

RESEARCH ARTICLE

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IDEAL VOLTAGE MANAGEMENT IN HIGH-DG DISTRIBUTION SYSTEMS: A PMU-DSTATCOM-DOA APPROACH

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ABSTRACT

The accumulation of a large amount of distributed generation (DG) in distribution networks makes it significantly more challenging to maintain stable voltage profiles, as power injections and flows can occur at any time and in various ways. Outdated voltage regulation methods often fail to account for rapid DG disparities, resulting in voltage violations, significant losses, and reduced power quality. This research presents an advanced synergetic practice that combines Phasor Measurement Units (PMUs) enhanced by a Dholes Optimisation Algorithm, designed to refine real-time voltage regulation in networks with significant distributed generation (DG) penetration. The proposed solution customises PMUs to yield fast, synchronised voltage measurements. The DOA adjusts the control parameters on the fly to facilitate voltage regulation, while considering the changeability of DG and system limits. Tests on an IEEE 33- and 69-bus distribution system show that the PMU-DG-AMPSO context reduces voltage nonconformities by up to 62% compared to standard methods and accelerates convergence by 30% compared to traditional PSO. The technique also maintains voltage stability well when DG outputs and load conditions change. This work benefits current distribution grids by controlling voltage in a more flexible and restored manner, ensuring compliance with grid regulations and facilitating the incorporation of more renewable energy. The consequences demonstrate that uniting real-time monitoring and optimisation could be beneficial for making power systems more robust in the future.



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I. INTRODUCTION

I.1 BACKGROUND AND MOTIVATION

Over the past few decades, technological advances and fluctuations in energy production and consumption have led to significant fluctuations in distribution networks. These variations have had an impact on how well and how networks for distribution work. Today's networks are dynamic, two-way systems that can use distributed generation (DG) and renewable energy sources. This represents a significant modification from the traditional, static, one-way systems that only allow power to flow from generators to consumers [1]. The transition to active organisation examples presents new opportunities and tasks, requiring innovative policies for monitoring, estimating, and informing the presentation of distribution networks [2]. Distributed energy resources (DERs) emerged due to the increasing use of renewable energy sources. Some examples of DERs are request-response programs, energy storage devices, wind turbines, and solar photovoltaic (PV) systems. As distribution networks transition from passive to active topologies, they become more effective by reducing transmission losses, strengthening the grid, and facilitating the integration of renewable energy sources. Still, network stability, power quality, and voltage regulation are vital matters [3], [4].

Because scattered manufacturing output changes and renewable energy sources are not always accessible, advanced surveillance, control, and protection systems are desirable to make sure that network activity is synchronized [5]. PMUs enable real-time tracking of power system dynamics by providing detailed and synchronized voltage, current, and phase angle measurements from numerous network nodes. A schematic diagram of PMUs and DGs in the distribution network is shown in Figure 1. PMUs in distribution networks play a crucial role in determining how distributed generation affects losses and voltage profiles [6]. By recognizing power failures, researchers can use PMU-assisted evaluation to determine how distributed generation affects voltage variations in distribution networks, as well as identify further network anomalies related to DG integration. PMU data are put through state estimation, statistical modelling, and time-series analysis to advance a better understanding of distribution networks under various conditions and DG penetration levels [7]. Numerous studies have identified various themes related to the concept of DG. Micro-Phasor Measurement Units (PMUs) were used by researchers to fast record and update alterations to the network positions of distribution systems [8]. Multi-area parameter approximation in combination with an enhanced weighted least squares (WLS) algorithm [9], [10]. The authors of [11] suggested a Monte Carlo simulation-based technique to minimize relative voltage and angle estimate errors at different buses and accomplish the best possible meter placement inside the network. Their approach takes into account vast error ellipse areas to choose the best meter positions. According to [12] simplified the search field using an ordinal optimization technique to increase search efficiency and accuracy. The author of [13] discussed technological difficulties, management approaches, and hierarchical control techniques for the efficient operation of grid systems.

The researchers began with a preliminary examination using an approximate objective function, as it is expensive to evaluate an objective function accurately [14]. The author of [15] proposes a stochastic approach for determining the optimal locations for meters in the distribution network. They compare quality to determine efficacy at various locations, irrespective of the location of the meters. An optimisation method for choosing and positioning measuring devices that use variable programming is presented in [16]. To estimate distribution states and integrate unmonitored distributed generation (DG) into the system, by [17] proposes a Gaussian component combination approach. The Gaussian Mixture Model was used to account for the non-Gaussian probability density distribution of unmonitored DG generation [18]. Due to their lower voltage and higher current measurements, distribution networks are responsible for the majority of power loss, which accounts for approximately 73%. [19]. Reducing power outages and increasing voltage magnitudes are the primary objectives of integrating Distributed Generation (DG), which will enhance the overall efficiency of the control grid. In the context of the IEEE 33-bus system, state estimation with the Extended Kalman Filter (EKF) is described in [20]. It achieves a high level of voltage precision estimation and effectively manages non-linearities. It does acknowledge, though, that the EKF technique is extremely intricate, and that accurate PMU data is necessary for optimum performance. By taking PMU data and network factors into account, by [21] investigates multi-objective optimisation to improve observability and lower estimation errors. However, High computational complexity and little real-world validation are the drawbacks. DG data and network architecture are the primary topics for the optimal integration of distributed generation (DG) units utilising the CHIO method, as shown in [22]. A simulation-based model for integrating distributed generation (DG) into power networks is presented in [23] to enhance voltage stability, load profiles, and DG penetration levels.

