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Optimal Integration of D-STATCOMs in Radial and Meshed Distribution Networks Using a MATLAB-GAMS Interface

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Abstract: This paper proposes an interconnection of the MATLAB and GAMS software interfaces, which were designed based on a master-slave methodology, to solve the mixed-integer nonlinear programming (MINLP) model problem associated with the problem regarding the optimal location and sizing of static distribution compensators (D-STATCOMs) in meshed and radial distribution networks, considering the problem of optimal reactive power flow compensation and the fact that the networks have commercial, industrial, and residential loads for a daily operation scenario. The objective of this study is to reduce the annual investment and operating costs associated with energy losses and the installation costs of D-STATCOMs. This objective function is based on the classical energy budget and the capacity constraints of the device. In the master stage, MATLAB software is used to program a discrete version of the sine-cosine algorithm (DSCA), which determines the locations where the D-STATCOMs will be installed. In the slave stage, using the BONMIN solver of the GAMS software and the known locations of the D-STATCOMs, the MINLP model representing the problem under study is solved to find the value of the objective function and the nominal power of the D-STATCOMs. To validate the effectiveness of the proposed master-slave optimizer, the 33-node IEEE test system with both radial and meshed topologies is used. With this test system, numerical comparisons were made with the exact solution of the MINLP model, using different solvers in the GAMS software, the genetic-convex strategy, and the discrete-continuous versions of the Chu and Beasley genetic algorithm and the salp swarm optimization algorithm. The numerical results show that DSCA-BONMIN achieves a global solution to the problem under study, making the proposed method an effective tool for decision-making in distribution companies.

Keywords: GAMS computational tool; MATLAB computational tool; distribution networks; interface interconnection; distribution static compensators; sine and cosine algorithm; radial and meshed topology; minimizing annual operating costs

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1. Introduction

1.1. General Context

Currently, power distribution systems are characterized by high power losses, which are very high-power components compared to transmission lines, given the power levels used and the radial topology with which these systems are built [1,2]. Therefore, to avoid overloading the power distribution lines and take full advantage of their capacity, utilities present solutions whose implementation can be costly and time-consuming in some cases. An example of this involves system expansions through the construction of new lines. Alternatively, there are operational measures with the same objective, such as topology changes via network switching and active and reactive power flow control, among others [3].

The distribution system delivers electricity to millions of end users. In the Colombian context, electricity is supplied to medium- and small-sized sectors, i.e., with operating voltages typically between 15 and 10 kV [4]. One of the best options to reduce energy losses is distributed generation (DG). When building distribution networks, a radial topology is often used to reduce the financial costs of conductors and safety equipment. Nevertheless, their initial investment and installation costs can be very high, especially when compared to the installation of capacitor banks and strategies, such as grid reconfiguration [5]. Moreover, one of the disadvantages of distribution networks when it comes to installing capacitor banks is that it does not allow considering the daily demand of active, reactive, and customer energy for a scenario in which reactive power is injected in fixed steps [6,7].

The economic factor is important for utilities, especially regarding energy losses at the time of distribution. This can directly affect the finances of the company in charge of supervising and maintaining the system. In addition, thanks to the increase in unbilled energy, tariffs for the service's end users can be increased to compensate for economic losses. In Colombia, the energy losses of the electricity system are between 1.5% and 2.0% of the total energy produced. In medium-sized grids, energy losses can vary from 5% to 18% [2]. According to the regulating bodies, loss levels below 10% correspond to networks where maintenance has been carried out simultaneously with device replacements, and scores above 10% are associated with poor management of distribution systems [2].

1.2. Motivation

In recent years, power electronics-based compensation has become essential to solving the problems of shunt capacitor-based compensation devices [8,9]. These devices are known as static power compensators (D-STATCOMs). The main characteristics of these compensators include the injection of variable reactive power due to the variation in amplitude and phase angle regarding the connected network. All of this is associated with the behavior of the demand [10]. These devices are placed at the network nodes to significantly reduce network losses. However, proper integration is necessary when determining their sizing and location in order to reduce network losses. Some of the advantages of implementing D-STATCOMs in a distribution network are: (i) low cost, (ii) high reliability, and (iii) long lifespans (between 5 and 15 years) [11]. For this reason, in this document, D-STATCOMs are integrated into AC distribution networks with radial and meshed topologies, aiming to reduce the operating costs of the system, i.e., the costs of purchasing power at the slack node or substation, together with the costs of installation, operation, and maintenance of the D-STATCOMs.

Similarly, to find a solution, this research proposes a reduction in the total operating costs of AC distribution systems with radial and meshed topologies when integrating D-STATCOMs, which is achieved through the application of a discrete version of the sine-cosine algorithm (DSCA), in conjunction with the BONMIN solver, considering the behavior of the end users' demand curve. Most distribution networks have radial topologies, except for a small percentage with meshed topologies, which implies large voltage drops and power losses due to their high resistance/reactance ratio [12]. This, together with the fast-growing demand and the slow expansion of the electricity system, has generated a series of inconveniences in distribution systems as a sector, as well as for the end users of the system [13,14]. To find an adequate solution to these problems, it is of vital importance that, in addition to the existing infrastructure, control devices can be integrated to offer a technical-economic solution via the implementation of a structured system, as is the case of the incorporating D-STATCOMs into distribution systems. This arises from the need to increase efficiency through effective control of network power, as the optimal allocation of these devices maximizes load capacity, minimizes power losses, compensates for reactive power, and improves stability and power quality [15].

Integrating D-STATCOMs is a key solution to improve the performance of distribution systems with radial and meshed topologies. However, the best location for installing these devices must be first identified, as well as the right size, in order to reduce the existing issues of distribution networks. This makes the network more effective by increasing the network capacity and system reliability.

1.3. Literature Review

Different methods and proposals for integrating D-STATCOMs into AC distribution networks have been presented in the literature. In 2012, the authors of [16] presented a combination of a genetic algorithm and particle swarm optimization to minimize power losses in the network and improve voltage regulation and stability within the framework of system operation and security restrictions in radial distribution systems. In the same year, the authors of [17] proposed a mathematical model represented by an MINLP algorithm, which was implemented in test systems of 33 and 69 nodes. After comparing the results with those of different methods described in the scientific literature, their approach showed superior efficiency and accuracy in terms of power loss reductions.

The authors of [18] worked on an optimization algorithm for ant colonies, which integrates a fuzzy technique with several objectives. This article proposed the implementation of PV sources and D-STATCOMs in the IEEE 33-node system, in which these devices are reconfigured and assigned to meet the objectives of improving voltage profiles and minimizing grid losses. In the same year, the authors of [19] proposed the reduction of power losses in radial networks using a heuristic method based on power loss and voltage metrics for the optimal placement and sizing of D-STATCOMs in radial networks. Nevertheless, the authors only considered the most demanding conditions for the 33-node system when performing the computational validations.

In [12], the authors presented a combination between a second-order cone-based mathematical programming method and a genetic algorithm for sizing and locating D-STATCOMs in distribution networks. They made use of commercial, industrial, and residential demand curves in the IEEE 33 and 69 test systems, demonstrating the efficiency of the proposed methodology in comparison with the solution of the model in the GAMS software. The authors of [20] aimed to determine the optimal sizing and positioning of D-STATCOMs in distribution networks through an optimization method based on a multi-objective particle swarm algorithm. The study aimed to stabilize the voltage index and load factor, as well as to minimize the active losses in the distribution network. It should be noted that the method considered the possibility of adapting the network for different demand conditions, and the algorithm only works under load conditions. Therefore, when working with the maximum load, the D-STATCOMs can be oversized. Finally, the authors of [21] modified the sine-cosine algorithm to minimize power losses and improve voltage profiles.

In 2021, the authors of [10] addressed the D-STATCOMs integration problem by applying a discrete-continuous version of the Chu and Beasley genetic algorithm. This work aimed at minimizing the total annual operating costs associated with the power losses and installation costs of D-STATCOMs. Numerical results in the 33-node test system with both radial and meshed topologies demonstrated the efficiency and robustness of the proposed methodology when compared to other methods reported in the literature. In the same year, reductions in investment and operating costs were achieved via the discrete-continuous vortex search algorithm [22], genetic algorithms, conic programming [23], and the solution of the exact MINLP model in GAMS software [24]. In 2022, the authors [25], by means of second-order conic mixed-integer programming, sought to minimize energy losses and reduce investment and operating costs.

A summary of the implemented algorithms, methodologies, and objective functions, along with their year of publication, can be found in Table 1.

Table 1. Overview of methodologies used in the literature for sizing and locating D-STATCOMs.

