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Distribution Network Reconfiguration Using Selective Firefly Algorithm and a Load Flow Analysis Criterion for Reducing the Search Space

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ABSTRACT This paper proposes an alternative to solve the distribution network reconfiguration (DNR) problem, aiming real power losses' minimization. For being a problem that has complexity for its solution, approximate techniques are adequate for solving it. Here, the proposition is a technique based on the firefly metaheuristic, named selective firefly algorithm, where the positioning of these insects is compressed in a selective range of values. The algorithm is applied to the DNR, and all its implementation and adequacy to the problem studied are presented. To define the search space, the methodology presented initially considers a set of candidate switches for opening based on the studied systems' mesh analysis. To reduce these possibilities, a refinement through a load flow analysis criterion (LFAC) is proposed. This LFAC considers the real power losses on each branch for a configuration with all switches closed, then, selecting possible switches to elimination from the set previously established. To demonstrate the behavior and the viability of the LFAC, it was initially applied on a 5 buses' and 7 branches' system. Also, to avoid getting stuck on results that may be considered not good, a disturbance resetting the population is set to occur every time a counter reaches a pre-defined number of times that the best solution does not change. Results found for simulations with 33, 70, and 84 buses are presented and comparisons with selective particle swarm optimization (SPSO) and selective bat algorithm (SBAT) are made.

INDEX TERMS Selective firefly algorithm, metaheuristics, distribution network reconfiguration, reducing search space.

NOMENCLATURE

F_t :	system total real power losses on t configuration;
c_{km} : $k-m$	switch state (closed = 1 or open = 0);
g_{km} : $k-m$	branch conductance;
V_k : k	bus voltage;
V_m : m	bus voltage;
θ_{km} :	angular difference between $k-m$ buses;
N_t :	branch numbers on t configuration;
A :	bus incidence matrix;
$V_k^{min} and V_k^{max}$: k	bus lower and upper voltage limits;
P_k : k	bus real power injection;
P_{km} : $k-m$	branch real power flow;
Q_k : k	bus reactive power injection;
Q_{km} : $k-m$	branch reactive power flow;
θ_k : k	bus phase angle;
θ_m : m	bus phase angle;
Q_k^{sh} : k	bus reactive power due to shunt element;
Ωk :	set of buses neighbors to k bus;
I_0 :	light intensity of a firefly at the source ($r = 0$);
β_0 $\mathcal{V}$	attractiveness of a firefly at the source ($r = 0$);
γ :	absorption coefficient;

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x :	is the kth component of the spatial coordinate x_i and x_j of the ith and jth firefly;
d :	last spatial coordinate (dimension) of the ith and jth firefly;
n_{os} :	number of switches to be opened;
n_s :	number of total switches of the system;
n_b :	number of total buses of the system;
nm :	indicate the analyzed mesh, where nm varies from 1 to n_{os};
V_{nm} :	indicate the vector of the analyzed n mesh;
Cm_{nm} :	indicate the last switch to be opened on the analyzed nm mesh;
p :	percentage of switches that can be excluded without prejudice to the system;
$n_{e_{cp}}$:	number of switches to be excluded on the studied case with the lowest possible reduction;
$n_{t_{cp}}$:	total number of switches of the studied case with the lowest possible reduction;
n_{ce} :	maximum number of switches to be excluded;
V'_n :	vector established on the second stage, eliminating the switches ranked by its losses;
c_i :	switch i, from the higher losses ranking established for the system;
n_{ce} :	position of the last switch to be excluded of the higher losses ranking established through the LFAC;
X_i :	matrix of the fireflies positioning at iteration i of the firefly algorithm;
σ_i :	matrix of the sigmoid approximation of fireflies positioning at iteration i of the firefly algorithm;
$Losses$:	final losses vector of each firefly at iteration i of the firefly algorithm.

I. INTRODUCTION

Electrical power systems are composed of three parts: generation units, transmission systems and electrical energy distribution systems (EEDS). The EEDS typically operate on radial topology, with medium voltage three pole disconnect switches installed on network strategical points, aiming to facilitate its maneuver on operations and maintenance service, insulating loads on casual contingencies. Opening and closing these disconnect switches end up modifying the network topology and, depending on its configuration, the ohmic losses resulting from Joule effect can decrease or increase [1].

Due to the Joule effect, not all the electric energy distributed on the network is used by the consumers. Consequently, the supplier companies do not receive for all the electricity delivered to the clients. Considering this energetical waste a continuous phenomenon, the DNR aiming losses minimization is one of the most important problems that must be solved by the energy distribution service companies. The state changing (open or closed) technique of the disconnect switches, known as reconfiguration, is one of the most economic optimization techniques to reduce the ohmic losses. These techniques are:

1) Add or replace phase-shifting and step-up transformers, to elevate the network voltage profile, compensating voltage drops on its more critical sections. This optimization technique is one of the most expensive, because of transformers excessive costs. Furthermore, labor costs are indispensable for installing these devices.

2) Replace all electrical cables, increasing its transversal section. This causes a decrease in its electrical resistance, and consequently, reduces the Joule effect. Depending on the network extension, it becomes a financially unfeasible solution.

3) Insert a capacitor bank to correct the power factor of consumer loads. As the transformers, capacitors also have a high cost on electrical network optimization.

4) Insert distributed generation (DG), improving the balance between active and reactive power on the electric network. Besides the excessive costs of these generators, their allocation demands a complex study of all system constraints, otherwise, DG could decrease the electrical network performance.

5) Modify the disconnect switches state, through its opening and closing, searching for a better-quality combination regarding the optimization of the electrical network state. It is important to state that this reconfiguration technique does not demand installation or replacement of devices on the electrical network.

Without a doubt, the DNR shows itself as the most attractive option when is aimed the optimization of the network and at the same time, save natural resources, equipment and labor costs, providing technical and financial improvements. Furthermore, the reconfiguration also promotes electrical voltage profile improvements, fitting the supply to levels established by regulatory agencies. With DNR is also possible to improve consumer load balance between EEDS feeders, avoiding overloads. Another advantage is the possibility of combination with other optimization techniques, as DG allocation [2]–[4].

Although economic, the DNR technique demands a solid study of the resulting system topology, because there are a great number of possible solutions that are unfeasible. Among the impracticable cases are: meshed topologies, disconnected buses (islanding) or not fulfilling the limits imposed by the regulatory agencies.

The DNR problem has been studied through years, the first papers dating from the 70's [5] and 80's [6]–[8], where the authors use classic techniques and heuristics. In the 90's some papers still presented studies based on the previously cited authors proposed methods, as on [9]–[11]. For being the first methods developed, these were implemented generally in small systems. It is important to point out that some classic techniques demand a lot of time on its execution limiting their usage for the DNR problem in larger systems. However, still in the 90's, the first papers using metaheuristics and evolutionary algorithms starts to be published, as presented on [12]–[16]. In the 2000's these techniques became more often studied, as verified on [17]–[20]. Still in the 2000's, a specific type of metaheuristic became common on solving the DNR problem, being named bio-inspired metaheuristics, as presented on [21]–[24], also being used in the last decade as seen on [1], [25]–[33]. Due to the fact that these metaheuristic techniques help achieve good results, especially for larger systems, but does not guarantee the best one, and to the fact that they have other limitations such as needing a correct parameter adjustment [27], finding new ways to improve the search space exploration [34], etc., the majority of the papers cited shows pros and cons. One of the major concerns that are not addressed on some recent papers [25], [30], [32] is the convergence rate. Also, the number of iterations needed to achieve the best result is an obstacle [32]. Some of these papers does not assess real systems [25], [29]. Then, despite this being a subject widely studied, the presented limitations, the fact that DNR is one of the most efficient and economical solutions to minimize the real power losses, and the fact that new artificial intelligence techniques are being developed and used in the most diverse electric power system areas such as optimal PMU placement [35], planning and economical dispatch [36], [37], shows that a vast field for novel studies searching best solutions still exists.

