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Power Transformer Fault Diagnosis Using Recurrent Neural Network And Fuzzy Inference System

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Abstract— **Power transformer is one of the most vital components in electric power systems. Considering huge financial impact on consumers during the unplanned outage caused by faults, an artificial intelligent system that combines the recurrent neural network (RNN) and fuzzy inference system (FIS) is developed in this research work. The operating condition considered includes normal condition, over current due to overload faults, external short circuit faults, terminal faults, winding faults, incipient faults and low energy discharge and high energy discharge faults conditions. MATLAB/SIMULINK software were used to model the power system network which includes 132 kV transmission lines from Itu Transmission Control of Nigeria (TCN) to Uyo 132 kV TCN and a star/delta 330/132/33 KV, 450MVA, 50Hz power transformer at Uyo TCN. These models were used to generate transformer current signals (data) for each of the faults considered. The generated features were used to developed RNN-FIS models for the fault's diagnostic and classification. The overall performance accuracy of the RNN-FIS found to be effective from the error deviation values of the diagnostic code, it was observed that the error deviation value was 0.013 for low energy faults occurrence. The result shows it is at a tolerate value. The average prediction accuracy achieved with RNN-FIS was 98.7%. The intelligent hybrid of RNN-FIS diagnostic model has proven to be useful in the diagnosis of the selected transformer faults.**

Keywords— Power Transformer, Fault Diagnosis, Recurrent Neural Network, Fuzzy Inference System, Recurrent Algorithm

1. INTRODUCTION

Every year, Nigeria power industry continues to record power deficit when the supplied energy is compared with the demand [1,2,3,4,5,6,7,8,9,10]. In view of the inadequate power supply from the national grid, the teeming consumer population resort to soar power system, wind power system, diesel generators and other alternative off grid power supply system [11,12,13, 14,15,16,17, 18,19,20,21, 22,23, 24,25, 26,27, 28,29, 30,31, 32,33]. Studies have shown that among the causes of recurring power shortage from the national grid are low power generation compared with the required power demand, poor transmission and distribution network infrastructure, energy theft, among others [34.35.36,37]. There is also significant power loss in the system [38,39,40,41,42,43,44,45,46,47,48]. Accordingly, in this paper, the focus is on power transformer fault diagnosis.

Notably, power transformer is one of the essential assets and vital component in the generation, transmission and distribution levels of a power system. Furthermore, it is of critical importance to ensure its stable, reliable and safe operation. Power transformers are regarded as one of the most important and expensive unit in power network, a sudden failure that causes by faults implies that, the transformer need to be taken out of service, often associated with considerable cost for the company. Faults in transformer causes breakdown in power system which lead to financial and economic losses to the sector and frustration to the consumer [51]. Power system stability mostly depends on the operation of series of component within the system. However, it is subjected to different types of faults which may cause restriction in power supply; eventually result in severe economic losses as well as social impacts [52].

Many fault diagnosis methods are available; but only few could detect the fault in power transformer. As a result, effective fault diagnosis approaches were introduced and analyze the power transformer internal faults, and eliminate the associated impacts to the lowest level [53]. Fault in a power transformer is classified as internal and external faults, and Fault diagnosis of power transformer become increasingly essential to keep power system in reliable, stable and efficient operation of power grid, more new technology of transformer fault diagnosis, such are neural network (NN), artificial neural network (ANN), artificial intelligence (AI), and clustering neural network (CNN) [54,55]. Moreover, its supply differences give undesirable factors for the accurate prediction and assessment of power transformer fault. Therefore, it is a critical important to develop effective fault diagnosis of power transformer method for electric power system. So, it is pertinent and necessary to detect fault early by using fault diagnosis system of power transformer [56,57].

2. REVIEW OF RELATED WORKS

Power transformer fault detection (diagnostics) using radial basis function (RBF) neural network was discussed in [58,59]. The authors achieved a high degree of fault diagnostic performance accuracy of 82.2%. There is meant to be mis-identification of fault when artificial intelligent model is utilized. [60] explored the study of artificial bee colony algorithm (ABC) with other machine learning methods for internal fault detection of a power transformer using differential protection scheme with a sampling frequency of 1 kHz. However, the diagnostic accuracy of random forest which was 85% needs to be increased to ensure efficient transformer fault identification. [61] utilized artificial neural network-based fault diagnosis system on power transformers. The accuracy obtained was 0.72 (72%) which was low when compared with other previous studies. [62] proposed transformer fault diagnostics with dissolved gas analysis (DGA) for detecting the incipient fault of oil-filled power transformers. Though the results showed a promising study but the chances of fault mis-identification is high as the accuracy of the faults diagnostics is less than 95%.

3. METHODOLOGY

A three phase, three windings connected in star- star-delta situated in the transmission station in Afaha-Ube, Uyo was used as the case study to this research. It is energized by a 330 kV network, rated at 450 MVA, 330KV/132KV/33KV (voltage stepped down from 330KV to 132KV). The model of this transformer was obtained and simulated in MATLAB 2019a. Six transformer faults were introduced to this transformer with a sole aim of using a hybrid of intelligent models of fuzzy inference system and recurrent neural network (FIS-RNN) model in diagnostic performance of the transformer. The flow chart below summarizing the research methodology is shown in Figure 1.

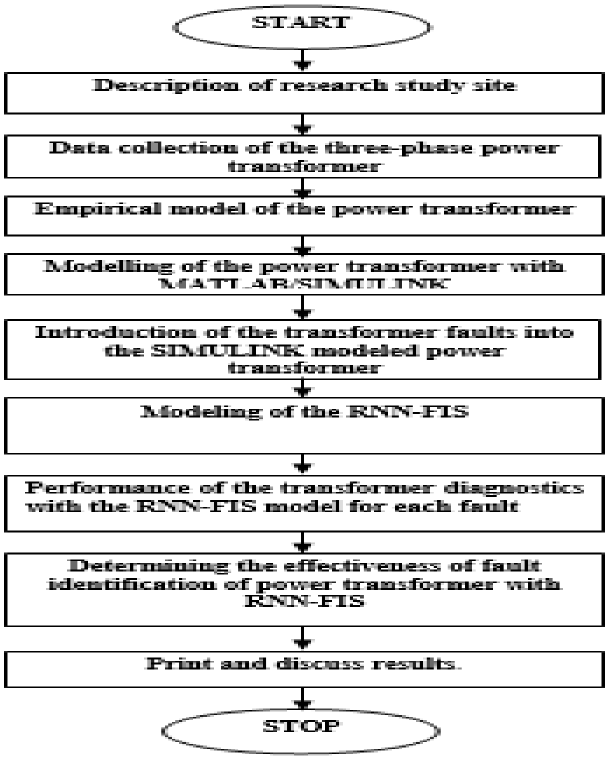

Figure 1: Research procedure

The transmission substation in Uyo is located in Ring Road off Ikot Ekpene Road, Uyo at 5.042792 Longitude and 7.902335 Latitude. The three-phase power transformer in this substation receives 330KV from Alaoji and Ibom Power Plants and steps it down to 132 kv and 33 kV, and distributes to other places in Akwa Ibom state. The rating of the transformer is 450MVA. The data of the following parameters of the power transformer collected from the power station is shown in Table 1.