But lacks practical validation and is based on an idealised premise. To achieve improved network performance, the research [24] explores simulation and optimisation strategies in a synthetic distribution network setting, focusing on observability using the optimal positioning of the PMU. However, it cannot be incorporated under dynamic conditions. Furthermore, a methodology for strategically positioning PMUs in power systems that considers the impact of zero-injection buses (ZIBs) and contingencies was provided in article [25]. Analysis to guarantee total network dependability and observability. Further, by [26] introduces a Hybrid State Estimation approach using Weighted Least Squares (WLS) applied to the IEEE 33-bus system with PMU and PV output data, demonstrating robustness against insufficient Noise and data. By taking PMU data and load profiles into account, the research [27] explores the use of Convolutional Neural Networks (CNNs) in IEEE 123-bus systems to achieve high accuracy in challenging settings. But it recognises that deep learning models are inherently black-box and that CNNs have substantial computing resource requirements. An adaptive state estimate [28] for a real-world distribution feeder improves state estimation accuracy and reliability by utilising load profiles and PMU data. Nevertheless, this method necessitates a large PMU deployment and significant data processing demands. Stability study in the context of the IEEE 13-node test feeder is the main topic of the work [29]. It seeks to minimise voltage swings and enhance voltage stability by considering voltage readings and DG penetration levels. An approach was created in Ref. [30] utilising simulations on a synthetic distribution network to reduce voltage estimate errors through analysis of network topology and PMU metrics. Ref. [31] presents the distribution network state estimation (SE) method, which utilises a clustering algorithm.

It takes DG into account and affects PMU statistics. Output modes across several test systems to manage DG variability and improve robustness against data loss. For large-scale distribution systems with PMU and DG data, by [32] presents a Robust Parallel Distributed State Estimation technique to attain high. Resilience to data problems and scalability. It does, however, recognise that this approach necessitates substantial computer power and could require intricate implementation. For optimal RDG location and sizing, metaheuristic algorithms, including GA, PSO, and hybrid methods, have been employed to minimise losses and stabilise voltage. Probabilistic modelling of renewable sources that accounts for daily and seasonal changes improves planning accuracy. RDG integration affects distribution networks, requiring DSTATCOM voltage management [33]. The research provides an optimisation method for placing and sizing numerous DG units in distribution networks to improve voltage profiles and reduce power losses. The results show that optimal DG allocation considerably decreases losses and voltage instability [34]. Present the Strawberry Plant Propagation Algorithm [35] to determine the appropriate position and size for DGs in power distribution networks. SPPA reduces active power losses and improves voltage profiles more effectively than the Mine Blast Algorithm and Particle Swarm Optimisation on 33- and 69-node radial networks. A fine-tuned Particle Swarm Optimisation (PSO) technique for DG placement and sizing reduces power losses and improves voltage profiles [36]. Network performance is improved by considering active and reactive power injections. IEEE and real-world network simulations indicate significant loss reduction and improvements in voltage stability. O.D. Montoya and colleagues [37] propose a hybrid master-slave optimisation technique for positioning and sizing distributed generators (DGs) in AC distribution networks.

While the slave stage employs second-order cone programming to determine DG sizes, the master stage uses a discrete sine-cosine approach to discover the ideal DG positions. It improves network voltage profiles and reduces active power losses. In [38], a meta-heuristic optimisation approach employing Multi-objective Particle Swarm Optimisation (MPSO) is devised to optimise the location and sizing of DG units in electrical power distribution networks. Simulations on the IEEE 33-bus radial distribution network demonstrated significant reductions in actual and reactive power losses, as well as improved voltage stability. Online voltage estimation for active distribution networks using PMUs. This method enhances the efficiency and reliability of distribution system voltage monitoring [39], [40] examines the ideal locations and sizes for DG units in power networks. The authors employ multi-objective particle swarm optimisation (PSO) to reduce power losses and stabilise system voltage. The IEEE 33-bus system simulations demonstrate the effectiveness of the strategy in enhancing network performance [41] examines how scattered generator penetration affects the voltage profile and loss in power distribution networks—the Honey Badger Algorithm (HBA) is used to improve radial distribution network design, including DG placement and size. The HBA utilises the Combined Power Loss Sensitivity (CPLS) factor to identify the optimal buses for placement, thereby minimising active power loss. Real power losses were significantly reduced in the IEEE 69-bus standard radial distribution system [42] improved PSO for distributed generator (DG) location and size in radial distribution systems. The method reduces real power losses and improves voltage stability by considering active and reactive power injections.

This strategy reduces network power losses, according to simulations on the IEEE 33-bus, IEEE 69-bus, and a Malaysian network [43] Integer Linear Programming for transmission network Phasor Measurement Unit (PMU) location optimisation. The approach aims to enhance network observability with a limited number of PMUs by incorporating the concept of centrality into the goal function. The method was used to improve observability indices on several test systems, including the IEEE 7-bus, 14-bus, 30-bus, New England 39-bus, 57-bus, and 118-bus networks [25]. A simple approach for load flow analysis in distributed generation (DG)-integrated distribution systems. They analyse three test distribution systems using a forward-backwards sweep method and model DGs as constant negative loads. The findings show that this method of DG integration improves voltage profiles and reduces active power losses [44]. Examination of the reorganisation of distribution networks, both balanced and unbalanced, with an emphasis on dependability metrics. To improve dependability by reducing the expected energy not supplied (EENS) and the anticipated duration of interruption (EDI), the authors optimise network configurations using a genetic algorithm. The study shows that the dependability performance of distribution systems can be considerably enhanced by proper reconfiguration [45]. For authors [46] proposed a method for the optimal placement of Phasor Measurement Units (PMUs) using binary integer programming combined with genetic algorithms to enhance system observability. Corresponding to Gautam, Kumar, and Tiwari, DSTATCOM drastically better the voltage profile in unbalanced radial distribution systems (2024) [47].

