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Fuzzy risk index for power transformer failures due to external short-circuits

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ABSTRACT

A novel methodology to assess the risk of power transformer failures caused by external faults, such as short-circuit, taking the paper insulation condition into account, is presented. The risk index is obtained by contrasting the insulation paper condition with the probability that the transformer withstands the short-circuit current flowing along the winding during an external fault. In order to assess the risk, this probability and the value of the degree of polymerization of the insulating paper are regarded as inputs of a type-2 fuzzy logic system (T2-FLS), which computes the fuzzy risk level. A Monte Carlo simulation has been used to find the survival function of the currents flowing through the transformer winding during a single-phase or a three-phase short-circuit. The Roy Billinton Test System and a real power system have been used to test the results.

1. Introduction

During an external short-circuit the windings of power transformers are subjected to electromagnetic forces. These forces cause windings displacements and deformations. Such a phenomenon influences the reliable operation of power transformers [1].

If a short-circuit occurs at the secondary side of the transformer, the short-circuit current can flow through the windings. This current is several times the rated current of the transformer. Due to this increased short-circuit current the transformer winding is prone to undergo mechanical fatigue due to the electromagnetic forces, which are proportional to the square of the short-circuit current [2].In case of a winding damage, long transformer downtimes are to be expected since the repairing time can be very long and in some cases the fault disables completely the equipment [3].

On the other hand, when the transformer's insulating paper condition reaches a questionable aging level, the ability of the equipment to withstand an external short-circuit decrease significantly. This is due to the fact that cellulose in poor condition can cause an internal fault due to transient stresses [4].

The mechanical strength of the insulating paper can be assessed by measuring the degree of polymerization (DP). The DP represents the number of monomers β of glucose $C_6H_{10}O_5$ present in the paper cellulose molecules [5]. During the manufacturing process of a transformer, the DP of the paper is between 1000 and 1300, but its aging in service conditions reduces it considerably. The mechanical strength of the paper falls down to 20% of its initial value when the DP is 150. Below this value, the paper does not have any mechanical strength. Usually, it is considered that with DP below to 200 the paper loses all its mechanical properties and the equipment is susceptible to damage [6]. However, from the point of view of short-circuits it is considered that the transformer has reached its end of life when the DP has reached a value lower than or equal to 450 [7].

A novel methodology to assess the power transformer failure risk under short-circuits is presented in this work. This methodology takes into account the condition of the paper insulation on the basis of its DP and the probability (So) that the current (I_{kk}), circulating through the transformer during short-circuits, be grater than a specific value. In order to find this probability a Monte Carlo simulation, using a test system, was performed. Also, it is implemented the analysis in a real power system. Subsequently, the values of DP and probability are used as input of a T2-FLS (Type-2 fuzzy logic systems), which evaluates the risk level of the device. The results show that it is feasible to evaluate the risk level of a power transformer due to external short-circuit faults. For the sake of simplicity, only single-phase and three-phase faults were simulated.

The structure of the paper is as follows. The procedure for obtaining the survival function (S) of the short-circuit current (I_{kk}) is shown in Section 2. The calculation algorithm for I_{kk} and S is also shown in this section. Section 3 gives a brief overview of fuzzy inference systems. The T2-FLS used for the risk analysis is shown in

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Section 4. In Section 5, the procedure to determine the membership function of *So* from the ordered pair ($I_{kk} - S$) is described. Section 6 gives the results obtained. Finally, the conclusions are presented in Section 7.

2. Short-circuit current probability

Power systems behaviour is stochastic in nature and therefore it is natural to consider that the assessment of such systems should be based on techniques that take this characteristic into account (i.e., probabilistic techniques) [8].

The probability distributions are typically defined in terms of the probability density function (PDF). However, there are various probability functions used in different applications. One of these functions is the survival function. The survival function is used widely in reliability analysis and related fields. Concretely, the survival function $S(x)$ describes the probability that a variable X takes a value greater than a number x, i.e.,:

$$S(x) = P[X > x] \tag{1}$$

In order to obtain the distribution S within the context of the transformer fault risk evaluation caused by external short-circuits, a Monte Carlo simulation was performed. This simulation makes possible to take into account the uncertainty of the power system configuration (changes in the system configuration), the uncertainty of the fault type (single-phase or three-phase), the line that experiences the fault, the phase involved in the fault (during the event of a single-phase fault), and the percentage of the line under faulted condition. By means of this procedure the different values of I_{kk} with their respective probability values (greater than) are found. A similar approach which uses a Monte Carlo sampling for the evaluation of reliability indexes can be found in Ref. [9]. The procedure for obtaining the S function is presented following.

2.1. State sampling approach

A system state depends on the combination of all component states. Each component state can be determined by sampling the probability that the component is in such state [9]. The behaviour of each component can be described by a uniform distribution in the interval (0, 1). It is assumed that each component has two states: in-service and out-of-service, and that the component faults are independent events. Assume S_j as the state of the jth component and FP_j as its state probability. A random number U_j distributed uniformly between (0 and 1) is evaluated for the jth component state. Then, the state of S_j of the jth component will be

$$S_j = \begin{cases} 0 & (\mathrm{In-service})\,\mathrm{if}\, U_j \geq \mathrm{FP}_j \\ 1 & (\mathrm{Out-of-service})\,\mathrm{if}\, 0 \leq U_j < \mathrm{FP}_j \end{cases} \tag{2}$$

The probability that the component is out-of-service could be represented by means of the forced outage rate (FOR) defined by the following equation:

$$\mathrm{FOR} = \frac{\lambda}{\lambda + \mu} \tag{3}$$

where λ is the expected failure rate and μ is the expected repair rate of each component of the system.

By substituting FOR by FP_j (2), for each component, as well as comparing this value with the uniformly distributed number U_j, the component state is obtained. So, the network configuration to be used in the short-circuit simulations is obtained in this manner.

Table 1
Probability of short-circuit occurrence [11].

Short-circuit	Occurrence (%)
Three-phase-to-ground	1.5
Three-phase	1.5
Line-to-line-to-ground	6.0
Line-to-line	10.0
Single-phase	81.0

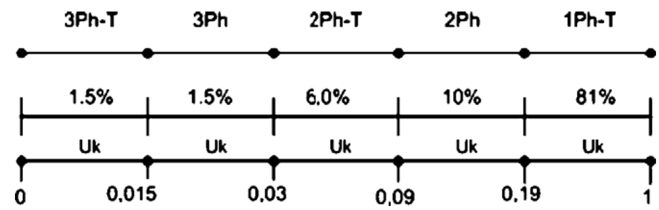

Fig. 1. Representation of the intervals that determine the type of fault [11].

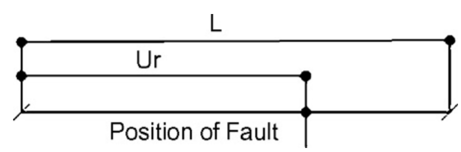

Fig. 2. Representation of the intervals that determine the location of fault.

2.2. Calculation of the failure probability and type of fault

The previous procedure is also used while considering a short-circuit affecting a certain line. In this case, the probability that this line is affected by a fault is obtained using Eq. (4). The faulted line is chosen comparing this value with a uniformly distributed number between zero and one.

$$P_{\mathrm{fault}k} = \frac{L_k}{\sum_{j=1}^{N} L_j} \tag{4}$$

where $P_{\mathrm{fault}k}$ is the probability of fault in line k; L_k is the length of line k and $\sum_{j=1}^{N} L_j$: *Sumatory of the length of all lines of the system*

The use of a uniform distribution for the location of faults in transmission lines describes the typical lack of predictability in this matter [10]. Consequently, Eq. (4) simply models the probability by assuming that the number of faults is proportional to the length of the line, which makes sense, since it is to be expected that lines having greater lengths have greater number of faults, and therefore its probability of failure has to be greater. An opposite condition occurs in lines having smaller lengths.

