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A modified and extended genetic algorithm for optimal distributed generation grid-integration solutions in direct current power grids

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ABSTRACT

The integration of distributed generation into direct current power grids presents a critical challenge in modern energy systems, as it directly impacts grid reliability, efficiency, and the successful transition to renewable energy. This study addresses the problem of optimizing distributed generation placement and sizing in direct current grids, a key issue for reducing power losses and improving energy distribution. To tackle this, a modified and extended genetic algorithm was developed, capable of handling both continuous and discrete variables simultaneously. The algorithm was tested on two standard direct current grid systems, a 21-bus microgrid and a 69-bus network. The results demonstrated significant improvements over existing methods, reducing power losses by 84.5% in the 21-bus microgrid and by 95% in the 69-bus direct current network, with notably reduced computation times. These findings indicate that the proposed algorithm not only optimizes distributed generation integration effectively but also offers superior performance compared to traditional approaches, without the need for additional methods or software. The novelty of this work lies in its ability to handle complex, nonlinear optimization problems within direct current grids using a single, efficient approach, advancing beyond previous efforts by achieving better results with fewer computational resources.

1. Introduction

In the global context of an ongoing energy transition, where nations are striving to reduce their reliance on traditional fossil fuels in favor of cleaner and more sustainable energy sources. This energy transition is critical for addressing environmental challenges, such as greenhouse gas emissions and air pollution [1]. Wind, solar, geothermal, and hydropower are essential to the energy transition, offering sustainable energy solutions. [2].

One pivotal facet of this energy transition is the integration of renewable energy sources as distributed generators (DGs) into existing energy grids. Historically, energy production and distribution relied heavily on large centralized power plants interconnected by extensive power grids. However, the emergence of DGs presents an opportunity to provide localized energy access and reduce dependence on centralized sources. Integrating these generators into AC or DC microgrids requires careful planning to ensure grid stability and reliability. DGs offer multiple advantages, including enhanced energy security, reduced losses, and improved reliability in energy generation and grid operation [3].

An effective strategy for integrating DGs into the energy grid involves the deployment of microgrids, which are small-scale networks that encompass power generation, energy storage, and diverse loads. Microgrids can operate independently or in conjunction with the main grid. Notably, DC power grids have gained prominence due to their streamlined planning and operational efficiency [4]. Unlike AC grids, DC grids eliminate the need to manage reactive power, ensuring more efficient integration of renewable energy sources [5]. Many renewables, such as solar and wind, inherently generate DC power, further facilitating seamless integration [6]. Additionally, DC networks exhibit greater resilience against issues like voltage drops and frequency oscillations, which can impact AC grids adversely. Furthermore, DC grids offer enhanced flexibility for load management and DG utilization.

Optimal DG Grid-Integration Models are mathematical tools employed to optimize the incorporation of renewable energy sources into existing electrical grids [3]. These models aim to minimize electricity generation costs or power losses while maximizing renewable energy utilization, while considering constraints like network capacity, energy demand, and grid stability [7]. Typically, these models are formulated as Mixed Integer Nonlinear Programming (MINLP) problems, as they involve both continuous and integer variables and nonlinear relationships among system components [3]. In terms of thermal processes, integrating DGs through the optimization algorithm reduces power losses, which directly impacts the heat generated in electrical components. Power loss in grid systems, especially resistive losses in conductors and conversion inefficiencies, typically manifests as heat. By minimizing these losses, the optimization algorithm contributes to lowering thermal stress on cables and power converters. Solutions derived from these

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algorithms offer valuable insights for designing future energy systems and informing energy transition policies.

Various approaches, including branch and bound [8], genetic algorithms [9], particle swarm optimization (PSO) [10], tabu search [11], population-based incremental learning (PPBIL) [7] and even machine learning approaches [12], have been applied to solve these optimization problems in AC power grids. However, the potential application of these methods in DC networks remains largely unexplored, with limited research focused on the optimal integration of DGs in DC grids [13].

