A Method for Optimal Distributed Generation Allocation Considering Load Demand Uncertainties

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Abstract—**This paper presents a method for optimally allocating distributed generators in power distribution networks for total loss minimization using genetic algorithms technique. In the optimization process, load demand uncertainties throughout the day were considered with the aim of representing appropriately the real operation of the distribution system, which allows a more careful evaluation of the optimal bus to allocate the DG. The proposed approach was implemented on the IEEE 13, IEEE 34, and IEEE 123 bus test systems, which possess characteristics inherent in distribution grids.**

Index Terms—**Distributed generators, power distribution systems, load demand uncertainties, loss minimization, optimization.**

I. Introduction

In [1], Distributed Generation (DG) is defined as a source of energy connected directly to the distribution network or to the customer's measurement location. The distinction between the distribution and transmission networks is based on the legal definition, which is normally part of the regulation of the electricity market in each country.

Among the main benefits provided by the insertion of DG in the electrical system, we can highlight the reduction of active power losses, improvement of the voltage profile, and environmental gains, when using renewable sources such as solar photovoltaic (PV) and wind energy as primary sources [2]-[4]. To take advantage of these potential benefits, one of the main steps is to deal with the placement and sizing problem of distributed sources, which consists of solving an optimization problem whose decision variables are the location and size of the DGs [5], [6].

In this context, many works have been developed in the literature, producing different approaches to the DG allocation problem. In the works reported in [7]-[10], the use of the Genetic Algorithm (GA) is proposed to determine the optimal location and size of the DGs, with the main objective being to minimize the active power losses of the system. In [11], a cooperative reinforcement learning algorithm for solving the economic dispatch is proposed, to minimize the operation costs of micro-networks. The micro-grid model consists of distributed generation units and energy storage devices. For the analysis and validation of the proposed algorithm, the authors performed simulations based on real load data and comparisons with fuzzy-Q learning and with the Scenario-based algorithm, showing that their methodology is effective in minimizing the costs of DG dispatch in micro-networks. As a limitation, the author does not take into account active and reactive power losses. In [12], fuzzy logic is used to solve the DG allocation and sizing problem. The authors take into account a reliability index that represents the cost of non-supplied energy. Thus, one of the objectives of the optimization problem is to improve the reliability of the network. To minimize active power losses, [13] propose the power loss index (PLI) for the allocation of DG units together with the flower pollination algorithm (FPA) metaheuristic approach. The research carried out in [14], [15] bring a multi-objective approach to insert and dimension DG in radial distribution systems. The three weighted goals are to reduce active power losses, improve the voltage profile, and increase a voltage stability index. In [16]-[18], the siting and sizing of DG units is implemented using a hybrid algorithm that uses particle swarm optimization (PSO) to locate the DGs and GA to determine the size.

Table I brings several works referring to the optimal allocation of DGs that directly or indirectly influenced this work, showing the adopted objective function(s), some comments relevant to the modeling and the adopted solution method.

In this paper, a method for the allocation of three-phase generators distributed in electrical distribution systems is developed, that seeks to minimize the total system active power losses. The optimization method is based on the metaheuristic technique of the genetic algorithm. In this approach, the uncertainties and variations in load demand are considered which makes the model be a close representation of the actual operation of electric energy distribution systems.

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TABLE I: EXAMPLES OF WORKS REGARDING THE OPTIMAL ALLOCATION OF DGs

Solution method and reference	Objective Function	Comments about the modelling
Artificial Bee Colony [19]	Minimize active power losses.	Two load scenarios, comparison with exhaustive search.
Fuzzy Genetic Algorithm [20]	Maximize the voltage stability margin and revenue total net.	Fuzzifier the two objective functions into one and then apply weighted sum, three possible load levels, do analysis for meshed systems.
Multi-objective Particle Swarm Optimization [21]	Maximization of DG's entrepreneur's total net revenue, minimization.	Calculation of operational and technical indexes for decision making, also determines the price of the energy sale contract, three load levels, DG capacity factor equal to 1, without differentiating the sources.
Ant Colony Optimization [22]	Maximize the present value of the network.	Applies penalties on objective function, using multiple scenarios.
Dynamic programming [23]	DG total cost minimization	Losses were monetized and included in the total DG cost.
Teaching Learning-Based Optimization [24]	Minimization of active energy losses, the grid voltage profile and the inverse of the voltage stability index.	Comparison with PSO and GA, one load level.
Evolutionary Algorithm and Game theory [25]	Minimizing active energy losses, voltage stability index, total voltage variation and energy purchase costs and maximizing the total net revenue of the GD entrepreneur.	Two stage contract price and allocation optimization, comparison with GA and PSO with weighted sum, contract price according to DG power.
Technique for Order Preference by Similarity to Ideal Solution [26]	Minimization of losses, maximization of voltage profile improvement.	DG allocation and sizing.
Cuckoo Search Algorithm [27]	Power losses minimization.	It uses the voltage stability index and loss sensitivity factor as algorithm parameters, it allocates and sizes in addition to DG, a synchronous compensator.

