Research on Engineering Structures & Materials
www.jresm.org
Research Group

Research Article

Optimal distributed generation sizing and placement in radial distribution systems using hybrid BFS–PSO for loss minimization and voltage stability enhancement

Vipin Kumar Azad [*,1,a], Krishnarti De [2,b], Suman Majumder [2,c]

[1]*Department of Electrical & Electronics Engineering, NIT Mizoram, India*
[2]*Department of Electrical Engineering, NIT Mizoram, India*

Article Info

Article History:

Received 05 Mar 2026

Accepted 11 June 2026

Keywords:

Distributed generation, Particle swarm optimization; Backward/forward sweep; Voltage stability enhancement; Power loss minimization

Abstract

The integration of Distributed Generation (DG) into existing electrical networks is critical, as it can either enhance or degrade grid performance. Therefore, prior to DG integration, a thorough assessment involving load flow analysis and stability evaluation is essential. Since the location and sizing of DG units significantly influence voltage stability and network performance, this study employs a quantitative optimization-based approach using a hybrid Backward–Forward Sweep (BFS) and Particle Swarm Optimization (PSO) framework to determine the optimal placement and sizing of DG units in radial distribution systems. The proposed method is validated using the IEEE-33 bus system, where optimal DG allocation achieves a 49.71% reduction in power losses and a 6.85% voltage improvement at the weakest bus. The algorithm is further applied to real-world power networks in Mizoram, India, specifically the Bawktlang–Saiphai and Bawktlang–Bukpui networks. In the Bawktlang–Saiphai network, the proposed approach results in an 87.90% reduction in power loss and a 23.16% increase in voltage at the weakest bus, while in the Bawktlang–Bukpui network, power losses are reduced by 83.48%, leading to a 36.58% voltage improvement. The proposed framework is applicable to radial distribution systems and may be extended to similar regional and practical distribution networks for enhanced operational performance and voltage stability.

1. Introduction

Electricity demand increases with population, economic growth, urbanization, electrification of transportation, and government policies to tackle global warming [1-4]. Growing electricity demand causes the distribution system's voltage to drop and power loss to increase [5-6]. The enhanced grid capacity can be achieved through traditional methods such as grid extension or enforcement, but these approaches are opposed due to their costs and potential environmental impacts [7]. In modern power grids, Distributed Generation (DG) has become increasingly important, as it plays a vital role in transitioning to more sustainable, decentralized energy systems [8]. With the growing emphasis on renewable energy integration, DG technologies such as solar photovoltaics (PV), wind turbines, and biomass are being deployed closer to the point of consumption [9]. This integration is helping to reduce transmission losses, enhance grid flexibility, and support the global push towards cleaner, low-carbon energy solutions [10]. Incorporating a DG into the consumer side can improve power system operations, including voltage stability and infrastructure upgrades, as well as having a good economic and environmental impact [7]. By decentralizing power generation, DG can also enhance grid resilience, making it less vulnerable to large-scale outages and disruptions, particularly in disaster-prone areas.

*Corresponding author: krishnarti.eee@nitmz.ac.in
[a]orcid.org/0009-0005-3863-1152; [b]orcid.org/0000-0002-7634-1923; [c]orcid.org/0000-0002-8843-9047
DOI: http://dx.doi.org/10.17515/resm2026-1545en0305rs

DG has gained considerable attention for its potential to improve the economic and technical performance of power systems while reducing reliance on fossil fuels [11]. Selective research has been conducted on DG planning, optimal sizing and placement. The placement and sizing of DG are optimized to achieve minimum power losses in the distribution network, improving the voltage profile and promoting renewable energy integration [12-13]. Researchers on DG have explored several optimization techniques such as analytical methods, meta-heuristic algorithms and hybrid methods [11]. The analytical methods include Linear programming (LP), Non-linear programming (NLP), Loss Sensitivity Factor (LSF). Meta-heuristic Algorithms include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), etc. Whereas hybrid methods combine analytical and meta-heuristic techniques such as GA-PSO, GA-ABC, Hybrid Chaotic Bat Algorithm etc. [5]. Analytical methods such as LP, NLP, and LSF rely on mathematical formulations but often struggle with local optima and may not guarantee the best DG placement [14]. Meta-heuristic algorithms, such as GA and ABC require extensive parameter tuning, demand high programming skills for implementation, and incur high computational costs [15]. Hybrid methods, such as GA-PSO, GA-ABC, and Hybrid Chaotic Bat Algorithm, combine analytical and meta-heuristic techniques to enhance performance but often introduce additional computational complexity.

The Backward Forward Sweep (BFS) method is an efficient approach for power flow analysis in radial distribution networks and is particularly effective for optimal DG placement [16-17]. Meanwhile, PSO is widely recognized for its computational efficiency, as it employs a simple mathematical structure with fewer control parameters and avoids complex genetic operations. Consequently, PSO exhibits faster convergence and reduced computational time compared to Genetic Algorithm (GA) and Differential Evolution (DE) in various engineering optimization problems [18, 19, 20]. However, PSO method may suffer from premature convergence based on the initial control settings. The study results revealed that PSO is most sensitive to the inertia weight (w) and the acceleration coefficients (c1, and c2) [21]. The convergence behavior of PSO is significantly influenced by the selection of control parameters, particularly the inertia weight and acceleration coefficients. Proper tuning of these parameters ensures a balanced trade-off between exploration and exploitation, thereby improving the likelihood of convergence to a near-optimal or global solution.

By combining BFS with PSO, an effective framework for DG placement is achieved, efficiently handling load flow analysis while optimizing DG sizing. Distribution networks are typically radial or weakly meshed with high R/X ratios, under which conventional transmission-oriented load flow methods (e.g., Newton–Raphson) often exhibit poor convergence. The BFS algorithm is specifically designed for such systems and has been widely validated as a robust, fast, and numerically stable load flow method, avoiding Jacobian matrix formation and thereby reducing computational complexity [22]. The BFS method is employed due to its suitability for radial distribution systems with high R/X ratios and its computational efficiency compared to conventional load flow methods. Particle Swarm Optimization (PSO), on the other hand, provides an effective balance between exploration and exploitation, with advantages such as low parameter dependency, fast convergence, and ease of implementation compared to many recent metaheuristic algorithms [23]. PSO is adopted because of its fast convergence, minimal parameter tuning requirements, and proven effectiveness in solving non-linear DG optimization problems. While several newer algorithms (e.g., Grey Wolf Optimizer, Harris Hawks Optimization, and Differential Evolution variants) have been proposed in recent literature, they often involve:

- Increased algorithmic complexity
- Higher parameter tuning sensitivity
- Greater computational overhead
- Less consistent convergence behavior for power system constraints

In contrast, the hybrid BFS–PSO framework offers:

- Algorithmic simplicity and ease of integration with load flow
- Lower computational burden, suitable for large-scale or real-time applications
- Consistent convergence performance for non-linear, constrained problems in radial networks

Recent studies have further advanced DG planning using hybrid and intelligent optimization techniques. For instance, hybrid metaheuristic approaches have demonstrated significant improvements in power loss reduction and voltage profile enhancement, although they often involve higher computational complexity and parameter sensitivity [24]. Comprehensive reviews highlight the increasing importance of distributed generation and renewable integration in modern power systems, particularly in addressing challenges related to grid stability and scalability [25,26]. Additionally, recent works have explored the interaction between distributed generation and demand-side management, emphasizing the need for optimized integration strategies [27]. IEEE-based studies have also demonstrated the effectiveness of Backward–Forward Sweep (BFS) approaches in enhancing voltage stability and minimizing power losses in radial distribution networks [28].

Therefore, the central research problem addressed in this study is: How can Distributed Generation be optimally sized and located in radial distribution networks to minimize power losses and improve voltage stability while ensuring practical applicability in real-world rural power systems? Addressing this problem is important because effective DG planning can enhance network efficiency, support renewable energy integration, reduce operational costs, and improve electricity supply reliability in remote and underserved regions. To address this challenge, the present study develops and validates a hybrid Backward–Forward Sweep and Particle Swarm Optimization (BFS–PSO) framework using both the IEEE-33 bus test system and actual 33 kV distribution networks in Mizoram, India.

Based on the identified research gaps, this study has the following primary objectives:

- To quantitatively evaluate the impact of Distributed Generation (DG) placement and sizing on voltage profile improvement (p.u.) and real power loss reduction (kW) in radial distribution networks;
- To develop and implement a hybrid Backward–Forward Sweep and Particle Swarm Optimization (BFS–PSO) framework for determining the optimal DG size (MW) and placement location (bus number) that minimizes total real power loss;
- To validate the proposed optimization methodology using the IEEE-33 bus system and practical 33 kV distribution feeders in Mizoram, India, through comparative analysis of network performance before and after DG integration;
- To assess voltage stability enhancement under varying DG penetration levels using the Voltage Stability Margin Index (VSMI);
- To investigate the suitability of renewable-based DG systems, particularly solar photovoltaic (PV) integration, for improving voltage regulation, reducing line losses, and enhancing power supply reliability in remote and mountainous distribution networks.

The BFS technique is used for load flow analysis, whereas PSO is used to find the optimal size and location of a DG. The IEEE-33 standard test bus system is used to evaluate the proposed technique. Later, four cases are considered assuming the DG sizes – i.e 1MW, 2MW, 3MW and 4MW. The case studies show the variation of DG location and voltage with DG size. The proposed algorithm is validated by simulating the existing power networks from Bawktlang to Saiphai and from Bawktlang to Bukpui in Mizoram, India. Saiphai and Bukpui are located far from the generating station and therefore voltage drops and line losses are common issues. The biggest challenge in Bawktlang to Bukpui network is likely voltage drops due to long distances and rugged terrain. Without proper compensation, the voltage profile may degrade along the line. At present, no DG is connected in both the power networks. There is potential to integrate renewable energy sources such as solar PV into the network to alleviate supply issues and reduce dependency on the central grid. Mizoram's mountainous terrain and decentralized population centers make DG solutions particularly attractive for improving reliability and reducing line losses.

On applying the proposed algorithm to the IEEE-33 bus, it yields a 6.85% improvement in voltage at the weakest bus and a 49.71% reduction in power losses. This method is employed to analyze two electricity networks in Mizoram, India: Bawktlang-Saiphai and Bawktlang-Bukpui. In the Bawktlang-Saiphai network, the technique enhances the weakest bus voltage by 23.16% and cuts power losses by 87.90%. For the Bawktlang-Bukpui network, it achieves a 36.58% improvement in voltage and reduces power losses by 83.48%. This research offers insights on the following: -

- Highlights the suitability of renewable-based DG, especially solar PV, for enhancing power supply reliability in remote and mountainous regions.
- Provides practical guidance for integrating solar PV and other renewable energy sources into rural distribution networks to support decentralized and sustainable power systems.
- Offers actionable insights for policymakers and planners to improve rural electrification, voltage profiles, and loss minimization in geographically challenging areas.

The work in this paper includes Load flow analysis using BFS for the IEEE-33test bus system, DG size calculation and its placement using optimization technique (i.e., PSO), performance analysis of the IEEE-33 test bus system in terms of voltage profile without and with DG, power loss minimization, and Voltage Stability Index without and with DG. The rest of the paper is organized as follows. Section 2 discusses the materials and methods used in the research and development of an algorithm for optimal DG sizing and placement. Section 3 shows the results and findings. Section 4 provides the conclusion of the study.

2. Materials and Methods

This section lays the groundwork for DG placement optimization, explaining how the methodology determines the optimal size and location of DG units. The following key points is analyzed in this section;

- The BFS-based load flow analysis for evaluating system performance in terms of voltage profile, power loss, and stability.
- The PSO-based optimization framework is to determine the optimal size and placement of DG.

2.1 Backward-Forward Sweep (BFS) Method

BFS is grounded in Kirchhoff's current and voltage laws and is particularly suitable for radial distribution networks due to its numerical stability, low computational burden, and ability to handle high R/X ratios. This justifies its selection for accurate load flow analysis in the studied systems. The BFS load flow method assumes a radial topology, steady-state operation, and constant-power loads, and convergence is verified using a predefined tolerance criterion.

