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A Review on Techniques Used for Solving the Economic Load Dispatch Problems: Categorization, Advantages, and Limitations

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ABSTRACT

The increasing global demand for electric power presents significant challenges for power utilities, as they must balance the need for reliable and sustainable power generation with the goal to minimize generation costs. This challenge has led to studying Economic Load Dispatch (ELD), which aims to optimize power generation at minimal fuel costs. This paper presents a comprehensive review of several primary techniques used in solving ELD problems, including traditional methods such as the Lambda Iteration, Gradient, and Newton-Raphson techniques, as well as modern optimization methods like Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Sine Cosine Algorithm (SCA), and Gravitational Search Algorithm (GSA). The paper also provides a comparative analysis using tables and chart in section three outlining the advantages, disadvantages, and limitations of each technique discussed in section two. Additionally, this review examines the applications of these techniques on IEEE test systems in various studies, highlighting their effectiveness on practical utility making it easier for researchers to make a choice in selecting a technique for their ELD problem.

1. INTRODUCTION

Electricity plays a vital role in our day-to-day life activities which helps to improve the standard of living and boost the economy of both developed and developing countries all over the world [1]–[3]. The main aim of modern electric power utilities is to provide a high-quality, reliable power supply to the consumers at the lowest possible cost while operating to meet the limits and constraints imposed on the generating units committed to that load [4]. These goals of the power utilities lead to the introduction of the economic load dispatch known as the Economic Load Dispatch ELD, analysis, and These constraints define the ELD problem which aims to determine the optimal output power combination for all active generating units committed [5]. The central goal of the ELD s to establish the power of all committed generating units so that generating cost is minimized as the load demand and inequality constraints are satisfied [6][7]. This approach of the ELD minimizes total fuel costs while adhering to one equality constraint and several inequality constraints. Economic load dispatch ELD, is a crucial optimization technique in power system operation [8][9]. Its primary goal is to minimize the generation costs of thermal units while enhancing overall system efficiency all while meeting load demand and adhering to equality and inequality constraints [8][10]. Many investigations on ELD, problems have been carried out of date using different techniques to solve the issues ranging from the conventional methods applied to linear non convex systems and modern methods applied to the non-linear convex systems.

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In this paper the major techniques used in solving ELD problems are discussed in section two and these techniques are categorized into two classes for easy analysis. Section three contains a detailed review on the methods used in solving the ELD problems including tables which outlines the pros and cons of the reviewed techniques and also presenting a performance chart that clearly shows the effectiveness of each technique when applied to a similar test system. This paper helps researchers to make a choice for optimization technique to use when solving ELD problem.

The structure of this paper consists of section 2 on the method containing the Economic Load Dispatch and Review Methodology, Section 3 contains the results and discussion, and Section 4 contains the conclusion. Finally, Chapter 5 contains Acknowledgements

2. METHOD

There are different methods used in solving (ELD) problems depending on the relative accuracy and computational burden, different programs are used in dispatch or pre- dispatch stages. Various methods used in early days and present days depend upon the type and size of the system to be analyzed and the behavior of the fuel-cost curves of the generating units either linear monotonically or non–linear [11]. These techniques are categorized into two sets of methods, which is outlined below:

(1) Traditional method or Conventional techniques.

(2) Advanced method or Meta-heuristics techniques.

The nonlinear and non-convex nature of fuel-emission objectives makes the traditional methods inappropriate for tackling ELDP which led to the high use of advance techniques to solve the problems [12]. In this paper we brought out some significant methods used in solving ELD problems from the two categories listed above and summarize their advantages and disadvantages based on their application as reviewed from our literature review section. But before that we have to go through the general steps to approach the ELD problems by understanding the objectives and the mathematical tools guiding this studies.

