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Improvement of Reliability Indices and Costs in Distribution Systems Considering Multiple Scenarios Through Switch Reallocation

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Abstract
This paper presents a method for improving indices and costs associated with reliability in radial distribution systems through switch placement using genetic algorithms. On this paper, the switch allocation problem will be solved with a method that allows novelties that can improve the quality of the solutions obtained. First, the possibility of switch allocation on both sides of each section of a feeder is proposed. Second, a method to quantify the non-supplied energy in terms of dollars per kWh of interruption is expanded, allowing a versatile way to simulate cases in which individual customers have different economic impacts when in situation of interrupted power delivery. The proposed algorithm is also versatile when additional restrictions are applied, such as fixing the number of switches or imposing SAIDI limits. Optimal switch locations are defined to improve restoration and reduce costs associated with reliability. Simulations in test and real feeders are performed, and the presented results show significant improvements.

Keywords Distribution systems · Reliability · SAIFI · SAIDI · Optimization · Genetic algorithms

1 Introduction

The goal of a power system is to deliver electric energy to its customers. This delivery must meet some power quality criteria that although vary from country to country, usually involve limits for acceptable power interruption durations from the final customers perspective. While a power system is basically composed of generation, transmission and distribution systems, it is reported that distribution systems account for up to 90% of all customer reliability problems (Billinton 1994 and Billinton 1996), which means that improving distribution reliability is the key to improving customer reliability. Distribution reliability is, therefore, one of the most important topics in the electric power industry due to its high impact on the cost of electricity and its high correlation with customer satisfaction (Brown 2009).

A distribution system usually operates in radial topology, meaning that each component has a unique path to a power source. The radial topology is preferred because of simple protection and coordination schemes and reduced short circuit current (Lavorato et al. 2012). Constant search for better configuration methods of distribution networks and more efficient methods of protection of these networks have been made, with the aim of improving their overall reliability. Good reviews on this subject are present in Sultana et al. (2016) and Mishra et al. (2016).

The installation of switches in the feeders and the use of schemes of reconfiguration through normally open tie points are common methods that have already been used for many years to improve the reliability of a distribution network. These methods improve the feeders' reliability because in the case of fault occurrences, the utilities can restore power to some of its nodes with the use of switches, by trying to isolate the fault area and restore power to the greatest number of customers as possible. Some methods for optimizing the distribution networks regarding its switches positioning for this purpose have been proposed, such as (Chen et al. 2006; Sohn et al. 2006; Chen et al. 2006; Moradi and Fotuhi-Firuzabad 2008; Tippachon and Rerkpreedapong 2009; de Souza et al. 2015; Alam et al. 2016; López et al. 2016; Ray et al. 2016; Popović et al. 2017; Girón et al. 2018; Rodrigues et al. 2019; Vaz et al. 2019; Seta et al. 2020): simulated annealing, binary programming, classic programming, genetic algorithms, immune system, particle swarm, ant colony and path relinking. It is noted that these works tend

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to the use of heuristic methods to solve the problem more efficiently, and that the feeder's models are based on graphs, with nodes representing customers. On the sections between nodes, switches can be allocated on their beginnings, and the multiple possibilities of allocations are tested to find the optimal solution. It is worth mentioning that, although there is no guarantee that the solutions found by these heuristic methods are indeed the global optimum, the literature usually uses the term "optimization" in these cases to evidence the search for this global optimum, so that the solutions found can be considered at least near-optimal (Araujo et al. 2013).

The aforementioned works are interesting, but the used methods could be improved in some ways. On this paper, the switch allocation problem will be solved with a method that allows flexibilities that can improve the quality of the solutions obtained.

- First, we will extend the possibilities of switch allocation on both sides (SABS) of each section of a feeder (and not only the beginning of each section, as is done in most of the literature). For example: in a section that starts in "node 5" and ends in "node 6", generally, the optimization methods used in the literature will only consider allocating switch in this beginning of this section, nearer to node 5, and will not consider allocating at the end of this section, nearer node 6. It will be shown that this possibility allows a greater number of candidate solutions to be analyzed, thus increasing the possibility of finding a better solution with reduced increase in computational effort when using heuristic techniques. To do this in traditional methods, it is necessary to increase the number of nodes in the system to represent these extra switches, which increases the computational time as shown in Sect. 3.5.
- Second, it is noted that the most of the methods found in the literature, which quantifies the non-supplied energy in terms of dollars per kWh of interruption, in order to minimize global costs (regarding equipment and interruption costs), tend to use only one fixed value of $/kWh interrupted, for all the customers in the feeder. Although this can work well for feeders that have all (or almost all) of its customers being of a same profile (i.e., all customers are residential, or all are commercial, or all are industries of a same type), this type of analysis can be greatly compromised when the load characteristics of the customers are not homogeneous. The load curves of residential, commercial and industrial customers can vary a lot (Willis 1996), and the $/kWh of interruption can also vary a lot even in the same category. So, we will model the equation that compares the candidate solutions in a way that can easily individualize the cost per power interrupted for each customer present on the feeder. Genetic algorithms will be used as a heuristic method for comparing different candidate solutions, which are associated with different switch placements.
- Third, the proposed method will be versatile when additional restrictions are needed. For example, the user may need to impose a fixed number of switches for use or a limit to SAIDI (social constraint). These are real distribution systems planning issues, as sometimes the operator is not interested in changing the number of switches in a feeder and only wants to optimize the existing switches allocation, or when there are financial penalties to feeders that have SAIDI values greater than a fixed value. A practical algorithm needs to allow these restrictions to be imposed in a versatile way, and this is the intention of the proposed method. These kinds of restrictions can be easily imposed using penalty factors in the genetic algorithm fitness function that is used.

Therefore, with the use of the proposed method, which will encompass all of these flexibilities, more candidate solutions to the switch allocation problem can be evaluated, and therefore better results can be achieved. The simulations conducted here will also compare the same system in multiple scenarios, in order to compare different situations that can appear in real cases of distribution systems.

2 SABS Method

2.1 Modeling the Sections with Four Possibilities of Switch Placement

As described in the Introduction, the majority of the methods in the literature involve the optimization of switch allocation considering only the placement of switches in the beginning of each section of the feeder, not taking into account the possibility of switch placement also at the end of the sections. By not using this possibility, the search for the optimal solution for the feeder is compromised, because a great number of solution possibilities will not be analyzed.

