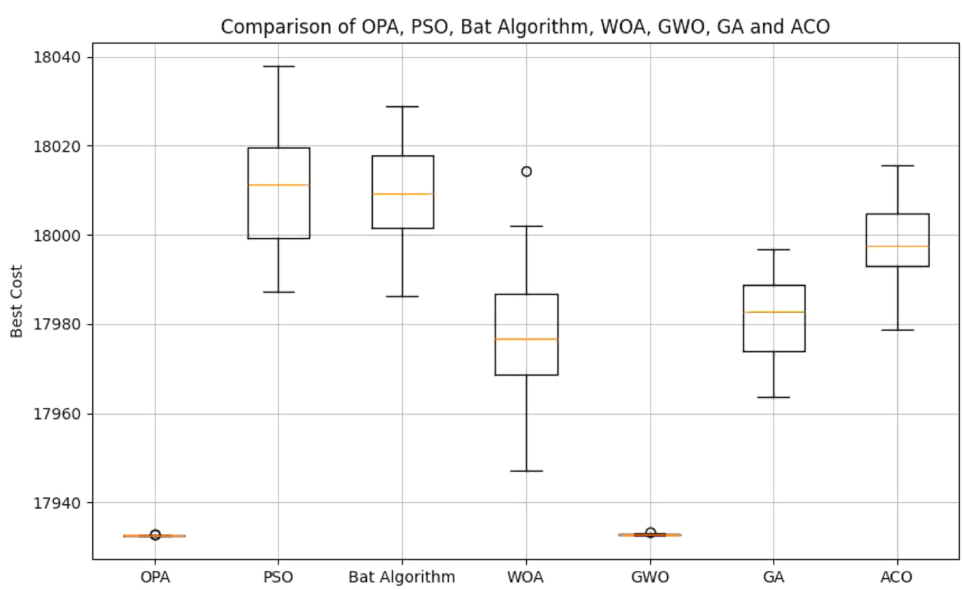

Fig. 4. Box Plot Comparison on 13 Generators

study demonstrates that parameter optimization in the OPA method can markedly enhance performance, particularly in the economic dispatch problem involving a system with six producing units. Through appropriate parameter tuning, a reduced optimal cost and enhanced stability can be achieved, demonstrating significant potential for improving the optimization outcomes of the OPA method.

