Vokasi Unesa Bulletin of Engineering, Technology and Applied Science (VUBETA)
https://journal.unesa.ac.id/index.php/vubeta
Vol. 1, No. 1, 2025, pp. 306~318 DOI: 10.26740/vubeta.v2i2.38275
ISSN: 3064-0768

The Use of Genetic Algorithm Optimization Approach In Comparison With Lambda Iteration Technique to Solve Economic Load Dispatch Problem

Sabo Aliyu [1], Sadiq N. Buba[1,2*], Olutosin Ogunleye[1], Kabir Mohammed [1], Samuel Ephraim Kalau[1], Daramdla P. Olaniyi[1]

[1]Department of Electrical and Electronics Engineering, Faculty of Engineering, Post graduate school, Nigerian Defense Academy, Nigeria.
[2]Kaduna Electricity Distribution Company, Kaduna State, Nigeria

Article Info

Article history:

Received January 14, 2025
Revised March 19, 2025
Accepted March 28, 2025

Keywords:

Economic Load Dispatch,
Genetic Algorithm,
Lambda Iteration,
IEEE 39-bus system,
Optimization

ABSTRACT

The increasing demand for efficient and reliable power generation systems has amplified the importance of solving the Economic Load Dispatch (ELD) problems. This study compares the performance of two optimization techniques—Genetic Algorithm (GA), a robust metaheuristic approach, and Lambda Iteration, a traditional iterative method—on the IEEE 39-bus 10-generator test system. The analysis focuses on fuel cost minimization and computational efficiency. GA achieves a significant reduction in total fuel cost to \$1390.29, outperforming Lambda Iteration's \$2324.22. However, Lambda Iteration demonstrates faster convergence at 0.2 seconds compared to GA's 1.2 seconds. The results underscore the trade-offs between cost efficiency and computational speed, providing valuable insights into the suitability of advanced optimization methods like GA for complex ELD problems and the practicality of Lambda Iteration for simpler systems.

1. INTRODUCTION

Electrical power is a crucial energy source that plays a significant role in the growth and development of nations, both developed and developing, across the globe [1]. Its vital role in daily activities has driven a sharp rise in power demand, leading to a corresponding expansion in the size of power systems [2]-[4]. The electrical power as an energy source must be generated, transmitted, and distributed via a medium known as the electrical network or grid for utilization. This energy generation on a larger scale is faced with different challenges, one of which is the cost of generation [2][5][6]. Many power companies are trying to find new ways to optimize the cost of generation while maintaining all other operational constraints. This need for optimal power generation at minimal cost led to the study of the economic load dispatch problem (ELD) [1][4][5]. Economic Load Dispatch (ELD) is one of the most crucial optimization problems in power system operation, aimed at minimizing the total fuel cost while satisfying the power demand and operational constraints [6][2][4]. Economic Load Dispatch (ELD) is used in power systems to identify the most cost-effective generation schedule for a group of power plants, ensuring that the load demand is met [6]. The primary goal of ELD is to minimize the total fuel cost of power generation while adhering to various constraints, such as generator capacity limits and transmission line capabilities [3][7]. In solving the ELD problems different optimization techniques have been used for other system sizes ranging from Traditional methods like Lambda Iteration and Newton-Raphson up-to the modern optimization techniques like Genetic Algorithms (GA), Particle swarm optimization (PSO), Artificial Bee Colony (ABC) etc [4][7]-[9]. From the related literatures we reviewed we found that researchers used both traditional and meta-heuristic technique to solve the ELD problems of different system sizes both small, medium and large systems [1][3][9]. For example, a vectorized lambda-iteration method is proposed to solve a three-generator test system, which serves as an advanced Lambda iteration technique. This technique can scale the computational challenges for large-scale systems, and the

*Corresponding Author
Email: sadiqnguraa@gmail.com

result obtained shows that this technique achieves faster convergence and reduced computational time, but the algorithm is complex [10].

A meta-heuristic method, particle swarm optimization, is applied to solve a system of six generating units. It was able to solve the problem at a fast convergence time but the algorithm is faced with an issue of stuck at local optima [4][11]. To solve the ELD problem of two sets of three and six generating units, ant lion optimization algorithm (ALOA) and bat algorithm (BA) techniques were used as advanced techniques. The result was optimal, although equivalent and unequal specifications must be addressed [9]. The multiple of hybrid lambda-iteration method and bee colony optimization (MHLBCO) was also used to solve the ELD problem with a smooth cost function [12]. This study proposes Genetic Algorithms (GA) and the Lambda Iteration method to solve the ELD problem, using the IEEE 39-bus test system as a benchmark for comparison. These techniques were evaluated based on their efficiency and suitability for optimization in power systems [13]. Traditional techniques like Lambda Iteration provide fast results for simple, convex systems, whereas meta-heuristic methods like Genetic Algorithms (GA) are more suitable for complex, non-linear problems. This paper compares GA and LI for solving the ELD problem in the IEEE 39-bus system, emphasizing cost efficiency and convergence time.

The primary objective of this study is to investigate the cost-effectiveness and computational performance of the GA and LI methods. With its population-based heuristic approach, GA is expected to yield lower costs due to its ability to avoid local minima. In contrast, LI's deterministic nature offers faster convergence for simpler problem structures. To provide a broader perspective, section two provides a detailed step-by-step explanation of how these methods work. In contrast, section three presents us with the results in tables and charts that clearly show the effectiveness of each technique. Section 4 describes and summarizes the results obtained, demonstrating the superiority of one method over the other in terms of cost-effectiveness and convergence time. This paper showed the strength and reliability of GA over the Lambda iteration technique when applied to large-scale systems.

