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Original Research Article

Economic Dispatch in Microgrids with Renewable Energy Resources Using Artificial Intelligence Techniques

***Gwaivangmin, B.I., Bakare, G.A., Haruna, Y.S. and Amoo, A.L.**

Department of Electrical and Electronics Engineering, Abubakar Tafawa Balewa University, Bauchi, Nigeria.
*gwaivangminb@gmail.com

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ABSTRACT

This study addresses the global challenge of scarce and expensive electricity by investigating artificial intelligence techniques for optimizing economic load dispatch in microgrids with renewable energy sources. The study explores methods to minimize power generation costs within these systems. The analysis showed that a Hybrid Genetic Algorithm - Firefly Algorithm (HGA-FFA) approach emerges as the most cost-effective solution. HGA-FFA achieves the lowest total cost, significantly lower than competing methods. A Hybrid Genetic Algorithm - Particle Swarm Optimization (HGA-PSO) method proved to be a strong alternative, striking a balance between optimization complexity and cost. The traditional Genetic Algorithm (GA), while effective, exhibits the highest total cost, making it the least economical option among the three. Therefore, for minimizing economic load dispatch costs in similar microgrid scenarios, HGA-FFA is the optimal choice, followed by HGA-PSO. While GA remains a viable approach, its economic efficiency falls short of the hybrid methods.

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1. INTRODUCTION

The growing integration of renewable energy sources (RES) into microgrids introduces complexities in optimizing economic dispatch (ED). Microgrids, localized grids with independent or grid-connected operation, can benefit significantly from RES integration. This is due to the potential for reduced operational costs and environmental footprint, as highlighted by research (Ramesh et al., 2023 and Wang *et al.,* 2024). However, the intermittent nature of many RES presents challenges for ED optimization within microgrids.

The intermittent and variable nature of RES complicates economic dispatch (ED) in microgrids. To address this challenge and achieve cost-effective and reliable energy distribution, advanced optimization techniques are necessary. Artificial intelligence (AI) has emerged as a powerful tool in this domain, offering solutions for optimizing ED in microgrids with RES integration (Younes *et al.*,2014, Carpinteiro *et al.,* 2021;2022).

Traditional optimization methods often struggle with the non-linear, multi-objective, and dynamic characteristics of ED problems in microgrids with RES. These limitations necessitate robust and flexible solutions. AI-based methods address this gap effectively. Genetic algorithms (GAs) and their advanced variants, like particle swarm optimization-enhanced GAs (PSO-GA) and ant colony optimization-enhanced GAs (ACO-GA), have demonstrated significant potential in this area (Wang *et al.,* 2021; Yang *et al.,* 2022).

Genetic algorithms (GAs) are a powerful class of evolutionary algorithms inspired by natural selection (Holland, 1992). They excel at navigating large search spaces and identifying near-optimal solutions through mechanisms like selection, crossover, and mutation. This makes GAs well-suited for addressing the complexities of economic dispatch (ED) in microgrids with renewable energy sources (RES). The non-linear and multifaceted nature of the ED problem in such settings is effectively handled by GAs, offering a viable solution for RES integration, as demonstrated in recent research (Haupt and Haupt ,2004., Wu *et al*., 2016; Cui *et al.,* 2023;).

While GAs offers a robust solution for ED in microgrids with RES integration, researchers have explored hybrid approaches to further enhance performance. Particle swarm optimization enhanced genetic algorithms (PSO-GA) combine the global search strengths of GAs with the local search proficiency of PSO (Kennedy and Eberhart, 1995). PSO mimics the social behavior of flocking birds or schooling fish to refine solutions, leading to faster convergence and improved accuracy for ED problems, as demonstrated by recent studies (Clerc and Kennedy, 2002; Li *et al.,* 2024). Similarly, ant colony optimization enhanced genetic algorithms (ACO-GA) integrate the exploration and exploitation capabilities of ant colony optimization (ACO) with the evolutionary strategies of GAs. ACO, inspired by the foraging behavior of ants, efficiently navigates the search space, making it suitable for complex optimization tasks like ED in microgrids (Dorigo and Stützle, 2004; Wang *et al.,* 2022).

The hybrid ACO-GA approach enhances the exploration capabilities of GAs, reducing the likelihood of premature convergence and improving the overall quality of the solutions (Mahapatra *et al.,* 2022).

