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A Multi-objective Approach for Optimized Monitoring of Voltage Sags in Distribution Systems

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Abstract
Voltage sags are among the most relevant power quality disturbances. Furthermore, they also have high occurrence rates. Their stochastic nature makes monitoring difficult and causes significant losses to power utilities and customers. This paper presents an approach to overcome the problem of allocating power quality monitors. To do so, our approach accounts for topological coverage, unmonitored voltage sags, and the total cost of required equipment. We used NSGA-II to build our approach due to its efficiency in dealing with combinatorial problems. We also used the Monte Carlo simulation method to model the time series in our approach due to the random nature of power quality disturbances. To evaluate our approach, we simulated the IEEE 13-, 34- and 37-bus distribution systems using the DigSILENT Power Factory 15.1 software. The evaluation results show that our approach supported cost reduction associated with the installation of power quality monitors, both in terms of identifying adequate number and position of the performance monitors.

Keywords Genetics algorithms · Monitors allocation · Monte Carlo method · Power quality

List of symbols

$A(X)$	Ambiguity vector
$D(X)$	Descendants vector
D_{total}	Total number of descendants of the system
e	Remainder voltage threshold
F	Fault node
$f_1(x)$	Monitoring cost objective function
$f_2(x)$	Topological coverage quality objective function
$f_3(x)$	Sag coverage objective function
k	Node under observation
$L(X)$	Load vector
L_{total}	Total load in the system
CM_e	Coverage matrix given a threshold e
VMDF	Voltage matrix during fault
VMDF^T	Transpose of the voltage matrix during fault
n	Number of nodes in the system
N_{sample}	Sample size in MCM
N_{mcm}	Number of executions of MCM
N_{pop}	Population size in the NSGA-II
C	Monitor installation cost vector
P_t	Parent population of generation t in NSGA-II
Q_t	Child population of generation t in NSGA-II
R_t	Auxiliary population of generation I in NSGA-II
V	Observability vector
$\overline{V}$	Vulnerability vector
U	Non-monitored sags vector
w_1	Weight of load coverage
w_2	Weight of descendants coverage
w_3	Weight of ambiguity
X	Allocation vector
σ_x	Sample standard deviation in MCM
$\sigma_{\overline{x}}$	Approximation error of MCM

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1 Introduction

Electric Power Systems (EPS) are subject to a number of electric disturbances (Bollen and Gu 2006; Dugan et al. 2012). Among them, voltage sags are considered one of the most serious problems regarding power quality (PQ), since in addition to being difficult to monitor due to their stochastic nature (Cebrian et al. 2010; Espinosa-Juárez and Hernandez 2007), they are the most frequent events in electric systems (Bollen and Gu 2006; Gupta and Fritz 2016), causing great financial losses to consumers due to equipment malfunctioning or interruptions in the industrial process (Branco et al. 2015).

Therefore, constant monitoring of PQ is an essential part of identifying the existing disturbances and of correcting possible defects in the monitoring plan of the events. One way to perform this monitoring procedure is through the installation of tools capable of monitoring power quality in the distribution system (DS). However, the complete monitoring of a DS incurs a high cost, and due to practical and economic reasons its application could be infeasible (Kempner et al. 2014).

As an alternative, monitoring could be performed considering only some strategic points in the system, which would consequently create additional problems with the approach, such as determining the number and the location of these monitoring points. Due to technical and operational reasons, there is no previous knowledge, regarding PQ, about where the monitors should be installed in such a way as to provide the best overview of the situation faced by the EPS (Branco et al. 2015).

In order to solve this problem, many methodologies for allocating PQ monitors in EPSs are found in the literature. For example, the authors of Espinosa-Juarez et al. (2009) have proposed an approach for allocating monitors that is capable of assuring a complete coverage of the voltage sags. In order to do that, they used a reachability matrix of the monitors, determined through analytical expressions. In Almeida and Kagan (2011), the authors have used genetic algorithms and fuzzy set theory to determine the minimum amount and the location of the necessary monitors to cover voltage sags and swells in a DS. In Liao et al. (2016), on the other hand, the authors have developed an optimized allocation methodology based on gradient method and particle swarm, building in the network topology and historical experiences with the search process using generating trees. Another approach (Hong and Chen 2011) proposes the use of a genetic algorithm, along with a modified clustering algorithm, to determine the location of the monitors in the network.

Based on this literature review, an aspect present in all studies was the need of always providing solutions with the best possible cost, considering the cost–benefit ratio of the investment and the monitoring quality resulted from the investment. As a consequence, when a solution demands a slightly higher financial investment, but, in return, provides a better than or the same cost–benefit ratio, the solution with lowest cost could be discarded.