2.2 Particle Swarm Optimization (PSO)

PSO is based on collective intelligence and swarm behavior theory, where particles iteratively update their positions using cognitive and social learning mechanisms. Its suitability is justified by its fast convergence, reduced parameter complexity, and effectiveness in solving non-linear optimization problems, such as DG sizing and placement. The PSO framework assumes a bounded and continuous search space, a well-defined objective function, and parameter stability with convergence ensured through monitoring of the global best solution

2.2.1 Hybrid BFS–PSO Framework

The hybridization leverages the analytical accuracy of BFS and the global search capability of PSO, making it theoretically appropriate for minimizing power loss while maintaining voltage stability in radial distribution systems.

The BFS-based load flow analysis is explicitly linked to the objective of evaluating system performance in terms of voltage profile, power loss, and stability. The PSO-based optimization framework is clearly aimed at determining the optimal size and placement of DG. The case study of real-world networks in Mizoram is explicitly connected to the objective of validating the proposed method under practical operating conditions. The first step towards the study is data analysis of IEEE-33 standard test bus systems and the bus network of Mizoram Power Systems (Aizawl Project Circle- I: Part A & B). Analyzing data on electricity consumption patterns helps identify where demand is highest, and parts of the network where power losses (technical losses due to resistance in power lines) are highest. Further, by analyzing demand patterns, network performance, and environmental factors, utilities can make informed decisions on the most effective placement and size of DG.

2.3 IEEE-33 Standard Test Bus System

Bus data and line data for the IEEE-33 standard test bus are adopted from established benchmark datasets widely used in recent literature [29]. Fig. 1 illustrates the IEEE-33 bus radial distribution network used as the benchmark test system. This standard configuration provides a validated platform for evaluating the effectiveness of the proposed BFS–PSO method in minimizing power loss and improving voltage profile.

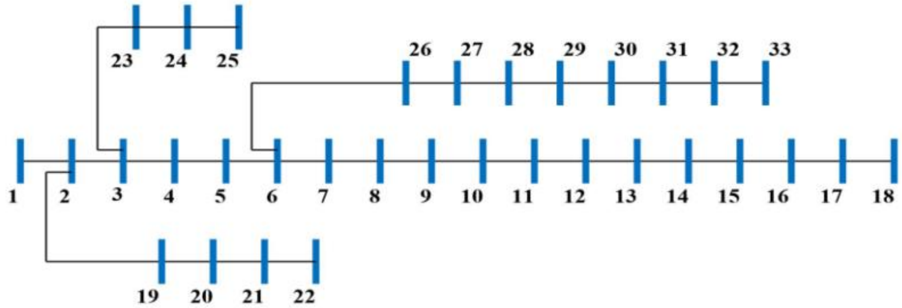

Fig. 1. IEEE-33 standard test bus system

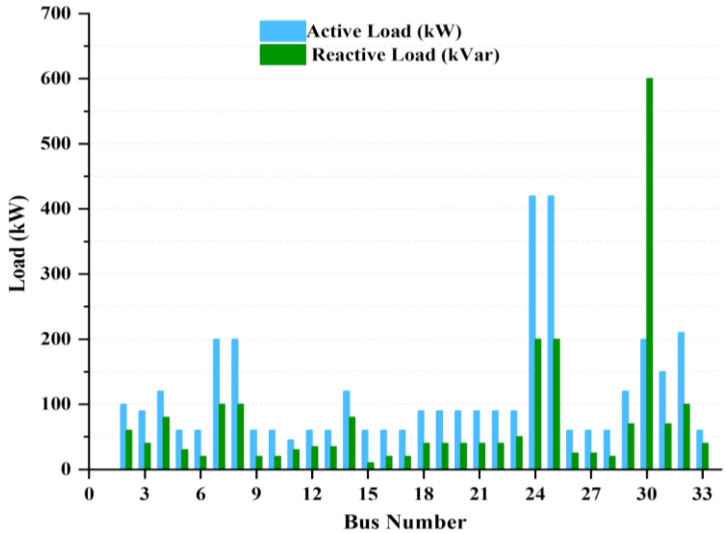

Fig. 2. Connected Load at IEEE-33 Bus

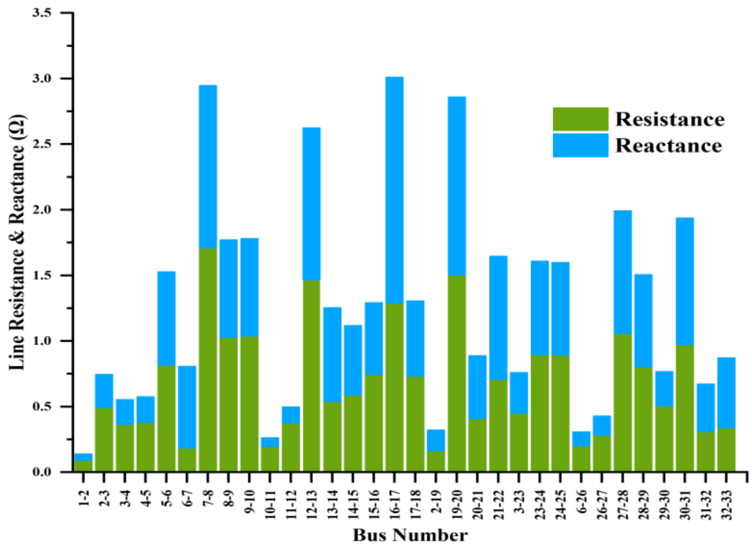

Fig. 3. Line Impedance for IEEE-33 bus system

The IEEE 33-bus system is used to study power flow by calculating voltages, currents, and power flows under various operating conditions. The IEEE-33 bus system is selected because it serves as a standard benchmark, enabling validation and comparison with the existing literature. Fig. 2 shows the distribution of active and reactive loads across the IEEE-33 buses. This load profile is essential for accurately performing load flow analysis and identifying buses with higher demand that influence DG placement. Bus 1 is a slack bus supplying system power, while buses 2–33 are load buses. Fig. 3 presents the branch impedance values (resistance and reactance) for each line segment. These parameters directly affect power loss and voltage drop, making them critical inputs for load flow and optimization analysis. Resistance causes heat-related losses, while reactance affects voltage stability and power flow dynamics in the system.

2.4 Case Study of Mizoram Power System (Aizawl Project Circle- I)

The case study of Mizoram Power System (Aizawl Project Circle – I), comprising the Bawktlang to Saiphai and Bawktlang to Bukpui power networks in Mizoram, is chosen for several technical and geographical reasons. Figs. 4 and 5 depict the single-line diagrams of the Bawktlang–Saiphai and Bawktlang–Bukpui networks, respectively. These real-world radial feeders form the basis for validating the proposed method under practical operating conditions in geographically challenging terrain. Both networks traverse hilly and forested areas, which can affect the electrical grid's performance due to long transmission distances, voltage drops, and higher line losses. This makes them ideal for studying rural electrification, which is a key goal in India's energy policy, and thus, Bawktlang to Saiphai presents ideal test cases for exploring DG.

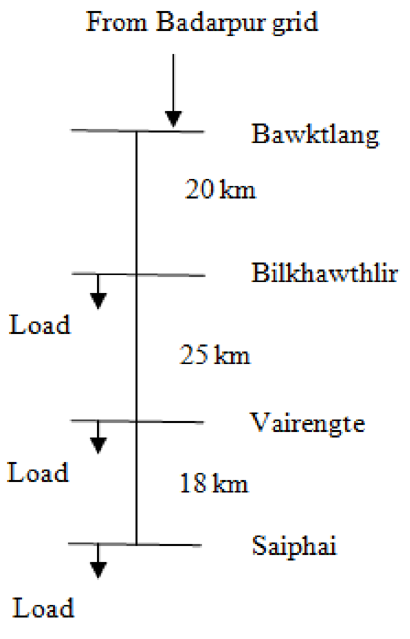

Fig. 4. Single Line Diagram of 33kV bus system from Bawktlang to Saiphai

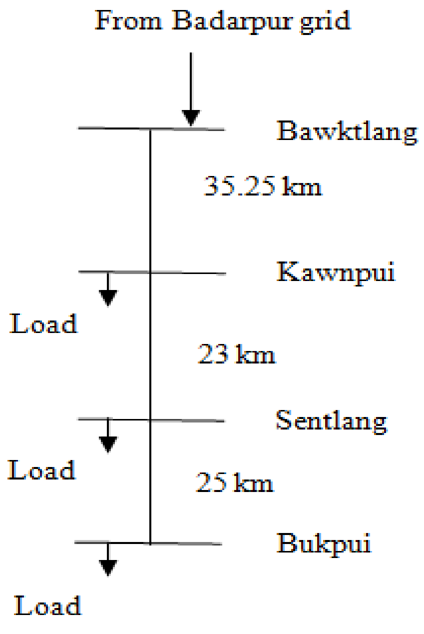

Fig. 5. Single Line Diagram of 33kV bus system from Bawktlang to Bukpui

2.4.1 Bus Data of Bawktlang to Saiphai and Bawktlang to Bukpui

The power demand in these rural areas would primarily be residential, with some agricultural and small commercial loads. The connected load might fluctuate, especially during certain seasons, due to agricultural use. The load profile is typically characterized by low demand in the morning and peak demand in the evening. Table 1 presents the peak demand of the four buses in 2023, collected from the Mizoram State Electricity Board. The total active and reactive power connected in Bawktlang to the Saiphai network is 3710 kW and 1630 kVAr, respectively. Similarly in Table 2, which represents the bus data of Bawktlang to Saiphaihas a total of 3870 kW of active power and 1719 of reactive power respectively. An average power factor of 0.9 is considered in the analysis.

Table 1. Bus data of Bawktlang to Saiphai power network

Bus	kW	kVAr
Bawktlang	0	0
Bilkhawthlir	693	308
Vairengte	2617	1162
Saiphai	400	160
Total	3710	1630

Table 2. Bus data of Bawktlang to Saiphai power network

Bus	kW	kVAr
Bawktlang	0	0
Kawnpui	1990	884
Sentlang	1200	533
Bukpui	680	302
Total	3870	1719

2.4.2 Line Data of Bawktlang to Saiphai and Bawktlang to Bukpui

The line impedance (resistance and reactance) of the Bawktlang-Saiphai network depends on the length of the distribution lines and the type of conductors used (typically ACSR). In rural areas, line impedances are crucial for calculating voltage drops and losses over long distances, which are typically high in such settings. ACSR Dog conductor, commonly used for 33 kV lines, is ideal for Mizoram's hilly terrain due to its lightweight and high tensile strength. The conductor has an aluminum area of 105.04 mm2, 6 strands of aluminum with a 4.72 mm diameter, and steel reinforcement with 7 strands and a 1.57 mm diameter. Table 3 represents the line resistance and reactance of Bawktlang to the Saiphai power network and that of Bawktlang to Bukpuiin Table 4.

Table 3. Line data of Bawktlang to Saiphai power network

From	To	R_T (Ω)	X_T (Ω)
Bawktlang	Bilkhawthlir	16.752	21.060
Bilkhawthlir	Vairengte	20.940	26.325
Vairengte	Saiphai	15.077	18.954

Table 4. Line data of Bawktlang to Bukpui power network

From	To	R_T (Ω)	X_T (Ω)
Bawktlang	Kawnpui	29.525	37.118
Kawnpui	Sentlang	19.265	24.219
Sentlang	Bukpui	20.94	26.325

3. MATLAB Simulation

A MATLAB simulation setup is employed for optimizing the placement and sizing DG in a power system, such as the IEEE-33 bus system. The process involves several key steps – assumption, constraints, objective function, method for finding location and sizing of DG and stability method. The following assumptions are made to simplify the modeling process while ensuring the feasibility and accuracy of the DG placement optimization. These assumptions balance theoretical soundness, computational simplicity, and practical relevance.

