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Matheuristic Algorithm Based on Neighborhood Structure to Solve the Reconfiguration Problem of Active Distribution Systems

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***Abstract*— The problem of reconfiguration for active distribution systems is formulated as a stochastic mixed-integer second-order conic programming (MISOCP) model that simultaneously considers the minimization of energy power losses and CO2 emissions. The solution of the model determines the optimal radial topology, the operation of switchable capacitor banks, and the operation of dispatchable and non - dispatchable distributed generators. A stochastic scenario-based model is considered to handle uncertainties in load behavior, solar irradiation, and energy prices. The optimal solution of this model can be reached with a commercial solver; however, this is not computationally efficient. To tackle this issue a novel methodology which explores the efficiency of classical optimization techniques and heuristic based on neighborhood structures, referred as matheuristic algorithm is proposed. In this algorithm. the neighborhood search is carried out using the solution of reduced MISOCP models that are obtained from the original formulation of the problem. Numerical experiments are performed using several systems to compare the performance of the proposed matheuristic against the direct solution by the commercial solver CPLEX. Results demonstrate the superiority of the proposed methodology solving the problem for large-scale systems.**

Keywords*— CO_2 emissions mitigation, distribution systems reconfiguration, matheuristic, mixed-integer second-order conic programming, neighborhood search.

I. INTRODUCTION

A. Motivation and literature review

The optimal operation of distribution systems (DSs) is an important research area that seeks to increase economical, technical, and environmental benefits. Nevertheless, optimizing a DS is a complex task, due to the presence of sectionalizing and tie switches that change the network topology, the multiplicity of distributed technologies that inject power in the lines and the stochasticity of parameters that are part of the operational environment.

From a classical optimization approach, there are different ways to model this problem, however the mixed integer nature of variables and the stochasticity of certain parameters, add it a high complexity. Today's computational tools offer us different types of commercial solvers for mathematical programming. However, the implementation of new technologies in distribution systems has also advanced rapidly and analyze the mathematical model of a real system produces a heavy computational effort for the solver. In this way, are necessary new and efficient approaches to reach a suitable operational state of the networks.

Based on what was explained in the previous paragraphs, some of the elements that add complexity to the mathematical model are the binary variables related to the change of topology, the integer variables related to the state of switchable capacitors and the analysis of a set of scenarios that represent the stochasticity of parameters such as load, solar radiation and energy cost. Each of these elements can be specifically addressed during the solution process to reduce computational effort and get a good-quality results.

The distribution network reconfiguration (DNR) problem, is an extensively researched topic that has been treated mainly in two ways [1], mathematical programming [2], and metaheuristic approaches [3]. For large systems however, the optimal solution still represents a problem. Additionally, the use of renewable energy sources that is growing globally led by the continued installation of approximately 100 GW of grid-connected photovoltaics (PV) per year [4], makes the uncertainty of output from renewable primary sources an important aspect. This is combined with the variability of demand to increase the challenges associated with obtaining an efficient solution to the problem.

Nowadays, several concerns have emerged due to high greenhouse gases emissions from the sector of electricity generation; therefore, it has been necessary to create policies that encourage the use of renewable generation to reduce the CO_2 emissions produced by the burning of fossil fuels. In this regard, the inclusion of renewable energy sources (RES) in the DSs can help to mitigate the impact to use fossil fuels as primary generation sources [5].

All these factors should be considered when devising a procedure that optimizes the operation of DSs to minimize the cost of energy losses as well as the penalty for CO_2

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emissions. Generally, the reconfiguration problem has been studied as a strategy to minimize active energy losses, however, having different schemes working together, it is appropriate to be able to extend it to consider other objectives that also economically impact the operation of the DS.

