SSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 13, Issue 3, pp: (92-99), Month: July - September 2025, Available at: www.researchpublish.com

SOLVING POWER ECONOMIC DISPATCH PROBLEM USING FIREFLY ALGORITHM-BASED COST OPTIMIZATION MODEL

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DOI: https://doi.org/10.5281/zenodo.15878584

Published Date: 14-July-2025

Abstract: **The Power Economic Dispatch (PED) problem plays a crucial role in the optimal allocation of generating resources to meet electricity demand while minimizing operational costs in power systems. This project presents the application of the Firefly Algorithm (FA), a bio-inspired optimization technique, to solve the PED problem with an emphasis on cost minimization. The Firefly Algorithm, known for its efficiency in exploring complex solution spaces, was adapted to optimize the dispatch of power generation units considering various constraints, such as generation limits and demand requirements. The objective is to minimize the total fuel cost of power generation, which can significantly enhance the operational efficiency of power systems. The model was implemented and tested on a set of benchmark test systems, demonstrating the superiority of Firefly Algorithm in terms of solution quality and computational efficiency compared to traditional optimization methods. The results confirm that the Firefly Algorithm-based cost optimization model provides a promising approach for solving the PED problem, with potential applications in real time energy management and grid optimization. Additionally, the paper highlights the potential of the Firefly Algorithm to be adapted and scaled for other power plants, demonstrating its flexibility and adaptability to different system sizes and operational conditions. This makes it a promising tool for optimizing generation costs in power plants seeking to minimize their operational costs while maintaining the reliability and stability of the grid.**

Keywords: **Economic Dispatch, Firefly Algorithm, Cost Optimization Model, Power Distribution for Stations, Particle Swarm Optimization (PSO), Power Allocation.**

I. INTRODUCTION

1.1 Nigeria's electricity sector is responsible for generating, transmitting, and distributing electric power, but the output remains significantly below the level required to meet both household and industrial demands. The country has 23 power-generating plants linked to the national grid, with a total capacity of 11,165.4 MW. These facilities are operated by generation companies (GenCos), independent power producers, and the Niger Delta Holding Company. In 2012, the sector struggled to distribute just 5,000MW—far below the 40,000 MW needed to meet the population's basic energy needs fall is further aggravated by unplanned load shedding, partial or total system failures, and grid collapses (Adedeji, 2023). This shortfall is further aggravated by unplanned load shedding, partial or total system failures, and grid collapses (Adedeji, 2023). To bridge the gap, many households and businesses rely on generators, which supplied an estimated 6,000 MW in 2008 (Al Hadi et al., 2023). Nigeria has long faced a persistent electricity crisis (AfricanNews, 2022), with its power grid collapsing twice in one week in 2022 and three times in a single week in October 2024. Firefly Algorithm (FFA) is one of the recent swarm intelligence methods developed by Yang in 2008 and is a nature-inspired, meta-heuristic algorithm that can be applied for solving the hardest optimization problems (also NP-hard problems) Patel et al. (2024). Firefly algorithm is inspired by the behavior of fireflies and their attraction to light (Singh et al., 2023). This paper aim to develop an optimization model for solving the Power Economic Dispatch problem to minimize production costs while meeting demands and satisfying operational constraints. design a cost optimization Power Economic Dispatch model using Firefly Algorithm implement the model and evaluate the it using standard metrics. An instability within the system was identified, leading to the enforcement of operational restrictions and limits, followed by the implementation of a planned corrective measure. The analysis of line losses produced excellent results, which will enhance the safety and efficiency of the Nigerian 330KV system, ultimately contributing to the improvement of the country's future power infrastructure.

1.2 Objectives of the Paper

The specific objectives of this research are to:

(a.) design a cost optimization Power Economic Dispatch model using Firefly Algorithm;

(b.) implement the model in (i); and

(c.) evaluate the model using standard metrics.