- Slack Bus: Bus number 1 is designated as the slack bus to account for transmission losses. Bus 1 is traditionally chosen as the slack bus because it often represents the main grid connection, where fluctuations can be handled most effectively.
- DG Location for IEEE-33 Bus:
- Lower bound for bus location: 2

- Upper bound for bus location: 33
- Base Values:
- Apparent power, Sbase = 100 MVA
- Voltage, Vbase = 11 kV
- PSO parameters:

The convergence of PSO is generally analyzed based on the dynamic system interpretation of particle velocity and position updates, where stability is governed by the appropriate selection of control parameters such as inertia weight and acceleration coefficients. It has been shown that, under suitable parameter settings (e.g., properly chosen inertia weight and cognitive/social coefficients), the particle trajectories converge to a stable equilibrium point. In particular, the use of a linearly decreasing inertia weight helps balance global exploration and local exploitation, thereby enhancing convergence characteristics. Additionally, commonly adopted parameter ranges (e.g., inertia weight in the range of 0.4–0.9 and acceleration coefficients around 2) are known to ensure stable convergence behavior in practical applications [30, 31]. In this work, these well-established parameter settings are employed to ensure reliable convergence of the PSO algorithm. Furthermore, the convergence behavior has been empirically verified, as the objective function consistently stabilizes within a finite number of iterations across multiple runs. While a formal mathematical proof of convergence is beyond the scope of this application-oriented study, the adopted PSO configuration follows standard practices reported in the literature, which are known to provide stable and robust convergence for power system optimization problems.

- Number of DG, m=1 (i.e., number of search variables equals the number of DG).
- Population size, n=100.
- Inertia weight; w_{max} = 0.9, w_{min}= 0.4.
- Acceleration factors: c_1= 2, c_2=2.

3.1 Constraints

Optimal DG placement is a multi-variable optimization problem subject to various constraints on both DG size and distribution system operation [11]. If the DG is too large (i.e., produces more power than the total demand plus losses), it could lead to reverse power flow in the distribution system. In this article, a single Distributed Generation (DG) unit modeled as PV bus is considered in this study to simplify the analysis and clearly evaluate its individual impact on system performance parameters such as voltage profile and power losses. In practical scenarios, installing multiple DG units is often constrained by economic and planning considerations, and utilities may initially deploy DG in a phased manner. Therefore, analyzing a single DG provides a fundamental baseline for understanding its effectiveness before extending the study to multiple DG placements. Operational constraints, including DG size limits and permissible voltage bounds (0.85–1.10 p.u.), are explicitly stated and enforced in all simulations. The assumptions and stability thresholds for the Voltage Stability Margin Index (VSMI) are clarified and consistently applied.In addition, reactive power support has not been explicitly modeled in this study because the solar DG units are assumed to operate at unity power factor. This assumption is commonly adopted to simplify the analysis and to focus on the impact of active power injection on system performance, such as voltage profile and power loss reduction. Although modern inverter-based DGs are capable of providing reactive power support, incorporating such control strategies would introduce additional complexity and is considered as a scope for future work.

Additionally, Reverse power flow (RPF) is managed through coordinated control of network devices and distributed generation. In this study, RPF is addressed through optimal DG placement and sizing, ensuring that generation does not exceed local load demand. In addition, voltage constraints are enforced within permissible limits, indirectly mitigating adverse effects of reverse power flow such as voltage rise. In practical systems, RPF can be further managed using smart inverter control (e.g., Volt–VAR and Volt–Watt strategies), on-load tap changers, and energy storage systems [38]. However, detailed modeling of these control mechanisms is beyond the scope of the present work and can be considered in future studies.

- DG Size: The DG size must be less than or equal to the sum of system demand and power loss.

- DG Size ≤ (P_{loss} + P_{load})
- Objective function

The objective function is essential because it defines the goal of the optimization process. The objective here is to minimize total real power loss by optimally placing a DG unit. This is achieved by minimizing the branch current. The node current I in jth bus in kth iteration is given by equation (1).

$$I_j^{(k)} = \frac{(P_{L_j} - x) + jQ_{L_j}}{V_j^{(k-1)}} \tag{1}$$

Where x is the size of the DG. $P_{L_j}$and $Q_{L_j}$are the real and reactive power at bus j. V_j is the voltage at bus j. The real power loss in the ith branch is calculated by using equation (2),

$$P_i = \left(I_i^{(k)}\right)^2 \times Re(Z) \tag{2}$$

Where Z is the branch impedance. The total real power loss is expressed by equation (3),

$$P = \sum_{i=1}^{n} P_i \tag{3}$$

The next step is to find optimal DG size and its placement in the radial network.

3.2 Optimal Location and Sizing of DG Method

In a power system, the optimal location and size of a DG unit refer to determining the best placement (bus) and capacity of the DG unit to achieve minimum power loss. MATLAB software is used to find the optimal location and size of single DG in 33 bus system through BFS method and PSO optimization technique. BFS method is used for the load flow analysis. PSO is used to optimize the DG size. The DG size range varies from 0 p.u. to 0.0405166 p.u. The maximum range is chosen such that it is equal to the sum of power loss (before DG connection) and total load connected in the bus. The PSO searches for the minimum power-loss and optimal DG size within the provided range. The simulation result also shows the optimal location of the DG. The simulation result is discussed in result section. The next step is to analyze the voltage stability of the proposed system.

3.3 Stability Method

Stability refers to the ability of a system to maintain a steady state or return to one after a disturbance. Voltage stability is another critical aspect, especially in systems with DG. It refers to the system's ability to maintain steady voltage levels across all buses under varying generation and load conditions. In the IEEE-33 bus system, voltage stability analysis focuses on maintaining voltage levels within acceptable limits under both normal and abnormal conditions.

In modern power systems, voltage stability is typically assessed using voltage magnitude as a key indicator of proximity to collapse. As the system approaches its maximum load ability limit (nose point of the PV curve), voltage decreases progressively and eventually collapses. In practical operation, this critical region is commonly observed around 0.8–0.85 p.u., where insufficient reactive power support leads to instability and rapid voltage decline [30-33]. It should be noted that the exact voltage collapse point is system-dependent; however, the range of 0.8–0.85 p.u. is widely accepted in practical stability assessment as an operational threshold indicating proximity to voltage instability.

Therefore, threshold typically lies around 80-85% of the nominal voltage. Beyond this, voltage collapse occurs. And overvoltage occurs at 110% of the nominal voltage. Therefore, if the VSMI is more than 0.15 p.u then grid will be unstable. Also, if VSMI is less than -0.10 p.u., then the grid will be unstable. Hence for stability of grid, the value of VSMI should lie in between -0.10 to 0.15 p.u. Fig. 6 illustrates the classification of voltage stability regions based on the Voltage Stability Margin Index (VSMI). This framework is used to assess whether the system operates within stable voltage limits under different DG integration scenarios.Voltage Stability Margin Index is given by equation (4).

$$VSMI = \frac{|V_{desired} - V_{operating}|}{V_{desired}} \tag{4}$$

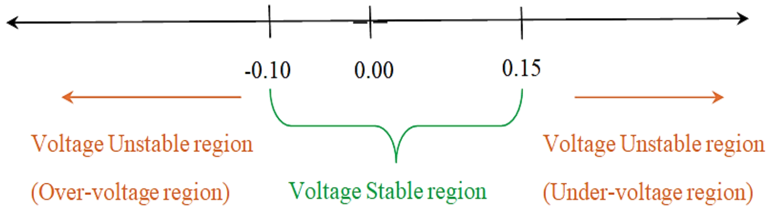

Fig. 6. Voltage Stability of the grid based on VSMI, which highlights grid stability across three regions: Over-voltage (unstable) beyond -0.10, Stable between -0.10 and 0.15, and Under-voltage (unstable) beyond 0.15

The modeling framework assumes a radial distribution network, balanced loading conditions, and steady-state operation. These assumptions are consistent with standard IEEE test feeders and the selected Mizoram distribution networks, which inherently follow radial topology. All system quantities are expressed in per-unit values to ensure numerical stability and comparability across different operating conditions. All candidate DG solutions are constrained to satisfy operational limits, including DG size less than or equal to total system demand plus losses and bus voltage limits within 0.85–1.10 p.u., ensuring physical feasibility of the results. The voltage stability assessment assumes steady-state voltage conditions, and the VSMI thresholds (−0.10 to 0.15 p.u.) are consistently applied to evaluate system stability across all simulation scenarios. The next sub-section discusses the load flow study using bus data and line data.

3.4 Load Flow Study

After collecting line and load data for IEEE-33 bus, the next step is to analyze the data using load flow. The load flow analysis is a crucial tool in the planning, design, and operation of electrical power systems, as it helps maintain voltage within acceptable limits, ensure balanced power flows, and identify potential overloads or voltage instability. In load flow analysis, particularly in power systems, the BFS method is commonly used for solving radial distribution networks. Fig. 7 represents a generalized radial distribution network model used for load flow formulation. This structure underpins the application of the BFS method for iterative voltage and current calculations.

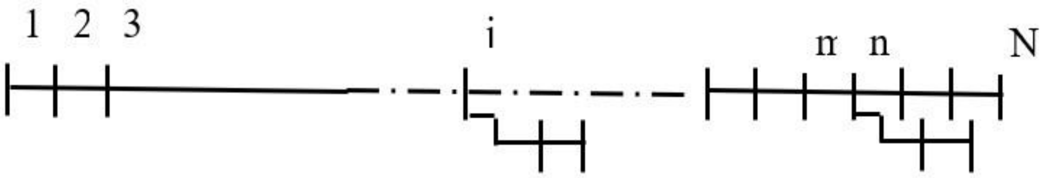

Fig. 7. Generalized radial bus network, represents a generalized radial bus network, commonly used in power distribution systems

Fig. 8 presents the flowchart of the backward–forward sweep method, detailing the iterative process for computing bus voltages and branch currents. This figure clarifies the computational steps involved in load flow analysis. The flowchart illustrates the procedure for determining the bus voltages and branch currents of a radial distribution network using the BFS method. The algorithm iteratively updates the voltages and currents until the specified convergence criterion is satisfied. The algorithm begins by initializing the necessary system parameters required for the load flow analysis. At first step, each bus voltage is initialized as 1.0 p.u. At the second step, the iteration count begins from 1. For the third step, load current is calculated using the formula given in the flowchart. In the fourth step, branch current is calculated using Kirchhoff's current law. Here 'S' represents the sum of all currents emanated from bus n for mn branch (refer fig.7). In the backward sweep stage, the branch currents are calculated starting from the terminal nodes towards the slack bus. The current flowing through branch $m - n$is determined by summing the load current and the currents of downstream branches. In the fifth step, each bus voltage is calculated.

