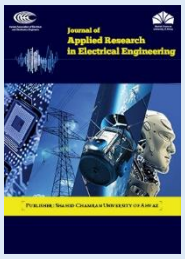
Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Using Mixed Integer Nonlinear Programming in Reconfiguring Electricity Distribution Systems with the Presence of Distributed Generation Resources

Azadeh Barani [1], Majid Moazzami [1,*], Ghazanfar Shahgholian [2], and Fariborz Haghighatdar Fesharaki [2]

[1] *Department of Electrical Engineering, Na.C., Islamic Azad University, Najafabad, Iran*

[2] *Smart Microgrid Research Center, Na.C., Islamic Azad University, Najafabad, Iran*

** Corresponding Author: majid.moazzami@iau.ac.ir*

Abstract: Reconfiguration of electrical distribution systems with distributed generations (DGs) involves changing the state of the grid switch to optimize its performance, often minimizing power losses and voltage deviations, while improving reliability. DGs, such as solar or wind power, add complexity to the process due to their variable output, requiring advanced algorithms to find optimal configurations that balance power flow, ensure voltage stability, and respect protection system constraints. The benefits of DG reconfiguration include: reduced losses, improved voltage, increased reliability, and improved operational efficiency. In this paper, a mixed-integer nonlinear programming (MINLP) model is presented for the dual-objective optimization of power distribution system rearrangement and the simultaneous location of DG, utilizing GAMS software. The objective of this model is to minimize active power losses and voltage deviation by considering power dissipation and voltage/current components as functions of their real and imaginary parts. The method, which has been tested on a 33-bus electrical system, shows a significant reduction in power losses (72.97%) and voltage deviation (94.77%). The key aspects of the model are: dual-objective function, MINLP formulation, GAMS software, network modeling, and simultaneous optimization. The simulation results demonstrate the effectiveness of the MINLP model in improving the voltage profile and reducing losses in distribution networks, especially with the integration of DG.

Keywords: active power losses, distributed generation, distribution system reconfiguration, nonlinear programming, voltage changes.

Article history
Received 30 August 2025; Revised 22 June 2026; Accepted 30 July 2026; Published online 19 November 2026.
© 2026 Published by Shahid Chamran University of Ahvaz & Iranian Association of Electrical and Electronics Engineers (IAEEE)
How to cite this article
A.Barani, M.Moazzami, G.Shahgholian, and F.Haghighatdar fesharaki," Using mixed integer nonlinear programming in reconfiguring electricity distribution systems with the presence of distributed generation resources," *J. Appl. Res. Electr. Eng.*, vol. 5, no. 1, pp. 25-37, 2026.
DOI: https://doi.org/10.22055/jaree.2026.50507.1257

Check for updates

1. INTRODUCTION

Radial power distribution systems have a simple and cost-effective design, but they result in higher energy losses and are less reliable than other configurations, such as the ring system. To address these problems, the integration of distributed generation (DG) and energy storage (ESS) systems into radial networks has been proposed to reduce power losses, improve voltage profiles, and increase overall system reliability. Single power supply, low initial cost, and simple maintenance are the characteristics of radial systems, while high power losses and lower reliability are their disadvantages [1-6].

Two major challenges in power distribution systems are maintaining an optimal voltage profile and minimizing power losses, which can be helped by strategically installing DG resources and reconfiguring the system topology [7,8]. Rearranging power distribution systems, also known as network reconfiguration, is crucial because it reduces energy losses, enhances voltage stability, balances loads across

feeders, and improves overall reliability. By dynamically adjusting power flow, it optimizes system performance, makes it easier to integrate renewable energy sources like solar and wind power, and can even delay the need for new infrastructure [9,10].

Locating DG is crucial because strategic placement minimizes power losses, improves grid voltage stability, and enhances overall system reliability, especially during outages. Optimal placement also reduces stress on transmission infrastructure, enables better integration of renewable energy sources like solar and wind, and supports rural electrification and microgrid formation. Without proper location, the benefits are diminished, leading to potential drawbacks like increased congestion and voltage issues, underscoring the importance of accurate planning [11,12].

DG location and distribution system reconfiguration are considered dual-objective optimization problems. To find optimal solutions to these problems, researchers use various optimization methods, including heuristic algorithms and newer techniques such as arithmetic optimization algorithms (AOA) [13-15] and training-learning-based optimization (TLBO) [16-18].

Optimal energy flow management from distributed energy resources (DER) and electric vehicles (EVs) in a 33-bus distribution system using a congestion algorithm to reduce overload in scenarios with inherent uncertainty in output power is presented in [19], where the role of electric vehicles as mobile energy storage for peak load management is demonstrated. Simulation results show that this method effectively reduces overload problems caused by electric current flow.

A common approach in power systems is presented in [20], where the reconfiguration of power distribution systems is modeled as a mixed integer linear programming (MILP) problem, to consider the integration of DG. This method uses linear approximations to represent the system demands and operating conditions, and allows the use of efficient MILP solvers to find optimal configurations, which improve system performance by reducing losses and increasing reliability. The model explicitly considers the presence of DG, which can lead to two-way power distribution and changing network dynamics. The model also considers standard operating constraints and conditions of the power distribution system to ensure the realistic nature of the solution.

A method for reconfiguring power distribution systems is presented in [21], to improve reliability and efficiency by changing the network topology using existing switches, eliminating the need for new infrastructure. The process involves an advanced optimization technique called the Krill Herd sine-cosine algorithm using differential evolution to find the best configuration, which has been tested on 33-bus and 66-bus systems, and shows improved performance at different load levels. Simulation results show that the proposed method improves the reliability and efficiency of the distributed system. Also, by using existing infrastructure, this approach offers a cost-effective alternative to expensive infrastructure upgrades.

A computational method using the whale optimization algorithm (WOA) to simultaneously optimize the distribution network reconfiguration and the placement of DGs to minimize power losses and improve the steady-state voltage profile is proposed in [22]. This approach has been validated on standard test systems, and its superior performance is demonstrated by comparing it with other meta-heuristic algorithms, showing a significant reduction in power losses and improved voltage stability. Simulation results show that the voltage profiles are significantly improved, such that the greater penetration of DG sources increases the overall voltage stability.

Table 1 summarizes the performance comparison of various algorithms from other references in solving this type of problem. As observed, the proposed method offers a more comprehensive approach compared to the other methods discussed. Heuristic algorithms typically require limited computational effort and are capable of delivering solutions rapidly. Nevertheless, especially in large-scale and highly complex systems, they are often constrained by inherent limitations that may lead to low-quality or, in some cases, even infeasible solutions. Moreover, the fundamental characteristic of metaheuristic optimization approaches is that they concentrate their effort on addressing the distribution network reconfiguration and DG placement problem through an iterative, strategy-driven process of design and evolution. This indicates that such methods essentially decompose the problem into a leader-follower framework, where the metaheuristic technique constitutes the primary (leader) layer and the secondary layer corresponds to conventional power-flow calculations. Although these methods generally perform effectively for optimization problems involving binary decision variables, their focus remains predominantly on algorithm design, which does not guarantee an integrated or universally robust solution. A method may perform exceptionally well for a specific problem instance, yet fail to provide optimal results when the problem characteristics change.

