Optimal Reconfiguration of the Eletric Power Distribution Network with High Photovoltaic Generation and Overvoltage

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Abstract. Distribution Network Reconfiguration (DNR) is the most common method employed by distribution network operators to achieve optimal system operation. The proliferation of Renewable Energy Sources (RES), particularly photovoltaic (PV) energy generation, in modern distribution networks has introduced novel challenges in network planning and operation. In this context, this paper introduces a DNR strategy involving the manipulation of network topology through switch opening and closing, integrated with a Modified Flower Pollination Algorithm (FPA-M). The primary aim is to minimize active power losses and regulate voltage levels at distribution system buses, particularly under high PV generation. The problem formulation takes the form of a Mixed Integer Nonlinear Programming (MINLP), encompassing continuous and discrete variables. The FPA-M method is an efficient meta-heuristic algorithm inspired by flower pollination processes. Compared to alternative methods, the FPA-M boasts a single control parameter and proves highly effective in optimization problems. The study's central contribution lies in enhancing algorithm performance and reducing computational effort through a refined determination of the search space. The proposed approach is evaluated across diverse operational scenarios, including load curves and PV data collected from the Federal University of ABC. Tests are conducted on a 33-bus distribution system, and results are benchmarked against other methodologies from the literature. The findings underscore that the amalgamation of FPA-M with DNR yields substantial energy loss reductions, effectively maintaining voltage levels within acceptable bounds throughout the evaluation period.

Keywords: Distribution Network Reconfiguration, Power Loss, Voltage, Optimization, Flower Pollination Algorithm, Photovoltaic Energy.

1 Introduction

The growing interest in carbon-free energy sources has led to a transformation of electricity distribution systems, with the incorporation of Distributed Generation (DG) and capacitor banks (BCs) in networks. This is due to the rapid growth in energy demand and the challenges in building new substations. The DGs provided several benefits such as voltage support, alleviating distribution congestion, reducing energy losses, improving system reliability and reducing operating costs.

However, the insertion of DGs also presents challenges, such as overvoltages and voltage variations in the electrical network [1]. The study of electrical energy distribution systems with the insertion of DG faces important challenges and conflicts. DG can cause financial and technical problems due to the increase in connections of generating sources, such as overvoltages that impair the Quality of Electric Power (QEP). In addition, the intermittency of energy sources, such as photovoltaic panels, can lead to voltage variations in the electrical network. The non-optimal use of GD can generate counterproductive results. If a distribution network cannot accommodate excessive power generation from DGs, it will encounter an increase in voltage at the point of common coupling and an increase in power loss. As a result, some corrective actions must be taken. Otherwise, the expected benefits of GDs are not realized [2].

The DNR problem has been studied extensively since 1975 by Merlin and Back [3]. Due to its important role in the operation of the distribution system with GD has become one of the main attractive research contents [2], [4] and [5]. In [1] they focus on the optimal use of existing GDs in non-optimal locations, therefore, DNR is proposed

according to generation and load levels, according to authors, the resulting dynamic configuration can alleviate the problem of voltage rise and reduce energy losses. According to [5] the DNR and GD operation reduce energy losses more efficiently than when only GD is used. In addition, DNR mitigates improper placement of DG in such systems, which are subject to variable high penetration loads. In this [3] study, the SFS algorithm was applied to solve the DNR problem with the integration of DGs, aiming to minimize the real energy loss and improve the voltage profile. In [1] it focuses on the optimal use of existing GDs in non-optimal locations, therefore, it is proposed a DNR according to the generation and load levels and with the resulting dynamic configuration that can alleviate the voltage problem and reduce losses power. Based on the literature review, it can be seen that, for renewable energy sources such as wind and PV, the ideal location and sizing should be replaced by their optimized use.
The works mentioned in the specialized literature present DNR and GDs with the objective of minimizing energy losses in the network and voltage increase in the system buses using different programming techniques. However, all these works do not address DNR with high power of GDs and overvoltage adjustment in the distribution network. Thus, in this work, a DNR and a method based on the FPA-M metaheuristic are proposed to overcome the problem of energy losses and overvoltage (voltage control) in distribution networks of 33 buses and 37 lines. The work also presents a contribution in determining the Search Space Reduction (REB) incorporated into the FPA-M to reduce the optimization time and meet the radiality of the system.