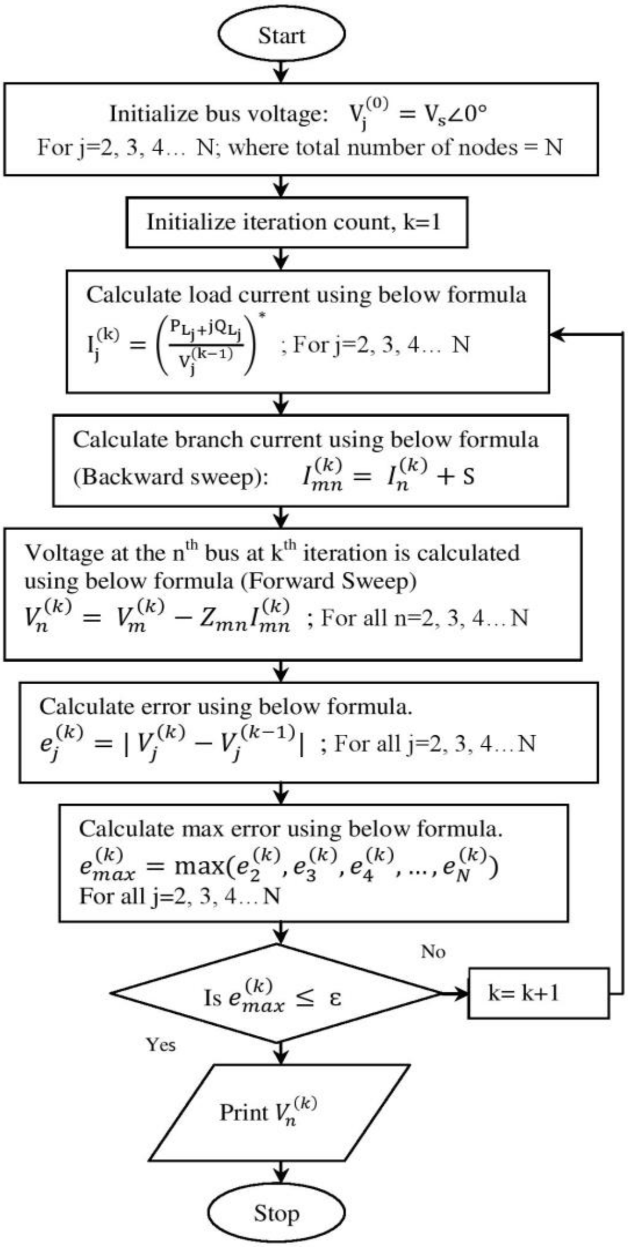

Fig. 8. Flowchart for Backward-Forward Sweep method [34], illustrates the BFS method used for load flow analysis in power distribution networks

In the next step, the calculated bus voltage at the kth iteration is compared with the previous iteration and stored as an error. The maximum error is then chosen and compared with the tolerance value. If the error is within the prescribed limit, then the bus voltage is printed; otherwise, it is moved to the next iteration. The BFS method assumes a radial network structure and steady-state operating conditions with constant power loads. Convergence of the load flow solution is verified using a predefined tolerance criterion, ensuring numerical stability and reliability of computed bus voltages and branch currents. The next subsection discusses the optimization technique for optimal DG sizing and its optimal position in the network.

3.5 Optimization Technique

After doing the load flow study, voltage, current, power loss (I^2R) is obtained. The next task is to find the optimal DG size and its location. Fig. 9 illustrates the PSO algorithm workflow, including particle initialization, fitness evaluation, and iterative updates. This process is central to determining the optimal DG size and placement. Position of particle (i) is adjusted as;

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{5}$$

Velocity of particle (i) is updated as follows:

$$v_i^{(t+1)} = w\, v_i^{(t)} + c_1 r_1 \,(p_{(i,lb)}^{(t)} - x_i^{(t)}) \;+\; c_2 r_2 \,(p_{(gb)}^{(t)} - x_i^{(t)}) \tag{6}$$

where i is the i^th particle, t is the generation counter, $v_i^{(0)}$ is a randomly set value, w adds to the inertia of the particle, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are random numbers ϵ [0,1], $p_{(i,lb)}^{(t)}$ is the local best or personal best of the i^th particle and $p_{(gb)}^{(t)}$ is the global best. $w\, v_i^{(t)}$ It is called the momentum part or the inertia component and provides memory of the previous flight direction as well as prevents the particle from drastically changing direction. $c_1 r_1 \,(p_{(i,lb)}^{(t)} - x_i^{(t)})$ It is called the cognitive part and provides memory of the previous best position as well as quantifies performance relative to past performances. $c_2 r_2 \,(p_{(gb)}^{(t)} - x_i^{(t)})$ is called social part and quantifies performance relative to neighbors. For the power loss minimization problem, the function is given by equations (7) and (8).

$$p_{(i,lb)}^{(t+1)} = \{x_i^{(t+1)}, \quad if\ f\left(x_i^{(t+1)}\right) < f\,(p_{(i,lb)}^{(t)}) p_{(i,lb)}^{(t)}, \qquad otherwise \tag{7}$$

$$p_{(gb)}^{(t)} \epsilon \left\{ f\,(p_{(gb)}^{(t)} = \left\{ f\,(p_{(gb)}^{(t)} \right\} \right\} \tag{8}$$

Where N is the number of particles in the swarm.

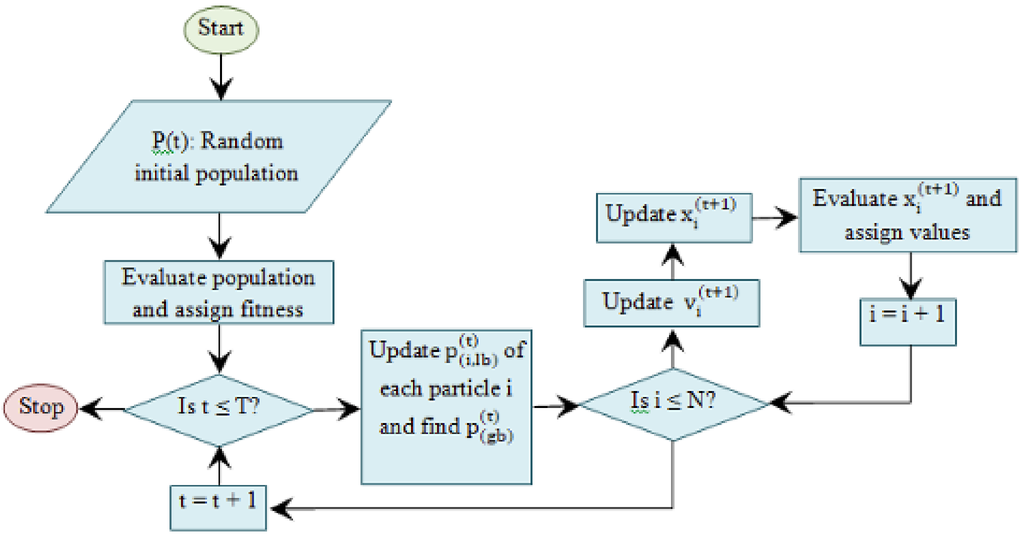

Fig. 9. Flowchart of PSO algorithm, outlines the steps involved in the PSO algorithm used for optimal DG placement and sizing in power systems

The PSO-based optimization assumes a continuous and bounded search space for DG size, with all candidate solutions constrained within physically feasible limits. The objective function (real power loss minimization) is continuous and well-defined, enabling stable convergence. The selected PSO parameters (inertia weight, acceleration coefficients, and population size) are chosen based on established literature to ensure convergence stability and to avoid premature stagnation. Convergence is verified by monitoring the stability of the global best solution across successive iterations.

3.6 Interaction Between PSO and Power Flow

Fig. 10 shows the interaction between BFS load flow analysis and PSO optimization. This integrated framework enables simultaneous evaluation of network performance and optimization of DG parameters. PSO generates candidate DG sizes, while BFS evaluates network performance through load flow analysis. The objective function, which minimizes power loss, is computed for each candidate. PSO then updates the DG size based on the objective function and iterates until the optimal DG size is determined, minimizing power loss. The pseudocode for PSO is given in [14]. The analysis begins with the BFS method where load flow analysis is performed without DG integration to calculate base bus voltage, branch current, and real power losses.

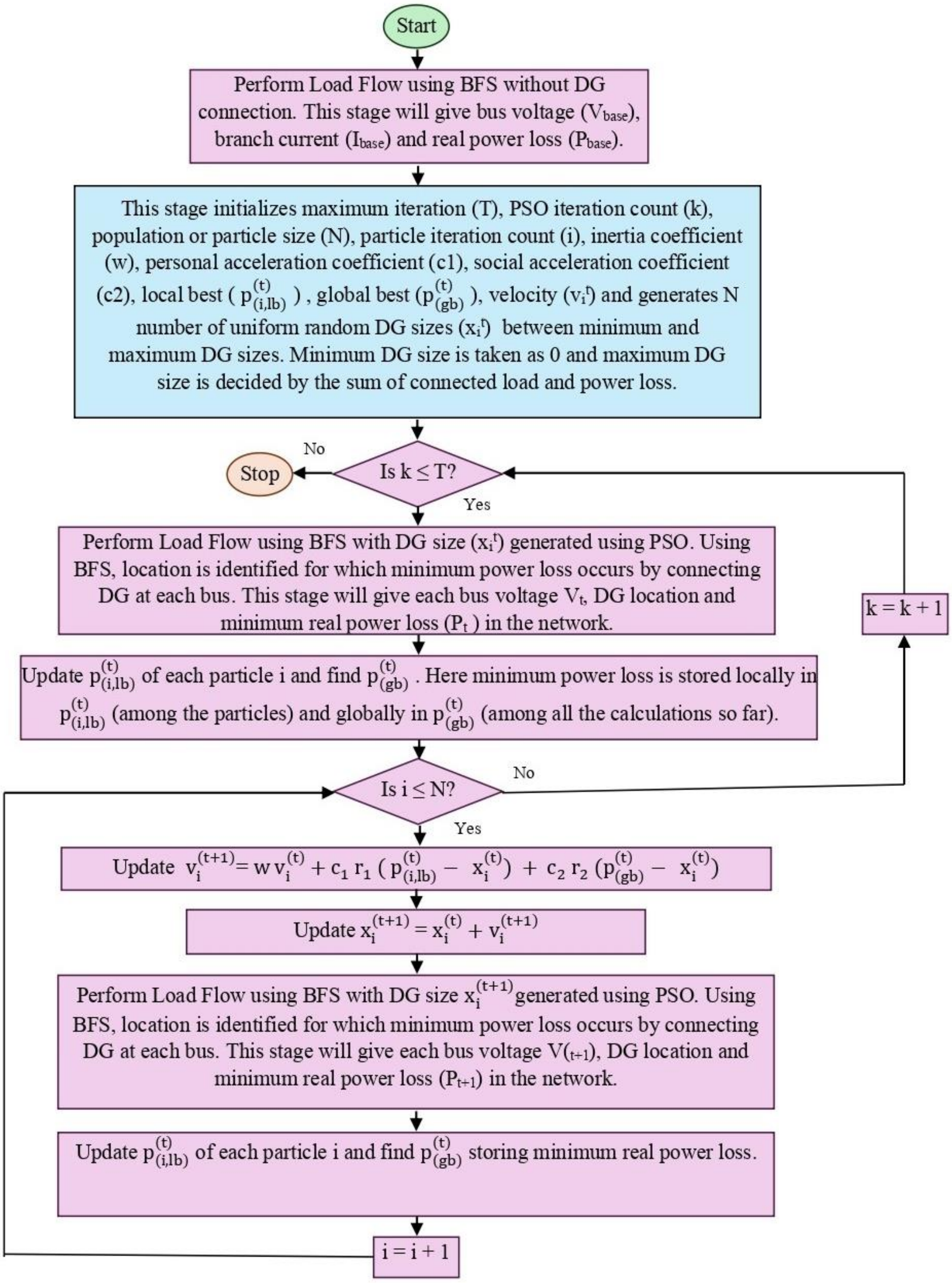

Fig. 10. Flowchart for interaction between PSO and power flow

Subsequently, the PSO parameters are initialized, including the maximum number of iterations, the current iteration, the particle count, and the inertia, personal acceleration, and social acceleration coefficients. Particles representing DG sizes are initialized with positions and velocities, constrained within a range from 0 to a maximum value based on the connected load and power loss. The PSO optimization loop continues until the maximum iteration count is reached. During each iteration, BFS is used for load flow analysis with DG sizes generated by PSO, determining the bus voltage, DG location, and size that minimize real power loss. Fitness values are updated by identifying the local best position for each DG size (also called particle) and the global best position among all particles. Particle velocities and positions are updated iteratively using PSO equations that incorporate inertia, personal best influence, and social best influence. This process ensures continuous refinement of the solution. The final output identifies the optimal DG size and placement, minimizing power losses and improving voltage stability. The hybrid BFS-PSO approach is efficient, enabling simultaneous optimization of objectives, making it well-suited for radial power distribution networks.

It is important to note that this study uses deterministic simulation and optimization techniques; therefore, classical statistical assumption tests (e.g., normality or homoscedasticity) are not applicable. Instead, model validity is ensured by satisfying physical constraints, verifying convergence, and ensuring consistent results across multiple simulation scenarios, which are standard practices in power system analysis. This section discusses the methodology used in the analysis. The next section shows the result obtained from the study.