In summary, The proposed system was modeled using a traditional dataset from Transmision Company of Nigeria (TCN) which was obtained directly by permission.

The Problem is about distributing the required load demand among power generating units while minimizing the cost of power generation and adhering to operational constraints. The Firefly Algorithm (FA), a nature-inspired optimization technique, can be applied to solve this problem by optimizing the cost function.

II. LITERATURE REVIEW

Basu et al., (2024) Fuzzy-Logic Controlled Genetic Algorithm (FCGA) was applied to environmental/economic dispatch.

Objectives: Application of Fuzzy-Logic in order to control environment/economic dispatch.

Motivation: The algorithm retained the advantages of the GAs over the traditional ELD methods and eliminated the main disadvantage of the binary coded GAs (long execution time).

Methodology: Two fuzzy controllers were designed to adaptively adjust the crossover probability and mutation rate during the optimization process based on some heuristics. Adequacy tests also showed promising results but heavily dependent on the right levels of input.

Contribution to knowledge: The authors proposed real coded genetic algorithm that relies on elitism, arithmetic crossover and mutation to proffer solution to economic dispatch problem. Both solutions underperformed with large population.

Limitation: Power flow in the branch is the limitation of power economic dispatch for minimizing the dispatch cost.

Result: The solution adapted the technique with an actual application on the optimization of the operation planning for a cascaded system composed of interconnected hydroelectric plants.

Kumar et al (2023), shift in the paradigm from conventional to green energy demands the reformulation of sophisticated optimization problems to optimally utilize both conventional and distributed energy sources.

Objectives: To shift from conventional to reformulation of sophisticated optimization for distributed energy sources.

Motivation: The major reasons for opting for renewable sources are their negligible emissions and environmental constraints.

Methodology: This section describes the basic forms of different aim and objectives, functions and constraints associated with such optimization problems and highlights various additions to augment the nature of the practical problem.

Contribution to knowledge: To deal with this intermittent nature of renewable sources, researchers have developed various optimization models and forecasting algorithms.

Limitation: The production of sources largely depends on external atmospheric conditions, and the power output can fluctuate in nature for different scheduling intervals.

Result: effectively coordinate different energy sources in a hybrid power system.

Walters, et al (2020), developed a Simple Genetic Algorithm (SGA) with two different encoding schemes for solving the Economic Load Dispatched (ELD) problem

Objectives: To use encoding schemes in Simple Genetics Algorithm for Economic Load Dispatched problem. Motivation: the ability to handle any type of unit characteristics in genetic algorithm-based approach for large-scale economic dispatch subject to the network losses.

Methodology: The GA tested for ELD problem with and without losses for smooth and non smooth cost curves using three machine test systems for five different cases.

Limitation: The algorithm used only test for five (5) cases.

Result: Though the comparison of obtained results with those of lambda –iteration method establishes the fast and robust nature of the approach.

Rasheed (2020) with the increase in penetration of distributed generation sources to the conventional grid, a large set of optimization problems has been derived based on the economic dispatch of conventional and non-conventional energy sources.

Objectives: To optimize the conventional grid base on economic dispatch energy source

Methodology: Author dealt with hybrid energy systems which include photovoltaic (PV) energy sources, wind energy systems, and battery energy storage systems (BESS), in addition to thermal and hydroelectric sources.

Contribution to Knowledge: Dispatch of conventional and non-conventional sources were based on the different forecasting techniques.

Limitation: The majority of these suggested problems deal with the intermittent and variable nature of the renewable energy sources coupled with the addition of certain constraints related to each distributed energy source.

Result: Large set of optimization problems was derived.

El-Sayed, 2020, Dispatch Problem Modeling introduced the output power of the PV module is determined using the irradiance and temperature levels for different scheduling intervals.

Objective: To introduce the output power of the PV module using the irradiance and temperature levels for different scheduling intervals.

Motivation: to determine the characteristics of the PV module is the single diode model However, the single diode model introduces a challenge to optimally selecting the different parameters.

