



A NEW MUTATION STRATEGY FOR THE DIFFERENTIAL EVOLUTION METAHEURISTIC APPLIED TO THE RECONFIGURATION OF POWER DISTRIBUTION NETWORKS

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ABSTRACT

This work presents a comparative evaluation between two mutation variants of the Differential Evolution (DE) metaheuristic and a newly proposed strategy, applied to the problem of Distribution Network Reconfiguration (DNR). Reconfiguration is employed to make network operation more efficient and economical. The objective is to identify which of these approaches provides better performance in terms of number of iterations, average convergence time, and quality of the obtained solutions, under the same initial assumptions. For the analyses, the 33-, 70-, and 84-bus systems, widely adopted in the literature, were used along with a framework developed to ensure a fair comparison. The results show that the proposed strategy achieves superior performance, especially in more complex distribution networks.

Keywords — Distribution Network Reconfiguration, Differential Evolution, Mutation Strategies.

1 INTRODUCTION

The Distribution Network Reconfiguration (DNR) problem has been studied for over three decades, since the seminal work of Baran and Wu [1989]. Due to its high complexity, with a solution space of the order of 2^{nr} (where nr is the number of switchable branches), several methodologies have been proposed to address this challenge [Gerez et al., 2019; Tiguercha et al., 2017; Gomes et al., 2021, 2023]. DNR is considered an economically viable strategy since it relies on the operation of existing sectionalizing switches to improve network efficiency and reduce operational costs.

Deterministic and stochastic approaches have been applied to DNR. While deterministic methods can provide exact solutions, they often require commercial solvers such as CPLEX or KNITRO. In contrast, metaheuristics have gained popularity for offering a balance between solution quality and computational effort, being easily implemented in open-source environments without the need for advanced mathematical modeling [Silva et al., 2016].

Several classes of metaheuristics exist, inspired by natural processes, collective behavior, physical phenomena, human cognition, natural evolution, and ecological interactions [Yang, 2010]. Among them, Differential Evolution (DE) has shown promising results in solving DNR due to its efficiency in handling large search spaces with binary variables [Su and Lee, 2003; Chiou et al., 2005; Sureshkumar and Vijayakumar, 2015]. DE, introduced by Storn and Price [1995], relies on evolutionary concepts of mutation and recombination to generate new solutions and improve exploration of the search space.

This work conducts a comparative analysis of two DE mutation variants and introduces a new strategy tailored for DNR. In addition, a programming framework is proposed to standardize the initial population conditions, mitigating the randomness effect



that often biases comparative evaluations. The results aim to provide insights into DE's behavior in complex distribution networks and demonstrate the benefits of the proposed mutation strategy.

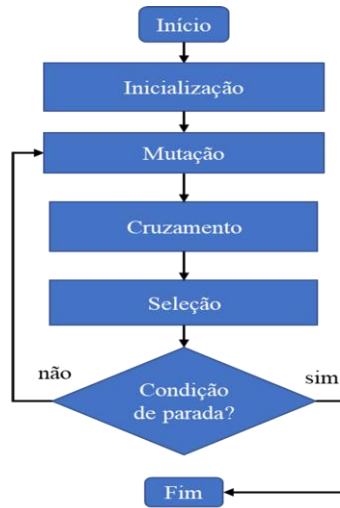
2. DIFFERENTIAL EVOLUTION AND MODIFICATIONS

The Differential Evolution (DE) algorithm, proposed by Storn and Price [1995], follows three main steps in its iterative process: mutation, crossover, and selection, preceded by an initialization phase where the population is randomly generated to ensure diversity.

- **Mutation:** Two classical strategies are considered. M1 directs solutions toward the best individual, accelerating convergence but reducing exploration [de Carvalho et al., 2016], while M2 follows the original DE formulation, ensuring diversity [Storn and Price, 1995]. A new hybrid strategy, MP, alternates between M1 and M2 to balance exploration and exploitation.
- **Crossover:** Combines target and mutant vectors to form a trial vector, guided by a crossover probability (CR).
- **Selection:** Compares trial and target vectors, keeping the best for the next generation.

This iterative process continues until a stopping criterion, here defined as the number of generations, is reached.

