A Comparative Study on Different Optimization Algorithms for Solving Economic Dispatch Problem

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***Abstract*— Economic dispatch is one of the mathematical optimization problems in power system operation and planning. It aims to find the most efficient output for generating units that meets the demand of the load at the lowest possible cost while satisfy all operational constraints. This paper examines numerous methods to address the economic dispatch problem, including deterministic approaches like the Lagrange multiplier method, metaheuristic optimization algorithms such as the Genetic Algorithm, the Firefly Algorithm, the Harris-Hawks optimization algorithm, and their hybridizations. The study also utilizes PowerWorld Simulator, a software package that solves economic dispatch problems using sequential linear programming. Two different case studies have been conducted on IEEE 5-bus and 30-bus test systems for demonstrating the effectiveness of the proposed algorithms. The results of various case studies showed that the deterministic methods are the most effective for solving the economic dispatch problem. It was also shown that the hybrid algorithms, which combine the strengths of different optimization techniques, can achieve a significant enhancement in total cost compared to the conventional metaheuristic methods.**

Keywords—Economic Dispatch, Firefly Algorithm, Harris Hawks Algorithm, Genetic Algorithm, PowerWorld Simulator.

I. INTRODUCTION

Power generation and distribution systems must be cost-effective in order to be sustainable and reliable. To achieve this, it is essential to schedule the real and reactive power output from each generation unit in order to minimize operating costs within power networks [1]. Economic dispatch (ED) involves finding the optimal output levels for power generation units within power networks. The aim is to reduce the generation cost while fulfilling load demand and operational constraints such as power balance constraint and generation capacity constraint [2].

Recently, many researchers have paid more attention to address the ED problem under different operational constraints for power networks. Different mathematical programming and optimization techniques have been utilized to address the ED problem, including classical deterministic numerical methods, metaheuristic algorithms, and hybrid methods [3]. The classical deterministic numerical methods include the Lagrange multipliers method (LMM) [4], the lambda-iteration method [5], the interior point method [6], linear programming algorithm [7], nonlinear programming [8] algorithm, the quadratic programming algorithm [9], the dynamic programming method [10], and the decomposition technique [11].

To obtain the optimal solution to the nonlinear equations of ED problem, many metaheuristic optimization methods have been proposed in the literature [12]–[20]. These techniques include Particle Swarm Optimization (PSO) [12], Genetic Algorithm (GA) [13], Differential Evolution (DE) [14], Biogeography-Based Optimization [15], Simulated Annealing [16], Firefly Algorithm (FA) [17], Cuckoo Search Algorithm [18], Teaching Learning Based Optimization [19], and Gravitational Search Algorithm [20]. These approaches are able to effectively handle non-differentiable and discontinuous cost curves while obtaining global or near-global solutions.

Various hybrid optimization techniques have also been utilized to optimize the ED problem. These approaches combine the strengths of different optimization techniques to achieve better performance, such as evolutionary programming with sequential quadratic programming (EPSQP) [21], particle swarm optimization with sequential quadratic programming (PSO-SQP) [22], hybrid GA-DE [23], and hybrid Artificial Bee Colony and Artificial Rabbits Optimization [24].

In this study, we focus on solving the conventional ED problem by using various approaches, including the Lagrange multiplier method (LMM), the Genetic Algorithm, the Firefly Algorithm, the Harris-Hawks Optimization algorithm (HHO), and the hybrid combinations of these metaheuristic algorithms. Furthermore, the PowerWorld Simulator (PWS), which utilizes sequential linear programming, is used to address the problem. To show the effectiveness of these approaches, two different case studies have been conducted on IEEE 5-bus and 30-bus test systems. The main contributions of this work can be summarized as follows:

- Compare various optimization algorithms and simulation software to explore which algorithm provide the most optimal solution for conventional economic dispatch problem.
- Evaluate the performance of the proposed algorithms and simulation software on two different power systems.

The rest of this paper is organized as follows. Section II describes the economic dispatch problem and its mathematical formulation. Section III provides an overview of the proposed algorithms used to address the problem. Section IV presents analysis the obtained results with the proposed algorithms for each test system. Finally, Section V concludes the paper.