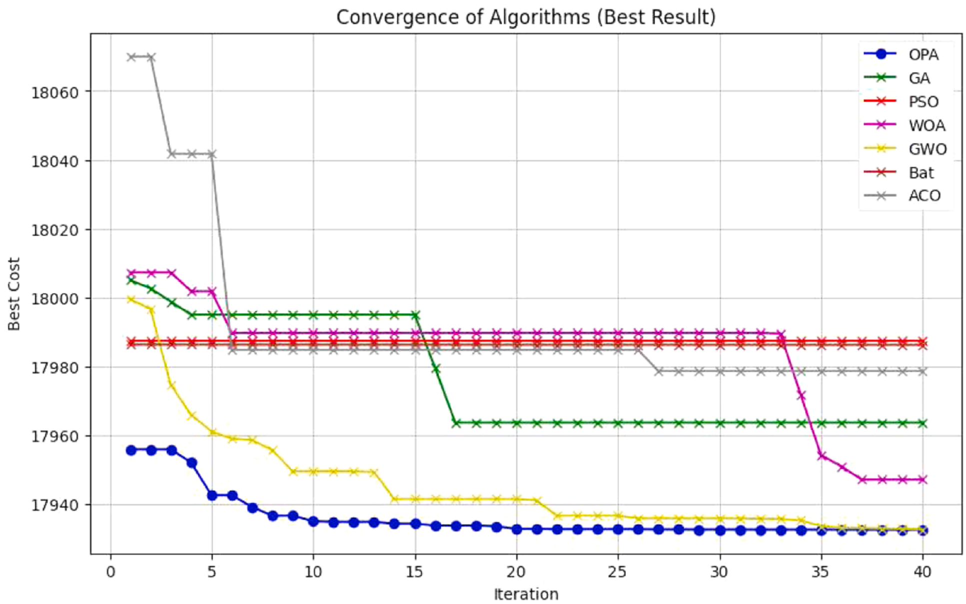

Fig. 5. Convergence curves on 13 Generators

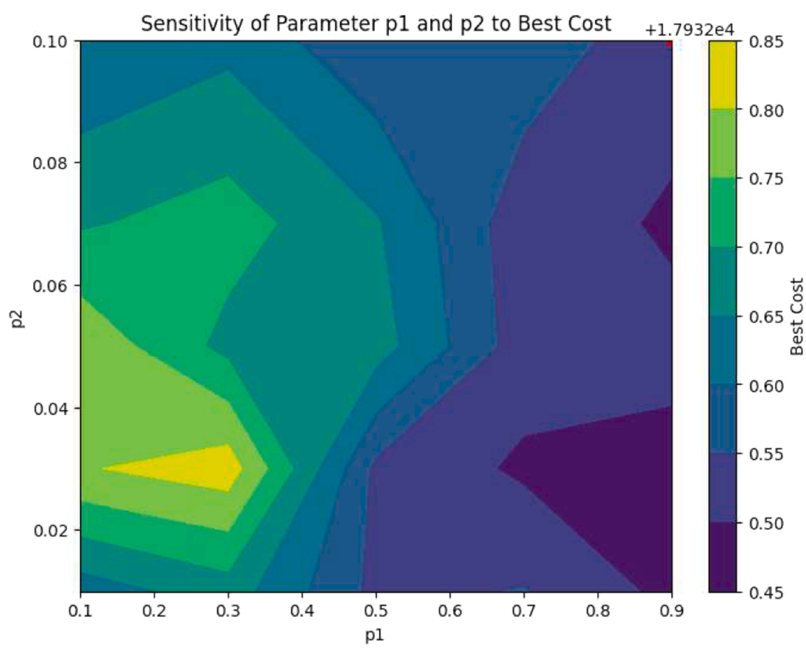

Fig. 6. Parameter Sensitivity Graph on 13 System Units

4.2. 13-unit system

The 13 generators in the 13-unit system collectively require a total load of 1800 MW. Table 7 displays the power output of each unit utilizing the five optimization procedures. Table 8 displays the minimum cost of the system following 30 trials, the average cost derived from these trials, the standard deviation, and the computation time for each technique. Fig. 3 illustrates the box plot for each algorithm assessed over 40 iterations. Fig. 4 illustrates their convergence curves.

The study found that OPA was the best way to solve the ED problem because it had the lowest cost (17932.4954), the most stable average cost (17932.5566), and the smallest standard deviation (0.0586). With a slightly higher average cost (17932.8416) and higher standard deviation (0.1926), GWO emerged as a strong contender. On the other hand, GA showed better results with a minimum cost of 17963.6191, even though its standard deviation was higher (9.2587). ACO demonstrates advantageous characteristics relative to PSO and the Bat Algorithm; yet, it displays reduced convergence speed and increased variability. Regarding computational duration, GA is the most rapid at 0.0554 seconds, followed by WOA at 0.0633 seconds. The computing length of OPA is 1.0397 seconds, a duration that aligns with its exceptional accuracy and stability. A boxplot study shows that OPA is more consistent with the most tightly shaped cost distribution that doesn't have any outliers, but GWO is also stable. Convergence research Fig. 5 shows that OPA gets to the best cost (∼17932) in just 10 iterations, which is faster than other methods. GWO and GA are also competitive, but not as reliable, options. These findings show that OPA is the most dependable and efficient method for addressing the ED problem involving 13 generators.

