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Comparison of Sine-Cosine and Bat Algorithm for Distributed Generation Placement

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ABSTRACT — The enhancement of electricity distribution is a crucial factor in supporting sustainable development and reducing energy access inequality. To ensure the reliability and stability of energy systems, the integration of distributed generation (DG) has a significant role. Numerous studies have explored optimal DG placement using metaheuristic methods. The study evaluated the performance of both algorithms based on key indicators, including voltage profile improvement and power loss reduction, under normal load conditions and under a 10% load increase to simulate future demand growth. The methods employed were the sine-cosine algorithm (SCA) and the bat algorithm (BA). By comparing these two methods, this study aims to optimize the placement and sizing of DG units, with a case study based on the IEEE 9 bus system configuration. Load flow analysis was performed using Electric Transient Analysis Program (ETAP) software to validate the effectiveness of optimized DG placement under various scenarios. Key performance indicators, namely losses reduction and improvement of voltage profile, were evaluated to determine the relative strengths of each algorithm. The results show that both SCA and BA are effective in optimizing DG implementation. Specifically, SCA achieved reductions in active power losses by up to 85% and reactive power losses by 93%, outperforming BA in certain scenarios. Both algorithms enhance system reliability and stability. These findings highlight the potential of metaheuristic algorithms to address the challenges of modern energy systems and contribute to the broader goal of developing sustainable power systems.

KEYWORDS — Sine-Cosine Algorithm, Bat Algorithm, Distributed Generator, IEEE 9 Bus, Metaheuristic Method.

I. INTRODUCTION

Electricity distribution begins with power generation at the power plant, where the energy is produced using various sources, such as coal, nuclear, natural gas, hydro, wind, or solar. The electricity is generated at high voltage to minimize losses during transmission. Throughout the process, grid management and control systems monitor and optimize operations to ensure stability, reliability, and efficiency, utilizing modern technologies like the smart grid and distributed generation (DG) to satisfy the expanding demands of contemporary energy systems as the population grows.

The increasing electricity demand and the global transition toward cleaner and more sustainable energy systems have emphasized the importance of DG in modern power networks. DG, which are small-scale electricity generation units typically located close to the load center, offer several advantages, including reduced transmission losses, enhanced reliability, and the integrated renewable energy sources. Usually, in medium and low voltage systems an unbalanced voltage. Continued operation under these conditions will exacerbate the stability of the power system and degrade the quality of the electrical energy supplied.

Therefore, considering sustainable options, such as integrated DG into the current power infrastructure, is becoming more important [1]. Reliability, security, technological advancements, regulatory considerations, and emission reduction are the driving forces behind the rising levels of renewable energy penetration. Researchers are focusing on incorporating renewable energy sources, such as wind power and solar, into the optimization process as DG technologies develop [2].

The sizing and placement of DG units significantly influence the overall efficiency, reliability, and stability of the power system [3]. Improperly placed or sized DG units can lead to adverse effects, such as increased power losses, voltage instability, and higher operational costs [4]. To enable its interconnection at nearly any point within the power grid, the IEEE classified DG facilities as power generation facilities with a significantly smaller capacity than centralized power plants, often 10 MW or less. Based on [1], developing a distributed controller for DC microgrids can, in addition to achieving limited voltage regulation, dynamically minimize the overall cost of generation. The proposed controller's performance has been verified by extensive switch-level simulations, and additional strategies, such as load shedding, in the future [5].

In low and medium voltage distribution networks, [6] has suggested a technique for the best positioning and expansion of distributed renewable energy generation and battery energy storage systems, minimizing investment and operating costs while maximizing distribution system operator profits. Their novel decomposition method efficiently determines the optimal battery energy storage system (BESS) operating scheme, achieving near-global optimal solutions and demonstrating effectiveness on a large-scale, real-world distribution system.

There are several combinations for DG planning in the distribution power system: dimension, position, quantity, and kind; simply size; only location; both size and location; and both size, location, and number [7]. Depending on the type of power they provide, DG systems can be classified into three categories. In the first category, the systems only inject real power. Second, systems only inject reactive power, and the third systems capable of injecting both reactive and active power. This categorization highlights the versatility and complexity of DG planning, particularly as renewable energy integration becomes increasingly critical for sustainable power system development [8].

II. RELATED WORKS

There are several methods proposed, both in artificial intelligence (AI) and calculus, based on small and large systems. Various kinds of AI computational techniques have been applied for optimizing the size and location of DGs as genetic algorithm (GA) [9]–[13], artificial bee colony (ABC) [14], [15], particle swarm optimization (PSO) [2], [16], [17], neural network [18], [19] and the hybrid optimization method [20], [21], [8] combines two or more AI methods to leverage their strengths and overcome individual limitations.