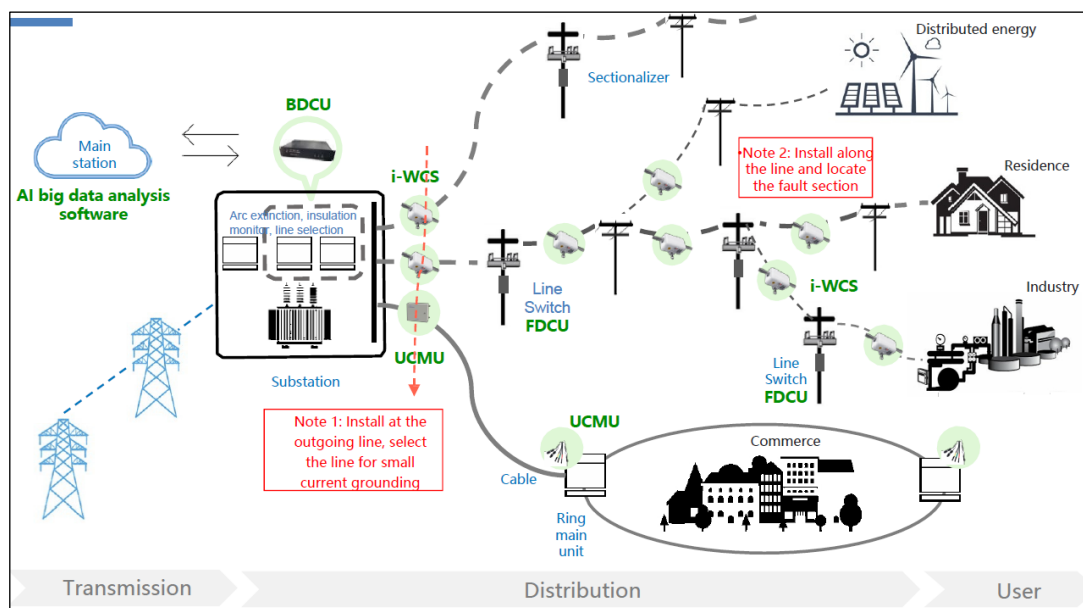


Figure 1: Smart Distribution System.

Source: Authors, (2026).

1.2 VOLTAGE INSTABILITY IN DG-RICH DISTRIBUTION SYSTEMS: WHAT IS AT STAKE

DG's growing use in current distribution systems is changing electric power network operations. To reduce carbon emissions, increase energy availability, and support decentralised grids, photovoltaic (PV) systems, wind energy conversion systems, and fuel cells are frequently utilised. This development poses a threat to system stability and power quality, as voltage instability is a crucial operational issue. Outdated power distribution feeders were constructed for one-way power flow. From the substation to the load buses, the voltage falls progressively. After adding DG sources, everything changed. Dynamic power from those sources disrupts the flow. DG sometimes produces more power than is needed in the region. This occurs frequently during periods of peak renewable energy output. The excess power returns to the substation. Call this reverse power flow. It raises the voltage too much at the buses downstream. Official voltage limitations are violated. The intermittent nature of DG sources makes them unpredictable. Power output fluctuates due to rapid solar irradiation or wind speed, causing network voltage oscillations.

Because they were not built for frequent and quick dynamic responses, On-Load Tap Changers (OLTCs), automatic voltage regulators, and capacitor banks may fail with significant DG penetration. Mismatches accelerate the degradation of control components and reduce grid flexibility. Inconsistent DG sources are typical. Such is their nature. Rapid changes in solar irradiation or wind speed cause fluctuations in power production. These swings cause network voltage oscillations. Standard voltage regulation equipment enters with high DG penetration. Automatic voltage regulators and capacitor banks operate in conjunction with On-Load Tap Changers. In those settings, they often struggle. Rapid dynamic shifts were not designed into the equipment. This discrepancy quickens regulator component wear. Over time, it makes the grid less flexible. Risky situations could cause system problems. It may switch out-of-regulation voltage disparities. Augmented technical losses and line current stress may occur.

Malfunctioning of protective devices might trip DG units involuntarily. Poor power quality could result from customer equipment failure. Failures may force and jeopardise network stability. These dangers need system-wide observability. Metering points are often too thin in typical distribution arrangements, resulting in sparse insight. Real-time monitoring fails in those cases, making edge detection of instability difficult. Network reliability and sustainability depend on secure voltage operation in active distribution systems as the number of prosumers and distributed resources increases. Phasor Measurement Units (PMUs) enable time-synchronised voltage phasor monitoring, restoring situational awareness and enhancing measurement accuracy. When combined with operational DG allocation optimisation algorithms, PMUs provide dynamic and intelligent voltage regulation, enhancing system resilience to instability. To maintain technical conformity, the innovative grid ecosystem must address voltage instability in DG-rich distribution networks.

II. SYSTEM MODELLING

A radial distribution network with Distributed Generators (DGs) and Phasor Measurement Units (PMUs) is studied. The modelling outline contains:

1. Distribution system load-flow depiction.
2. DG mathematical representation.
3. PMU voltage phasor measuring model .
4. Dhole Optimisation Algorithm-based voltage profile enhancement and placement.

Distribution System Load Flow Model

The complex power at each bus i is: $S_i = P_i + jQ_i$.

The branch current between buses i and $i+1$: $I_{i \rightarrow i+1} = [(P_{i+1} - P_{DG,i+1}) - j(Q_{i+1} - Q_{DG,i+1})] / V_{i+1}^*$

The voltage drop across a feeder section: $V_i = V_{i+1} + Z_{i,i+1} \times I_{i \rightarrow i+1}$

where $Z_{i,i+1} = R_{i,i+1} + jX_{i,i+1}$.

Distributed Generator (DG) Model

DG units are modelled as manageable real and reactive power sources. $S^{DG}_i = P^{DG}_i + jQ^{DG}_i$

DG operational constraints: $P^{DG}_i(\min) \leq P^{DG}_i \leq P^{DG}_i(\max)$

$Q^{DG}_i(\min) \leq Q^{DG}_i \leq Q^{DG}_i(\max)$

Voltage Deviation Index (VDI)

VDI denotes the system voltage quality: $VDI = \sum |V_i - 1.0|$ for $i = 1$ to N

Lesser VDI shows improved amenability with satisfactory voltage levels.