The sensitivity graph Fig. 6 of parameters p_1 and p_2 for ED over 13

Table 9
Actual output from the system's 15 generators

Algorithm	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
PSO	637	413	127	126	156	357	363	156	57	66	35	55	37	15	23
Bat algorithm	289	408	116	91	416	444	455	89	113	57	47	28	29	16	22
WOA	434	446	87	127	172	446	437	298	154	143	62	65	78	15	26
GWO	424	455	130	130	283	458	465	60	25	25	51	54	25	15	15
GA	429	366	120	119	222	458	455	71	90	90	49	70	28	16	39
ACO	381	444	130	130	169	444	444	60	60	46	80	80	46	55	55
OPA	454	454	129	129	271	459	464	60	25	25	41	58	25	15	15

Table 10
Economic Dispatch on 15 Generators

Algorithm	Minimum Cost	Mean	Std	Computation Time
PSO	32479.77291159878	32623.175772738516	64.57281947957246	0.1150459369023641
Bat Algorithm	32517.27926269168	32736.693165221626	92.45938874166197	0.10075624783833821
WOA	32274.77527602057	32417.488311981335	90.06626186968653	0.04204538663228353
GWO	32260.96554107122	32373.93983597075	246.29498176071982	0.20730963548024495
GA	32452.48462298998	32591.145301781602	59.11278287536433	0.05900542736053467
ACO	32536.403120208663	32688.53318748755	76.27128490028328	0.9935892422993978
OPA	32257.018569117114	32257.602241102897	0.3277700800721914	0.9067840178807577

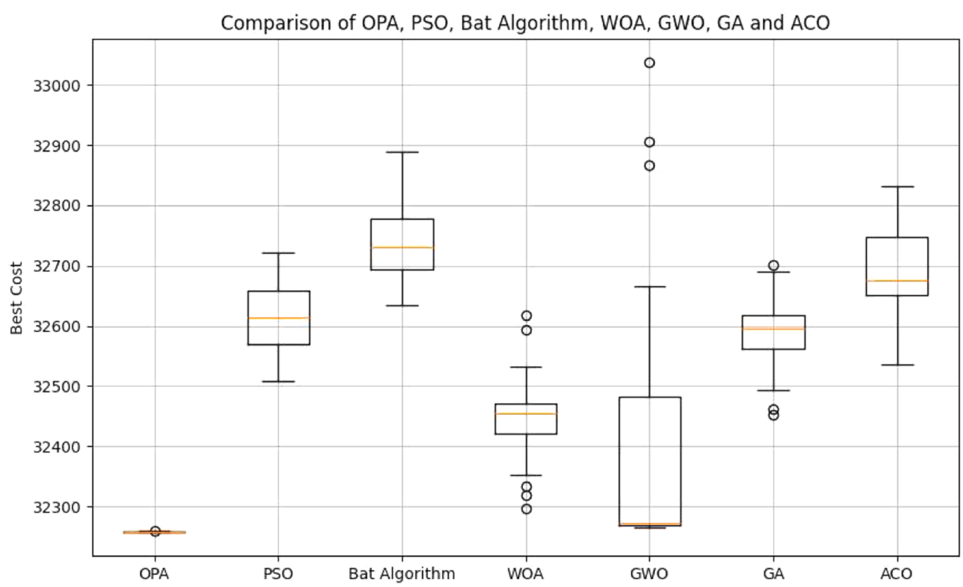

Fig. 7. Box Plot Comparison on 15 Generators

system units shows that the best cost changes depending on how p_1 and p_2 are combined. The experimental findings indicate that utilizing the parameter settings from Yuxin's work yields a maximum cost of 17932.495398652336, produced by the OPA method. Subsequent optimization yields a superior cost of 17932.485745827937, utilizing parameter values $p_1 = 0.9$ and $p_2 = 0.01$. The sensitivity graph indicates that within the range of p_1 from 0.2 to 0.4 and p_2 from 0.03 to 0.05, there is a notable variation in the optimal cost, with the most favorable outcomes occurring within these parameters. Simultaneously, as p_1 ascends to 0.9 and p_2 descends to 0.01, it is evident that the optimal cost diminishes, signifying that this parameter combination yields more stable and superior outcomes. The results of this 13-unit system demonstrate that the OPA algorithm can enhance its performance for solving economic dispatch problems in larger systems.

