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# Optimizing Economic Load Dispatch in Microgrids using Orangutan Optimization Algorithm

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***Abstract:-*** In recent years, the integration of renewable energy sources into microgrids has grown substantially, emphasizing the urgent need for efficient power generation management and cost optimization. To address this challenge, this paper introduces the Orangutan Optimization Algorithm (OOA) as an effective approach for solving the Economic Load Dispatch (ELD) problem in microgrids. A microgrid, comprising distributed energy resources and interconnected loads, functions as a coordinated system within well defined electrical boundaries. It incorporates diverse micro-sources such as distributed generators, solar photovoltaic units, and wind turbines, along with various types of loads. The proposed OOA is implemented in MATLAB to solve the ELD problem under different power demand scenarios across a 24 hour operating horizon. The simulation results reveal that OOA achieves notable cost reductions of about 25.83% compared to other benchmark algorithms, including the Whale Optimization Algorithm (WOA), Cuckoo Search Optimization (CSO), Differential Evolution (DE), and Particle Swarm Optimization (PSO). These findings confirm the superior effectiveness of the OOA in optimizing economic load dispatch in microgrid environments.

***Keywords:*** *ELD, Orangutan Optimization Algorithm, Optimization, Microgrid, Wind Turbine, Solar Power.*

## 1. Introduction

Microgrids are decentralized power systems designed to operate on a localized scale, typically serving specific communities or regions. They play a vital role in the generation, distribution, and regulation of electrical power between producers and consumers. By integrating distributed generation (DG) units, comprising renewable energy sources such as wind and solar power, along with conventional generation technologies, microgrids aim to minimize operational costs, reduce power losses, and lower infrastructure investment requirements [1]. According to a report by Markets and Data, the global microgrid market is projected to grow from an estimated USD 2.63 billion in 2025, expanding at a compound annual growth rate of approximately 14.56% through 2033. This robust growth is primarily driven by rapid urbanization, industrialization, and the increasing integration of renewable energy sources such as solar power, further supported by favorable government policies and rising investments in sustainable energy infrastructure.

To enhance the operational management of DG units and conventional power sources within a microgrid, the ELD approach can be utilized. ELD aims to optimally allocate power generation among available units to meet the system's total demand at the minimum operational cost, while simultaneously satisfying all technical and operational constraints [2]. However, achieving distributed economic load dispatch in microgrids poses considerable challenges due to the inherent variability and

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randomness of RES. Resources such as wind and solar power exhibit intermittent and non-dispatchable behavior, resulting in frequent fluctuations and uncertainties. These challenges are further amplified by forecasting errors arising from limitations in weather prediction models and data inaccuracies. In addition, technological factors, such as equipment efficiency variations and operational practices contribute to further uncertainty in system performance.

To mitigate these issues, researchers have employed various methodologies, including statistical and probabilistic approaches, scenario-based analysis, forecasting models, stochastic optimization, sensitivity analysis, and risk assessment techniques. Among these, Robust Optimization (RO) has emerged as an effective strategy for handling uncertainties in day-ahead scheduling. RO develops optimal operational strategies by considering potential worst-case scenarios, thereby ensuring reliable and cost-effective microgrid operations despite fluctuations in both energy generation and demand [3]. To overcome these challenges, controllable power sources such as utility grids, Energy Storage Systems (ESS), and diesel generator units can be strategically scheduled to complement the intermittent output of renewable energy sources during critical load conditions. Through the Point of Common Coupling (PCC), the microgrid integrates a network of distributed energy resources—including solar photovoltaic (PV) units, wind turbines, Combined Heat and Power (CHP) systems, and energy storage devices—to collectively supply electricity to various connected loads [4]. A significant advantage of a microgrid lies in its capability to effectively utilize renewable energy sources, resulting in reduced operational costs and enhanced power generation efficiency. Typically, a microgrid functions in two modes—grid-connected and islanded mode [5]. In the grid-connected mode, the PCC serves as the interface between the microgrid and the main utility grid. Conversely, in islanded mode, the microgrid operates autonomously, independent of the central grid.