This work presents a multi-objective approach to solve the problem of power quality monitor allocation in distribution systems, considering topological aspects, voltage sags and monitoring costs. The applied approach uses the fault position method (FPM) (Bollen 2000) for determining the points of occurrence of voltage sags in the DS. However, the Voltage matrix during fault (VMDF) generated is not only based on the application of short-circuits (Das 2016), but on the time series of occurrences of faults, whose behavior was modeled using Monte Carlo method (MCM) (Newman et al. 1999), aiming toward a VMDF that represents the real behavior of the system. Thus, the objective here is to provide solutions that maximize the quality of the system's topological coverage, minimize the number of non-monitored voltage sags and minimize the monitoring costs. The non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al. 2002) algorithm was chosen to solve the multi-objective problem given its efficiency in dealing with combinatorial problems.

The proposed approach was tested with IEEE 13-, 34- and 37-bus distribution systems (Kersting 1991), simulated on DigSILENT Power Factory 15.1 software and, as a result, the methodology provides a set of optimized solutions considering, simultaneously, the many aspects, in such a way that it allows for a more careful analysis of the cost–benefit ratio to be performed with each proposed scenario. The main contributions of this work are:

- The use of Monte Carlo Method, along with Fault Position Method, for determining the monitoring points based on the system's real behavior; and
- The establishment of an optimized allocation methodology of monitors that simplifies the decision-making process guided by the concessionary company's budget available for investment.

The rest of the article is organized as it follows: Sect. 2 brings some of the necessary theoretical fundamentals for the understanding of this work. Section 3 details the functioning of the approach. Subsequently, the results are presented in Sect. 4. Finally, Sect. 5 presents the conclusions and future studies.

2 Theoretical Fundamentals

2.1 Short-Duration Voltage Variations

Short-duration voltage variations (SDVV) are phenomena associated with variations of RMS voltage values, characterized by voltage levels being constantly above or below the nominal range during a period of time greater than 0.5 cycles and less than 1 min.

These variations can be designated according to the duration of the events as: instantaneous (0.5 to 30 cycles), momentary (30 cycles to 3 s) or temporary (3 s to 1 min). The main causes of such disturbances are fault conditions, transformer energizing, starting of large motors, and intermittent loss of connection of the cables in the system (Mahela et al. 2015).

With respect to the voltage amplitude, SDVVs can be classified as:

- Voltage sag is the most significant disturbance in electric networks (Bollen 2000; Singh et al. 2014), and it consists in a reduction in the RMS voltage value from 10 to 90% of the nominal voltage. As a consequence, these disturbances may cause problems in many types of devices, such as computers, sensitive loads, micro-processed components, programmable logic controllers (PLCs), among others;
- Voltage swell is characterized by an increase in the RMS voltage of the system in between 10 and 80% of the nominal voltage. It may occur during any phase of a three-phase circuit during a short-circuit, but it is not as common as voltage sags.
- Interruption of short duration is less common. Interruptions are local events characterized by a reduction of RMS voltage to critical levels (less than 10% of the nominal voltage).

2.2 Fault Position Method

The fault position method (Conrad et al. 1991) was proposed to calculate voltage sags in large transmission systems. This method consists of a short-circuit simulation in each of the system's nodes (one at a time), followed by the calculation of the residual voltage in all remaining nodes. Thus, it is possible to determine the voltage sags in the whole electric system under analysis, for any fault situation at any node.

Figure 1 illustrates a flowchart of the fault position method, according to which for each fault position F (usually a system node) a short-circuit situation is simulated and the voltages in all other nodes are calculated and stored. The algorithm is executed until all fault positions are covered, which is to say, until the short-circuits have been calculated in all desired nodes.

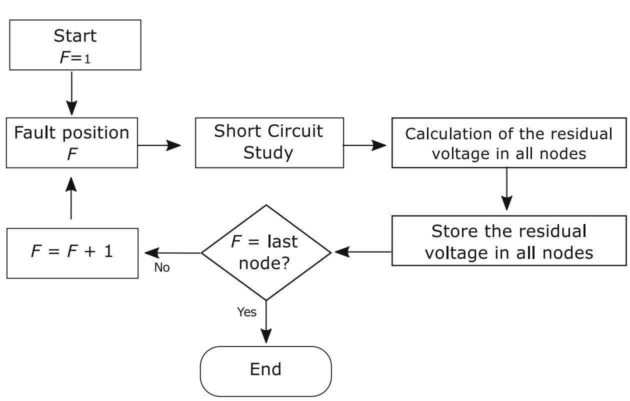

Fig. 1 Flowchart of the fault position method algorithm

With all residual voltages, the VMDF is built, in which the columns make it possible to determine the areas affected by the faults applied to each of the nodes and the rows make it possible to determine the vulnerability area of each node.