Method/Algorithm	Objective Function	Year	Ref.
Genetic algorithm	Minimization of power losses	2011	[26]
Artificial neural networks	Mitigation of voltage sags under faults	2012	[27]
Immune algorithm	Minimization of power losses and reduction of investment and operating costs	2014	[28]
Particle swarm optimization	Minimization of power losses and voltage profile improvement	2014	[29]
Ant colony optimization	Minimization of power losses and voltage profile improvement	2015	[18]
Sensitivity indices	Minimization of power losses and voltage profile improvement	2015	[30]
Harmony search algorithm	Minimization of power losses	2015	[31]
Heuristic search algorithm	Minimization of power losses	2016	[32]
Imperialist competitive algorithm	Minimization of energy costs and voltage profile improvement	2017	[33]
Discrete-continuous vortex search algorithm	Investment and operating costs reduction	2017	[34]
Modified crow search algorithm	Reducing line losses, maximizing economic benefits, improving voltage profiles, and reducing pollution levels	2018	[35]
Particle swarm optimization	Reduction of power losses and voltage profile improvement	2019	[20]
Hybrid analytical-coyote	Minimization of active power losses and voltage profile improvement	2019	[36]
Modified sine-cosine algorithm	Minimization of power losses and voltage profile improvement	2020	[37]
Discrete-continuous vortex search algorithm	Reduction in investment and operating costs	2021	[2]
GAMS software for the solution of the exact MINLP model	Reduction in investment and operating costs	2021	[38]
Mixed-integer second-order conic programming	Minimization of power losses and reduction of investment and operating costs	2022	[25]

Note that the objective functions of most methodologies in Table 1 were to minimize power losses and reduce investment costs. The metaheuristic nature of the methodologies can also be highlighted, as is the case of genetic algorithms, which improve the adaptation probability of each individual, thus improving efficiency; that of the immune algorithm, which improves efficiency by protecting the host from negative selection, thus making it able to regroup; and that of particle swarm optimization, ant colony optimization, and the modified crow search algorithm, which are based on the behavior of living beings and their mechanism for biological evolution. Moreover, the harmony search, heuristic search, and imperialist competitive algorithms must all compare multiple solutions that are found in different ways. In the current literature, it is common to use combinatorial optimization methods to solve the problem regarding the optimal location and sizing of D-STATCOMs in distribution networks. This research proposes a newly developed, mathematics-inspired combinatorial methodology, together with the use of the GAMS software, within the framework of master-slave optimization.

1.4. Contributions and Scope

To find a strategy that allows reducing the computational resources and time required to carry out an optimization process, the idea is to communicate two specialized software applications in order to achieve an optimal global solution. As shown above, several optimization methods have been implemented to solve the D-STATCOMs sizing and placement problem. However, most of these solutions can get stuck in local optima, which is why this study implements an optimization methodology that connects the GAMS and MATLAB software interfaces through a master-slave methodology. The benefits of this methodology include the fact that the D-STATCOM's placement and sizing problems can be staged. The master stage, which uses the DSCA to solve the D-STATCOMs placement problem, is programmed in MATLAB software. Then, using the BONMIN solver in the GAMS software and the locations provided by the master stage, the mathematical model that represents the problem are solved, finding the optimal size of the D-STATCOMs and the value of the objective function that meets all the technical-operating conditions of the system. Listed below are the main contributions of this research article:

i. A complete description of the mathematical formulation representing the problem under study while considering different load types in a daily operation scenario.
ii. The implementation of a new optimization methodology that uses MATLAB and GAMS software interfaces in order to find the optimal global solution to the problem of sizing and locating D-STATCOMs in electrical distribution networks with a meshed or radial topology.
iii. A new form of the master-slave method to solve the mathematical model representing the studied problem. In the master stage, MATLAB software is used as a tool to develop the discrete version of the sine-cosine algorithm, with the aim of determining the locations of the D-STATCOMs. In the slave stage, the GAMS software is used to solve the MINLP model that represents the problem, thus finding the nominal power of the D-STATCOMs and the total annual operating costs of the network.

The advantages of the proposed research should be highlighted, given the benefits of these optimization methods for solving optimization problems that belong to the family of MINLP models. A novel interface between MATLAB (which uses the sine-cosine algorithm) and GAMS (which solves the nonlinear programming model for each combination of binary variables) is proposed. Moreover, the numerical results of this research study can be considered a new reference to the problem regarding the location and sizing of D-STATCOMs and their implementation in electrical distribution networks.

Finally, it is worth mentioning some aspects not considered in the article, such as demand uncertainty and simulation times. Moreover, the period of analysis of this study is one year, in which three types of sectors is considered (industrial, commercial, and residential) for two types of configurations (mesh and radial).

1.5. Document Structure

In this article, Section 2 presents the mathematical formulation associated with the problem of integrating D-STATCOMs in power grids, with the objective function of minimizing the total annual costs of operation. Section 3 presents the implemented MATLAB-GAMS interface. This interface was developed using a master-slave methodology that combines DSCA and the GAMS BONMIN solver. Section 4 presents the main characteristics of the 33-node test systems with a radial and meshed configuration, the daily demand curves for different zones (i.e., commercial, industrial, and residential), and the parameter information needed to determine the value of the objective function. Section 5 analyzes the results obtained, as well as the convergence of the proposed methodology. Finally, Section 6 presents the conclusions and future research derived from this work.

2. Mathematical Formulation

This section introduces the mathematical model that represents the problem regarding the sizing and placement of D-STATCOMs in meshed or radial power distribution systems. As this problem contains discrete variables (i.e., the location of D-STATCOMs at specific nodes) and continuous variables (i.e., the size of the D-STATCOMs), it can be expressed with a mixed-integer nonlinear programming (MINLP) model [38]. Additionally, the sum of the costs of energy losses during a whole year of operation and the annualized investment costs associated with installing the D-STATCOMs are considered the objective function. The investigated problem is shown below.

2.1. Formulation of the Objective Function

To solve the optimization problem, an objective function, i.e., the annualized costs function of the energy losses (f_1) and the annualized investment costs function of the D-STATCOMs (f_2), are determined via Equations (1) and (2), respectively.

$$f_1 = C_{kWh} T \sum_{h \in \mathcal{H}} \sum_{k \in \mathcal{N}} \sum_{m \in \mathcal{N}} Y_{km} V_{kh} V_{mh} \cos(\delta_{kh} - \delta_{mh} - \theta_{km}) \Delta h, \tag{1}$$

$$f_2 = T\left(\frac{k_1}{k_2}\right) \sum_{k \in \mathcal{N}} \left(\alpha\left(Q_k^{DS}\right)^2 + \beta Q_k^{DS} + \gamma\right) Q_k^{DS}, \quad (2)$$

where C_{kWh} is the average cost per kWh; T is a constant related to the study period (i.e., 365 days); Y_{km} is the admittance magnitude of the line linking nodes m and k with an angle θ_{km}; V_{kh} and V_{mh} are the voltages related to nodes m and k in period h with angles δ_{kh} and δ_{mh}, respectively; δ_h corresponds to the period in which the electrical variables are assumed to be constant (i.e., 1 h); k_1 refers to the annualized investment costs constant; and k_2 is the D-STATCOM lifetime constant. The parameters α, β, and γ are continuous and positive, and they represent the variable installation costs of a D-STATCOM of nominal power Q_k^{DS}. Finally, $\mathcal{H}$ and $\mathcal{N}$ are the sets containing all the network periods and nodes, respectively. To obtain the general objective function of problem (3), the algebraic sum of Equations (1) and (2) is performed.

$$\min \ A_{cost} = f_1 + f_2, \quad (3)$$

with A_{cost} being the predicted annual costs of the distribution network, which depend on the installation costs and the power losses of the D-STATCOMs. The objective function denoted in (3) and its two components f_1 and f_2 are defined in (1) and (2), respectively, both of which are nonlinear and non-convex functions of the main decision variables. f_1, due to the presence of products between tensions and trigonometric functions, is nonlinear and non-convex [39].Similarly, f_2 is nonlinear, and because it has a cubic function in its formulation, it is non-convex [40].