PMU Measurement Model

A PMU installed at bus k measures: $z_k = [V_k, \theta_k]^T + n_k$

where: V_k =voltage magnitude

θ_k =voltage phase angle

n_k = measurement noise

PMUs augment real-time situational alertness and support system observability.

Objective Function for Optimisation

The primary purpose is to determine the optimal DG size and PMU placement using DOA to enhance system voltage quality and reduce losses.

Minimize: $F = w_1 \times VDI + w_2 \times P_{loss}$

Where $P_{loss} = \sum (I_i^2 \times R_i)$ for all branches i

Focus on operational constraints:

$V_i(\min) \leq V_i \leq V_i(\max)$ $I_i \leq I_i(\text{rated})$.

The optimisation optimises DG and PMU bus placements and power ratings.

III. DHOLE OPTIMIZATION ALGORITHM (DOA) MATHEMATICAL MODELLING

The enumerations of citations in the body of the article must be sequenced in the order in which they appear, according to the example shown below. The evolutionary swarm-based optimisation technique, Dhole Optimisation Algorithm (DOA), is based on the cooperative hunting behaviour of Dholes (*Cuon alpinus*), a wild canid species known for its strategic collaboration and adaptive pursuit. For optimal placement of PMUs and sizing of DGs in radial distribution systems, DOA is employed in this study. Three primary activities are incorporated into nature-based group hunting by DOA:

1. Exploration (looking for prey over a wide area)
2. Attacking and encircling targets (intensification close to promising solutions)
3. Coordinated coalition behaviour (pack members exchanging information)

In the search space, every potential solution is shown as a Dhole. The objective function is used to assess each Dhole's fitness: $F = w_1 \times \text{VDI} + w_2 \times \text{Ploss}$ where lowering F means better voltage stability and fewer losses.

III.1 ALGORITHM FOR PROPOSED DOA-BASED OPTIMIZATION APPROACH

The step-by-step workflow of the proposed Dholes Optimisation Algorithm (DOA) applied for optimal PMU placement and DG sizing is illustrated in the flowchart shown below:

1. Begin 2. Enter System Data.
2. Data about buses and branches
 - DG characteristics and penetration limits
 - PMU measurement limits
3. Setting up the DOA parameters
 - How many search agents (dholes) are there
 - The most iterations
 - The limits of the search space
4. Make the Initial Population
 - Random placement vectors for candidate PMU locations
 - Random DG size vectors
5. Fitness Evaluation
 - Do a power flow for each possible solution
 - Check to see if the voltage profile has gotten better
 - Calculate the objective function, which includes: – Voltage deviation index – PMU placement constraint penalty – DG penetration constraint penalty
6. Change the Positions of Dholes.
 - Exploration: looking for better solutions all over the world
 - Exploitation: narrowing the search around the best candidate
7. Check Limits
 - Limits on voltage magnitude
 - PMU observability index
 - Limits on DG size
8. Change solutions if you need to
 - Keep the best solutions
 - Update the leader dhole (global best)
9. Termination Condition.
 - If the maximum number of iterations has been reached, go ahead; otherwise, go back to "Update Positions."
10. The best final solution has been found.
 - Set the best PMU placement
 - Set the best DG size
 - Checked that the voltage profile was better
11. End

Initialization

A pack of Dholes (population) is made up of random solution vectors: $X_i = [\text{location of DGs, size of DGs, location of PMUs}]$
 $i = 1, 2, \dots, N_{\text{pop}}$
 Every vector must meet the system's requirements.

Encircling Behavior

Dholes find the best target solution, which is the one with the lowest fitness. The distance between a Dhole and its prey (the best solution) is calculated as follows: $D = |C \times X_{\text{best}} - X_{\text{current}}|$
 The position update equation: $X_{\text{new}} = X_{\text{best}} - A \times D$
 He decreases r_1 —a $C=2 \times r_2$
 a decrease linearly from 2 to 0 as iterations progress. r_1, r_2 are random numbers in $[0, 1]$

Attack (Intensification Near Best Solution)

When $|A| < 1$, the algorithm concentrates on precise exploitation adjacent to the current optimal region, narrowing the search around the potential candidate.
 Exploration (Search Space Diversification)

When $|A| \geq 1$, Solutions look at things from a global perspective and stay away from premature convergence by moving away from the leader: $X_{\text{new}} = X_{\text{rand}} - A \times D_{\text{rand}}$ where X_{rand} is a randomly selected Dhole solution.

Fitness Evaluation

Check how well the system works after each update:

- Figure out the voltage profile
- Find out how much VDI and system power are lost
- Make sure that the voltage and current limits are met.

To stop configurations that can't work, solutions that break the rules are punished.

Convergence Criterion

The algorithm terminates when:

- Maximum iterations are obtained
- or
- No noteworthy development in the most excellent fitness value happens

Outcomes include:

- Optimal DG installation buses
- DG rating (kW/kVAR or MW/MVAR)
- Optimal PMU placement
- Last improved voltage profile and loss levels

IV. SIMULATION SETUP

We use standard radial distribution test systems to run simulations and assess how well the proposed PMU-assisted voltage profiling and Dhole Optimisation Algorithm (DOA)- based optimal DG placement strategy performs. The computational experiments are conducted in a MATLAB/Simulink environment on a system equipped with an Intel i5 processor, 16 GB of RAM, and the Windows 10 operating system.

