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Voltage Stability Enhancement in Power Distribution Systems using an Improved Blue Monkey Optimization-Based D-SVCs Integration Approach

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ABSTRACT

This paper presents an Improved BM (IBM) optimization algorithm for enhancing voltage stability and reducing power losses in distribution networks through optimal placement and sizing of Distribution Static Var Compensators (D-SVCs). The IBM algorithm modifies the original Blue Monkey metaheuristic by incorporating a random inertia weight to accelerate convergence and improve exploration-exploitation balance. Benchmark function tests demonstrated the IBM's better performance over the original BM and Particle Swarm Optimization (PSO) in solution accuracy, stability, and convergence speed. The proposed method was applied to the IEEE 33-bus system under varying load conditions, achieving optimal D-SVC placements at buses 7, 14, and 31, with reductions of 22.17% and 18.15% in active and reactive power losses, respectively, and an increase in minimum voltage from 0.9131 p.u. to 0.9590 p.u. Comparative analysis with the Modified Artificial Rabbit Optimization (MARO) method confirmed the IBM's consistent performance advantage, including better Fast Voltage Stability Index (FVSI) values. The results validate the IBM algorithm as an effective and robust tool for reactive power compensation optimization in modern power distribution systems.

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1. INTRODUCTION

In modern distribution systems, maintaining voltage levels stable and achieving good power quality are key for delivering electricity reliably and efficiently to customers [1]. However, this has become of the challenging issues as power grids face unpredictable and constantly changing loads, caused by factors such as fluctuating energy demand [2]. These factors usually lead to voltage issues such as voltage sags and swells, which can have dire consequences on the power quality level, affect sensitive equipment, and reduce the overall reliability of the distribution system [3].

Poor distribution systems voltage profiles also contributes to more reactive power to flow and increase real power losses that flow along the distribution lines, which is not just inefficient, it also raises costs for both utilities and consumers [4]. A promising potential approach to tackle these challenges is by the use of Distribution Static Var Compensators (D-SVCs) [5]. These devices help stabilize voltage and improve system power quality. However, to truly get the most out of D-SVCs, especially in such a dynamic environment, there is a need for an effective optimization algorithm technique [6]. This algorithm-based technique is required to determine the best size and location of the D-SVCs in the distribution system to achieve better benefits such as helping to fine-tune voltage control, boost system performance, and reduce power losses under a wide range of system load conditions [7].

To contribute to the ongoing research trend of adopting algorithm-based techniques in optimizing distribution systems with D-SVCs, this work seeks to propose a novel optimization technique based on the Blue Monkey (BM) algorithm [8]. The IBM algorithm is a nature-inspired metaheuristic algorithm that had its inspiration from the social behavior of the Blue Monkeys in wildlife. This IBM algorithm has the potential to be adopted in optimizing distribution systems similar in the case of capacitor integration optimization in distribution system using the adaptive gorilla troop optimizer [9]. Also, the elephant herding optimization has been adopted to optimize the sizing and placement of series capacitors in radial distribution systems [10]. The integration of D-STATCOM into a distribution system has been optimized using pelican optimization algorithm inspired by the pelican birds [4]. These successful applications of nature-inspired algorithms evidence the potentials of such algorithms in optimizing power distribution systems. However, these algorithms are subjected drawbacks such as entrapment in local optimal, slow convergence, etc that usually require modifications to make them suitable for the application [11].

The Blue Monkey (BM) algorithm, inspired by the behavior of the blue monkeys within the groups in which they live, has demonstrated remarkable potentials in solving various optimization problems especially in engineering related fields [12][8]. However, its rigorous tests on standard mathematical benchmark test functions have established its potentials as well as its drawbacks, that is the BM algorithm has shown extremely slow convergence across the test functions consistently [8]. The BM is, therefore, modified to remedied this weakness of slow convergence and the modified version is used to optimize the placement and sizing of D-SVCs in distribution networks.

2. METHOD

This section presents the original BM algorithm, the proposed modification to enhance the convergence performance, and the application to optimize the D-SVCs integration into distribution systems.

2.1. Problem Formulation:

To solve any optimization problem using a metaheuristic algorithm, it is a requirement to formulate the optimization problem, considering the target factors or parameters, into a mathematical objective function. The focus of this work is to enhance the system voltage; as a result, the objective function is formulated based on the system voltage deviations as follows in Equation (1).

$$f_{obj} = \sum_{j=1}^{N} \left| V_{ref} - V_j \right| \quad (1)$$

Where N represents the number of system buses, V_j represents the voltage magnitude at the bus i expressed in per unit, and V_{ref} represents the reference voltage taken to be 1 p.u.

The objective function, Equation (1), is minimized as much as possible by using the proposed IBM algorithm, subject to the standard constraints of the power system [1].

2.1.1. Model of D-SVC:

The D-SVC is one of the shunt-connected reactive power compensation devices capable of providing flexible reactive compensation in distribution networks. It is capable of providing effective system voltage regulation by injecting and absorbing according to when required in the capacitive mode and inductive mode, respectively [13]. The general circuit structure is illustrated in Figure 1 as follows.

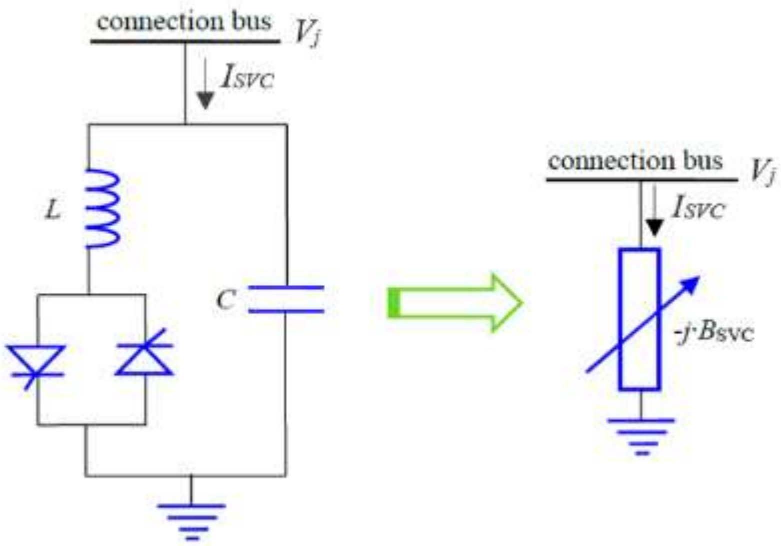

Figure 1. Circuit structure and Equivalent model of D-SVC

Where B_{D_SVC} represents the equivalent susceptance of the D-SVC, the V_j is the voltage at bus j and I_{D_SVC} represents the D-SVC current. The reactive power Q_{D_SVC} injected or absorb by the D-SVC is related to these parameters based on Equations (2) and (3).