Reference [22] provides a thorough review of metaheuristic optimization techniques for the application of metaheuristic algorithms to the optimal integration issue and its dynamic implementation to objective function solutions. While various optimization algorithms have been proposed to address the placement and sizing of DG units, comparative studies evaluating advanced metaheuristic approaches remain limited [22]. Sine-cosine algorithm (SCA) and bat algorithm (BA) are effective metaheuristic algorithms commonly used for solving complex optimization problems like DG placement. This research aims to bridge this gap by conducting a systematic comparison of the SCA and BA for optimizing the DG.

The novelty of this research is the performance evaluation of these algorithms, focusing on key metrics such as power loss reduction, voltage, stability, and computational efficiency. Moreover, the determination of DG sizing also considers the project load growth [23]. To enhance the robustness of the analysis, the authors have incorporated load growth forecasting based on the Electricity Power Supply Business Plan (Rencana Usaha Penyediaan Tenaga Listrik RUPTL) 2021–2030 [24] and Decree from the Ministry of Energy and Mineral Resources [25], which estimates an annual increase in electricity demand of approximately 6.4% in Indonesia, ensuring that the proposed optimization solutions remain effective and adaptable under future load conditions, complemented by a power quality analysis to assess voltage stability and power factor.

Furthermore, optimization studies focus on integrating, such as load flow analysis using Electric Transient Analysis Program (ETAP) software to validate computational results and ensure real-world applicability. A case study system was simulated using the IEEE 9 bus system. Although small, it serves as an excellent testbed for exploring optimization challenges in power systems under realistic conditions.

By optimizing DG's placement, this research has significant social implications, such as improving the supply of electrical energy more reliably, so that areas located far from the generation system is rarely disrupted. Additionally, optimizing DG's placement can raise local communities through inclusive home industries, economic growth, public services, and education. A power distribution network may experience a voltage breakdown due to severe reverse power caused by a DG unit's constant actual power penetration. The performance and dependability of a distribution network may be impacted by the erratic power supply for DG devices powered by renewable energy sources. In order to address these problems with the best possible integration of electrical equipment, optimization techniques have been created [22].

This study aims to explore the application of SCA and BA. BA algorithm for optimizing the placement and sizing of DG units in electrical networks. Both SCA and BA are population-based metaheuristic optimization algorithms that iteratively improve candidate solutions toward the global optimum. Besides that, BA and SCA algorithms rely on stochastic processes, using random numbers to guide the search process and ensure diversity in candidate solutions, where the best solution found so far influences the population's future movement [26]. These algorithms are two popular metaheuristic algorithms that have been widely used for various optimization problems [27]. The research introduces or focuses on novel performance metrics, such as voltage profile improvement, power loss minimization, or system reliability; and analysis on how effectively each algorithm meets these objectives.

SCA generates candidate solutions by oscillating between sine and cosine functions, enabling exploration and exploitation of the search space [28]. By leveraging the capabilities of the SCA, this research seeks to minimize power losses, improve voltage profiles, and enhance the overall performance of the system. Since 2020, SCA has gained increased attention for its application in power systems, particularly for the optimal integration of DG in distribution networks. Its ability to handle large-scale optimization problems, such as power loss minimization and voltage stability improvement, makes it a preferred choice for researchers [22].

In contrast, the BA mimics the echolocation behavior of bats, dynamically adjusting parameters such as frequency, loudness, and pulse rate to balance exploration and exploitation effectively [29]. This algorithm has been widely applied in power systems, particularly for optimizing the placement and sizing of DGs and other electrical units in distribution networks. Its ability to minimize power losses, improve voltage stability, and enhance operational efficiency has made it a valuable tool for addressing challenges in renewable energy integration and grid reliability. However, challenges such as parameter tuning and susceptibility to local optima require further refinement to enhance its scalability and effectiveness in real-world applications [30].

This paper provides a comparative analysis of the SCA and BA for optimizing DG placement in the IEEE 9 bus system. The primary contribution is showing the effectiveness of both algorithms in reducing losses, which also evaluates the performance of these algorithms in minimizing power losses and ensuring voltage stability while adhering to system constraints. By comparing these two methods, the study aims to provide insights into their relative strengths and weaknesses, offering valuable guidance for researchers and practitioners in selecting appropriate optimization tools for power system applications.

