International Journal of Scientific Engineering and Science
Volume 8, Issue 8, pp. 8-16, 2024. ISSN (Online): 2456-7361

# Optimal Sizing of Solar Off Grid Microgrid Using Modified Firefly Algorithm

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***Abstract***— *This paper presents a novel approach for determining the optimal sizing of solar off-grid microgrids through the utilization of a modified Firefly Algorithm (FA). Off-grid microgrids, powered primarily by solar photovoltaic (PV) systems, offer a sustainable solution for providing electricity to remote areas. However, the optimal design and sizing of such microgrids remain a challenging task due to the dynamic nature of renewable energy sources and varying energy demands. In this study, a Modified Firefly Algorithm (MFA) has been designed especially for optimizing the sizing of solar off-grid microgrids. MFA improves the convergence speed and solution quality, even in a complex multi-objective optimization problem. The effectiveness of the proposed approach is demonstrated through a case study involving the design and optimization of a solar off-grid microgrid. Comparative analysis with standard firefly algorithm (FA) illustrates that Modified Firefly Algorithm (MFA) achieves optimal sizing solutions with improved efficiency and accuracy. The findings of this research contribute to advancing the design and implementation of sustainable energy solutions powered by renewable energy sources.*

***Keywords***— *Convergence Speed, Modified Firefly Algorithm, Optimization, Renwable Energy, Sizing Microgrid.*

## I. Introduction

The increasing demand for reliable and sustainable energy solutions has increased interest in off-grid microgrids powered by solar photovoltaic (PV) systems. These microgrids offer a good alternative for providing electricity to remote areas and underserved communities where access to the main power grid is limited or non-existent [1], [2]. However, the design and optimization of solar off-grid microgrids is challenging due to the intermittent of energy sources and the variation in energy demands. Al-Shahri, et al. [3] presented a comprehensive review of challenges and issues in optimization of PV systems. Size Optimization of photovoltaic (PV) systems has several challenges that include:

a) Limited available space, especially in urban areas or on existing structures like rooftops, can restrict the size of PV systems and make optimization challenging.
b) Determining the optimal size requires accurately estimating energy demand, which can vary seasonally, daily, or even hourly, depending on factors such as weather, and energy-consuming activities.
c) As the size of the PV system increases, the complexity of design, installation, and maintenance also grows, requiring more sophisticated engineering and management solutions.
d) Solar energy generation is intermittent and variable due to factors such as cloud cover, and shading making it challenging to accurately predict the optimal system size to match energy demand.
e) Balancing the upfront costs of installing a larger PV system with the long-term benefits of increased energy production and savings can be challenging, especially when considering factors such as financing options, incentives, and payback periods.
f) The efficiency and performance of PV technology may impose limitations on the size optimization of PV systems, as higher efficiency panels or advanced technologies may be more expensive or less readily available.
g) Larger PV systems may require more frequent maintenance and operational monitoring to ensure optimal performance, adding to the overall complexity and cost of system optimization.

Achieving optimal sizing of components such as solar panels, batteries, and inverters is crucial to ensure the cost effectiveness, reliability and performance of these microgrid systems. Mathew, Mobi, et al. [4] presented a comprehensive review of various methods for sizing approaches for PV systems.

The optimal design of PV systems has important implications for the design and implementation of sustainable energy solutions. This will pave the way for the widespread use of solar-powered microcomputers as an efficient way to power remote and remote locations.

Ridha, et al. [5] presented the advantages of optimized PV system. Optimizing the design of photovoltaic (PV) systems can offer numerous advantages, including:

a) Optimized designs ensure that the PV system is configured to capture the maximum amount of sunlight available at a specific location, leading to higher energy generation.
b) By fine-tuning the design parameters such as panel orientation, tilt angle, and system layout, efficiency can be maximized, resulting in better overall performance.
c) Optimized designs can help reduce overall system costs by minimizing unnecessary components, optimizing the use of materials, and maximizing energy production per unit cost.
d) Higher energy production and lower costs result in improved Return on Investment, making the investment in PV systems more financially attractive over the system's lifespan.
e) Optimal design ensures efficient use of available space, whether it's a rooftop, ground area, or integrated into building architecture, allowing for the installation of more panels and increased energy output.
f) A well-designed PV system considers factors such as weather conditions, shading, and system layout to minimize

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Volume 8, Issue 8, pp. 8-16, 2024. ISSN (Online): 2456-7361

potential sources of degradation or failure, leading to increased reliability and longevity.

g) Optimal designs are often scalable and can be adapted to various scales and applications, allowing for flexibility in system size and configuration based on specific needs and constraints.
h) Optimized PV designs can be seamlessly integrated with energy storage systems, allowing for better utilization of generated energy and increased self-consumption, further enhancing the economic viability of solar power.