Among some of the relevant works that address the DNR problem for loss minimization through mathematical programming, it can mentioned the MISOCP proposed model for loss reduction presented in [2], this is characterized by being the first convex reconfiguration model proposed, which accurately calculates power losses, unlike previous works that only proposed approximations. In [6], the real and imaginary parts of the variables are separated to obtain a mixed-integer linear programming (MILP) model. Due to the advantages of convexity, the development of new conical models has advanced and they have been used according to the study approach. Two clear examples of the advantages offered by this type of modeling are [7] that use the big-M method and piecewise linearization to losses minimization and, [8] that joint the reconfiguration and placement of capacitors problems. The broad application of metaheuristics to solve the reconfiguration problem is demonstrated in [3], where the authors present a review about the used methodologies, some of they are Simulated annealing (SA), Tabu search (TS), Evolutionary algorithm (EA), Generic algorithms (GA), and others. The authors in [9] propose a differential evolution algorithm to minimize losses. The CO_2 emissions minimization is currently a topic under intense study but there is not a deep analysis of the relationship between it and the reconfiguration. Works that consider this link are: [10] that uses a multi verse optimization (MVO) algorithm to solve the reconfiguration problem and shows that emissions are reduced in a directly proportional way with losses; on the other hand, [11] formulates the emissions minimization as a part of the objective function that reduce the operational overall costs.

B. *Research gap and novelty contributions*

Matheuristic algorithms are optimization tools that joint metaheuristics and mathematical programming, to solve complex optimization problems. As such, the matheuristic concept has been successfully applied for much mathematical programming problems and is associated with the improvement of MIP solvers. However, the matheuristics have not been significantly explored on DSs field.

Due to the above, this work contributes with a new neighborhood matheuristic algorithm (NMA) to solve the reconfiguration problem of active DSs. The mathematical model of the problem is a MISOCP stochastic scenario-based model that minimizes the total cost of energy losses and the taxation produced by emissions of CO_2. The model solution determines the optimal operation of switchable capacitor banks (SCB), dispatchable DGs, and PV units.

The remainder of the paper is organized as follows: Section II presents the mathematical model of the problem; the proposed methodology approach is shown in Section III; Section IV presents the obtained results for different systems and a comparing analysis of performance between the implemented methodology and mathematical programming CPLEX solver. Finally, conclusions are drawn in Section V.

II. Problem Formulation

A. *Uncertainty*

In this work it is necessary to model the uncertainty for the three stochastic parameters, cost of energy, electrical load and solar radiation. It is carried out using the k-means clustering technique that takes samples of historical measurements and generates k-scenarios of operation in order to represent a specific period [5]. This clustering technique arrange data according to their similarities with a good performance and simplicity [12], obtaining as a result a reduced set of centroids determined by the mean square distance between the samples.

The time range considered for the analyses in this work in specific was 2160 hours (three months) that correspond to a year season. This set of historical data were taken from [13] and correspond to a Brazilian littoral's São Paulo state. Then, the data is processed according to Fig. 1 where the k-means method obtains two groups of twelve scenarios (centroids). Each group represents a typical day and the probability of occurrence of a scenario that belongs to the first group is the complement to the respective probability of the scenario belonging to the second one. The day and night are considered due to the PV generation.

B. *Objective function*

The stochastic programming model optimizes the operational cost of the system, simulating a day of operation by 24 weighted scenarios. This objective is obtained minimizing the cost of active power losses and the cost of CO_2 emissions penalty, as is showed in Equation (1).

$$Min\ \mathcal{F} = \sum_{s\in\Omega_C} Prob_s \cdot T_s \cdot (C_s^{Loss} + C_s^{Emis}) \tag{1}$$

where:

$$C_s^{Loss} = C_s^L \left(\sum_{ij\in\Omega_B} R_{ij} \cdot I_{ij,s}^{sqr} \right) \quad \forall\, s \in \Omega_C \tag{2}$$

$$C_s^{Emis} = C^{tax} \left(\sum_{i\in\Omega_{SS}} e^{gs} P_{i,s}^S + \sum_{i\in\Omega_{DG}} e^{gg} P_{i,s}^{DG} \right) \quad \forall\, s \in \Omega_C \tag{3}$$

In the objective function $\mathcal{F}$ (1), C_s^{Loss} represents the total cost for active power losses and C_s^{Emis} represents the total tax per carbon emissions. In these equations, Ω_C is the set of stochastic scenarios, Ω_B is the set of branches, Ω_{SS} is the set of substation nodes, and Ω_{DG} is the set of nodes with DG installed. The parameter $Prob_s$ is the probability of occurrence of the scenario s, T_s is the duration of each period (2 hours), C_s^L is the price per unit of energy, C^{tax} is the tax per ton of produced carbon, R_{ij} is the resistance of branch ij, e^{gs} and e^{gg} are the CO_2 emission factors, kg of CO_2 per kWh generated at substations and dispatchable generators, respectively. Continuous variables $P_{i,s}^S$ and $P_{i,s}^{DG}$ are the active