2.2. Set of Constraints

The constraints of the problem regarding the sizing and location of D-STATCOMs in distribution networks are related to the main operating limits of the system, such as the balance of reactive and active power, the voltage control limits, and the power limits that can be provided by D-STATCOMs, among others. Equations (4)–(8) define the constraints of the problem studied in this article.

$$P_{kh}^g - P_{kh}^d = \sum_{k \epsilon \mathcal{N}} \sum_{m \epsilon \mathcal{N}} Y_{km} V_{kh} V_{mh} \cos(\delta_{kh} - \delta_{mh} - \theta_{km}), \{\forall k \in \mathcal{N}, h \in \mathcal{H}\}, \quad (4)$$

$$Q_{kh}^g + Q_k^{DS} - Q_{kh}^d = \sum_{k \epsilon \mathcal{N}} \sum_{m \epsilon \mathcal{N}} Y_{km} V_{kh} V_{mh} \sin(\delta_{kh} - \delta_{mh} - \theta_{km}), \{\forall k \in \mathcal{N}, h \in \mathcal{H}\}, \quad (5)$$

$$V_{min} \le V_{kh} \le V_{max}, \{\forall k \in \mathcal{N}, h \in \mathcal{H}\}, \quad (6)$$

$$Z_k Q_{min}^{DS} \le Q_k^{DS} \le Z_k Q_{max}^{DS}, \{\forall k \in \mathcal{N}\}, \quad (7)$$

$$\sum_{k \in \mathbb{N}} Z_k \le N_A^{DS}, \quad (8)$$

where P_{kh}^g is the active power injected in period h by a standard generator connected to node k; Q_{kh}^g is the reactive power injected by a conventional generator connected to node k in period h; P_{kh}^d is the active power demanded during period h by the loads connected to node k; Q_{kh}^d is the reactive power demanded during period h by the loads connected to node k; Q_k^{DS} is the reactive power generated by the D-STATCOM at node k; V_{min} is the minimum voltage at the system nodes; and V_{max} is the maximum voltage at the system nodes. A binary variable is defined for whether a D-STATCOM is connected at node k, Z_k ($Z_k = 1$) or not ($Z_k = 0$). Finally, N_A^{DS} is the number of D-STATCOMs available for installation.

2.3. Model Interpretation

In Equations (1)–(8), the mathematical model is described, which includes continuous variables related to the magnitudes, angles of voltages, and active and reactive power production. This is a MINLP model that includes binary variables associated with the placement of the D-STATCOMs in the network. In addition, due to active and reactive power balance constraints and the trigonometric functions and voltage products, this model is nonlinear [2].

To understand the MINLP model described in Equations (1)–(8), some aspects must be clarified. Equation (3) describes the total costs of one year of operating the distribution network, which consists of Equation (1), representing the yearly cost of power purchased at conventional generation node terminals, and Equation (2) expresses the costs of installing the D-STATCOMs. Equations (4) and (5) are observed for each node and period of the reactive and active power balance. Variable Q_k^{DS} is considered in Equation (5), which injects the reactive power of the D-STATCOMs positioned at the nodes. It is essential to clarify that the power varies as a function of the daily demand curve. As imposed by the regulatory authorities of the electricity sector [41], (6) is the inequality that defines, for each node, the lower and upper voltage limits of each period. The nominal reactive power limits for each D-STATCOM and variable Z_k, which is binary, indicate whether the D-STATCOM is located at node k. This is observed in constraint (7). The limit of D-STATCOMs installed in the grid is defined by inequality (8), where N_A^{DS} is the maximum number of D-STATCOMs allowed.

3. Proposed Hybrid Optimization Approach

A master-slave methodology is employed in this study to solve the D-STATCOM's optimal placement and sizing problem. This methodology uses an interface connection that involves GAMS and MATLAB as the basis of operation. The master stage proposes the implementation of a discrete version of the sine-cosine algorithm in MATLAB software. The DSCA is responsible for defining the locations where the available D-STATCOMs will be installed. In the slave stage, the GAMS software uses the known locations to determine the nominal power of each D-STATCOM, which is defined via Equations (4)–(8), as well as to find the value of the objective function given in Equation (3).

3.1. Master Stage: DSCA

The DSCA, a metaheuristic optimization technique, explores and exploits the solution space using trigonometric sine and cosine functions whose amplitude varies over a number of iterations [42]. One of the key features of the DSCA is that it is a population-based optimization technique, so the optimization process starts with random solutions. This set is repeatedly evaluated using an objective function and improved by applying a set of evolution rules, which are shown below.

3.2. Initial Population

The initial population of individuals in the DSCA takes the structure shown in (9):

$$X^t = \begin{bmatrix} X_{11}^t & X_{12}^t & \cdots & X_{1N_v}^t \\ X_{21}^t & X_{22}^t & \cdots & X_{2N_v}^t \\ \vdots & \vdots & \ddots & \vdots \\ X_{N_i1}^t & X_{N_i2}^t & \cdots & X_{N_i,N_v}^t \end{bmatrix} \tag{9}$$

In Equation (9), it is observed that X^t is the population of individuals at iteration t, N_i is the number of individuals that make up the population, and N_v is the variable number or the size of the solution space for this study—it is the total number of D-STATCOMs to be deployed in the grid (N_A^{DS}). To create the initial population of individuals (10), a matrix of discrete random numbers within the lower and upper bounds defined for the D-STATCOM placement problem is employed.

$$X^0 = round(y_{\min} ones(N_i, N_v) + (y_{\max} - y_{\min}) rand(N_i, N_v)) \tag{10}$$

Equation (10) considers $ones(N_i, N_v)$ to be an array of ones in matrix form. $rand(N_i, N_v)$ is a matrix of random numbers between 0 and 1 generated from a uniform distribution.

$round()$ is a function that rounds each population element to the nearest integer. Finally, $y_{\min}$ and $y_{\max}$ are vectors representing the lower and upper bounds of the decision variables associated with the location of the D-STATCOMs at the demand nodes.

Finally, each individual of the population in the objective function has to be evaluated by the slave stage. At this point, the best solution is chosen as the best individual found so far (i.e., X_{best}^t).

3.3. Evolution Criteria

The DSCA is designed to evolve while considering a simple sine-cosine rule, where there is a 50% probability of evolving with the sine function and a 50% probability of evolving with the cosine function, as shown in Equation (11) [42]. With this equation, it is possible to create new descendant individuals P_i^{t+1} from X_{best}^t.

$$P_i^{t+1} = \begin{cases} round(X_i^t + r_2 \sin(r_3)|r_4 X_{best}^t - X_i^t|) & \text{if } r_1 < 0.5 \\ round(X_i^t + r_2 \cos(r_3)|r_4 X_{best}^t - X_i^t|) & \text{if } r_1 \geq 0.5 \end{cases} \tag{11}$$

In Equation (11), P_i^{t+1} is the value obtained by the evolutionary method. It is a possible solution that can substitute X_i^t. Parameter r_1 is a constant number from 0 to 1, which ensures the equivalence of the transformation between the sine and cosine trigonometric functions [43]. Parameter r_2 is a variable that determines where the resulting new individual should move, i.e., the closest possible to the best solution P_{best} in the solution space [43], as shown in (12).

$$r_2 = a - t\frac{a}{t_{max}} \tag{12}$$

In Equation (12), t is the current iteration, t_{max} is the maximum number of iterations, and a is a constant used for this article, with a value of 2, as recommended in [43]. r_3 is a random number between 0 and 2π that determines how far or how close the new potential solution moves with regard to the current best solution [43]. Finally, r_4 is a random number between 0 and 1.

3.4. Updating the Individuals

Finally, an individual X_i^t from the current population is replaced if and only if the value of the objective function of a potential individual P_i^{t+1} is smaller (i.e., minimization problem); otherwise, this individual remains in the population. This behavior is reflected in (13).

$$X_i^{t+1} = \begin{cases} P_i^{t+1} & \text{if } F(P_i^{t+1}) < F(X_i^t) \\ X_i^{t+1} & \text{otherwise} \end{cases} \tag{13}$$

In Equation (13), $F(\cdot)$ represents the objective estimate of an individual in the slave stage. Once the individuals in the population have been updated, the best individual in the new population X^{t+1} is taken as X_{best}.

Algorithm 1 summarizes the DSCA's implementation to solve the D-STATCOM location problem. The first thing to do is store the information related to the optimization problem so that the initial report is generated from Equation (9). In line three, the time must be set to zero so that the value of the objective function of each individual in the slave stage can then be evaluated with the aim of selecting the best solution. However, in line six, by making the time equal to one so that the values are generated, the power of each individual is determined according to Equation (11), and the value of the objective function of the potential individual in the slave stage is evaluated. This process and the previous one are carried out to compare the results, and if a better solution is found, it is replaced, with the last value being the best solution obtained so far. Thus, the individual is retained in the population.

Algorithm 1: Pseudo-code for the proposed DSCA approach in optimization problems.

Data: The information related to the optimization problem is stored, as well as the DSCA criteria; Generate the initial information from Equation (9);
Do $t = 0$;
Evaluate the value of each individual's objective function in the slave stage;
Select the best solution from the population as X^t_{best};
for $t = 1 : t_{max}$ **do**
    for i=N_i **do**
        Generate the values r_1, r_2,r_3, and r_4;
        Determine the potential individual P_i^{t+1} from Equation (11);
        Evaluate the objective function value of the potential individual in the slave stage;
        if $F(P_i^{t+1}) < F(X_i^t)$ **then**
            Replace the individual in the population with the potential individual;
        else
            Retain the individual in the population;
        Select the best solution from the new population as X_{best};
Result: Take X_{best} as the result and solution for the optimization problem.