$$Q_{D\_SVC} = -B_{D-SVC}.V_j^2 \quad (2)$$

$$I_{D\_SVC} = -B_{D-SVC}.V_j \quad (3)$$

The D-SVC flexibly functions in capacitive mode by injecting reactive power and in inductive mode by absorbing reactive power from the system, depending on the system state. The susceptance of the D-SVC is constrained within a given reactive range given in Equation (4).

$$-Q_{D-SVC}^{max} < Q_{D-SVC} < +Q_{D-SVC}^{max} \quad (4)$$

Where, $-Q_{D-SVC}^{max}$ and $+Q_{D-SVC}^{max}$ are the injected reactive power limits (inductive and capacitive modes) of the D-SVCs, respectively.

2.1.2. Backward / Forward Sweep (BFS) load flow:

A load flow method is required to assess system performance at each iteration of the proposed Improved Blue Monkey (IBM) algorithm. The Backward/Forward Sweep (BFS) load flow method is selected due to its high efficiency and fast convergence, particularly in radial distribution networks [14].

The BFS method operates in two main iterative stages: the backward sweep, which calculates branch currents by aggregating load currents from the end nodes towards the substation, and the forward sweep, which updates bus voltages by propagating voltage drops from the substation outwards using known line impedances [15]. Starting with an initial voltage estimate (usually 1.0 p.u.), the process repeats until bus voltages converge within an acceptable tolerance, ensuring that the power flow equations are accurately satisfied.

2.2. Proposed IBM Algorithm-based Method

2.2.1. The Original BM Algorithm

This algorithm inspiration can be traced back to the intelligent social behavior of a monkey breed known as the Blue Monkeys. The Blue Monkey (Cercopithecus mitis) forms alliances with red-tailed monkeys (Cercopithecus Ascanius) to enhance protection [8]. Their social structure is predominantly female, as males leave the group upon maturity. Adult male blue monkeys have minimal involvement with offspring. Due to their territorial nature, young males are compelled to leave quickly, increasing their chances of survival by challenging dominant males from other groups. If successful, they assume leadership, securing resources and social benefits. Blue monkeys tend to occupy forested areas, drawn by abundant fruit and large fruit patches.

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Unlike many monkey species, they thrive in female-led groups where females remain in their natal groups, while males seek new groups after reaching maturity. This behavior prevents inbreeding. Social interactions among blue monkeys are brief, occurring mainly during play or grooming sessions. Female monkeys take charge of infant care, fostering strong maternal bonds and teaching young monkeys to socialize [8].

Group Division:

The BM algorithm mimics the social behaviors of blue monkeys. To model their interactions, monkeys are grouped and dispersed across the search area. Monkeys venture out in search of food, with dominant males protecting their territories. Young males must depart quickly to succeed in their quest for leadership. If they defeat a dominant male, they lead the group, securing essential resources. Typically, each group consists of one male and numerous females and offspring [8].

Positions Update:

The position of each monkey in a group is updated based on the best-performing monkey in that group [8]. The update mechanism follows Equations (5) and (6) below:

$$Rate_{i+1} = (0.7 \times Rate_i) + (W_{leader} - W_i) \times rand \times (X_{best} - X_i) \tag{5}$$

$$X_{i+1} = X_i + Rate_{i+1} \times rand \tag{6}$$

Where the $Rate$ Signifies the power of the monkey, the W_{leader} and W_i denote the weights of the leader and the monkey, respectively. The variable X represents the position of the monkey, with X_{best} indicating the best position in the group. And finally, $rand$ is a random value between 0 and 1. The position update in Equations (5) and (6) are applicable to the mature monkey group member but the offsprings.

In the case of the younger members of the group termed the offsprings, their positions are updated using Equations (7) and (8) as follows.

$$Rate_{i+1}^{ch} = \left(0.7 \times Rate_i^{ch}\right) + \left(W_{leader}^{ch} - W_i^{ch}\right) \times rand \times \left(X_{best}^{ch} - X_i^{ch}\right) \tag{7}$$

$$X_{i+1}^{ch} = X_i^{ch} + Rate_{i+1}^{ch} \times rand \tag{8}$$

Where $Rate_i^{ch}$ represents the child power rate, W_{leader}^{ch} is the leader child weight, W_i^{ch} is the child weight and all weights are random numbers between [4, 6]. Also, X_i^{ch} is the child position, X_{best}^{ch} is the leader child position and $rand$ represents an arbitrary number between [0,1]. The positions of the blue monkeys are updated iteratively throughout the algorithm. The implementation procedure is detailed in the next section.

Implementation of the Blue Monkey Optimization Algorithm

The implementation of the BM algorithm is achievable by following a certain laid down procedure. The procedure is guided by well-established steps which are presented as follows:

1. Initialize the population of monkeys and offspring.
2. Set initial power rates and weights.
3. Randomly divide monkeys into teams; offspring remain in one group.
4. Calculate the fitness of all monkeys and offspring.
5. Identify the best and worst fitness values in each group.
6. Set the iteration counter to 1.
7. Repeat the following until the maximum number of iterations is reached:
   - 7.1. Replace the worst fitness values with the best from the offspring group.
   - 7.2. Update the position (X) and rate (Rate) of monkeys using the defined equations 6 and 5 respectively.
   - 7.3. Update offspring positions (X) and rates (Rate) using equations 8 and 7 respectively.
   - 7.4. Recalculate fitness and update the best solution if improved.
   - 7.5. Increment the iteration counter.
8. Return the optimal solution.

2.2.2. Propose Modification of the BM Algorithm

The original BM algorithm has shown good performance in solving varieties of standard benchmark functions [8]. This demonstrates its potential in solving optimization problems in various fields. However, the BM algorithm has shown relatively slow convergence across the test functions, consistently requiring higher number of iterations to achieve good results [8]. This is a substantial weakness that can lead to the production of suboptimal solutions in real-life optimization problems.