Micro-source controllers are employed to regulate both the distributed generation units and the connected loads, ensuring stable operation. When isolated, the microgrid supplies power exclusively to critical loads, maintaining system reliability during grid disturbances. This operational flexibility enables microgrids to mitigate energy shortages and reduce transmission losses by integrating Distributed Energy Resources such as renewable-based micro-sources at multiple nodes across the network [6].

By leveraging diverse RESs, DER-integrated microgrids not only decrease the cost of electricity generation but also significantly reduce greenhouse gas emissions. Consequently, they ensure a steady supply of reliable, high-quality power to essential loads [7].

Furthermore, microgrids have proven to be an effective solution for reducing power losses, enhancing system reliability by preventing blackouts, and facilitating the integration of non-conventional energy sources supported by advanced control and management technologies [8–10].

Identifying the primary constraints in the power scheduling problem of a Microgrid Cluster (MGC) system is crucial to ensuring the system's overall reliability, stability, and operational efficiency [11]. These constraints are generally categorized into power balance constraints and equipment constraints.

The power balance constraints guarantee that the total generated power consistently equals the total load demand throughout the operation period. Maintaining this balance prevents both power shortages and excessive generation, thereby promoting stable and economical system performance [12].

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On the other hand, equipment constraints safeguard the system's operational integrity by ensuring that each component operates within its permissible technical limits. Adhering to these constraints helps maintain system stability, prevent equipment damage, and prolong the lifespan of critical assets [13].

Determining an optimal solution approach for the economic dispatch problem in MGCs has become a central topic in contemporary research, with a wide range of optimization algorithms explored to address this challenge. Traditional methods such as Linear Programming (LP) [14] and Nonlinear Programming (NLP) [15], though straightforward and computationally efficient, are inadequate for handling the increasing complexity, nonlinearity, and uncertainty inherent in modern power system architectures [16-18]. In recent years, Machine Learning (ML) techniques have gained significant traction in solving scheduling and optimization challenges within microgrids and MGCs [19]. Advanced deep learning models, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Deep Reinforcement Learning (DRL) frameworks, have demonstrated the ability to autonomously learn optimal operational strategies that enable MGs to adapt dynamically to changing environmental conditions and market fluctuations.

Despite their potential, these approaches often require large datasets, lengthy training processes, and high computational capacity, which can limit their practicality in real-time or resource-constrained applications [20]. In addition to classical optimization and Machine Learning approaches, metaheuristic algorithms have gained widespread application in MGC systems due to their strong capability to handle nonlinear, nonconvex, and multi-objective optimization problems efficiently. This study focuses on analyzing the ELD of a microgrid configuration using the OOA [21]. The considered microgrid setup comprises two diesel generators, two wind power units, and two solar photovoltaic units. The research develops the structural framework of the microgrid system and conducts a comprehensive assessment of key constraints, including those related to equipment capacity, energy storage, and power balance. The proposed approach seeks to achieve an optimal balance between economic efficiency and operational stability of the power system.

The remainder of this paper is organized as follows: Section 2 presents the Problem Formulation, offering a detailed description of the specific issue under investigation. Section 3 focuses on the OOA, providing an in-depth explanation of its working principles and implementation process. The system description is detailed in Section 4, simulation results and analysis are thoroughly discussed in Section 5. Finally, Section 6 concludes the paper by summarizing the key findings and highlighting the main implications of the study.