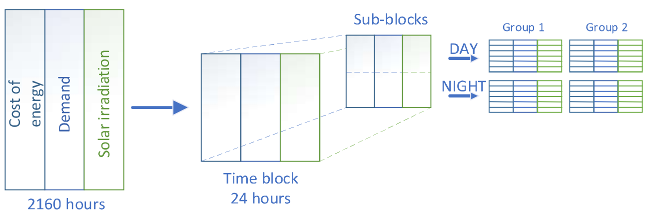

Fig. 1. Scenarios generation by *k-means* method.

power injected by substations and DG units, $I_{ij,s}^{sqr}$ is the square of the current magnitude through a branch.

Equation (2) determines the total cost for energy losses in each scenario. Equation (3) determines the total tax per carbon emissions.

C. Operational state of the network

The operational state of radial DSs is determined using the following constraint that represent the steady state of the system.

$$\sum_{ki \in \Omega_B} P_{ki,s} - \sum_{ij \in \Omega_B} \left(P_{ij,s} + R_{ij} I_{ij,s}^{sqr}\right) + P_{i,s}^{S} + P_{i,s}^{DG} + P_{i,s}^{PV} = P_{i,s}^{D} \quad \forall i \in \Omega_N, \forall s \in \Omega_C \quad (4)$$

$$\sum_{ki \in \Omega_B} Q_{ki,s} - \sum_{ij \in \Omega_B} \left(Q_{ij,s} + X_{ij} I_{ij,s}^{sqr}\right) + Q_{i,s}^{S} + Q_{i,s}^{DG} + Q_{i,s}^{scb} + Q_{i,s}^{PV} = Q_{i,s}^{D} \quad \forall i \in \Omega_N, \forall s \in \Omega_C \quad (5)$$

$$V_{i,s}^{sqr} - V_{j,s}^{sqr} + \mu_{ij,s} = 2\left(R_{ij} P_{ij,s} + X_{ij} Q_{ij,s}\right) + Z_{ij}^{sqr} I_{ij,s}^{sqr} \quad \forall ij \in \Omega_B, \forall s \in \Omega_C \quad (6)$$

$$\left|\mu_{ij,s}\right| \leq (\overline{V}^2 - \underline{V}^2)(1 - k_{ij}) \quad \forall ij \in \Omega_B, \forall s \in \Omega_C \quad (7)$$

$$I_{ij,s}^{sqr} V_{j,s}^{sqr} \geq P_{ij,s}^2 + Q_{ij,s}^2 \quad \forall ij \in \Omega_B, \forall s \in \Omega_C \quad (8)$$

In (4)–(8), the set Ω_N is the set of nodes of the system. The parameter X_{ij} is the reactance of branch ij, Z_{ij}^{sqr} is the squared impedance of ij, $P_{i,s}^{D}$ and $Q_{i,s}^{D}$ are the active and reactive demand at each load node, $\overline{V}$ and $\underline{V}$ are the maximum and minimum voltage magnitude limits respectively. The continuous variables $P_{ij,s}$ and $Q_{ij,s}$ are the active and reactive power flow magnitude through the branch ij. $V_{i,s}^{sqr}$ indicates the squared voltage magnitude, $\mu_{ij,s}$ is a slack variable, $P_{i,s}^{S}$ and $Q_{i,s}^{S}$ are the active and reactive power injected by the substation at node i, $P_{i,s}^{DG}$ and $Q_{i,s}^{DG}$ represent the active and reactive power injected at each dispatchable DG node, $P_{i,s}^{PV}$ and $Q_{i,s}^{PV}$ are the active and reactive power injected by photovoltaic panels respectively, $Q_{i,s}^{cb}$ and $Q_{i,s}^{scb}$ are the reactive power injected by a CB and SCB respectively, and finally, k_{ij} is a binary variable that indicates the status of the switches, i.e., if $k_{ij} = 1$ then, the switch ij is closed and the branch is operating, otherwise, if $k_{ij} = 0$ then, the switch is open.