Methodology: The other methods involve modeling the characteristics of the PV module using the fractional integral polynomial method or using the double diode model to augment the efficiency of the single-diode based circuit.

Contribution to Knowledge: The basic objective function which models the cost equation for the PV plant represents a linear relation between a defined tariff rate and the output power.

Limitation: The constraints for hydro and thermal generation remain the same.

Result: Evaluate and compare various optimization algorithms for a specific optimization problem.

Dinh et al (2020) in CONSTRAINTS FOR THE HYDRO AND THERMAL UNITS

Introduction: The remaining constraints remain the same for the hydro and thermal units as discussed previously in the respective sections. This represents the simplest form of the solar-hydrothermal dispatch problem discussed in the literature.

Objectives: The basic objective function introduced can be modified by taking into consideration different practical constraints. For instance, the authors updated the objective function for thermal generation by including the emission values while considering the PV energy source.

Methodology: The authors modify the problem by considering the wind energy source in addition to solar, thermal, and hydro energy sources.

Contribution to Knowledge: The authors in have suggested the economic dispatch of the system consisting of solar and electric vehicles. The authors in consider the pumped hydro storage in addition to the solar and thermal energy sources.

Limitation: A large number of objective functions have been discussed for this particular dispatch problem by introducing small changes in the original objective function.

Result: The dispatch for the PV energy source with conventional sources.

Oluwadare, et al., (2016) formulation developed Genetic Algorithm (GA)-based model as a solution to the problems of economic power dispatch.

Objective: the authors presented a GA-based solution for the operational planning of hydro-thermal power systems to get around the deficiencies in nonlinear programming-based approaches.

Motivation: The model considered GA as numerical optimization algorithms based on the principle inspired from the genetic and evolution mechanisms observed in natural systems and population of living being.

Methodology: Genetic Algorithm (GA) are essentially derived from a simple model of population genetics and are associated with three prime operators; namely reproduction, crossover, and mutation.

Limitation: unable to provide global optimal solution, got stuck at local optimal.

Contribution to knowledge: The implementation of the model produced an application whose performance showed superior performances of the new model over some existing ones.

Result: Three power generating systems and three Nigerian Thermal Power Plants showed superior performances of the new model over some existing ones.

III. METHODOLOGY

3.1 System Architecture

The plan for solving the Power Economic Dispatched (PED) problem with a firefly algorithm for cost-cutting is shown in Figure 3.1. The firefly algorithm works by putting together a few key parts: the data input, the power system model, the optimization process, and the results we get out. The system architecture is designed to efficiently manage economic power dispatch by integrating multiple layers of data processing and optimization.