## II. Literature Review

Researchers have developed numerous problem-solving techniques for solving complex engineering problems. In general, these methods can be divided into two main categories i.e. heuristics and meta-heuristics. Heuristics are problem-solving techniques that aim to find satisfactory solutions quickly when an exhaustive search is impractical. They are practical rules of thumb that guide decision-making processes, often relying on experience, intuition, or common sense rather than a systematic algorithmic approach. Heuristics are useful in situations where finding an optimal solution is computationally expensive or impossible.

Metaheuristics, on the other hand, are higher-level strategies used to optimize heuristic methods [6]. They provide a framework for guiding the exploration of the solution space, often borrowing concepts from nature, such as genetic algorithms, simulated annealing, or particle swarm optimization. Metaheuristics offer a more systematic approach to problem-solving compared to heuristics alone, enabling the efficient exploration of large solution spaces and the discovery of near-optimal solutions for complex problems [7]. Fig. 1 shows some well-known heuristic and meta heuristic techniques from the literature.

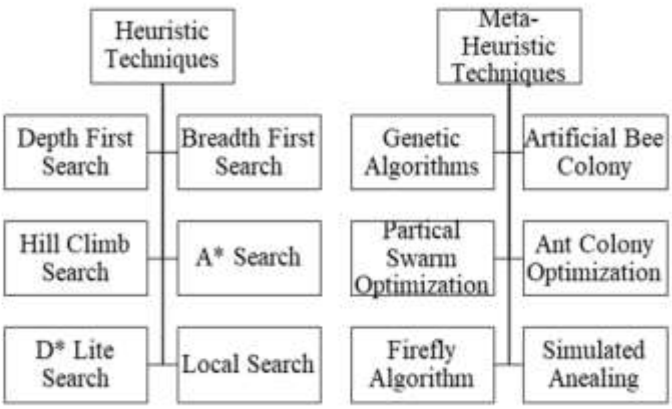


Fig 1. Problem Solving Techniques.

Traditional methods for sizing off-grid microgrids often rely on heuristic approaches or simulation-based techniques. Fioriti, Davide, et al. [8] and Bektas, Zeynep, et al. [9] presented heuristic approaches to size microgrid while considering multiple design options. These options may not always result in the most efficient or cost-effective solutions. To address this issue, optimization algorithms have emerged as powerful tools for determining the optimal configuration of microgrid components.

Khan, Baseem, et al. [10] presented a comprehensive analysis for selecting meta heuristic technique to smart microgrid optimization problem. Gao, Kaiye, et al. [11] well elaborated the optimization of microgrid operation along with its sub components. They also highlighted that genetic algorithms and simulated annealing algorithms are the most commonly used optimization algorithms for microgrid operations. S. Leonori, et al. [12] used genetic algorithm for optimization of energy management of microgrid. Diab, Ahmed A. Zaki, et al. [13] presented to minimize the cost of energy (COE) supplied by the system while increasing the reliability and efficiency of the system due to the loss of power supply probability (LPSP). [13] compared results of Whale Optimization Algorithm (WOA), Water Cycle Algorithm (WCA), Moth-Flame Optimizer (MFO), and Hybrid particle swarm-gravitational search algorithm (PSOGSA) for designing the optimized microgrid.

Among these algorithms, the Firefly Algorithm (FA) has garnered attention for its ability to efficiently solve complex optimization problems inspired by the flashing behavior of fireflies in nature. Vasanth, J. Deepak, et al. [14] used firefly algorithm for minimization of operational cost of a microgrid. Ibrahim, Ibrahim M.et al. [15] integrated Particle Swarm Optimization (PSO) with Firefly Algorithm (FA) i.e. a hybrid form of firefly algorithm for finding optimal size of microgrid system. Problem is implemented in MATLAB and the main objective of the proposed study is to obtain the optimal size of the MG system which minimizes the total costs and the total emissions. Yang, YuDe et al. [16] presented an improved meta heuristic optimization algorithm based on the firefly algorithm, called multidimensional firefly algorithm (MDFA), for solving day-ahead scheduling optimization in a microgrid.

Based on the literature review, it has been observed that firefly algorithm has gathered immense attention of researchers for solving multiple problems related to microgrid parametric optimization. This paper introduces a novel approach for the optimal sizing of solar off-grid microgrids using a modified Firefly Algorithm. The proposed algorithm is tailored to address the specific challenges associated with optimizing the design of off-grid microgrids, including the integration of multiple objectives such as system cost, reliability, and performance. By leveraging the unique characteristics of the Firefly Algorithm and incorporating enhancements to improve convergence speed and solution quality, the proposed approach aims to overcome the limitations of existing optimization techniques and provide more accurate and efficient solutions.

Through a comprehensive case study, this research demonstrates the effectiveness of the modified Firefly Algorithm in optimizing the sizing of solar off-grid microgrids. Comparative analysis with other optimization methods showcases the superiority of the proposed approach in achieving optimal solutions that meet the diverse requirements of off-grid electrification projects. The findings of this study have significant implications for the design and implementation

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of sustainable energy solutions, paving the way for the widespread adoption of solar off-grid microgrids as a viable means of electrifying remote and off-grid communities.

