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OPTIMIZING DISTRIBUTED GENERATOR ALLOCATION IN POWER NETWORKS USING GENETIC ALGORITHMS: A FOCUS ON LOSS MINIMIZATION AND LOAD UNCERTAINTY

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Abstract:
This paper introduces an innovative method for strategically allocating distributed generators (DGs) within power distribution networks to achieve total loss minimization. Utilizing the genetic algorithms technique, this method takes into account load demand uncertainties that vary throughout the day, thus providing a realistic representation of operational dynamics within distribution systems. This consideration is crucial for accurately determining the most effective placement of DG units to optimize network performance and efficiency. The optimization framework developed in this study incorporates a robust analysis of fluctuating load demands, which is essential for adapting to the unpredictable nature of power usage and generation. By integrating these variables, the proposed method not only aims to reduce power losses but also enhances the reliability and sustainability of the power distribution networks. To validate the effectiveness of this approach, it was applied to three different IEEE bus test systems—the IEEE 13, IEEE 34, and IEEE 123 bus systems. Each of these systems exhibits unique characteristics typical of distribution grids, making them ideal for demonstrating the versatility and applicability of the proposed optimization strategy. The results from these test cases highlight significant improvements in loss reduction and system stability, underscoring the potential of genetic algorithms in complex network configurations. This study not only advances the methodology for DG allocation but also contributes to the broader goal of improving grid management and resilience in the face of varying demand patterns. It lays the groundwork for future research aimed at integrating renewable energy sources and new technologies into the power distribution framework, moving towards more adaptive and intelligent energy systems.
Keywords—*Distributed generators, power distribution systems, load demand uncertainties, loss minimization, optimization, genetic algorithms.*

I: Introduction

In [1], Distributed Generation (DG) is defined as an energy source that is directly linked to either the distribution network or the customer's measuring point. The differentiation between the distribution and transmission networks is established according to the legal definition, often included in the regulations governing the electrical market in each nation.
The incorporation of DG into the electrical system offers many advantages, including less active power losses, enhanced voltage profile, and environmental benefits when using renewable sources like solar photovoltaic (PV) and wind energy. The range is from 2 to 4, inclusive. In order to exploit these potential advantages, a key step is to address the issue of placing and

scaling dispersed sources. This involves solving an optimisation problem, where the decision variables are the position and size of the DGs [5], [6].

Within this framework, several studies have been conducted in the academic literature, resulting in various methodologies for addressing the DG allocation issue. The studies conducted in references [7]-[10] suggest the use of the Genetic Algorithm (GA) to identify the most favourable position and dimensions for the DGs. The primary aim is to minimise the active power losses in the system. A cooperative reinforcement learning technique is introduced in [11] to minimise the operating expenses of micronetworks by addressing the economic dispatch problem.

The micro-grid concept comprises decentralised generating units and energy storage devices. The authors conduct simulations using actual load data to analyse and validate their proposed algorithm. They compare it with fuzzy-Q learning and the Scenario-based approach. The results demonstrate that their technique effectively reduces the costs of DG dispatch in micro-networks. One shortcoming of the author's work is the omission of active and reactive power losses. Fuzzy logic is used in [12] to address the issue of allocating and determining the size of DG (Distributed Generation). The authors consider a dependability index that quantifies the expense associated with energy that is not provided. One of the main goals of the optimisation challenge is to enhance the network's dependability. In order to reduce active power losses, [13] suggest using the power loss index (PLI) in combination with the flower pollination algorithm (FPA) metaheuristic technique to allocate DG units. The study conducted in [14], [15] employs a multi-objective method to include and size distributed generation (DG) in radial distribution networks. The three primary objectives are to minimise active power losses, enhance the voltage profile, and maximise the voltage stability index. The process of determining the location and capacity of DG units is carried out by a hybrid algorithm that combines particle swarm optimisation (PSO) for locating the DGs and genetic algorithm (GA) for determining their size. This method is implemented in sections 16 to 18.

Table I presents a collection of studies that have impacted this study, focusing on the optimum allocation of DGs. The table includes information on the objective function(s) used, important remarks about the modelling process, and the solution approach used.
This work presents a developed approach for allocating three-phase generators in electrical distribution systems. The objective of the method is to minimise the overall active power losses in the system. The optimisation approach relies on the genetic algorithm, which is a metaheuristic methodology. This technique takes into account the uncertainties and changes in load demand, resulting in a model that closely represents the real functioning of electric energy distribution networks.