4. Results and Discussion

This section presents the results and findings of the study. The first sub-section gives the result of DG sizing and its placement in the IEEE-33 test bus, the second sub-section shows DG placement variation based on DG Size, and the last sub-section gives the optimal DG for the Mizoram Power System.

4.1 Optimal DG for IEEE-33 bus

The result for simulation of optimal placement and sizing of DG using BFS and PSO technique is given in Table 5. The result shows that the best DG size for IEEE-33 bus is 0.028135 p.u. (2813.5 kW) on the base of 100 MVA and 11kV. The results indicate that optimal DG placement at bus 6 significantly reduces real power loss by 49.71% while improving the minimum bus voltage by 6.85%, demonstrating the effectiveness of the proposed method. The optimal DG size obtained from the simulation is 0.028135 p.u. (2813.5 kW), which reduces the total real power loss from 331.66 kW to 166.78 kW, corresponding to a 49.71% reduction, indicating a substantial practical effect of DG integration. The minimum bus voltage improves from 0.8575 p.u. (9.43 kV) to 0.9162 p.u. (10.08 kV) at Bus 18, representing a 6.85% increase, demonstrating a meaningful enhancement in voltage profile. Annual energy loss decreases from 2.91 GWh to 1.46 GWh, resulting in an absolute saving of 1.45 GWh per year, which highlights the significant operational benefit of optimal DG placement. Overall, the integration of DG at Bus 6 yields a large effect in terms of both loss minimization and voltage stability improvement.

Table 5. Simulation result of single DG placement in IEEE-33 bus

Sl. No.	Parameters	Output
1.	The Best DG Size (in p.u.)	0.028135 (2813.5 kW)
2.	The minimum power loss with the Best DG Size inserted (in p.u.)	0.0016678 (166.78 kW)
3.	Power loss without DG insertion (in p.u.)	0.0033166 (331.66 kW)
4.	Percentage of power loss reduction	49.71%
5.	The best location to insert DG of optimal size is at bus number	6
6.	Lowest voltage before DG insertion (occurs at Bus number 18) in p.u.	0.85750 (9.43 kV)
7.	Lowest voltage after DG insertion (occurs at Bus number 18) in p.u.	0.91620 (10.08 kV)
8.	Percentage of voltage improvement at the worst Bus	6.85%
9.	Energy loss per year without DG	2.91 GWh
10.	Energy loss per year with DG	1.46 GWh
11.	Energy saving per year when DG is implemented	1.45 GWh

The DG is placed at optimal location of bus number 6. Fig. 11 compares the voltage profile of the IEEE-33 bus system before and after DG integration. The improvement toward the nominal voltage level demonstrates the effectiveness of the proposed method. The voltage profile after DG integration shifts closer to the nominal value of 1 p.u. across all buses, indicating improved voltage regulation. It is clear that the lowest voltage occurs at bus no. 18, and that the voltage profile improves after DG insertion. The voltage profile improvement is about 6.85% at the weakest bus (i.e. bus number 18). Fig. 12 shows the variation of the voltage stability index before and after DG placement. The shift toward stable regions confirms that DG integration enhances system stability. As it goes far away from zero line, the system approaches instability.

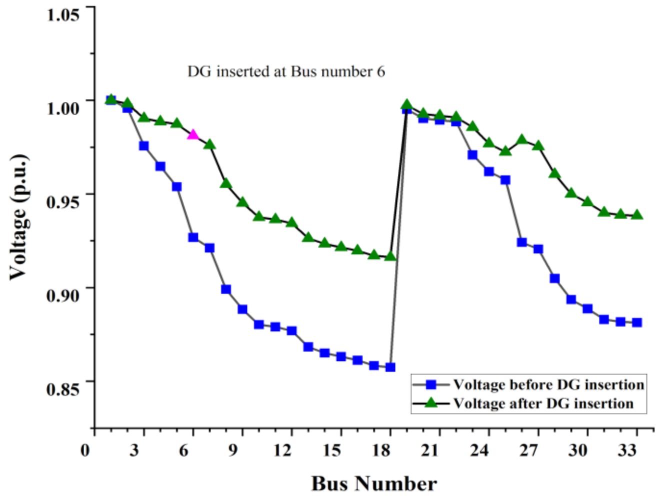

Fig. 11. Voltage profile of IEEE-33 bus system before DG insertion and after DG insertion, the green triangular dot line shows that the voltage profile after DG insertion improves as it is nearer to 1 p.u. as compared to the blue squaredot line which shows the voltage profile before DG insertion

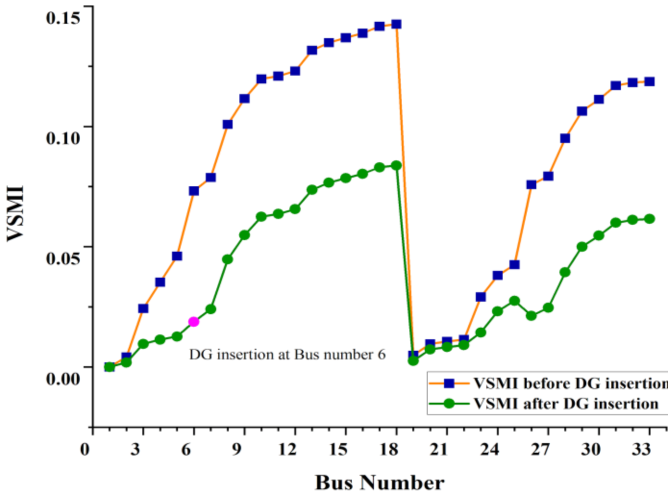

Fig. 12. Voltage Stability Index for the IEEE-33 bus system before DG insertion and after DG insertion. A voltage stability index margin near zero means good stability

The green circular dot line indicates the voltage stability margin index when DG is integrated. Whereas blue square dot line shows voltage stability margin index before DG implementation. Therefore, the DG implementation improves the voltage profile and stability of the power network. Therefore, the DG implementation improves the voltage profile and stability of the power network. With the optimal DG size of 2.8 MW installed at bus number 6, the real power loss is reduced to 166.78 kW, compared to 331.66 kW without DG. This corresponds to a real power loss reduction of 49.71%.

The computational performance of the hybrid method depends on two main components: the PSO optimization process and the BFS load flow analysis used for fitness evaluation. The BFS load flow method is particularly well-suited for radial distribution systems and exhibits linear computational complexity with respect to the number of buses, making it highly efficient for large-scale networks.

As the network size increases, the computational burden grows proportionally due to additional branch and node calculations, but remains tractable. On the other hand, the PSO algorithm has a computational complexity proportional to the swarm size and number of iterations, and is largely independent of network topology. The overall complexity of the BFS–PSO framework can therefore be expressed as a function of:

- Number of particles,
- Number of iterations,
- Cost of BFS load flow (which scales approximately linearly with system size).

Thus, the total computational effort increases in a near-linear manner with network size, primarily driven by the load flow evaluation within the fitness function. Additionally, the BFS–PSO approach does not require matrix factorization or Jacobian computations, which enhances its suitability for large-scale radial distribution systems. The method is also amenable to parallel implementation, as fitness evaluations for different particles can be performed independently, further improving scalability. Although the proposed method is validated on the IEEE 33-bus system, its formulation is general and can be extended to larger systems (e.g., 69-bus or higher) without structural modifications. It is acknowledged that computational time will increase with system size; however, the increase remains manageable due to the efficient BFS load flow and the simplicity of PSO.

The integration of optimally sized DG (2.8135 MW at Bus 6) results in a 49.71% reduction in real power loss, decreasing from 331.66 kW to 166.78 kW. This level of improvement is consistent with recent studies employing metaheuristic optimization techniques, which typically yield loss reductions of 30%-60% for IEEE-33 bus systems. For instance, recent works have reported comparable reductions using hybrid optimization frameworks [35, 36]. The obtained result falls within this established range, thereby validating the effectiveness of the proposed BFS–PSO approach. In terms of voltage performance, the minimum bus voltage improves from 0.8575 p.u. to 0.9162 p.u. (6.85% increase). Similar studies report voltage improvements in the range of 4–10% for standard test systems [25], indicating that the proposed method achieves competitive performance. This improvement is attributed to the synergistic integration of accurate load flow analysis (BFS) with global optimization capability (PSO). Furthermore, the Voltage Stability Margin Index (VSMI) shows improved system stability after DG integration. This aligns with recent findings that optimal DG placement enhances voltage stability in radial networks, particularly under high R/X conditions [37].

4.2 DG Placement Variation Based on DG Size

The placement of a DG unit becomes critical when its size is fixed, as it directly affects the network's power losses and voltage profile. The optimal location for the DG is found using the BFS and the PSO optimization techniques. The DG is placed such that there occurs a minimum real power loss after its placement. Figs. 13–16 illustrate voltage profiles for different DG sizes (1–4 MW) and their corresponding optimal locations. These comparisons highlight the impact of DG size on voltage improvement and system performance. From the simulation result as shown in fig.13-16, it is observed that if a DG of 1MW is to be placed in the IEEE 33 bus system, then the optimal location would be Bus number 12. Similarly, if DG of 2MW is placed at Bus 8, DG of 3MW is placed at 6 and DG of 4MW should be placed at Bus number 6 for lesser power loss and improved voltage profile.

The results indicate that real power loss decreases progressively as DG size increases from 1 MW to 3 MW, after which it increases at 4 MW, demonstrating a non-linear relationship between DG size and system performance. The minimum power loss is achieved at a 3 MW DG size, indicating that this configuration provides the greatest reduction in system losses compared to the other tested sizes. Voltage magnitude at the weakest bus shows consistent improvement across all DG sizes, with values approaching the nominal 1.0 p.u., indicating a positive and measurable effect on voltage stability. However, when DG size exceeds the connected load (e.g., 4 MW), the real power loss increases, suggesting diminishing returns and potential adverse effects due to reverse power flow." These results demonstrate that DG size has a significant effect on both loss reduction and voltage profile, with optimal performance observed near 3 MW.

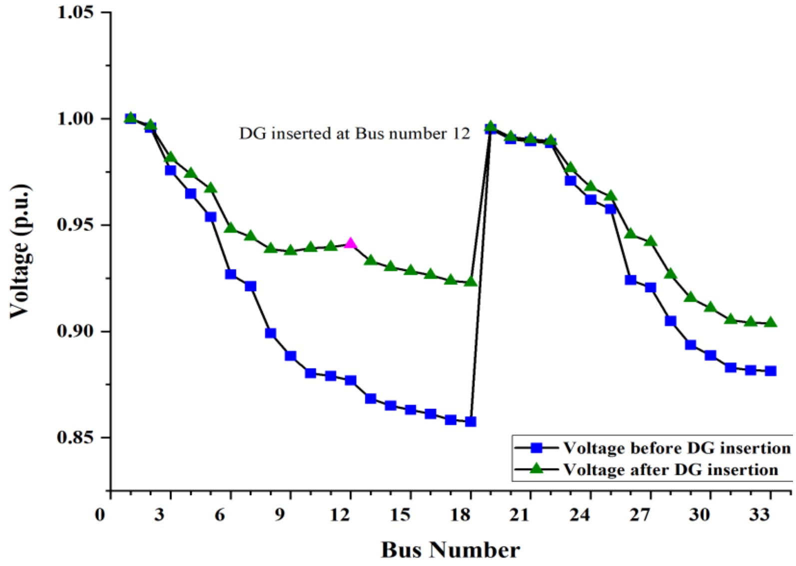

Fig. 13. Voltage profile pre and post Placement of DG of 1 MW at Bus Number 12; when 1MW isto be integrated in IEEE-33 test bus, the optimal location would be at Bus number 12

