IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 27 August 2023, accepted 16 September 2023, date of publication 26 September 2023, date of current version 3 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3319456

RESEARCH ARTICLE

Simultaneously Distributed Generation Allocation and Network Reconfiguration in Distribution Network Considering Different Loading Levels

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This work was supported by the Researchers Supporting Project, King Saud University, Riyadh, Saudi Arabia, under Grant RSPD2023R868.

ABSTRACT This paper introduces a novel application of the recently developed meta-heuristic algorithm called Geometric Mean Optimization (GMO). The algorithm combines the unique properties of the geometric mean operator in mathematics with the power loss sensitivity index (PLSI) to address various optimization problems in distribution networks. Specifically, the paper focuses on the problems of optimal network reconfiguration (NR), optimal distributed generation (DG) unit allocation with optimal power factor (OPF) and unity power factor (UPF), as well as simultaneous optimal NR and DG unit allocation while considering UPF and OPF. The proposed technique considers operational constraints and three loading levels (0.5 p.u loading - light load level, 1.0 p.u loading - nominal load level, and 1.6 p.u loading - heavy load level) to solve single and multi-objective functions such as maximizing voltage stability index (VSI) and minimizing total active power loss (TAPL) and voltage deviation (VD) in the distribution network (DN). To evaluate the effectiveness of the proposed technique, experiments were conducted on IEEE 33 bus and 69-bus networks. The results of simultaneous optimal NR and DG unit allocation with OPF showed significant improvements in terms of VSI, TAPL, and VD compared to other scenarios, including optimal simultaneous NR and DG unit allocation with UPF, only DG unit allocation with UPF and OPF, and only NR and base case. Moreover, when considering multiple objectives, the simultaneous allocation of NR and DG units with OPF consistently yielded better results for all load conditions. Furthermore, the proposed technique was compared to existing algorithms in the literature, specifically for the objective of TAPL at the nominal load level. The comparison demonstrated that the combined technique outperformed other methods in terms of TAPL for all cases, highlighting its efficacy. The proposed technique exhibited high accuracy and convergence speed, making it a favorable choice for simultaneous optimal NR and DG unit allocation with UPF and OPF across different load conditions.

INDEX TERMS Distributed generation, distribution network, geometric mean optimization, network reconfiguration, power loss sensitivity index.

I. INTRODUCTION

The power distribution network (DN) serves as the crucial link connecting the power system to numerous consumers, and its significance and function cannot be substituted. While they are often designed in a meshed configuration, they commonly function in a radial arrangement due to various factors, including cost savings, current control for power management, limited coordination of protection systems, reduced failure rates, and voltage mode control [1].

The associate editor coordinating the review of this manuscript and approving it for publication was Lei Chen.

Due to the ongoing increase in power consumption across different sectors, radial distribution networks (DN) often operate near their voltage stability limits [2]. This results in higher financial losses and reduced system efficiency. To address this issue, several approaches have been proposed to mitigate total active power loss (TAPL), voltage deviation (VD), and improve the voltage stability index (VSI) in radial DN. These approaches include the allocation of distributed generation (DG) units based on renewable energy sources (RES), capacitor installation, network reconfiguration (NR), and voltage regulation [3].

In recent years, there has been significant interest in the combined implementation of distributed generation (DG) allocation and network reconfiguration (NR) solutions, considering their close relationship with implementation costs and the development context of power sources. With the rapid growth in electricity demand, increasing environmental concerns, and government policies promoting renewable energy technologies, the first solution has gained prominence. By carefully selecting the optimal location and size of DGs and designing an efficient radial structure, significant reductions in power loss and improvements in technical indicators can be achieved.

On the other hand, the second technique involves altering the radial structure of the distribution network (DN) by changing the status of network switches. This approach takes advantage of the inherent annular structure of the DN, which can be operated in a radial configuration without the need for additional equipment investments. However, implementing each technique separately on a DN may lead to suboptimal results, as the optimal solutions of one technique may no longer be valid or effective after implementing the other technique on the same DN [4].

The available literature can be broadly categorized into three groups, depending on the approaches employed for addressing the challenge of integrating Distributed Generators (DGs) and Non-Revenue (NR) considerations. These categories are as follows:

✓ Heuristic and metaheuristic strategies, documented in references [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], and [23].
✓ Analytical techniques, discussed in references [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], and [40].
✓ Hybrid techniques, explored in references [41], [42], [43], [44], [45], [46], [47], [48], and [49].

Figure 1 illustrates the various methodologies utilized to address the integration of DGs and NR considerations, whether approached separately or concurrently.

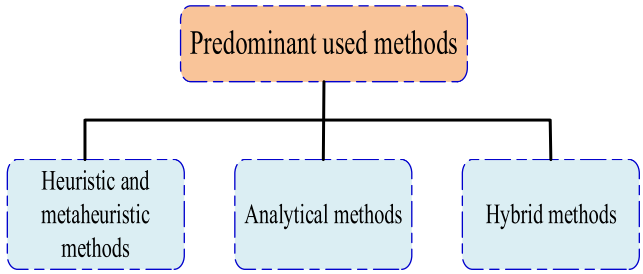


FIGURE 1. Classification of used methods.

A diverse range of heuristic and metaheuristic methods has been employed in the literature. In [5], an innovative approach known as the Mayfly Algorithm (MA) was introduced to optimize Non-Revenue (NR) aspects with the aim of minimizing power losses. In [6], the Salp Swarm Algorithm (SSA) was highlighted as an effective and contemporary optimization technique for efficiently addressing radial distribution NR problems, ultimately reducing Total Annual Power Loss (TAPL). In [7], switch exchanges were executed based on an estimate of the sensitivity of active power loss, focusing on power loss minimization.

In [8], a knowledge-based network was developed to identify pairs of switching statuses that ensure the radial topology of the network. However, it is worth noting that while knowledge-based heuristic techniques are considered natural and straightforward, they may not consistently yield optimal results for highly intricate systems [9].

To tackle these complex issues, various metaheuristic methods have been applied. These include the Modified Flower Pollination Algorithm (MFPA) [10], Evolution Strategies (ES) [11], and Differential Evolution (DE) [12]. Moreover, the literature has explored the utilization of the Harris Hawks Optimizer (HHO) [13], a Hybrid Approach (HA) [14], the Harmony Search Algorithm (HSA) [15], the Ant Colony Search Algorithm (ACSA) [16], the Backtracking Search Optimization Algorithm (BSOA) [17], the Grey Wolf Optimizer (GWO) [18], the Henry Gas Solubility Optimization (HGSO) method, and the Artificial Ecosystem-Based Optimization (AEO) algorithms to minimize power losses through optimal allocation of Distributed Generation (DG) units [19].

In [20], an efficient algorithm (EA) was proposed specifically for minimizing power losses in Distribution Networks (DN). The Particle Swarm Optimization (PSO) method was explored in [21], while the Electrostatic Discharge Optimization Algorithm (ESDOA) was introduced to enhance Voltage Stability Index (VSI) and reduce power losses [22]. Additionally, in [23], researchers introduced the Tree Growth Algorithm (TGA) to address the DG allocation problem in Distribution Networks (DNs) with the objective of minimizing power losses.

Numerous mathematical techniques have been extensively utilized for addressing NR (Network Reconfiguration) and DG (Distributed Generation) allocation problems, each offering various levels of precision and effectiveness. These methods encompass mixed-integer linear programming (MILP) [24], second-order mixed-integer cone programming (MISOCP) [25], nonlinear programming (NLP) [26], fuzzy adaptation of evolutionary programming (FAEP) [27], linear programming [28], [29], hybrid MILP [30], [31], nonlinear solving programming [32], [33], quadratic solving programming [34], [35], Kalman's filter algorithm [36], dynamic programming (DP) [37], improved MILP [38], improved analytical approach [39], multi-period optimal power flow (MP-OPF) [40], and more.

It is evident that the formulation of NR and DG allocation problems becomes intricate due to the constraints linked to nonlinear optimization, nonlinear constraints, and discrete variables encountered when employing these techniques. Consequently, applying these methods to NR and DG allocation problems remains a challenging endeavor.

To tackle these complexities, a hybrid optimization approach has emerged, combining various algorithms to enhance the efficiency of solving DG allocation problems while minimizing power losses in the distribution network (DN). For instance, the hybrid salp swarm algorithm (HSSA) is employed to minimize power losses in DN [41]. In another approach, the NR method is leveraged to minimize line power loss costs in DN [42], while a genetic algorithm-enabled particle swarm optimization (PSOGA) is utilized for NR with the same objective [43]. In pursuit of Transmission and Distribution System Analysis for Power Losses (TAPL) minimization, a hybrid chaotic golden flower algorithm (CGFA) is presented [44]. Additionally, a hybrid Fuzzy-flower pollination algorithm (FFPA) is developed to offer a versatile solution [45].

Authors have also explored the fusion of multiple algorithms to enhance performance. For instance, a hybrid algorithm incorporating both PSO and ant colony optimization (ACO) outperforms individual algorithms in [46]. Performance evaluations have been conducted on PSO and genetic algorithms (GA), revealing PSO's superiority and its capacity to mitigate some of the drawbacks of the individual algorithms [47]. Furthermore, a hybrid chaotic grasshopper optimization algorithm (CGOA) is suggested for DG allocation [48], and the combination of PSO with gravitational search (GS) algorithm is proposed and evaluated for efficiency [49].

Several studies have addressed the concurrent optimization of Distributed Generation (DG) allocation and Network Reconfiguration (NR) problems, employing a range of metaheuristic algorithms. These include the Fireworks algorithm (FWA) [50], the Intersect mutation differential evolution (IMDE) algorithm [51], the adaptive modified whale optimization algorithm (A-MWOA) [52], the Refined genetic algorithm (RGA) [53], the Improved sine-cosine algorithm (ISCA) [54], and the Efficient harmony search algorithm (EHSA) [55].

In a different study [56], researchers introduced the adaptive cuckoo search (ACSA) algorithm to minimize power losses in distribution networks (DNs) by simultaneously reconfiguring the network and allocating DG resources. In [57], an enhanced Elitist-Jaya (IEJAYA) algorithm was proposed for DG integration and network restructuring. Another study [58] implemented a modified rainfall optimization (MRO) algorithm to address the simultaneous optimization of NR and DG placement in radial DNs. In [59], the arithmetic optimization algorithm (AOA) was introduced to minimize Transmission and Distribution System Analysis for Power Losses (TAPL) and voltage deviation (VD) while improving voltage stability index (VSI) in radial DNs. Furthermore, an Artificial Bee Colony algorithm (ABCA) was presented in [60] to minimize power loss through NR and DG allocation in DNs. In [4], the coyote algorithm (COA) was introduced to minimize TAPL in DNs. Additionally, a novel chaotic search group algorithm (CSGA) [61] aimed to minimize TAPL in DNs, while a three-dimensional group search optimizer (3D-GSO) technique [62] was proposed for the concurrent planning of DG units and NR. A mixed-integer linear programming (MILP) model [63] was developed for the simultaneous planning of DG units and NR with the goal of minimizing TAPL and VD in DNs.