4.3. 15-unit system

The system consists of fifteen thermal units, and the specific parameters can be referenced in [16]. This test setting encompasses all the nonlinear features and practical limitations associated with the ED problem. The load demand is 2630 MW. Fig. 8

The investigation reveals that OPA is the most efficient method for the ED issue involving 15 generators Tables 9 and 10, boasting the lowest cost (32257.0186) and the most consistent average cost (32257.6022) with a minimal standard deviation (0.3278), thereby confirming its exceptional stability. GWO emerged as a viable alternative with a marginally elevated cost (32260.9655) but increased variability (246.2950), while WOA showed commendable performance (32274.7753), albeit with a lower consistency (90.0663). GA yielded competitive findings (32452.4846), although its standard deviation (59.1128) constrained its reliability. ACO outperforms PSO and the Bat Algorithm; nonetheless, its slower convergence and elevated standard deviation suggest reduced stability. On the other hand, PSO (32623.1758) and the Bat Algorithm (32736.6932) have high costs that change a lot, which proves that they are unstable. Regarding calculation time, WOA is the most rapid at 0.0420 seconds, followed by GA at 0.0590 seconds, whereas OPA requires more time at 0.9068 seconds due to its meticulous optimization procedure. Notwithstanding the increased

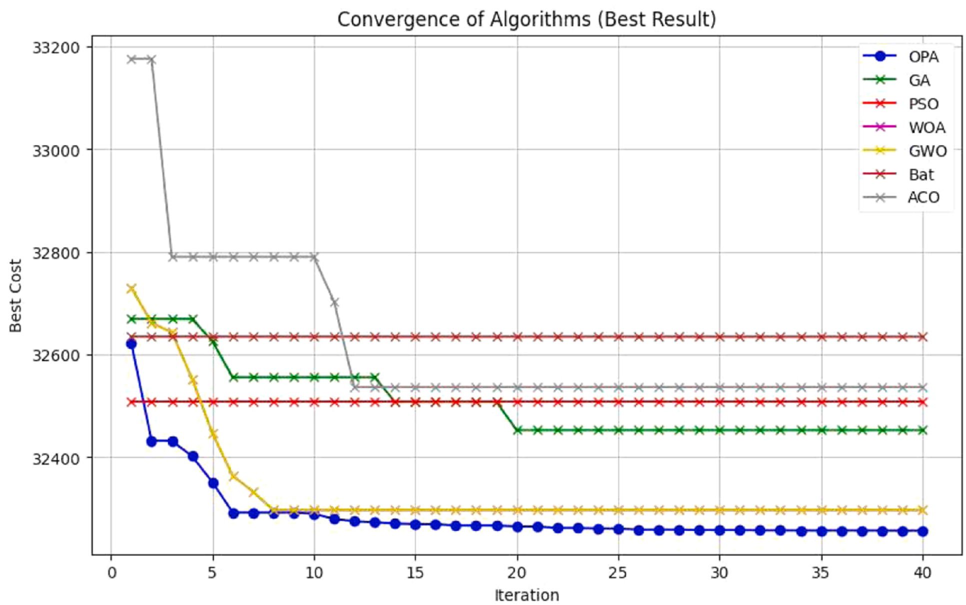

Fig. 8. Convergence curves on 15 Generators

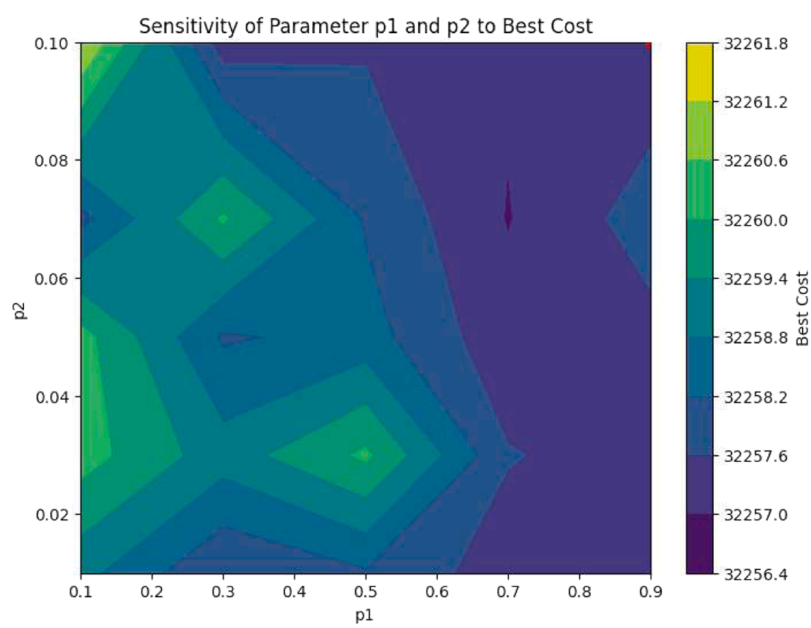

Fig. 9. Parameter Sensitivity Graph on 15 System Units

computing time, OPA typically yields improved outcomes, validating the trade-off. The boxplot study reinforces OPA's superiority, demonstrating the smallest cost distribution without outliers; hence, it affirms its exceptional consistency (Fig. 7). GWO exhibited stability with increased variability, whereas WOA, GA, and ACO demonstrated broader dispersion (Fig. 7). The PSO and Bat Algorithm exhibit the broadest distributions, indicating a deficiency in consistency. The convergence graph illustrates the efficacy of OPA, achieving optimal cost (∼32257) after 10 rounds (Fig. 8). GWO approaches convergence at approximately 32260 after approximately 15 iterations; however, it exhibits diminished consistency. WOA stabilized at approximately 32274 across 20 iterations, indicating moderate performance. GA and ACO exhibited slower convergence, stabilizing at around 32452 and 32536, respectively. The PSO and Bat Algorithm did not attain competitive prices, stabilizing at elevated values with negligible enhancement. These results show that OPA is the most reliable and effective way to solve the ED problem with 15 generators. It is better than all the other options in terms of correctness, stability, and convergence rate.