In the case of DC networks, the optimal DG grid-integration models have not been fully explored [13]. The few works that have been proposed to solve the above problem can be classified into four main groups: exact MINLP methods [3], approximation-based methods [14], multi-objective approaches [15] and sequential methods [13,16]. In the first group, the authors in [3] presented solutions based on exact MINLP methods for optimal integration of DGs in DC grids. In addition, in [17] proposed a mixed-integer semidefinite programming model to tackle this problem, employing a branch and bound method for the binary components and convex optimization techniques for the nonlinear programming aspects. However, these methods include complex mathematical developments and must be used specialized software to solve the problem. The second group includes methods that apply convex approximations of the exact MINLP problem with the purpose of ensuring better quality solutions. However, they could be time-consuming, depend on the size of the given problem and a parallelization is extremely difficult. In the third group, approaches can be found that address the integration of distributed energy resources in DC networks by considering optimization problems with several objective functions. For example, the authors in [15] introduced a multi-objective version of the PSO to address technical, economic and environmental elements in the objective function. Finally, in the fourth group, different authors have proposed optimization methods based on sequential programming, which are seen as a variable-based decomposition of the MINLP problem and are called as master–slave approaches, that is, the master step addresses the problem of the location of the distributed resource, while the slave stage deals with their sizing of DGs [13]. Despite having two stages for the solution of the MINLP problem, these methods have shown to be a promising alternative for the analysis of the integration of DGs in power networks. All these methodologies have yielded significant insights into optimizing the integration of distributed generation in DC grids. However, exact MINLP methods, while guaranteeing optimal solutions, demand substantial computational resources. Conversely, multi-objective techniques can evaluate multiple criteria and produce a set of solutions (Pareto frontier). Despite this advantage, they often encounter conflicts between objectives and require specialized expertise for both their application and the interpretation of the Pareto frontier. Sequential methodologies, on the other hand, have emerged as dominant solutions due to their computational efficiency and flexibility.

Master–slave approaches can combine methods like genetic algorithms and the black hole algorithm to address the sizing of DGs in DC networks. However, these approaches may not address the challenge of determining the optimal location for these DGs [18]. On the other hand, in [13], a thorough comparison of various techniques for solving the optimal integration problem of DGs is presented. The authors explore several methods, including the genetic algorithm and vortex search algorithm, genetic algorithm and particle swarm optimization, two-phased genetic algorithm, population-based incremental learning algorithm, parallel Monte Carlo simulation, and others. In [16], the authors used a master–slave approach to optimize the operation of energy storage systems, employing the PSO algorithm in the master stage and the power flow method based on successive approximations in the slave stage. The objective function focused on reducing energy purchase costs at the main node of the electrical network. To validate the efficiency and robustness of their methodology, the authors compared its performance against three metaheuristic algorithms, also evaluating the solution's repeatability and computation times. The authors in [19] introduced a hybrid methodology combining the PPBIL algorithm and PSO. Using a master–slave structure, the PPBIL master stage determines the generator locations, while the PSO slave stage calculates their sizes, focusing on minimizing power loss within the constraints of DC grids in a distributed generation setting. Finally, Montano et al. in [20] proposed to use the arithmetic optimization algorithm and PSO algorithm to solve the optimal power flow problem in DC networks. This proposed approach produced high-quality solutions with low standard deviation. However, the overall computation time, particularly for large networks, can be longer. This is especially noticeable in scenarios where the search space becomes large due to higher DG penetration.

While previous studies have proposed various sequential methods to address this challenge, they often require specialized software or multi-step approaches, leading to longer computation times, increased complexity and involve adjusting multiple parameters, which makes it more challenging for non-experts to apply. Research on unified, population-based algorithms that can efficiently solve this problem in DC grids is still limited. Due to the foregoing, this paper proposes the use of a single, population-based algorithm, specifically genetic algorithms, underscores an innovative approach to optimizing DG integration, that is, it determines the most favorable locations and sizes for DGs within the context of DC power grids. The novel optimization technique using an extended genetic algorithm not only advances the technical integration of distributed generation into DC grids but also significantly addresses the associated thermal challenges. Genetic algorithms possess the remarkable ability to explore solution spaces with a degree of randomness while accommodating the complex interplay of both nonlinear and integer constraints. This approach can be adjusted and scaled to address problems for DC grids of different sizes and complexities, making efficient use of available computational resources. This unique methodology offers a promising solution to a complex and pressing problem. Therefore, this paper proposes to use an extended and improved version of the genetic algorithm presented in [21]. To validate the efficacy of this novel approach, two DC test networks are used: a 21-bus DC microgrid and a 69-bus DC network employed by [2]. The main contributions of this paper include the following:

- An optimal method for integrating distributed resources into DC networks is discussed.
- A novel optimization approach using genetic algorithms is introduced.
- The proposed algorithm combines discrete and continuous variables seamlessly.
- Experiments on two test systems validate the approach, showing improved resource integration.

