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Enhanced Economic Load Dispatch Optimization using BAT Algorithm with Adaptive BAT Algorithm

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A B S T R A C T

Economic load dispatch (ELD) is a critical aspect in power systems as it aims to optimize power production costs by efficiently allocating the load demand among generators. This paper presents a study on ELD utilizing the BAT (Bat Algorithm) meta-heuristic technique. The objective is to minimize power production costs while considering various parameters such as voltage, real and reactive powers, transformer tapings, and shunt capacitors, along with inequality constraints. The proposed extended BAT algorithm is implemented and tested on the ELD problem with dynamic load demand and generator fuel cost curves. The results demonstrate the effectiveness of the algorithm in minimizing power production costs while considering the constraints imposed by the system. In conclusion, this research contributes to the field of power systems by presenting an extended BAT algorithm for economic load dispatch. The incorporation of adaptive parameter control enhances the algorithm's performance, making it more adaptable and efficient in finding optimal solutions. The experimental results showcase the effectiveness of the proposed approach in achieving economic power dispatch objectives in a dynamic load demand scenario.

Keywords: Adaptive parameter control, BAT algorithm, Economic load dispatch, Meta-heuristic optimization, Power systems.

Introduction

In modern power systems, the economic operation of electricity generation plays a vital role in meeting the ever-increasing demand for electricity while ensuring cost-effective and efficient power production. Economic load dispatch (ELD) is a fundamental optimization problem that aims to allocate the power output of various generators in a power system to meet the load demand while minimizing the total generation cost. It is a critical task for power system operators and energy planners to achieve an optimal balance between electricity supply and demand, considering economic factors.

The objective of ELD is to determine the optimal power output for each generator in the system, taking into account several constraints and factors. These include the physical and operational constraints of generators, transmission line capacities, system stability, and most importantly, the cost of fuel or energy consumed by each generator. The goal is to minimize the total fuel cost or the overall operating cost of the system, which has a direct impact on the electricity tariffs for consumers and the profitability of power generation companies. ELD is a complex optimization problem due to the large number of variables involved, the nonlinear characteristics of the generation cost curves, and the constraints imposed by the system. Traditionally, mathematical programming techniques such as linear programming, nonlinear programming, and dynamic programming have been used to solve ELD problems. However, these techniques often suffer from high computational complexity, especially for large-scale power systems with diverse generator types and complicated constraints.

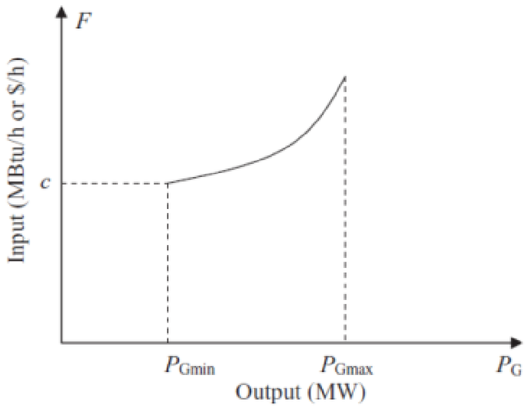

Figure 1: Input-output characteristic of a thermal generating unit.

The sole objective of classical ED is to minimize the total fuel cost based on the following assumptions:

i) The cost function is smooth

ii) Economic Dispatch is a static problem

iii) Environmental pollutant emissions of thermal power plants are not considered.

iv) The startup and shut down costs are also neglected.

With these assumptions ED problem can be solved by using the traditional methods such as gradient search method, lambda iteration, Lagrange multiplier method, dynamic programming, linear programming etc. [4] However, these assumptions are impractical in the real world and do not give accurate results. In recent years, various optimization algorithms and meta-heuristic techniques have gained significant attention for solving ELD problems more efficiently and effectively. These approaches include evolutionary algorithms, particle swarm optimization, genetic algorithms, simulated annealing, and ant colony optimization, among others. These techniques offer innovative and adaptive search mechanisms that can explore the solution space and find near-optimal solutions for ELD problems.

