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A Novel Solution Method for the Distribution Network Reconfiguration Problem Based on a Search Mechanism Enhancement of the Improved Harmony Search Algorithm

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Abstract: This paper addresses the problem of Distribution Systems Reconfiguration (DSR), which consists of finding the state of switching devices (open or closed) in a given distribution network, aiming to minimize active power losses. DSR is modeled as a mixed-integer non-linear optimization problem, in which the integer variables represent the state of the switches, and the continuous variables represent the power flowing through the branches. Given the multi-modal and non-convex nature of the problem, an improved harmony search (IHS) algorithm is proposed to solve the DSR problem. The main novelty of this approach is the inclusion of a Path Relinking phase which accelerates convergence of the DSR problem. Several tests were carried out in four benchmark distribution systems, evidencing the effectiveness and applicability of the proposed approach.

Keywords: distribution networks; metaheuristics; optimization; power losses; reconfiguration



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1. Introduction

Distribution systems play a key role in the electricity supply chain. Their main purpose consist on meeting the customer's demand after receiving the bulk electrical energy from a transmission or sub-transmission substation. To reduce operation costs and facilitate the coordination of protections, distribution systems are usually built in a mesh way, but operate radially [1,2]. Such constructive characteristic also facilitates solving restoration and reconfiguration problems [3]. Given its importance, distribution network operators must be attentive to new tools and procedures that allow them to improve the quality and efficiency of supply [4]. Minimizing active power losses is one of the ways to improve the efficiency of distribution systems. Different ways of minimizing active power losses in distribution networks are reported in the specialized literature. These include the repowering of conductors [5], location of new elements such as distributed generation (DG) [6,7] and network reconfiguration [8,9]. The latter consists of opening and closing switches, keeping the radial topology of the network with the main objectives of loss reduction and voltage improvement.

Distribution systems reconfiguration (DSR) is a large-scale, non-convex optimization problem whose solution is a challenging task. Several researchers have proposed different approaches to solve the DSR problem, among which metaheuristic techniques stand up. In [10], the DSR is formulated as a mixed integer programming problem for loss minimization and solved through a genetic algorithm (GA). The authors also included a penalty for voltage drop violations. In [11,12], the DSR problem is solved by means of a simulated annealing (SA) technique. Although this algorithm is efficient, its implementation is limited to small-scale test systems.

In [13], a binary integer programming method of feeder reconfiguration is presented for loss minimization in distribution systems. Within this methodology, it is taken into account the fact that the composition of loads in every feeder may be different, and their loading patterns may also vary with time; nonetheless, presenting power losses in this way is complicated for medium and large-sized distribution systems. To overcome this issue, the authors in [14] proposed a network partitioning theory able to achieve online distribution system reconfiguration for loss reduction. In this case, the distribution network is split into several groups of buses and the power losses between these groups are minimized.

In [15], the authors propose a non-linear heuristic constructive method for distribution system reconfiguration. In this case, the configuration with the smallest discrete increase in active power losses is selected by picking up and adding loads as incremental steps. The authors of [16] introduced a new approach to solve the DSR problem. In this case, the standard Newton method with second derivatives was used to compute branch currents; in addition, the increase in power losses of each branch was estimated through quadratic terms of the branch current. This approach turned out to be effective for real-size distribution systems. In order to reduce the computing time and number of power flows evaluated, the authors in [17] modeled the DSR as an optimal power flow problem through sensitivity analysis.

Radiality constraints have always posed a major challenge when modeling distribution system optimization problems. In [18], the authors proposed a new way to include radiality constraints in the DSR problem. Such constraints are considered in a simple and efficient way through a proper handling of transfer nodes (nodes without load). Nonetheless, this strategy increases computation time. In [19], distribution systems are modeled as planar graphs and their radiality constraints are considered as a spanning tree optimization problem using graph theory. This formulation allows for the reduction of the reconfiguration time of planar networks; nonetheless, it cannot be applied to non-planar distribution systems.

Taylor and Hover [20] proposed second-order cone programming models for distribution system reconfiguration and present quadratically constrained and second-order cone approximations to power flow in radial networks. These type of models guarantee convexity but require high computational resources; therefore, they are limited to small and medium-size distribution systems. To overcome this issue, the authors in [21] proposed a mixed-integer linear programming model for finding the tree of minimum active power losses. Nonetheless, this methodology depends on a set of parameters that must be tuned for each specific system. In addition, according to [8], the approximations implemented may degrade the performance of the model when solving highly non-linear combinatorial problems.

In [22], a mixed integer linear programming (MILP) model is proposed to solve the DSR problem considering load variations and uncertainty; nonetheless, the piecewise linear approximations implemented in the model reduce the accuracy of solution and limit the application to small-scale distribution systems. In [23], the authors include demand response (DR) in the reconfiguration problem not only to reduce power losses but also to increase network reliability. Following a similar approach, the authors in [24] propose a dynamic DSR approach also considering battery energy storage systems and renewable resources; nonetheless, the application is carried out from the standpoint of the distribution system operator and is also limited to small and medium-size distribution systems. In [25], an Improved Harmony Search (IHS) algorithm is developed to solve the DSR problem. The authors also present an effective system impedance matrix based process to detect isolated nodes as a strategy to meet the radiality constraint.

