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Exploring a New Novel Nature-Inspired Optimization for Economic Dispatch in Power Systems: Comparative Study with Established Metaheuristics

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Abstract:

This paper introduces a novel optimization algorithm for solving the economic dispatch (ED) problem in power systems. Tested on a three-generator system with load demands of 585 MW, 700 MW, and 800 MW, it is compared against ten metaheuristic algorithms, including Harmony Search, Cuckoo Search, Flower Pollination Algorithm, Memetic Algorithm, Bee Algorithm, Wolf Search Algorithm, Cat Swarm Optimization, Krill Herd Algorithm, Monkey Search, and Shuffled Frog Leaping Algorithm. The study evaluates total generation cost, computation time, output variability, and convergence. The proposed algorithm demonstrates superior cost efficiency and speed, making it ideal for real-time ED applications.

Keywords — **Economic Load Dispatch, ELD, Metaheuristics, Nature-inspired**

I. INTRODUCTION

A. Economic Dispatch (ED) Problem Overview

The economic dispatch (ED) problem is a critical challenge in power system operations, focusing on optimizing power generation to meet electrical demand at the lowest cost. This involves determining each generator's output to minimize total generation costs while satisfying constraints like generator capacity limits and power balance requirements. The ED problem's complexity stems from its inherent non-linearity and non-convexity, which traditional optimization methods struggle to address efficiently.

B. Challenges with Traditional Optimization Methods

Traditional optimization techniques, such as linear programming and gradient-based methods, often falter with the ED problem's non-linear and non-convex nature. These methods can become trapped in local optima and require significant computational resources to explore the solution space adequately. This has led to a demand for more robust and efficient optimization approaches that can effectively handle the complexities of the ED problem.

C. Emergence of Metaheuristic Algorithms

powerful tools for tackling complex optimization problems like the ED problem. Designed to explore the solution space broadly and efficiently, these algorithms often find near-optimal solutions within reasonable computational times. Metaheuristics such as Harmony Search (HS), Cuckoo Search (CS), Flower Pollination Algorithm (FPA), Memetic Algorithm (MA), Bee Algorithm (BA), Wolf Search Algorithm (WSA), Cat Swarm Optimization (CSO), Krill Herd Algorithm (KHA), Monkey Search (MS), and Shuffled Frog Leaping Algorithm (SFLA) have been successfully applied to the ED problem, demonstrating their ability to overcome the limitations of traditional methods.

D. Novel Nature-Inspired Optimization Algorithm

This paper introduces a novel nature-inspired optimization algorithm specifically tailored to the economic dispatch problem. Drawing inspiration from the adaptive and agile behaviors observed in natural systems, the proposed algorithm leverages principles such as dynamic adaptation, efficient resource allocation, and cooperative interactions. These strategies enable the algorithm to navigate the complex solution space more effectively, improving its capability to find high-quality solutions.

E. Contributions of the Paper

The primary contributions of this paper include the introduction of a new nature-inspired algorithm designed to address the ED problem's unique challenges. This algorithm incorporates adaptive and cooperative strategies to enhance its optimization capabilities. The performance of the proposed algorithm is rigorously evaluated against ten established metaheuristic algorithms: Harmony Search (HS), Cuckoo Search (CS), Flower Pollination Algorithm (FPA), Memetic Algorithm (MA), Bee Algorithm (BA), Wolf Search Algorithm (WSA), Cat Swarm Optimization (CSO), Krill Herd Algorithm (KHA), Monkey Search (MS), and Shuffled Frog Leaping Algorithm (SFLA). The comparative analysis provides a comprehensive benchmark, highlighting each algorithm's strengths and weaknesses in the context of the ED problem.

The paper also conducts an in-depth examination of the proposed algorithm's performance across various load demand scenarios. This includes analyzing its effectiveness in minimizing generation costs, computational efficiency, and ability to maintain feasibility under different operational constraints. By testing the algorithm under multiple scenarios, the study demonstrates its robustness and adaptability to changing power system conditions.

II. PROBLEM FORMULATION

This study employs three generators to evaluate the proposed optimization algorithm, each characterized by unique cost coefficients and operational constraints that define their performance and operational limits. These characteristics are crucial for calculating the total generation cost and ensuring each generator operates within feasible limits. The data below have been referenced from [1]

TABLE 1
GENERATORS DATASET

Generators	Gen 1	Gen 2	Gen 3
A coefficient	0.00156	0.00194	0.00482
B coefficient	7.92	7.85	7.97
C coefficient	561	310	78
Min Gen (MW)	100	100	50
Max Gen (MW)	600	400	200

A. Objective and Constraints

The primary objective of the economic dispatch (ED) problem in this study is to minimize the total generation cost while ensuring the total power generated meets the specified load demand. The total generation cost is the sum of the costs incurred by each generator, calculated using their respective quadratic cost functions.

