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ORIGINAL RESEARCH

Switch Allocation Problem in Power Distribution Systems with Distributed Generation

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Abstract

Research on distributed generation in power systems is of great interest due to its potential benefits in reducing environmental impact and improving overall system reliability and efficiency. The switch allocation problem (SAP) encompasses a series of decision-making faced by power distribution utilities concerning: (i) the number; (ii) type (manual or remote-controlled); (iii) capacity; and (iv) location of switches in a network to minimize operational costs while maintaining acceptable levels of reliability. This work proposes an efficient solution methodology for SAP that can solve large networks with distributed generation. The methodology is based on memetic algorithms embedded with a hierarchical population and local search procedures. Statistical analysis is conducted to determine the optimal values of hyperparameters. A case study on a real-life network (5523 nodes) from the state of São Paulo (Brazil) shows the methodology providing substantial cost reductions compared to the real-world solution implemented by the utility, and the potential benefits resulting from the presence of distributed generation. Also, the proposed approach was evaluated with six well-known instances present in the literature. The proposed methodology solved most of these instances in under minutes and achieved a substantial reduction of the reliability index metric employed, namely, SAIDI.

Keywords Combinatorial optimization · Switch allocation problem · Network reliability · Distributed energy resources · Memetic algorithms

1 Introduction

Power distribution systems are responsible for delivering energy coming from transmission lines through substations and distributing it to the final consumers. Distribution companies must hold the standards established by regulatory agencies by pursuing solutions with reasonable compromises between operational costs and reliability. A common practice to increase network reliability is to restrain the effects

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of outages, which can be accomplished by a suitable allocation of sectionalizing switches. These devices operate in a normally closed state, and they can be opened to isolate a contingency and reduce the area affected by interruptions. The costs of sectionalizers are significant, thus their number and location on a network are decisions that must be made on reliability and economic grounds.

The Switch Allocation Problem (SAP) is an NP-hard [1] combinatorial optimization problem that searches for (i) optimal locations; (ii) amount; and (iii) types of switches on a distribution network to minimize costs while maintaining a desired level of reliability. The SAP is generally intractable for exact algorithms on large instances, as shown by studies that adopted mixed-integer linear programming models [2–5]. Nevertheless, it is still possible to search for high-quality solutions by employing heuristic approaches such as Particle Swarm Optimization [6, 7], Artificial Bee Colony [8], and Artificial Immune System [9].

The SAP was solved heuristically considering real-world networks by different approaches such as Tabu Search [10], NSGA II [11], Genetic Algorithms (GA) [12], Memetic Algorithms [13], and GRASP [14]. Studies considering large networks (more than 1000 buses) are scarce [10, 13], and they typically restrain the types of equipment being allocated. For example, some works consider only sectionalizing remote-controlled switches (RCS) [8, 10, 15–17] while others only take into account deploying RCS [18, 19]. There are also works that focus on sectionalizing switches [6, 9].

Power distribution systems have been evolving into *smart grids* through recent advances in information technology, sensor networks, and distributed generation (DG) from renewable sources of energy. DG is a paradigm in which power sources are decentralized and placed near the consumers, in primary or secondary distribution lines. This work considers the potential benefit of DG in improving reliability and decreasing non-supplied energy in distribution networks. Some works consider DG and use GA as a solution approach [20, 21]. However, most of these consider small networks or other equipment such as automatic reclosers [22] and protection devices [23].

In [24], an immune algorithm is proposed to calculate the optimal configuration of switching devices with regards to minimizing the total cost of customer service outage and investment cost of line switches. The work described in [25] determines the optimal locations and sizes of DG using a Modified Teaching-Learning Based Optimization (MTLBO) algorithm. The approach was evaluated against two different test systems and the results obtained demonstrated the respective effectiveness by being able to find acceptable solutions using few evaluations. The authors applied the proposed methodology using the data of a real-world distribution system consisting of 11 feeders, 92 segments, and 90 load points, obtaining cost reductions of 57%.

In [26], a MILP model was proposed to determine the number and placement of RCS. The method was tested against real-world data of the Helsinki distribution network composed of 474 feeders serving 2369 sary substations. The approach resulted in cost reductions of 6%.

In [27], a two-stage optimization method for optimal DG was proposed considering the integration of energy storage. The first stage determines the locations and capacities of DG in order to maximize profit and voltage stability. The second stage applies a multi-objective ant lion optimizer to obtain Pareto-optimal solutions. The results have shown that the method was superior to the NSGA-II, MOPSO, and MOHS techniques.

Proper placement of DG for minimizing power losses was analyzed in [28] using the War Optimization metaheuristic. The authors show their approach was able to find better solutions more often than when compared against metaheuristics such as PSO.

A modified Taguchi-based approach for optimal DG was discussed in [29]. The approach introduced two modifications to deal with local trapping and suboptimal solutions. Namely, a roulette wheel selection criterion was applied which was then followed by the application of the modified Taguchi method. The approach was validated using two networks comprised of 33-bus and 118-bus radial distribution systems.

In the past three years, we can summarize some recently related works. In [30] it is considered the allocation of protection devices and one switch. A mixed-integer linear program formulation was proposed considering islanding with one DG in distribution systems. A network of 10 buses was used in tests. In [21], a method based on NSGA-II solved an expansion planning problem considering reliability, DG, capacitor, and switch placement. The authors employed a 90-bus network to evaluate their methodology. A fuzzy mixed-integer linear programming algorithm was proposed in [31] to determine the optimal number, type, and location of different types of automation devices. A test network with 33 buses was used to evaluate the method. The work described in [32] presents a framework to optimize the replacement of sectionalizing manual switches by RCS. The results were obtained using a 119-bus network. In [33], a method was presented to determine the optimal location of sectionalizing RCSs in the presence of DGs. A genetic algorithm with PSO was proposed and a 33-bus network was used for tests. DG was allocated at the end of the process to improve reliability, and islanding was allowed if some operational conditions were satisfied.