The main objective of this study is to determine the strategic buses for the allocation of DGs that provide the lowest electrical losses in the analyzed systems. To solve the optimization problem, a program for inclusion of DGs and calculation of the three-phase power flow is used, which is coupled to a GA routine

II. BASIC ASSUMPTIONS

A. Distributed Generators

The definition of DG does not define the degree of energy generation, since the maximum degree depends on the conditions of the local distribution grid, for example. However, it is useful to introduce categories of varying degrees of distributed generation. The authors in [1] suggest the following categories:

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

In this study, the power dispatched by the generators can be 50, 100, 150 and, 200 kW, all with unity power factor, connected only in three-phase buses, serving as an active power source for the system. Fig. 1 shows a synchronous machine representation for distributed generators in distribution systems.

The implementation of the DGs and the solution of the power flow to the networks are carried out using OpenDSS. The machines are modeled with balanced constant active power injection for a specified power factor. The synchronous generators are modelled as negative loads.

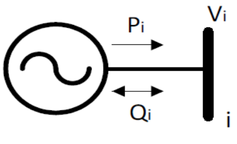


Fig. 1. Representation of a distributed generator connected to a busbar of an electrical system.

B. Demand Randomness and Loading Scenarios

In the actual operation of electrical distribution systems, the demand of the loads has a certain degree of uncertainty, due to measurement errors and also to the incessant loading variation in each bus [28], [29]. In addition, there are also varying loading conditions (light, medium and heavy) of the networks throughout the day.

Thus, it is necessary to incorporate the randomness of demand and loading scenarios in the power flow for a more realistic analysis of the distribution systems. This randomness can be introduced by multiplying the load demand at each node of the systems by a set of randomly drawn numbers within value ranges that represent, in addition to the uncertainty of demand, the network loading scenario. The drawing of numbers can be implemented through a function in Matlab®, as well as the file for defining the power of the loads in each simulation, which will be included in OpenDSS [30].

III. PROPOSED METHOD FOR DGs LOCATION & SIZING TO MINIMISE LOSSES IN DISTRIBUTION SYSTEMS

The problem addressed in this work can be defined as the determination of the optimal buses for the installation of DGs for active power loss minimization, taking into account the uncertainties of the demand and loading levels of the systems throughout the day, while maintaining voltage within acceptable limits.

A. Optimization Problem

The active power losses can be computed as:

$$P_{L_k} = g_{k,ij} \left| V_{k,i} - V_{k,j} \right|^2 \tag{1}$$

where P_{L_k} is the active power loss corresponding to element k (kW), $g_{k,ij}$ is the conductance of element k, $V_{k,i}$ is the voltage modulus of bus i, from which element k exits, $V_{k,j}$ is the voltage modulus of bus j, from which element k exits.

The optimization problem can be modeled as

$$\text{OBF} = \min \sum_{k=1}^{N} P_{L_k} \quad \text{subject to} \quad V_{\min} \le V_i \le V_{\max} \qquad (2)$$

where N is the set of lines belonging to the system.

Equation (2) represents the objective function, OBF, subject to the voltage restriction for the evaluation of the optimal parameters chosen in each generation of the genetic algorithm.

Due to the non-linear nature of the optimization problem to minimize losses, classical optimization techniques, despite the guarantee of an optimal solution, require that all possible combinations of the search space for solutions are evaluated. This results in a high computational cost, making them unfeasible for energy systems. Thus, meta-heuristic techniques are suitable for solving the problem, enabling a convenient reduction of the search space, implying a more efficient investigation of solutions close to optimality, making them computationally viable. However, metaheuristic methods do not guarantee optimal solutions. For this work, the Genetic algorithm technique was chosen.

B. Proposed Method

The optimization problem is solved through a GA, having its routine implemented code in Matlab®. The objective function of the problem seeks to minimize the total active power losses in the test systems with the allocation of already configured DGs. The sequence of allocation of DGs and their respective dispatchable powers in the systems are indicated by the GA. After that, the power flow is executed in OpenDSS, from which the total losses for the respective DG allocations provided by the GA are obtained. These losses depend on the operating state of each bus at a given moment, varying according to the voltage magnitude and angle, and power injection of the DGs at each instant.

This section sets out to show how the approach works. Fig. 2 shows the GA flowchart. The description of each step of the executed routine is as follows.

GA.1 – Start: Initialization of the GA routine in Matlab and definition of the desired number of simulations.

GA.2 – Amount of DGs to be allocated: The number of DGs to be allocated in the systems is defined as input data by the user.