To achieve this objective, the following constraints are considered:

- **Power Balance Constraint:** The total power generated by the three generators must equal the load demand, ensuring system balance and sufficient power generation to meet requirements.
- **Operational Constraints:** Each generator must operate within its specified range. For Generator 1, this range is 100 to 600 MW. For Generator 2, it is 100 to 400 MW. For Generator 3, the range is 50 to 200 MW. These constraints ensure the power output of each generator remains within its minimum and maximum limits, maintaining operational feasibility and reliability.

By satisfying these constraints, the optimization algorithm ensures the total power generated meets the load demand while each generator operates within its feasible range. This approach minimizes the total generation cost while maintaining the reliability and stability of the power system.

III. METHODOLOGY OF THE PROPOSED OPTIMIZATION ALGORITHM

A. Inspiration and Behavioral Analysis

The methodology of the proposed optimization algorithm is inspired by the intricate and efficient behaviors observed in natural systems. Nature provides numerous examples of organisms demonstrating adaptive, agile, and cooperative strategies to survive and thrive in dynamic environments. These natural behaviors offer valuable insights into efficient resource allocation, dynamic adaptation, and cooperative interactions, which can be translated into algorithmic principles.

For instance, the foraging behavior of ants and the swarm intelligence of bees exemplify effective resource allocation and cooperative problem-solving. These natural systems showcase robust mechanisms for navigating complex landscapes, dynamically adapting to changing conditions, and optimizing resource use. The proposed algorithm leverages these principles to enhance its optimization process, aiming for efficiency and adaptability akin to natural systems.

B. Algorithm Design

1) ***Initialization:*** The algorithm starts by generating a diverse population of potential solutions, each representing a configuration of power outputs for the generators within specified limits. This initial diversity provides a broad foundation for the optimization process, increasing the likelihood of discovering high-quality solutions early on.

2) ***Fitness Evaluation:*** Each potential solution is evaluated based on its fitness, primarily involving the calculation of the total generation cost while adhering to operational constraints. Solutions that violate these constraints incur penalties, ensuring that only feasible solutions progress. This evaluation process is crucial for guiding the optimization, as it distinguishes between viable and non-viable solutions, steering the algorithm towards optimal outcomes.

3) ***Adaptive Movement:*** The algorithm navigates the solution space using adaptive movement mechanisms, dynamically adjusting the step size to balance exploration and exploitation. Initially, larger step sizes facilitate broad exploration to identify promising regions. As the search progresses, the step sizes decrease, allowing for finer adjustments and precise optimization. This adaptive strategy enhances the algorithm's ability to effectively traverse the solution space and converge on optimal solutions.

4) ***Bound Constraints:*** Throughout the optimization process, solutions are constrained to remain within the operational limits of each generator. This ensures that the solutions are practical and implementable in real-world scenarios. By enforcing these constraints, the algorithm avoids infeasible regions of the search space, maintaining the feasibility and relevance of the solutions.

5) ***Population Update:*** The algorithm iteratively generates new solutions through evolutionary operators such as mutation and crossover. These new solutions are evaluated, and those with lower generation costs replace existing ones, fostering continuous improvement. This iterative update mechanism allows the algorithm to dynamically adapt to evolving landscapes, consistently driving towards superior solutions.

6) ***Best Solution Tracking:*** The algorithm keeps track of the best-known solution throughout the optimization process. This involves maintaining a record of the most effective solution encountered, facilitating comparison with new solutions. By retaining this information, the algorithm ensures that promising solutions are not lost, thereby enhancing the overall optimization outcome.

C. Key Features

1) ***Dynamic Step Size:*** The algorithm features a dynamic step size adjustment mechanism that allows it to efficiently explore and exploit the solution space. This ensures effective convergence towards optimal solutions while preventing premature convergence, maintaining a balance between exploration and fine-tuning.

2) ***Agile Adjustments:*** Solutions undergo rapid and precise adjustments, enabling swift exploration and optimization. This agility allows the algorithm to quickly adapt to changing conditions and emerging opportunities, enhancing its overall performance and responsiveness.