2. METHOD

The economic load dispatch (ELD) problem aims to minimize the generation cost while satisfying operational constraints, and traditional methods such as the lambda-iteration method (LIM) have been widely used due to their simplicity and computational efficiency in small systems [1][13][14]. However, LIM struggles to address non-convex cost functions, non-linear constraints, and large-scale systems [13][15]. Conversely, meta-heuristic techniques like genetic algorithms (Gas) have proven effective in handling the complexities of non-linearities and non-convexity, offering better convergence and accuracy [5][16][17]. Studies have demonstrated the potential of hybrid approaches, where the computational speed and efficiency of LIM are combined with the global search capabilities of GAs to achieve superior performance in large-scale, non-linear ELD problems [13][8][14]. Further research also emphasizes the application of GAs for multi-objective optimization, such as integrating renewable energy sources or addressing environmental constraints [5][15]. By leveraging the strengths of both methods, GAs effectively solve the limitations of LIM, ensuring scalability, adaptability, and robustness in solving complex ELD problems [18]-[20]. This integration highlights that GAs critical role in achieving optimal solutions for real-world, large-scale power system operation is crucial and makes it stand out compared to other techniques [1].

Out of all the methods used in solving the ELD problems, we chose to use the Genetic Algorithm approach compared with the lambda-iteration technique to solve the ELD problem of the IEEE 39-bus 10-generator test system. In this section we explains the two methods used in solving the ELD problem and the software environment used for the simulation (Matlab), and we also provide a systematic way of using the two methods to solve the ELD problem, including their respective mathematical problem formulation and flow charts.

2.1 Simulation Environment and Implementation:

The simulations were performed using MATLAB R2023a, leveraging built-in functions and custom scripts for both GA and Lambda Iteration methods. For the GA, the `ga ()` function from MATLAB's Global Optimization Toolbox was utilized, with the parameters set as shown below. For the lambda-iteration, custom MATLAB scripts were developed to adjust the lambda value based on system constraints iteratively.

- Software: MATLAB R2023a
- Population Size (GA): 100
- Crossover Rate: 0.8
- Mutation Rate: 0.05
- Convergence Criteria: 100 generations or negligible improvement
- Processor: Intel Core i7, 16 GB RAM
- Operating System: Windows 10 Pro

2.2 Genetic Algorithm:

The genetic algorithm (GA) is a robust meta-heuristic optimization technique inspired by the principles of natural selection and genetics [1][16]. It maintains a set of candidate solutions called a population and repeatedly modifies them to a new population derived from the older ones [4]. It is particularly effective for solving non-linear and non-differentiable problems like ELD. The arising question will be How does GA solve the ELD problem? Yes, GA solves the ELD problem by encoding generator power outputs into chromosomes and iteratively improving them using selection, crossover, and mutation to minimize the objective function. It handles constraints using penalty functions or repair mechanisms. Below is a mathematical formulation for solving the ELD using GA.

2.2.1 Objective function:

The objective function is to minimize the total cost of generation at the optimal power output:

$$C(P) = \sum [ai * Pi^2 + bi * Pi + ci], \text{ for } i = 1 \text{ to } N \tag{1}$$

where:
- C(P): Total generation cost ($/h)
- ai, bi, ci: Cost coefficients of generator i
- Pi: Power generated by generator i
- N: Number of generators

2.2.2 Constraints:

- Power Balance Constraint:

$$\sum Pi = PD + PL \tag{2}$$

where
-PD is the total load demand
-PL is the power loss
-∑ Pi is the total power generation.

- Generator Limits constraints:

$$Pmin,i \le Pi \le Pmax,i \tag{3}$$

where: Pmin,i and Pmax,i are the minimum and maximum power outputs of generator i, respectively.

2.2.3 Key Terms Used in the Genetic Algorithm:

Below is a simple table outlining the key terms, also known as the element of genetic algorithm method which will be related to the parameters of the objective function of the economic load dispatch. We try to describe these two to give a better understanding of how the heuristic method is used to solve ELD problems.

Table 1. Key Terms of Genetic Algorithm to ELD

s/n	Terms used in GA	Meaning of each term specified	How these terms are related to ELD objective function.
1	Population	A group of candidate solutions (chromosomes)	Representing power generation levels.
2	Chromosome	A single candidate solution	Encoded as a vector of power outputs.
3	Fitness Function	A measure of how well a candidate solution meets the objective	This represent the Generation cost
4	Selection	The process of choosing parent solutions for reproduction based on fitness.	The process of choosing better solution based on the generation cost obtain
5	Crossover	A genetic operation where two parent solutions are combined to produce offspring.	Process of combining two output generation to form a better one
6	Mutation	A genetic operation that introduces random changes to maintain diversity in the population.	Randomly changing parameters to maintain the power generation.
7	Generations	Iterations of the GA process	Number of iteration

.