There are several limitations related to all metaheuristic techniques: (i) global optimal solutions are not guaranteed, (ii) several parameters must be fine-tuned for the proper performance of the metaheuristic and (iii) they usually imply high computational cost. In this paper, we deal with this last issue. This paper presents an efficient way of solving the DSR problem by means of an IHS algorithm. The main contribution of this paper is

the improvement of the algorithm presented in [25]. In the proposed approach, a Path Relinking phase is added which accelerates the convergence of the algorithm. The tests carried out in several benchmark distribution systems allow for the conclusion that the proposed methodology is an effective way of approaching the DSR problem in medium-sized and large distribution systems. Finally, it is worth mentioning that the performance improvement of the HS algorithm implemented in this paper can be extrapolated to other applications different from the DSR problem.

2. Reconfiguration in Distribution Systems

The DSR problem presents high mathematical complexity. This is due to the fact that it involves binary and continuous decision variables along with non-linear constraints and objective function. Furthermore, a normal operative condition must be guaranteed when solving the DSR problem, which is verified by solving the system power flow.

Basically, the traditional DSR study seeks to find an optimal topology that generates the lowest possible losses in the system under study. The system topologies are generated by opening/closing the disconnecting switches present in the system branches. The DSR problem does not involve the installation of new equipment or new power generation. The only costs of the DNR are the ones associated with opening or closing switches, which are negligible. Within the mathematical optimization models reported in the technical literature to solve the DSR problem, the model proposed in [18] stands out. The proposed mathematical formulation is given by Equations (1)–(7).

$$\min P_{loss}^{total} = \sum_{(i,j) \in \Omega_l} [\alpha_{ij} g_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij})] \quad (1)$$

subject to:

$$P_{S_i} - P_{D_i} - \sum_{i \in \Omega_b} \alpha_{ij} P_{ij} = 0; \quad \forall i \in \Omega_b \quad (2)$$

$$Q_{S_i} - Q_{D_i} - \sum_{i \in \Omega_b} \alpha_{ij} Q_{ij} = 0; \quad \forall i \in \Omega_b \quad (3)$$

$$V_{min} \leq V_i \leq V_{max}; \quad \forall i \in \Omega_b \quad (4)$$

$$x_{ij} (I_{Re_{ij}}^2 + I_{Im_{ij}}^2) \leq I_{max_{ij}}^2; \quad \forall (ij) \in \Omega_l \quad (5)$$

$$\sum_{(ij) \in \Omega_l} \alpha_{ij} = (n_b - 1) \quad (6)$$

$$\alpha_{ij} \in [0, 1]; \quad \forall (ij) \in \Omega_l \quad (7)$$

Equation (1) represents the objective function, which is the minimization of the total active power losses of the distribution system. In this case, Ω_l is the set of system branches, α_{ij} is a binary variable that indicates if the switch of the corresponding branch ij is open (zero) or closed (one), g_{ij} is the line conductance and V_i and V_j are the voltage magnitudes at nodes i and j , respectively. Finally, θ_{ij} is the difference of the voltage angles between nodes i and j .

The constraint given by Equation (2) represents the active power balance in the nodes of the distribution system. P_{S_i} and P_{D_i} represent the active power generated and demanded at node i , respectively; while P_{ij} is the active power flow from node i to node j . Note that the power flow is multiplied by the binary variable that indicates whether the corresponding switch of the branch is open or closed. Equation (3) represents the reactive power balance which is analogous to the aforementioned constraint regarding active power. In this case, Q_{S_i} and Q_{D_i} represent the reactive power generated and demanded at node i , respectively; while Q_{ij} is the active power flow from node i to node j . Note that this variable is also multiplied by α_{ij} to indicate whether or not there is reactive power flow in branch ij .

Equation (4) represents the limits of voltage magnitudes, where V_{min} and V_{max} indicate the minimum and maximum limits of V_i , respectively. Constraint given by (5) represents

the maximum current capacity of branch ij . In this case, x_{ij} is the reactance of branch ij , $I_{Re_{ij}}$ and $I_{Im_{ij}}$ are the real and imaginary components of the current in branch ij , respectively and $I_{max_{ij}}$ is the maximum current allowed in branch ij . Equation (6) corresponds to the basic radiality constraint of the distribution system where n_b represents the number of nodes. Finally, (7) is the declaration of the binary variable α_{ij} associated with the state of the switch (open/closed) in branch ij .