Table 1: Review of Techniques for Optimal Allocation of Distributed Generators (DGs)

Method and Reference	**Objective Function**	**Model Characteristics**
Artificial Bee Colony [19]	Minimize active power losses.	Analyzed under two load scenarios; compared with exhaustive search methods.
Fuzzy Genetic	Maximize voltage stability	Integrates dual objectives using a

Algorithm [20]	margin and net revenue.	fuzzifier into a weighted sum; tested on three load levels in meshed systems.
Multi-objective Particle Swarm Optimization [21]	Maximize net revenue and minimize costs for DG entrepreneurs.	Includes operational and technical index calculations for decision-making, fixed DG capacity factor; pricing based on energy sale contracts across three load levels.
Ant Colony Optimization [22]	Maximize network present value.	Incorporates penalties into the objective function and accommodates multiple scenario assessments.
Dynamic Programming [23]	Minimize total DG cost.	Incorporates monetized losses into total DG cost calculations.
Teaching Learning-Based Optimization [24]	Minimize active energy losses, improve grid voltage profile, and enhance voltage stability index.	Compares results with Particle Swarm Optimization (PSO) and Genetic Algorithms (GA); considers a single load level.
Evolutionary Algorithm and Game Theory [25]	Minimize active energy losses and energy purchase costs; maximize voltage stability, total voltage variation, and net revenue.	Utilizes a two-stage contract price and allocation optimization; compares with GA and PSO using a weighted sum approach, sets contract price relative to DG power.
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [26]	Minimize losses and maximize voltage profile improvement.	Focuses on both DG allocation and sizing.
Cuckoo Search Algorithm [27]	Minimize power losses.	Utilizes voltage stability index and loss sensitivity factor for algorithm parameters; considers allocation and sizing of DGs and a synchronous compensator.

This table presents a summarized view of various methodologies used for the optimal placement and sizing of distributed generators in power distribution networks, highlighting the main objectives and distinctive features of each modeling approach.

The primary goal of this research is to identify strategic buses for the placement of Distributed Generators (DGs) that result in the minimal electrical losses within the systems studied. To address this optimization challenge, a specialized software program is utilized. This program facilitates the integration of DGs and conducts a three-phase power flow analysis, which is integrated with a Genetic Algorithm (GA) routine.

II. Basic Assumptions

A. Categories of Distributed Generators

Although the concept of DG doesn't specify the extent of energy generation—which varies depending on local grid conditions—it is beneficial to categorize the degrees of distributed generation. As proposed by the authors in [1], these categories are:

- Micro distributed generation: [1W ~ 5kW]
- Small distributed generation: [5kW ~ 5MW]
- Medium distributed generation: [5MW ~ 50MW]
- Large distributed generation: [50MW ~ 300MW]

In our analysis, the distributed generators dispatch power levels of 50, 100, 150, and 200 kW, each operating at a unity power factor and connected exclusively to three-phase buses. These serve as active power sources within the system.

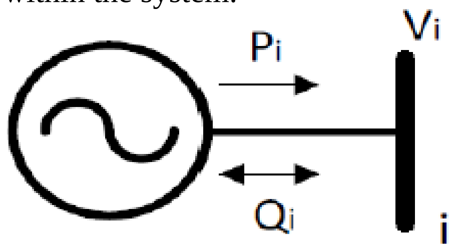


Figure 1 illustrates a synchronous machine setup for DGs in distribution networks.

DG implementation and power flow solutions within the networks are executed using OpenDSS. The generators are modeled to inject a balanced, constant active power at a specific power factor, essentially functioning as negative loads in the system.

B. Demand Randomness and Loading Scenarios

Operational realities of electrical distribution systems feature inherent uncertainties in load demands due to factors like measurement errors and constant variations at each bus [28], [29]. Furthermore, the network experiences different loading conditions—light, medium, and heavy—throughout the day. It is crucial to incorporate this randomness and variability of loading scenarios into the power flow calculations to enhance the accuracy of system analyses. This incorporation of randomness can be achieved by multiplying the load demand at each node by a series of randomly generated numbers. These numbers reflect not only the demand uncertainty but also the different loading conditions of the network. The generation of these numbers can be managed using a function in MATLAB®, along with the configuration files that define the power load for each simulation in OpenDSS [30].

