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Applying the Crow Search Algorithm for the Optimal Integration of PV Generation Units in DC Networks

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Abstract: This paper presents an efficient master–slave methodology to solve the problem of integrating photovoltaic (PV) generators into DC grids for a planning period of 20 years. The problem is mathematically formulated as Mixed-Integer Nonlinear Programming (MINLP) with the objective of minimizing the total annual operating cost. The main stage, consisting of a discrete-continuous version of the Crow search algorithm (DCCSA), is in charge of determining the installation positions of the PV generators and their corresponding power ratings. On the other hand, at the slave level, the successive approximation power flow method is used to determine the objective function value. Numerical results on 33- and 69-bus test systems demonstrate the applicability, efficiency and robustness of the developed approach with respect to different methodologies previously discussed in the scientific literature, such as the vortex search algorithm, the generalized normal distribution optimizer and the particle swarm optimization algorithm. Numerical tests are performed in the MATLAB programming environment using proprietary scripts.

Keywords: DC networks; PV generators; crow search algorithm; discrete-continuous codification; master–slave optimization; successive approximation power flow method; electrical systems planning

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1. Introduction

1.1. General Background

Due to technological advances in the field of power electronics, the implementation and use of DC networks have been growing in recent years, with which it is expected to bring electricity to end-users at medium and low voltage levels through DC transmission and sub-transmission systems [1,2]. In comparison with traditional AC systems, DC systems have the following advantages [3–5]: (i) higher efficiency, since the absence of reactive elements (i.e., inductive reactances and reactive power flows) reduces power losses and improves voltage profiles; (ii) reduced operating and investment costs associated with network maintenance; and (iii) simpler integration of distributed energy resources, such as distributed generation based on renewable resources and energy storage systems, since most of these devices operate in DC. This last advantage has enabled researchers around the world to develop strategies that allow the transition from classical, fossil fuel-based centralized generation systems to decentralized power generation systems based on renewable resources such as photovoltaic (PV) or wind energy [6,7]. This will not only help to meet the energy demands of end-users; it will also reduce dependence on fossil fuels and, at the same time, the environmental impact of their use.

The integration of distributed energy resources such as PV generation poses challenges for engineers in charge of the planning, design, and operation of electrical systems since an inadequate integration of these resources leads to the following problems [8]: (i) the degradation of voltage profiles, (ii) the overloading of distribution lines, (iii) increased energy losses, and (iv) the deterioration of power quality, among others. However, it is evident that appropriate integration of photovoltaic generators into power grids considerably improves the technical-operational conditions of the system and makes it possible to reduce the greenhouse gas emissions caused by fossil sources [9].

1.2. Motivation

Being a country located between the tropics of Cancer and Capricorn, Colombia has an abundant solar resource, which is the reason why, through legislation, as is the case of Law 1715 of 2014, the number of projects for the integration of PV generators into conventional electricity grids has increased in recent years [10,11]. However, the currently installed capacity of PV generation is far from the maximum usable capacity, representing 0.76% of the total energy generated in the country (these data come from the observation of the energy matrix reported by XM during 2019, before the pandemic). For this reason, the main motivation of this research study is to propose alternatives that allow taking advantage of the country's abundant solar resource, thus allowing an energy transition that reduces the emissions of polluting gases while providing a high-quality service to the end-users to be achieved that is as economical as possible. Note that the optimal integration of PV generators in DC networks is a complex problem from the point of view of mathematical modeling, as it is represented by a mixed-integer nonlinear programming (MINLP) model that combines discrete and continuous variables. As a result of the above, it is necessary to develop efficient solution strategies that address the problem with high-quality results and reduced computation times. Therefore, this research also aims to propose an optimization methodology to solve the problem under study by finding the best possible solution with low computational costs.

1.3. State of the Art

To address the problem of integrating generators based on renewable energy resources into DC networks, different methodologies have been recently reported in the specialized literature. Some of these research works are presented below.

In [12], a methodology is presented to assess the technical-economic feasibility of integrating and operating large-scale photovoltaic generators in AC/DC distribution networks. The objective functions considered are the minimization of operating costs and energy losses of the grid. To solve this problem, the non-dominant sorting genetic algorithm-II is used. Numerical performance achieved on the 33-bus IEEE test feeder demonstrates the feasibility of the suggested method. In [13], hybridization between the particle swarm optimization algorithm and the gravitational search algorithm is suggested to address the integration problem of renewable energy sources based mainly on photovoltaic and wind generation. The main goal for this work is to reduce energy losses in the grid and increase profits for renewable energy owners. Numerical performance on the 69-bus IEEE test system shows the effectiveness and applicability of the suggested methodology in terms of the solution compared to other population-based metaheuristic algorithms. In reference [14], the problem of integrating distributed generators (mainly based on solar and wind power) into DC grids is represented by a mixed-integer nonlinear linear programming (MINLP) model. This work aims to minimize the installation costs of distributed generators and save in power purchasing. The authors used the GAMS software to solve the mathematical model. Numerical performance on the 21-bus test feeder shows the application and effectiveness of the suggested approach. In [15], a method on the basis of the equilibrium optimization algorithm is proposed for the efficient location and size of PV generators and batteries in distribution grids. The purposes of this work include minimizing the cost of energy not supplied, the investment costs associated with the installation of the PV generators and batteries, their operating costs, the power losses through the distribution lines, and the CO_2 emissions produced in relation to the network and the systems. Numerical results on 30- and 69-bus feeders demonstrate the efficiency and robustness of the suggested methodology with respect to other algorithms reported in the specialized bibliography, such as genetic algorithms, particle swarm optimization, differential evolution and gray wolf optimization.

The authors of [16] address the problem of integrating of distributed generators in DC networks through a mixed-integer semi-definite programming model. This model is solved using the MATLAB CVX tool, with which the authors manage to minimize the power losses of the system. Numerical performance achieved on 21-bus and 69-bus test feeders demonstrates the efficiency of the suggested method in terms of solution quality compared to classical metaheuristic methods. In [17], a mixed-integer convex model is proposed to solve the problem of integrating generators based on renewable resources and energy storage systems in DC distribution networks. The aim of this work is to reduce the costs associated with energy losses. This model is solved using the MATLAB CVX tool, with excellent numerical results of 21- and 69-bus feeders showing the effectiveness and implementability of the suggested method. In reference [18], the problem regarding the integration of distributed generation sources in DC networks is addressed through a second-order conic programming model. This model seeks to minimize the power losses in the system lines. Numerical results on 21 and 69 bus feeders demonstrate the effectiveness and robustness of the suggested method compared to solutions representing the MINLP model of the problem.