2.3 Monte Carlo Method

Monte Carlo Method is a numerical method developed with the goal of exploring and solving mathematical problems through simulations involving random variables. Statistical simulations contrast with conventional discretization methods since, in many cases, can be directly applied, thus eliminating the need to describe the mathematical functions that represent the behavior of the system (Newman et al. 1999; Li and Billinton 2013). However, the historical behavior of the system must be known in order to correctly model the random variables involved.

The basic functioning of MCM can be understood in four steps, as it follows:

1. Model the problem by defining a probability density function (PDF) that represents the behavior of each variable;
2. Generate random values as described by the PDF for each variable of the problem;
3. Calculate the deterministic result by substituting the variables by the generated results;
   Steps 2 and 3 must be repeated a certain number of times.
4. Aggregate and manipulate the results from the sample in such a way as to obtain an estimate of the solution for the problem.

As the solutions obtained through the method are approximated, there is an approximation error ($\sigma_{\overline{x}}$) that could be represented by Eq. 1:

$$\sigma_{\overline{x}} = \frac{\sigma_x}{\sqrt{N_{\text{sample}}}} \quad (1)$$

in which σ_x is the standard deviation and N_{sample} is the size of the sample.

By analyzing Eq. 1, it is possible to note that the error is inversely proportional to the size of the sample. Thus, the size of the sample should be sufficiently large in order to reduce the error associated with it.

3 Proposed Approach

This section contains the proposed approach for the optimized PQ monitor allocation problem in distribution systems. All steps of the approach are detailed, starting with the computational representation adopted for the DS's in

Sect. 3.1. Next, the aspects considered regarding the topological coverage and sags in Sects. 3.2 and 3.3, respectively, are considered. The elaboration of the multi-objective optimization problem is defined in Sect. 3.4. Finally, the complete flowchart of the proposed approach is presented in Sect. 3.5.

3.1 Computational Representation of the Distribution System

Solving a multi-objective optimization problem (MOP) requires, at first, the definition of an adequate structure for the computational representation of the problem. In this approach the tree data structure (Hopcroft 1983) was chosen to represent the DS. This choice was based on the existing equivalence between a DS and the tree structure. As an example, it is possible to establish the following relationships: a system's nodes could be linked to the nodes in a tree, the links between the nodes could be seen as the edges that connect the nodes and the presence of a hierarchy of the many levels of the system is the primary characteristic of a tree. This structure's efficiency in representing a DS has been explored by other authors in studies in the literature, as in Won and Moon (2008).

Another necessary representation when working with Genetic Algorithms is that of a solution. In this approach, the nodes are considered installation points for PQ monitors. Thus, the indication of whether a certain b_i node is or is not monitored is performed through an allocation vector (X), which contains an element for each node in the DS. Therefore, the allocation vector has a dimension equal to the number of nodes in the distribution system. The possible values for the vector were defined as either 0 (zero) or 1 (one), where zero represents the absence of a monitor in the corresponding node and one, the opposite situation, as shown in Eq. 2.

$$x_i = \begin{cases} 1, & \text{if there is a monitor installed on bus } i \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

3.2 Aspects Related to the Topological Coverage

Traditionally, the choice of the best points for PQ monitoring in a DS is based on specialized knowledge acquired by the engineers (professionals and researchers) along years of practice, considering: topology of the system, how the event of interest is manifested and how it spreads over the system (Branco et al. 2015).

When developing a non-supervised allocation approach, the specialized expertise should be translated into rules that make performing a quantitative analysis possible. Thus, some rules can be used in order to support the definition of the monitor installation points in the system, as presented next:

– *Rule number 1* If there are n lines connected to a node, then, there are n possible monitor installation points. However, it is only necessary to know the currents of $(n - 1)$ of these lines, since one of the lines can be computed knowing all the others [Kirchhoff's Current Law—KCL (Nilsson 2008)]. The situation in which it is not possible to determine all currents in the lines connected to a certain node is known as a topological ambiguity (Won et al. 2006).
– *Rule number 2* It is important to install monitors in the load derivations, as most of the damages caused by PQ related problems appear in consumer loads, making these locations important monitoring points.
– *Rule number 3* The monitors must be installed in branches with many descendants, which makes it possible to monitor a larger area. Based on this rule, the monitors tend to be installed in points that are close to the power source.