3.5. Slave Stage: GAMS

The GAMS software specializes in design for modeling real-world optimization problems in a simple programming language. This software executes linear, nonlinear, and mixed-integer optimization problems, finding solutions of excellent quality solutions with reduced processing times and low standard deviations, sometimes reaching the optimal solutions to the problem [44]. This computational tool offers the user an interface to easily enter the mathematical model of the problem, giving the user a choice between different solvers and displaying the model's behavior and the resulting variables. Thus, it allows the user to obtain the result of a robust mathematical model in a few seconds through mathematical operations and iterations. One of the advantages of this software is that it makes it easy for the user to check the progress of the answer by comparing the initial solution with the final one.

The objective of the slave stage executed by the GAMS software is to evaluate the optimization model using the locations generated by the DSCA in order to determine the sizes of each D-STATCOM and, with these two parameters, to evaluate the objective function, which is fitted to the constraints according to Section 2. After this operation, GAMS returns the total cost associated with the objective function, and this value is sent to MATLAB as an input parameter when executing the DCSA.

3.6. Interface Connection

To link the interfaces of the two applications, file compatibility between the two programs must be considered. In this sense, the Excel software is used as an intermediate stage to ensure an effective exchange of information between MATLAB and GAMS, so the linking of the interfaces is performed through files in *.xlsx* format, in which the data necessary for the evaluation of the MINLP mathematical model defined in Section 2 are sent and received. However, as shown in Figure 1, it is necessary to use a function that allows the reading and writing of these files in the software.

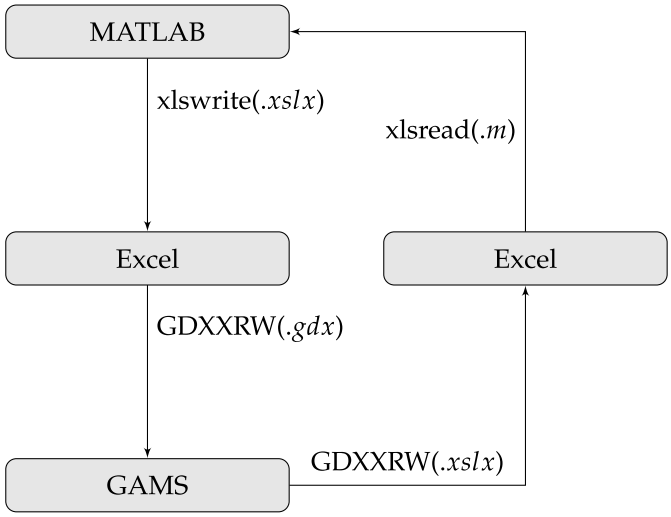

Figure 1. Diagram of the information exchange in the MATLAB–GAMS interface.

The GAMS software uses the GDXXRW feature, which allows reading and writing Excel spreadsheets [45], as well as a *.gdx* file extension to read multiple data ranges in *.xslx* format. Conversely, this function allows writing these data in *.xslx* format from the GAMS software for further processing in Excel. With MATLAB, the xlswrite and xlsread functions are used. The former allows writing data with the *.m* extension in the Excel files used to write the D-STATCOM locations. The latter function allows reading the *.xlsx* file in MATLAB. This function is used to read the value of the objective function resulting from the optimization carried out in GAMS [45]. One of the advantages of this information exchange is that the connection between the two interfaces allows *.xlsx* and *.csv* files to be executed so that large amounts of data can be processed in reduced computation times. However, it should be noted that the GDXXRW function is only available for devices running the Windows operating system [45].

Figure 1 summarizes the methodology used in this research, depicting the duty cycle based on the implemented methodology. The MATLAB computational tool performs the function of evaluating the objective function associated with the total costs, as described in Equation (3) within the DSCA and, as a result, it generates the initial locations of the D-STATCOMs, which are sent to the Excel tool to be later read by GAMS. Afterward, the locations are evaluated, taking into account the constraints in terms of optimal power flow, power balance, and reactive power injected by the D-STATCOMs and the new value of the objective function, which is then sent to an Excel file to be read by MATLAB, which restarts the process and evaluates the number of iterations.

4. Test Systems

To apply the methodology of this case study, a 32-node, 32-line grid distribution network, referred to as the IEEE 33-node system, was tested. This system has a 12.66 kV voltage at the substation node, an active power consumption of 3715 kW, and a reactive power of 2300 kvar at its peak hour. In addition, the total network losses during the peak hour are 210.9876 kW [2]. For this study case, the distribution system was divided into three different zones: (i) commercial zone (red), (ii) industrial zone (blue), and (iii) residential zone (green). Similarly, this test system's radial and meshed versions were considered to solve the D-STATCOM placement and sizing problem. Figures 2 and 3 show the electrical diagram of the IEEE 33-node test system in its radial and meshed versions [46], respectively. Note that, for the case of the meshed network, nodes 12, 18, 22, 25, 29, and 33 are active, thus forming closed cycles.

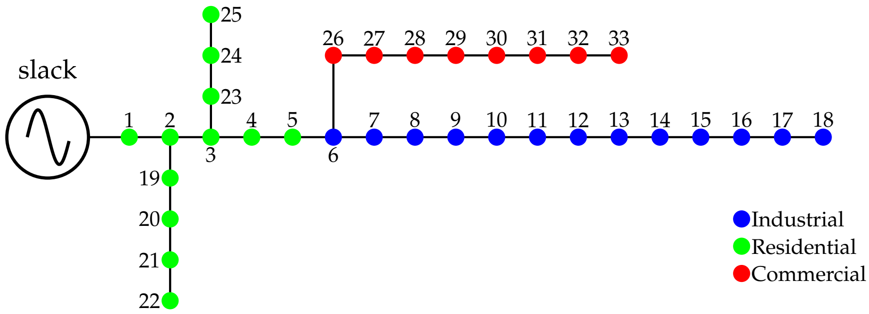

Figure 2. Electrical diagram of the IEEE 33-node radial test system.

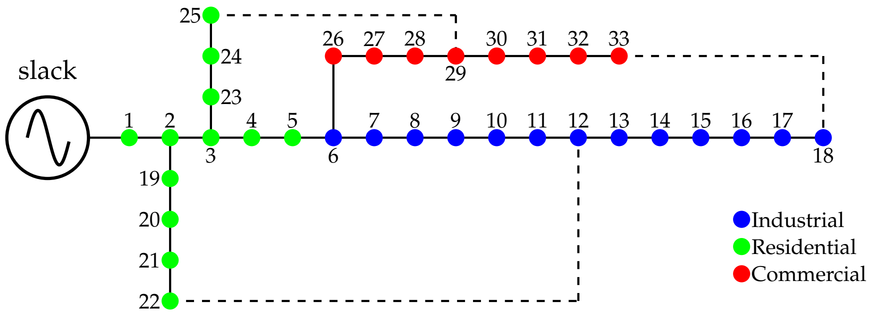

Figure 3. Electrical diagram of IEEE 33-node meshed test system.

Table 2 provides the resistance and reactance values of the distribution lines, as well as the demand of bus j, which make up this 33-bus IEEE test system. Note that the values of the active and reactive power correspond to the peak values.

Similarly, Table 3 shows the electrical parameters of the distribution lines that allow the test system to be connected in a meshed topology (dotted lines).

As mentioned above, the proposed networks (Figures 2 and 3) have three zones with different load types, so each of these areas has a different daily demand curve. Figure 4 contains the daily demand data for these load types.

Finally, Table 4 presents the parameters used to evaluate the objective function in Equation (3). In addition, the basic voltage and power data of the grid are shown. A number of these values are taken from [2].

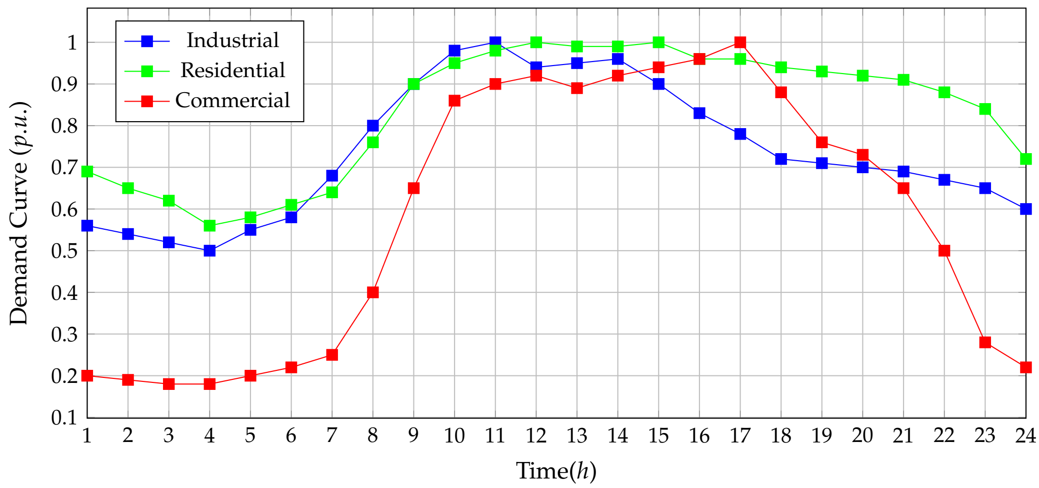

Figure 4. Load curves: industrial, commercial, and residential.

