Case Study of Comparison DGA Methods for Faults Diagnosis in Power Transformer Using Intelligent Expert System

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***Abstract*— Accurate diagnoses of faults in power transformers for life-long maintenance is ever-demanding. Transformers insulation excellence is known to deteriorate over time because of temperature fluctuations and moisture contents, which significantly affects its durability and functionality. Developing an intelligent program for precise and efficient determination of transformers faults types in the early stages are the key challenges in protecting transformers from potential failures that occur during operation to avoiding economic losses. The dissolved gas analysis (DGA) being a reliable method is used to develop an intelligent expert system for faults diagnoses in power transformers. The developed algorithm used two approaches including Expert System based Adaptive Neuro-Fuzzy Inference System (ANFIS) and Expert System based on ANN as per the standards of IEEE, C57-104, and IEC 60599 specifications. Experimental results revealed that the proposed expert system based on ANN is highly accurate in terms of diagnosing the faults in power transformers. Results of the proposed method are statistically analyzed and compared with the existing techniques.**

Keywords— dissolved gas analysi; fault diagnosis; power transformer; intelligent expert system

I. INTRODUCTION

The quest of finding an accurate fault diagnostics and assessing the oil quality of high voltage electrical power transformer for life-long safeguard is never-ending. The longevity of transformers function is critically decided by the quality of its insulation.

Generally, this insulation deteriorates over time span due to fluctuating temperature, moisture and oxygenation [1]. The quality of oil decides the working efficiency of the transformer [2]. Thus, judgment of faults is one of the most important factors in protecting transformers from potential failures that often occur during operation. Power transformers are exceptionally expensive and the damage in insulation system causes high economic loss [3]. In the past, several methodologies are adopted for the transformer faults diagnosis and subsequently different smart standards are developed with the approved specifications including IEEE standard C57-104 and IEC standard 60599 [4, 5]. Despite many efforts, a method for efficient and precise determination of the nature of faults and subsequent rectification mechanism for superior performance of the transformers is far from being achieved.

The DGA in transformers oil is performed by taking some oil sample, where the concentration ratios of the generated gases in the oil sample are determined. These gases are formed due to the occurrences of high temperatures, partial discharge process, arcing, and corona. These factors lead to the decomposition of the oil (hydrocarbons) and generate various harmful combustible and non-combustible gases. Combustible gases (CG) are Carbon Monoxide (CO), Hydrogen (H_2), Methane (CH_4), Acetylene (C_2H_2), Ethylene (C_2H_4), Ethane (C_2H_6), Propene (C_3H_6), Propane (C_3H_8). Non Combustible gases (NCG) are Oxygen (O_2), Nitrogen (N_2), Carbon Dioxide (CO_2) [6]. The generation rate as well as their proportions is decided by the oil temperature variation and aging effects. The allowed limits for these gas ratios and their rate of formation in the transformer oil is set by the standard (IEEE standard C57-104). [7]

In this paper case study for power transformer an intelligent expert system relying on the DGA, where the concentrations of these harmful hydrocarbons in the transformer oils can easily be determined without isolating them. Rogers's ratio, IEC ratio and Doernnburg ratio methods is employed to develop a computer algorithm for diagnosing

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the power transformer faults. Being based on ANN and ANFIS, the proposed algorithm is intelligent enough for fault diagnosis. The software is trained by a back propagation algorithm and matched with IEC standard 60599, which can identify the nature of faults. Furthermore, the trained algorithm of following IEEE standard C57-104.

II. METHODOLOGY

In this study, the use of two approaches of intelligent approach in expert systems, namely ANN and ANFIS, known to be expert systems consist of two parts, knowledge base and inference engine in addition to the user interface through which gases enter the values and show us the results of the diagnosis. Either was programmed using the following approaches:

A. ANFIS Expert System

Expert Systems fall under the artificial intelligence category of computer applications. Designing an ES needs the knowledge of studying human experts who make decisions and translates the findings into rules that a computer can understand. The term ANFIS is derived from adaptive network-based fuzzy inference engine. This system is designed to allow if-then rules and membership functions to be constructed based on the historical data of established metrics. It is designed with an adaptive nature for automatic tuning purposes [8]. The design provides an interface, where the user can input gas values derived from the analysis of samples of transformer oil through dissolved gas ratios. Subsequently, the user can choose the method to be used in the analysis process.