Recently, the problem of integrating PV generators into DC networks has been solved by considering economic approaches based mainly on master–slave methodologies working with discrete-continuous coding. This type of codification allows siting and sizing problems to be solved in a unified manner, improving the exploration and exploitation of metaheuristic algorithms while reducing their computation times. An example of this is the work published by [19], which proposes a leader–follower optimization method consisting of the discrete-continuous version of the vortex search algorithm (DCVSA) and the successive approximations power flow method. The main idea of this work is to reduce the total annual operating costs, taking into account the investment, operation and maintenance costs of the power generation systems. The numerical performance on the 33-bus and 69-bus test feeders demonstrates the feasibility and effectiveness of the developed methodology. Finally, as in the previous case, the study by [20] uses the discrete-continuous version of the generalized normal distribution optimizer (DCGNDO) to solve the PV-generator integration problem. This work's main objective is to minimize the total annual operating costs. The results obtained in the 33- and 69-bus tests demonstrate the developed methodology's applicability and efficiency compared with the DCVSA.

1.4. Contributions and Scope

Considering the review literature review presented in the previous subsection, the main contributions of this document are presented as follows:

- A new optimization approach to solve the mathematical model representing the optimal integration of PV generators into DC grids. This methodology combines the discrete-continuous version of the crow search algorithm with the successive approximation power flow method within the framework of a master–slave optimization strategy.
- A solution strategy that finds the optimal global solution to the problem of integrating PV generators into DC networks, improving the results reported by the specialized literature regarding solution quality and repeatability.
- A new optimization approach based on the leader–follower operation scheme that allows solving a high-complexity optimization problem with reduced processing times

(less than 1.5 min) and consistent numerical performance in the DC versions of the 33- and 69-bus test feeders.

It is worth mentioning that this research is in the area of distribution system planning, which means that all the optimization algorithms (proposed and comparative methodologies) are evaluated based on simulations (offline validations) with the information provided by the distribution company regarding the generation and demand profiles being these data-averaged values obtained from historical information. In addition, once the expected size and location of the PV plants are determined, the distribution company will implement the physical stage, i.e., the construction of the PV plants; once these are ready to operate, then efficient day-ahead economic/technical/environmental dispatch methodologies for real-time operation must be implemented. This means that more research is required to plan and operate renewables in monopolar DC networks, which is an opportunity to continue contributing to the development of sustainable electrical networks in future works. However, numerical results in the studied test feeders demonstrated that in the case of the optimal location and sizing of PV plants in DC networks, all the combinatorial methods reach efficient numerical results, and the difference among them is minimal, which implies that with this research, the solution of the studied problem can be considered closed.

1.5. Document Organization

The rest of the paper is structured as follows: Section 2 provides a full description of the MINLP model representing the problem under study, i.e., the optimal integration of PV generators into DC distribution networks with the objective of reducing total annual operating costs; Section 3 describes the general implementation of the discrete-continuous version of the crow search algorithm and the successive approximation power flow method in order to evaluate the objective function; Section 4 presents the main characteristics of the DC versions of the 33- and 69-bus test feeders, the typical PV generation and demand curves for a Colombian region and the parametric information used to calculate the objective function value; Section 5 shows the numerical results, validations, analysis and discussion obtained for the optimal integration of PV generators for both test systems; and Section 6 lists the main conclusions of this study and future works.

2. Mathematical Formulation

The problem of the integration of PV generators into DC networks is presented here. The problem is mathematically formulated as Mixed-Integer Nonlinear Linear Programming (MINLP) where the decision variables are put in relation to the choice of the bus where the PV generator is placed, and the nonlinearity of the model arises in the power flow formulation due to the nonlinear nature of its general equation [21]. The objective function and the set of constraints of the optimization model representing the problem of integrating PV generators in DC distribution systems are described below.

2.1. Formulation of the Objective Function

The objective function corresponds to the minimization of the total annual operating cost of the DC network, which consists of three parts: annual power purchase costs for the substation bus, annual investment costs and maintenance costs for the PV generators. The components of the objective function are shown in (1) to (4).

$$\min \; A_{cost} = A_1 + A_2 + A_3, \tag{1}$$

$$A_1 = C_{kWh} T C_a C_c \left(\sum_{h \in \mathcal{H}} \sum_{k \in \mathcal{N}} p_{k,h}^{cg} \Delta h \right), \tag{2}$$

$$A_2 = C_{pv} C_a \left(\sum_{k \in \mathcal{N}} p_k^{pv} \right), \tag{3}$$

$$A_3 = C_{O\&M} T \left(\sum_{h \in \mathcal{H}} \sum_{k \in \mathcal{N}} p_{k,h}^{pv} \Delta h \right), \tag{4}$$

with

$$C_a = \left(\frac{t_a}{1 - (1 + t_a)^{-N_t}} \right),$$

$$C_c = \left(\sum_{t \in \mathcal{T}} \left(\frac{1 + t_e}{1 + t_a} \right)^t \right).$$

Here, the value of the objective function is given by A_{cost} and represents the total annual operating costs of the system. A_1 is the value of the annualized energy purchasing costs at the substation bus. A_2 is the value of the annualized investment costs, while A_3 is the value of the operation and maintenance costs of the PV generators. C_{kWh} is the average energy purchase price of the substation bus. T represents the average number of days per year. C_a is the annuity factor that allows finding the value of the periodic payments to be made by the network operator, depending on the expected internal interest rate t_a and the planning period N_t. C_c is a factor related to the increase in electricity costs during the planning period, which depends on the expected annual energy cost increase rate specified by the network operator t_e. $p_{k,h}^{cg}$ is the active power produced by each conventional generator connected to bus k during time period h. Δh is the length of the time period in which the electrical variables are assumed to be constant. C_{pv} is the average installation cost of 1 kW of solar power. p_k^{pv} is the nominal power of the PV generator connected to bus k. $C_{O\&M}$ is the maintenance and operation cost of the PV generator set, and $p_{k,h}^{pv}$ is the active power generated by each connected PV unit at bus k in the time interval h. Finally, $\mathcal{N}$, $\mathcal{H}$, and $\mathcal{T}$ are the sets containing all the buses in the network, the time periods in a daily operation scenario and the number of years in the planning horizon, respectively.