Whatever is the method chosen to reconfigure the EEDS, the premise is that in a network with $\boldsymbol{n}$ switches, the amount of configuration possibilities is given by $\mathbf{2^n}$. Due to this exponential characteristic of the problem, depending on the $\boldsymbol{n}$ value, it becomes difficult to test all existing switching possibilities to verify which one would minimize the Joule effect in larger systems. To overcome this, an option is reduce the search space, which can improve the computational time and effort spent on locating these solutions [38].

Here is proposed an algorithm based on the firefly metaheuristic (selective firefly) to solve the DNR problem with a technique to reduce the search space through a proposed criterion. This reduction is done in two steps: the first aim to form sets of buses corresponding to the network meshes (mesh analysis), and the second seeks to apply the LFAC in the network in order to identify the most propitious branches to be opened and thus, discard the least favorable to openness. With the application of the LFAC, the search space decreases even more, favoring the obtainment of optimal network configuration.

The great contribution of this paper is the combination of the selective firefly algorithm with a heuristic based on a power flow analysis criterion, promoting a synergy of the two techniques in the search for a solution to the DNR problem. The LFAC is presented as a new and alternative method to enhance the reduction in the search space. Also a strategy to disperse the population in search of better solutions is used. Simulations results endorse the proposal of this paper, showing its advantages, such as the easiness to implement the technique, the time results (number of iterations and computational time) considering the platform here used for implementation and the improvement of convergence specially in larger systems using the LFAC, and disadvantages, such as the need to set the selective firefly algorithm parameters empirically and the limitations of the LFAC considering unknown systems.

The paper structure was organized in a logic way, being: section II presents the mathematical modeling of the problem; section III describes the selective firefly algorithm and its parameters; section IV presents the LFAC in a detailed way; section V demonstrates the algorithm here developed for the problem solution; section VI shows the obtained results through the methodology for 33, 70 and 84 bus systems and a comparison with other algorithms; and finally, section VII describes the paper conclusions.

II. RECONFIGURATION PROBLEM MATHEMATICAL MODELLING

Being this an optimization problem, DNR is subject to the imposed constraints to determine the best configuration for the system based on the losses reduction (objective function). The following relation represents the given problem:

$$\boldsymbol{Minimize \rightarrow F_t = \sum_{k=1}^{N_t} c_{km} g_{km} (V_k^2 + V_m^2 - 2V_k V_m cos\theta_{km})} \tag{1}$$

Subject to :

$$\boldsymbol{det(A) = 1 \; or - 1} \tag{2}$$

$$\boldsymbol{V_k^{min} \leq V_k \leq V_k^{max}} \tag{3}$$

$$\boldsymbol{P_k = \sum_{m \in \Omega k} P_{km}(V_k, V_m, \theta_k, \theta_m)} \tag{4}$$

$$\boldsymbol{Q_k = \sum_{m \in \Omega k} Q_{km}(V_k, V_m, \theta_k, \theta_m)} \tag{5}$$

For being a problem with integer and continuous variables, and due to its non-linear basic formulation, it is characterized as a case of Mixed Integer Non-Linear Programming (MINLP), thus, a non-trivial problem, needing the use of computational techniques to solve it [39]. Due to the presented characteristics, the paper here presented proposes the solution of the referred problem through the firefly bio-inspired metaheuristic.

III. SELECTIVE FIREFLY ALGORITHM

The firefly metaheuristic technique was initially formulated by Yang, a researcher from Cambridge University [40], and it is based on the firefly social and environmental interaction. Through its behavior observation, Yang studied these characteristics in a way to mathematic represent them.

According to [40], the algorithm is based on three basic points:

- there is no distinction between insect gender;
- attractiveness is proportional to brightness;
- brightness is affected by the landscape of the objective function.

From a mathematical point of view there are two extremely important parameters: light intensity $\boldsymbol{I}$ and attractiveness $\boldsymbol{\beta}$ where both varies with the distance $\boldsymbol{r}$. The first can be given through (6) below, and being the attractiveness proportional to the light intensity, it can be represented through (7).

$$I(r) = I_0 \cdot e^{-\gamma r^2} \tag{6}$$
$$\beta(r) = \beta_0 \cdot e^{-\gamma r^2} \tag{7}$$

The distance r presented on (6) and (7) is given by the equation expressed in (8), which represents the distance between two fireflies i and j, that is, the spatial distance between two points.

$$r_{i,j} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{8}$$

These parameters definition allow the mathematical representation of the movement and positioning of these fireflies on a posterior instant given by (9) below, and composed of three terms, each one presenting a specific characteristic which delimits these insects positioning.

$$x_i^{t+1} = x_i^t + \beta_0 \cdot e^{-\gamma r_{ij}^2} \cdot \left(x_j^t - x_i^t\right) + \alpha V_i \tag{9}$$

The first term represents the firefly positioning at an t instant, x_i^t, the second term, represents the distance between two fireflies due to its attractiveness, and, the third term, represents the positioning randomness of these fireflies through a vector.

To put this positioning on a range of discrete values, an approximation through a sigmoid function is normally used based on the presented by [41] for the particle swarm optimization (PSO) algorithm, where the authors make use of the function in a way that is possible to compress the position values in 0 or 1 through (10) and (11) presented below:

$$\sigma\left(x_i^{t+1}\right) = \frac{1}{1 + e^{-(x_i^{tC1})}} \tag{10}$$

$$x_i^{t+1} \begin{cases} 1 & \text{if } rand < \sigma\left(x_i^{t+1}\right) \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Still, it is needed a new approximation to insert the firefly positioning in a range of selective values. The selective firefly algorithm here proposed was based on the presented by [42] for the PSO algorithm due to its resemblance with the firefly algorithm. The studies presented by [43] and [44] shows that this technique is suitable to the firefly metaheuristic. This is needed due to the nature of the problem here presented, where a higher range of integer values is needed.

Equation (12) presents the sigmoid function used to perform the approximation on a given d_n dimension. Relation (13) establishes the choice of the positioning based on the value determined on (12).

$$\sigma\left(x_i^{t+1}\right) = d_n \cdot \frac{1}{1 + e^{-(x_i^{tC1})}} \tag{12}$$

$$x_i^{t+1} \begin{cases} S_{d1} \text{ if } \sigma\left(x_i^{t+1}\right) < 1 \\ \quad\ldots \\ s_{dn} \text{ if } \sigma\left(x_i^{t+1}\right) < d_n \end{cases} \tag{13}$$

There are some variations of the sigmoid function presented on (10), where the term $e^{-(x_i^{t+1})}$, is substituted by $e^{-(2x_i^{t+1})}$, or by $e^{-(\frac{x_i^{t+1}}{2})}$, thus, modifying the contour of the sigmoid as seen on Figure 1.

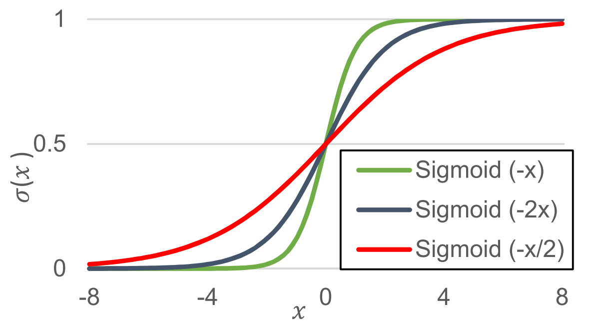

FIGURE 1. Sigmoid variations contours.

For the presented paper, two of these where used, one for the 33 and 70 buses cases, with the (12) term $e^{-(x_i^{t+1})}$ being replaced by $e^{-(2x_i^{t+1})}$ and another, with the term $e^{-(x_i^{t+1})}$ being replaced by $e^{-(\frac{x_i^{t+1}}{2})}$ for the 84 buses case. These selections demonstrated better solutions for the studied cases, mostly due to the problem characteristic, where in cases with more possible configurations (84 buses), the term $e^{-(\frac{x_i^{t+1}}{2})}$ allows a major set of solutions when the approximation is performed. On the other hand, in cases with a minor number of possible configurations (33 and 70 buses), the term $e^{-(2x_i^{t+1})}$ allows that the approximation don't get deviated to a point with a result that may be considered bad.