This study is aimed at optimizing the economic dispatch of power generation at the University of Jos to minimize costs over a 24-hour period.

2. METHODOLOGY

This study would implement economic load dispatch (ELD) as a strategy to optimize power supply for the University of Jos. This approach will integrate three key elements:

i. Demand prediction**:** Real-data validated forecasts of electricity demand on the 11kV dedicated feeder.

ii. Demand response strategies**:** Techniques to encourage users to adjust their consumption patterns and optimize system efficiency.

iii. Meteorological data**:** Solar irradiance is used to model solar power generation.

These elements will provide crucial inputs for the university's hybrid power system ELD. By incorporating them, the system can predict the availability and variability of solar energy. This information is then fed into the ELD algorithm, allowing it to optimize the allocation of power generation among the four sources:

i. Solar PV

ii. Pumped hydro energy storage

iii. Diesel generator

iv. Public power supply

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The study will reportedly utilize three optimization algorithms (GA, GA-PSO, GA-FFA) coded in Python. These algorithms aim to minimize the total cost of power generation by optimizing the dispatch (allocation) of power from each generating unit, considering their economic efficiency.

2.1. Economic Load Dispatch (ELD) for 11 kV Dedicated Feeder of University of Jos

This section outlines the mathematical formulation and pseudocode for the ELD strategy applied to the University of Jos, 11kV dedicated feeder.

According to Victoire *et al.* (2004), Mohammadi-Ivatloo *et al.* (2013), Basetti *et al.* (2021) and Marhatang *et al.* (2022) ELD aims to allocate power generation among different sources in such a way that the overall cost is minimized while meeting the demand and operational constraints. In this case, we consider multiple power sources: Solar PV, Pumped Hydro Energy System (PHES), Diesel Generator, and Public Power Supply.

Objective function:

It is to minimize the total cost F_T given by:

$$F_T = MIN(\sum_{k=1}^{4} F_k[P_k]) \tag{1}$$

Where $F_k(p_k)$ is the cost function for the k-th generator:

$$F_k(p_k) = a_k + b_k p_k + c_k p_k^2 \tag{2}$$

Where $a_{k,}b_k, c_k$: Cost coefficients for the k-th generator

The ELD problem consists in minimizing subject to the following constraints: -

Power balance constraints:

$$\sum_{k=1}^{4} P_k - (P_D) = 0 \tag{3}$$

Where P_D: Total power demand

Generator Capacity Constraints:

$$P_k^{min} \leq P_k \leq P_k^{max} \tag{4}$$

Without transmission losses:

In this case, we assume that the transmission losses are negligible, so the total power generated equals the total power demand directly.

$$\sum_{k=1}^{4} P_k - (P_D) = 0 \tag{5}$$

The ELD problem can be formulated as:

$$F_T = \min\left(F_{solar}(P_{solar}) + F_{phess}\left(P_{phess}\right) + F_{diesel}(P_{diesel}) + F_{public}\left(P_{public}\right)\right) \tag{6}$$

Subject to:

$$P_{solar} + P_{phess} + P_{diesel} + P_{public} = P_D \tag{7}$$

Where, P_{solar}: Power from Solar PV, P_{phess}: Power from Pumped Hydro Energy Storage System

P_{diesel}: Power from Diesel Generator, P_{public}: Power from Public Power Supply

$$P_k^{min} \leq P_k \leq P_k^{max} \qquad for\ k\ \in \{solar, phess, diesel, public\} \tag{8}$$

With transmission losses:

When considering transmission losses, let $P_L$represent the transmission losses. The power balance equation is modified to account for these losses.

$$\sum_{k=1}^{4} P_k - (P_D + P_L)\ = 0 \tag{9}$$

Transmission losses can be approximated as a function of the power generation, often using the Kron's loss formula:

$$P_L = \sum_{i=1}^{4}\sum_{j=1}^{4} P_i B_{ij} P_j \tag{10}$$

Where;

B_{ij} are the loss coeficients

The ELD Problem can be formulated as follows:

$$F_T = \min\left(F_{solar}(P_{solar}) + F_{phess}\left(P_{phess}\right) + F_{diesel}(P_{diesel}) + F_{public}\left(P_{public}\right)\right) \tag{11}$$

Subject to:

$$P_{solar} + P_{phess} + P_{diesel} + P_{public} = P_D + \sum_{i=1}^{4}\sum_{j=1}^{4} P_i B_{ij} P_j \tag{12}$$

$$P_k^{min} \leq P_k \leq P_k^{max} \qquad for\ k\ \in \{solar, phess, diesel, public\} \tag{13}$$

The parameters used:

Particle Swarm Optimization (PSO):

i. Swarm size: 20 particles.
ii. Inertia weight (w): 0.5.
iii. Cognitive parameter (c1):1.5.
iv. Social parameter (c2): 1.5
v. Maximum number of iterations: 100 iterations.