The probability of occurrence of any type of short-circuit is specified according to Table 1. The probability intervals are shown in Fig. 1, just as proposed in Ref. [11], and is modelled by means of a generator of uniformly distributed random numbers between zero

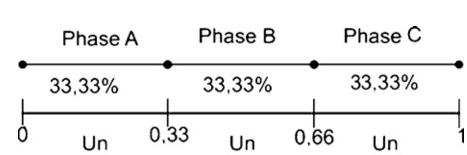

Fig. 3. Representation of the intervals that determine. The phase involved in the fault.

and one (U_k). As it was mentioned in the previous section, only single-phase and three-phase faults are considered. The former being the most common fault [10] and latter the most severe.

A similar procedure is used while considering the randomness of the fault location in the line. The percentage of length of line failed is modelled by means of uniformly distributed random numbers between zero and one (Ur). That is, the location of the fault in the line is considered to have a uniform probability, as shown in Fig. 2. The same assumption is made while choosing the faulted line.

The choice of the failed phase is done in the same way, i.e., considering the probability intervals shown in Fig. 3. This selection provides robustness to the methodology, since in the case of analyzing asymmetrical networks the results of the algorithm will reflect the changes in the fault currents.

The algorithm used to apply the previously described procedure is shown in Fig. 4. For the sake of simplicity, the 60909 IEC standard, 2001 [12] is used to calculate the short-circuit current.

The λ and μ inputs represent the expected failure rate and the expected repair rate of each system component, respectively. The maximum number of fault simulations (α) that the algorithm has to perform depends on the convergence level of the Monte Carlo simulation, as it will be shown later.

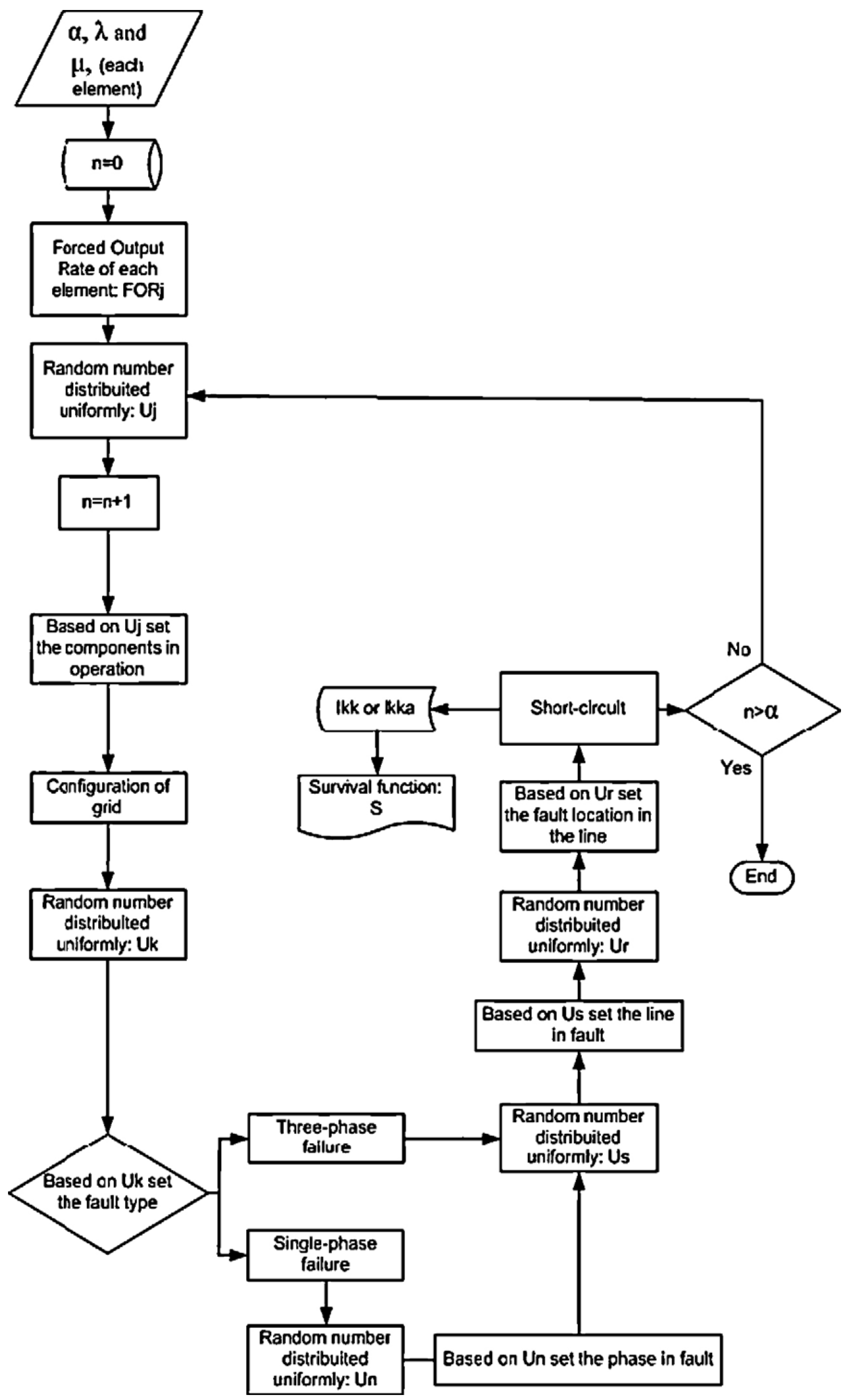

Fig. 4. Algorithm to obtain I_{kk} and S.

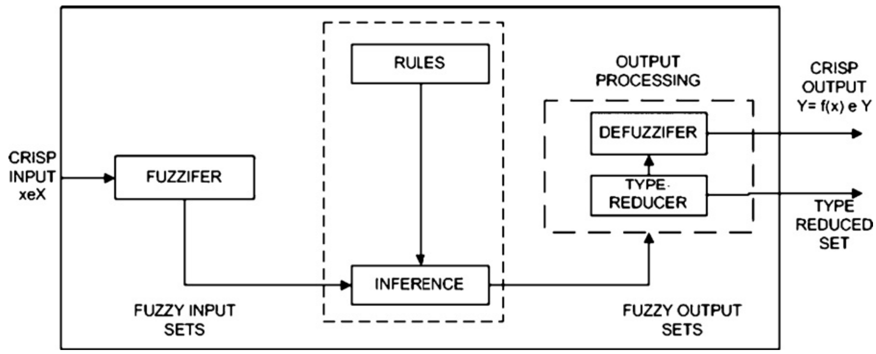

Fig. 5. Structure of a T2-FLS [13].

3. Fuzzy logic systems: a brief overview

Before continuing, it is considered worth to present a brief description of the type-2 fuzzy sets and T2-FLS. A rigorous description of the FLS mathematical theory and applications can be found in Ref. [13].

The main advantage of the fuzzy systems theory is that it approximates the behaviour of a system in cases where analytical functions or numerical relations for describing its behaviour do not exist [14]. Therefore, fuzzy systems have a high potential as a tool to understand systems for which behaviour models have not been developed, i.e., complex systems. The relationship between cause and effect in these systems is generally non-understood, but usually it can be observed.

The concept of the fuzzy sets theory can be used in several ways for system modelling [15]. Several subsystems in control engineering and system theory can be "fuzzified", and different kinds of fuzzy systems can be applied to model them.