## III. PROBLEM FORMULATION

Problem formulation and modeling for size optimization of a microgrid PV system involves defining the key variables and constraints to achieve optimal performance, considering the subsystems of the PV system [17]. These subsystems typically include photovoltaic panels, inverters and batteries or possibly backup generators [18]. Each subsystem introduces its own set of parameters and limitations that are integrated into the optimization model. For instance, the capacity and efficiency of the photovoltaic panels, the efficiency and power rating of the inverters, the storage capacity and efficiency of the batteries, and the constraints on backup generator usage all influence the overall system design. Balancing these factors requires careful consideration of the interplay between energy generation, storage, and distribution within the microgrid, aiming to maximize efficiency, minimize costs, and ensure reliable power supply under various operating conditions [19]. PV system has been modeled using following equations from [20].

The output power of a PV module is estimated from (1) based on the solar irradiation at time t, and the efficiency of the PV module is given by (2).

$$P_{PV}(t) = \eta_{PV}.A_{PV}.G(t) \quad (1)$$

$$\eta_{PV} = \eta_{STC}.\eta_{MPPT}[1-\alpha(T_C - T_{ATC})] \quad (2)$$

where $A_{PV}$ is the area of a PV module in (m2 ), G(t) is the hourly total solar irradiance in (W/m2 ), $\eta_{PV}$ is the efficiency of the PV array, $\eta_{STC}$ is reference efficiency of the PV cell at standard temperature condition (STC), $\eta_{MPPT}$ is the efficiency of the maximum peak power tracker, $T_C$ is the temperature of the PV cell in (˚C), $T_{STC}$ is the reference temperature of the PV cell at STC (25˚C), and α is the temperature coefficient of the PV cell (typically 0.4%/˚C – 0.6%/˚C for silicon cells).

The discharging and charging energies of the ESS at time t can be obtained from (3) and (4), respectively.

$$E_{ESS}^{d}(t) = E_{ESS}(t-1) - \frac{[E_{Load}(t) - E_{PV}(t) - E_{WT}(t)]}{\eta_d} \quad (3)$$

$$E_{ESS}^{c}(t) = E_{ESS}(t-1) + [E_{PV}(t) + E_{WT}(t) - E_{Load}(t)].\eta_c \quad (4)$$

where $E_{ESS}(t-1)$ is the energy at time $t-1$ in (kWh); $E_{PV}, E_{WT}, E_{Load}$ are the PV energy, WT energy and load energies, respectively; $\eta_d$ and $\eta_c$ are the discharge and charge efficiencies of the ESS, respectively.

Loss of power supply (when demand exceeds the energy generated) can be expressed as:

$$LPS(t) = P_{Load}(t) - [P_{PV}(t) + P_{WT}(t) + P_{ESS}^{d}(t)].\eta_{inv} \quad (5)$$

where $\eta_{inv}$ is the efficiency of the inverter. The Loss of Power Supply Probability (LPSP) for a given time period T can be defined as the ratio of all LPS (t) values for that period to the sum of the load demands as in (6).

$$LPSP = \frac{\sum_{t=0}^{T} LPS(t)}{\sum_{t=0}^{T} P_{Load}(t)} = \frac{\sum_{t=0}^{T} Power\ Failure\ Time}{T} \quad (6)$$

After the modeling PV systems, firefly and modified firefly algorithm [21] has been used to find the optimum solution for the desired problem. For firefly algorithm, the main update formula for any couple of two fireflies i and j at $x_i$ , $x_j$ , is:

$$x_i^{Itr+1} = x_i^{Itr} + \beta\left(x_i^{Itr} - x_j^{Itr}\right) + \alpha\epsilon_i^{Itr} \quad (7)$$

where α is a parameter controlling the step size, $\beta = \beta_0 e^{-\gamma r^2}$ is the attractiveness with $\beta_0$ represents the attractiveness at distance $(r=0)$ and $\gamma$ represents the light absorption coefficient. $\epsilon_i$ is randomization where the vector of random variables being drawn from a distribution (e.g., Gaussian distribution). The distance between any pair of fireflies i and j at $x_i$ , $x_j$ , can be the Cartesian distance $r_{ij}$.

These equations show that FA is dependent upon three tunable parameters i.e. $\alpha, \gamma$ and $\epsilon$. It is too difficult to tune these parameters manually. In modified FA, these parameters are updated adaptively. In this case tunable parameters can be calculated using the following equations.

$$\alpha(Itr_i) = \exp\left(1 - \left(\frac{Itr_{max}}{Itr_{max} - Itr_i}\right)^c\right) \quad (8)$$

$$\beta = \beta_0 e^{-\gamma r^2} \quad (9)$$

$$r = \|x_i - x_j\| \quad (10)$$

$$\gamma(Itr_i) = 1 - \exp\left(1 - \left(\frac{Itr_{max}}{Itr_{max} - Itr_i}\right)^c\right) \quad (11)$$

where c represents the integer number to determine the speed of decaying. In the search process, two updating equations are explained and chosen randomly and are presented as:

$$x_{i+1} = \begin{cases} \beta(i)x_i + x_j(1-\beta(i)) + \alpha(i)\epsilon_i & rand > 0.5 \\ \frac{NG-i}{NG}(1-\delta)x_i + \delta x_{best} & Elsewhere \end{cases} \quad (12)$$

where δ represents the gray coefficient and NG is the number of generations.