The definitions presented allow the application of the selective firefly algorithm to the DNR problem.

IV. SEARCH SPACE DETERMINATION

Through the technique presented in the previous section, it is possible the development of the algorithm applied on the DNR.

Some considerations though, must be taken in for the algorithm to present a performance which respects the imposed conditions to the problem solution from a technical point of view. Defining the search space is one of the most important steps so that the solutions found satisfy these conditions. The technique here proposed can be split basically into two fundamental stages to be presented on this section.

A. FIRST STAGE

Initially, on a first stage, a search space is defined through a mesh analysis. The number of switches that must be opened to obtain radial configurations as solutions for the problem, can be determined by (14) below:

$$n_{os} = n_s - n_b + 1 \tag{14}$$

The number of switches defined by (14) are equal to the number of meshes presented on herein studied systems, representing the problem dimension, and are fundamental to implement the technique here proposed.

Through an analysis performed on the network in its meshed configuration, a set of vectors that represent each one of the system meshes is determined, where its formation depends on the value given by (14) and mesh dimension (number of switches composing it). Equation (15) basically represents the composition of each one of the formed vectors.

$$\boldsymbol{V}_{nm} = [\boldsymbol{C1}_{nm}, \boldsymbol{C2}_{nm} \ldots \boldsymbol{Cm}_{nm}] \tag{15}$$

Through the previously presented analysis, the set of candidate switches to be opened on this first stage is determined.

The analysis of the possibilities established through the methodology shows that the search space is reduced in comparison with the number of possible configurations considering all system switches.

Still, in some systems, the search space can present a considerable set of possibilities even after its initial reduction. To overcome this, a decrease of this search space is proposed through the LFAC, which takes in consideration the losses on a meshed system.

B. SECOND STAGE

When a system is operated as a meshed grid, real power losses are minimum, and the opening of a switch that presents a higher current value (and consequently of active losses) is responsible for deviating the current flow to branches with higher losses, thus, having a negative impact on the system power flow and real power losses [45]. Therefore, the second stage proposes the determination of real power losses through an AC power flow (Newton-Raphson method) considering the studied systems on its meshed configurations and the posterior decreasing ranking of switches (represented by branches) based on the losses determined on each one of it.

The previous analysis allows to conclude that, branches (switches) that have a higher value of losses considering the system meshed, normally do not become part of the best solution, thus, staying on the same state initially considered, allowing its exclusion of the vectors established on the first stage of the technique and consequently diminishing the search space.

The exclusion limit is given by the best solution found through the first stage, being identified the switch that belongs to the solution vector which has the higher value of active losses on the ranking formed by the meshed system. To determine a coherent and unique amount for all systems, the case that presents the lower possible percentage of search space reduction is taken as basis.

$$\boldsymbol{p} = \frac{\boldsymbol{n}_{e_{cp}}}{\boldsymbol{n}_{t_{cp}}} \tag{16}$$

Through this, it is possible to determine the maximum number of switches candidates for exclusion without a negative impact on the system. This number is determined for each case through (17).

$$\boldsymbol{n}_{ce} \cong \boldsymbol{n}_s \cdot \boldsymbol{p} \tag{17}$$

Having established the ranking of switches and the amount to be excluded, the new mesh vectors are determined through (18).

$$\boldsymbol{V}'_n = \boldsymbol{V}_n - \sum_{i=1}^{n_{ce}} \boldsymbol{c}_i \tag{18}$$

Tests performed for this paper allows the selection of up to 30% of the total switches to be excluded based on the higher losses ranking and the exclusion of the switches contained on the established range of the vectors formed on the first stage of the technique here presented. Although in some unknown systems the best solution could be excluded, the percentage of reduction here imposed shows that the rule proposed can be used without prejudice to theses system when using a previously known case as basis for defining this number.

C. 5 BUSES AND 7 BRANCHES ILLUSTRATIVE EXAMPLE

To exemplify, a basic 5 buses and 7 branches system presented initially on [46] is used, and its meshes are represented on Figure 2 below:

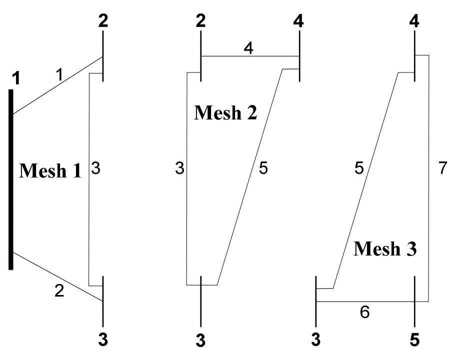

FIGURE 2. 5 buses and 7 branches system mesh composition.

The set of vectors and switches determined by Figure 2 mesh analysis and through the application of (14) and (15) presented on the first stage of the technique here proposed are the following:

$$\begin{aligned} \boldsymbol{V_1} &= [1 \quad 2 \quad 3] \\ \boldsymbol{V_2} &= [3 \quad 4 \quad 5] \\ \boldsymbol{V_3} &= [5 \quad 6 \quad 7] \end{aligned}$$

On the second stage, the ranking of the switches based on active losses is defined as showed in Table 1.

On the case presented, considering the 30% limit established, switches 1 and 2 are excluded due to presenting the higher value of active losses, thus, altering the initial composition of the vectors to the following:

$$\begin{aligned} \boldsymbol{V_1} &= [3] \\ \boldsymbol{V_2} &= [3 \quad 4 \quad 5] \\ \boldsymbol{V_3} &= [5 \quad 6 \quad 7] \end{aligned}$$

The number of possible configurations considering all switches as candidates ($\boldsymbol{2^7}$), the possibilities presented

TABLE 1. Switches ranking based on branches real power losses (meshed system-LFAC).

Switch	*Losses (MW)*
2	2.12561568
1	0.5229157
5	0.15501953
6	0.10451301
3	0.02674822
4	0.01698286
7	0.01084279

applying only the first stage of the technique and finally, the second stage of the methodology are the following for the 5 buses and 7 branches system: 128, 27 and 9. It is noticed the considerable decrease of the number of solution candidate switches, consequently diminishing the search space. It is possible than to apply the firefly technique together with the proposition of this section.

V. SELECTIVE FIREFLY ALGORITHM APPLIED TO DNR

The algorithm here proposed was named Firefly-DNR and developed on Matlab environment. It was used together with an AC Power Flow (Newton-Raphson method) to determine real power losses, contained on a specific pack of an algorithm designed for electrical power system analysis named MATPOWER and developed by [47]. Figure 3 shows a flowchart that represents the methodology here developed.

The fundamental flowchart steps can be divided as the following:

Step 1: System data insertion by the user and random determination of the firefly spatial positioning represented through real values contained in a range determined by the user.

Step 2: Search space and mesh vectors determination applying the first and second stage of the technique presented in section IV.

Step 3: Application of the firefly technique described in section III for DNR, where new topologies for the studied systems are determined. Each firefly represents a system solution and its positioning represents the opened switches. Its approximation is made based on the presented in section III, that is, through its brightness, here represented by real power losses, where the fireflies with higher losses value tend to get closer to the ones with lower losses levels. The feasibility validation of new topologies found by the fireflies applying the constraints described in section II and the determination of real power losses through a power flow performed by MATPOWER are made. Each time a new solution isn't found, the algorithm increment a counter. If the counter reaches a limit defined by user, all the population is reset. This is made to "disperse" the fireflies into the search space, avoiding the solution to get stuck in some points. This step is executed until the maximum number of iterations defined by the user is reached.

Step 4: After performing all defined iterations, the best topology found, its respective real power losses and the lower voltage levels are presented.