For the solution of the DSR problem, the constraint given by Equation (6) alone is not enough to ensure the radiality of the network under study, in the sense that a configuration may present islanding (nodes electrically disconnected from the rest of the network) even when meeting condition (6). For this reason, it is necessary to complement the verification of constraint (6) with the use of methods for detecting islanding, which are usually based on graph theory. In this work, we used the method proposed in [25] to test the radiality of each new configuration obtained in the process of finding the optimal solution of the DSR problem.

3. Implemented Algorithms

Three algorithms were implemented to solve the DSR problem, namely: Harmony Search, Improved Harmony Search and Improved Harmony Search with Path Relinking. It is worth mentioning that all metaheuristic techniques, these included, present certain drawbacks such as the fact of not guaranteeing global optimal solutions, the fine-tuning of several parameters and high computational cost. The contribution of this paper is focused on this last issue. The implemented algorithms are described below.

3.1. Harmony Search (HS)

The Harmony Search (HS) optimization method, proposed in [26], is inspired by the improvisation and memorization process of musical groups, in which each decision variable of the optimization problem is equivalent to a musical instrument, while the fitness or objective function corresponds to the appreciation of the listeners. An iteration of the solution process is analogous to the improvisation of musicians in the search for new harmonies, and the optimal solution of the problem corresponds to the perfect harmony achieved. HS algorithm presents five main control parameters: Harmony Memory Size (HMS), which determines the amount of solutions stored in memory; Harmony Memory Consideration Rate (HMCR), which defines the probability of creating a new solution based on those stored in memory; Pitch Adjustment Rate (PAR), that acts as a perturbation mechanism; BandWidth (BW) which determines the adjustment range of the value of each decision variable (in the case of continuous variables); and Number of Improvisations (K), which acts as a stopping condition for the iterative process.

Infeasible solutions obtained during the iterative process of the HS algorithm are discarded. The set of best feasible solutions is stored in a matrix called Harmony Memory (HM). Equation (8) exemplifies the HM matrix for an optimization problem with N decision variables $x_i \in X_i, i = 1, \dots, N$ where X_i corresponds to the range of possible values for each variable x_i . In the HM matrix, each column refers to the value of the i -th decision variable of the problem and each row corresponds to the vector of the j -th solution x_j with objective function value $f(x^j), j = 1, \dots, HMS$.

$$HM = \begin{bmatrix} x_1^1 & \cdots & x_i^1 & \cdots & x_N^1 & f(x^1) \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ x_1^j & \cdots & x_i^j & \cdots & x_N^j & f(x^j) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ x_1^{HMS} & \cdots & x_i^{HMS} & \cdots & x_N^{HMS} & f(x^{HMS}) \end{bmatrix} \quad (8)$$

HS algorithm starts by initializing the general control parameters (HMS, HMCR, PAR, BW and K) and the initial randomly generated HM matrix. At each iteration of

the HS algorithm, a new solution vector $x^{new} = (x_1^{new}, \dots, x_i^{new}, \dots, x_N^{new})$ is obtained based on three rules: memory consideration, pitch adjustment and random selection. Algorithm 1 shows the search mechanism for new solutions, where $rand1$ and $rand2$ are random numbers of uniform distribution between 0 and 1. For each new solution x^{new} that meets the constraints of the problem (feasibility analysis), the value of the objective function or fitness criterion is calculated and, if the new solution is better than the worst fitness solution stored in the HM matrix, the new solution enters the set of solutions of the HM matrix in place of the worst solution. The process is repeated until the adopted number of improvisations K is reached and the solution that presents the best objective function or fitness criterion is chosen as the optimal solution of the optimization problem.

Algorithm 1: HS search process for new solutions.

```

1 for  $i \leftarrow 1$  to  $N$  do
2   if ( $rand_1 < HMCR$ ) then (memory consideration)
3      $x_i^{new} \leftarrow x_i \in [x_i^1, x_i^2, \dots, x_i^{HMS}]^T$  (random selection)
4     if ( $rand_2 < PAR$ ) then (pitch adjustment)
5        $x_i^{new} \leftarrow x_{(i+c)}$ ,  $c \in [-1, 1]$  (discrete variable)
6        $x_i^{new} \leftarrow x_i \pm bw \times rand_2$  (continuous variable)
7     end if
8   else (no memory consideration)
9      $x_i^{new} \leftarrow x_i \in X_i$  (random selection)
10  end if
11 end for

```

3.2. Improved Harmony Search (IHS)

As discussed in [25], applying HS to the DSR problem may require too many iterations when the search space is too large (typically, large networks), such that the HS algorithm may get stuck momentarily in local minima or even fail to find the global minimum. To overcome these difficulties, improvements in the solution finding process of the HS algorithm were proposed in the literature. In [27], a dynamic modification of the PAR and BW parameters in each iteration is proposed, as a way to mitigate the difficulty of the basic version of HS in obtaining optimal solutions as a result of the parameters remaining fixed throughout the improvisation process. In [28], a modification of the pitch tuning process is proposed, where the value of PAR is dynamically adjusted based on a range of values and the maximum number of improvisations.