An inertia weight (α) is introduced in this work to fix this weakness by accelerating the convergence process through a random exploration technique [16]. In this proposition, a random inertia weight concept is adopted and integrated into the position update of the monkeys [17]. The proposed change is presented as follows in Equation (9).

$$X_{i+1} = \alpha X_i + Rate_{i+1} \times rand \quad (9)$$

Where the weight α is defined as follows in Equation 10.

$$\alpha(t) = 0.5 + \frac{rand}{2} \quad (10)$$

This modification enhances the exploration ability of the algorithm by ensuring a more thorough exploration of the search space for better values at each iteration. This proposition helps avoid the production of suboptimal solutions to optimization problems. To verify the improvement effect, there is a need to test this proposed variant, called the Improved Blue Monkey algorithm (IBM algorithm), on standard mathematical benchmark test functions. The implementation procedure of the proposed IBM algorithm is presented in Figure 2 below as a flowchart.

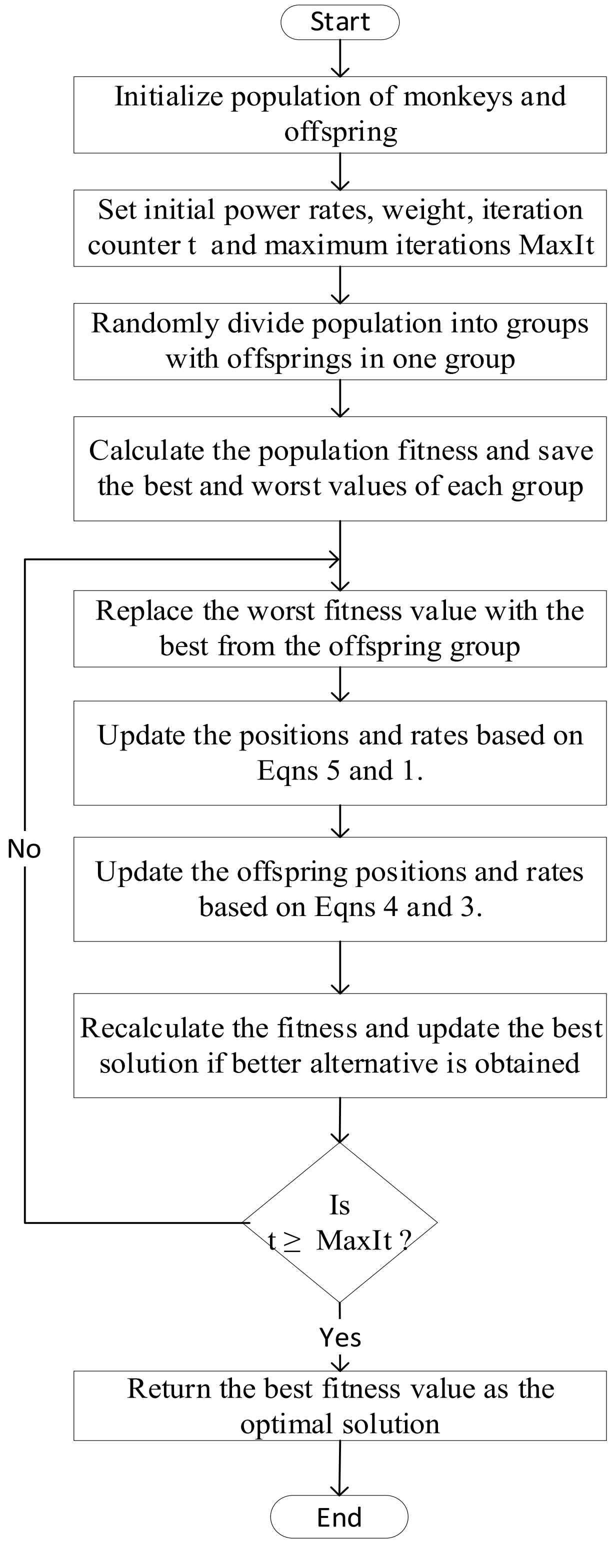

Figure 2. Implementation of IBM Algorithm

Preliminary Testing of the IBM Algorithm on Benchmark Functions:

The proposed IBM algorithm is pre-tested on standard mathematical benchmark test functions to verify its improved performance relative to the original BM algorithm before it is used on the optimization of the D-SVCs in distribution systems. The benchmark test functions considered in this test are sampled from the literature of the original BM algorithm [8].

Table 1. Unimodal Benchmark Functions

Function	Test Name	Dimension	Search Range	Global Optimal
F1	Sphere	30	-100, 100	0
F2	Schwefel 2.22	2	-100, 100	0
F3	Schwefel 2.21	2	-100, 100	0
F4	Schwefel 1.2	2	-100, 100	0
F5	Ackley 2	2	-32, 32	-200

2.3. IMB Algorithm-based Method:

The IBM algorithm-based method involves first initializing random locations and sizes for the D-SVCs within the distribution network. The BFS load flow analysis is executed to determine the system voltage performance by computing the objective function values based on Equation (1). The best-performing sizes and locations are recorded.

The D-SVCs' sizes and locations are considered the population for the IBM algorithm. The exploration and exploitation phases are executed to update the population. The updated population is evaluated using the objective function, and the best-performing sizes and locations are updated if a relatively better-performing result is obtained.

The population re-updating and re-evaluation are repeated iteratively till the stoppage condition of the IBM algorithm is met. The best performing SVCs' sizes and positions are produced as the optimal solution for the optimization problem. The method is comprehensively presented in the flowchart below in Figure 3.