Table 1: Comparison of the proposed method with several other references

Ref.	Objective Function Type		Objective Function		Reconfiguration	Placement of DGs	Rectangular-Coordinate AC Formulation (No Linearization)
	Single-objective	Bi-objective	Power Loss	Voltage Deviation			
[23]	*	*	*	-	*	*	-
[24]	*	-	*	*	-	*	-
[25]	*	-	*	-	*	*	-
[26]	*	*	*	-	*	*	-
[27]	*	*	*	-	*	*	-
[28]	*	-	*	-	*	*	-
[29]	-	*	*	*	*	*	-
Proposed method	*	*	*	*	*	*	*

On the other hand, classical optimization techniques such as MILP suffer from intrinsic limitations when applied to nonlinear and complex problems due to their linear structure. These methods rely on coarse approximations that often introduce inaccuracies, resulting in suboptimal solutions and inadequate modeling capability for highly complex systems. In contrast, nonlinear optimization methods preserve the inherent nonlinear nature of the problem and consequently offer higher accuracy and more optimal solutions.

Given the challenges associated with solving the problem using metaheuristic optimization approaches and the limited research addressing the simultaneous optimal distribution network reconfiguration and DG placement, this study develops a mixed-integer nonlinear programming (MINLP) model to effectively address this combined problem. The core contribution of the proposed work is the development of a unified formulation for the integrated distribution network reconfiguration and DG placement problem, utilizing a rectangular-coordinate AC representation based on the real and imaginary components of voltages and currents. This formulation avoids explicit voltage-angle variables and trigonometric expressions, resulting in a compact mathematical representation while preserving the physical fidelity of AC network modeling. To address the inherent modeling challenges of the integrated distribution network reconfiguration and DGs allocation problem, an integrated framework is developed using a rectangular-coordinate AC formulation. The proposed representation eliminates the need for explicit voltage-angle variables and trigonometric expressions, resulting in a mathematically streamlined optimization model while preserving the physical characteristics and accuracy of AC network modeling. Under both single-objective and bi-objective frameworks, the proposed model minimizes active power losses and voltage deviation, ultimately enhancing the network voltage profile.

It is worth noting that the proposed formulation avoids explicit voltage-angle variables and trigonometric expressions, leading to a more compact mathematical representation of the optimization model. While this modeling approach may simplify the formulation and implementation process, a comprehensive computational complexity comparison with alternative formulations is beyond the scope of the present study.

The key contributions of this study are summarized as follows:

- Introducing an integrated MINLP mathematical framework for solving the combined network reconfiguration and DGs placement problem, utilizing a rectangular-coordinate AC formulation that avoids explicit voltage-angle variables and trigonometric expressions without relying on linearization approximations, with the objectives of reducing power losses, mitigating voltage deviations, and improving voltage profiles.
- Evaluating the proposed model on a medium-scale distribution system to optimize network configuration and determine the optimal locations and capacities of DG units across various scenarios.
- Demonstrating the significant impact of the proposed formulation in reducing active power losses and improving the voltage profile within the combined reconfiguration-DG placement problem.
- Showing the effectiveness of the proposed formulation in obtaining high-quality solutions for distribution network optimization through a non-linear AC representation without linearization approximations.

The GAMS software was employed for the implementation of the proposed model in this study. The model's validity and accuracy were rigorously assessed using a standard 33-bus distribution system, a well-established test case in power system engineering.

2. PROPOSED METHOD

The problem of simultaneously reconfiguring AC distribution systems and locating DGs is solved using the GAMS software, a General Algebraic Modeling System known for handling complex optimization problems like mixed integer programming, quadratic programming, and nonlinear programming. This approach is suitable because it accommodates both discrete and continuous variables, as well as nonlinear objective functions and constraints. The branch and bound algorithm is employed to systematically search for the optimal solution. Table 2 describes in detail the steps of writing a program in this software.

the problem involves both continuous variables (like DG capacity) and discrete variables (like switch status for reconfiguration), and can have nonlinear objective functions and constraints, making GAMS an appropriate choice.

The steps of the branch and bound method for finding the optimal solution to an objective function are as follows:

Start (Create a Root Problem): The process begins by defining the original optimization problem, which serves as the root node of the search tree.

Solve the root problem continuously: a relaxed version of the root problem is solved, typically by ignoring integer constraints or other complicating factors, to obtain a continuous solution. This solution provides an initial bound (upper or lower, depending on maximization or minimization) for the optimal objective function value.

Check the solution: the continuous solution obtained in step 2 is examined. If it satisfies all original constraints (e.g., integer requirements), it is a feasible solution to the original problem and a candidate for the optimal solution. If not, further steps are required.

Branch (create sub-problems): if the continuous solution is not feasible (e.g., a variable is fractional when it should be integer), the current problem is "branched" into multiple sub-problems. This involves adding new constraints to force the problematic variable into feasible ranges (e.g., adding constraints $x \leq \text{floor(value)}$ and $x \geq \text{ceil(value)}$ for a

fractional variable x). Each sub-problem represents a distinct branch in the search tree.

Bounding: for each new sub-problem created in step 4, a bound is calculated, often by solving its continuous relaxation. This bound helps determine if the sub-problem could potentially lead to a better solution than the best one found so far.

Remove branches (pruning): sub-problems are pruned (removed) from consideration if their calculated bound indicates that they cannot contain a solution better than the current best known feasible solution. This significantly reduces the search space.

Select a sub-problem: from the remaining active sub-problems, one is selected for further exploration. The selection strategy can vary (e.g., depth-first, breadth-first, best-bound).

Return to step 2: the selected sub-problem is then treated as the new "current problem", and the process returns to step 2, where its continuous relaxation is solved, and the cycle continues until no active sub-problems remain or an optimal integer solution is found and verified.

Table 2: Steps to write a program in GAMS software

Stage	Subject	Actions Taken
1	Definition of variables	Discrete variables: state of disconnections and connections (zero or 1), and the number of DGs Continuous variables: the size of DGs, current in branches, and voltage in buses
2	Definition of the objective function	Minimizing active power losses and voltage deviation
3	Definition of constraints	Network constraints: power balance constraints, voltage constraints, and current constraints Technical constraints: size constraints of DGs and state constraints of switches
4	Modeling	Using equation, variable, and model commands to define variables, equations, and models Using nonlinear GAMS functions to express nonlinear relationships
5	Solving the model using the branch and bound method	Using MINLP solvers such as linear, interactive, and discrete optimizer (LINDO)

A step-by-step guide to solving optimization problems in GAMS using the Branch and Bound Method:

This section describes the implementation of the GAMS model, including the optimization problem solving process using the branch and bound method.

i. Program Execution Flow

The flow of the GAMS model execution is as follows:

1. Start
2. Program Execution
3. Setting up maps & sets in the optimization problem
4. Defining scalar, tables, and parameters
5. Writing equations to solve the optimization problem
6. Writing the optimization model (objective function and constraints)
7. Solving the proposed model using the branch and bound method
8. Reporting the solution
9. Analyzing the results of the optimization
10. End Program

ii: Optimization Solution Method (Branch and Bound Example)

The following illustrates the detailed steps involved in solving the optimization problem, particularly when employing the Branch and Bound method for MINLP:

Executing the Branch and Bound method

1. MINLP for evaluating the performance of the distribution system
2. Nonlinear Programming without Integer Presences
3. Optimal solution?
   - If No:
4. Is the answer not optimal? (Further investigation or adjustments needed)
   - If Yes:
5. Is the optimal answer correct?
   - If No: (Indicates an issue with the model or solution)
   - If Yes:
6. Select an integer variable to branch?
   - If Yes:
7. Have all search branches beenexplored?
   - If Yes:
     End of Branch andBound method
   - If No:
     Select a pending searchbranch
     (Continueexploration)
8. Return to step 2 until all branches are checked or a correct solution with an optimal value is found

This process provides a clear visual roadmap of the process of implementing and solving the model, and increases the interpretability and reproducibility of the research.