2.2. Set of Constraints

Equations (5) to (11) show the set of constraints representing the problem of integrating a PV generator into a DC grid.

$$p_{k,h}^{cg} + p_{k,h}^{pv} - P_{k,h}^{d} = \sum_{j \in \mathcal{N}} G_{kj} v_{k,h} v_{j,h}, \{\forall k \in \mathcal{N}, \quad \forall h \in \mathcal{H}\}, \tag{5}$$

$$p_{k,h}^{pv} = p_k^{pv} C_h^{pv}, \{\forall k \in \mathcal{N}, \quad \forall h \in \mathcal{H}\}, \tag{6}$$

$$P_k^{cg,\min} \leq p_{k,h}^{cg} \leq P_k^{cg,\max}, \{\forall k \in \mathcal{N}, \quad \forall h \in \mathcal{H}\}, \tag{7}$$

$$y_k P_k^{pv,\min} \leq p_k^{pv} \leq y_k P_k^{pv,\max}, \{\forall k \in \mathcal{N}\}, \tag{8}$$

$$v_k^{\min} \leq v_{k,h} \leq v_k^{\max}, \{\forall k \in \mathcal{N}, \quad \forall h \in \mathcal{H}\}, \tag{9}$$

$$\sum_{k \in \mathcal{N}} y_k \leq N_{pv}^{ava}, \tag{10}$$

$$y_k \in \{0, 1\}, \{\forall k \in \mathcal{N}\}. \tag{11}$$

Here, $P_{k,h}^{d}$ is the active power required by the bus k in time period h. $v_{k,h}$ and $v_{j,h}$ denote the voltages of buses k and j in time period h, respectively, and G_{kj} is the conductance value associated with buses k and j. C_h^{pv} is the expected PV electricity production curve in the area of influence of the power system. $P_k^{cg,\min}$ and $P_k^{cg,\max}$ are the active power limits associated with each conventional generator connected at bus k. $P_k^{pv,\min}$ and $P_k^{pv,\max}$ are the active power limits associated with the PV generator connected at bus k. On the other hand, y_k is a binary variable responsible for finding the location of a PV generation unit at bus k. v_k^{min} and v_k^{max} are the minimum and maximum voltage regulation limits allowed by all the buses that make up the electrical system. Finally, N_{pv}^{disp} is a constant parameter related to the maximum number of PV generators that can be installed in the grid.

2.3. Model Analysis and Interpretation

The mathematical model displayed in (1) to (11) can be interpreted as follows. Equation (1) defines the objective function of the problem, which is the sum of the annual energy purchasing costs at the substation bus, as shown in Equation (2), with the annual investment costs of the PV generators, as proposed in (3), and maintenance and operating costs, as indicated in (4). Constraint (5) presents the active power balance for each system bus in each time period. This equation is the most challenging constraint of the problem studied, and since it is non-linear and non-convex, it must be solved adequately by numerical methods [4]. Equation (6) states that the active power generation of PV generators varies as a function of their rated power and the expected generation curve in the grid's influence zone. Inequality constraint (7) defines the lower and upper active power injection limits of conventional generators. Inequality (8) is also a constraint that determines the minimum and maximum active generation boundaries of the PV generators to be installed throughout the system. Similarly, (9) is a box constraint that defines the lower and upper bounds of voltage regulation for all busbars and time periods, while (10) defines the maximum number of PV generators available for installation in the grid. Finally, (11) shows the binary nature of the decision variable y_k.

The main complications of the presented model are (i) the existence of non-linearities and non-convexities in the active power balance equation and (ii) the mixture of integer and continuous variables. Therefore, to solve the problem under study, a master–slave optimization methodology based on the discrete-continuous version of the crow search algorithm (DCCSA) and the successive approximations method version is proposed, which has not been previously presented in the specialized literature and constitutes one of the main achievements of this work.

3. Proposed Methodology

This section presents a master–slave methodology applied to solve the problem of integrating PV generators into DC networks. In the master stage, the buses where the PV generators are placed are defined, along with their rated power. In the slave stage, the power flow constraints defined in the MINLP model are evaluated to determine the value of the objective function. Each component of the proposed methodology is presented in the following sections.

3.1. Master Stage: Discrete-Continuous Crow Search Algorithm

The DCCSA is a bio-inspired metaheuristic algorithm that is based on the rational behavior of crow flocks [22]. Crows are characterized by being ambitious birds, as they chase each other to stock up on the best food. In addition, crows watch where other birds hide their food in order to steal it when they are away [23]. Consequently, after having stolen the food, crows take the necessary measures to avoid becoming another victim, moving their hiding place or changing their route [24]. This behavior can be mathematically modeled by following simple rules that allow for a correct exploration and exploitation of the solution space [22]:

- ✓ Crows live in swarms
- ✓ Crows can remember where food sources are
- ✓ Crows chase each other to commit theft

✓ Crows guard their hideouts against robbery using stochastic behavioral factors

3.1.1. Initial Population

DCCSA is a population-based algorithm consisting of crows randomly placed in the environment, which allows the algorithm to begin the process of exploring and exploiting the solution space. The starting population of crows adopts the structure displayed in (12):

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

where X^t is the population of crows in iteration t, N_i is the number of individuals in the population and N_v is the number of variables or the size of the solution space. To create the initial population of crows, (13) is used, which generates an array of random numbers in the lower and upper bounds that contain possible solutions for the PV generator integration problem.

$$X^0 = x_{\min} ones(N_i, N_v) + (x_{\max} - x_{\min}) rand(N_i, N_v), \tag{13}$$

where $ones(N_i, N_v) \in \mathbb{R}^{N_i \times N_v}$ is an array containing ones; $rand(N_i, N_v) \in \mathbb{R}^{N_i \times N_v}$ is an array filled with random numbers between 0 and 1 that are generated by a uniform distribution; and $x_{\min} \in \mathbb{R}^{N_v \times 1}$ and $x_{\max} \in \mathbb{R}^{N_v \times 1}$ are vectors representing the lower and upper boundaries of the solution space, as shown below:

$$x_{\min} = \begin{bmatrix} x_{1,\min} \\ x_{2,\min} \end{bmatrix}, y_{\max} = \begin{bmatrix} x_{1,\max} \\ x_{2,\max} \end{bmatrix}.$$

Here, $x_{1,\min} \in \mathbb{R}^{N_{pv}^{ava} \times 1}$ and $x_{1,\max} \in \mathbb{R}^{N_{pv}^{ava} \times 1}$ represent the lower and upper limits of the decision variables associated with the location of the PV generators at the demand buses. On the other hand, $x_{2,\min} \in \mathbb{R}^{N_{pv}^{ava} \times 1}$ and $x_{2,\max} \in \mathbb{R}^{N_{pv}^{ava} \times 1}$ are the lower and upper bounds of the decision variables related to the size of the PV generation units.