In the field of artificial intelligence there are several forms to represent the knowledge [14]. The most usual way to represent the human knowledge is perhaps to formulate it by means of rules written in natural language based on IF-THEN expressions, as that shown by the following equation:

$$\text{IF } x_1 \text{ is } \tilde{A}_1 \text{ and}\ldots\text{and } x_L \text{ is } \tilde{A}_L \text{ THEN } y \text{ is } \widetilde{B}_r \tag{5}$$

where $\tilde{A}_L$ is the lth fuzzy set representing the antecedent of the rth rule and $\tilde{B}_r$ is the fuzzy set representing the rth consequent from the rth rule.

The FLS are used to represent and numerically manipulate linguistic rules in a natural way. They are also useful because of their ability to handle problems which the conventional control theory cannot focus successfully. Also, the latter requires a valid and precise model which not always exists [16].

On the other hand, a type-2 fuzzy set $\tilde{A}$ can model the uncertainty related to the meaning of words using a function of three-dimensional property which is fuzzy and is defined by mean of (6) and (7).

$$\tilde{A} = \frac{\displaystyle\int_{x \in X} \mu_{\tilde{A}}(x)}{x} \tag{6}$$

$$\mu_{\tilde{A}}(x) = \frac{\displaystyle\int_{u\hat{\text{I}}J_x} f_x(u)}{u}, \quad J_x \subseteq [0, 1] \tag{7}$$

where $\mu_{\tilde{A}}(x)$ is the *secondary membership function* for an element $x \in X$. The domain (J_x) and the amplitude ($f_x(u)$) of $\mu_{\tilde{A}}(x)$, are the *primary membership* of x and the *secondary grade*, respectively.

The union ($\bigcup$) of all primary memberships of $\tilde{A}$ is a region called *fingerprint of uncertainty* (FOU) which is defined in Eq. (8). The upper

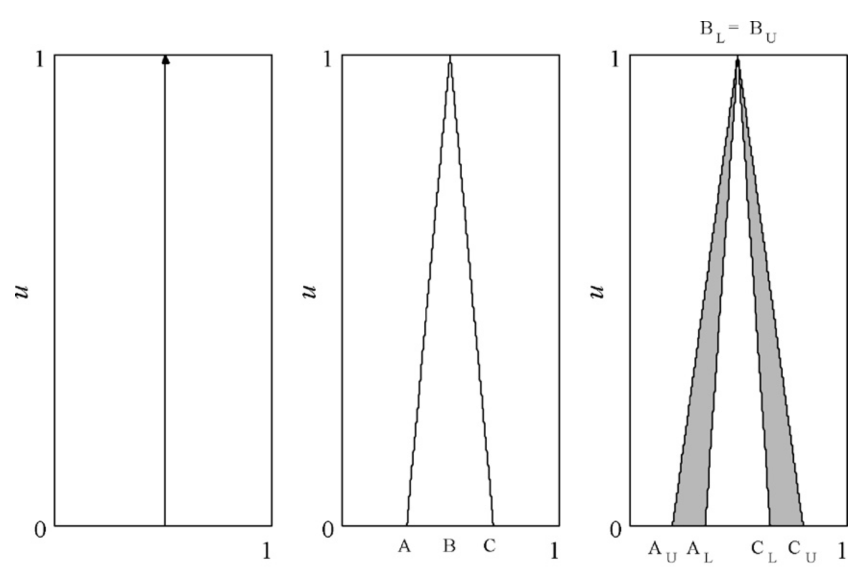

Fig. 6. Memberships functions of type-2 singleton (left), type-1 triangular fuzzy set (middle) and FOU of interval type-2 triangular fuzzy set (right).

Table 2
Example of base of rules from T2-FLS for the analysis of risk.

Rule	Antecedents		Consequent
	DP	*So*	I_R
1	Unacceptable	Low	Medium
2	Questionable	Low	Medium
3	Acceptable	Low	Low
4	Unacceptable	Medium	High
5	Questionable	Medium	Medium
6	Acceptable	Medium	Low
7	Unacceptable	High	High
8	Questionable	High	Medium
9	Acceptable	High	Low

and lower limits of the FOU are called upper and lower membership functions of $\tilde{A}$, respectively, and they are defined in Eqs. (9) and (10).

$$\mathrm{FOU}(\tilde{A}) = \bigcup_{x\in X} J_x \tag{8}$$

$$\bar{\mu}_{\tilde{A}}(x) = \overline{\mathrm{FOU}(\tilde{A})} = \bigcup_{x\in X} \overline{J_x} \quad \forall x \in X \tag{9}$$

$$\underline{\mu}_{\tilde{A}}(x) = \underline{\mathrm{FOU}(\tilde{A})} = \bigcup_{x\in X} \underline{J_x} \quad \forall x \in X \tag{10}$$

T2-FLSs can be classified into two types: general type and interval type. The former uses fuzzy sets whose secondary grade can take any value in the interval between (0, 1), and the latter uses fuzzy sets whose secondary degrees are equal to 1. In this work only type-2 fuzzy sets of interval type are used, because they are computationally more efficient than those of general kind [13].

The structure of a T2-FLS is shown in Fig. 5. This figure shows the different parts of a T2-FLS. A description of these parts can be found in [13]. The rules depend on the basis of rules of the particular system. In the following section the base of rules of the T2-FLS used for the risk analysis has two antecedents and one consequent (see Table 2).

The inputs of a T2-FLS can be modelled by type-2 singletons, type-1 fuzzy sets or interval type-2 fuzzy sets, depending on the nature of uncertainty. These are shown in Fig. 6.

The shaded area of the FOU models the uniformity of the secondary grades of an interval type-2 fuzzy set ($f_x(u) = 1, \forall \in J_x$). The output of a T2-FLS is a crisp value (y_{ic}) and a type-1 interval ($y_i = [y_{iL}, y_{iU}]$) called *type-reduced fuzzy set*, which is shown in Fig. 7. This interval is a measure of the uncertainty of the crisp output, in a similar way that for models based on probability, where the standard deviation is a measure of the uncertainty of the average.

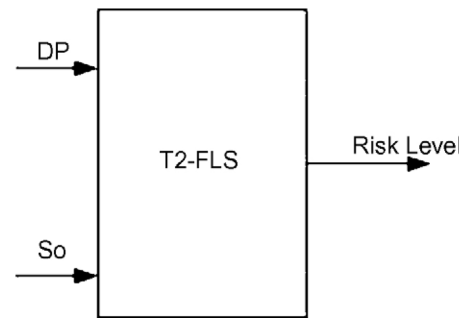

Fig. 8. T2-FLS for risk analysis due to short-circuits.

4. T2-FLS for the risk analysis of transformer failure due to short-circuit

A T2-FLS is used to evaluate the fault risk due to short-circuits, since it has suitable characteristics of T-2 FLS for this purpose. Furthermore, at present there is no model considering the state of the paper insulation and the probability that the equipment withstands an external short-circuit. This T2-FLS can be seen in Fig. 8. Its base of rules is shown in Table 2.

Each rule has two antecedents (DP y *So*) and one consequent, the risk level (I_R), which is a type-1 fuzzy set (see Fig. 7) or a crisp value (y_{ic}). The membership function of DP is derived from its crisp value and the type-1 fuzzy sets shown in Fig. 9.

In Ref. [17], ranges of DP are defined according to the loss of the paper mechanical strength caused by aging. However, to take into account the insulation weakness when a short-circuit occurs, the subdivision shown in Fig. 9 is proposed by the authors. These fuzzy sets are constructed using the criterion mentioned in Ref. [7], where it is stated that “from the point of view of short-circuits; it is considered that a power transformer has arrived at its ending of life when the DP has reached a value smaller than or equal to 450”.