The rest of this paper is organized as follows. Section 3 presents the mathematical modeling of the problem of optimal placement and sizing of distributed resources in DC networks by means of a MINLP problem. Then, in Section 4, the methodology based on genetic algorithms is briefly explained to solve the problem described in Section 3. Section 5 presents a discussion of the results achieved by implementing the method outlined above on various DC grids. Section 6 concludes with a summary of findings and suggestions for future research.

2. DC grid model

As previously noted, a DC grid constitutes a network encompassing renewable energy resources, energy storage systems, electric vehicles, and controlled loads, as illustrated in Fig. 1. This network is versatile, capable of operating in island mode or establishing connections with the AC network via a bidirectional AC/DC converter. The appeal of DC networks stems from the properties discussed earlier.

As highlighted by Garces in [4], these networks not only hold research significance but also offer practical utility. For instance, in [22],

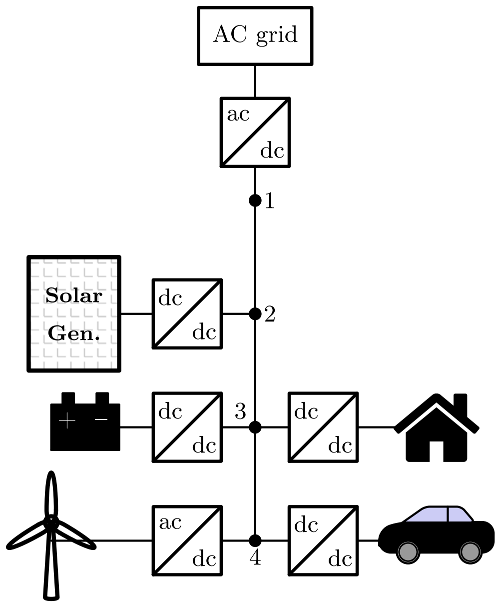

Fig. 1. DC Grid Example.

the authors introduced a Low Voltage DC distribution system featuring four-wire ground cables, developed in collaboration with Elenia Oy and ABB Oy Drives. The NASA International Space Station itself operates on two DC systems [23]. Furthermore, numerous data centers worldwide have adopted DC distribution systems, including the Duke Energy data center in Charlotte [24] and the University of California's Datacenter [25]. Given these real-world applications, it remains crucial to delve deeper into the analysis of these emerging technologies within power systems.

Let us consider a DC grid with master–slave operation, which can be represented as follows [3],

$$\mathbf{I} = V_0\mathbf{G}_0 + \mathbf{G}\mathbf{V}, \tag{1}$$

where $\mathbf{G}_0 \in \mathbb{R}^{n\times 1}$ and $\mathbf{G} \in \mathbb{R}^{n\times n}$ are nodal admittance matrices[1]; V_0 is a known voltage at the Master Terminal; $\mathbf{V} \in \mathbb{R}^{n\times 1}$ and $\mathbf{I} \in \mathbb{R}^{n\times 1}$ are the nodal voltages and currents, respectively. From the model shown in Eq. (1), the power injected to the DC grid can be computed as the product between the nodal voltages and currents, that is

$$\mathbf{P} = \mathbf{f}(\mathbf{V}) = V_0\mathbf{G}_0 \odot \mathbf{V} + \mathbf{G}\mathbf{V} \odot \mathbf{V}, \tag{2}$$

where $\mathbf{P} \in \mathbb{R}^{n\times 1}$ includes all the injected active powers, and $\odot$ is the Hadamard product (i.e. the element-wise product of matrices).