## 2. Problem Formulation

The objective of this research is to optimize the operation of a microgrid system comprising multiple generation sources, including conventional and renewable units, to minimize operational costs while meeting load demands and satisfying system constraints. The microgrid under consideration consists of two Diesel Generation Units (DGs), two Wind Turbine (WT) Units and two Solar Photovoltaic (PV) Units. The goal is to achieve cost-effective energy dispatch considering both economic and operational constraints. The following elements are considered in the problem formulation:

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### 2.1 Objective Function

The primary objective is to minimize the total operational cost of the microgrid over a planning horizon $T$:

$$\text{Minimize } C_{\text{total}} = \sum_{t=1}^{T}\left(C_{\text{DG}}(P_{\text{DG},t}) + C_{\text{WT}}(P_{\text{WT},t}) + C_{\text{PV}}(P_{\text{PV},t})\right) \quad (1)$$

Where:

- $C_{\text{DG}}(P_{\text{DG},t})$= Fuel cost of diesel generators at time $t$
- $C_{\text{WT}}(P_{\text{WT},t})$, $C_{\text{PV}}(P_{\text{PV},t})$= Operating costs of WT and PV units which is usually negligible but may include maintenance costs.
- $P_{\text{DG},t}, P_{\text{WT},t}, P_{\text{PV},t}$= Power outputs of respective units at time $t$

### 2.2 Power Balance Constraint

At each step, the total generated power must meet the microgrid load demand $P_{\text{load},t}$:

$$\sum_{i=1}^{2} P_{\text{DG},i,t} + \sum_{j=1}^{2} P_{\text{WT},j,t} + \sum_{k=1}^{2} P_{\text{PV},k,t} = P_{\text{load},t} \quad (2)$$

### 2.3 Generator Operating Constraints

Each diesel generator has minimum and maximum power output limits:

$$P_{\text{DG},i}^{\min} \leq P_{\text{DG},i,t} \leq P_{\text{DG},i}^{\max}, i = 1,2 \quad (3)$$

Similarly, WT and PV units are constrained by available renewable resources:

$$0 \leq P_{\text{WT},j,t} \leq P_{\text{WT},j}^{\text{avail}}, j = 1,2 \quad (4)$$

$$0 \leq P_{\text{PV},k,t} \leq P_{\text{PV},k}^{\text{avail}}, k = 1,2 \quad (5)$$

### 2.4 Ramp Rate Constraints (for DGs)

Diesel generators cannot change their output instantaneously beyond a certain ramp rate:

$$-R_{DG,i}^{down} \leq P_{DG,i,t} - P_{DG,i,t-1} \leq R_{DG,i}^{up} \quad (6)$$

### 2.5 Renewable Generation

The output from WT and PV units is uncertain and modeled based on historical wind speed and solar irradiance data:

$$P_{\mathrm{WT},j,t} = f_{\mathrm{wind}}(v_t) \tag{7}$$

$$P_{\mathrm{PV},k,t} = f_{\mathrm{solar}}(I_t) \tag{8}$$

Where $v_t$and $I_t$are the wind speed and solar irradiance at time $t$, respectively.

## 3. Orangutan Optimization Algorithm

The inspiration behind the OOA is clearly elaborated, followed by an in-depth explanation of the theoretical foundations of the method. Subsequently, the OOA's step-by-step procedure is systematically formulated through mathematical modeling, ensuring its effective applicability to a wide range of optimization problems.

### 3.1 Algorithm initialization

The OOA is a bio-inspired metaheuristic technique modeled on the natural behavior of orangutans. In this algorithm, each orangutan represents a candidate solution within the search space, where every individual occupies a distinct position defined by its decision variables. Collectively, these individuals form the OOA population.

The position of each orangutan is expressed as a matrix $P$, given in Eq. (9):

$$P = \begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ \cdot \\ Y_S \end{bmatrix}_{S\times D} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,D} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,D} \\ \vdots & \vdots & \ddots & \vdots \\ p_{S,1} & p_{S,2} & \cdots & p_{S,D} \end{bmatrix}_{S\times D} \tag{9}$$

Here, $S$denotes the number of orangutans (population size), and $D$represents the number of decision variables. Initially, the positions of all orangutans are generated randomly to ensure diversity within the search space, as shown in Eq. (10):

$$p_{j,d} = L_d + \epsilon \cdot (U_d - L_d) \tag{10}$$

where $L_d$and $U_d$are the lower and upper bounds of the $d^{th}$variable, and $\epsilon \in [0,1]$is a random number.

