Multilayer Fuzzy System Applied to Locate Faults in Distribution Systems Using Only Voltage Measurements

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***Abstract*—Smart grids are a more and more present concept in electrical systems. In the context of smart grids, alike in the present topology of electrical systems, it is necessary to guarantee quality and reliability of energy provision. Thus, this work has the objective to locate faults ins energy distribution systems using only post-fault voltage data. This data will be collected on the medium voltage side of distribution transformers, a likely place for installation of concentrating devices of smart grids, and will be applied to a multilayer fuzzy inference system. The scenario studied is a feeder of an actual distribution system, with 1600 buses and 505 transformers. The obtained results are still very imprecise to faults too close or too far from the measurement point, but they are satisfactory for a specific range of fault distances. Improvements are going to be made to obtain more accurate results.**

Keywords-Distribution system; Fault location; Fuzzy inference systems.

I. INTRODUCTION

Electrical power systems have been facing different technical, economic and environmental changes, mainly in response to the increasing energy demand, the efforts to incorporate renewable generation sources and the intensification of reliability of energy supply. A feasible way to alleviate the problems caused by such changes is the use of Distributed Generation (DG) [1][2].

DG is defined as small generating units installed in distribution systems near load centers. Its main advantages are: reduction of losses in the system, improvement of voltage profile and power quality indices, increase of energy supply trustworthiness, reduction of operating and environmental costs (less penalties for emission of pollutants, because of the use of a renewable source) and market opening [1][3].

The energy generated with DG can be used to feed the energy needs of the producer, but it also can be sold to the grid when convenient. However, for the implantation of DG to be allowed, there is a set of rules that must be followed by the producer. One of them says that when an abnormal condition is verified, the DG must be disconnected from the grid [3][4].

A fault in the system is an abnormal condition, since it is a sudden voltage sag which leads to high currents. Faults are events that happen randomly, and are very prejudicial to the grid, especially due to these overcurrents. To save the system from potential damage, the protection system must work correctly and must isolate the fault from the grid [5][6].

However, isolating the faulty point is not the solution to the problem. Some faults must be located and repaired before reconnecting that point to the grid. This is where the objective of this paper lies. This paper aims to develop a multilayer Fuzzy Inference System (FIS) to locate faults in distribution systems using only voltage measurements. It is expected that the FIS can estimate the fault location no matter the distance to a reference point, which in this paper is any transformer in a simulated distribution system identical to a real one.

This paper is organized as follows: Section II contains the state-of-the-art regarding fault locations in distributions systems and the original contribution of this paper. Section III describes the multilayer FIS used. Section IV exposes the methodology used to obtain the results, which are in Section V. Finally, Section VI contains the conclusions of this paper.

II. STATE OF THE ART AND ORIGINAL CONTRIBUTION

Currently, there are several methodologies for locating faults in electrical systems to reduce the reestablishment time of electrical energy in the region where the fault occurred, and each of these techniques has advantages, disadvantages and particularities [7][8]. These methods can be divided into three main categories: based on apparent impedance, based on traveling waves, and methods using artificial intelligence.

Apparent impedance-based methods consider that the distance between a given measuring point, usually the substation, and the fault point is proportional to the apparent impedance seen from the measurement point, calculated at the time of the fault, as explained in [9]-[13]. An advantage of this method is that it does not require a geo-referencing system with synchronized measurements to detect the point of the fault, since the measurement of parameters in one grid terminal is sufficient, but in contrast its disadvantage is the estimation of multiple possible points of fault, due to the branching of the radial distribution systems [7][8]. Other important aspects are that the fault impedance and the fault current impact the calculation of the apparent impedance.

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The fault impedance is always unknown and the fault current is influenced by several factors of the system, such as the load and the presence of distributed generation [14].

The methods based on traveling waves rely on the analysis of the waveform of the voltage that travels to both sides of the grid, being reflected and refracted in its discontinuities while its amplitude is attenuated. The method consists in measuring the time between the first and the second incidence of the wave originated with the fault, which travels back and forth from the fault point to the terminal, as presented in [15]-[21].

One of the main difficulties in applying this method comes from the branching of the distribution systems, since each connection of the system is a point of discontinuity where the traveling wave will be reflected and refracted [7][8]. In this case, a possible approach is the use of the wavelet transform, which can detail the characteristics of traveling waves in the time and in the frequency domains in order to determine at what moment of time a high frequency transient, i.e., a fault, happens [18][20]. The main advantage of this methodology, compared to the method based on the apparent impedance, is that the multiple estimation does not occur, instead a single location of the fault point is found [22]. At the same time, there are the disadvantages of this second method, which are the need for syncing the measurements in two terminals, or alternatively, using a high frequency of data acquisition [20].