For instance, refer to Fig. 1. It shows two possible allocations of normally closed (NC) switches for a same feeder. Note that the first one has two NC switches, both at the beginning of their sections; the second one also has two NC switches, at the same sections of the first one, but one of these switches (the blue one) is at the end of its section. The switching maneuvers for restoration purposes in case of faults in these feeders, because of this simple change of position on one switch, are quite different. For a fault between nodes 4 and 6, regarding the protection scheme, in both feeders the circuit breaker (CB) will open, leading to an initial power interruption on all nodes from 2 to 10. However, regarding system reconfiguration, there are differences:

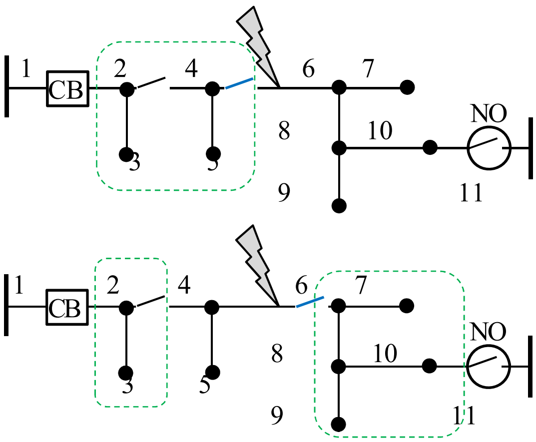

Fig. 1 Comparison between two possible switch allocations in a feeder

- the first feeder can have the NC switch between nodes 4 and 6 opened, allowing the closing of the circuit breaker and consequently the restoration of power for nodes 2, 3, 4 and 5. The nodes 6, 7, 8, 9 and 10 will continue to be in situation of power interruption until the fault is repaired.
- the second feeder can have both the NC switches between nodes 2 and 4 and between nodes 4 and 6 opened, allowing the closing of both the CB and the normally open (NO) switch, thus leading to restoration of power for nodes 2, 3, 6, 7, 8, 9 and 10. Only nodes 4 and 5 will continue to be in situation of power interruption until the fault is repaired.

Note that, in this simple example, the number of restored customers, by switching maneuvers, varied greatly—just by considering the placement of a switch at the end of a section. Depending on the number of customers and loads attached to each of the nodes, one or another of these feeders can be more reliable or more economic in terms of cost of non-supplied energy. Of course, this analysis was made only for one faulty section, which leads us to think that the complete analysis of faults in every section of the feeders will yield results that can vary greatly, especially when dealing with bigger feeders with lots of NC switches and branches.

With this in mind, we will model each section of a feeder in a way that permits the evaluation of four possibilities: switches on neither ends of the section; switch only on the beginning of the section; switch only on the end of the section; switch on both ends of the section. To do this, in the genetic algorithm used, each chromosome will be generated with genes regarding the existence or not (1 or 0) of switches at each end of each section of the feeder. For example, if certain distribution feeder has 7 sections, 8 nodes (numbered from 1 to 8) and 2 NC switches, one being installed closer to the "from" node of sections 2–3 and other being installed closer to the "to" node of sections 3–5, its chromosome is represented by Fig. 2.

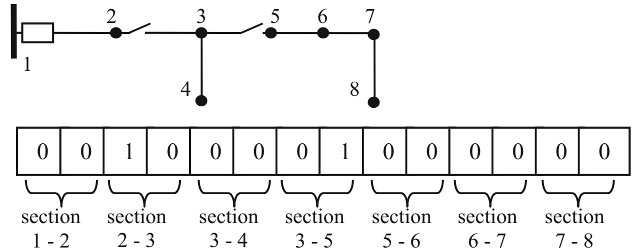

Fig. 2 A feeder and its associated chromosome structure for example

2.2 Fitness Function and Genetic Algorithm

The discrete search space (related to the switch allocation possibilities), χ, is related to a real number by its fitness function, f, as defined in (1). The objective of the genetic algorithm is to find the minimum argument of the fitness function, therefore finding the fittest solution in its search space. Defining X as a vector of decision variables within χ, and noting that X is an integer, binary vector (as in Fig. 2), the objective is given by (2).

The fitness function used in the present genetic algorithm is given in (3), and it aims to minimize the annual cost of reliability of a distribution system (regarding the switches placement and their costs along with costs associated with power interruptions). Other reliability-related devices present on feeders (such as circuit breakers, reclosers and fuses) are assumed to be fixed, which means fixed costs that won't vary in any scenario, thus not impacting in the search for the optimal placing of switches. In (3), C is the number of installed NC switches, CC is the average cost of a NC switch (installation and maintenance, cost per year, assumed to be 2500.00 US$/year—Sohn et al. 2006), P_j is the average load (kW) connected to the load point j, D_j is the duration of power interruption (hours per year) for load point j, ACDF_j is the customer damage function per hour and power of failure (in $/kWh—Sohn et al. 2006) for load point j, and n is the number of load points of the feeder.

As f in this case is given by (3), the objective then can be written as (4), which is subject to the individual interruption times for each customer j, D_j. Equation (4) aims to minimize the annual cost of reliability of a DS, regarding: (1) the switches placement and their costs; (2) the cost due to power interruptions. The formulation expresses a probabilistic, integer, non-linear and combinatorial optimization problem. Constraints used for programming the algorithm are better explained next. The variables of the problem are switch numbers and allocations. SAIDI and SAIFI can also be calculated along with costs. D_j depends on the impacts suffered by customer j because of each sustained fault i that can happen on the L sections of the feeder and will be better explained in Sect. 2.3.

Equation (5) indicates that the cost of interruption of event i will only be considered as an increment of impact $D_{j,i}$ for customer j after a user-indicated interruption time (t), e.g., interruptions of more than 3 min.

Equation (6) indicates that SAIDI must be less than or equal to a used-indicated maximum SAIDI ($\mathrm{SAIDI_{MAX}}$). This equation is considered as an optional user-indicated social constraint, which avoids that less important consumers will be severely harmed in relation to large consumers. This issue is analyzed in Sect. 3, simulations 5 and 6.