The results of this study are expected to contribute valuable insights into the strategic deployment of DG units, aligning with the broader objectives of achieving sustainable and resilient power systems. This dual approach of theoretical and practical validation.

III. SYSTEM MODEL

The goal of this system is to optimize the sizing and placement of DG within an electrical power system, specifically the IEEE 9 bus system, to minimize power losses while ensuring the system's operational constraints. The integration of DG into the system provides several benefits, including reduced transmission losses and improved voltage stability. However, the optimal placement and sizing of DG units is a challenging task due to the nonlinear and complex nature of power flow in electrical networks.

In this study, the optimization problem is formulated with the following objectives. First, the total power losses across the system could be minimized by determining the optimal locations and capacities for DG units. Second, the system must adhere to several constraints, including voltage limits at each bus, power balance, and operational limits of DG units. The problem was solved using two different optimization methods, comparing their effectiveness in minimizing power losses and maintaining system stability. The authors proposed a 10% load increase in the system to evaluate the resilience of the optimization algorithm under future load growth scenarios. This assumption was made based on the RUPTL 2021–2030 projection, which estimates an annual load growth of approximately 6.4% in Indonesia. By adopting a slightly higher load increase, the analysis aims to more rigorously test the robustness and adaptability of the proposed optimization methods under elevated demand conditions.

By solving this problem, the optimal configuration for DG placement is determined, providing valuable insights into the impact of DG integration on overall system performance. The following sections elaborate on the mathematical representation of the objective function and its integration into the optimization framework.

A. OBJECTIVE FUNCTION

Reducing the system's overall power losses is the primary objective of DG deployment. Power losses in a power system are generally caused by the resistance in transmission lines and the load flow in the system. The objective function can be expressed in (1).

$$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} G_{ij} \left(V_i^{\,2} + V_j^{\,2} - 2V_iV_j \cos\theta_i - \theta_j\right) \quad (1)$$

where P_{loss} is total power losses (in Mw), N is total number of busses in the system, G_{ij} is conductance between busses i and j, V_iV_j is voltage magnitude at bus i and bus j, and θ_i, θ_j is voltage angles at bus i and bus j.

B. LOAD FLOW

One of the essential phases in power system research is load flow analysis, which enables the calculation of voltage magnitudes, phase angles, power flows, and losses in the network under steady-state conditions. The software's load flow analysis module is employed to simulate the power flow under various operating conditions, including pre- and post-optimization scenarios. This simulation framework enables a comprehensive evaluation of DG placement and sizing, ensuring the validity and practicality of the optimization outcomes. The integration of ETAP provides high fidelity to real-world conditions, enhancing the relevance of the study's results.

The load flow analysis in this work was conducted using the ETAP software, which provides robust simulation tools for validating the results obtained from the optimization process. ETAP was utilized to calculate voltage level, active power (W) and reactive power (VAR) and losses at each bus in the network, providing critical insights into the system's performance. By simulating the placement and sizing of DG units, load flow also helps identify optimal system efficiency. Load flow analysis also assesses the reactive power contributions of DG units, ensuring proper reactive power management to maintain system reliability and a stable power factor. Furthermore, it examines how DG's integration affects existing infrastructure, such as lines and transformers, preventing overloading and ensuring compatibility.

In this load flow system, the adaptive Newton-Raphson method was used. This method was employed within ETAP for its superior convergence characteristics and computational efficiency [31]. In the simulation, the maximum number of iterations was set to 99. ETAP is designed such that if the solution does not converge within the specified number of iterations, the process will automatically stop, and the software will notify the user.

The adaptive Newton-Raphson method was chosen because it dynamically adjusts the step size and direction based on the system's nonlinearity, thereby improving the stability of the solution process, especially for networks with high penetration of distributed generation. This method ensures faster convergence compared to traditional Newton-Raphson methods and reduces the risk of divergence in systems with challenging initial conditions or poorly scaled variables. The load flow analysis results, including voltage profiles, line flows, and power losses, served as critical inputs for evaluating the feasibility and performance of the optimized DG placement.

C. POWER LOSSES

Power losses in a transmission system refer to the energy lost as electrical power when transmitted from the generation source to the end-users through the transmission lines. Power losses in an electrical network primarily occur due to the resistance in transmission lines. As electric current flows through the lines, a portion of the energy is dissipated as heat due to the resistance, and this energy cannot be utilized by the load. In addition, the magnitude of power losses in the transmission networks depends on the type and length of the conductor. Loss of electrical energy needs to be predicted and anticipated so that it occurs within normal and reasonable limits. Power losses in the transmission system are represented in (2).

$$P_{loss} = I^2 . R \quad (2)$$

where P_{loss} denotes power losses in the transmission line (W), I denotes current (A) that flows in the conductor, and R denotes resistance (Ω).