Kirchhoff's current law is represented as the active and reactive power balances for each node in (4) and (5), respectively. The Kirchhoff's voltage law is represented in (6), where the slack variable $\mu_{ij,s}$ is calculated according to the status of the switches (6). The flow of current through a branch is calculated by the conic inequality constraint (6) which guarantees optimality and convexity in term of the continuous variables of the problem.

D. Radiality constraints

Representing a DS as a spanning tree connected to a substation is a feasible way to maintain the radiality of the network [2]. For this, it is necessary to introduce two binary variables β_{ij} and β_{ji} that indicate the direction of power flow through branch ij.

If a line belongs to the spanning tree, i.e., $k_{ij} = 1$, then the variable $\beta_{ij} = 1$ indicates that j is the parent node of i, or in otherwise, if $\beta_{ji} = 1$ this means that i is the parent node of j:

$$\beta_{ij} + \beta_{ji} = k_{ij} \qquad \beta_{ij}, \beta_{ji}, k_{ij} \in \{0,1\} \qquad \forall ij \in \Omega_B \quad (9)$$

$$\sum_{j \in \Omega_N \mid ij \in \Omega_B \text{ or } ji \in \Omega_B} \beta_{ij} = 1 \quad \forall ij \in \Omega_B \quad (10)$$

$$\beta_{ij} = 0 \quad \forall ij \in \Omega_B \mid i \in \Omega_{SS} \quad (11)$$

$$\beta_{ji} = 0 \quad \forall ij \in \Omega_B \mid j \in \Omega_{SS} \quad (12)$$

Constraint (9) indicates that if a line is active $k_{ij} = 1$, it must have only one direction of flow, otherwise if $k_{ij} = 0$. Constraint (10) imposes that each load node must have one parent. Finally, equations (11) and (12) express that a substation cannot have a parent node. This formulation guarantees the radial connectivity of the grid even in networks with DGs.

E. Distributed generation

The operation of synchronous machines is modeled by (13)– (15).

$$\left(P_{i,s}^{DG}\right)^2 + \left(Q_{i,s}^{DG}\right)^2 \leq (S_i^{DG})^2 \quad \forall i \in \Omega_{DG}, \forall s \in \Omega_C \quad (13)$$

$$P_{i,s}^{DG} \geq 0 \quad \forall i \in \Omega_{DG}, \forall s \in \Omega_C \quad (14)$$

$$-P_{i,s}^{DG} \cdot tan\left(cos^{-1}\varphi_i^{C,DG}\right) \leq Q_{i,s}^{DG} \leq P_{i,s}^{DG} \cdot tan\left(cos^{-1}\varphi_i^{I,DG}\right) \quad \forall i \in \Omega_{DG}, \forall s \in \Omega_C \quad (15)$$

Constraint (13) limits the active and reactive power injection regarding the capacity of the machine S_i^{DG}, connected to node i. (14) indicates that the active power must have a positive value, finally, (15) determine the injection of reactive power in the network between the limits defined by the capacitive $\varphi_i^{C,DG}$ and inductive $\varphi_i^{I,DG}$ power factors respectively.

The power generated by a photovoltaic panel is presented in (16) and ((17).

$$0 \leq P_{i,s}^{PV} \leq \overline{P_i^{PV}} \quad \forall i \in \Omega_{PV}, \forall s \in \Omega_C \quad (16)$$

$$-P_{i,s}^{PV} \cdot \tan\left(cos^{-1}\varphi_i^{C,PV}\right) \leq Q_{i,s}^{PV} \leq P_{i,s}^{PV} \cdot \tan\left(cos^{-1}\varphi_i^{I,PV}\right) \quad \forall i \in \Omega_{PV}, \forall s \in \Omega_C \quad (17)$$

Constraints (16) and ((17) impose the limits of injection for the active and reactive power respectively where $\varphi_i^{C,PV}$ and $\varphi_i^{I,PV}$ are the power factors.