Equation (7) represents the schema theorem (Whitley 1994 and Reeves 2010), which combines the effects of selection, crossover and mutation in a simple genetic algorithm between generations of solutions, where P_c is the probability of crossover, P_m the probability of mutation, $o(H)$ the number of defined positions on the schema, $\delta(H)$ the defining-length of the schema, and $m(H,t)$ is the number of instances the schema H has in generation number t.

$$f : \chi \mapsto \mathbb{R} \tag{1}$$

$$\text{Objective} = \underbrace{\arg\min f}_{X\in\chi} \tag{2}$$

$$f = \text{Cost} = C \cdot \mathrm{CC} + \sum_{j=1}^{n} P_j \cdot \mathrm{ACDF}_j \cdot D_j \tag{3}$$

$$\underbrace{\arg\min}_{X\in\chi}\left[C \cdot \mathrm{CC} + \sum_{j=1}^{n} P_j \cdot \mathrm{ACDF}_j \cdot D_j\right] \tag{4}$$

$$D_j = \sum_{i=1}^{L} D_{j,i}, \quad D_{j,i} = \begin{cases} D_{j,i}, & \text{if } t \geq 3\text{min for fault } i \\ 0, & \text{else} \end{cases} \tag{5}$$

$$\mathrm{SAIDI} \leq \mathrm{SAIDI_{max}} \tag{6}$$

$$m(H,t+1) \geq m(H,t) \cdot \frac{f(H)}{\bar{f}} \cdot \left\{1 - \left(P_c \cdot \frac{\delta(H)}{l-1}\right) - o(H) \cdot P_m\right\} \tag{7}$$

Note that, in order to evaluate the fitness function of a candidate feeder, all of the values of interruption durations D_j for each of its load points must be first calculated. This calculation is performed by an analytical simulation, which evaluates the impact of each fault i on the sections of the candidate feeder on each load point j that belongs to this feeder. This analytical simulation will be described next. Note also that the formulation of this fitness function easily allows ACDF_j, which is the cost S/kWh of interruption for load point j, to be individualized for each load point present in the feeder—which is one of the objectives of this paper, described in the Introduction. This individualization is important, and the following example in Brown (2009) is very clear about this: a semiconductor factory may incur a high initial cost due to a ruined process and a small time-dependent cost due to lost production; a plastic extrusion facility may incur small costs for short interruptions, but incur an extremely high cost if the interruption is long enough for plastic to solidify within extrusion equipment; a refrigeration warehouse may not incur any cost for short interruptions, but at certain point, food will begin to spoil and severe economic losses will occur, reaching its peak when all the food is spoiled. Therefore, to make the search for the optimal solution for the switch placement problem more aligned with real-world problems, the methods should bring the analysis of varying the customer damage functions, in \$/kWh interrupted, according to the load characteristics of each node. Finally, as the intention of this optimization is to allocate switches which have switching times greater than momentary interruptions times, only sustained interruptions will be taken into account.

2.3 Analytical Simulation for Calculation of D_j

The first step to evaluate the individual impacts of each fault on each customer is the analysis of which customers will be impacted when the fault occurs and, among these, which customers can have its power restored, and by which method. In this context, the presented algorithm will generate, for each fault, five important sets of customers:

Ω_N: customers which will not suffer any impact regarding this fault. These are the customers that are not downstream of the protection device which opened because of the fault.
Ω_P: customers which will suffer at least a momentary impact regarding this fault. These are the customers that are downstream of the protection device which operated and opened because of the fault.
Ω_U: customers which can have its power restored by upstream restoration. These are the customers that are located in an area of the feeder between the operated protection device and the first NC switch upstream of the fault, which can be opened to isolate them from the fault area, allowing the protection device to be closed and reset.
Ω_D: customers which can have its power restored by downstream restoration. These customers are located in an area of the feeder that has simultaneously a NC switch downstream of the fault and a NO switch separating this area from an adjacent feeder, so the NC switch can be opened to isolate the fault area and the NO switch closed for power transference, if the power and voltage constraints are not exceeded.

The algorithm, upon each fault occurrence and according to its location, will then generate different sets Ω_N, Ω_P, Ω_U and Ω_D, through graph navigation and search. The following notation will be adopted: among the total of L fault event in a component, each individual fault event i ($i = 1, 2, 3, \ldots, L$) will generate the sets $\Omega_{N\,(i)}$, $\Omega_{P\,(i)}$, $\Omega_{\mathrm{U}\,(i)}$ and $\Omega_{\mathrm{D}\,(i)}$.

After evaluating these Ω sets, it is clear that, for each fault event i, each individual customer j among the total number of customers n ($j = 1, 2, \ldots, n$) can belong or not to the sets $\Omega_{N(i)}$, $\Omega_{P(i)}$, $\Omega_{\mathrm{U}(i)}$ or $\Omega_{\mathrm{D}(i)}$. The algorithm, in order to identify for each customer if it belongs to a certain set, generates Boolean values:

$$B_{N(i,j)} = \begin{cases} 1, \text{ if } j \in \Omega_{N(i)} \\ 0, \text{ else} \end{cases}$$
$$B_{P(i,j)} = \begin{cases} 1, \text{ if } j \in \Omega_{P(i)} \\ 0, \text{ else} \end{cases}$$
$$B_{\mathrm{U}(i,j)} = \begin{cases} 1, \text{ if } j \in \Omega_{\mathrm{U}(i)} \\ 0, \text{ else} \end{cases}$$
$$B_{\mathrm{D}(i,j)} = \begin{cases} 1, \text{ if } j \in \Omega_{\mathrm{D}(i)} \\ 0, \text{ else} \end{cases} \tag{8}$$