Each orangutan's fitness is then evaluated using the objective function $f(\cdot)$, represented by vector $F$in Eq. (12):

$$F = \begin{bmatrix} f(Y_1) \\ f(Y_2) \\ \vdots \\ f(Y_S) \end{bmatrix}_{S\times 1} \tag{12}$$

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Fitness values determine the quality of each solution. During each iteration, the best and worst orangutans are identified, and their positions are updated accordingly. This iterative process allows the OOA to balance exploration and exploitation, gradually converging toward the optimal solution.

### 3.2 Phase 1: Foraging Strategy

Foraging Phase of OOA- In nature, orangutans spend much of their time searching for food such as fruits and leaves. This extensive foraging results in wide-ranging movement and exploration across their habitat. In the OOA, this behavior is simulated to strengthen the algorithm's exploration ability, allowing it to efficiently scan the global search space.

During the first phase, each orangutan updates its position to mimic food-searching activity. Let $Q_{Fi}$denote the set of potential food source locations for the $i^{th}$orangutan, and $Z_p$represent an orangutan with a superior fitness value compared to the $i^{th}$individual.

The movement of each orangutan is modeled as:

$$z_{i,d}^{(1)} = y_{i,d} + \mu \cdot (Q_{Fi,d} - \eta \cdot y_{i,d}) \tag{13}$$

$$Y_i^{(1)} = f(x) = \begin{cases} Z_i^{(1)}, & \text{if } f(Z_i^{(1)}) \leq f(Y_i) \\ Y_i, & \text{otherwise} \end{cases} \tag{14}$$

Here,

- $z_{i,d}^{(1)}$is the updated value of the $d^{th}$variable for the $i^{th}$orangutan,
- $\mu$is a random number in [0,1],
- $Q_{Fi,d}$denotes the $d^{th}$dimension of a selected food source,
- $\eta \in \{1,2\}$is a random integer controlling movement intensity, and
- $f(\cdot)$represents the objective function.

If the new position $Z_i^{(1)}$yields a better fitness value, it replaces the previous position $Y_i$. This adaptive movement ensures continuous exploration of new areas, enhancing the search efficiency of the OOA.

### 3.3 Phase 2: Nesting Skill (Exploitation phase)

Nesting Phase of OOA- Besides foraging, orangutans display high intelligence through their nesting behavior, building nests daily in nearby trees using branches and leaves. This local activity represents a focused search in their surroundings. In the OOA, this behavior enhances exploitation, refining solutions and improving local search accuracy. In the second phase, each orangutan updates its position toward a nearby region to simulate nesting. The movement is defined as:

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$$z_{i,k}^{(2)} = y_{i,k} + (1 - 2\,\phi_{i,k}) \cdot \frac{U_k - L_k}{\tau} \tag{15}$$

$$Y_i = f(x) = \begin{cases} Z_i^{(2)}, & \text{if } f(Z_i^{(2)}) \le f(Y_i) \\ Y_i, & \text{otherwise} \end{cases} \tag{16}$$

where

- $z_{i,k}^{(2)}$ is the updated $k^{th}$ variable of the $i^{th}$ orangutan,
- $\phi_{i,k}$ is a random number within [0,1],
- $L_k$ and $U_k$ are the lower and upper bounds of the $k^{th}$ variable,
- $\tau$ is the current iteration number, and
- $f(\cdot)$ denotes the objective function.

If the new position $Z_i^{(2)}$ produces a better fitness value, it replaces the current position $Y_i$. This process improves local exploitation, guiding the search toward the optimal region efficiently.