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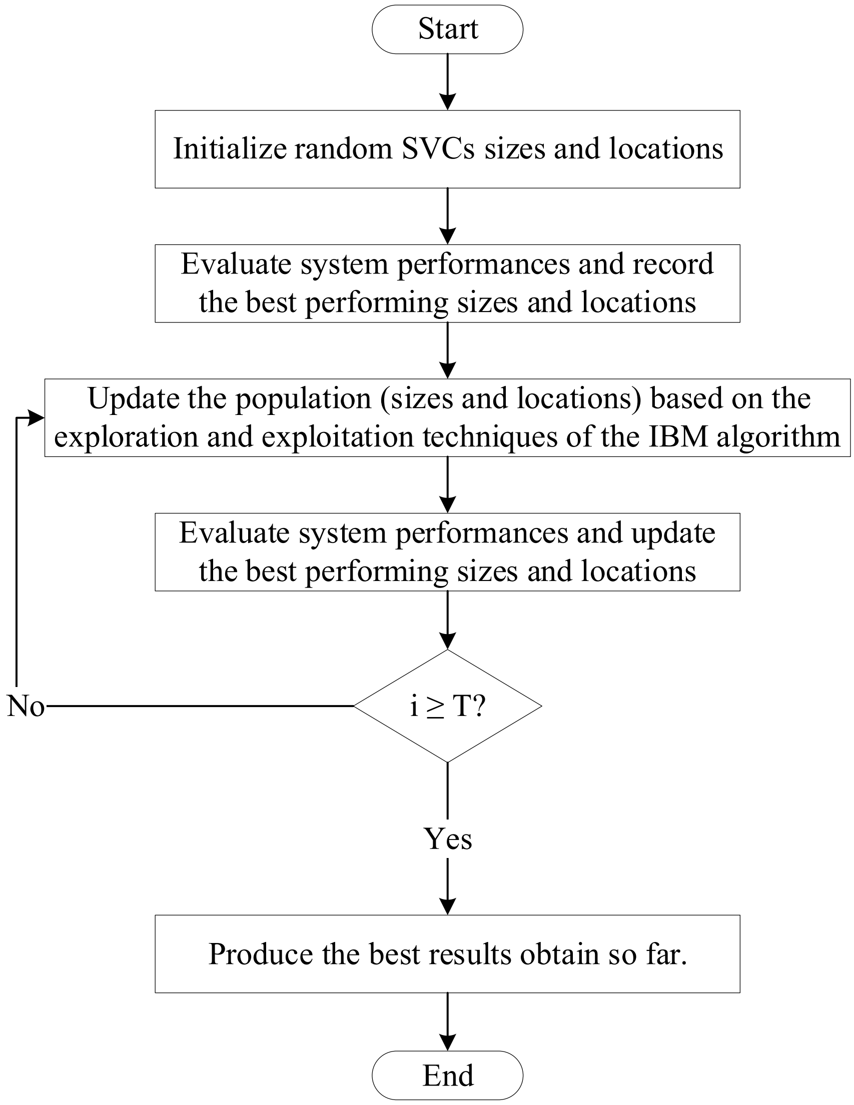

Figure 3. Proposed IBM Algorithm-based Method

Test System (The IEEE 33-bus System):

The IEEE 33-bus test system is a standard radial distribution network widely used for research in power system analysis and optimization [18]. It comprises 33 buses, 32 distribution lines, and a single substation at bus 1, operating at a base voltage of 12.66 kV. The system has a total load demand of approximately 3.715 MW and 2.3 MVAR. Its structure reflects typical real-world distribution networks, making it suitable for studies on power loss reduction, voltage profile improvement, and integration of distributed energy resources. Due to its simplicity and practical relevance, it serves as a reliable benchmark for validating various analytical and optimization techniques. The system is illustrated in the single-line diagram in Figure 4.

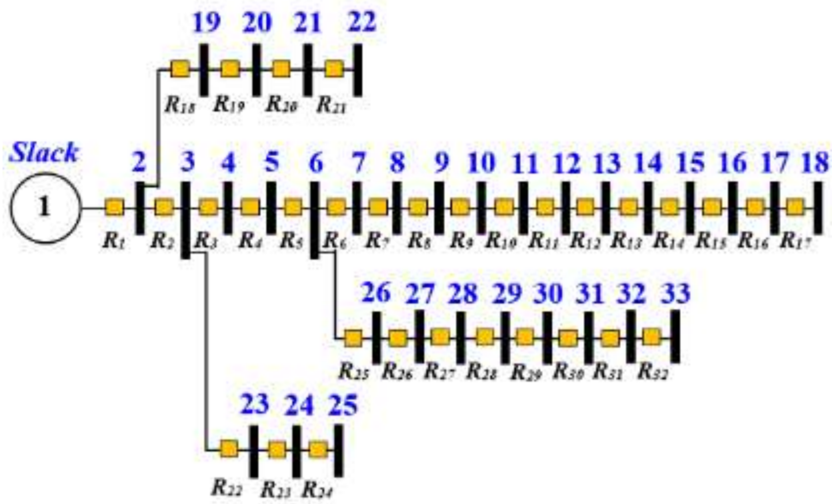

Figure 4. The standard IEEE 33-bus system

The average hourly daily loading conditions of the IEEE 33-bus data expressed in percentage are presented in Table 2 below [19]. This presents the hourly varying power demand in the system.

Table 2. Hourly Loading Data of IEEE 33-bus System

Hour	Loading (%)	Hour	Loading (%)
1	64	13	99
2	60	14	100
3	58	15	100
4	54	16	97
5	56	17	96
6	58	18	96
7	64	19	83
8	66	20	82
9	72	21	82
10	85	22	87
11	99	23	78
12	100	24	71

Test Implementation:

The proposed IBM algorithm-based method is tested on the standard IEEE 33-bus system by code implementation in MATLAB software. The method was used to optimize the IEEE 33-bus system with three (3) D-SVCs integrated at optimal locations. The compensation sizes (amount of reactive power injected) were also determined by the method. The performance was tested under 24 hours of varying loading conditions of the system, and the various performance parameters (power losses, minimum voltage, and system voltage profile) were analyzed.

3. RESULTS AND DISCUSSION

The simulation outcome is presented comprehensively based on the two main test scenarios. The first presents the performance of the IBM algorithm on the standard benchmark functions for the preliminary test. The second part presents the performance of the IBM algorithm-based method of optimizing D-SVCs in a distribution system (the IEEE 33-bus system).

3.1. Performance on benchmark functions

To effectively establish proper performance analysis of the proposed IBM algorithm, it was implemented by coding in MATLAB software as well as the original BM algorithm. The simulation on each benchmark function was repeated 30 times, and the average and standard deviation (Std) were computed and recorded. The performances of the IBM algorithm, the BM algorithm, and the Particle Swarm Optimization (PSO) algorithm [8] are compared in Table 3 to justify the effectiveness of the proposed modification.