Table 2. Electrical parameters for the 33-bus IEEE network with a radial structure.

Bus i	Bus j	R_{ij} (Ω)	X_{ij} (Ω)	P_j (kW)	Q_j (kvar)
1	2	0.0922	0.0477	100	60
2	3	0.4930	0.2511	90	40
3	4	0.3660	0.1864	120	80
4	5	0.3811	0.1941	60	30
5	6	0.8190	0.7070	60	20
6	7	0.1872	0.6188	200	100
7	8	1.7114	1.2351	200	100
8	9	1.0300	0.7400	60	20
9	10	1.0400	0.7400	60	20
10	11	0.1966	0.0650	45	30
11	12	0.3744	0.1238	60	35
12	13	1.4680	1.1550	60	35
13	14	0.5416	0.7129	120	80
14	15	0.5910	0.5260	60	10
15	16	0.7463	0.5450	60	20
16	17	1.2890	1.7210	60	20
17	18	0.7320	0.5740	90	40
2	19	0.1640	0.1565	90	40
19	20	1.5042	1.3554	90	40
20	21	0.4095	0.4784	90	40
21	22	0.7089	0.9373	90	40
3	23	0.4512	0.3083	90	50
23	24	0.8980	0.7091	420	200
24	25	0.8960	0.7011	420	200
6	26	0.2030	0.1034	60	25
26	27	0.2842	0.1447	60	25
27	28	1.0590	0.9337	60	20
28	29	0.8042	0.7006	120	70
29	30	0.5075	0.2585	200	600
30	31	0.9744	0.9630	150	70
31	32	0.3105	0.3619	210	100
32	33	0.3410	0.5302	60	40

Table 3. Additional electrical parameters for the 33-bus IEEE network with a meshed structure.

Bus i	B j	R_{ij} (Ω)	X_{ij} (Ω)
12	22	2	2
18	33	0.5	0.5
25	29	0.5	0.5

Table 4. Data on the D-STATCOM parameters for calculating the investment costs.

Parameter	Value	Unit	Parameter	Value	Unit
C_{kWh}	0.139	USD-kW/h	T	365	days
Δ_h	1	h	α	0.3	USD/Mvar^3
β	-305.1	USD/Mvar^2	γ	127.380	USD/Mvar
N_A^{DS}	3	-	ΔV	± 10	%
$Q_{\min}^{DS}$	0	kvar	$Q_{\max}^{DS}$	2000	kvar
V_{base}	12.66	kV	S_{base}	10.000	kVA

5. Numerical Results, Analysis, and Discussions

This section presents the numerical results obtained by applying the proposed methodology to solve the D-STATCOM's optimal integration problem in the two aforementioned test systems, as well as their validation, analysis, and discussion. All numerical simulations were performed by interfacing MATLAB version R2022a and the GAMS software on a computer with an AMD Ryzen 5 5500U processor, Radeon Graphics at 2.10 Ghz, 20 GB of RAM, and a 64-bit Windows 11 Pro operating system.

To evaluate the performance of the proposed solution methodology, composed of the DSCA (MATLAB) in the master stage and the BONMIN solver (GAMS) in the slave stage, the results are contrasted with the following methodologies (which have been used previously to solve the problem addressed in this research): (i) the XPRESS, SBB, DICOPT, and LINDO solvers of GAMS (exact solution of the MINLP model); (ii) the genetic-convex algorithm [34]; (iii) the continuous, discrete version of the Chu and Beasley genetic algorithm (DCCBGA) [47]; and (iv) the salp swarm optimization algorithm (SSA) [47].

5.1. Radial Configuration

To validate the effectiveness of the proposed solution methodology and visualize the best results for this configuration, the proposed methodology was executed one time for 100 iterations, whose different solutions could be observed, as shown in Table 5. Here, the evaluated fitness function (operation costs), node locations, and sizes of the D-STATCOM are shown.

Table 5. List of best results obtained for a radial configuration with the proposed methodology.

Solution No.	Node Location	Sizes (Mvar)	Energy Loss Costs (USD/Year)	Investment Costs (USD/Year)	Annual Cost (USD/Year)
1	[13, 30, 24]	[0.2503, 0.6923, 0.0668]	93,867.77	12,843.90	106,711.67
2	[13, 15, 30]	[0.1476, 0.1054, 0.6983]	94,574.27	12,103.25	106,677.52
3	[14, 8, 30]	[0.1992, 0.1174, 0.6721]	93,949.70	12,579.28	106,528.98

The following remarks can be made from Table 5:

✓ The solution with the best annual operating costs is number 3, with 106,528.98 USD per year. For this solution, the selected nodes are 14, 8, and 30, which connect D-STATCOMs of 0.1992, 0.1174, and 0.6721 Mvar. This scenario reduces the annual operating costs by 18.42% when compared to the base case.

✓ The worst cost function achieved by the DSCA-BONMIN corresponds to solution 1. In this scenario, nodes 13, 30, and 24 connect D-STATCOMs of 0.2503, 0.6923, and 0.0668 Mvar. The difference between the best and worst fitness functions is 182.69 USD per year of operation.

✓ Node 30 appears for all solutions to the problem. Node 13 appears in solutions 1 and 2. The former is located in the commercial zone, and the latter is in the industrial zone. Finally, nodes 8 and 14, which are within the optimal solution, are also located in the industrial zone, which means that the most suitable locations for a D-STATCOM are in the industrial and commercial zones (Figure 2).

✓ The difference between solution 3 (the best) and solution 1 (the worst) is approximately 183 USD per year of operation, which corresponds to 0.1712%. Therefore, when it comes to minimizing operating costs in this distribution network with a higher number of nodes at a higher number of iterations, the annual cost solutions can be considered efficient, which indicates the accuracy of the implemented algorithm.

✓ In the solutions, the costs associated with energy losses are 87.96% (solution 1), 88.77% (solution 2), and 88.19% (solution 3). In turn, the investment costs are 12.03% (solution 1), 11.34% (solution 2), and 11.80% (solution 3), which corresponds to the fact that the costs associated with energy losses represent a higher percentage of the total cost than those related to investment.

Table 6 presents the results regarding the location, size, and annual operating costs of the D-STATCOMs, as obtained with the proposed methodology and the methods used for comparison.

Table 6. Results obtained by the metaheuristic optimizers and the proposed methodology for the radial configuration.

Methodology	Node Location	Sizes (Mvar)	Annual Cost (USD/Year)	Reduction (%)
Benchmark case	-	-	130,580.82	-
XPRESS	[13, 16, 32]	[0.1822, 0.0727, 0.2328]	112,376.45	13.94
SBB, DICOPT, and LINDO	[13, 16, 32]	[0.1850, 0.0825, 0.4478]	109,768.70	15.94
Genetic-Convex [34]	[14, 30, 32]	[0.2896, 0.5593, 0.1177]	109,455.96	16.18
DCCBGA [47]	[14, 25, 30]	[0.2327, 0.1056, 0.5403]	108,196.46	17.14
DSCA-BONMIN	[14, 8, 30]	[0.1992, 0.1174, 0.6721]	106,528.98	18.42

Based on the information in Table 6, the following can be concluded:

✓ The GAMS solvers used to solve the MINLP model are stuck when in local optima compared to the developed DSCA-BONMIN methodology. The SBB, DISCOPT, and LINDO solvers reduce the annual operating costs of the distribution network by 15.94%, while the XPRESS solver only reduces it by 12.94%. In addition, the solvers identify similar locations and sizes for the D-STATCOMs.

✓ The DCCBGA methodology reduces the annual operating costs of this radial distribution network by 17.14%, which is an improvement compared to the GAMS solvers and the genetic-convex methodology. However, the DSCA-BONMIN proposed in this article reduces annual costs by 1,667.48 USD compared to the DCCBGA. This result represents a reduction of 18.42% in the objective function value with respect to the base case, which represents savings of 24,051.84 USD for the network operator.

✓ A remarkable aspect of the DSCA-BONMIN methodology is the existence of D-STATCOMs in the commercial and industrial zones (Figure 2), similar to the GAMS solvers and the genetic-convex methodology and unlike the DCCBGA methodology, where there are D-STATCOMs in each zone. Furthermore, the sizes of the D-STATCOMs located by the DCCBGA and DSCA-BONMIN are similar. The only representative differences are the change from node 25 to node 8, and a reduction of 14.39% for the first location, 11.17% for the second, and 24.39% for the third with regard to the size in each of the locations. These differences represent the improvement in the annual operating costs.