Each individual generated by (13) must respect the coding shown in (14), which allows for determining the optimal location and size of PV generation units to be installed in the DC network.

$$X_i^t = \left[5,\ z,\ ...,\ 18\ |1.6593,\ p_z^{pv},\ ...,\ 2.210\right]; i = 1, 2, ..., N_i. \tag{14}$$

Finally, in each iteration t, every crow in the population is able to memorize the position of the hiding place of its food, as presented in (15), which stores the location of the best food cache that each crow has found so far.

$$M^t = \begin{bmatrix} x_{11}^t & x_{12}^t & \cdots & x_{1N_v}^t \\ x_{21}^t & x_{22}^t & \cdots & x_{2N_v}^t \\ \vdots & \vdots & \ddots & \vdots \\ x_{N_i1}^t & x_{N_i2}^t & \cdots & x_{N_i,N_v}^t \end{bmatrix} \tag{15}$$

3.1.2. Crow Movement

To start the DCSSA, a crow j is supposed to want to visit its hideout, which is located at position M_j^t. On the other hand, crow i decides to follow j to approach its hiding place. Two situations may arise in this context: (i) search and (ii) evasion.

1. Case 1: Search
From this situation, crow j does not know that crow i is chasing it. Therefore, crow i manages to approach crow j's hideout, thus switching its position in the solution space. The new location can be represented mathematically, as shown in (16).

$$X_i^{t+1} = X_i^t + rand\ fl\ (M_j^t - X_i^t), \tag{16}$$

where $rand$ is a random number between 0 and 1 generated by uniform distribution, and fl is the flight length of the crow i.
2. Case 2: Evasion
In this situation, crow j knows that crow i is chasing it. Consequently, the crow j tries to trick the crow i by moving to a random position in the solution space in order to protect its hiding place from being sacked.
The two possible situations that may arise can be summarized as shown in (17).

$$X_i^{t+1} = \begin{cases} X_i^t + rand\ fl\ (M_j^t - X_i^t) & \text{Si } r_j \geq A_p \\ \text{random} & \text{otherwise} \end{cases} \tag{17}$$

Here, r_j is a random number between 0 and 1 that is generated by a uniform distribution, and A_p is the probability that crow j notices that crow i is following it.

3.1.3. Memory Updating

From the situations described above, the position of the crows is modified. Therefore, the new position of the food source must be updated. Therefore, if the new meal location adaptation function is better than the previously memorized position adaptation function, the crow updates its memory with the new position, as depicted in (18).

$$M_i^{t+1} = \begin{cases} X_i^{t+1} & \text{Si } F_F(X_i^{t+1}) < F(M_i^t) \\ M_i^t & \text{otherwise} \end{cases}, \tag{18}$$

where $F_f(\cdot)$ represents the adaptation function to be minimized.

3.2. Slave Stage: Successive Approximations Power Flow Method

The successive approximation method for solving the power flow in DC power systems was originally presented in [25]. This method allows iterative solving of the active power balance equation shown in (5). Therefore, it permits the slave phase to estimate the value of the adaptation function for each individual that composes the crow population, ensuring that the constraints presented in the MINLP model are respected, as previously mentioned in Section 2. The recursive formula that allows the solving of the power flow formulated in (5) is presented in (19).

$$\mathbb{V}_{d,h}^{m+1} = -\mathbf{G}_{dd}^{-1}\left[\mathbf{diag}^{-1}(\mathbb{V}_{d,h}^{m})(\mathbb{P}_{d,h} - \mathbb{P}_{pv,h}) + \mathbf{G}_{ds}\mathbb{V}_{s,h}\right]. \tag{19}$$

Here, m is the iteration counter and $\mathbb{V}_{d,h}$ is the vector containing the voltage at the demand buses for each period h. $\mathbf{G}_{ds}$ is the component of the conductance matrix that associates the slack bus with the demand buses, while $\mathbf{G}_{dd}$ is the component of the conductance matrix that relates the demand buses to each other. $\mathbb{P}_{d,h}$ is the vector containing the active power consumed at the load buses for each period h. $\mathbb{P}_{pv,h}$ is the vector containing the active power generated by each PV generator for each period h. $\mathbb{V}_{s,h}$ is the vector containing the voltage at the substation bus terminals for each period h, which is a known parameter of the power flow solution. Finally, $\mathbf{diag}(z)$ is a diagonal matrix made up of the elements of vector z.

To determine the convergence of the iterative process, the criteria specified in (20) is employed, in which the maximum difference in the magnitudes of the demand voltages (i.e., $\mathbb{V}_{d,h}$) for each period h of two consecutive iterations is less than a given tolerance.

$$\max_h \left\{ |\mathbb{V}_{d,h}^{m+1} - \mathbb{V}_{d,h}^{m}| \right\} \leq \zeta \tag{20}$$

In (20), ζ is defined as the convergence error, which takes the value 1×10^{-10} for this study.