Table 3. Simulation Results on Benchmark Functions

Function	IBM		BM		PSO	
	Average	Std	Average	Std	Average	Std
F1	7.5011E-14	8.0394E-14	9.03693E-11	1.78213E-10	2.54E-08	7.98E-08
F2	1.1199E-94	3.1013E-94	3.8784E-66	7.1281E-66	2.03E-51	1.10E-50
F3	4.0067E-84	5.3142E-84	1.8251E-53	3.9978E-53	75.79913	99.69846
F4	1.5996E-140	7.2471E-140	3.2449E-82	1.2054E-81	9.14E-46	5.01E-45
F5	-200	0	-200	0	1.95E-15	1.66E-15

The results across the five benchmark functions presented in Table 3 shows a successive superiority of the proposed IBM algorithm over both the original BM algorithm and PSO. The IBM attained solutions that were repeatedly closer to the global optimum, coupled with lower standard deviations, indicating a robust and stable convergence pattern across several independent runs. The improved performance of the IBM algorithm is attributed to the modifications introduced into the original BM algorithm, which improve both the exploration and exploitation phases of the search process.

In the case of functions F1, F2, F3, and F4, the IBM algorithm outperformed the other algorithms in obtaining the best average and std values. The original BM algorithm followed with the next better performance and the PSO produced the worst results among them. In the case of function F5, both the proposed IBM algorithm and the original BM algorithm produced a very competitive results by obtaining the global optima of the test function, while the PSO produced a sub-optimal value.

Further comparisons in terms of the convergence process on some benchmark functions between the original BM algorithm and the proposed IBM algorithm are presented below.

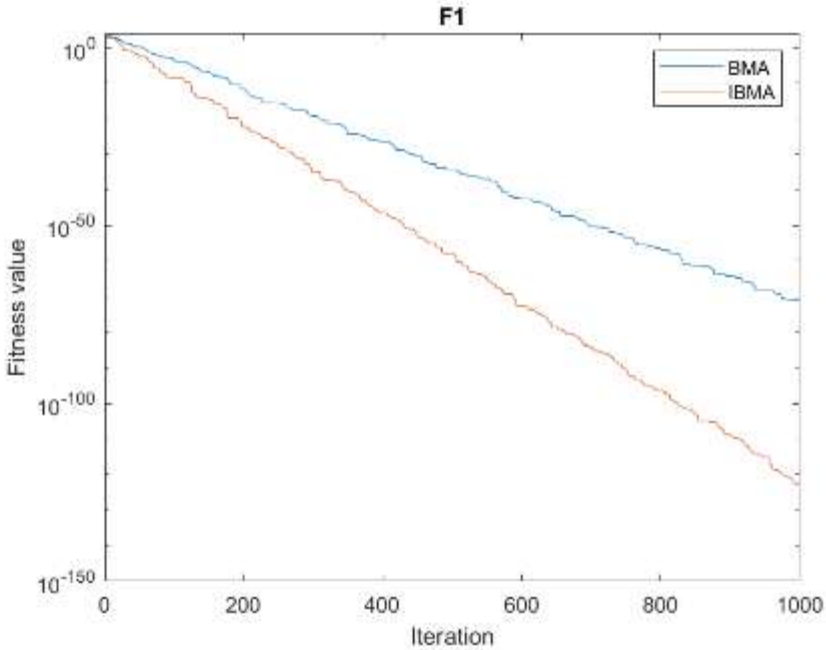

Figure 5. Convergence Process on Sphere.

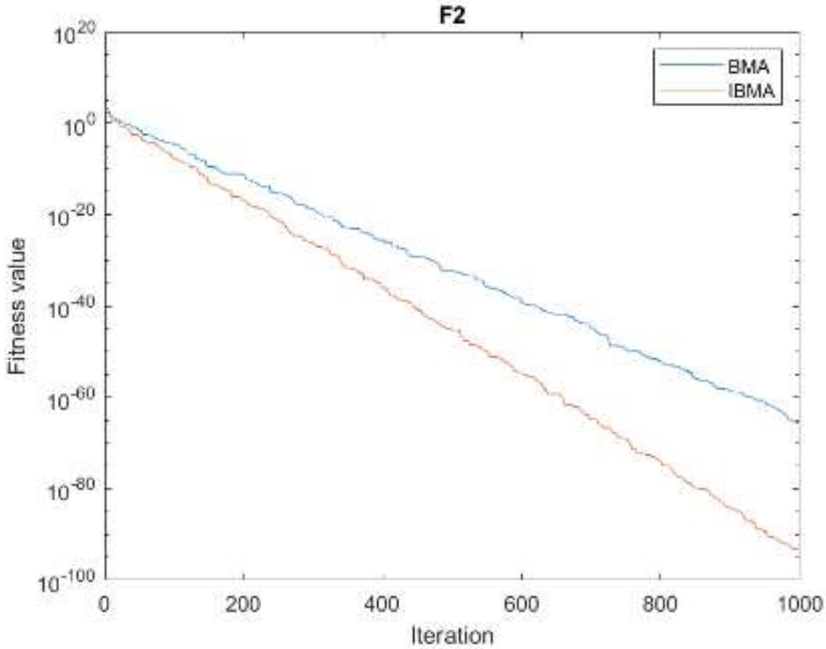

Figure 6. Convergence Process on Schwefel 2.22

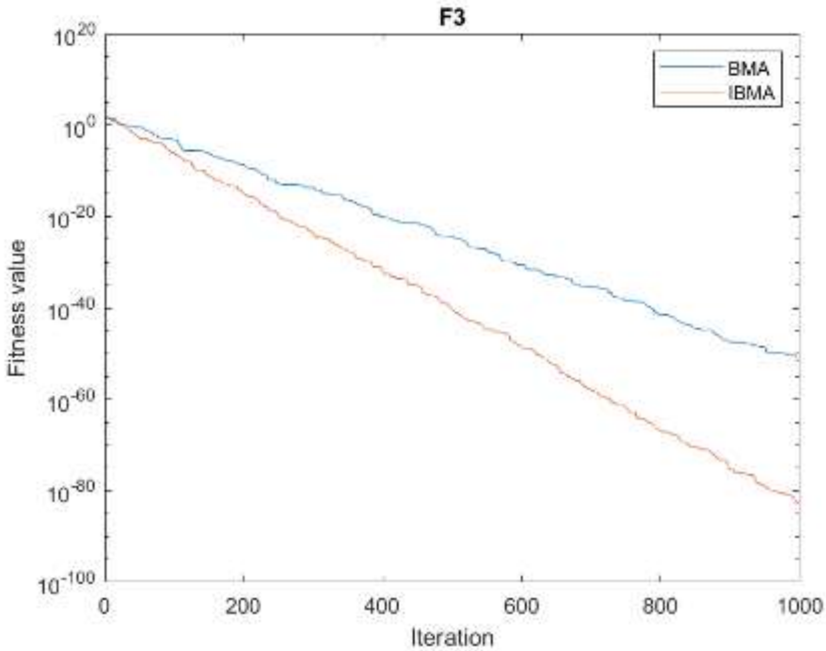

Figure 7. Convergence Process on Schwefel 2.21

From Figures 5, 6, and 7, the convergence processes on F1, F2, and F3 have been illustrated to show the performance comparison of the IBM and BM algorithms. The IBM algorithm has shown a relatively fast convergence process to better optimal solutions than the BM algorithm. This further demonstrates the impact of the proposed modification integrated into the IBM algorithm.