Selecting appropriate algorithms is a critical consideration when employing metaheuristic-based approaches because the effectiveness of these algorithms can vary depending on the problem at hand. While metaheuristic techniques can excel in certain scenarios, they may yield suboptimal results in others. Hence, it is essential to identify the most suitable algorithm when employing metaheuristic-based approaches to address specific problems.

This study seeks to address the simultaneous NR and DG allocation problem with optimal power factor (OPF) and unity power factor (UPF) operation of DG units under varying load conditions. It introduces a novel Geometric Mean Optimization (GMO) algorithm in conjunction with a Power Loss Sensitivity Index (PLSI) to achieve this goal. Notably, this research marks the first implementation of GMO with PLSI to simultaneously optimize DG allocation and NR while reducing TAPL and VD and improving VSI, all while adhering to practical constraints like power balance, voltage, current limits, and DG sizing. The proposed approach, combining GMO and PLSI, was evaluated on the standard IEEE 33 and 69 bus networks for solving NR, DG allocation with UPF and OPF, and the simultaneous NR and DG allocation with UPF and OPF, considering both multi-objective and single-objective optimization objectives. Thanks to its accuracy and rapid convergence, this method consistently achieves near-optimal solutions.

The main contributions of this paper can be summarized as follows:

- ✓ The paper introduces a novel approach that combines the GMO algorithm with PLSI to address the simultaneous optimization problem of distributed generation (DG) allocation and network reconfiguration (NR). The approach considers multiple objectives, specifically the minimization of total active power loss (TAPL) and voltage deviation (VD), as well as the improvement of voltage stability index (VSI).
- ✓ The proposed combined technique is successfully applied and tested on small and medium-sized 33 and 69-bus networks. The objective is to optimize the simultaneous allocation of DG units and NR while considering both unit

power factor (UPF) and optimal power flow (OPF) under different load levels.

✓ A comparative analysis is performed among various scenarios, including NR alone, DG allocation with UPF and OPF, simultaneous DG allocation with UPF, and simultaneous DG allocation with OPF and NR. The results demonstrate that the simultaneous DG allocation with OPF and NR is highly efficient in terms of achieving the goals of TAPL and VD minimization, as well as VSI improvement.

✓ Furthermore, the proposed technique is compared with existing techniques from the literature, specifically for the goal of TAPL at the nominal load level. The comparison reveals that the proposed technique outperforms other modern techniques in terms of delivering the most accurate results for the tested networks.

The paper is organized as follows: Section II introduces the PLSI method. In Section III, the problem formulation of the study is presented. The proposed technique and its solution process are described in Section IV. Section V presents the numerical results and discussions. Finally, Section VI presents the conclusions of the paper.

II. POWER LOSS SENSITIVITY INDEX (PLSI)

In this paper, PLSI is employed to identify suitable bus candidates for integrating DG units into the distribution network (DN). This approach is adopted to streamline the search process, thereby expediting the solution time. Figure 2 provides a depiction of a simplified two-bus grid-connected DN, serving as an illustrative example to demonstrate the implementation of PLSI for this purpose.

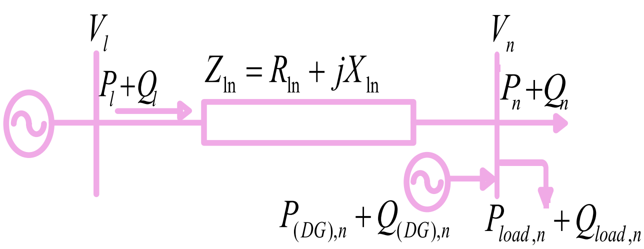


FIGURE 2. The equivalent single line diagram of two bus of DN that are connected to the grid and DG unit.

where, P_l and P_n are two active power flows of the buses l and n, Q_l and Q_n are two reactive power flows of the buses l and n, V_l and V_n are the magnitudes of voltage of buses l and n. $R_{\ln}$ and $X_{\ln}$ are the resistance and reactance of the line between buses l and n. $P_{DG,n}$ and $Q_{DG,n}$ are generated active reactive power output of DG unit, $P_{load,n}$ and $Q_{load,n}$ are active and reactive power loads at bus n.

To calculate power loss on line ln following equation is used:

$$P_{\ln-loss} = \frac{(P_n^2 + Q_n^2)*R_{\ln}}{(V_n)^2} \tag{1}$$

To calculate the PLSI, we use (2)

$$\frac{\partial P_{\ln-loss}}{\partial Q_n} = \frac{2Q_n*R_{\ln}}{(V_n)^2} \tag{2}$$

Figures 3 and 4 illustrate the PLSI results for the 33-bus and 69-bus test networks. Following the calculation of PLSI values for the buses, a descending sorting process is applied. Buses with higher PLSI values are identified as more favorable locations for DG integration. This selection process considers up to 50% of the network buses, as detailed in prior studies [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [60], [64].

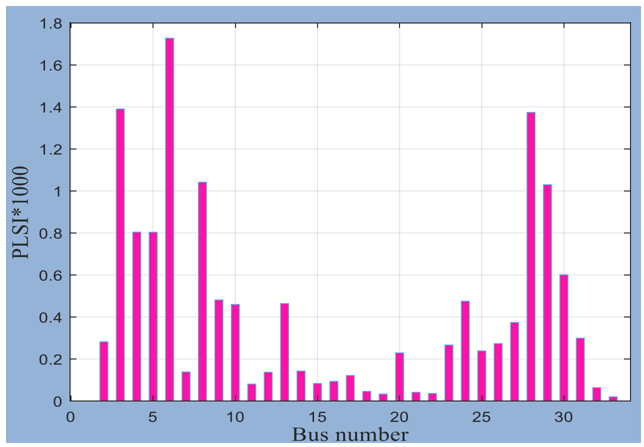


FIGURE 3. A 33-bus test network's PLSI values.

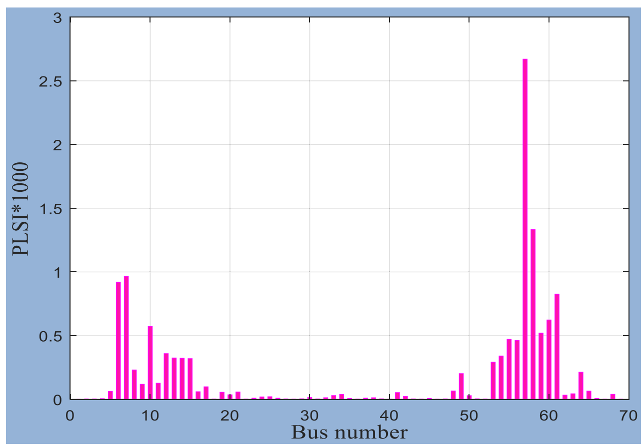


FIGURE 4. A 69-bus test network's PLSI values.

III. PROBLEM FORMULATION

Minimizing total active power loss (TAPL) (F1), reducing voltage deviation (VD) (F2), and enhancing voltage stability index (VSI) (F3) within a distribution network (DN) can be accomplished through the optimal placement of distributed generation (DG) units, while taking into account operational constraints.

The TAPL, which can be mathematically expressed as follows [65]:

$$F_1 = TAPL = \sum_{m=1}^{N_L} P_{\ln-loss}(m) \tag{3}$$

where, N_L is the total line number in the test network.

The voltage deviation (VD) of a network can be expressed in the following formula [59]:

$$F_2 = \Delta VD = \sum_{n}^{N_{bus}} (V_{sluck} - V_n)^2 \tag{4}$$

where, V_{sluck} represents substation bus voltage and in this study it equal to 1.0 p.u. To eliminate the possibility of a negative VD value, a square indicator is added to the formula.

The bus VD is the refers to the quality of voltage across the network buses. In order to achieve a regulated voltage profile across the network, bus voltage regulation is an essential duty of utilities.

The voltage stability index (VSI) is also calculated to show the impact of the allocation of DG units and NR simultaneously on network stability. The network is considered more stable if the VSI value is closer to one. VSI is calculated at bus n as follows [66]:

$$F_3 = VSI(n) = |V_l|^4 - 4 * (P_n * X_{\ln} - Q_n * R_{\ln})^2 - 4 * (P_n * R_{\ln} + Q_n * X_{\ln}) * |V_l|^2 \tag{5}$$

A. OBJECTIVE FUNCTION

A weighted sum approach (WSA) is used in this study to integrate all the objective functions simultaneously into a single objective. An objective function for the problem can be represented as follows:

$$OF = Min(w_1 * F_1 + w_2 * F_2 + w_3 * 1/F_3) \tag{6}$$

where, $w1$, $w2$, and $w3$ are the weighting factors. All of the objectives' functions are assumed to have equal weights in this paper. A weight factors should be equal to one when its total absolute value is added up, as shown in the equation displayed below [59], [60]:

$$|w_1| + |w_2| + |w_3| = 1 \tag{7}$$

B. EQUALITY RESTRICTIONS

The power balance must be met the following constraints [5], [6]:

$$P_{sub} + \sum_{l=1}^{M_{DG}} P_{DG}(l) = \sum_{l=1}^{L} P_{\ln-loss}(l) + \sum_{l=1}^{M} P_{load}(l) \quad (8.1.)$$

$$Q_{sub} + \sum_{l=1}^{M_{DG}} Q_{DG}(l) = \sum_{l=1}^{L} Q_{\ln-loss}(l) + \sum_{l=1}^{M} Q_{load}(l) \quad (8.2.)$$

where, P_{sub} and Q_{sub} are displays the substation's reactive and active power. M_{DG} is the total installed DG number, M is representing the total line number.

C. INEQUALITY RESTRICTIONS

1) VOLTAGE LIMITS

The bus voltages must be in its minimum and maximum limits.

$$V_{\min} \le |V_n| \le V_{\max} \tag{9}$$

2) THE INTEGRATED DG UNITS POWER OUTPUT CONSTRAINTS AS FOLLOWS [9]

$$P_{DG}^{\min} \le P_{DG}(n) \le P_{DG}^{\max} \quad (10.1.)$$

$$Q_{DG}^{\min} \le Q_{DG}(n) \le Q_{DG}^{\max} \quad (10.2.)$$

where, $P_{DG}^{\min}$, $P_{DG}^{\max}$ and $Q_{DG}^{\min}$, $Q_{DG}^{\max}$, are power limits for DG units in terms of their active and reactive power at lower and upper levels, respectively.

3) THE DG UNITS POWER FACTOR CONSTRAINTS AS FOLLOWS

$$PF_{DG,\min} \le PF_{DG,n} \le PF_{DG,\max} \tag{11}$$

where, $PF_{DG,\min}$ and $PF_{DG,\max}$ are minimum and maximum limits of power factor.