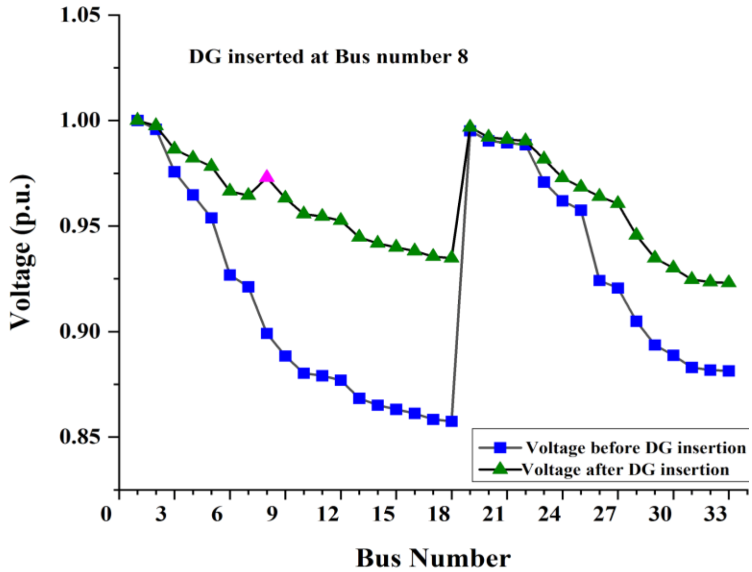

Fig. 14. Voltage profile pre and post Placement of DG of 2 MW at Bus Number 8; when 2MW is to be integrated in IEEE-33 test bus, the optimal location would be at Bus number 8

The optimal DG size for the IEEE-33 bus system with a connected load of 3.72 MW is 2.8 MW. Four cases are considered, with two sizes below and two sizes above the optimal value. In real-world scenarios, the DG size may be constrained to 1, 2, or 3 MW due to financial, spatial, or other limitations. The analyzed cases demonstrate how DG placement is influenced by its size and explore the effect of DG size on the voltage profile and real power loss. The DG size is varied in 1 MW increments from 0 to 4 MW (just above the connected load). The study also shows that connecting a 4 MW DG—exceeding the total load of 3.72 MW—results in higher real power losses than connecting a 2 MW or 3 MW DG. In each of the four cases, i.e. insertion of 1MW or 2MW or 3MW or 4MW DG, minimum voltage occurs at Bus Number 18.

Fig. 17 shows the relationship between DG size and real power loss. The curve demonstrates that an optimal DG size exists, beyond which losses increase due to system constraints. Real power loss decreases with increasing DG size up to 3 MW, beyond which it increases, indicating the existence of an optimal DG size for loss minimization. Fig. 18 presents the variation of minimum bus voltage with DG size. The results indicate that appropriate DG sizing significantly improves voltage levels toward the desired nominal value. The analysis demonstrates that optimal DG sizing is crucial for minimizing power loss and improving voltage profiles, with 3 MW the most effective size in this case, achieving the lowest power loss and bringing the minimum voltage closest to the nominal value. The next sub-section discusses about the optimal DG placement in Mizoram Power System.

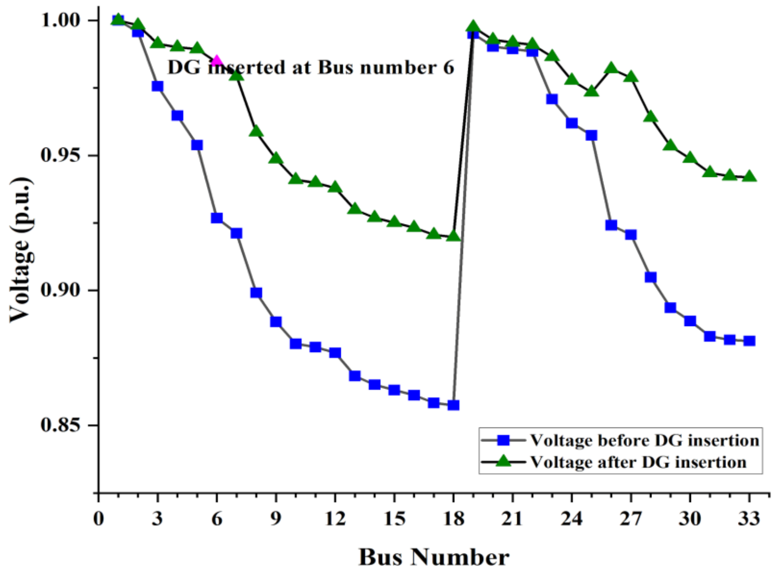

Fig. 15. Voltage profile pre and post Placement of DG of 3 MW at Bus Number 6. When 3MW is to be integrated in IEEE-33 test bus, the optimal location would be at Bus number 6

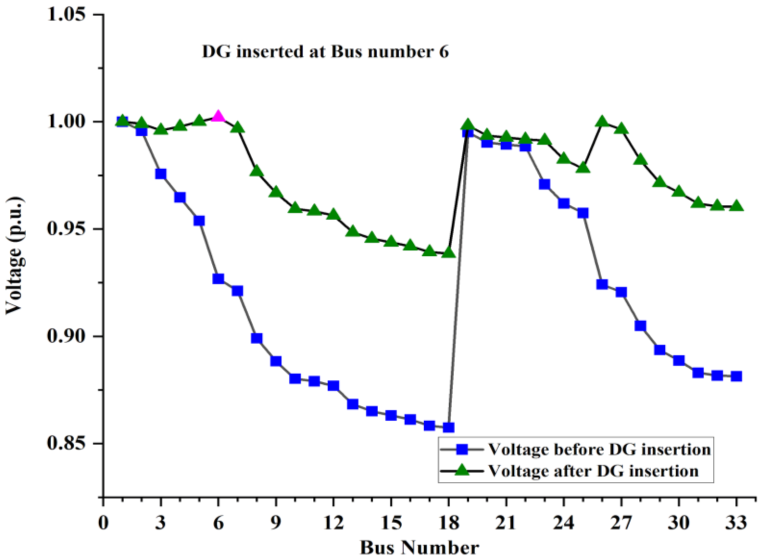

Fig. 16. Voltage profile pre and post Placement of DG of 4 MW at Bus Number 6. When 4 MW is to be integrated in IEEE-33 test bus, the optimal location would be at Bus number 6

The analysis of DG size variation (1–4 MW) reveals that real power loss decreases with increasing DG size up to 3 MW, after which it increases at 4 MW. This confirms the existence of an optimal DG size threshold, beyond which performance deteriorates due to reverse power flow and increased losses. This trend is consistent with recent studies showing that excessive DG penetration leads to network inefficiencies and constraint violations [27]. These findings reinforce the importance of optimal sizing in DG planning. Additionally, the optimal DG location shifts from Bus 12 (1 MW) to Bus 6 (≥3 MW) with increasing DG size. This behavior aligns with theoretical expectations based on loss sensitivity and load distribution, and is supported by recent optimization-based studies highlighting the dependence of DG placement on system topology and loading conditions [35]. The voltage profile analysis further shows that the minimum bus voltage approaches the nominal value (1 p.u.) with DG integration, confirming improved voltage regulation, which is essential for reliable distribution system operation.

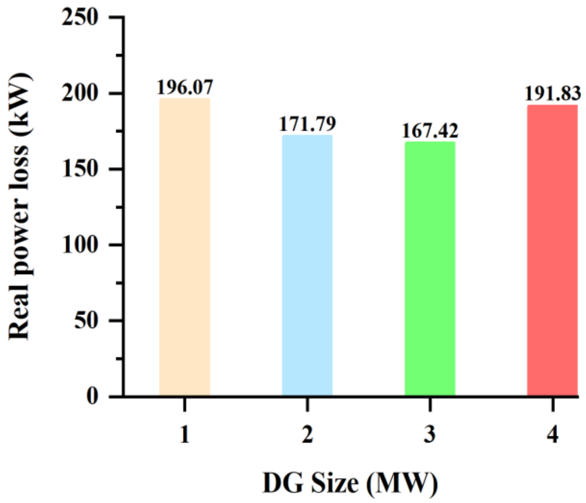

Fig. 17. Real Power Loss vs. DG Size. Graph shows that real power loss is minimum when 3MW is inserted as compared to 1 to 4MW

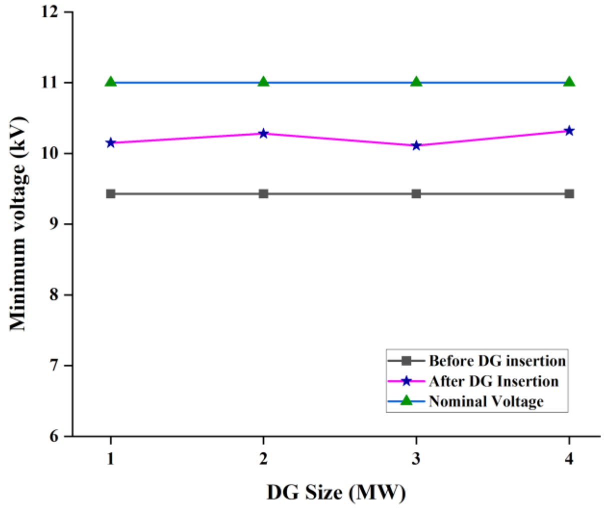

Fig. 18. Minimum voltage vs. DG Size. Minimum bus voltage approaches towards desired bus voltage when DG is integrated

4.3 Optimal DG for Mizoram Power System (Aizawl Project Circle- I)

Table 6 presents the results of simulating the proposed algorithm on the Aizawl Project Circle-I networks. For Part A (Bawktlang to Saiphai), an optimal DG size of 3388.90 kW at bus 3 achieves an 87.90% reduction in power loss and a 23.16% improvement in voltage at the weakest bus. Similarly, for Part B (Bawktlang to Bukpui), an optimal DG size of 3171.70 kW at bus 3 results in an 83.48% reduction in power loss and a 36.58% improvement in voltage at the weakest bus. Significant reductions in power loss (up to 87.90%) and substantial improvements in voltage confirm the practical effectiveness of the proposed approach in real distribution networks.

Table 6. Simulation result of single DG placement in Mizoram Power System (Aizawl Project Circle- I)

Sl. No.	Parameters	Bawktlang to Saiphai network	Bawktlang to Bukpui network
1.	The Best DG Size (in p.u.)	0.91345 (3388.90 kW)	0.81956 (3171.70 kW)
2.	The minimum power loss with the Best DG Size inserted (in p.u.)	0.025499 (94.60 kW)	0.048758 (188.69 kW)
3.	Power loss without DG insertion (in p.u.)	0.21072 (781.77 kW)	0.2952 (1142.42 kW)
4.	Percentage of power loss reduction	87.90%	83.48%
5.	The best location to insert DG of size 0.028135 p.u. is at bus number	3	3
6.	Lowest voltage before DG insertion (occurs at Bus number 4) in p.u.	0.74972 (24.74 kV)	0.65124 (21.49 kV)
7.	Lowest voltage after DG insertion (occurs at Bus number 4) in p.u.	0.92346 (30.47 kV)	0.88933 (29.35 kV)
8.	Percentage of voltage improvement at the worst Bus	23.16%	36.58%
9.	Energy loss per year without DG	6.84 GWh	10.00 GWh
10.	Energy loss per year with DG	0.83 GWh	1.65 GWh
11.	Energy saving per year when DG is implemented	6.01 GWh	8.35 GWh

For the Bawktlang–Saiphai network, the optimal DG size of 3388.90 kW reduces real power loss from 781.77 kW to 94.60 kW, corresponding to an 87.90% reduction, indicating a very strong effect of DG integration. The minimum bus voltage increases from 0.7497 p.u. (24.74 kV) to 0.9235 p.u. (30.47 kV), representing a 23.16% improvement, demonstrating a substantial enhancement in voltage stability. Annual energy loss decreases from 6.84 GWh to 0.83 GWh, yielding a net saving of 6.01 GWh, which reflects a significant operational and economic benefit. For the Bawktlang–Bukpui network, the optimal DG size of 3171.70 kW reduces real power loss from 1142.42 kW to 188.69 kW, corresponding to an 83.48% reduction, indicating a strong performance improvement. The minimum bus voltage improves from 0.6512 p.u. (21.49 kV) to 0.8893 p.u. (29.35 kV), representing a 36.58% increase, which highlights a significant enhancement in voltage profile. Annual energy loss is reduced from 10.00 GWh to 1.65 GWh, resulting in an annual energy saving of 8.35 GWh, demonstrating a substantial system-level benefit.