A genetic optimization algorithm with Steepest Descent was proposed in [34] to find the optimal location and control of automatic and manual cross-section switches and protection relay systems in the distribution power system. The methodology also considers a DG system with the island state of generation units. Tests were performed in the distribution network of Ahvaz city in Iran. In [35], a MILP model was proposed to allocate tie and sectionalizing switches, which could be either RCS or manual. Five networks were tested with 37, 85, 137, 145, and 230 nodes. In [36], an NSGA-II with multi-scenario (MSNSGA-II) was used for the placement of RCSs to enhance the efficiency and reliability of unbalanced distribution systems. The authors considered the uncertainty in the load and renewable energy sources along with network reconfiguration. Tests were performed with the IEEE 34-bus and IEEE 123-bus systems.

Our Contributions The SAP is clearly a hard combinatorial optimization problem, and solving it on large instances with DG builds up its complexity. To meet this challenge, we have developed a memetic algorithm with a hierarchical population and local search procedures. The motivation for this approach follows from the reduced number of individuals required in the population for convergence. This can reduce considerably the computational effort, considering the size of the networks being solved. Moreover, the adoption of the local search was conducted with parsimony, intensifying a small number of selected individuals. Formally, the methodology minimizes the solution cost constrained by network reliability targets. The solution determines the amount, location, type (manual or RCS), and capacity of the switches. The methodology was evaluated using a set of six general instances available for research on power distribution systems with 32, 83, 135, 201, 873, and 10476 buses/nodes.[1]A case study considers the allocation of sectionalizers in a large real network with 7 feeders and 5523 nodes[2]. This contrasts with the aforementioned literature that focuses on smaller instances. We also present a comprehensive statistical analysis for the procedural tuning of a set of algorithmic hyperparameters. In summary, our contributions rely on the scope (allocation of manual and remote-controlled switches considering DG), efficiency (tackling large real-life networks), and robustness (statistical analysis to guide our approach) of the methodology.

This paper is organized as follows: Sect. 2 presents the underlying concepts of the SAP; Sect. 3 describes the mathematical model behind our approach; Sect. 4 describes the solution methodology; Sect. 5 details the hyperparameter optimization procedure; Sect. 6 shows the computational experiments and the analysis of the results; Sect. 7 provides our concluding remarks.

2 Problem Presentation

To solve the SAP it is essential to analyze three costs, namely: (i) switch acquisition; (ii) switch maintenance, and (iii) costs of energy not supplied. It would be possible to have a solution with no switches and, therefore, no acquisition cost. However, this would lead to extensive impact upon failure and, consequently, poor standard reliability and high costs due to unsupplied energy. On the other hand, a solution consisting of a switch in each line of the network would theoretically lead to the best reliability but, as a result, acquisition costs would be maximal.

2.1 Distributed Generation

Centralized Generation (CG) [37] is concentrated in large power plants that supply energy to consumers. The energy flows through high-voltage transmission lines. Voltage is then reduced in the primary and secondary distribution systems until reaching the final consumer. Typical examples of generation facilities in centralized systems are fossil-fuel-fired plants and hydroelectric dams, both of which have considerable environmental impacts. In addition, these types of systems also incur

[1] REDS: REpository of Distribution Systems

[2] Public repository: https://github.com/lauraassis/SAP.

significant electrical losses that could be reduced if the electricity was to be produced closer to the final consumer [38]. DG can reduce losses in transmission and distribution systems by being placed near the end-consumer, in the primary or secondary distribution system. However, DG usually has a lower capacity than CG and can thus only feed a fraction of consumers. Typical examples of DG include small hydraulic turbines, photovoltaic systems, and wind turbines.

DG is also susceptible to islanding, a condition in which a distributed generator continues to provide electricity to a consumer that is no longer connected to the main power supply. Despite not being the prevalent practice in utilities, several works consider the impact of islanding dynamics in the reliability evaluation of distribution networks, with restoration from renewable-based DG [30, 33, 39, 40]. More information on the impact of islanding maneuvers on reliability indices is presented in [39].

2.2 Problem Representation

Since most power distribution systems are radial, they can be modeled as a connected directed tree $T(V, A)$, where V is the set of n nodes and A is the set of m arcs. The root of the tree represents the main power supply. A node $i \in V$ denotes a load point or connection point, and an arc $(i,j) \in A$ symbolizes an electrical connection between node i and j. In order to simplify the SAP with DG in large networks, it is possible to reduce the number of nodes (load points) by grouping the ones nearby that cannot be electrically isolated through a switch or a protection device. This network reduction allows for more reasonable computational times. The set of grouped nodes is called a *sector* that is constituted by a subset of nodes $V_k \subset V$, with $k \in S$, where S represents all the sectors. An example is presented in Fig. 1 consisting of 7 load points that can be grouped into 4 sectors. The corresponding tree representation can be found in Fig. 2. Larger networks have the potential for more significant reductions, which would result in lower computational effort. For each sector k it is possible to define the active power P_k as the sum of power from its constituent nodes p_i as described in Eq. (1). An analogous process can be used to define the reactive power Q_k of a sector in terms of its nodes q_i, as detailed in Eq. (2). The total number of consumers N_k in a sector k, is the sum of the consumers from all nodes of this sector, as shown in Eq. (3).

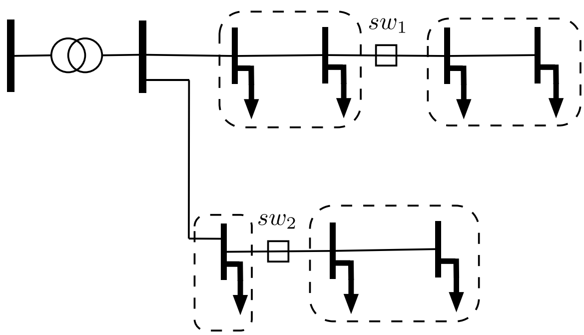
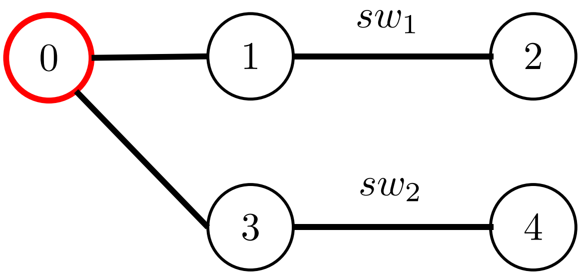