3. Mathematical modeling

Optimizing the integration of distributed resources can be achieved through a MINLP model, which is a mathematical optimization model that minimizes a nonlinear objective function while considering linear and nonlinear constraints. In this model, certain variables are restricted to integer and continuous values that correspond to the location and sizing of the resources, respectively [13]. Solving such problems is challenging due to nonlinear objectives, constraints, and integer variables, which increase computational complexity and time [3]. Based on the models proposed in the specialized literature, all agree that the objective function of this model is the reduction of power losses [13]. On the other hand, it is possible to include as restrictions: the energy balance in each system node, voltage profiles, thermal limits in the conductors, limits of power injected in the distributed generators and their locations. For this study, the model used by [13] will be closely followed, i.e., the optimal model for integrating distributed generation is given by,

$$\min P_{\text{loss}} = \min \mathbf{V}^{\top}\mathbf{G}\mathbf{V}, \tag{3}$$

$$s.t,$$

$$P_{g_i} - P_{d_i} = \sum_{j\in\mathcal{N}} G_{ij} v_i v_j, \tag{4}$$

$$v_{\min} \le v_i \le v_{\max}, \tag{5}$$

$$\left|I_{ij}\right| \le I_{ij,\max}, \tag{6}$$

$$P^{DG}_{\min_i} x^{DG}_i \le P^{DG}_i \le P^{DG}_{\max_i} x^{DG}_i, \tag{7}$$

$$\sum_{i\in\mathcal{N}} P^{DG}_i x^{DG}_i \le P^{DG}_{\max}, \tag{8}$$

$$x^{DG}_i \in \{0,1\} \tag{9}$$

where $P_{\text{loss}} \in \mathbb{R}_+$ is a real positive number that represents the active power losses in the DC network, $\mathbf{v} \in \mathbb{R}^n$ is a vector that includes all the grid nodal voltage, $\mathbf{G}_L \in \mathbb{R}^{n\times n}$ is the conductance matrix that relates all the conductive effects of the line connections. P_{g_i} and P_{d_i} are the generated and demanded power at node i, respectively. G_{ij} is the element appearing in the ith row and jth column of $\mathbf{G}_L$. $\mathcal{N}$ corresponds to the set of nodes of the grid. v_i and v_j are the nodal voltages at buses i and j, respectively. I_{ij} is the current between the nodes i and j. P^{DG}_i is the generated power by a DG connected to node i. x^{DG}_i is a binary variable that represents the location of the DGs at node i, that is, x^{DG}_i takes the value 1 if it is located at node i and 0 otherwise.

The MINLP problem described in Eqs (3) to (9) can be interpreted in the following manner: the objective of the model is to minimize active power losses, as indicated in Eq. (3), while ensuring the energy balance of the system, as specified in Eq. (4). This ensures that all the active power generated is efficiently consumed. Additionally, the voltage profile within DC networks must remain within predefined minimum and maximum limits, as denoted in Eq. (5), in order to address stability concerns within these networks [1]. Similarly, the model enforces compliance with thermal limits in the system conductors, as outlined in Eq. (6). Finally, the problem also mandates that distributed generation is dispatched only within permissible limits and is situated at appropriate system nodes, in accordance with Eqs (7) to (9). Based on the MINLP problem shown in Eqs (3) to (9), which has a convex objective function, and nonlinear and non-convex constraints associated with the energy balance, this paper uses a methodology that supports this type of constraint together with binary variables.

4. Applied methodology

To solve the MINLP problem associated to the optimal location and sizing of DGs in DC grids, this paper proposes to use a modified and extended genetic algorithm (MEGA) presented by Deep et al. in [27] to deal with integer restrictions or decision variables. The crossover operator, called Laplace crossover, uses uniform and Laplace distributions to generate new offsprings from two parents, while the mutation operator applies a power distribution to create a mutated solution within a parent's vicinity, that is,

$$y^1_i = z^1_i + \beta_i \left|z^1_i - z^2_i\right|, \tag{10}$$

$$y^2_i = z^2_i + \beta_i \left|z^1_i - z^2_i\right|, \tag{11}$$

where y^1_i and y^2_i are two off-springs generated from two parents z^1_i and z^2_i. β_i is a random variable that follows a Laplace distribution, which is computed as,

$$\beta_i = \begin{cases} a - b\log\left(u_i\right), & r_i \le 1/2, \\ a + b\log\left(u_i\right), & r_i > 1/2, \end{cases} \tag{12}$$

[1] For the DC grids analyzed here, it is considered that: the graph is connected ($\mathbf{G}$ is not singular), and the system is represented in per-unit [26].