Genetic Algorithm (GA):

i. Population size:20

ii. Maximum Generation: 100

iii. Mutation rate: 0.1

Firefly Algorithm

i. alpha: 1.0 # attraction coefficient

ii. beta_min : 0.2 #minimum beta (initial light intensity)

iv. gamma: 0.01 # light absorption coefficient

2.2. Demand Response

To inform the analysis, a 24-hour electricity demand forecast and comprehensive meteorological data (NASA,2023) are provided in Table 1. Weather information influencing solar power generation was also included.

Table 1: the 24 hours Data used for the Economic Load Dispatch

Time (h)	Load demand (kW)	Cloudiness index	Temperature (^oC)	Solar irradiance (W/m^2)
1:00-2:00	340.330	1	18	0
2:00-3:00	311.010	1	18	0
3:00-4:00	332.010	1	18	0
4:00-5:00	548.710	0.98	17	0
5:00-6:00	655.410	1	17	109
6:00-7:00	945.010	0.95	18	385
7:00-8:00	1204.120	1	20	543
8:00-9:00	1280.330	0.41	23	708
9:00-10:00	1139.920	0.38	26	773
10:00-11:00	1041.220	0.68	27	745
11:00-12:00	890.040	0.52	28	742
12:00-13:00	780.820	0.67	29	662
13:00-14:00	765.100	0.55	29	635
14:00-15:00	868.800	0.13	29	449
15:00-16:00	890.400	0.42	28	223
16:00-17:00	932.770	0.05	27	0
17:00-18:00	917.520	0	24	0
18:00-19:00	908.500	0.02	22	0
19:00-20:00	938.770	0.16	20	0
20:00-21:00	848.310	0.71	20	0
21:00-22:00	629.920	0.88	20	0
22:00-23:00	563.960	1	19	0
23:00-24:00	413.250	0.8	19	0
24:00-1:00	341.25	1	19	0

2.3. Simulation of GA ELD

The simulation of GA economic dispatch is shown in Figure 6.

Pseudocode for GA ELD

The flowchart shown in Figure 1 outlines the process of economic load dispatch using Genetic Algorithm (GA.

Here are the steps involved in the process, based on the flowchart shown in Figure 1.

1. Start

2. Load Data**:** This step loads data, likely from an external source, into a temporary location (24 hours).
3. Initialize Population: This step initializes a population, possibly referring to a set of records for processing.
4. Generation = 1? This step checks if it's the first generation of processing.
    - If Yes, proceed to step 5 (Evaluate Fitness).
    - If No, skip to step 9 (Check Dispatch Feasible).
5. Evaluate Fitness: This step evaluates the fitness of the data, possibly checking if it meets certain criteria for loading.
6. Selection**:** This step involves selecting data based on the evaluation in the previous step.
7. Crossover: This step may refer to combining data elements or records.
8. Mutation: This step may introduce modifications to the data.
9. Check Dispatch Feasible (24 hours)**:** This step checks if the data is feasible for dispatching to the database after 24 hours of processing.
    - If Yes, proceed to step 10 (End).
    - If No (Infeasible), the process may terminate here or loop back to an earlier step (not shown in the flowchart).