III. PROPOSED METHODOLOGY FOR OPTIMAL DG PLACEMENT AND SIZING TO REDUCE LOSSES IN DISTRIBUTION SYSTEMS

The focus of this study is to identify the optimal locations (buses) for the placement of Distributed Generators (DGs) in order to minimize active power losses. This involves considering uncertainties in demand and load levels throughout the day, while ensuring that voltage levels remain within acceptable limits.

A. Formulation of the Optimization Problem

Active power losses can be calculated using the formula:$PLk=gk,ij(Vk,i-Vk,j)2$ where PLk denotes the active power loss for element k (in kW), gk,ij is the conductance of element k, and Vk,i and Vk,j are the voltage magnitudes at buses i and j, respectively, from which element k exits. The optimization challenge is modeled as: min$f()$subject to minOBFsubject to$Vmin \le Vi \le Vmax$ where N represents the set of lines within the system. Equation (2) illustrates the objective function (OBF), constrained by voltage limits to assess optimal parameters in each generation of the genetic algorithm.

Due to the nonlinear nature of this optimization problem, traditional optimization methods, while ensuring an optimal solution, become computationally expensive as they evaluate every possible combination within the search space. Metaheuristic techniques, hence, are preferred for their ability to effectively reduce the search space, thus providing a more efficient exploration of near-optimal solutions, and are computationally feasible for energy systems. Nevertheless, these methods do not guarantee the absolute best solution. For this study, the genetic algorithm (GA) was selected for its robustness.

B. Implementation of the Proposed Method

The optimization task is addressed using a GA, with the routine implemented in Matlab®. The objective function aims to minimize total active power losses in the test systems through strategic DG placement, which is directed by the GA. Subsequent to determining the sequence and power levels of DG placement, power flow calculations are performed using OpenDSS to evaluate total losses for the configurations suggested by the GA. These losses vary depending on each bus's operational state at any given time, influenced by voltage magnitude and angle, and power injections from the DGs.

Figure 2 presents the GA flowchart, with a detailed description of each step in the implemented routine:

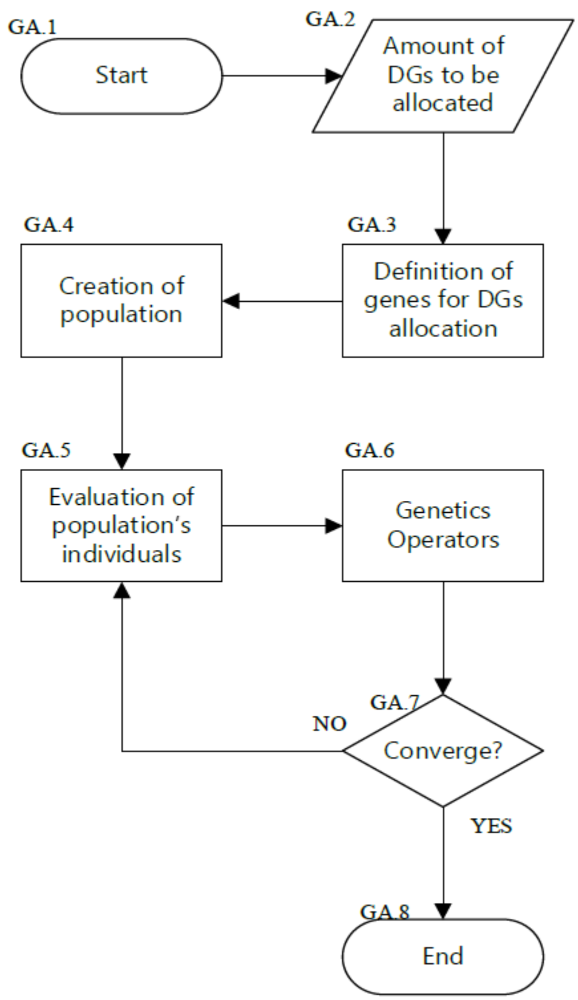


Fig. 2. Genetic algorithm flowchart.