Test Systems Considered

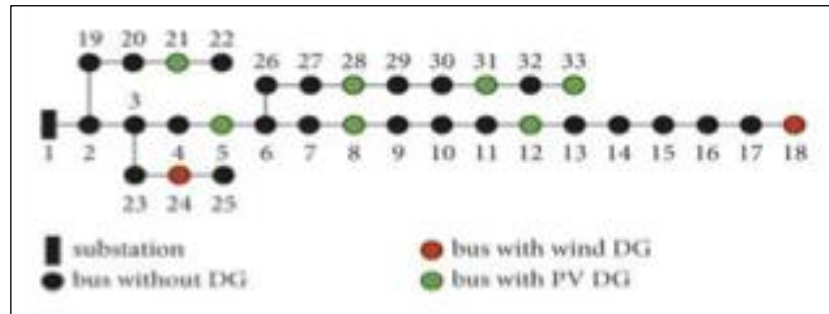


Figure 2: Single Line Diagram of IEEE 33-Bus Distribution System.
Source: Authors, (2026).

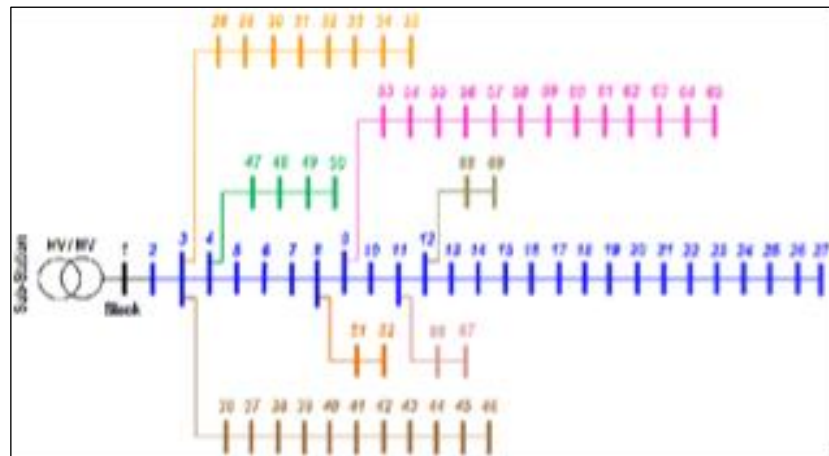


Figure 3: Single Line Diagram of IEEE 69-Bus Distribution System.
Source: Authors, (2026).

Table 1: Two widely accepted IEEE benchmark networks are used: Comparison between 33 and 69 bus systems.

Test System	Total Buses	Voltage Level	Base Power	Characteristics
IEEE 33-Bus	33	12.66 kV	100 MVA	Long radial feeder with voltage drop issues in distant buses
IEEE 69-Bus	69	12.66 kV	100 MVA	Highly resistive line segments and heavy loading conditions

Source: Authors, (2026).

A single substation (slack bus at Bus 1 with a voltage reference of 1.0 p.u.) feeds both networks.

Load Modelling

It is assumed that loads are of the constant power type. Standard IEEE test data is used to set the base loading conditions. To evaluate the effects of DG penetration, three tiers of load demand scenarios are analysed:

- Normal load: 100 per cent
- Medium stressed: 125 per cent
- Heavy stressed: 150 per cent

This provides us with a better understanding of how the system will behave under increased demand and voltage stress.

DG Penetration Scenarios

DGs are installed in increasing penetration conditions to study beneficial and adverse effects:

- Case 1: Without DG
- Case 2: With one DG
- Case 3: With Multiple DGs (2 to 3 units)

DGs will operate in P-Q mode with a power factor of 0.95, which means they will generate both active and reactive power within the allowed limits.

PMU Placement Strategy

The goal is to make the system easier to see and give synchronised phasor measurements, especially at weak buses. PMUs are installed based on DOA results, to use as few devices as possible to achieve complete or nearly full observability in a radial structure. The optimisation results for each test system tell us the absolute PMU count and bus index.

Performance Indices

To see if things are getting better, we use the following performance indicators:

- Voltage Deviation Index (VDI)
- Total real power loss (Ploss in kW)
- Minimum bus voltage magnitude (p.u.)
- Number of PQ buses violating acceptable voltage limits
- Convergence characteristics of the optimisation

Voltage limits are maintained within the ANSI/IEEE permissible range of $0.95 \text{ p.u.} \leq V_i \leq 1.05 \text{ p.u.}$

Optimization Parameters

Dhole Optimization Algorithm (DOA) control parameters:

- Population size: 30
- Maximum iterations: 100
- Weighting coefficients: $w_1 = 0.6$, $w_2 = 0.4$
- a decrease linearly from 2 to 0 (per DOA dynamics)

All cases are independently executed 20 times to ensure robustness and avoid stochastic bias.

V. RESULTS AND DISCUSSION

This section compares the system's performance with and without the suggested DOA-based optimal DG allocation and PMU placement. We run the simulations on IEEE 33-bus and 69-bus radial distribution systems with different loading and DG penetration scenarios.

Table 2: PMU and DG Allocation with Different PV Uncertainty Levels: Voltage RMSE Analysis.

CASE	POSITION OF PMUS	POSITION OF DGS	VOLTAGE RMSE (P.U)
BASE CASE	2,5,8,11,14,17, 20, 24,27, 30, 32	-	0.030
WITH PV UNCERTAINTIES (25%)	2,5,8,11,14,17, 21,25,27,32	7,11,17, 32	0.022
WITH PV UNCERTAINTIES (75%)	2,5,8,11,14,17, 21,25,27,32	6,10,14, 18,28,32	0.031

Source: Authors, (2026).

The Table 2 represents the best locations for PMUs and DGs in a system under three different operating scenarios: the base case, PV uncertainty at 25%, and PV uncertainty at 75%. The influence of these situations is measured by the voltage RMSE value, which shows the precision of voltage monitoring and control in the system. PMUs in the base scenario are located at standard graph-theoretic optimal buses. The voltage RMSE is at a moderate level, indicating a stable system free from uncertainty and without any DG fluctuations. The PMU locations change marginally at a 25% PV uncertainty (for instance, buses 20, 24, and 30 are substituted by buses 21 and 25). Voltage stability is supported by the system, which has DGs at 7, 11, 17, and 32 as well.