In general, the observed results validate that the proposed modifications in the IBM have effectively enhanced its balance between exploration and exploitation. As a result, the IBM demonstrates superior optimization capability, solution stability, and convergence reliability, making it a more suitable choice for solving both simple and complex optimization problems compared to the original BM and PSO.

3.2. Performance on IEEE 33-bus system:

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The performance of the proposed method in optimizing the integration of three (3) D-SVCs in the standard IEEE 33-bus system is presented. The performance of the system at its normal loading condition as well as under varying loading conditions are presented. The optimized system is compared with the base system and compared with other methods in literature.

3.2.1. Performance Comparison with Base Case:

In Table 4, the performance of the proposed IBM algorithm-based method is compared with the performance of the base case system in terms of system active and reactive power losses, and the minimum system voltage expressed in per unit.

Table 4. Results Comparison with Base-case

Algorithm	Base Case	IBM Algorithm
D-SVC Location (Size/kVar)	-	7 (637.5), 14 (844.9), 31 (980)
Losses (kW)	202.6771	157.7368
% Loss reduction (Active)	-	22.1733%
Losses (kVar)	135.1410	110.6161
% Loss reduction (Reactive)	-	18.1476%
Vmin (p.u.)	0.9131	0.9590

The IBM algorithm has yielded significant improvements in system performance. In the base case, no D-SVCs were installed. However, with the application of the IBM optimization technique, D-SVCs were strategically placed at buses 7, 14, and 31, with respective reactive power ratings of 637.5 kVar, 844.9 kVar, and 980 kVar, respectively. These locations were identified as weak points in the network requiring reactive compensation to enhance voltage stability and reduce losses.

The simulation results indicate a substantial reduction in both active and reactive power losses. The active power losses decreased from 202.6771 kW in the base case to 157.7368 kW after optimization, representing a 22.17% reduction. Similarly, reactive power losses were reduced from 135.1410 kVar to 110.6161 kVar, marking an 18.15% decrease. These reductions demonstrate the algorithm's effectiveness in minimizing energy losses and improving overall efficiency in the distribution network.

In addition to loss reduction, the IBM algorithm significantly improved the voltage profile of the system. The minimum bus voltage increased from 0.9131 p.u. in the base case to 0.9590 p.u. after D-SVC integration. This enhancement in voltage level suggests improved voltage regulation and better power quality for end-users. Overall, the IBM algorithm proves to be a robust tool for optimizing the placement and sizing of D-SVCs, leading to improved operational performance and stability of the distribution system. The profiles of the two (2) scenarios are compared in Figure 8 below.

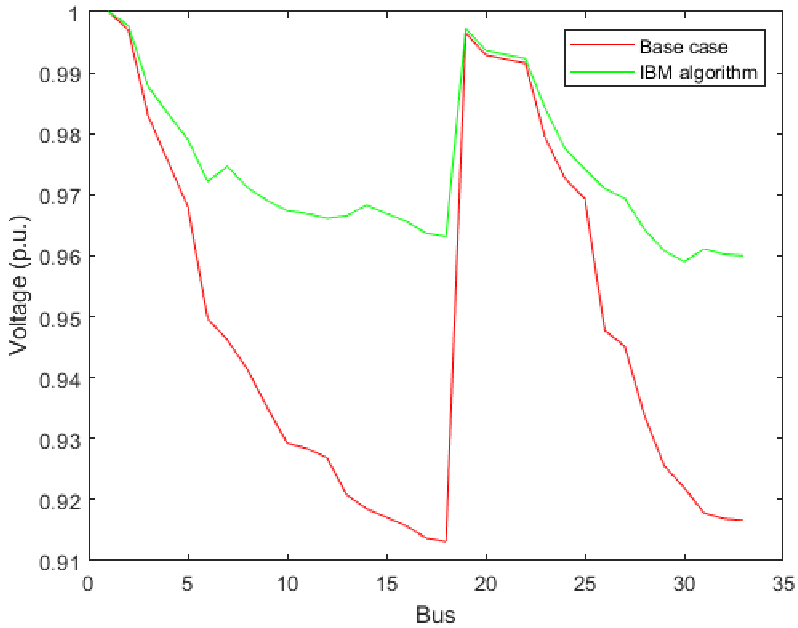

Figure 8. Voltage Profiles (Base case, IBM algorithm)

3.2.2. Performance Comparison with Existing Method:

The performance of the proposed IBM algorithm-based method is benchmarked against an existing method in the same domain that was recently published in the literature. The existing method is the Modified Artificial Rabbit Optimization (MARO)-based method [19]. The comparison is presented in Table 5 below.

Table 5. Results Comparison (Base-case, MARO, and IBM)

Algorithm	Base Case	MARO Algorithm [19]	IBM Algorithm
D-SVC Location (Size/kVar)	-	8(631), 14(522) 30(1120)	7(637.5), 14(844.9), 31(980)
Losses (kW)	202.6771	160.4864	157.7368
% Loss reduction (Active)	-	20.8167%	22.1733%
Losses (kVar)	135.1410	111.2989	110.6161
% Loss reduction (Reactive)	-	17.6424%	18.1476%
Vmin (p.u.)	0.9131	0.9527	0.9590

The performance of the proposed IBM algorithm was further evaluated by comparing it with the MARO algorithm, an existing method reported in [19]. Both algorithms were assessed based on their effectiveness in reducing power losses and improving the voltage profile, using the base case scenario as the reference.