2.1. Problem Formulation:

The factors affecting power generation at the lowest cost include the operating efficiency of generators, fuel prices, and transmission losses. Even the most efficient generating unit may not guarantee minimum fuel costs if it is in an area with high fuel prices [13]. The Economic Load Dispatch (ELD) problem is a study which involves determining the optimal power generation levels for a set of generators in a power system while minimizing the total generation cost, subject to various operational and system constraints, and it also helps to increase the reliability of the system [14]–[16]. The main objective of this study is to allocate generation so that the total fuel cost is minimized while satisfying the power demand and operational limits of the generators. In this section we are going to explain the critical steps used in solving the ELD problems for both conventional and some of the advance techniques.

2.1.1. Objective function:

The main goal of ELD is to minimize the total cost of power generation for a particular set of generators committed [10][17]. These can be represented mathematically as:

$$F(P) = \sum_{i=1}^{N} F_i(P_i) \quad (1)$$

Where $F(P)$ is the total fuel cost. $F_i(P_i)$ *is* the fuel cost function of the i-th generating unit. P_i is the power generated by the i-th generator. N is the number of generating unit

For analysis, each fuel cost function is modeled as a quadratic function as shown below:

$$F_i(P_i) = a_i P_i^2 + b_I P_i + c_i \quad (2)$$

Where a_i, b_i *and* c_i *a*re the cost coefficients for the i-th generator. These coefficient are the factors contributed to the fuel cost.

2.1.2. Constraints:

The ELD optimization problem is subjected to the following constraints which has to be certified for better optimal output:

a) Power Balance Constraint: This constraints equate the total power generated from all the generating units to be equal to the load demand. This constraint is represented mathematically below:

$$\sum_{i=1}^{N} P_i = P_D \quad (3)$$

Where P_D is the total power load demand from the system. $\sum_{i=1}^{N} P_i$ is the total power generated from the unit.We should note that the above equations are assumed for an ideal system, whose losses are neglected.

b) Generator Capacity Limit Constraint: This constraint explains the limits of each generator committed. It shows that each generating unit has a minimum and maximum capacity limit that must be respected during operation to obtain a reliable and optimal power output, below is a mathematical expression that certifies this constraint;

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (4)$$

Where P_i^{min} *and* P_i^{max} are the minimum and maximum power output limits for the ith generator.

c) Ramp Rate Limit: there are systems that use ramp rate limit in other to determine how fast the output of a generator can be adjusted:

$$|P_i(t+1) - P_i(t)| \leq R_i \quad (5)$$

Where R_i are The ramp rate unit for generator i.

2.1.3 Formulation of Transmission Line Losses

In a situation whereby transmission losses are considered, the power balance constraints are modified to include the power losses along the lines denoted as (PL), and this changes the power balance constraints as follows:

$$\sum_{i=1}^{N} P_i = P_D + P_L \quad (6)$$

Where PL is the total transmission line losses.

2.1.4 Non-Smooth Fuel Cost Functions:

For systems with more realistic scenarios, the fuel cost functions may include valve-point effects, which introduce ripples in the cost curve, which can also be called the non-linear systems. This can be represented as:

$$F_i(P_i) = a_i P_i^2 + b_I P_i + c_i + \left| e_i \sin\left(f_i\left(P_i^{min} - P_i\right)\right) \right| \quad (7)$$

Where e_i & f_i are the valve-point effect coefficient.

2.2 Review Methodology:

ELD problems as the central figure in this paper has different methods used by many group of researchers in achieving a single goal which is minimization of generating cost and optimizing the output power [15][16]. In this particular sub-section we will go through some of the related works conducted by other researchers applying different technique in solving the ELD problems ranging from the traditional methods to some of the advance methods. Below is the review carried on some of the techniques used in solving ELD problems.