End

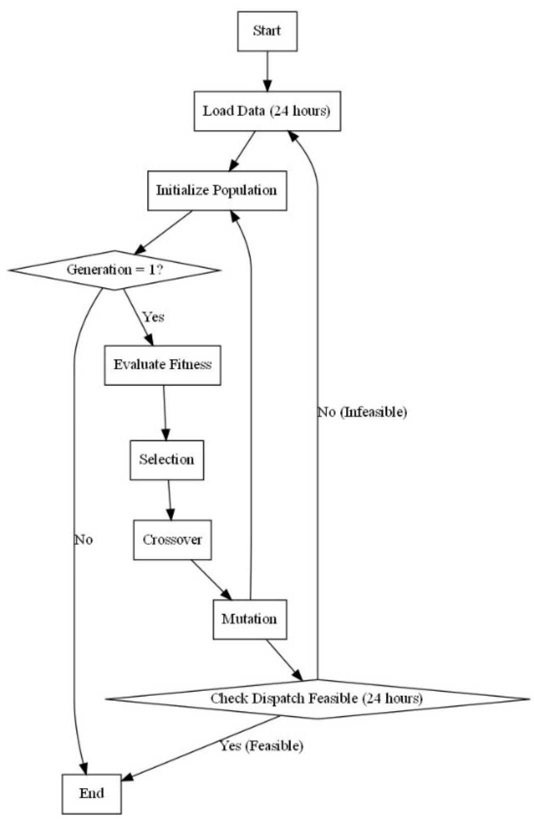

Figure 1 Diagram for simulation of GA ELD

2.4. Simulation of GA-PSO ELD

The flowchart for the simulation of GA-PSO economic load dispatch is shown in Figure 2.

Pseudocode for GA-PSO ELD

The flowchart shown in Figure 2 outlines the process of combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for a hybrid optimization approach. Let's break down the steps in the flowchart:

1. Start: The algorithm begins.
2. Load Data (24 hours): Data for a 24-hour period is loaded into the system.
3. Initialize Particles (PSO) and Initialize Population (GA):
    - PSO: Initialize the particles for the PSO part of the algorithm.
    - GA: Initialize the population for the GA part of the algorithm.
4. Check for Feasible Solution:
    - After initialization, the system checks for a feasible solution. If no feasible solution is found, the process ends.
5. Generation = 1?:
    - The algorithm checks if the current generation is the first one.
    - If it is the first generation, it proceeds to evaluate fitness for both PSO and GA.
6. Evaluate Fitness (PSO) and Evaluate Fitness (GA):
    - PSO: Evaluate the fitness of the particles.
    - GA: Evaluate the fitness of the population.
7. Update Particles (PSO): Update the positions and velocities of the particles based on their fitness.
8. Selection (GA), Crossover (GA), and Mutation (GA):
    - Selection: Select individuals from the population based on their fitness.
    - Crossover: Perform crossover operations to produce new offspring.
    - Mutation: Introduce mutations to maintain genetic diversity.
9. Combine Best Individuals (Optional): Optionally combine the best individuals from both PSO and GA to form a new population.
10. Check for Feasible Solution: Again, check if a feasible solution has been found.
    - If a feasible solution is found, the process ends.

If no feasible solution is found, the algorithm proceeds to the next generation and repeats the steps.