4) LINE CAPACITY CONSTRAINTS

The line must meet the following capacity limits:

$$S_{\ln} \le S_{\ln(rated)} \tag{12}$$

5) RADIAL TOPOLOGY CONSTRAINTS

There must be no isolated buses within the DN topology, and its topology must be radial [5], [6].

$$\begin{aligned} &\det[A] = 1 or -1 \quad \text{for radial toplogy} \\ &\det[A] = 0 \quad \text{for nonradial toplogy} \end{aligned} \tag{13}$$

IV. THE GEOMETRIC MEAN OPTIMIZATION (GMO) ALGORITHM

The Geometric Mean Optimization (GMO) algorithm is a recently created meta-heuristic optimization technique inspired by the distinctive characteristics of the geometric mean operator in mathematics [67]. By employing this operator, it becomes feasible to assess the suitability and diversity of search agents simultaneously. GMO calculates the weight of each agent by considering the geometric mean of the scaled objective values (OV) of its counterparts, signifying that the agent is aptly positioned to direct other agents in the optimization problem-solving process. This guidance is based on the geometric mean of their scaled OV.

To implement the GMO algorithm, the following steps should be adhered to:

A. INITIALLY, SEARCH AGENTS' VELOCITY AND POSITIONS ARE GENERATED RANDOMLY

$$\begin{aligned} &V_i^0 \quad U(V_{\min}, V_{\max}) \\ &X_i^0 \quad U(X_{\min}, X_{\max}) \end{aligned} \tag{14}$$

where, $X_{\min}$, $V_{\min}$ and $X_{\max}$, $V_{\max}$ are the lower and upper limits of the optimization dimension.

B. THEN, THE FITNESS FUNCTION VALUES ARE CALCULATED FOR ALL SEARCH AGENTS TO FIND THE PERSONAL BEST POSITION OF ALL SEARCH AGENTS

$$fit(X_i) \tag{15}$$

C. IN THIS STEP, THE FUZZY MEMBERSHIP FUNCTION (MF) IS CALCULATED FOR ALL OPPOSITE AGENTS OF A SPECIFIC AGENT BY MULTIPLYING THE OV

$$MF_j^t = \frac{1}{1+\exp\left[-\frac{4}{\sigma^t\sqrt{e}} * (X_{best,j}^t - \mu^t\right]}; \quad j = 1, 2, \ldots N \tag{16}$$

where $X_{best,j}^t$ is the personal best agent's OV at the tth iteration; σ^t and μ^t are the all personal best search agents' standard deviation (SD) and mean values of the fitness function, MF_j^t is the MF value of the jth personal best agent, e is Napier's constant, and N is the total number of search agents.

D. IN THIS STEP, THE DUAL-FITNESS INDEX (DFI) IS EXPRESSED FOR SEARCH AGENTS

$$DFI_i^t = MF_1^t * \ldots * MF_{i-1}^t * MF_{i+1}^t * \ldots * MF_N^t = \prod_{\substack{j=1\\ j\neq i}}^{N} MF_j^t \tag{17}$$

E. DFI INDEXES IS SORTED IN DESCENDING ORDER TO CHOOSE THE FIRST NBEST ELITE AGENTS

F. IN THIS STEP, THE GUIDE AGENTS CALCULATE AS FOLLOWS

$$Y_i^t = \frac{\sum_{j\in Nbest, j\neq i} DFI_j^t * X_j^{best}}{\sum_{j\in Nbest} DFI_j^t + \varepsilon} \tag{18}$$

where Y_i^t is unique global guide agent position at iteration t for the agent i, X_j^{best} is the personal best position of the jth search agent, and ε is a tiny positive number it added to avoid the singularity.

G. IN THIS STEP, THE GUIDE AGENTS Y_i^t ARE MUTATED IN A GMO PROCESS. FOR THIS MUTATION GAUSSIAN MUTATIONS ARE CONSIDERED. THE FOLLOWING EQUATION IS USED TO FOR THIS TYPE OF MUTATION TO BE IMPOSED ON THE GUIDE AGENTS

$$Y_{i,mut}^t = Y_i^t + w * randn * (sd_{\max}^t - sd^t) \tag{19}$$

where $randn$ is normally distributed random number, sd^t is the SD for the personal best agents at the tth iteration, $sd_{\max}^t$ is maximum SD values of the personal best agents. w is mutation step size. Based on the lapse of iterations, the mutation step size is calculated using the following formula:

$$w = 1 - \frac{t}{T_{\max}} \tag{20}$$

where, t and $T_{\max}$ are current and maximum iteration numbers.

H. FINALLY, THE SEARCH AGENTS' VELOCITY AND POSITIONS UPDATE USING THE FOLLOWING EQUATION

$$V_i^{t+1} = w * V_i^t + \varphi * (Y_{i,mut}^t - X_i^t);$$
$$\varphi = 1 + (2 * rand - 1) * w \tag{21}$$
$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{22}$$

where, V_i^t is ith velocity of search agent's at the tth iteration, V_i^{t+1} is the velocity at $(t+1)$th iteration, $Y_{i,mut}^t$ is global guide position for the agent i and X_i^t is a position of the ith agent's, φ is a scaling parameter, and $rand$ is a random number within (0, 1).

The overall procedure of the proposed technique used in this study in order to solve the optimization problem is shown in Fig. 5. Used parameters and operational constraints of the proposed technique and objective functions are tabled in Table 1.

TABLE 1. Operational constraints and used parameters.

Parameters	Values	
Total search agents' number	For 33-bus 70	For 69-bus 100
Total iterations number	100	
ε	0	
Voltage constraints	$0.9\,p.u. \leq V_i \leq 1.05\,p.u.$	
DG power generation limits	$0.2MW \leq P_{DG,m} \leq 3MW$	

V. RESULTS AND DISCUSSION

The proposed technique is assessed by conducting an evaluation using the standard IEEE 33 and 69 bus test networks. The simulation is carried out using MATLAB R2021b software. To showcase the effectiveness of the proposed approach, various scenarios are considered:

✓ Scenario 1: In this scenario, the system operates at a light load level of 0.5 p.u.
✓ Scenario 2: This scenario represents the nominal load level with a loading of 1.0 p.u.
✓ Scenario 3: The system is subjected to a heavy load level of 1.6 p.u. in this scenario.

To thoroughly evaluate the proposed approach, the following cases are examined:

✓ First Case: This is the base case.
✓ Second Case: Only NR (Newton-Raphson) is applied.
✓ Third Case: Three distributed generators (DGs) are allocated with Unity Power Factor (UPF).

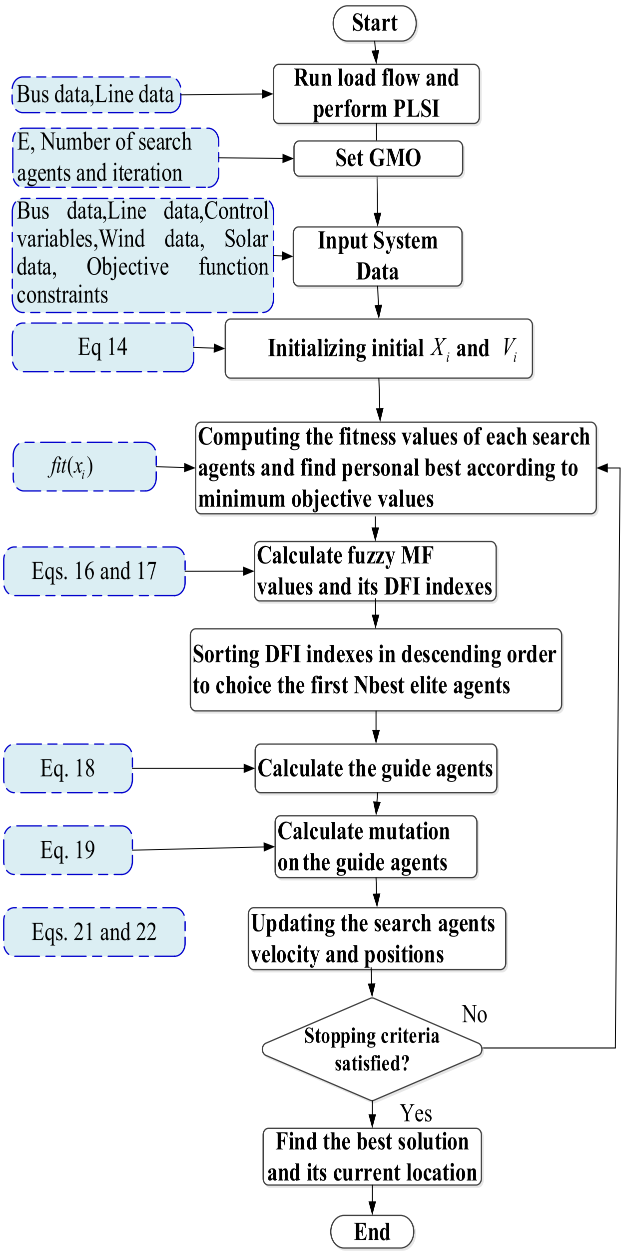


FIGURE 5. The overall process flowchart of solving the optimization problem using the proposed algorithm.

- ✓ Fourth Case: Three DGs are allocated with Optimal Power Flow (OPF) considerations.
- ✓ Fifth Case: DG allocation is performed simultaneously with UPF and NR.
- ✓ Sixth Case: DG allocation is carried out simultaneously with OPF and NR.

Figures 6 and 7 provide single-line diagrams of the test networks, which operate at a base voltage (kV) of 12.66 kV and a base apparent power (MVA) of 100 MVA for both the 33 and 69 bus distribution networks.

The initial test network is an IEEE 33-bus configuration featuring five open switches identified as s33, s34, s35, s36, and s37. For three distinct load levels, the active and reactive power demands of this initial network are as follows: 1857.5 kW and 1150.0 kVAr, 3715.0 kW and 2300.0 kVAr, and 5944.0 kW and 3680.0 kVAr.

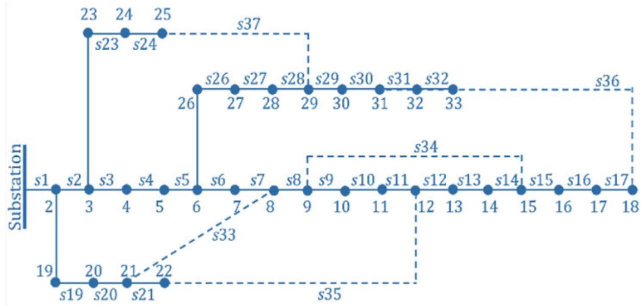


FIGURE 6. The line diagram of the 33-bus network.