Having solved the power flow in all time periods h using the successive approximation power flow method, the next step is to estimate the power generated at the terminals of the substation bus, as shown in (21).

$$\mathbb{P}_{s,h} = \mathbf{diag}(\mathbb{V}_{s,h})(\mathbf{G}_{ss}\mathbb{V}_{s,h} + \mathbf{G}_{sd}\mathbb{V}_{d,h}). \tag{21}$$

Here, $\mathbb{P}_{s,h}$ is the vector containing the active power generated at the slack bus for each period h. $\mathbf{G}_{ss}$ is the component of the conductance matrix associated with the slack bus, while $\mathbf{G}_{sd}$ is the component of the conductance matrix that relates the slack bus to the demand bus. Note that when solving (21), it is possible to obtain the value of A_1. The solution given by each individual in the master phase that follows the encoding given by (14) allows us to obtain the values A_2 and A_3. However, in order to discard potentially infeasible solutions that do not meet the constraints of the solution space, the objective function shown in (1) is substituted by the fitness function described in (22) [26,27].

$$\begin{aligned} F_f =& A_{cost} + \beta_1 \max_h \{0, \mathbb{V}_{d,h} - v^{\max}\} - \beta_2 \min_h \left\{0, \mathbb{V}_{d,h} - v^{\min}\right\} \\ & - \beta_3 \min_h \left\{0, \mathbb{P}_{s,h} - P_k^{gc,\min}\right\} \end{aligned}. \tag{22}$$

In (22), F_f is the value of the adaptation function, and β_1, β_2 and β_3 are penalty factors applied to the objective function. These penalty factors are activated when the solution specified in the master stage does not meet the voltage regulation or generation capacity constraints of the slack bus. For this research article, the value of these penalty factors is taken as 1×10^6. One of the main advantages of using an adaptation function is that it allows the optimization approach to explore and exploit the solution space efficiently, given that if all the constraints specified in the MINLP model are satisfied, the final value of F_f is equal to the value of the objective function [28].

Figure 1 presents the general implementation of the proposed master–slave methodology for the integration of PV generation units into DC grids.

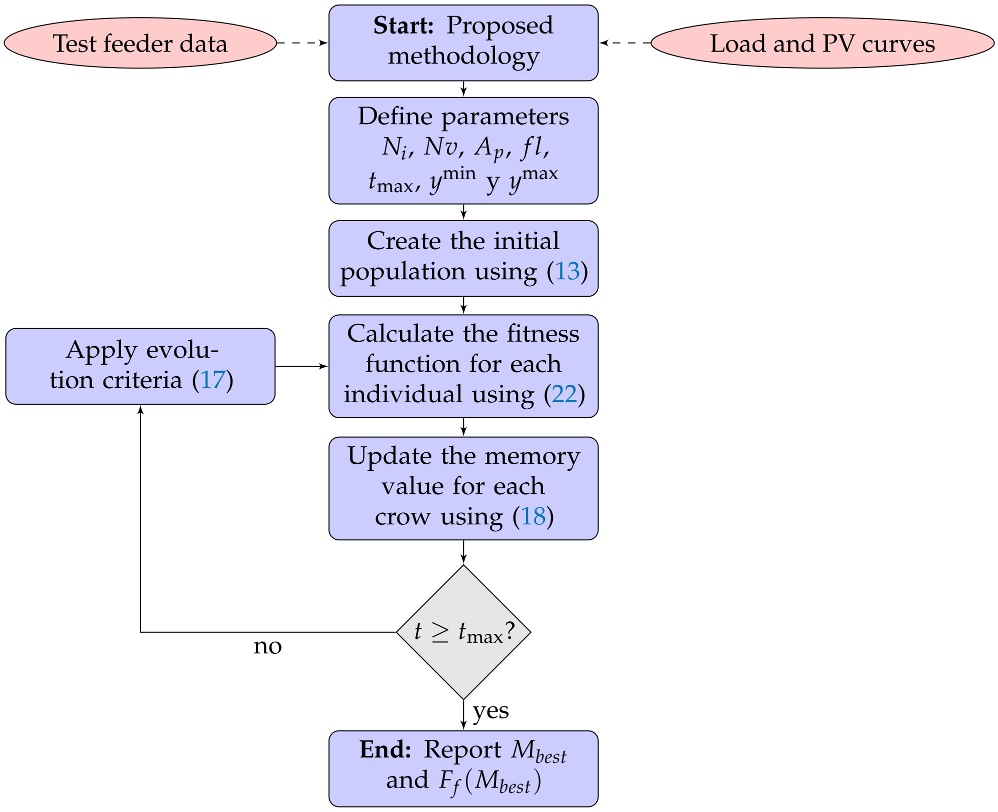

Figure 1. General application of the master–slave approach to address the problem of optimal integration of PV generating units in DC networks.

4. Test Feeders

To solve the problem under study, the DC versions of the 33- and 69-bus feeders (both with a radial topology) were used [29]. The main characteristics of each test feeder are presented below.

4.1. 33-Bus Test Feeder

This test feeder is an adaptation of the 33-bus ac test feeder commonly used to solve the problem of integrating PV generators into electrical systems. This feeder was originally proposed in [30]. Initially, it consists of 33 buses and 32 distribution lines, as shown in Figure 2a. To transform this feeder into a DC network, a voltage base of 12.66 kV and a power base of 100 kW are used. Additionally, the reactance component of all the distribution lines is neglected, as well as the reactive power consumption in all the buses that make up the feeder. In the maximum consumption scenario, the system loads consume 3715 kW. The parametric information for this system can be consulted in [31].

4.2. 69-Bus Test Feeder

This test feeder is an adaptation of the 69-bus AC test feeder commonly used to solve the problem of integrating PV generators into distribution systems, which was originally proposed in [32]. Initially, this feeder consists of 69 bus and 68 distribution lines, as shown in Figure 2b. To transform this feeder into a DC network, a voltage base of 12.66 kV and a power base of 100 kW are used. As in the previous feeder, the reactance component of all the distribution lines and the reactive power consumption in all the buses that make up the system are neglected. In the maximum consumption scenario, the system loads consume 3890.7 kW. The parametric information of this system can be found in [31].

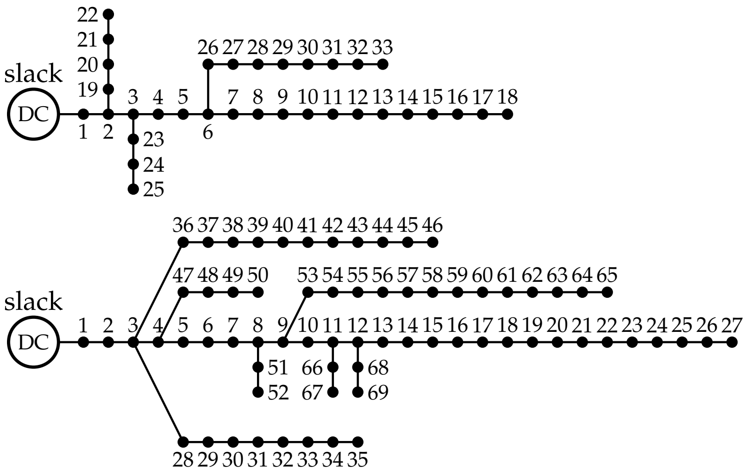

Figure 2. Electrical schematic of the test feeders: (**a**) 33-bus and (**b**) 69-bus.