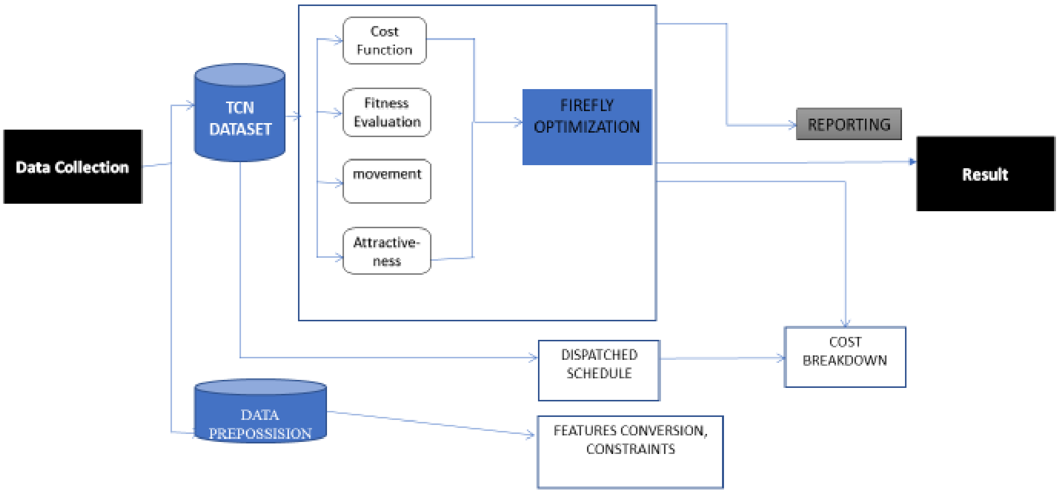

Figure 3.1: System Architecture for Power Economic Dispatch using Firefly Algorithm

3.2 DATA COLLECTION

Data was collected from power-generating stations in Osun State, with Osogbo serving as the Southwest regional headquarters, to study how power is generated, managed, and dispatched to various major locations within Osogbo, towns across the state, and even to other states within Southwest Nigeria. The power is generated and dispatched to places such as Cottage Ede, Ede Township, Iwo, Ejigbo, and Ife-Odan. The goal is to analyze the conventional methods used and introduce Firefly Algorithms for improved effectiveness. Computerized findings based on the traditional methods was used to develop optimization models using soft computing techniques (i.e., Firefly Algorithms), executed through Python programming. A comprehensive review of the existing power economic dispatch system was also carried out. Data has been collected from power-generating stations in Osogbo, and the collected data undergone several processes, including extraction, pre-processing, and feature selection, to identify the key features for use in the optimization process.

1) Objective:

One way to apply the Firefly Algorithm in this context could be to optimize or analyze the discrepancies (difference) between allocation and actual values. Specifically, the goal might be to:

1. Minimize the difference between allocated and actual values over the time periods.
2. Maximize the usage of available allocation across the station periods.

2) Procedure for Firefly Algorithm Application:

Here's a simplified version of how Firefly Algorithm might be used for this analysis:

1. Objective Function: Define an objective function to minimize the difference column. For example:

Objective Function=∑(Allocation−Actual)2\text{Objective Function} = \sum (\text{Allocation} - \text{Actual})^2 Objective Function=∑(Allocation−Actual)2

This measures the squared difference between the allocated and actual values across time periods.

2. Firefly Initialization: Each "firefly" represents a possible solution, where each solution corresponds to a set of values or parameters for the allocation and actual values. A firefly will try to adjust the allocation values to minimize the objective function.

3. Attraction and Movement: The fireflies will move towards other fireflies with lower objective function values (i.e., smaller differences between allocation and actual), using the brightness of other fireflies to guide their movement.

4. Convergence: After multiple iterations, the algorithm will converge to a solution where the difference between the allocation and actual values is minimized, meaning the fireflies will "settle" on a set of optimal allocation values.

5. Result: The algorithm's outcome would provide insights into how to adjust the allocations to match the actual values more closely, potentially improving efficiency or resource distribution at the station.

3) Result Analysis:

Based on the data from the table, the DIFFERENCE column shows the discrepancy between allocation and actual values at each time period. The Firefly Algorithm could potentially identify patterns in these differences or suggest optimized allocations that minimize these differences.

The objective of the Firefly Algorithm in this case is to minimize the difference between the allocated and actual values for each time period. We can use the sum of squared differences as the objective function.

a) Objective Function:

Let's define the objective function f(x)f(x)f(x) for a given set of time periods:

f(x)=∑i=1N(Allocatedi−Actuali)2f(x) = \sum_{i=1}^{N} (\text{Allocated}_i - \text{Actual}_i)^2f(x)=i=1∑N(Allocatedi −Actuali)2 (3.1)

Where:

- NNN is the total number of time periods (in your case, 24 rows corresponding to each hour of the day).
- Allocatedi\text{Allocated}_iAllocatedi is the allocated value for the iii-th period.
- Actuali\text{Actual}_iActuali is the actual value for the iii-th period.