3. OBJECTIVE FUNCTION

The objective function in the optimal rearrangement and location of DGs is formulated to achieve two primary goals: the reduction of active power losses and the minimization of voltage deviation within the distribution network. The reduction of active power losses is a key component of the objective function. This is typically represented by minimizing the sum of active power losses across all branches of the network. The active power loss in a branch can be calculated using the current flowing through the branch and its resistance. The minimization of voltage deviation is another crucial aspect of the objective function. This involves ensuring that the voltage magnitudes at all buses within the network remain within acceptable operational limits and are as close as possible to the nominal voltage. Voltage deviation can be quantified by calculating the difference between the actual voltage at each bus and a reference voltage, often squared to emphasize larger deviations. The objective function for the optimal rearrangement and location of DGs is designed to minimize active power losses and voltage deviation, thereby improving the overall efficiency and stability of the distribution network [30,31].

$$\min z_1 = P_{loss} = \sum_{l \in L} R_l I_l^2 \quad (1)$$

$$\min z_2 = VD = \sum_{k=1}^{T_{bus}} (1 - V_k)^2 \quad (2)$$

where P_{loss}, R_l, I_l, and V_k are the active power loss, the resistance of branch l, the current flowing in branch l, and the voltage of the system buses, respectively. The bi-objective function is defined as the following equation.

$$\left\{ \begin{matrix} \min z_3 = z = (w_1 \times z_1 + w_2 \times z_2) \\ w_1 + w_2 = 1 \end{matrix} \right\} \quad (3)$$

where w_1 and w_2 are weight coefficients that change uniformly between zero and 1. Initially, w_1 and w_2 are set to one and zero, respectively, and are decreased and increased in different steps of 0.05, respectively, to reach the values of zero and 1. Current and voltage constraints are considered according to the following equations.

$$-I_l^{\max} \le I_l \le I_l^{\max}, \forall l \in L \quad (4)$$

$$V_k^{\min} \le V_k \le V_k^{\max}, \forall k \in N \quad (5)$$

where I_l^{max}, V_k^{min}, and V_k^{max} are the maximum thermal limit in branch l, the minimum voltage on the system buses, and the maximum voltage on the system buses, respectively, which are considered to be 0.90 and 1.10 per unit, respectively [32].

Constraints for active and reactive power balance are formulated utilizing the real and imaginary components of the voltage and current variables, as presented in following equations.

$$P_g^k - P_d^k = \sum_{l \in L} A_{kl} (V_k^r I_l^r + V_k^i I_l^i), \forall k \in N \quad (6)$$

$$Q_g^k - Q_d^k = -\sum_{l \in L} A_{kl} (V_k^r I_l^i - V_k^i I_l^r), \forall k \in N \quad (7)$$

where P_g is the active power in the reference bus, Q_g the reactive power in the reference bus, P_d^k the active power consumed in the bus k, Q_d^k the reactive power consumption in the bus k, V_k^r the real component of the voltage variable in the bus k, V_k^i The imaginary component of the voltage variable in the bus k, I_l^r is the real component of the current variable in the l branch, I_l^i is the imaginary component of the current variable in the l branch and the A_{kl} matrix of the node with the branch. It is desirable that in the crossing matrix of the branch with node A, A_{kl} is equal to +1 if branch l originates from bus k, equal to -1 if branch l terminates at bus k, and equal to 0 otherwise.

The real and imaginary components of the l branch are written as following equations.

$$I_l^r = \frac{y_l}{R_l^2 + X_l^2} \sum_{k \in N} A_{kl} (R_l V_k^r + X_l V_k^i), \forall l \in L \quad (8)$$

$$I_l^i = \frac{y_l}{R_l^2 + X_l^2} \sum_{k \in N} A_{kl} (R_l V_k^i - X_l V_k^r), \forall l \in L \quad (9)$$

where y_l is a binary variable that indicates the connection or non-connection of the l branch. If y_l is equal to one and branch l is connected, and if $y_l=0$, branch l is disconnected. Furthermore, X_l denotes the reactance of branch l. It should be noted that A_{kl} and y_l represent different quantities within the proposed formulation. The parameter A_{kl} is an element of the network incidence matrix and describes the topological relationship between branch l and bus k. In contrast, y_l is a binary decision variable indicating the operational status of branch l. Consequently, these quantities serve different purposes in the optimization model and are not generally expected to have identical absolute values. Keep in mind that N is a set of system buses.

The following equation is defined to ensure the radiality of the distribution system.

$$\sum_{l \in L} y_l = |N| - 1 \quad (10)$$

It should be noted that Equation (10) is employed as a radiality-supporting condition within the proposed network reconfiguration framework. In conjunction with the power balance equations, branch-current relations, voltage constraints, and network operating limits, this condition effectively guides the optimization toward feasible radial operating structures. Nevertheless, from a strict graph-theoretic perspective, additional connectivity or spanning-tree constraints may provide a more rigorous guarantee of radiality and can be incorporated in future developments of the proposed model.

It is worth noting that this research pursues the optimization of DG placement and sizing with the dual objectives of reducing active power losses and minimizing voltage deviation in distribution networks. The selection of these two parameters as the primary objective functions (equations (1)-(3)) is based on their direct significance in enhancing energy efficiency, reducing operational costs, and improving power quality in modern networks. This approach enables the provision of a focused and implementable mathematical model. Nevertheless, we acknowledge that a comprehensive assessment of power system performance necessitates the consideration of additional indicators. The following points are regarded as potential limitations of the current model and pave the way for future research:

Reactive Power Loss: While reactive power losses are an inherent part of power systems, the focus of this study on active power losses stems from the fact that their impact on overall energy efficiency reduction, as well as their direct correlation with operational costs, is of high priority in many modern distribution network scenarios. Accurate modeling of reactive power losses, depending on the details of the network impedance and the profile of reactive loads, can significantly increase the complexity of the model.

Reliability Indices: A comprehensive assessment of network reliability (e.g., SAIFI and SAIDI) typically requires complex simulations and the consideration of various fault and outage scenarios. While improvements in losses and voltage can indirectly contribute to reliability, directly integrating these indices into the primary objective function of this study was beyond its scope and initial focus. This research provides a technical foundation for performance improvement that future studies can complement by adding reliability analyses.

Economic Costs: Economic considerations, including the investment, operation, and maintenance costs of DGs, are ultimately essential for any practical implementation.

However, this study concentrated on the technical aspects of optimization. It is assumed that after identifying technically optimal solutions, their economic evaluation can be undertaken in subsequent stages. Developing more comprehensive models that can simultaneously address both technical and economic objectives is a subject for future research. By focusing on these two key parameters, this research offers a practical framework for the preliminary assessment of DG impact on network efficiency. It is anticipated that future studies, by expanding the objective function to incorporate reactive power losses, reliability indices, and economic costs, will move towards developing more comprehensive and multifaceted solutions.

4. Analysis of Simulation Results

In this section, the effect of the proposed model on the 33-bus test system is shown. The reconfiguration starts with all switches and connections in the ring distribution system closed. The switches are opened one by one until the rings are eliminated, and the system becomes radial. The switch that causes the least active power losses and voltage deviation should be opened. Network reconfiguration refers to the process of selecting appropriate switches to be opened or closed in order to minimize total active power losses and voltage deviations while maintaining the operational constraints of the network. Network reconfiguration involves strategically opening or closing switches to change a distribution system's topology, with the goal of improving operational efficiency by reducing power losses and maintaining stable voltage levels. The study uses a radial distribution system for which Table 3 provides details.