From Table 2, the membership functions of *So* are obtained using the procedure shown in Section 5. The consequents are modelled by means of type-2 fuzzy sets of interval type (see Fig. 6, right). Each consequent is described by three linguistic terms (High, Medium, Low), whose membership function is obtained by means of expert surveys regarding the value of these linguistic terms within the interval 0–10. The extreme linguistic terms (High and Low) are modelled by means of trapezoidal type-2 fuzzy sets. The term “Medium” is modelled using a triangular type-2 fuzzy set. The type-2 fuzzy sets of these linguistic terms are shown in Fig. 10.

The result of this T2-FLS is an interval similar to that shown in Fig. 7. The consequent is the type-reduced fuzzy set and it is obtained using the extended *sup-star* composition,

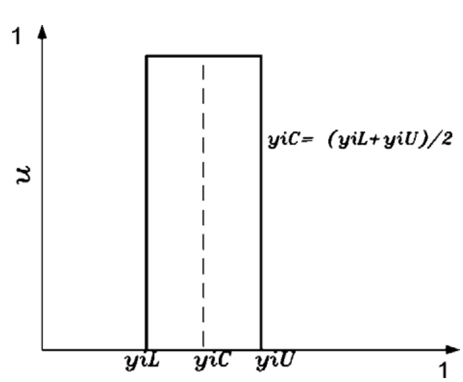

Fig. 7. Type-reduced fuzzy set.

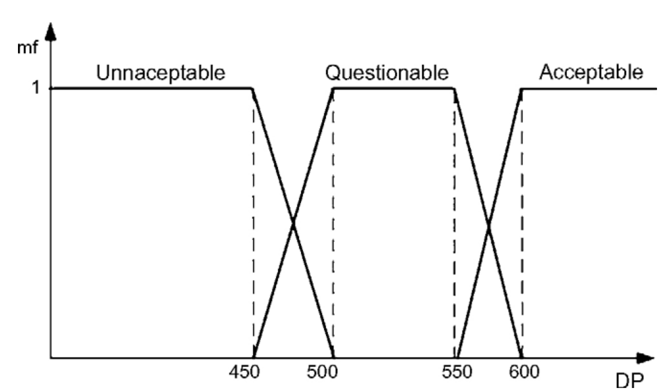

Fig. 9. Type-1 fuzzy sets for membership function of DP.

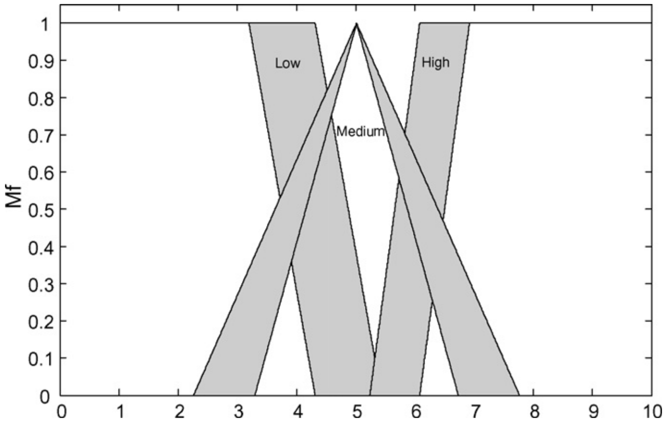

Fig. 10. Type-2 fuzzy sets of linguistic terms used as consequent in the T2-FLS.

under maximum-product norms and centre of type-reduction sets [13].

5. Obtaining the membership function S_o

To obtain the membership function of a variable, a procedure in the context of the extraction of knowledge from numerical data set can be used. In this way a rule-based system could be obtained [19].

A simple solution for obtaining the membership function *So* is therefore obtained from the values of *S* and I_{kk}, both determined by means of the procedure shown in Section 2. With the aim to obtain *So*, the artificial neural network (ANN) shown in Fig. 11 is used together with the *K*-means clustering method [14]. The *K*-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem [18]. The clustering procedure classifies a given data set in a certain number of clusters (assumed *k* clusters), which is established a priori ($k = 3$ in our case). The main idea is to define *k* centroids, one for each cluster, so that the sum of squares of the distances between each data point and the centre of the cluster is minimized.

Once the data have been distributed in the clusters, an ANN is created and trained using the data collected in the simulation. With this aim several configurations of ANN were trained being the feed-forward backpropagation ANN constituted by 4 layers-2 hidden inputs and three outputs showed the best performance. This network is trained either setting the consequent to zero, if the data does not belong to a particular region, or to one, if the data belong to it. This is shown in the example of Fig. 12.

The partition of *So* is made by means of three linguistic terms: “High”, “Medium” and “Low” represented by the regions R_1, R_2 y R_3, respectively (see Fig. 11). This kind of division can be extended so

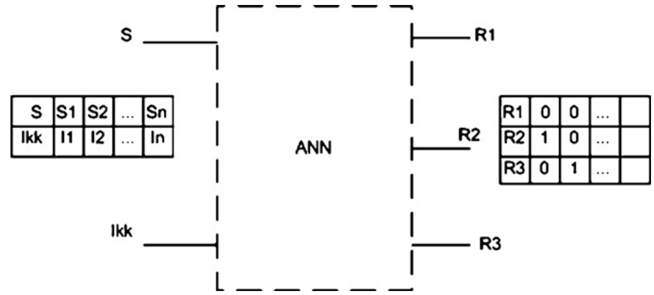

Fig. 12. Training the ANN.

as to use more membership functions, e.g. Medium Low, Medium High, etc. However, in our case, this would not be suitable because the known phenomenon called *curse of dimensionality*, which refers to the exponential growth of the number of rules with the number of input variables, should be avoided. The mentioned partition is enough to allow the expert to evaluate the risk using a minimum quantity of rules without loss of objectivity in the decision.

Once the ANN has been trained, it is possible to obtain the membership function of *So* by means of the given ordered pair (I_{kk}, *So*). This ordered pair used as input, can be obtained considering that the transformer has a rated short-circuit current (I_{CCRated}) [20]. The power transformer shall withstand this current if DP > 450.

By contrasting the value of the rated short-circuit current with the survival function S, partitioned in the three aforementioned regions, the membership function of *So* used as antecedent in the base of rules (Table 2) can be obtained.

6. Results

In order to illustrate the procedure described in the previous sections, firstly a simulation using the Digsilent Power Factory software® has been performed. The system used in the simulations is the Roy Billinton Test System (RBTS) proposed in [9]. The referred system consists of six buses as depicted in Fig. 13. On the other hand, it is implemented the algorithm for the analysis of risk in the electric power system of Honduras (see Fig. 21). In this case, the risk analysis is used on the 230/138 kV, 100 MVA, TSY power transformer located at Suyapa substation.

6.1. Simulation

The failure and repair rates of all lines, transformers and generators are considered in the simulation. The symmetrical short-circuit current (I_{kk}) due to three-phase faults as well as the asymmetrical short-circuit current (I_{kka}) due to single-phase faults flowing through the secondary winding of the 75 MVA power transformer TT2 (see Fig. 13) is analyzed. For the sake of clarity and conciseness

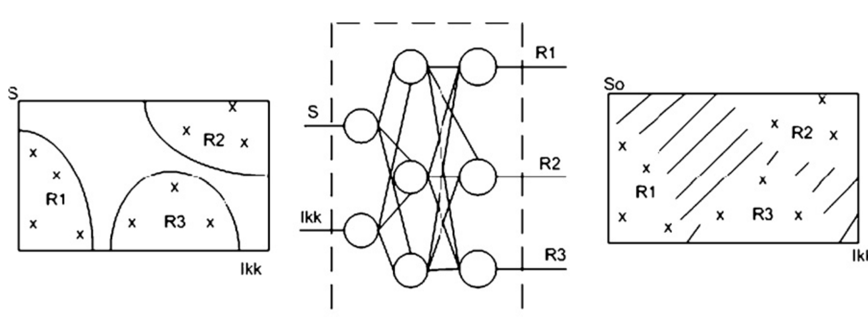

Fig. 11. ANN used to obtain *So* [14].