TABLE I, TABLE II and TABLE III show the key parameters of PV panels, inverter and BSS of microgrid system.

TABLE I. PV parameters.

| Parameter | Value | Units |
|---|---|---|
| Area of Panel | 2.9094 | m2 |
| Rated Capacity | 0.66 | KW |
| Temperature Coefficient | -0.34 | % / C |
| Operating Temperature | 43 | C |
| Efficiency | 0.2125 | % |
| Panel Lifetime | 25 | Years |
| Capital Cost | 147 | $/KWh |
| Replacement Cost | 110 | $/KWh |
| Operational / Maintenance Cost | 10 | $/Year |

TABLE II. Inverter parameters.

| Parameter | Value | Units |
|---|---|---|
| Capacity | 100 | KWh |
| Lifetime | 25 | Year |
| Capital Cost | 280 | $ |
| Replacement Cost | 280 | $ |
| Operational / Maintenance Cost | 10 | $/KW |
| Loss of Power Supply Probability (LPSP) | 0.01,0.1 | --- |

TABLE III. BSS parameters.

| Parameter | Value | Units |
|---|---|---|
| Nominal Voltage | 600 | V |
| Nominal Power Capacity | 100 | KWh |
| Nominal Current Capacity | 167 | Ah |
| Round Trip Efficiency | 90 | % |
| Maximum Charge Current | 167 | A |
| Initial State of Charge | 100 | % |

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| | | |
|---|---|---|
| Minimum State of Charge | 20 | % |
| Maximum Discharge Current | 500 | A |
| Lifetime | 5 | Year |
| Capital Cost | 100 | $/KW |
| Replacement Cost | 100 | $/KW |
| Operational / Maintenance Cost | 10 | $/KW |

## IV. PROPOSED ALGORITHM

The goal is to minimize the total cost of the microgrid configuration, including initial investments and operational expenses, while ensuring system reliability through a low Loss of Power Supply Probability (LPSP). Amara, et al. [22], Azaza, et al. [23] and Huang et al. [24] used LPSP as a technical reliability criteria while optimizing microgrid sizing. The challenge lies in the complex, nonlinear nature of the problem, influenced by variable energy demands, renewable energy supply and many other operational and technical challenges as highlighted by Azeem, et al. [25], Saeed, et al. [26] and Choudhury, et al. [27].

The FA mimics the attraction behavior of fireflies, where each firefly represents a potential solution, moving towards brighter ( more optimal) [28]. The algorithm's simplicity is balanced by its innovative approach to solution search, with attractiveness based on the inverse of the objective function (total cost) [29]. TABLE IV shows the pseudocode of standard firefly algorithm.

TABLE IV. Pseudocode for standard firefly algorithm.

```
function FireflyAlgorithm(problem) returns a solution
  X ← initialize fireflies with random state
  for each Gen do
   for each i^th Firefly do
   for each j^th Firefly do
    if fitness(i^th Firefly) > fitness(j^th Firefly) then
        r ←  Euclidian distance b/w i^th and j^th firefly
        β ←  Attractiveness based on r
        step ←Calculate step size based on α
        p ←random number b/w 0~1
        if p > 0.5 then Update firefly position based on β
        else Update firefly position based on bestfitness
            Update fitness of i^th firefly
                Solution ←firefly with best fitness
   return solution
```

Khan, et al. [29], Kumar, et al. [30] and Tilahun, et al. [31] presented a comprehensive review on firefly algorithm and its modified form that researches proposed for enhancing FA performance. Enhancing the standard FA, the MFA incorporates additional strategies like local search mechanisms to improve solution quality and convergence speed. This approach is designed to address the FA's limitations, such as premature convergence and exploration inefficiency. Fig. 2 shows the flowchart of standard FA along with proposed MFA.

## V. RESULTS AND DISCUSSIONS

Several parameters govern the functioning of firefly algorithm, each playing a crucial role in determining its efficiency and effectiveness. The *light absorption coefficient* (γ) regulates the attractiveness of fireflies towards each other, influencing their movement towards brighter individuals in the search space. The attractiveness can be adjusted to control exploration and exploitation, balancing the exploration of new regions with the exploitation of promising solutions. The *step size coefficient* (α) controls the degree of randomness in fireflies' movement, allowing for a balance between exploration and exploitation. Additionally, the *population size* and *maximum number of iterations* are crucial parameters that affect the algorithm's convergence and computational efficiency. Fine-tuning these parameters is essential to achieve optimal performance in solving various optimization problems.

Fig. 3 illustrates the system configuration where FA and MFA were applied to optimize the system using load and meteorological data obtained from previous research [32].