Remark 1. *In this research work, the equivalent DC system electrical configuration is assumed to be monopolar, i.e., the voltage difference between the positive pole and the neutral conductor is the same as that assigned in the AC network [33].*

4.3. Calculating the Objective Function

To estimate the value of the adaptation function described in (22), the information shown in Table 1 was employed [34,35]. The cost of electricity considered for this study is a real value reported in [36], which corresponds to the average cost of energy reported by the utility company CODENSA of Bogota, Colombia, in May 2019. We have taken this value to have a fair comparison between the proposed methodology and the methodologies previously used to solve the problem under study in DC grids since this electricity price was used by the different comparison methodologies

Table 1. Information used to calculate the objective function value.

Parameter	Value	Unit	Parameter	Value	Unit
C_{kWh}	0.1390	USD/kWh	T	365	days
t_a	10	%	N_t	20	years
Δh	1	h	t_e	2	%
C_{pv}	1036.49	USD/kWp	$C_{O\&M}$	0.0019	USD/kWh
N_{pv}^{ava}	3	-	ΔV	± 10	%
$P_k^{pv,\min}$	0	kW	$P_k^{pv,\max}$	2400	kW
β_1	1×10^6	USD/V	β_2	1×10^6	USD/V
β_3	1×10^6	USD/W	-	-	-

To determine the effect of integrating PV generators into the test feeders presented in the previous subsection, the generation and demand curves for the city of Medellín, Colombia, were used (see Figure 3). These curves were first reported in [37].

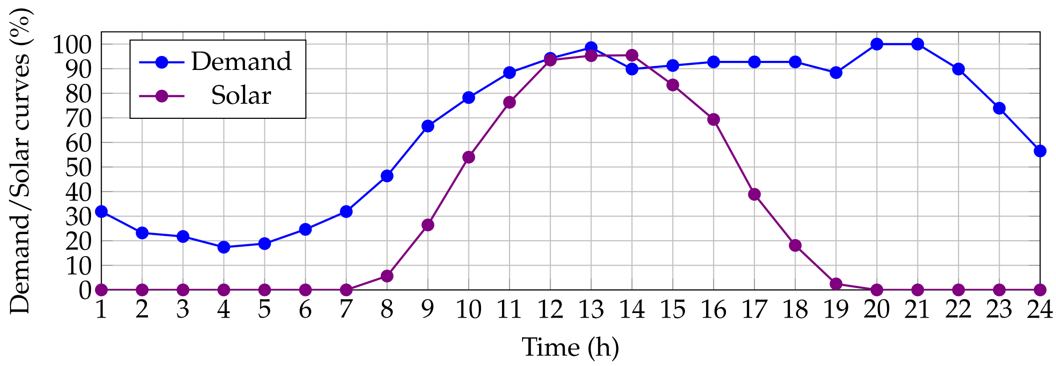

Figure 3. Daily demand and generation curves for Medellín, Colombia.

5. Numerical Results and Discussions

All simulations were implemented in the MATLAB programming environment, version 2022*a*, using proprietary scripts on a desktop computer with an Intel(R) Core(TM) i9-11900 processor CPU@2.50Ghz, 64.0 GB RAM and a 64-bit Windows 10 pro operating system. In order to demonstrate the performance of the suggested optimization approach, the DCCSA has been compared with the next methodologies, which were previously employed to address the problem under study in both AC and DC networks: (i) the BONMIN solver of the specialized GAMS software (exact solution of the MINLP model) [38], (ii) the discrete-continuous version of the Chu & Beasley Genetic Algorithm (DCCBGA) [38], (iii) the discrete-continuous version of the vortex search algorithm (DCVSA) [19], (iv) the discrete-continuous version of the generalized normal distribution optimizer (DCGNDO) [20], and (v) the discrete-continuous version of the parallelized particle swarm particle optimization algorithm (DCPPSO) [39]. Finally, for both test feeders, the installation of three PV generation units with a maximum size of 2400 kW was proposed.

5.1. DCCSA Parameters

To address the problem of the optimal integration of PV generators into DC networks, we used the information contained in Table 2.

Table 2. Parameters of the discrete-continuous crow search algorithm used in the master stage.

Parameter	DCCSA
Number of individuals (N_i)	62
Maximum iterations ($t_{\max}$)	622
Flight length (fl)	1.8468
Awareness probability (A_p)	0.0145

For the choice of the parameters listed in Table 2, the DCCSA was tuned using the CBGA [40] with an initial population of 50 individuals and a maximum number of iterations of 350. The tuning stage consists of using a metaheuristic algorithm in a previous stage, in the case of this study, the CBGA, to find the optimal parameters of the DCCSA to achieve a balance between thee exploration and exploitation of the algorithm. This is performed in order to guarantee the convergence of the algorithm and to ensure that the algorithm finds the global optimal solution (or very close optimal solutions) for the problem of integration of PV generators into DC networks. Similarly, another advantage of tuning metaheuristic algorithms is that it increases repeatability, i.e., each time the algorithm is run, it will always find the same or a very close solution. The parameters for tuning were: (i) the population size (N_i), with a range of [1–100] individuals; (ii) maximum number of iterations (t_{max}), with a range of [1–1000]; (iii) the flight length (fl), with a range of [0–3.5]; and (iv) the awareness probability (A_p), with a range of [0–1]. These parameters were selected due to the influence that each of them has on the performance of the algorithm since the modification of each of these parameters directly affects the exploration and exploitation of the DCCSA [22].

