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Fuzzy logic applied to the diagnosis of technical conditions of distribution transformers

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Abstract

The distribution transformers are one of the most important elements for the operation of the distribution networks, considering their quantity and dispersion in the network, and that the failures cause great economic losses, both from the point of view of the transformer itself and of the cost of the energy left to serve. The technical condition of the distribution transformers depends on multiple external factors that influence the loss of useful life of the same, and therefore, it is necessary to relate them for a correct diagnosis. In the present work, a method based on fuzzy logic is developed for the diagnosis of distribution transformers, considering the international regulations that govern its operation. The resulting procedure was implemented using the fuzzy toolbox of MATLAB programming tools version 9.8 (R2020a). A random sample of transformers in three distribution circuits was evaluated, and the results correspond to that established in the IEEE C57.91 standard of 2011.

Keywords: Distribution transformers, Diagnosis, Electrical distribution networks, Fuzzy logic, Technical condition

Introduction

Putting a distribution transformer out of service represents a serious problem for electricity distribution companies since it always brings with it a more or less prolonged service interruption in sectors with social or economic impact. However, the case becomes more dramatic when the interruption of the transformer's operation is caused untimely by an equipment failure, since the aforementioned inconveniences; we would have to add the cost of repairing or replacing the transformer, which results in. It is vitally important to monitor the technical status of this equipment in a distribution network.

Transformer diagnosis methods are in constant development and are typically based on analysis of chemical indicators of the oil, using, for example, methanol (MeOH) and 2-furfural (2FAL) as indicators of the aging state of the transformer [1–3]; other research has been directed to the identification and analysis of partial discharge (PD) pulses [4, 5], and in the last two decades, some processing tools based on the time domain, frequency domain, or hybrid domains have been developed for detecting and analyzing PD signals; the Fourier transform, the short-time Fourier transform, the waveform transform, and the Gabor transform are some examples of techniques used [6, 7]. More recently, frequency response analysis (FRA) has been used worldwide. The reliability of this method has been shown to diagnose transformer conditions, especially mechanical vibrations. The FRA technique is performed by comparing the response result in the initial condition of the transformer with its current condition. The interpretation of the transformer condition from the response is based on frequency sub-bands. Each frequency sub-band indicates the vibration of any part of the transformer and electrical faults [8–12].

In [13, 14], a proactive diagnostic approach is presented based on the detection of short-circuit faults in the input terminals of power transformers based on the neutral current or a transformer model. Transformer modeling using finite elements has also been used for this purpose [15, 16].

However, to reliably assess the health condition of a transformer, all available evidence from various sources should be integrated. This includes online and offline measurements, operation and maintenance data, failure statistics, on-site inspection, and expert experience. The health index, an overall assessment of the transformer's health condition, can be obtained by combining such condition data with electronics [17].

A little discussed approach is the life cycle cost analysis; in [18] is presented an experience in managing the complete life cycle to improve performance and reliability. Using failure mode, effect, and criticality analysis based on the previous failure data, lifecycle management strategies have been identified but only limited to an element of the transformer, the on-load tap changer (OLTC). This approach is further discussed in [19], proposing a life cycle cost analysis method of distribution transformers considering high overload capacity and vegetable insulating oil; however, this method is oriented to transformer selection, not to diagnosis of technical condition.

Diagnosing distribution transformers is challenging due to their large quantity and decentralized location in the distribution network. The diagnostic techniques require measurements of various parameters, making them more suitable for power transformers located in substations. However, online monitoring schemes based on microcontrollers and IoT have been proposed as a solution [20, 21]. In [22], an online condition monitoring system (OCMS) algorithm for the health index determination of substation or service transformers is implemented in C+ +using Raspberry Pi2 modified version of Debian GNU/Linux. The proposed OCMS is a cost-effective, online, and accurate tool, and it has several features like proposing corrective actions for the benefit of power utilities but requires strong measurement infrastructure for distribution networks.

To solve this problem, artificial intelligence techniques have been used, to design an approach that allows the detection of problems in transformers that can lead to accurate fault prediction without continuous human monitoring [23]. In this sense, various techniques have been used such as neural networks [24], text mining with machine learning [25, 26], fuzzy logic [27, 28], or combined techniques such as neurofuzzy networks [29].

In [30], a method for calculation of a health index for oil-immersed transformers rated under 69 kV using fuzzy logic is presented, but the method relies on the use of furan analysis, dissolved gas analysis, and other oil analysis results which is a disadvantage in having to take oil samples from each of the transformers evaluated.

In the present work, a fuzzy model based fundamentally on the distribution transformer's thermal behavior is proposed to diagnose its technical condition.

Methods

The proposed fuzzy model characterizes the state of the distribution transformer in a more reliable way, applying an interpretation methodology, contained in the international standards and the records of transformer failures of the distribution companies.

Based on a literature survey conducted in [22], antecedent variables for transformer failure have been identified. The survey included major causes reported by utilities around the world. Historical data or offline parameters discussed below need to be considered for the computation of health index.

- Age: The age of the transformer is the number of years it has been in service since installation. Typically, for service transformers, this is about 15–20 years [31].
- Loading history: Loading history refers to the history of all loads on the transformer, which is important in determining the amount of fatigue endured. It directly affects both the probability of failure and the lifetime of the transformer. Continuous loading at the rated capacity causes the winding conductor temperature to increase, leading to the hottest-spot temperature [32, 33].
- Location: Maintenance data from various utility companies show that transformers installed at different locations have different failure rates. Transformers are ranked by A for agriculture load, B for business load, I for industrial load, and R for residential load. However, rankings can vary between different utilities.