F. Capacitor banks

The operation of SCBs is modeled by (18)–(19).

$$Q_{i,s}^{scb} = n_{i,s}^{scb} \cdot q_i^{scb} \quad \forall i \in \Omega_{scb}, \forall s \in \Omega_C \quad (18)$$

$$0 \leq n_{i,s}^{scb} \leq \overline{n}_i^{scb} \quad \forall i \in \Omega_{scb}, \forall s \in \Omega_C \quad (19)$$

In these constraints, Ω_{scb} is the set of nodes with a SCB, the parameter q_i^{scb} is the capacity of each capacitor unit, $\overline{n}_i^{scb}$ is the number of installed units. Integer variable $n_{i,s}^{scb}$ determines the number of connected units at node i and scenario s. The constraints (18) represents the power injected by the CBs and (19) limits the number of connected modules at node i.

III. Matheuristic Approach Applied to the Network Reconfiguration Problem

The reconfiguration model (1)–(19) presented in the previous section is highly complex which directly impacts the computational time required to solve it by a commercial solver. In this regard, matheuristics optimization techniques appear to be suitable alternative to solve the problem. These techniques combine classic optimization and heuristic algorithms to solve high complexity problems [14]. This combination results in a process with efficiency driven by the heuristics while maintaining the accuracy of classic optimization [15]. In this way, during the solution process, the heuristics oversees exploring new search spaces and escaping from local optimum, while the mathematical model is iteratively evaluated exploiting their characteristics, on these different neighborhoods.

The proposed neighborhood matheuristic algorithm (NMA) is based on neighborhood search around a current solution, then an efficient strategy to determine a high-quality neighbor solution is required. In this work, this neighborhood search is based on the solution of simplified MISOCP models obtained from (1)–(19). These MISOCP models; simpler than the original, allow to explore the search space through changes in a current solution. The following subsections present details of proposed matheuristic algorithm.

A. Reduction of the search space

Since the DNR model (1)–(19) is used to define the neighborhood structures, it is convenient to reduce the search space to reduce the computational effort. In this regard, the optimal operation of the SCBs that is defined using integer variables, could be an issue to find efficient solutions. Therefore, constraints (20) and (21) are introduced.

$$n^{scb}_{i,s-1} - \eta_i \le n^{scb}_{i,s} \le n^{scb}_{i,s-1} + \eta_i \qquad \forall i \in \Omega_{scb}, \forall s \in \Omega_C \qquad (20)$$

$$\sum_{i\in\Omega_{scb}} n^{scb}_{i,s-1} - \overline{\eta} \le \sum_{i\in\Omega_{scb}} n^{scb}_{i,s} \le \sum_{i\in\Omega_{scb}} n^{scb}_{i,s-1} + \overline{\eta} \qquad \forall s \in \Omega_C \qquad (21)$$

For each SCB node, constraint (20) ensures that the change in the number of active modules between two scenarios is in unit steps. Between one scenario and the next, constraint (21) controls the variation in the total number of modules connected to the system. This variation can be of $\overline{\eta}$ units.

B. Neighborhood structure

An efficient criterion to generate neighboring solutions, directly influences the development time of an algorithm. For the reconfiguration case, efficiency can be obtained by touring a neighborhood structure where all possible solutions are radials. In the relevant literature, branch-exchange is the most popular technique to obtain radial neighbor topologies for the DNR problem [16]. It consists of closing a (normally open) tie switch forming a loop, and opening a (normally closed) sectionalizing switch that belongs to the loop. Based on this idea, a neighborhood depends on an algorithm to recognize the loops and the candidate lines to be opened. In order to perform this procedure, the implemented algorithm uses the variables β_{ij} and β_{ji} from (9)-(12) as is shown in the Fig. 2 and it is following explained.