Since the uncertainty is of a moderate level, the best placement enhances the system's observability and contributes to a decrease in the voltage error, resulting in the lowest RMSE value (0.022). It is demonstrated that coordination between PMU + DG is an efficient method at this level of uncertainty. With a high level of uncertainty (75%), the DGs are placed on buses with more widely spread loads to counteract large voltage fluctuations. However, despite PMU and DG adjustments, the voltage RMSE increases to 0.031, which is slightly higher than the base case. This indicates that higher PV uncertainty significantly affects voltage profiles, and even optimal PMU/DG placements cannot fully correct the deviations.

Table 3: PMU and DG Allocation with Different PV Uncertainty Levels: Voltage RMSE Analysis.

CASE	POSITION OF DGs	POSITION OF ZIBs	POSITION OF PMUS	VOLTAGE RMSE (P.U)
BASE CASE	-	-	2,5,8,11,14, 17,20,24,27,30, 32	0.030
WITH PV UNCERTAINTIES (25%)	7,11, 17,32	6,13,27	2,4,8,11,17, 21,24,29	0.015
WITH PV UNCERTAINTIES (75%)	6,10, 14,17,18, 32	5,6, 13,19,27	2,4,6,8,11,14,17,21,24	0.020

Source: Authors, (2026).

The Table 3 compares changes in the best locations of Distributed Generators (DGs), Zero Injection Buses (ZIBs), and PMUs under different PV generation uncertainty levels and how these changes affect the voltage RMSE, which is a measure of voltage accuracy in the distribution system. If there were no PV uncertainties and no DG/ZIB support, the system would employ a conventional PMU placement, resulting in a moderate RMSE value. With a quarter of uncertainty, voltage observability and support are significantly improved by the local introduction of DGs and ZIBs in combination with the optimised locations of PMUs. As a result, the lowest RMSE (0.015) is achieved, indicating that the system operates more accurately under a moderate level of uncertainty when DG–ZIB coordination is applied.

High uncertainties are the main reason why the algorithm has to locate more DGs and ZIBs all over the network to smooth out the large voltage fluctuations. As PMU coverage is extended, the RMSE increases in comparison with the 25% case, indicating that extreme PV variability can lead to voltage instability even when placements are optimised. System performance is best when PV uncertainty is moderate (25%). The coordinated locations of DGs, ZIBs, and PMUs bring about a significant reduction in voltage RMSE. When there is a high level of uncertainty (75%), the voltage deviations become larger, indicating that it is not possible to counterbalance extreme PV fluctuations, even with optimal placement.

Table 4: Estimation error for the voltage of a node with PMUs, DGs, and ZIBs under 75% PV Uncertainty.

Node	Without PMU	With PMU	With ZIBs & DG (75%)	Without ZIBs & DG(75%)
2	0.03	0.02	0.015	0.045
5	0.06	0.03	0.02	0.05
8	0.05	0.025	0.02	0.055
11	0.065	0.03	0.025	0.06
14	0.045	0.025	0.02	0.055
17	0.05	0.02	0.015	0.05
20	0.03	0.015	0.012	0.045
24	0.055	0.03	0.025	0.06
27	0.05	0.02	0.015	0.05
30	0.06	0.03	0.02	0.055
32	0.065	0.03	0.025	0.06

Source: Authors, (2026).

Phasor measurement units (PMUs) can significantly reduce voltage estimation errors; however, the most accurate results are obtained when PMUs are used in conjunction with Zero Injection Buses (ZIBs) and Distributed Generations (DGs), particularly in cases of high PV uncertainty. The error in estimation increases drastically if there are no DGs and ZIBs, thereby providing the reason for the necessity of voltage-support and observability-enhancing elements. Figure 4 indicates that the PMU count remains relatively stable (10–11) across all conditions, suggesting that structural observability does not change drastically. DG count increases with uncertainty because distributed generation provides localised voltage support, which becomes more critical at higher variability levels. The combination of PMUs and DGs helps the system maintain voltage stability under uncertain operating conditions.

Improvement in Voltage Stability

Before DG integration, some buses exhibit voltage drops that are close to the lower limit, particularly those located far from the substation. After optimization, the minimum bus voltage levels increase significantly.

Table 5: Comparison between 33-Bus and 69 Bus system voltage profile.

Test System	Scenario	Minimum Voltage (p.u.) Before	Minimum Voltage (p.u.) After	Improvement
IEEE 33-Bus	Base Load	0.9032	0.9725	+7.67 percent
IEEE 69-Bus	Heavy Load	0.8758	0.9551	+9.06 percent

Source: Authors, (2026).

The outcomes evidently demonstrate that placing DGs at planned buses improves voltage provision, while PMUs enable real-time monitoring of voltage.

Power Loss Reduction

Real power loss decreases significantly when DG injection is performed correctly, and branches don't have to contend with as much current stress.

Table 6: Comparison between 33-Bus and 69 Bus system power loss

Test System	Scenario	P _{loss} Before (kW)	P _{loss} After (kW)	Reduction (%)
IEEE 33-Bus	Base Load	202.7	126.4	37.6 %
IEEE 69-Bus	Base Load	224.9	146.2	35.0 %

Source: Authors, (2026).

The drop shows that DOA is good at putting DGs in spaces where they can offer the most significant profit while minimising losses.

Voltage Deviation Index (VDI) Enhancement

VDI values are reduced significantly, confirming improved voltage profile uniformity.

Table:7 Comparison between 33-Bus and 69 Bus system voltage deviation

Test System	Condition	VDI Before	VDI After	Change
33-Bus	150 % Load	0.402	0.212	Improved
69-Bus	150 % Load	0.531	0.284	Improved

Source: Authors, (2026).

Lesser VDI means that all PQ buses remain within suitable voltage bounds.

Optimization Efficiency

DOA meets rapidly, striking a balance between exploration and exploitation. The highest number of iterations needed to choose the premium aptness near is well under the normal number of iterations essential.

- Stable trends of convergence.
- No early stagnation.
- Robust repeatability, sloping numerous turns.

