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Transformer faults identification via fuzzy logic approach

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ABSTRACT

The need for a constant electricity supply is at an alarming rate especially in the 21st century due to the high rate of increase in industrialization across the globe. Conventional protection schemes such as differential relays, Buchholz relay, and other techniques such as genetic algorithms and artificial neural networks, do not match the precision and reliability needed for transformer fault indentification, due to their complexity in computation, tedious training system, time consumption, and need the of human experts. The method proposed in this research is the use of a fuzzy inference system in detecting potential faults in power system transformers. The faults in the transformer were observed and analyzed using a simulation system of MATLAB/Simulink software. The suggested approach ensures swift identification of faults as it relies on if-then rules and only uses current and voltage measurements with 100% independence toward the power flow direction, making it highly reliable and simple to implement compared to other techniques for transformer fault identification.

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1. INTRODUCTION

Electricity is no longer a privilege but a right, considering its importance toward human endeavors. It plays a key role in the survival of our educational, health, financial, and industrial sectors and also in our homes which we use to solve our daily needs [1]. Modern electrical power systems are complicated networks that usually require highly and more précised protection schemes that would prevent them from failing or breaking down completely [2], [3]. Transformer being the substantial and crucial element of an electrical system, is subjected to a series of problems, resulting in power outages, which when they occur, can affect the economic and social development of any nation across the globe [4]. Faults in power system transformers are issues of serious concern, the need to preserve an uninterrupted flow of electricity is of paramount importance due to its effect on social and economic development [5].

Traditional fault protection schemes like differential relays, buchholz relays, dissolved gas analysis, and other techniques like; wavelets transform, adaptive extended Kalman filter, artificial intelligence, probabilistic neural networks, and genetic algorithms used in the detection and protection of faults in transformers are no longer guaranteed due to the complex nature of modern high-voltage transformers [6], [7]. With technological advancement and increasing demand in the power sector, a more reliable and sophisticated detection and protection scheme is needed in the power sector, to shadow the menace that may result from various faults occurring in power system transformers [8]-[10]. A lot of research was conducted concerning the identification of faults in transformers. One noticeable technique is the use of neural networks in classifying faults in transformers [11]. The approach has to some extent exhibited success, but yet, too much training is required by the system to produce effective results, which is not healthy in terms of transformer safety. Moreover, relevant research using wavelet transform to detect faults in transformers was carried out [12]. Thus, the process is highly complex due to too much computational analysis involved. Similarly, a fuzzy neural technique was used in the detection of symmetric and unsymmetrical faults in power transformers [13], but the approach required ample time for adequate training of the artificial neural network.

Peng *et al.* [14] carried out research on transformer protection using differential relays, the suggested approach accurately distinguishes internal failures from other circumstances. Furthermore, the magnetizing inrush throughout energizing and the decrease in voltage during breakdowns do not affect the scheme. The suggested approach can safely safeguard the transformer while requiring little calculation and is simple to apply in practice. However, the techniques exhibit some limitations, by indicating an inability of protection strategy during external problems, resulting in false alarms and frequent tripping.

Liu *et al.* [15], provided promising results for early identification of potential issues and improving routine upkeep in transformers. Yet, it's quite challenging during implementation due to too much computation and expert knowledge requirement. Siregar and Lumbanraja [16], combined three (3) methods in detecting transformer faults, the methods proposed have an insufficient cooling system, resulting in unwanted failure. Similarly, Mohammed *et al.* [17], on transformer fault detection was proposed, yet, the approach suffers due to complexity, accuracy dependence on input data quality, potential modeling inaccuracies, and challenges in capturing real-world dynamics for effective optimization and fault diagnosis. In their paper Buchholz relay response and innovative non-electric-parameter protection, the approach detects internal faults through gas and oil anomalies, preventing catastrophic failures in transformers effectively [18]. Thus, it is limited to the detection of internal faults.