In [29], an alternative version of HS entitled Improved Harmony Search (IHS) is presented, applied to the discrete-time chaotic system synchronization problem. The authors propose the variation of PAR based on Equations (9) and (10) at each iteration i .

$$PAR(i) = PAR_{\min} + (PAR_{\max} - PAR_{\min}) \times degree \quad (9)$$

$$degree = [F_{\max}(i) - \text{mean}(F)] \div [F_{\max}(i) - F_{\min}(i)] \quad (10)$$

In this case, PAR_{\min} and PAR_{\max} represent the smallest and largest value assigned to the PAR fit, respectively, $F_{\min}(i)$ and $F_{\max}(i)$ correspond to the smallest and largest objective or fitness function value stored in the HM matrix, respectively, and $\text{mean}(F)$ is the average value of all the objective or fitness functions stored in the HM. As shown by Equations (9) and (10), the adaptive nature of PAR is attributed to the *degree* variable, which depends only on data from the HM memory matrix for its adjustment to each improvisation/iteration of the algorithm. Algorithm 2 presents the implementation of the IHS metaheuristic for discrete decision variables.

Algorithm 2: IHS search process for new solutions.

```

1 for  $i \leftarrow 1$  to  $K$  do
2    $grade_1 \leftarrow Calc(\min(fitness(HM)), \max(fitness(HM)), average(fitness(HM)))$ 
3    $PAR_i \leftarrow Calc(PAR_{min}, PAR_{max}, grade_i)$ 
4   if  $rand_1 < HMCR$  then (memory consideration)
5      $x_i^{new} \leftarrow x_i \in [x_i^1, x_i^2, \dots, x_i^{HMS}]^T$  (random selection)
6     if  $rand_2 < PAR$  then (pitch adjustment)
7        $x_i^{new} \leftarrow x_{(i+c)}, c \in [-1, 1]$ 
8     end if
9   else (no memory consideration)
10     $x_i^{new} \leftarrow x_i \in X_i$  (random selection)
11  end if
12 end for

```

3.3. Path Relinking

In [25], the IHS algorithm is applied to the DSR problem, where a higher convergence speed compared to the basic HS is verified by the authors of the paper. This work aims to propose an improvement of the IHS algorithm with the introduction of the search mechanism known as Path Relinking.

Path Relinking is a generalization of the application of Scatter Search. This search method has two principles: (1) the capture of information contained separately in original vectors and (2) the heuristic selection of elements that need to be recombined to generate new vectors of individuals. According to [30], Path Relinking is an evolutionary method that operates with a population of solutions rather than a single solution, which allows the combination of pre-existing solutions, generating new solutions by exploring paths that can connect to high-quality solutions. The sweeping flow method under study is as follows: it starts by choosing an initial solution, calculating the symmetric difference between the two solutions. By definition, the symmetric difference is the cardinality of the set of moves required to go from the initial solution to the target solution. The closure of the process occurs when the symmetric difference between the target solution and the final solution is less than or equal to zero.

Figure 1 illustrates the basic steps performed by Path Relinking for the network reconfiguration problem. The algorithm starts by randomly selecting a predefined number of solutions stored in the HM, then the necessary moves are calculated to reach the target solution from these initial solutions, which corresponds to the best solution obtained so far by the algorithm. Then, the algorithm selects the movement that provides the best objective function (highlighted line), and from there the procedure is repeated until the initial solution is equal to or better than the target solution.

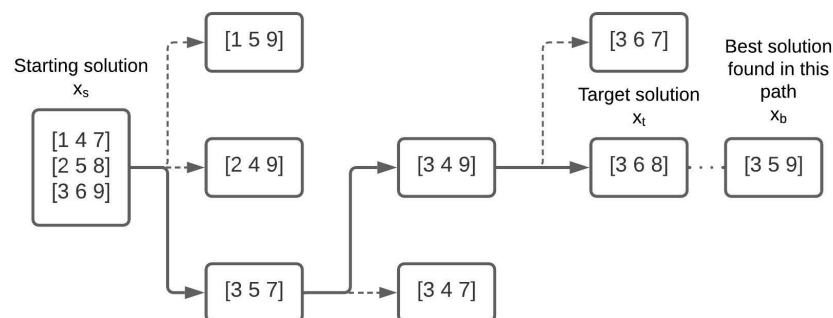


Figure 1. Example of Path Relinking applied to the DSR problem.