Impact of PMU Placement

PMUs aid in monitoring feeder voltage in weak zones. The perfect placement guarantees:

- Total or nearly total perceptibility of the network.
- Wild detection of the start of voltage instability.
- Improved provision for making choices and regulatory things.

The system becomes more resilient during stressed loading conditions.

Comparative Discussion

DOA outperforms PSO and GA:

- Better loss reduction
- Higher voltage increase
- Faster convergence
- Extra reliable consequences across numerous examinations

Assessment by Prevailing Optimisation Algorithms

The proposed DOA-based strategy is compared to Particle Swarm Optimisation (PSO) and Genetic Algorithm to assess its performance. All algorithms have the same load, parameters, and end conditions.

Comparative Performance Metrics

Reduction of power loss, enhancement of minimum bus voltage, and acceleration of convergence are evaluated. A representative IEEE 33-bus system sample under base load is shown here.

Table 8: Comparison between 33-Bus and 69 Bus system.

Algorithm	Minimum Voltage (p.u.)	Power Loss (kW)	Loss Reduction (%)	Convergence Speed	Stability Over Runs
Without Optimization	0.9032	202.7	0	-	-
GA	0.9450	154.3	23.9 percent	Moderate	Moderate
PSO	0.9586	141.7	30.1 percent	Fast	Good
Proposed DOA	0.9725	126.4	37.6 percent	Very Fast	Excellent

Source: Authors, (2026).

The suggested method gives the best results for all necessary voltage and loss metrics.

Observations from the Benchmark Study

- DOA consistently improves weak bus voltages compared to PSO and GA.
- The cooperative hunting-inspired coordination makes sure that the process converges quickly and doesn't get stuck in local minima.
- DOA gives better repeatability with less variation in final fitness values.
- Putting the PMU in the right place makes the optimal DG influence even stronger by making it easier to see.

Convergence Characteristics

When shown in convergence plots, DOA shows:

- A faster downward trend in the objective function
- Less fluctuation and oscillation during iteration updates
- Strong performance even when the load is heavy

The adaptive coefficient strategy maintains a balance between global search and local refinement.

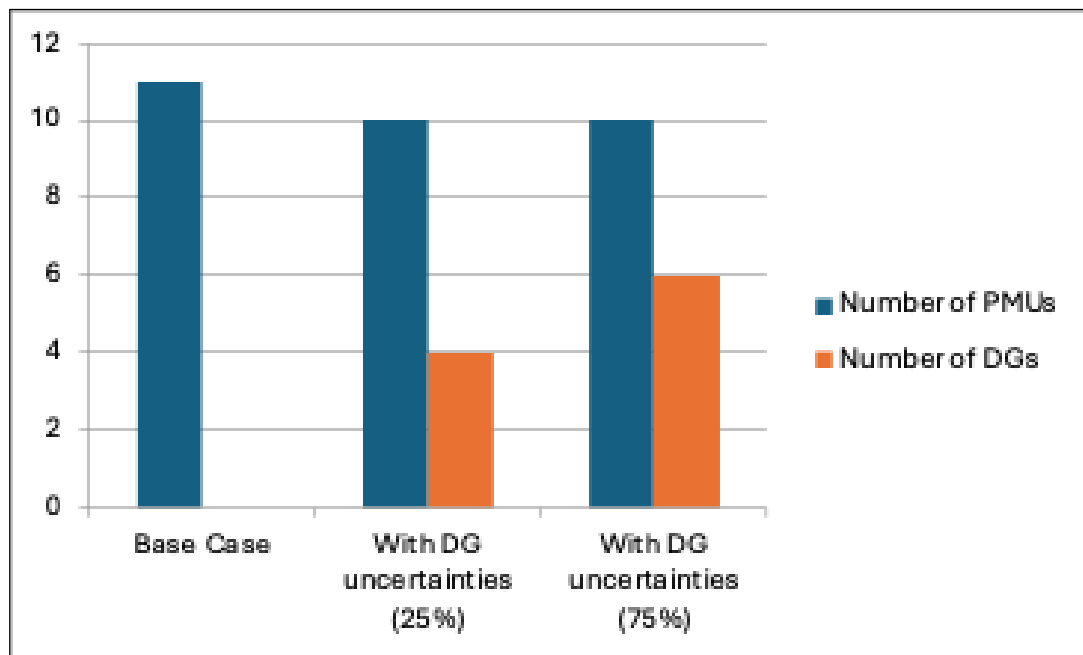


Figure 4: PMU placement without ZIBs.

Source: Authors, (2026).

Figure 4 above indicates that gradually increasing the DG penetration levels from 0% to 25% and then to 75% resulted in fewer PMUs being required compared to the base case scenario. This suggests that the presence of distributed generation units, though uncertain, can still partially contribute to system observability. At the same time, the quantity of DGs grows along with the uncertainty level in a one-to-one ratio. Figure 5 below illustrates that incorporating DGs and ZIBs in the presence of PV uncertainty leads to a significant variation in the number of PMUs required to achieve total network observability. Moderate PV uncertainty (25%) significantly lowers the PMU requirement compared to high PV uncertainty (75%), where the extra variability necessitates an increase in the number of measuring units.

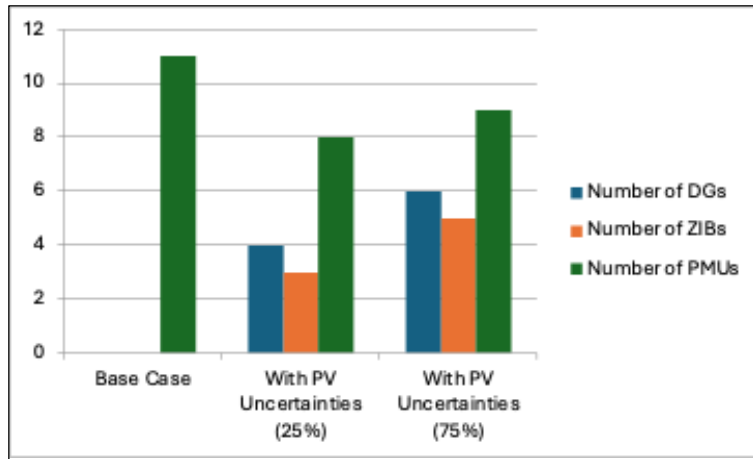


Figure 5: Effect of rising PV unpredictability on the necessary quantity of DGs, ZIBs, and strategically positioned PMUs to ensure complete network observability.