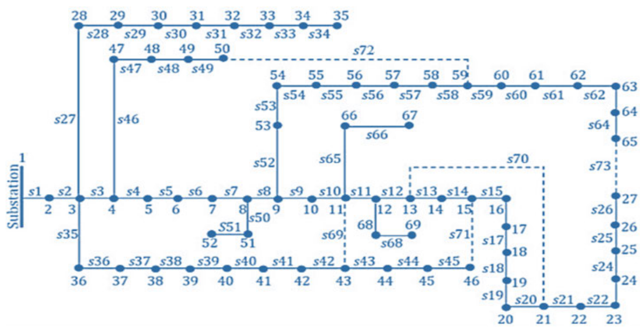


FIGURE 7. The line diagram of the 69-bus network.

At these three load levels, the initial active power losses in the network are recorded as 48.7898 kW, 210.9983 kW, and 603.4557 kW, respectively. The lowest voltage levels within the network are 0.95395 p.u, 0.90371 p.u, and 0.83581 p.u, corresponding to the three load levels. Additionally, the lowest Voltage Stability Index (VSI) values for the test network are 0.82815 p.u, 0.66697 p.u, and 0.488002 p.u across the same load levels. The Voltage Deviation (VD) within the network is observed to be 0.03076 p.u, 0.13388 p.u, and 0.3863506 p.u, respectively, for the three different load levels.

For more detailed information about this test network, please refer to [68].

The second test network consists of a standard IEEE 69-bus configuration, featuring five open switches labeled as s69, s70, s71, s72, and s73. For this network, the active and reactive power loads vary across three different load levels, with values of 1901 kW and 2329.9 kVAr, 1347 kW and 3801.5 kVAr, as well as 6084 kW and 4311 kVAr, respectively.

Additionally, the initial active power losses at these load levels are measured at 51.6063 kW, 225.0014 kW, and 652.5322 kW. The lowest voltage levels observed in this test network are 0.95664 per unit (p.u), 0.909 p.u, and 0.84397 p.u, corresponding to the three load levels, respectively.

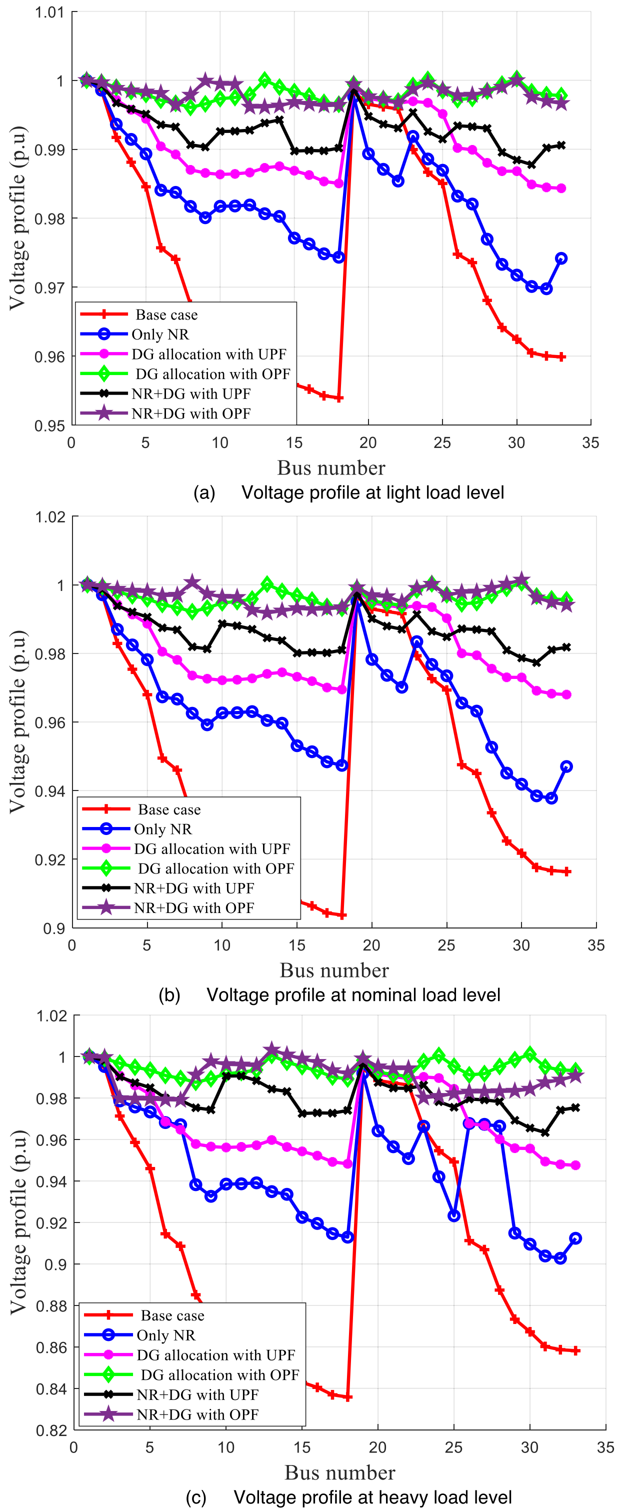


FIGURE 8. Effect of NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF on voltage profile of 33-bus DN.

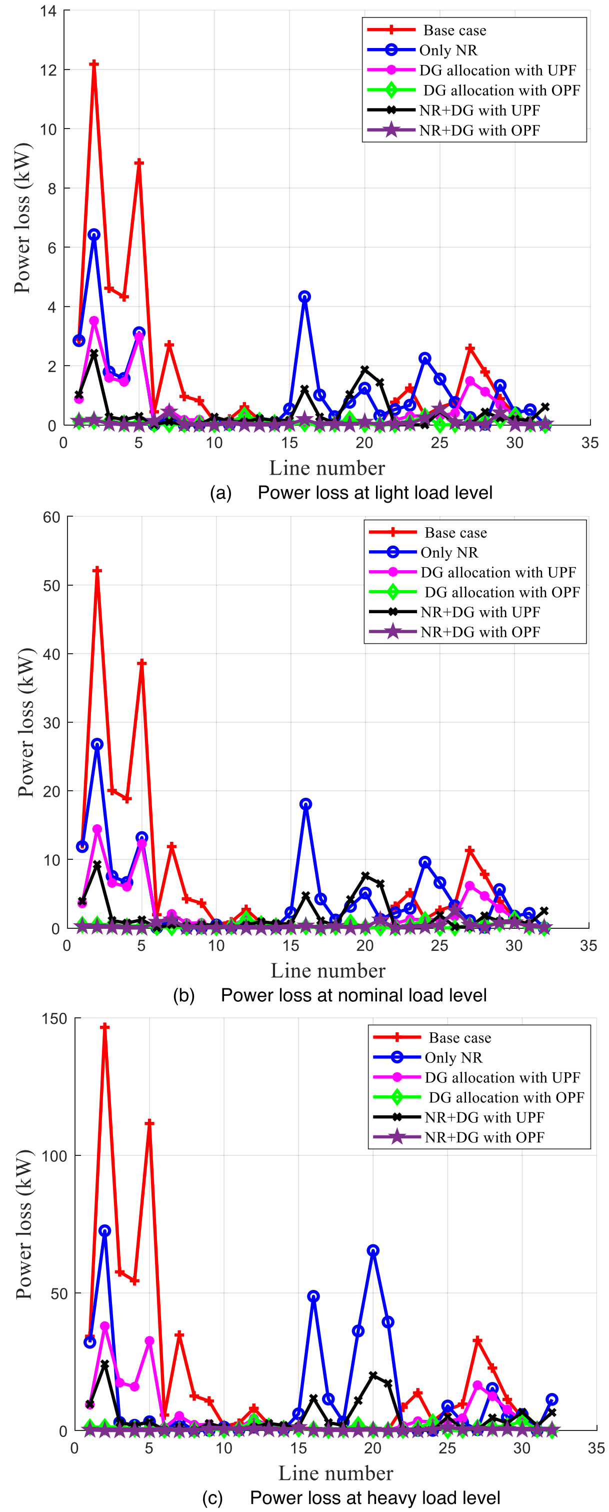


FIGURE 9. Effect of NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF on line power loss of 33-bus DN.

Furthermore, the lowest Voltage Stability Index (VSI) values for the test network are 0.8375036 p.u, 0.68274785 p.u, and 0.5073609 p.u, again for the three different load levels, respectively. Lastly, the Voltage Deviation (VD) for this network is reported as 0.02291670 p.u, 0.09964988 p.u, and 0.2876265 p.u, corresponding to the same three distinct load levels. For additional details about this test network, please refer to [69].

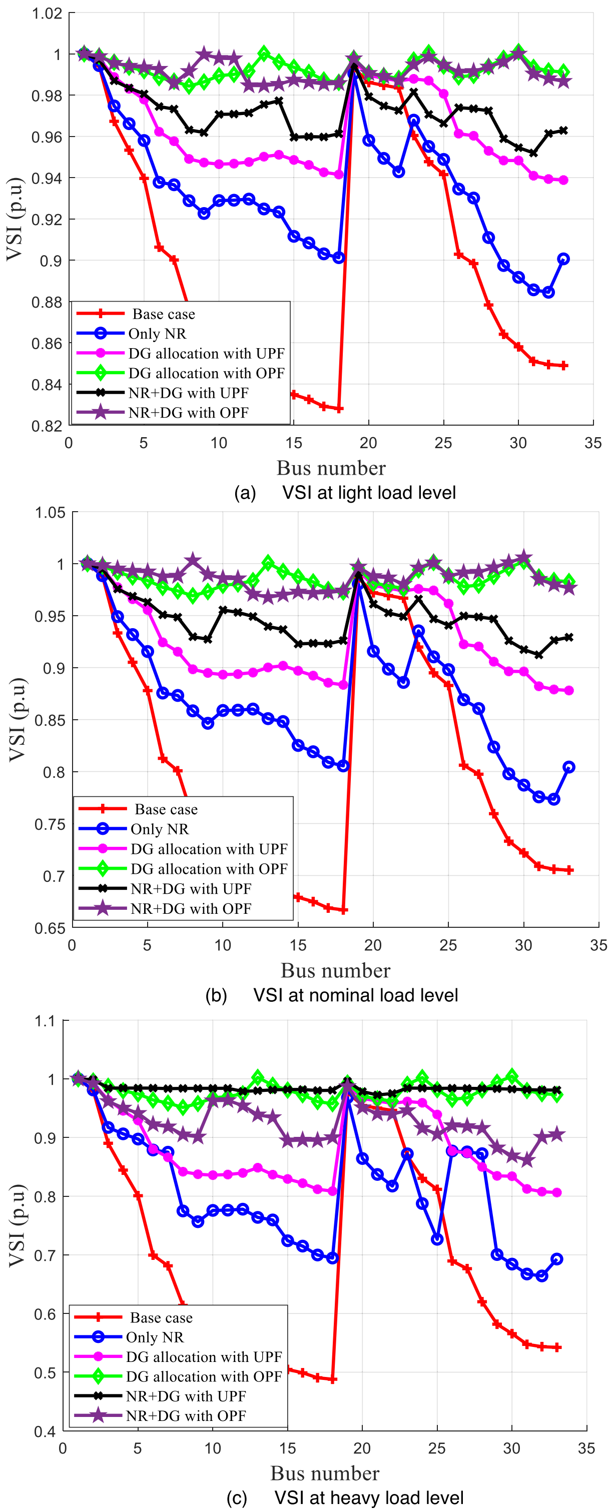


FIGURE 10. Effect of NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF on VSI of 33-bus DN.

