Intelligent Systems for the Detection of Internal Faults in Power Transmission Transformers

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1. Introduction

This chapter presents an approach based on expert systems, which is intended to identify and to locate internal faults in power transformers, as well as to provide an accurate diagnosis (predictive, preventive and corrective), so that proper maintenance can be performed. In fact, the main difficulty in using conventional methods, based on analysis of acoustic emissions or dissolved gases, lies in how to relate the measured variables when there is an internal fault in a transformer. This kind of situation makes it difficult to design optimized systems, because it prevents the efficient location and identification of possible defects with sufficient rapidity. In addition, there are many cases where the equipment must be turned off for such tests to be carried out. Thus, this chapter proposes an architecture for an intelligent expert system for efficient fault detection in power transformers using different diagnosis tools, based on techniques of artificial neural networks and fuzzy inference systems. Based on acoustic emission signals and the concentration of gases present in insulating mineral oil and electrical measurements, intelligent expert systems are able to provide, as a final result, the identification, characterization and location of any electrical fault occurring in transformers.

With the changes occurring in the electricity sector, there is a special interest on the part of power transmission companies in improving and defining strategies for the maintenance of power transformers. However, when a fault occurs in a transformer, it is generally removed from the system and sent to a maintenance sector to be repaired. With this in mind, some feasibility studies have been conducted, aimed at supporting the electrical system in order to maintain the supply of energy, reducing operation costs and maintenance. Among these investigations, researches have been accomplished into the identification of internal faults in power transformers. In this case, the analysis of dissolved gases [1]-[5] and/or of acoustic emissions [6]-[10] can be highlighted. Within the context of economic viability, it is worth noting the increasing difficulty of removing an operating power transformer and placing it under maintenance. Thus, the above techniques, which evaluate parameters or quantities that indicate the current state of the transformer, have emerged as a more attractive alternative.

Although some papers deal with the development of tools for monitoring sensors [3], very few papers can be found on the efficient use of both sensor types (dissolved gases and acoustic emissions) in the same study. This is probably due to the fact that the cost associated with the acquisition of these sensors is very high. Another factor that should be highlighted is the growing use of intelligent tools for identifying and locating of internal faults [1-2, 5, 7].

The increasing use of intelligent tools is due to the fact that conventional techniques are not always able to achieve high accuracy rates of fault identification. In one of the most outstanding studies in the area [1], which makes a comparison between conventional and intelligent tools, the authors propose a method based on obtaining association rules that perform the best analysis of dissolved gases and satisfactorily ensure reliable identification of failures. The authors compared the proposed technique with other conventional methods (Rogers and Dornenburg) and intelligent techniques (Neural Networks, Support Vector Machines and *k*-Nearest Neighbors). A total of 1193 samples from dissolved gas sensors were acquired, which were divided into two sets of data in order to evaluate each technique used, i.e., one for training (1016 samples) and the other for validation (177 samples). After all training and validation processes had been conducted, the following accuracy rates were obtained: Artificial Neural Networks (62.43%), Support Vector Machines (82.10%), k-Nearest Neighbors (65.85 %), Rogers (27.19%), Dornenburg (46.89%) and Association Rules (91.53%). According to the results, it can be clearly seen that intelligent systems outperform conventional methods.

In addition to this paper, in [2], the authors make a more detailed analysis of gases. In this analysis, a total of 10 kinds of fault were considered, namely: partial discharge, thermal failures lower than 150°; thermal failures greater than 150° and lower than 200°; thermal failures greater than 200° and lower than 300°; cable overheating; current in the tank or iron core, overheating of contacts; low energy discharges, high energy discharges, continuous sparkling (a luminous phenomenon that results in the breakdown of the dielectric by discharge through the insulating oil), and partial discharge in solid insulation. It is worth mentioning that the method applied in this study was based on a fuzzy inference system, which was tested under controlled fault conditions. Other tests were also realized in Hungarian substation transmission transformers, where the method performed well against the uncontrolled failure scenarios.

However, studies [1] and [2] present a gap with regard to internal fault diagnosis for power transformers, because they only identify the type of failure and do not locate the partial discharges.

In order to provide a better fault diagnosis for power transformers, some studies have used acoustic emissions to locate faults due to partial discharges. Among these investigations, in [8], the authors propose a geometric analysis of the arrival times of acoustic emission signals in order to properly locate the sources of partial discharges. In the proposed methodology, they use both time measurements from sensors and pseudo-measurements, which provide greater precision in the tracking system of partial discharges.

In the context of these studies, this chapter aims to determine the necessary procedures for the development of a methodology based on information from sensors for both dissolved gases and acoustic emissions. The purpose of this methodology is achieve satisfactory results for identifying internal faults, and, in the case of faults due to partial discharges, to locate them accurately to help in the process of decision-making related to the maintenance of transmission transformers.

The tasks of identifying and locating internal faults in power transformers are extremely important, since they have a very high aggregate cost for purchase and for maintenance. Dissolved gas analysis and the analysis of partial discharges by means of acoustic emission sensors are essential for maintaining the equipment, and can bring many benefits, such as reducing the risk of unexpected failures, extending the useful life of a transformer, decreasing maintenance costs and reducing maintenance time (due to the precise location of the failure). Furthermore, with the processing of these data by means of intelligent expert systems, it becomes possible to provide answers to help in the decision-making process about the power transformer analyzed.

2. Internal Faults in Transformers

The diagnosis of the status and operating conditions of transformers is of fundamental importance in the reliable and economic operation of electric power systems. The aging and wear and tear of transformers determine the end of their useful life; thus, the occurrence of faults can affect the reliability or availability of the power transformer. Understanding the mechanisms of deterioration and having technically feasible and economically viable repair strategies enables us to correlate faults with the operating evolution of the equipment in service [11].

Many techniques have been proposed to ensure the integrity, reliability and functionality of power transformers, all of which seek trinomial low cost, efficiency and rapid diagnosis. Among several techniques available for detecting internal faults in power transformers, acoustic emission analysis can be highlighted because it is not invasive, allowing analysis to be conducted on the equipment during normal operation [12].

A power transformer can be affected by a variety of internal faults, such as partial discharge, electrical arcs, sparks, corona effects, and overheating. Of these, Partial Discharge (PD) can be highlighted, since it is directly related to the insulation conditions of a power transformer, which in turn trigger the occurrence of more severe faults. PD in high voltage systems occurs when the electric field and localized areas suffer significant changes which enable an electric current to appear [6].