For this, four input variables are defined as follows:

- Operating time of the transformer
- The temperature of the hottest point
- Percentage of loss of useful life of the transformer
- Failure rate of the transformers of the circuit to which the transformer belongs

In addition, these conditions must be fulfilled at the same time, that is, the implication rules are related to each other with the AND connective.

The engine of an inference process is composed of a base of implication rules of the IF–THEN type. Since the reasoning, in this case, is not precise, a consequent can be inferred, even though the antecedents of the rule do not fully verify it. The said consequent will be more similar to the consequent of Formal Logic the more exactly the antecedents are fulfilled [34]. In this case, for practical application in equipment maintenance, the consequent does not require a numerical value but rather the concrete and at the same time fuzzy response of the type:

- Declare the transformer in good technical condition.
- Declare it at risk of failure.
- Declare it in imminent failure.

The main difficulty consists in correctly selecting the intervals within which the input variables are considered acceptable, as well as expressing the degree of such acceptability using the corresponding fuzzy set membership functions. Status scales "low," "medium," and "high" were used to identify the membership levels of the different input variables.

At the output, the program presents the user with the degree to which the transformer under analysis needs or does not need a maintenance intervention, in addition to allowing the behavior of the partial indicators to be observed, thanks to the possibility of seeing the corresponding graphs.

Therefore, taking into account the years of service and the difficult climatic conditions (high ambient temperatures, humidity), attention to such equipment should be increased. This attention should focus on the evaluation of the state of each transformer to determine the order of priority in its maintenance.

"Fuzzification" of input and output variables

In the fuzzification process, crisp inputs from the domain are transformed into fuzzy inputs with the help of the membership function. The input variables are compared with the membership functions on the antecedent part of fuzzy rule to obtain the membership values of each linguistic label [35].

The "fuzzification" of the first of the variables, "operation time of the transformers," is expressed through three triangular membership functions whose equations are shown below.

$$TEXP\ Low\begin{cases} -2x/TEXP_{global}+1 \quad if \quad 0 \leq x \leq TEXP_{ave} \\ 0 \quad if \quad x \geq TEXP_{ave} \end{cases} \tag{1}$$

$$TEXP\ Medium\begin{cases} 2x/TEXP_{global} \quad if \quad TEXPprom_{min} \\ -2x/TEXP_{global}+1 \quad if \quad TEXP_{ave} \leq x \leq TE_{max} \end{cases} \tag{2}$$

$$TEXP\ High\begin{cases} 2x/TEXP_{global}-1 \quad if \quad TEXP_{ave} \leq x \leq TEXP_{global} \\ 1 \quad if \quad x \geq TEXP_{global} \end{cases} \tag{3}$$

where

$TEXP_{global}$: Average global operating time of the transformers installed in the distribution network (years).

$TEXP_{ave}$: Average operating time of failed transformers (years).

$TEXP_{min}$: Average operating time of failed transformers minus three times the standard deviation (years).

$TEXP_{max}$: Average operating time of failed transformers plus three times the standard deviation (years).

The triangular membership function is a function of three parameters, actually a linear approximation of bell curves. The parameters of the membership functions are obtained through control charts as shown in Fig. 1, based on the information provided by the historical records of transformer failure in the distribution companies, using the average value of the operating time of the failed transformers and the standard deviation.

Figure 2 shows the graphical representation of the three membership functions of the exploitation time variable.

The variable temperature of the hottest point in the period of maximum demand is represented by three trapezoidal functions. This type of function represents sets in which for points of the domain near the central value, the degree of membership remains equal to

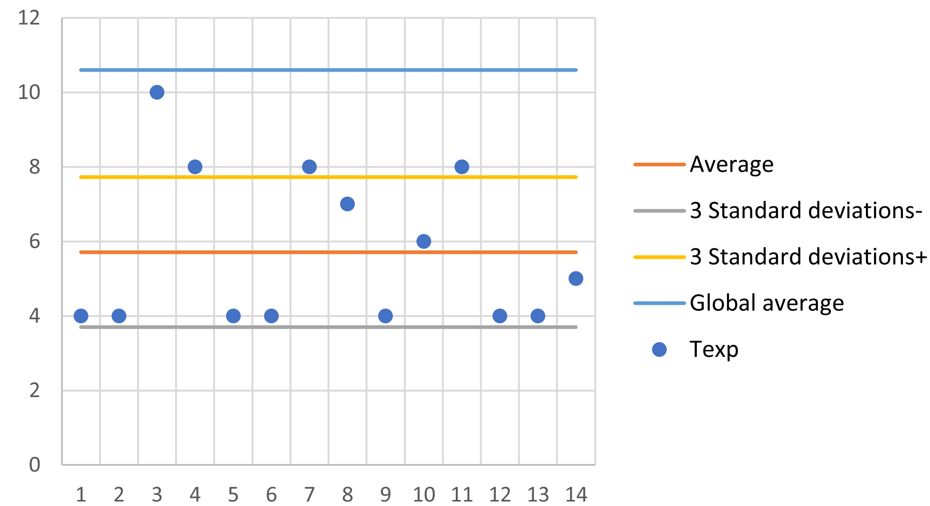

Fig. 1 Example of control chart based on the historical records of transformer failure in a distribution circuit