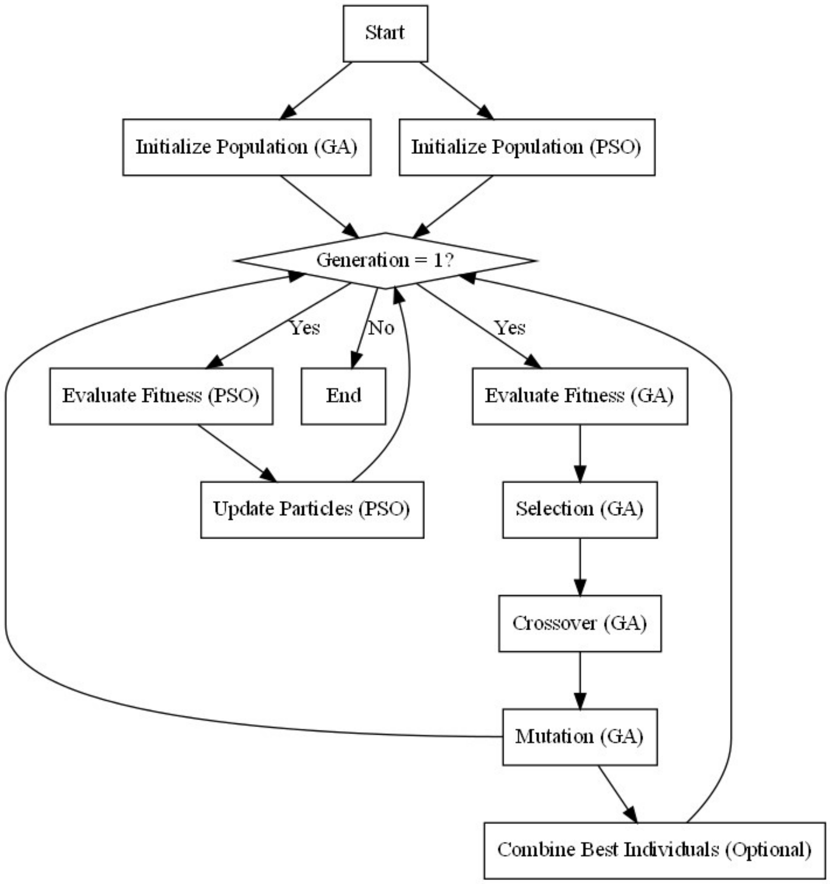

Figure 2: Diagram for simulation of GA-PSO ELD

2.5. Simulation of GA-FFA ELD

The flowchart for the simulation of GA-PSO economic load dispatch is shown in Figure 3.

Pseudocode of GA-FFA ELD

The flowchart shown in Figure 3 describes the integration of the Firefly Algorithm (FFA) and Genetic Algorithm (GA) for optimization. Let's break down and analyze the steps involved in this hybrid approach:

1. Start: The process begins.
2. Load Data (24 hours): Data for a 24-hour period is loaded into the system.
3. Initialize Fireflies (FFA) and Initialize Population (GA):
   - FFA: Fireflies are initialized for the Firefly Algorithm.
   - GA: The population is initialized for the Genetic Algorithm.
4. Check for Feasible Solution:
   - After initialization, the system checks for a feasible solution. If no feasible solution is found, the process ends (Infeasible).
5. Generation = 1?:
   - The algorithm checks if the current generation is the first one.

- If it is the first generation, it proceeds to evaluate light intensity for FFA and evaluate fitness for GA.

6. Evaluate Light Intensity (FFA) and Evaluate Fitness (GA):
    - FFA: Evaluate the light intensity of the fireflies.
    - GA: Evaluate the fitness of the population.
7. Movement of Fireflies (FFA): Fireflies are moved based on their light intensities.
8. Selection (GA), Crossover (GA), and Mutation (GA):
    - Selection: Select individuals from the population based on their fitness.
    - Crossover: Perform crossover operations to produce new offspring.
    - Mutation: Introduce mutations to maintain genetic diversity.
9. Combine Best Solutions (Optional): Optionally combine the best solutions from both FFA and GA to form a new population.
10. Check for Feasible Solution: Again, check if a feasible solution has been found.
    - If a feasible solution is found, the process ends (Feasible).

If no feasible solution is found, the algorithm proceeds to the next generation and repeats the steps.