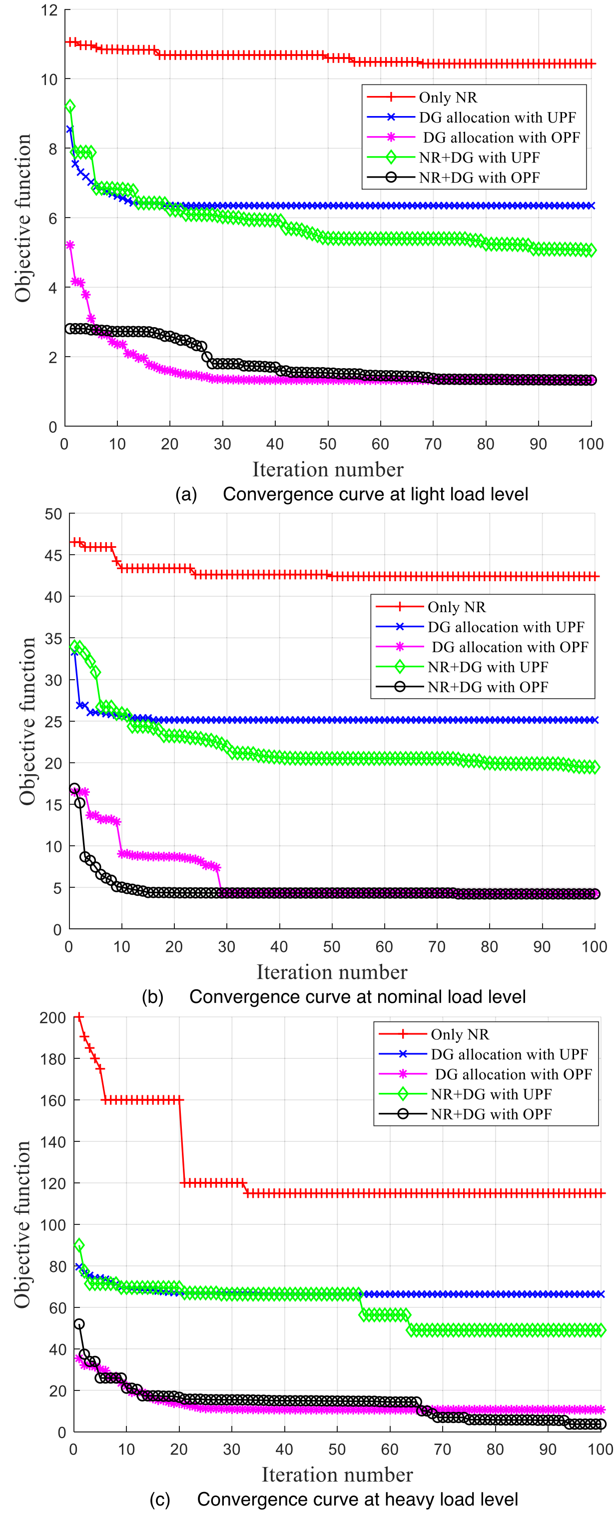


FIGURE 11. Convergence curve of 33-bus DN on NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF.

A. THE IEEE 33-BUS NETWORK

1) SIMULTANEOUS OPTIMIZATION OF TAPL, VD, AND VSI

Table 2 presents the outcomes achieved using the proposed method across various scenarios encompassing diverse load conditions. These scenarios include the base case, NR, allocation of three DG units with UPF, allocation of three DG units with OPF, as well as the simultaneous allocation of DG units with UPF and NR, and the simultaneous

TABLE 2. Obtained simulation results of the 33-bus network under different loading levels considering simultaneous optimization of TAPL, VD and VSI.

Cases	Parameters/Load level	Light load level (0.5)	Nominal load level (1.0)	Heavy load level (1.6)
Base case	Open switches	s33, s34, s35, s36, s37	s33, s34, s35, s36, s37	s33, s34, s35, s36, s37
	TAPL (kW)	48.7898	210.9983	603.4557
	Min voltage (p.u)@bus	0.95395@18	0.90371@18	0.83581@18
	Min VSI (p.u)	0.82815	0.66697	0.488002
	ΔVD (p:u:)	0.03076	0.13388	0.3863506
Only NR	Open switches	s37, s14, s32, s7, s9	s9, s14, s32, s37, s7	s32, s14, s7, s28, s9
	TAPL (kW)	33.269	139.5513	381.2399
	Min voltage (p.u) @bus	0.96977@32	0.93778@32	0.90271@32
	Min VSI (p.u)	0.88445	0.773405	0.6640491
	ΔVD (p:u:)	0.01160	0.048825	0.1206579
Only DG allocation with unity PF	Bus /DG Size (KW /P.F)	30 14 24 527/1 383/1 542/1	24 14 30 1097/1 771/1 1068/1	30 24 13 1722/1 1775/1 1299/1
	Open switches	s33, s34, s35, s36, s37	s33, s34, s35, s36, s37	s33, s34, s35, s36, s37
	TAPL (kW)	17.6351	72.7911	193.8922
	Min voltage (p.u) @bus	0.98434@33	0.96799@33	0.94757@33
	Min VSI (p.u)	0.93881	0.87797	0.80620823
	ΔVD (p:u:)	0.00375	0.0156513	0.04171801
Only DG allocation with optimal PF	Bus /DG Size (KW /P.F)	30 24 13 514/0.71352 534/0.90068 396/0.90506	13 30 24 795/0.9048 1030/0.71339 1070/0.90035	24 30 13 1717/0.90033 1654/0.71364 1278/0.90422
	Open switches	s33, s34, s35, s36, s37	s33, s34, s35, s36, s37	s33, s34, s35, s36, s37
	TAPL (kW)	2.9203	11.7411	30.2407
	Min voltage (p.u) @bus	0.99606@8	0.99217@8	0.98759@8
	Min VSI (p.u)	0.98435	0.969026	0.951273
	ΔVD (p:u:)	0.0001580	0.00062228	0.0015439
Simultaneous DG allocation with unity PF and NR	Bus /DG Size (KW /P.F)	14 25 33 250.47/1 624.47/1 341.19/1	25 10 33 1376.77/1 554.64/1 689.17/1	33 11 25 1129.33/1 1206.45/1 2232.62/1
	Open switches	s7, s9, s14, s28, s31	s7, s9, s14, s28, s31'	s7, s9, s14, s28, s31
	TAPL (kW)	13.4861	54.4039	147.2994
	Min voltage (p.u) @bus	0.98777@31	0.9773@31	0.96335@31
	Min VSI (p.u)	0.95195	0.912250	0.8613626
	ΔVD (p:u:)	0.001946	0.0071379	0.0143
Simultaneous DG allocation with optimal PF and NR	Bus /DG Size (KW /P.F)	9 30 24 487/0.90721 637/0.78821 306/0.8398	30 8 24 1084/0.72877 1080/0.90513 992/0.89853	9 13 33 414/0.7 2531/1 1497/0.7
	Open switches	s6, s12, s11, s23, s25	s25, s13, s5, s37, s11	s2, s8, s12, s25, s7
	TAPL (kW)	2.9185	10.6414	11.774
	Min voltage (p.u) @bus	0.99613@13	0.9918@13	0.97902@7
	Min VSI (p.u)	0.984593	0.9675944	0.9186783
	ΔVD (p:u:)	0.00018605	0.0005755	0.0053006

allocation of DG units with OPF and NR in the 33-bus network. The proposed approach demonstrates its effectiveness by delivering superior results in the realm of multi-objective optimization for distribution networks, achieved through the optimal allocation of DG units using OPF and NR techniques.

The test network's total active power loss (TAPL) for different load levels is decreased to 33.269 kW,139.5513 kW and 381.2399 kW. The test network's voltage deviation (VD) is decreased to 0.01160 p.u, 0.048825 p.u, and 0.1206579 p.u, and the test network's lowest voltage stability index (VSI) is enhanced to 0.88445p.u, 0.773405p.u, and 0.6640491 p.u, respectively, when NR is executed.

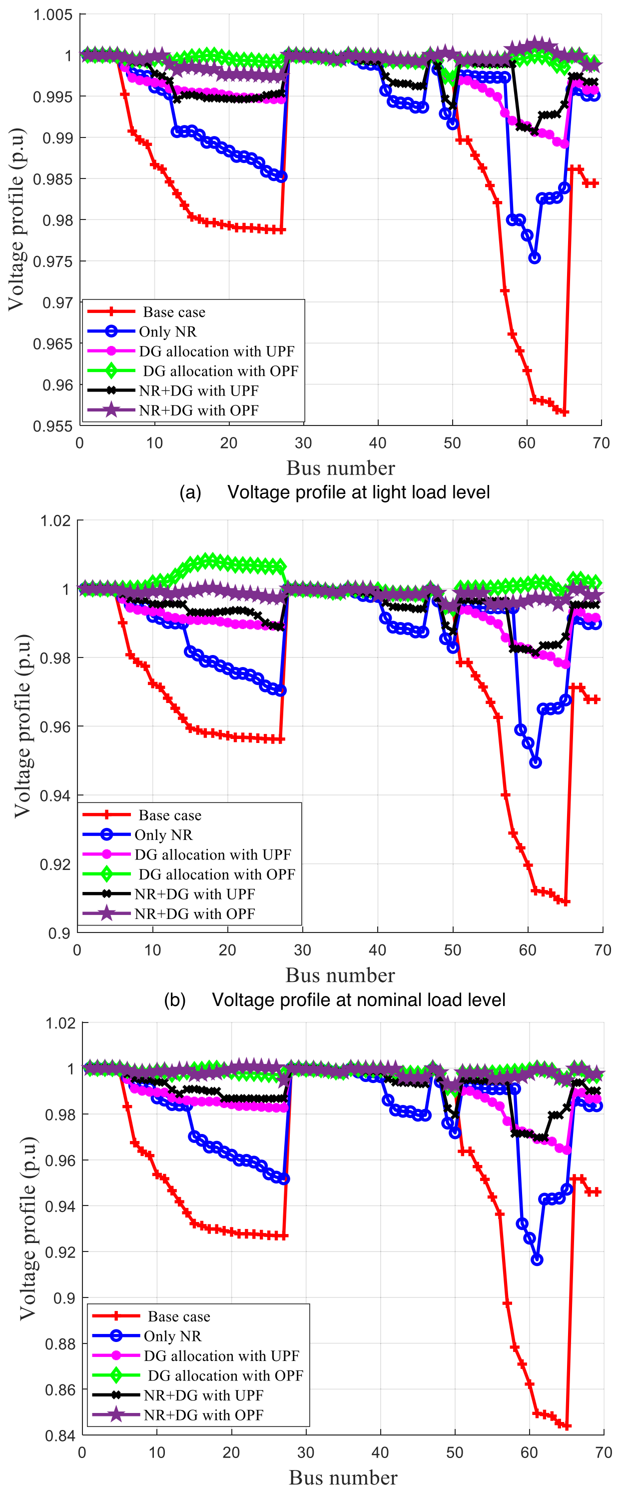
After performing only three DG allocation with UPF in the test network for different load levels, TAPL is decreased to 17.6351 kW, 72.7911 kW and 193.8922 kW. The VD of the test network is decreased to 0.00375p.u, 0.0156513 p.u, and 0.04171801 p.u, respectively. The lowest VSI of the test network is enhanced to 0.93881 p.u, 0.87797 p.u, and 0.80620823 p.u, respectively.