In the example of Fig. 3a, the system has a radial topology with two open lines L8 and L9. If line L9 is closed, as shown in Fig. 3b, the algorithm identifies the pair of connected nodes, $i = 5$ and $j = 9$ and searches a path from each of them until a substation. For the node 5, $\beta_{15} = 0$; $\beta_{51} = 1$, which indicates that the parent of the node 5 is the node 1, then line L2 is marked and the algorithm identifies that this parent node is a substation. The same procedure is repeated from node 9. In this case, $\beta_{89} = 0$ and $\beta_{98} = 1$, indicate that the parent of 9 is the node 8, then L6 is marked; however, this is not a substation node, thus the new analyzed node is $i = 8$; the variables $\beta_{28} = 0$; $\beta_{82} = 1$, show that the parent node of 8 is the node 2. Thus, L7 is marked; this parent node is a substation, so consequently the process stops. As result, the

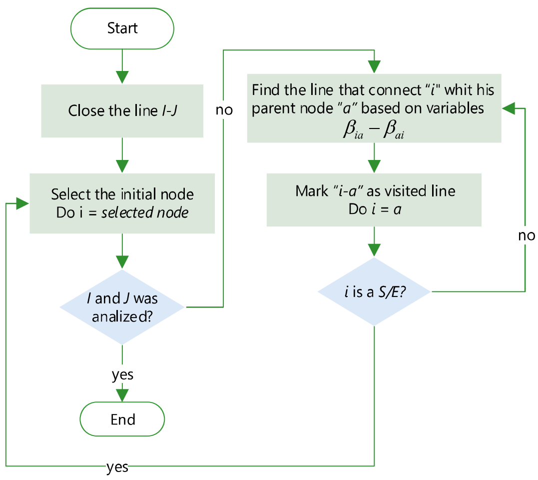

Fig. 2. Loop recognition algorithm.

vector of candidate lines to be opened (VL) contains L2, L6 and L7, as is shown in Fig. 3b. The set of lines that do not belong to VL are fixed in their current open/closed status, and the solution of the MISOCP model (1)-(21) determines the optimal neighbor radial solution by opening one of the lines in VL. Note that, the optimal solution also allows changes on SCBs. In this example, it was possible to reduce the number of candidate lines from 9 to 3. If some lines are closed simultaneously, the process is repeated simultaneously too.

C. Heuristic and mathematical programming interoperation

Heuristic approach is an optimization technique characterized by its greedy behavior. The process is always generating a better neighbor solution than the previous one. Once it is not possible to generate a better neighbor solution, the process stops. In general, the last found solution by the above process, is a local optimum. To tackle this, it can be applied some principle to escape from this not global optimum and the heuristic process can continue.

For this work, was used the concept of memory, in the same way that Tabu search method does. When the process arrives at a local optimum, it cannot return to previously visited solutions. These visited solutions, are saved in the memory and remain forbidden for the rest of the process. In this way, the process escapes from a local optimum by moving towards the next best unvisited neighbor solution. This allows the algorithm to visit a low-quality neighbor solution, then, the heuristic keeps moving throughout new neighborhoods.

The proposed heuristic methodology is a combination between a heuristic method and mathematical programming forming the matheuristic method.

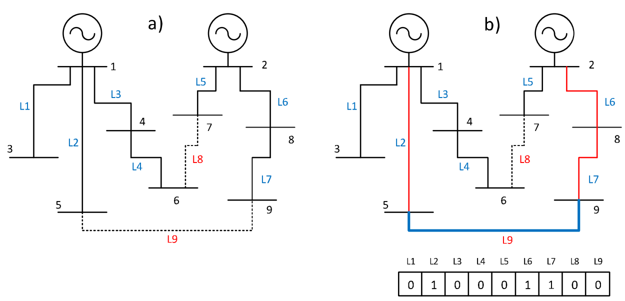

Fig. 3. Example of loop recognition. a) Initial topology. b) Recognition of the candidate lines to be opened.

As is shown in Fig. 4, the implemented algorithm starts defining the objective function of the initial topology and saves the current open lines vector and $n_{i,s}^{scb}$ variables in memory. Then, the neighborhood structure uses the current topology to generate 'n' neighbors closing 'k' different lines. The algorithm chooses the best neighbor for each neighborhood and updates the memory including the current visited solution. Each enhanced objective function value is defined as incumbent and it is not necessary that the best-neighbor be better than the incumbent to advance in the development; allowing for a reduction in the quality of solutions to explore new search spaces. The neighborhood structure varies according to the 'k' parameter that closes a different number (for this work $1 <= k <= 3$) of lines per iteration giving dynamism during the move among solutions.