Fig. 1 Distribution network and its representation of sectors (*sw* are switches)

Fig. 2 Graph representation of a distribution network for Fig. 1



$$P_k = \sum_{i \in V_k} p_i \tag{1}$$

$$Q_k = \sum_{i \in V_k} q_i \tag{2}$$

$$N_k = \sum_{i \in V_k} n_i \tag{3}$$

3 Problem Formulation

Reliability indices are metrics typically used to assess the state of distribution networks. Two of the most widely used indices are expectations of probability distributions [13, 41], namely, System Average Interruption Duration Index (SAIDI) (Eq. (4)) and Energy Not Supplied (ENS) (Eq. (5)).

$$\text{SAIDI} = \frac{\sum_{k \in S} U_k N_k}{\sum_{k \in S} N_k} \tag{4}$$

$$\text{ENS} = \sum_{k \in S} U_k P_k \tag{5}$$

U_k is the total duration of interruptions perceived by sector k, as shown in Eq. (6). This expression makes use of: (i) Λ_l, the average failure rate per year for sector $l \in S$ and λ_i, the average failure rate for node $i \in V$, as depicted in Eq. (7); and (ii) time $t_{kl} = t_d + t_r$, which is the expected duration of interruption in sector k due to failure in sector l, where t_d is the average time to detect (localize) the failure and t_r is the average time to repair the equipment causing the failure.

$$U_k = \sum_{l \in S} \Lambda_l t_{kl} \tag{6}$$

$$\Lambda_l = \sum_{i \in V_l} \lambda_i \tag{7}$$

In what concerns interruption times, when it is possible to isolate the failure by opening a sectionalizing switch, the affected clients have their energy restored in t_d time. Similarly, if there is DG in a sector affected by a fault, then the sector load can be reestablished with the customers incurring a t_d time to be energized. If a sectionalizing switch cannot isolate the fault and there is no DG to supply power, then the clients will experience a time $t_d + t_r$ to have their power restored.

Figure 3 presents a power distribution network with DG that exemplifies the restoration time calculation procedure in the event of a fault. When a failure occurs in sector 2, the substation (sector 0) protection device opens automatically and sectors [0, 4, 5, 6] are unaffected. In time t_d the switches sw_1 and sw_2 are opened, isolating the failure in sector 2. Sectors [1, 3] then have their energy reestablished, namely sector 1 is re-energized by the substation while sector 3 is re-energized through DG in an islanding operation, which is dependent on the DG being capable of feeding sector 3. Sector 2 must wait for the repair. A summary of the interruption times perceived by each sector is presented in Table 1.

The mathematical model presented in this paper is based on the one proposed in [13]. The decision variables $x_{ij}^{sw} \in X$ represent the type and location of the switches. If a sectionalizing switch of type sw is allocated on arc (i, j), then $x_{ij}^{sw} = 1$, otherwise $x_{ij}^{s} = 0$ (Constraint (11)). The objective function presented in Eq. (8) minimizes the ENS, and switches costs, where c_e is the cost of energy not supplied and c_{sw} is the cost (acquisition and maintenance) of switches type sw. Constraint (9) limits the SAIDI value in order to maintain the required reliability level. Constraint (10) guarantees that the switch capacity must be respected according to the maximum flow per arc. In these constraints, SW is the set of available switches.

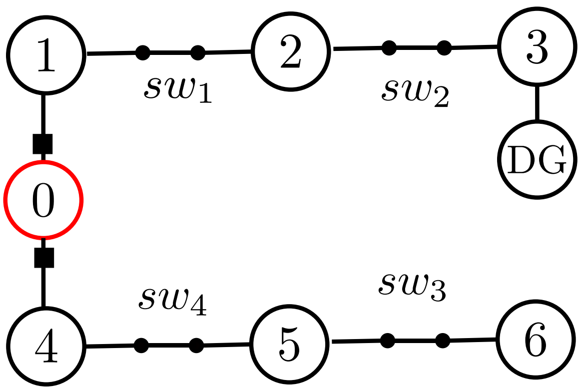


Fig. 3 Impact of DG after a failure

Table 1 Restoration time considering a failure in sector 2

Sector	Restoration Time ($t_{k,2}$)
0	$t_{0,2} = 0$
1	$t_{1,2} = t_l$
2	$t_{2,2} = t_d + t_r$
3	$t_{3,2} = t_d$
4	$t_{4,2} = 0$
5	$t_{5,2} = 0$
6	$t_{6,2} = 0$

$$\min \quad c_e \mathrm{ENS}(X) + \sum_{(i,j)\in A} \sum_{sw \in SW} c_{sw}(x_{ij}^{sw}) \tag{8}$$

$$\begin{aligned} & s.t. \\ & \mathrm{SAIDI}(X) \leqslant \mathrm{SAIDI}_{lim} \end{aligned} \tag{9}$$

$$f_{ij} x^{sw} \leq F_{sw} \quad \forall\, (i,j) \in A, \forall\, sw \in SW \tag{10}$$

$$x_{ij}^{sw} \in \{0, 1\} \quad \forall\, (i,j) \in A, \forall\, sw \in SW \tag{11}$$

The idea of the model is to give a simple representation that encapsulates the main aspects of the decision-making on switch allocation, which are the overall costs, reliability, and switch types (manual or remote and the capacity). For simplicity, the model leaves the power flow equations implicit. In practice, the power flow on each arc f_{ij} is calculated using a single-line backward-forward sweep method [42]. Also, without loss of generality, all the networks used in this work are balanced and with constant power demand in all buses.

4 Solution Methodology

Memetic Algorithms (MAs) [43] are derived from GAs, where a local search technique is added to intensify the search. Our solution methodology is based on MA and expands on the concepts presented in [13]. The main differences reside in the introduction of DG in the network with islanding and using statistical analysis to fine-tune the set of values of the methodology hyperparameters. The following sections briefly define the main concepts supporting GAs and MAs.