The integration of DG can significantly reduce these losses by supplying power closer to the load centers. The total power loss (P_{loss}) in the system are calculated based on the line conductance G_{ij} and the voltage and phase angle differences between buses. The expression for power losses is directly incorporated into the objective function, ensuring that the optimization process targets loss minimization [32].

D. CONSTRAIN

The optimization process must adhere to several system constraints to ensure feasible and practical solutions. These constraints include voltage limits, the voltage magnitude at each bus must remain within acceptable limits as (3).

$$V_{min} \leq V_i \leq V_{max} \quad (3)$$

Power balance, the total generation, including DG, must equal the total load demand plus losses as shown in (4).

$$\sum P_{gen} = \sum P_{load} + P_{loss}. \quad (4)$$

DG capacity limit, the power generated by DG units must be within their operational limits as shown in (5).

$$P_{DG,min} \leq P_{DG,i} \leq P_{DG,max} \tag{5}$$

by addressing these constraints, the optimization ensures that the DG placement improves system performance without violating operational or technical requirements.

IV. METHODOLOGY

This study proposed a systematic approach to analyze and optimize the placement and capacity of DGs within the IEEE 9 bus system configuration. The methodology involves several stages to ensure the accuracy and reliability of the result.

First, the system parameters, including single line diagram (SLD), load profile, line impedance, transformer specification, and generator data, were modeled using ETAP software. Second, the optimization process incorporated two metaheuristic algorithms. Each algorithm was initialized with parameters, including population size, iteration limits, and objective functions, tailored to the problem. Next, the results from both methods were compared based on their performance indicators. Finally, a comprehensive analysis was performed to assess the effectiveness of SCA and BA under various scenarios, including different load conditions and DG capacities.

A. DATA COLLECTION AND SYSTEM MODELLING

The IEEE 9 bus system was used as the test network for this study. Standard IEEE datasets were used to get the system parameters, such as line data, bus data, and load demand. All the impedance values were taken to match the system base, which was set at 100 MVA. The network parameters, including bus voltages, line impedances, transformer ratings, and load demands, were sourced from standard IEEE datasets to ensure accuracy and reproducibility.

Figure 1 shows an SLD representation of an electrical system for the IEEE 9 bus system. The system has 9 busses, with three generators in bus 1, 2, and 3. The specification of each generator is shown in Table I.

Table II shows the load parameter, while Table III shows transformer parameter data. On the IEEE 9 bus system, there are three transformers that act as step-up transformers. Table IV shows transmission line parameter data. Transmission line parameters include lengths, resistances and inductances on this conductor.

B. OPTIMIZATION TECHNIQUES

The study applied two optimization algorithms, SCA and BA, to compare metaheuristic methods and to solve DG placement problems. Each proposed algorithm utilized Python software and was validated using ETAP software for load flow analysis.

The steps of SCA in which a population of *N* candidates is randomly initialized within the search space are formulated in (6).

$$X_i(0) = X_{min} + r\,(X_{max} - X_{min}) \tag{6}$$

where $X_i(0)$ is the initial position of the i candidate, X_{min} and X_{max} are the bounds of the search space, and r is a random number in [0, 1].

The position update mechanism in SCA is governed by trigonometric sine and cosine functions. The updated position of each candidate is determined based on whether a random variable r_4 is less than or greater than 0.5. Specifically, the position is adjusted using (7).

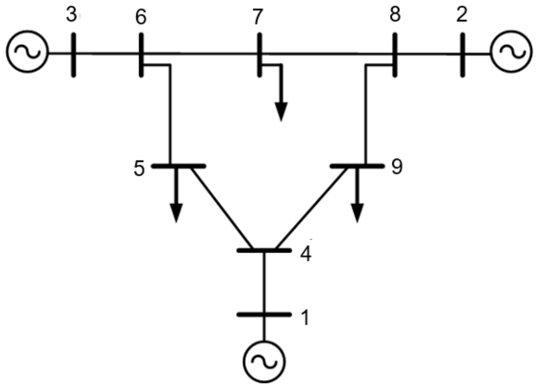

Figure 1. Single line diagram of the IEEE 9 bus.