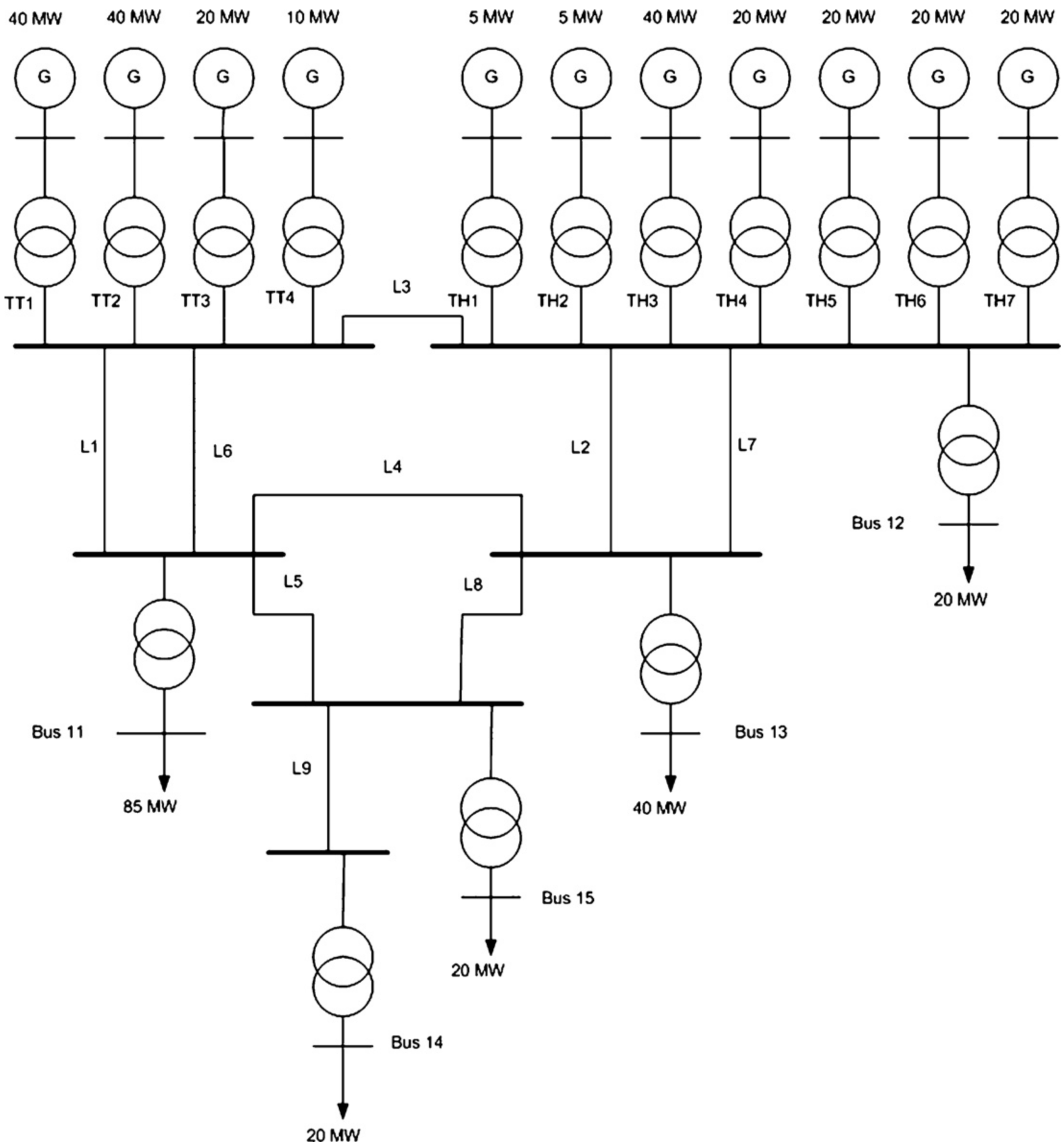

Fig. 13. Test feeder RBTS.

only the results for three-phase faults are presented. The amount of three-phase faults simulated was 3000, whereas the single-phase faults were 162,000. The procedure to be followed is basically the same for each transformer of the system.

By applying the algorithm of Fig. 4 and after a specific number of iterations, it is possible to analyze the convergence of the I_{kk} average value. Such convergence of the transformer TT2 while analysing three-phase faults is shown in Fig. 14.

Once the convergence of Monte Carlo method is reached, I_{kk} and S are obtained. Fig. 15 shows the function S calculated from I_{kk} and from I_{kka} flowing through TT2. Furthermore, the probability density function of I_{kk} is shown in Fig. 16.

The ANN is trained using the ordered pair (Ikk, S). Thereafter, the partition of S shown in Fig. 17 is obtained.

In this case the inputs of the trained ANN were the times of I_{kk} which TT2 (Fig. 13) is capable of support (I_{SC} = 6.5 P.U.) and the corresponding value of probability (S = 0, see Fig. 15). In this way, the following membership functions were obtained: R_1 = 0, R_2 = 0.0076 y R_3 = 0.9877. So, the low probability zone (R_3) has the higher membership function. Therefore, it is “Low” the probability that similar or higher currents than the allowed one flow through the sec-

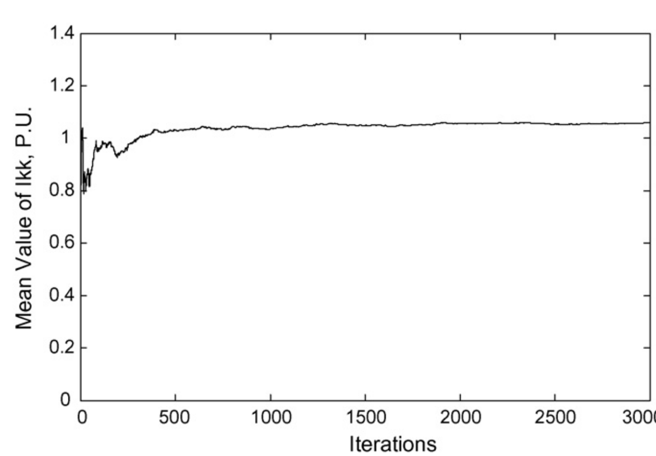

Fig. 14. Convergence of average value of I_{kk} for TT2.

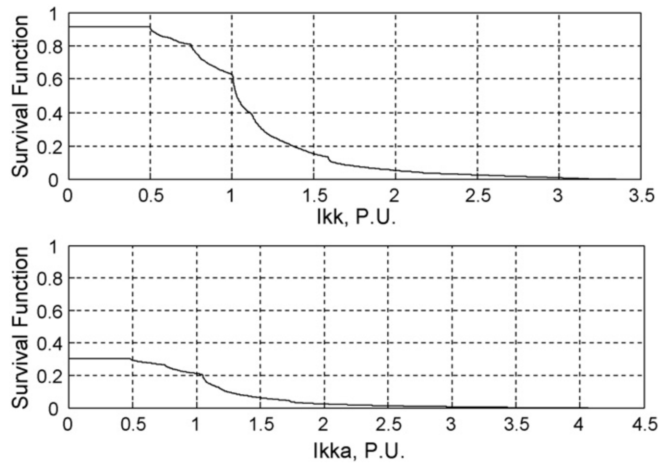

Fig. 15. Survival function for I_{kk} and I_{kka} circulating through transformer TT2.