These Boolean values finally can be used to calculate not only the D_j (annual duration of interruption of load point j) values, but also the annual failure rate F_j of each load point. These are calculated by the algorithm using Eqs. (9) and (10):

$$\begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_n \end{bmatrix} = \sum_{i=1}^{L} \begin{bmatrix} \lambda_i \cdot B_{P(i,1)} \\ \lambda_i \cdot B_{P(i,2)} \\ \vdots \\ \lambda_i \cdot B_{P(i,n)} \end{bmatrix} \tag{9}$$

$$\begin{bmatrix} D_1 \\ D_2 \\ \vdots \\ D_n \end{bmatrix} = \sum_{i=1}^{L} \begin{bmatrix} \lambda_i \cdot r_i \cdot B_{P(i,1)} & -\lambda_i \cdot (r_i - s_{\mathrm{NC}}) \cdot B_{U(i,1)} & -\lambda_i \cdot (r_i - s_{\mathrm{NO}}) \cdot B_{D(i,1)} \\ \lambda_i \cdot r_i \cdot B_{P(i,2)} & -\lambda_i \cdot (r_i - s_{\mathrm{NC}}) \cdot B_{U(i,2)} & -\lambda_i \cdot (r_i - s_{\mathrm{NO}}) \cdot B_{D(i,2)} \\ \vdots & & \vdots \\ \lambda_i \cdot r_i \cdot B_{P(i,n)} & -\lambda_i \cdot (r_i - s_{\mathrm{NC}}) \cdot B_{U(i,n)} & -\lambda_i \cdot (r_i - s_{\mathrm{NO}}) \cdot B_{D(i,n)} \end{bmatrix} \tag{10}$$

where s_{NC} is the time needed to open the NC switch used in an upstream restoration maneuver; s_{NO} is the time needed to perform power transference in an downstream restoration maneuver; λ_i (failures/year) and r_i (hours/failure) are statistical parameters of the fault, respectively failure rate and mean time to repair, which are parameters inserted in the algorithm along with other feeder's data.

By knowing the values of F_j and D_j, it is possible to calculate other reliability indexes for this system. Two of the most used are the SAIFI and SAIDI, which are simply the arithmetic means, respectively, of the F_j and D_j of all of the n customers connected to the feeder, given in Eqs. (11) and (12). Also, at this point, the fitness function (3) can be finally

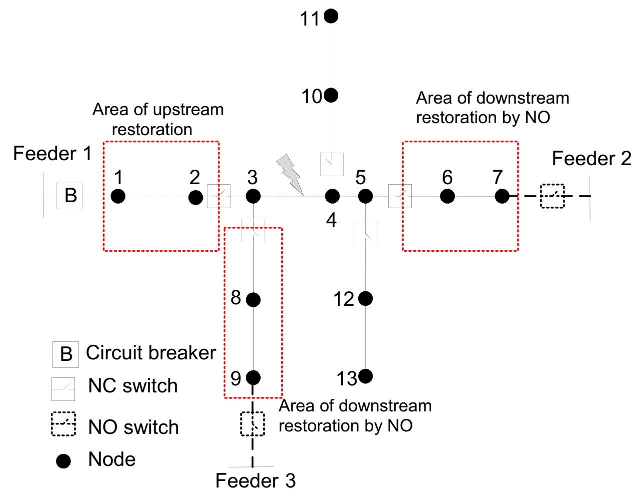

Fig. 3 Example. Fault occurring between nodes 3 and 4

evaluated, so it will be known for each candidate feeder, along with its values of SAIFI and SAIDI.

$$\mathrm{SAIFI} = \frac{\sum_{j=1}^{n} F_j}{n} \tag{11}$$

$$\mathrm{SAIDI} = \frac{\sum_{j=1}^{n} D_j}{n} \tag{12}$$

Before analyzing the other steps of the algorithm, let us be clearer with all the definitions of sets and Boolean values showed above with a feeder of example presented in Fig. 3. Each fault event on this feeder generates different sets and Boolean values. Let us see an example of a fault occurring on the section between nodes 3 and 4, and let us suppose that the number of this fault (among all L fault events) is $i = 2$. Therefore, the values for fault $i = 2$ are:

$\Omega_{N(2)} = \{\emptyset\}$, because all the customers will be initially affected by the fault, as all of them are downstream of the circuit breaker (which opens because of this fault);
$\Omega_{P(2)} = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13\}$, which are all the customers that will be affected by the fault;
$\Omega_{\mathrm{U}(2)} = \{1, 2\}$, which are all the customers that can be restored by upstream restoration;
$\Omega_{\mathrm{D}(2)} = \{6, 7, 8, 9\}$, which are all the customers that can be restored by other feeders with the use of NO switches.

The Boolean values B for this fault for all j customers will be the ones listed on Table 1.

After generating these Boolean values for each customer and each fault (thus classifying which customers will or will not be impacted, and, if impacted, will or will not be restored before fault clearing, and by which method), the customer impact analysis can then be quantified with rates and time parameters. For n customers and a total of L annually fault

Table 1 Boolean B values for fault 2 for each customer on example feeder

j:	1	2	3	4	5	6	7	8	9	10	11	12	13
$B_{P\,(2,j)}$	1	1	1	1	1	1	1	1	1	1	1	1	1
$B_{U\,(2,j)}$	1	1	0	0	0	0	0	0	0	0	0	0	0
$B_{D\,(2,j)}$	0	0	0	0	0	1	1	1	1	0	0	0	0

events, each single fault i among L impacts differently each customer j among all n customers. Starting with $F_j = 0$ and $D_j = 0$, the algorithm sums the possible increments in all these n indexes after each fault occurrence in the period of a year, doing this for all the L faults and with each fault i generating different increments for each different customer j because of the different Boolean values above described. The impacts also depend on the parameters of the fault, which are its failure rate λ_i and mean time to repair r_i. Equations (9) and (10) are used by the algorithm to sum all possible increments (taking into account lesser increments in case of any possible restoration maneuvers, activated in the equations by Boolean values), so the algorithm generates a final n-sized array of individual indexes F_j and D_j.

2.4 Flowchart and Other Details Regarding the Genetic Algorithm

The flowchart of the proposed genetic algorithm for solving the problem is shown in Fig. 4, and it synthesizes all of the described steps of the algorithm.