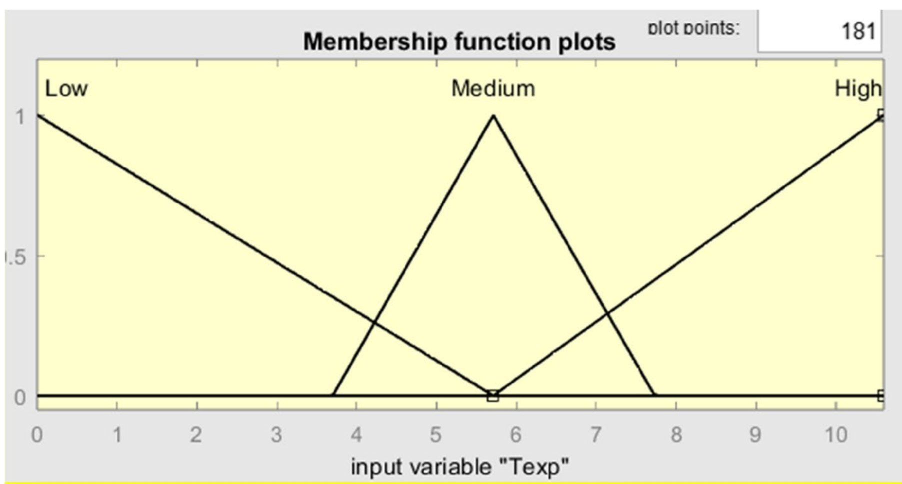

Fig. 2 Graphical representation of the fuzzification of the exploitation time variable

one, which is interpreted as a saturation zone, which is in correspondence with the transformer operating temperature behavior described in [33], whose expressions are as follows:

$$TLow\begin{cases} 1 \quad if \quad HST \le 110^0C \\ (130^0C - HST)/(130 - 110) \quad if \quad HST \in (110^0C, 130^0C) \end{cases} \tag{4}$$

$$TMedium\begin{cases} 0 \quad if \quad (HST \le 120^0C \ or \ HST \ge 180^0C) \\ (HST - 140^0C)/(140^0C - 120^0C) \quad if \quad HST \in (120^0C,\ 140^0C) \\ 1 \quad if \quad HST \in (140^0C,\ 160^0C) \\ (180^0C - HST)/(180^0C - 160^0C) \quad if \quad HST \in (160^0C,\ 180^0C) \end{cases} \tag{5}$$

Table 1 Insulation aging acceleration factor for continuous operation at the hottest spot temperature during one load cycle [33]

Hottest spot temperature °C (HST)	Insulation aging acceleration factor (IAAF)
110	1.00
120	2.71
130	6.98
140	17.2
150	40.6
160	92.1
170	201.2
180	424.9
190	868.8
200	1723

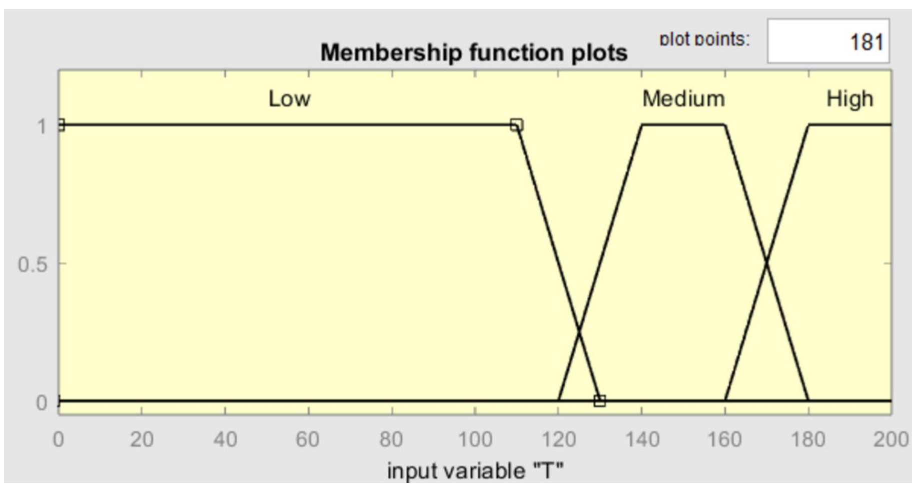

Fig. 3 Graphical representation of the fuzzification of the variable temperature of the hottest point

$$THigh\begin{cases} 0 \quad si \quad HST \leq 160^0C \\ (HST - 180^0C)/(180^0C - 160^0C) \quad si \quad HST \in (160^0C,\ 180^0C) \\ 1 \quad si \quad HST \geq 180^0C \end{cases} \tag{6}$$

where

HST: Maximum temperature calculated during a 24-h load cycle, using the calculation method established in annex G of the standard IEEE C57.91 of 2011 [33].

The limits of the trapezoidal functions were established according to Table 1, shown below.

Figure 3 shows the graphical representation of the three membership functions of the variable temperature of the hottest point.