According to [13], PD can be grouped into 8 classes:

- Point to Point discharges in insulating oil: these PDs are related to insulation defects between two adjacent turns in the winding of a transformer;
- Point to Point discharges in insulating oil with bubbles: this kind of fault is also caused by PD between two adjacent winding turns, but the condition of insulation degradation allows the formation of gas bubbles;
- Point to Plan in insulating oil: defects in the winding insulation system can cause PD between it and the grounded parts of the transformer tank;
- Surface Discharges between two electrodes: the most common kind of PD, occurring between two electrodes insulated with oil-paper called triple point, where the electrode surface is in contact with dielectric solids and liquids;
- Surface Discharges between an electrode and a multipoint electrode: the PD relating to these elements differ from the previous one with regard to the intensity distribution of the electric field. Both are insulated with oil-paper;
- Multiple Discharges on the plan: multiple damaged points in the winding insulation may cause PD between it and the grounded parts of the transformer tank;
- Multiple Discharges on the plan with gas bubbles: the PD in this case occurs at various damaged points in the winding insulation and the grounded parts of the transformer tank, but in the presence of gases dissolved in insulating oil;
- Discharges caused by particles: in this case, the insulating oil is contaminated with particles of cellulose fiber formed by the degradation process of the oil-paper insulation system, due to the aging of the power transformer. Such particles are in constant motion in the oil, causing PD;

3. Laboratory Aspects for Internal Fault Experiments in Power Transformers

It is important to specify equipment, methods and parameters, which vary according to the type of defect that is to be analyzed. In simple terms, the monitoring system can be better understood through Figure 1.

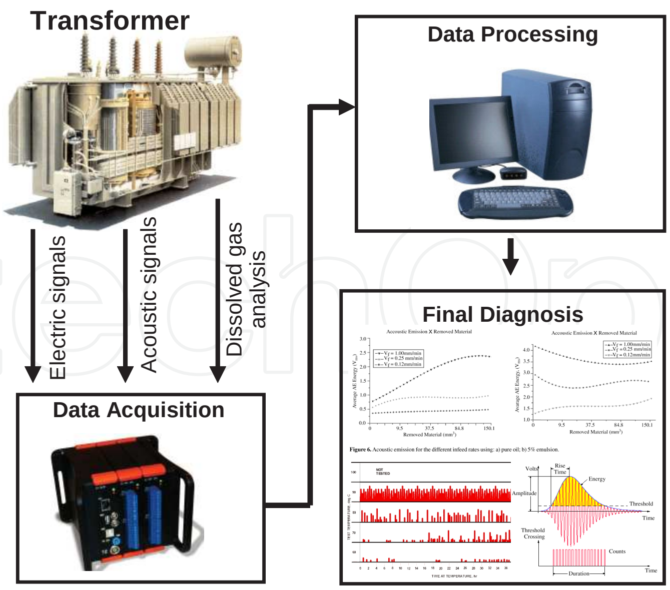

Figure 1. Laboratorial setup diagram.

The structures highlighted (inside the black boxes) are those that present the greatest challenges for configuration and parameterization, which are entirely dependent on the type of tests to be accomplished.

The most complete and detailed tests are (given their wide coverage of internal faults) more complex and expensive due to the various devices necessary used for the fault detection and location process, because more sensors and also data acquisition hardware are necessary.

3.1. Electrical measurements

Electrical parameters are also necessary for a correct characterization of internal transformer faults, especially when dealing with systems that require databases for normal operating conditions and with situations when a system has to be restored following a disturbance. This is the case of artificial neural networks, which require quantitative data for the learning process. It is necessary to measure voltages and three-phase primary and secondary currents, totaling 12 electrical parameters. The acquisition frequency in this case must not be high, because the purpose is to investigate the most predominant harmonic components in the electrical system.

3.2. Acoustic measurements

The acoustic signals are captured by acoustic emission sensors distributed evenly throughout the tank, which are externally connected to the power transformer. Such sensors have several characteristics that require a correct specification:

- Number of sensors per transformer: The number of sensors needed to detect internal faults in transformers varies according to the size of the equipment, amount of available channels and the type of fault to be detected. For the fault location task, for example, it takes a greater number of sensors, so that the entire volume of the transformer can be monitored. Thus, a total of 16 to 20 sensors is normally used [14];

- Pre-amplification: This item is extremely important because only the amplified acoustic signals are sent to the acquisition hardware, which removes extraneous noises;

- Operating frequency: This is strongly dependent on the type of fault to be monitored. Mechanical faults are associated with frequencies ranging from 20 kHz to 50 kHz, while electrical ones vary between 70 kHz and 200 kHz;

- Resonance frequency: This parameter defines the frequency where the signal gain is maximum. For maximum performance, it is necessary for the resonance frequency of the sensor to be tuned to the phenomenon to be monitored. The most common sensors have a resonance frequency of 150 kHz.

The experimental apparatus for supporting experiments aimed at testing computer systems developed for identifying and locating partial discharges in power transformers consists of a metal tank, in which all the devices responsible for the acquisition of acoustic and electrical signals are mounted. Figure 2 illustrates a tank specially prepared for this purpose.

Figure 2. Tank for experimental testing.

Figure 3 illustrates the attachment of an acoustic emission sensor mounted on the outside of the metal tank, whose signals are transmitted via cable to the acquisition system.

Figure 3. Acoustic emission sensor fixed to the outside of the tank.

Figure 4 illustrates a device made in order to produce partial discharges in the tank. The mechanism can also be moved within the tank, in all directions, by means of a rail and pulley system.

Figure 4. Device to produce partial discharges in the tank.

3.3. Measurements of dissolved gases

Measurement of dissolved gases in insulating oil can be acquired from chromatographic analysis of the oil, which is often performed in the laboratory. However, there are now some commercial devices that sense some gases dissolved in the oil. These devices can be used to monitor a power transformer in real time. It is worth mentioning that, through the analysis of dissolved gases, it is possible to obtain a first indication of a malfunction, which is usually related to electrical discharges and overheating.

Figure 5 shows the installation (in the tank) of the gas sensor, which is responsible for acquiring information on the quantities of gases dissolved in the insulating oil in order to relate them to internal defects.

Figure 5. Gas analysis sensor installed in the experimental tank.

3.4. Equipment for data acquisition

As seen above, the frequencies for electrical signals differ greatly from those found in acoustic signals, whose acquisition hardware can be divided into two according to technical and financial aspects:

- Hardware for electrical signals: for power quality purposes established in the Brazilian standard PRODIST [15], the 25th harmonic is the last one of interest. Thus, according to the Nyquist criterion, a minimal acquisition rate of 3 kHz is required. For electrical parameters it is also possible to use hardware with an A/D multiplexed converter, which reduces the cost of equipment;

- Hardware to acoustic signals: one of the factors that make this hardware expensive is the need to use an A/D converter for each channel. The sources of acoustic emissions also vary between 5 kHz and 500 kHz, where an acquisition frequency in MHz is necessary.

3.5. Computer for receiving and processing data

The computer is responsible for storing acoustic, electrical and dissolved gas data coming from the hardware acquisition. The hardware bus speed and the disk storage capacity must also take into account the amount of planned experiments, although a high performance disk is unnecessary, since a SCSI bus can be used.