Table 1: Data acquired for modelling

Parameters	Values
Nominal power (rating)	60MVA
Resistance of winding	11.11 ohm
Voltage of winding 1	330kV
Inductance of winding	10.118 H
Resistance of winding	20.235 ohm
Voltage of winding	2132 kV
Inductance of winding	20.25 H
Resistance of winding	30.36 pu
Voltage of winding	333 kV
Inductance of winding	30.019 pu
Frequency	50 Hz

The main function of transformers is to step up or step-down inlet voltages values to the required voltage of that environment. The primary winding core draws current when it is connected to an alternating voltage source. The sinusoidal current produces a sinusoidal flux φ that is expressed as:

$$\varphi = \varphi_m sinwt \quad (1)$$

where φ_m is the magnetic flux and w is the angular velocity. The instantaneous emf induced in the primary winding e_i is given as:

$$e_i = -N_i \frac{\Delta\varphi}{\Delta t} \quad (2)$$

where N_i is the number of loops in the primary coil and e_i is the emf induced in the primary coil. The instantaneous emf induced in the secondary winding e_s is given as:

$$e_s = -N_s \frac{\Delta\varphi}{\Delta t} \quad (3)$$

where N_s is the number of loops in the secondary coil and e_s is the emf induced in the secondary coil. Substituting Equations 1 into 2 gives:

$$e_i = -N_i \frac{d}{dt}(\varphi_m sinwt) \quad (4)$$

$$e_i = -N_i w \varphi_m \, coswt \quad (5)$$

$$e_i = -N_i w \varphi_m \sin(wt - 90) \quad (6)$$

The primary EMF maximum E_{mi} is given as:

$$E_{mi} = N_i w \varphi_m \quad (7)$$

Whose root mean square (RMS) E_i is given as:

$$E_i = \frac{E_{mi}}{\sqrt{2}} \quad (8)$$

Substituting equation (7) into (8) gives:

$$E_i = \frac{N_i 2\pi f \varphi_m}{\sqrt{2}} \quad (9)$$

where $w = 2\pi f$ with f being the frequency.
Similarly, for the secondary coil,

$$E_s = \frac{N_s 2\pi f \varphi_m}{\sqrt{2}} \quad (10)$$

Taking the ratio of Equation 2 and Equation 3 gives number of turns in the transformer as:

$$\frac{e_i}{e_s} = \frac{N_i}{N_s} = a \quad (11)$$

Dividing Equation (9) by Equation (10) gives:

$$\frac{E_i}{E_s} = \frac{N_i}{N_s} = a \quad (12)$$

Where a is the ratio of the turns in the transformer.
Assume negligible resistance, the electrical output of a transformer is equal to its input. Equating the power input and output gives:

$$P_i = I_i V_i cos\varphi = I_s V_s cos\varphi = P_s \quad (13)$$

The Simulink model of the three-phase power transformer is shown in Figure 2.

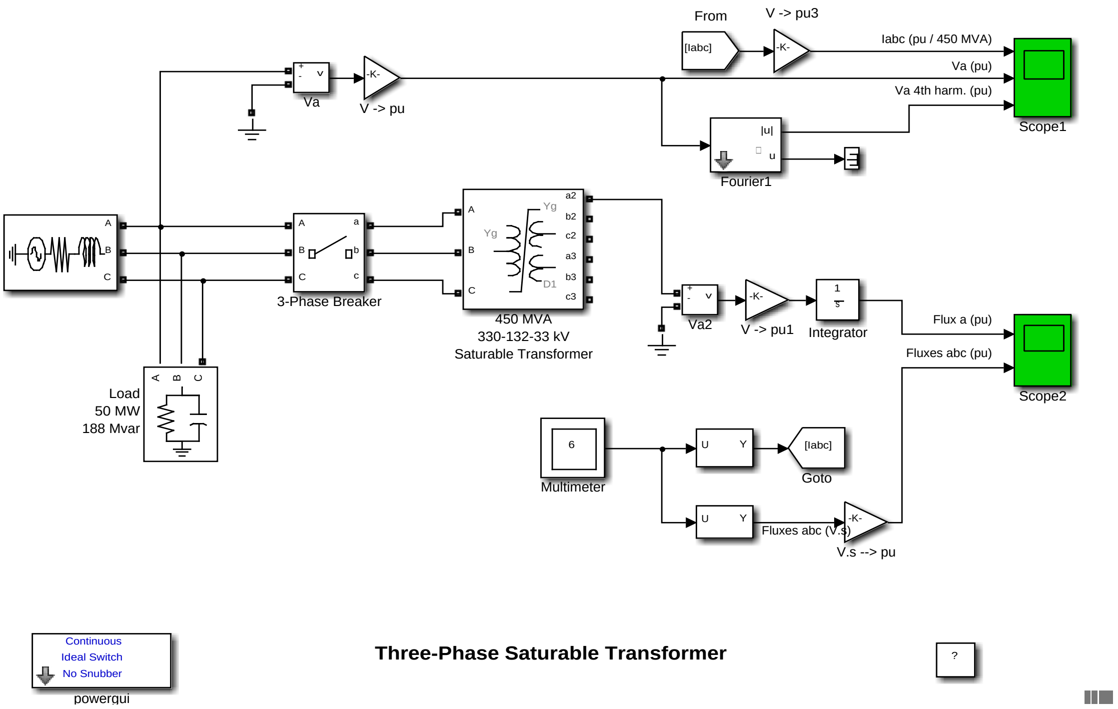

Figure 2: Three-Phase saturable transformer

A three-phase transformer is energized on a 132 kV network. The transformer rated 450MVA, 330KV/132 kV/33 kV consists of three windings connected in Star (Y) /Star (Y)/Delta (Δ). The power system is simulated by an equivalent circuit consisting of an inductive source (short-circuit power of 1200 MVA) and a parallel RC load. The capacitor reactive power has been selected in order to produce a resonance at 50 Hz. The transformer saturation characteristics is approximated by a single slope Xsat of 0.32 pu, corresponding to an air core reactance Xac = 0.40 pu (Xac = Xsat+Xh = 0.32+0.08 = 0.40 pu.) seen from the primary. Three residual fluxes (-0.8, - 0.4 and 0.4 pu) are specified for phases A, B and C.

The multimeter and scope blocks are used to monitor extra signals without using measurement blocks. The 6 signals at the multimeter output includes the 3 currents from the circuit breaker and 3 fluxes which are inside of the saturable transformer core.