2 Mathematical Proposed Model for DNR

The objective of FPA-M is to minimize the objective function and simultaneously meet the operational constraints of the system. The objective function is given by eq. (1).

$$Minimize\ OF = \sum_{i=1}^{n_l} \beta_i (R_i I_i^2) \tag{1}$$

Where: OF- Active power losses in the network; β_i Binary variable related to the switch (open or closed);
I_i- Electric current in branch i; n_l - Number of network lines; R_i- Resistance in branch i.

The objective function of the protection problem eq. (1) is subject to the following constraints:

2.1 Power flow constraints

Also within these restrictions are active and reactive power balances of the nodes of the system under study, given by the equations 2 and 3.

$$P_{G_k} + P_{PV_k} - P_{L_k} = V_k \sum_{m \in k} V_m (G_{km} cos\theta_{km} + B_{km} sin\theta_{km}) \tag{2}$$

$$Q_{G_k} - Q_{L_k} = V_k^t \sum_{m \in \Omega_\kappa} V_m (G_{km} \sin\theta_{km} - B_{km} \cos\theta_{km}^t) \tag{3}$$

Where: P_{G_k}, Q_{G_k} - Active and reactive power at the bus k; P_{PV_k} - Photovoltaic generation at the bus k;
V_k, V_m - Voltage magnitude at buses k and m, respectively; G_{km}, B_{km} - The real and imaginary parts of element km in the nodal admittance matrix. ($Y = G + jB$);
θ_{km} - Angular difference between bus k and m.

2.2 Voltage magnitude restrictions

Equation eq. (4) represents the minimum and maximum limits imposed on the voltage profile.

Considered as a restriction of the problem, the value of the voltage in the nodes must be within the operational limits to guarantee the stability of the system, therefore, the levels established by the National Agency of Electric Energy (ANEEL), which determines the adequate operating range for the distribution network with nominal operation between 1kV and 69kV according to eq. (4) which represents the maximum and minimum voltage levels allowed in each node.

$$V_k^{min} \leq V_k \leq V_k^{max} \tag{4}$$

Where:
V_k^{min} - Minimum voltage limit at bus k; V_k^{max} - Maximum voltage limit at bus k.

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2.3 Radiality constraint

The majority of distribution systems are required to operate with a radial topology. This requirement is fulfilled in this modeling by employing the following strategy. The fundamental matrix (FM) of meshes is derived by identifying the system meshes. Candidate solutions are then generated with the constraint that only one switch should be open in each mesh. The FM plays a crucial role in the optimization process as it ensures radiality and, at the same time, reduces the search space, as discussed by the authors in [6].

For instance, there are three meshes: $M_1 = [1\ 2\ 3]$; $M_2 = [3\ 4\ 5]$; and $M_3 = [5\ 6\ 7]$. The meshes are represented as sequences of real numbers. To achieve a radial system, one element from each row is selected (corresponding to an open switch), ensuring no repetition of elements.
Where: M_N - Switch vector of mesh N, S_N^l - Switch l in mesh N and MD_N - Size of the vector belonging to mesh N.
Since a switch can only assume the states of open or closed, in a system with n switches, there are 2^n reconfiguration possibilities. By using the FM, the number of possibilities decreases considerably. This strategy, in addition to reducing the search space, ensures the radiality of the system [6]. In this work, this part will be addressed by the FPA meta-heuristic.