3.6. Analysis and diagnosis

The implementation of this structure is very challenging, because it consists of a combination of techniques to efficiently identify and locate faults in power transformers. Among these techniques, those based on intelligent systems have efficiently increased the performance of processes involving the detection and location of faults [13].

4. Data Analysis from Acoustic Emission Signals

Altogether, we collected 72 oscillograph records of partial discharges. Each of these records depicts a time window of one second. In general, many occurrences of partial discharge are registered in these time slots.

In addition to this phenomenon, the data acquisition system also recorded mechanical waves that were used to evaluate the gauging of acoustic emission sensors. These waves are the result of the break, near the surface where the sensor is installed, of graphite with specifications given by the manufacturer of acoustic emission sensors. The graphs resulting from this test are highlighted in Figure 6.

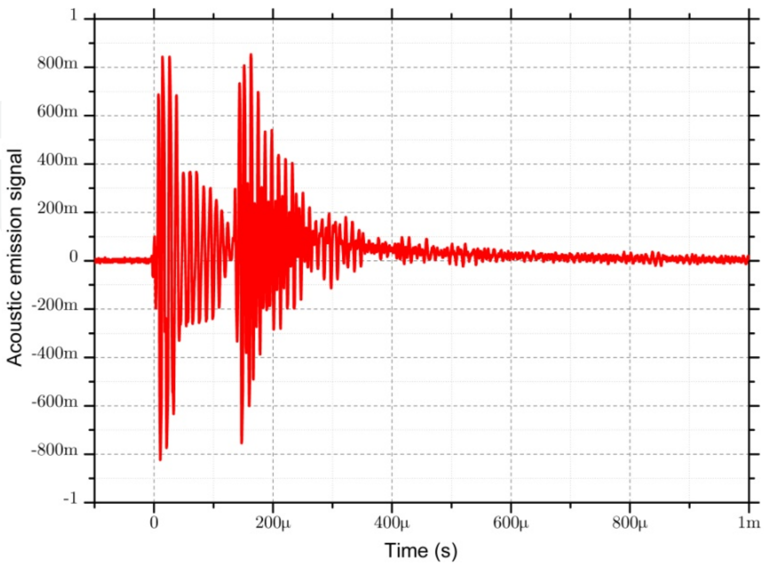

Figure 6. Acoustic emission signal resulting from the gauging process of sensors.

As shown in this figure, the signal is thus composed of two well-defined moments. The first of these relates to the instant when there was a mechanical disruption of graphite, while the second stage is the result of the impact of the pencil with the surface where the acoustic emission sensor is installed.

Figure 7 shows in more detail the first moment of the mechanical wave in Figure 6, while Figure 8 illustrates how the mechanical waves are related to the currents resulting from partial discharges.

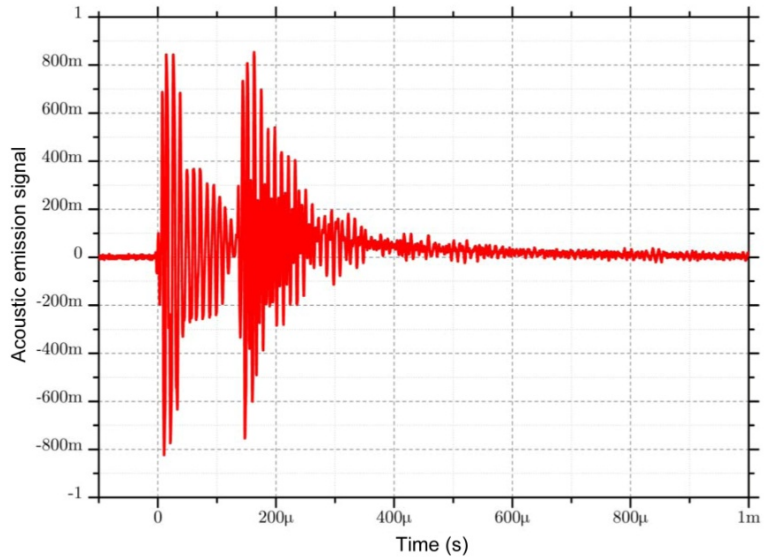

Figure 7. Details of the acoustic emission signal resulting from the gauging process of sensors.

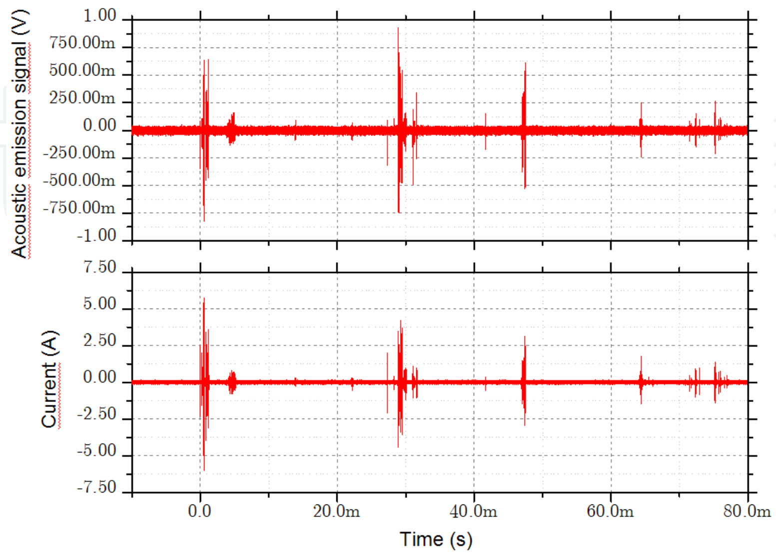

Figure 8. Relationship between partial discharge current and acoustic emission waves.

From Figure 8 we can see that each partial discharge results in a highly correlated mechanical wave. The graphs shown in Figure 9 highlight this relationship more clearly.

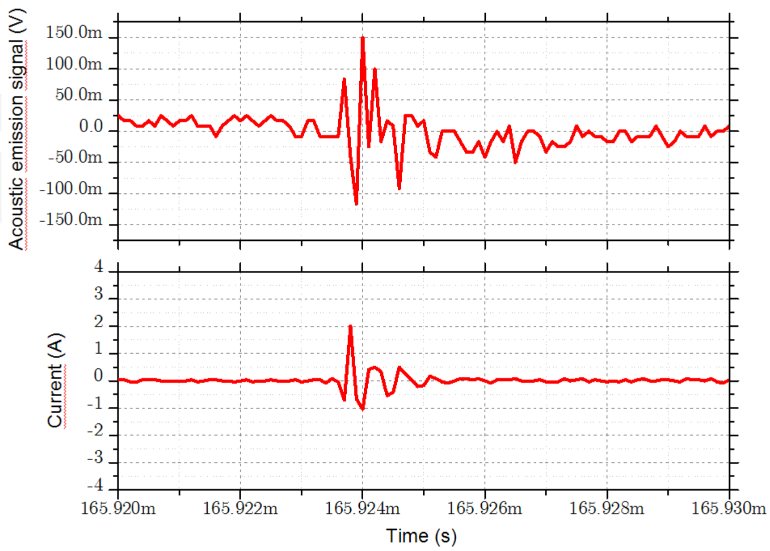

Figure 9. Detail of relationship between partial discharge current and acoustic emission.