II. PROBLEM FORMULATION

Economic dispatch is the process of obtaining the best output of a set of power generation units to meet the total forecasted load at the minimum cost, given operational constraints. The cost function of power generation in a power system is usually modeled as a quadratic function as given by [25], [26]:

$$c_i(P_i) = A_i P_i^2 + B_i P_i + C_i \tag{1}$$

where P_i represents the output of the i-th power generator. A_i, B_i and C_i are the coal consumption characteristic coefficients of the i-th generator. The optimal power output dispatch aims to minimize the overall cost of the power grid by finding the most suitable output levels for all generators within the system, as defined in the following equation [27]:

$$OF = \min \sum_{i=1}^{n} c_i(P_i) \tag{2}$$

where n is the number of power generation units in the system. The ED optimization algorithm solves the optimization problem in (2) to determine the optimal output power levels for all generators in the system. This ensures that the power grid operates efficiently and meets the load demand, while minimizing the total cost of generation.

The objective function in (2) has two constraints. The first constraint refers to the power balance constraint, ensures that the total power generated by all power plants in the system matches the total power demand. This can be expressed as follows [28].

$$\sum_{i=1}^{n} P_i - P_D = 0 \tag{3}$$

where $\sum_{i=1}^{n} P_i$ is the total power generation, and P_D is the system load. The second constraint is the generation capacity constraint, which limits the generation capacity of each unit so that it is not exceeded. This can be expressed as follows [29]:

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

where P_i^{min} and P_i^{max} are the minimum and maximum generation limit of i-th generator, respectively.

III. Optimization Algorithms and Simulation Software

The next step after formulating the ED problem is to solve it using optimization algorithm, mathematical approach, or simulation software. The techniques utilized to solve the ED problem are introduced and discussed in the following sections.

A. Lagrange Multiplier Method (LMM)

LMM is a mathematical approach that can successfully resolve optimization problems with constraints. It is particularly useful for finding local maxima and minima for functions while satisfying equation constraints [30]. To achieve this, the LMM adds a penalty term to the objective function for each constraint. The Lagrange multiplier is a constant that ensures that the new objective function is minimized when the constraints are satisfied [31]. In applications such as ED, the LMM proves beneficial in determining optimal generation levels for each generator within a power system.

B. Genetic Algorithm (GA)

GA is a metaheuristic optimization algorithm that was first proposed by John Holland in the 1960s [32]. It is inspired by natural evolution process, where organisms with the best characteristics are more likely to survive and reproduce. A random population of solutions is first generated by the algorithm. A vector of generation levels for each generator makes up each solution. Based on the value of its objective function, each solution's fitness is evaluated. The solutions with the highest fitness are more likely to be selected for reproduction. The algorithm then selects two parents from the population based on their fitness. The parents reproduce to produce offspring. The offspring inherit their genes from their parents. Some of the offspring are mutated. Mutation is a process that changes the genes of an offspring [33]. Mutation introduces new genetic material into the population and prevents the population from converging to a local optimum [34]. The offspring are then evaluated and added to the population. The process is repeated until a solution with the desired fitness is found [35]. The proposed algorithm is terminated under various conditions, such as when a maximum number of iterations is reached, after a certain time, or when the fitness threshold is reached. The algorithm can also be terminated if the objective function has not significantly improved over a certain period of time.

C. Firefly Algorithm (FA)

FA is a nature-inspired algorithm that mimics the flashing behavior of fireflies to solve complex optimization problems [36], [37]. It was developed by Yang et al. in 2007 and has been shown to be effective in solving several optimization problems [38], [39]. It works by simulating the movement of fireflies in a dark environment. Each firefly has a brightness that is inversely proportional to its distance from other fireflies. The higher the brightness of a firefly, the more appealing it becomes to other fireflies. This means that fireflies are more likely to move to the brighter fireflies, which are also the solutions with the optimal objective function values [40]. In minimization problems, the firefly with the highest light intensity has the smallest objective function. In other words, the firefly with the best solution is the most attractive to the other fireflies. This process of attraction and movement continues until a firefly obtain a solution with a sufficiently small objective function [36]. In comparison to other optimization techniques, one of the FA key advantages is its ability to simultaneously find all local optima as well as the global optimum. This is because fireflies are not restricted to moving to the nearest brighter firefly. Instead, they can move to any firefly that has a better solution, regardless of its distance. This makes FA a good choice for problems with multiple local optima. Another advantage of FA is that it is relatively simple to implement. It does not require any complex mathematical concepts or algorithms, making it a good choice for engineers and scientists who are not experts in optimization. Finally, FA is well-suited for parallel implementation, meaning that different fireflies can work almost independently of each other. This makes FA a very efficient algorithm for solving large optimization problems [41].