4.1 Chromosome

Population-based algorithms use individuals to represent solutions to the problem under consideration, and each individual is represented by a chromosome. The

arcs	(0,1)	(1,2)	(2,3)	(0,4)	(4,5)	(5,6)
Chromosome	0	1	5	0	1	1

Fig. 4 Chromosome representation of the solution depicted in Fig. 3

chromosome is modeled by a gene sequence represented by an integer array where each gene maps an arc in the network where a sectionalizing switch can be allocated. Each gene (allele) value gives the type $s \in SW$ of a switch placed in the corresponding network arc. If a chromosome position assumes value 0, there is no switch allocated in the corresponding arc. Figure 4 shows an encoded solution of the network presented in Fig. 3.

4.2 Fitness

Evolutionary algorithms execute for a predetermined number of iterations. The fitness of every individual is calculated at each iteration. The fitness function used in this work is the inverse of the objective function presented in Eq. (8).

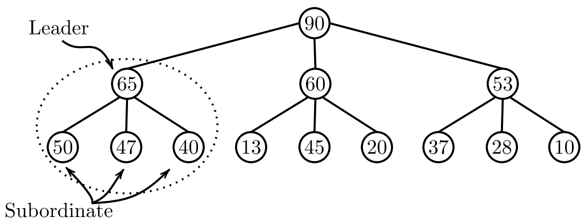
4.3 Hierarchical Population

The population is hierarchically structured with 13 individuals, arranged as illustrated in Fig. 5. The population forms a ternary tree, where all leaders have higher fitness than all of their subordinate individuals, so the best individual is always located on the tree root. Using this type of structure it is possible to achieve similar quality solutions to traditional unstructured populations, which require more individuals [44].

4.4 Crossover

Each pair of individuals (leader, subordinate) has their genetic code combined, generating offspring. A one-point crossover is performed, where a random point is chosen from the chromosome, and the offspring receives the first part from the leader parent and the second part from the subordinate parent. If the offspring has better fitness than its subordinate parent, then the latter is replaced by its offspring. In this way, the two best individuals are kept in the population.

Fig. 5 Population hierarchy



4.5 Mutation

According to a mutation rate (m_r), a gene of the chromosome is selected to be mutated, with one of the following possible outcomes:

1. if there is no switch then, with a specific rate (pm_r), allocate a manual one.
2. if there is a remote-controlled switch (RCS) then, replace it with a manual switch.
3. if there is a manual switch then, remove it or replace it with an RCS, with the same probability.

4.6 Constructive Heuristic

The constructive heuristic generates the initial population. Each of the 13 individuals is generated by randomly selecting an arc to receive a suitable switch from the set $S = \{1, \cdots, |SW|\}$. Each arc has a different probability of receiving a switch. This is done according to the potential benefit value B^s_{ij} that this switch will bring to system reliability, as shown in Eq. (12).

$$B^s_{ij} = \frac{1}{m}\left(\frac{\mathrm{SAIDI}_{max} - \mathrm{SAIDI}^s_{ij} + 1}{\mathrm{SAIDI}_{max} - \mathrm{SAIDI}_{min} + 1} + 1\right), \tag{12}$$

where B^s_{ij} is the benefit of placing a switch of type s in an arc (i, j), SAIDI^s_{ij} is the SAIDI value with the network containing only a switch s in the arc (i, j), SAIDI_{max} and SAIDI_{min} is the maximum and minimum SAID value for the network, respectively.

4.7 Local Search Procedure

After the crossover and mutation operations, the Local Search (LS) is performed by searching in the individual neighborhood (of size N_v) for a better solution. Three different movements form the proposed local search:

1. **Insertion** — allocate an adequate manual switch with a lower cost in one arc;
2. **Removal** — remove a switch from one arc;
3. **Exchange** — swap the switches between two arcs.

Since LS is computationally demanding it is not applied to all individuals. In this work, in each MA generation, two individuals of the population are chosen, (i) an individual randomly selected; and (ii) the highest fitness individual. The LS is executed until a better solution is found or if the maximum number of movements (M_{max}) is reached. If the latter occurs, the individual keeps its previous genes, i.e., the individual remains unchanged.

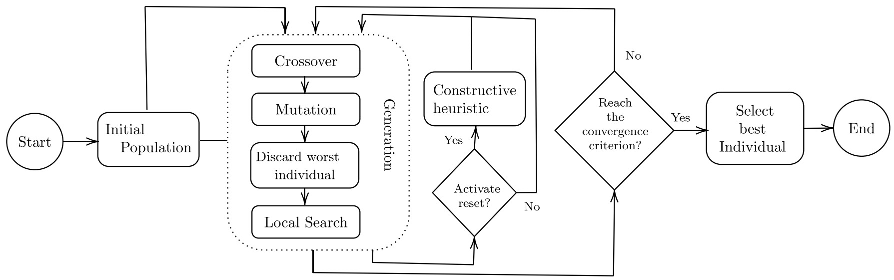


Fig. 6 Memetic algorithm diagram

4.8 Memetic Algorithm Diagram

The MA diagram is shown in Fig. 6. In the first steps, an initial population is created, and the individuals are sorted by their fitness. For each MA generation, the population is submitted to crossover and mutation genetic operations, and then a local search is performed. The stopping criterion of the MA is to achieve a maximum number of generations. If the fitness of the best individual value does not change for a predefined number of generations, a reset operation is performed. Then, a new population is generated by the constructive heuristic, and the evolution process begins again. The best individual is always preserved.

4.9 Feasibility

After the evolutionary process, the generated individual may be infeasible regarding constraint (9). If this happens, a constructive heuristic is utilized to allocate more switches until the individual becomes feasible.

5 Hyperparameter Optimization

The MA uses a set of hyperparameters whose values influence algorithmic performance and solution quality. Each hyperparameter can be tested for a potential set of values. This leads to several possible combinations for hyperparameter values. A grid search (exhaustively exploring a subset of the hyperparameters) can be employed to find the best combination. The set of values shown in Table 2

Table 2 Hyperparameter set and the search space

Hyperparameter	Description	Search Space
m_r	Mutation rate	$\{0.1, 0.2, 0.3, 0.4, 0.5\}$
pm_r	Manual switch allocation rate after mutation	$\{0.1, 0.2, 0.3\}$
N_v	Neighborhood size	$\{1, 2, 3\}$
M_{max}	Maximum movements	$\{50, 100, 150\}$
G_r	Maximum movements no improvements for reset	$\{5, 10, 15, 20, 25, 30\}$

Table 3 Network used in the hyperparameter optimization — R9

Attribute	Value
Feeders	4
Load (MW)	12.13
DG capacity (MW)	0
Length (Km)	145
Nodes	1887

is based on that defined in [13]. Network R9 of the repository was used for the hyperparameters optimization process. As a result, this network was not utilized to evaluate the efficiency of our method in order to avoid possible biased results. Table 3 presents the main characteristics of network R9.