- **GA.1 - Start**: Initialization of the GA in Matlab and setting the desired number of simulations.
- **GA.2 - DG Allocation**: Defining the number of DGs to be placed as input by the user.
- **GA.3 - Chromosome Definition**: Chromosomes represent allocation possibilities (system buses) and power dispatch possibilities from DGs, as illustrated below: $Xn=[P1 |Bus1|P2|Bus2|\ldots|Pn|Busn]$ Here, Xn is the chromosome, $Busi$ is the ith bus, Pi is the power from the DG to $Busi$, and n corresponds to the number of DGs and their respective dispatch powers.
- **GA.4 - Population Creation**: Creation of the initial population of chromosomes, with genes randomly drawn in the first iteration. Genetic operators are then applied to evolve the population.
- **GA.5 - Evaluation of Individuals**: Each candidate's allocation of DGs is decoded and power flow executed individually. Performance is assessed using the objective function (OBF), assigning fitness through the GA fitness function. The fittest individuals have a higher probability of influencing future populations.
- **GA.6 - Genetic Operations**: Operations include crossover (combining genes from parent chromosomes), mutation (random gene alterations), and elitism (ensuring the best individuals continue to the next generation), all aimed at deriving superior individuals for subsequent generations.

These steps continue until convergence to an acceptable solution is achieved, ensuring a diverse genetic pool and a broad search scope.

GA.7 – Convergence Criteria: This step involves verifying the convergence of the Genetic Algorithm. The criteria for determining convergence might include reaching a maximum number of iterations or observing that the population has become stagnant. For this study, the convergence criterion of population stagnation was used.

GA.8 – Conclusion and Results Presentation: Upon meeting the convergence criteria, this step showcases the optimal solution derived by the GA, which includes the ideal location and power settings for the machines that result in minimized total losses. Figure 3 illustrates the flowchart for the integration of uncertainties in load demand and the various loading scenarios encountered throughout the day. This procedure was implemented using Matlab®.

DU.1 – Random Number Generation: In this research, Matlab's **rand** function is employed to generate random numbers ranging from 0 to 1.

DU.2 – Loading Scenario Specification: This step involves defining the loading scenarios that will be simulated. Loading ranges from 0.2 to 1.5, with specific intervals defined for different conditions: 0.2 to 0.5 for light loading, over 0.5 to 0.8 for medium loading, and over 0.8 to 1.0 for heavy loading. Additionally, a range from 0.5 to 1.5 is included to encompass medium and heavy loads, as well as potential overloading scenarios.

DU.3 – Random Number Utilization: Following the specification of the desired load, the **rand** function is used to select random numbers within the established range. These numbers represent not only the uncertainty in demand but also the specific loading scenario to be simulated. This randomization helps define the power demands for each load in the subsequent simulation.

DU.4 – Load Demand Specification: The randomly drawn numbers are then multiplied by the active and reactive power values for each load in the system. This step determines the network load and introduces demand randomness into the power flow calculations, enhancing the realism of the simulation.

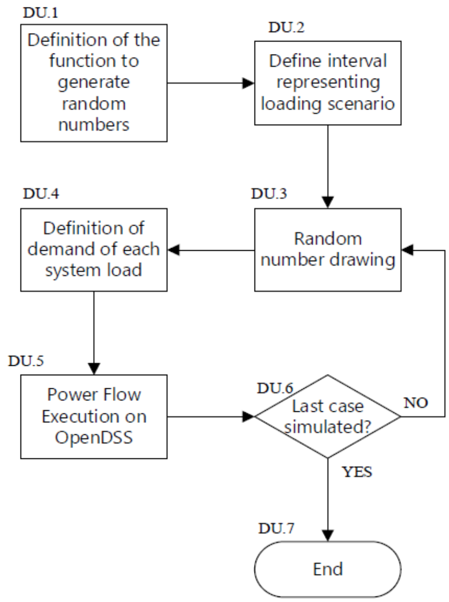


Fig. 3. Flowchart for representation of uncertainties in demand.

DU.5 – Power Flow Execution: In this phase, after the genetic algorithm has specified the optimal configuration (chromosome), and the machines have been assigned to their respective nodes, OpenDSS is tasked with executing the power flow, incorporating the previously defined uncertainties in load demands.

DU.6 – Simulation Case Verification: This step checks whether the desired number of simulations has been completed. If the target number of simulations has been reached, the program concludes. If not, the process cycles back to step DU.3 to continue with further simulations.

DU.7 – Conclusion and Restart: Upon completing the planned number of simulations, it becomes necessary to define a new network loading scenario. This action sets the stage for restarting the process, allowing for continuous adaptation and optimization based on updated scenarios and conditions.

IV. RESULTS

The methodology outlined in Section III was evaluated using the IEEE 13-, 34-, and 123-bus systems [31]. These tests were conducted on a computer equipped with an Intel Core i5 processor running at 2.3 GHz, 4 GB of RAM, Windows 10 Pro operating system, Matlab R2015a, and OpenDSS version 8.1.6.1 (64-bit build). The duration of computational processing varied across the different test systems.