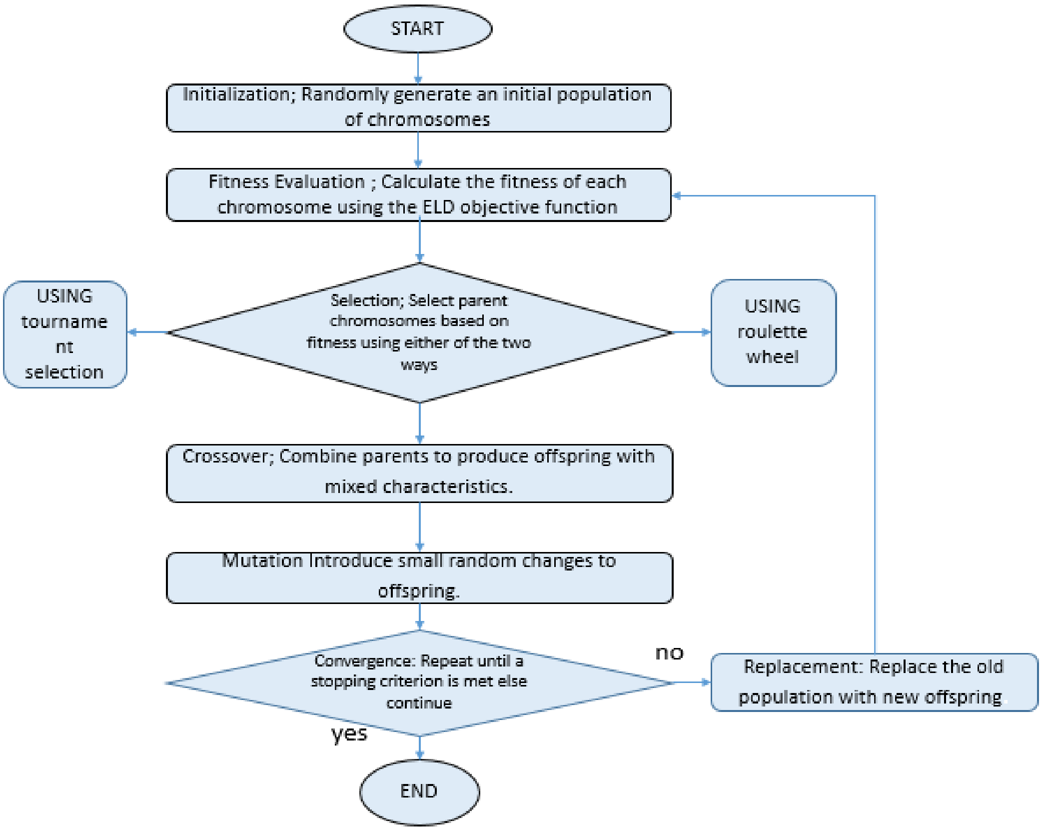


Figure 1. Flow chart of GA when applied to solve ELD

1. **Initialization**:
   Randomly generate an initial population of chromosomes (potential solutions), each representing a candidate power dispatch configuration.
2. **Fitness-evaluation**:
   Calculate the fitness of each chromosome by evaluating the ELD objective function. This function typically includes generation cost, system constraints, and power balance.
3. **Selection**:
   Choose parent chromosomes based on their fitness values using methods like:
   - Roulette Wheel Selection: Higher fitness increases the likelihood of selection.
   - Tournament Selection: A subset of chromosomes competes, and the fittest is selected.
4. **Crossover (Recombination)**:
   Combine selected parents to produce offspring. Common techniques:
   - **Single-point crossover**: Swap segments of chromosomes after a selected point.
   - **Uniform crossover**: Mix parent characteristics randomly.
5. **Mutation**:
   Introduce small random changes to offspring genes to maintain diversity and explore the solution space. This prevents premature convergence.
6. **Replacement**:
   The next generation can be formed by replacing the current population with offspring, possibly retaining a few elite individuals (elitism) to ensure the best solutions are not lost.
7. **Convergence**:
   Repeat steps 2–6 until a stopping criterion is met, such as the following;
   - A predefined number of generations.
   - A fitness threshold.
   - Insignificant improvements over successive generations

2.3 Lambda Iteration Method:

The Lambda Iteration Technique is a conventional approach and is one of the most commonly used techniques in solving the ELD problem [4]. It is based on the principle of equal incremental cost, which ensures that the cost of generating additional power is the same for all participating generators. This method assumes a quadratic cost function and linear constraints, making it effective for simpler, convex ELD problems.

2.3.1 Objective Function of Lambda Iteration:

Minimize the total fuel cost using the mathematical relation below:

$$F(Pgi) = \Sigma\, Fi(Pgi) = \Sigma\, (ai\, Pgi^2 + bi\, Pgi + ci) \tag{4}$$

where:

- F(Pgi): total fuel cost (in $/h or equivalent units)
- Fi(Pgi): fuel cost of generator i
- Pgi: power output of the generator
- ai, bi, ci: cost coefficients of generator i
- N: total number of generators

2.3.2 Constraints:

1. Power Balance Constraint

The total power generated must equal the total power demand plus losses:

$$\Sigma\, Pgi = PD + PL \tag{5}$$

where:

PD is the ttotal power demand and PL is the transmission line losses (can be approximated or neglected in simplified systems).

2. Generator Operating Limits

Each generator must operate within its specified limits:

$$Pgi\_min \leq Pgi \leq Pgi\_max \tag{6}$$

The lambda-iteration method iteratively adjusts the Lagrange multiplier (denoted as λ) to balance power generation and demand while minimizing cost. The condition for economic dispatch and the incremental cost function is given below:

$$\partial Fi(Pgi) / \partial Pgi = \lambda \;\; \forall I \tag{7}$$

$$\partial Fi / \partial Pgi = 2ai\, Pgi + bi = \lambda \tag{8}$$

Table 2. Steps used in lambda iteration to solve ELD

s/n	Stages involved	Corresponding action to be taking
1	Input Data	-Cost coefficients ai, bi, ci for each generator - Power demand PD - Generator limits Pgi_min, Pgi_max
2	Initialization	- Initialize λ (Lagrange multiplier) - Set tolerance ε for convergence
3	Calculate Power Outputs	- For each generator, calculate Pgi using: Pgi = (λ - bi) / 2ai
4	Check Operating Limits	- If Pgi < Pgi_min, set Pgi = Pgi_min - If Pgi > Pgi_max, set Pgi = Pgi_max
5	Compute Total Power	- Compute the total generated power: P_total = ΣPgi

.

6	Check Power Balance	- Calculate the mismatch: $\Delta P = PD - P\_total$ - If $\lvert\Delta P\rvert \le \varepsilon$, go to Step 8.
7	Update Lambda	-Adjust λ using a suitable updating rule, e.g; $\lambda\_new = \lambda\_old + k\Delta P$
8	Output Results	- Print the power output Pgi for each generator - Print the total cost using: $F\_total = \Sigma Fi(Pgi)$

The flow chart below Figure 2 shows how the lambda-iteration technique adjusts the Lagrange multiplier iteratively to ensure that the total power output matches the demand while also minimizing the fuel cost. By iteratively recalculating the power outputs and updating λ, the method achieves an optimal and feasible economic dispatch solution.