2.4 Search space determination

The electric power distribution system typically operates as a radial system, where power is supplied from a single source and distributed through an interconnected network of lines. This configuration simplifies the system and reduces the complexity of operations and maintenance. However, in some cases, it may be necessary to determine the optimal path for power distribution, taking into account specific system constraints. One approach to achieve this is by incorporating a search algorithm. Therefore, incorporating the FPA or similar optimization algorithms can assist in determining the best path for energy distribution in a radial system, considering system constraints and reducing exhaustive search through the vast number of possibilities. Given the number of possibilities being 2^n, the FPA aims to find the best possible solution among the topology possibilities of the system to be used.

3 Modified FPA

FPA is a bio-inspired meteheuristic on flower pollination and has been studied by [7]. The FPA optimization process consists of finding the best solution for a certain problem. therefore, pollen transfer, when it occurs over short distances, can be used to implement a local optimization process, whereas the long distance transfer can implement global optimization. The global pollinition can be implemented by eq. (5)

$$X_i^{t+1} = X_i^t + L(X_i^t - g_*) \tag{5}$$

Where X_i^t is the pollen i or (solution vector) X_i in iteration t. g_* is the best solution found among all, so far. The L parameter is the pollination strength, which is a value generated by the Lévy distribution. Local pollination can be represented by eq. (6).

$$X_i^{t+1} = X_i^t + \varepsilon(X_j^t - X_k^t) \tag{6}$$

Where X_j^t e X_k^t are pollen de diferentes plantas da mesma espécie, na mesma iteração. Por fim, ε corresponde a uma distribuição normal uniforme no intervalo [0,1]. In general, metaheuristic algorithms start with random solutions and, at the same time, over time, they seek to improve them by moving towards the optimal solution. And it is common for the randomly generated initial solutions to be far from the optimum. O worst case occurs when they are in the opposite position of the optimal solution. in cases like this, optimization can take a long time or even make the process unfeasible. An alternative to this would be to carry out a search, simultaneously, in all directions or simply perform the search in the opposite direction. this last alternative can be accomplished using the concept of Opposition-Based Learning [8].
The Levy flight is based on the Levy distribution, which follows a power-law and exhibits properties of long-distance jumps. This distribution is used to generate random steps during the search process. By incorporating the Levy flight into the FPA, individuals (flowers) are capable of making broader and more random movements, enabling a more efficient exploration of solutions across the entire search space. Equation 7 represents the Levy flight.

$$L \sim \frac{\lambda\tau(\lambda)(sin\frac{\pi\lambda}{2})}{\pi}\frac{1}{S^{2+\lambda}}, S \gg S_0 > 0 \tag{7}$$

Where λ is the scaling factor to control the step size, $\tau(\lambda)$ is a gamma function, whose distribution is valid for large steps $S \gg$, S being the flight step size ($S_0 > 0$), which can take small values, such as [0,1].

3.1 Photovoltaic Geration injeted

The photovoltaic generation allocated in the grid has a 24-hour power per PV unit. It is important to highlight that the treatment of PV data is obtained through a solarimetric station on Campus de Santo André UFABC-SP, with inclined and horizontal radiation data, cell temperature and environment, it was possible to determine PV output power through eq. (8) used in this work [9].

$$P_P V = \frac{Solar_r ad}{1000}(1 + \Delta_t(T_t^{cell} - T_A) \tag{8}$$

Where $P_P V$ is Photovoltaic Generation Power, $Solar_r ad$ solar radiation, $Delta_t$ constant given by -0.0046, T_t^{cell} cell temperature over time and T_A air temperature. The Fig. 1 depicts the curves of standard and horizontal