Figure 1 – Flowchart of the DE metaheuristic



3 SOLUTION METHODOLOGY

3.1 Proposed Mathematical Model

The Distribution Network Reconfiguration (DNR) problem aims to minimize energy losses and improve the voltage profile at the buses while satisfying the system constraints. This objective can be formulated as follows (Eq. 1).

$$\text{Minimize } P_p = \sum_{i=1}^{n_l} \beta_i R_i I^2 \quad (1)$$

where:

P_p – total active power losses in the system configuration;



I – electric current flowing through branch;

n_l – number of lines in the network;

R_i – resistance of branch;

β_i – binary variable representing the status of the switch on line (1 if closed, 0 if open).

3.2 Load Flow Constraints

These constraints ensure the active and reactive power balance at each bus of the network, as given by Eqs. (2) and (3).

$$PG_k - PC_k = V_k \sum_{m \in k} V_m (G_{km} \cos \theta_{km} + B_{km} \sin \theta_{km}) \quad (2)$$

$$QG_k - QC_k = V_k \sum_{m \in k} V_m (G_{km} \sin \theta_{km} - B_{km} \cos \theta_{km}) \quad (3)$$

Where:

$PG_k - QG_k$ – active and reactive power generated at bus k , respectively;

$PC_k - QC_k$ – active and reactive power consumed at bus k , respectively;

V_k, V_m – voltage magnitudes at buses k and m , respectively;

G_{km}, B_{km} – real and imaginary parts of the admittance matrix element ($Y=G+jB$);

θ_{km} – voltage angle difference between buses k and m .

3.3 Voltage Magnitude Constraints

The Brazilian Electricity Regulatory Agency (ANEEL) defines the appropriate operating voltage range for distribution networks.

Equation (4) represents the minimum and maximum voltage limits at each bus.

$$V_{min} \leq V_k \leq V_{max} \quad (4)$$

3.4 System Radiality

Distribution systems typically operate in a radial configuration, with energy flowing from the main supply point to the end buses, serving loads without forming loops. Enforcing the radiality constraint simplifies system operation and control, but it increases the complexity of the problem, especially for medium- or large-scale networks. This constraint can be expressed by Eq. (5).

$$\det(A) = 1 \text{ or } -1 \quad (5)$$

where A is the nodal incidence matrix. These constraints are widely used in DNR modeling [Gerez et al., 2019; Silva et al., 2020], although additional constraints may be included depending on network complexity.

3.5 Solution Algorithm

This section presents a flowchart organizing the execution of the three mutation strategies used to compare their performance. To ensure a fair analysis, the same initial population is considered, generated randomly. The steps are summarized in the flowchart shown in Fig. 2. The DE parameters were determined empirically.

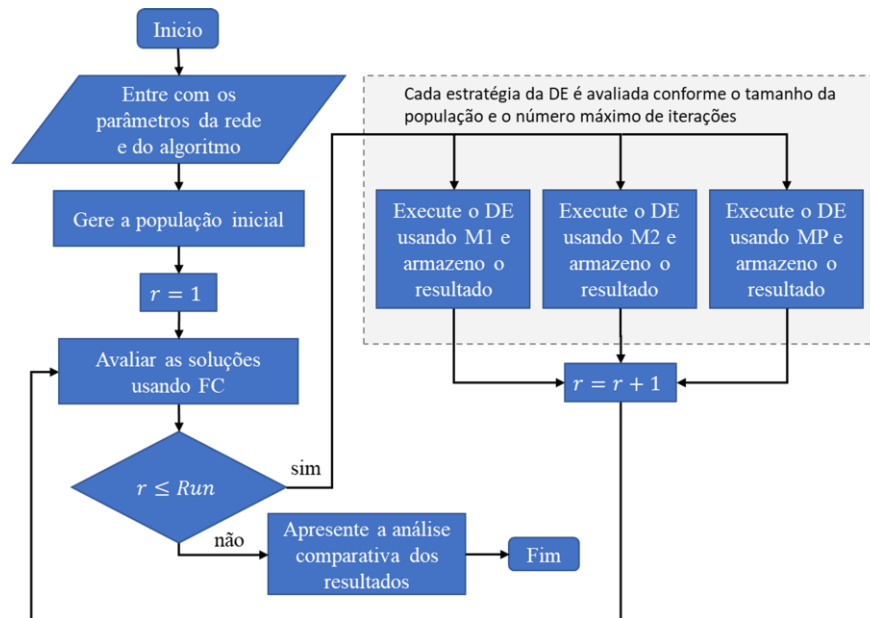
4. RESULTS ANALYSIS

The analyses were carried out on three distribution networks: 33, 70, and 84 bus systems. The DE parameters were set, after preliminary analysis, as $CR=0.3$ and $F=0.3$. Voltage limits were defined as $V_{max}=1.05$ pu and $V_{min}=0.90$ pu, and in all cases, the substation voltage was fixed at 1 pu. The Newton-Raphson load flow method with a precision of 10^{-6} was used, implemented



Matpower [Zimmerman et al., 2011]. Simulations were performed on a computer with Intel® Core™ i7 @1.8GHz, 8 GB RAM, Windows 11 Home 64-bit, 1 TB HDD, 256 GB SSD, using OCTAVE.