GA.3 – Chromosome definition: the proposed chromosome structure that will be used in the optimization process consists of allocation possibilities (system buses) and the possibilities of dispatching power from the DGs, as shown in the vector below:

$$X_n = \left[\text{Bus}_1 \mid P_1 \mid \text{Bus}_2 \mid P_2 \mid \ldots \text{Bus}_n \mid P_n \mid\right]$$

where X_n is the chromosome, Bus_i is the i^{th} bus, P_i is the active power from the DG to Bus_i, and n corresponds to the number of DGs to be allocated and their respective powers to be dispatched.

The chromosome presents the premises of interest for each individual in the population evaluated in the objective function (OBF), the allocation buses and, available powers. Each individual offers a new configuration for the system, where each DG allocated in buses (only three-phase buses) of the system will contribute to the active power injection according to the power indicated by the GA.

GA.4 – Population creation: In this step, the initial population of individuals (chromosomes) is created, and in the first iteration, genes are randomly drawn.

From there, the genetic operators - described in GA.6 act to update individuals.

GA.5 – Evaluation of individuals: In this step, individuals are decoded and the allocation of DGs is carried out to execute the power flow with each candidate individually. Once this is done, each individual has their performance calculated by the OBF presented previously in (2), attributing a fitness through the GA fitness function. The fittest individuals are those that provide the best results in the assessment, with a greater probability of permanence for the future composition of new populations.

GA.6 – Genetic operations: The genetic operators used are the crossover or crossing, which generates new individuals from the combination of genes from the "parent" chromosomes. The mutation, which carries out random changes in the genes of each individual in the population. And finally, elitism, which guarantees the permanence of the fittest individuals to form the next population.

Genetic operations are applied in order to obtain new and better individuals from those who already make up each population. Thus, while convergence to a viable solution is not achieved, operators are executed to enable genetic diversity and allow for a more comprehensive search space.

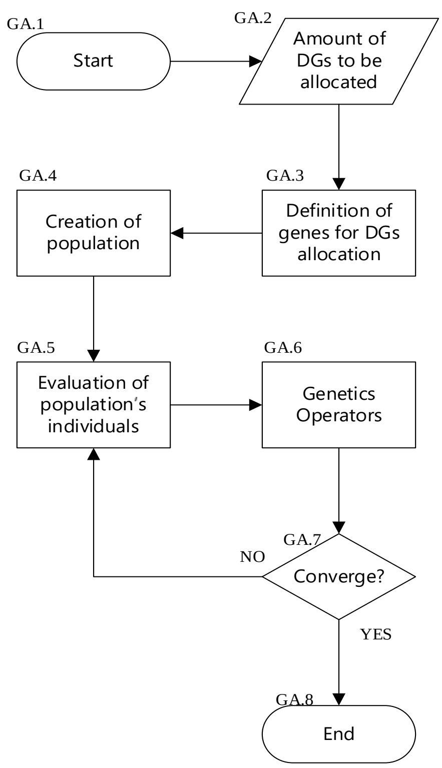


Fig. 2. Genetic algorithm flowchart.

GA.7 – Convergence criterion: In this module, the convergence of the GA is verified. The criteria used for convergence can be the maximum number of iterations or population stagnation. For this work, the criterion adopted was that of population stagnation.

GA.8 – Finalization and presentation of results: In this step, after reaching the convergence criterion, the viable solution indicated by the GA with optimal location and power of the machines and minimized total loss is presented.

Fig. 3 shows the flowchart for the representation and inclusion of uncertainties in the demand of each load and also the loading scenarios throughout the day. Then, the procedure was implemented in Matlab®.

DU.1 – Function to generate random numbers: In this study, the rand function in Matlab is used to generate random numbers between 0 and 1.

DU.2 – Definition of the loading scenario: In this step, the loading scenario to be simulated at intervals between 0.2 and 1.5 is defined. For the present work, the range between 0.2 and 0.5 was considered for light loading, the range between over 0.5 and 0.8 for medium loading, and the range between over 0.8 and 1.0 for heavy loading. A range between 0.5 and 1.5 was also included covering, in addition to medium and heavy loads, the possibilities of overloading defined as a random load scenario.

DU.3 – Random number drawing: Once the desired load is defined, the *rand* function in Matlab is implemented in order to draw random numbers within the corresponding range. These numbers are used to represent, in addition to the uncertainty in demand, the loading scenario to be simulated and subsequently, the demands on each load for the corresponding simulation.

DU.4 – Demand definition: The drawn numbers are multiplied by the active and reactive power of each load in the systems, defining the network load and demand randomness, which will be incorporated into the power flow.