As presented in [31], several alternatives can be considered and combined in Path Relinking implementations:

- Periodical relinking: the mechanism is not applied continuously but periodically (i.e., every predefined number of iterations of the main algorithm).
- Forward relinking: the mechanism is applied using the worst one between x_s and x_t as the initial solution and the other one as the target solution.
- Backward relinking: the mechanism is applied using the best one between x_s and x_t as the initial solution and the other one as the target solution.
- Back and forward relinking: two different trajectories are explored, the first one using x_s as the initial solution and the second one using x_t for this condition.
- Mixed relinking: two paths are explored concurrently, the first one starting from x_s and the second from x_t , until they meet at an intermediate solution equidistant from x_s and x_t .
- Randomized relinking: instead of selecting the best movement, one is randomly selected from a list of candidates with the most favorable movements on the path being investigated.
- Truncated relinking: the total trajectory between x_s and x_t is not explored but only part of it.

In this work, the alternatives Backward relinking, Periodical relinking, Randomized relinking and Truncated relinking are implemented simultaneously. Path Relinking is carried out within the IHS algorithm with the intention of performing a perturbation in the HM matrix and thus accelerating the process of finding better solutions. For each test system, a different frequency (called PR rate) is defined for the execution of Path Relinking, corresponding to a fixed number of iterations of the IHS algorithm that are executed before applying the Path Relinking process. For the initial solutions, 25% of the best solutions are stored in the current HM matrix and the current best solution is selected as the target solution. If the solution found in the local search has a better objective function than the worst solution stored in the HM, it will replace that solution in the HM. The search process continues until a new solution better than the target solution is found. If it is not found, the process is terminated after performing a predefined number of iterations (in this work, it is set at 5% of the maximum number of iterations of the IHS algorithm). Algorithm 3 describes the implemented Path Relinking mechanism.

Algorithm 3: Path Relinking search process for new solutions.

```

1 Input: starting solution  $x_s$  and target solution  $x_t$ 
2 Output: best solution  $x_b$  in path from  $x_s$  to  $x_t$ 
3 while  $\Delta(x_i, x_t) > 0$  : difference between  $x_i$  and  $x_t$ 
4    $x_i \leftarrow rand(x_s)$ 
5   if  $\Delta(x_i, x_t) < 0$  : difference between  $x_i$  and  $x_t$ 
6      $x^{HMS} \leftarrow x_i$  ( $x^{HMS}$  worst solution)
7     break
8   else if  $\Delta(x_i, x_s) < 0$  : difference between  $x_i$  and  $x_s$ 
9      $x^{HMS} \leftarrow x_i$  ( $x^{HMS}$  worst solution)
10  end if
11  if  $5\% \cdot K = true$ 
12    break
13  end if
14 end while

```

In order to illustrate the improvements made to the IHS algorithm, Figure 2 presents the flowchart of the proposed methodology for solving the DSR problem.

Table 1. Results obtained for different test systems.

Test System	Base Configuration		Proposed IHS Solution			Loss Reduction (%)
	Open Switches	Losses (kW)	IHS Parameters	Best Configuration	Losses (kW)	
14-Bus	s11; s13; s16	511.43	N = 3 HMS = 5 HMCR = 0.85 K = 130	s7; s12, s16	466.13	9.77
33-Bus	s33; s34; s35; s36; s37	202.68	N = 3 HMS = 20 HMCR = 0.85 K = 2000	s7; s9, s14; s32; s37	139.55	31.15
84-Bus	s84; s85; s86; s87; s88; s89, s90; s91; s92; s93; s94; s95; s96	531.99	N = 3 HMS = 20 HMCR = 0.85 K = 5000	s7; s13; s34; s39; s55; s62	469.87	11.68
119-Bus	s119; s120; s121; s122; s123; s124; s125; s126; s126; s127; s128; s129; s130; s131; s132; s133	1298.1	N = 3 HMS = 20 HMCR = 0.85 K = 15,000	s23; s25; s34; s39; s42; s50; s58; s71; s74; s95; s97; s109, s121; s129; s130	854.03	34.21

The 14-bus test system was first introduced by [32]. It is composed of 16 branches and 14 buses. The system operates at a nominal voltage of 23 kV and has a total active load of 28.7 MW. Table 2 presents the comparative results between HS, IHS and IHS with the addition of Path Relinking for Average, Standard Deviation and processing time. It is worth mentioning that the IHS with Path Relinking (labeled in Table 2 as IHS+Path) showed convergence to the optimal solution in all runs performed. For this analysis, a maximum number of 300 iterations and a PR rate equal to 50 were used.

Table 2. Convergence analysis results for the 14-bus test system.

Algorithm	Average	Standard Deviation	Time (s)
HS	49.5050	48.1178	5.5016
IHS	43.5250	47.0691	5.4253
IHS+Path	40.4000	41.9686	4.9657

Figure 3 presents a histogram that quantifies the frequency of convergence of the algorithms for the 14-bus test system. To elaborate the histogram, 10 classes containing intervals of 30 iterations were used. Based on the frequency distribution shown, it is observed for all cases that the optimal solution is found in the execution of at most 30 iterations. It should be noted that the use of IHS with the addition of Path Relinking presents better results than HS and IHS because in 102 out of 200 runs, the algorithm is able to find the optimal solution performing a smaller number of iterations.