The sensitivity graph Fig. 9 of parameters p_1 and p_2 for ED over 15 system units shows that changing the parameters has a big effect on the optimal cost. Yuxin's essay's parameter values yielded an optimal cost of 32257.018569117114. Subsequent optimization yielded a reduced optimal cost of 32256.967447080402, achieved with parameter values $p_1 = 0.7$ and $p_2 = 0.07$. The graph shows that the optimal values for p_1 and p_2 are within the range of 0.7 and 0.07, respectively, allowing for cost minimization beyond the parameters presented in Yuxin's work. This proves that changing some parameters makes OPA algorithms work much better and more efficiently, especially for more complicated ED problems, as this 15-unit system shows.

5. Conclusion

This research shows that the Orca Predation Algorithm (OPA) consistently does a better job than other methods, such as PSO, the Bat Algorithm, WOA, GWO, GA, and ACO, when it comes to solving ED problems for systems with 6, 13, and 15 units in all possible configurations. OPA achieved the lowest cost, the most constant average cost, and the least fluctuation, confirming its remarkable stability and reliability. In the 6-unit system, OPA got the best price of $15,275.9305 very precisely, beating out its competitors because it had the lowest standard deviation and the fastest convergence. In the 13-unit system, OPA maintained the lead with an ideal cost of 17932.4954 and consistent performance, although GWO presented a viable alternative, albeit with slightly greater variability. In the 15-unit system, OPA worked amazingly well, getting the best results with the lowest cost (32257.0186) and the most consistent costs. This solidified its reputation as the most reliable algorithm. While GWO exhibited commendable convergence speed, its greater variability and certain outliers underscored the superior consistency of OPA. WOA and GA yielded competitive outcomes in certain instances; nonetheless, they exhibited inferior stability and precision compared to OPA. Simultaneously, ACO demonstrated superior performance compared to PSO and the Bat Algorithm, but with delayed convergence and increased variability. The PSO and Bat Algorithm consistently produced bad results with wide variation, proving that they are not useful for solving ED problems. Although OPA had outstanding performance, its computational duration surpassed that of alternative approaches. The remarkable precision and stability of OPA justify this trade-off. Researchers may find ways to get around this problem in the future by finding ways to speed up OPA's calculations through parallelization or hybrid methods. Also, looking into how OPA can be used in bigger, more complicated systems with cost functions that aren't convex can show how useful it is for real-world power system optimization.

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CRediT authorship contribution statement

Vivi Aida Fitria: Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Arif Nur Afandi:** Validation, Methodology. **Aripriharta:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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