3.3 Aspects Related to the Coverage of Voltage Sags

In order to calculate voltage sags, this approach is based on the fault position method presented in Sect. 2.2. The VMDF generated with this approach is based on a historical series of occurrences of faults in a DS with the purpose of determining the real behavior of the system. The historical fault series was modeled using MCM, and the types of faults considered were: single-phase, two-phase (LL and LLG) and three-phase (LLL and LLLG). MCM has the advantage of being usable to estimate the expanded uncertainty in situations where the distribution function is not normal. The coverage of the many fault types has the advantage of increasing the robustness of the approach.

The VMDF must be transposed (VMDF^T) so that the allocation is performed respecting the vulnerability area of the system. Next, a threshold e must be defined for the elaboration of the coverage matrix (CM_e), which has the same dimensions as the VMDF and indicates in which points of the DS voltage sags for the defined threshold occur. The construction of CM_e is performed by assigning the value of 1 to the positions corresponding to values below threshold e and the value of 0 to the positions with values greater than or equal to the threshold, as shown in Eq. 3:

$$\text{cm}_{e_i} = \begin{cases} 1, & \text{if } vmdf_i^T < e \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

vmdf_i^T is the element i in the VMDF^T and e is the threshold value that indicates below which voltage magnitude the power quality monitor should start registering occurrences.

In order to determine the number of voltage sags covered by a set of monitors, it is sufficient to calculate the internal product of the CM_e and the allocation vector (X), as in Eq. 4, which will result in the observability vector (V), in which the positions with values greater than zero represent the nodes in which voltage sags can be monitored by the allocated monitors, considering the established threshold.

$$V = \mathrm{CM}_e \cdot X \tag{4}$$

Nonetheless, it is important to note that not all positions of vector V with value equal to zero mean, necessarily, non-monitored voltage sags. An element v_j could be equal to zero because all elements of a row in matrix CM_e are also equal to zero, which, as result, means that there are no voltage sags in that row in matrix CM_e with values below the established threshold. So, it is important to assure that this situation does not influence the calculation of the number of voltage sags that are not noticed by an arrangement of monitors. This assurance can be achieved by multiplying matrix CM_e by a vector with all positions equal to 1, as shown in Eq. 5. The result makes it possible to say that if a position in the vulnerability vector ($\overline{V}$) is equal to zero, that is due to the fact that this row in matrix CM_e has all elements equal to zero, indicating that no node undergoes voltage sags (considering the threshold of study) when a short-circuit conducted at the node in the same location of vector $\overline{V}$.

$$\overline{V} = \mathrm{CM}_e \cdot 1 \tag{5}$$

With vectors V and $\overline{V}$, the number of nodes in the DS by which the voltage sags could be monitored, considering the location scenario given by X, is given by Eq. 6, generating the non-monitored sags vector (U):

$$u_i = \begin{cases} 1, & \text{if } v_i = 0 \text{ and } \overline{v}_i > 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

In which positions with values greater than 1 indicate the nodes where there will be the most voltage sags that will not be observed by any installed monitor.

3.4 Elaboration of the Multi-objective Problem

The proposed approach has the purpose of performing the allocation of PQ monitors, aiming at minimizing the cost, maximizing the quality of the topological coverage of the system and minimizing the number of non-monitored voltage sags. Thus, for each of the three objectives an evaluation function was elaborated, as it follows.

3.4.1 Monitoring Cost

The installation cost of the monitors, in each of the possible monitoring points, is given by the cost vector C, as in Eq. 7:

$$c_i = \text{cost to monitor the node } i \tag{7}$$

The total monitoring cost, on the other hand, is calculated by multiplying the allocation vector and the cost vector. So, the first objective function is indicated in Eq. 8:

$$f_1(x) = \sum_{i=1}^{n} c_i \cdot x_i \tag{8}$$

in which n is the number of nodes in the system.