Similar to the behavior of a transformer's operating temperature, the variable "percentage of loss of useful life" is also represented by a trapezoidal function, whose expressions are as follows:

$$LULP_{Low}\begin{cases} 1 \quad if \quad LULP \leq 0.0133 \\ (0.05 - LULP)/(0.05 - 0.0133) \quad if\ LULP \in (0.0133, 0.05) \end{cases} \tag{7}$$

$$LULP_{Medium}\begin{cases} 0 \quad if \quad (LULP \leq 0.0133\ or\ LULP \geq 0.3) \\ (LULP - 0.05)/(0.05 - 0.0133) \quad if \quad LULP \in (0.0133,\ 0.05) \\ 1 \quad if \quad LULP \in (0.05,\ 0.1) \\ (0.3 - LULP)/(0.3 - 0.1) \quad if \quad LULP \in (0.1,\ 0.3) \end{cases} \tag{8}$$

$$LULP_{High}\begin{cases} 0 \quad if \quad LULP \leq 0.1 \\ (LULP - 0.3)/(0.3 - 0.1) \quad if \quad LULP \in (0.1,\ 0.3) \\ 1 \quad if \quad LULP \geq 0.3 \end{cases} \tag{9}$$

where

LULP: Loss of life percentage calculated over a 24-h load cycle.

The limits of the trapezoidal functions were established according to Sect. 5.3 of the IEEE C57.91 standard of 2011 [33].

Figure 4 shows the graphical representation of the three membership functions of the variable percentage of loss of useful life.

Transformer parameters such as hottest point temperature and percentage of loss of useful life are calculated using the expressions from the IEEE C5791 standard [33]. The calculations are based on the transformer's characteristic data, load profile, and monthly billing data. The load profile is obtained from the type of customer the transformer supplies, which is recorded in the utility's network management system (SIGERE). A detailed calculation methodology can be found in [36].

Finally, the membership functions of the input variable circuit transformers' failure rate are obtained through fuzzy clustering [37], from the statistical information on failed transformers per circuit, related to the total number of transformers that the circuit has.

With these data, 3 groups with similar characteristics (cluster) are formed, which correspond to the 3 failure levels. The maximum, centroid, and minimum values of each cluster constitute the parameters of each membership function of the variable. It is represented by three triangular membership functions.

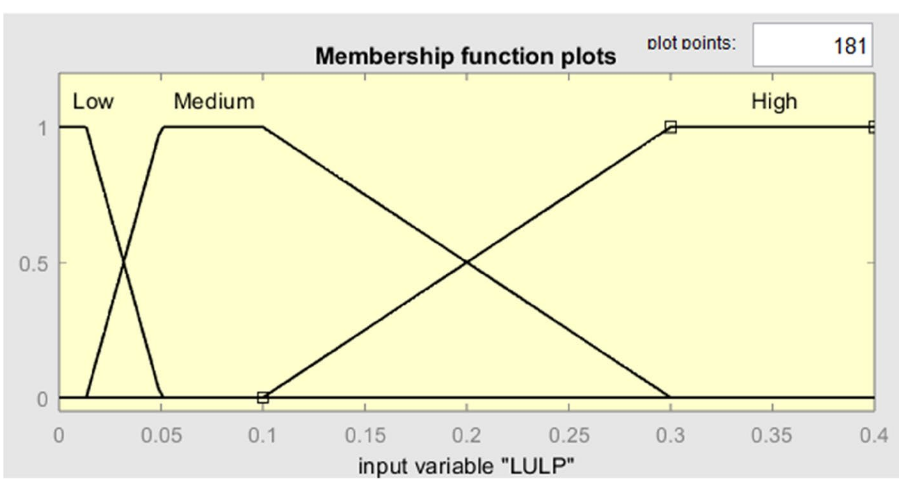

Fig. 4 Graphical representation of the fuzzification of the variable percentage of loss of useful life

The shape of the membership function is given by cluster plot; an example of cluster 1 plot is shown in Fig. 5.

The expressions of the membership functions are shown below.

$$Failure\ rate_{Low}\begin{cases} -2x/Nf+1 \quad if \quad 0\leq x\leq Nf_{centroid1} \\ 0 \quad if \quad x\geq Nf_{centroid1} \end{cases} \tag{10}$$

$$Failure\ rate_{Medium}\begin{cases} 2x/Nf_{centroid2} \quad if \quad Nf_{min1}\leq x\leq Nf_{centroid2} \\ -2x/Nf_{centroid2}+1 \quad if \quad Nf_{centroid2}\leq x\leq Nf_{max2} \end{cases} \tag{11}$$

$$Failure\ rate_{High}\begin{cases} 2x/Nf_{centroid3}-1 \quad if \quad Nf_{min3}\leq x\leq Nf_{centroid3} \\ 1 \quad if \quad x\geq Nf_{centroid3} \end{cases} \tag{12}$$

where

N_f: Circuit transformers' failure rate.

$N_{fcentroid1}$: Cluster 1 circuit transformers' failure rate centroid.

$N_{fcentroid2}$: Cluster 2 circuit transformers' failure rate centroid.

$N_{fcentroid3}$: Cluster 1 circuit transformers' failure rate centroid.

Figure 6 shows the graphical representation of the three membership functions of the circuit transformer' failure rate variable.

The consequent set, in this case, is defined by three states, which correspond to the risk levels established (without considering regular maintenance) in the standard [38] and is represented by three trapezoidal membership functions whose expressions are shown below.