Intelligent systems used in fault location can profit from the advantages and avoid the disadvantages of both preview methods by using known historical data to be trained, as explained in [23]-[27]. In [28], for example, the fault distance is calculated through the apparent impedance method, which leads to multiple possible fault points. After that, an Artificial Neural Network (ANN) is trained to recognize patterns using voltage sag data in the moment of the fault so the correct fault point among all can be determined.

In [29] the authors use as inputs of an ANN the parameters of the wavelet transformation applied to the line currents of the 34-bus IEEE feeder. Likewise, in [30], a neuro-fuzzy system receives wavelet parameters of voltage and current, obtaining 80% accuracy index when DG is present in the distribution system, and 90% accuracy index when DG is absent.

When analyzing the most recent researches related to fault location in distribution systems it is noticed that their indexes of accuracy are quite satisfactory. The most used methodology consists of intelligent systems whose inputs are post-fault, voltage and/or current wavelet parameters [29][31]. An important detail is that in most of recent works the current measurement is considered as something essential for the correct and precise location of the fault [7][8].

The original contribution of this work comes from the fact that only voltage data is used to locate the fault in a distribution system. This consideration is important because of the following reason: in Brazil, the National Agency of Electrical Energy (ANEEL) considered as minimum requirements to a smart meter to acquire voltage, active power and reactive power data [32]. Current measurements are not included in the minimum requirements of smart meters, thus not using them in fault location methods increase the applicability of this work in a future Brazilian smart grid scenario.

III. MULTILAYER FUZZY INFERENCE SYSTEM

The FIS may be treated as systems that use the concepts and operations defined by the fuzzy set theory and by the fuzzy reasoning methods, since they use the fuzzy inference process to perform their operational functions. Basically, these operational functions include the inputs fuzzification of the system, the inference rules associated to it, the aggregation of rules and the later defuzzification of the aggregation results, which represent the outputs of the FIS [33].

Considering the operational functions performed by the FIS, it is convenient to represent them by a three-layer model. Thus, a FIS may be given by the sequential composition of an input layer, an inference layer and an output layer.

A. Input Layer

The system inputs fuzzification has the purpose of determining the membership degree of each input related to the fuzzy sets associated to each input variable. To each input variable, as many fuzzy sets as necessary can be associated. This way, given a FIS with only one input, to which there are *N* fuzzy sets defining it associated, then the output of the first layer is a column vector with *N* elements, which are representing the membership degrees of this input in relation to those fuzzy sets.

If we define the input of this FIS with one only input x, then the input layer output of the FIS is the vector I_1, that is

$$I_1 = (\mu_{A_1}(x)\ \ \mu_{A_2}(x)\ \ \cdots\ \ \mu_{A_N}(x))^T \tag{1}$$

where $\mu_{Ak}(\cdot)$ is the membership function defined to x input, which is referring to the k-th fuzzy set associated to this input.

The generalization of the input layer concept for a FIS having p input variables can be achieved if we consider each input of this FIS being modeled as a sub-layer of the input layer. Considering this, the output vector of the input layer $I(x)$ is then defined by

$$I(x) = (I_1(x_1)^T\ \ I_2(x_2)^T\ \ \cdots\ \ I_P(x_P)^T)^T \tag{2}$$

where x_i is the i-th input of the FIS and $I_k(\cdot)$ is the k-th vector of membership functions associated to the x_k input.

B. Inference Layer

The set of rules has fundamental importance to the correct functioning of the FIS. There are several methods for the extraction of fuzzy rules from the tuning set.

In this paper, the FIS has initially all the possible inferred rules. Therefore, the tuning algorithm has the task of weighting the inference rules. The weighting of the inference rules is an adequate way to represent the most important rules in the FIS, or even to allow that conflicting rules are related to each other without any verbal completeness loss.

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Thus, it is possible to express the *i*-th fuzzy rule as (3), where $R_i(\cdot)$ is the function representing the fuzzy weight value of the *i*-th fuzzy rule, w_i is its weight factor and $r_i(\cdot)$ represents its fuzzy value.

$$R_i(I(x)) = w_i \ r_i \ I(x) \tag{3}$$

C. Output Layer

The output layer of the FIS aims to aggregate the inference rules, as well as the defuzzification of the fuzzy set generated by the aggregation of inference rules.