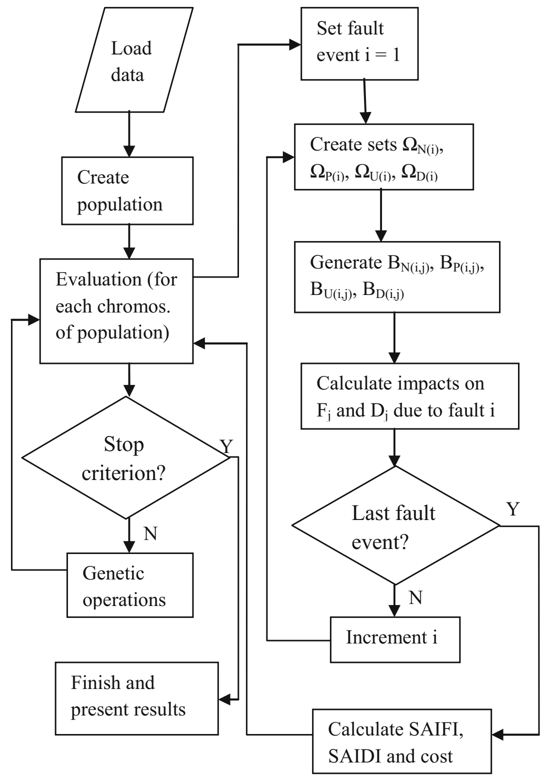

Fig. 4 Flowchart of the proposed genetic algorithm

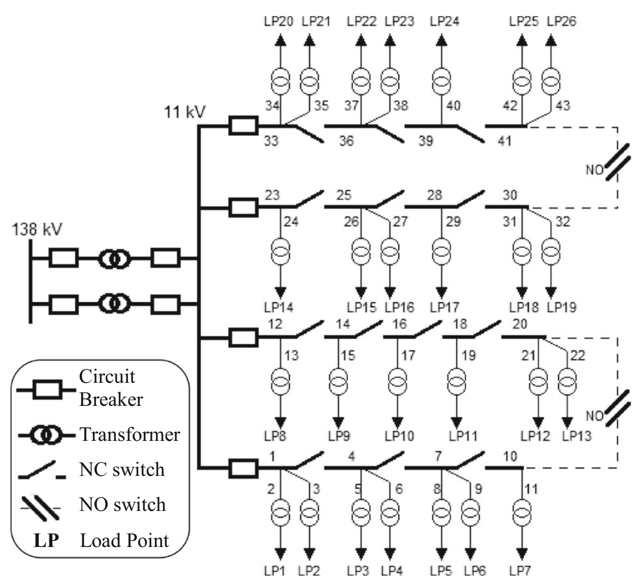

Fig. 5 The RBTS-Bus 5 test system

3 Results

In this section, the results obtained with the methods proposed in test systems and in real systems will be presented. The algorithm was implemented and simulated in MATLAB R2018a®, using an 8 Gb IntelCore® i7 personal computer.

3.1 Method Validation on a Test System

The proposed method was tested on the RBTS-Bus 5 Test System, shown in Fig. 5, and which data was presented in Billinton and Jonnavithula (1996).

Firstly, validation of the reliability assessment of the proposed method could be obtained by analyzing SAIFI, SAIDI and EENS indices obtained from the proposed method and comparing it to the original values. The obtained data is considered to be equal, which validates the proposed analytical simulation method for calculating reliability indices. The results of these test simulations are shown in Table 2.

Secondly, the proposed optimization function was used on this test system. Results obtained for feeders F1 and F2 of this test system (F1: feeder which has load points from LP1 to LP7; F2: feeder which has load points from LP8 to LP13) were compared to the results obtained in Ma et al. (2010), which also used a method based on genetic algorithms on these feeders. The conditions were the same as the most complex simulated case on the aforementioned paper, which considers fuses in each load branch and transformers

Table 2 Results for RBTS-Bus 5 test system

	SAIFI (f/year)	SAIDI (h/year)	EENS (MWh/year)
Original data	0.23	3.55	40.1
Proposed algorithm, original test feeder switch allocation	0.23	3.54	40.0

Table 3 Results on the optimization of feeders F1 and F2 of RBTS-Bus 5

	Locations of sectionalizing switches	Annual total cost	EENS (kWh/year)
Ma et al. (2010)	Sections 4, 7, 10, 14 (all in the beginning of the sections)	116,028.01	23,566.00
Proposed method	Beginning of sections: 4 and 14 End of sections: 7 and 10	111,998.00	22,607.00

failure rates. The outage costs and switch costs were also the same used in Ma et al. (2010). Comparison of the results is shown in Table 3. It is interesting to note that the switch allocation sections were the same, but two of these switches were allocated at the end of theirs sections, which could lead to better restoration maneuvers; this way, the investment in switches were the same, but the non-supplied energy was lower, therefore the costs of non-supplied energy were also lower, leading to lower total costs. While the costs and EENS reductions on this case were not so high, note that the test feeders are small, and therefore the impacts on bigger systems can be of great significance.

3.2 Real Feeder Data and Configuration

The real feeder data used to perform the simulations here are presented in Tippachon (2009). It is a real distribution network, which scheme is reproduced on Fig. 6. Among the data presented in Tippachon (2009), it is important to mention: failure rates are $\lambda = 0.17$ failures/year per section km; fault repair time is 2 h/failure; switching operations requires 30 min to be performed; average ACDF for all customers $= 1.865$ \$/kWh; switch cost = US\$2500.00; original feeder has SAIFI $= 8.67$ faults/year; original feeder has SAIDI $=$ 10.02 h/year. Data regarding sections of the feeder are given on Table 4. It is also important to mention that both the values of ACDF and switch costs were extracted from the same reference where the tested feeder data were extracted, which means that these used costs are consonant with the feeder's economic aspects (except in the last simulations, in which some made-up ACDF values will be considered, for interesting reasons that will be explained).