The flux on phase A is also obtained by integrating the phase A voltage at the unloaded output of winding two. The voltage is converted into p.u and also, the flux is converted to p.u. with gain blocks using proper scaling. The contents and data supplied to each of the Simulink blocks in Figure 2 are displayed in the subsequent figures. The three phase power block parameters are shown in Figure 3.

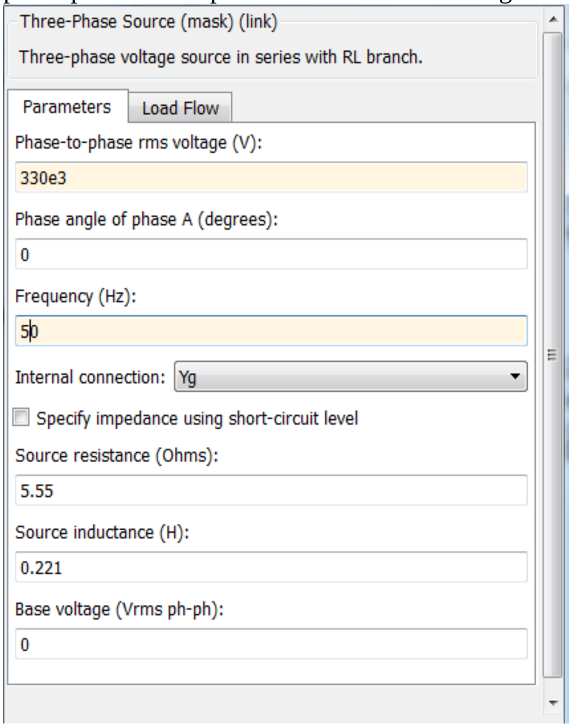

Figure 3: Power source block.

From Figure 3, it can be seen that the voltage used for powering the transformer was 330kv supplied from Alaoji at Nigerian frequency of 50Hz. The three-phase transformer model block is shown in Figure 4.

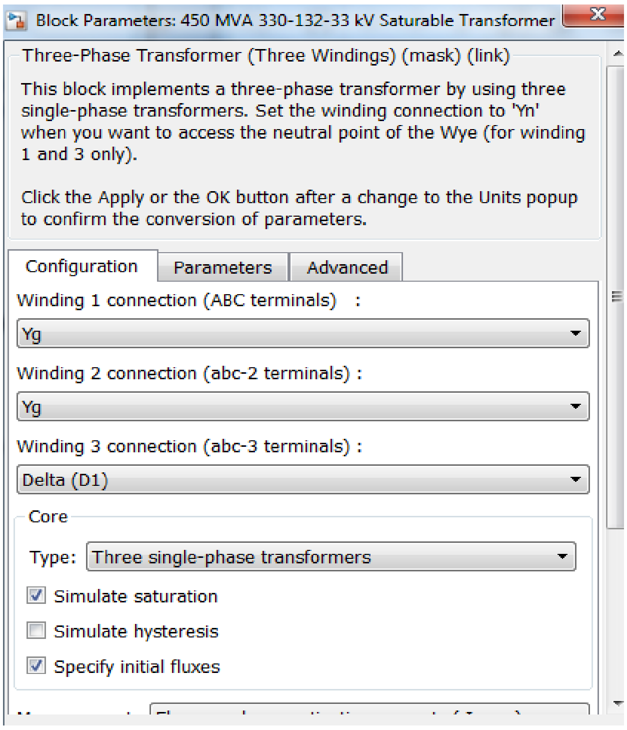

Figure 4: Configurations of the transformer

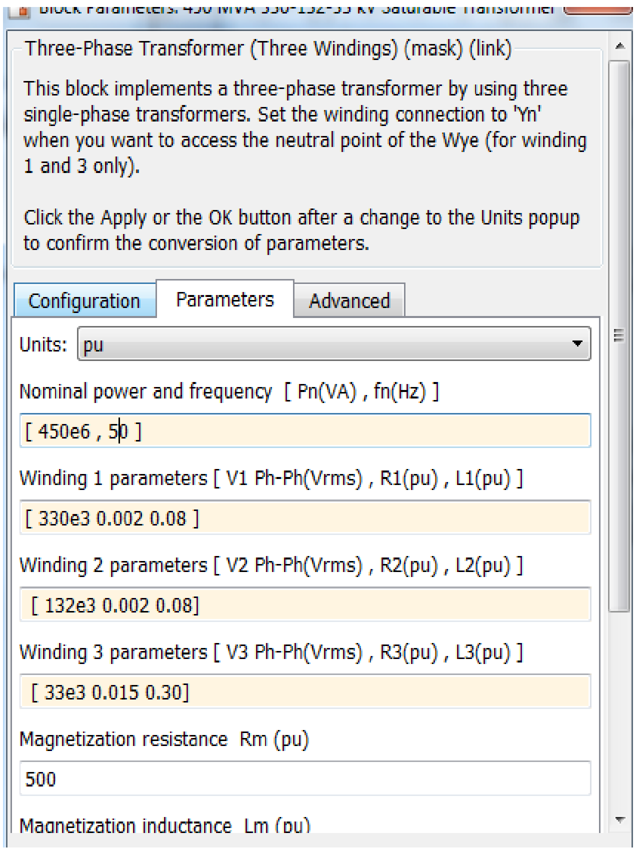

Figure 5: Transformer parameters

Before simulation, different types of faults were introduced to the Simulink model in Figure 2. The three current signals generated from the scope of the model was exported to the command window of the MATLAB environment which was used as input to the RNN-FIS model to be described in the next subsection. The fault introduced were: over current due to overloads and external short circuits, terminal faults, winding faults, incipient fault, low energy discharge and high energy discharge faults.

For the fault diagnostic performance of a power transformer, a hybrid of RNN and FIS model used and implemented in MATLAB/SIMULINK software. The flow algorithm indicating the procedure of modelling the RNN-FIS in MATLAB for identifying different transformer faults are shown in Figure 6.

To generate a higher accuracy in prediction, sugeno inference rules was used instead of the default inference rules mamadani. The FIS environment with the inputs and targeted output is shown in Figure 8. The membership function used for the inputs and output are shown in Figure 9 to Figure 11. From Figure 11, the membership function used for the diagnostics codes is a constant membership function. The reason for using a constant membership function for the output variable was for proper alignment of the inference rule to the input. The sugeno generated inference rules is shown in Figure 12.