In order for the tests to have statistical confidence through the z-test [45], each hyperparameter combination would have to be executed 30 times. Since the number of hyperparameter combinations is $5 \times 3 \times 3 \times 3 \times 6 = 810$ this would result in a total of 24300 algorithm executions. However, due to the problem's complexity, each simulation requires a large amount of time to run and it is therefore not practical to run the full set of executions. Alternatively, we adopted simplifications to reduce the number of combinations. The following sections describe these simplifications.

5.1 Step 1

The first simplification step consisted in fixing $G_r = 10$. This hyperparameter determines whether or not the algorithm should be restarted. As a result, the number of hyperparameter combinations was reduced to $5 \times 3 \times 3 \times 3 = 135$. Preliminary, each combination was executed a single time, and the five best hyperparameter combinations are shown in Table 4.

5.2 Step 2

Step 2 executed each of the five best combinations presented in Table 4 for 30 times. The results obtained are presented in Fig. 7, which depicts the solution evolution cost for each hyperparameter combination. Each color represents a combination, with the information for the best individual (lower costs) of each

Table 4 Top 5 results from step 1

Combination	m_r	pm_r	N_v	M_{max}	Cost (R$)
#1	0.2	0.2	1	50	53788.04
#2	0.1	0.3	1	50	54809.58
#3	0.1	0.2	1	50	56051.08
#4	0.1	0.1	1	50	56100.04
#5	0.2	0.1	3	50	56609.74

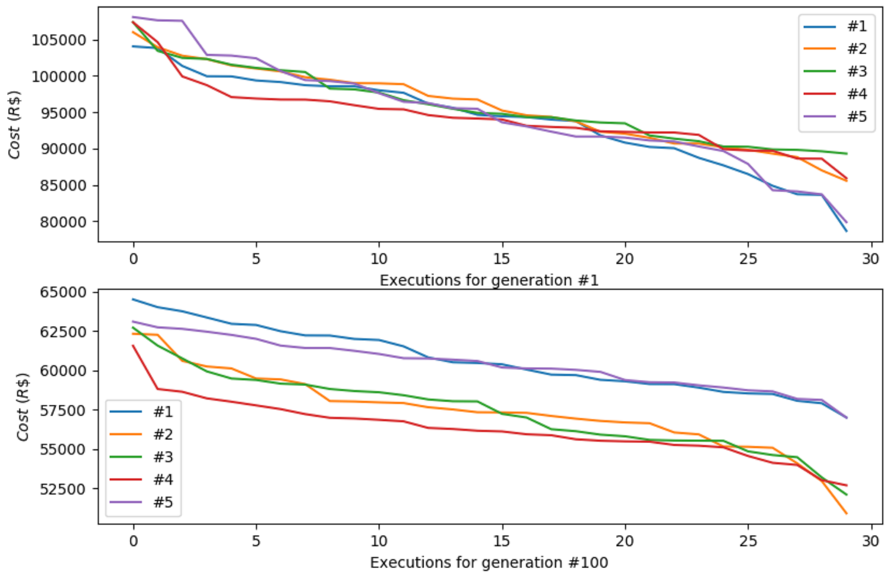


Fig. 7 *Fitness* evolution by generation from step 2

sample. Figure 8 shows a box plot for each hyperparameter combination, with the quartiles highlighting the median and outliers, showing that combinations 1 and 5 are clearly dominated by the others.

To compare the mean value among combinations, first, we check if they have normal distributions using *Shapiro-Wilk* test [46]. Subsequently, it is possible to use the *Levene* test [47] to check if the results for each combination have the same variance. We then apply a hypothesis z-test to verify if they have different means. All the statistical tests have a confidence level of 5%. The tests performed demonstrated that each combination has a normal distribution and the same variance. Table 5 shows the mean and standard deviation for each combination of Table 4. The z-test also demonstrated that combinations 3 and 4 could not be distinguished in terms of the mean value. As a result, it is not possible to assess with certainty which one outperforms the other, thus both combinations appear to be equally good. Our final hyperparameter choice was combination 3.

5.3 Step 3

The last step consisted in finding an optimal choice for G_r, with six different values being considered, namely, $G_r = \{5, 10, 15, 20, 25, 30\}$. Each combination was executed 30 times, leading to a total of $6 \times 30 = 180$ runs. The same analysis from step 2 was performed in order to obtain the lower mean. The box plot for each combination is shown in Fig. 9.