Figure 10 illustrates the average frequency spectrum of an acoustic emission signal coming from a standard partial discharge. Through this frequency behavior, it can be seen that there is high signal energy at approximately 95 kHz and within the range between 160 kHz and 180 kHz. These values are of great importance in distinguishing partial discharge signals from other interferences.

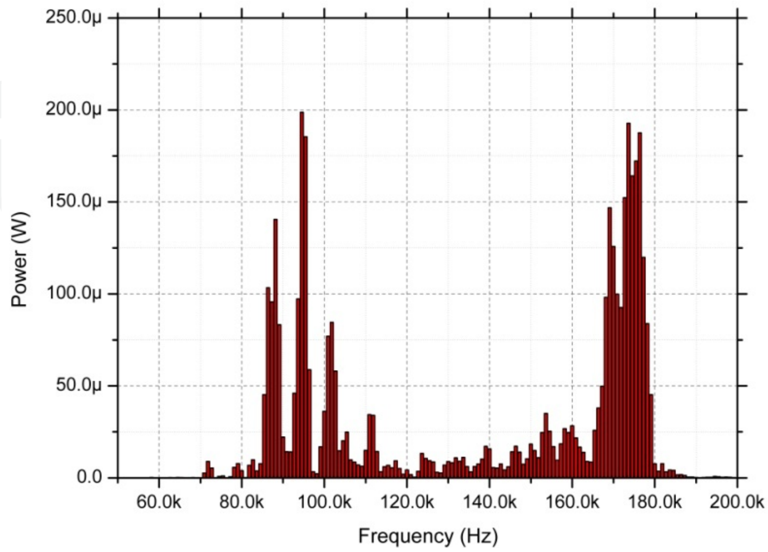

Figure 10. Average frequency spectrum of acoustic emission signal coming from a partial discharge.

In order to verify the behavior of the sensors for the tests, the voltage and current signals are processed in order to find the frequency response of these devices. In Figure 11 the amplitude versus frequency for the first calibration test has been recorded. The top of the graph highlights the energy and voltage signals sampled, and at the bottom there is the amplitude versus frequency. From the signal analysis it is then possible to observe a maximum response around 400 Hz and 100 kHz.

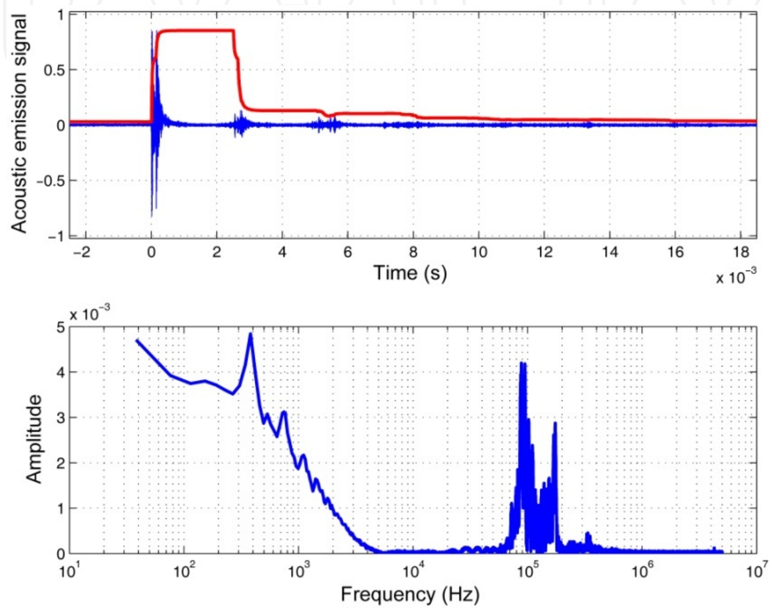

Figure 11. Frequency response of the acoustic emission signal.

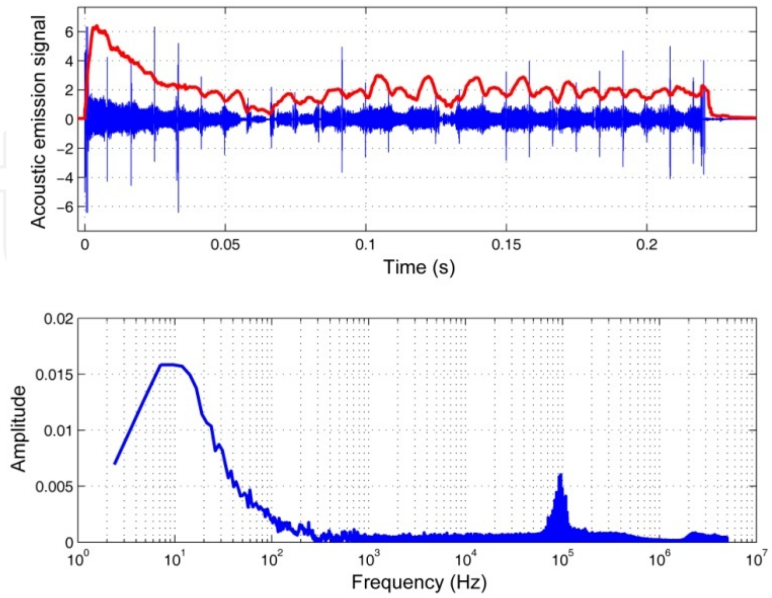

Figure 12. Detail of frequency response of the acoustic emission signal (segment 1).

In Figure 12, the signals were assigned in segments where the amplitude was more significant for detection purposes, which now represents the presence of different peak amplitudes at various frequencies.

The energy signal shows an envelope having important information, making clear the differences between the acoustic emission signal and the reflections that are also registered. In order to better evaluate these peaks, segments of interest were amplified and the frequency response was recalculated for this section, as reported in Figure 13.