Figure 2 – Flowchart of the proposed solution algorithm



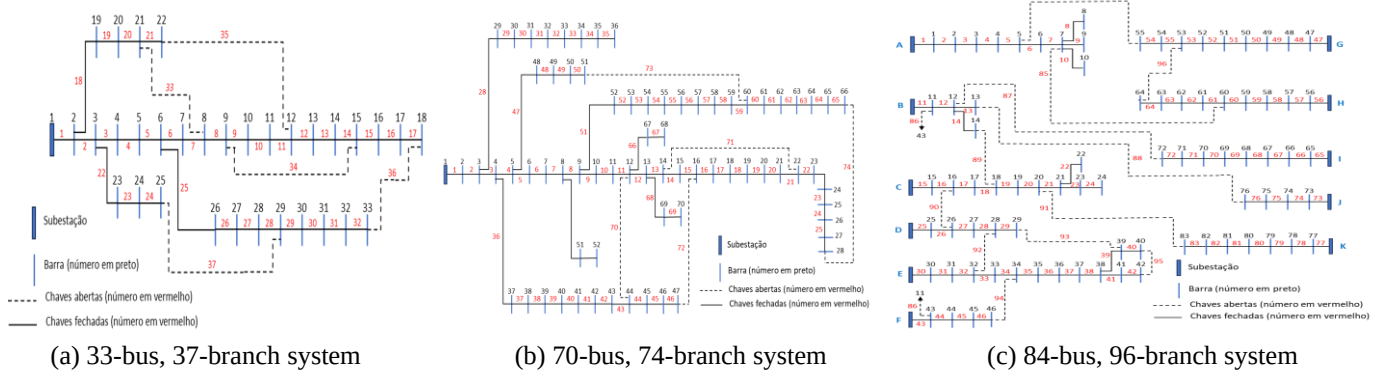
4.1 33 Bus System

The 33-bus, 37-branch system proposed by Baran and Wu [1989] operates at a nominal voltage of 12.66 kV. It includes 32 normally closed and 5 normally open tie switches (Fig. 3a). When all switches are closed, the system forms five loops. Total active and reactive power demands are 3715 kW and 2300 kVAr, respectively.

4.2 70 Bus System

The 70-bus system, originally proposed by Chiang and Jean-Jumeau [1990], has a base voltage of 12.66 kV and a base power of 10 MVA. It contains 5 normally open and 69 normally closed switches. The total system load is 1108 kW and 898 kVAr. Figure 3b illustrates the 70-bus system.

Figure 3 – Analyzed systems





In real systems, only some branches are switchable. The search space, ignoring the radiality constraint, is 2^{n_r} where n_r is the number of switchable branches. Considering only the number of switches that should be open, the search space is given by the combination $C(n_r, n_b - 1)$. For feasible solutions, the search space can be estimated by the total number of spanning trees (n_a) in the system graph, as discussed by Possagnolo [2015]. Table 1 presents these values for the analyzed systems.

Table 1 – Solution space size for different coding and search approaches

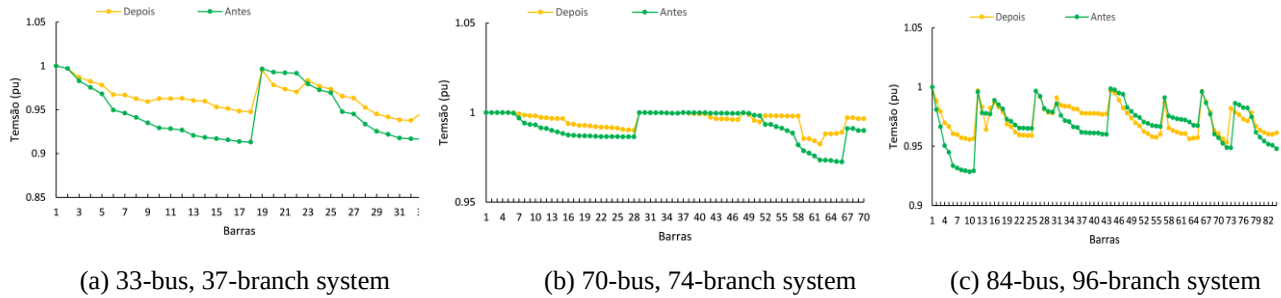
System	n_r	2^{n_r}	$C(n_r, n_b - 1)$	Number of spanning trees n_a
33 bus	37	1.3744×10^{11}	435.897	50.751
70 bus	74	1.8889×10^{22}	185.250.786	407.920
84 bus	96	7.9228×10^{28}	4.0363×10^{15}	3.5196×10^{11}