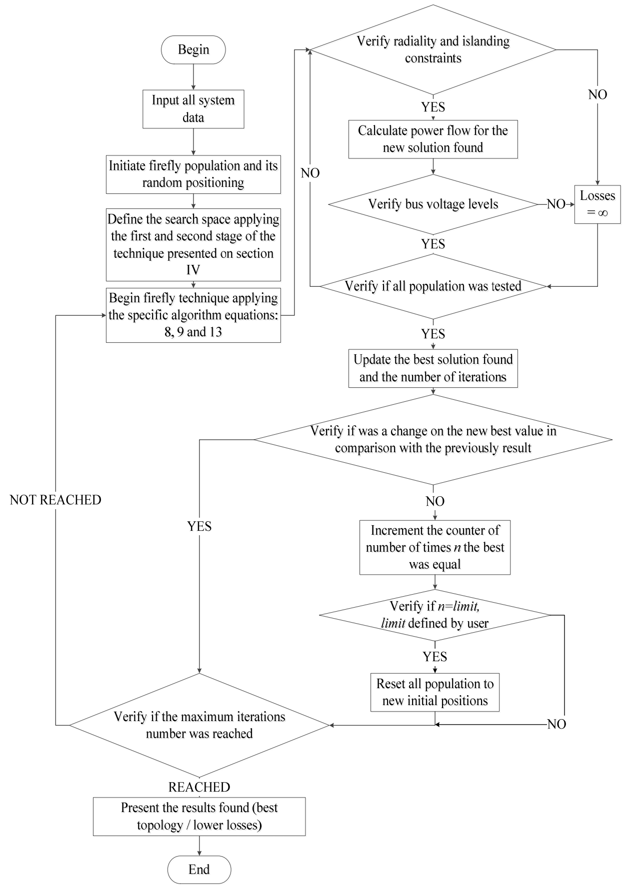

FIGURE 3. Representative Firefly-DNR flowchart.

A. FIREFLY – DNR EXAMPLE (5 BUSES SYSTEM)

To show these steps, a DNR using Firefly-DNR on a 5 bus and 7 branches example is briefly described.

Initially all the data needed is set (parameter values, number of buses and branches, dimension of the problem, number of iterations, etc.), the random positioning of each particle is set on a matrix (real number between [0,1]) with each position further representing a switch and each firefly a solution. For the example, consider that a set of random numbers could be defined as:

$$X_0 = \begin{bmatrix} 0,2259 & 0,2581 & 0,0855 \\ 0,1707 & 0,4087 & 0,2625 \\ 0,2277 & 0,5949 & 0,8010 \\ 0,4357 & 0,2622 & 0,0292 \\ 0,3111 & 0,6028 & 0.9289 \\ 0,9234 & 0,7112 & 0,7303 \\ 0,4302 & 0,2217 & 0,4886 \\ 0,1848 & 0,1174 & 0,5785 \\ 0,9049 & 0,2967 & 0,2373 \\ 0,9797 & 0,3188 & 0,4588 \\ 0,4389 & 0,4242 & 0,9631 \\ 0,1111 & 0,5089 & 0,5468 \end{bmatrix}$$

A random initial best position is set for the 5 bus and 7 branches, for example 2 - 4 - 6. After this, the search space used for the example is defined using the technique

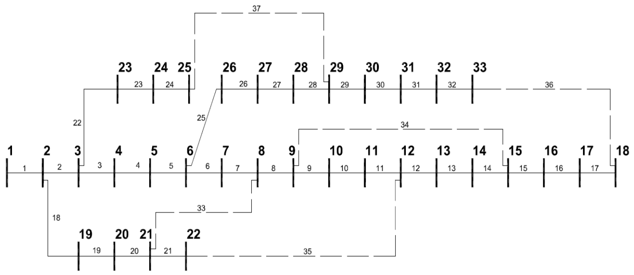

FIGURE 4. 33 buses and 37 branches system.

TABLE 2. 33 buses system – vectors first and second stage.

Vectors	First Stage	Second Stage
V_1	*[8 9 10 11 21 33 35]*	*[8 9 10 11 21 33 35]*
V_2	*[2 3 4 5 6 7 18 19 20 33]*	*[6 7 18 33]*
V_3	*[9 10 11 12 13 14 34]*	*[9 10 11 12 13 14 34]*
V_4	*[6 7 8 15 16 17 25 26 27 28 29 30 31 32 34 36]*	*[6 7 8 15 16 17 25 26 27 28 30 31 32 34 36]*
V_5	*[3 4 5 22 23 24 25 26 27 28 37]*	*[25 26 27 28 37]*

described in section IV. For this case (5 buses), the vectors are the same as the ones of section IV. Then, the particles are approximated through its brightness (losses). For the first iteration the particles stay in the same position, then, $X_0 = X_1$, because the load flow and losses calculation are further performed, as shown on Figure 3. Once the particles change its positioning, the sigmoid function is applied to perform the approximation presented on section III. For the example, the sigmoid at the first iteration is given by:

$$\sigma_1 = \begin{bmatrix} 1 & 2 & 2 \\ 1 & 3 & 2 \\ 1 & 3 & 3 \\ 1 & 2 & 2 \\ 1 & 3 & 3 \\ 1 & 3 & 3 \\ 1 & 2 & 3 \\ 1 & 2 & 3 \\ 1 & 2 & 2 \\ 1 & 2 & 3 \\ 1 & 3 & 3 \\ 1 & 3 & 3 \end{bmatrix}$$

Each of σ_1 matrix lines represents which switch is chosen from the vectors established on the second stage described on section IV, for example, the first line of σ_1, [1 2 2] indicates that the first line of X_1 will be represented by [3 4 6], that is, the elements of the first column of V_1, of the second column of V_2 and the second column of V_3 established

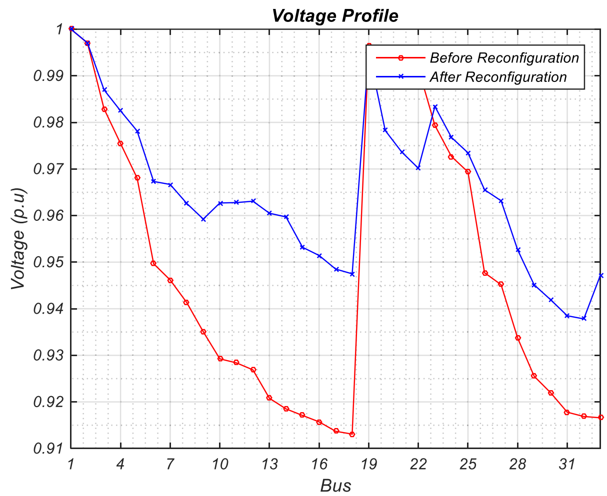

FIGURE 5. 33 buses and 37 branches system voltage profile.

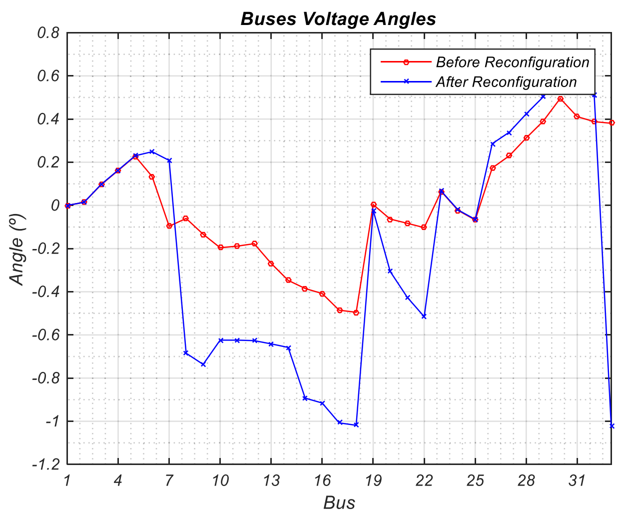

FIGURE 6. 33 buses and 37 branches system buses voltage angles.

on section IV. Thus, X_1 is represented by:

$$X_1 = \begin{bmatrix} 3 & 4 & 6 \\ 3 & 5 & 6 \\ 3 & 5 & 7 \\ 3 & 4 & 6 \\ 3 & 5 & 7 \\ 3 & 5 & 7 \\ 3 & 4 & 7 \\ 3 & 4 & 7 \\ 3 & 4 & 6 \\ 3 & 4 & 7 \\ 3 & 5 & 7 \\ 3 & 5 & 7 \end{bmatrix}$$

The radiality constraint is verified for each one of the particles (lines of X_1 matrix), and if not radial, the losses associated with the referred positioning receive a high order value. The load flow is performed to determine the losses of

TABLE 3. 33 buses system loss comparison, configurations and percentage loss reduction through first and second stage search space.