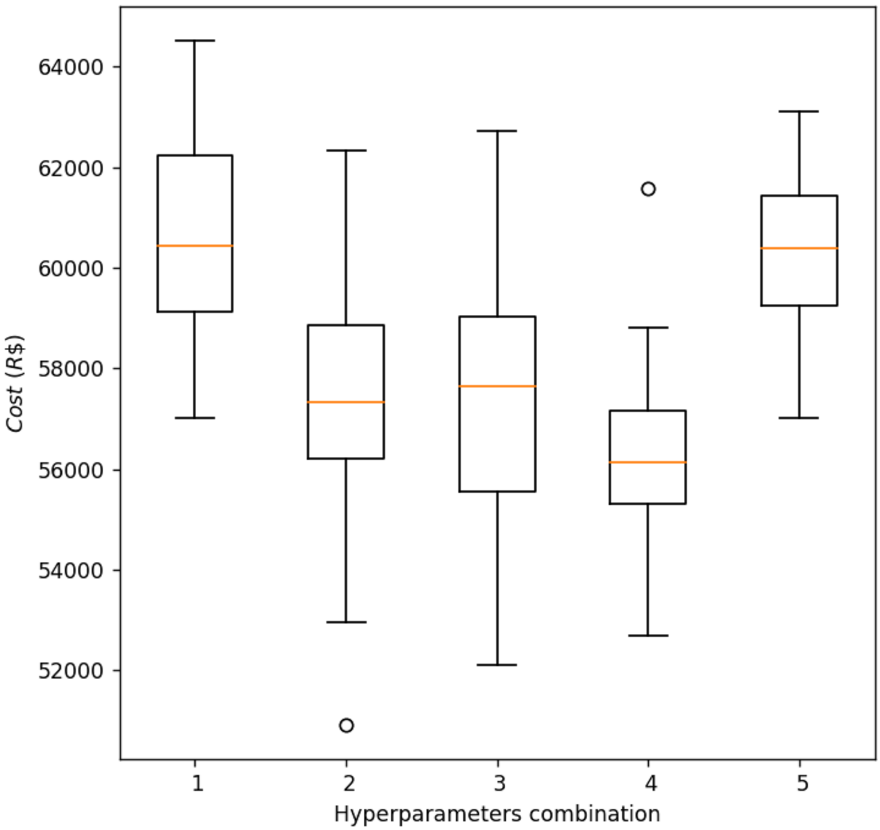


Fig. 8 Box plot for samples of each hyperparameter combination from step 2

The tests showed that all samples are normally distributed with the same variance. A hypothesis test was then performed comparing the lowest sample mean (Table 6). The results demonstrated that the values $\{20, 25, 30\}$ exhibit the best results, with no statistical difference among them. Our final choice consisted of $G_r = 20$. Table 7 describes the final hyperparameter configuration. The G_v parameter refers to the stopping criterion and its value is correlated to the computational time. As a side note, each execution required approximately one hour to run. The total number of executions was 465, a 98.1% reduction compared to the original number of hyperparameter combinations (24300).

Table 5 Mean (μ_x) and standard deviation (σ_x) of the samples by hyperparameter combination on Table 4

Combination	#1	#2	#3	#4	#5
μ_x	60673.51	57408.93	57357.62	56272.08	60390.18
σ_x	2035.82	2496.63	2459.63	1814.76	1541.25

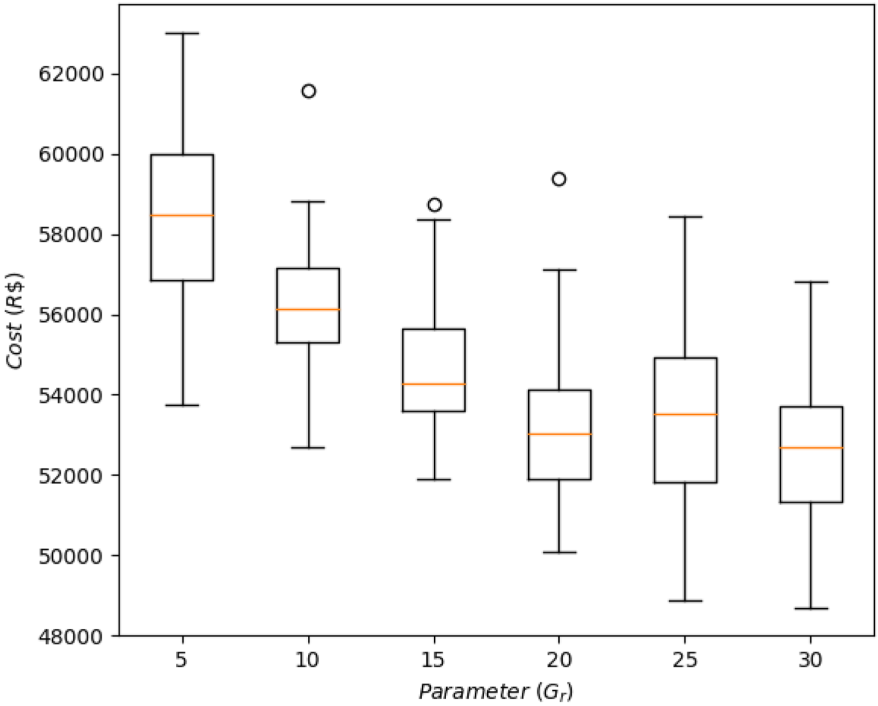


Fig. 9 Samples box plot for each value of G_r

6 Computational Experiments

The performance of the proposed methodology was evaluated experimentally with a PC equipped with an Intel Core i7 7500U running at 2.70GHz with 8GB of RAM and Ubuntu 18.04. The code was developed in C++ language. Each instance is executed in an individual core. Since there are 8 cores available, it was possible to process 8 instances simultaneously. The model parameters are presented in Table 8 and the set of six switch types considered are described in Table 9. The costs of the sectionalizing switches are annually based and include the acquisition and maintenance costs. The values reported in Tables 8 and 9 were the same practiced by the utility operating the network of the computational study.

Table 6 Mean (μ_x) and standard deviation (σ_x) of the samples by hyperparameter combination from step 3

G_r	5	10	15	20	25	30
μ_x	58334	56272	54717	53200	53650	52600
σ_x	2263	1814	1703	2033	2163	1892

Table 7 Final hyperparameter set

Hyperparameter	Value
G_v	100
M_{max}	50
m_r	0.1
N_v	1
pm_r	0.1
G_r	20

6.1 Test Scenarios

Table 10 shows the characteristics of a real large network[3] from the state of São Paulo in Brazil that was used in the tests. The tests considered three scenarios for the São Paulo network, which were compared with the solution previously implemented by the utility:

- **Utility Solution:** corresponds to the actual solution that the utility implemented for the network.
- **Scenario 0 (S0):** corresponds to a network without DG.
- **Scenario 1 (S1):** approximately mimics current DG in Brasil employing 0.43% of DG [48, 49].
- **Scenario 2 (S2):** uses a more considerable amount of DG, namely, 3.43%, in order to accommodate future growth.

Each DG was randomly allocated regarding position and capacity. A variation in the energy produced by DG is to be expected in real-world conditions, e.g., solar-based systems do not generate energy at night, but it is possible to model this type of production during daylight hours with cloudy conditions. However, since this work considers a planning scenario, we opted to employ a simplified version of distributed power generated that represents the amount produced for a year. The solution network obtained is presented in Fig. 11, where each color represents different feeders and the green dots depict DG allocations for scenario 1. Fig. 11

Table 8 Model parameters

Hyperparameter	Value
Energy cost	R\$100.00
Load factor	0.6
Annual interest rate	10%
Amortization period	15 years
Location time (t_l)	0.91 hours
Repair Time (t_r)	2.28 hours

[3] network R8 of the repository.