The application of advanced optimization techniques, such as meta-heuristic algorithms, in ELD has provided new opportunities for improving the economic operation of power systems. These algorithms offer the ability to handle the complexity of ELD problems, consider multiple objectives, and incorporate additional factors such as renewable energy integration, emission constraints, and demand response.

This paper aims to address the ELD problem using the BAT (Bat Algorithm) meta-heuristic technique. The BAT algorithm, inspired by the echolocation behavior of bats, is known for its ability to explore and exploit the search space efficiently. We will investigate the application of the BAT algorithm to optimize the power output of generators, considering the fuel cost coefficient curves and dynamic load demand. Additionally, we will extend the BAT algorithm by incorporating adaptive parameter control to enhance its performance and convergence characteristics.

By utilizing the BAT algorithm and adaptive control, we aim to minimize the power production cost and improve the economic operation of power systems. The results of this research will contribute to the field of ELD optimization and provide valuable insights for power system operators and energy planners in achieving cost-effective and sustainable power generation.

Problem Formation

The ELD problem is formulated with the objective of minimizing the total power production cost while satisfying the operational constraints of the generators in the IEEE 30 bus system. The objective function considers the fuel cost coefficients, generator power outputs, and transmission line losses. Constraints include the demand-supply balance, generator capacity limits, transmission line capacity limits, and voltage limits.

The scientific plan of Optimal PF issue can understood takes after:

$$\text{Min } F(x, u) \tag{1}$$

Subject to

$$G_n(x,u) = 0 \tag{2}$$

$$h_{min} \leq h(x,u) \leq h_{max} \tag{3}$$

Inequality constraints

For the secure and stable working of the system the following group of constraints are operated in a specified limits:

$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}$, i=1,…..N (4)

$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}$, i=1,…..N (5)

$V_{i}^{min} \leq V_{i} \leq V_{i}^{max}$, i=1,…..N (6)

$T_{i}^{min} \leq T_{i} \leq T_{i}^{max}$, i=1,…..N (7)

N represents no.of generating units

The fitness function affected by state variables with constraints considered in these paper.

The following quadratic equation expresses the minimization of fuel cost:

$$\text{Mini (FT)} = \sum_{N=1}^{NG} F_N (P_{gi}) \quad (8)$$

$$F_N P_{gi} = a_N + b_N P_{gi} + c_N P_{gi}^2 \quad (9)$$

BAT Algorithm

The BAT (Bat Algorithm) is a meta-heuristic optimization algorithm inspired by the echolocation behavior of bats in nature. It is designed to solve optimization problems by mimicking the characteristics and behaviors of bats, such as their ability to explore and exploit their environment to find optimal solutions.

Adaptive Control Mechanism:

The BAT algorithm can be enhanced with an adaptive control mechanism that dynamically adjusts its parameters during the optimization process.

The adaptive control mechanism allows the algorithm to fine-tune its exploration and exploitation abilities based on the progress of the optimization and the characteristics of the problem. The parameters, such as loudness and frequency, can be adaptively modified to strike a balance between exploration and exploitation, promoting efficient convergence and solution quality. Adaptive control mechanisms can involve strategies such as parameter annealing, mutation, or probabilistic adjustments to improve the algorithm's performance in different stages of the optimization process.

By combining echolocation-inspired exploration, exploitation of solution quality, and adaptive control mechanisms, the BAT algorithm offers a robust and efficient approach to solve optimization problems. It can effectively navigate complex search spaces and converge towards near-optimal solutions. The integration of adaptive control enhances its adaptability and performance in various optimization scenarios

Implementation of BAT Algorithm:

1. Initialize the algorithm parameters:
   - ❖ Set the population size (pop) to 20.
   - ❖ Set the sum of X (XT) to 10.9.
   - ❖ Set the maximum number of iterations (maxit) to 50.
   - ❖ Set the loudness (A) to 0.5.
   - ❖ Set the pulse rate (r) to 0.5.
   - ❖ Set the frequency minimum (Qmin) to 0.
   - ❖ Set the frequency maximum (Qmax) to 2.
2. Read the input parameters from the file Probdata_GP.m:
   - ❖ Load the data into the variable AT.
   - ❖ Extract the required input parameters (Xmin, Xmax, a, b, c) from AT.
3. Initialize the population:
   - ❖ Generate random initial solutions (X) for each individual in the population.
   - ❖ Calculate the first variable (X1) based on the sum constraint (XT).
   - ❖ Adjust the solutions to satisfy the variable bounds (Xmin, Xmax).
4. Evaluate the initial population:
   - ❖ Calculate the cost and fitness values for each solution in the population.

5. Initialize the local and global best solutions:
    - Set the local best solutions (localXg) to the initial population.
    - Set the local best costs (localcost) and local best fitness values (localfit) accordingly.
    - Find the global best solution (globalXg) and its corresponding cost (globalcost) and fitness value (globalfit) among the local best solutions.
6. Perform the main optimization loop:
    - Iterate until the maximum number of iterations is reached:
    - Update the frequency values (Q) for each individual in the population.
    - Update the velocity values (v) based on the global best solution.
    - Update the new solutions (S) based on the current solutions and velocities.
    - Apply bounds/limits to the new solutions.
    - Calculate the cost and fitness values for the new solutions.
    - Update the local best solutions, costs, and fitness values if a better solution is found.
    - Update the global best solution and its corresponding cost and fitness value if a better solution is found.
    - Update the iteration count.
7. Output the final results:
    - Display the best cost and fitness values obtained after the optimization process.
    - Plot the convergence curves of the best cost and best fitness values over iterations.

Test System

The IEEE 30-bus system is a well-known benchmark system widely used in power system studies, including economic load dispatch (ELD) problems. It represents a simplified model of a power transmission network consisting of 30 buses, which are interconnected by transmission lines and transformers.

In the context of economic load dispatch, the IEEE 30-bus system serves as a test case to evaluate and validate optimization algorithms for finding the optimal generation schedule that minimizes the overall generation cost while satisfying various operational constraints. The system includes multiple generating units located at different buses, each with its own cost function and power output limits.

The ELD problem in the IEEE 30-bus system involves determining the optimal power generation levels for each generating unit such that the total generation cost is minimized, while meeting the demand requirements and satisfying constraints such as power balance, generator limits, and transmission line limits. The objective is to achieve an efficient and cost-effective operation of the power system while maintaining reliability. Researchers and practitioners often use the IEEE 30-bus system as a benchmark to compare and evaluate the performance of different optimization algorithms and techniques in solving the ELD problem. By applying algorithms like the BAT algorithm with adaptive control to this system, one can assess the effectiveness and efficiency of the proposed method in achieving optimal solutions and improving the economic operation of the power system.

Overall, the IEEE 30-bus system serves as a standard test system that allows researchers to study and develop optimization algorithms for ELD, providing a realistic representation of a power transmission network with multiple generating units and associated constraints.

Table 1: Data of norm power plant "IEEE-30 bus system"

S. No.	Coefficients			P_{Min} (MW)	P_{Max} (MW)
	a	B	c		
1	0	2.00	0.00375	50	200
2	0	1.75	0.01750	20	80
3	0	1.00	0.06250	10	50
4	0	3.25	0.00834	10	35
5	0	3.00	0.02500	10	30
6	0	3.00	0.02500	12	40