Case 33 Buses	Losses (kW)		Open Switches		Percentage Loss Reduction (%)	
Run	*First Stage*	*Second Stage*	*First Stage*	*Second Stage*	*First Stage*	*Second Stage*
1	*139.55*	*139.55*	*7-9-14-32-37*	*7-9-14-32-37*	*31.15*	*31.15*
2	*145.3*	*142.80*	*6-11-14-32-37*	*7-11-32-34-37*	*28.31*	*29.54*
3	*151.5*	*139.55*	*7-14-32-35-37*	*7-9-14-32-37*	*25.25*	*31.15*
4	*139.55*	*139.55*	*7-9-14-32-37*	*7-9-14-32-37*	*31.15*	*31.15*
5	*139.55*	*139.55*	*7-9-14-32-37*	*7-9-14-32-37*	*31.15*	*31.15*
6	*184.8*	*139.55*	*14-20-28-32-35*	*7-9-14-32-37*	*8.82*	*31.15*
7	*151.5*	*139.55*	*7-14-32-35-37*	*7-9-14-32-37*	*25.25*	*31.15*
8	*139.55*	*139.55*	*7-9-14-32-37*	*7-9-14-32-37*	*31.15*	*31.15*
9	*139.55*	*139.55*	*7-9-14-32-37*	*7-9-14-32-37*	*31.15*	*31.15*
10	*139.55*	*139.55*	*7-9-14-32-37*	*7-9-14-32-37*	*31.15*	*31.15*
Standard Deviation / Average Reduction (%)	*NA*	*NA*	*NA*	*NA*	*6.99 / 27.45*	*0.51 / 30.99*

each particle.

$$\boldsymbol{Losses} = \begin{bmatrix} \mathbf{3.83} \\ \mathbf{16.04} \\ \mathbf{9.95} \\ \mathbf{3.83} \\ \mathbf{9.95} \\ \mathbf{9.95} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.83} \\ \mathbf{3.62} \\ \mathbf{9.95} \\ \mathbf{9.95} \end{bmatrix} \boldsymbol{MW}$$

The next step is checking if the solutions found are within the voltage range defined. Again, solutions that present voltages outside the limits established receive high order losses. Losses are then put in a crescent order, the best solution found is stored, and iteration number is incremented. If the best solution does not change within a pre-determined number of iterations defined by user, all the particles are dispersed to new random positions to avoid getting stuck in some points, as described on the Step 3 of the technique. The algorithm return to the stage where the particles are approximated, and the process restart until the maximum number of iterations is reached.

For the 5 buses case it is possible to see the particles "getting closer" through the analysis of their positioning at the end of each iteration and its associated losses:

$$\boldsymbol{X_2} = \begin{bmatrix} \mathbf{3\ 4\ 7} \\ \mathbf{3\ 4\ 7} \\ \mathbf{3\ 4\ 7} \\ \mathbf{3\ 4\ 7} \\ \mathbf{3\ 5\ 7} \\ \mathbf{3\ 5\ 7} \\ \mathbf{3\ 4\ 7} \\ \mathbf{3\ 4\ 7} \\ \mathbf{3\ 5\ 6} \\ \mathbf{3\ 5\ 7} \\ \mathbf{3\ 4\ 7} \\ \mathbf{3\ 5\ 7} \end{bmatrix} \boldsymbol{Losses} = \begin{bmatrix} \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{9.95} \\ \mathbf{9.95} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{16.04} \\ \mathbf{9.95} \\ \mathbf{3.62} \\ \mathbf{9.95} \end{bmatrix} \boldsymbol{MW}$$

TABLE 4. 70 Buses system – vectors first and second stage.

Vectors	*First Stage*	*Second Stage*
V_1	*[4 5 6 7 8 9 10 11 36 37 38 39 40 41 42 43 70]*	*[4 5 9 11 36 37 38 39 40 43 70]*
V_2	*[12 13 14 15 44 45 46 70 72]*	*[14 15 44 45 46 70]*
V_3	*[14 15 16 17 18 19 20 21 71]*	*[14 15 16 17 18 19 20 21 71]*
V_4	*[10 11 12 13 22 23 24 25 26 27 53 54 55 56 57 58 59 60 61 62 63 64 65 71 74]*	*[11 22 23 24 26 27 53 54 56 62 63 64 71]*
V_5	*[4 5 6 7 8 9 47 48 49 50 53 54 55 56 57 58 59 73]*	*[4 5 9 47 53 54 56]*

At the end of the 5th iteration all particles reached the best position:

$$\boldsymbol{X_5} = \begin{bmatrix} \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \\ \mathbf{3} & \mathbf{4} & \mathbf{7} \end{bmatrix} \boldsymbol{Losses} = \begin{bmatrix} \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \\ \mathbf{3.62} \end{bmatrix} \boldsymbol{MW}$$

The open switches for the 5 buses case are 3 - 4 - 7 and associated losses are 3.62 MW, with minimum voltage of 1.0378 p.u at bus 2. These results are the same found on [46].

VI. SIMULATIONS AND RESULTS

To validate the presented technique, simulations were performed in some systems (33, 70 and 84 buses), and its results herein presented. The algorithm parameters were fixed at $\boldsymbol{\alpha} = 0.95$, $\boldsymbol{\beta} = 1$ and $\boldsymbol{\gamma} = 1$ for all cases ($\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ empirically

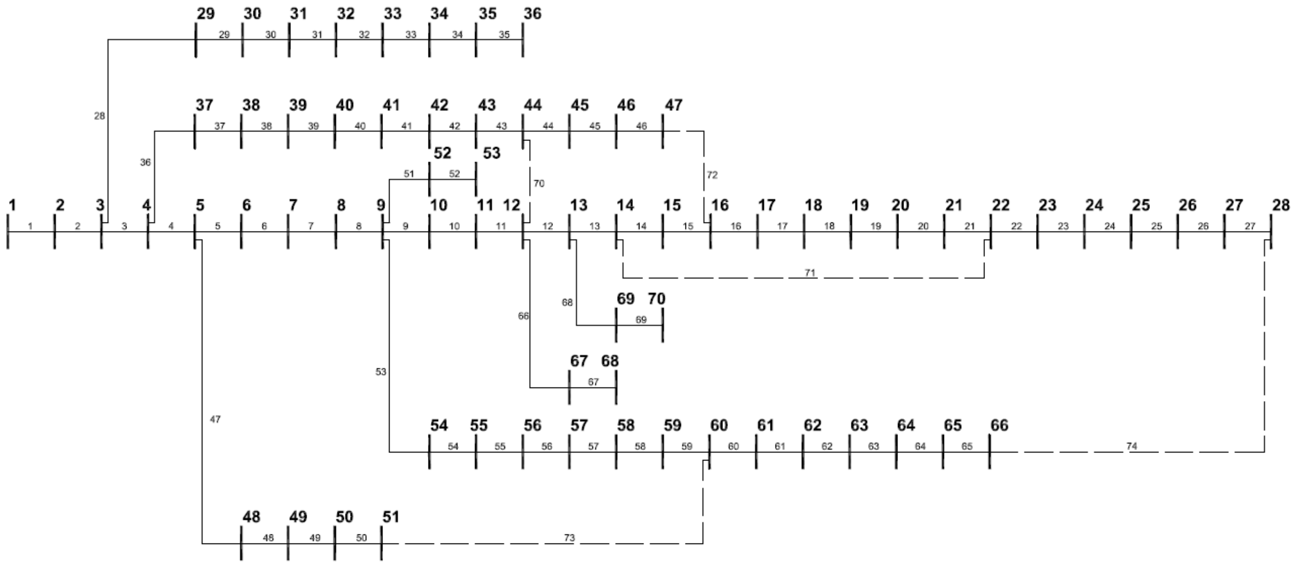

FIGURE 7. 70 buses and 74 branches system.