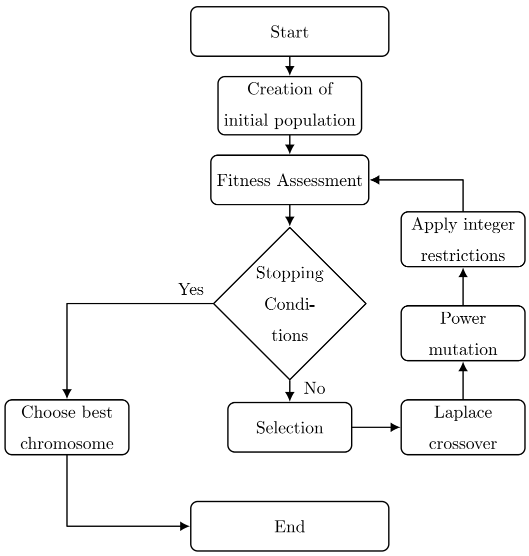

Fig. 2. Flowchart of MEGA applied to solve the MINLP problem in Eqs. (3) to (9).

where, a represents the location parameter and $b > 0$ represents the scaling parameter. u_i and r_i denote uniform random variables. In case there is an integer decision variable, $b = b_{int}$, otherwise $b = b_{real}$.

For the mutation operator, MEGA uses a power distribution to create a muted solution, that is,

$$z = \begin{cases} \bar{z} - s\left(\bar{z} - z^l\right), & t < r, \\ \bar{z} + s\left(z^u - \bar{z}\right), & t \geq r, \end{cases} \tag{13}$$

where, z represents a solution within the vicinity of a parent solution $\bar{z}$. The variable s follows a power distribution with the form $s = \left(s_1\right)^p$, where s_1 is a uniform random variable, and p corresponds to the mutation index. Finally, $t = \frac{\bar{z}-z^l}{z^u-\bar{z}}$, z^l and z^u are the lower and upper limits of the decision variable, this whole process is called power mutation. In the case of the truncation operator, MEGA applies the following rule: if z_i is a integer then $\bar{z}_i = x_i$, otherwise, $\bar{z}_i$ is equal either $\lfloor z_i \rfloor$ or $\lfloor z_i \rfloor + 1$ each with probability 0.5, where $\lfloor z_i \rfloor$ is the integer part of z_i. In MEGA, tournament selection operator is applied as reproduction operator. The MEGA application can be summarized as shown in Fig. 2.

5. Results and discussion

In order to analyze the behavior of MEGA applied to the problem of optimal DG location and sizing, two DC networks, which have been widely used in the literature, were employed. Specifically, a 21-bus DC microgrid and a 69-bus DC grid were used as presented in [13]. The 21-bus DC microgrid includes 21 buses, 20 branches and a slack bus at bus 1 as shown in Fig. 3. Base voltage and power are set to 1 kV and 100 kW, respectively. On the other hand, the 69-bus DC grid is composed by 69 buses, 68 branches and a slack bus at bus 1 as shown in Fig. 4. For this DC grid, a base voltage and a power are set to 12.66 kV and 100 kW, respectively. In the scenario of no inclusion of DGs, the active power losses are 27.6 kW and 153.84 kW for the microgrid and the 69-bus DC grid, respectively.

In order to assess the effectiveness of MEGA, its solution quality and computational time have been compared against various methodologies proposed in [13] and [19] for the optimal placement and sizing of DGs in DC networks. Grisales et al. in [13,19] employed different sequential programming approaches. For the location problem, they utilized the genetic algorithm (GA), a population-based incremental learning (PBIL) algorithm, and a parallel version of the Monte Carlo algorithm (PMC). To address the sizing problem, they employed the particle swarm optimization (PSO), black hole (BH) optimization algorithm,

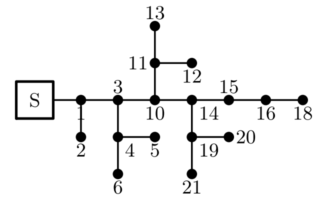

Fig. 3. 21-bus test DC microgrid.