Finally, Figure 5 shows the convergence graph of the methodology implemented for the 33-node IEEE test system in its radial version, from which the following can be concluded. The DSCA-BONMIN finds a value of 106,711.67 USD/year for this system in its first iteration. In the second iteration, it finds a lower objective function value, with 106,677.52 USD, demonstrating the efficiency of the methodology. Around iteration 19, the DSCA-BONMIN continues to reduce the value of the objective function, which indicates that the proposed methodology is rapidly converging to the global optimum.

The above confirms that the DSCA-BONMIN is an effective and robust tool to solve the problem regarding the location and sizing of D-STATCOMs in distribution systems in order to reduce the annual operating costs. This makes the proposed methodology the best option to solve the studied problem in 33-node IEEE test systems with a radial topology and obtain the best solution from an economic point of view while respecting all of the system operator's constraints.

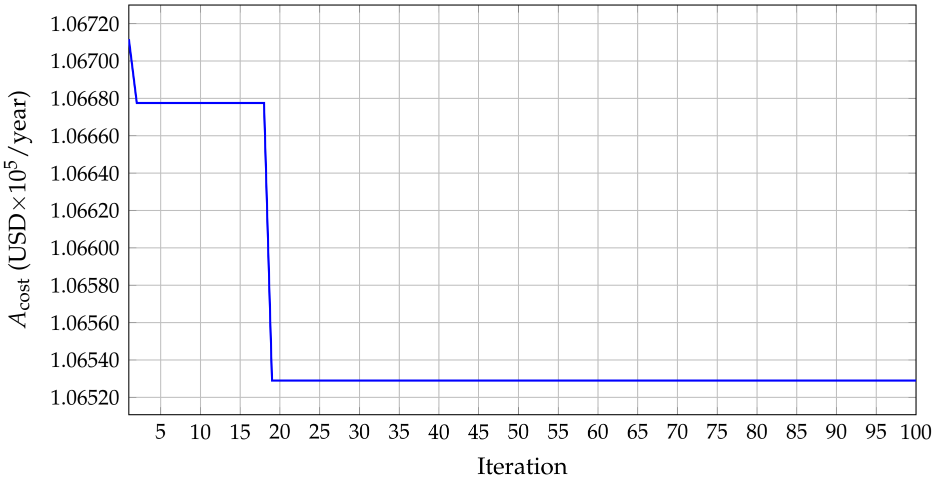

Figure 5. Convergence curve of the IEEE 33-node system with a radial configuration.

5.2. Meshed Configuration

As in the previous case, for this configuration, the proposed methodology was executed one time for 100 iterations, and the results obtained are shown in Table 7. In this case, the number of solutions was higher than those found in Section 5.1. These results are presented together with the sizes and locations of the D-STATCOMs nodes.

Table 7. Results obtained by the metaheuristic optimizers and the proposed methodology for the meshed configuration.

Solution No.	Node Location	Sizes (Mvar)	Energy Loss Costs (USD/Year)	Investment Costs (USD/Year)	Annual Cost (USD/Year)
1	[30, 19, 32]	[0.5107, 0,0.2348]	68,433.39	9488.47	77,921.86
2	[30, 33, 27]	[0.5238, 0.2113, 0.0266]	68,201.11	9694.85	77,895.96
3	[30, 18, 22]	[0.5644, 0.1890, 0]	68,299.6	9588.11	77,887.74
4	[4, 14, 30]	[0, 0.1510, 0.6358]	67,860.69	10,011.27	77,871.96
5	[9, 30, 33]	[0.0846, 0.5163, 0.1941]	67,656.69	10,120.19	77,776.88
6	[15, 30, 33]	[0.1049, 0.5279, 0.1480]	67,776.07	9,938.80	77,714.87
7	[14, 33, 30]	[0.1104, 0.1524, 0.5256]	67,649.24	10,035.84	77,685.08

Based on the information in Table 7, it can be concluded that:

- ✓ The results confirmed that, for this scenario, node 30, being in all the solutions obtained by the proposed methodology, is the most sensitive to the minimization of operating costs. Additionally, the two other nodes found in most of the reported solutions are node 33, with a percentage of 57.14%, and node 14, with 28.57%, which are related to the total responses. This occurs when considering discriminated sectors and hourly load profiles. As for nodes 30 and 33, they are nodes located in the commercial zone, and node 14 belongs to the industrial zone (Figure 3).
- ✓ The difference between solution 7 (the best) and solution 1 (the worst) is 236.78 USD, which corresponds to a 0.3039% improvement between the first and the optimal solutions obtained. As a result, as the number of iterations increases, the solutions in Table 7 improve in quality. This result confirms the accuracy of the DSCA-BONMIN method when it comes to minimizing operating costs in this distribution network.
- ✓ In the solutions, with regard to the total costs, the costs associated with energy losses represent 87.82% (solution 1), 87.55% (solution 2), 87.68% (solution 3), 87.14% (solution 4), 86.98% (solution 5), 87.21% (solution 6), and 87.08% (solution 7); and the investment costs represent 12.17% (solution 1), 12.44% (solution 2), 12.31% (solution 3), 12.85% (solution 4), 13.01% (solution 5), 12.78% (solution 6), and 12.91% (solution 7).

This means that the costs of energy losses represent a higher percentage of the total cost than the investment costs.

Table 8 shows the results for the location, size, and annual costs of the D-STATCOMs, as obtained by the comparison methodologies and the one proposed in this research.

Table 8. Results obtained by the metaheuristic optimizers and the proposed methodology for the meshed configuration.

Methodology	Node Location	Sizes (Mvar)	Annual Cost (USD/Year)	Reduction (%)
Benchmark case	-	-	86,882.81	-
XPRESS	[13, 16, 32]	[0.2000, 0.0453, 0.3923]	79,535.02	8.46
SBB, DICOPT, and LINDO	[13, 16, 32]	[0.0960, 0.0531, 0.4480]	79,350.36	8.67
SSA [47]	[32, 30, 14]	[0.2023, 0.3944, 0.1462]	77,870.17	10.37
DCCBGA [48]	[14, 30, 32]	[0.1134, 0.4705, 0.1503]	77,809.98	10.44
DSCA-BONMIN	[14, 33, 30]	[0.1104, 0.1524, 0.5256]	77,685.08	10.59

Based on the information in Table 8, the following was concluded:

- ✓ In comparison with the developed DSCA-BONMIN methodology, the local optima used by the GAMS solvers stagnate. The SBB, DISCOPT, and LINDO solvers reduced the annual network operating costs by 8.67%, while XPRESS only reduced them by 8.46%. The solvers define the exact same nodes for reactive compensation. The dimensions of the D-STATCOM range from 0.104 Mvar at node 13, 0.0078 Mvar at node 16, and 0.0557 Mvar at node 32. The most noticeable size variation takes place at node 13, suggesting that this compensator overcomes the higher capital costs that are not included in the energy loss cost.
- ✓ The SSA methodology reduces the annual operating costs by 10.37%, and the DCCBGA methodology shows a 10.44% reduction in the operating costs of this meshed distribution network, where the locations of the nodes are the same, unlike the sizes, which vary by 0.0328 Mvar at node 14, 0.052 Mvar at node 32, and 0.0761 Mvar at node 30. Of all, the most notable size difference is at node 30, suggesting that this compensator offsets the higher capital cost, which is not included in the reduction of the energy losses cost.
- ✓ The DSCA-BONMIN methodology reduces the annual operating costs by 1667.48 USD compared to DCCBGA. This result represents a reduction of 10.59% in the objective function evaluated for the base case, as well as savings of 9197.73 USD for the network operator.
- ✓ A notable aspect of the DSCA-BONMIN methodology is the existence of D-STATCOMs in the commercial and industrial zones (Figure 3), similar to the SSA and DCCBGA. In addition, the sizes of the D-STATCOMs located by the DCCBGA and DSCA-BONMIN are similar. The only representative differences with respect to the methodology to be compared are the change from node 32 to node 33 and reductions of 2.65% for node 14 and 11.711% for node 30 with respect to the size of each of the locations mentioned. Therefore, these differences represent an improvement in annual operating costs.

Finally, Figure 6 shows the convergence graph of the implemented methodology for the 33-node IEEE test system in its meshed version, from which the following can be concluded. In its first iteration, the DSCA-BONMIN finds a value of 77,921.86 USD/year. In the third iteration, it reduces the value of the objective function to 77,895.96 USD/year, thus showing the efficiency of the proposed methodology. In the fourth iteration, it shows a reduction to 77,871.9 USD/year. As of iteration 7, there is an annual cost of 77,871.96 USD/year. In iteration 28, there is a cost of 77,871.96 USD/year. In iteration 42, there is a reduction to 77,714.87 USD/year. Around iteration 93, the DSCA-BONMIN finds the lowest objective function value for the system, which is 77,685.08 USD/year. This indicates that the proposed methodology, by increasing the number of iterations, quickly converges to the global optimum.