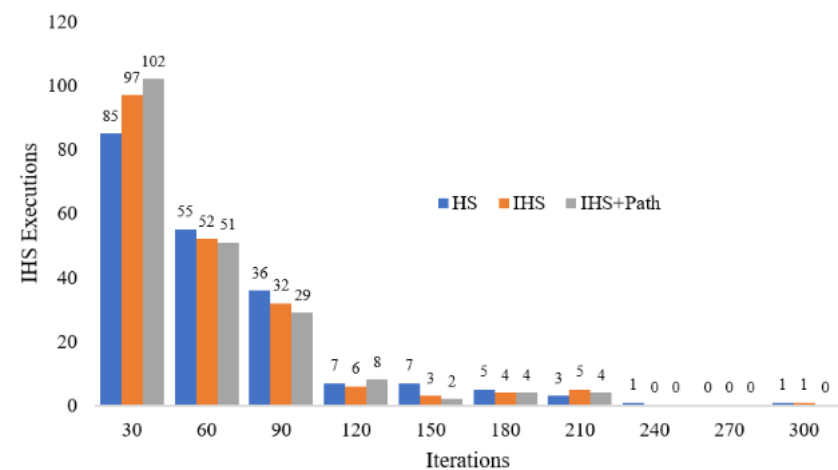


Figure 3. Convergence frequency of different algorithms for the 14-bus test system.

Figure 4 illustrates the convergence of the metaheuristics techniques implemented for a random execution. The first harmony of the HM matrix is plotted on the graph for each iteration, in order to find the optimal solution, and it can be seen that the IHS with Path Relinking presents the best results and the HS presents the worst performance. These results prove that the use of Path Relinking together with a metaheuristic such as IHS is effective in reducing the computational effort when dealing with small systems such as the 14-bus test system.

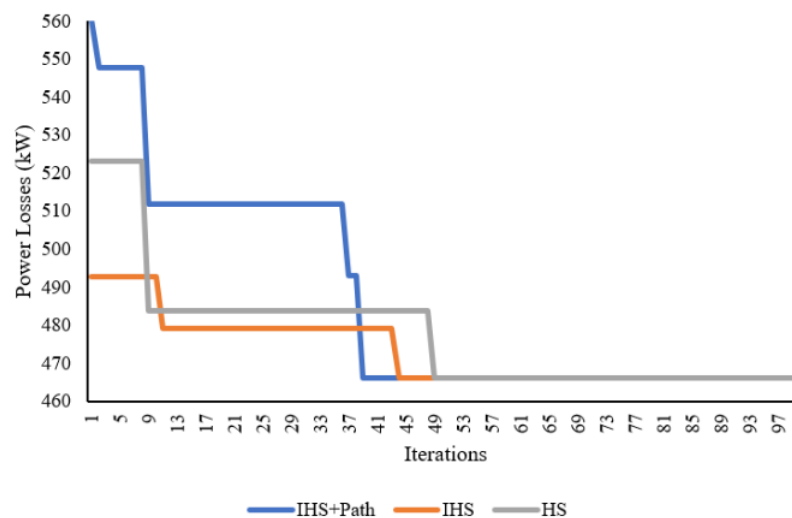


Figure 4. Convergence of the algorithms implemented for the 14-bus test system.

The 33-bus test system has 37 branches operating at a nominal voltage of 12.66 kV and features a total active demand of 3715 kW. The data of this system can be found in [33]. A maximum of 2000 iterations was used as stopping criterion and a PR rate equal to 50 was adopted, obtaining the results presented in Table 3.

Table 3. Convergence analysis results for the 33-bus test system.

Algorithm	Average	Standard Deviation	Time (s)
HS	256.9150	152.5867	90.7441
IHS	249.4050	144.6317	83.8367
IHS+Path	248.2450	155.7405	85.5317

Figure 5 shows the histogram that quantifies the frequency of convergence of the algorithms implemented for the 33-bus test system. This histogram presents 10 classes containing intervals of 100 iterations. Based on the frequency distribution depicted in Figure 5, the optimal solution is found by the algorithms after running more than 100 iterations. It can be seen that in the classes where fewer iterations are performed, the IHS+path algorithm had the highest frequency of occurrence.

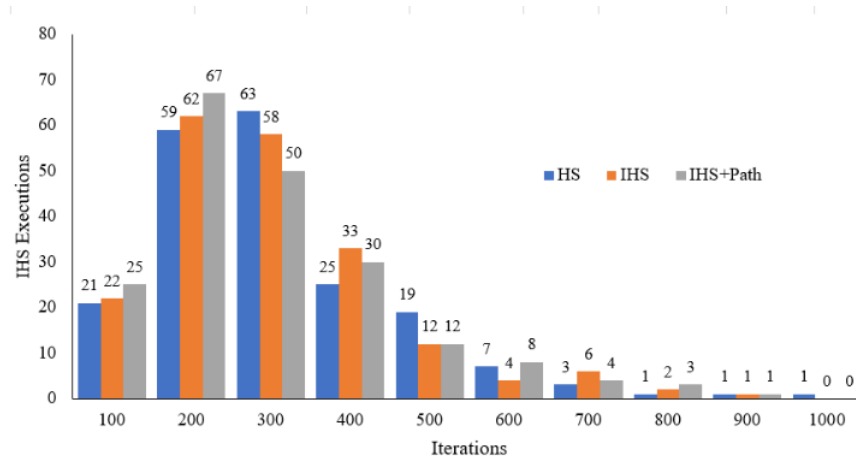


Figure 5. Convergence frequency of different algorithms for the 33-bus test system.