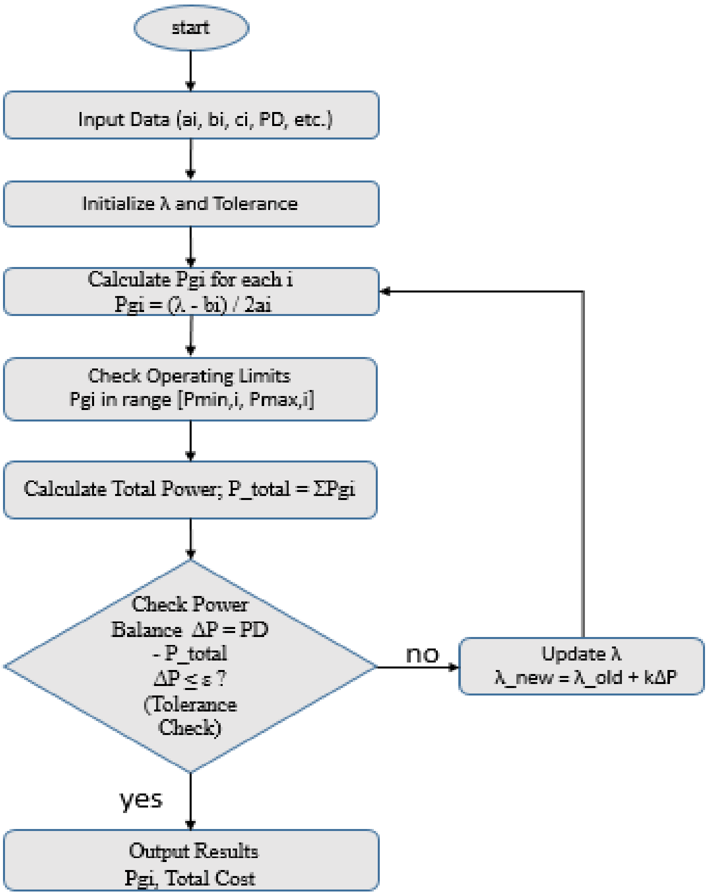


Figure 2. Lambda iteration flow chart

3. RESULTS AND DISCUSSION

This section presents the experiment performed on the IEEE 39-bus system, using GA and the Lambda iteration technique. To perform this experiment, we used the MATLAB software environment, which is one of the best tools for power system analysis, and the result presented in this work is the simulation result obtained from the software. Both techniques were simulated, and the output results were compared based on the fuel cost of generation, power output generation, and the rate at which each method converges. After the experiment, we use tables and graphs to present the results and a detailed discussion for deep insight.

3.1 System Overview:

In this research work, we use the IEEE 39-bus system to test the performance of the two methods discussed earlier in section two: the GA and the lambda-iteration technique. The New England 39-bus system, the IEEE test system, is a widely used benchmark for power system analysis. It includes 39 buses, 10 generating units, and 46 transmission lines [21]. The system provides a test environment for evaluating economic load dispatch, power flow, and stability studies. The figure and table below provide us with the schematic Network and generating unit information needed to perform the analysis, including cost coefficients for the quadratic fuel cost function and the minimum and maximum power output constraints.

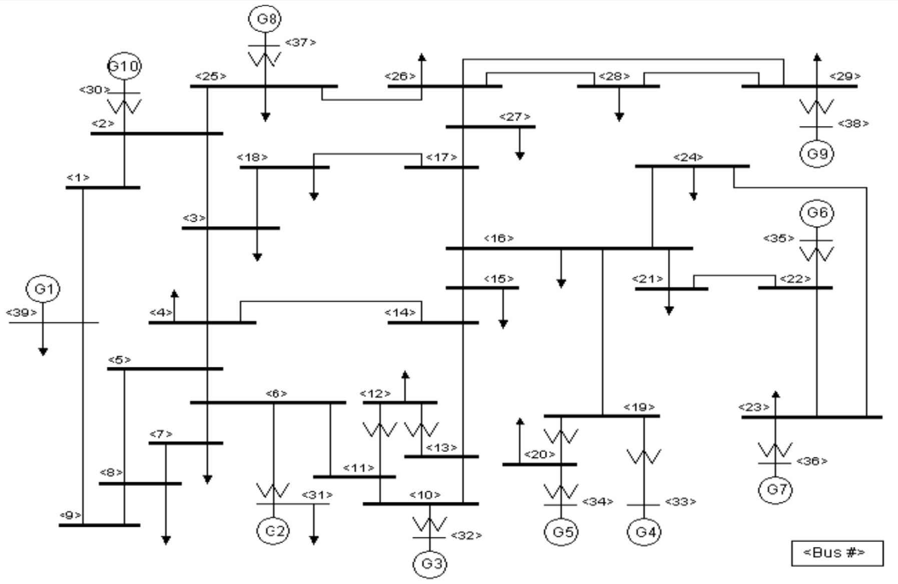


Figure 3.1. IEEE 10-generator 39-bus system network [21]

Table 3.1. IEEE 10-generator 39 bus system

Generator	Bus	a	B	c	P_min, i (MW)	P_max, i (MW)
G1	30	0.00375	2.00	0.00	50	200
G2	31	0.01750	1.75	0.00	20	100
G3	32	0.06250	1.00	0.00	15	80
G4	33	0.00834	3.25	0.00	10	60
G5	34	0.02500	3.00	0.00	10	60
G6	35	0.02500	3.00	0.00	12	60
G7	36	0.02000	2.50	0.00	10	60
G8	37	0.01000	2.00	0.00	20	80
G9	38	0.03226	1.00	0.00	25	100
G10	39	0.01000	1.00	0.00	30	120

PD = 500 MW.

3.2 Using the Lambda Iteration Method:

In this section, we apply the lambda iteration technique to solve the economic load dispatch problem for the IEEE 39-bus system. The results include the power output of each generator, the total fuel cost, and the system's convergence performance.

Table 3.2. Lambda iteration result.