D. Harris Hawks Optimization Algorithm (HHO)

HHO is a recent nature-inspired optimization technique that simulates the cooperative hunting strategies of Harris's hawks to solve complex optimization problems [42]. One of the unique features of HHO is its time-varying rule, which allows it to flexibly shift from exploration to exploitation as the algorithm progresses. This makes HHO more adaptable to difficult problems. Another advantage of HHO is its progressive convergence process. The algorithm starts with a exploration phase, where it searches for a wide range of solutions. As the algorithm progresses, it enters an exploitation phase, where it focuses on improving the best solutions it has found so far. HHO has been shown to produce high-quality results on a variety of problems. It is also relatively easy to implement and use. The exploitation phase of HHO is particularly effective because it greedily picks the best solutions explored so far and ignores low-quality solutions. This helps HHO to quickly converge to the best solution [43], [44].

E. Hybrid Algorithms

Hybridization is used to improve optimization results by combining the discussed metaheuristic algorithms. The following sections describe each of the hybrid algorithms proposed in this study.

1) Hybrid Harris Hawks – Genetic Algorithm (HHO-GA): It combines the strengths of the HHA and GA to optimize power generation levels more effectively and efficiently. The optimization process alternates between HHA and GA in each iteration. During even iterations, HHA initializes the population of candidate solutions, represented by hawks' positions in the search space. The update rule of HHA guides the hawks to explore the search space by adjusting their positions based on random vectors and the current best solution. This exploration phase helps the algorithm cover a wide range of potential solutions, enabling it to escape local optima and discover promising regions. During odd iterations, GA introduces a new population of candidate solutions, utilizing genetic evolution mechanisms like selection, crossover, and mutation. The fitness evaluation drives GA towards improved solutions, making use of information from previous iterations to fine-tune the results. By combining HHA and GA alternately, this hybrid approach benefits from efficient exploration and exploitation, leading to better convergence towards the optimal solution for power generation levels.

2) Hybrid Firefly – Genetic Algorithm (FA-GA): Similar to HHS-GA, the FA-GA combines the strengths of FA and GA to optimize power generation levels more effectively. The optimization alternates between FA and GA, where FA initializes the population of potential solutions using fireflies' positions. Fireflies' positions are updated using attraction and light absorption coefficients, facilitating exploration and escaping local optima. In odd iterations, GA introduces a new population, employing genetic operations for refining solutions based on historical information. This sequential combination of algorithms enables the hybrid FA-GA algorithm to find better solutions than either FA or GA alone.

3) Hybrid Harris Hawks – Firefly Algorithm (HHO-FA): Converting the current solution into one or more enhanced solutions can improve the performance of the optimization algorithm. A combination between the HHS and FA algorithms is utilized to perform this improvement. HHA explores the search space, identifying promising regions, and the best solution obtained is used to initialize FA. FA improves the solutions, encouraging further exploration while avoiding local optima. By combining these algorithms sequentially, the hybrid approach aims to achieve high-quality solutions for power generation level optimization.

F. PowerWorld Simulator(PWS) – Sequential Linear Programming

PWS is a powerful and user-friendly power system simulation software [45]. It can efficiently solve power flow problems for systems with up to 100,000 buses [46]. PWS also has a wide range of other features, including integrated ED, economic analysis of area transactions, power transfer distribution factor calculation, short circuit analysis, and fault analysis [47]. Furthermore, PWS has the capability to simultaneously solve the ED problem to optimally allocate generation in an area. This is conducted using sequential linear programming (SLP). SLP works by linearizing the problem around an operating point and then solving the resulting linear problem. This process is repeated until the solution converges. SLP is a powerful tool for solving the ED problem, as it can handle complex systems with multiple constraints [4].