Source: Authors, (2026).

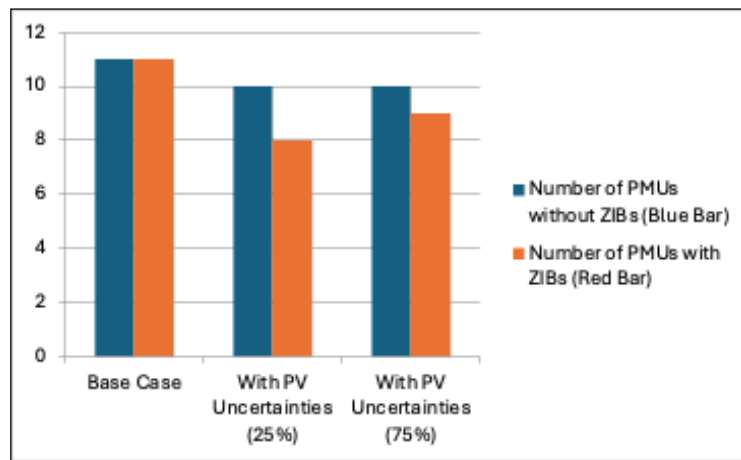


Figure 6: Comparative study on the ideal number of PMUs needed considering with and without ZIBs under varying PV uncertainty levels.

Source: Authors, (2026).

The above figure. Figure 6 clearly shows that the inclusion of ZIB information invariably leads to a decrease in PMU requirement throughout the different scenarios. The observability gain is highest with moderate PV uncertainty (25%), but it remains beneficial over the entire range of uncertainty (75%). This supports the idea that ZIBs are crucial in reducing PMU deployment costs while ensuring total system observability during the uncertain period of renewable generation.

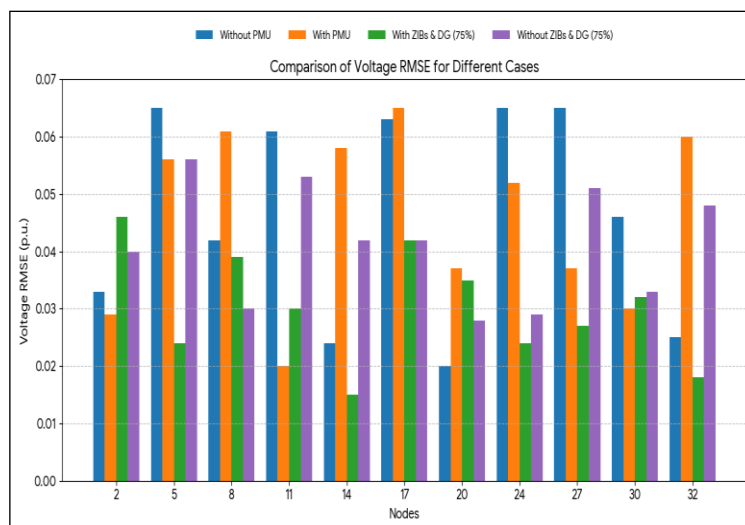


Figure 7: Comparison of voltage RMSE values across selected nodes for four cases: without PMU, with PMU, with ZIBs & DG (75%), and without ZIBs & DG (75%).

Source: Authors, (2026).

Figure 7 above displays that the maximum voltage estimation error (RMSE) occurs when no PMUs are utilised at all. The addition of PMUs results in a significant improvement in accuracy. In contrast, the integration of DGs and ZIBs at 75% DG penetration yields the lowest RMSE among the majority of nodes that exhibit good observability and enhanced state estimation performance.

VI. CONCLUSION AND FUTURE SCOPE

This study employed the Dhole Optimisation Algorithm (DOA) and PMU-assisted voltage profiling to optimise the location and sizing of distributed generation (DG) in radial distribution systems. The suggested solution reduces power loss, improves bus voltage stability, and puts PMUs for good observability. The simulation outcomes of the IEEE 33-bus and 69-bus test systems revealed significant reductions in the least voltage, VDI, and total real power loss compared to the base state. The optional method exhausted PSO and GA in resolution quality, convergence speed, and steadiness across execution runs. PMUs improved situational awareness, making weak network locations easier to monitor and strengthen. DOA is dependable and realistic for optimising various purposes in distribution system preparation subjects with numerous DG-rich scenarios.

Future Scope

There are numerous approaches to enlarge the procedure:

1. Counting vagueness in renewable DG with probabilistic or stochastic outlines.
2. Altering PMU placement to topology variations like reconfiguration and outages.
3. Use unfair and meshed distribution networks for extra-accurate real-world outcomes.
4. Employed with DSTATCOMs and OLTC transformers for Volt/VAR control.
5. Hardware-in-the-loop or real-time simulation with synchro phasor data.
6. In view of DG penetration and load development across several stages.

Through these improvements, the framework can enable utilities to operate smarter, more resilient, and greener electricity distribution networks.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Ramisetty Madhan Mohan and Pradeepa S.

Methodology: Ramisetty Madhan Mohan and Pradeepa S.

Investigation: Ramisetty Madhan Mohan and Pradeepa S.

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Supervision: Pradeepa S and Praphulla Rao

Approval of the final text: Ramisetty Madhan Mohan, Pradeepa S, Praphulla Rao, Nethravathi S and Venkatesh Boddapati.

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