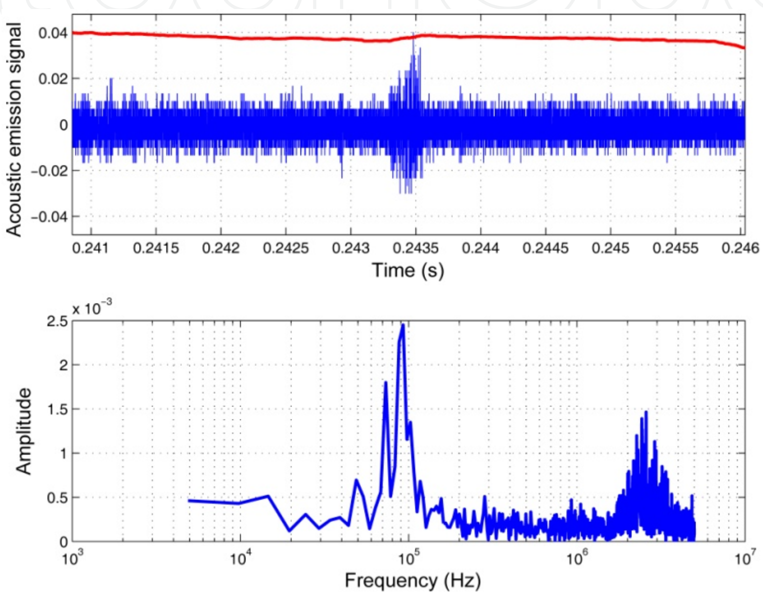

Figure 13. Detail of frequency response of the acoustic emission signal (segment 2).

In the segment highlighted in Figure 12, there is clearly a large concentration of low frequencies, with maximum amplitude at 10 Hz. In contrast, Figure 13 presents a large concentration at 100 kHz and another at approximately 2.5 MHz.

It is worth noting that, in the light of the two analyses, the signal with higher energy, recorded in the first segment, has an extremely low frequency wave. Thus, the propagation velocity tends to be higher due to the proximity to the spectrum of mechanical waves. However, for higher frequencies, typically observed in electromagnetic waves, there is a decrease of the signal energy, because this wave will suffer large attenuation when propagating through the insulating oil. Thus, the signal perceived by the acoustic emission sensor has already suffered severe degradation before being detected. This attenuation phenomenon is of great importance for the location process of partial discharges when installing more sensors in the experimental tank. In fact, since the speed of wave propagation in the insulating oil is known, it is then possible to estimate the location of the source of discharge.

The energy calculation is performed to obtain the full power of a signal. However, some signals are negative and therefore a quadratic sum of the sampled points must be calculated, as shown in the following equation:

$$E = \sum_{i=1}^{N} \sum_{j=1}^{M} \text{sinal}_{i,j}^2 \tag{1}$$

where N is the i-th window, and M represents the j-th point of the data window (consisting of 1101 points per window).

Thus, it may be noted that each data window corresponds to an acoustic emission signal measured by a given sensor. In this case, 8 sensors are used and, therefore, for each partial discharge we have 8 data windows. In addition, 10 samples for each partial discharge are still considered, which were obtained at different moments. Thus, the energy calculation for each of the 8 acoustic emission sensors is shown form Figures 14 to 21. Moreover, three different experiments were compared, where there was variation in the depth of the partial discharges in the oil tank used during the tests.

Experiment 1 represents a partial discharge located at 5 cm from the surface of the insulating oil, while experiments 2 and 3 are respectively located at 21.5 and 40 cm from the surface of the insulating oil.

Experiment 3 also had a small variation in the distance of the partial discharge from the front of the experimental tank, where it was moved 1 cm with respect to the original position of tests 1 and 2.

It is important to mention that this displacement is made in such away that the partial discharge of experiment 3 could be detected by sensors closer to the front wall of the tank, where it was expected that sensors 1 and 2 allocated on the wall would be more sensitive in experiment 3 rather than in experiments 1 and 2.

From Figures 14 and 15 it is possible to observe the energy response supplied by sensors 1 and 2 (for each of 10 samples), which represents the greatest contribution of experiment 1 in sensitizing them, while sensor 3 shows an energy response which makes it difficult to define which experiment caused the highest sensitization (Figure 16).

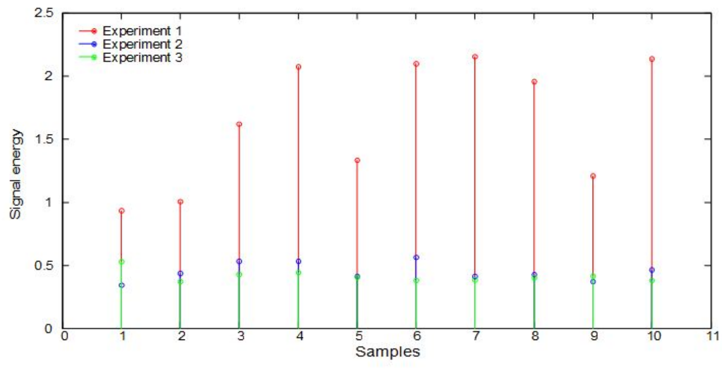

Figure 14. Energy response calculated for sensor 1 (mounted on the front wall - bottom right) during experiments 1, 2 and 3.

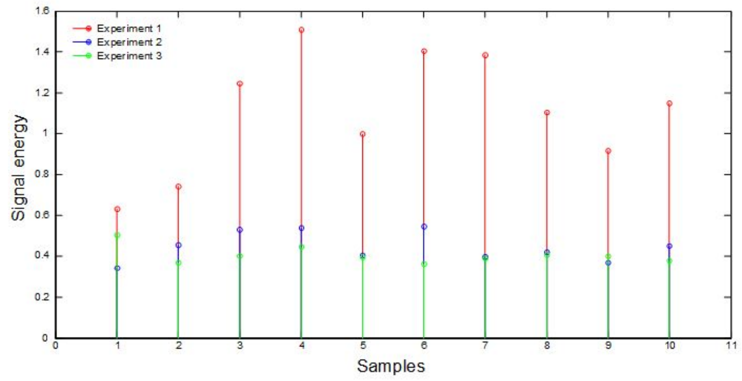

Figure 15. Energy response calculated for sensor 2 (mounted on the front wall - top left) during experiments 1, 2 and 3.

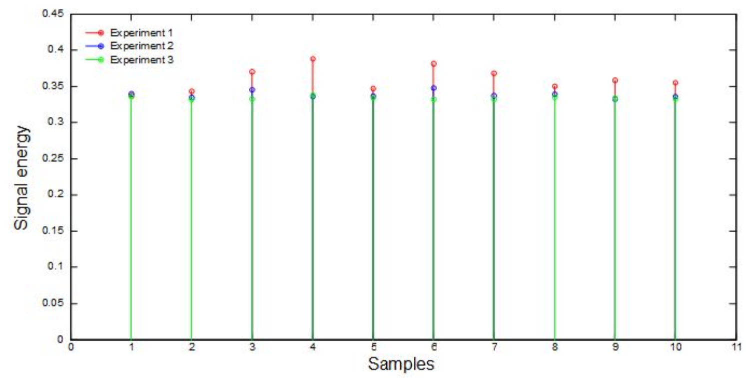

Figure 16. Energy response calculated for sensor 3 (mounted on the side wall-lower right corner) for experiments 1,2 and 3

The sensor 4 showed an energy response similar to that already shown for sensors 1 and 2 (Figure 17).