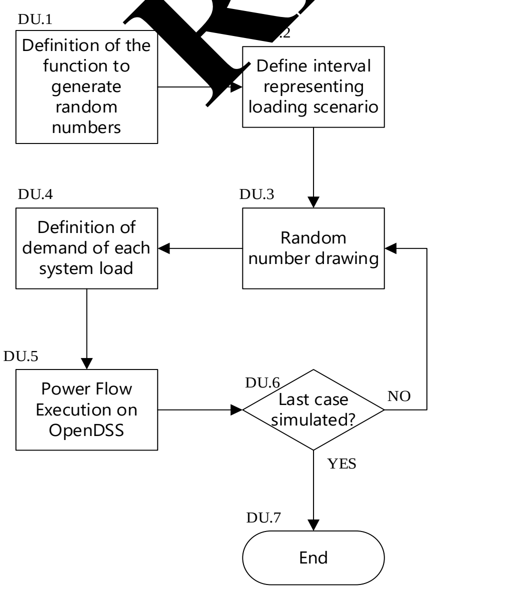


Fig. 3. Flowchart for representation of uncertainties in demand.

DU.5 – Power flow execution: In this step, with the chromosome indicated by the GA already decoded, the machines allocated in the respective nodes, and the uncertainties incorporated to the demands, OpenDSS executes the power flow.

DU.6 – Verification of simulated cases: it is verified if the desired number of simulations had been carried out. If so, the program ends its execution, if not, it returns to step DU.3.

DU.7 – Finalization: at the end of the desired number of simulations, it is necessary to define the new desired network loading scenario so that the process is restarted.

IV. RESULTS

The method proposed in Section III. was tested using IEEE 13-, 34-, and 123-bus systems [31]. The simulations were run on an Intel Core i5, 2.3 GHz, 4 GB RAM, using Windows 10 Pro operating system, with Matlab R2015a and OpenDSS version 8.1.6.1 (64-bit build). The computational time required by the simulations varies for each test system.

For the case studies, the GA was run 400 times in each system, being 100 times for each loading scenario. In each simulation, the loads can assume different values, within the range that defines the network operation scenario, causing the genetic algorithm, at the end of each simulation, to indicate different bars. Due to the stochastic nature of the GA, together with the incorporation of uncertainties in the load demand, an extensive number of simulations is necessary, favoring a more prudent evaluation of the optimal buses for the allocation of DGs in each system. The buses most indicated by the GA were selected as the optimal bus in each studied test system.

The developed program allows the user to define any number of DGs to be allocated. For the simulations, the number of machines allocated was defined to allow for a greater diversity of bus indications. In all cases studied, the number of DGs specified was 6.

For the purpose of validating the proposed method, simulations were carried out with generators allocated to the three buses most indicated by the GA in each system. Simulations were also carried out for the base cases, in which there are no DGs. The scenarios chosen for simulation were heavy and random load scenarios, as they represent more critical scenarios for the operation of the network. For each case (base and allocation) ten simulations were run and the arithmetic average of the values obtained were made (due to the consideration of randomness in the load demand), and then, finally, the results were displayed in tables for case comparison and evaluation of the method.

A. Case of Study – IEEE 13 Buses Test System

Fig. 4 presents the single-line circuit of the 13-bus IEEE system, the base topology of the system in question. This is a small feeder model with a nominal voltage of 4.16 kV for analysis in distribution systems. It is characterized by having overhead and underground lines, a voltage regulator at the substation, shunt capacitors, a transformer, high and unbalanced load.

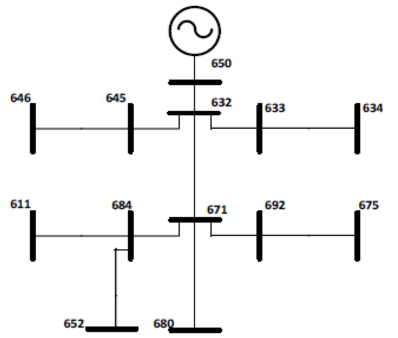
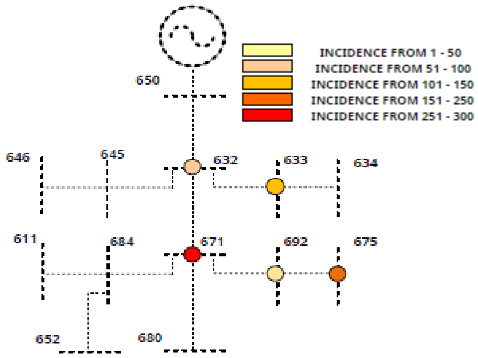
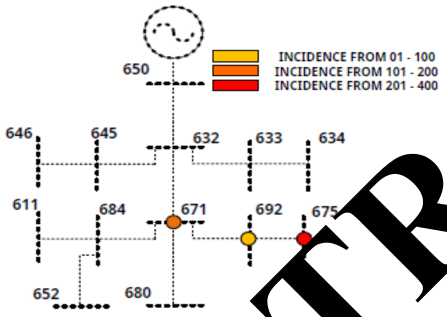


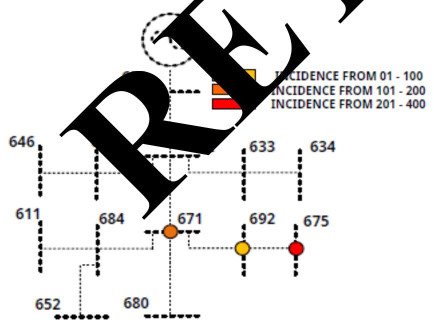
Fig. 4. IEEE 13 bus test systems.