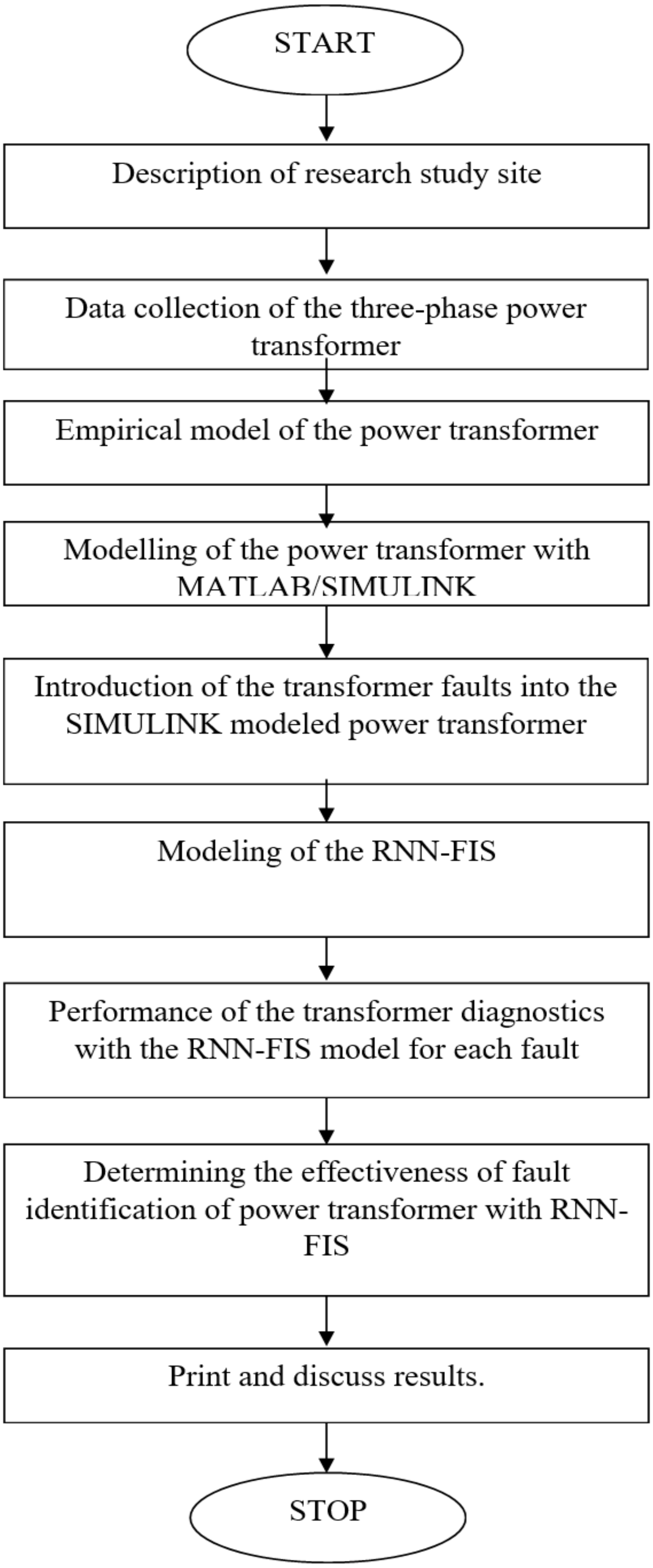

Figure 6: Flow algorithm for RNN-FIS modelling

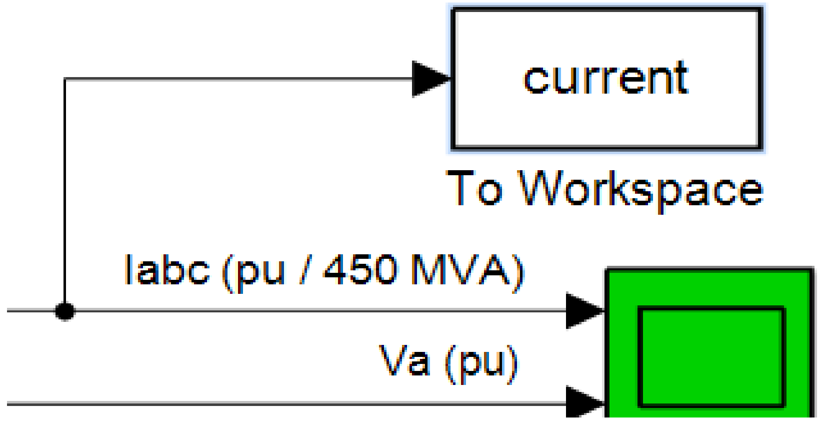

Figure 7: Simout block in Simulink

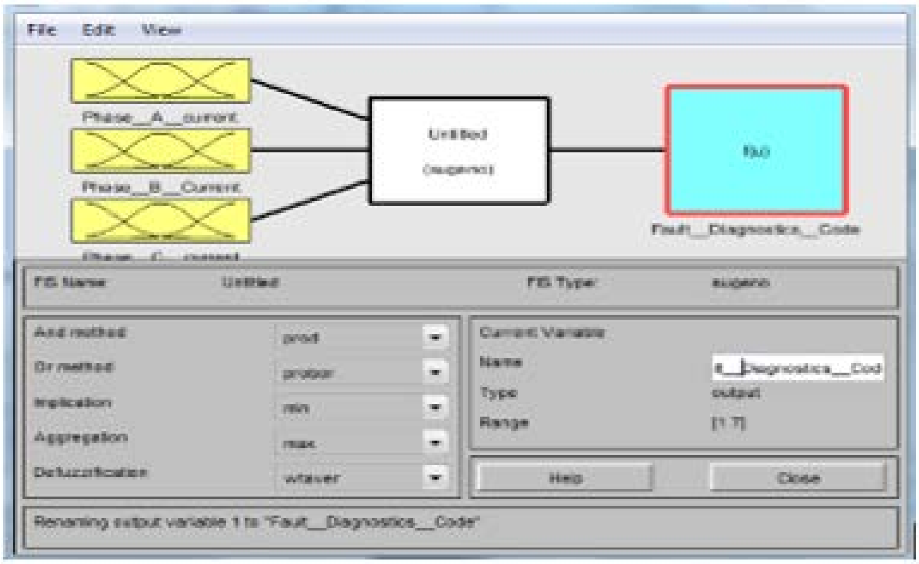

Figure 8: Inputs and Output targets for FIS

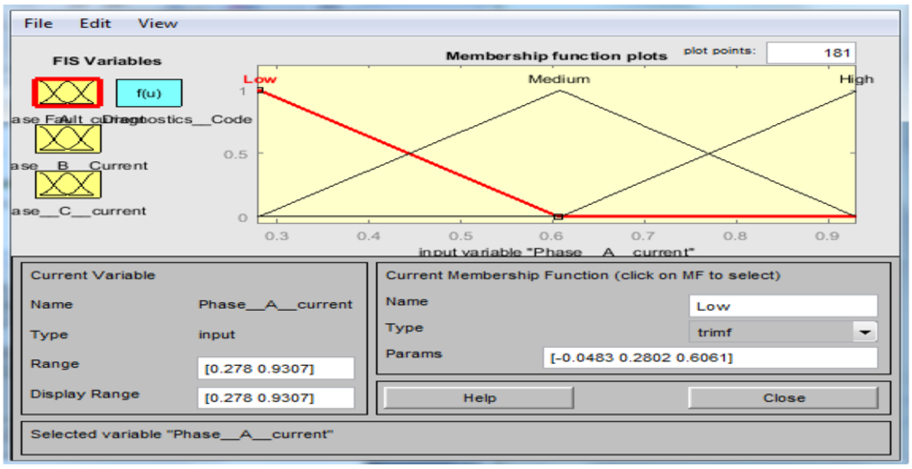

Figure 9: Membership function for transformer Current at Phase A

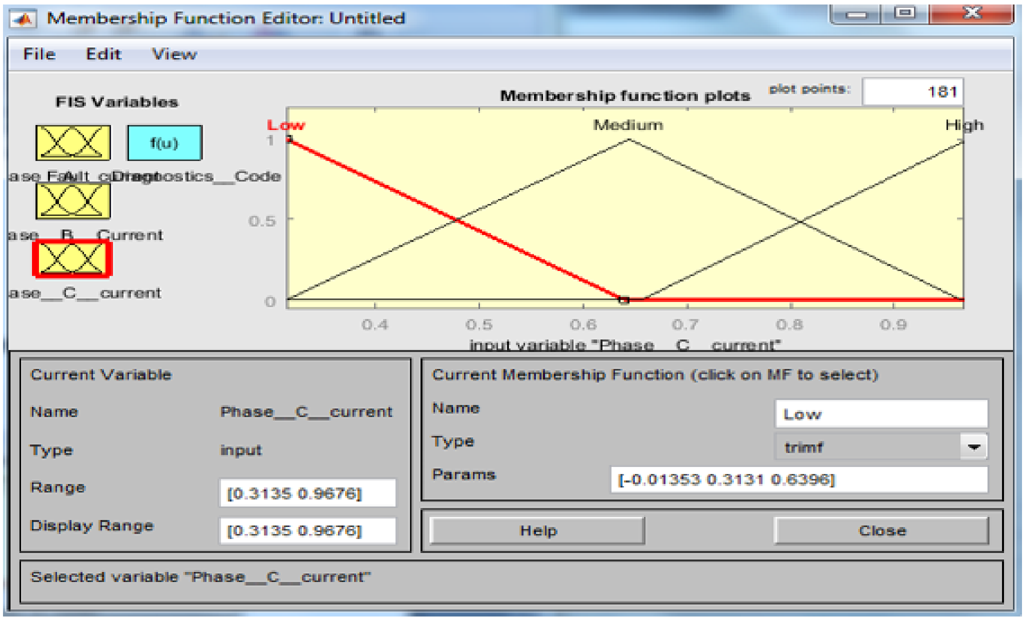

Figure 10: Membership function for transformer Current at Phase C.

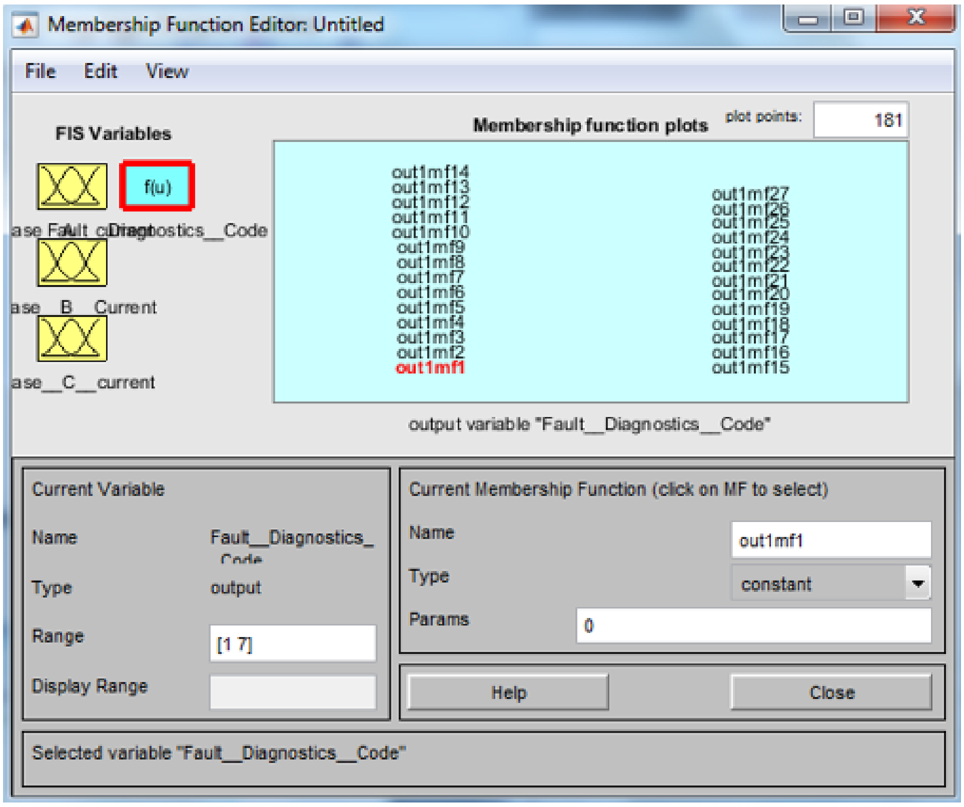

Figure 11: Membership function for diagnostics codes.

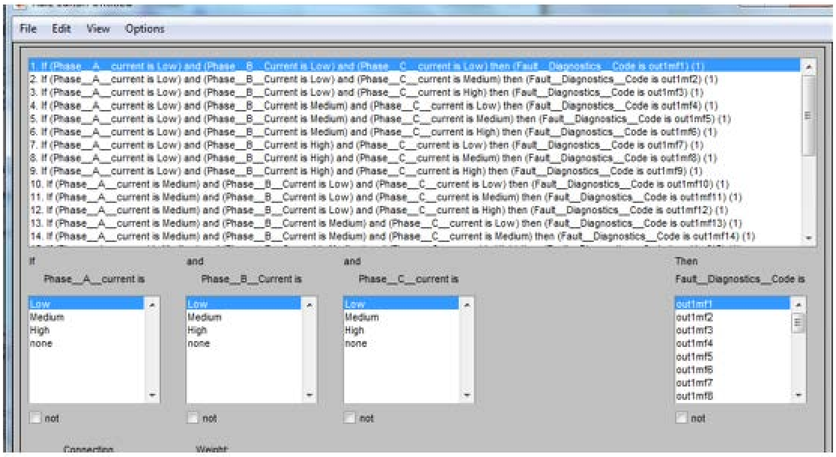

Figure 12. FIS Sugeno inference rules

4. RESULTS AND DISCUSSION

The different transformer faults current signal was simulated in MATLAB/SIMULINK and the code for identifying the type of fault occurrence is shown in Table 2. The model represented in SIMULINK was the power transformer located at Afaha-Ube transmission substation in UYO. The various faults considered includes; transformer at normal condition, the current of the transformer when there is over current fault, when there is terminal fault, occurrence of winding fault, incipient fault, low energy fault and a high energy fault occurrence in the transformer.