S/N	Generators committed	Power output (MW)	Fuel cost ($)
1	G1	200.0000	550
2	G2	88.4671	291.8
3	G3	30.7708	89.95
4	G4	60.0000	225
5	G5	36.9270	144.9
6	G6	36.9270	144.9
7	G7	58.6587	215.5
8	G8	80.0000	224
9	G9	59.6148	174.3

.

10	G10	120.0000	264
Total	10 generators	771.3654 MW	2324.22 $

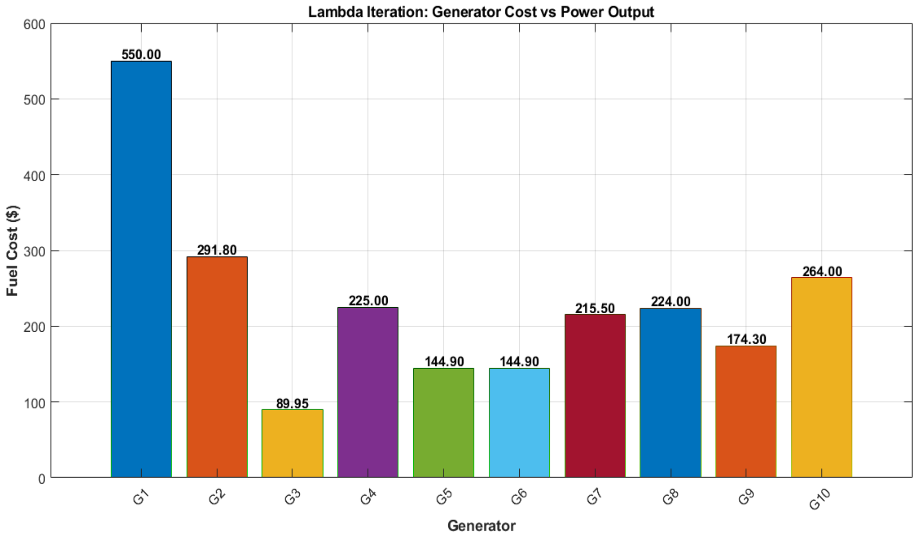


Figure 3.2. Lambda iteration result bar chart

The lambda-iteration method efficiently solves the economic load dispatch (ELD) problem by distributing the load among the ten generators in a cost-optimal manner. As shown in Table 3.2, the method allocates the highest output to G1 (200 MW) due to its low cost coefficients, while smaller generators such as G3 and G4 contribute less power to minimize the total cost. The total fuel cost achieved using this method is $2324.22, and the total power generation amounts to 771.3654 MW, which is higher than the 500 MW demand, likely accounting for losses. The corresponding bar chart (Figure 3.2) visually illustrates the power distribution, showing G1 as the dominant contributor, followed by G2 and G10. The lambda-iteration converged in just 0.2 seconds, as indicated in the comparison table (Table 3.4), demonstrating its computational efficiency. This makes it a preferred method for systems with simpler constraints and convex cost functions.

3.3 Using the Genetic Algorithm Method:

This section presents the application of the genetic algorithm (GA) to the same IEEE 39-bus system. The GA results highlight the optimized power outputs, minimized fuel cost, and the computational time required for convergence.

Table 3.3. Genetic Algorithm result

S/N	Generators committed	Power output (MW)	Fuel cost ($)
1	G1	112.14	271.44
2	G2	52.992	141.88
3	G3	33.12	101.68
4	G4	19.555	66.742
5	G5	21.583	76.393
6	G6	27.959	103.42
7	G7	55.92	202.34
8	G8	24.73	55.577
9	G9	67.663	215.36
10	G10	84.338	155.47
Total	10 generators	500.00 MW	1390.29 $