IV. Tests and Results

The MISOCP model, defined by (1)–(19), and the proposed NMA approach were implemented in AMPL. The solver CPLEX was used to optimize the models considering as stopping criteria an optimality gap of 0.1% or a maximum CPU time of 6 hours. Numerical experiments were carried out in a computer with Intel(R) Xeon(R) CPU E5-2650 v4 @ 2.20GHz processor and 64 GB of RAM. The tests are performed to compare the quality of solutions and the CPU time.

The CO_2 emission factor of the system is $e^{gs} = 2.17\ kg\ CO_2/\ kWh$ and the emission factor of dispatchable generators is $e^{gs} = 0.63\ kg\ CO_2/\ kWh$. The cost per ton of CO_2 produced is $C^{Emis} = 10\ US\$/\ Ton$.

In this paper, the data of solar irradiation were obtained from [13] and the k-means clustering technique is used to reduce the historical data to a suitable set of stochastic scenarios. This historical data comprises cost of energy, load level and solar irradiation. The quantity of analyzed hours was 2160 to represent a typical day of a quarter. In Fig. 5 is showed the stochastic scenarios obtained by k-means clustering method.

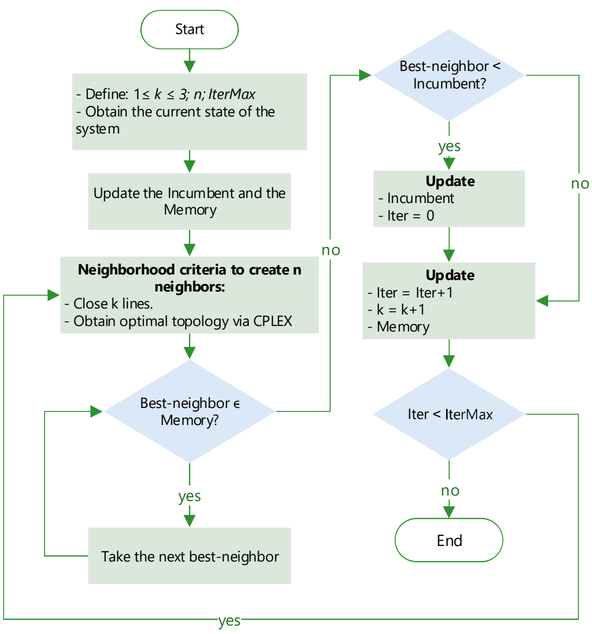

Fig. 4. Proposed matheuristic algorithm.

For all the dispatchable DG units the set power factor are $\varphi_i^{C,DG} = \varphi_i^{I,DG} = 0.8$, while for the PV units are $\varphi_i^{C,PV} = \varphi_i^{I,PV} = 0.9$. These data are the same for all the test systems.

A. 33 Bus System

This system was presented in [17]. Additionally, the following equipment were considered: a dispatchable DG of 250 kVA at node 23, two fixed CB of 150 kVAr at nodes 10 and 27, a SCB with 4 units of 150 kVAr each at node 19, finally, a photovoltaic panel with 250 kVA at node 32.

B. 69-Bus System

This system from [18], has three dispatchable DGs 300 kVA connected at nodes 6, 20 and 34. Two fixed CBs of 150 kVAr at nodes 17 and 20; two fixed CBs of 300 kVAr at nodes 53 and 68, a SCB with 4 units of 150 kVAr each at node 13. Finally, four photovoltaic units of 1 MVA at nodes 24, 28, 50 and 66.

C. 118-Bus System

This system from [19], has four dispatchable DGs of 250 kVA connected at the nodes 11, 25, 35 and 86, eight fixed CBs of 120 kVAr respectively at the nodes 9, 30, 48, 57, 58, 59 73 and 88. Two SCBs of 4 units and 120 kVAr each at the nodes 7 and 73. Six photovoltaic panels of 1MVA at nodes 17, 28, 50, 61, 107 and 111.

D. 136-Bus System

This system from [20], has three dispatchable DGs of 250 kVA at nodes 15, 42 and 63 and two DGs of 400 kVA at nodes 83 and 156. Six fixed CBs of 150 kVAr at nodes 18, 35, 48, 55, 87, 135 and 155. Two SCBs with 2 units of 120 kVAr each at nodes 5 and 21. Two SCBs with 4 units of 120 kVAr each at nodes 59 and 136. Finally, six photovoltaic panels of 1 MVA connected at nodes 12, 30, 83 and 87.