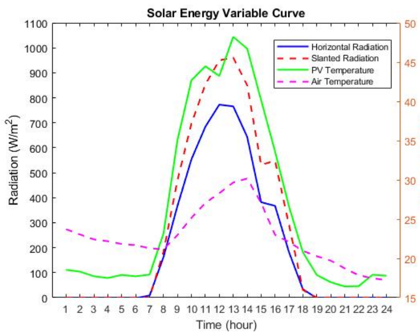

Figure 1. solar energy variable curve

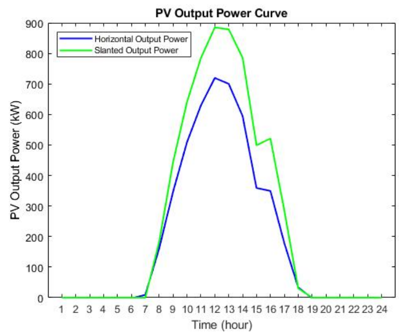

Figure 2. PV output power curve

radiation, as well as cell and air temperatures, measured over a 24-hour period using the solar metric station at UFABC. Eq. (8) was employed to transform these curves into PV output power. In Fig. 2, two PV output power curves are presented for inclined and horizontal radiation. It's noteworthy that the behavior of the curves is driven by higher values of the variables. The same trend is observed in the output power curve illustrated in Fig. 2; as radiation increases, generated power also increases.

4 Simulation, Results and Discussion

The results of aplication to FPA-M models for 33 bus network were compared with the results presented in [3], [4], [6] and [8] are show in Table 2. The simulations were performed on a computer with an Intel® Core™ i7 CPU @ 1.8 GHz, 8 GB of RAM, 256 GB SSD and Windows 11 Home 64 bits. Figure 3 shows a system with 33 nodes and 37 lines, as proposed by [10]. The system operates at a nominal voltage of 12.66 kV, with an active load of 3715 kW and a reactive load of 2300 kVAr. The open switches are represented by dashed lines.

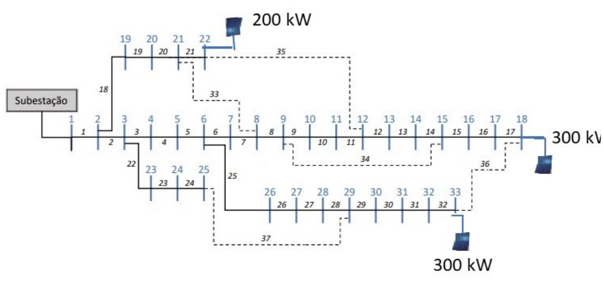

Figure 3. Sistema de 33 nodes and 37 lines

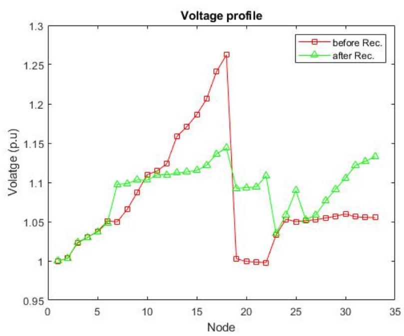

Figure 4. high voltage profile

Table 1 presents some basic parameters used in FPA-M. Each round involves 10 simulations and parameter updates. It is important to clarify that, in this context, the term number of tests refers to the quantity of iterations or repetitions performed during each round. For example, each round entails conducting 10 simulations and

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subsequently updating the algorithm's parameters. The flowers mentioned represent the candidate solutions that the algorithm employs to explore the search space in pursuit of an optimal solution. They indicate the number of solutions present in the algorithm's population. Additionally, the probability parameter $P[0, 1]$ is responsible for controlling local and global pollination within the algorithm.

Table 1. Basic parameters of MFPA used

N° of tests	N° of simulations	flowrs	P $[0, 1]$	maximum iteration	% of hits	switches
1	10	50	0.75	100	60	9-14-16-28-33
2	10	100	0.75	150	80	9-14-16-28-33
3	10	150	0.75	200	90	9-14-16-28-33
4	10	200	0.75	250	100	9-14-16-28-33