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4) Step 3: Calculate the Brightness

The brightness of a firefly is related to the value of the objective function. A firefly with a smaller objective function value (i.e., smaller differences between allocation and actual) is brighter, while one with a larger objective function value is dimmer.

- The brightness of firefly iii is given by:

Brightnessi=11+f(xi)\text{Brightness}_i = \frac{1}{1 + f(x_i)}Brightnessi=1+f(xi)1 (3.5)

Where f(xi)f(x_i)f(xi) is the objective function value for firefly iii.

5) Step 4: Move Towards Brighter Fireflies

Once the initial population of fireflies is generated, the next step is for each firefly to move towards brighter fireflies. The movement of a firefly is determined by the following equation:

xi=xi+β·(Brightnessj−Brightnessi)+α·random noisex_i = x_i + \beta \cdot (\text{Brightness}_j - \text{Brightness}_i) + \alpha \cdot \text{random noise}xi=xi+β·(Brightnessj−Brightnessi)+α·random noise (3.6)

Where:

- xix_ixi is the position of the firefly iii.
- β\betaβ is the attractiveness of the firefly (usually inversely proportional to the distance).
- α\alphaα is a randomization parameter that introduces some randomness to the movement.

6) Step 5: Iterations

This process of calculating the brightness, moving fireflies towards brighter ones, and updating their positions continues for a set number of iterations or until the algorithm converges to a solution. During each iteration, fireflies with smaller objective function values will pull other fireflies towards them.

7) Step 6: Convergence

Over multiple iterations, the fireflies will converge towards an optimal or near-optimal solution, meaning the differences between allocated and actual values will be minimized. The final set of allocation values produced by the algorithm will be the optimized solution.

1. Initialization: Suppose we start with an initial allocation vector for each firefly that is the
   - Firefly 1: [26.8, 26.8, 26.8]
   - Firefly 2: [26.8, 26.8, 26.8]
   - Firefly 3: [26.8, 26.8, 26.8] (3.7)
2. Calculate the Objective Function: Compute the objective function for each firefly based on their allocation values.

For Firefly 1:

f(x1)=(26.8−26.30)2+(26.8−21.70)2+(26.8−16.50)2=0.25+27.04+106.09=133.38f(x_1) = (26.8 - 26.30)^2 + (26.8 - 21.70)^2 + (26.8 - 16.50)^2 = 0.25 + 27.04 + 106.09 = 133.38f(x1)=(26.8−26.30)2+(26.8−21.70)2+(26.8−16.50)2=0.25+27.04+106.09=133.38

3. Move Fireflies: Fireflies with lower objective values (if any) will attract other fireflies to their position. If a firefly has a better allocation (lower difference), it will move towards it. (3.8)
4. Convergence: After several iterations, the fireflies will adjust their allocation values such that the total d between allocation and actual values is minimized. For example, the optimized allocation values might be something like:
   - Firefly 1: [26.5, 26.5, 26.5] (a better allocation matching actual values more closely)
5. Final Results: The algorithm would return the final optimized allocation values for all time periods, which minimize the overall difference.

8) Conclusion:

By following these steps, the Firefly Algorithm will help in determining the optimal allocation to minimize the discrepancies between the allocated and actual values across the time periods.

The results showcase the potential of the algorithm to manage a real-world power dispatch problem by balancing multiple objectives (minimizing costs, maintaining allocation adherence, and adhering to station constraints). By observing high costs in specific periods (e.g., 1:00 AM), the data provides valuable feedback to system operators to investigate: Are these costs due to penalties for allocation mismatches? Are cost parameters (e.g., station fuel costs) accurately represented? The data offers a clear starting point to refine the algorithm in adjust station prioritization to distribute load more evenly, reduce high costs by improving station constraints or rebalancing cost parameters and improve penalty settings for mismatch to better align Total Actual with Allocation. This table provides operators and planners with critical information for scheduling and budgeting. For instance: identifying high-cost periods to adjust operations and planning station maintenance schedules based on utilization trends.