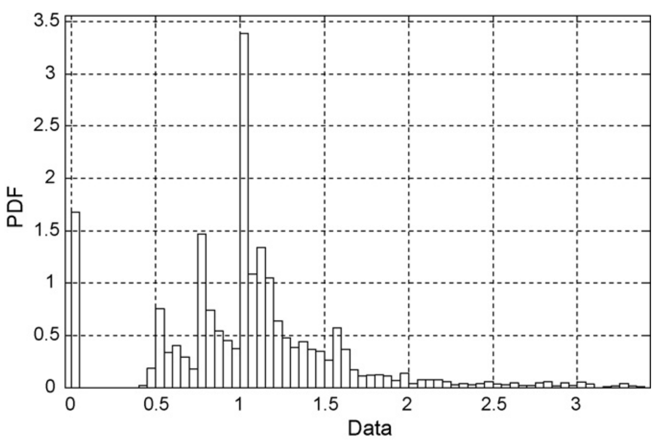

Fig. 16. PDF for I_{kk} (P.U.) flowing in TT2 transformer.

ondary winding of the transformer, during a three-phase fault. Similar results are obtained by using the data of single-phase faults. Because I_{kk} is inversely proportional to the system impedance and considering that the system grows over time, I_{kk} will decrease with the growth of the system. This entails that the membership function of R_1–R_3 will change over time as well as the fuzzy risk. Thus, the fuzzy risk index is a dynamical index.

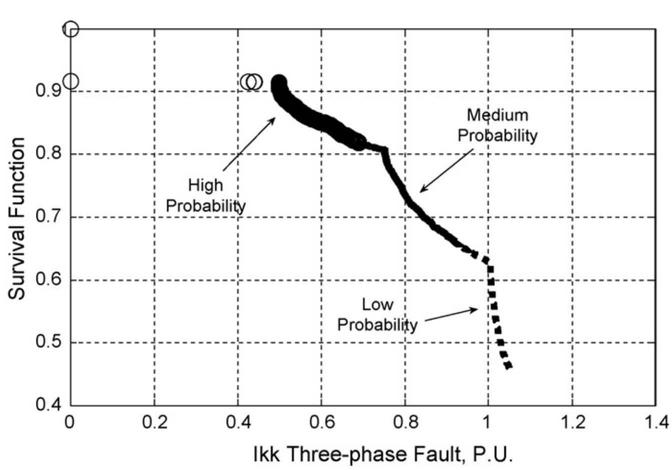

Fig. 17. Partition of S in three regions.

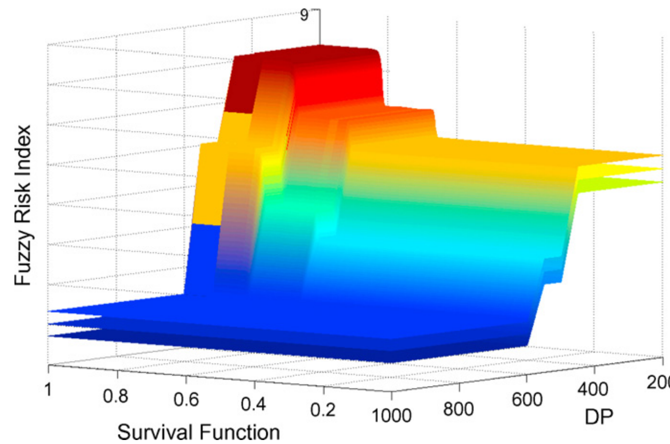

Fig. 18. Fuzzy risk index type-2 for TT2 transformer under three-phase fault.

The fuzzy risk profile for the power transformer TT2 is shown in Fig. 18. This fuzzy risk is obtained from all possible values of DP and S of the three-phase faults. Specifically, the type-reduced fuzzy set and the crisp value (middle), which resulted from the T2-FLS, are shown in Fig. 18. Similar results can be obtained if the procedure is applied to the remaining power transformers of the system either for three-phase or single-phase faults.

Fig. 18 shows also that if the DP is high, the risk is always low. On the other hand, the values of DP between 450 and 600 cause a "Medium" risk; thus, a rise of the risk with respect to the minimum value is observed. Furthermore, if the probability and the DP are low, the fuzzy risk obtained will be lower than the fuzzy risk for higher probabilities. This is shown in more detail in Fig. 19. Finally, if the probability *So* is high and the value of DP is low, the values of the fuzzy risk are high (see Fig. 18).

On the other hand, if is used a Type-1 FLS the fuzzy risk profile for the power transformer TT2 is shown in Fig. 20. In this case the uncertainty of the meaning of words is not modelling, because only Type-2 fuzzy sets and T2-FLS provide flexibility for modelling this uncertainty as well as the uncertainty of data.

6.2. Application on an electric power system

The algorithm for the risk analysis is implemented in the electric power system of Honduras. A section of this system is showed in

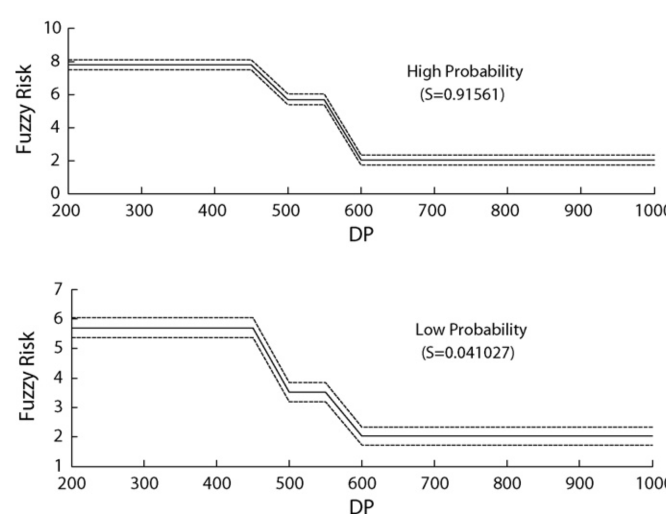

Fig. 19. Two profiles of fuzzy risk index for TT2 under three-phase fault and S constant.

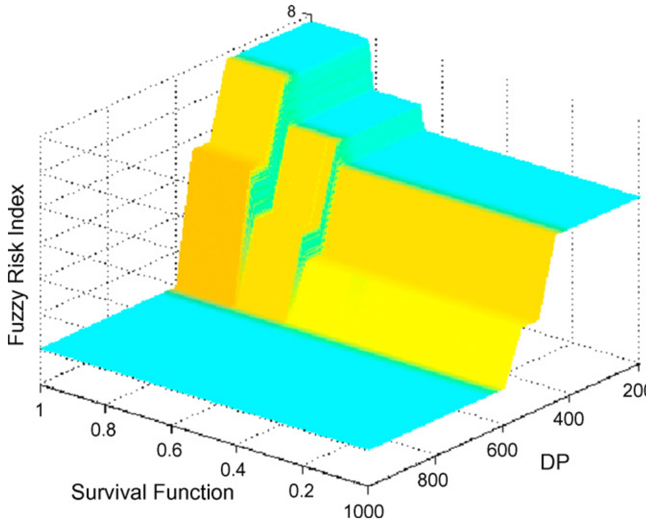

Fig. 20. Fuzzy risk index type-1 for TT2 transformer under three-phase fault.