IV. Simulation Results

This section presents the results of using the proposed algorithms for solving the ED problem. These algorithms were tested on two case studies. The results were obtained using a precise simulation program developed in MATLAB software version 2021a.

A. IEEE 5-bus test system

The proposed algorithms' efficiency in minimizing the total system cost is evaluated using IEEE 5-bus test system with 3 generation units. The examination has been conducted on the IEEE 5-bus test system as depicted in Fig. 1. It shows its component parts, which consists of 3 thermal generation units.

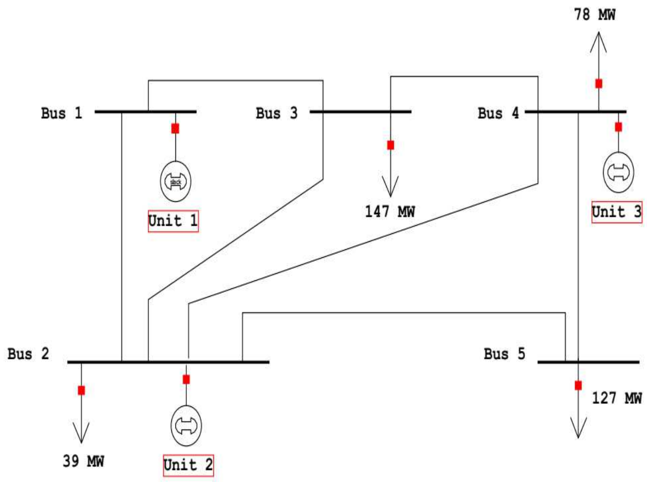

Fig. 1. Single line diagram of the 5-bus test system.

The generator parameters for the system under study are shown in Table 1. The case considered three generating units to meet the demand of 392 MW.

TABLE I. Cost coefficients and Power Limits for the 3 Units.

Unit	Generation Limit		Fuel Cost Coefficients		
	Pmin (MW)	*Pmax (MW)*	*A ($/MW)*	*B ($/MWh)*	*C ($/h)*
1	100	400	0.016	10	373.5
2	150	500	0.018	8.0	403.6
3	50	300	0.018	12	253.2

The actual power generation by each unit is presented in Table II. It is shown that the PWS and LMM methods achieved the lowest total system cost, followed by the HHO-GA, FA-GA, HHO-FA, HHO, GA and FA algorithms. The FA algorithm achieved the highest total system cost. The PWS and LMM algorithms are both deterministic methods, while the other algorithms are metaheuristic methods. This demonstrates that deterministic methods can be effective for solving the ED problem. The comparative tests performed on IEEE 5 bus test system have illustrated the effectiveness of the proposed hybrid methods as shown in Fig. 2, which shows that the improvement in total cost achieved by the proposed methods. The hybrid methods achieved significant improvements in total cost over the metaheuristic methods on the IEEE 5-bus test system. The HHO-GA algorithm achieved a 0.8% reduction in total cost over the GA algorithm, from 5730.57$/h to 5724.37$/h. The FA-GA algorithm achieved a 1.1% reduction in total cost over the GA algorithm, from 5730.57$/h to 5725.93$/h. The HHO-FA algorithm achieved a 0.3% reduction in total cost over the FA algorithm, from 5732.46$/h to 5729.50$/h. These improvements in total cost may seem small, but they can lead to significant savings for power utilities, especially over the long term.

TABLE II. SIMULATION RESULTS FOR TEST SYSTEM I.

Method	P_1 (MW)	P_2 (MW)	P_3 (MW)	Total Cost *($/h)*
PWS	141.12	180.99	69.88	5724.30
LMM	141.12	180.99	69.88	5724.30
HHO-GA	139.39	181.78	70.82	5724.37
FA-GA	133.34	186.76	71.89	5725.93
HHO-FA	131.22	194.69	66.08	5729.50
HHO	131.34	195.37	65.29	5729.90
GA	149.23	165.59	77.17	5730.57
FA	159.05	173.95	59.01	5732.46