Figure 6 shows the convergence of a random run of each of the implemented algorithms. It can be observed that the three algorithms present similar convergences; nonetheless, the IHS with Path Relinking achieves a faster convergence.

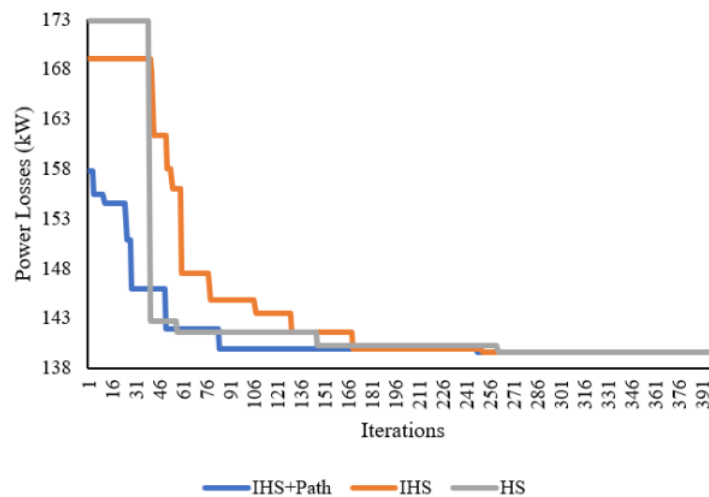


Figure 6. Convergence of the algorithms implemented for the 33-bus test system.

The 84-bus test system was presented by [34]. The base voltage adopted for this system is 11.4 kV. This test system features 11 feeders, 96 disconnecting switches and a maximum active power of 28.351 MW. In this case, a maximum number of 7000 iterations was used as stopping criteria and a PR rate equal to 25, obtaining the results presented in Table 4.

Table 4. Convergence analysis results for the 84-bus test system.

Algorithm	Average	Standard Deviation	Time (s)
HS	1411.5650	618.1724	15,701.49
IHS	1315.8550	519.0843	16,265.06
IHS+Path	1295.6300	551.3007	13,990.85

Figure 7 presents the convergence histogram of the algorithms implemented for the 84-bus test system, in which the frequency with which each algorithm converges to the optimum is quantified. To obtain the histogram, 10 classes containing intervals of 450 iterations were used. Based on the frequency distribution shown in Figure 7, the optimal solution is mostly found between 901 and 1350 iterations, with the IHS with Path Relinking algorithm presenting the highest frequency.

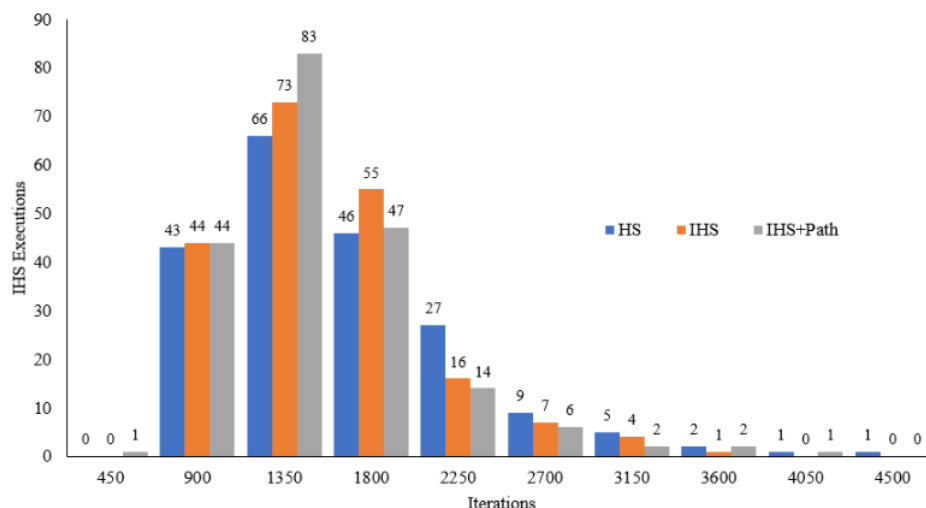


Figure 7. Convergence frequency of different algorithms for the 84-bus test system.

In large systems, such as the 84-bus test system, the need for high computational performance is evident by observing the time spent (See Table 4) to perform the required tests.