Research on conventional methods of DGA for fault detection in power transformers shows a promising result by monitoring gases produced by incipient faults, revealing transformer health. Thus, it exhibits limited sensitivity to early faults and dependence on expert analysis [19]-[21], improves transformer fault diagnosis by integrating sensor data for increased reliability. However, the challenge in terms of computational complexity, resource demands, system overhead, and increased cost makes the approach questionable. Wu *et al.* [22], used GI-XGBoost in transformer fault identification, the approach optimizes parameters for the robust search, improving fault diagnosis accuracy. However, it is challenging in interpreting1 features that leds to transformers' fault. Moradzadeh *et al.* [23] used a deep learning method for locating short circuit faults within transformer windings on a turn-to-turn basis. The method enhanced precision and efficiency in identifying faults, leading to faster and more accurate fault localization. Despite its ability to detect faults, it demands resources, and expertise, which are too costly and challenging [24]-[26].

In light of the literature reviewed above, all the approaches exhibit different shortcomings ranging from time consumption, errors due to human experts, tedious computational analysis, false alarm notification, and inability to work under uncertainty scenarios. Thus, the idea of ''transformer faults identification via fuzzy logic approach'' came into existence due to its simplicity, ability to provide solutions to uncertainty issues, and less computational analysis compared to traditional methods and other soft-computing techniques [27], [28]. The subsequent sections of this manuscript are scheduled as follows: the proposed methodology is deliberated in section two, section three analyses and discusses the findings of the results, and section four (4) draws a conclusion, with suggestions for future improvement of the method proposed.

2. METHOD

Method proposed in this research is the use of a fuzzy inference system in detecting potential faults in power system transformers. The fuzzy logic approach is considered due to its straightforward implementation and less computational effort compared to other soft computing techniques. In the method proposed, the parameters used for its implementation are; two variables, calibrated as "error" for input current and "error dot" for the rate of change in current with respect to time with values ranging from -1.5 to 1.5 and -10 to 10 respectively were used as the input values, nine (9) IF and Then rules, and a triangular membership function with linguistic variables (low, zero, and high). The fuzzy sets crisp output, and its corresponding membership function is determined by the centroid defuzzification approach. The faults in the transformer will be observed and analyzed using a simulation system of MATLAB/Simulink software that contains a toolbox of fuzzy logic (mamdani type).

Identifying faults in a power transformer using fuzzy logic involves the following process as shown in Figure 1. Figure 1(a) parameters such, as temperature, oil quality, and load condition are measured as the input variables. These measurements are pre-processed and then translated (Fuzzified) into descriptive language. Afterwards, a set of rules based on knowledge that links the linguistic variables to potential fault conditions is established. Through inference, these rules are applied to the input data generating outputs that indicate the likelihood of specific faults. To get an assessment of the transformers' condition, the outputs are aggregated. For precise insights, a defuzzification process, that is, converting the fuzzy results into clear values is performed. Continuous monitoring and adjustment of the sets and rules ensure accurate fault detection. When the output value (fuzzy output) is greater or less than the value of the threshold, then, a signal is sent to the relay, and immediate action is taken. Ultimately, this approach based on its logic enables us to detect faults in power transformers efficiently leading to prompt maintenance actions and preventing catastrophic failures.

In Figure 1(b), CT1 and CT2 represent the primary and secondary current transformers, and CB (1 and 2) represents operating and restraining auxiliaries' currents in the current transformers. The combined input as well as output current is given by,

$$\frac{I_1}{I_2} = \frac{N_2}{N_1} \tag{1}$$

where; I_1 & I_2 are currents entering the transformer's primary and secondary coils, and N_1 & N_2 are the Number of loops in the coils.
Making I_1 the subject, in (1) becomes;

$$I_2 = I_1 \times \frac{N_1}{N_2} \tag{2}$$

where; I_2 = Error (Input Current). By differentiating I_2 with respect to time t, equation 2 becomes,

$$I_2 = \frac{dI_2}{dt} = I_3 \tag{3}$$

where; I_3 = Error-Dot. (rate of change of current with time taken).

In the fuzzy logic protective relay shown in Figure 1(b), the collected input variables are combined, and their dI (differential currents) are calculated and forwarded to the model (fuzzy system). ± 0.5 threshold value is coordinated to the fuzzy logic system. When the output value (fuzzy output) is greater or less than the value of the threshold, a signal will be sent to the relay to switch off or trip the system.