The Inference engine is used to design the process of search within the knowledge base to match for the diagnosis and to give correct results. MATLAB programming language is used to appropriately designing the environment. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping is then used as a basis for making decisions. The process of fuzzy inference involves membership functions, logical operations, and if-then rules enlisted in table 1. FIS maps 5 input characteristics to get the membership functions in rules to output the membership function to single-value output [9]. The shape of membership functions depends on the parameters. ANFIS chooses the parameters of membership functions automatically during the learning phase to match the system's output with the target output. ANFIS is used for modeling the system where input/output data are available for modeling but no predetermined model for the system exists. Parameters of membership functions are defined to fit the membership functions of the input/output data as depicted in figure (1).

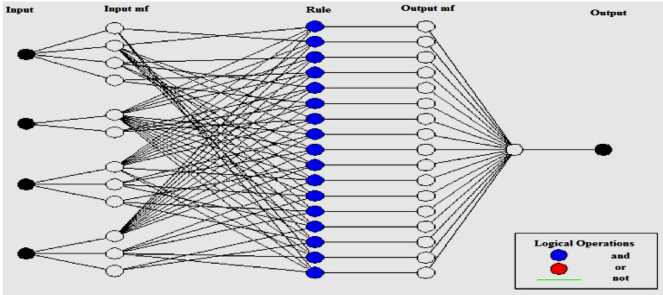

Figure 1: Typical ANFIS structure

Table 1: set of IF- Then rules for Roger's ratio method based on ANFIS

No. of Rule	Condition
Rule 1	If (R1 is 0) and (R2 is 0) and (R3 is 0) and (R4 is 0) then (condition is 0)
Rule 2	If (R1 is 5) and (R2 is 0) and (R3 is 0) and (R4 is 0) then (condition is 1)
Rule 3	If (R1 is 1) and (R2 is 0) and (R3 is 0) and (R4 is 0) then (condition is 2)
Rule 4	If (R1 is 2) and (R2 is 0) and (R3 is 0) and (R4 is 0) then (condition is 2)
Rule 5	If (R1 is 1) and (R2 is 1) and (R3 is 0) and (R4 is 0) then (condition is 3)
Rule 6	If (R1 is 2) and (R2 is 1) and (R3 is 0) and (R4 is 0) then (condition is 3)
Rule 7	If (R1 is 0) and (R2 is 1) and (R3 is 0) and (R4 is 0) then (condition is 4)
Rule 8	If (R1 is 0) and (R2 is 0) and (R3 is 1) and (R4 is 0) then (condition is 5)
Rule 9	If (R1 is 1) and (R2 is 0) and (R3 is 1) and (R4 is 0) then (condition is 6)
Rule 10	If (R1 is 1) and (R2 is 0) and (R3 is 2) and (R4 is 0) then (condition is 7)
Rule 11	If (R1 is 0) and (R2 is 0) and (R3 is 0) and (R4 is 1) then (condition is 8)
Rule 12	If (R1 is 0) and (R2 is 0) and (R3 is 1) and (R4 is 1) then (condition is 9)
Rule 13	If (R1 is 0) and (R2 is 0) and (R3 is 2) and (R4 is 1) then (condition is 9)
Rule 14	If (R1 is 0) and (R2 is 0) and (R3 is 1) and (R4 is 2) then (condition is 9)
Rule 15	If (R1 is 0) and (R2 is 0) and (R3 is 2) and (R4 is 2) then (condition is 10)
Rule 16	If (R1 is 5) and (R2 is 0) and (R3 is 0) and (R4 is 1) then (condition is 11)
Rule 17	If (R1 is 5) and (R2 is 0) and (R3 is 0) and (R4 is 1) then (condition is 11)

And the inputs of ANFIS are set equal to those of ANNs for the same DGA methods as enlisted in table2. The input and output membership function shown in table 3 and figure (2,a, b, c)