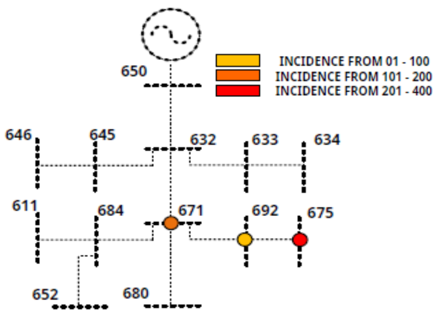
(a) Light Load)



(b) Average load



(c) Heavy Load



(d) Random load

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

In Fig. 5, the incidences of the optimal buses indicated by the GA are presented. Each of the figures corresponds to a loading scenario. Incidence means how many times a given bus was indicated as optimal. The number of incidences for each bus may vary depending on the loading scenario, the red colors show the buses that have the highest incidence and yellow the lowest.

According to the simulations results, the most appropriate buses for allocation of DGs in the IEEE 13-bus test system are 675, 671, and 692. In each loading scenario, the indicated powers vary, mainly for Light load. However, considering the other scenarios, the most indicated and selected power for each machine was 200 kW.

In Table II, it is observed that the Allocation 01 (heavy loading) and Allocation 02 (random loading) cases, which represent the optimal allocation of DGs, compared to the base cases 01 (heavy loading) and 02 (random loading), present reduction in total losses of 28.87% and 28.43%, respectively, validating the method discussed.

TABLE II: 13 BUS TEST SYSTEM: RESULTS COMPARISON

Loading condition	Scenario	Active power losses (kW)
Heavy loading	Base case without DGs	85.552
	With DGs	60.851
Random loading	Base case without DGs	109.045
	With DGs	78.042

B. Case of Study – IEEE 34 Buses Test System

Fig. 6 shows the single-line diagram of the IEEE 34-bus system. This system is a real feeder, rated at 24.9 kV and characterized by being long, lightly loaded, having two voltage regulators, a transformer to supply a short feeder section at 4.16 kV, shunt capacitors, and unbalanced loads.

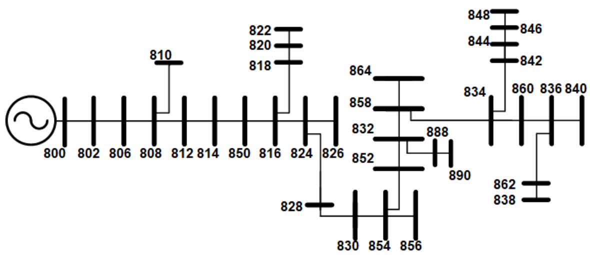


Fig. 6. IEEE 34 bus test system.

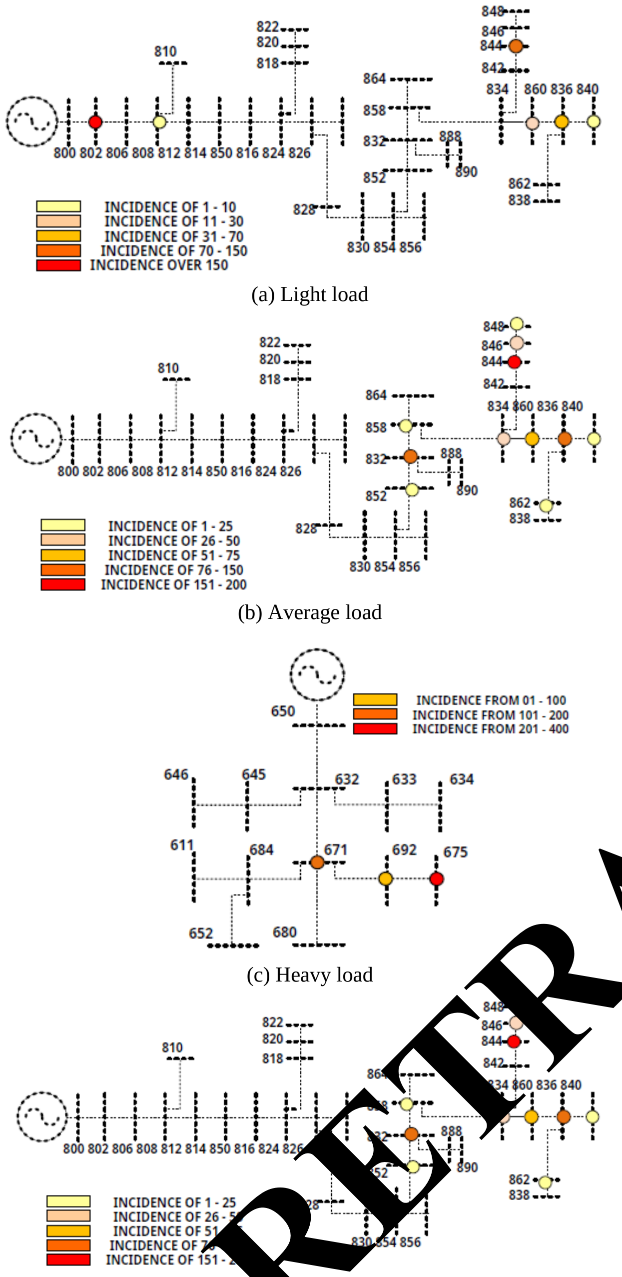
The incidences of the optimal buses indicated in the IEEE 34 bus system considering the availability of 6 DGs for allocation in the network are presented in Fig. 7.