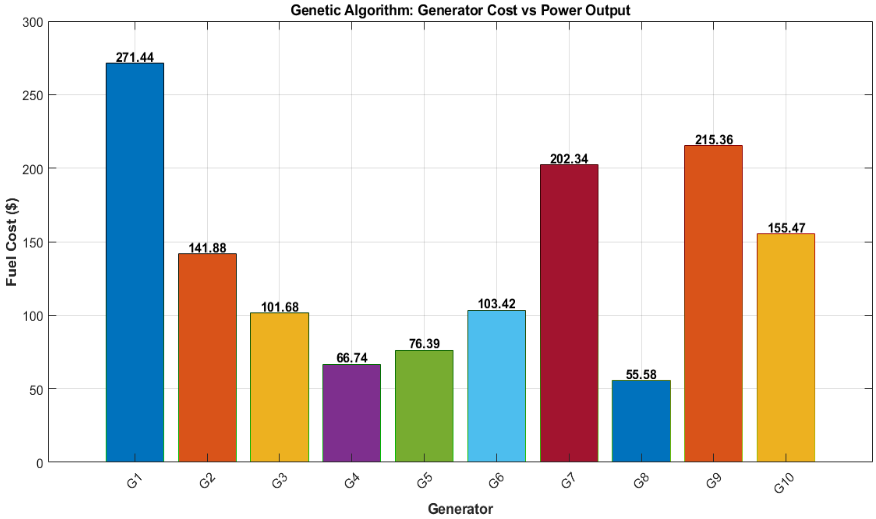


Figure 3.3. Genetic Algorithm result bar chart

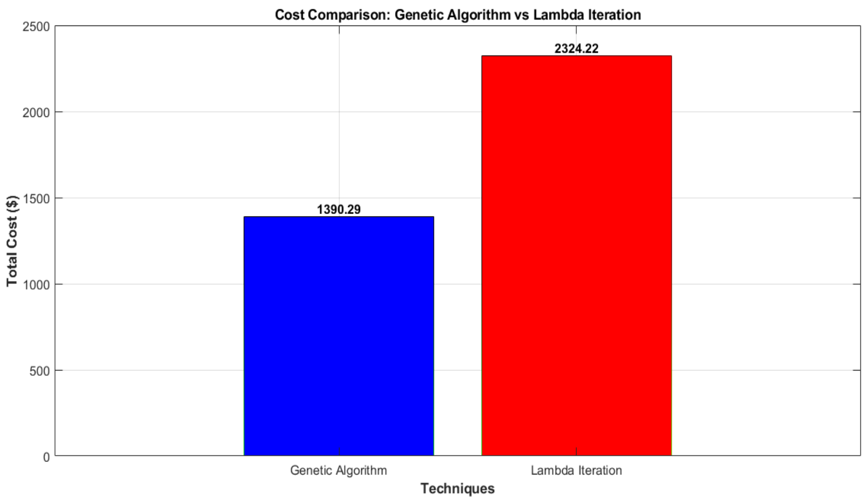
The genetic algorithm (GA) provides a more advanced solution by optimizing the fuel cost while maintaining the system demand of 500 MW, as reflected in Table 3.3. Unlike the lambda-iteration, GA adapts better to the nonlinearities and complexities of the system. The power outputs for each generator were more evenly distributed, with G1 contributing 112.14 MW and G9 contributing 67.66 MW, reflecting the algorithm's flexibility in minimizing costs. The total fuel cost using GA was significantly reduced to $1390.29, a clear improvement over the lambda-iteration results. The corresponding bar chart Figure 3.3 shows how the GA balances power outputs among generators while adhering to constraints. However, the method requires a longer convergence time of 1.2 s, as noted in Table 3.4, due to the iterative nature of the genetic operators (selection, crossover, and mutation) and their exploration of a larger solution space. This trade-off between computational time and cost efficiency highlights GA's suitability for complex ELD problems.

3.4 Comparison of Results Obtained:

Here, we compare the results obtained from the lambda iteration technique and the genetic algorithm. The comparison focuses on fuel costs, power output distributions, and convergence times, providing insights into the strengths and limitations of each method.

Table 3.4. Comparison of Results Obtained from The Two Techniques.

S/N	Technique	Total Cost ($)	Generator Outputs (MW)	Convergence time (sec)
1	Lambda Iteration	2324.22 $	771.3654 MW	0.4 (sec)
2	Genetic Algorithm	1390.29 $	500.00 MW	1.2 (sec)



.

Figure 3.4. Comparison Bar-Chart

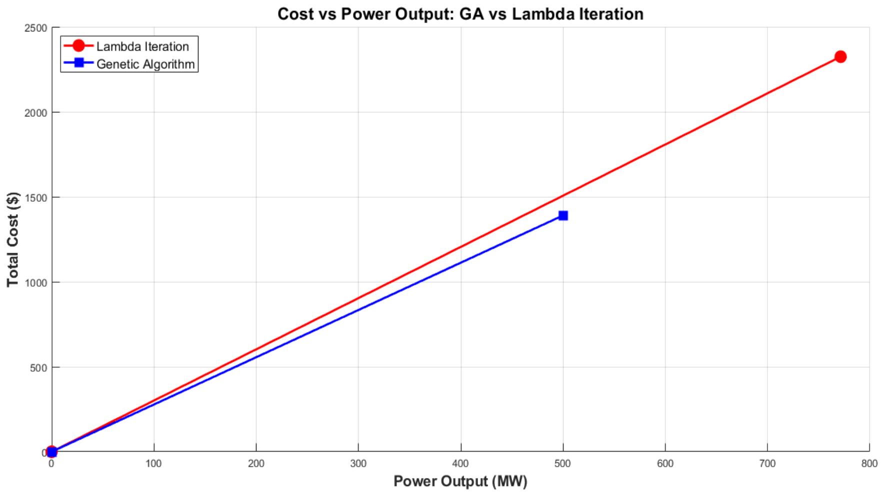


Figure 3.5. Comparison graph.

The comparison reveals that GA significantly reduces fuel costs to $1390.29, whereas the Lambda Iteration generates a higher cost of $2324.22 (Table 3.4). This cost advantage is due to the GA's ability to explore non-convex solution spaces and avoid local minima. However, the Lambda Iteration maintains an advantage in speed, converging in just 0.4 seconds compared to GA's 1.2 seconds. The comparison bar chart (Figures 3.4 & 3.5) vividly illustrates these differences, with GA achieving lower costs across the board but at the expense of higher computational time. While lambda-iteration is straightforward and efficient for simpler problems, GA is more versatile and practical for systems like the IEEE 39-bus system, where cost minimization is critical. Building on these findings, a more detailed comparative analysis is provided below to evaluate the trade-offs between the two techniques.

3.5 Comparative Analysis:

This section compares the performance of the Genetic Algorithm (GA) and the Lambda Iteration method in solving the Economic Load Dispatch (ELD) problem for the IEEE 39-bus 10-generator test system. The analysis focuses on key metrics such as the total fuel cost, power output distribution, and computational efficiency.

a. Fuel Cost Optimization:

The GA achieved a total fuel cost of $1390.29, significantly outperforming the Lambda Iteration method, which resulted in a higher cost of $2324.22. The ability of GA to explore a broader solution space and avoid local optima contributed to its superior cost minimization performance. GA is particularly effective for ELD problems with non-linear cost functions or complex constraints. In contrast, the lambda-iteration is more suited to convex optimization problems due to its reliance on a quadratic cost function and the principle of equal incremental cost. While it provides a feasible solution, its inability to handle non-linearities limits its effectiveness in minimizing costs for more complex systems.

b. Computational Efficiency:

Lambda Iteration demonstrated a significant advantage in computational efficiency, with a convergence time of 0.2 s compared to 1.2 seconds. This is due to its straightforward iterative process, which requires fewer computational resources and operates efficiently under simplified conditions, such as excluding transmission line losses and ramp rate constraints in this study. On the other hand, GA's longer convergence time can be attributed to its reliance on population-based search mechanisms, including selection, crossover, and mutation, which explore and exploit the solution space. While computationally intensive, this approach enables the GA to find global optima, particularly for non-convex problems.

c. Power Distribution Patterns:

GA's ability to distribute power more evenly across all generators highlights its adaptability in minimizing fuel costs while maintaining system constraints. Unlike the Lambda Iteration, which disproportionately allocates power to generators with lower cost coefficients, GA optimally adjusts power output across all units, preventing excessive reliance on specific generators. This ensures better load balancing, reduces stress on individual units, and improves long-term operational stability, essential in a power system.

d. Applicability to System Complexity:

Given the absence of transmission line losses and ramp rate constraints in this study, both methods performed well within their respective capacities. However, GA's superior performance in cost minimization underscores its potential for more complex ELD problems, where such constraints are included. Lambda Iteration, while faster, is better suited for simpler systems where computational speed is a priority and the cost function is convex.

e. Key Trade-offs:

The Genetic Algorithm (GA) requires 1.2 seconds to converge, while Lambda Iteration (LI) completes in just 0.4 seconds. This difference arises from their distinct optimization approaches. GA operates using a population-based search, meaning it iteratively evaluates multiple candidate solutions, applying selection, crossover, and mutation, which increases computational complexity. In contrast, Lambda Iteration directly adjusts the Lagrange multiplier. It uses a deterministic approach, allowing it to converge quickly in convex cost functions but limiting its flexibility in handling non-linear constraints.

f. Parameter Sensitivity:

Varying crossover and mutation rates tested the performance stability. The comparative analysis indicates that GA significantly reduces the generation costs but requires more computational time. The sensitivity analysis revealed that GA's performance is more stable when the crossover rate is between 0.6 and 0.85. In contrast, LI showed consistent performance across different system conditions.

g. Practical Implications:

These findings have significant implications for modern power systems. GA's ability to optimize costs while maintaining flexibility makes it highly suitable for hybrid power systems integrating renewable energy sources such as wind and solar. Additionally, its effectiveness in handling complex, non-linear constraints positions it as a strong candidate for real-time economic load dispatch (ELD) applications in smart grids. On the other hand, Lambda Iteration remains a viable option for simpler grid configurations where rapid convergence is a priority. Potential applications include the following;

- Optimization of generation schedules in hybrid power systems.
- Cost reduction strategies for grids integrating renewable energy sources.
- Real-time ELD in micro-grids with variable demand patterns.

4. CONCLUSION AND LIMITATION

This study demonstrates the application of the genetic algorithm and lambda-iteration techniques to solve the Economic Load Dispatch problem for the IEEE 39-bus 10-generator test system. The results underscore GA's effectiveness in minimizing fuel costs, achieving a total cost reduction of $1390.29 compared to Lambda Iteration's $2324.22. However, the Lambda Iteration excels in computational efficiency, converging in 0.2 seconds versus GA's 1.2 seconds. These findings emphasize the trade-offs between the advanced optimization capabilities and computational simplicity. GA is more suitable for systems with non-linearities and complex constraints, whereas Lambda Iteration is preferred for its rapid convergence in simpler, convex systems. Future work could explore hybrid approaches to leverage the strengths of both methods for enhanced ELD problem-solving.

ACKNOWLEDGEMENTS

First, I would like to express my sincere gratitude to those who have supported and contributed to the successful completion of this research. First, I would like to thank my mentor, Dr. Sabo Aliyu, for his invaluable guidance, insightful suggestions, and continuous encouragement throughout this study. His expertise and advice greatly enhanced the quality of this work. I am also profoundly grateful to my esteemed colleagues Kabir Mohammed, Samuel Ephraim Kalau, and Daramdla P. Olaniyi for their collaborative efforts, insightful discussions, and unwavering support. Their contributions were crucial to developing this paper, and I truly appreciate their time and input.

REFERENCES

[1] A. Sabo, "A Review on Techniques Used for Solving the Economic Load Dispatch Problems: Categorization, Advantages, and Limitations", *Vokasi Unesa Bulletin of Engineering, Technology and Applied Science*, vol. 2, no. 1, pp. 36–47, 2025. https://doi.org/10.26740/vubeta.v2i1.35591

[2] S. Gihare and P. Arun, "An Analysis of Optimization Based Algorithms Economic Load Dispatch in Power Systems,"

International Journal of Advances in Engineering and Management, vol. 6, no. 08, pp. 116–121, 2024. https://doi.org/10.35629/5252-060811612.

[3] S. Jain and D. K. T. Chaturvedi, "Review on Economic Load Dispatch and Associated Artificial Intelligence Algorithms," *Smart Moves Journal Ijoscience*, vol. 7, no. 3, pp. 34–42, 2021. https://doi.org/10.24113/IJOSCIENCE.V7I3.370

[4] Z. N. Jan, "Economic Load Dispatch using Lambda Iteration, Particle Swarm Optimization & Genetic Algorithm," *International Journal for Research in Applied Science and Engineering Technology*, vol. 9, no. 8, pp. 972–977, 2021. http://dx.doi.org/10.22214/ijraset.2021.37527

[5] K. E. Fahim, L. C. D. Silva, F. Hussain, and H. Yassin, "A State-of-the-Art Review on Optimization Methods and Techniques for Economic Load Dispatch with Photovoltaic Systems: Progress, Challenges, and Recommendations," *Sustainability*, vol. 15, no. 15, 2023. http://dx.doi.org/10.3390/su151511837

[6] M. B. B. M. 1D, R. K. Viral, P. M. Tiwari, "Solving Economic Load Dispatch Problem with Integrated Renewable Resources: A Comparative Analysis on Optimization Algorithms," *Journal of Electrical Systems*, vol. 20, no. 7s, pp. 3730–3739, 2024.