TABLE I
GENERATOR'S DATA

Information	Gen 1	Gen 2	Gen 3
S (MVA)	512	270	125
V (kV RMS L-L)	24	18	15.5
Xd (pu)	1.7	1.7	1.22
X'd (pu)	0.27	0.256	0.174
X'' (pu)	0.2	0.185	0.134
T'do (s)	3.8	4.8	8.97
T''do (s)	0.01	0.01	0.033
Xq (pu)	1.65	1.62	1.16
Xq' (pu)	0.47	0.245	0.25
Xq'' (pu)	0.2	0.185	0.134
T'qo (s)	0.48	0.50	0.50
T''qo (s)	0.0007	0.0007	0.0007
H (s)	2.6312	3.1296	4.768
D (pu)	2	2	2

TABLE II
LOAD PARAMETER

Item	Load Bus_5	Load Bus_6	Load Bus_7
P	125 MW	90 MW	100 MW
Q	50 MVAR	30 MVAR	35 MVAR

TABLE III
TRANSFORMATOR PARAMETER

Items	Trafo 1	Trafo 2	Trafo 3
$V_{primary}$ (kV)	24	18	15.5
$V_{secondary}$ (kV)	230	230	230
R1 (pu)	1×10^{-10}	1×10^{-10}	1×10^{-10}
L1 (pu)	2.88×10^{-20}	3.13×10^{-2}	2.93×10^{-2}
R2 (pu)	1×10^{-10}	1×10^{-10}	1×10^{-10}
L2 (pu)	2.88×10^{-20}	3.13×10^{-2}	2.93×10^{-2}
Rm	$5.00 \times 10^{+30}$	$5.00 \times 10^{+3}$	$5.00 \times 10^{+3}$
Lm	$5.00 \times 10^{+30}$	$5.00 \times 10^{+3}$	$5.00 \times 10^{+3}$

$$X_i(t+1) = \begin{cases} X_i(t) + r_i\,.\sin(r_2)\,.\,|r_3P - X_i(t)|, if\ r_4 < 0.5 \\ X_i(t) + r_i\,.\,\mathrm{scos}(r_2)\,.\,|r_3P - X_i(t)|, if\ r_4 < 0.5 \end{cases} \tag{7}$$

where t is current iteration, r_1, r_2, r_3 are random numbers in [0.1], and P is a randomly selected position in the population.

SCA employed a dynamic control mechanism for the exploration-exploitation trade-off to facilitate convergence. The parameter r_1, which dictates the amplitude of updates, decreases linearly over iterations, the formula is shown in (8).

TABLE IV
LINE PARAMETER

Bus		Distance (km)	*R0* (Ω/km)	*L0* (Ω/km)	*R1* (Ω/km)	*L1* (Ω/km)
From	*To*					
4	5	89.98	0.5881	0.00398	0.00588	0.00133
4	6	97.336	0.924	0.00398	0.924	0.00133
5	7	170.338	0.994	0.00398	0.0994	0.00133
6	9	179.86	1.15	0.00398	0.115	0.00133
7	8	76.176	0.590	0.00398	0.0590	0.00133
8	9	106.646	0.590	0.00398	0.0590	0.00133

$$r_1 = r_1^{max} - \frac{t}{T}(r_1^{max} - r_1^{min}) \quad (8)$$

allowing r_1 to reduce gradually from its maximum to minimum value over the maximum number of iterations *T*. This gradual reduction shifts the algorithm's focus from broad exploration in the early stages to local exploitation in later iterations. Finally, the fitness of each solution was evaluated based on the objective function. The solution with the best fitness value was stored as the optimal solution. SCA iteratively refines the population's positions, leveraging its simplicity and effectiveness in solving optimization problems. The SCA and BA offer distinct mechanisms for addressing complex optimization challenges.

The BA is inspired by the echolocation behavior of bats and begins by initializing a population of candidate solutions, referred to as bats. Each bat's position $X_i(0)$ and velocity $V_i(0)$ are randomly initialized within the search space, with the position calculated similarly to SCA using (5). This random initialization ensures diverse candidate solutions, which is critical for effective exploration.

The BA algorithm introduces a frequency parameter to guide the search. At each iteration, the frequency f_i of each bat is updated using (9).

$$f_i = f_{min} + r\,(f_{max} - f_{min}) \quad (9)$$

where f_{min} and f_{max} define the frequency range. The velocity of each bat is subsequently updated using (10).

$$V_i(t+1) = V_i(t) + (X_i(t) - X_*)\,f_i \quad (10)$$

where X_* is the best global solution. The position update is computed as in (11).

$$X_i(t+1) = X_i(t) + V_i(t+1). \quad (11)$$

Equation (10) ensures that bats adjust their positions based on their current velocities and the influence of the global best solution. To enhance exploitation, the BA incorporates a local search step. A random walk around the best solution X_* is performed using $X_* + €A_i$, where € is number in [-1,1] and A_i represents the loudness of the bat. This local search step ensures refinement in the vicinity of promising solutions, enabling the algorithm to fine-tune the results effectively.