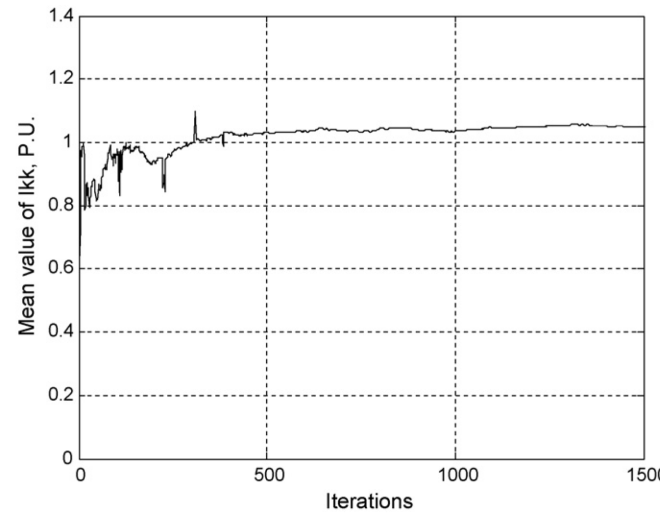

Fig. 22. Convergence of average value of I_{kk} for TSY.

Fig. 21. The symmetrical short-circuit current (I_{kk}) due to three-phase faults flowing through the secondary winding of the 100 MVA power transformer TSY (see Fig. 21) is analyzed.

By applying the algorithm and after a specific number of iterations, it is possible to analyze the convergence of the I_{kk} average value. Such convergence is shown in Fig. 22.

Fig. 23 shows the function S calculated from I_{kk} flowing through TSY. Furthermore, the probability density function of I_{kk} is shown in Fig. 24.

The ANN is trained using the ordered pair (Ikk, S). Thereafter, the partition of S shown in Fig. 25 is obtained.

The inputs of the trained ANN were the times of I_{kk} (I_{SC} = 7.11 P.U.) of TSY transformer and the corresponding value of probability (S = 0, see Fig. 23), the following membership functions were obtained: $R_1 = 0$, $R_2 = 0.041$ y $R_3 = 0.9965$. In this way, the low probability zone (R_3) has the higher membership function. Therefore, it is “Low” the probability that similar or higher currents than the allowed one

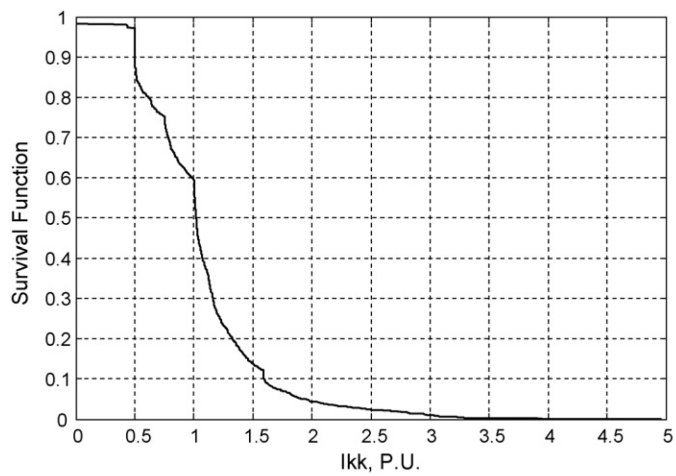

Fig. 23. Survival function for I_{kk} circulating through transformer TSY.

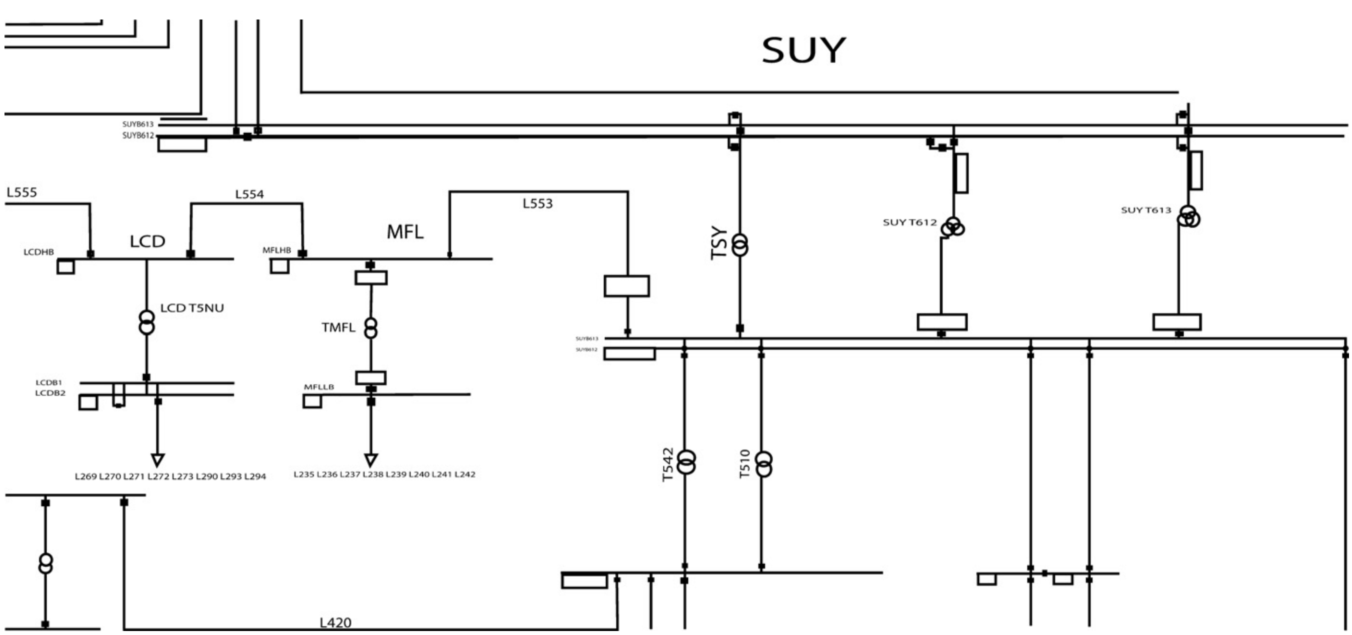

Fig. 21. A section of the electric power system of Honduras.

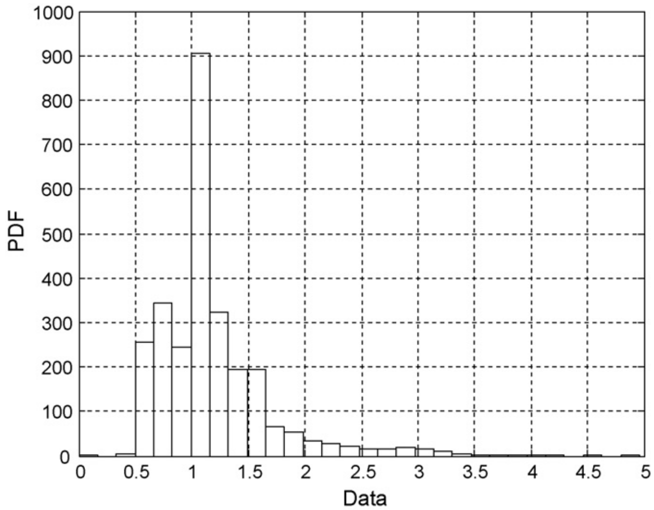

Fig. 24. PDF for I_{kk} (P.U.) flowing in TSY transformer.

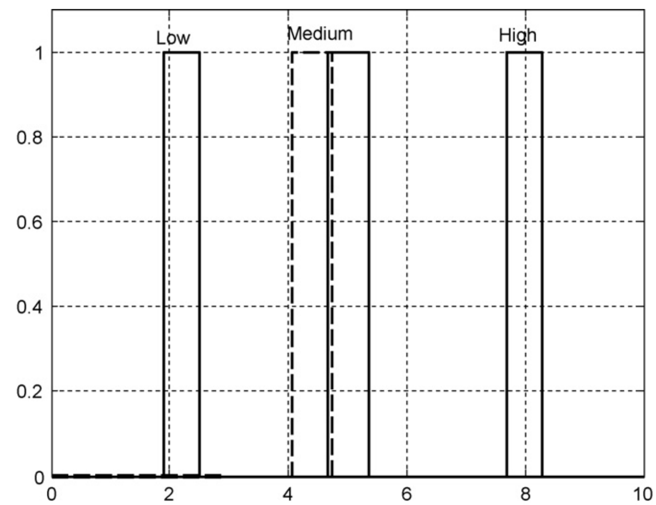

Fig. 27. Type-reduced fuzzy set for medium risk of TSY.