Table 2 presents the system data before and after reconfiguration, based on the literature [Silva et al., 2020]. For these systems, the optimal reconfiguration yields a reduction of 31.15% for the 33-bus system, 54.82% for the 70-bus system, and 11.68% for the 84-bus system. The values reported in the literature were adopted as the reference optimal solutions.

Table 2 – Results before and after reconfiguration

System	Description	Initial	Final
33 bus	Open Switches	33 - 34 - 35 - 36 - 37	7 - 9 - 14 - 32 - 37
	Minimum voltage (pu)	0,913	0,938
	Losses (kW)	208,48	139,55
70 bus	Open Switches	70 - 71 - 72 - 73 - 74	15 - 56 - 62 - 70 - 71
	Minimum voltage (pu)	0,973	0,982
	Losses (kW)	20,87	9,43
84 bus	Open Switches	84 - 85 - 86 - 87 - 88 - 89 - 90 - 01 - 92 - 93 - 94 - 95 - 96	9 - 13 - 34 - 40 - 42 - 55 - 62 - 72 - 83 - 86 - 89 - 90 - 92
	Minimum voltage (pu)	0,973	0,982
	Losses (kW)	532,00	469,87

Figure 4 – shows the bus voltages before and after reconfiguration for the three systems



4.3 Comparative Analysis

Comparative analyses were performed considering 30, 60, and 80 individuals for the three systems. In all tests, the maximum number of iterations was set to 80, and each algorithm was executed 30 times per case. These values were chosen empirically to provide a proper assessment of algorithm performance. The comparisons include: Success rate per run, Average number of iterations to reach the optimal solution per run and Average time to reach the optimal solution per run. The highest computational effort is associated with the load flow calculation, which is an iterative process. The results are shown in Table 3, with cells highlighted in blue for 100% success rate and in bold blue for cases with 100% success achieved in shorter time.



Table 3 – Simulation results for different systems and mutation strategies

Metric		33 bus			70 bus			84 bus		
		M1	M2	MP	M1	M2	MP	M1	M2	MP
Solutions	30	19	29	29	17	27	25	24	25	24
	50	29	30	30	29	30	30	22	27	30
	80	30	30	30	30	30	30	28	29	30
Iterations	30	7.79	20.31	12.45	14.94	32.67	23.44	19.13	75.60	35.54
	50	4.97	17.60	9.07	8.31	31.33	18.50	18.05	73.37	36.30
	80	4.40	15.97	8.93	5.83	24.37	11.20	17.39	71.59	31.17
Time	30	1.12	10.38	4.65	12.50	41.65	14.48	4.76	24.04	17.45
	50	0.70	2.76	1.97	2.52	10.52	7.79	6.97	32.76	21.42
	80	0.83	3.27	2.69	2.72	11.95	6.09	10.21	45.56	23.84

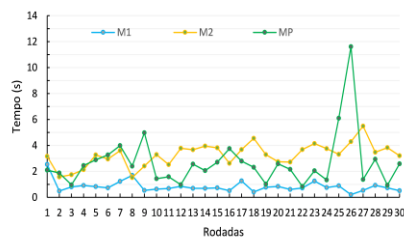
4.3.1. 33 Bus System Analyzing Table 3, the DE algorithm using the M1 strategy showed the best performance for a population of 80 individuals. In all 30 runs, it reached the expected solution with a very low average number of iterations, resulting in an average convergence time of only 0.83 seconds. The MP strategy ranked second, achieving 100% success with only 50 individuals and an average convergence time of 9.07 seconds. The average time per iteration, including load flow execution, was 0.003 seconds. Exhaustively testing all feasible solutions () as in Table 1 would require approximately 2.45 minutes. Figure 5a shows the comparison of the three DE mutation strategies in terms of convergence time for a population of 80 individuals.