Additionally, the BA algorithm dynamically adjusts two key parameters: loudness A_i and pulse rate r_i. Loudness decreases over iterations, as in (12).

$$A(t+1) = \alpha A_i(t) \quad (12)$$

while the pulse rate increases as (13)

$$r_i(t+1) = r_i\,(0)(1 - e^{\gamma t}) \quad (13)$$

where α and γ are constants. These adjustments simulate the behavior of real bats, with reduced loudness and increased pulse rates indicating a transition from exploration to exploitation.

BA algorithm evaluates the fitness of each candidate solution using the objective function. The best solution is updated iteratively, and the algorithm terminates when the maximum number of iterations or a convergence criterion is met. BA is particularly effective in handling complex and multimodal optimization problems due to its robust global and local search mechanisms.

C. LOAD FLOW ANALYSIS

Load flow is an essential tool for researching, planning, and evaluating power systems. It enables power system engineers to assess the safety of the power system's configuration and operation under various loading scenarios. Modelling and simulation are required to ascertain the power flow and losses in such a system [33]. The ETAP software's adaptive Newton-Raphson method approach is used to analyze load flow in order to validate the optimization outcomes. This method ensures accurate calculation of voltage profiles, line flows, and power losses under different DG configurations, due to its high accuracy and rapid convergence properties, even for large-scale and highly nonlinear power systems. In this study, load flow analysis was conducted to validate the placement and sizing of DG units determined by the SCA and BA. The validation step confirmed the feasibility and performance of the solutions proposed by the optimization algorithms.

Load flow analysis is a fundamental step in assessing the performance of an electrical power system under the influence of DG. To ensure the system ran within allowable bounds, this analysis established the voltage magnitude and phase angle at each bus as well as the power flows over transmission lines.

The inclusion of DG in the IEEE 9 bus system modified the power flow by reducing line losses, improving voltage profiles, and enhancing overall system stability. To evaluate the effectiveness of the SCA and BA, the optimized DG parameters were applied, and the corresponding load flow results were analyzed. Key performance indicators included active power losses, voltage stability indices, and system efficiency.

By comparing the load flow results for DG placement derived from the two optimization techniques, this study highlights the practical implications of the SCA and BA in achieving optimal power system performance.

V. RESULTS AND DISCUSSION

The results of the load flow analysis and optimization procedure were obtained under three scenarios: normal condition, integration of DG using the BA and SCA with normal loads, and use of an increased 10% load using optimization SCA and BA. The comparative analysis evaluated the performance of each method in terms of system voltage profile improvement, power loss reduction, and overall system efficiency.

The results of the DG placement simulation based on the algorithm are shown in Table V, which illustrates the voltage profile of the IEEE 9 bus system. To ensure consistency in analysis and facilitate comparison across various system elements, the voltage profile is represented in per unit (pu) units.

A. THE RESULT OF SCENARIO 1

Prior to the DG integration, the voltage levels on the lower buses ranged from 0.95 pu. Such conditions highlight the

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necessity of DG placement to improve system voltage stability and ensure compliance with operational standards. The voltage deviations were observed on several buses, particularly on bus 4, 5, and 6, where the voltage dropped as low as to 0.93 pu. This indicates a need for voltage support on these buses. In the context of DG integration and voltage profile analysis, maintaining voltage levels within these limits is critical. If the voltage deviates significantly from the nominal range, either under or over the acceptable limits, it can lead to a variety of operational, safety, and performance issues in the electrical system. Both undervoltage and overvoltage conditions negatively affect system reliability, equipment longevity, and operational efficiency. Ensuring voltage levels remain within standards, such as SPLN 1:1995 (+5%, -10%), is crucial for safe and effective power system operation.

The voltage drops occurring on buses 4, 5, and 6 were attributed to the excessive length of the transmission line. Long transmission lines or poor conductor quality can result in significant voltage drops due to high resistance. If this problem is not resolved and keeps happening, it can lead to several adverse effects, including damage to electrical equipment, reduced operational efficiency, and increased power losses. Over time, this can cause the systems to become unstable, disrupt the consumer power supply, and deteriorate the system's reliability.