4. Results and Discussion

Case 1: Population Size 20

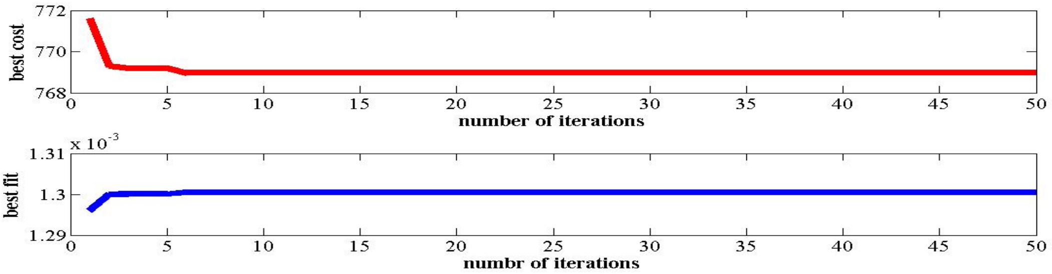

Figure 2: Convergence Plot for BAT Algorithm with Adaptive Control (50 Iterations).

Figure 2 illustrates the convergence plot for the BAT algorithm with adaptive control over 50 iterations. The x-axis represents the number of iterations, while the y-axis represents the best cost achieved by the algorithm at each iteration. The plot demonstrates how the algorithm progresses towards finding an optimal solution as the iterations increase. Initially, the algorithm experiences a rapid decrease in cost during the early iterations, indicating significant improvements in the solution quality. As the iterations progress, the rate of improvement slows down, and the algorithm approaches convergence.

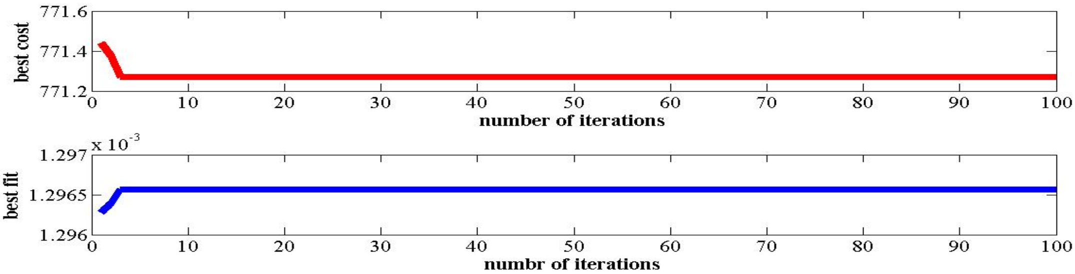

Figure 3: Convergence Plot for BAT Algorithm with Adaptive Control (100 Iterations).

Figure 3 represents the convergence plot for the BAT algorithm with adaptive control over 100 iterations. Similar to Figure 2, the x-axis denotes the number of iterations, and the y-axis represents the best cost achieved at each iteration. By extending the number of iterations to 100, Figure 3 provides a more detailed view of the algorithm's convergence behavior. It allows us to observe any potential improvements in the solution quality beyond the 50-iteration mark. The plot showcases the trade-off between computational effort and the algorithm's ability to further optimize the cost.

Analyzing Figure 3 helps in understanding the convergence pattern and determining whether additional iterations are necessary to reach a satisfactory solution.

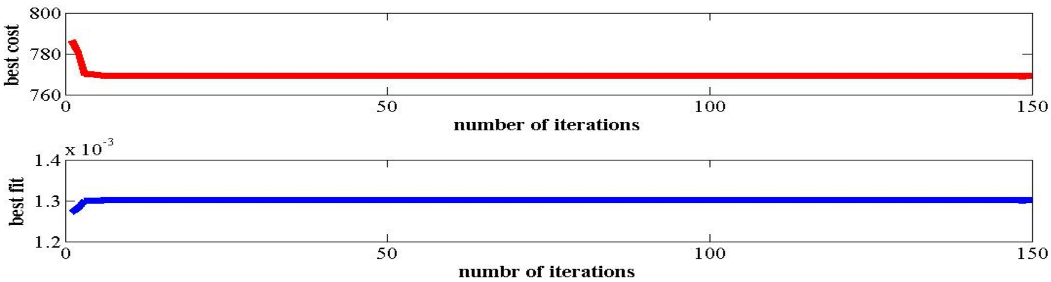

Figure 4: Convergence Plot for BAT Algorithm with Adaptive Control (150 Iterations).