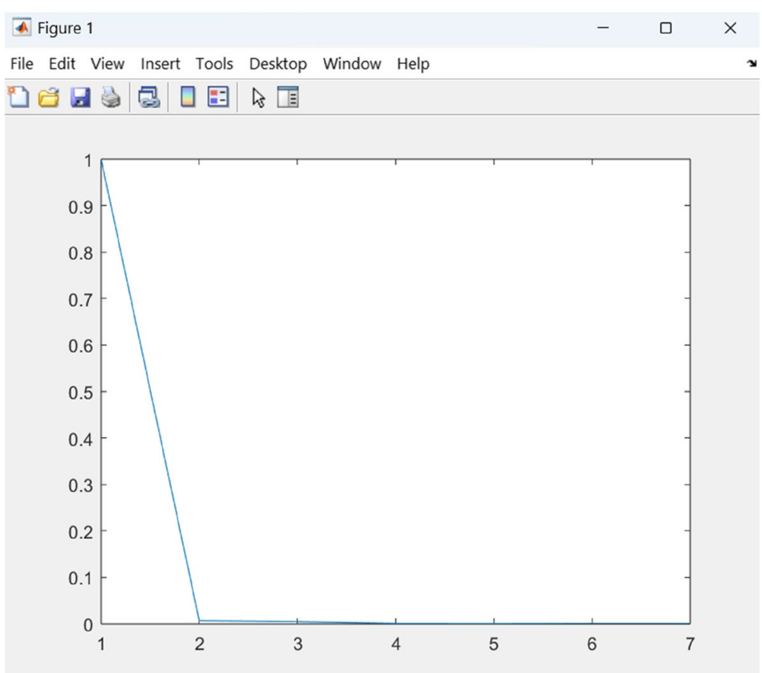

Fig. 5 Example of cluster plot corresponding to the shape of cluster 1 "low failure rate"

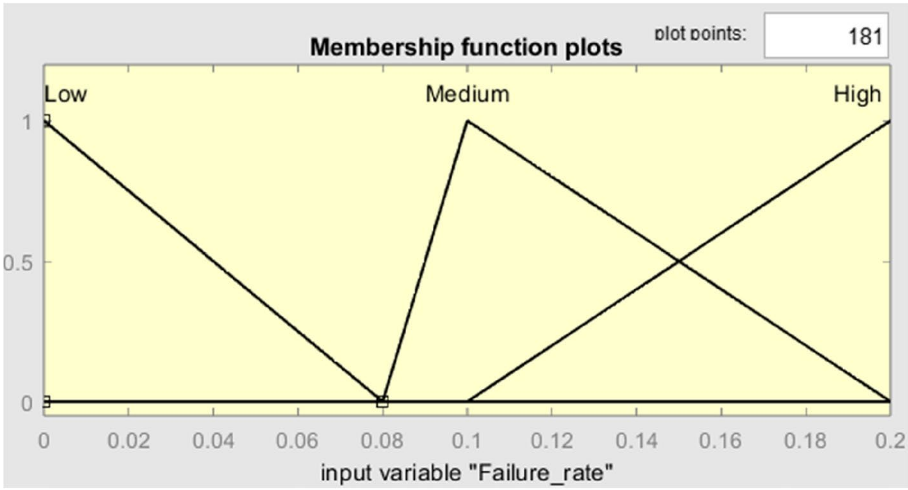

Fig. 6 Graphical representation of the fuzzification of the variable circuit transformer's failure rate

$$Good\ condition\begin{cases} 1 \quad if \quad LULPA \leq 4.85\% \\ (18.25\% - LUPLA)/(18.25\% - 4.85\%) \quad if \quad LULPA \in (4.85\%, 18.25\%) \end{cases} \tag{13}$$

$$In\ risk\begin{cases} 0 \quad if \quad (LULPA \leq 7.3\%\ or\ LULPA \geq 109.5\%) \\ (LULPA - 36.5\%)/(36.5\% - 7.3\%) \quad if \quad LULPA \in (7.3\%,\ 36.5\%) \\ 1 \quad if \quad LULPA \in (36.5\%,\ 73\%) \\ (109.5\% - LULPA)/(109.5\% - 73\%) \quad if \quad LULPA \in (73\%,\ 109.5\%) \end{cases} \tag{14}$$

$$Imminent\ failure\begin{cases} 0 \quad if \quad LULPA \leq 73\% \\ (LULPA - 109.5)/(109.5\% - 73\%) \quad if \quad LULPA \in (73\%,\ 109.5\%) \\ 1 \quad if \quad LULPA \geq 109.5\% \end{cases} \tag{15}$$

where

LULPA: Percentage of annual useful life loss, output variable that integrates into the result of the effect of the operating time of the transformers, and the incidence of transformer failures in a circuit.

Figure 7 shows the graphic representation of the three membership functions of the consequent, which allows establishing the technical condition of the transformer.

Inference system

The inference system's rule base for determining the distribution transformer's technical status has 81 implication rules. These implication rules relate the variables of the antecedent, (operation time of the transformers, temperature of the hottest point in the period of maximum demand, percentage of loss of useful life, the failure rate of circuit transformers), with the variable of the consequent (technical state of the transformer).

Based on the results of the literature survey [22], age and hottest point temperature are given the highest priority due to their influence on the health of the insulation. The useful life loss results are given second priority, while the failure rate of the circuit is allocated lower priority. The sum of the pondered weights of each antecedent variable should be equal to one.