The maximum number of iterations establishes a limit on the maximum number of iterations each individual flower can perform before being considered stagnant. The success rate indicates a measure of success in evaluating solutions. These are some of the basic parameters used in MFPA. Each of them plays a significant role in configuring and fine-tuning the algorithm's performance, influencing the exploration of the search space and the ability to find optimal or near-optimal solutions. It's important to adjust these parameters appropriately for each specific problem, considering its characteristics and requirements. Table 1 illustrates the convergence analysis of four rounds, as presented in the table. It's observed that in the first round, the convergence is at 60%, while in the subsequent rounds, the convergence is considered more than satisfactory. In the presented Figure 5, two voltage curves are depicted considering a maximum allocation of 800 kW PV, distributed across nodes 18, 22, and 33 of the used system. It's evident that the first curve highlighted in red illustrates minimal voltage variation without the load curve and without Reactive Power Distribution Network (RDN). The minimum and maximum voltages are observed to be at 1 p.u and 1.26 p.u, respectively. The second curve shown in figure 6, highlighted in green, represents the voltage with the application of RDN to PV and without the load curve. This intervention lowered the maximum voltage to a value below 1.15 p.u. However, it's crucial to note that the maximum voltages still exceed the limits defined by the regulatory agency ANEEL for the distribution network, which are 0.93 p.u and 1.05 p.u. To address this high-voltage issue, various scenarios were analyzed for improvement. Table 2 presents the results for Case I, including both the initial outcomes and those achieved through the employed technique. These results have been compared with other studies and techniques available in the literature. It's noted that the attained RDN outcomes, in the absence of load and PV curves, are consistent with findings from other investigations that utilized various techniques. Table 3 explores three distinct cases in a 24-hour analysis. In Case II, the system was assessed considering the load curve, but without the presence of PV and RDN. In Case III, the analysis was conducted with the load curve, the absence of PV, and considering the application of RDN. Finally, in Case IV, the load curve, PV, and RDN were all taken into account. Table 3 presents the energy loss values over a 24-hour period, along with minimum voltages, highest active losses, and open switches for each case. It is notable that the voltage readings, active losses, and open switch statuses mainly occur at 22 hours for all cases.

Table 2. comparisons with other techniques

Cases	item	SFS [3]	ED [4]	FPA [8]	PSO [6]	FPA-M
Case I	Opened switches	33-34-35-36-37	33-34-35-36-37	33-34-35-36-37	33-34-35-36-37	33-34-35-36-37
	$P_L(kW)$	202.68	202.68	202.68	202.68	202.68
	$V_{min}(pu)$	0.913	0.9232	0.913	0.913	0.913

Table 3. Energy losses during 24h with different cases

Cases	losses kWh	voltage $p.u$	losses in X hour	open switches
Case II	4934.942	0.86451	488.81	6 - 8 - 9 - 30 - 37
Case III	2736.3536	0.8964	245.5299	9 - 14 - 16 - 28 - 33
Case IV	1897.07011	0.94386	163.8101	10 - 14 - 16 - 28 - 23

Based on the obtained results and conducted analyses, it can be stated that this approach can be deemed a promising starting point for optimizing the high-voltage system with PV. The detailed analyses of scenarios involving PV and RDN, along with the combination of these factors, enabled a deeper understanding of the impacts on voltages, energy losses, and other crucial parameters. When assessing the effects of various strategies, such as the application of load curves and RDN in the system, measures were identified that can contribute to keeping voltages within acceptable limits and reducing losses.