4.3.2. 70 Bus System from Table 3, the M1 strategy again achieved the best performance for 80 individuals, converging after an average of 5.83 iterations and an average time of 2.72 seconds. The MP strategy, also with 80 individuals, required 11.20 iterations on average, converging in 6.09 seconds. The average time per iteration was 0.006 seconds, twice that of the 33-bus system due to the larger network. Exhaustive evaluation of all feasible solutions () would take approximately 42.47 minutes. Figure 5b presents a comparison of the three mutation strategies in terms of iterations to convergence for 80 individuals.

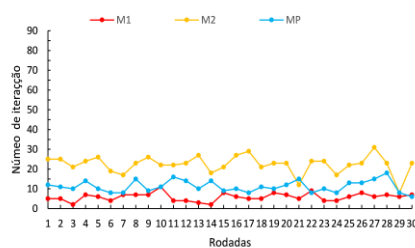
4.3.3. 84 Bus System For the 84-bus system, the MP strategy performed best with 50 individuals, converging after 36.30 iterations on average and an average time of 21.42 seconds. Strategies M1 and M2 did not achieve 100% success, showing that MP is more effective for larger, more complex systems. The average time per iteration was 0.009 seconds, three times higher than for the 33-bus system. Exhaustive evaluation of all feasible solutions () would take 9,250 years, making brute-force search infeasible.

Figure 5 compares the three DE mutation strategies in terms of iterations to convergence for 50 individuals, showing that M1 and M2 sometimes reached the 80-iteration limit without converging.

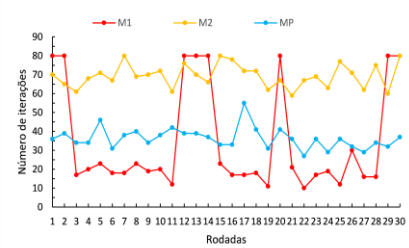
Figure 5 – Comparison of the three DE mutation strategies (80 individuals for 33- and 70-bus systems, 50 for 84-bus system)



(a) Convergence time 33-bus



(b) Iteration to convergence 70-bus



(c) Iteration to convergence 84-bus

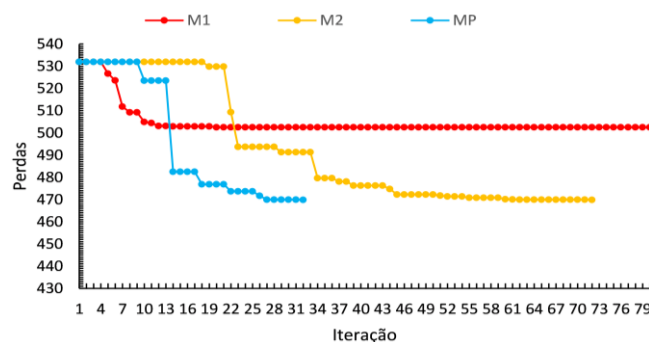


4.4 General Analysis

Overall, the DE algorithm performed well (Table 3). The choice of mutation strategy depends on system complexity and search space size. The MP strategy showed consistently good results across all systems, proving to be the best option for the 84-bus system. M1 converges quickly but may get trapped in local minima. M2 has a higher success rate than M1 but requires more iterations. MP finds the optimal solution with fewer iterations compared to M2.

Figure 6 illustrates a comparison for the 84-bus system with 50 individuals: M1 failed to converge (losses of 502.594 kW), M2 converged after 72 iterations, and MP reached the optimum in just 32 iterations.

Figure 6 – Comparative convergence for 50 individuals – 84-bus system



5. CONCLUSION

The comparative analysis of DE mutation strategies for RRDEE problems showed consistent results. All strategies performed well, with MP standing out, achieving 100% success in 30 runs for populations of 50 and 80 individuals across all evaluated systems. Thus, DE proves to be a robust and reliable approach for RRDEE and similar engineering problems. The choice of the most suitable mutation strategy should consider the size and complexity of the system. The importance of a robust algorithm becomes evident when dynamic reconfiguration is considered, especially in networks with renewable generation such as photovoltaic solar. In these networks, the load/generation profile varies throughout the day, requiring efficient and adaptive methods to ensure optimized operation. For future work, it is recommended to perform a sensitivity analysis for the DE parameters F and CR , and to investigate the performance of DE variants in larger distribution networks.

Acknowledgment:

I thank CAPES for the financial support that made this work possible.

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