E. Discussion

TABLE I shows a comparison between the NMA and CPLEX solver solutions for (1)–(19). For the 33-bus and 69-bus systems, the proposed NMA algorithm finds the same solutions as CPLEX, while for the 118-bus system, the NMA the solution is only US$ 0.09 better than the CPLEX's solution. On the other hand, better solutions are obtained for

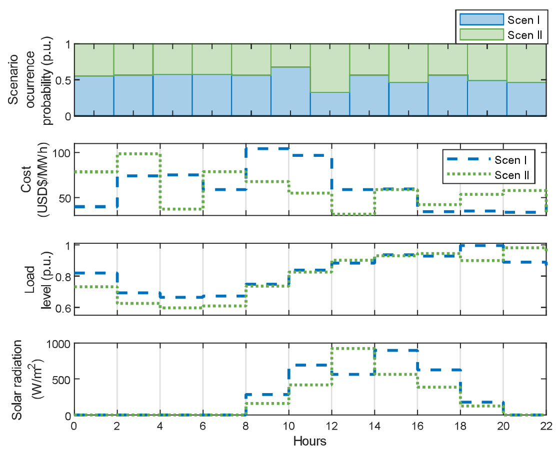

Fig. 5. Parameter values a) Probability occurrence of the scenarios. b) Cost of the energy. c) Load level and d) Solar irradiance.

TABLE I.
COMPARISON OF RESULTS OBTAINED BY CPLEX AND PROPOSED MATHEURISTIC

System	Results	Before Reconfig.	CPLEX	Matheuristic
33-Bus	OF (US$)	903.68	853.60	853.60
	Iterations	-	-	3
	Time (s)	-	217.53	204.46
69-Bus	OF (US$)	860.60	563.94	563.94
	Iterations	-	-	4
	Time (s)	-	5,788.83	2,667.00
118-Bus	OF (US$)	5,350.61	5,025.02	5,024.93
	Iterations	-	-	12
	Time (s)	-	21,600	5,322.47
136-Bus	OF (US$)	3,631.22	3,595.95	3,132.15
	Iterations	-	-	16
	Time (s)	-	21,600	5,625.12

TABLE II.
CO_2 TAX AND LOSSES COST FOR THE TESTED SYSTEMS BEFORE AND AFTER OF RECONFIGURATION

	33-Bus		69-Bus		118-Bus		136-Bus	
Results	*BR*	*AR*	*BR*	*AR*	*BR*	*AR*	*BR*	*AR*
CO_2	141.32	99.7	338.47	90.92	865.03	593.98	200.82	110.08
Losses	762.36	753.9	522.13	473.02	4485.58	4430.95	3430.4	3022.07
Total	903.68	853.6	860.6	563.94	5350.61	5024.93	3631.22	3132.15

the 136-bus systems where NMA's solution is 12.9% better than the CPLEX one.

A similar context occurs for the time of solution; for the two last systems, the imposed 6 hours' time limit was required to stop the CPLEX process while the NMA obtained solutions in 75.36% and 73.96% less time. This demonstrates the efficiency of the methodology as an alternative to solve complex problems.

In addition, TABLE II shows the reduction in the objective function, CO_2 tax and cost of losses are compared before the reconfiguration (BR) and after (AR) where the major reduction is obtained for the 136 Bus system with a reduction of approximately \$500. The major reduction in CO_2 was obtained for the 118 Bus system where the reduction was \$271.05.

V. Conclusions

Conforming to the results, this NMA presents quality solutions in less computational time than CPLEX solver. This superiority occurs as the size of the system increases. Regarding the objective function, it was possible to achieve a noticeable reduction in the operating cost considering that the increased presence of DG results in a reduction of up to \$ 270 from gas emissions taxes in a hypothetical day. On the other hand, the proposed neighborhood structure and search space reduction can be applied to other planning problems that require radial topologies. Similarly, the proposed approach can be used to implement other matheuristic algorithms based on neighborhood structures.

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