In the FIS design, the choice of not only the aggregation method but also the defuzzification method constitutes a very important decision. The aggregation method of the fuzzy inference rules must be in such a way that the fuzzy set resulting from aggregation is capable of adequately representing the knowledge contained in this set of fuzzy rules. By analogy, the method chosen for the defuzzification must express, in a crisp value, the fuzzy set resulting from the fuzzy aggregation.

D. Adjustment of the Fuzzy Inference System

To summarize what was exposed until now in this Section, Figure 1 illustrates how the layers are disposed. In this example, two inputs were provided and three rules activated.

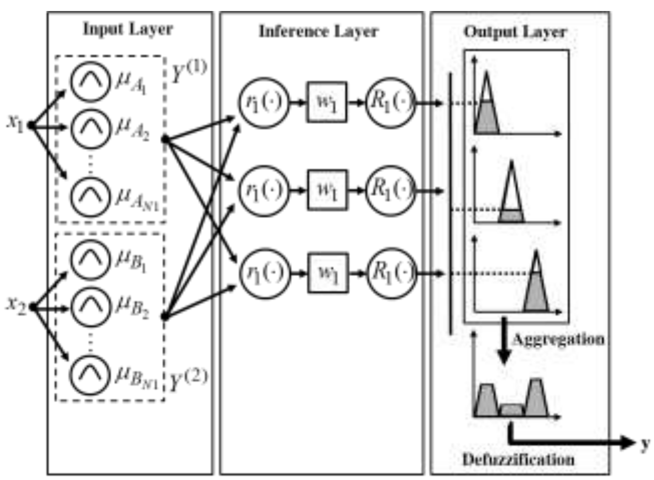

Figure 1. Multilayer fuzzy inference system [33].

The formalization of a FIS in the form of a multilayer system can be justified not only by the different operational division of each one of these layers, but also by the presence in each of them of different free parameters.

This way, the mapping *f* between the input space *x* and the output space *y* may be defined by (4), where mf_{1n}, *w* and mf_{out} respectively represent the vectors of the input membership functions parameters, the weight of the inference rules and the output membership functions parameters.

$$y = f(x, \ mf_{1n}, \ w, \ mf_{out}) \tag{4}$$

Therefore, mf_{1n}, *w* and mf_{out} represent the free parameters of the FIS and for this reason it is more suitable to rewrite (4) as presented in

$$y = f(x, \ \theta) \tag{5}$$

where θ is the vector resulting from concatenation of the free parameters involved to system, that is

$$\theta = \left({mf_{1n}}^T \ w^T \ {mf_{out}}^T \right) \tag{6}$$

The definition of the energy function to be minimized remains in function of the fuzzy mapping. Considering that the tuning set *{x,y}* is fixed during the whole adjustment process, it may be written as (7), where ξ represents the energy function associated to the FIS *f*.

$$\xi_{(x,y)} = \xi_{(x,y)}(\theta) \tag{7}$$

In problems like this, involving the minimization of energy functions, it is desired that, after any iteration, the energy function value is lower than that value obtained in the previous iteration. There are several techniques used to solve unconstrained optimization problems. A detailed description of the unconstrained optimization techniques may be found in [34]. The choice of the most adequate technique to be used is conditioned to the form by which the energy function is defined. For example, the Gauss-Newton method for the unconstrained optimization may be more applicable in problems where the energy function is defined as (8), where *e(i)* is the absolute error of the *i*-th tuning pattern.

$$\xi(\theta) = \frac{1}{2} \sum_{i=1}^{m} e^2(i) \tag{8}$$

In this paper, a derivation of the Gauss-Newton method is used for the FIS. The Gauss-Newton expression to update the vector $\boldsymbol{\theta}$ is defined by (9), where *g* is the gradient of ξ expressed in (7) and *J* is the Jacobian matrix of *e* presented in (8).

$$\theta_{next} = \theta_{now} - \frac{1}{2} \left(J^T J \right)^{-1} g \tag{9}$$

The optimization algorithm used was the Levenberg-Marquardt method [35]. The Levenberg-Marquardt method can handle well ill-conditioned matrices $J^T J$ by altering (9) to

$$\theta_{next} = \theta_{now} - \frac{1}{2} \left(J^T J + \lambda I \right)^{-1} g \tag{10}$$

The calculation of the matrices *J* and the vectors *g* were performed through the finite differences method.