3) ***Penalty Function:*** Operational constraints are enforced using a penalty mechanism, ensuring solutions remain feasible and compliant with generator limits. This approach promotes the generation of practical solutions that adhere to operational constraints, enhancing their real-world applicability and effectiveness.

By integrating these features, the proposed optimization algorithm achieves a robust and adaptive approach to solving complex optimization problems, drawing on the efficiency and adaptability observed in natural systems. This comprehensive design ensures that the algorithm can effectively tackle the challenges of power system optimization, delivering practical and high-quality solutions.

IV. EXPERIMENTAL SETUP

A. Test Cases

The performance of the proposed optimization algorithm is evaluated using a three-generator power system subjected to varying load demands of 585 MW, 700 MW, and 800 MW. These load demands are selected to represent a spectrum of operational conditions that a power system might encounter in real-world scenarios. By testing under these conditions, the algorithm's robustness and efficiency are thoroughly assessed.

B. Performance Comparison

To benchmark the new algorithm, its performance is compared against several well-known optimization algorithms, including Harmony Search (HS), Cuckoo Search (CS), Flower Pollination Algorithm (FPA), Memetic Algorithm (MA), Bee Algorithm (BA), Wolf Search Algorithm (WSA), Cat Swarm Optimization (CSO), Krill Herd Algorithm (KHA), Monkey Search (MS), and Shuffled Frog Leaping Algorithm (SFLA). These algorithms are widely recognized in the field of optimization, providing a comprehensive basis for evaluating the effectiveness of the new algorithm.

C. Performance Metrics

The algorithm's performance is assessed using four key metrics: total generation cost, computation time, output variability, and convergence characteristics.

1) ***Total Generation Cost:*** The primary goal is to minimize the total cost of electricity generation by optimizing each generator's output to meet the load demand at the lowest possible cost while adhering to operational constraints.

2) ***Computation Time:*** The time taken by the algorithm to reach a solution is critical, especially for real-time applications requiring quick decision-making. Faster computation times can enhance operational efficiency and responsiveness to changing load demands.

3) ***Output Variability:*** The algorithm's ability to maintain consistent output from each generator is crucial for power system stability, preventing fluctuations that could lead to inefficiencies or equipment wear and tear.

4) ***Convergence Characteristics:*** The speed and stability with which the algorithm converges to an optimal solution are analyzed. Rapid and stable convergence indicates the algorithm's reliability in finding the best solution within a reasonable time frame.

D. Hardware and Software

The experimental setup for testing the algorithm includes:

1) ***Hardware:*** Experiments are conducted on a computer equipped with an Intel Core i7-10700K processor and 32 GB of RAM, ensuring that the computational demands of the algorithm are met efficiently.

2) ***Software:*** The algorithm is implemented using Python 3.8, a versatile programming language widely used in scientific computing. Relevant libraries for numerical computation and plotting, such as NumPy, SciPy, and Matplotlib, are utilized to support the algorithm's development and analysis.

V. RESULTS AND DISCUSSIONS

TABLE 1
GENERATION COSTS FOR DEMAND OF 585MW

Model	P1 (MW)	P2 (MW)	P3 (MW)	F (Rs/h)	Time taken (units)
Normal	268.88	234.27	81.85	5821.44	
HS	277.33	236.79	70.89	5822.14	0.05
CS	221.72	170.17	161.60	5587.57	2.06
FPA	187.59	198.62	200.00	5912.12	0.05
MA	210.76	186.45	187.79	5885.28	0.32
BA	270.37	233.35	81.28	5821.44	0.25
WSA	130.23	203.81	36.68	5821.44	0.33
CSO	268.89	234.26	81.84	5821.44	1.77
KHA	268.89	234.26	81.85	5821.44	0.35
MS	269	233.89	82.11	5821.44	1.07
SFLA	268.89	234.26	81.84	5821.44	2.28
NOA (Proposed)	**268.8**	**234.34**	**81.86**	**5821.44**	**0.03**