Table 2: Code for Different Types of Fault Occurrence

S/N	Transformer faults	Fault Current signal			Fault diagnostic code
		A	B	C	
1	Normal condition	96.77	32.04	-127	1
2	Over current	207	136.1	- 343.1	2
3	Terminal	-0.9186	-0.3317	1.23	3
4	Winding	19.6	24.5	-44.1	4
5	Incipient	18.65	24.94	-43.6	5
6	Low energy	19.45	25.24	-44.69	6
7	High energy	208.41	34.5	-342.9	7

From Table 2, it is expected that when any of the transformer fault occurs, it will be identified by the diagnostic codes shown in the last column. Table 2 was used in generating the RNN-FIS intelligent model for diagnosing transformer faults. The current signals were the independent variable while the diagnostic code being the output variable. Figure 13 shows the Simulink model of the transformer at normal condition with the diagnostic model inserted.

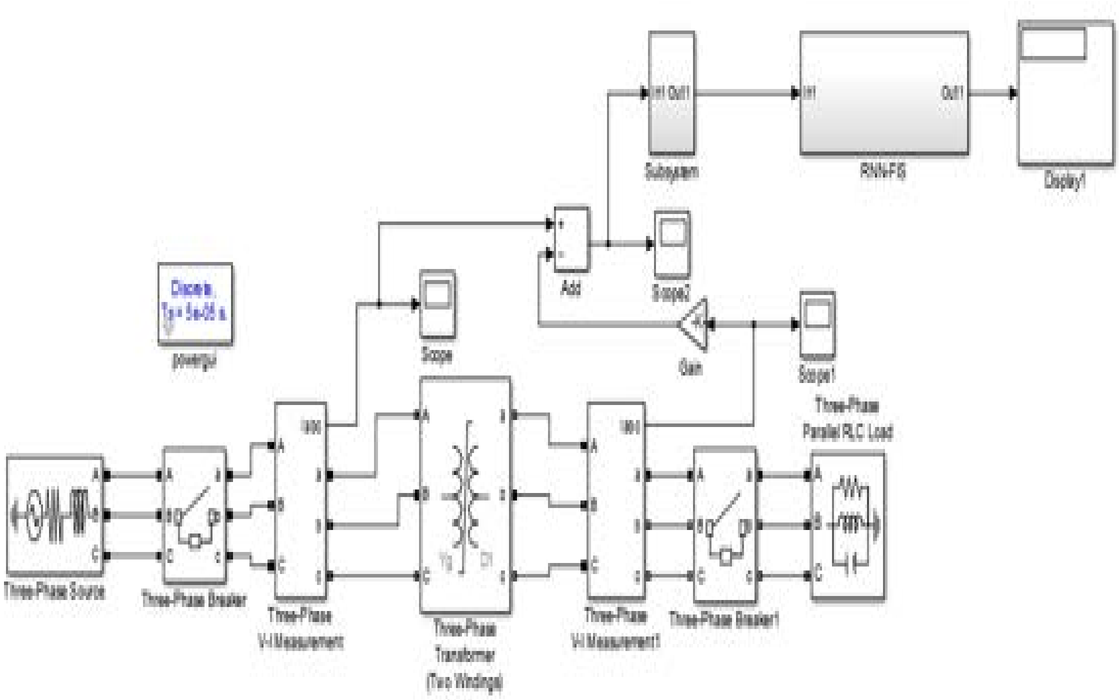

Figure 18: Transformer model with the fault identifier.

The aftermath of the simulation of the SIMULINK model shows in Figure 15 is displayed in Figure 14. The RNN-FIS block in the model is used in identification and diagnostics of the various types of fault occurrence in the transformer. According to the Simulink model presented in Figure 13, the current signal of the transformer indicated as ‘’three-phase transformer (two windings)’’ is measured and sent to the fault identifier (RNN-FIS) where the faults will be diagnosed and displayed. However, the RNN-FIS main function is to obtain the current signal sent and ascertain the type of fault by displaying the code for each fault occurrence. The various fault occurrence diagnosis performed by the RNN-FIS block model are reported in the subsequent figures. The operation of the transformer at normal condition has been diagnosed by the RNN-FIS model is shown in Figure 14.

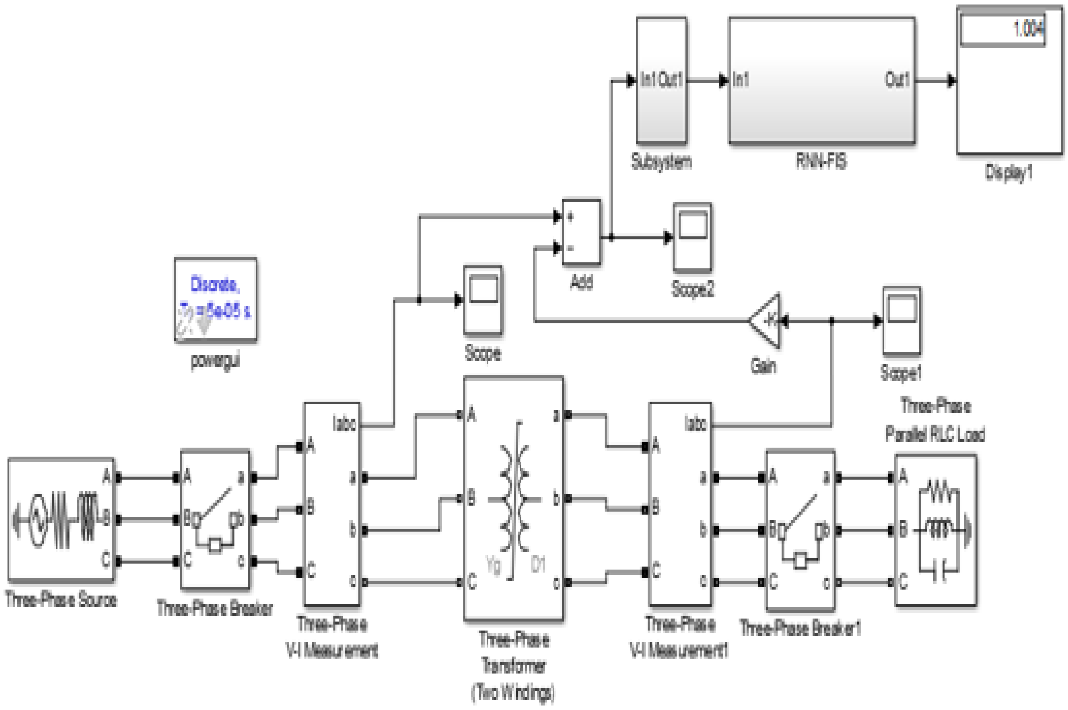

Figure 14: Simulated Transformer Model at Normal condition.