## 4. System Description

The OOA has been employed to address the ELD problem within a microgrid environment. For this study, the hourly load demand profile given in Table 1 and corresponding wind speed data and irradiance for the selected day shown in Table 2 were sourced from [22]. In addition the cost coefficients and generation capacities of all distributed energy resources are given in Table 3. The operational wind turbine parameters—namely the cut-in speed (5 m/s), rated speed (10 m/s), cut-out speed (15 m/s), and the specific wind speed conditions—were also obtained from [22]. The irradiance levels required for modeling the photovoltaic generation units were similarly referenced.

Table 1. Hourly Demand Profile

| Time (hrs) | Load (kW) | Time (hrs) | Load (kW) |
|---|---|---|---|
| 1 | 718 | 13 | 1050 |
| 2 | 701 | 14 | 978 |
| 3 | 709 | 15 | 1003 |
| 4 | 720 | 16 | 1020 |
| 5 | 758 | 17 | 1024 |
| 6 | 770 | 18 | 1031 |
| 7 | 795 | 19 | 1048 |
| 8 | 996 | 20 | 1715 |
| 9 | 1342 | 21 | 1721 |
| 10 | 1502 | 22 | 1689 |
| 11 | 1494 | 23 | 1394 |
| 12 | 1410 | 24 | 1042 |

Table 2. Hourly Irradiance and Wind speed data

| Time (hrs) | Irradiance (W/m²) | Wind Speed (m/s) | Time (hrs) | Irradiance (W/m²) | Wind Speed (m/s) |
|---|---|---|---|---|---|
| 01 | 0.0 | 8.634 | 13 | 815.881 | 7.456 |
| 02 | 0.0 | 8.132 | 14 | 818.287 | 4.543 |
| 03 | 0.0 | 7.876 | 15 | 732.597 | 5.003 |
| 04 | 0.0 | 6.132 | 16 | 565.549 | 5.453 |
| 05 | 0.0 | 9.356 | 17 | 455.152 | 6.875 |
| 06 | 32.177 | 4.1 | 18 | 139.981 | 7.011 |
| 07 | 203.341 | 4.568 | 19 | 37.669 | 6.653 |
| 08 | 406.681 | 5.731 | 20 | 0.0 | 7.875 |
| 09 | 575.917 | 4.122 | 21 | 0.0 | 7.943 |
| 10 | 733.158 | 5.134 | 22 | 0.000 | 5.642 |
| 11 | 872.775 | 5.456 | 23 | 0.000 | 6.624 |
| 12 | 737.838 | 6.765 | 24 | 0.000 | 6.112 |

Table 3. Cost Coefficients and Generation Capacities

| Generator Type | a | b | c | Minimum Power (KW) | Maximum Power (KW) |
|---|---|---|---|---|---|
| Diesel Gen. 1 | 0.007 | 0.233 | 0.433 | 0 | 400 |
| Diesel Gen. 2 | 0.004 | 0.145 | 0.273 | 0 | 800 |
| Wind 1 | 0 | 0 0.022 | 0 | 0 | 300 |
| Wind 2 | 0 | 0.032 | 0 | 0 | 300 |
| Solar 1 | 0 | 0.018 | 0 | 0 | 40 |
| Solar 2 | 0 | 0.014 | 0 | 0 | 40 |

## 5. Results and Discussion

The resulting optimal generation schedule derived using the OOA, along with the corresponding total operational cost, is summarized in Fig. 1. The generation profile indicates a balanced hybrid operation of the microgrid, where diesel generators and renewable resources complement each other to meet hourly demand. The diesel generators show noticeable variability, with Pdiesel1 maintaining moderate generation throughout the day and increasing output during certain hours to meet system demand. Pdiesel2, in contrast, exhibits pronounced peaks at hours 10, 12, 20, and 21**,** indicating that it is likely dispatched during periods of higher load or low renewable availability. These sharp increases highlight their role as a flexible and responsive generation unit.