Figure 4 presents a flowchart where the operating principle of the tuning stage can be observed. In this stage, the CBGA is responsible for generating the optimal DCCSA parameters (i.e., N_i, t_{max}, f_l and A_p) represented by the red arrow. These parameters enter the master–slave stage to evaluate the value of the objective function of the problem under study represented by the green arrow. Once the iterative process is finished, the tuning stage finds the DCCSA parameters that allow finding the best value of the objective function. Regarding the parameters of the algorithms used for comparative purposes, they were taken from the original papers in which they were used for the first time to solve the problem of the location and sizing of PV generators in DC networks.

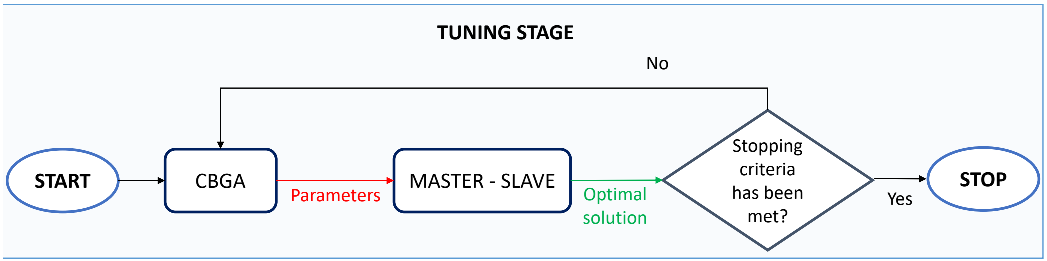

Figure 4. Operating principle of the tuning stage.

Likewise, it was also proposed to carry out 100 consecutive evaluations of the developed method to find the best, average and worst values of the objective function. In addition, the standard deviation of the two proposed test feeders and the average calculation time taken by the algorithm to find the optimal location and size of the PV generator were calculated.

5.2. Results from the First Test Feeder

5.2.1. Numerical Results

Table 3 shows the numerical values found by applying the proposed approach in the DC version of the 33-bus test feeder. The data in this table are listed from left to right as follows: the methodology used, the buses where the PV generators were installed and their rated power and the total annual operating costs.

Table 3. Numerical performance for the DC version of the 33-bus feeder.

Method	Site and Size (bus, MW)	A_{cost}(USD/Year)	Reduction(%)
Bench. Case	-	3,644,043.01	0
BONMIN	$\{18(1.4301), 32(2.0611), 33(0.1437)\}$	2,664,089.12	26.8919
DCCBGA	$\{11(1.1630), 14(0.9435), 31(1.4828)\}$	2,662,724.82	26.9294
DCVSA	$\{9(0.5803), 15(1.2914), 31(1.7156)\}$	2,662,425.32	26.9376
DCGNDO	$\{10(0.9743), 16(0.9202), 31(1.6925)\}$	2,662,371.59	26.9391
DCPPSO	$\{10(0.9680), 16(0.9189), 31(1.6999)\}$	2,662,371.59	26.9391
DCCSA	$\{10(0.9742), 16(0.9198), 31(1.6930)\}$	2,662,371.59	26.9391

The numerical results from the 33-bus test feeder show the following:

- ✓ All metaheuristic algorithms outperform the solution provided by BONMIN (i.e., the exact solution of the MINLP model), corroborating that the existence of binary variables leads the exact solution methods to be trapped in local optima.
- ✓ DCCSA, DCGNDO and DCPPSO are the methodologies that reach the best solution, achieving a reduction of 981,671.42 USD/year with respect to the benchmark case, confirming that the global optimal solution for the 33-bus test feeder is 2,662,371.59 USD/year

and is reached by locating the PV generation units at buses 10, 16 and 31, with a total rated capacity of 3586.97 kWp.

✓ The methodologies used to achieve the integration of PV generators allow savings of more than 26.85% compared to the benchmark case, with DCCSA, DCGNDO and DCPPSO being the methodologies that achieve the greatest reduction of 26.9391%. When these methodologies are compared to the other solution methodologies, there is a reduction in annual operating costs of approximately 0.0472% with respect to BONMIN, 0.0097% with respect to DCCBGA and 0.0015% with respect to DCVSA.

5.2.2. Statistical Analysis

Table 4 shows the results obtained by performing 100 consecutive evaluations of the master–slave approach in the 33-bus test feeder. The data in this table are listed from left to right as follows: the methodology used, the best solution found, the percent standard deviation and the average computation time.

Table 4. Numerical performance comparison in the 33-bus feeder after 100 consecutive evaluations.

Method	Best(USD/Year)	SDT(%)	Avg. Time(s)
BONMIN	2,664,089.12	0	1.29
DCCBGA	2,662,724.82	0.0557	2.43
DCVSA	2,662,425.32	0.0620	76.86
DCGNDO	2,662,371.59	0.0601	159.99
DCPPSO	2,662,371.59	0.0398	16.81
DCCSA	2,662,371.59	0.0058	20.86

The results in Table 4 show the following:

✓ DCCSA, DCGNDO and DCPPSO, in comparison with the methodologies reported in the literature, provide better results in terms of annual operating costs. They outperform BONMIN by 0.0645%, DCCBGA by 0.0133% and DCVSA by 0.0020%.

✓ Regarding computation times, BONMIN, DCCBGA and DCPPSO are faster than the proposed methodology, reducing processing times by 93.8016%, 88.3510% and 19.4160%, respectively, in comparison with DCCSA. However, as it is a planning problem, 20 s is a low processing time compared to the planning horizon, and DCCSA can solve the PV generator integration problem for DC networks while providing quality solutions with low computation times.

✓ Regarding the standard deviation, the superiority of the proposed DCCSA can be understood, achieving a reduction of 867.5515% with respect to DCCBGA, 977.5298% with respect to DCVSA, 943.9829% with respect to DCNGDO and 591.9624% with respect to DCPPSO. A comparison with respect to BONMIN was not made because when the MINLP model is exactly solved, its solution will always be the same.

The aforementioned demonstrates the effectiveness and robustness of DCCSA in solving the challenges of integrating PV generators into DC grids in order to reduce annual operating costs. The suggested method provides the best performance in terms of optimal solution and reproducibility with a short processing time. This makes it the best option to solve the problem of 33-bus test feeders, achieving an adequate solution not only from an economic point of view but also from a technical-operational point of view.

5.3. Results from the Second Test Feeder

5.3.1. Numerical Results

The numerical values found by the application of the proposed methodology on the DC version of the 69-bus test feeder are shown in Table 5. This table shows the same information as Table 3.