TABLE 5. 70 buses system loss comparison, configurations and percentage losses reduction through first and second stage search space.

Case 70 Buses	Losses (kW)		Open Switches		Percentage Loss Reduction (%)	
Run	*First Stage*	*Second Stage*	*First Stage*	*Second Stage*	*First Stage*	*Second Stage*
1	*9.43*	*9.96*	*15-56-62-70-71*	*11-14-56-62-71*	*54.82*	*52.28*
2	*9.44*	*9.43*	*14-58-62-70-71*	*15-56-62-70-71*	*54.77*	*54.82*
3	*10.33*	*9.44*	*9-15-58-62-71*	*14-56-62-70-71*	*50.5*	*54.77*
4	*9.44*	*9.43*	*14-56-62-70-71*	*15-56-62-70-71*	*54.77*	*54.82*
5	*9.45*	*9.44*	*13-58-62-70-71*	*14-56-62-70-71*	*54.72*	*54.77*
6	*11.24*	*9.44*	*12-57-65-70-71*	*14-56-62-70-71*	*46.14*	*54.77*
7	*11.24*	*9.43*	*18-57-63-70-72*	*15-56-62-70-71*	*46.14*	*54.82*
8	*9.44*	*9.43*	*14-57-62-70-71*	*15-56-62-70-71*	*54.77*	*54.82*
9	*9.46*	*9.43*	*13-14-59-62-70*	*15-56-62-70-71*	*54.67*	*54.82*
10	*10.08*	*9.43*	*10-15-57-64-71*	*15-56-62-70-71*	*51.7*	*54.82*
Standard Deviation / Average Reduction (%)	*NA*	*NA*	*NA*	*NA*	*3.58 / 52.3*	*0.8 / 54.55*

defined and β default value for most applications [40]). The voltage constraints were limited at 0.93 p.u. and 1.05 p.u., and the population and the maximum iterations number defined respectively on 4 and 8 times the dimension of the studied problem n_{os}. Also, comparisons were made under the same conditions (population size, iterations and search space) for two different algorithms: selective particle swarm optimization (SPSO) based on [42] and selective bat algorithm (SBAT) based on [48].

A. 33 BUSES AND 37 BRANCHES DISTRIBUTION SYSTEM

The 33 buses studied system, presented in Figure 4, was initially proposed by [8], and its initial open switches and associated real power losses are respectively 33 - 34 - 35 - 36 - 37 and 202.68 kW. The minimum voltage on the referred configuration is found at bus 18 with a value of 0.91309 p.u. The best solution found in the literature [29], [49]–[51] through DNR points out to opening 7 - 9 - 14 - 32 - 37 switches, fitting with the herein presented, which also points out to the same solution with associated real power losses of 139.55 kW and minimum voltage of 0.93782 p.u at bus 32.

Table 2 presents the vectors formed considering only the first stage and the ones formed through the second stage (LFAC), that is, the complete process, thus allowing to verify the diminish of the search space of each stage.

Table 3, shows the results found (real power losses and opened switches) for the referred system using the search space considering only the first stage of the technique and using the one defined through second stage. Also is showed the percentage reduction of real power losses between the results obtained using the proposed technique and the initial ones for 10 runs.

For assessing the constraints imposed to the optimization problem, Figure 5 shows that, not only the losses were reduced, but the voltage profile considering the best result was improved trough the reconfiguration process.

TABLE 6. 84 buses system – vectors first and second stage.

Vectors	First Stage	Second Stage
V_1	[1 2 3 4 5 47 48 49 50 51 52 53 54 55 84]	[4 50 52 53 54 55 84]
V_2	[1 2 3 4 5 6 7 56 57 58 59 60 85]	[4 6 7 58 59 60 85]
V_3	[11 43 86]	[43 86]
V_4	[11 12 65 66 67 68 69 70 71 72 87]	[65 67 69 70 71 72 87]
V_5	[11 12 73 74 75 76 88 13]	[13 74 75 76 88]
V_6	[11 12 14 15 16 17 18 89]	[14 89]
V_7	[15 16 25 26 90]	[90]
V_8	[25 26 27 28 30 31 32 92]	[28 32 92]
V_9	[15 16 17 18 19 20 77 78 79 80 81 82 83 91]	[19 20 79 80 81 82 83 91]
V_{10}	[25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 93]	[29 33 34 35 36 37 38 39 92 93]
V_{11}	[30 31 32 33 34 43 44 45 46 94]	[32 33 34 43 44 94]
V_{12}	[39 40 41 42 95]	[39 40 41 42 95]
V_{13}	[47 48 49 50 51 52 53 56 57 58 59 60 61 62 63 64 96]	[50 52 53 58 59 60 61 62 63 64 96]

Figure 6 shows the voltage angles for each one of the system buses before and after the reconfiguration process.

It is noted that the use of a refinement of the technique through the exclusion of switches with higher real power losses levels (LFAC), brings an improvement to the algorithm performance regarding its regularity point of view, being possible not only to find the best result, but diminish the discrepancy between this value and the results found on other runs. The average computational time for computing all iterations for the 10 runs was 8.121 s, and on its best execution took 6 iterations and 1.338 s to reach this point.

B. 70 BUSES AND 74 BRANCHES DISTRIBUTION SYSTEM

The second system herein studied, presented in Figure 7, was introduced by [13] and its initial topology considers the switches 70 – 71 – 72 – 73 – 74 opened, associated losses of 20.78 kW and minimum voltage of 0.97255 p.u at bus 66. The results that are pointed out as the bests in the literature indicate the opening of switches 15 – 59 – 62 – 70 – 71 [52] and 15 – 58 – 62 – 70 – 71 [50] with losses of approximately 9.43 kW. For the Firefly-DNR the best results found points out to opening switches 15 – 56 – 62 – 70 – 71, losses of 9.43 kW and minimum voltage of 0.98240 p.u at bus 62

Table 4 shows the vectors constructed considering the two stages, demonstrating the search space reduction.

Table 5 shows the results encountered for 10 runs of the Firefly-DNR considering the first stage only and the second stage (LFAC), as well as the standard deviation between the results found and the average result.

This system specifically presents a set of solutions that have associated losses close to one another, as pointed out by the solutions presented by [50], [52] and here presented, which indicates different sets of switches with approximately

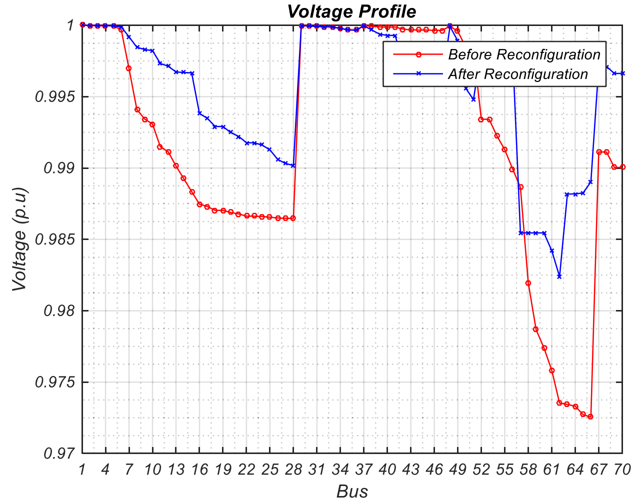

FIGURE 8. 70 buses and 74 branches system voltage profile.