2.2.1 Conventional Methods:

Lambda (λ) technique: In the Lambda iteration method, lambda represents the variable introduced to tackle constraint optimization problems, commonly known as the Lagrange multiplier. It is crucial to recognize that lambda can be determined by solving equations. To ensure that all inequality constraints are met at each iteration, the equations are solved using an iterative approach. This method employs an equal increment cost criterion for systems without transmission losses and incorporates penalty factors B matrix to account for losses [18]. Also, a conventional method known as the (λ) lambda iteration method is used to analyze a 14-bus IEEE distribution system, and based on their research and method used, they were able to minimize the total cost of generation and also reduce total losses at the bus. Even though the method they used is a conventional method it is easier to understand and it is simpler than any other method which gives it advantage over others for beginners to use. (λ) lambda iteration method is used to solve the economic load dispatch problem to improve the efficiency of the generators at minimum cost [19]. At the same time, another load flow technique known as fast decouple is also used to minimize the losses along the lines and busses [20]. The research conducted by this group has some limitations when it comes to large or medium power system networks, and it is not favorable for non-linear systems.

Gradient technique: This method is based on the idea that we can find the minimum of a function, f(x), by following a series of steps that consistently move downward [21]. In this approach, the fuel cost function is selected to be quadratic function. However, when valve point loading effects are considered, the fuel cost function becomes increasingly nonlinear [22]. The gradient method is a highly effective numerical technique for nonlinear optimization compared to the lambda technique in terms of speed and convergence [23]. At the same time, it is primarily designed for unrestricted optimization. Two variations of the gradient method are proposed to solve the economic dispatch problem of three generators, which seeks to minimize the fuel consumption of generators and the overall system's operating costs by determining the power output of each generating unit committed, subject to certain constraints. Generally, the cost function of a thermoelectric generator is quadratic. However it can be a cubic or more complex function; if that happens, it will be impossible to use the gradient method to solve the problem since it is not in linear form, Therefore other advance optimization techniques such as the Genetic Algorithm GA, particle swarm optimization PSO, etc will be used to solve the problem, also two approaches are used to compare the gradient methods, the first widely used in the solution of the economic dispatch solving the problem with the fixed descent parameter ($\alpha^k = \alpha$), and the second approach, finding the successive $\alpha^k$from a linear search these two approaches are used to solve a standard problem of three generating units as a test to the system.

Newton Raphson technique: Newton’s method goes a step beyond the simple gradient method and tries to solve the economic dispatch by observing that the aim is to continuously drive the gradient of the function to zero. Generally, Newton’s method will solve for the correction that is much closer to the minimum generation cost in one cost in one step than the gradient method [24]. Based on the research it proves that the newton’s technique supersedes the remaining conventional methods due to its fast and reliable result closeness to the optima.

2.2.2 Advance Methods:

Genetic Algorithms (GA): Meta- heuristic approaches are predominantly used to solve the ELD problem due to their optimization efficiency [25]. The genetic algorithm is a search algorithm based on the mechanics of natural selection and natural genetics [26]. A Genetic Algorithm (GA) is one of the meta-heuristic technique used as a computational search method to identify exact or approximate solutions for optimization and search problems, they are also classified as global search heuristics. They are executed through computer simulations, where a population of abstract representations (known as chromosomes or genotypes) of potential solutions (referred to as individuals, organisms, or phenotypes) to an optimization problem evolves. Another set of researchers used the GA technique in comparative with the lambda iterative method to solve two systems of 5 and 10 generators, based on the result obtained GA solution has the best result [27]. In other to solve ELD problem containing multiple unit of 3 and 6 generators Genetic Algorithm method was proposed and the result was optimally suitable [28]. A research was carried out combining the GA and firefly algorithm to solve the ELD problem coupled with environmental emission problem and they were able to address both problems efficiently to an optimal result [29]. GA is one of the widely heuristic techniques used in solving ELD problems but GA is a probabilistic algorithm. The result obtained is a probability of the expected result, the GA is one of the most prominent techniques for solving ELD problems [11].