For the simulations in this system, buses 844, 836, 832 and 860 were obtained as optimal. Again, the indicated powers vary according to the load scenario, however, considering all scenarios, the optimal power indicated for each machine was 200 kW.

The results in Table III show, as expected, a significant reduction in active losses in the network, with 56.17% for the heavy load scenario and 39.96% for the random load scenario.

TABLE III: 34 BUS TEST SYSTEM: RESULTS COMPARISON

Loading condition	Scenario	Active power losses (kW)
Heavy loading	Base case without DGs	225.78
	With DGs	98.95
Random loading	Base case without DGs	240.80
	With DGs	174.57



(a) Light load

(b) Average load

(c) Heavy load

(d) Random load

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

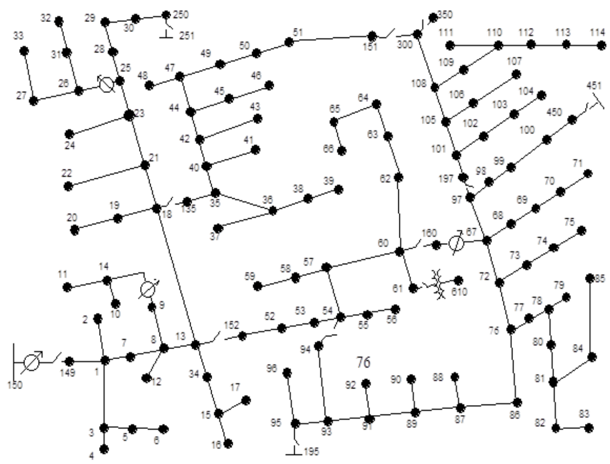


Fig. 8. IEEE 123 bus test system.

C. Case of Study – IEEE 123 Buses Test System

Fig. 8 shows the single-line of the IEEE 123 bars system, which operates at a nominal voltage of 4.16 kV, providing problems related to voltage drops that must be solved by installing equipment and actuating control devices. The system is characterized by having overhead and underground lines, voltage regulators, unbalanced loads with constant power, impedance, and current nature.

Fig. 9 and Fig. 10 show the buses indicated by the GA and their incidences for Heavy and Random load condition respectively.

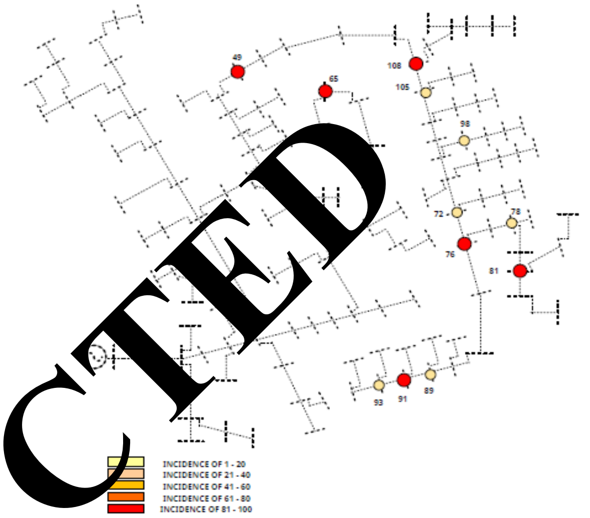


Fig. 9. Incidences of strategic buses in the IEEE 123 Buses (Heavy Load) system.

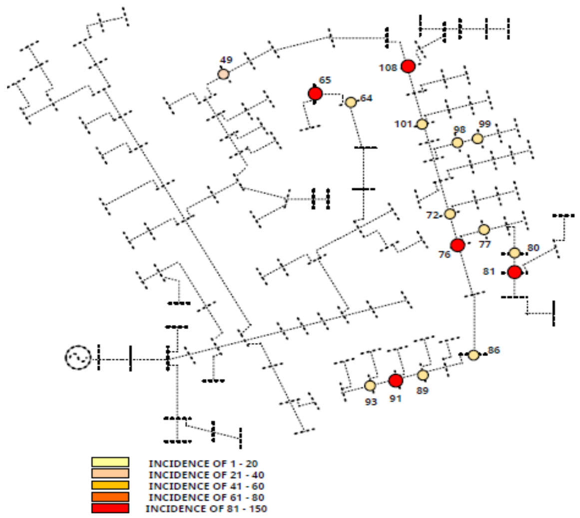


Fig. 10. Incidences of strategic buses in the IEEE 123 Buses (Random Load) system.