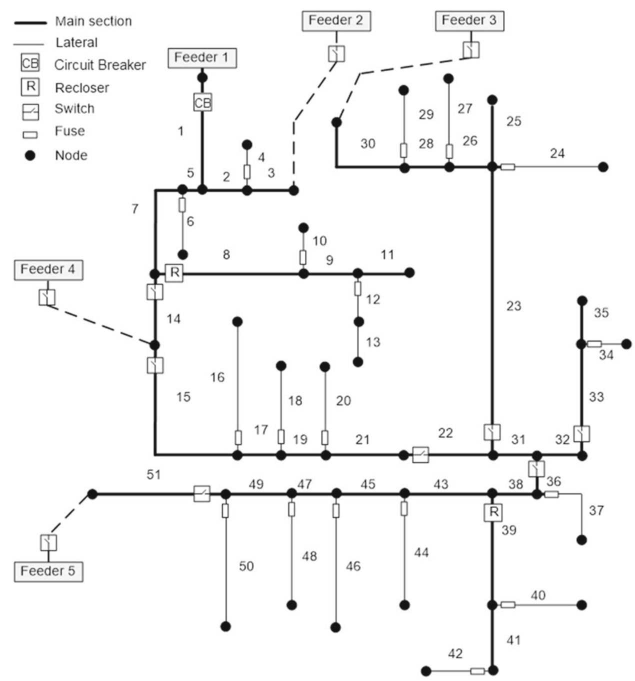

Fig. 6 Real 22 kV feeder

3.3 Description of the Simulations on the Real Feeder

As it was described in the Sect. 1, this paper has a goal of simulating and analyzing the switch allocation problem in multiple scenarios. The selected scenarios for simulations are described next, and all of them will yield results of switch allocation spots, SAIFI, SAIDI and costs:

Simulation 1 switch placement optimization; any number of switches may be present, but only at the beginning of each section. Original ACDF $= 1.865$ \$/kWh is used for all nodes.

Simulation 2 switch placement optimization; any number of switches may be present, at any extreme (beginning or end) of each section. Original ACDF $= 1.865$ \$/kWh is used for all nodes.

Simulation 3 switch placement optimization; preserve the original number of seven switches (only reallocate them), at any extreme (beginning or end) of each section. This is done by imposing a penalty factor for any solution which has a number of switches different from 7. Original ACDF

Table 4 Feeder data (Sct is the section; Lg is the length of the section in km; Ld is the load of the section in kVA; *N* is the number of consumers in the section)

Sct	Lg	Ld	N	Sct	Lg	Ld	N
1	3.4	0	0	27	0.9	110	80
2	0.5	0	0	28	4.2	590	120
3	0.1	0	0	29	0.7	90	93
4	0.4	150	55	30	2.3	170	145
5	0.5	0	0	31	2.8	480	65
6	1	220	89	32	1.5	2400	80
7	1	0	0	33	1.3	210	102
8	3	1250	145	34	0.6	50	20
9	0.5	90	85	35	0.5	100	30
10	0.3	90	1	36	0.1	0	0
11	1.2	445	200	37	2.5	100	65
12	1	720	2	38	3.2	480	50
13	1	30	55	39	0.8	500	1
14	0.3	0	0	40	3	450	220
15	2.9	150	55	41	2.7	150	95
16	3	50	57	42	3	110	125
17	1.7	60	105	43	9.3	60	167
18	1.3	310	243	44	3.5	150	141
19	2	340	147	45	1.2	50	21
20	1.4	30	47	46	2	140	93
21	1	2130	107	47	0.9	36	106
22	0.4	250	30	48	1.3	60	90
23	2.3	780	117	49	1.3	30	17
24	4	610	135	50	5	160	145
25	0.7	80	95	51	2	1350	67
26	1.5	60	50				

= 1.865 \$/kWh is used for all nodes. This scenario is important because most of the works that present optimal solutions for cost optimizations only bring the global optimum solution, i.e., the solution with the least total cost (equipment + cost of interruptions). While the best global cost is great for theoretical purposes and planning of new feeders, it should be noted that many electric distribution companies are also interested in the solutions that don't demand change on the number of equipment installed on an already existing feeder. For example, if a real existing feeder has 11 switches and its global optimum solution has 13 switches, maybe the distribution company will prefer a local optimum 11-switches solution instead of the global optimum, as there will be no need to go through the process of buying and installing new equipment, which sometimes can be inconvenient (if the company is public and has to go through bidding processes for buying new equipment, for example).

Simulation 4 switch placement optimization; any number of switches may be present, at any extreme (beginning or end) of each section, and customers will have different costs of interruption. The ACDF values used in this simulation will be estimated arbitrarily, taking into account some power interruption costs details explained in Brown (2009). So, it will be considered that:

- the single customer of load 500 kW at the end of section 39 is of industrial type, with huge economic losses in case of power interruptions, with ACDF = 10 US\$/kWh.
- the customers of total load 150 kVA at the end of section 41 consist of a group of small factories, with ACDF = 8 US\$/kWh.
- the customers at the end of sections 16, 18 and 20 are a group of commercial structures, which incur in average economic losses if their power is interrupted, with an ACDF = 5 US\$/kWh.
- the rest of the customers are all of residential type, having small ACDF = 1.6 US\$/kWh (it is a bit below the original average ACDF of the feeder because it is not an average of all possible customers anymore. These customers are exclusively residential).

Simulation 5 switch placement optimization; any number of switches may be present, at any extreme (beginning or end) of each section. Customers' data will vary greatly from the original data, in order to check how the switches placement will behave in a feeder which has industrial poles separated from residential/commercial areas. In this context, it will be considered that:

- the areas downstream of the two feeder reclosers (nodes at the end of the sections 8, 9, 10, 11, 12 and 13; and nodes at the end of the sections 39, 40, 41 and 42) will consist of two poles of industrial customers. Each node of these poles will represent a single customer of load 500 kW and high ACDF, considered to be 10 US\$/kWh;
- all the other nodes that had loads will now be groups of residential-type customers. Each of these nodes will be associated with 10 customers, with a total load of 50 kW per node, and a low ACDF, considered to be 1 US\$/kWh.

Simulation 6 same as Simulation 5, but with the addition that only solutions with SAIDI values lesser or equal to 6.0 will be considered.

Regarding the genetic algorithm module, crossover rates will be 80%; mutation rates will be low, selected at a rate of 0.05%; elitism will be 2%; population size will be 500 for first generation; stopping criterion will be maximum number of generations or stagnation. Each scenario is simulated many times, in order to find best optimum solutions.