3.4.2 Quality of the Topological Coverage

In order to build this evaluation function, it was necessary to establish a method of measuring each of the rules presented in Sect. 3.2. So, regarding *Rule number 1*, a node b_i is said to be ambiguous if it is impossible to determine the currents of all the lines connected to it, as in Eq. 9:

$$a_i = \begin{cases} 0, & \text{if } b_i \text{ can have its current determined} \\ 1, & \text{otherwise} \end{cases} \tag{9}$$

Thus, the total ambiguity in a DS with n nodes, given a monitor layout X, is given by:

$$A(X) = \sum_{i=1}^{n} a_i \cdot x_i \tag{10}$$

With respect to *Rule number 2*, we have that if the existing amount of load in a node b_i is given by l_i, the total monitored loads in a DS, given a monitor layout X, is expressed by:

$$L(X) = \sum_{i=1}^{n} l_i \cdot x_i \tag{11}$$

In this model, the sum of the powers of the loads connected in the three phases was considered to be the total load connected to node b_j. The loads distributed along the lines were considered to belong to the original nodes of the line.

Finally, *Rule number 3* is measured by the size of the area that can be monitored from a node b_i, which means, by the amount of descendants of a node b_j added to the node itself, here denoted by d_i. Thus, the total monitored area of a DS, given a monitor layout X, is given by:

$$D(X) = \sum_{i=1}^{n} d_i \cdot x_i \tag{12}$$

The objective function that evaluates the quality of the topological coverage of a DS, given a monitor layout X, is built by combining Eqs. 10, 11 and 12 and its value was normalized in the interval from 0 to 1, as in Eq. 13:

$$f_2(X) = \frac{L(X)}{L_{\text{total}}} * w_1 + \frac{D(X)}{D_{\text{total}}} * w_2 + \left(1 - \frac{A(X)}{n}\right) * w_3 \tag{13}$$

in which L_{total} is the total load in the DS, D_{total} is the total number of descendants in the DS, n is the number of nodes and w_1, w_2 and w_3 represent weights, with $w_1+w_2+w_3 = 1$.

3.4.3 Number of Non-covered Sags

The third objective function (Eq. 14) is simply the sum of all elements in vector U, obtained as described in Sect. 3.4.3.

$$f_3(x) = \sum_{i=1}^{n} u_i \tag{14}$$

So, the objective function of the MOP is defined in Eq. 15.

$$\begin{aligned} &\text{minimize}\ (f_1(x)) \\ &\text{maximize}\ (f_2(x)) \\ &\text{minimize}\ (f_3(x)) \end{aligned} \tag{15}$$

3.5 Flowchart of the Proposed Approach

Figure 2 illustrates the function for the entire approach. Initially, MCM is conducted N_{mcm} times in order to establish which types of faults will be studied during the FPM. At the end, there will be N_{mcm} VMDFs, one from each execution. The average of all VMDFs is, then, calculated, in order to generate a single VMDF, which will be used in the allocation study. After that, the threshold e is defined and the CM_e is elaborated. The optimization module, composed by NSGA-II, receives the generated CM_e and the DS computational model as inputs, as described in Sect. 3.1, and processes the information in order to obtain the solutions belonging to the Pareto Frontier, which are returned to the user at the end of the execution. With all the solutions on the Pareto Frontier, the power utility can adopt a monitoring strategy that takes into account the number of non-covered sags, the total monitoring cost, the topological ambiguity, the total monitored charges and the size of the monitoring area.

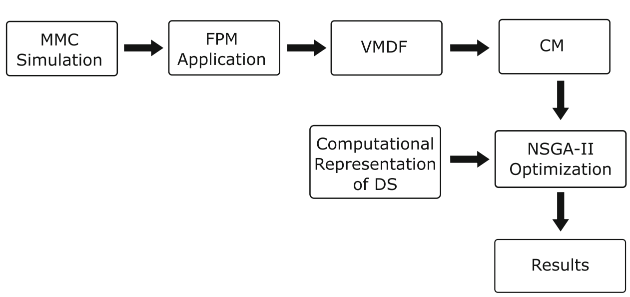

Fig. 2 Flowchart of the functioning of the proposed approach

Table 1 NSGA-II parameters

Parameter	Value
Population size	500
Maximum number of iterations	500
Selection method	Tournament (16)
Crossover method	Single point
Probability of crossover	85%
Mutation method	Bit flip
Mutation probability	1%

Table 2 Some solutions returned by the approach for thresholds equal to 0.9 and 0.6 p.u. for IEEE 13-bus DS

#	Limit	Solution	Cost	Non-monitored sags	Topological coverage
1	0.9 p.u.	1000000000000	1	0	0.143
2	0.9 p.u.	1001100100000	4	0	0.616
3	0.9 p.u.	1101100100000	5	0	0.721
4	0.9 p.u.	1101101110110	9	0	0.929
5	0.6 p.u.	0100000000000	1	6	0.155
6	0.6 p.u.	1111000000000	4	0	0.358
7	0.6 p.u.	1111100000000	5	0	0.595
8	0.6 p.u.	1111100110110	9	0	0.912

4 Results

For validation purposes, the approach proposed in this article was tested in the IEEE 13-, 34- and 37-bus distribution systems (Kersting 1991).