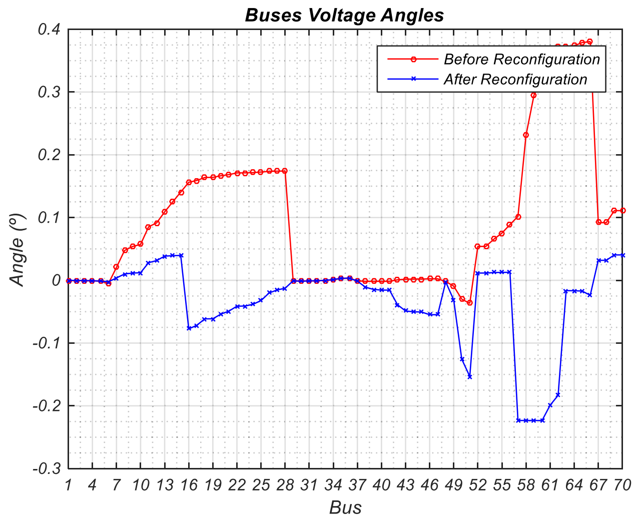

FIGURE 9. 70 buses and 74 branches system buses voltage angles.

the same real power losses. Along with the real losses reduction, the voltage profile was increased and attended the constraints imposed by the problem. Figures 8 and 9 presents the voltage profile and voltage angle magnitudes for the best result in each bus of the studied system. The results showed on Table 5 indicates again, the improvement of the results found between the first and second stage. The average computational time for computing all iterations for the 10 runs was 14.679 s, and on its best execution took 5 iterations and 2.282 s to reach this point.

C. 84 BUSES AND 96 BRANCHES DISTRIBUTION SYSTEM

Finally, a practical 84 buses and 96 branches system located in Taiwan as presented on [22] was tested. The initial open switches and losses considering the system at this state are respectively 84 - 85 - 86 - 87 - 88 - 89 - 90 - 91 - 92 - 93 – 94 - 95 - 96, losses of 531.99 kW and minimum voltage of 0.92852

TABLE 7. 84 buses system loss comparison, configurations and percentage losses reduction through first and second stage search space.

Case 84 Buses	Losses (kW)		Open Switches		Percentage Loss Reduction (%)	
Run	*First Stage*	*Second Stage*	*First Stage*	*Second Stage*	*First Stage*	*Second Stage*
1	*470.06*	*470.06*	*7-13-34-39-42-55-63-72-83-86-89-90-92*	*7-13-34-39-42-55-63-72-83-86-89-90-92*	*11.64*	*11.64*
2	*476.64*	*470.19*	*7-13-34-39-64-72-84-86-89-90-91-92-95*	*7-13-34-39-55-63-72-83-86-89-90-92-95*	*10.40*	*11.62*
3	*471.41*	*469.88*	*7-33-39-55-63-72-83-86-88-89-90-92-95*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*11.39*	*11.68*
4	*470.01*	*470.01*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*7-13-34-42-55-62-72-83-86-89-90-92-93*	*11.65*	*11.63*
5	*470.19*	*469.88*	*7-34-39-42-55-62-72-83-86-88-89-90-92*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*11.62*	*11.68*
6	*470.06*	*470.41*	*7-13-34-39-42-55-63-72-83-86-89-90-92*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*11.64*	*11.58*
7	*471.66*	*470.01*	*7-33-63-72-83-84-86-88-89-90-92-93-95*	*7-13-34-39-55-62-72-83-86-89-90-92-95*	*11.34*	*11.65*
8	*489.39*	*469.88*	*7-32-36-55-72-82-86-88-89-90-92-95-96*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*8.01*	*11.68*
9	*469.88*	*469.88*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*11.68*	*11.68*
10	*480.77*	*469.88*	*7-33-36-41-64-72-84-86-88-89-90-91-92*	*7-13-34-39-42-55-62-72-83-86-89-90-92*	*9.63*	*11.68*
Standard Deviation / Average Reduction (%)	*NA*	*NA*	*NA*	*NA*	*1.22 / 10.9*	*0.03 / 11.65*

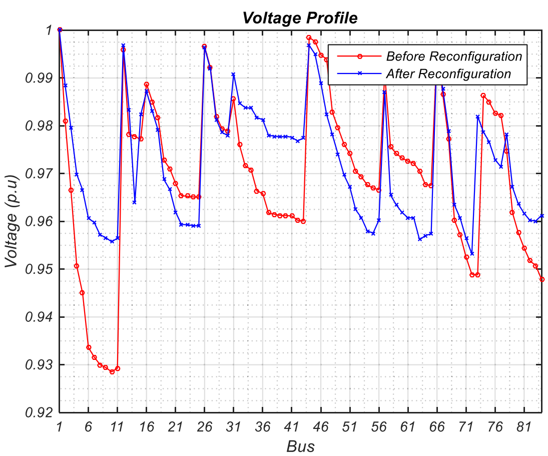

FIGURE 10. 84 buses and 96 branches system voltage profile.

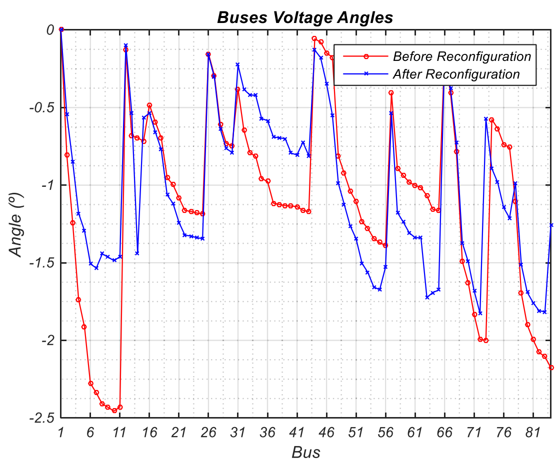

FIGURE 11. 84 buses and 96 branches system buses voltage angles.

p.u at bus 10. The best result found is the same as the ones from [20], [27], [34] pointing out to opening switches 7 - 13 - 34 - 39 - 42 - 55 - 62 - 72 - 83 - 86 - 89 - 90 - 92, losses of 469.88 kW and minimum voltage of 0.95319 p.u at bus 72.

Table 6 presents the vectors established. The results found for losses and the percentage reduction determined comparing these results with the initial state are shown in Table 7. Again, not only the losses were reduced, but

TABLE 8. Comparison for all systems results for Firefly-DNR, SPSO and SBAT.

33 BUS SYSTEM (10 RUNS)						
FIRST STAGE	*BEST (kW)*	*WORST (kW)*	*AVG. LOSS (kW)*	*MIN. ITER*	*MAX. ITER*	*RUNS BEST*
Firefly-DNR	*139.55*	*184.80*	*147.04*	*9*	*18*	*60%*
SBAT	*139.55*	*143.16*	*140.72*	*15*	*23*	*30%*
SPSO	*139.55*	*141.20*	*140.40*	*13*	*18*	*30%*
SECOND STAGE	*BEST (kW)*	*WORST (kW)*	*AVG. LOSS (kW)*	*MIN. ITER*	*MAX. ITER*	*RUNS BEST*
Firefly-DNR	*139.55*	*142.80*	*139.88*	*6*	*19*	*90%*
SBAT	*139.55*	*142.42*	*140.48*	*10*	*33*	*40%*
SPSO	*139.55*	*141.20*	*140.36*	*8*	*16*	*40%*
70 BUS SYSTEM (10 RUNS)						
FIRST STAGE	*BEST (kW)*	*WORST (kW)*	*AVG. LOSS (kW)*	*MIN. ITER*	*MAX. ITER*	*RUNS BEST*
Firefly-DNR	*9.43*	*11.24*	*9.95*	*21*	*21*	*10%*
SBAT	*9.43*	*9.52*	*9.45*	*6*	*10*	*60%*
SPSO	*9.78*	*11.73*	*11.10*	*-*	*-*	*0%*
SECOND STAGE	*BEST (kW)*	*WORST (kW)*	*AVG. LOSS (kW)*	*MIN. ITER*	*MAX. ITER*	*RUNS BEST*
Firefly-DNR	*9.43*	*9.96*	*9.49*	*5*	*39*	*60%*
SBAT	*9.43*	*9.52*	*9.43*	*8*	*32*	*80%*
SPSO	*9.43*	*11.73*	*9.83*	*29*	*38*	*40%*
84 BUS SYSTEM (10 RUNS)						
FIRST STAGE	*BEST (kW)*	*WORST (kW)*	*AVG. LOSS (kW)*	*MIN. ITER*	*MAX. ITER*	*RUNS BEST*
Firefly-DNR	*469.88*	*470.41*	*474.01*	*97*	*97*	*10%*
SPSO	*503.14*	*530.08*	*515.16*	*-*	*-*	*0%*
SBAT	*471.25*	*520.14*	*484.13*	*-*	*-*	*0%*
SECOND STAGE	*BEST (kW)*	*WORST (kW)*	*AVG. LOSS (kW)*	*MIN. ITER*	*MAX. ITER*	*RUNS BEST*
Firefly-DNR	*469.88*	*470.41*	*470.01*	*23*	*103*	*50%*
SPSO	*470.35*	*519.33*	*484.48*	*-*	*-*	*0%*
SBAT	*469.88*	*502.59*	*473.90*	*42*	*65*	*40%*

the voltage profile were improved, as showed in Figure 10. Figure 11 illustrate the voltage angles in each bus for the best result found. Figure 12 shows the tested system.