IV. METHODOLOGY

Aiming to locate faults in a distribution system, this paper uses simulations of faults in a real system, which is in Biritiba-Mirim (Brazil). This distribution system contains 505 transformers and 1600 buses. Each simulation consisted in applying a fault to one bus and measuring the medium-side voltages in each transformer, in addition to zero and

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positive impedances between each transformer and the fault. This way, more than 800,000 sets of data were gathered. All the voltage data collected are: module, real part and imaginary part of phase, line and sequence voltages. Since phase A is the reference, its imaginary part is zero and the real part is equal to the module. This way, there are 25 different vectors of voltage data that will be the inputs of the FIS.

The medium voltage side of transformers was chosen as the points to collect data because of two main reasons. First, the transformers are a likely spot to place the data concentrators of a smart grid [36]. Second, the work presented in [37] develops and designs a Phasor Measurement Unit (PMU) that fits perfectly for data acquisition in the purpose of this paper. Although it is placed in the low voltage side of transformers (220 V), it can collect all 25 different voltages used in the magnitude of 13.8 kV by considering the transformer model.

The outputs of the FIS are the modules of the zero and positive impedances in fault condition. These variables are used to calculate the apparent impedance, which is directly proportional to the fault distance between a transformer (measurement point) and the fault point. The equations below shows these relations between the distance D, the apparent impedance Z_{ap}, the zero and positive sequence impedances Z_0 and Z_1, the fault voltage V_A and current I_a and the zero sequence current i_0 [38].

$$D \ \alpha \ Z_{ap} = \frac{V_A}{I_a + \left(\frac{Z_0 - Z_1}{Z_1} \right) i_0} \qquad (11)$$

$$D \ \alpha \ \frac{Z_1}{Z_0 - Z_1} \qquad (12)$$

Some considerations were made in this study. It was considered that the system is balanced, equilibrated and symmetric before the fault. The fault is phase-A-to-ground with no resistance. The system is unloaded.

V. RESULTS

The results were obtained by training and testing the FIS with 5 inputs and 12 rules, once for calculating Z_0 and another for calculating Z_1. These 5 inputs were selected among all the 25 measured voltages by the method developed in [39].

For Z_0, the voltages selected as inputs of the FIS were V_A, V_{1i}, V_{0r}, V_{Br} e V_{1r}. The rules and membership functions are in Figure 2, while the estimation result is in Figure 3. For estimating Z_1, the inputs were V_A, V_{1i}, V_{BCr}, V_{2i} e V_{0r}. The results are in Figure 4 while the FIS configuration is in Figure 5.

Figures 2 and 5 show 6 columns (5 inputs and 1 output) and 12 rows (rules). In each but the last column there is a red line which represents the value of each input. This value can vary from 0 to 1 individually, since all data is in pu, but they are all assumed 0.5 here as an example. In each row, there are all the membership functions that are activated by the values of the inputs in the corresponding rule. The yellow region in each membership function is the pertinence of that function. In the last row and column, there is a thick red line that represents the value of the output after the aggregation of all membership functions of the output. This value is the impedance in pu.

Figures 3 and 4 show how many estimations exist by interval of impedance. By analyzing them, it is possible to see that the FIS was not able at all to estimate impedances in the intervals [0.0 0.1] pu and [0.6 1.0] pu. Instead, the FIS placed them in the ranges of impedances [0.1 0.2] pu and [0.3 0.6] pu, making their estimation not as correct as they should be. The only interval were the estimations matched reasonably the real impedances is the [0.2 0.3] pu interval in both cases.

With these estimation data, the distance between the fault and the measurement point can be calculated, using (12). Then, they are compared to the real distance of the fault. This comparison is showed in Figure 6, which can be analyzed similarly to Figures 3 and 4, and in in Figure 7, which is the histogram of the error, indicating the number of estimations that provided similar intervals of errors (in km).