For simplification reasons, we considered, in all tests, that the monitor installation costs in any node are the same and with unitary values. This simplification does not affect the validation of the approach and also facilitates the identification of the number of necessary monitors.

The behavior of each DS, in view of occurrences of faults, was simulated on DigSILENT Power Factory 15.1 software. MCM was applied to the modeling of the behavior of occurrences of faults in the DS, considering that the frequencies of occurrence of single-phase, two-phase and three-phase faults were 80, 15 and 5%, respectively. The fault impedance considered was 0 ohms in all simulations and the voltage value of bar was considered the minimum value among three phases.

The values of the weights w_1, w_2 and w_3 used, in Eq. 13, were the same and equal to 0.33. In the approach it was considered a period of 1000 time units in the MCM simulations. The optimization algorithm used was NSGA-II (Deb et al. 2002), and its parameters were adjusted as in Table 1.

In the experiments, allocation studies were conducted considering less severe sags, with threshold e of 0.9 p.u., and

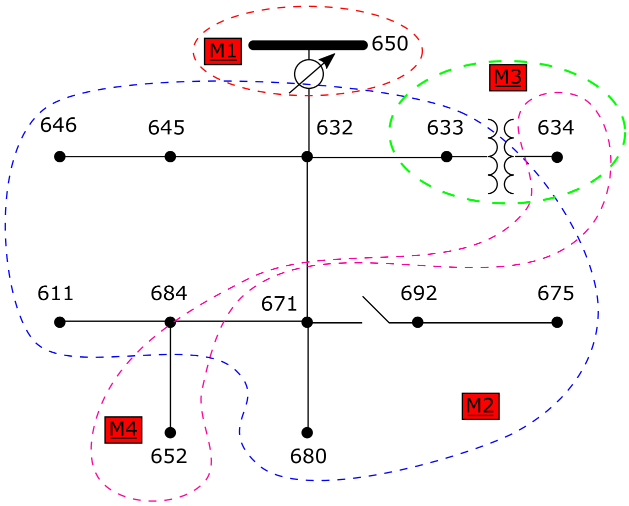

Fig. 3 Monitors' location and coverage in solution number 6

more severe sags, with threshold e of 0.6 p.u. The results obtained with each DS are presented in the next subsections.

4.1 IEEE 13-Bus DS

Table 2 shows some solutions extracted at the end of the allocation study in the IEEE 13-bus DS. By analyzing the solutions with threshold e of 0.9 p.u., it is possible to note that a single monitor is enough to cover all voltage sags (solution number 1). However, the quality of the topological coverage of the solution with a single monitor is low (0.143). This is due to the fact that the topological coverage is directly proportional to the number of allocated monitors, so solutions with a smaller number of monitors lead to a lower cost, but represent a low coverage quality. The decision of which criterion to be prioritized depends on the financial availability of the power utilities and on the degree of efficiency desired. The solution should be determined by an analyst at the end of the study.

As for the threshold e of 0.6 p.u., the solution with a single monitor (solution number 5) is not capable of covering all sags, leaving six events unmonitored in the DS, and also shows the lowest topological quality of the sample (0.155). In this threshold configuration, the minimum number of equipment needed to cover all sags is four (solution number 6), giving more than the double of the topological coverage of the solution with a single monitor (0.358). Figure 3 shows the installation location of the monitors according to solution number 6, and also their coverage areas.

4.2 IEEE 34-Bus DS

Coincidentally, as in the previous system, the IEEE 34-bus DS needs the same number of monitors in order to cover all sags, an equipment for a threshold e of 0.9 p.u. and four for a threshold e of 0.6 p.u. Table 3 shows some solutions for this circuit.

By analyzing the quality of the topological coverage, it is noticeable that as the number of monitors increases, the gain is reduced until it reaches a point in which the necessary investment does not justify the achieved benefits. This becomes clear when comparing the rate of increase of the topological coverage in solutions 1 and 2, where the increase of one monitor incurs a gain of approximately 188%. In solutions 5 and 8, an increase of 14 monitors means a gain of only 10.88%. The same phenomenon can be observed when threshold e equals 0.6 p.u. Therefore, through the proposed approach it is possible not only to identify a set of optimized solutions for a monitoring plan, but also to detect the existence of saturation areas, thus allowing decisions to be more easily made and avoiding waste of resources that do not translate into real gain in monitoring quality.