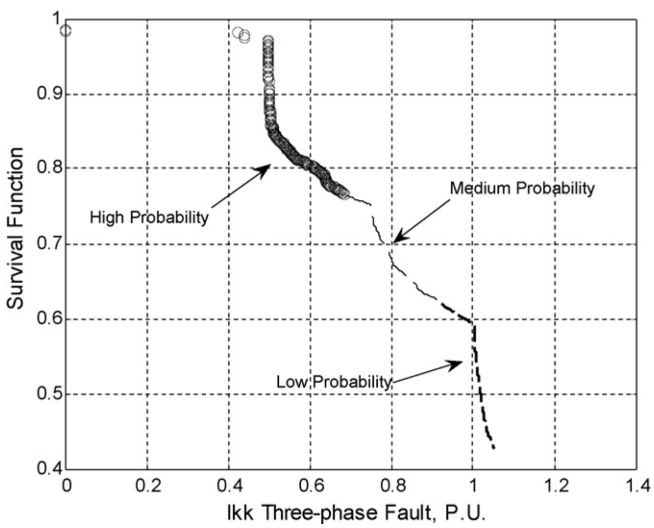

Fig. 25. Partition of *S* in three regions. TSY.

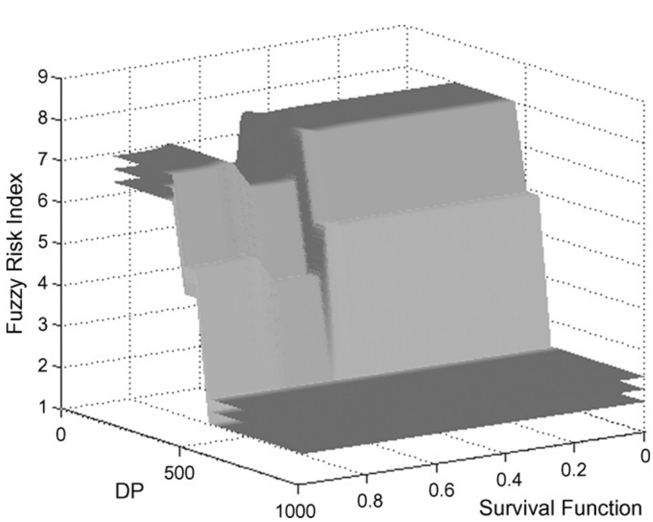

Fig. 26. Fuzzy risk index type-2 for TSY transformer under three-phase fault.

flow through the secondary winding of the transformer, during a three-phase fault.

The fuzzy risk index profile for the power transformer TSY is shown in Fig. 26. This fuzzy risk index is obtained from all possible values of DP and S of the three-phase faults. On the other hand, the result of tests applied to TSY shown that DP was 500. In this way, the inputs for the T2-FLS were DP = 500 and S= Low. Therefore, the fuzzy risk index is “medium”, which is a result expected by the maintenance personnel because of the condition of the insulation paper. Finally, Fig. 27 shows the interval obtained for “medium” risk. Formally, the centroid of the consequent representing the fuzzy risk “medium” is 4.3944 and the solution interval [Risk Medium_L, Risk Medium_R] is [4.0600, 4.7289].

7. Conclusions

A novel methodology to assess the risk of power transformer failures, due to external faults such as short-circuits, regarding the condition of the paper insulation was in this paper presented.

The methodology takes into account the paper insulation condition and the stochastic nature of the fault.

The fuzzy risk index provides a quantitative measure of the equipment reliability at the installation location. This tool will be very useful for power transmission utilities, which at present time does not have a tool to assess the failure risk of power transformers caused by external faults, which includes the condition of the paper insulation as an important influencing factor.

References

[1] Z. Liang, J. Li, R. Tang, Axial vibrations of power windings under short-circuit conditions, in: IEEE Electrical Machines and Systems, 2003. ICEMS 200. Sixth International Conference on, vol. 1, 9–11 November, 2003, pp. 332–335.

[2] Y.H. Oh, K.D. Song, B.Y. Lee, K.Y. Parks, Displacement measurement of high-voltage winding for design verification of short-circuit strength of transformer, in: Transmission and Distribution Conference and Exposition, 2003 IEEE PES, vol. 2, 7–12 September, 2003, pp. 831–835.

[3] M. Wang, et al., Review of condition assessment of power transformers in service, IEEE Electrical Insulation Magazine 18 (6 (November–December)) (2002) 12–25.

[4] J. Schneider, et al., Asset management techniques", Electrical Power and Energy Systems 28 (2006) 643–654.

[5] IEC Measurement of the Average Viscometric Degree of Polymerization of New and Aged Cellulosic Electrically Insulating Materials. IEC 60450, Second edition 2004-04.

[6] A.M. Emsley, et al., Degradation of cellulosic insulation in power transformers. Part 2. Formation of furan products in insulating oil, IEE Proceedings Science and Measurement Technology 147 (3 (May)) (2000) 110–114.

[7] CIGRÉ Working Group A2.18, Guide for Life Management Techniques For Power Transformers, CIGRÉ Broschure 227, 20 January 2003, CIGRÉ: Paris, France.
[8] R. Billinton, R.N. Allan, Reliability Evaluation of Power Systems, Plenum Press, USA, 1996.
[9] R. Billinton, W. Li, Reliability Assessment of Electric Power Systems Using Monte Carlo Methods, Plenum Press, New York, 1994.
[10] G.J. Anders, Probability Concepts in Electric Power Systems, John Wiley and Sons, New Jersey, USA, 1990, pp. 509–530.
[11] U.A. Bordalo, A.B. Rodrigues, M.G. Da Silva, A new methodology for probabilistic short-circuit evaluation with applications in power quality analysis, IEEE Transactions on Power Systems 21 (2 (May)) (2006).
[12] IEC short-circuit currents in three-phase a.c. systems. IEC 60909, 2001.
[13] J.M. Mendel, Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions, Prentice Hall, New Jersey, USA, 2004.
[14] Timothy J. Ross, Fuzzy Logic with Engineering Applications, 2nd edition (August 16, 2004), John Wiley and Sons: New Jersey, USA, ISBN-10: 0470860758, ISBN-13: 978-0470860755.
[15] Robert Babuska, "Fuzzy modeling and identification", Ph.D. Dissertation, University of Delft, 1996, pp. 51.
[16] Q. Liang, N.N. Karnik, J.M. Mendel, Connection admission control in ATM networks using survey-based type-2 fuzzy logic systems,", IEEE Transactions on Systems, Man and Cybernetics. Part C: Applications and Reviews 30 (3 (August)) (2000).
[17] M. Horning, J. Kelly, S. Myers, R. Stebbins, Transformer Maintenance Guide, S.D. Myers Inc, Ohio, USA, 2004.
[18] A tutorial on clustering algorithms. Available: http://www.elet.polimi.it/upload/matteucc/Clustering/tutorial_html/kmeans.html.
[19] Tzu-Ping, S.-M. Chen, A new method for constructing membership functions and fuzzy rules from training examples", IEEE Transactions on Systems, Man, and Cybernetics. Part B: Cybernetics 29 (1 (February)) (1999).
[20] IEEE Standard General Requirements for Liquid-Immersed Distribution, Power and Regulating Transformers. IEEE Std. 57.12.00-1993.

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