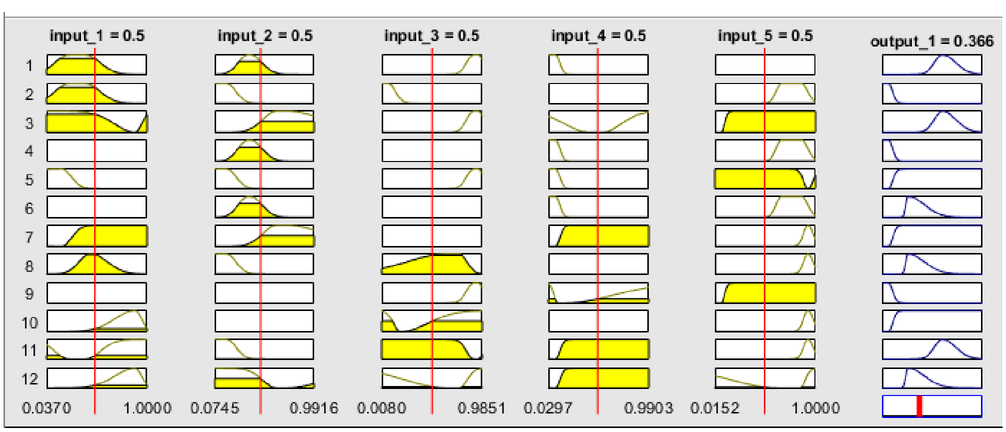

Figure 2. FIS configuration for estimating Z_0.

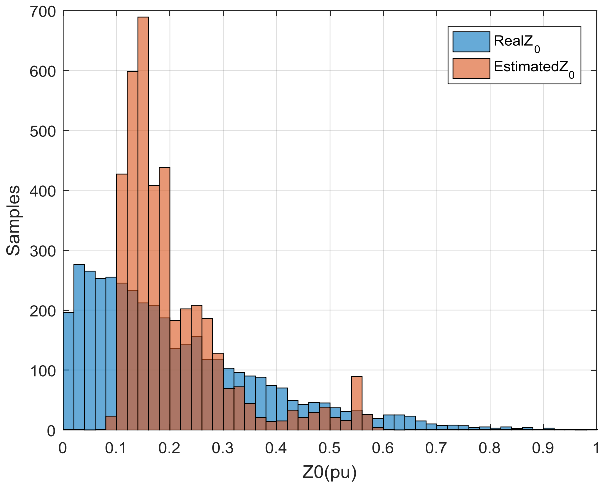

Figure 3. Z_0 estimatiom.

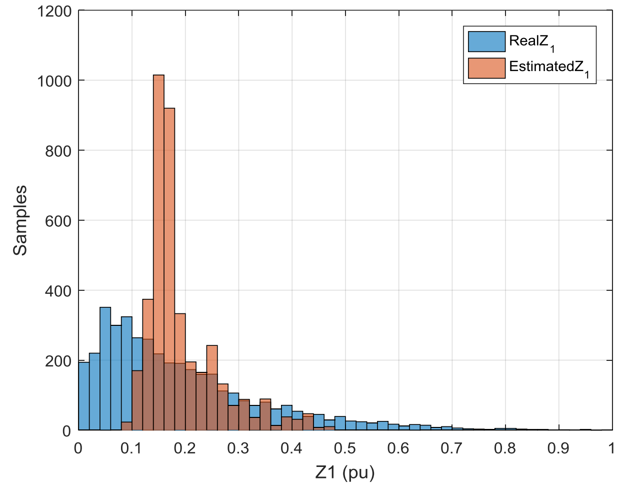

Figure 4. Z_1 estimation.

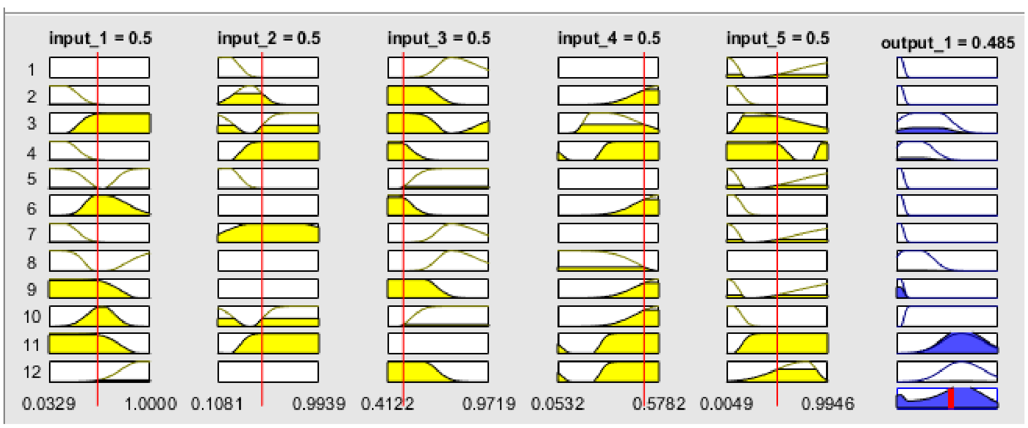

Figure 5. FIS configuration for estimating Z_1.