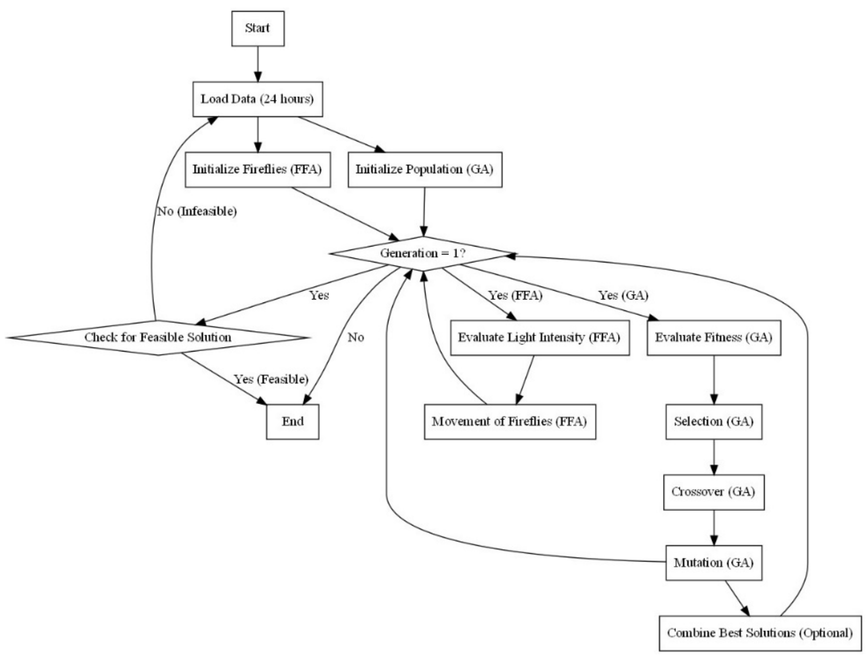

Figure 3 Diagram for simulation of GA-FFA ELD

3. RESULTS AND DISCUSSION

3.1. Simulation Results of the GA Model

Ratshilengo et al. (2021) compared three models for short-term solar irradiance forecasting in South Africa: Genetic Algorithm (GA), K-Nearest Neighbor (KNN), and Recurrent Neural Network (RNN). The GA model emerged as the most accurate, making it a promising tool for power utilities to optimize grid operations and integrate solar energy. Guzman et al. (2020) presented a method to accurately simulate PV systems with limited information, using genetic algorithms to optimize key parameters for precise digital twin creation. The data collected were simulated using, GA toolbox for anaconda (Spyder) on the python platform. The load demand data of the demand response, solar irradiance data, GA parameters, the other data related to the four sources of power generation were used to write a code in python with the economic load dispatch model and the results are shown in Figure 4. Figure 4 shows a hybrid system. Public power supply forms the baseload at 1000 kW. Solar PV contributes most during the day, peaking at 800 kW at noon. Data for PHESS (Pumped Hydroelectric Storage) is unavailable. Diesel generators act as backup, with a slight increase at night. Public power provides the base (peaking at 700 kW), supplemented by solar during the day (peaking at 600 kW at noon). Hydro offers constant support around 400 kW. Diesel acts as a balancing source, fluctuating inversely with solar to meet demand variations, especially when solar is low.

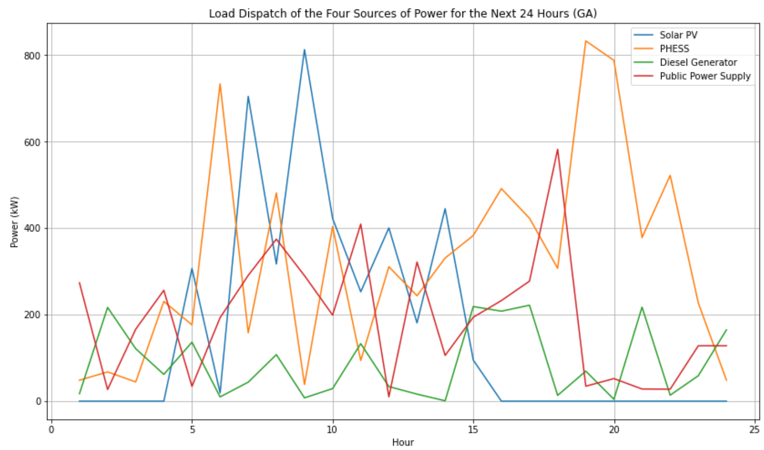

Figure 4: GA load dispatch of the four sources of power for the next 24 hours

3.2. Simulation Results of the GA-PSO Model

Vafaeva et al. (2024) in their study optimized the size of a solar-wind hybrid microgrid using Particle Swarm Optimization (PSO) to improve energy production, economic feasibility, and environmental impact. PSO outperforms other optimization techniques like GA and SA by enhancing energy production, reducing LCOE, and improving payback time. The optimized design also considers land use efficiency and community acceptance. The data collected were simulated using, GA-PSO toolbox for anaconda (Spyder) on the python platform.

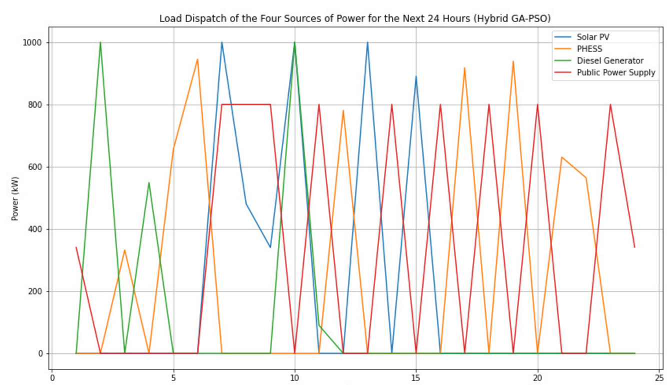

Figure 5: GA-PSO load dispatch of the four sources of power for the next 24 hours

The load demand data of the demand response, solar irradiance data, GA-PSO parameters, the other data related to the four sources of power generation were used to write a code in python with the Economic load dispatch model and the result are shown in Figure 5. Figure 5 shows a hybrid system.