Table 5 Simulation results

Simulation	Sections with NC switch in their beginning	Sections with NC switch in their ends	SAIFI	SAIDI	Total annual cost ($)
1	7–14–21–23–26–31–33–36–43–45–51	–	8.6441	6.0519	185,800.00
2	14–22–26–33–36–43	7–19–23–28–31–38–45–51	8.6441	5.6413	177,730.00
3	14–26–31–36–43	21–49	8.6441	6.5428	190,470.00
4	14–22–26–33–36–41–43	7–17–21–23–28–31–38–45–51	8.6441	5.5181	190,020.00
5	11–14–23–41–43	7–38	8.6441	7.9345	281,660.00
6	11–14–23–28–41–43–45	7–19–31–38	8.6441	5.8529	286,010.00

3.4 Simulation Results and Discussion

Results of the simulations are summarized on Table 5.

When comparing the results that use the original ACDF value for all customers (which are original network, Simulation 1, Simulation 2 and Simulation 3), it can be clearly seen that the result yielded in Simulation 2, which is the optimization without restriction on number of used switches and without restriction of in which part of the section a switch can be placed (beginning or end) is the best solution regarding total costs. This could be predicted even before the simulations were done, and the reason for this is that the universe of possible solutions is expanded, allowing the algorithm to search for the optimal solution in a wider gamma of possibilities. In this case, from the simulation done, the lower cost solution was also the lower SAIDI solution—which could not be predicted beforehand, because the minimization of total costs, depending on the feeder data, could lead to greater SAIDI values. Simulations 4 and 5, which uses different data for ACDF (loads and number of customer in each node are also different in Simulation 5), will not be directly compared to other simulations regarding costs and SAIDI, but the analysis of their individual results (especially their switches allocation) bring some interesting details.

Simulation 1 is the optimization of placement of any number of switches, but restricting their placements only to the beginning of each section—which, as explained already in this paper, is what was done in all switch placement optimization algorithms found in the literature. This restriction leads to good costs and SAIDI values, but it leads to worse results comparing to Simulation 2, which analyzes switch placement possibility in both extremes of each section. As stated before, the method proposed in this paper allows the simulations to be performed in any or both of the extremes of the sections of the network.

Simulation 3 is the best result that one could obtain fixing the number of switches in 7 (original number of switches present in the feeder). This was done by imposing a penalty factor for any solution that had a number of switches different from 7. As was explained before, this type of analysis can be interesting to electric companies, which could not be interested of varying the number of switches present in the network, being interested only in making the most of the already existing switches. This could happen for varying reasons; for example, the process of biding, buying, transporting, etc., of new equipment, mostly in the case of public electric companies which depend of taxpayers' money. As stated before, the method proposed in this paper allows the simulations to either be free to analyze any number of switches that will be present on the optimal solution or to fix this number by using penalty factors.

Simulations 4 and 5, as previously stated, have results that cannot be directly compared to the other results because of their use of different ACDF and load values for different types of customers, instead of a global average value. As previously stated, the objective function used in this paper can easily use different damage values for different customers. This was not found in the researched literature, though it can be very important in real case scenarios, because some customers or city areas may have more important loads than others—as the case of hospitals or some kinds of industries. In the present case, it is interesting to note that the optimal switch placement of Simulation 4 was almost equal to the optimal switch placement of Simulation 2, the only differences being 3 more switches in the case of Simulation 4 (allowing more restoration possibilities for the areas which customers have greater ACDF values) and little variation from the placement of most of the switches. Note that both solutions have in common switches in the beginning of sections 14–22–26–33–36–43 and switches in the end of sections 7–23–28–31–38–45–51, a coincidence of placement of 13 switches, which means that these switch spots are really important for the best maneuvers that can be performed for power restoration, even though the ACDF values are different from both simulations.

In the case of Simulation 5, which uses not only different ACDF values but also different number of customers and total load value for its nodes, the results are very different from the original ones, but it is an interesting fact that, in the optimized solution in these conditions, both the industrial poles (the areas downstream of the two reclosers, present in sections 8 and 39) have NC switches surrounding the initial nodes of the reclosers (end of section 7 and beginning of section 14, for the first industrial pole, and end of section 38 and beginning of section 43, for the second industrial pole), which increases the possibilities of these both areas be restored in the case of most faults that could occur in the feeder, leading to the preservation of power delivery to the industrial poles. Besides, both of these poles have now also a NC switch in their last main sections (sections 11 and 41), which improves the reliability of these poles in the case of faults occurring downstream of both the reclosers. And, as the ACDF of residential customers, along with their loads, are quite low in this simulation, it seems that in this case it is not worth to prioritize residential areas and their interruption times. Note the high SAIDI for this feeder, along with a single switch at the beginning of section 23, which is the only switch not directly near to any of the two industrial poles that concentrated all the other switches. Either way, this switch allows that any fault on section 23 or on its downstream may be isolated by that switch, allowing a clear path of upstream restoration for both industrial poles and also some residential customers.

In Simulation 6, we used the exact same customer parameters used in Simulation 5, with the difference that we imposed a restriction on SAIDI. As Simulation 5 brought a high SAIDI value, in Simulation 6 this value needs to be lower than 6.0, to simulate the condition that a feeder with industrial poles needs to have the lower costs as possible, but without penalizing its residential customers with high interruption periods. Naturally, the cost of the feeder obtained as result in this simulation is higher than in Simulation 5, which had no restrictions when evaluating its costs; but the SAIDI now is under the imposed limit. In fact, the increase in the cost was only of 1.54%, while the reduction in SAIDI was of 26.23%, which means a great social benefit. The switches allocation under these conditions are interesting, as the same switches positioning of Simulation 5 are used (switches at the beginning of sections 11, 14, 23, 41 and 43, and switches at the end of sections 7 and 38) along with 4 new switches, which are positioned at the beginning of sections 28 and 45, and at the end of sections 19 and 31. This new configuration allows the switching operations for restoration of both industrial poles in most of the faults that can occur in the feeder sections, as stated in Simulation 5 for its switches' allocation, and also general switching maneuvers that will restore a great range of residential customers in case of faults: note that the 4 new switches can divide the main section in some segments, allowing more fault isolation schemes.