For each test system, the Genetic Algorithm (GA) was executed 400 times—100 times for each predefined loading scenario. Due to the variability in network conditions, each simulation permitted the loads to fluctuate within a predetermined range, influencing the GA's results at the conclusion of each run. This stochastic approach, combined with the inclusion of load demand uncertainties, necessitated a large number of simulations to ensure a thorough evaluation of the most suitable bus locations for Distributed Generator (DG) allocation. The buses most frequently recommended by the GA were deemed optimal for DG placement in each test system.

The software developed for this study allows users to specify any number of DGs for allocation. In the simulations conducted, the number of machines designated was chosen to maximize the diversity of bus recommendations. In every scenario analyzed, six DGs were allocated.

To validate the effectiveness of the proposed method, simulations were also performed with generators positioned at the three most recommended buses by the GA for each system. Additional simulations were conducted for base cases, where no DGs were installed, to serve as controls. The more challenging heavy and random load scenarios were selected for these simulations because they represent conditions that are particularly demanding for network operations. For both the base and allocation cases, ten simulations were conducted, and the results were averaged to account for the inherent randomness in load demands. Finally, the results were compiled and presented in tables, allowing for a comparative evaluation and thorough assessment of the method's performance.

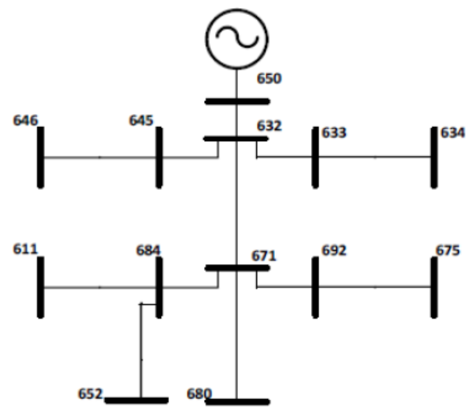
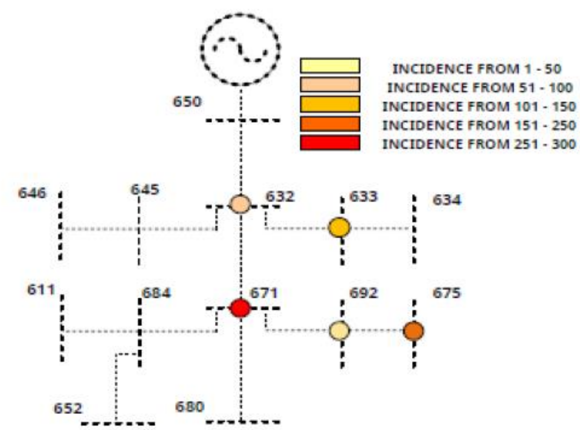
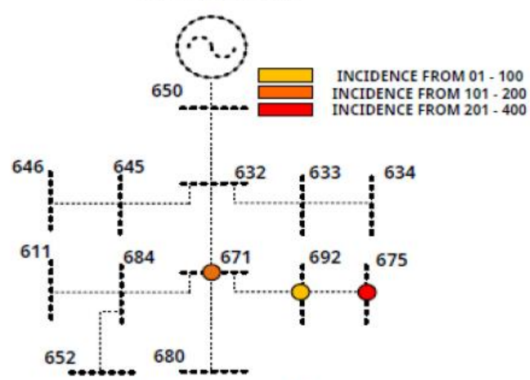


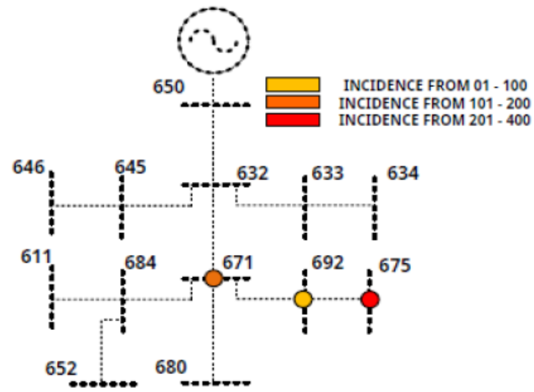
Fig. 4. IEEE 13 bus test systems.