Table 2: Inputs of the expert system for DGA

Method	Trapezoidal input membership	
	Number of inputs	*Inputs*
Roger's ratio method	4	$\frac{CH_4}{H_2}, \frac{C_2H_6}{CH_4}, \frac{C_2H_4}{C_2H_6}, \frac{C_2H_2}{C_2H_4}$
IEC ratio method	4	$\frac{C_2H_2}{C_2H_4}, \frac{CH_4}{H_2}, \frac{C_2H_4}{C_2H_6}$
Doernenburg ratio method	10	CH_4, H_2, C_2H_6, C_2H_4, C_2H_2, CO, $\frac{CH_4}{H_2}, \frac{C_2H_2}{C_2H_4}, \frac{C_2H_2}{CH_4}, \frac{C_2H_6}{C_2H_2}$

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Table 3 Input and output Membership function of ANFIS ES

Membership function		Type of membership functions	Number of membership Functions
Input membership functions	MFs for R1 = $\frac{C_2H_2}{C_2H_4}$	Trapezoidal	3
	MFs for R2 = $\frac{CH_4}{H_2}$	Trapezoidal	3
	MFs for R3 = $\frac{C_2H_4}{C_2H_6}$	Trapezoidal	3
Output membership functions		Constant with the input membership functions	9

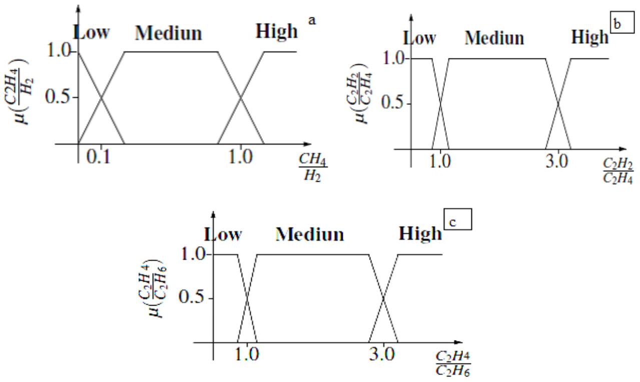

Figure 2; Input membership functions for ANFIS

The user interface of the ANFIS expert system is designed using GUI access in the MATLAB environment. The user input interface allows the inputting of parameters such as gas values, analysis methods (Rogers ratio, IEC ratio and Doernenburg's ratio), gas ratios, fault type diagnosis shown figure 3.

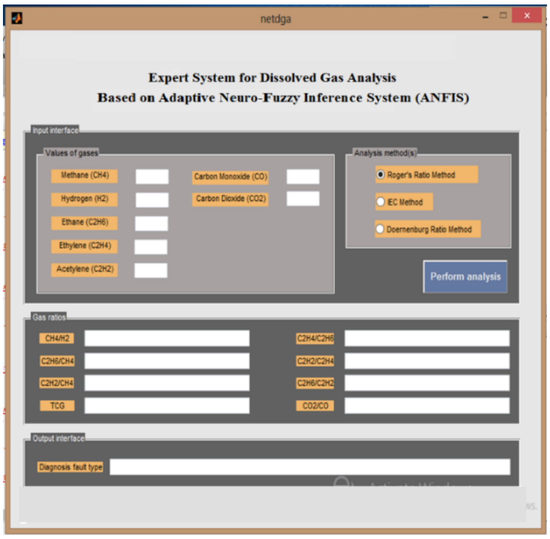

Figure 3: User interface of ANFIS expert system

A. ANN Expert System

Expert systems that rely on ANNs are not much different from other expert systems in terms of components and general structures. But they are different in the programming process, where the inference engine operates in a manner that is designed using ANNs [10]. The expert system uses ANN technology in the diagnosis, through the back propagation algorithm.

Modeling the ANN, multilayer feed forward back propagation network structure can be described using the following expressions whose pictorial presentation is displayed in Figure(4).

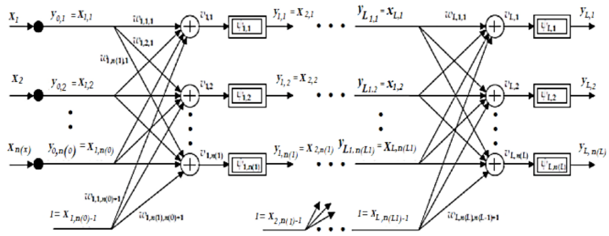

Figure 4: Multilayer perceptron NN

In developing the expert system, three feed-forward back-propagation ANNs are created. As aforementioned, they are based on DGA algorithms (Roger's ratio, IEC 60599, and Doernenburg's ratio). The modeling of the ANNs includes the following ;

Inputs of Roger's ratio method, IEC ratio method and Doernenburg's ratio method based NNs are four gas ratios, six gas values, and four gas ratios, respectively. In ANFIS represents inputs for all three constructed neural networks. Number of neurons in the output layer of each AN is equal to number of identifiable faults on which the network based: 12 for Roger's ratio based NN, 9 for IEC ratio based NN and 4 for Doenrenburg's ratio based NN as illustrated in figures 5,6 and 7.