In this study, two scenarios were examined based on the LPSP values of 0.01 and 0.1. Both scenarios utilized identical initial settings for the algorithms, including the number of fireflies, problem dimensions, and maximum generations as detailed in TABLE V.

TABLE V. Algorithm parameters

| Parameter | Value |
|---|---|
| Number of Fireflies | 20 |
| Problem Dimensionality | 2 |
| Maximum Generations | 30 |
| Lower Bound of Decision Variable | 1 |
| Upper Bound of Decision Variable | 6000 |
| Attractiveness at r=0 ($\boldsymbol{\beta_0}$) | 1 |
| Light Absorption Coefficient ($\boldsymbol{\gamma}$) | 0.1 |
| Step Size Coefficient ($\boldsymbol{\alpha}$) | 0.2 |
| c | 1 |
| Gray Coefficient (δ) | 0.5 |

The distinction lies in the MFA's integration of a local search phase post-movement, aiming to refine solutions and potentially escape local optima. A similar concept for integration of harmony search with firefly algorithm has also been used by Satapathy, et al. [33] for solving an optimization problem in same field of microgrids.

The performance of the microgrid, optimized using the FA and MFA for both scenarios with LPSP values of 0.01 and 0.1, is captured in Fig. 4, Fig. 5, Fig. 6, and Fig. 7 respectively. Figures depict the interplay between photovoltaic generation, demand, and battery storage over time. PV generation indicated by blue crosses, reflects the output from the solar panels.

The spikes in generation correspond to daylight hours, showing significant variability that is typical for solar energy, which is dependent on sunlight conditions. Demand, shown with red circles, represents the energy required by the connected load. It appears fairly constant over time, with some variations indicating peak usage periods or variable loads within the microgrid. Battery status, illustrated with green line, indicates the energy stored in the system's batteries. The charging and discharging cycles are evident as the status fluctuates, often decreasing during high demand or low PV generation periods and increasing when excess energy is available.

TABLE VI provides a comparative analysis of the performance of the FA and MFA in optimizing a solar off-grid microgrid system under the two different scenarios based on

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ISSN (Online): 2456-7361

LPSP values. It presents key metrics for each case and algorithm, including the number of PV units, BSS units, converters, total cost, and the number of iterations that are required to reach the optimal solution.

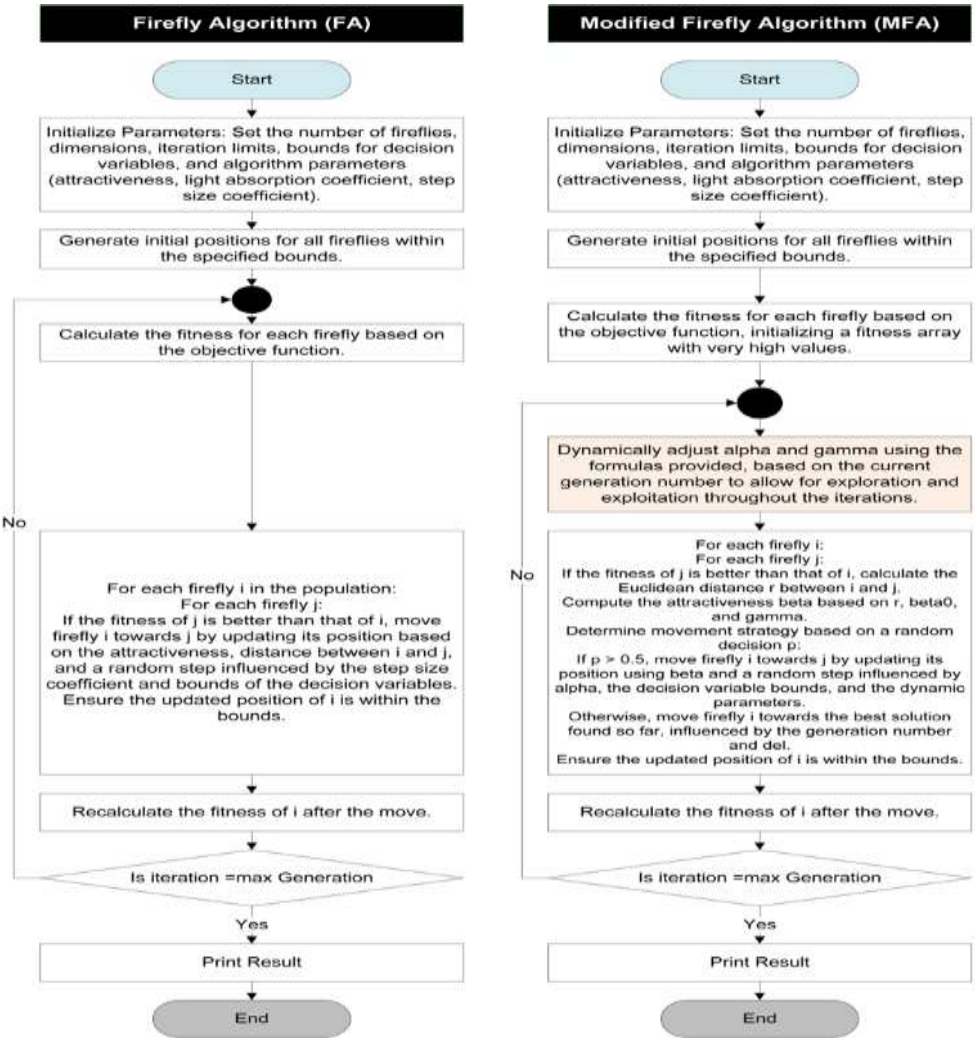

Fig. 2. FA and proposed MFA flowchart.