Table 9 Switch types

Switch	Capacity (A)	Type	Cost (R$)
C100	100	Manual	2817.00
C200	200	Manual	3817.00
C400	400	Manual	5017.00
C600	600	Manual	6185.00
A400	400	RCS	25000.00
A600	600	RCS	35000.00

presents an overall view of the SAP solution for the São Paulo network. This figure includes a zoom in the area where the feeders intersect, containing a larger number of switches. Each scenario was executed 30 times and compared using a z-test.

Figure 10 shows the box plot of the solution costs obtained in the three scenarios. There are noticeable cost reductions and reliability improvements when considering DG in the network. This was confirmed by the hypothesis test.

The average annual cost and algorithm execution time are presented in Table 11. When comparing the Utility Solution with the optimized solution for S0, the cost reduction obtained was 18.7%, showing a sizeable room for improvements for the solution actually being employed by the utilities in Brazil. Considering scenarios S1 and S2, with DG, the cost reductions were even more substantial, achieving, 24.2% and 31.6%, respectively. These results make a strong case in favor of the use of DG and islanding operations to improve network reliability or even maintain a target reliability index using a more cost-efficient switch allocation.

The average SAIDI values obtained by the memetic algorithm, and presented in Table 11, have similar values since the same target was used for all scenarios, showing that the algorithm satisfied the reliability constraint. It is worth pointing out that the reported average time refers to the multiple executions (30 repetitions) of the methodology.

Another pertinent comparison of our approach is with the results obtained by Assis et al. [13], as they also solved the same network using a memetic algorithm. One relevant difference between the approaches is that the authors did not perform any adjustment of the hyperparameters of their algorithm. Thus, the comparison with their methodology provides insights into the benefits brought by the tuning of the hyperparameters using statistical analysis. The results show that the cost

Table 10 Network information — R8

Attribute	Value
Feeders	7
Load(MW)	28.088 (100%)
Annual interest rate	10%
DG capacity (MW) — Scenario 1	0.149 (0.53%)
DG capacity (MW) — Scenario 2	0.936 (3.33%)
Length (Km)	391
Nodes	5523

Table 11 Results obtained by the memetic algorithm

	Utility Solution	Scenario 0	Scenario 1	Scenario 2
ENS Cost (R$)	21116.93	20075.89	19978.33	20214.44
Switches Cost (R$)	117846.26	92903.27	85304.29	74831.93
Total Annual Cost (R$)	138963.19	112979.17 (−18.7%)	105282.62 (−24.2%)	95046.37 (−31.6%)
Avg. time per execution	-	5.15 h	4.91 h	4.75 h
Avg. SAIDI	6.92	6.29	6.29	6.32

we obtained for Scenario 0 was 4.40% less than the results reported in [13]. It is worth mentioning that this cost reduction is only a lower bound of the actual benefit since Assis et al. [13] also considered the normally opened switches in their solution. When observing the results for scenarios 0, 1, and 2, a question arises: would increasing the penetration of DG in the network, such as 10% to 20% of the total load, affect the switch's rating, size, cost, and locations? This is an important consideration, and we anticipate that it would. Table 11 provides insights into this

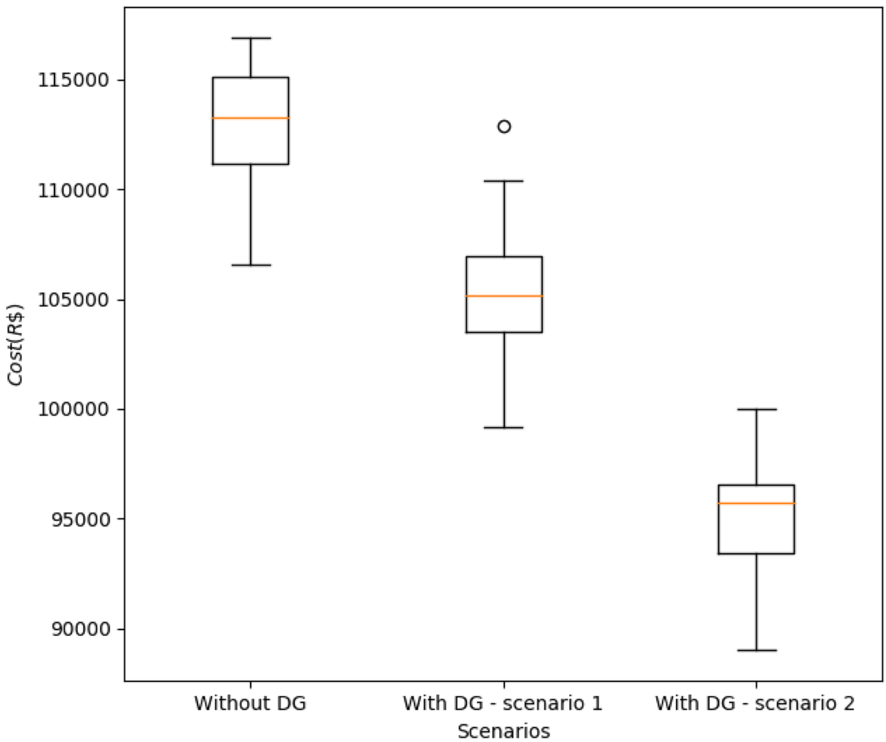
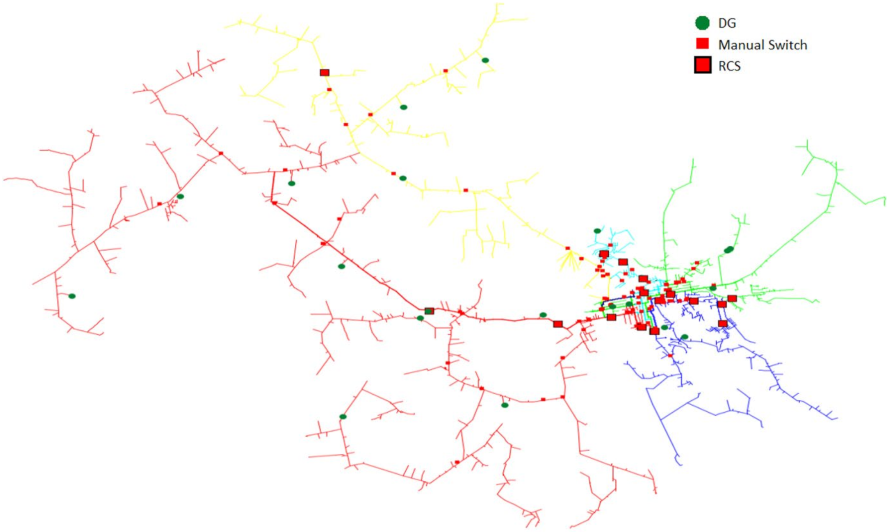
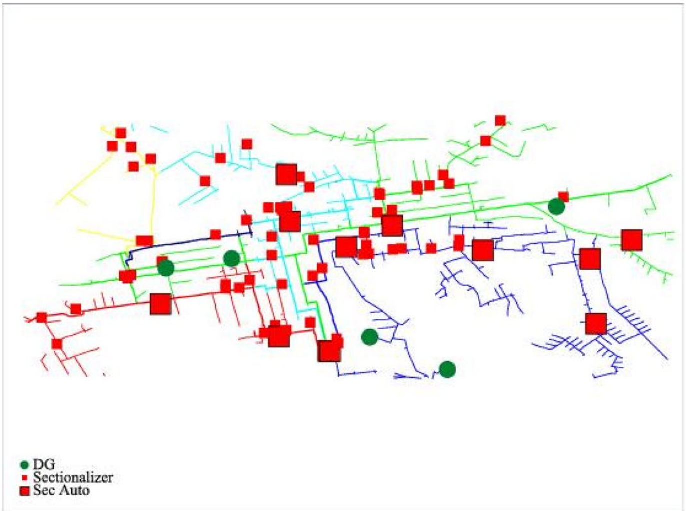