In the base case, the system experienced active and reactive power losses of 202.6771 kW and 135.1410 kVar, respectively, with the minimum bus voltage recorded at 0.9131 p.u. When the MARO algorithm was applied, D-SVCs were optimally placed at buses 8, 14, and 30, with corresponding sizes of 631 kVar, 522 kVar, and 1120 kVar. This configuration resulted in a 20.82% reduction in active power losses and a 17.64% reduction in reactive power losses. The minimum bus voltage also improved to 0.9527 p.u., reflecting better voltage support across the network.

In comparison, the IBM algorithm yielded improved results. It placed D-SVCs at buses 7, 14, and 31, with respective sizes of 637.5 kVar, 844.9 kVar, and 980 kVar. This setup achieved a 22.17% reduction in active power losses and an 18.15% reduction in reactive power losses, both slightly better than the MARO algorithm. Additionally, the minimum bus voltage increased to 0.9590 p.u., the highest among all scenarios, indicating enhanced voltage stability. The voltage profiles under the three conditions are illustrated in Figure 9 below.

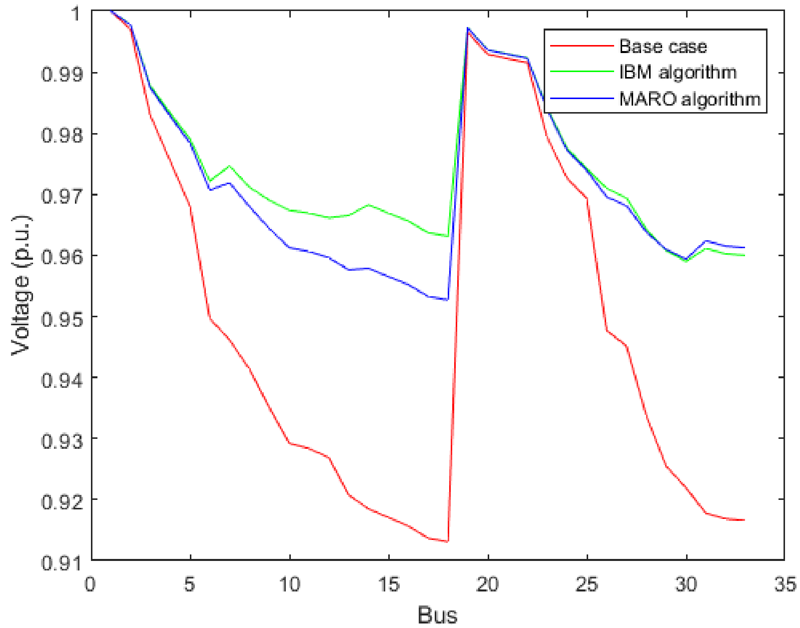

Figure 9. Voltage Profiles (Base case, MARO algorithm, and IBM algorithm)

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The Fast Voltage Stability Index (FVSI) was used to compare the voltage stability of a power system under the three different conditions: the Base Case, MARO, and the proposed IBM method. In this analysis, lower FVSI values indicate better voltage stability [20]. The results in Figure 10 show that the proposed IBM method consistently achieved the lowest FVSI values across most lines, indicating the highest level of voltage stability.

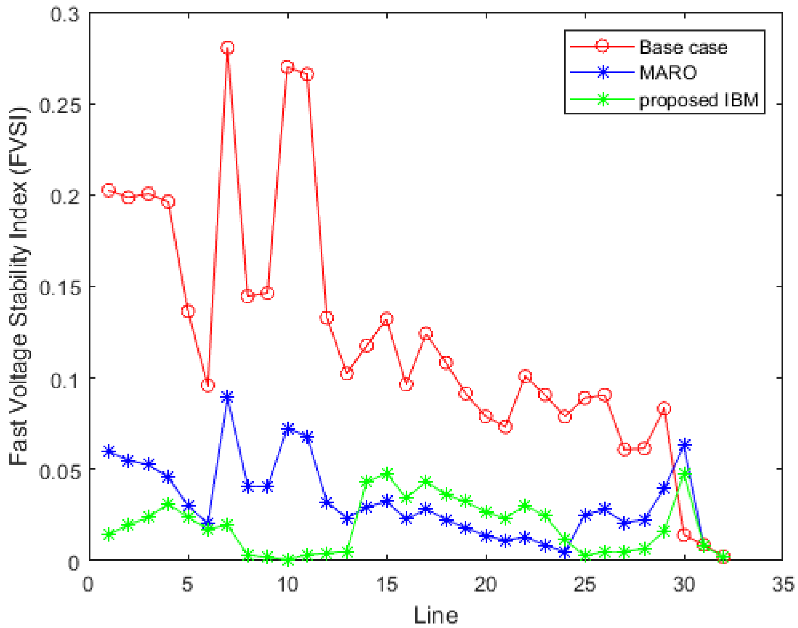

Figure 10. FVSIs of system lines

The Base Case recorded the highest FVSI values, especially between lines 1 and 10, with some values reaching up to 0.28. This suggests that the system under the Base Case is less stable. The MARO method showed some improvement over the Base Case, but it had occasional spikes in FVSI values, making it less consistent. In contrast, the proposed IBM method maintained low and steady FVSI values across almost all lines.

Toward the end of the network, between lines 30 and 33, all three methods produced low FVSI values. However, the proposed IBM method still performed slightly better. Overall, the results indicate that the proposed IBM method provides the best voltage stability, followed by MARO, while the Base Case is the least stable.

Overall, both optimization approaches significantly enhanced the distribution system's efficiency and voltage stability compared to the base case. However, the IBM algorithm demonstrated a marginal yet consistent performance advantage over the MARO algorithm in all key performance indicators, confirming its effectiveness in optimizing the integration of D-SVCs in distribution networks.

3.3. Performance of IBMO Algorithm under Varying Loading Conditions:

The performance of the system under varying loading conditions is presented in this section. The first condition looked at the active power losses of the system on an hourly basis, while the second condition looked at the minimum bus voltage of the system on an hourly basis. These two parameters of the system are compared under the base case and the proposed IBMO algorithm-based situation.