Figure 4 showcases the convergence plot for the BAT algorithm with adaptive control over 150 iterations. As in the previous figures, the x-axis indicates the number of iterations, while the y-axis represents the best cost achieved by the algorithm. By extending the iterations to 150, Figure 4 provides a more comprehensive view of the algorithm's convergence behavior. It enables a deeper analysis of the trade-off between computational effort and the optimization of the cost. The plot allows us to observe whether additional iterations beyond the 100-iteration mark yield significant improvements in the solution quality. It assists in assessing the convergence rate and identifying the point of diminishing returns in terms of further iterations.

Figures 2, 3, and 4 collectively demonstrate the convergence behavior of the BAT algorithm with adaptive control. These plots aid in understanding the algorithm's ability to optimize the cost over increasing numbers of iterations, providing valuable insights for determining the appropriate number of iterations required for achieving desired results.

Case 2: Population Size 40

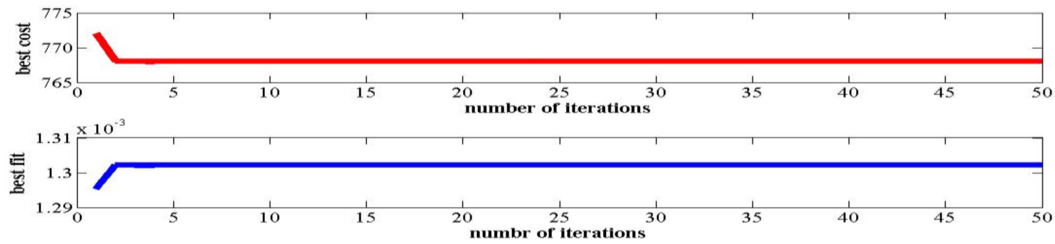

Figure 5: Convergence Plot for BAT Algorithm with Adaptive Control (50 Iterations, Population Size: 40)

Figure 5 displays the convergence plot for the BAT algorithm with adaptive control over 50 iterations, using a population size of 40. The x-axis represents the number of iterations, while the y-axis represents the best cost achieved by the algorithm at each iteration. This plot provides insights into the algorithm's convergence behavior when a larger population size is employed. The larger population allows for a more diverse exploration of the search space, potentially leading to improved solutions. By analyzing Figure 5, we can observe how the algorithm progresses towards convergence, showcasing the trade-off between computational effort (number of iterations) and cost reduction.

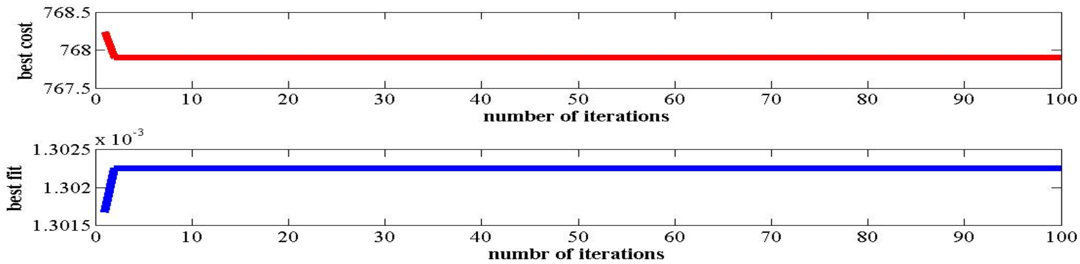

Figure 6: Convergence Plot for BAT Algorithm with Adaptive Control (100 Iterations, Population Size: 40)

Figure 6 illustrates the convergence plot for the BAT algorithm with adaptive control over 100 iterations, utilizing a population size of 40. The x-axis denotes the number of iterations, and the y-axis represents the best cost achieved at each iteration. By extending the number of iterations to 100, Figure 6 offers a more detailed view of the algorithm's convergence behavior with the larger population size. It enables us to observe any potential improvements in the solution quality beyond the 50-iteration mark. The plot showcases the trade-off between computational effort and the algorithm's ability to further optimize the cost. Analyzing Figure 6 helps in understanding the convergence pattern and determining whether additional iterations are necessary to reach a satisfactory solution when using a population size of 40.