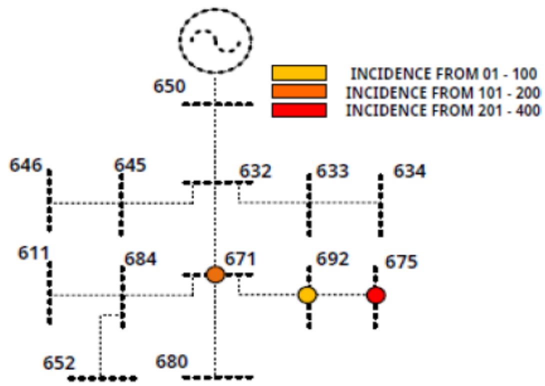
(a) Light Load)



(b) Average load



(c) Heavy Load



(d) Random load

Fig. 5. Incidences of strategic buses in the IEEE 13 Bus system

In Figure 5, the frequency with which specific buses were identified as optimal by the Genetic Algorithm (GA) is depicted for various loading scenarios. The term "incidence" here refers to the number of times a particular bus was selected as optimal. The frequency of these incidences varies with the loading scenario; buses with the highest frequencies are marked in red, and those with the lowest in yellow.

The simulation results indicate that the most suitable buses for the placement of Distributed Generators (DGs) in the IEEE 13-bus test system are buses 675, 671, and 692. The recommended power settings for the DGs fluctuate, particularly under light load conditions. However, across other scenarios, the consistently selected power for each DG was 200 kW.

Table II demonstrates the effectiveness of the DG allocations under heavy and random loading scenarios, termed Allocation 01 and Allocation 02, respectively. These scenarios exhibit a significant reduction in total losses—28.87% for heavy loading and 28.43% for random loading—when compared to the base cases without DGs. This substantiates the viability of the method under discussion.

Table II: Comparison of Results for the 13 Bus Test System

Loading Condition	**Scenario**	**Active Power Losses (kW)**
Heavy Loading	Base Case	85.552
	With DGs	60.851
Random Loading	Base Case	109.045
	With DGs	78.042

B. Case Study – IEEE 34 Bus Test System

Figure 6 presents the single-line diagram of the IEEE 34-bus system, a real feeder rated at 24.9 kV. This system is characterized by its length, light loading, the presence of two voltage regulators, a transformer serving a short feeder section at 4.16 kV, shunt capacitors, and unbalanced loads.