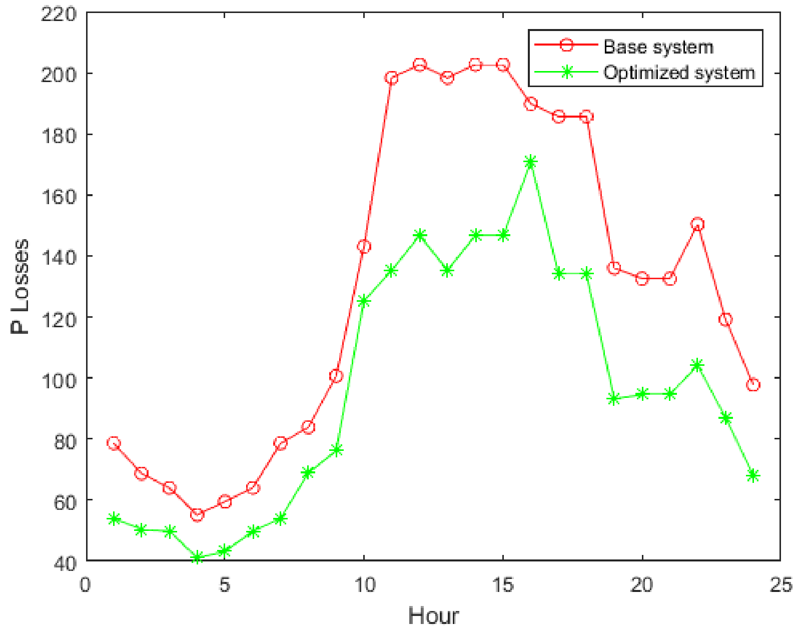

Figure 11. Hourly System Power Losses

Figure 11 compares the total active power losses of the system under optimized and the base system without optimization on an hourly basis for 24 hours.

The hourly active power loss profile of the IEEE 33-bus system was analyzed by comparing the base case with the optimized system, as shown in the provided plot. The results reveal a clear distinction between the two scenarios across the 24 hours, highlighting the effectiveness of the optimization approach in reducing power losses throughout the day.

In the early hours, from 1:00 AM to around 6:00 AM, both the base and optimized systems experience relatively low active power losses due to light load conditions. However, even during this period, the optimized system consistently records lower losses, ranging between approximately 45 kW and 60 kW, compared to the base system's 60 kW to 80 kW. This indicates that the optimization remains beneficial even under low-demand scenarios.

As the system load begins to increase from 7:00 AM onwards, there is a corresponding rise in power losses for both cases. The base system experiences a sharp increase in losses, reaching a peak of over 200 kW between 12:00 PM and 4:00 PM. In contrast, the optimized system shows a more moderate increase, with losses peaking at approximately 170 kW during the same period. This reduction of about 30–35 kW during peak hours demonstrates the optimization’s ability to significantly mitigate losses when the system is under heavy loading conditions.

During the evening hours, from around 5:00 PM to midnight, the base system maintains moderately high-power losses, fluctuating between 130 kW and 150 kW. The optimized system, however, exhibits a steeper decline in losses over the same period, eventually dropping below 100 kW by the end of the day. This sustained reduction throughout the evening further confirms the optimization strategy's effectiveness.

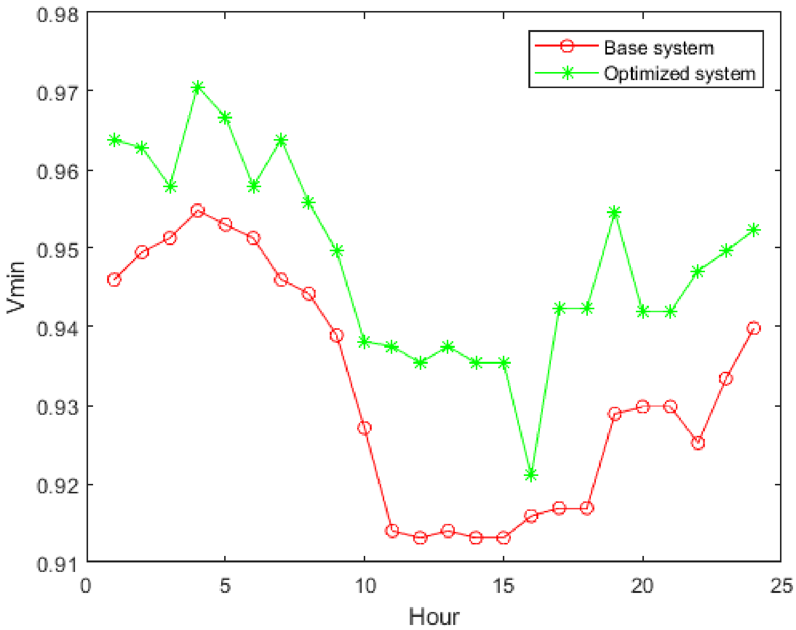

Figure 12. Hourly Minimum Bus-Voltage (p.u.)

The plotted results in Figure 12 show the variation of the minimum bus voltage over 24 hours for both the base system (without D-SVCs) and the optimized system (with D-SVCs installed through the proposed method). The comparison reveals consistent improvements in voltage levels across all hours under the optimized condition.

In the base system, the minimum voltage starts around 0.945 p.u. in the early morning and gradually declines, reaching its lowest point of approximately 0.913 p.u. between 12:00 PM and 5:00 PM. This dip aligns with peak demand hours, where higher loading causes voltage drops across the network. After this period, the voltage begins to recover slightly but remains below 0.94 p.u. for most of the evening.

The optimized system maintains higher voltage levels throughout the day. Minimum voltages in the early morning are consistently above 0.96 p.u., and even during the peak demand period, the voltage remains relatively stable, dropping only to about 0.936 p.u., above the minimum in the base case. By the evening, the optimized system shows a clear recovery, with voltages rising again above 0.95 p.u.

4. CONCLUSION

An algorithm-based method of optimizing distribution with D-SVCs is proposed. The integration of Distribution Static Var Compensators (D-SVCs) optimized using the Improved Blue Monkey (IBM) algorithm has proven to be an effective strategy for enhancing voltage stability and reducing power losses in distribution systems. By applying the proposed method to the IEEE 33-bus test system, the research demonstrated significant improvements in system performance, including a 22.17% reduction in active power losses and an 18.15% reduction in reactive power losses, alongside a notable increase in minimum bus voltage from 0.9131 p.u. to 0.9590 p.u. Compared to the base case and the MARO method, the IBM algorithm consistently yielded better results across all performance metrics that including better FVSI as well. Under varying loading conditions, the optimized system maintained lower power losses and improved voltage profiles throughout the day. These findings underscore the potential of the IBM algorithm as a reliable and competitive tool for optimizing reactive power compensation in modern power distribution networks. The IBM algorithm is, therefore, recommended for adoption in solving various optimization problems such as reactive power planning in radial distribution systems.

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