For each identifiable fault, the output of only one neuron in the output layer of the network equals to one, while all other outputs are zero. Codifications of outputs of Roger's ratio method based NN, IEC ratio method based NN, and Doenrenburg's ratio method based NN.

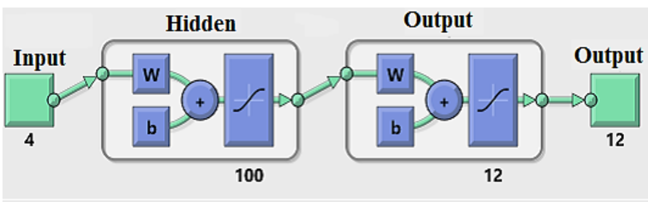

Figure 5: Roger's ratio method based ANN architecture

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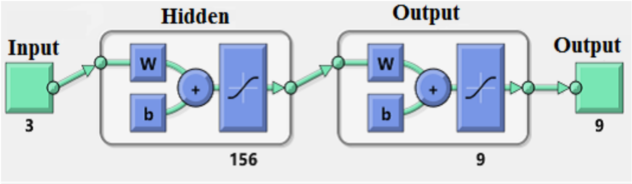


Figure 6: IEC ratio method based ANN architecture

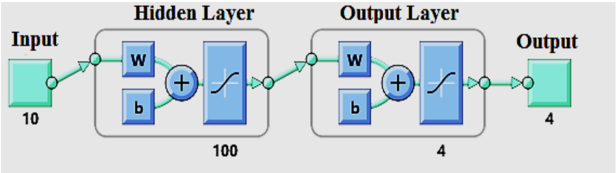


Figure 7: Doernenburg's ratio method based ANN architecture

The systems training is based mostly on virtually generated data which are extracted from Roger's ratio, IEC ratio, and Doernenburg's ratio based algorithms. Performance can be greatly improved using more data collected from real transformers. This would open the way to developing the system that is able to diagnose even the faults, unidentifiable by any of these three methods. This is because of NN's learning and generalizations ability.

The total number of samples for each ANN. During preprocessing, the training data is divided into three sets including training dataset, validation dataset, and testing dataset. Each of them are normalized to the range of [-1,1]. The first dataset is used for network training, and the second one for network validation during the learning process. The third dataset is not used in the training process. Later, it is used for testing the network. Normalization to range [-1,1] is useful to speed up the training process. This also decreases the possibility of getting stuck in local minimum as summarized in Table 4.

Table 4: Number of samples in each dataset after data division.

Dataset type	**RRM based ANN**	**IEC based ANN**	**DRM based ANN**
Training dataset	1820	1750	560
Validation dataset	390	375	120
Testing dataset	390	375	120

The interface user of the ANN expert system is designed using the GUI access provided in the MATLAB environment. Figure 8, shows that the user input interface allows several items to be entered, including gas values, analysis methods, gas ratios, fault type diagnosis.

Figure 8: Interface module of the ANN expert system

III. RESULTS

A fifty samples are used as the input data. This data is a concentration of dissolved gases ratios in the insulating oil of power transformers in substations in Malaysia. The actual results were obtained by Tenaga Nasional Berhad (TNB) (Malaysian National Electricity Company), through the user fault diagnosis sustenance of the high voltage power transformers enlisted table 5. Done collect data from the maintenance department for the past five years.

After inserting the values of dissolved gases in the oil in the system intelligent expert in both cases based on the ANFIS and ANN. A sample of fault diagnoses can be seen as tables 6. The all results shown in chart figure 9.