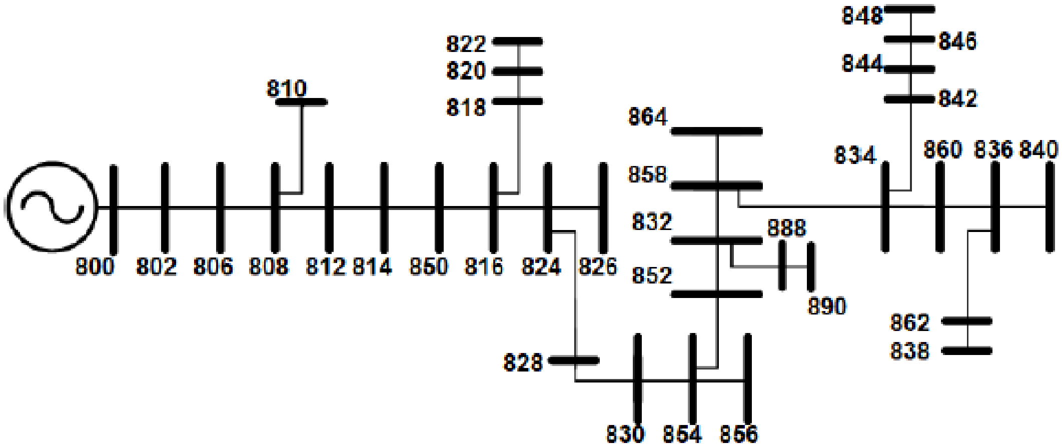


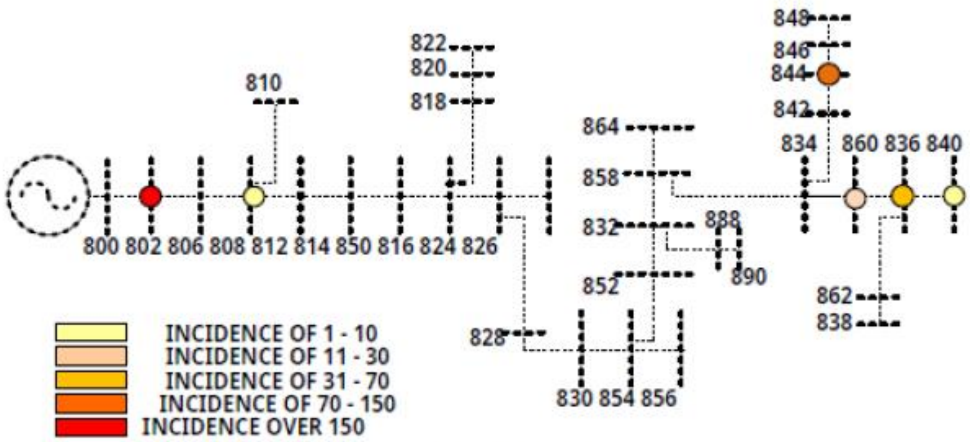
Fig. 6. IEEE 34 bus test system.

In the IEEE 34 bus system, the allocation of 6 Distributed Generators (DGs) and their optimal placement are illustrated in Figure 7. During the simulations of this system, buses 844, 836, 832, and 860 were identified as optimal locations for DG installation. Although the recommended power levels for the DGs varied depending on the specific load scenario, a consistent optimal power output of 200 kW for each DG was identified across all scenarios. This demonstrates the robustness of the simulation process in pinpointing the most effective bus locations for DG placement to optimize network efficiency. The outcomes displayed in Table III highlight a substantial decrease in active power losses across different loading scenarios for the IEEE 34 bus test system, as anticipated. Specifically, there is a 56.17% reduction in losses under the heavy load scenario and a 39.96% reduction under the random load scenario, demonstrating the effectiveness of Distributed Generator (DG) allocation in enhancing network efficiency.

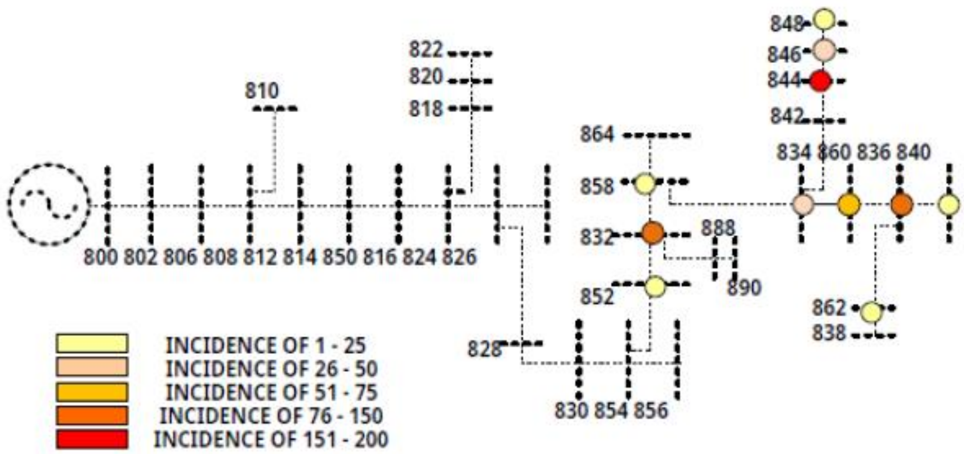
Table III: Comparison of Results for the 34 Bus Test System

Loading Condition	Scenario	Active Power Losses (kW)
Heavy Loading	Base Case	225.78
	With DGs	98.95
Random Loading	Base Case	240.80
	With DGs	174.57

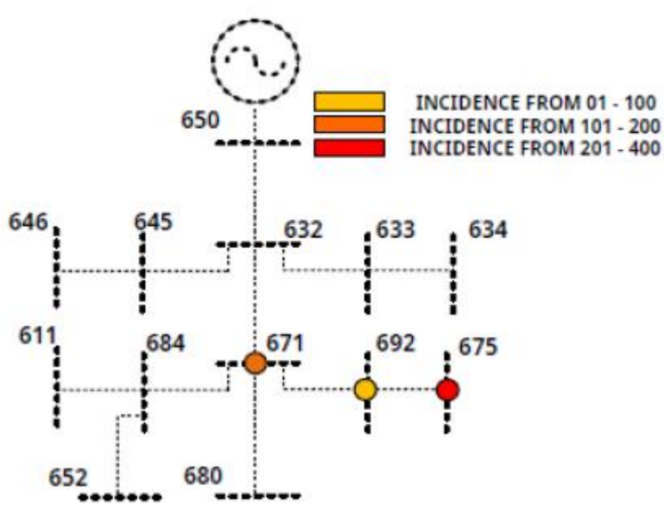
These results validate the strategic placement of DGs within the network to optimize power distribution and minimize losses, particularly in scenarios that demand more from the network.