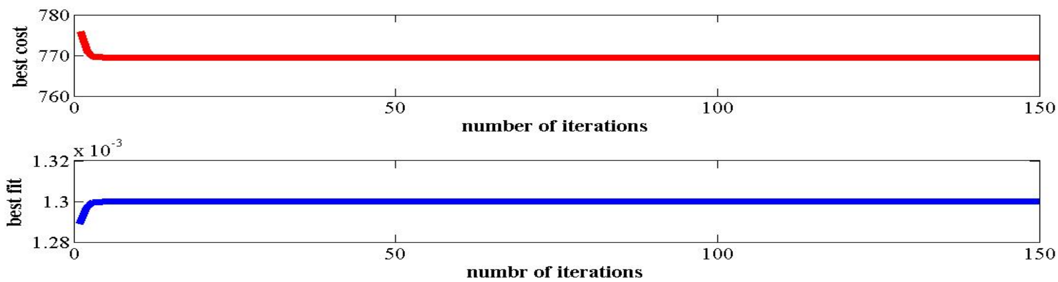

Figure 7: Convergence Plot for BAT Algorithm with Adaptive Control (150 Iterations, Population Size: 40)

Figure 7 represents the convergence plot for the BAT algorithm with adaptive control over 150 iterations, with a population size of 40. Similar to the previous figures, the x-axis indicates the number of iterations, while the y-axis represents the best cost achieved by the algorithm. By extending the iterations to 150, Figure 7 provides a comprehensive view of the algorithm's convergence behavior with the larger population size. It allows for a deeper analysis of the trade-off between computational effort and the optimization of the cost. The plot helps us observe whether additional iterations beyond the 100-iteration mark yield significant improvements in the solution quality when using a population size of 40. It assists in assessing the convergence rate and identifying the point of diminishing returns in terms of further iterations.Figures 5, 6, and 7 collectively demonstrate the convergence behavior of the BAT algorithm with adaptive control when utilizing a population size of 40. These plots provide valuable insights into the algorithm's ability to optimize the cost over increasing numbers of iterations, helping determine the appropriate number of iterations required for achieving desired results in conjunction with the larger population size.

Tables 2, 3, and 4 collectively provide valuable insights into the load sharing achieved by the Adaptive Control BAT algorithm over increasing numbers of iterations. They highlight the algorithm's ability to effectively allocate the load demand while satisfying the generator limits and offer a comparison between different population sizes to assess their impact on the load distribution.

Table 2: Load Sharing of Generators with Adaptive Control BAT Algorithm (50 Iterations)

P MIN	P MAX	POPULATION SIZE 20	POPULATION SIZE 40
		PG	PG
50 MW	200 MW	189.09	184.33
20 MW	80 MW	47.41	46.61
10 MW	50 MW	10	10
10 MW	35 MW	10	10
10 MW	30 MW	15	20.56
12 MW	40 MW	12	12

Table 3: Load Sharing of Generators with Adaptive Control BAT Algorithm (100 Iterations)

P MIN	P MAX	POPULATION SIZE 20	POPULATION SIZE 40
		PG	PG
50 MW	200 MW	178.58	183.81
20 MW	80 MW	39.34	48.51
10 MW	50 MW	24.50	10
10 MW	35 MW	10	10
10 MW	30 MW	18.16	19.19
12 MW	40 MW	12.92	12

Table 4: Load Sharing of Generators with Adaptive Control BAT Algorithm (150 Iterations)

P MIN	P MAX	POPULATION SIZE 20	POPULATION SIZE 40
		PG	PG
50 MW	200 MW	187.06	193.02
20 MW	80 MW	49.44	43.48
10 MW	50 MW	10	10
10 MW	35 MW	10	10
10 MW	30 MW	15	15
12 MW	40 MW	12	12