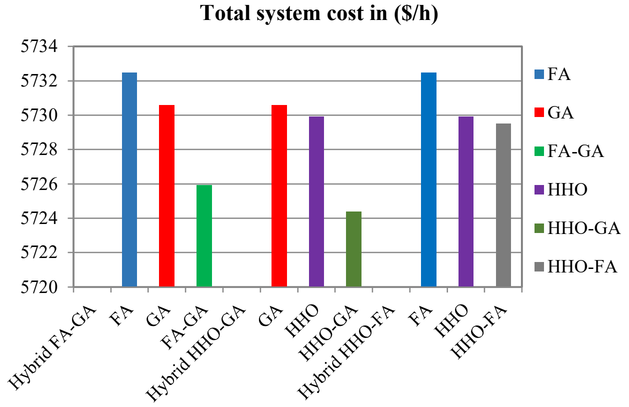

Fig. 2. Improvement of the proposed hybrid algorithms compared to the metaheristic algorithms for test system I.

B. *IEEE 30-bus test system*

Fig. 3 depicts the single-line diagram of the IEEE 30-bus network, which consists of 6 thermal generation units. The aim is to optimize the generation levels of the generation levels, with the main goal of minimizing the total cost of generation. The generators data and line and bus data of test bus system have been taken from [48], the generators power production cost and its power generating limits are given in Table III. The load demand of 500 MW is connected with the 6- generating power system.

TABLE III. COST COEFFICIENTS AND POWER LIMITS FOR THE 6 UNITS.

Unit	Generation Limit		Fuel Cost Coefficients		
	Pmin (MW)	*Pmax (MW)*	*A ($/MW)*	*B ($/MWh)*	*C ($/h)*
1	10	125	0.15247	38.53970	756.7989
2	10	150	0.10587	46.15916	451.3251
3	35	225	0.02803	40.39655	1049.998
4	35	210	0.03546	38.30553	1243.531
5	130	325	0.02111	36.32782	1658.569
6	125	315	0.01799	38.27041	1356.659

The results of the simulation for IEEE 30-bus test system are demonstrated in Table IV. The table shows the production of each generating unit in MW and the total system cost for each algorithm.

The results show that the LMM and PWS methods achieved the lowest total system cost of $26,970.4 and $27,003.5, respectively. This indicates their effectiveness in solving the ED problem for this case study. The hybrid methods HHO-GA, HHO-FA, and FA-GA also achieved very good results, with total system costs of $27,016.8, $27,022.2, and $27,005.3, respectively. These hybrid methods are able to combine the strengths of different metaheuristic algorithms, which enables them to find better solutions than the individual metaheuristic algorithms. The GA algorithm also achieved good results, with a total system cost of $27,019.7. However, the hybrid methods were able to achieve slightly better results than the GA algorithm. The FA and HHO algorithms achieved the highest total system costs, with values of $27,028.0 and $27,041.3, respectively.