The application of the proposed method to real distribution feeders (Bawktlang–Saiphai and Bawktlang–Bukpui) yields power loss reductions of 87.90% and 83.48%, respectively, along with voltage improvements of 23.16% and 36.58%. These improvements are significantly higher than those observed in standard test systems and are consistent with recent studies on real distribution networks, where loss reductions exceeding 80% have been reported under optimal DG integration [26]. The higher improvements are attributed to long feeder lengths, higher initial losses, and weaker voltage conditions, which amplify the benefits of DG integration. The substantial voltage improvement in the Bukpui feeder (36.58%) aligns with findings that weak rural networks are more sensitive to DG integration, leading to more pronounced voltage stabilization effects [27].

4.4 Mitigating Solar Power Variability

This paper presents a methodology for optimizing the placement and sizing of DG using the BFS and PSO technique in MATLAB. Tested on the IEEE-33 bus system, the algorithm then was applied to real-world. To investigate the impact of distributed generation (DG) uncertainty arising from solar intermittency, a deterministic scenario-based analysis is carried out by reducing solar generation from its optimal value in steps of 100%, 75%, 50%, and 25%. This approach effectively captures the variability in solar irradiance due to changing weather conditions, time of day, and seasonal effects. The impact of reduced solar generation on the voltage profile of the IEEE 33-bus system is illustrated in Fig. 19. Under nominal conditions (optimal DG size of 2.8 MW), the system maintains a better voltage profile. However, as solar generation decreases, a progressive voltage drop is observed across the network. The most severe degradation occurs under 100% reduction (complete loss of solar generation), where the system operates close to its lower voltage limits.

Fig. 20 presents the variation in the Voltage Stability Margin Index (VSMI) under different levels of solar generation. It is evident that with decreasing solar output, the VSMI shifts progressively toward the unstable region, indicating a reduction in system voltage stability. This behavior reflects the system's increasing proximity to voltage collapse due to insufficient reactive power support and higher loading on the grid. The effect of solar intermittency on power losses is depicted in Fig. 21. The results show a consistent increase in real power losses as solar generation decreases. This is attributed to higher grid current to compensate for reduced local generation, thereby increasing line losses. The results clearly demonstrate that DG uncertainty significantly affects system performance. A reduction in solar generation leads to voltage degradation, decreased stability margin, and increased power losses. This indicates that the optimal DG size obtained under nominal conditions is sensitive to solar intermittency and may not guarantee optimal or secure operation under uncertain conditions.

To mitigate the adverse effects of solar variability, Energy Storage Systems (ESS) are integrated with the solar DG. ESS provides fast response capabilities to balance generation fluctuations, regulate voltage and frequency, and smooth power output. By storing excess energy during periods of high solar generation and supplying it during periods of low solar generation, ESS enhances system reliability and operational flexibility.

Furthermore, ESS enables improved grid support by reducing dependence on conventional generators during solar deficits and allowing better utilization of renewable energy. It also facilitates peak load management and enhances the economic viability of solar integration through energy arbitrage. The optimal battery size can be calculated based on the following assumptions:

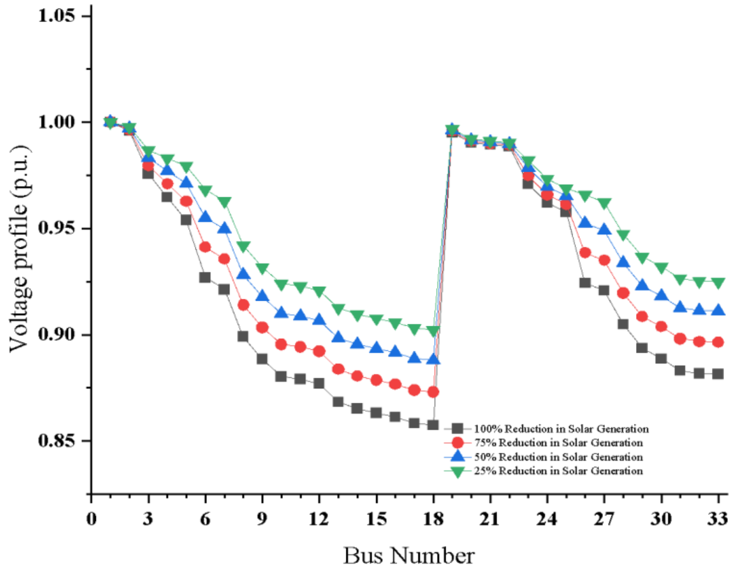

Fig. 19. Impact of solar generation reduction on voltage profile in IEEE-33 bus system

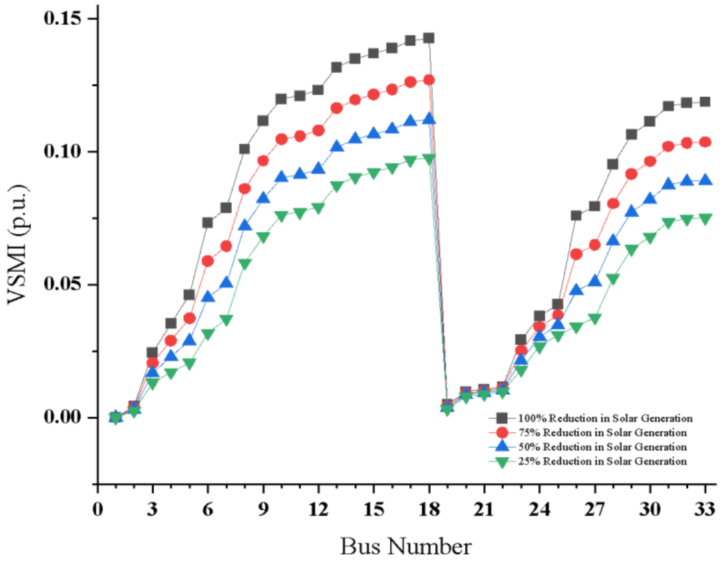

Fig. 20. Impact of solar generation reduction on voltage stability margin index in IEEE-33 bus system

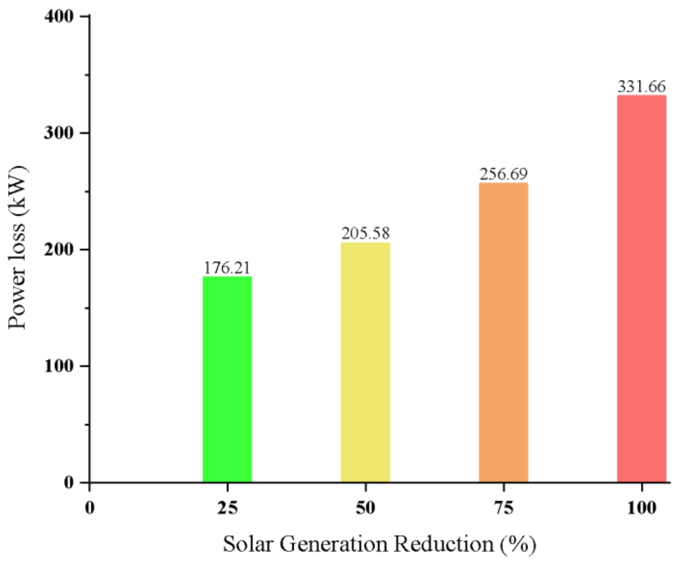

Fig. 21. Impact of solar generation reduction on power loss in IEEE-33 bus system

- The total energy from solar DG will be stored in the battery and then flow to the load.
- State of charge (SOC) variation ranges from 10% - 90% [27].
- Battery efficiency (EB) considered is 80% [39].
- The optimal size of the battery is given by equation (9) [3], [25], [39]

$$Battery\ size = \frac{Optimal\ DG\ Size\ \times E_B}{SOC_{Final} - SOC_{Initial}} \tag{9}$$

where SOC_{Final} = 90%; $SOC_{Initial}$ = 10%; E_B = 80%; Optimal DG size = 0.028135 p.u. Putting these values in equation (1) gives the battery size of 0.028135 p.u (on base 100 MVA and 11kV).

In addition to ESS, alternative arrangements are considered to handle different levels of solar power reduction. In the case of complete loss of solar generation (100% reduction), grid support or hybrid generation systems (e.g., wind or thermal) are required to meet demand. For partial reductions (75%, 50%, and 25%), varying levels of ESS support are necessary to maintain system stability and performance. Although a probabilistic approach (e.g., Monte Carlo simulation) could provide a more comprehensive representation of DG uncertainty, the adopted scenario-based method effectively captures critical operating conditions and worst-case scenarios. Thus, it can be concluded that solar intermittency introduces significant variability in system performance, and appropriate mitigation strategies such as ESS are essential to ensure reliable and stable operation of modern power systems [40-42]. The following are the limitations of the study;

- Methodological limitations: The study is based on simulation using the IEEE-33 bus system and selected real feeders, which may not fully capture dynamic operational uncertainties (e.g., load variability, renewable intermittency).
- Contextual limitations: The findings are derived from distribution networks in Mizoram, characterized by hilly terrain and specific load patterns; thus, generalization to urban or highly meshed networks may be limited.
- Analytical limitations: The optimization focuses primarily on real power loss minimization and voltage improvement; other objectives, such as economic cost, reliability indices, and multi-DG scenarios, were not explicitly considered.

Compared with several recent hybrid and intelligent optimization techniques reported in the literature, the proposed BFS–PSO framework provides a comparatively lower computational burden and simpler implementation while maintaining strong convergence characteristics and effective loss minimization capability. Furthermore, whereas many existing studies primarily focus on standard IEEE benchmark systems, the present work demonstrates the applicability of the proposed framework on practical 33 kV rural distribution networks with long feeder distances and hilly terrain conditions, thereby enhancing its practical significance. The study also assumes balanced operating conditions and steady-state analysis; therefore, transient stability effects, protection coordination issues, and communication-related constraints associated with smart grid implementation were not explicitly investigated. Moreover, uncertainty associated with renewable generation and demand variability was represented using scenario-based analysis rather than full probabilistic modeling.

The findings suggest that utilities operating long radial feeders can prioritize DG deployment at weak buses identified through optimization studies to reduce technical losses and improve voltage stability. Policymakers may utilize the results to support decentralized renewable energy planning in remote regions through targeted incentives, feeder modernization programs, and integration of community-scale solar PV with energy storage systems. Additionally, the proposed framework can assist researchers and system planners in developing multi-objective DG planning strategies incorporating reliability, economics, and renewable uncertainty considerations.

5. Conclusion

This study proposed a BFS–PSO-based framework for optimal sizing and placement of Distributed Generation (DG) in radial distribution systems. The methodology was validated on the IEEE-33 bus system and subsequently applied to real distribution networks in Mizoram, India, namely the Bawktlang–Saiphai and Bawktlang–Bukpui feeders. The primary finding of this work is that the proposed BFS–PSO framework significantly improves network performance by reducing power losses and enhancing voltage stability. In the IEEE-33 bus system, the proposed method achieved a 49.71% reduction in power losses and a 6.85% improvement in voltage at the weakest bus. In practical feeder systems, even greater improvements were observed, with 87.90% and 83.48% reductions in power losses and 23.16% and 36.58% voltage improvements in the Bawktlang–Saiphai and Bawktlang–Bukpui networks, respectively.

Whereas voltage profile depends on the bus loading and line reactance. Under load variation, the power system operating conditions change dynamically. An increase in load demand leads to higher current flow, which causes increased voltage drop across transmission and distribution lines, thereby deteriorating the voltage profile. It also results in higher real and reactive power losses due to increased line currents. Conversely, a decrease in load improves the voltage profile and reduces system losses. Therefore, load variation significantly affects system voltage, power losses, and overall stability.