TABLE IV: 123 BUS TEST SYSTEM: RESULTS COMPARISON

Loading condition	Scenario	Active power losses (kW)
Heavy loading	Base case without DGs	76.91
	With DGs	51.41
Random loading	Base case without DGs	97.35
	With DGs	62.95

For the simulations carried out in the 123-bus system, the optimal buses were obtained as buses 65, 76, 49, and 108. As for the other systems studied, the indicated powers vary according to the load, being in the case of the 123 buses, the widest range of indications happening for the light load scenario. Still, considering all the simulated scenarios, the optimal power is specific and adequate for each DG for 200kW.

The results obtained in Table III, shown that for the case study system, there was a relevant reduction in total active losses in the network, with a reduction of 33.15% for the heavy load scenario and for the random load scenario of 35.33%, once again showing the effectiveness of the method in this proposed work.

V. Conclusion

In this paper, an approach for optimal allocation of distributed generators in power distribution systems using genetic algorithm has been presented. In the optimization process, the randomness of each load, as well as the system's light, medium and heavy loading conditions were considered. The objective of the optimal allocation of DGs was the minimization of total active losses, respecting the operational restrictions of the systems.

With this method, it was possible to obtain several strategic buses for the allocation of generators, observe which buses are most suitable and most appropriate for this purpose, and also which is the optimal bus (most suitable, considering all loading scenarios, including overloads) for installation of DGs. It was also possible to observe the influence of loading scenarios and demand uncertainties in the indication of the optimal buses and the power dispatched by each DG. In scenarios with light loading, the indicated powers vary more and the indications of the buses for DG installation they happen in a more dispersed way in the systems, and when the network load increases, they are concentrated in common regions of each system, more specifically at the end of the feeder branches. Another observation was that some buses that were previously indicated in some load scenarios were not indicated in others, or were indicated with a lower incidence.

The results for purposes of comparison, evaluation of the optimal installation of DGs, and their contribution to reducing losses attest to the effectiveness of the method covered with a significant reduction in losses in each system studied, allowing the installation of generators efficiently, improving the performance of the distribution systems.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Azaldo MACHAVA conducted the research and wrote the paper; Keren KABERERE and Gil VILANCULOS supervised the work; all authors had approved the final version.

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References

[1] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: A definition," *Electr. Power Syst. Res.*, vol. 57, no. 3, pp. 195-204, Apr. 2001.

[2] M. C. V. Suresh and E. J. Belwin, "Optimal DG placement for benefit maximization in distribution networks by using Dragonfly algorithm," *Renewables Wind. Water, Sol.*, vol. 5, no. 1, p. 4, Dec. 2018.

[3] H. Kuang, S. Li, and Z. Wu, "Discussion on advantages and disadvantages of distributed generation connected to the grid," in *Proc. Int. Conf. on Electrical and Control Engineering*, 2011, pp. 170–173.

[4] V. V. S. N. Murty and A. Kumar, "Optimal placement of DG in radial distribution systems based on new voltage stability index under load growth," *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 246–256, July 2015.

[5] F. C. R. Coelho, I. C. da Silva Junior, B. H. Dias, W. Peres, V. H. Ferreira, and A. L. M. Marcato, "Optimal distributed generation allocation in unbalanced radial distribution networks via empirical discrete metaheuristic and steepest descent method," *Electr. Eng.*, vol. 103, no. 1, pp. 633–646, 2021.

[6] F. C. R. Coelho, "Alocação de geração distribuída em sistemas de distribuição de energia elétrica via otimização bioinspirada na ecolocalização de morcegos," Universidade Federal de Juiz de Fora, 2013.

[7] A. W. S. Almeida, C. F. M. Toledo, and M. S. Arantes, "Optimal allocation and sizing of distributed generation for loss minimization using a multi-population genetic algorithm," in *Proc. IEEE Congress on Evolutionary Computation (CEC)*, 2020, pp. 1–7.

[8] L. W. Oliveira, F. V Gomes, E. J. Oliveira, Â. R. Oliveira, A. M. Variz, and H. A. Silva, "Power distribution systems planning with distributed thermal and wind generation," in *Proc. IEEE Eindhoven PowerTech*, 2015, pp. 1–6.

[9] M. H. Moradi, M. Abedinie, and H. B. Tolabi, "Optimal multi-distributed generation location and capacity by genetic algorithms," in *Proc. Conference Proceedings IPEC*, 2010, pp. 614–618.