Based on the SCA and BA algorithms for DG's location, DG is located on the same bus, namely bus 6. However, in terms of capacity, the SCA and BA methods have different results. The SCA method determined the DG capacity to be 250 kW, while the BA method determined the DG capacity to be 299 kW.

B. RESULTS OF SCENARIO 2

The second scenario is an integrated DG using the normal load (Table II). SCA algorithm demonstrates significant improvements in the voltage profile across the IEEE 9 bus system. One of the notable benefits of the SCA method is its ability to address low-voltage issues on critical buses. For instance, bus 4 and bus 5, which initially had the lowest voltage levels of 0.95 pu, experienced an improvement to 0.99 pu and 0.98 pu, respectively. These values are close to the nominal voltage level of 1.00 pu, indicating a substantial improvement in the system's voltage stability. This improvement reduces the risk of undervoltage-related issues, such as motor inefficiencies, overheating, or equipment damage, thereby contributing to a more reliable operation.

Moreover, the SCA demonstrates its stability by maintaining the voltage levels of several buses at their nominal values. Bus 1 and bus 7, for instance, remain at 1.00 pu, showing that the optimization process does not disrupt well-performing nodes. The algorithm's capability to fine-tune the DG placement and capacity ensures that the overall system operates within acceptable voltage limits without causing overvoltage or undervoltage in any of the buses.

The BA demonstrated remarkable performance in optimizing the voltage profile across the IEEE 9 bus system, surpassing the results achieved by the SCA algorithm. One of its standout features is the ability to improve voltage levels across all buses, bringing them closer to or slightly above the nominal value of 1.00 pu. This optimization not only stabilizes the system but also enhances its resilience, particularly in areas with initially poor voltage performance. For example, bus 4 and bus 5, which initially exhibited the lowest voltage levels of 0.9 pu, saw significant improvements to 1.01 pu each, fully recovering from undervoltage conditions and reaching a more robust operational range. However, a notable drawback of the BA algorithm was the emergence of overvoltage conditions in several buses, including bus 2 (1.10 pu), bus 3 (1.07 pu), bus 7 (1.07 pu), bus 8 (1.07 pu), and bus 9 (1.06 pu). This algorithm is better suited for scenarios requiring substantial improvements in specific areas of the network.

TABLE V
VOLTAGE PROFILE

Bus ID	Before DG (pu)	Normal Load With DG		Load Increase 10% With DG	
		SCA	***BA***	***SCA***	***BA***
Bus 1	1.00	1.00	1.00	1.00	1.00
Bus 2	1.04	1.00	1.10	1.06	1.04
Bus 3	1.02	1.02	1.07	1.04	1.01
Bus 4	0.93	0.99	1.01	1.01	0.93
Bus 5	0.95	0.98	1.01	1.01	0.94
Bus 6	0.95	1.00	1.00	1.00	0.94
Bus 7	1.01	1.00	1.07	1.04	1.01
Bus 8	1.01	1.01	1.07	1.04	1.00
Bus 9	1.00	1.01	1.06	1.03	1.00

A comparative analysis of the two algorithms reveals that both SCA and BA effectively improve the voltage profile, but their performance characteristics differ. To mitigate this problem, the optimization process needs to be refined to include tighter voltage constraints to ensure that no bus exceeds the allowable voltage range. Additionally, integration of voltage control devices, such as on-load tap changers or reactive power compensators can help regulate voltage levels effectively.

C. RESULTS OF SCENARIO 3

In the third scenario, an additional 10% load was applied across the system to represent anticipated future load growth. This adjustment was made to rigorously assess the capability of the SCA and BA algorithms to maintain voltage stability and system performance under elevated operation.

In the voltage profile, SCA exhibited strong resilience (Table V). Most buses maintained their voltages close to the nominal value, with critical buses, such as bus 4 and bus 5, improving to 1.01 pu, and bus 6 stabilizing at 1.00 pu. These results indicate that the SCA optimization effectively accommodates higher demand without compromising voltage stability, enhancing system reliability even under dynamic conditions. The ability of SCA to sustain acceptable voltage levels across the network demonstrates its robustness against load variability and its suitability for future load growth scenarios.