[7] S. Kumar, V. Kumar, N. Katal, S. K. Singh, S. Sharma, and P. Singh, "Multiarea Economic Dispatch Using Evolutionary Algorithms," *Mathematical Problems in Engineering*, vol. 2021, no. 7, pp. 1-14, 2021. http://dx.doi.org/10.1155/2021/3577087

[8] K. E. Fahim, L. C. De Silva, V. Andiappan, S. A. Shezan, and H. Yassin, "Research Article A Novel Hybrid Algorithm for Solving Economic Load Dispatch in Power Systems," I*nternational Journal of Energy Research*, vol. 2024, 2024. https://doi.org/10.1155/2024/8420107

[9] R. A. Abttan, A. H. Tawafan, and S. J. Ismael, "Economic Dispatch by Optimization Techniques," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 3, pp. 2228–2241, 2022. http://doi.org/10.11591/ijece.v12i3.pp2228-2241

[10] R. R. N. Ikhsan, J. Raharjo, and B. Rahmat, "Vectorized Lambda Iteration Method for Swift Economic Dispatch Analysis," *Evergreen*, vol. 11, no. 1, pp. 435–447, 2024. http://dx.doi.org/10.5109/7172306

[11] Z. N. Jan and D. S. Saini, "Economic Load Dispatch Using Computational Techniques," *International Journal For Research in Applied Science and Engineering Technology*., vol. 10, no. 12, pp. 831–834, 2022. http://dx.doi.org/10.22214/ijraset.2022.47977

[12] A. Aurasopon and C. Takeang, "Multiple Hybrid of Lambda Iteration and Bee Colony Optimization Method for Solving Economic Dispatch Problem," *International Journal on Electrical Engineering and Informatics*, vol. 13, no. 1, pp. 57–72, 2021. http://dx.doi.org/10.15676/ijeei.2021.13.1.3

[13] J. Uhaa and A. Engla, "Lambda Iteration and Genetic Algorithms Application to solve the Economic Load Dispatch Problem of Seven Nigerian Thermal Power Plants," *Journal of Energy Technology and Policy*, vol. 11, no. 4, pp. 45–54, 2021.

[14] W. Aribowo, "Comparison Study on Economic Load Dispatch Using Metaheuristic Algorithm," *Gazi University Journal of Science*, vol. 35, no. 1, pp. 26–40, 2022. http://dx.doi.org/10.35378/gujs.820805

[15] H. Nourianfar and H. Abdi, "Environmental/Economic Dispatch Using a New Hybridizing Algorithm Integrated with an Effective Constraint Handling Technique," *Sustainabillity*, vol. 14, no. 6, 2022. https://doi.org/10.3390/su14063173

[16] N. Kumar, "A Genetic Algorithm Approach for the Solution of Economic Load Dispatch Problem," *International Journal on Computer Science and Engineering*, vol. 4, no. 6, pp. 1063–1068, 2012.

[17] A. M. Kabir *et al.*, "Optimized Economic Load Dispatch with Multiple Fuels and Valve-Point Effects using Hybrid Genetic–Artificial Fish Swarm Algorithm," *Sustainabillity*, vol. 13, no. 19, pp. 1–27, 2021. http://dx.doi.org/10.3390/su131910609

[18] M. S. Brar and G. S. Brar, "Economic Load Dispatch using IYSGA," *European Journal of Theoretical and Applied Sciences*, vol. 2, no. 1, pp. 595–606, 2024. http://dx.doi.org/10.59324/ejtas.2024.2(1).52

[19] M. Khan, M. A. Shafi, and M. S. K. Khosa, "An Analysis of Stochastic Wind Power Approach for Economic Load Dispatch Optimization using Genetic Algorithm," *Southern Journal of Engineering & Technology*, vol. 1, no. 2, 2023.

[20] F. Marzbani and A. Abdelfatah, "Economic Dispatch Optimization Strategies and Problem Formulation: A Comprehensive Review," *Energies*, vol. 17, no. 3, pp. 1–31, 2024. http://dx.doi.org/10.3390/en17030550

[21] T. Athay, R. Podmore, and S. Virmani, "A Practical Method for the Direct Analysis of Transient Stability," *EEE Transactions on Power Apparatus and Systems*, vol. PAS-98, no. 2, pp. 573–584, 1979. https://doi.org/10.1109/TPAS.1979.319407

BIOGRAPHIES OF AUTHORS

Engr. Dr. Sabo Aliyu (Ph.D) MIEEE. PES. (Member, IEEE) completed his Bachelor's degree in Electrical Engineering from the Prestigious Ahmadu Bello University, Zaria, Kaduna State, Nigeria in 2011. Engr. Dr. Sabo Aliyu completed his M.Sc and Ph.D Degrees in Electrical Power Systems Engineering from Universiti Putra Malaysia. His main research areas include the application of Neuro-Fuzzy Controller to power system, Computational Intelligence techniques, Power System Oscillation Damping Controller Designs, Power Systems Optimizations, Power Flow and Optimal Power Flow, Power Quality, and Robust controllers with several online publications. Engr. Dr.Sabo Aliyu is currently a Senior Lecturer at Nigerian Defence Academy, Kaduna State, Nigeria. He is a registered Engineer under the Council for the Regulation of Engineering in Nigeria (COREN).

Sadiq .N. Buba is a Protection Engineer at Kaduna Electricity Distribution Company, (KAEDCO) Nigeria. He received his B.Eng. from Modibbo Adama University of Technology Yola in Electrical and Electronics Engineering department in the year 2020. He is presently an M.Eng student in the department of Electrical and Electronics Engineering (Power and Machine major) from the post graduate school Nigeria defense academy, Nigeria. He is also a member of International Association of Engineers (IAENG). Contact email: sadiqnguraa@gmail.com .

Olutosin Ogunleye is a Senior Research Fellow at the Centre for Innovation and Creativity, Nigerian Defence Academy. He obtained B.Eng. in Electrical/Electronic Engineering and M.Eng Electronic/Communications Engineering from the Nigerian Defence Academy in 1998 and 2012 respectively. He also bagged a doctorate in Energy Studies from the Faculty of Multidisciplinary Studies, University of Ibadan, Nigeria in 2021. He has attended energy conferences within and outside Nigeria and his research interests include solar thermal systems and energy security. He is a corporate member of the Nigerian Society of Engineers, Nigeria Institute of Management and a chartered engineer of the Council for the Regulation of Engineering in Nigeria. He is also a fellow of the Army War College (fwc) Nigeria and fellow of the National Defence College (fdc) Nigeria.