Particle Swarm Optimization (PSO): James Kennedy and Russell Eberhard introduced particle swarm optimization PSO as a technique designed to solve complex, non-linear optimization problems [30]. Inspired by the collective behaviors of animals such as bird flocking and fish schooling, PSO does not require knowledge of the gradient of the objective or error function. It efficiently identifies optimal solutions and is known for its quick convergence, providing high-quality results in a short amount of time [31][32]. A research focuses on the IEEE 14-bus system, where the economic scheduling of three generator units is carried out using the PSO technique and SCA [11]. The results of both methods are compared, with all analyses conducted using MATLAB software. Based on their research PSO technique showed high quality solution and stable convergence over SCA. They were able to reduce the generating cost and obtain an optimal result. A modified particle swarm optimization to solve three different ELD problem, using the MPSO were able to solve single and multi-objective problems [21].

Sine Cosine Algorithm (SCA): The Sine Cosine Algorithm SCA is an optimization technique based on a population of randomly selected search agents [14]. The algorithm works in two stages: exploration and exploitation. In the exploration phase, SCA generates solutions with high randomness, allowing it to explore areas of the search space where the global solution is more likely to be found. During the exploitation phase, the algorithm refines these solutions by making minor, less random changes than in the exploration stage [31]. Four key parameters guide the algorithm: e1, which determines the next position relative to the solution and destination; e2, which dictates the distance search agents move towards the solution; e3, which adjusts the emphasis on the destination based on its value; and e4, which switches between sine and cosine functions to help reposition the agents near the global solution, giving the algorithm its name [14]. A research conducted using COA method to solve ELD problems of 13-unit, 38-unit, and 40-unit thermal test systems, and it was proven that the COA being almost as competitive in a total fuel cost as the metaheuristic optimization techniques, especially for problems with the less-constrained, but with far reduced computation time [33].

Evolutionary Programming (EP), Simulated Annealing (SA): Simulated Annealing is a stochastic optimization method inspired by the natural crystallization process, where metals undergo gradual cooling [34]. In metallurgy and material science, annealing involves heating and slowly cooling a material to produce a crystal with minimal defects. The concept of thermodynamic annealing, which deals with systems in thermal equilibrium, is closely related to combinatorial optimization, where the goal is to find the global minimum of a function based on numerous parameters. Two research were conducted using SA technique to solve ELD problem and the research paper introduces the Simulated Annealing SA algorithm which is an optimization method inspired by the annealing process in thermodynamics, to address the economic load dispatch ELD problem, their approach demonstrates its ability to yield optimal results while considering operational constraints in ELD and the effects of valve point loading [35]. In other to validate the robustness of the algorithm, they tested it on four standard cases, systems with 3, 13, and 40 generating units with valve point effects, as well as an 18-unit thermal system from Crete Island with convex fuel cost characteristics. The primary advantage of the Simulated Annealing SA approach is its low memory requirement. But its disadvantage is that when there are numerous local minima, finding the global minimum of a multidimensional function becomes a challenging task [36]. The goal of optimization is to ensure quick convergence and effective exploration of the solution space [37]. SA enhances this process by using a probability function to accept or reject new solutions, allowing it to avoid getting trapped in local minima. This technique is more efficient than other related techniques used such as the firefly Algorithm, Gravitational search Algorithm, Artificial Bee colony, etc [38]. Another research was carried out using Simulated Annealing Optimization (SA) algorithm to address economic load dispatch ELD problems.