In contrast, the BA algorithm exhibited a decline in voltage regulation performance under increased load. Several buses, particularly bus 4 and bus 5, experienced voltage drops to 0.93 pu and 0.94 pu, respectively, indicating a return to undervoltage conditions. Although some buses, such as bus 1 and bus 7, maintained stable voltage levels, the overall performance of the BA algorithm under higher loading conditions was less stable compared to SCA. This suggests that while BA is effective under normal load conditions, its adaptability under increased system stress is limited, making SCA a more reliable option for ensuring voltage stability in systems experiencing future load growth.

TABLE VI
LOSSES REDUCTION

Condition		Losses		Reduction Losses (%)	
		MW	*MVAR*	*MW*	*MVAR*
Before DG		34.7	31.16	-	-
Normal load with DG	SCA	5.35	2.06	85	93
	BA	30.96	11.98	11	61
Load increase 10% with DG	SCA	30.8	11.88	11	62
	BA	34.7	29.01	0	6.9

The analysis of system losses reinforcing the significance of voltage optimization in power systems is shown in Table VI. The analysis of losses reduction highlights the effectiveness of the SCA and BA in optimizing active and reactive power losses within the system. Under normal conditions, active power losses were recorded at 34.7 MW, while reactive power losses stood at 31.16 MVAR. After optimization using the SCA, active power losses dropped significantly to 5.35 MW, representing an 85% reduction, and reactive power losses decreased to 2.06 MVAR, an impressive 93% reduction. This substantial improvement underscores the SCA ability to optimize DG placement and capacity effectively, resulting in a significant improvement in system efficiency.

On the other hand, the BA showed a more modest improvement. Active power losses were reduced to 30.96 MW, translating to an 11% reduction, while reactive power losses dropped to 11.98 MVAR, corresponding to a minimal 11% reduction. Although the BA improved voltage profiles, as discussed previously, it was less effective in minimizing losses than the SCA. The discrepancy in performance suggests that the BA optimization process prioritizes voltage stability over loss reduction, whereas the SCA achieves a more balanced approach, addressing both voltage improvement and losses reduction comprehensively. When the system load was increased by 10%, the performance of both algorithms declined. With load growth, the SCA method maintained a relatively strong performance, reducing active and reactive power losses by 11% and 62%, respectively.

The connection between voltage improvement and loss reduction is evident in this context. The significant reduction in losses achieved by the SCA corresponds with its ability to bring voltage levels near the nominal value, thereby reducing power dissipation across the network. Conversely, while the BA enhances voltage stability at specific buses, its relatively lower impact on loss reduction indicates that its optimization strategy may not fully address areas with high power dissipation. Overall, the results demonstrate that the SCA outperforms the BA in optimizing both voltage profiles and power losses, making it a more effective solution for enhancing system performance. These results highlight the effectiveness of both optimization methods in adapting to increased load scenarios, with the SCA slightly outperforming the BA in overall voltage regulation.

VI. CONCLUSION

The comparative analysis of the SCA and BA algorithms demonstrates that both methods contribute to the improvement of voltage profiles and the reduction of system losses following DG integration. The SCA algorithm consistently outperforms the BA algorithm, achieving substantial reductions in both active and reactive power losses, as well as maintaining voltage levels closer to the nominal value across all scenarios. Under normal load conditions, the SCA method achieved an 85% reduction in active power losses and a 93% reduction in reactive power losses, while also improving voltage stability without causing overvoltage conditions. In contrast, the BA method, although effective in mitigating undervoltage, introduced slight overvoltage and achieved only modest reductions in system losses. When subjected to a 10% load increase, the SCA algorithm demonstrated greater robustness by maintaining acceptable voltage levels and sustaining notable reductions in system losses, whereas the BA method exhibited a decline in performance, particularly with voltage drops and minimal loss reduction. Overall, the findings highlight that the SCA algorithm provides superior performance in enhancing both the efficiency and stability of the power system under both normal and elevated load conditions, making it a more reliable and adaptable optimization strategy for future power system operations.

The integration of ETAP software for load flow validation has ensured the practical relevance of the optimization results. Future research can explore hybrid optimization techniques and the inclusion of real-world constraints to further enhance system performance.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. All authors have contributed to the research independently.

AUTHORS' CONTRIBUTIONS

Conceptualization, Lindiasari Martha Yustika and Jangkung Raharjo; methodology, Rifki Rahman Nur Ikhsan; software implementation and validation, Lindiasari Martha Yustika and Rifki Rahman Nur Ikhsan; formal analysis and investigation, I.G.P.O Indra Wijaya; resources and data curation, Lindiasari Martha Yustika, Jangkung Raharjo, Rifki Rahman Nur Ikhsan, and G.P.O Indra Wijaya; supervision, Jangkung Raharjo.

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