a continuous version of the GA (CGA), and vortex search algorithm. The top 7 methods, based on the lowest power losses, were compared, i.e., from [13], GA/VSA, PIBL/PSO, PIBL/GA, PIBL/BH, PMC/PSO, GA/PSO and GA/GA have been used. With the goal of comparing these methods, the operating conditions explained by [13] have been implemented, that is, the maximum power assigned to the DGs are 150 kW and 1200 kW in the 21-bus and 69-bus test systems, respectively. In both test systems, the minimum power is set to 0 kW, while the maximum allowable distributed power generation is capped at 40% of the total power generated by the slack bus. Additionally, the voltage limits for DC grid nodes range between 0.9 pu and 1.1 pu, and the maximum branch current limits are 520 A and 335 A for the microgrid and 69-bus DC grid, respectively. Finally, the number of DGs to 3 has set, since the vast majority of solutions presented by [13] established three DG locations. All tests and simulations were conducted on an Intel Core i7 PC with a 2.1 GHz processor.

Table 1 shows the results obtained for the optimal location and sizing of DGs in the 21-bus DC microgrid and 69-bus DC grid. From Table 1, the methodology used, the sizing (active power generation) of the DG and in parentheses its optimal location are presented. Then, the value of the active power losses and computation time are found. The Table 1 also shows the value of the computation time after using each of the solution approaches. All this for the DC microgrid. Then, in Table 2, the previous results are presented but using the 69-bus DC network. From the Table 1, it can be seen that the MEGA achieved an optimal placement of DGs similar to that of GA/VSA and PIBL/BH for the 21-bus DC microgrid. However, MEGA achieved an 84.5% reduction in active power losses, outperforming the 78.5% reduction obtained by GA/VSA. Additionally, MEGA took 2.53 s to provide the optimal solution to the problem posed in this study. MEGA achieved lower computation times than those reported in [13].

On the other hand, Table 2 shows the results of the optimal placement and sizing of DGs using the 69-bus DC grid. Table 2 shows that MEGA managed to locate three DGs at nodes 18, 61 and 63 with 395.55 kW, 777.86 and 778.55 kW of active power generation, respectively. With the above solution, MEGA took 7.84 s to obtain an active power loss of 7.66 kW. That is, MEGA was able to obtain an active power losses reduction of about 95%. Although the locations of the DGs are different, MEGA obtained the best solution in terms of active power loss and computation time.

Figs. 5 and 6 show the voltage profile for the two test systems when DGs are not considered and when they are considered. The red and blue lines correspond to the system voltage profile with/without considering, respectively. As shown in these figures, the voltage profile improves with DG integration. In other words, the above notation highlights that the optimal integration of distributed resources supports the secure operation of these DC networks. This confirms the viability of using a unified approach for both location and sizing in DG optimization, a departure from the traditional multi-stage methodologies.

6. Conclusions

This paper proposed to use an extended and improved version of the genetic algorithm in order to solve the mixed integer nonlinear

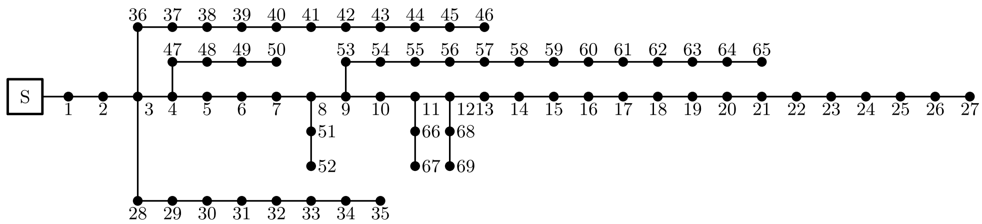

Fig. 4. 69-bus test DC network.

Table 1
Optimal DG placement and sizing in the 21-bus DC microgrid, showing power generation and losses.