Public power supply provides the baseload at around 1000 MW. Solar PV contributes the most during the day, peaking at 1000 MW at noon. Data for PHESS (Pumped Hydroelectric Storage System) is unavailable. Diesel generators act as backup, seeing a slight increase at night. Public power serves as the baseload, while solar power provides the most during the day, peaking at 1200 MW. Hydro power offers constant support around 700 MW, and diesel is used as a backup source.

3.3. Simulation Results of the GA-FFA Model

Alfaraj (2024) compared the accuracy of satellite and ground-based solar irradiance data for PV system simulations. Ground-based data is more accurate but less widely available, while satellite data is less accurate but covers larger areas. The study uses Python-based PVLib for simulations and recommends ground-based data for precise PV system design and satellite data for regional assessments. The data collected were simulated using, GA-FFA toolbox for anaconda (Spyder) on the python platform. The load demand data of the demand response, solar irradiance data, GA-FFA parameters, the other data related to the four sources of power generation were used to write a code in python with the Economic load dispatch model and the result are shown in Figure 6. Public power serves as the baseload, while solar power provides the most during the day, peaking at 1200 MW. Hydro power offers constant support around 700 MW, and diesel is used as a backup source. Figure 6 shows a hybrid power system utilizing public power (1000 MW) as the base with solar providing the most during the day (peaking at 1200 MW), hydro offering constant support (700 MW), and diesel acting as a backup source for night time increases in demand.

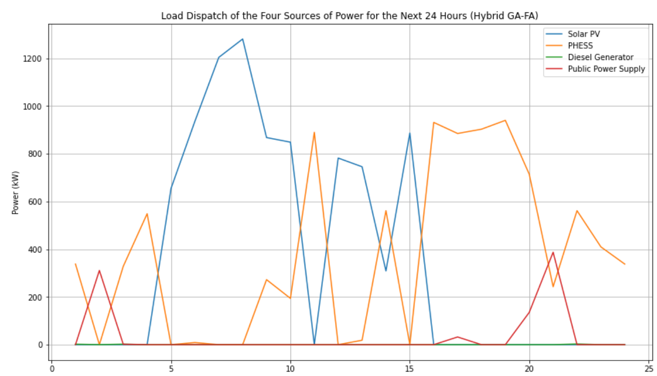

Figure 6: GA-FFA load dispatch of the four sources of power for the next 24 hours

The analysis of Table 2 reveals that the Hybrid Genetic Algorithm - Firefly Algorithm (HGA-FFA) is the most cost-effective method, with the lowest total cost of 2,753,990.11. The Hybrid Genetic Algorithm - Particle Swarm Optimization (HGA-PSO) method follows, with a total cost of 3,463,365.39 offering a balance between optimization complexity and cost. The Genetic Algorithm (GA) method has the highest total cost of 3,494,203.80, indicating it is the least cost-efficient among the three. Therefore, the HGA-FFA method is the best choice for minimizing the economic load dispatch cost in this scenario, followed by HGA-PSO, while GA, though effective, is not as economical.

Table 2: Minimized economic load dispatch cost

Power source dispatch economic method	Total cost of economic dispatch method (N)
HGA-FFA	2,753,990.11
HGA-PSO	3,463,365.39
GA	3,494,203.80

4. CONCLUSION

In conclusion, this study explored the potential of artificial intelligence in mitigating the global challenge of limited and expensive electricity. By focusing on optimizing economic load dispatch in microgrids with renewable energy sources, the research aimed to minimize power generation costs within these systems. The investigation revealed that a Hybrid Genetic Algorithm-Firefly Algorithm (HGA-FFA) approach emerged as the most cost-effective solution. HGA-FFA achieved a significantly lower total cost compared to competing methods. While a Hybrid Genetic Algorithm-Particle Swarm Optimization (HGA-PSO) method presented itself as a strong alternative, balancing optimization complexity with cost, the traditional Genetic Algorithm (GA), although effective, exhibited the highest total cost. Therefore, for similar microgrid scenarios aiming to minimize economic load dispatch costs, HGA-FFA is the recommended approach, followed by HGA-PSO. While GA remains a viable technique, its economic efficiency is surpassed by the hybrid methods investigated in this study. Future research directions could involve exploring the application of these hybrid algorithms to larger and more complex microgrid systems, along with investigating their performance under real-world operating conditions.

5. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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