Table 5. Numerical results for the DC version of the 69-bus feeder.

Method	Site and Size (Bus, MVAr)	A_{cost}(USD/Year)	Reduction(%)
Bench. Case	-	3,817,420.38	0
DCCBGA	$\{19(0.7908), 61(1.7891), 64(1.1474)\}$	2,785,598.86	27.0293
DCVSA	$\{23(0.7720), 62(2.3403)63(0.6185)\}$	2,785,538.58	27.0309
BONMIN	$\{27(0.4971), 61(2.4000), 65(0.8531)\}$	2,785,208.63	27.0395
DCGNDO	$\{19(0.4970), 61(2.4000), 64(0.8470)\}$	2,785,011.53	27.0447
DCPPSO	$\{22(0.5310), 61(2.4000), 64(0.8105)\}$	2,784,987.68	27.0453
DCCSA	$\{21(0.4855), 61(2.4000), 64(0.8598)\}$	2,784,979.35	27.0455

The following can be concluded from the information presented in Table 5:

- ✓ The developed DCCSA is the methodology that achieves the best solution for the 69-bus test feeder, i.e., a reduction of approximately 1,032,441.03 USD/year with respect to the benchmark case, which indicates that the optimal solution to the problem addressed in this study is 2,784,979.35 USD/year and is reached by locating the PV generators at buses 21, 61 and 64, with a total rated capacity of 3745.29 kWp.
- ✓ The comparison methodologies used to achieve the problem addressed allow savings of more than 27% with respect to the benchmark case, with DCCSA being the methodology that achieves the greatest reduction (i.e., 27.0455%). Similarly, when comparing the proposed methodology to the other solution methodologies reported in Table 5, reductions in the objective function value of approximately 0.0060% with respect to BONMIN, 0.0162% with respect to DCCBGA, 0.0146% with respect to DCVSA, 0.0008% with respect to DCGNDO and 0.0002% with respect to DCPPSO were obtained.

5.3.2. Statistical Analysis

As in the previous case, the effectiveness and robustness of the DCCSA for solving the problem under study were determined by performing 100 consecutive evaluations of the suggested approach in the 69-bus test feeder, whose results can be seen in Table 6. This table presents the same information as Table 4.

Table 6. Numerical performance comparison of the 69-bus feeder after 100 consecutive evaluations.

Method	Best(USD/Year)	SDT(%)	Avg. Time(s)
DCCBGA	2,785,598.86	0.1289	7.74
DCVSA	2,785,538.58	0.0975	269.22
BONMIN	2,785,208.63	0	2.03
DCGNDO	2,785,011.53	0.2384	376.88
DCPPSO	2,784,987.68	0.0226	28.24
DCCSA	2,784,979.35	0.0178	69.96

These results show the following:

- ✓ DCCSA, in comparison with all of the methodologies reported in the literature, provides better results in terms of the evaluation of the objective function. It outperforms BONMIN by 0.0082%, DCCBGA by 0.0222%, DCVSA by 0.0201%, DCNGDO by 0.0012% and DCPPSO by 0.0003%.
- ✓ As for the processing times, it can be seen that BONMIN, DCCBGA and DCPPSO are faster than the proposed methodology, reducing processing times by 97.0996%, 88.9359% and 59.6316%. It is also important to note that the DCCSA solves this highly complex optimization problem with the best results in less than 1.5 min.
- ✓ With regard to the standard deviation, the superiority of the proposed DCCSA is appreciated, achieving a reduction of 624.1573% with respect to DCCBGA, 447.7528%

with respect to DCVSA, 1239.3258% with respect to DCNGDO and 26.9663% with respect to DCPPSO. As mentioned in the previous subsection, no comparison was made with BONMIN.

The results presented above highlight that the developed DCCSA exhibits the best performance in terms of its solution and repeatability, with low processing times, making it the best choice to solve the problem of integrating PV generators into the 69-bus test feeder.

6. Conclusions and Future Work

This research document presents a master–slave approach to address the problem regarding the integration of PV generators into DC grids. In the master phase, the DCCSA is in charge of determining the bus where the photovoltaic generators will be installed, along with their rated powers, while the slave phase calculates the value of the adaptation function using the successive approximation power flow method. The DCCSA parameters were tuned using the CBGA. The numerical performance demonstrated the implementability and effectiveness of the optimization approach developed for the 33- and 69-bus DC test feeders when compared to different methodologies reported in the specialized literature, such as the BONMIN solver of GAMS, the Chu & Beasley genetic algorithm, the vortex search algorithm, the normal distribution optimizer and the particle swarm optimization algorithm.

In this regard, the following remarks can be made:

✓ The DCCSA achieves a reduction in the total annual operating costs of approximately 981,671.42 and 1,032,441.03 USD/year for each test feeder. These values represent reductions of 26.9391% and 27.0455%, respectively.

✓ The developed DCCSA obtains lower standard deviation values for the DC version of the 33- and 69-bus test feeders, showing improvements of 591.9624% and 26.9663% concerning the DCPPSO (i.e., second-best results), respectively. These standard deviation results confirm the repeatability and robustness of the proposed DCCSA in solving the PV generation unit integration problem, ensuring that, in each evaluation, the response is within a radius of 153 USD/year for the 33-bus feeder and 637 USD/year for the 69-bus feeder.

✓ The computation times taken by the proposed methodology to solve the MINLP model are 20.86 and 69.96 s for the 33 and 69-bus test feeders, respectively. This demonstrates that the developed methodology is a robust tool that allows the solving of highly complex mathematical models, ensuring quality answers when compared to other methods reported in the literature, as well as with low processing times. This allows the conclusion that the developed DCCSA is the best solution methodology to solve the problem herein addressed.

As future work, the following can be proposed: (i) reformulating the mathematical model of the problem under study while considering freeing the PV generators, i.e., disabling the maximum power point tracking of the PV generators; (ii) reformulating the mathematical model of the problem under study while considering the integration of batteries; (iii) including the problem of optimal conductor selection in the planning of DC networks, taking the investment costs of each conductor into account; and (iv) the reformulation of the studied problem via mixed-integer convex approximations by ensuring the global optimum finding with gradient-based algorithms combined with branch and cut optimization techniques.

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