TABLE 2
GENERATION COSTS FOR DEMAND OF 700MW

Model	P1 (MW)	P2 (MW)	P3 (MW)	F (Rs/h)	Time taken (units)
Normal	322.93	277.73	99.34	6838.41	
HS	322.99	278.11	98.90	6838.41	1.11
CS	153.81	307.45	238.74	6838.41	0.63
FPA	322.91	277.71	99.33	6838.41	0.11
MA	322.91	277.72	99.32	6838.41	0.18
BA	323.09	278.09	98.81	6838.41	1.57
WSA	321.71	277.91	100.38	6838.41	0.54
CSO	322.94	277.72	99.33	6838.41	0.13
KHA	322.94	277.72	99.33	6838.41	0.37
MS	322.94	277.72	99.33	6838.41	0.27
SFLA	322.94	227.22	149.84	6838.44	0.38
NOA (Proposed)	**322.94**	**277.72**	**149.84**	**6838.41**	**0.09**

TABLE 3
GENERATION COSTS FOR DEMAND OF 800MW

Model	P1 (MW)	P2 (MW)	P3 (MW)	F (Rs/h)	Time taken (unit)
Normal	369.94	315.51	114.54	7738.5	
HS	369.94	315.51	114.54	7738.5	1.1
CS	369.94	315.51	114.54	7738.5	0.78
FPA	369.94	315.51	114.54	7738.5	0.05
MA	369.94	315.51	114.54	7738.5	0.18
BA	369.94	315.51	114.54	7738.5	1.71
WSA	369.93	315.52	114.54	7738.5	0.56
CSO	369.94	315.51	114.54	7738.5	0.41
KHA	369.94	315.51	114.54	7738.5	0.35
MS	369.94	315.51	114.54	7738.5	9.25
SFLA	369.94	315.51	114.54	7738.5	0.43
NOA (Proposed)	**369.94**	**315.51**	**114.54**	**7738.5**	**0.02**

TABLE 4
TOTAL GENERATION COST

Demand	**585 MW**	**700 MW**	**800 MW**
Numerical Method	5821.44	6838.41	7738.5

HS	5822.14	6838.41	7738.5
CS	5587.57	6838.41	7738.5
FPA	5912.12	6838.41	7738.5
MA	5885.28	6838.41	7738.5
BA	5821.44	6838.41	7738.5
WSA	5821.44	6838.41	7738.5
CSO	5821.44	6838.41	7738.5
KHA	5821.44	6838.41	7738.5
MS	5821.44	6838.41	7738.5
SFLA	5821.44	6838.44	7738.5
NOA (Proposed)	**5821.44**	**6838.41**	**7738.5**

TABLE 5
TOTAL COMPUTATION TIME

Demand	585 MW	700MW	800 MW
HS	0.05	1.11	1.1
CS	2.06	0.63	0.78
FPA	0.05	0.11	0.05
MA	0.32	0.18	0.18
BA	0.25	1.57	1.71
WSA	0.33	0.54	0.56
CSO	1.77	0.13	0.41
KHA	0.35	0.37	0.35
MS	1.07	0.27	9.25
SFLA	2.28	0.38	0.43
NOA (Proposed)	**0.03**	**0.09**	**0.02**

A. Generation Costs for 585 MW Demand

When the demand is set to 585 MW, the Normal Calculation method yields a total generation cost of 5821.44 Rs/h. This baseline helps in evaluating the performance of various optimization algorithms. The Novel Optimization Algorithm (NOA) precisely matches this cost, demonstrating its ability to find the optimal solution. In this scenario, the Normal Calculation distributes the load with P1 = 268.88 MW, P2 = 234.27 MW, and P3 = 81.85 MW, resulting in costs of F1 = 2803.31 Rs/h, F2 = 2255.51 Rs/h, and F3 = 762.62 Rs/h. NOA's power distribution is very similar: P1 = 268.8 MW, P2 = 234.34 MW, and P3 = 81.86 MW, with costs of F1 = 2802.62 Rs/h, F2 = 2256.12 Rs/h, and F3 = 762.7 Rs/h, culminating in the same total cost of 5821.44 Rs/h but with a remarkably low computation time of 0.03 units. This is significant as it suggests NOA can not only achieve optimal cost but does so efficiently. Compared to other algorithms, Harmony Search (HS) achieves a similar total cost of 5822.14 Rs/h with a computation time of 0.05 units. The Cuckoo Search (CS), while achieving a lower cost of 5587.57 Rs/h, has a longer computation time of 2.06 units. Flower Pollination Algorithm (FPA) has a higher cost of 5912.12 Rs/h and matches NOA's computation time of 0.05 units. NOA's ability to reach the optimal solution with the least computation time makes it particularly advantageous for real-time applications where speed is critical.