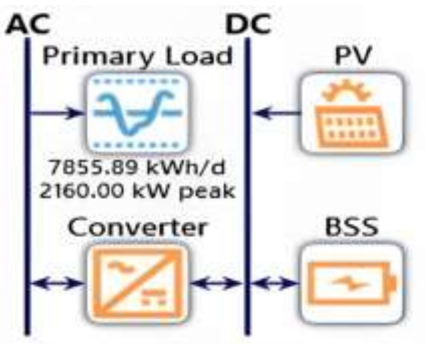

Fig. 3. System configuration.

In Case 1, with an LPSP of 0.01, the MFA required fewer photovoltaic units, battery storage units, and converters, resulting in a lower total cost ($3,917,511) and 15 iterations compared to the Standard FA. Similarly, in Case 2, with an LPSP of 0.1, the MFA again outperformed the Standard FA, achieving cost savings ($2,360,733) and efficiency improvements with fewer components and less iterations. These results demonstrate the ability of MFA to optimize microgrid configurations. Fig 8 (a), (b) and Fig 9 (a), (b) show the iteration for the two cases.

The MFA consistently outperformed the standard FA in finding lower-cost configurations for the microgrid. Key observations include:

a) Enhanced Exploration and Exploitation: The MFA's hybrid nature allowed for a more comprehensive exploration of the search space and a more effective exploitation of promising regions.
b) Diversity Preservation: By incorporating local searches, the MFA maintained solution diversity, reducing the risk of premature convergence.
c) Adaptability: The flexibility of the MFA to incorporate problem-specific knowledge or additional optimization

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techniques proved advantageous in navigating the complex optimization landscape of microgrid systems.

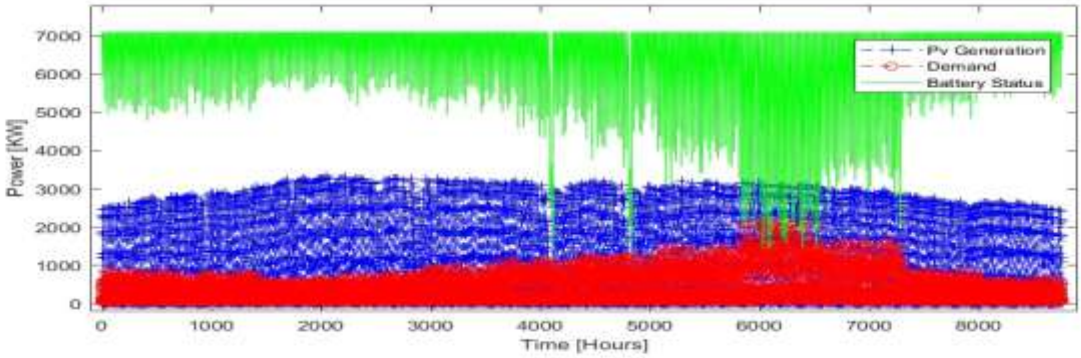

Fig. 4. System performance of Standard FA with LPSP = 0.01.