It specifies that the active power of DG units injected into each bus to which they are connected is between 0 and 1.5 MW. This selection is based on a comprehensive technical assessment. The specified range was determined to cover a broad array of common and economically sensible operational scenarios typical for medium-voltage distribution networks. Extensive literature review suggests that the installed capacity of DG in comparable networks predominantly lies within this interval. This methodology enables a precise and reliable evaluation of DG's beneficial effects on key grid performance metrics, including power loss reduction, voltage profile enhancement, and improved system reliability under typical operating conditions. The outcomes derived from this range offer a robust basis for operational decision-making and investment strategies related to DG deployment. Regarding sensitivity analysis concerning higher DG penetration levels, while this is crucial for a complete assessment of DG's potential, the results obtained within the 0-1.5 MW range represent stable and economically favorable operational conditions.

However, to provide a more comprehensive perspective, we qualitatively examine advanced scenarios. Increasing DG capacity beyond 1.5 MW holds the potential for further improvements in the aforementioned metrics. Yet, at very high penetration levels (e.g., exceeding 2-3 MW in this specific system), more complex challenges may emerge. These could include the need for advanced control strategies for voltage and frequency stability, intricate reactive power management, sophisticated protection coordination, and significant infrastructure investments to accommodate bidirectional power flow.

Although these aspects extend beyond the focused scope of the current research, they warrant consideration in future, long-term studies aimed at maximizing the full potential of DG. For the purpose of this study, a deterministic approach was adopted for the simultaneous DG placement and distribution network reconfiguration. Although renewable generation such as wind and solar is inherently uncertain, in the present work these sources were modeled based on their average output over a defined time horizon to maintain the focus on the optimization and structural aspects of the network. Future extensions of the proposed framework may incorporate probabilistic or robust representations of renewable energy sources in order to better capture generation uncertainty and further enhance the reliability and resilience of the obtained solutions.

Additionally, the base voltage for the per-unit calculations is 12.66 kV, and the base apparent power is 1 MVA. The data for the lines and loads of the test system are sourced from [33,34]. The system being described is a power distribution network featuring 33 buses, 37 lines, 5 tie switches, and 32 sectionalizing switches, with total loads of 3.715 MW and 2.300 MVAR (Fig. 1). The core issue is voltage droop caused by inductive loads, which can be mitigated by integrating DG to lower through-currents and power losses. Connecting DGs to the system can help reduce the voltage droop.

In a power system scenario with open tie switches in the base case, active power losses were 0.2109 MW with a voltage deviation of 0.1338 per unit and a minimum voltage of 0.9040 per unit, according to case (1). Subsequent cases showed a reduction in power losses, with case (2) achieving 0.1396 MW and case (3) improving significantly to 0.0786 MW, demonstrating a positive response to the proposed model.

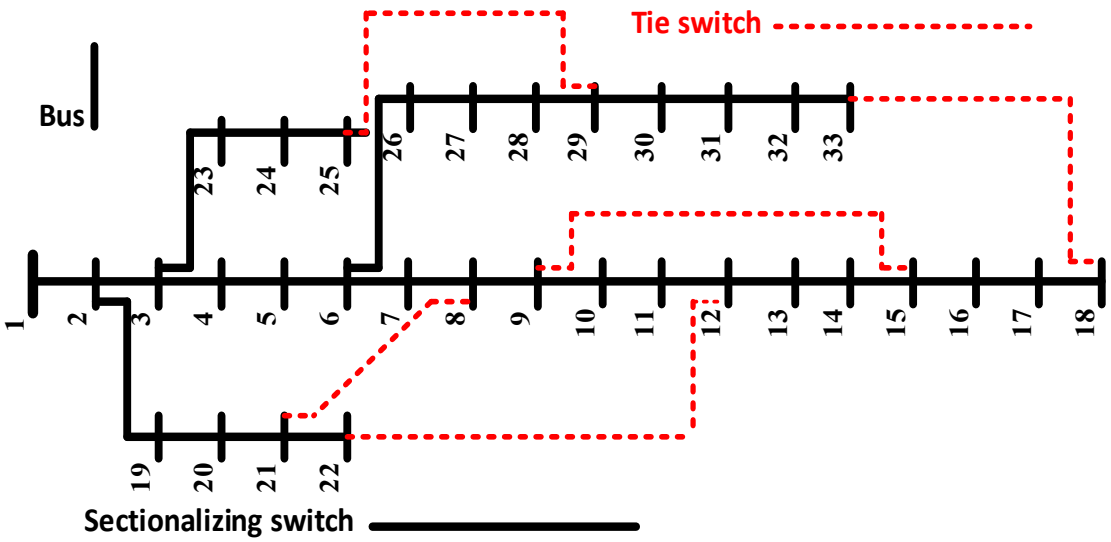


Fig. 1. Test system under study

Table 3: Scenarios studied in the radial distribution system

Scenario	Objective Function	Case
1	Total active power loss reduction	1- Without considering the reconfiguration and location of DGs (base system) 2- Reconfiguration 3- Location of DGs
2	Voltage deviation reduction	1- Without considering the reconfiguration and location of DGs (base system) 2- Reconfiguration 3- Location of DGs
3	Total active power loss reduction and voltage deviation reduction	1- Without considering the reconfiguration and location of DGs (base system) 2- Reconfiguration 3- Location of DGs 4- Simultaneous reconfiguration with DGs location

Table 4: Comparison of results of different methods for the 33-bus test system considering the power loss objective function (Scenario 1)

Case	Method	Open switches	DGs size (MW)- (location)	Lowest voltage (per unit)	Power losses (MW)
2	MINLP	7-9-14-32-37	-	0.9380	0.1396
	[35]		-	0.9378	0.1398
3	MINLP	33-34-35-36-37	0.834(32)- 1.349(23)- 0.970(10)	0.9630	0.0786
	[36]		0.9250(11)- 0.8630(16)- 1.2000(32)	0.9808	0.1034
	[37]		1.0672(32)- 0.1984(18)- 0.6521(14)	0.9705	0.0899

Table 5: Comparison of results of different methods for the 33-bus test system considering the voltage deviation objective function (Scenario 2)

Case	Method	Open switches	DGs size (MW)- (location)	Lowest voltage (per unit)	Voltage deviation (per unit)
2	MINLP	7-9-14-32-37	-	0.9380	0.04870
	[38]		-	0.9413	0.04412
3	MINLP	33-34-35-36-37	1.121(31)- 1.462(26)- 1.194(12)	0.9840	0.00080
	[39]		1.0081(30)- 1.1980(29)- 1.1320(14)	-	0.0010
	[40]		1.2743(28)- 1.1702(29)- 1.0998(13)	-	0.00085

Table 6: Pareto solutions using the weighting method and MRID under case (4) in the third scenario

Pareto's answer	Assigned weights		Objective function values		Relative ideal distance
	w_1	w_2	Voltage deviation (per unit)	Power losses (MW)	
1	1.00	0.00	0.0120	0.0547	0.0115
2	0.75	0.25	0.0070	0.0570	0.0069
3	0.65	0.35	0.0060	0.0600	0.0076
4	0.45	0.55	0.0050	0.0690	0.0150
5	0.25	0.75	0.0020	0.0730	0.0184
6	0.10	0.90	0.0008	0.0800	0.0253
7	0.00	1.00	0.0005	0.0930	0.0383