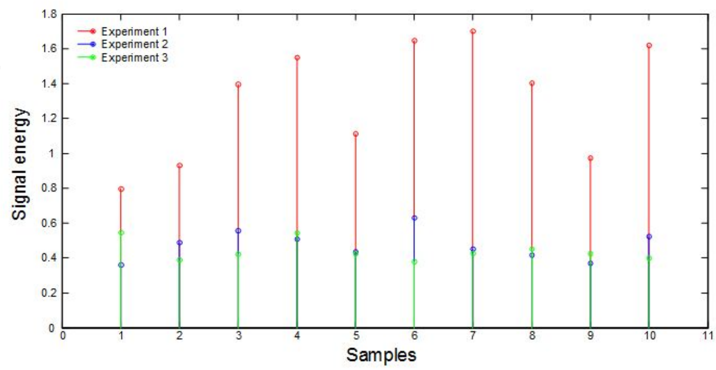

Figure 17. Calculated energy response for sensor 4 (mounted on the side wall - upper left) during experiments 1, 2 and 3

By means of the energy response supplied by sensor 5 (Figure 18) it can be seen that there is a certain emphasis on the response of experiment 1, but its energy levels are very close to those of experiments 2 and 3.

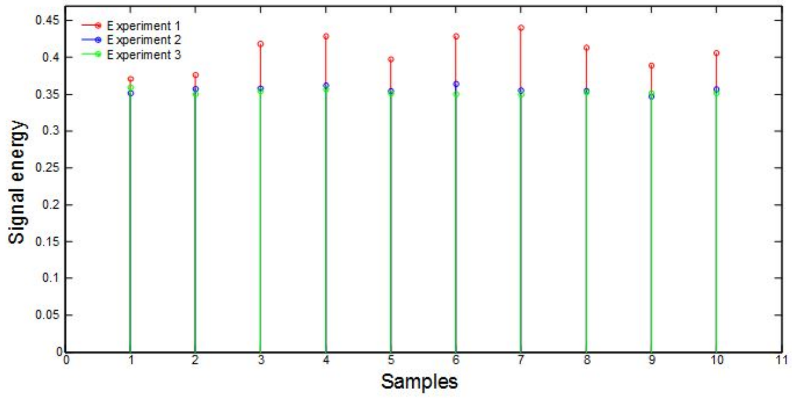

Figure 18. Energy response calculated for sensor 5 (mounted on the rear wall - bottom right) during experiments 1, 2 and 3.

The energy response of sensor 6 (Figure 19) in almost all samples presented responses similar to those obtained by sensors 1 and 2. However, in the first sample it can be seen that there are very similar levels of energy in the three experiments, although sensor 6 was a little more sensitive in experiment 3.

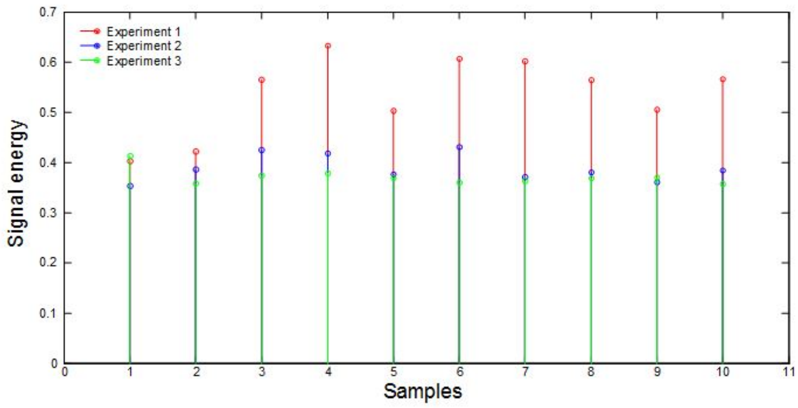

Figure 19. Energy response calculated for sensor 6 (mounted on the rear wall - top left) during experiments 1, 2 and 3

Sensor 7 presented the most complex energy response (Figure 20) because its response was unbiased for most samples. This is one factor that shows the complexity involved in the treatment of acoustic emission signals, making the application of intelligent systems very promising.

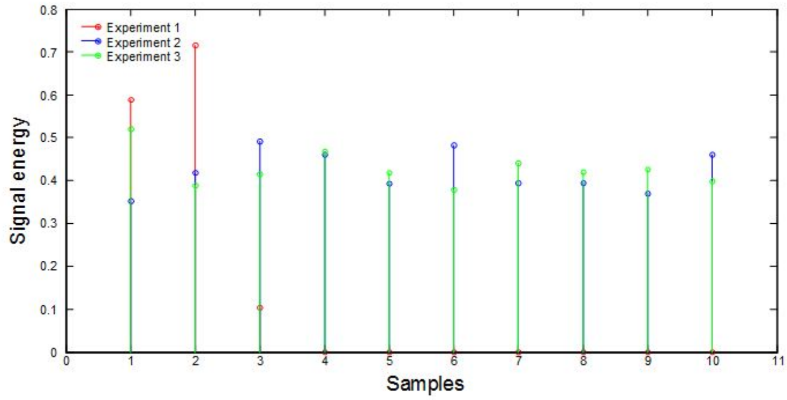

Figure 20. Energy response calculated for sensor 7 (mounted on the side wall - bottom left) during experiments 1, 2 and 3

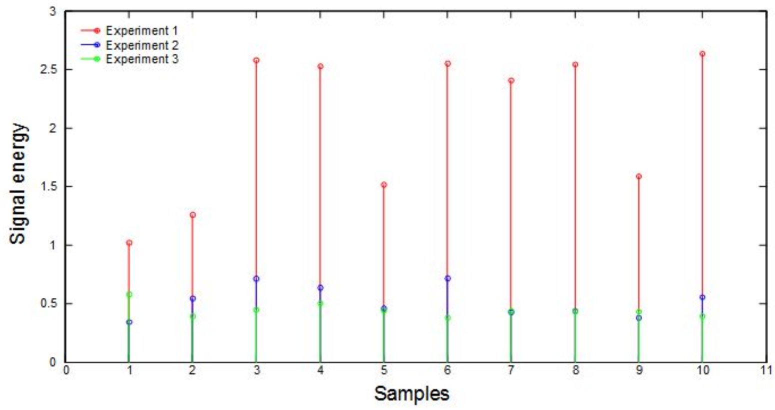

Figure 21. Energy response calculated for sensor 8 (mounted on the side wall - upper left) during experiments 1, 2 and 3.