Through the results analysis it is noticed that the use of the refinement (LFAC) provided the improvement of the results consistency showing a better convergence for the presented technique. The average computational time for computing all iterations for the 10 runs was 106.7 s, and on its best execution took 23 iterations and 23.597 s to reach this point.

D. COMPARISON BETWEEN TECHNIQUES

To show the improvement achieved through the LFAC here proposed and the performance of the Firefly-DNR, comparisons with simple implementations of two other algorithms were made, namely SPSO and SBAT. The SPSO is based on the collective behavior of groups of fishes and birds and the SBAT is based on eco-location of micro bats. The two techniques proposed use the selective characteristic here presented for the Firefly-DNR. Table 8 shows the comparison of results for the three algorithms on the first (mesh analysis) and second stage (LFAC) of the technique.

Analysis of Table 8 data allow to verify the results already presented for the Firefly-DNR. In general, the technique here proposed showed a better behavior for the majority of systems, being the only one to find in 10 runs the best solution through the two sets of search spaces defined (before and after the LFAC) for all the studied systems. It also indicates the improvement of results for all the techniques after the LFAC was applied. It is worth to point out the good result found with SBAT for the 70 bus system, showing a better convergence rate for this specific system (60% before LFAC and 80% after LFAC). For the SPSO, although it did not found the best result for some systems, the best ones found were better than the initial configuration presented for the systems tested.

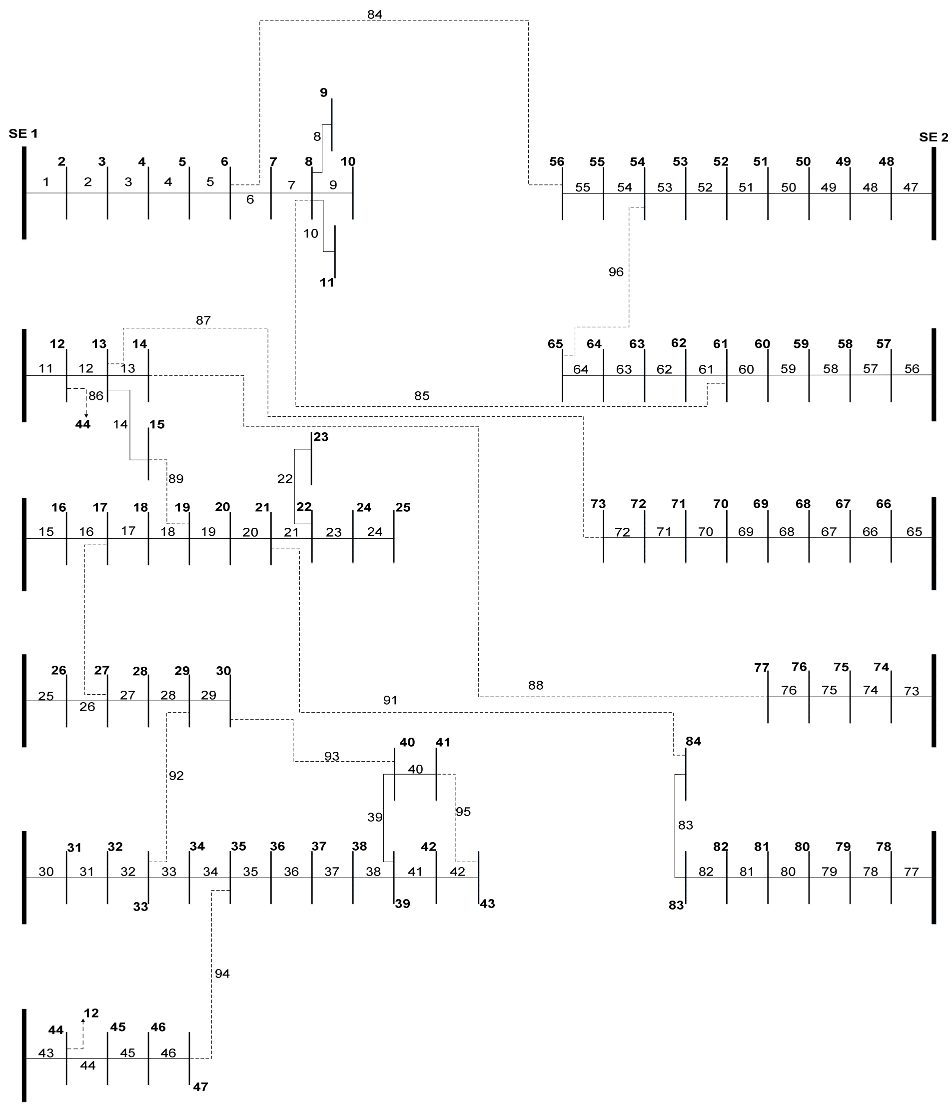

FIGURE 12. **84 buses and 96 branches system.**

Through all the results achieved, the Firefly-DNR appears as the most reliable considering the implementation developed in this paper for the three techniques tested and all the systems studied.

As stated, the Firefly-DNR achieved a good convergence rate after the LFAC for all systems. Specifically for the 84 bus system, was the only one to find the best solution before and after the LFAC, suggesting it as the most applicable to real systems, considering also its average losses for the two stages (474.01 kW and 470.01 kW). The SBAT also appears as a good alternative for use in real systems, considering its results of 40% of convergence in the second stage, and average losses for the two stages (484.13 kW and 473.90 kW) in the 84 buses system. The SPSO appears to need more improvement to achieve better results.

The average computational time for the 33, 70 and 84 buses system for the SPSO was respectively 6.173s, 12.525s and 89.955s. For the SBAT considering the same systems was respectively 6.025s, 12.592s and 83.246s.

VII. CONCLUSION

The use of the technique developed for this paper, initially allowed the presentation of an alternative metaheuristic applied to DNR through a reduced search space, considering on a first moment (first stage) the systems meshed and its meshes containing the candidate switches for composing the set subject to reconfiguration. On this first stage the technique already presented results compatible with the specialized literature.

However, due to the problem nature and some systems sizes, the proposition of using a refinement to the technique provided notable improvements from the performance and results point of view, presenting a better consistency and smaller discrepancy between results improving the algorithm convergence.

The comparison of the Firefly-DNR results with SBAT and SPSO, points out to the choice of the firefly algorithm as a good alternative for achieving good results considering its easy implementation and understanding.

The results presented in this paper indicate that the gain in combining the firefly and LFAC techniques may allow its application on the DNR problem for distribution systems with different characteristics of the presented here, such as larger systems with more switches, load varying systems, distributed generation and other operational restrictions. Also, the sensitivity between sigmoid functions presented in section III for compressing the positioning used on the selective firefly algorithm can be further explored in other applications.

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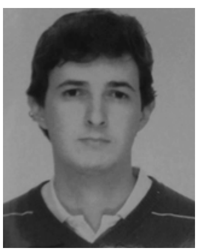

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