Table 7: System performance under different conditions considering the two-objective function of losses and voltage deviation (Scenario 3)

Case	Open switches	DGs size (MW)- (location)	Lowest voltage (per unit)	Power losses (MW)	Voltage deviation (per unit)
1	33-34-35-36-37	-	0.9040	0.2109	0.1338
2	7-9-14-32-37	-	0.9380	0.1400	0.0487
3	33-34-35-36-37	1.090(31)- 1.033(13)- 1.500(3)	0.9790	0.0840	0.0060
4	11-28-30-33-34	1.134(25)- 1.006(18)- 1.234(5)	0.9770	0.0570	0.0070

The analysis shows a clear trend of reducing active power losses as the system moves from the base configuration (case (1)) to the reconfigured states in cases (2) and (3), with the latter yielding the most substantial improvement in power loss reduction. Table 4 presents a comparison of the open switch positions after network reconfiguration, together with the bus locations and capacities of DG units, as well as the minimum voltage and active power losses of the distribution system in the first scenario.

A comparison of voltage deviations for the second scenario is presented in Table 5. The voltage deviation in case (2) was found to be 0.04870 per unit using MINLP, while in case (3), it was reduced to 0.0008 per unit with the proposed method.

For the third scenario, different cases are considered, and the optimal response is obtained by minimizing the total system losses and minimizing the voltage deviation. The minimum losses are 0.0547 MW, but the voltage deviation reaches 0.0005 per unit. The optimal responses obtained for case (4) using the objective weighting method (equation (3)) are presented in Table 6 using this method, the ideal solution (power losses equal to 0.0547 MW (w_1,w_2=1,0) and voltage deviation equal to 0.0005 per unit (w_1,w_2=0,1)) has been determined, and the Pareto front solution with the minimum relative ideal distance (MRID) (equation (11))is considered the best effective solution (BES).

$$RID = \sqrt{(z_1^{Ideal} - z_1^*)^2 + (z_2^{Ideal} - z_2^*)^2} \quad (11)$$

Where z_1^* and z_2^* are Pareto front solutions.

MRID is a metric to select the "best" solution from the Pareto front by finding the point closest to the ideal solution, considering the relative scaling of the objectives. BES is the final, most preferred solution selected from the Pareto front, which balances the objective functions.

The most favorable results obtained for active power losses and voltage deviation are 0.0570 MW and 0.0070 per unit, respectively. As illustrated in Fig. 2, among the optimal candidates, Pareto solution 2 is chosen as the most suitable one. The Pareto front corresponding to the third scenario under case (4) is depicted in Fig. 3, where the best achieved solution is also highlighted. It is noteworthy that although the Pareto front exhibits a downward trend between total active power loss and voltage deviation, the trend of changes in the relative ideal distance is not necessarily monotonic. In fact, the relative ideal distance is calculated from the Euclidean distance to the ideal point and usually reaches its minimum value at a point on the front where the most balanced value of both objective functions is achieved. Therefore, as we continue to move along the Pareto front, the relative ideal distance may decrease and then increase again. A summary of the outcomes for the third scenario across all four cases, used to assess the effectiveness of the proposed approach in reducing network losses, minimizing voltage deviations, and enhancing the voltage profile, is provided in Table 7. Fig. 4 demonstrates the variations in the voltage profile with respect to the base case, clearly indicating an improvement in the system voltage. A notable reduction in active power losses is achieved, accompanied by a consistent decrease in voltage deviation and enhancement in the voltage profile. The final results show that power losses decrease to 0.0570 MW, while the voltage deviation and minimum voltage reach 0.0070 per unit and 0.9770 per unit, respectively. There was a significant decrease in active power losses and a noticeable trend of reducing voltage deviation and improving the voltage profile.

The case (4) demonstrates the best performance in terms of reducing active power losses and voltage deviation, according to the data presented in Figures 5 and 6 of the study. This conclusion is drawn because case (4) shows favorable results for these key performance indicators when compared to other cases considered in the study.

The results obtained for the 33-bus test system indicate that the proposed MINLP formulation provides improved solution quality with respect to power loss reduction and voltage profile enhancement when compared with the linearized MILP model reported in [29]. Although the two approaches are based on different mathematical representations, the observed improvements may be associated with the proposed model's ability to retain AC network characteristics without relying on linearization approximations. For reference, the MILP model in [29] achieved a 58.71% reduction in power losses and a minimum system voltage of 0.960 per unit.

Fig. 7 illustrates the enhancement in the minimum voltage observed in the power system during the third scenario. Furthermore, case (4) demonstrates particularly favorable outcomes contributing to this improvement.

The complete solution process required a total computation time of 3.8 second, which reflects the efficiency of the method in managing the nonlinearity and combinatorial complexity inherent in the problem. Throughout the optimization procedure, standard convergence tolerances commonly applied in MINLP solvers were employed to ensure numerical accuracy and solution stability. These tolerances, applied to both the objective function and system constraints, enabled the algorithm to consistently converge to a reliable solution, from which the substantial reductions in active power losses and voltage deviation were obtained. The effectiveness of the proposed framework is demonstrated using the 33-bus benchmark distribution system. Although the formulation is general and can be extended to larger

networks, further validation on larger-scale systems is required before drawing definitive conclusions regarding scalability.

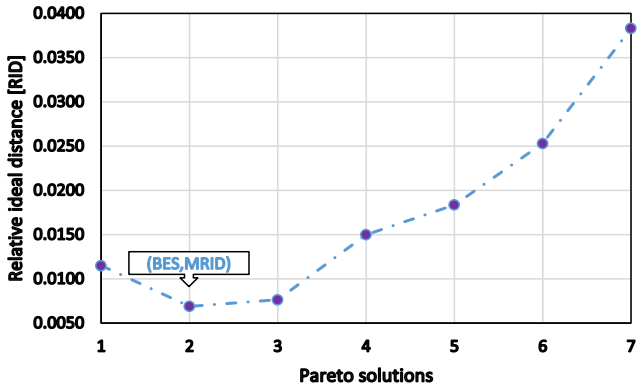


Fig. 2. Diagram of the MRID and determination of the BES for the 33-bus test system under case (4) in the third scenario

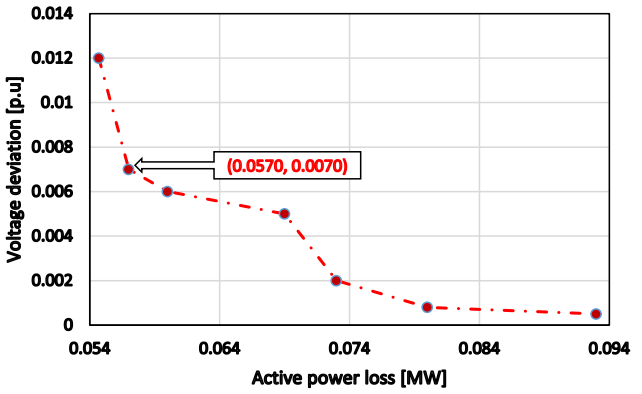


Fig. 3. Pareto-optimal front for the 33-bus test system under case (4) in the third scenario