Wind generation from Pwind1 and Pwind2 remains consistently present, though with varying magnitudes across the day. Both wind units contribute modestly during early hours, rise moderately around late morning, and continue offering steady support through the evening. The presence of continuous wind output indicates its importance as a reliable renewable resource, despite natural fluctuations.

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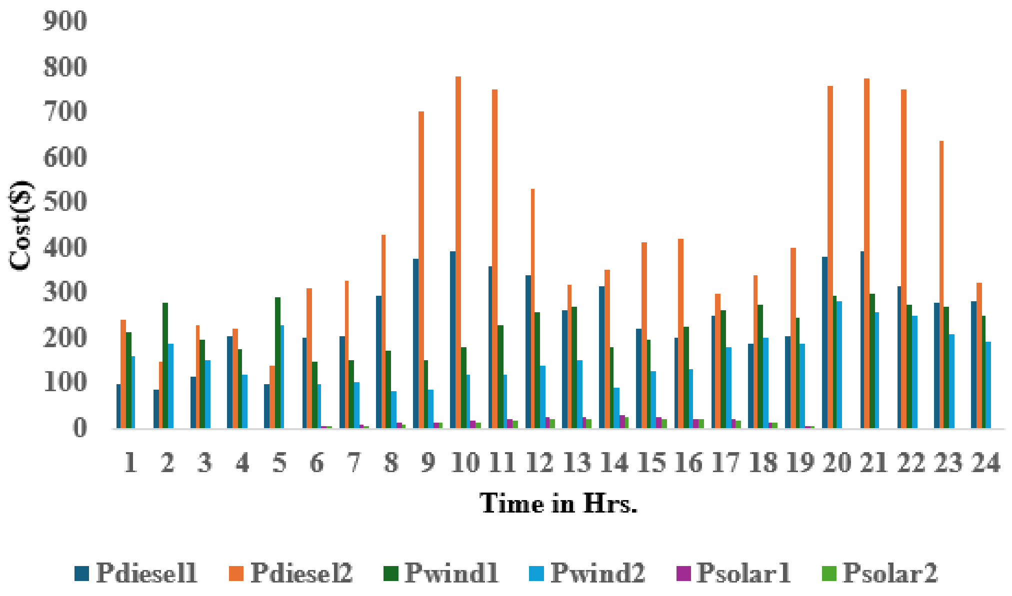

Fig. 1 Optimal Generation Schedule of Energy Sources for 24 Hours

Solar generation follows the expected diurnal pattern: Psolar1 and Psolar2 remain at zero during nighttime hours and begin producing power from hour 6 onward. Their output increases steadily, peaking between hours 10 to 14**,** before tapering off toward sunset. Compared to wind and diesel, the solar contribution is relatively modest, suggesting either lower solar irradiance or a smaller installed photovoltaic capacity.

Overall, the generation reflects a well-coordinated hybrid microgrid where diesel units provide essential dispatchable support to maintain system balance, while wind and solar resources contribute significantly during their respective availability periods. The combined renewable output reduces diesel dependency during mid-day but requires diesel ramp-up during early morning, late evening, and periods of lower renewable generation. This pattern underscores the importance of robust scheduling strategies and optimization techniques to ensure reliable and cost-effective operation of the microgrid.

This variability underscores the importance of smart scheduling, potential integration of energy storage, and the use of effective economic dispatch optimization techniques to achieve cost-efficient and stable microgrid operation.

Table 4. Comparative Cost Analysis

| **Optimization Algorithm** | **OOA** | **WO** | **CS** | **DE** | **PSO** |
|---|---|---|---|---|---|
| **Cost ($)** | 42448 | 56313 | 56382 | 57102 | 57236 |

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The comparative assessment of the simulated results is presented in Table 4, and it shows that OOA has obtained the least cost. Furthermore, Fig. 2 illustrates the convergence characteristics of PSO, CSA, DE, WOA, and OOA. The convergence trends reveal that OOA rapidly approaches near-optimal solutions in the early iterations. The analysis also shows that WOA exhibits strong robustness with respect to initial population settings and consistently surpasses the performance of the other metaheuristic algorithms reported in the literature.