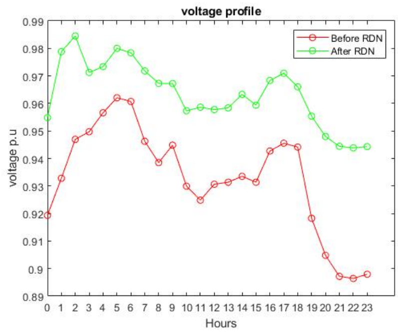

Figure 5. Voltage profire before and after DNR

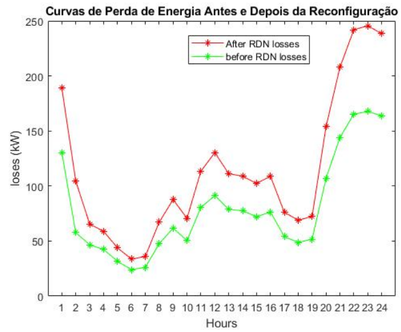

Figure 6. Active losses before and after DNR

5 Conclusion

The FPA-M optimization approach, combined with distribution network reconfiguration (DNR), has proven to be highly effective in enhancing the performance of the high-voltage system with the inclusion of photovoltaic (PV) generation. Through a detailed analysis of different scenarios, including the presence of PV and load curve considerations, it was possible to gain an in-depth understanding of critical system variables such as voltages and energy losses. The optimization of high-voltage systems plays a crucial role in ensuring the efficient and reliable operation of the electrical grid. Considering the interaction between complex variables, such as load curves and DNR, enabled the identification of solutions that not only meet voltage and loss requirements but also contribute to a smoother integration of intermittent and renewable sources. These results underscore the importance of refined approaches that encompass a wide range of factors and strategies. Additionally, the conclusion highlights the feasibility of enhancing efficiency and reliability in electrical systems through the adoption of advanced optimization technologies. In summary, this analysis provides valuable insights for future research and development in the field of electrical systems optimization, especially those incorporating renewable energy sources. Furthermore, there is an opportunity to expand this work to larger-scale systems in the future, which could further enrich our understanding and contribute to significant advancements towards more sustainable and efficient energy systems.

References

[1] R. B. Navesi, D. Nazarpour, R. Ghanizadeh, and P. Alemi. Switchable capacitor bank coordination and dynamic network reconfiguration for improving operation of distribution network integrated with renewable energy resources. . *Journal of Modern Power Systems Clean Energy*, vol. 10, n. 3, pp. 637–646, 2022.

[2] B. A. K. and S. A. V. M. K. Optimal distributed generation and network reconfiguration strategy to enhance system performance under time varying voltage dependent loads. *ieee - National Power Systems Conference*, vol. 10, n. 3, pp. 1–11, 2022.

[3] T. T. Tran, K. H. Truong, and D. N. Vo. Stochastic fractal search algorithm for reconfiguration of distribution networks with distributed generations. *Production and hosting by Elsevier*, vol. 11, n. 1, pp. 389 – 407, 2020.

[4] C. Qian and A. Wang. Drobust distribution network reconfiguration in thepresence of distributedgenerationunder uncertainty in demand and load variations. *Artificial Intelligence and Internet of Things Engineering ieee*, vol. 3, n. 1, pp. 234 – 240, 2022.

[5] M. Mahdavi, K. Schmitt, and F. Jurado. Distribution network reconfiguration based on improved differential evolution ant colony algorithm. *IEEE Transactions on Power Delivery*, vol. 3, n. 1, pp. 1 – 16, 2023.

[6] L. I. Silva, E. A. Belati, C. Gerez, and I. C. S. Junior. Reduced search space combined with particle swarm optimization for distribution system reconfiguration. *Electrical Engineering*, vol. , pp. 1127–1139, 2020.

[7] X.-S. Yang. Flower pollination algorithm for global optimization. *International Conference on Unconventional Computing and Natural Computation ,Springer Berlin Heidelberg*, vol. , pp. 240–249, 2012.

[8] Y. R. Gomes, E. A. Belati, and R. Vargas. Flower pollination algorithm for distribution system reconfiguration problem. *2021 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America)*, vol. , pp. 1–5, 2021.

[9] S. Montoya-Bueno, J. I. Muoz, and J. Contreras. A stochastic investment model for renewable generation in distribution systems. *IEEE Transactions on Sustaina.*, vol. 6, n. 4, pp. 1466 – 1474, 2015.

[10] M. Baran and F. Wu. Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Trans. Power Deliv.*, vol. 4, n. 2, pp. 1401–1407, 1989.

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