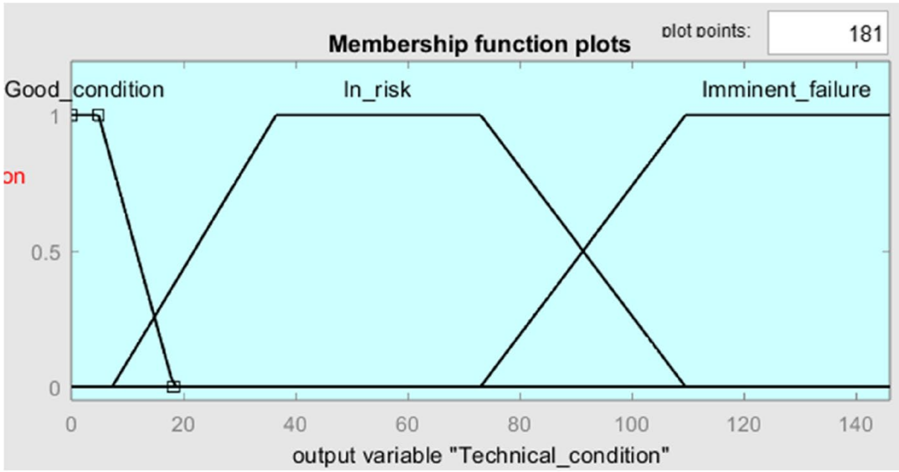

Fig. 7 Graphical representation of the variable of the consequent "technical condition of the transformer"

When applying any of the implication rules mentioned above, a result that is difficult to apply in practice is obtained: a value of the antecedent infers a fuzzy set of values of the consequent; this can be seen in Fig. 8, where an example of the rule is base.

This figure shows the rule editor where each of the 81 rules relating each variable of the antecedent to the variable of the consequent is written using the AND connective, for example, rule 1 shown in the figure in the rule editor would be as follows:

IF the operating time (TEXP) is low AND hottest point temperature (T) is low AND life useful loss percentage (LULP) is low AND the circuit transformer failure rate (failure rate) is low, THEN transformer technical condition is GOOD.

The rule viewer is also shown where it can be appreciated which membership value takes each of the antecedent variables and the consequent variable in each of the rules for a set of input data for each of the antecedent variables. The example in the figure refers to a transformer with 4.5 years of operation, 100 °C hottest point temperature during the maximum demand of the daily load cycle, 0.2% loss of useful life, and a failure rate of 0.15 failed transformers per installed transformer in the circuit.

When a single value of the consequent is needed to be able to use it as a definition of the risk of failure, a special operation is defined, called "defuzzification"; in this case, the center of gravity method was used.

This method expresses the weighted average concept of the fuzzy set of the consequent, where the weight is the area under the curve of its membership function.

$$u = \frac{\int_{u_{\min}}^{u_{\max}} \mu(x_i) \cdot x_i}{\int_{u_{\min}}^{u_{\max}} \mu(x_i)} \tag{16}$$

When the membership functions of the linguistic values "i" of the consequent have symmetry concerning a vertical axis, with the central value ci, the defuzzification is obtained as the weighted average of said central values, using as weight the area under the curve of membership:

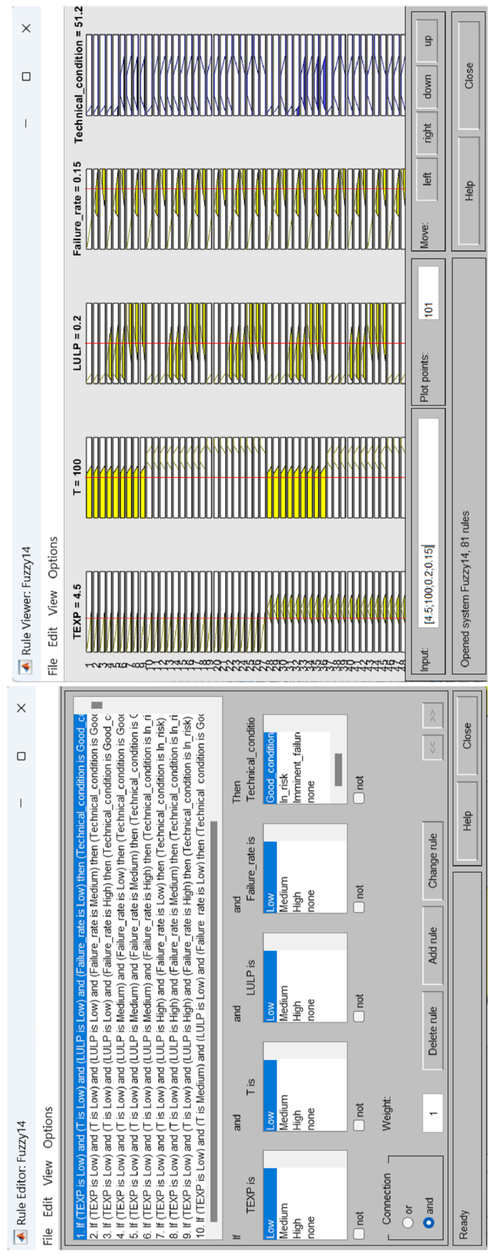

Fig. 8 Example of the implication rule base, in the Mamdani inference system

$$u = \frac{\sum_{i=1}^{u} C_i \cdot A_i}{\sum A_i} \tag{17}$$

When the linguistic values of the consequent are singletons (which is equal to the use of the implication of the drastic product) with their respective central values, the areas Ai degenerate into numbers μi(u), that is, into values of the membership of the antecedent, and the expression is as follows:

$$u = \frac{\sum_{i=1}^{u} \mu_i \cdot C_i}{\sum_{i=1}^{u} \mu_i} \tag{18}$$

The method assesses each factor's risk individually and sums them up to find the cumulative risk, which is better than generalized aggregation. Fuzzy logic's AND operators can quickly reach maximum membership value (equal to unity), losing details of risk assessment for different situations.