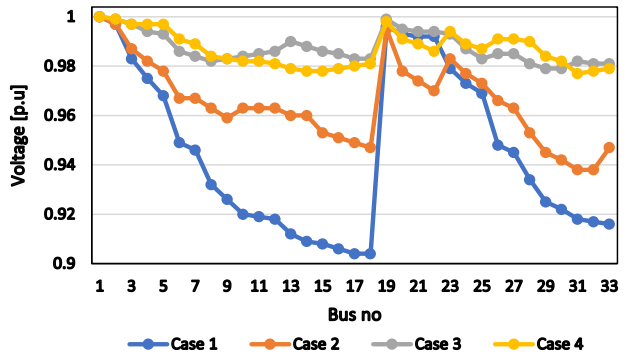


Fig. 4. Voltage profile in the 33-bus test system under different cases in the third scenario

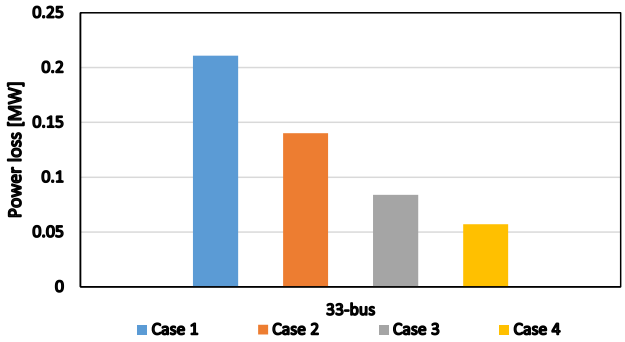


Fig. 5. Power losses in the 33-bus test system under different cases in the third scenario

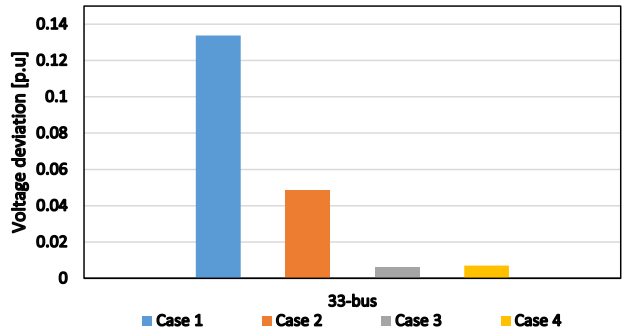


Fig. 6. Voltage deviation in the 33-bus test system under different cases in the third scenario

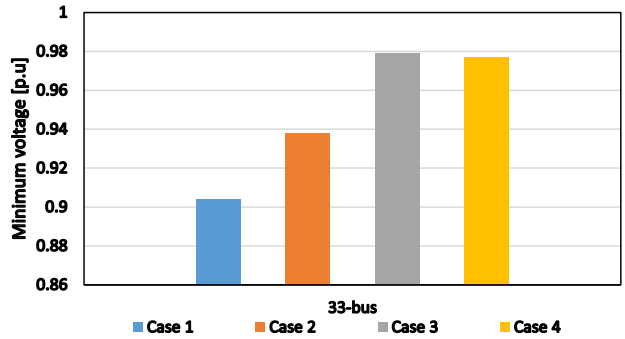


Fig. 7. Minimum voltage in the 33-bus test system under different cases in the third scenario

Given the structure of the optimization model and the solver's performance, the methodology is anticipated to retain its effectiveness when applied to distribution systems of greater size, particularly when enhanced with more advanced solvers or computational acceleration techniques. This supports the broader applicability of the approach to real-world and industrial-scale distribution networks.

It should be noted that, for initial and fundamental evaluation, the 33 bus system was chosen as a standard and well-recognized platform. This selection enabled us to rigorously assess the core capabilities of our algorithm within a controlled environment, effectively analyzing its performance against topological complexities and load variations, and subsequently comparing our findings with prior benchmarks. A distinguishing feature of the proposed approach is the use of a rectangular-coordinate AC formulation based on the node-branch incidence matrix, which avoids explicit voltage-angle variables and trigonometric expressions within the optimization model. The

results obtained for the 33-bus test system demonstrate the applicability of the proposed framework and provide an initial indication of its potential suitability for larger distribution networks. Nevertheless, further investigation on larger-scale systems is required to comprehensively assess its computational performance and scalability. To further evaluate the applicability of the proposed framework, ongoing research is focused on extending the analysis to larger benchmark systems, including the 69-bus distribution network. These studies are expected to provide additional insights into the computational characteristics, solution quality, and practical applicability of the proposed methodology under more complex network conditions. The corresponding results will be reported in future work.

5. CONCLUSION

This paper presents a dual-objective optimization model implemented with GAMS for simultaneous reconfiguration of a 33-bus radial distribution network and strategic placement of DGs to minimize power losses and improve voltage profile. The combined approach showed significant improvements, especially a reduction of about 73% in active power losses and a reduction of about 95% in voltage deviation, which confirms its effectiveness in enhancing network performance. In summary, the results obtained from this study are:

- Simultaneous network reconfiguration with DGs placement significantly improved active power losses, voltage deviation, and overall voltage profile.

- For the dual-objective condition, the third scenario (minimizing total active power losses and voltage deviation) yielded very good results.

- The integrated approach achieved a significant reduction in total active power losses, reaching 72.97%.

- The voltage deviation was reduced by 94.77%.

While the simulation results on the standard 33-bus system confirm the high efficiency of our hybrid reconfiguration and DG placement methodology, its successful implementation in real-world power systems necessitates careful consideration of several operational factors. These include practical constraints such as switching limitations in network equipment, the intermittent and often unpredictable nature of DG intermittency which can impact grid stability, and the inherent uncertainty in accurate load demand forecasting (uncertainty in load demand). The methodology proposed in this paper provides a flexible optimization framework, laying a suitable foundation for managing these uncertainties. However, future research should specifically concentrate on developing adaptive and robust algorithms capable of addressing these real-world complexities.

For future research endeavors, it is recommended that this methodology be evaluated on larger distribution systems with more intricate topologies. Furthermore, investigating the transient dynamic effects arising from sudden changes in DG generation or consumer load, and developing strategies for optimal power flow management during transient states, represent valuable avenues for future work. Additionally, integrating this approach with advanced network state estimation systems and leveraging artificial intelligence for more precise load and DG generation forecasting would constitute logical next steps toward enhancing the reliability and efficiency of industrial-scale distribution systems. Furthermore, Future research may include a systematic comparison of the proposed formulation with conventional AC MINLP and polar-coordinate models in terms of computational complexity, solution time, and scalability under different network sizes and operating conditions.

ACKNOWLEDGMENTS

This study is an extract from a doctoral dissertation at the Islamic Azad University, Najafabad Branch. We would like to thank the respected referees and colleagues in the journal for their guidance. We would also like to thank the respected colleagues in the field of research at the Najafabad Branch.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Azadeh Barani: Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft, Writing – review & editing. **Majid Moazzami**: Supervision, Writing – original draft, Writing – review & editing. **Ghazanfar Shahgholian**: Supervision, Writing – original draft, Writing – review & editing. **Fariborz Haghighatdar Fesharaki**: Supervision, Writing – original draft, Writing – review & editing.

Declaration Of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

REFERENCES

[1] A. Fathollahi, "Machine learning and artificial intelligence techniques in smart grids stability analysis: A review," *Energies*, vol. 18, no. 13, Art. no. 3431, 2025. DOI: https://doi.org/10.3390/en18133431.

[2] B. Ghosh, A. K. Chakraborty, and A. R. Bhowmik, "A technique to boost reliability and efficiency of a radial distribution network by considering the effect of protective devices and system restructuring," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 5, Art. no. 100210, 2023. DOI: https://doi.org/10.1016/j.prime.2023.100210.