- The objective of optimal DG sizing and placement is addressed in Section 3.1 (IEEE-33 bus results) and Section 3.3 (real network results).
- The objective of analyzing the impact of DG size variation is addressed in Section 3.2, where multiple DG sizes (1–4 MW) are evaluated.
- The objective of improving voltage profile and reducing power loss is supported throughout Section 3 via quantitative comparisons before and after DG integration.
- The objective of validating the methodology on real distribution networks is fulfilled through the case studies of the Bawktlang–Saiphai and Bawktlang–Bukpui systems.

These results demonstrate that DG placement and sizing are strongly dependent on network characteristics, feeder loading, and system parameters. The successful application of the proposed method to real distribution systems highlights its practical value, particularly for rural and geographically challenging networks where voltage drops and line losses are significant concerns.

This research contributes by providing a computationally efficient and scalable optimization framework that combines the robustness of BFS load flow analysis with the fast convergence characteristics of PSO. Unlike many studies limited to benchmark systems, this work validates the proposed approach using practical distribution networks, thereby extending its applicability to real-world planning scenarios. Future research should focus on:

- Incorporating uncertainty through stochastic modeling of renewable generation and load variations;
- Integrating machine learning and adaptive hybrid optimization techniques; and
- Evaluating real-time implementation through hardware-in-the-loop and digital twin platforms.

The findings indicate that renewable-based DG, particularly solar PV systems, can play an important role in improving voltage stability, reducing losses, and enhancing reliability in remote and hilly distribution networks.

Acknowledgement

The authors are thankful to Power & Electricity Department, Government of Mizoram, India, for providing the necessary information on the substations and help required for this paper. The authors also express gratitude towards NIT Mizoram for providing the necessary support.

References

[1] De K, Majumder S, Kumar P, Rayudu R. Effect of an electric vehicle bus network on Guwahati grid. In: Proc IEEE Innovative Smart Grid Technologies Asia (ISGT-Asia); 2017; Auckland, New Zealand. p. 1-6. https://doi.org/10.1109/ISGT-Asia.2017.8378335

[2] Hiruta Y, Ishizaki NN, Ashina S, Takahashi K. Regional and temporal variations in the impacts of future climate change on Japanese electricity demand: simultaneous interactions among multiple factors considered. Energy Convers Manag X. 2022;14:100172. https://doi.org/10.1016/j.ecmx.2021.100172

[3] Majumder S, De K, Kumar P, Rayudu R. A green public transportation system using E-buses: a technical and commercial feasibility study. Sustain Cities Soc. 2019;51:101789. https://doi.org/10.1016/j.scs.2019.101789
[4] Azad VK, De K, Majumder S. Ethanol blending and its environmental impacts: a case study of India. Energy Sustain Dev. 2024;79:101385. https://doi.org/10.1016/j.esd.2024.101385
[5] Khenissi I, Guesmi T, Alshammari BM, Alqunun K, Almalaq A, Alturki M, et al. A hybrid chaotic bat algorithm for optimal placement and sizing of DG units in radial distribution networks. Energy Rep. 2024;12:1723-1741. https://doi.org/10.1016/j.egyr.2024.07.042
[6] De K, Majumder S, Kumar P. Analysis of the resilience of an electric-based transportation system. IET Electr Syst Transp. 2020;10(1). https://doi.org/10.1049/iet-est.2018.5087
[7] Kapeller R, Cohen JJ, Kollmann A, Reichl J. Incentivizing residential electricity consumers to increase demand during periods of high local solar generation. Energy Econ. 2023;127:107028. https://doi.org/10.1016/j.eneco.2023.107028
[8] Rani P, Parkash V, Sharma NK. Technological aspects, utilization and impact on power system for distributed generation: a comprehensive survey. Renew Sustain Energy Rev. 2024;192:114257. https://doi.org/10.1016/j.rser.2023.114257
[9] Singh S, Singh S. Advancements and challenges in integrating renewable energy sources into distribution grid systems: a comprehensive review. ASME J Energy Resour Technol. 2024;146(9):090801. https://doi.org/10.1115/1.4065503
[10] Minas AM, García-Freites S, Walsh C, Mukoro V, Aberilla JM, April A, et al. Advancing Sustainable Development Goals through energy access: lessons from the Global South. Renew Sustain Energy Rev. 2024;199:114457. https://doi.org/10.1016/j.rser.2024.114457
[11] Nappu MB, Arief A, Ajami WA. Energy efficiency in modern power systems utilizing advanced incremental particle swarm optimization-based OPF. Energies. 2023;16(4):1706. https://doi.org/10.3390/en16041706
[12] Hota A, Mishra S. A forward-backward sweep based numerical approach for active power loss allocation of radial distribution network with distributed generations. Int J Numer Model Electron Netw Devices Fields. 2020;34. https://doi.org/10.1002/jnm.2788
[13] Bawazir RO, Cetin NS. Comprehensive overview of optimizing PV-DG allocation in power system and solar energy resource potential assessments. Energy Rep. 2020;6:173-208. https://doi.org/10.1016/j.egyr.2019.12.010
[14] Kumar M, Soomro AM, Uddin W, Kumar L. Optimal multi-objective placement and sizing of distributed generation in distribution system: a comprehensive review. Energies. 2022;15(21):7850. https://doi.org/10.3390/en15217850
[15] Shami M, et al. Particle swarm optimization: a comprehensive survey. IEEE Access. 2022. https://doi.org/10.1109/ACCESS.2022.3142859
[16] Kawambwa S, et al. An improved backward/forward sweep power flow method based on network tree depth for radial distribution systems. J Electr Syst Inf Technol. 2021;8:7. https://doi.org/10.1186/s43067-021-00031-0
[17] Azad VK, De K, Majumder S. Optimal positioning of distributed generation based on its penetration using backward-forward sweep method. In: Proc IEEE Guwahati Subsection Conf (GCON); 2023; Guwahati, India. p. 1-5. https://doi.org/10.1109/GCON58516.2023.10183476
[18] Borni A, Bessous N, Zaghba L, Bouchakour A, Agmas MS, Ali E, et al. Enhancing grid connected wind energy conversion systems through fuzzy logic control optimization with PSO and GA techniques. Sci Rep. 2025;15(1):27678. https://doi.org/10.1038/s41598-025-12593-4
[19] Maheshwari A, Jaiswal S, Sood YR, Raj H, Sabyasachi S. A comprehensive review on metaheuristic optimization methods for efficient power system operation. In: Khadse CB, Kale IR, Shastri AS, editors. Intelligent Methods in Electrical Power Systems. Singapore: Springer; 2024. https://doi.org/10.1007/978-981-97-5718-3_1
[20] Veni SV, Jayachandran J, Malathi S, Prakash RA, Jayavignesh J, Prabaharan N. Dynamic power management based on model predictive control and PSO for hybrid microgrid. Sci Rep. 2025;15(1):39225. https://doi.org/10.1038/s41598-025-23204-7
[21] Clerc M, Kennedy J. The particle swarm-explosion, stability, and convergence in a multidimensional complex space. IEEE Trans Evol Comput. 2002;6(1):58-73. https://doi.org/10.1109/4235.985692
[22] Rupa JM, Bompard EF. A new formulation of three-phase load flow for radial distribution networks. In: Proc IEEE Power Engineering Society Winter Meeting; 2000. Vol. 3. p. 1715-1720.
[23] Sengupta S, Basak S, Peters RA. Particle swarm optimization: a survey of historical and recent developments with hybridization perspectives. Mach Learn Knowl Extr. 2019;1(1):157-191. https://doi.org/10.3390/make1010010

[24] Kalidasan M, Guna Sekar T, Mohanasundaram T. Power loss reduction and voltage profile enhancement by reconfiguration of radial distribution system with hybrid optimization method. Therm Sci Eng Prog. 2025;57:103105. https://doi.org/10.1016/j.tsep.2024.103105
[25] Salazar Vanegas CE, Gallego Pareja LA, Gómez Carmona O. A multi-period MILP model for optimal integration of battery energy storage systems and distributed generation in power distribution systems. Results Eng. 2025;27:106806. https://doi.org/10.1016/j.rineng.2025.106806
[26] Saxena V, Manna S, Rajput SK, Kumar P, Sharma B, Alsharif MH, et al. Navigating the complexities of distributed generation: integration, challenges, and solutions. Energy Rep. 2024;12:3302-3322. https://doi.org/10.1016/j.egyr.2024.09.017
[27] Demirci O, Taskin S, Schaltz E, Acar Demirci B. Review of battery state estimation methods for electric vehicles - Part I: SOC estimation. J Energy Storage. 2024;87:111435. https://doi.org/10.1016/j.est.2024.111435
[28] Kumar A, et al. Load flow analysis and voltage stability improvement in radial distribution networks using backward-forward sweep method. In: Proc IEEE Global Conf Adv Technol (GCON); 2023.
[29] Baran ME, Wu FF. Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Trans Power Deliv. 1989;4(2):1401-1407. https://doi.org/10.1109/61.25627
[30] Tarekegn D, et al. Optimal parameter selection and convergence analysis of particle swarm optimization for energy system applications. Front Energy Res. 2023;11:1159410.
[31] Nigatu DT, et al. Particle swarm optimization-based parameter tuning and convergence enhancement techniques for engineering optimization applications. Results Eng. 2024;22:100696.
[32] Wang X, et al. Improved particle swarm optimization techniques and parameter adaptation strategies: a review. Energy Inform. 2023;6:279.
[33] Wang D, Tan D, Liu L. Particle swarm optimization algorithm: an overview. Soft Comput. 2021;25:1-22.
[34] Santoso B, Sarijaya D, Sakti FP. Optimal sizing and placement of wind-based distributed generation to minimize losses using flower pollination algorithm. J Teknol Rekayasa. 2018;3(2):167-176. https://doi.org/10.31544/jtera.v3.i2.2018.167-176
[35] Rajakumar P, Balasubramaniam PM, Aldulaimi MH, Arunkumar M, Ramesh S, Alam MM, et al. An integrated approach using active power loss sensitivity index and modified ant lion optimization algorithm for DG placement in radial power distribution network. Sci Rep. 2025;15:10481. https://doi.org/10.1038/s41598-025-87774-2
[36] Zhang Y, et al. Hybrid intelligent optimization framework for distributed energy management and power loss minimization in distribution systems. Glob Energy Interconnect. 2025.
[37] Singh AK, et al. Optimal distributed generation placement for voltage stability enhancement and loss reduction in radial distribution systems. IEEE Access. 2022;10:14632-14647.
[38] Pereira IS, da Costa Vergara G, López-Lezama JM, Muñoz-Galenao N, Garcés Negrete LP. Strategies to mitigate reverse power flow in distribution networks with high penetration of solar photovoltaic generation. Energies. 2026;19(4):1069. https://doi.org/10.3390/en19041069
[39] Dutta S, Majumder S, De K. Parameter sizing in bi-directional charging for compact EVs. In: 2024 IEEE Silchar Subsection Conference (SILCON 2024); 2024; Agartala, India. p. 1-6. https://doi.org/10.1109/SILCON63976.2024.10910648
[40] Dutta S, Adikari S, Debnath T, Pal RS, Amitabh K, Chauhan M, et al. Recent trends and open challenges in battery management systems: a comprehensive review with hardware-in-the-loop simulation for electric vehicle applications. Res Eng Struct Mater. 2026. https://doi.org/10.17515/resm2026-1349en1119rv
[41] Dutta S, Majumder S, De K, et al. Electric vehicle battery recycling for sustainability: environmental and water benefits. Clean Techn Environ Policy. 2026;28:28. https://doi.org/10.1007/s10098-025-03402-7
[42] Borahel RDS, Telli GD, Bolzoni AA, Isoldi LA, dos Santos ED, Luiz Rocha AO. Numerical analysis of the impact of PCM reservoir width on lithium-ion battery cooling: a constructal design study. Res Eng Struct Mater. 2025;11(5):2421-2435. https://doi.org/10.17515/resm2025-557en1202rs