This observation becomes clearer after analyzing the graph in Fig. 4, in which three sets of solutions can be seen. In the first one, there are three solutions with 0–9 monitors and with a considerable gain in quality of topological coverage. In the second group, composed by solutions with 10–25 equipment, the gain decreases compared the previous one, but can still be considered. In the third and last group, with solutions with over 25 monitors, the gain is no longer perceivable.

4.3 IEEE 37-Bus DS

In the last analyzed circuit, using both thresholds considered, a single monitor is enough to perform the coverage of all sags. Table 4 presents some solutions for the circuit.

Regarding Table 4, it is important to notice that the solutions with the same costs could take to completely different situations. A possible scenario can be found in solutions 12, 13 and 14, all of which have a cost of two, although the number of non-monitored sags varies substantially from a complete coverage of the system to a situation with 34 non-monitored events, without showing considerable increase in the quality of topological coverage.

Another important point is the solutions that, however different, give the same number of non-monitored sags and topological coverage, which allows the concessionary company to select solutions whose logistics is more viable to the installation teams.

Figure 5 shows the Pareto Frontier returned by the optimization algorithm of a 0.9 p.u. voltage threshold. Its analysis makes it possible to conclude that the cheapest solutions are on the right side. On the upper side are the solutions with the best coverage of sags and best topological coverage, which show a color close to yellow. Additionally, it is possible to perform a joint analysis of the objective. For example, the

Table 3 Some solutions returned by the approach for thresholds equal to 0.9 and 0.6 p.u. for IEEE 34-bus DS

#	Limit	Solution	Cost	Non-monitored sags	Topological coverage
1	0.9 p.u.	0000000000000000000000000000000010	1	0	0.067
2	0.9 p.u.	0000000000000000010000000000000010	2	0	0.193
3	0.9 p.u.	0000000000000001001000000000000010	3	0	0.298
4	0.9 p.u.	0000000000100001001000000000000010	4	0	0.371
5	0.9 p.u.	1110111111110001101001001000001010	19	0	0.900
6	0.9 p.u.	0000000000100001001000000000000010	24	0	0.976
7	0.9 p.u.	1111111111111111111111111000001110	28	0	0.994
8	0.9 p.u.	1111111111111111111111111101111111	33	0	0.998
9	0.6 p.u.	0000000001000000000000000000000000	1	17	0.062
10	0.6 p.u.	0000000001000000000000000010000000	2	4	0.073
11	0.6 p.u.	0000000001000000000000000010000010	3	1	0.149
12	0.6 p.u.	0000000001000000000000000110000010	4	0	0.150
12	0.6 p.u.	1110111111110001101001001110001010	20	0	0.902
13	0.6 p.u.	1111111111111011010101001110001010	24	0	0.958
14	0.6 p.u.	1111111111111011011111111110001110	28	0	0.989
15	0.6 p.u.	1111111111111111111111111111101111	33	0	0.998

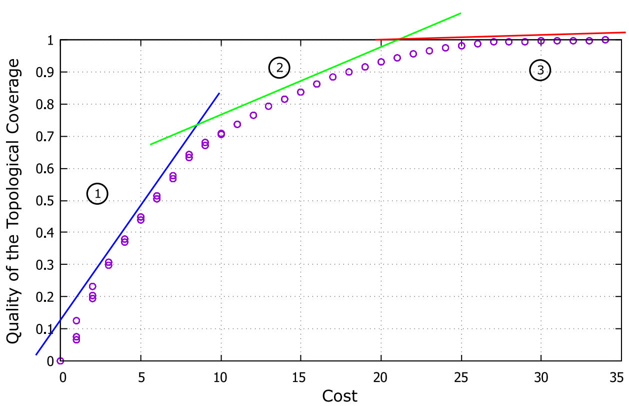

Fig. 4 Graph representing the monitoring cost by the quality of the topological coverage in IEEE 34-bus DS, considering a voltage threshold of 0.9 p.u.

solutions with lowest cost and best coverage of sags are in the upper right corner and there is no solution with low cost and high topological coverage, which was to be expected after analyzing the design of the problem.