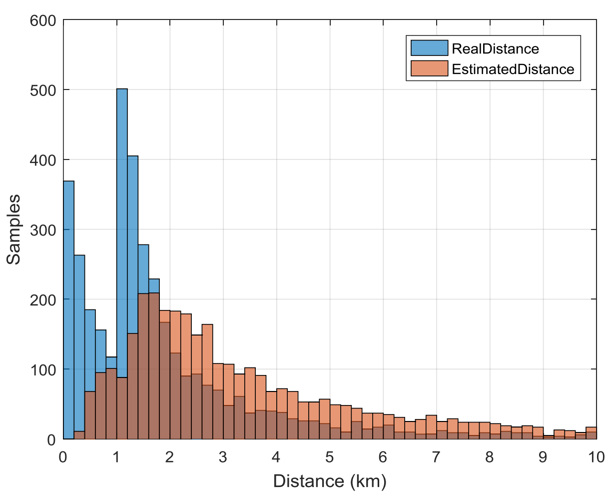

Figure 6. Comparison between estimated and real fault distances.

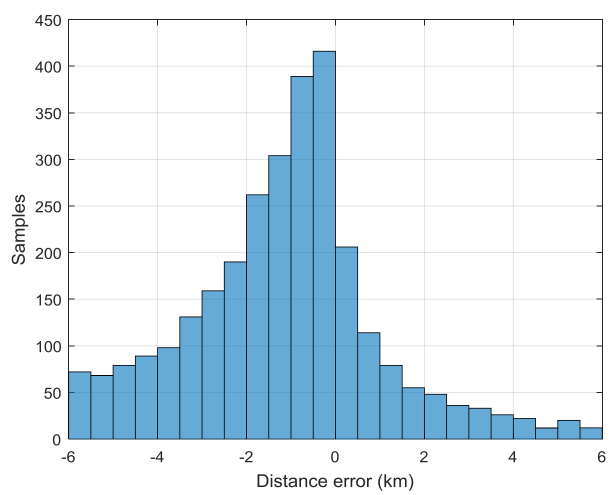

Figure 7. Histogram of distance estimation error.

Circa 400 samples (10% of the training data) resulted in errors close to zero, approximately the same amount of samples whose estimated distance is between 1.6 km and 2.0 km, that is the interval of distances with the smallest estimation error.

VI. CONCLUSION

This paper developed a fault location method in distribution systems using only voltage measurements. A Fuzzy Inference System was trained with these voltage data and provided as outputs the zero and positive impedances, which were used to calculate the distance from each transformer of the grid to the fault point.

In a first glance at Figure 6, the results look far from being satisfactory to completely fulfill the objective of this work. Yet, this work has some good results, as explained below.

Taking a closer look on Figure 6, there is a range of distances, [1.6 2.0] km, where the estimation has little error. This is the only acceptable range because the FIS could only estimate the zero and positive impedances more accurately in the narrow interval associated with this distance range, that is the [0.2 0.3] pu impedances interval. Knowing this, after a fault happens, when calculating the distance from every transformer to the fault, most of them will locate the fault incorrectly. Transformers closer than 1.6 km from the fault will accuse that the fault is even closer, and transformers further from 2.0 km will indicate an even longer distance to the fault. Nevertheless, there is a circle of transformers with radius varying between 1.6 km and 2.0 km that will give a precise fault location, which is the center of this circle.

However, even after this analysis, there is more room for improving the results of this work in future ones. First, locating the fault using the thought exposed above is only conceivable if the correct number of measurement points is used. In this paper, 505 transformers were not enough to locate the fault regardless of its distance, but this number is fine to locate faults within the distance described above. Changing this number may improve the results, that is, may widen the range of precise distance estimations.

Second, the FIS must be restructured. Changing the number of transformers implies in a different set of data used to train the Fuzzy Inference System, making it necessary to alter the number of rules, membership functions, inputs and epochs of training for optimizing the results.

The third possible improvement regards the distribution system, that is rather simplified. It is convenient to add more characteristics of the system, such as unbalanced voltages, fault impedance and presence of loads to obtain a more applicable result in a real distribution system.

Additionally, there is still an important factor of this present work to investigate. Very low or very high impedances could not be estimated by the FIS, and the reasons for this are unknown. A hypothesis is that the distribution system is too complex for a fault to be located without clustering this system to be trained by different FIS. Making the FIS capable of accurately estimating these extreme impedances will certainly grant a more precise fault location.

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