The 119-bus test system was presented by [35]. The base voltage adopted for this system is 11 kV and it has 133 branches with their respective disconnecting switches. The total installed active load is 22.71 MW. For this system, a maximum of 12,000 iterations was used as a stopping criterion and a number of 50 iterations was adopted as the PR execution rate, obtaining the results presented in Table 5.

Table 5. Convergence analysis results for the 119-bus test system.

Algorithm	Average	Standard Deviation	Time (s)
HS	2366.8350	1911.1893	41,873.63
IHS	2227.0750	1851.4560	41,519.57
IHS+Path	2147.8500	1698.3796	40,645.44

Figure 8 presents the convergence histogram of the algorithms implemented. This histogram illustrates the frequency of convergence of each algorithm for 10 classes containing intervals of 800 iterations. Based on the frequency distribution shown in Figure 8, the optimal solution is found after running more than 800 iterations. In this histogram, the convergence of the IHS and IHS with Path Relinking algorithms is similar for that interval with the highest frequency of occurrence.

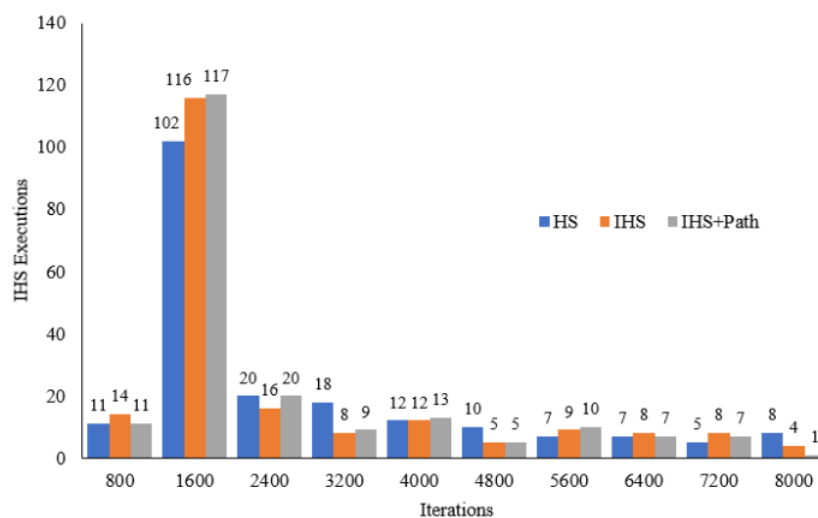


Figure 8. Convergence frequency of different algorithms for the 119-bus test system.

Comparison of Results

As described previously, for all the systems tested, the IHS algorithm with the addition of Path Relinking presented better results with a decrease in the number of iterations of the simulations. The test systems of 14, 84 and 119 buses obtained more expressive reductions in the average number of iterations, as demonstrated in Tables 2, 3 and 5. On the other hand, the 33-bus test system presented a small improvement in relation to HS and IHS. Table 6 presents the reduction of the average number of iterations in relation to HS according to the results presented in Tables 2–5.

Table 6. Convergence analysis results for the 119-bus test system.

	14-Bus	33-Bus	69-Bus	119-Bus
HS	12.08 %	2.92 %	6.78 %	5.90 %
IHS+Path	18.39 %	3.37 %	8.21 %	9.25 %

Based on the obtained results, it was found that all simulations performed using the IHS algorithm with the addition of the proposed Path Relinking are able to accurately obtain the optimal configuration of each system as reported in [25,36–38].

5. Conclusions

The use of metaheuristics to solve the distribution system reconfiguration problem is very common among researchers in the area. Since their use demands a high computational effort and a long period of time for data processing, this paper shows that, by implementing Path Relinking within a metaheuristic, it is possible to reduce the time and computational effort involved in the analysis of electric power distribution networks, which facilitates the decision making process.

From the tests performed and the analysis of the results presented in this paper, it can be seen that, in fact, the execution of the implemented algorithms requires a high computational performance, where the tests demand approximately 12 h of execution to perform the 200 simulations required.

With the implementation of the proposed heuristic, IHS with the addition of Path Relinking, the execution time of the simulations was reduced and, consequently, the computational effort required for data analysis. Thus, it can be said that the proposed approach presents a better performance when compared to HS and IHS, sometimes more significant, as is the case of the 14-bus system and other times less expressive, such as the 33-bus test system. The histograms presented in the results section are distorted to the left. This

indicates that the frequency of convergence occurs in the first classes of the implemented heuristics. This finding highlights the optimality of the solutions, reducing the required computational effort.

Therefore, it is concluded that the addition of Path Relinking in IHS algorithm provides agility in obtaining results, especially for large systems, such as the 84-bus and 119-bus presented in this paper. This makes the research more accessible to the entire academic community, since with the reduction of computational effort the DSR problem can be applied in larger distribution systems or in low spec computers.

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