5 Conclusions

In this article we presented an approach for allocating power quality monitors for distribution systems through the application of multi-objective optimization techniques aiming at providing solutions that maximize the system's topological coverage, minimize the number of non-monitored voltage sags and minimize the monitoring costs. In the proposed methodology, the fault position method and Monte Carlo method were applied in order to elaborate a voltage matrix during fault with an average profile of the voltages observed with time, considering the probabilities of occurrence of faults in the circuits under study. The VMDF was used to determine the number of monitored sags by a set of arranged monitors. The number of monitors, on the other hand, determines the cost. In order to solve the multi-objective model proposed, the non-dominated sorting genetic algorithm II was used.

The results obtained illustrate the solution (with the number and the monitor installation points), the cost, the number of non-monitored sags, the topological coverage and the threshold for the elaboration of the coverage matrix. Thus, the power utility can adopt a monitoring strategy considering different objectives (or criteria) associated with the problem. This way, the decision about which criterion will be prioritized depends on the power utilities' financial availability and by the degree of efficiency desired. It is important to note that the proposed approach is not limited to identifying a set of optimized monitoring solutions; it allows the detection of saturation areas, aiming at avoiding waste of resources that do not translate into real gain of monitoring quality. Through the results, it was possible to verify that the solutions with equal costs may lead to completely different situations, which means that they can vary substantially from a complete coverage of the system to a situation in which the position of the monitors leads to sags not being detected by the allocation layout. The results also illustrate the existence of different solutions with the same values of topological coverage and number of non-monitored

Table 4 Some solutions returned by the approach with thresholds of 0.9 and 0.6 p.u. in IEEE 37-bus DS

#	Limit	Solution	Cost	Non-monitored sags	Topological coverage
1	0.9 p.u.	0000010000000000000000000000000000000	1	0	0.074
2	0.9 p.u.	1000000000000000000000000000000000000	1	3	0.158
3	0.9 p.u.	1000010000000000000000000000000000000	2	0	0.205
4	0.9 p.u.	1000000000000000000000000000000100000	2	3	0.210
5	0.9 p.u.	1000111010000000100001000010000100000	12	0	0.665
6	0.9 p.u.	1001111010000011100101110110001110010	19	0	0.863
7	0.9 p.u.	1011111111101001111101110111001110010	26	0	0.945
8	0.9 p.u.	1011111111101011111111111111011111110	32	0	0.984
9	0.9 p.u.	1111111111111111111111111111111111110	36	0	0.998
10	0.6 p.u.	0000100000000000000000000000000000000	1	0	0.071
11	0.6 p.u.	1000000000000000000000000000000000000	1	34	0.158
12	0.6 p.u.	1000100000000000000000000000000000000	2	0	0.202
13	0.6 p.u.	1000000000000000000000100000000000000	2	19	0.208
14	0.6 p.u.	1000000000000000000000000000000100000	2	34	0.210
15	0.6 p.u.	1001111010000011100101010110000100000	15	0	0.761
16	0.6 p.u.	1001111010000011100101010010000100010	15	0	0.761
17	0.6 p.u.	1001111010000011100101010010001100000	15	0	0.761
18	0.6 p.u.	1011111111101011111111110111011110110	30	0	0.973
19	0.6 p.u.	1011111111101011111111111111001110110	30	0	0.973
20	0.6 p.u.	1011111111101011111101111111011110110	30	0	0.973
21	0.6 p.u.	1011111111101011111111111111011110010	30	0	0.973

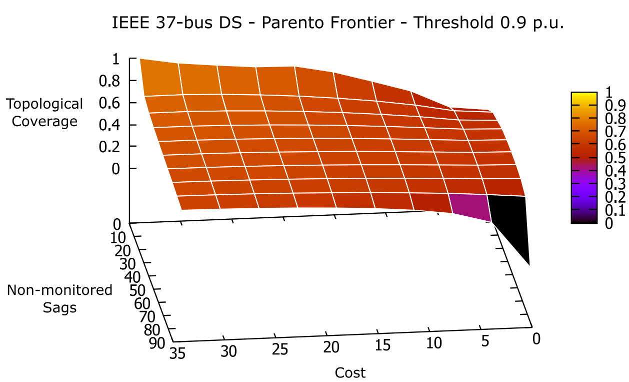

Fig. 5 Pareto Frontier obtained using a threshold of 0.9 p.u. in IEEE 37-bus DS

sags. So, the results make it possible to support decision-making.

One limitation of the proposed methodology is related to the need of using statistical data that is faithful to the reality of the occurrences of faults in the DS, since these data directly impact the generated VMDF and, as a consequence, the calculation of the voltage sags. In a future study, we intend to extend the approach in order to encompass the occurrence of faults on the lines, proposing a model for their behavior using MCM.

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