Gravitational Search Algorithm (GSA): GSA models is one of the advance techniques used in solving the ELD problems whereby the interactions among agents as gravitational forces, guiding the search process towards optimal solutions [17]. GSA was used as a new stochastic optimization algorithm inspired by the law of gravity and interaction between masses to solve ELD problems, called Gravitational Search Algorithm [39]. This proposed algorithm has been tested on some standard power systems including IEEE 6-bus 3 generator, IEEE 14-bus 5 generator, IEEE 30-bus 6 generator systems using different non-linear effect like valve point loading, ramp rate limits, prohibited zones etc. This result has been compared by many well-known heuristic search methods and it result provides the efficiency, robustness, fast convergence and proficiency of the proposed algorithm with less computational time over other existing algorithm. Another research was carried out using AFGSA antigravity-based fuzzy gravitational search algorithm [40]. AFGSA is designed based on the combination of the antigravity mechanism with the adaptive fuzzy parameter controller, these combination provide a better solution to the GSA whereby providing a balance between the exploration and exploitation of GSA this very solution provided by the AFGSA clearly shows that the AFGSA is an improved GSA [41]. MBGSA known as memory based gravitational search algorithm is also an optimization technique used in solving ELD problems and this technique clearly shows an advancement over the GSA when applied on similar systems [42]. The conventional Gravitational Search Algorithm (GSA) fails to keep track of the best agents across iterations, as their positions are determined by the current iteration as a result, it cannot guarantee that the agent new positions will outperform their previous ones while searching for the optimal solution [31]. Consequently, GSA risks losing the optimal solution identified in prior iterations, which hampers its effectiveness in tackling complex optimization challenges.

Artificial Bee Colony (ABC): The Artificial Bee Colony ABC algorithm is an optimization technique inspired by the behavior of bee colonies [43]. It involves worker bees gathering nectar, observer bees analyzing and guiding workers bees to new sources, and scout bees exploring independently for new nectar. In the algorithm, the location of nectar sources represents potential solutions to an optimization problem, and the amount of nectar reflects the quality of those solutions. Each solution is associated with a single worker bee, with the number of solutions equaling the number of employed bees [44]**.** The ABC algorithm is a population-based meta-heuristic technique that mimics the behavior of honey bee swarms. This method was applied to solve three systems consisting of 6, 18, and 20 units. The simulation results indicate that the ABC algorithm consistently provides superior statistical solutions, with a high likelihood of outperforming other intelligent techniques like differential evolution DE, artificial colony optimization ACO, the hybrid harmony search algorithm based on swarm intelligence HHS, and fuzzy adaptive chaotic ant swarm optimization FCASO An advance technique known as the combined heat and power was also used to solve an ELD problem [44]–[46].

3. RESULTS AND DISCUSSION:

In this section result were presented in a tabular form below outlining the advantages, disadvantages and limitations of each techniques discussed above. And also based on the data collected from the papers reviewed we were able to plot charts that clearly explain the performance of each technique when applied to an IEEE test system either small medium or large system making it easier for researchers to make a choice of which technique to use when dealing with similar system in terms of convergence.

Table 1. Comparative result for Conventional Techniques

S/N	Technique	Pros	Cons	Limitations	Similarities
1	Lambda Iteration	Simple and easy to implement	May not converge for complex systems	Suitable only for small and medium-sized systems	Similar to Gradient, both use traditional optimization methods
2	Gradient method	Fast convergence for smooth cost curve	Struggles with system whose cost function is non-linear	Requires differentiable objective function	Similar to lambda iteration relies on gradient information
3	Newton-Raphson	Fast and efficient convergence for certain cost curves	Requires second-order derivative information; complex computation	Can fail for poorly conditioned problems	Has similarities with Gradient in using derivative-based methods

From the table above it was observed that conventional techniques can be used to solve the ELD problems for system with linear fuel cost function but in reality, most of the systems fuel cost function is not linear in nature and because of this non-linearity the advance methods work better in providing solution compared to the traditional methods. Among the conventional methods, the newton Raphson method supersedes others when it comes to fast convergence, but it can fail for poorly conditioned problems since it depends on conditions, it also has similarities with the gradient methods in using derivatives. The lambda iteration technique is the most common conventional method used for its simplicity, but it is not suitable for big systems. The lambda iteration technique also has similarity to gradient method in terms of the optimization method used, these two techniques are widely used when solving simple systems either analytically or iteratively and optimal result will be obtained. The table above provides a comparative overview of optimization techniques commonly applied to solve economic load dispatch (ELD) problems. It highlights their advantages, disadvantages, limitations, and similarities with other methods. Here's a brief discussion on each method below:

1. **Genetic Algorithm (GA):**
    - **Pros:** Effective for non-linear and multi-modal problems, making it a robust choice for diverse optimization tasks.
    - **Cons:** Computationally expensive with slow convergence, particularly for fine-tuning solutions.
    - **Limitations:** Requires careful parameter tuning, especially for population size.
    - **Similarities:** Shares evolutionary principles with Particle Swarm Optimization (PSO) and Differential Evolution (DE).
2. **Particle Swarm Optimization (PSO):**
    - **Pros:** Simple implementation with fewer parameters to tune.
    - **Cons:** May converge prematurely and get trapped in local optima.
    - **Limitations:** Difficulty in handling boundary constraints.
    - **Similarities:** Related to GA as a nature-inspired method, sharing characteristics with swarm-based techniques like Artificial Bee Colony (ABC).
3. **Artificial Bee Colony (ABC):**
    - **Pros:** Known for its efficiency in global search and adaptability.
    - **Cons:** Experiences slow convergence in fine-tuning solutions.
    - **Limitations:** Sensitive to specific parameters like colony size.
    - **Similarities:** Resembles PSO and GA as part of swarm-based methodologies.
4. **Simulated Annealing (SA):**
    - **Pros:** Particularly effective in escaping local minima.
    - **Cons:** Requires careful cooling schedule adjustments to maintain performance.
    - **Limitations:** Sensitive to tuning of temperature and parameter scheduling.
    - **Similarities:** Closely related to the Gravitational Search Algorithm (GSA) due to its random search approach.
5. **Gravitational Search Algorithm (GSA):**
    - **Pros:** Excellent exploration capabilities.
    - **Cons:** May stagnate in local optima during later optimization stages.
    - **Limitations:** Faces challenges with slow convergence in final stages.
    - **Similarities:** Shares random exploration strategies with SA.
6. **Differential Evolution (DE):**
    - **Pros:** Highly effective for multi-modal and non-linear problems.

- **Cons:** Computationally intensive due to its population-based approach.
- **Limitations:** Sensitive to parameter settings such as mutation and crossover rates.
- **Similarities:** Shares adaptive mechanisms with PSO and GSA.

7. **Sine Cosine Algorithm (SCA):**
   - **Pros:** Incorporates a unique structure that avoids local optima more effectively than traditional techniques.
   - **Cons:** Faces challenges with fine-tuning solutions.
   - **Limitations:** Sensitive to initial parameter settings.
   - **Similarities:** Aligns with DE in using adaptive mechanisms for exploration.

These techniques demonstrate a trade-off between global search capability, computational efficiency, and sensitivity to parameters. Understanding their strengths and weaknesses can help researchers choose the most appropriate method for specific ELD scenarios.

Table 2. Comparative Result for Advance Techniques.

S/N	Technique	Pros	Cons	Limitations	Similarities
1	Genetic Algorithm	Good for non-linear and multi-modal problems	Computationally expensive, slower convergence	Requires tuning of multiple parameters like population size	Similar to Particle Swarm and Differential Evolution, all are evolutionary algorithms
2	Particle Swarm Optimization	Simple implementation, few parameters to tune	Can converge prematurely, may get stuck in local optima	Difficult to handle constraints effectively	Similar to Genetic Algorithm, both are nature-inspired methods
3	Artificial Bee Colony	Efficient for global search, adaptable	Slow convergence in fine-tuning solutions	Sensitive to parameters like colony size	Similar to Particle Swarm and Genetic Algorithm, all are swarm-based techniques
4	Simulated Annealing	Effective in escaping local minima	Slow convergence, parameter tuning is crucial	Requires careful cooling schedule for convergence	Similar to Gravitational Search Algorithm in random search nature
5	Gravitational Search Algorithm	Good exploration capabilities	May get stuck in local minima	Slow convergence in final stages	Similar to Simulated Annealing, both use random exploration
6	Differential Evolution	Effective for multi-modal and non-linear problems	Population-based, can be computationally expensive	Sensitive to parameters like mutation and crossover rates	Similar to Genetic Algorithm and Particle Swarm, uses population-based search
7	Sine Cosine Algorithm	Simple structure, avoids local optima better than some techniques	May struggle with fine-tuning solutions	Sensitive to initial parameter settings	Similar to Differential Evolution, both use adaptive mechanisms