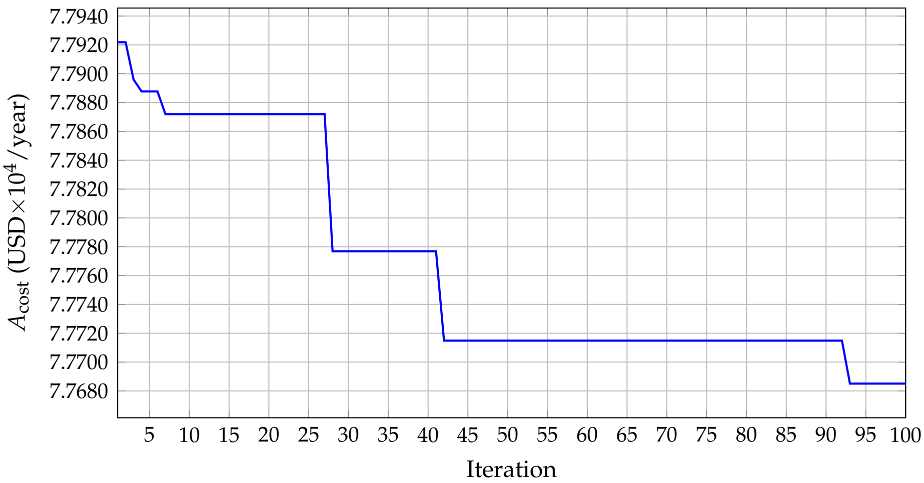

Figure 6. Convergence curve of the IEEE 33-node with a meshed configuration.

This confirms that the DSCA-BONMIN is an effective and robust tool to solve the problem regarding the location and sizing of D-STATCOMs in power distribution systems in order to reduce annual operating costs. Thus, the proposed methodology is the best option to solve the studied problem in 33-node IEEE test systems with a meshed topology, as it achieves the best solution from an economic point of view while respecting all of the system operator's constraints.

6. Conclusions and Future Works

This research managed to determine the siting and sizing of D-STATCOMs, even in light of the typical load variations associated with segregation by zones (commercial, residential, and industrial). This was achieved by linking two interfaces (MATLAB and GAMS) in conjunction with a master-slave strategy. The MATLAB software was entrusted with determining the best positions for the D-STATCOMs via a discrete version of the SCA. In the slave stage, the BONMIN solver of GAMS was used to evaluate the MINLP model of the studied problem while observing all of its constraints, thus obtaining the nominal power of each D-STATCOM the objective function value, i.e., the minimization of the annual operating costs, including the purchasing of electrical energy at the substation node terminals and the installation costs of the D-STATCOMs.

Numerical results validate the effectiveness and relevance of this approach as tested in the IEEE 33-node system with both radial and meshed topologies. The results obtained for both configurations differ, which is explained by the strong influence of network topology. However, the proposed optimization methodology is unaffected by this. The objective function of the radial topology was 106,528.98 USD/year, with a reduction of 18.42% with respect to the base case. For the meshed topology, this value was 77,685.08 USD/year, with a reduction of 10.59% with respect to the base case. That is to say, a difference of 28,843.9 USD per year of operation. This is due to the fact that the meshed topology improves the voltage profiles and allows better power flow distribution in the network.

The DSCA-BONMIN methodology performed better than the GAMS XPRESS, SBB, DICOPT, and LINDO solvers for both meshed and radial configurations. In both cases, the GAMS solvers were stuck on a locally optimal solution. This occurs because these solvers find an exact solution to the MINLP model representing the problem, which has a non-convex solution space, thus increasing the complexity of the problem. Additionally, the results obtained were compared with those of the genetic-convex, DCCBGA, and SSA methods for both configurations, managing to find a better solution. A benefit of connecting these two interfaces is that the solution of any mixed-integer nonlinear optimization problem can be scaled while dividing it by stages, which reduces the computational time and resources needed to solve the MINLP model. Furthermore, it allows the generating, evaluating, and further developing of all of the results obtained, making it possible to find the optimal global solution in a much shorter time.

This methodology can be used to solve other types of problems, such as (i) considering a 10- or 20-year planning perspective with regard to the coupling of D-STATCOMS and renewable energy sources in order to reduce the grid operation costs; (ii) employing the generalized normal optimizer and the arithmetic optimization algorithm, currently considered metaheuristic optimizers, to aid the solution of the master-slave optimization methods presented herein (moreover, for MINLP models, it is vital to consider the joint use of D-STATCOMs and batteries); (iii) considering longer time periods, be it weeks or months, and their effect on charging behaviors (a study dealing with uncertainties related to demand curves could address optimization issues); (iv) considering relevant load imbalances within three-phase networks caused by the installation of D-STATCOMs and evaluating their impact, as well as further analyzing the voltage stability of the network with these devices, along with the net present value (NPV), where the savings associated with network losses could be compared against the installation costs in order to assess the project's profitability and even calculate the break-even period; and (v) studying the network reconfiguration via sensitivity analysis in order to observe the effects of integrating D-STATCOMs into different network configurations.

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References

1. Cavellucci, C.; Lyra, C. Minimization of energy losses in electric power distribution systems by intelligent search strategies. *Int. Trans. Oper. Res.* **1997**, *4*, 23–33. [CrossRef]
2. Montoya, O.D.; Gil-González, W.; Hernández, J.C. Efficient operative cost reduction in distribution grids considering the optimal placement and sizing of D-STATCOMs using a discrete-continuous VSA. *Appl. Sci.* **2021**, *11*, 2175. [CrossRef]
3. Rawat, M.S.; Tamta, R. Optimal placement of TCSC and STATCOM for voltage stability enhancement in transmission network. In Proceedings of the 2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), Gorakhpur, India, 2–4 November 2018.
4. Alam, M.S.; Arefifar, S.A. Energy management in power distribution systems: Review, classification, limitations and challenges. *IEEE Access* **2019**, *7*, 92979–93001. [CrossRef]
5. Verma, H.K.; Singh, P. Optimal reconfiguration of distribution network using modified culture algorithm. *J. Inst. Eng. (India) Ser. B* **2018**, *99*, 613–622. [CrossRef]
6. Sultana, S.; Roy, P.K. Optimal capacitor placement in radial distribution systems using teaching learning based optimization. *Int. J. Electr. Power Energy Syst.* **2014**, *54*, 387–398. [CrossRef]
7. Sadovskaia, K.; Bogdanov, D.; Honkapuro, S.; Breyer, C. Power transmission and distribution losses—A model based on available empirical data and future trends for all countries globally. *Int. J. Electr. Power Energy Syst.* **2019**, *107*, 98–109. [CrossRef]
8. Satyanarayana, P.; Radhika, A.; Reddy, C.R.; Pangedaiah, B.; Martirano, L.; Massaccesi, A.; Flah, A.; Jasiński, M. Combined DC-Link Fed Parallel-VSI-Based DSTATCOM for Power Quality Improvement of a Solar DG Integrated System. *Electronics* **2023**, *12*, 505. [CrossRef]