[3] R. Fathi, B. Tousi, and S. Galvani, "Allocation of renewable resources with radial distribution network reconfiguration using improved salp swarm algorithm," *Applied Soft Computing*, vol. 132, Art. no. 109828, 2023. DOI: https://doi.org/10.1016/j.asoc.2022.109828.

[4] A. Fathollahi and B. Andresen, "Deep deterministic policy gradient for adaptive power system stabilization and voltage regulation," *e-Prime - Advances in Electrical*

Engineering, Electronics and Energy, vol. 9, Art. no. 100675, 2024. DOI: https://doi.org/10.1016/j.prime.2024.100675.

[5] S. A. Jazayeri, M. S. Moghaddam, M. Moazzami, G. Shahgholian, and M. Hashemi, "Enhancing renewable hosting capacity in smart grids: A robust optimization framework integrating hydrogen systems and demand response," *Energy Conversion and Management: X*, vol. 27, Art. no. 101063, 2025. DOI: https://doi.org/10.1016/j.ecmx.2025.101063.

[6] E. Aghadavoodi and G. Shahgholian, "A new practical feed-forward cascade analyze for close loop identification of combustion control loop system through RANFIS and NARX," *Applied Thermal Engineering*, vol. 133, pp. 381–395, 2018. DOI: https://doi.org/10.1016/j.applthermaleng.2018.01.075.

[7] S. Whaite, B. Grainger, and A. Kwasinski, "Power quality in DC power distribution systems and microgrids," *Energies*, vol. 8, no. 5, pp. 4378–4399, 2015. DOI: https://doi.org/10.3390/en8054378.

[8] A. Ahmadpour, H. Shayeghi, and E. Mokaramian, "Investigation of capacitor placement in variable loads to reduce the power loss of distribution systems using mixed-integer linear programming algorithm and re-gradation of loads," *Journal of Intelligent Procedures in Electrical Technology*, vol. 9, no. 36, pp. 51–61, 2019. Available: https://dorl.net/dor/20.1001.1.23223871.1397.9.36.6.1.

[9] M. Poursaberi and H. Barati, "Optimal reconfiguration of radial distribution system with the aim of reducing losses and improving voltage profiles using the improved lightning search algorithm," *Journal of Novel Researches on Smart Power Systems*, vol. 10, no. 1, pp. 1–12, 2021. Available: http://dorl.net/dor/20.1001.1.23222468.1400.10.1.2.7.

[10] M. Moazzami, M. J. Morshed, and A. Fekih, "A new optimal unified power flow controller placement and load shedding coordination approach using the hybrid imperialist competitive algorithm-pattern search method for voltage collapse prevention in power system," *International Journal of Electrical Power & Energy Systems*, vol. 79, pp. 263–274, 2016. DOI: https://doi.org/10.1016/j.ijepes.2016.01.022.

[11] J. Etedali, M. Moazzami, G. Shahgholian, M. Samiei-Moghaddam, and M. R. Moradian, "Three-level stochastic optimization framework for energy management in smart grids with integrated peer-to-peer trading," *Energy Conversion and Management: X*, vol. 30, Art. no. 101784, 2026. DOI: https://doi.org/10.1016/j.ecmx.2026.101784.

[12] S. M. Zanjani, M. Moazzami, and M. A. Honarvar, "Analysis and simulation of the static synchronous compensation effect in the distribution system with wind farms based on SCIG," *Signal Processing and Renewable Energy*, vol. 7, no. 2, pp. 17–32, 2023. DOI: https://doi.org/10.30495/SPRE.2023.1055998.

[13] E. S. Ghith and F. A. A. Tolba, "Tuning PID controllers based on hybrid arithmetic optimization algorithm and artificial gorilla troop optimization for micro-robotics systems," *IEEE Access*, vol. 11, pp. 27138–27154, 2023. DOI: https://doi.org/10.1109/ACCESS.2023.3258187.

[14] Y. J. Zhang, Y. X. Yan, J. Zhao, and Z. M. Gao, "AOAAO: The hybrid algorithm of arithmetic optimization algorithm with aquila optimizer," *IEEE Access*, vol. 10, pp. 10907–10933, 2022. DOI: https://doi.org/10.1109/ACCESS.2022.3144431.

[15] Y. P. Li, L. X. Zhang, and Z. J. Feng, "Arithmetic optimization algorithm based on Cauchy mutation trigonometric function search to solve combined economic emission dispatch problem," *IEEE Access*, vol. 11, pp. 136885–136909, 2023. DOI: https://doi.org/10.1109/ACCESS.2023.3338160.

[16] P. Lata and S. Vadhera, "Reliability improvement of radial distribution system by optimal placement and sizing of energy storage system using TLBO," *Journal of Energy Storage*, vol. 30, Art. no. 101492, 2020. DOI: https://doi.org/10.1016/j.est.2020.101492.

[17] K. Haghdar, "Optimal DC source influence on selective harmonic elimination in multilevel inverters using teaching–learning-based optimization," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 2, pp. 942–949, 2020. DOI: https://doi.org/10.1109/TIE.2019.2901657.

[18] A. S. K. Kannan, S. A. Balamurugan, and S. Sasikala, "A novel software package selection method using teaching–learning based optimization and multiple criteria decision making," *IEEE Transactions on Engineering Management*, vol. 68, no. 4, pp. 941–954, 2021. DOI: https://doi.org/10.1109/TEM.2019.2918050.

[19] L. Bagherzadeh and I. Kamwa, "Joint multi-objective allocation of parking lots and DERs in active distribution network considering demand response programs," *Energies*, vol. 16, no. 23, Art. no. 7805, 2023. DOI: https://doi.org/10.3390/en16237805.

[20] J. F. Franco, M. J. Rider, M. Lavorato, and R. Romero, "A mixed-integer LP model for the reconfiguration of radial electric distribution systems considering distributed generation," *Electric Power Systems Research*, vol. 97, pp. 51–60, 2013. DOI: https://doi.org/10.1016/j.epsr.2012.12.005.

[21] B. Ghosh, A. K. Chakraborty, and A. R. Bhowmik, "A technique to boost reliability and efficiency of a radial distribution network by considering the effect of protective devices and system restructuring," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 5, Art. no. 100210, 2023. DOI: https://doi.org/10.1016/j.prime.2023.100210.

[22] E. Mahdavi, S. Asadpour, L. H. Macedo, and R. Romero, "Reconfiguration of distribution networks with simultaneous allocation of distributed generation using the whale optimization algorithm," *Energies*, vol. 16, no. 12, Art. no. 4560, 2023. DOI: https://doi.org/10.3390/en16124560.

[23] T. T. Nguyen, A. V. Truong, and T. A. Phung, "A novel method based on adaptive cuckoo search for optimal network reconfiguration and distributed generation allocation in distribution network," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 801–815, 2016. DOI: https://doi.org/10.1016/j.ijepes.2015.12.030.

[24] A. A. Abou El-Ela, R. A. El-Sehiemy, and A. S. Abbas, "Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm," *IEEE Systems Journal*, vol. 12, no. 4, pp. 3629–3636, 2018. DOI: https://doi.org/10.1109/JSYST.2018.2796847.

[25] H. Teimourzadeh and B. Mohammadi-Ivatloo, "A three-dimensional group search optimization approach for simultaneous planning of distributed generation units and distribution network reconfiguration," *Applied Soft Computing*, vol. 88, Art. no. 106012, 2020. DOI: https://doi.org/10.1016/j.asoc.2019.106012.