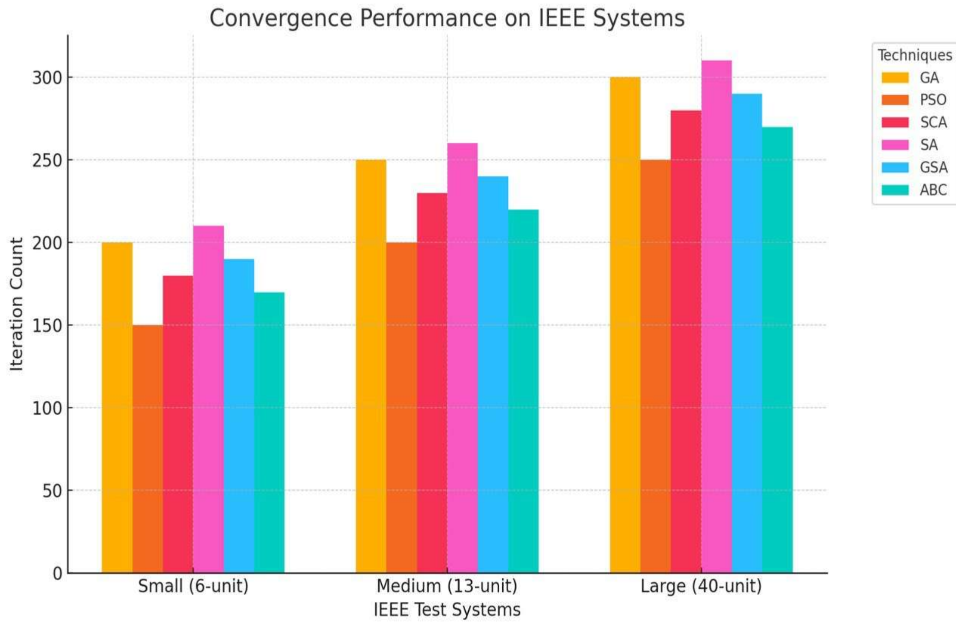

Figure 1. convergence performance graph of the metaheuristic methods.

This graph compares the convergence performance of six optimization techniques reviewed which are the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Sine Cosine Algorithm (SCA), Simulated Annealing (SA), Gravitational Search Algorithm (GSA), and Artificial Bee Colony (ABC) across IEEE test systems of varying sizes: small (6-unit), medium (13-unit), and large (40-unit). Below is a brief interpretation of the findings from the graph.

1. **Small System (6-unit):**
   - Most techniques achieve convergence within similar iteration counts, with ABC demonstrating relatively faster convergence compared to others.
   - SCA and SA require slightly higher iterations, suggesting challenges in fine-tuning on smaller systems.
2. **Medium System (13-unit):**
   - As the system size increases, SCA, SA, and GSA show increased iteration counts, highlighting their sensitivity to problem complexity.
   - ABC continues to perform well, indicating its robustness and adaptability to moderate system sizes.
3. **Large System (40-unit):**
   - All algorithms exhibit a significant increase in iteration count, reflecting the higher computational demand of larger systems.
   - SCA and SA require the highest iteration counts, suggesting they may struggle with scalability for larger systems.
   - GA, PSO, and ABC maintain relatively stable performance trends, showcasing their capability for larger-scale optimization.