9. Yarlagadda, V.; Geshmakumari, R.; Rao, J.V.; Gadupudi, L. Mitigation of Harmonics in Distributed System with D-GCSC fed Loads using closed loop control of DSTATCOM. In Proceedings of the 2022 IEEE Fourth International Conference on Advances in Electronics, Computers and Communications (ICAECC), Bengaluru, India, 10–11 January 2022; pp. 1–7. [CrossRef]
10. Muruganantham, B.; Selvam, M.M.; Gnanadass, R.; Padhy, N.P. Energy loss reduction and load balancing through network reconfiguration in practical LV distribution feeder using GAMS. In Proceedings of the 2017 7th International Conference on Power Systems (ICPS), Pune, India, 21–23 December 2017.
11. Comisión de Regulación de Energía y Gas (CREG). Resolución CREG 119. 2007. Available online: http://apolo.creg.gov.co/Publicac.nsf/Indice01/Resolucion-2007-Creg119-2007 (accessed on 29 December 2022).
12. Sharma, A.K. Optimal number and location of TCSC and loadability enhancement in deregulated electricity markets using MINLP. *Int. J. Emerg. Electr. Power Syst.* **2006**, *5*, 1–15. [CrossRef]
13. Sreedharan, S.; Joseph, T.; Joseph, S.; Chandran, C.V.; Vishnu, J.; Das P, V. Power system loading margin enhancement by optimal STATCOM integration—A case study. *Comput. Electr. Eng.* **2020**, *81*, 106521. [CrossRef]
14. Villalobos, M.A.M.; Suárez, J.F.P. Compensadores estáticos de potencia: Visión general y revisión del estado del arte. *Rev. UIS Ing.* **2010**, *9*, 9–21.
15. Wasiak, I.; Mienski, R.; Pawelek, R.; Gburczyk, P. Application of DSTATCOM compensators for mitigation of power quality disturbances in low voltage grid with distributed generation. In Proceedings of the 2007 9th International Conference on Electrical Power Quality and Utilisation, Barcelona, Spain, 9–11 October 2007.
16. Moradi, M.H.; Abedini, M. A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. *Int. J. Electr. Power Energy Syst.* **2012**, *34*, 66–74. [CrossRef]
17. Kollu, R.; Rayapudi, S.R.; Sadhu, V.L.N. A novel method for optimal placement of distributed generation in distribution systems using HSDO: DG PLACEMENT IN DISTRIBUTION SYSTEMS USING HSDO. *Int. Trans. Electr. Energy Syst.* **2014**, *24*, 547–561. [CrossRef]
18. Bagheri Tolabi, H.; Ali, M.H.; Rizwan, M. Simultaneous reconfiguration, optimal placement of DSTATCOM, and photovoltaic array in a distribution system based on fuzzy-ACO approach. *IEEE Trans. Sustain. Energy* **2015**, *6*, 210–218. [CrossRef]
19. Gupta, A.R.; Kumar, A. Energy savings using D-STATCOM placement in radial distribution system. *Procedia Comput. Sci.* **2015**, *70*, 558–564. [CrossRef]
20. Rezaeian Marjani, S.; Talavat, V.; Galvani, S. Optimal allocation of D-STATCOM and reconfiguration in radial distribution network using MOPSO algorithm in TOPSIS framework. *Int. Trans. Electr. Energy Syst.* **2019**, *29*, e2723. [CrossRef]
21. Garces, A. A linear three-phase load flow for power distribution systems. *IEEE Trans. Power Syst.* **2016**, *31*, 827–828. [CrossRef]
22. Shaw, R.; Attree, M.; Jackson, T. Developing electricity distribution networks and their regulation to support sustainable energy. *Energy Policy* **2010**, *38*, 5927–5937. [CrossRef]
23. Gomez-Gonzalez, M.; López, A.; Jurado, F. Optimization of distributed generation systems using a new discrete PSO and OPF. *Electric Power Syst. Res.* **2012**, *84*, 174–180. [CrossRef]
24. Hegazy, A.E.; Makhlouf, M.A.; El-Tawel, G.S. Improved salp swarm algorithm for feature selection. *J. King Saud Univ.-Comput. Inf. Sci.* **2020**, *32*, 335–344. [CrossRef]
25. Montoya, O.D.; Garces, A.; Gil-González, W. Minimization of the distribution operating costs with D-STATCOMS: A mixed-integer conic model. *Electric Power Syst. Res.* **2022**, *212*, 108346. [CrossRef]
26. Samimi, A.; Golkar, M.A. A novel method for optimal placement of STATCOM in distribution networks using sensitivity analysis by DIgSILENT software. In Proceedings of the 2011 Asia-Pacific Power and Energy Engineering Conference, Wuhan, China, 25–28 March 2011.
27. Tanti, D.; Verma, M.; Singh, D.B.; Mehrotra, O. Optimal Placement of Custom Power Devices in Power System Network to Mitigate Voltage Sag under Faults. *Int. J. Power Electron. Drive Syst.* **2012**, *2*, 267–276. [CrossRef]
28. Taher, S.A.; Afsari, S.A. Optimal location and sizing of DSTATCOM in distribution systems by immune algorithm. *Int. J. Electr. Power Energy Syst.* **2014**, *60*, 34–44. [CrossRef]
29. Devi, S.; Geethanjali, M. Optimal location and sizing of Distribution Static Synchronous Series Compensator using Particle Swarm Optimization. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 646–653. [CrossRef]
30. Gupta, A.R.; Kumar, A. Optimal placement of D-STATCOM in distribution network using new sensitivity index with probabilistic load models. In Proceedings of the 2015 2nd International Conference on Recent Advances in Engineering & Computational Sciences (RAECS), Chandigarh, India, 21–22 December 2015; pp. 1–6. [CrossRef]
31. Yuvaraj, T.; Devabalaji, K.; Ravi, K. Optimal Placement and Sizing of DSTATCOM Using Harmony Search Algorithm. *Energy Procedia* **2015**, *79*, 759–765. [CrossRef]
32. Muthukumar, K.; Jayalalitha, S. Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 299–319. [CrossRef]
33. Sedighizadeh, M.; Eisapour-Moarref, A. The imperialist competitive algorithm for optimal multi-objective location and sizing of DSTATCOM in distribution systems considering loads uncertainty. *INAE Lett.* **2017**, *2*, 83–95. [CrossRef]
34. Montoya, O.D.; Chamorro, H.R.; Alvarado-Barrios, L.; Gil-González, W.; Orozco-Henao, C. Genetic-Convex Model for Dynamic Reactive Power Compensation in Distribution Networks Using D-STATCOMs. *Appl. Sci.* **2021**, *11*, 3353. [CrossRef]

35. Sannigrahi, S.; Acharjee, P. Implementation of crow search algorithm for optimal allocation of DG and DSTATCOM in practical distribution system. In Proceedings of the 2018 International Conference on Power, Instrumentation, Control and Computing (PICC), Thrissur, India, 8–12 January 2018; pp. 1–6. [CrossRef]
36. Amin, A.; Kamel, S.; Selim, A.; Nasrat, L. Optimal Placement of Distribution Static Compensators in Radial Distribution Systems Using Hybrid Analytical-Coyote optimization Technique. In Proceedings of the 2019 21st International Middle East Power Systems Conference (MEPCON), Cairo, Egypt, 17–19 December 2019; pp. 982–987. [CrossRef]
37. Dash, S.K.; Mishra, S. Simultaneous Optimal Placement and Sizing of D-STATCOMs Using a Modified Sine Cosine Algorithm. In Proceedings of the Advances in Intelligent Computing and Communication, Bhubaneswar, India, 23 May 2021; Das, S., Mohanty, M.N., Eds.; Springer: Singapore, 2021; pp. 423–436.
38. Montoya, O.D.; Fuentes, J.E.; Moya, F.D.; Barrios, J.A.; Chamorro, H.R. Reduction of Annual Operational Costs in Power Systems through the Optimal Siting and Sizing of STATCOMs. *Appl. Sci.* **2021**, *11*, 4634. [CrossRef]
39. Yuan, Z.; Paolone, M. Properties of convex optimal power flow model based on power loss relaxation. *Electr. Power Syst. Res.* **2020**, *186*, 106414. [CrossRef]
40. Sharma, A.K.; Saxena, A.; Tiwari, R. Optimal placement of SVC incorporating installation cost. *Int. J. Hybrid Inf. Technol.* **2016**, *9*, 289–302. [CrossRef]
41. Comisión de Regulación de Energía y Gas (CREG). Resolución No. 024. 2005. Available online: http://apolo.creg.gov.co/Publicac.nsf/Indice01/Resolucion-2005-CREG024-2005 (accessed on 30 December 2022).
42. Mahdad, B.; Srairi, K. A new interactive sine cosine algorithm for loading margin stability improvement under contingency. *Electr. Eng.* **2018**, *100*, 913–933. [CrossRef]
43. Mirjalili, S. SCA: A Sine Cosine Algorithm for solving optimization problems. *Knowl. Based Syst.* **2016**, *96*, 120–133. [CrossRef]
44. Soroudi, A. *Power System Optimization Modeling in GAMS*; Springer: Berlin/Heidelberg, Germany, 2017; Volume 78.
45. Gams. GDXXRW. Available online: https://www.gams.com/latest/docs/T_GDXXRW.html (accessed on 30 December 2022).
46. Venkatesh, B.; Ranjan, R. Optimal radial distribution system reconfiguration using fuzzy adaptation of evolutionary programming. *Int. J. Electr. Power Energy Syst.* **2003**, *25*, 775–780. [CrossRef]
47. Castiblanco-Pérez, C.M.; Toro-Rodríguez, D.E.; Montoya, O.D.; Giral-Ramírez, D.A. Optimal Placement and Sizing of D-STATCOM in Radial and Meshed Distribution Networks Using a Discrete-Continuous Version of the Genetic Algorithm. *Electronics* **2021**, *10*, 1452. [CrossRef]
48. Mora-Burbano, J.A.; Fonseca-Díaz, C.D.; Montoya, O.D. Application of the SSA for Optimal Reactive Power Compensation in Radial and Meshed Distribution Using D-STATCOMs. *Algorithms* **2022**, *15*, 345. [CrossRef]