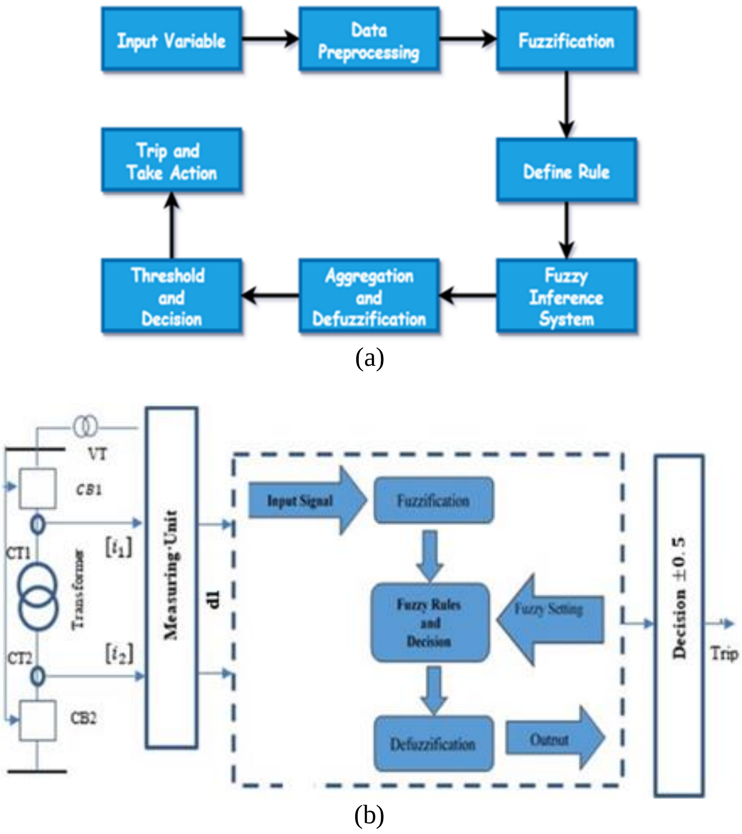


Figure 1. Fuzzy logic fault identification (a) block diagram and (b) protective relay circuit

2.1. Fuzzy logic faults protection rules

Nine fuzzy logic control rules were selected to carry out the entire operational activities and protection of the system using the IF-THEN rules. In Table 1, symbols I, d(I)/dt, NC, L, H, +VE, -VE, Z, and O/P are identified as; input current, current change rate with time, no change in current, low current, High current, positive, negative, zero and output respectively.

Table 1. IF and THEN rules for fault identification

SN	Antecedent block	Consequent block
1	If I = -VE & d(I)/dt = -VE	Then, O/P is L
2	If I = Z & d(I)/dt = -VE	Then, O/P is H
3	If I = +VE & d(I)/dt = -VE	Then, O/P is H
4	If I = -VE & d(I)/dt = Z	Then, O/P is L
5	If I = Z & d(I)/dt = Z	Then, O/P is NC
6	If I = +VE & d(I)/dt = Z	Then, O/P is H
7	If I = -VE & d(I)/dt = +VE	Then, O/P is L
8	If I = Z & d(I)/dt = +VE	Then, O/P is L
9	If I = +VE & d(I)/dt = +VE	Then, O/P is H

3. RESULTS AND DISCUSSION

The transformer fault protection scheme was designed using the fuzzy logic (FL) toolbox in MATLAB/Simulink. Based on the selected 9 (nine) rules in Table 2, rules number four, five, seven, and eight, are those rules that don't have zero in their outputs. Thus, leaving the fuzzy response output with no change in current (NC), and low current (LC). The response output will then undergo the processes of inference, coordinating, and defuzzification, to yield a definite result (crisp output). In the rule, the error is symbolized by (e), while the error- dot is symbolized by (er) as displayed in Table 2.

Similarly, the simulation output for the error (current) is obtained using Mamdani FIS with the range value of Error = [-1.5, 1.5] as arranged in Table 3. In Table 4, the range value [-10, 10], is used for the simulation of the Error-Dot member function (MF). The simulated results of the consequence membership degree for which the calculation of antecedents current and rate of change of current (Error and Error-Dot) is obtained using parameters in the Table 5.