Fig. 10 Results for the scenarios with and without DG



(a) Overall view.



(b) Zoom of the critical area.

Fig. 11 The best allocation of switches obtained for the São Paulo network — R9

phenomenon, showing that Scenario 0 (network without DG) has a higher switch cost compared to Scenario 1 (with 0.43% of DG). Furthermore, the switch cost in Scenario 2 (considering 3.43% of DG) is lower than that in Scenario 1. We believe that this impact could be even more significant if the tie switches are taken into account, and we discuss this further in our concluding remarks.

Table 12 Results obtained by the memetic algorithm for `REDS Repository` instances

Networks	END Cost (R$)	Switches Cost (R$)	Number Switches	Total Annual Cost (R$)	Initial SAIDI	MA SAIDI	SAIDI Reduction (%)	Time (s)
bus_32_1	432.00	5189.01	5	5621.00	2.21	1.27	42.5	0.45
bus_83_11	1252.58	16804.58	6	18057.16	0.62	0.54	12.9	0.42
bus_135_8	2274.29	27583.72	19	29858.01	1.77	1.23	30.5	1.74
bus_201_3	14474.27	24429.14	23	38903.41	7.53	4.86	35.4	7.65
bus_873_7	84096.85	102387.18	71	186484.02	13.02	6.71	48.4	147.55
bus_10476_84	986923.03	1161689.15	796	2148612.17	12.71	6.62	47.9	2009.47

6.2 Performance Evaluation Using Literature Instances

This section presents experiments that offer a more comprehensive analysis of our proposed methodology when employed against radial distribution system networks that are available online.[4] These experiments show the performance of the proposed methodology for well-known instances used in several optimization problems [50–54]. The tests were performed using the same parameters (Tables 7, 8, and 9) that were used with the real large network shown in the previous experiment. Distributed generation was randomly allocated with a capacity of approximately 20% of the total load of the network.

These computational experiments perform a full network optimization for the SAP. This means that there are no switches or protection devices previously placed in the network. Table 12 shows the results obtained for each network of the `REDS` repository. The two numbers in the instance name give the number of buses (nodes) and feeders, respectively.

The MA solved 5 instances out of 6 in less than 3 minutes. The largest network with 10.476 buses took less than 35 min to solve. The results show that our methodology was effective in reducing the SAIDI by substantial amounts compared to the network's initial states, as depicted by the column "SAIDI Reduction".

7 Final Remarks

This work provided a methodological framework to support the decision-making process related to switch allocation with DG for real-world networks. The adoption of DG in power systems is increasing among utilities, given its appeal towards a more sustainable and reliable energy distribution. This paper reflects this movement by addressing DG in the context of switch allocation and network reliability. A memetic algorithm was proposed to solve the SAP with DG considering both manual and remote-controlled switches. Computational tests were conducted using real-life networks from the state of São Paulo, Brazil, and also with some literature

[4] Instances from literature http://www.dejazzer.com/reds.html.

networks. Statistical methods validated the results and the efficiency of the methodology. The experimental results show the robustness of the methodology in reducing operational costs while targeting reliability levels. The MA was able to reduce by more than 18% the overall cost when compared with the solution put in practice by the utility. The cost reductions were even more significant for two scenarios combining efforts of DG and an appropriate switch allocation.

Regarding future research directions, there are several avenues that can be pursued. Firstly, it is important to evaluate how a further penetration of DGs affects the number, size, cost, and locations of switches. This analysis will provide valuable insights into the impact of increased DG integration on the power distribution network. Secondly, we can delve into the question of whether the allocation of tie switches (considering both manual and remote-controlled options) would be a worthwhile endeavor. Thirdly, it would be worthwhile to investigate the effects of weekly meshed networks that can offer valuable information for enhancing network performance. Lastly, integrating the switch allocation problem with the network reconfiguration problem in a multi-objective framework presents an exciting opportunity to address both reliability and power loss simultaneously.

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Data Availability The networks considered in this work are publicly available in these repositories: SAP Repository: https://github.com/lauraassis/SAP. REDS Repository: http://www.dejazzer.com/reds.html

Declarations

Conflict of Interest The authors declare no competing interests.

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