TAPL is decreased to 2.9203 kW, 11.7411 kW and 30.2407 kW. The VD of the test network is decreased to 0.0001580 p.u, 0.00062228 p.u, and 0.0015439 p.u, respectively. The lowest VSI of the test network is enhanced to 0.98435 p.u, 0.969026 p.u, and 0.951273 p.u, respectively, after performing only three DG allocation with OPF in the test network for different load levels.

When optimal three DG units with UPF and NR simultaneously is optimally executed in the test network, TAPL is decreased to 13.4861 kW, 54.4039 kW and 147.2994 kW. The VD of the test network is decreased to 0.001946 p.u, 0.0071379 p.u, and 0.0143 p.u, respectively. The lowest VSI of the test network is enhanced to 0.95195 p.u, 0.912250 p.u, and 0.8613626 p.u, respectively.

TABLE 3. A comparison of obtained results of the 33-bus network at nominal load level for TAPL.

Methods	Open switches	TAPL (kW)	Power loss reduction (%)	Min voltage (p.u) @bus	Bus /DG Size (KW /P.F)
Only NR					
Proposed method	s32, s9, s14, s7, s37	139.5513	33.86	0.93778@32	-
NR method [42]	s9, s28, s32, s14, s7	140.00	30.92	0.9416	-
HSA [15]	s10, s37, s36, s14, s7	142.67	29.67	0.9335	-
FWA [50]	s7, s14, s9, s32, s28	139.98	30.93	0.9413	-
ACSA [16]	s7, s14, s9, s32, s28	139.98	30.93	0.9413	-
FAEP [27]	s14, s9, s7, s28, s32	139.83	33.79	N/A	-
Only DG allocation with unity PF					
Proposed method	s33, s34, s35, s36, s37	72.7869	65.51	0.96795@33	'13 (802/1) 24(1091/1) 30 (1054/1)'
BSOA [17]	s33, s34, s35, s36, s37	89.05	57.79	0.9554	13 (632/1) 28 (487/1) 31 (550/1)
GWO [18]	s33, s34, s35, s36, s37	73.06	65.37	0.9709	13(850/1) 30(1100.77/1) 24 (1103.87/1)
HHO [13]	s33, s34, s35, s36, s37	73.4478	65.19	0.96979@bus 33	14 (790.31/1) 24 (870.08/1) 30 (1119.5/1)
HGSO [19]	s33, s34, s35, s36, s37	83.981	60.19	0.9547@ bus 33	12(919.25/1) 27(1237/1) 24 (504.82/1)
AEO [19]	s33, s34, s35, s36, s37	72.7902	65.50	0.96867@bus 33	24 (1097/1) 14(770.79/1) 30(1066/1)
Only DG allocation with optimal PF					
Proposed method	s33, s34, s35, s36, s37	11.740	94.44	0.99212 @ bus 8	24(1069.9/0.9) 30(1029.9/0.71) 13 (793.8/0.9)
BSOA [17]	s33, s34, s35, s36, s37	29.65	85.95	0.9795 @ bus 33	13 (698/0.86) 29(402/0.71) 31(658/0.7)
HSSA [41]	s33, s34, s35, s36, s37	11.741	94.44	0.9921 @ bus 8	13(877.2/0.91) 30(1445.6/0.72) 24(1178.2,0.89)
HHO [13]	s33, s34, s35, s36, s37	26.1092	87.63	0.99051@bus 33	25 (477.6/0.85) 30(913.14/0.85) 9(1403.44/0.89)
HGSO [19]	s33, s34, s35, s36, s37	28.1267	86.67	0.9851@bus25	16(540.68/0.87) 5(1567.66/0.86) 31(994.5/0.864)
AEO [19]	s33, s34, s35, s36, s37	11.7578	94.43	0.99203@ bus 8	24(1077.1/0.9012) 14(762.4034/0.9026) 30(1.0520/0.7207)
Simultaneous DG allocation with unity PF and NR					
Proposed method	s7, s9, s14, s28, s31	54.4039	74.22	0.9773@31	25('1376.77/1) 10(554.64/1) 33(689.17/1)
AOA [59]	s7, s9, s14, s28, s31	53.756	74.52	0.9756@ bus 31	1266.61(1)/25 624.47 (1)/33 527.32 (1)/12
ISCA [54]	s7, s9, s14, s28, s31	66.81	67.03	0.9611@ bus 31	30(648.46/1) 13(510.27/1) 16(532.46/1)
EHSA [55]	s7, s14, s10, s32, s28	73.05	63.95	0.97	32(525.8/1) 31(558.6/1) 33(584.0/1)
Simultaneous DG allocation with optimal PF and NR					
Proposed method	s25, s13, s5, s37, s11	10.6411	94.96	0.9918@13	'30('1084/'0.7297) 8(1080/0.90513) 24(992/0.89853)'
AOA [59]	s7, s9, s14, s28, s31	26.198	87.58	0.9885@28	1699.33 (0.95)/25 697.37 (0.95)/33 565.47 0.95)/12

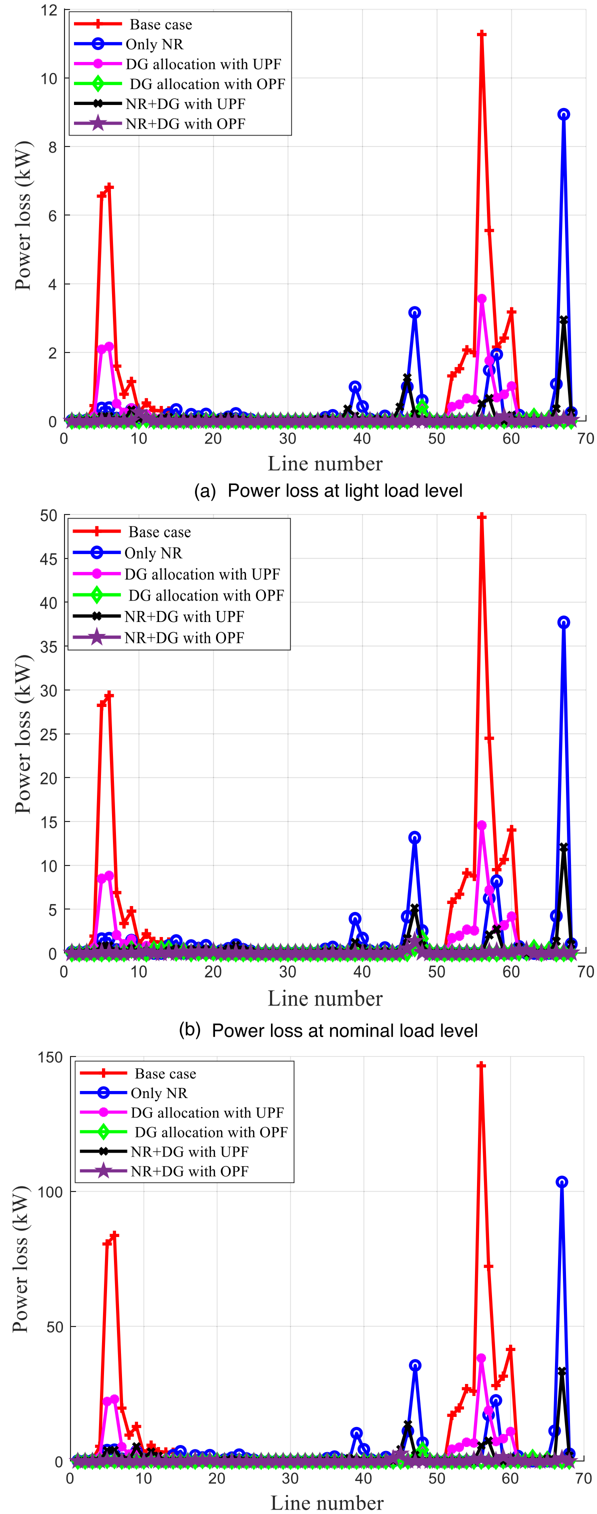


(a) Voltage profile at light load level

(b) Voltage profile at nominal load level

(c) Voltage profile at heavy load level

FIGURE 12. Effect of NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF on voltage profile of 69-bus DN.



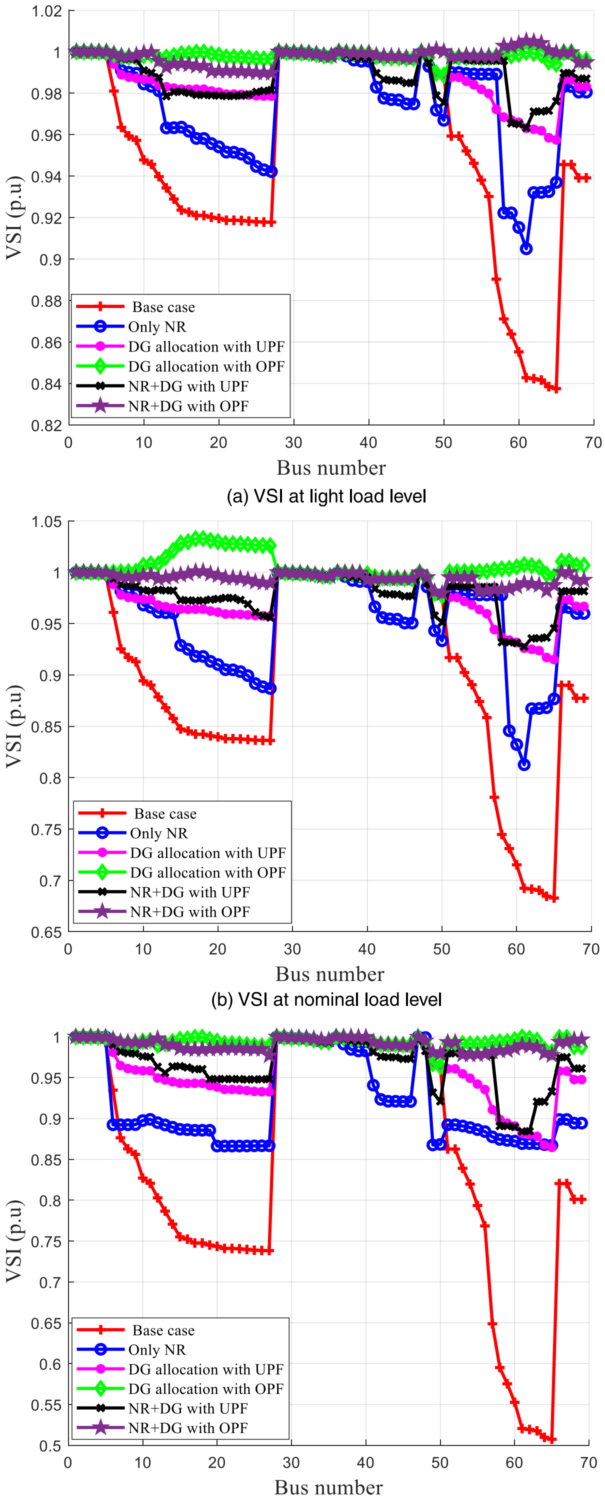
(a) Power loss at light load level

(b) Power loss at nominal load level

(c) Power loss at heavy load level

FIGURE 13. Effect of NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF on line power loss of 69-bus DN.