[26] U. Raut and S. Mishra, "An improved sine–cosine algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems," *Applied Soft Computing*, vol. 92, Art. no. 106293, 2020. DOI: https://doi.org/10.1016/j.asoc.2020.106293.

[27] T. V. Tran, B. H. Truong, T. P. Nguyen, T. A. Nguyen, T. L. Duong, and D. N. Vo, "Reconfiguration of distribution networks with distributed generations using an improved neural network algorithm," *IEEE Access*, vol. 9, pp. 165618–165647, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3134872.

[28] N. Bhatt and A. K. Chandel, "An intelligent water drop approach for simultaneous reconfiguration and DG integration in distribution system," *Energy Systems*, vol. 14, pp. 1–24, 2022. DOI: https://doi.org/10.1007/s12667-022-00521-8.

[29] L. A. G. Pareja, J. M. López-Lezama, and O. A. G. Carmona, "A mixed-integer linear programming model for the simultaneous optimal distribution network reconfiguration and optimal placement of distributed generation," *Energies*, vol. 15, no. 9, Art. no. 3063, 2022. DOI: https://doi.org/10.3390/en15093063.

[30] A. Mishra, M. Tripathy, and P. Ray, "A survey on different techniques for distribution network reconfiguration," *Journal of Engineering Research*, vol. 12, no. 1, pp. 173–181, 2024. DOI: https://doi.org/10.1016/j.jer.2023.09.001.

[31] M. Z. Iftikhar and K. Imran, "Network reconfiguration and integration of distributed energy resources in distribution network by novel optimization techniques," *Energy Reports*, vol. 12, pp. 3155–3179, 2024. DOI: https://doi.org/10.1016/j.egyr.2024.08.067.

[32] F. J. Ruiz-Rodríguez, S. Kamel, M. H. Hassan, and J. A. Dueñas, "Optimal reconfiguration of distribution systems considering reliability: Introducing long-term memory component AEO algorithm," *Expert Systems with Applications*, vol. 249, Art. no. 123467, 2024. DOI: https://doi.org/10.1016/j.eswa.2024.123467.

[33] S. Sultana and P. K. Roy, "Oppositional krill herd algorithm for optimal location of distributed generator in radial distribution system," *International Journal of Electrical Power & Energy Systems*, vol. 73, pp. 182–191, 2015. DOI: https://doi.org/10.1016/j.ijepes.2015.04.021.

[34] P. Moghari, R. M. Chabanloo, and H. Torkaman, "Distribution system reconfiguration based on MILP considering voltage stability," *Electric Power Systems Research*, vol. 222, Art. no. 109523, 2023. DOI: https://doi.org/10.1016/j.epsr.2023.109523.

[35] B. Venkatesh and R. Ranjan, "Optimal radial distribution system reconfiguration using fuzzy adaptation of evolutionary programming," *International Journal of Electrical Power & Energy Systems*, vol. 25, no. 10, pp. 775–780, 2003. DOI: https://doi.org/10.1016/S0142-0615(03)00046-2.

[36] M. H. Moradi and M. Abedini, "A combination of genetic and particle swarm optimization for optimal DG location and sizing in distribution system," *International Journal of Electrical Power & Energy Systems*, vol. 34, no. 1, pp. 66–74, 2012. DOI: https://doi.org/10.1016/j.ijepes.2011.08.023.

[37] A. M. Imran and M. Kowsalya, "Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization," *Swarm and Evolutionary Computation*, vol. 15, pp. 58–65, 2014. DOI: https://doi.org/10.1016/j.swevo.2013.12.001.

[38] I. Dey and P. K. Roy, "Simultaneous network reconfiguration and DG allocation in radial distribution networks using arithmetic optimization algorithm," *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 36, no. 6, Art. no. e3105, 2023. DOI: https://doi.org/10.1002/jnm.3105.

[39] S. Sultana and P. K. Roy, "Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 534–545, 2014. DOI: https://doi.org/10.1016/j.ijepes.2014.06.031.

[40] S. Sharma, S. Bhattacharjee, and A. Bhattacharya, "Quasi-oppositional swine influenza model based optimization with quarantine for optimal allocation of DG in radial distribution network," *International Journal of Electrical Power & Energy Systems*, vol. 74, pp. 348–373, 2016. DOI: https://doi.org/10.1016/j.ijepes.2015.07.034.

BIOGRAPHY



Azadeh Barani holds a PhD in Electrical Power Engineering. Her research focuses on multi-objective optimization of distribution network reconfiguration in the presence of electric vehicles. Since 2014, she has been a member of the Young Researchers' Club, the Elite Club, and the Iranian Wind Energy Association, consistently ranking among the top students in all stages of her academic studies.

From 2014 to 2017, she served as a teaching assistant for the Electromagnetics course at the Islamic Azad University, Bushehr Branch, and in 2018, she worked as a lecturer at the Islamic Azad University, Delvar Branch. Since 2018, she has been professionally engaged at the Control Systems and Water Energy Office of the Bushehr Province Water and Wastewater Company.

She has published numerous papers in national and international conferences as well as in peer-reviewed journals in the field of renewable energy. Her research interests include clean energy, optimization techniques, electric vehicles, and power system reliability.



Majid Moazzami was born in 1982. He received the B.Sc. and M.Sc. degree in Electrical Engineering from Azad Najafabad University (Isfahan-Najafabad/Iran) in 2004 and 2007 respectively.

He received PhD degree in Electrical Engineering department of Isfahan University. Since 2008, He is with the Department of Electrical Engineering of Islamic Azad University-Najafabad branch in Iran.

He is associated professor of IAUN and IEEE Senior Member. His main areas of research interest are Power system dynamics, stability and control, electricity markets, renewable energy & micro grids, and smart grids.



Ghazanfar Shahgholian was born in December 1968 in Isfahan, Iran. He graduated from Isfahan University of Technology (IUT) in 1992 with a degree in Electrical Engineering.

He received his MSc in Electrical Engineering in 1994 from Tabriz University, Tabriz, Iran and his PhD in Electrical Engineering in 2006 from Islamic Azad University (IAU), Science and Research Branch, Tehran, Iran. He is currently a professor in the Department of Electrical Engineering, Faculty of Engineering, IAU, Najafabad Branch.

He is also one of the founders of the Smart Microgrid Research Center, Najafabad Branch, Islamic Azad University. He is the author of 400 papers in journals and conference proceedings. His teaching and research interests include the application of control theory in power system dynamics, power electronics, and power system simulation. He is the founder and editorial board member of the Journal of Intelligent Methods in the Electricity Industry (JIPET). He has received various honours in the fields of teaching and research.



Fariborz Haghighatdar-Fesharaki was born in Isfahan, Iran, in 1981. He received the B.Sc. degree in Electrical Engineering from Najafabad Branch, Islamic Azad University, Iran, in 2005 and the M.Sc. (Honors) and PhD degrees, both in Electrical Engineering from University of Isfahan, Iran, in 2008 and 2014, respectively.

His research interests include power system quality assessment and computational methods in power system monitoring and operation. Currently, he is faculty of Electrical Engineering, Najafabad Branch, Islamic Azad University, Isfahan, Iran, from 2011 up to now.

Copyrights
© 2026 Licensee Shahid Chamran University of Ahvaz, Ahvaz, Iran. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution –NonCommercial 4.0 International (CC BY-NC 4.0) License (http://creativecommons.org/licenses/by-nc/4.0/).