Table 5; Actual results obtained by TNB

NO.of sample	Faults types
1	Fault in cellulose insulating paper
2	No fault
3	No fault
4	Fault in cellulose insulating paper
5	Fault in cellulose insulating paper
6	General conductor overheating
7	Fault in cellulose insulating paper
8	Core and tank circulating currents
9	No fault
10	No fault

Table 6; The results of ANFIS expert system

No.	**Fault type**		
	Rogers method	*IEC method*	*Doernenburg's method*
1	Fault in cellulose insulating paper	Fault in cellulose insulating paper	No fault
2	Arcing with power flow	No fault	Unidentifiable
3	No fault	No fault	No fault
4	Fault in cellulose insulating paper	Fault in cellulose insulating paper	Fault in cellulose insulating paper
5	Overheating-200 °C to 300°C	Fault in cellulose insulating paper	Fault in cellulose insulating paper t
6	General conductor overheating	General conductor overheating	General conductor overheating
7	Overheating-below 150 °C	Fault in cellulose insulating paper	Fault in cellulose insulating paper t
8	Core and tank circulating currents	Core and tank circulating currents	Core and tank circulating currents
9	No fault	No fault	No fault
10	No fault	Discharges of high energy	No fault

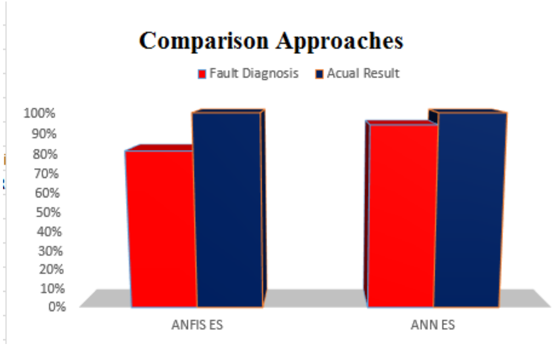


Figure 9: The result of comparison approaches

In IEEE Standard C57-104 defines the gases that are generated in the oil-immersed that can be used to suggested diagnose potential faults types in different temperature converters.

The results obtained using each of the three ratio methods were statistically analyzed (SPSS version 20.0) to determine the best approach for transformer fault diagnoses. The text results were converted to obtain accurate results. Fifty samples used for the test were transferred to the numbers, where faults were numbered from 0 to 7 in the case of diagnosis, as in the Table7.

Table7: Code of faults type suggested

Type of Faults	Symbol of Faults
Core and tank circulating currents	0
Continuous sparking to floating potential	1
Arcing (high intensity PD	2
Discharges of low energy	3
Partial discharges	4
Fault in cellulose insulating paper	5
Thermal fault	6
No fault	7

IV. Discussion of Results Analysis

The results obtained using each of the three ratio methods are statistically analyzed (SPSS version 20.0) to determine the best approach for transformer fault diagnosis. The text results are converted to obtain the accurate results. Fifteen samples used for the test are transferred to the numbers, where faults are numbered from 0 to 7 in the case of diagnosis see Table 4.

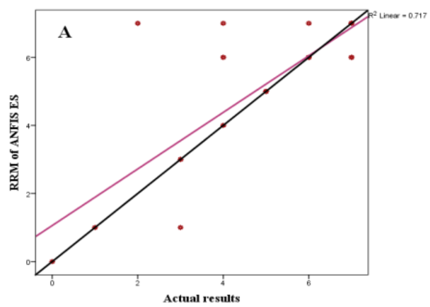
In the diagnosis of faults process, where the ANFIS expert system is used. A deviation between the standard lines of the actual values of the results line values are observed obtained in the program. It implies that there is an error rate as shown in Figure 10, A, B and C. Where the correlation between the actual results and the results obtained from ANFIS- ES of RRM, IEC RM and DRM for fault type diagnosis is displayed. The values for the mean (MEAN), root square (R2), Standard Error (SE) and the Probability Error (PE) are enlisted in Table 8.

Figure 11, A, B and C, illustrates the typical relationship between the actual results and the one obtained using ANN-ES for fault type diagnosis. Very tiny error in the diagnosis of faults process is evidenced, because the present technique used intelligent software in the expert systems. The values of MEAN, R2, SE, and the PE for are summarized in Table 8. Present results using ANN-ES for fault type diagnosis are observed to be much superior than those obtained using other approach. The proportion of very little error in the deviation line values for the standard line as well as also very small error in the values of MEAN, R2, SE, and the PE are noticeable Table 8.