This method results in the numerical assessment of the seriousness of the situation, whose additional advantage is the high power of discrimination.

Figures 9, 10, and 11 show the behavior of the consequent variable depending on the variation of the values of the antecedent variables, as it can appreciate in them that the variable that most influences the technical state of the transformer, considering that it all have the same weight, is the temperature of the hottest point.

Results and discussion

The method was applied to a random sample of 8 distribution transformers installed in 3 distribution circuits. From the physical characteristics, the materials used to build the transformer, and the load curves from their associated customers, the principles and formulas proposed in the references [39, 40] were applied to obtain the hottest point temperature.

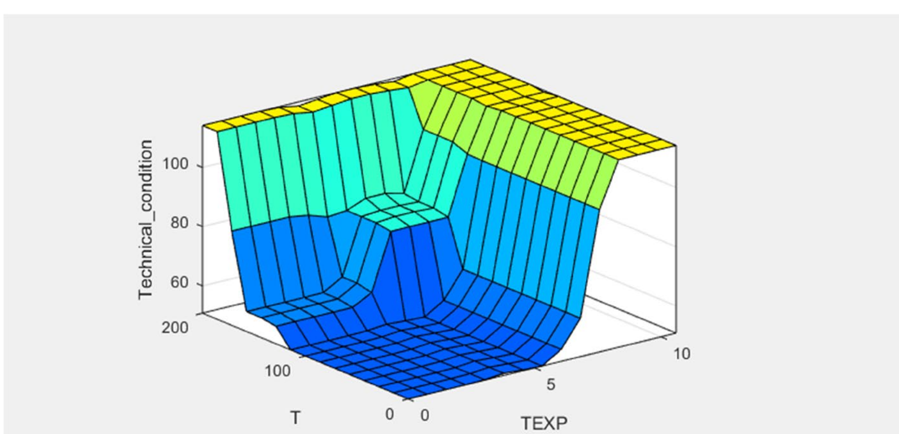

Fig. 9 The behavior surface of the consequent variable, depending on the variation of the antecedent variables "temperature of the hottest point" and "operation time of the transformers," in the Mamdani inference system

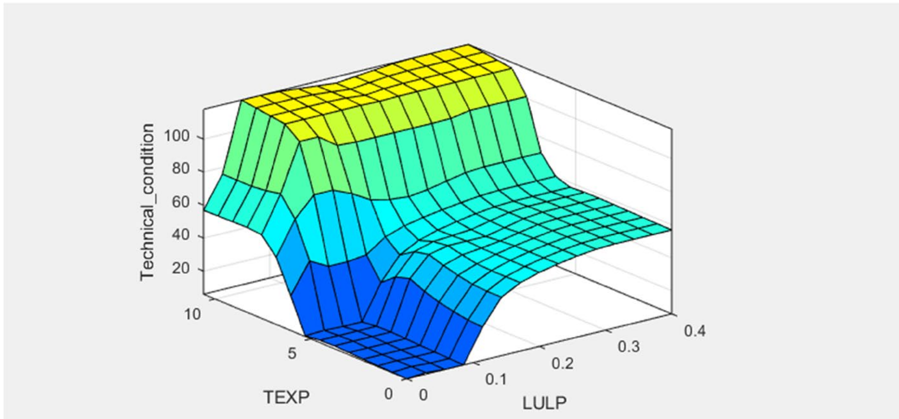

Fig. 10 The behavior surface of the consequent variable, depending on the variation of the antecedent variables "temperature of the hottest point" and "percentage of loss of useful life," in the Mamdani inference system

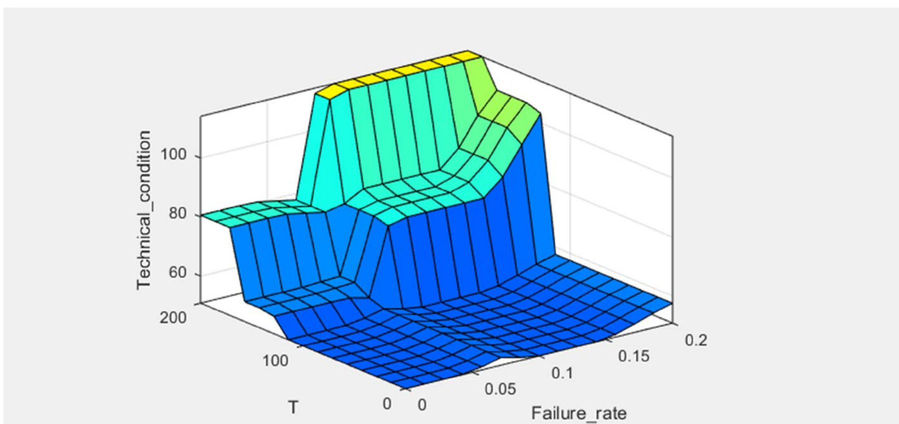

Fig. 11 The behavior surface of the consequent variable, depending on the variation of the antecedent variables "temperature of the hottest point" and "circuit transformers' failure rate," in the Mamdani inference system