TAPL is decreased to 2.9185 kW, 10.6414 kW and 11.774 kW. The VD of the test network is decreased to 0.00018605 p.u, 0.0005755 p.u, and 0.0053006 p.u, respectively. The lowest VSI of the test network is enhanced to 0.984593 p.u, 0.9675944 p.u, and 0.9186783 p.u, respectively, after performing simultaneously optimal three DG

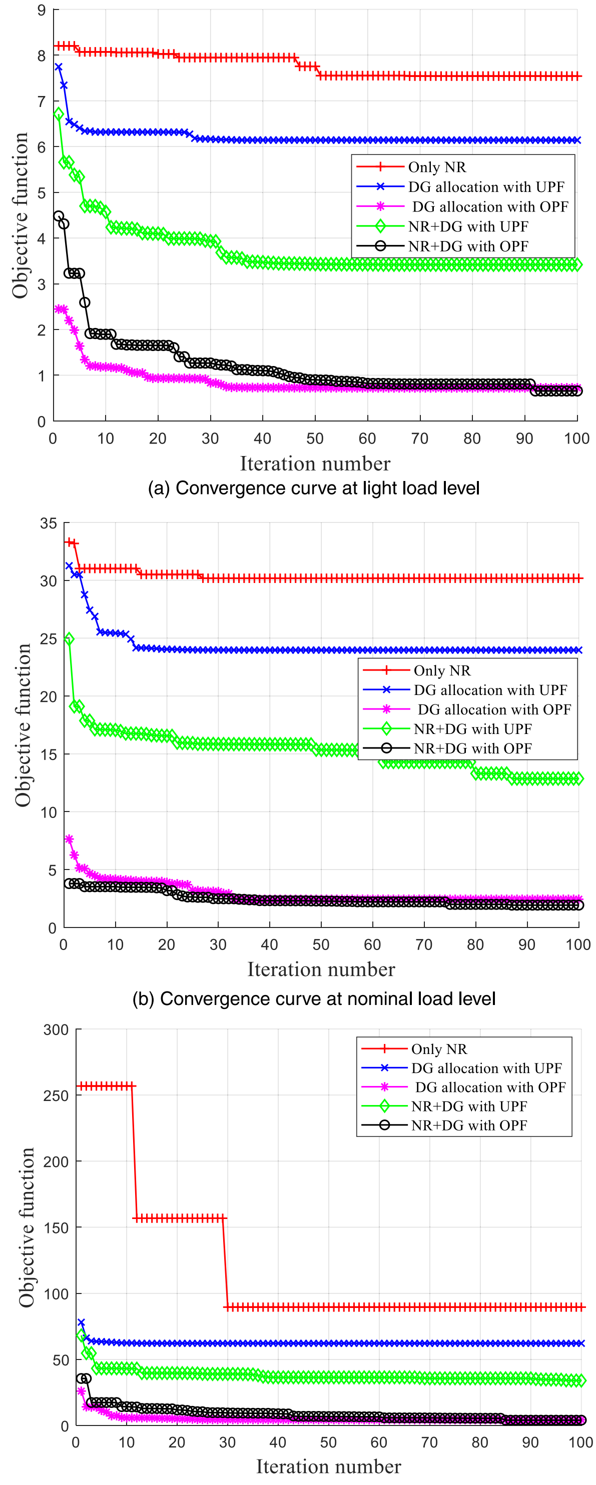


(a) VSI at light load level

(b) VSI at nominal load level

(c) VSI at heavy load level

FIGURE 14. Effect of NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF on VSI of 69-bus DN.



(a) Convergence curve at light load level

(b) Convergence curve at nominal load level

(c) Convergence curve at heavy load level

FIGURE 15. Convergence curve of 69-bus DN on NR, DG allocation with UPF, DG allocation with OPF, simultaneous NR+DG with UPF, and simultaneous NR+DG with OPF.

units allocation with OPF and NR is optimally executed in the test network for different load levels.

The results clearly demonstrate that the concurrent allocation of DG with OPF and network reconfiguration in a distribution network (DN) yields superior efficiency in multi-objective optimization. Furthermore, Figures 8-11 illustrate the influence of NR, the optimal integration of DG with UPF and OPF, the simultaneous allocation of DG with

TABLE 4. Obtained simulation results of the 69-bus network under different loading levels considering simultaneous optimization of TAPL, VD and VSI.

Cases	Parameters/Load level	Light load level (0.5)	Nominal load level (1.0)	Heavy load level (1.6)
Base case	Open switches	s69, s70, s71, s72, s73	s69, s70, s71, s72, s73	s69, s70, s71, s72, s73
	TAPL (kW)	51.6063	225.0014	652.5322
	Min voltage (p.u)@bus	0.95664@65	0.909@65	0.84397@65
	Min VSI (p.u)	0.8375036	0.68274785	0.5073609
	ΔVD (p:u:)	0.02291670	0.09964988	0.2876265
Only NR	Open switches	s57, s69, s12, s61, s70	s14, s58, s69, s61, s70	s14, s58, s69, s61, s70
	TAPL (kW)	23.6548	98.598	267.0943
	Min voltage (p.u) @bus	0.97535@61	0.94946@61	0.91646@61
	Min VSI (p.u)	0.904963	0.8125526	0.7051437
	ΔVD (p:u:)	0.00569859	0.02110687	0.0565237
Only DG allocation with unity PF	Bus /DG Size (KW /P.F)	18 61 11 190/1 850/1 255/1	11 18 61 528/1 380/1 1721/1	11 61 18 877/1 2801/1 611/1
	Open switches	s69, s70, s71, s72, s73	s69, s70, s71, s72, s73	s69, s70, s71, s72, s73
	TAPL (kW)	17.0434	69.4263	181.7813
	Min voltage (p.u) @bus	0.98919@65	0.97802@65	0.96427@65
	Min VSI (p.u)	0.95747027	0.91493232	0.8645491
	ΔVD (p:u:)	0.00136100	0.00555632	0.01444562
Only DG allocation with optimal PF	Bus /DG Size (KW /P.F)	61 18 66 840/0.81362 199/0.83305 215/0.81232	61 18 66 1696/0.84191 559 /0.91652 444/0.77186	66 18 61 692/0.81343 636/0.83244 2693/0.81391
	Open switches	s69, s70, s71, s72, s73	s69, s70, s71, s72, s73	s69, s70, s71, s72, s73
	TAPL (kW)	1.1475	6.2191	11.8455
	Min voltage (p.u) @bus	0.99714@50	0.99427@50	0.99078@50
	Min VSI (p.u)	0.988617	0.97727662	0.9636189
	ΔVD (p:u:)	0.000036151	0.000815867	0.00036674
Simultaneous DG allocation with unity PF and NR	Bus /DG Size (KW /P.F)	27 61 51 286/1 714/1 299/1	21 12 61 743.3/1 332.01/1 1445.54/1	61 11 27 2407/1 951/1 654/1
	Open switches	s69, s12, s58, s61, s13	s14, s57, s61, s69, s70	s57, s62, s18, s69, s13
	TAPL (kW)	9.0447	36.7738	98.97
	Min voltage (p.u) @bus	0.9907@61	0.98141@61	0.96973@62
	Min VSI (p.u)	0.96329746	0.92759046	0.8841887
	ΔVD (p:u:)	0.001038341	0.003852307	0.009296974
Simultaneous DG allocation with optimal PF and NR	Bus /DG Size (KW /P.F)	11 49 61 437/0.82169 314/0.70498 869/0.81303	61 18 66 1696/0.81413 559/0.82931 444/0.81737	61 22 66 2990/0.82387 771/0.8213 589/0.82154
	Open switches	s57, s8, s13, s18 s73	s39, s69, s54, s64, s70	s54, s42, s69, s14, s26
	TAPL (kW)	0.94946	4.6782	10.9769
	Min voltage (p.u) @bus	0.99743@27	0.9948@50	0.99238@50
	Min VSI (p.u)	0.9897713	0.97935849	0.969852
	ΔVD (p:u:)	0.0000854713	0.0002877	0.00041595

UPF and OPF, and NR in DN on various aspects such as voltage profile, branch power losses, voltage stability index (VSI), and the convergence curves of the objective function for three different load levels.

2) MINIMIZATION TAPL AT NOMINAL LOAD LEVEL FOR COMPARISON OBTAINED RESULTS WITH OTHER EXISTING ALGORITHMS IN THE LITERATURE

The proposed method excels in minimizing total active power loss (TAPL) within distribution networks (DN) by employing optimal NR, integrating optimal DG with UPF and OPF, and simultaneously allocating DG in conjunction with UPF and OPF along NR. Table 3 presents a comparative analysis between the results achieved through our proposed approach and those obtained from various existing algorithms in the literature under nominal load conditions.

When solely utilizing NR, our approach enables the attainment of a minimum TAPL of 139.5513 kW, representing a remarkable 33.86% reduction in power losses compared to NR alone [42], as well as surpassing the performance of HSA [15], FWA [50], ACSA [16], and FAEP [27] methods.

After performing only three DG allocation with UPF in the test network, the proposed technique gives a minimum TAPL is 72.7869 kW with a power loss reduction 65.51 % as compared to BSOA [17], GWO [18], HHO [13], HGSO [19], and AEO [19], respectively.

In the case of only three DG allocation with OPF in the test network for nominal load level obtained, TAPL is 11.740 kW with a power loss reduction 94.44% as compared to BSOA [17], HSSA [41], HHO [13], HGSO [19], and AEO [19], respectively.