Table 2. Fuzzy logic rule for fault output responses

N	Error (e) and error-dot (er)	Crisp output
1.	If error < 0 & error-dot < 0	Then, L (0.5 and 0.0) equal to 0.0
2.	If error = 0 & error-dot < 0	Then, H (0.5 and 0.0) equal to 0.0
3.	If error > 0 & error-dot < 0	Then, H (0.5 and 0.0) equal to 0.0
4.	If error < 0 & error-dot = 0	Then, L (0.5 and 0.5) equal to 0.5
5.	If error = 0 & error-dot = 0	Then, NC (0.5 and 0.5) equal 0.5
6.	If error > 0 & error-dot = 0	Then, H (0.5 and 0.0) equal to 0.0
7.	If error < 0 & error-dot > 0	Then, L (0.5 and 0.5) equal to 0.5

Table 3. MF for error input

MF	Symbol	Meaning	Range value
1	NB	Negative big	-1.5 1 -0.5
2	PB	Positive.big	0.5 1 1.5
3	Z	Zero	-0.5 0 0.5
4	P.S	Positive.small.	0 0.5 1
5	NS	Negative small	-1 -0.5 0

Table 4. Membership function for error-dot input

MF	Symbol	Meaning	Range value
1.	P	Positive	-10 -10 -5
2.	Z	Zero	- 5 0 5
3.	N	Negative	5 10 10

Table 5. MF for fault response output

MF	Symbol	Meaning	Range value
1.	L	Low current	-10 -50
2.	NC	No change	-505
3.	H	High current	5 10 10

From the readings in Tables 3-5, the simulation plots membership functions of error input variables, Error–Dot variable, and fuzzy rules fault output responses are shown in Figures 2, and 3, Figures 3(a) and (b) respectively.

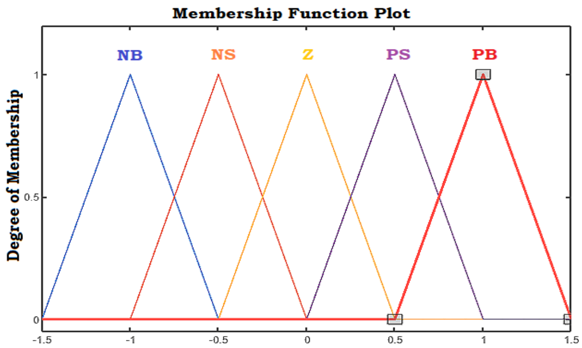
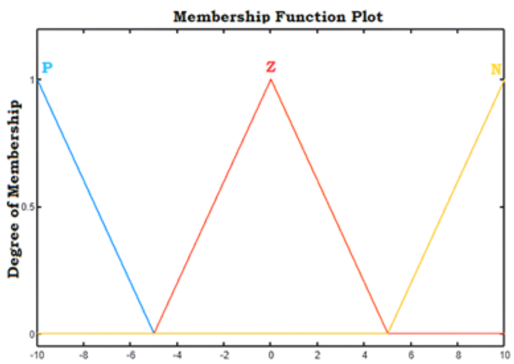
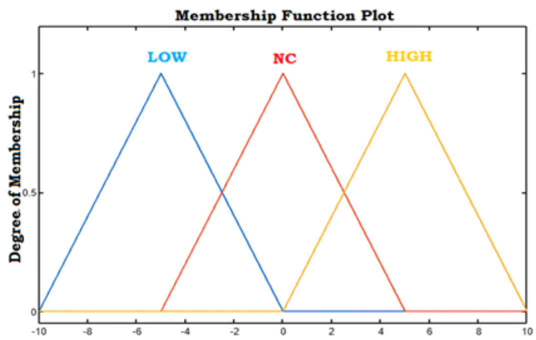


Figure 2. Plot Membership function for error input variables

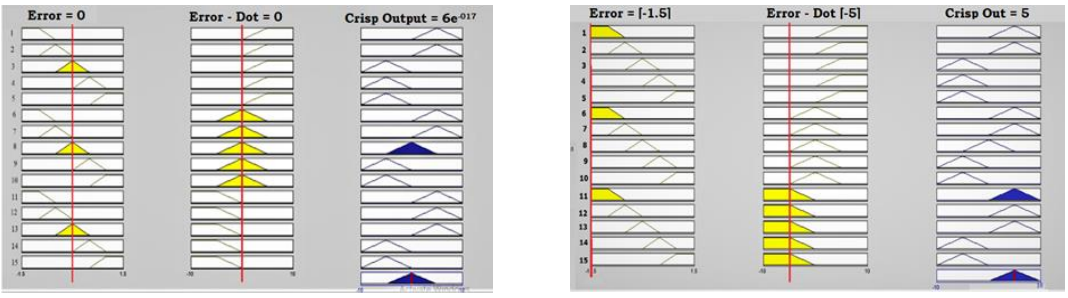


(a)