Once the temperature of the hottest point of the transformer is taken into account, the aging acceleration factor per hour was calculated, the aging factor over a period of time, and the percentage of life useful loss relating to a useful life of 180,000 h. Although this is a reference, it should not be confused with a real calculation of the useful life of the transformer, because although temperature is a fundamental factor that affects the insulation, it is not the only one, and transformers with insulation well below the minimum have been in service for years [33, 41].

The failure rate of the circuit transformers is calculated by dividing the number of failed transformers by the total number of installed transformers.

Table 2 shows the values of the input variables, and Table 3 shows the results obtained for each of them.

The results of the parameters obtained for each transformer, shown in Table 2, are entered as input data to the fuzzy inference system. Table 3 shows the value of the

Table 2 Values of the input variables for the test transformers

Code	TExp (years)	HST (°C)	LULP (%)	Circuit transformers' failure rate
CB-0082	4	54.32	0.0056	0.10
CB-0181	4	54.88	0.0064	0.09
CB-0033	10	68.6	0.0069	0.10
CB-0009	8	92.4	0.0059	0.15
CB-0086	4	54.1	0.006	0.053
CB-0036	4	115.7	0.049	0.059
CB0048	8	80.2	0.0078	0.062
CB0130	7	52.7	0.0064	0.10

Table 3 Results obtained for the test transformers

Code	LULPA (%)	Technical condition
CB-0082	7.81	Good
CB-0181	2.04	Good
CB-0033	6.27	Good
CB-0009	57.6	In risk
CB-0086	7.81	Good
CB-0036	77.81	In risk
CB0048	7.31	Good
CB0130	7.363	Good

consequent variable after the defuzzification process and the membership function "technical condition" to which each transformer belongs.

As can be seen in the results, there is a correspondence with what is established in the IEEE C57.91 standard of 2011; of the analyzed transformers, those whose temperature of the hottest point is close to or above 110 °C are at risk, which is the maximum permissible temperature for the continuous operation of the transformer, and the loss of annual useful life obtained through fuzzy logic is slightly higher than that obtained conventionally, due to the influence of the rest of the factors, such as the operating time of the transformers under study and the failure rate of the transformers of the circuit in which they are located.

Normally, before being damaged, a transformer trips or fails several times, especially when it is subjected to large overloads, so it would be convenient to review the correspondence between the transformer banks with tripping and those considered at risk.

For this purpose, the selected banks were monitored for 1 year; Table 4 shows the results.

The table shows that even though the temperature of the hottest point for a load cycle in the transformers at risk is below the limit established by the IEEE C57.91 standard of 2011, the protection devices of these transformers have operated at least once during the year.

Table 4 Number of protective device operations per year

Code	Technical condition	Number of protective device operations per year
CB-0082	*Good*	*0*
CB-0181	*Good*	*0*
CB-0033	*Good*	*0*
CB-0009	*In risk*	*1*
CB-0086	*Good*	*0*
CB-0036	*In risk*	*3*
CB0048	*Good*	*0*
CB0130	*Good*	*0*

Conclusions

The proposed fuzzy model allows working with standardized variables according to the IEEE C57.91–2011 standard, considering the technical and construction characteristics of all types of transformers, among which we can mention the nominal power, the nominal losses, the weight of the elements, monthly invoicing of the same, and the type of service that it provides.

Although there is a direct relationship between the temperature of the hottest point and the loss of useful life, the percentage of loss of useful life also depends on other factors such as the characteristics of the oil and humidity; other aspects, such as external faults and overvoltage, harm the condition of the insulating.

The loss of useful life depends not only on the value of the temperature as such but also on the time that the transformer is kept operating at said temperature; for this reason, it was decided to use the percentage of loss of useful life as an independent input variable in the fuzzy model.

The implementation of this method generates an impact that is given by the nonuse of resources such as fuel, wages, and means of measurement, such as thermographic cameras, massively, in the diagnosis of distribution transformers; it is only necessary to have the updated databases of the distribution circuits. In addition, due to early diagnosis, the cost of damaged transformers is avoided.

Abbreviations

PD	Partial discharge
FRA	Frequency response analysis
HST	Temperature of the hottest point
IAAF	Insulation aging acceleration factor
LULP	Loss of life percentage calculated over a 24-h load cycle
LULPA	Percentage of annual useful life loss, output variable that integrates into the result, the effect of the operating time of the transformers, and the incidence of transformer failures in a circuit.

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Authors' contributions

ES, research design, theoretical formulation, data collection and processing, analysis of the results, and writing the manuscript. JM, theoretical formulation, data collection and processing, and analysis of results. AS, data collection and processing and analysis of results. YF, data collection and processing and analysis of results. All authors read and approved the final manuscript.

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Availability of data and materials
The distribution transformers primary records data used to support the findings of this study have not been made available because these data were used for this research under a confidentiality agreement with the electrical distribution companies that supplied it.

Declarations

Competing interests
The authors declare that they have no competing interests.

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