TABLE 5. **A comparison of obtained results of the 69-bus network at nominal load level for TAPL.**

Methods	Open switches	TAPL (kW)	Power loss reduction (%)	Min voltage (p.u) @bus	Bus /DG Size (KW /P.F)
Only NR					
Proposed method	s55, s61, s70, s14, s69	98.598	56.18	0.94946@61	-
ABC [60]	s14, s58, s69, s61, s70	98.59	56.18	0.949	-
RGA [53]	s69, s17, s13, s55, s61	100.28	55.43	0.943	-
EHSA [55]	s69, s18, s13, s56, s61	99.35	55.85	0.942	-
Only DG allocation with unity PF					
Proposed method	s69, s70, s71, s72, s73	69.42553	69.14	0.97897 @ 65	18(380.3464/1) 11(526.9147/1) 61 (1718.8/1)
HSSA [41]	s69, s70, s71, s72, s73	69.4266	69.14	-	61(1719/1)
					17(380.5/1) 11(526.7/1)
PSO [21]	s69, s70, s71, s72, s73	73.1	67.51	-	66(700/1) 62(1900/1) 18 (300/1)
HHO [13]	s69, s70, s71, s72, s73	70.01	68.89	-	12(467.148/1) 15(346.77/1) 61(1734.2/1)
HGSO [19]	s69, s70, s71, s72, s73	72.338	67.85		15(598.634/1) 61(1796.9/1) 57(200/1)
EA [20]	s69, s70, s71, s72, s73	69.62	69.06	-	61(1795/1) 18(380/1) 11(467/1)
Only DG allocation with optimal PF					
Proposed method	s69, s70, s71, s72, s73	4.21	98.13	0.99427 @ 50	18(370.25/ 0.819) 11(508.44/0.836) 61(1670.84/0.810)
HSSA [41]	s69, s70, s71, s72, s73	4.269	98.10	-	61(2057.1/0.81) 17(454.9/0.84) 11(608.9/0.82)
PSO [21]	s69, s70, s71, s72, s73	39.2	82.58	-	61(1500/0.98) 59(600/0.98) 16 (500/0.98)
HHO [13]	s69, s70, s71, s72, s73	12.526	94.43	-	61(1412.4/0.766) 16(796.43/0.875) 47(1.0493/0.995)
HGSO [19]	s69, s70, s71, s72, s73	16.74	92.56		8(937.06 / 0.84) 61(1457.4 / 0.81) 59(200 /1)
EA [20]	s69, s70, s71, s72, s73	4.48	98	-	61(2113/0.82) 18(458/0.83) 11(668/0.82)
Simultaneous DG allocation with unity PF and NR					
Proposed method	s14, s57, s61, s69, s70	36.7738	83.66	0.98141@61	'21('743.3/1) 12(332.01/1) 61(1445.54/1)
ABC [60]	s12, s56, s69, s61, 7s0	39.63	82.39	0.982	61 (1394/1) 60 (820/1) 62 (432/1)
RGA [53]	s10, s16, s14, s55, s62	44.23	80.34	0.974	2065
EHAS [55]	s69, s17, s13, s58, s61	40.30	82.09	0.973	1871
CSA [56]	s69, s70, s14, s58, s61	37.02	83.54	0.9869@61	11 (541.3) 65 (553.6) 61(1724.0)
Simultaneous DG allocation with optimal PF and NR					
Proposed method	s42, s71, s15, s56, s12	3.9476	98.25	0.99486@50	'11(605/'0.81537) 20(400/0.83263) 61(1695/0.81375')
AOA [59]	s14, s56, s61, s69, s70	13.887	93.83	0.9917@62	12(433.50/0.95) 61(1669.30/0.95) 26(668.37/0.95)

When optimal three DG units with UPF and NR is optimally implemented in the test network, the proposed approach allows a minimum TAPL is 54.4039 kW with a power loss reduction 74.22% as compared to AOA [59], ISCA [54], and EHSA [55], respectively.

After performing optimal three DG unit allocation with OPF and NR is optimally implemented in the test network for nominal load level, the proposed technique gives a minimum TAPL is 10.6411 kW with a power loss reduction 94.96 % as compared to AOA [59], respectively.

The proposed method yields superior outcomes for reducing TAPL, demonstrating a substantial reduction in power loss while maintaining acceptable voltage magnitudes compared to compression techniques. Notably, when applying OPF to DG with NR, it results in the lowest TAPL among all scenarios. Moreover, DG coupled with OPF offers improved performance over DG coupled with UPF by reducing TAPL and enhancing the voltage profile, primarily due to its active power loss reduction capabilities and reactive power support.

B. THE IEEE 69-BUS NETWORK

1) SIMULTANEOUS OPTIMIZATION OF TAPL, VD, AND VSI

The obtained results of the proposed technique for different cases with different load level conditions, namely base case, NR, three DG allocation with UPF, three DG allocation with OPF, simultaneous DG allocation with UPF along NR, and simultaneous DG allocation with OPF along NR in the 69-bus network are listed in Table 4. As a result of the proposed approach, superior results are obtained in multi-objective optimization in DN by optimally allocating DG units with OPF and NR.

The test network's TAPL for different load levels is decreased to 23.6548 kW, 98.598 kW and 267.0943 kW. The VD of the test network is decreased to 0.00569859 p.u, 0.02110687 p.u, and 0.0565237 p.u, and the VSI of the test network is enhanced to 0.904963 p.u, 0.8125526 p.u, and 0.7051437 p.u, respectively, when there is NR is implemented.

After performing only three DG allocation with UPF in the test network for different load levels, TAPL is decreased to 17.0434 kW, 69.4263 kW and 181.7813 kW. The VD of the test network is decreased to 0.00136100 p.u, 0.00555632 p.u, and 0.01444562 p.u, respectively. The lowest VSI of the test network is enhanced to 0.95747027 p.u, 0.91493232 p.u, and 0.8645491 p.u, respectively.

TAPL is decreased to 1.1475 kW, 6.2191 kW and 11.8455 kW. The VD of the test network is decreased to 0.000036151 p.u, 0.000815867 p.u, and 0.00036674 p.u, respectively. The lowest VSI of the test network is enhanced to 0.988617 p.u, 0.97727662 p.u, and 0.9636189 p.u, respectively, after performing only three DG allocation with OPF in the test network for different load levels.

When optimal three DG units with UPF and NR simultaneously is optimally implemented in the test network, TAPL is decreased to 9.0447 kW, 36.7738 kW and 98.97 kW. The VD of the test network is decreased to 0.001038341 p.u, 0.003852307 p.u, and 0.009296974 p.u, respectively. The lowest VSI of test network is enhanced to 0.96329746 p.u, 0.92759046 p.u, and 0.8841887 p.u, respectively.

TAPL is decreased to 0.94946 kW, 4.6782 kW and 10.9769 kW. The VD of the test network is decreased to 0.0000854713 p.u, 0.0002877 p.u, and 0.00041595 p.u, respectively. The lowest VSI of the test network is enhanced to 0.9897713 p.u, 0.97935849 p.u, and 0.969852 p.u, respectively, after performing optimal three DG units allocation with OPF and NR simultaneously implemented in the test network for different load levels.

It can be seen from obtained results that the simultaneous DG allocation with OPF and NR in DN is more effective in multi-objective optimization. In addition, the impact of the NR, optimal DG integration with UPF and OPF, simultaneous DG allocation with UPF and OPF and NR in DN for three load levels on voltage profile, branch power losses, VSI, and objective function's convergence curves for each case are shown in Figs. 12-15.

2) MINIMIZATION TAPL AT NOMINAL LOAD LEVEL FOR COMPARISON OBTAINED RESULTS WITH OTHER EXISTING ALGORITHMS IN THE LITERATURE

The proposed technique achieves the best results regarding total active power loss (TAPL) minimization in DN by the optimal NR, optimal DG integration with UPF and OPF, and simultaneous DG allocation with UPF and OPF along NR. As shown in Table 5, a comparison is provided between the results acquired from the proposed technique and those obtained from other existing algorithms in the literature for the case of nominal load level.

When only NR is implemented, the proposed approach allows a minimum TAPL is 98.598 kW with a power loss reduction 56.18 % as compared to ABC [60], RGA [53] and EHSA [55] methods.

After performing only three DG allocation with UPF in the test network, the proposed technique gives a minimum TAPL is 69.42553 kW with a power loss reduction 69.14 % as compared to HSSA [41], PSO [21], HHO [13], HGSO [19] and EA [20], respectively.

In the case of only three DG allocation with OPF in the test network for nominal load level obtained, TAPL is 4.21 kW with power loss reduction 98.13 % as compared to HSSA [41], PSO [21], HHO [13], HGSO [19] and EA [20], respectively.

When optimal three DG units with UPF and NR is optimally implemented in the test network, the proposed approach allows a minimum TAPL is 36.7738 kW with power loss reduction 83.66 % as compared to ABC [60], RGA [53], EHAS [55] and CSA [56], respectively.

After performing optimal three DG unit allocation with OPF and NR is optimally implemented in the test network for nominal load level, the proposed technique gives minimum TAPL is 4.6782 kW with power loss reduction 97.92 % as compared to AOA [59], respectively.

From this compression, the proposed technique provides better results in minimization of TAPL with a higher reduction of power loss and an acceptable voltage magnitude. In contrast to the other cases, the OPF operation of DG with NR ensures the lowest value of TAPL. In addition, DG with OPF gives better performance than DG with UPF in terms of decreased TAPL and enhancement of voltage profile due to its reactive power support.

VI. CONCLUSION

This paper has introduced a novel approach that combines a GMO algorithm with the PLSI method to address various optimization problems related to network reconfiguration (NR) and allocation of distributed generation (DG) units. Specifically, the approach considers three DG units and incorporates both unit power factor (UPF) and optimal power flow (OPF), while taking into account operational constraints and three loading levels (light load, nominal load, and heavy load). The objective is to maximize voltage stability index (VSI) and minimize total active power loss (TAPL) and voltage deviation (VD) of distribution networks (DNs). To evaluate the effectiveness of the proposed method, standard IEEE 33 and 69-bus networks are used as test cases. The results demonstrate significant improvements in terms of VSI enhancement and TAPL and VD reduction when simultaneously optimizing NR and DG unit allocation with OPF, compared to the scenarios of simultaneous optimization with UPF only, as well as DG unit allocation with UPF and OPF, and NR optimization alone. The multi-objective nature of the problem is considered throughout the analysis. Furthermore, the proposed technique has been compared with other existing algorithms from the literature, specifically for the objective of TAPL at the nominal load level. The results show that the combined technique outperforms the existing techniques in terms of TAPL reduction for all the considered cases. The proposed technique exhibits good accuracy and convergence speed, making it a favorable choice for simultaneous optimal NR and DG unit allocation with UPF and OPF, regardless of the load conditions. Future work can focus on incorporating renewable energy sources, integrating energy storage systems, addressing uncertainties, assessing scalability, and applying the proposed technique to real-world distribution systems for validation. These directions aim to enhance the efficiency, reliability, and sustainability of optimal network reconfiguration and distributed generation unit allocation.

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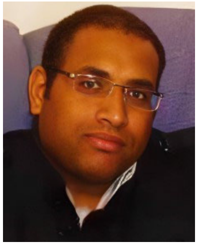

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