Through the above, we can say that the use of the IEC ratio method, they give good results compared with the other two methods, were diagnostic results are very good, especially when you used the expert system based on artificial neural networks. Where the error rate very small compared to the other method, but that does not mean dispensing for the other two methods. It is observed that the methods used in the diagnosis of faults sometimes share a certain diagnosis of fault and sometimes specializes in one method of the three ways to diagnose fault it.

Table 8: The values of MEAN, R2, SE and the PE for results of intelligent expert system

Parameter Name	MEAN	R^2	SE	P
RRM of ANFIS-ES	5.58	0.71	0.971	0.075
IEC RM ANFIS-ES	5.16	0.77	0.919	0.071
DRM ANFIS-ES	5.94	0.66	1.003	0.078
RRM of ANN-ES	5.52	0.93	0.486	0.038
IEC RM ANN-ES	5.52	0.95	0.347	0.027
DRM ANN-ES	5.46	0.73	0.947	0.073



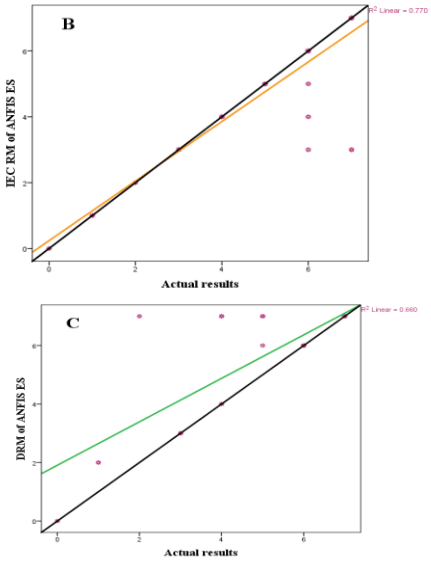


Figure 10, A, B and C: The correlation coefficients between the actual results and the results obtained from ANFIS Expert System of RRM, IECRM and DRM.

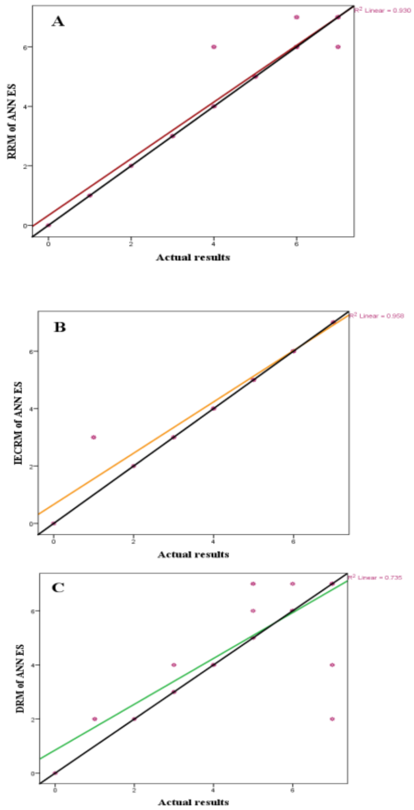


Figure 11, A, B and C: The correlation coefficients between the actual results and the results obtained from ANN Expert System of RRM, IECRM and DRM

V. Conclusion

The purpose of the present in this study, was to develop DGA based accurate intelligent expert system for power transformers faults diagnosis. Based on the statistical analyses of the experimental data the following conclusions are made: A DGA based intelligent expert system with ANN and ANFIS are succefully developed for precise fault diagnosis in power transformers. The used Rogers's ratio, IEC ratio and Doernenburg's ratio is written and the transformers faults type. The proposed ES based proposed intelligent algorithm are demonstrated to be accurate in determining the transformers fault types. A comparison of the three developed methods with the actual measurement revealed the superiority of the proposed methods in terms of accuracy and efficiency. Thus, the proposed intelligent expert system based ANN are more robust for implementation than the existing ANFIS expert system. The intelligent expert systems designed via MATLAB code based on GUI technique. They are used to build the user interface and the expert technology (ANN and ANFIS) in the design of inference engine and knowledge base. The implementation of these intelligent expert systems is affirmed to be successful for precise diagnoses of transformers faults type.

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