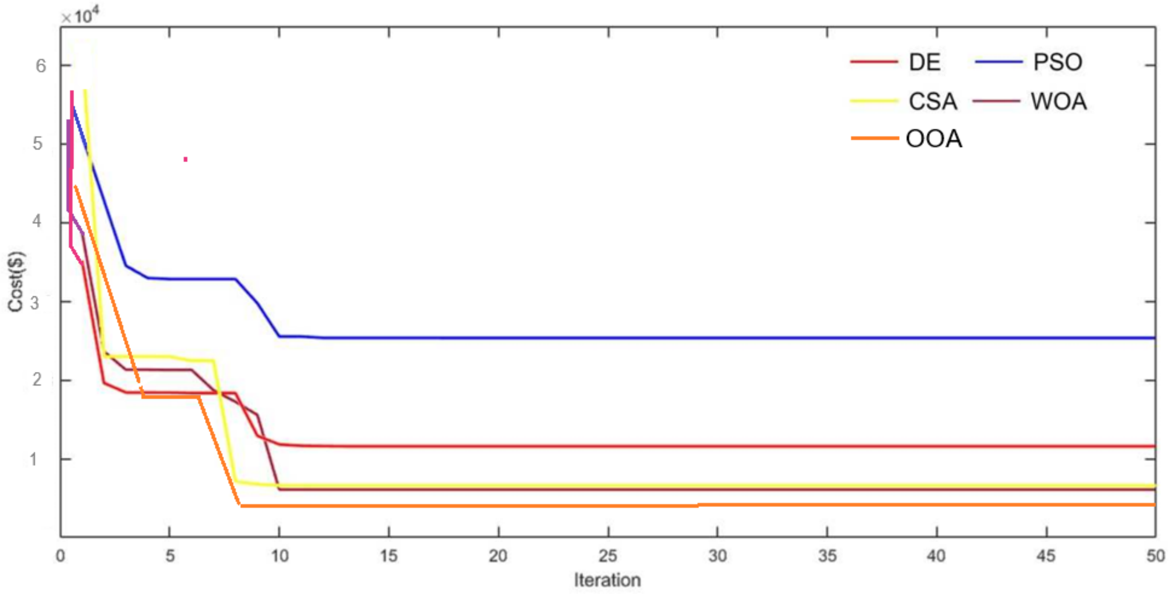

Fig.2 Comparative Convergence Curve for different Algorithms

## 6. Conclusion

This study has demonstrated the effectiveness of the OOA for solving the Economic Load Dispatch problem in renewable-integrated microgrids. Implemented over a 24-hour operating horizon, the proposed method successfully coordinates diesel generators with wind and solar resources to achieve a balanced and cost-efficient generation schedule. Comparative analysis shows that OOA attains the minimum operational cost of $42,448, yielding an average cost reduction of about 25.83% compared with PSO, DE, CS, and WOA. The rapid convergence and superior solution quality of OOA highlight its strong exploration–exploitation capability and robustness in handling the nonlinear and constrained nature of microgrid ELD problems. From an engineering perspective, the proposed approach offers a practical and computationally efficient tool for optimal scheduling of hybrid microgrids, enabling improved economic performance while maintaining system reliability under variable renewable generation.

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Future work can extend the proposed framework by incorporating energy storage systems, emission minimization objectives, and demand response programs to further enhance operational flexibility and sustainability. Additionally, the inclusion of stochastic modeling for renewable sources, electric vehicle integration, and real-time or market-based pricing mechanisms would improve the applicability of OOA to real-world smart microgrid operation and planning.

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