(b)

Once the variables, the IF and THEN rule, and the membership functions are defined as executed in Tables 1-4, with their corresponding graphs as captured in Figures 2, 3(a), and (b), the combined fuzzy rule and crisp value output for currents status of transformer is determined using the fuzzy rule editor. If the input value for current and rate of change of current (error and error-dot) are both zero (0), a single fuzzy set output is obtained by combining their outputs (fuzzy output sets) respectively. Such a scenario is acceptable when the power system transformer is operating within the desired range. In such circumstances, the defuzzification of fuzzy set output is done to obtain the accurate current output value of the transformer ($6e^{-017}$). The value $6e^{-017}$ signifies that there is no change of current in the transformer. This shows that the transformer is working normal level of current. Faults output response for no change in current and high current are show in Figure 4. A fuzzy set and crisp value for the no change response are shown in Figure 4(a). Similarly given that the input current is (-1.5) and rate of change of current is (-5), and an output crisp value of ‘‘5’’ is obtained after being defuzzified, this suggests the system is signalling the protective relay that there is the possibility of the system working under too high current. The graphical representation of the system is shown by the fuzzy rule editor captured in Figure 4(b).



(a) (b)

Figure 4. Faults output response for (a) no change in current and (b) high current

Also, when the input current for error and error-dot are 1.5 and -5 respectively, and the resulting crisp output is -5, after defuzzification, then this signifies that the system (power transformer) is experiencing low current. Figure 5, shows the simulated result for output response for low current.

Figures 4 and 5, display antecedent and consequent information for each rule, where each row represents a rule and each column a variable. The first two columns show antecedent membership functions, the third column shows consequent membership functions, and the sixteenth plot in the third column represents the aggregate decision for the inference system. A bold vertical line indicates defuzzified output.

Input values can be entered and adjusted by interacting with the plots. The intersection of the error index line with the membership function line determines the activation degree of a rule. A yellow patch under the membership curve enhances visibility. The implication process truncates the consequent based on the antecedent. Aggregation occurs, and the aggregate plot in the lower right corner depicts the defuzzified output value. Subsequently, following the establishment of the rule base and the identification of faults across various input values, the surface response was formulated, as depicted in Figure 6.

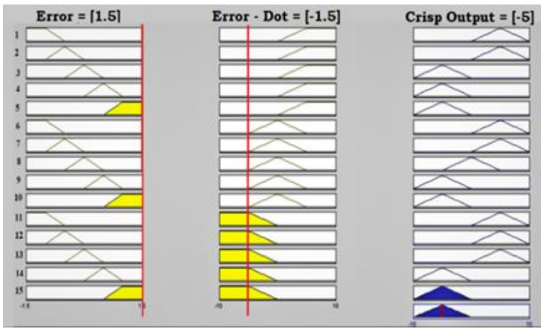


Figure 5. Output response for low current

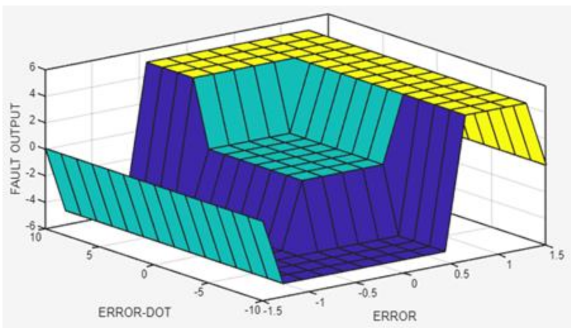


Figure 6. Surface response for faults identification

The simulation software evaluates and validates designed transformer fault protection scheme that involves testing during routine operations and various faults senarious. Analysis depicted in Figure 7, illustrates various faults senarious in power transformer. Fuzzy logic approach for faults inception time, and Estimated time of fault detection are shown in Figure 8. In Figure 8(a), the details time for fault inception is signal pricesily at 3 ms, and in Figure 8(b), the estimated time for fault detection is approximately 5.3 ms, indicating that, the proposed approach has the potentials of identifying incipient faults, and other types of trnsformer faults in real life scenario. Thus, making it realiable and effective toward protection of modern power system transformers.