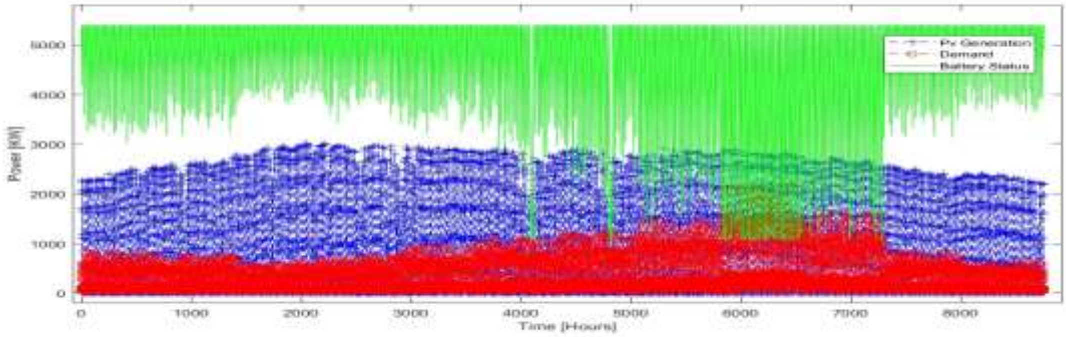

Fig. 5. System performance of MFA with LPSP = 0.01

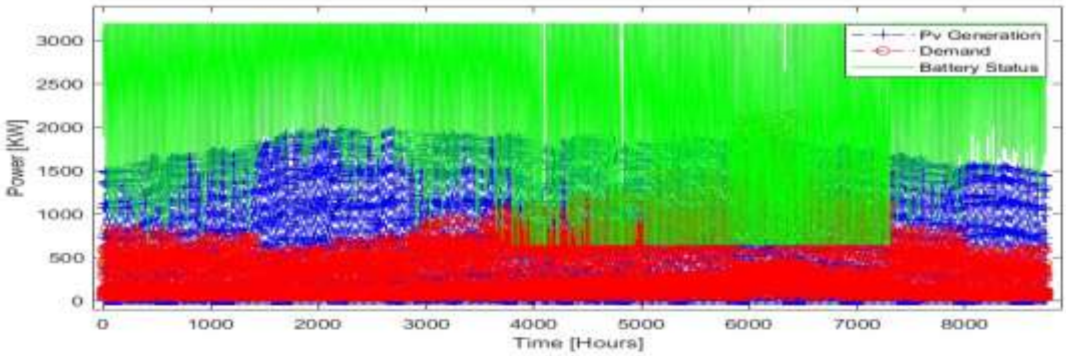

Fig. 6. System performance of Standard FA with LPSP = 0.1.

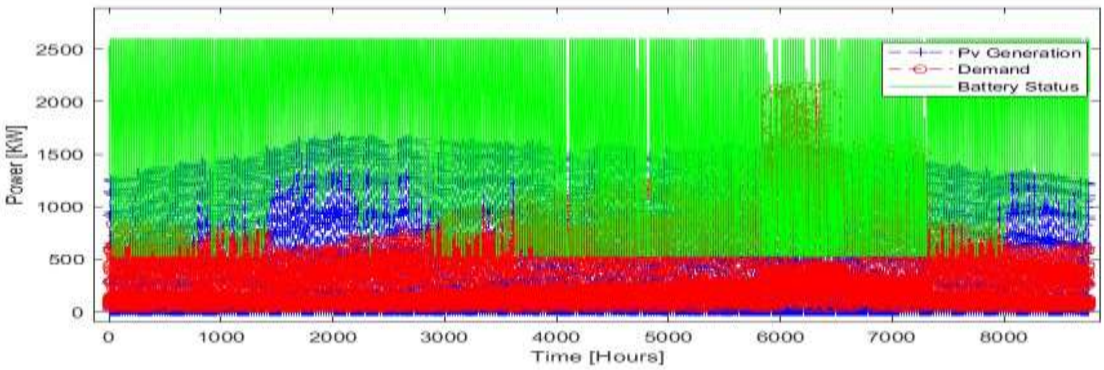

Fig. 7. System performance of MFA with LPSP = 0.1.

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TABLE VI. Performance results.

| Scenario | LPSP | Algorithm | PV (Unit) | BSS (Unit) | Converter (Unit) | Cost ($) | Iteration |
|---|---|---|---|---|---|---|---|
| Case 1 | 0.01 | Standard FA | 4634 | 71 | 10185 | 4208461 | 18 |
| | | Modified FA | 4211 | 54 | 8179 | 3917511 | 15 |
| Case 2 | 0.1 | Standard FA | 2765 | 32 | 5025 | 2468980 | 28 |
| | | Modified FA | 2321 | 26 | 4131 | 2360733 | 4 |

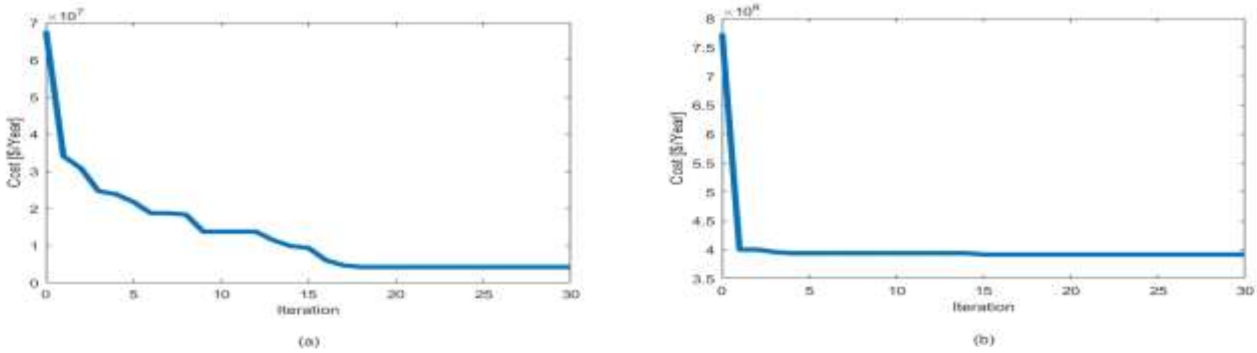

Fig. 8. Convergence comparison of Standard FA (a) and MFA (b) systems with LPSP=0.01.