Finally, sensor 8 presented an energy response (Figure 21) similar to that already obtained by other sensors, whose higher sensitization was caused by experiment 1.

5. Intelligent Systems

This section provides a theoretical foundation for fuzzy inference systems and artificial neural networks, as they are very prominent intelligent tools in the literature.

5.1. Fuzzy inference systems

Systems called fuzzy are built based on the theory of fuzzy sets and fuzzy logic, introduced by Zadeh in 1965, to represent knowledge from inaccurate and uncertain data. Fuzzy systems consist of a way to make a computational decision close to a human decision. Figure 22 shows a block diagram that expresses, in a simplified form, how a fuzzy system works.

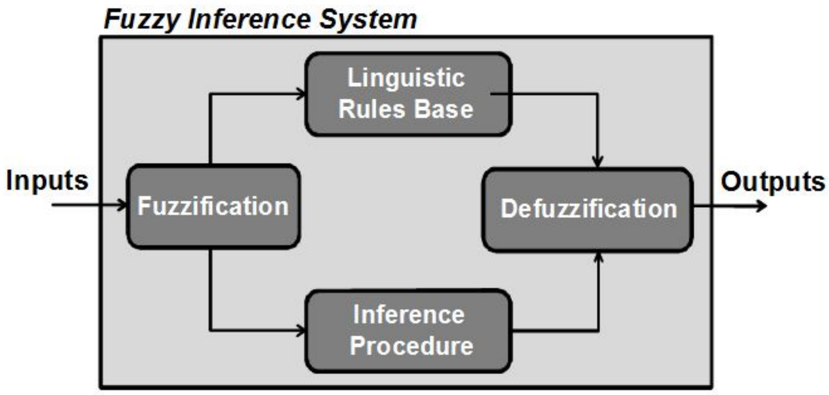

Figure 22. Diagram of a fuzzy inference system.

In the "Fuzzification" block, input values (in this case, information provided by the acoustic emission, gas concentration and electrical measurement sensors) are provided and conditioned, becoming fuzzy sets. Similarly, the "Defuzzification" block is responsible for transforming the outputs of the fuzzy system into non-fuzzy values (i.e., values which indicate the kind of internal fault and its location). The "Linguistic Rules Base" block has the function of storing the linguistic sentences and is fundamental to guarantee good system performance. The linguistic rules base and membership functions related to the inputs and outputs can be provided by experts or by automated methods, such as the ANFIS system (Adaptive Neural Fuzzy Inference System). On the other hand, the "Inference Procedure" block maps a system by using the linguistic rules. Thus, if rules are combined with input fuzzy sets acquired by the fuzzification interface, the system is then able to determine the behavior of the output variables of the system so that they can be defuzzified, generating the corresponding output to a given input value.

When using a fuzzy inference system, fuzzy rules and sets are adjusted and tuned by expert information. However, in some cases, because of the complexity and nonlinearity of the problem, it is necessary to use hybrid systems, such as ANFIS, where adjustments are performed in an automated manner according to the data set that represents the process. However, it is worth mentioning that, regardless of the setting, the whole fuzzy system has linguistic rules that can be represented as follows:

$$
\begin{aligned}
&R_i : \mathbf{If}\,Input\ 1\,\mathrm{is}\,x_1\,\mathbf{and}\,Input\ 2\,\mathrm{is}\,\mathrm{x}_2\\
&\mathbf{Then}\,Output\,\mathrm{is}\\
&\mathrm{y}_i = a\cdot x_1 + b\cdot x_2 + c
\end{aligned}
$$

Another factor that should be noted is the inference procedure, in which a variety of methods can be used. Currently, the most commonly used methods are those of Takagi-Sugeno and Mamdani.

5.2. Artificial neural networks

Artificial neural networks are computational models inspired by the human brain, which can acquire and retain knowledge. Among the various neural network architectures, there is the architecture of multiple layers, called MLP (Multilayer Perceptron). This type of architecture is usually used for pattern recognition, functional approximation, identification and control tasks [16]. The structure of a neural network can be developed according to Fig. 3.

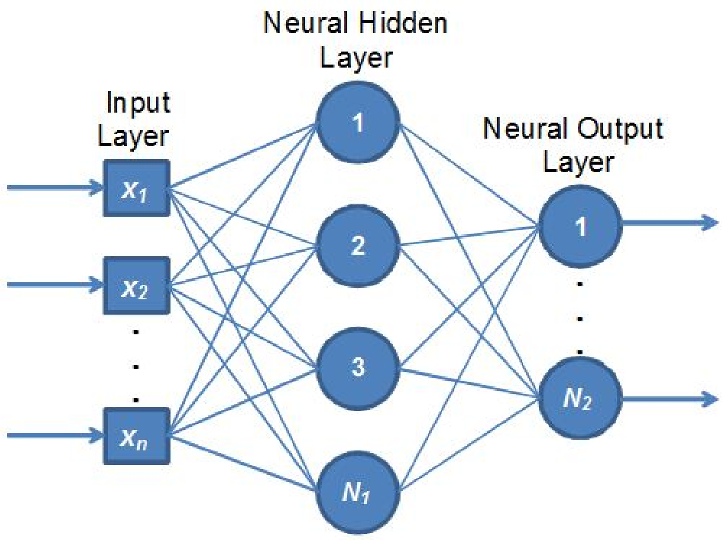

Figure 23. MLP neural network architecture.

As seen in Fig. 3, the neural network structure is basically composed of an input layer, hidden neural layers and an output neural layer. Also, between the layers, there is a set of weights, which are represented by a matrix of synaptic weights that will be adjusted during the training phase. It is further worth commenting that, for each of the neurons (hidden neural layers and output neural layer), it is necessary to implement activation functions in order to limit their output. In view of the basic configuration of the MLP neural network, other factors that should be explored are the training and validation stages.

During the training phase of MLP neural networks, some algorithms can be used. Currently, the backpropagation algorithm can be highlighted, which uses a descendent gradient calculation to reach the best adjustment of the synaptic weight matrix. In addition to the backpropagation algorithm, the Levenberg-Marquardt algorithm has been widely used because of its ability to accelerate the convergence process, due to the use of an approximation of Newton's method for non-linear systems [16].

On the other hand, the validation stage has the purpose of verifying the integrity of previously conducted training, so that the learning ability (generalization) of neural networks can be analyzed.

6. Intelligent Systems Used for the Identification and Location of Internal Faults in Power Transformers

As already mentioned in Section 1, a wide range of papers may be found in the literature, which are concerned with the identification and location of internal faults in transformers. However, there are very few papers which use intelligent systems applied to the same purpose, also taking into account experiments with acoustic emission sensors, electrical measurements and dissolved gases.