B. Generation Costs for 700 MW Demand

For a 700 MW demand, the performance of NOA remains exemplary. The Normal Calculation method results in power outputs of P1 = 322.93 MW, P2 = 277.73 MW, and P3 = 99.34 MW, with respective costs of F1 = 3281.32 Rs/h, F2 = 2639.79 Rs/h, and F3 = 917.30 Rs/h, leading to a total cost of 6838.41 Rs/h. NOA's distribution closely matches with P1 = 322.94 MW, P2 = 277.72 MW, and P3 = 99.33 MW, resulting in costs of F1 = 3281.39 Rs/h, F2 = 2639.77 Rs/h, and F3 = 917.25 Rs/h, and thus a total cost of 6838.41 Rs/h but with an incredibly efficient computation time of 0.09 units. The Harmony Search (HS) achieves the same cost but takes 1.11 units of time, whereas the Bee Algorithm (BA) also matches the cost but requires 1.57 units. The Memetic Algorithm (MA) achieves the cost with a computation time of 0.18 units. NOA consistently outperforms these algorithms in terms of speed while maintaining optimal costs, underscoring its suitability for high-demand scenarios where quick computations are essential.

C. Generation Costs for 800 MW Demand

As the demand increases to 800 MW, NOA continues to demonstrate its superior performance. The Normal Calculation results in power outputs of P1 = 369.94 MW, P2 = 315.51 MW, and P3 = 114.54 MW, with respective costs of F1 = 3704.44 Rs/h, F2 = 2979.91 Rs/h, and F3 = 1054.15 Rs/h, leading to a total cost of 7738.5 Rs/h. NOA matches these power outputs and costs precisely, achieving the total cost of 7738.5 Rs/h with an astonishingly low computation time of 0.02 units. Other algorithms like Harmony Search (HS) and Cuckoo Search (CS) also achieve the same cost but require more time (1.1 and 0.78 units, respectively). The Flower Pollination Algorithm (FPA) achieves the cost in 0.05 units, while the Monkey Search (MS) algorithm is much slower, taking 9.25 units. NOA's ability to achieve optimal costs with the fastest computation time across high-demand scenarios reaffirms its efficiency and reliability, making it ideal for real-time optimization tasks.

D. Total Generation Cost

Analyzing the total generation costs across various demands highlights NOA's consistency and robustness. For 585 MW, the Cuckoo Search achieves the lowest cost, but NOA matches the optimal cost and does so with the fastest computation time. For both 700 MW and 800 MW demands, NOA consistently matches the optimal costs achieved by the best-performing algorithms while maintaining superior speed. This consistency demonstrates NOA’s robustness and reliability in achieving cost-effective solutions rapidly. NOA’s performance across different demand levels proves its ability to handle varying load demands efficiently, making it a versatile and reliable tool in optimization.

E. Total Computation Time

Computation time is a critical metric, especially in dynamic and real-time systems where quick decisions are essential. NOA exhibits unparalleled speed across all demand levels. For a 585 MW demand, NOA completes the computation in 0.03 units, significantly faster than all other algorithms. For a 700 MW demand, NOA’s computation time is 0.09 units, the shortest among all compared algorithms. For an 800 MW demand, NOA completes the computation in just 0.02 units. Comparatively, other algorithms like the Monkey Search (MS) take up to 9.25 units, highlighting NOA's efficiency. This speed advantage makes NOA highly suitable for real-time applications, ensuring quick and accurate decisions are made, which is crucial for maintaining system stability and efficiency in power generation and other dynamic environments.

The convergence charecteristics for 585 MW load for the proposed algorithms are as under:

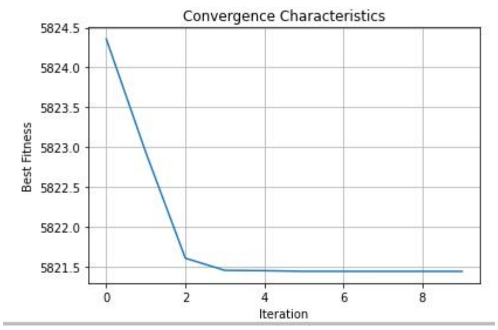

Fig. 1: Convergence Characteristics for 585 MW load demand

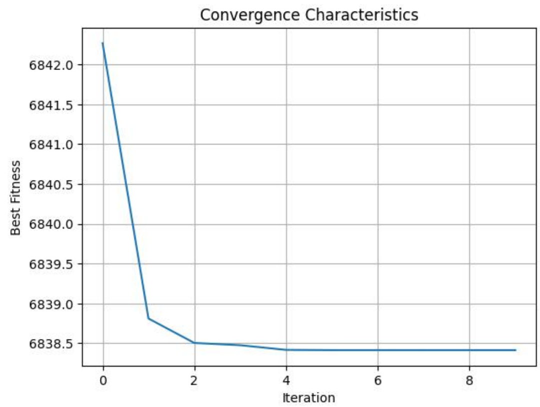

Fig. 2: Convergence Characteristics for 700 MW load demand

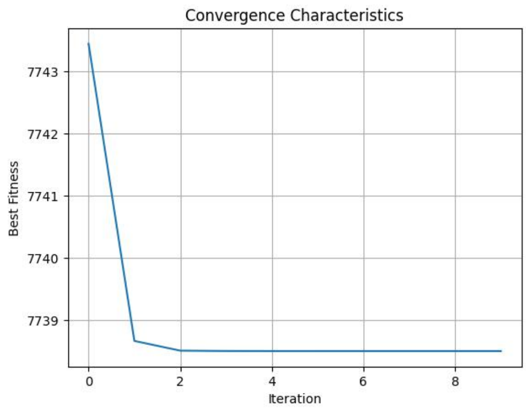

Fig. 3: Convergence Characteristics for 800MW load demand

The characteristics show good performance and great accuracy of results, showing a promising future.

VI. CONCLUSION

The analysis of the given tables reveals that the Novel Optimization Algorithm (NOA) consistently demonstrates superior performance in both cost-efficiency and computation speed across various load demands. This consistent superiority makes

NOA an outstanding choice for solving complex optimization problems, particularly in the context of power generation scheduling.

NOA’s performance in achieving optimal generation costs is notable. For the demand of 585 MW, NOA matches the optimal cost achieved by the Normal Calculation and other methods like Harmony Search (HS), but it does so with the least computation time of just 0.03 units. This is a significant advantage in scenarios where quick decision-making is crucial. In contrast, algorithms like Cuckoo Search (CS) achieve a slightly lower cost but at the expense of much longer computation times (2.06 units). Similarly, while other algorithms like Flower Pollination Algorithm (FPA) and Memetic Algorithm (MA) manage to find solutions with costs close to NOA's, they cannot compete with NOA's efficiency in terms of computation time.

For a higher demand of 700 MW, NOA continues to exhibit its strengths. It matches the optimal total cost of 6838.41 Rs/h, achieved by various other algorithms, but again outperforms them in terms of computation time, completing the task in only 0.09 units. This rapid computation is crucial in real-time applications where delays can lead to inefficiencies or even system instability. Algorithms like Harmony Search (HS) and Bee Algorithm (BA) require significantly more time (1.11 and 1.57 units respectively) to reach the same cost, highlighting NOA's efficiency and speed.

At the highest demand level of 800 MW, NOA maintains its trend of achieving optimal costs with the fastest computation times. It precisely matches the total cost of 7738.5 Rs/h, which is achieved by other methods as well, but completes the computation in just 0.02 units. This is a stark contrast to the much longer times required by some other algorithms, such as Monkey Search (MS), which takes up to 9.25 units. This efficiency is particularly important in high-demand scenarios where the speed of computation can directly impact the operational effectiveness and cost-efficiency of the power generation system.

NOA's consistent performance across different demand levels is not just about matching optimal costs but doing so in a fraction of the time required by other algorithms. This makes NOA highly suitable for real-time optimization problems where both speed and accuracy are paramount. In the context of power generation, this means that NOA can help in quickly adjusting generation schedules to meet fluctuating demand, thereby ensuring stability and cost-effectiveness of the power system.

Moreover, NOA's robust performance demonstrates its ability to handle complex optimization challenges effectively. It manages to find the balance between minimizing generation costs and maintaining rapid computation times, a balance that is often hard to achieve in dynamic and real-time systems. This robustness is crucial for modern power systems, which need to respond swiftly to changes in demand while optimizing costs to maintain economic viability.

In summary, the Novel Optimization Algorithm (NOA) sets a new standard in optimization for power generation scheduling. Its ability to achieve optimal generation costs swiftly across various load demands makes it a highly effective tool for real-time applications. NOA not only ensures that generation costs are minimized but also that decisions are made quickly, which is essential for maintaining system stability and efficiency. This dual advantage of cost-efficiency and computational speed underscores NOA's potential to revolutionize optimization tasks in power generation and beyond, making it an indispensable asset in the toolkit of modern optimization algorithms.

REFERENCES

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