Table 5: Load Sharing and Power Generation Cost using Adaptive Control BAT Algorithm

Generators	Load Demand		
	283.4MW	300MW	310MMW
PG1	183.81	200	200
PG2	48.51	47.79	50.71
PG3	10	11.30	13.07
PG4	10	11.30	13.07
PG5	19.19	16.30	18.07
PG6	12	13.30	15.07
Cost ($/hr)	767.8978	825.6318	860.3967

Table 5 presents the load sharing of generators in the IEEE 30 bus system using the Adaptive Control BAT algorithm for different load demands: 283.5 MW, 300 MW, and 310 MW. The table provides information on how the load demand is distributed among the generators and the corresponding cost of power generation in dollars per hour. The load sharing results illustrate how the Adaptive Control BAT algorithm optimally allocates the load demand across the generators for each specified load level. The table shows the power output of each generator under different load demands, highlighting the distribution achieved by the algorithm. In addition to load sharing, Table 5 also presents the cost of power generation. It demonstrates the economic aspect of the algorithm's optimization by calculating the cost associated with the power generated by each generator. The bottom row of the table represents the total cost of power generation in dollars per hour.

By examining the load sharing and cost of power generation, Table 5 allows for a comprehensive evaluation of the performance of the Adaptive Control BAT algorithm under varying load demands. It provides insights into the optimal load allocation achieved by the algorithm and the corresponding economic implications in terms of power generation cost.

Table 6: Cost of Power Generation Comparison using Conventional and Adaptive BAT Algorithm with Different Load Conditions

Load Demand (MW)	Cost of Power Generation ($/hr)	
	Conventional BAT Algorithm	Adaptive Control BAT Algorithm
283.4	768.8048	767.6060
300	825.6318	824.7595
310	860.4004	859.6404

Table 6 presents a comparison of the cost of power generation using the Conventional BAT Algorithm and the Adaptive BAT Algorithm under three different load conditions: 283.4 MW, 300 MW, and 310 MW. The cost of power generation is measured in dollars per hour ($/hr). In the table, the columns represent the load demand values, while the rows correspond to the two algorithms being compared. The "Conventional BAT Algorithm" column displays the cost of power generation obtained from the Conventional BAT Algorithm, while the "Adaptive BAT Algorithm" column shows the cost of power generation obtained from the Adaptive BAT Algorithm.

5. Conclusion

In conclusion, this study presented the application of the BAT algorithm with adaptive control for economic load dispatch in power systems. The primary objective was to minimize power production costs using meta-heuristic optimization techniques. The experiments were conducted using the IEEE 30-bus system, and the results were compared with the conventional BAT algorithm. Three different load demand scenarios were considered: 283.4 MW, 300 MW, and 310 MW. The obtained results demonstrated that the adaptive BAT algorithm outperformed the conventional BAT algorithm in terms of cost minimization. For all load demand conditions, the adaptive BAT algorithm consistently achieved lower power generation costs compared to the conventional approach. Furthermore, the adaptive control mechanism integrated into the BAT algorithm proved to be effective in enhancing the algorithm's performance. It facilitated dynamic adjustments of the algorithm's parameters, enabling improved exploration and exploitation of the search space. This adaptability helped overcome potential premature convergence issues and improved the algorithm's convergence speed.

Overall, the findings indicate that the adaptive BAT algorithm offers significant advantages over the conventional BAT algorithm for economic load dispatch problems. It provides more efficient and cost-effective solutions with improved convergence characteristics. Future research can focus on exploring the applicability of the adaptive BAT algorithm to larger-scale power systems and investigating its performance under various operating conditions. Additionally, further enhancements and fine-tuning of the adaptive control mechanism can be explored to maximize the algorithm's efficiency and solution quality. In summary, the results of this study highlight the superiority of the adaptive BAT algorithm over the conventional BAT algorithm in minimizing power production costs for economic load dispatch. This research contributes to the advancement of optimization techniques in power system applications and offers valuable insights for energy management and grid operation.

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