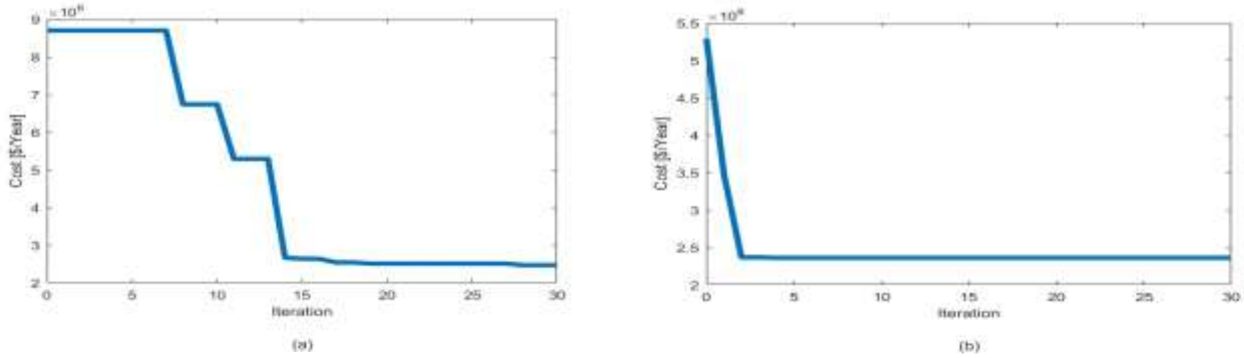

Fig. 9. Convergence comparison of Standard FA (a) and MFA (b) systems with LPSP=0. 1.

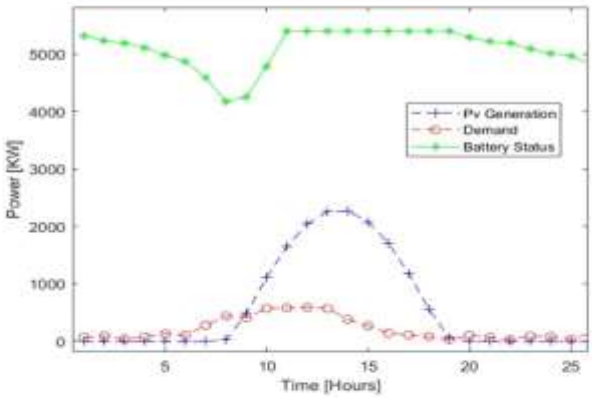

Fig. 10. 24-hour performance of the MFA with LPSP = 0.01.

Fig. 10 and Fig. 11 show the 24 hours performance of the MFA in both cases. In a 24-hour period, the graphs show the diurnal cycle of PV generation starting and ending at low points with a peak during the middle of the day, the demand would possibly show less variation, and the battery status would show charging during times of excess generation and discharging during high demand or low generation. It can be seen from blue line, which is Solar generation, it gives only energy to Grid from 08:00 am to 18:00 am and during this time demand is being given by Solar and battery is being charged which can be seen from red and green line respectively. In the absence of Solar energy, demand is being met by battery and it can be seen battery is being discharged as green line goes down.

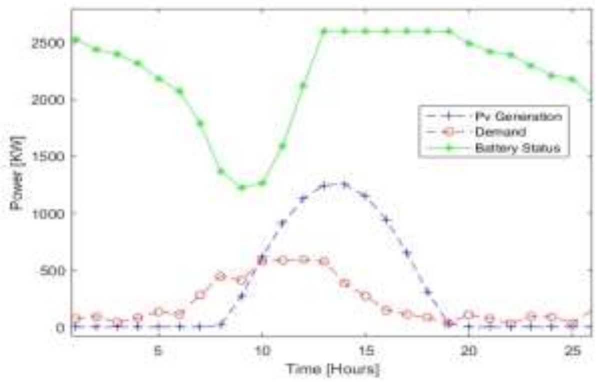

Fig. 11. 24-hour performance of the MFA with LPSP = 0.1.

The microgrid's performance over the studied period establishes a foundational understanding of the system's dynamics, presenting valuable insights for future optimization and scalability. The application of the FFA has proven effective

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in establishing an initial setup; however, continuous refinement of the algorithm parameters may yield improved results in terms of cost efficiency and power reliability.

Results show that MFA converged on a solution with fewer PVs, batteries, and reduced cost as compared to FA for same inputs settings.

## VI. Conclusion

This comparative study highlights the effectiveness of optimization modified strategies, particularly the Modified Firefly Algorithm, in enhancing microgrid configuration optimization. The MFA's ability to integrate standard FA principles with additional optimization mechanisms results in improved solution quality and faster convergence, offering a promising approach to designing cost-effective and reliable microgrids. Results show that the MFA finds optimum solution in fewer iterations than the standard FA. Future directions could explore further modification strategies and their application to broader aspects of energy system optimization, incorporating dynamic operational constraints and expanding renewable energy integration.

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