The SIMULINK model of the transformer at normal condition is shown in Figure 14. When the current signal from the power transformer was sent to the RNN-FIS model, it was able to diagnose to a near-accuracy extent that the transformer operates at normal condition (that is absence of any form of fault) by displaying the diagnostic code value of 1.004. The expected coded value of the transformer at normal condition that has been modelled in the RNN-FIS was 1.000. Hence, the deviation based on the outcome is 0.004. At this point, since the error is less than the tolerable threshold of 0.5, it implies that the diagnosis performed by the RNN-FIS model as pertains to normal condition of the transformer should be accepted and implemented. The simulated three-phase current signal of the transformer was obtained and displayed in Figure 15. This was done to ensure that the diagnostic report presented by the RNN-FIS is in line with current signal plots.

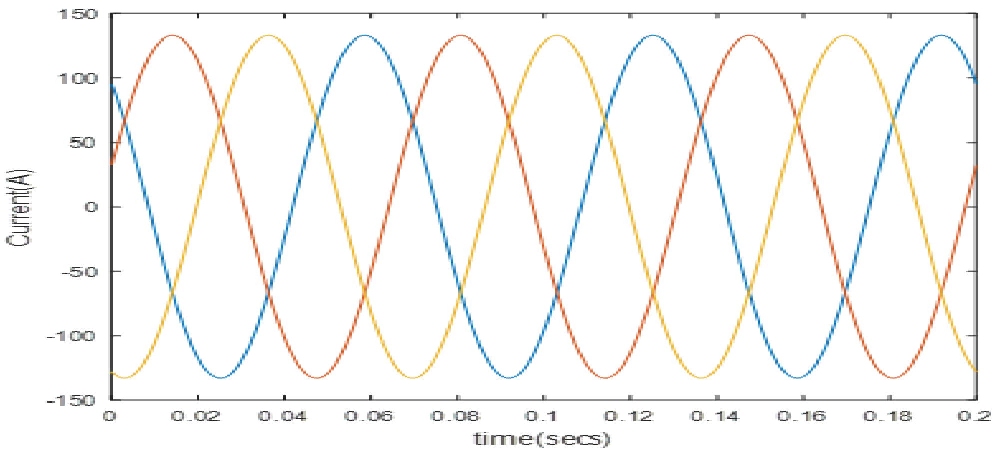

Figure 15: Simulated current signal at normal condition.

From the current signal shown in Figure 20, it can be seen that it represents the system at normal condition due to absence of any form of distortion in the signal. They can be taken to be confirmation of the diagnostic code presented by the RNN-FIS of being normal. Based on this, the proposed RNN-FIS model effectively identified and diagnosed the transformer at normal condition of operating at normal condition. The SIMULINK model of the power transformer when over current occurs and the diagnostic code presented by the RNN-FIS model is shown in Figure 16.

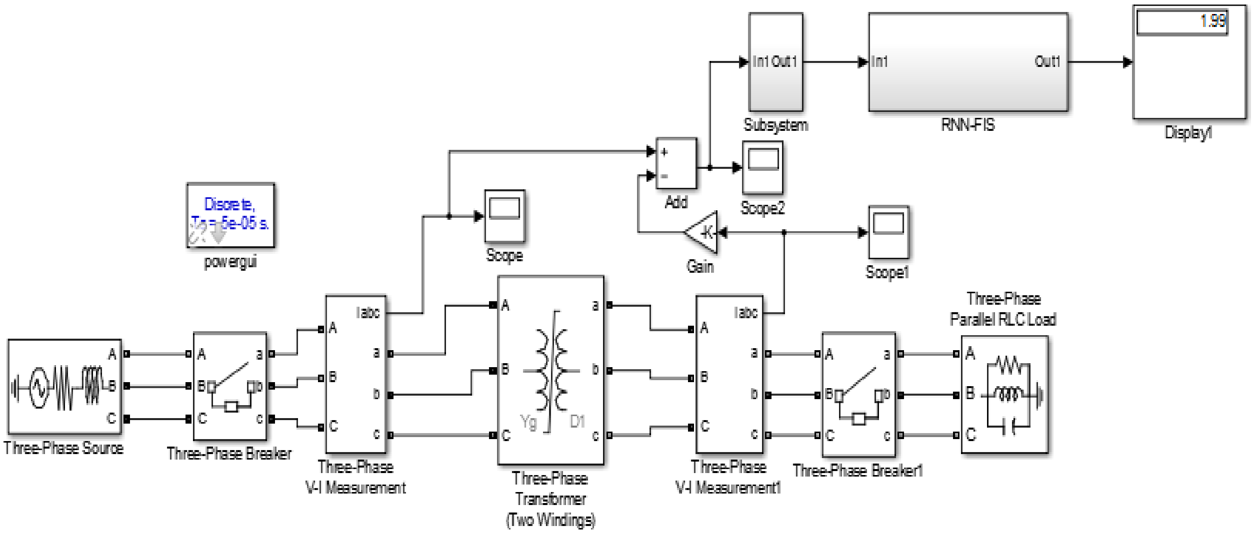

Figure 16: Fault diagnostics when over current fault occurred.

Figure 20 shows the SIMULINK model of the transformer during over current fault. When the current signal was sent to the diagnostic model (RNN-FIS), it displayed a diagnostic code 1.99 as against the diagnostic code of 2.00 used in the modeling of RNN-FIS. Based on this outcome, the deviation error was 0.01 (that is 2.00 – 1.99) which is lower than the error threshold of 0.5. This implies that the RNN-FIS proposed adequately identified and diagnostic the power transformer to have over current fault occurrence. The simulated plot of the current signal of the transformer was presented with the occurrence of over current fault and shown in Figure 17. This is too commensurate with the diagnostic report presented by the RNN-FIS as the system having transformer over current fault.