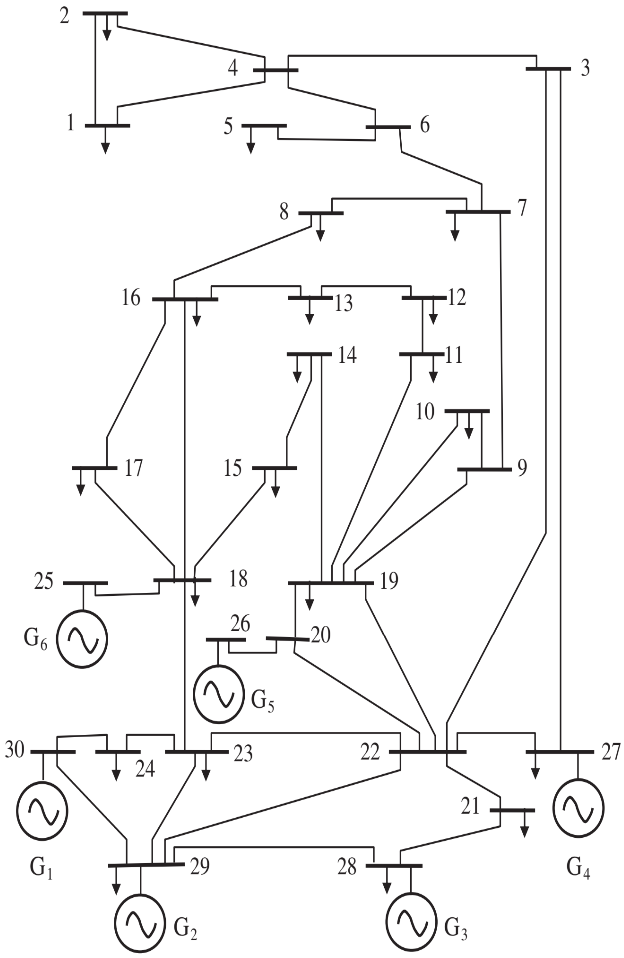

Fig. 3. Single line diagram of the IEEE 30-bus system [49].

TABLE IV. SIMULATION RESULTS FOR TEST SYSTEM II.

Method	P_1	P_2	P_3	P_4	P_5	P_6	Total Cost *($/h)*
PWS	16.62	10.00	61.56	77.99	178.1	154.93	26970.4
LMM	17.39	10.00	61.51	78.12	178.1	154.93	27003.5
FA-GA	17.10	10.00	60.76	73.83	185.2	153.08	27005.3
HHO-GA	18.43	11.05	47.15	75.56	181.9	165.83	27016.8
GA	18.24	10.02	60.07	67.01	199.7	145.00	27019.7
HHO-FA	21.64	12.57	69.22	72.56	176.9	147.12	27022.2
FA	24.17	10.03	51.64	63.69	175.6	174.89	27028.0
HHO	18.92	13.19	52.19	59.10	182.4	174.18	27041.3

To show the effectiveness of the proposed hybrid approaches, Fig. 4 presents the enhancement in total cost achieved by these hybrid techniques. It is shown that the HHO-GA algorithm achieved a 0.08% reduction in total system cost over the GA algorithm, from $27019.70 to $27016.80. The HHO-FA algorithm achieved a 0.10% reduction in total system cost over the FA algorithm, from $27028.00 to $27022.20. The FA-GA algorithm achieved a 0.05% reduction in total system cost over the GA algorithm, from $27019.70 to $27005.30. It clearly depicts that the hybrid algorithms, have achieved an improvement in the total cost compared to the conventional metaheuristic methods. This highlights the efficiency of these hybrid approaches in finding solutions that lead to significantly reduced overall costs.

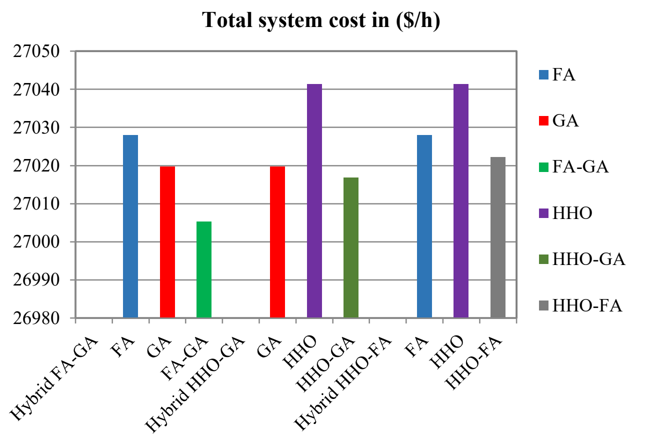

Fig. 4. Improvement of the proposed hybrid algorithms compared to the metaheristic algorithms for test system II.

V. CONCLUSION

This study investigated the application of various optimization algorithms to address the economic dispatch (ED) problem in power systems. The study used different methods, including deterministic techniques (LMM and PWS) and metaheuristic approaches (GA, FA, and HHO), both individually and in hybrid configurations(FA-GA, HHO-FA, and HHO-GA). The proposed algorithms were applied to the IEEE 5-bus and IEEE 30-bus test systems. The results showed that the deterministic methods were effective for solving the ED problem. The proposed hybrid methods achieved significant improvements in total cost over the conventional metaheuristic methods. Future research could investigate the performance of these hybrid methods on other power system test systems, including those with renewable energy sources and energy storage devices. Additionally, the proposed hybrid methods could be adapted to solve other power system optimization problems, such as unit commitment.

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