Method	Power generation (kW)			P_{loss} (kW)	CT (s)
No DGs	–	–	–	27.60	–
MEGA	102.75(12)	104.13(16)	91.03(19)	**4.27**	**2.53**
GA/VSA [13]	72.46(12)	114.04(16)	46.13(19)	5.96	5.90
PPBIL/PSO [19]	73.79(12)	118.34(16)	40.50(20)	5.96	126.52
PIBL/GA [19]	81.14(12)	110.27(16)	40.46(21)	6.01	222.48
PIBL/BH [19]	86.84(12)	91.90(16)	50.46(19)	6.18	203.03
PMC/PSO [13]	32.38(8)	111.37(14)	88.88(17)	7.21	124.38
GA/PSO [19]	31.61(3)	55.46(8)	145.5(17)	8.68	238.74
GA/GA [19]	59.30(9)	134.55(11)	38.77(13)	11.1	535.23

Table 2
Optimal DG placement and sizing in the 69-bus DC grid, showing power generation and losses.

Method	Power generation (kW)			P_{loss} (kW)	CT (s)
No DGs	–	–	–	153.84	–
MEGA	395.55(18)	777.86(61)	778.55(63)	**7.66**	**7.84**
GA/VSA [13]	177.56(22)	1054.56(61)	385.12(64)	13.79	29.69
PPBIL/PSO [19]	169.58(23)	1200(61)	247.65(67)	13.84	111.53
PBIL/GA [19]	148.99(27)	1167.96(62)	294.86(65)	14.86	220.82
PBIL/BH [19]	448.52(60)	395.63(62)	296.11(65)	36.11	197.063
PMC/PSO [13]	417.23(10)	1200(63)	–	15.75	138.68
GA/PSO [19]	179.33(14)	237.90(58)	1200(62)	17.49	839.67
GA/GA [19]	446.07(59)	1170.76(63)	–	19.02	1611.72

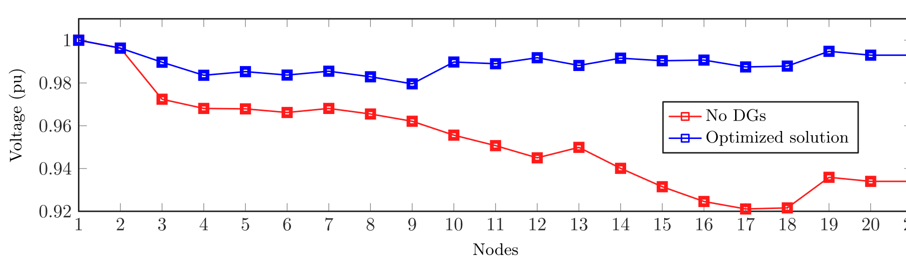

Fig. 5. Nodal Voltage profile of 21-bus DC microgrid with optimal integration of DGs. The red and blue lines correspond to the system voltage profile without considering and considering DGs, respectively.

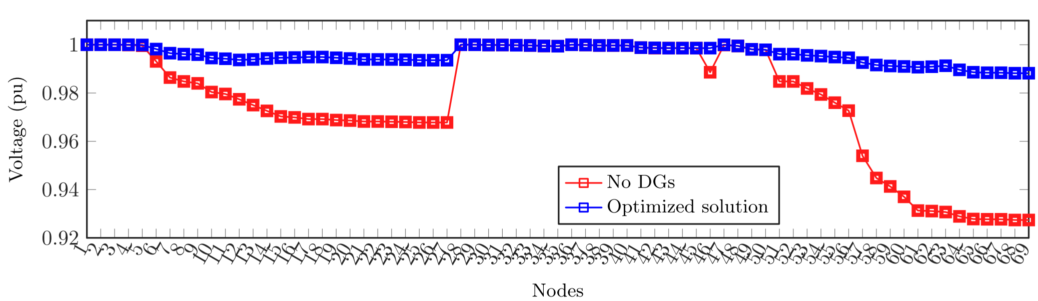

Fig. 6. Nodal Voltage profile of 69-bus DC grid with optimal integration of DGs. The red and blue lines correspond to the system voltage profile without considering and considering DGs, respectively.

programming problem associated with the optimal integration of distributed resources. Testing on two DC networks demonstrated that the proposed method surpassed traditional multi-step approaches in terms of both efficiency and computational time. Specifically, the proposed methodology achieved a reduction in active power losses of 84.5% and 95% for the 21-bus microgrid and 69-bus direct current grid, respectively. Additionally, this study demonstrated that this extended method is another alternative solution and does not require additional techniques to solve the problem. As future work, it is necessary to use systems of greater complexity, include the randomness of renewable energy sources and even analyze the performance of the technique in this type of problems applied to alternating current networks.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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