The convergence trends reveal that while traditional methods like GA and PSO remain versatile across all scales, swarm-based techniques like ABC consistently outperform others in terms of convergence speed. Conversely, SCA and SA exhibit scalability issues as system complexity increases, potentially due to limitations in their search mechanisms for fine-tuning solutions. This result underscores the importance of selecting an optimization technique tailored to the problem size and complexity to balance convergence efficiency and computational cost effectively.

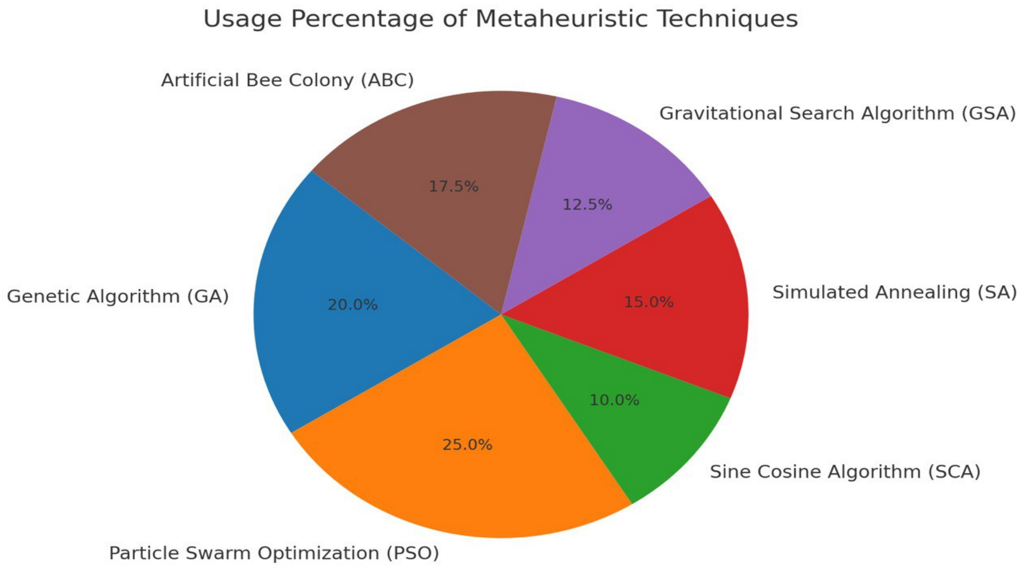

Figure 2. usage percentage chart of the reviewed techniques.

The pie chart above illustrates the usage percentage of metaheuristic techniques based on reviewed papers. Particle Swarm Optimization (PSO) is the most widely utilized (25%), indicating its popularity due to simplicity and effectiveness. Genetic Algorithm (GA) follows at 20%, reflecting its versatility. Artificial Bee Colony (ABC) accounts for 17.5%, showcasing its adaptability. Simulated Annealing (SA) and Gravitational Search Algorithm (GSA) represent 15% and 12.5%, respectively, indicating moderate use. The Sine Cosine Algorithm (SCA) has the least usage (10%), possibly due to its recent development or scalability issues as system complexity increases. Overall, PSO and GA dominate, underscoring their reliability across optimization tasks.

4. CONCLUSION AND LIMITATION

This paper focused on review of various techniques used in solving ELD, problems ranging from the conventional methods up to the advance methods as discussed in section two. From this research, we outlined the pros and cons of each technique based on the relevant works conducted by different researchers. The review indicates that advanced techniques perform better in solving system with non-linear fuel cost function compared to conventional methods. Additionally, based on the conducted studies, some advanced techniques outperform others when applied to similar systems in terms of convergence, speed response, and achieving optimal results. The aim of this paper is to review and compare the performance of the primary techniques used in solving ELD problems when applied on small, medium and large systems in other to come up with a result that help researchers in this field to select which technique to use when solving a similar problem and based on the review performed we were able to present tables and charts in the result section that fulfill our objectives.

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