Table 3.0: Result of a Day Power Dispatched from Five (5) Difference Stations Using Firefly

Start	End	Allocation	Station 1	Station 2	Station 3	Station 4	Station 5	Total Actual	Total Cost
00:00:00	01:00:00	26.80	2.75	4.40	1.55	1.65	2.47	12.82	1713.14
01:00:00	02:00:00	26.80	2.29	4.94	1.53	0.61	2.17	11.54	10921.47
02:00:00	03:00:00	26.80	2.53	5.07	1.70	0.93	1.82	12.05	21315.15
03:00:00	04:00:00	26.80	2.47	4.75	1.64	0.87	2.00	11.73	13318.03
04:00:00	05:00:00	26.80	2.33	4.73	1.47	0.73	2.19	11.45	7518.20
05:00:00	06:00:00	26.80	2.36	4.62	1.81	0.54	2.74	12.07	6918.89
06:00:00	07:00:00	24.80	2.79	4.37	1.72	1.42	1.28	11.58	6514.84
07:00:00	08:00:00	24.80	2.76	4.73	1.71	1.36	1.12	11.68	42313.18
08:00:00	09:00:00	24.80	2.81	4.59	1.71	1.46	0.81	11.38	30115.44
09:00:00	10:00:00	24.80	2.86	5.29	1.73	1.54	1.19	12.61	31315.85
10:00:00	11:00:00	24.80	2.98	3.91	1.79	1.76	2.21	12.65	31310.93
11:00:00	12:00:00	24.80	2.89	4.71	1.75	1.62	1.54	12.51	31512.15
12:00:00	13:00:00	24.80	2.72	4.27	1.66	1.20	-0.30	9.55	42715.14
13:00:00	14:00:00	24.80	2.98	3.23	1.79	1.75	2.17	11.92	4106.31
14:00:00	15:00:00	24.80	2.90	4.24	1.75	1.59	1.46	11.94	2507.39
15:00:00	16:00:00	24.80	2.86	4.06	1.73	1.50	1.04	11.19	44505.85
16:00:00	17:00:00	24.80	2.81	3.46	1.70	1.39	0.56	9.92	23105.15
17:00:00	18:00:00	24.80	2.90	3.27	1.75	1.58	1.41	10.91	24505.15

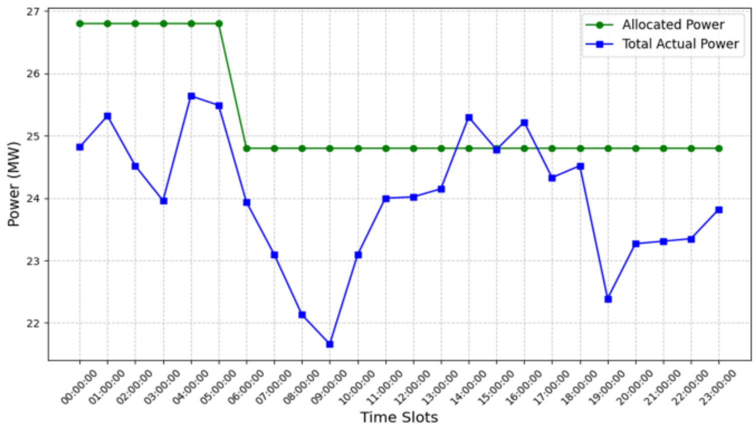

Figure 4.0: Total Power Across Time Slots

IV. CONCLUSION

The results achieved from the application of the FA-based model indicate that the Firefly Algorithm is highly effective in delivering optimal or near-optimal solutions for the economic dispatch problem.

The FA-based approach not only showed significant improvements in the total generation cost but also displayed robust convergence characteristics, even in the face of complex system constraints and the non-linearity inherent in the power generation process. Compared to conventional methods, the FA approach provided superior performance in terms of cost reduction and computational efficiency.

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