[10] I. Pisica, C. Bulac, and M. Eremia, "Optimal distributed generation location and sizing using genetic algorithms," in *Proc. 15th Int. Conf. Intell. Syst. Appl. to Power Syst.*, 2009, pp. 1–6.

[11] W. Liu, P. Zhuang, H. Liang, J. Peng, and Z. Huang, "Distributed economic dispatch in microgrids based on cooperative reinforcement learning," *IEEE Trans. neural networks Learn. Syst.*, vol. 29, no. 6, pp. 2192–2203, 2018.

[12] R. K. Samala and M. R. Kotapuri, "Optimal allocation of distributed generations using hybrid technique with fuzzy logic controller radial distribution system," *SN Appl. Sci.*, vol. 2, no. 2, pp. 1–14, 2020.

[13] G. Sabarinath and T. G. Manohar, "Optimal placement and sizing of distributed generation using flower pollination algorithm for power loss reduction maximization in distribution networks," in *Proc. 2nd IEEE Proc. of Int. Conf. on Power Electronics, Intelligent Control and Energy Systems*, 2018, pp. 253–256.

[14] A. Ali, M. U. Keerio, and J. A. Laghari, "Optimal site and size of distributed generation allocation in radial distribution network using multi-objective optimization," *J. Mod. Power Syst. Clean Energy*, vol. 9, no. 2, pp. 404–415, 2020.

[15] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, "Ant lion optimization algorithm for renewable distributed generations," *Energy*, vol. 116, pp. 445–458, Dec. 2016.

[16] M. P. HA, M. Nazari-Heris, B. Mohammadi-Ivatloo, and H. Seyedi, "A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks," *Energy*, vol. 209, Oct. 2020.

[17] K. Roy, L. Srivastava, and S. Dixit, "Optimal placement and sizing of distributed generation using multi-verse optimization," in *Proc. 12th Int. Conf. Comput. Intell. Commun. Networks*, 2020, pp. 268–272.

[18] S. Kansal, V. Kumar, and B. Tyagi, "Hybrid approach for optimal placement of multiple DGs of multiple types in distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 226–235, Feb. 2016.

[19] F. S. Abu-Mouti and M. E. El-Hawary, "Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm," *IEEE Trans. Power Deliv.*, vol. 26, no. 4, pp. 2090–2101, 2011.

[20] M. F. Akorede, H. Hizam, I. Aris, and M. Z. A. Ab Kadir, "Effective method for optimal allocation of distributed generation units in meshed electric power systems," *IET Gener. Transm. Distrib.*, vol. 5, no. 2, pp. 276–287, 2011.

[21] A. Ameli, S. Bahrami, F. Khazaeli, and M. R. Haghifam, "A multiobjective particle swarm optimization for sizing and placement of DGs from DG owner's and distribution company's viewpoints," *IEEE Trans. Power Deliv.*, vol. 29, no. 4, pp. 1831–1840, 2014.

[22] I. A. Farhat, "Ant colony optimization for optimal distributed generation in distribution systems," *Int. J. Comput. Inf. Eng.*, vol. 7, no. 8, pp. 1094–1098, 2013.

[23] M. J. Kasaei and J. Nikoukar, "DG allocation with consideration of costs and losses in distribution networks using ant colony algorithm," *Majlesi J. Electr. Eng.*, vol. 10, no. 1, pp. 51-56, 2016.

[24] B. Mohanty and S. Tripathy, "A teaching learning based optimization technique for optimal location and size of DG in distribution network," *J. Electr. Syst. Inf. Technol.*, vol. 3, no. 1, pp. 33–44, 2016.

[25] M. H. Moradi, M. Abedini, and S. M. Hosseinian, "A combination of evolutionary algorithm and game theory for optimal location and operation of DG from DG owner standpoints," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 608–616, 2015.

[26] T. Sattarpour, D. Nazarpour, S. Golshannavaz, and P. Siano, "A multi-objective hybrid GA and TOPSIS approach for sizing and siting of DG and RTU in smart distribution grids," *J. Ambient Intell. Humaniz. Comput.*, vol. 9, no. 1, pp. 105–122, 2018.

[27] T. Yuvaraj, K. Ravi, and K. R. Devabalaji, "Optimal allocation of DG and DSTATCOM in radial distribution system using cuckoo search optimization algorithm," *Modelling and Simulation in Engineering*, vol. 2017, p. 11, 2017.

[28] Z. Wang and F. L. Alvarado, "Interval arithmetic in power flow analysis," *IEEE Trans. Power Syst.*, vol. 7, no. 3, pp. 1341–1349, 1992.

[29] B. Borkowska, "Probabilistic load flow," *IEEE Trans. Power Appar. Syst.*, vol. 93, no. 3, pp. 752–759, 1974.

[30] OpenDSS. [Online]. Available: https://www.epri.com/pages/sa/opendss

[31] Resources | PES Test Feeder. [Online]. Available: https://site.ieee.org/pes-testfeeders/resources/

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