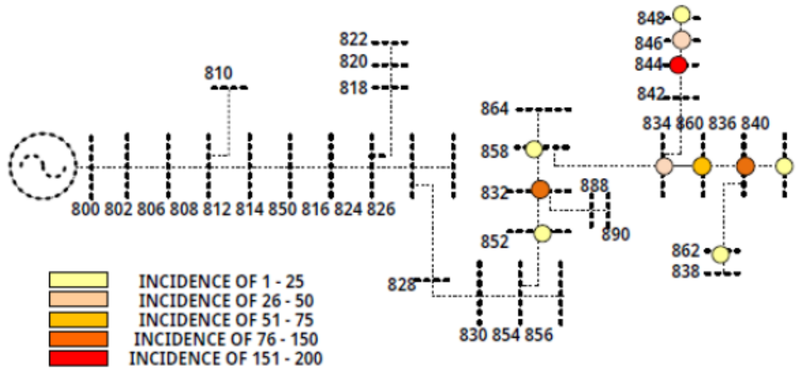
(a) Light load



(b) Average load



(c) Heavy load



(d) Random load

Fig. 7. Incidences of strategic buses in the IEEE 34 – bus system.

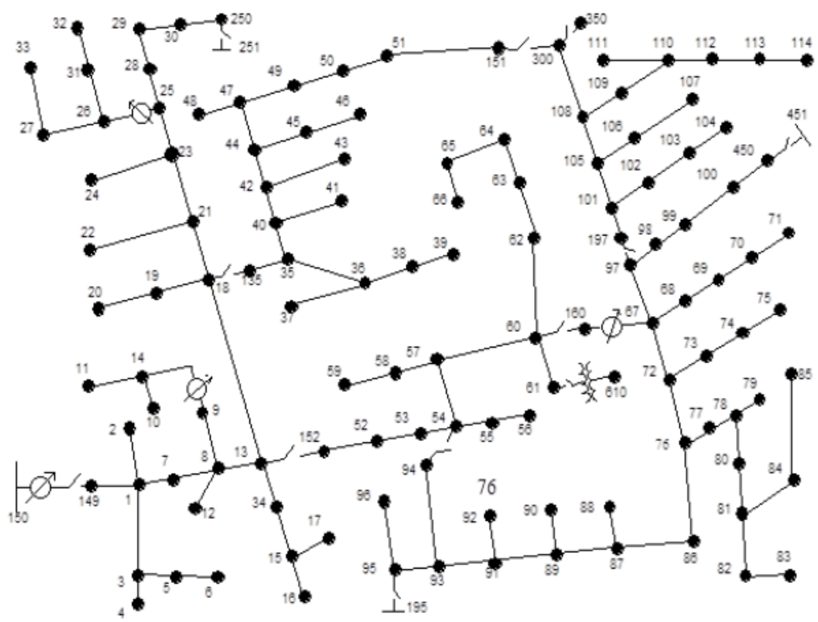


Fig. 8. IEEE 123 bus test system.

V. CONCLUSION

This paper detailed a strategy for optimally allocating distributed generators (DGs) in power distribution systems using a genetic algorithm. This method accounted for the inherent randomness in each load and catered to various loading conditions including light, medium, and heavy. The primary goal was to minimize total active power losses while adhering to the operational constraints of the systems. Through this approach, it was possible to identify several strategic buses for the placement of DGs, determine the most suitable and optimal buses for DG installation across all loading scenarios, including overload conditions. The study also highlighted how different loading scenarios and the uncertainties in demand influence the selection of optimal buses and the power output of each DG. Notably, under light loading conditions, the power recommendations varied more significantly, and the bus selections for DG installation were more dispersed across the systems. Conversely, as the loading intensity increased, the recommended buses tended to cluster in common regions, particularly towards the end of feeder branches. Additionally, it was observed that certain buses recommended in some load scenarios were either not recommended in others or were recommended less frequently. The comparative results and evaluations of the DG installations demonstrated the method's efficacy, showcasing a substantial reduction in losses for each system analyzed. This validates the method's utility in facilitating efficient generator installation and enhancing the overall performance of the distribution systems.

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