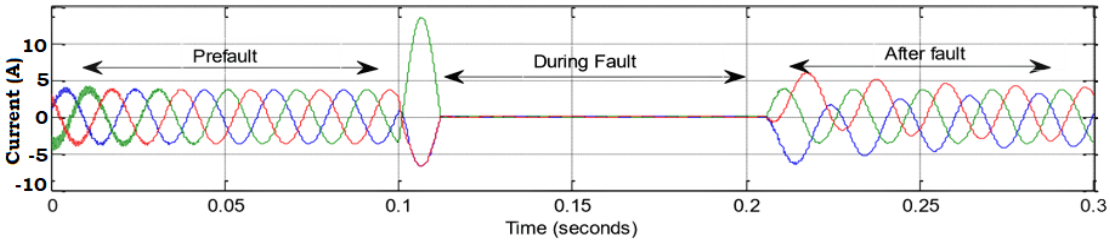
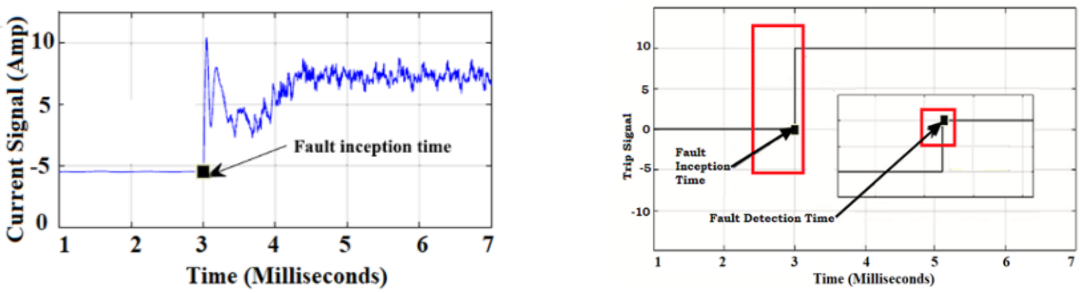


Figure 7. Various faults senarious in power transformer



(a) (b)

Figure 8. Fuzzy logic approach for (a) faults inception time and (b) estimated time of fault detection

3.1. Proposed methods comparison with existing methods

A comparative findings in terms of techniques used, and accuracy toward fault identification and protection in power transformers between existing methods by various authors and proposed is elaborated in Table 6. From the comparative of different techniques of faults identification in power transformer as shown Table 6. It is observed that fuzzy logic approach is highly reliable over other methods, due to its operational speed of faults identification in modern power system transformers within 5.3 ms, with an accuracy ranging from 96%-99% depending on the sensitivity the fault.

Table 6. Methods comparison

Authors	Techniques	Accuracy	Operation speed	Time taken
[14]	Differential protection	80%–90%	Fast	50 ms–100 ms
[21]	Sequential kalman filter	85%–90%	Moderate	500 ms–1 sec
[17]	Electrical transient analyser	70%–80%	Slow	5 secs–10 secs
[3]	Dissolved gas analysis	60%–80%	Slow	15 mins–30 mins
[18]	Buchholz relay	70%–80%	Moderate	100 ms–500 ms
[22]	GA-XG boost classifier	90%–95%	Fast	50 ms–100 ms
[Proposed]	Fuzzy inference system	96%–99%	Very fast	5 ms–10 ms

4. CONCLUSION

The use of fuzzy logic for fault detection is significantly important in the power system domain as it only uses the measurements of current and voltage with 100% independence toward the power flow direction. The model provides highly precise results and as well low-cost maintenance culture compared to the traditional methods and other soft computing techniques. The process implemented indicates how a fuzzy logic inference system is used for potential faults detection in transformers. Two input variables (error and error-dot) are used which both have values ranging [-1.5 to 1.5 and -10 to 10] respectively. The paper concludes that when the crisp output values after the defuzzification process are $6e\text{-}0^{17}$, +5, and -5, it indicates that the current flow in the power transformer is normal, high, and low respectively, and signals the protective relay within an approximate time of 5.3 ms, to take immediate action. The fuzzy logic model is reliable and highly precise toward the detection and protection scheme of modern power system transformers. The algorithm can be enhanced by including advanced type 2 and 3 fuzzy systems and employing deep learning control approaches that can accurately forecast power transformer defects.

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