Finally, some details regarding the genetic algorithms used for the simulations are:

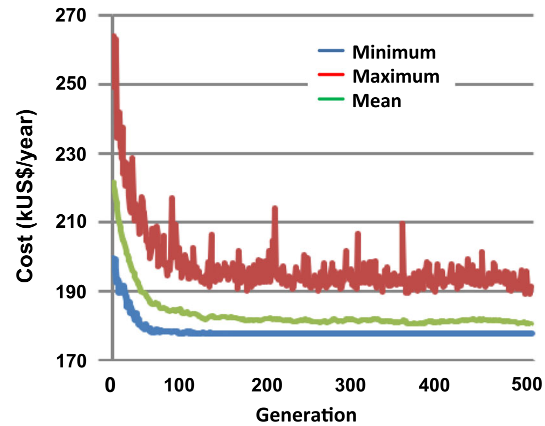

Fig. 7 Graph displaying the behavior of the minimum, maximum and mean values of the costs among the generations of Simulation 2

- the graph in Fig. 7 shows how the maximum, minimum and mean cost values among the generations behaved in Simulation 2, when we let the generations have a maximum value of 500. Stagnation of the minimum value, which was associated to the fittest solution, could be obtained with around 110 generations. A pattern like this one was observed in all the simulations that were conducted in this work. The analysis of these patterns, in these and other simulations, helped the authors to choose adjust the used parameters of the genetic algorithm, until the best solutions could be obtained rapidly;
- the used genetic algorithm configuration was the model known as SGA—Simple Genetic Algorithm. Since it is by definition an algorithm for maximizing a fitness function, and since the used cost function is a fitness function which aims minimization, during the process of assessing the fitness of the chromosomes, the genetic algorithm used the symmetrical of each candidate solution and to try to maximize this value. This leads to solutions with fitness values that are better as the lower are it costs;
- restrictions on allocating switches only at the beginning of sections were performed in the process of encoding the genes: a bit (0 or 1) indicates the possibility of allocating the switch only at the beginning of the corresponding section, while 2 bits (00, 01, 10 or 11) indicate the possibility of using no switches, one switch at the beginning, one switch at the end or two switches in both ends of the sections. Restrictions such as number of used switches or SAIDI limitations were performed in the objective function: if a restricted number of switches was intended, to the cost function it was added a term with the quadratic difference between the number of used and the number of desired switches, multiplied by a large scalar factor, so that these solutions would have their probabilities of genetic existence seriously prejudiced. A similar method was used with SAIDI limitations, in which solutions with SAIDI greater than the limit were penalized. Note that several practical restrictions can be performed in this way;
- in the tested systems, an exhaustive search was used to find the best solution. This took an extremely long computational time. As is known, in each execution of the genetic algorithm, a different solution can be found. For each tested

Table 6 Computational efficiency results

Simulation	Time (s)	Total annual cost ($)
S1	43.8	185,800.00
S2	50.7	177,730.00
S7	59.3	177,730.00

case, 30 GA were executed and an average of the optimality gap was calculated considering all the executions. This average value of the optimality gap was 1.07%.

3.5 Computational Efficiency

The computational efficiency of the proposed method was also verified. It is emphasized that this model was designed to take the advantage of the four-state switch possibilities, as it increases only the number of bits in each tested chromosome, instead of dealing with increased number of nodes in the feeder, when we allow the algorithm to allocate switches at both ends of each section.

For this verification, some simulation times were computed, which are shown in Table 6. Simulations 1 and 2 were the ones which results were already presented in Table 5, which are, respectively, the use of the proposed method when restricting the switch allocation possibilities only to the beginning of each section (Simulation 1) and when allowing the switch allocation possibilities to both ends of each section (Simulation 2), the last using the proposed method. Then, it was also added a new simulation, called S7, in which a traditional method is used (Ma et al. 2010), but extra nodes were created to permit switches at the beginning and at the end of the section. Note that the creation of new nodes, that virtually divide sections, could be a way to allow a traditional method to allocate switches at both ends of each real section (as the allocation of a switch in the beginning of these new extra sections are, in reality, a switch at the end of the original section). This way, the computational efficiency of the proposed method can be compared to the efficiency of a traditional method.

As can be seen, the proposed method achieved a better result than a traditional method. When the database of the traditional method was modified to allow switches at both ends of each section, both methods showed the same cost results (Simulation S2 and S7); however, the proposed method obtained a considerable computational time gain, which is approximately 17%. On the other hand, when comparing Simulations 1 and 2 (both using the proposed method), the allowance of switches at both ends of each section increases some computational time, but allows a good drop in costs, which can be viewed as a better solution from a practical point of view.

We also increased the size of the system by 2, in this new condition, the computational time increased to 67% (S2 × S7). That is, increasing the size of the system, the computational time increases considerably. Therefore, the decrease in computational time achieved by the proposed method can mean a great advantage on distribution systems planning.

4 Conclusions

This paper brings a new method for solving the switch placement problem for electric networks. Although this is a well-known problem of electric engineering, already analyzed in the literature, this paper presents a more versatile method that can solve this problem in different scenarios, according to the objectives aimed by the engineer.

The possibility of placing switches in both extremes of each section provides more candidate solutions for evaluation by the algorithm, which will probably produce better results in all cases. The possibility of fixing the number of switches to a certain number defined by the operator, in this method done by imposing penalty factors, can be of interest, as in real cases the number of switches to be used can be restricted. And the possibility of using different ACDF values can produce solutions closer to real needs, as different customers can have different importance of loads. In this paper, ACDF values can be easily modified and individualized in the proposed objective function.

Validation of the reliability assessment part of the algorithm was confirmed on a well-known test system. Comparison of one of the possibilities of the proposed method was done to another similar work, which showed benefits both in cost and non-supplied energy reductions. Simulations of different scenarios on a real feeder were performed, and, although it is impossible to guarantee that the produced results are optimal (because the optimization method is heuristic), it can be clearly seen that the optimization process used produced a great difference from the original cost value to the optimized one.

The processing time is not much increased when dealing with the possibility of allocating switches at both ends of each section, which makes this a good strategy for obtaining reduced cost solutions with just a little more computational effort. Reduction in several thousands of dollars per year can be obtained with just some more seconds in processing times.

The different scenarios analyzed are all of practical importance, and the proposed algorithm proved to be versatile for varying scenarios and conditions.

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