Among the most prominent papers found in the literature, we can highlight a few that use fuzzy inference systems and artificial neural networks for the analysis of dissolved gases [2, 17-19] and, for decision making, data from acoustic emission sensors [13].

As may be observed in papers [2, 17-18], which have fuzzy systems applied to the analysis of dissolved gases, the only notable difference lies in the fact that each one proposes different input variables to solve the problem and also different classes of faults. Thus, each paper has different settings of rules and of discourse universes for each input variable.

Therefore, a task of great importance is analyzing dissolved gases is the data preprocessing step, where the most relevant variables are obtained to characterize internal faults in power transformers.

As for those papers that analyze acoustic emission data, they typically employ conventional techniques [6-10]. However, the authors in [13] perform a series of experiments with partial discharges in insulating oil. However, these tests are not performed in order to apply the methodology to power transformers, but rather to identify partial discharges in any environment where oil is the insulator. Therefore, in order to identify the partial discharges, the authors use a MLP artificial neural network with backpropagation training, where the accuracy rates were above 97%.

Following the above context, it appears that the development of a method for identifying and locating internal faults in power transformers requires a number of steps, which are set out below:

- Allocation of sensors (acoustic emission and dissolved gases);
- Acquisition of data from sensors in accordance with the requirements commented upon in Section 3;
- Data preprocessing stage (definition of the most relevant variables and application of other necessary tools);
- Training or tuning of intelligent systems;

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- Data validation (use of other data than those used in training/tuning stage);
- Performance analysis of the methodology in relation to other methodologies found in the literature.

It is worth mentioning that, out of the 6 steps mentioned above, most attention should be given to the allocation and acquisition of data, because bad data acquisition can affect the whole process of identifying and locating faults. It is also important to emphasize that the calculations made during the preprocessing of the signals was devised in order to extract the characteristics that best represent the positioning of the partial discharge in relation to the acoustic emission sensor. However, for this first stage of testing the expert system and the hardware used in the acquisition of the signals, we used the experimental tank.

In order to better represent the embedded software, a block diagram detailing the calculations to be performed by the software is set out below (Figure 24).

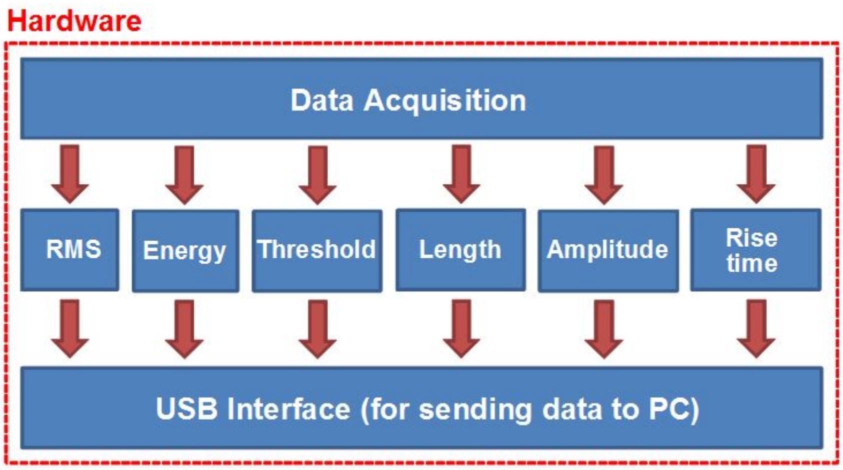

Figure 24. Overview of the embedded software.

As can be seen in Figure 24, it may be noted that the embedded software, after obtaining the acoustic signal, applies some computations in order to extract the characteristics that may represent the signal appropriately. Through these features, the expert system is able to distinguish these signals and to locate the source of partial discharges.

In this context, during the preprocessing step of the signs, the following calculations are performed: RMS, Energy, Length, Amplitude, Rise Time and Threshold. Finally, after obtaining the signal characteristics, they are sent to the computer through a USB (Universal Serial Bus).

Upon receipt of these data, the expert system is then responsible for providing information regarding the location of any partial discharge in the transformer. In order to better represent the overview of expert system, a block diagram is shown in Figure 25. In this figure, it may be noted that, after the received data concerning the characteristics commented upon previously, these are provided as input to the expert system.

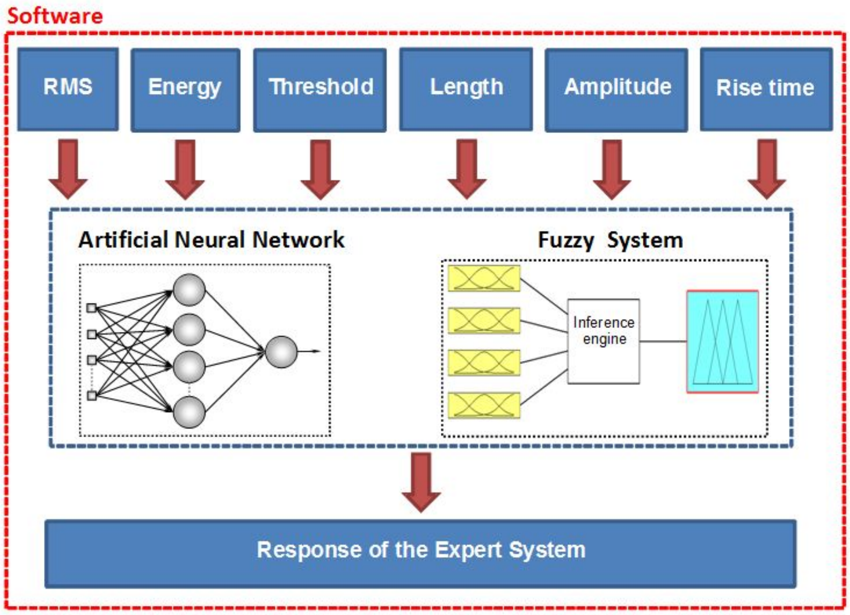

Figure 25. General diagram of the expert system.

In Figure 25 we can also observe that the expert system is composed of intelligent tools, such as artificial neural networks and fuzzy inference systems, which aim to locate partial discharges. Upon locating a partial discharge in transformer transmission, the operator may submit the equipment for maintenance (if necessary). Thus, the intelligent system here has the function of assisting the decision-making of the electric utility.

7. Conclusion

The tasks of identifying and locating internal faults in power transformers are extremely necessary, since this is one of the pieces of equipment that has the highest aggregated cost for both its purchase and maintenance.

Therefore, dissolved gas analysis and the analysis of partial discharges by means of acoustic emission sensors are essential for maintaining the equipment, which brings many benefits such as reducing the risk of unexpected failures and unscheduled downtime, extending transformer working life, reducing maintenance costs and minimizing maintenance time (due to failure location). Furthermore, processing this data by means of intelligent systems makes it possible to provide answers to help in decision-making about the analyzed power transformers.

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