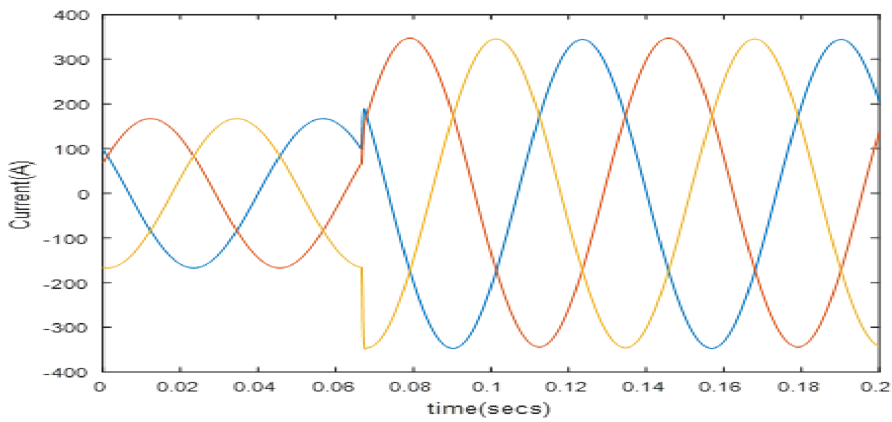

Figure 17: Current signal during over current fault occurrence in the transformer

The transformer with the presence of over current fault is shown in Figure 17. From the start-up of the transformer up to six seconds, the system operated at normal condition until a sudden current increase occurred at 0.06 seconds which led to the over current fault in the transformer having a current signal value than 300Amps. This implies that the presence of over current in the transformer was effectively detected and diagnosed by the RNN-FIS. For the terminal fault occurrence in the transformer, the SIMULINK model showing the implementation of the proposed RNN-FIS model for the diagnosis of the transformer is shown in Figure 18.

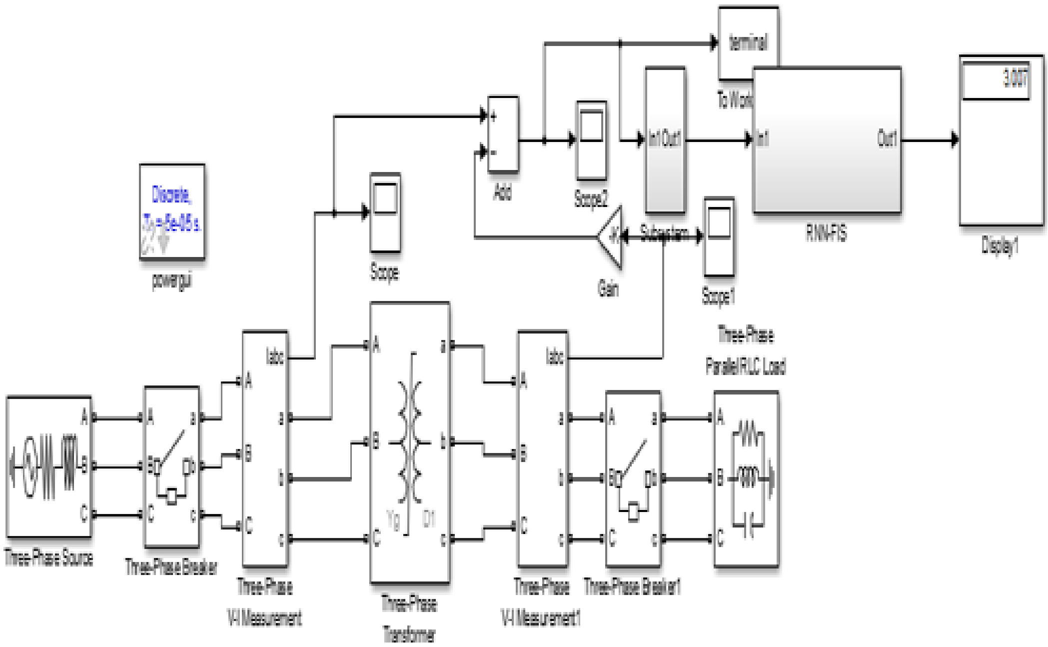

Figure 18: Fault diagnostics for terminal faults

Figure 18 shows that power transformer SIMULINK model and the RNN-FIS block for the identification of terminal fault. The diagnostic code displayed after the current signal from the transformer was sent to the model as shown was 3.007. The actual diagnostic code used in the modeling of the RNN-FIS model was 3.000. As such, the error deviation of the diagnostic code is 0.007 (that is 3.007-3.000). Since the error deviation is less than the deviation threshold of 0.5, it implies that the proposed intelligent hybrid model of RNN/FIS effectively diagnosed the transformer as having a terminal fault. The current trend when terminal fault occurs in the transformer is shown in Figure 19. This is to ensure that terminal fault occurred in the transformer has identified by the RNN/FIS model.

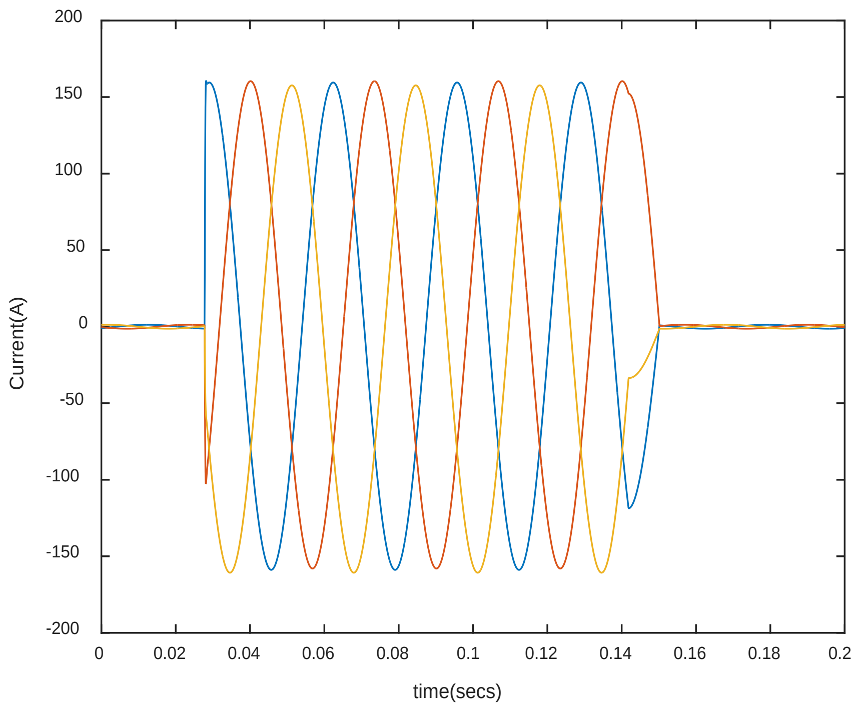

Figure 19: Current with terminal fault occurrence at the transformer

The current signal during the occurrence of terminal fault is presented in Figure 19. The transformer operated at interval between 0.03 seconds and 0.15 seconds which led to the occurrence of terminal fault. Hence, the RNN/FIS model were introduced and effectively identified and diagnosed the occurrence of terminal fault in the power transformer. The SIMULINK model with the RNN-FIS model for winding fault in the transformer is shown in Figure 20.

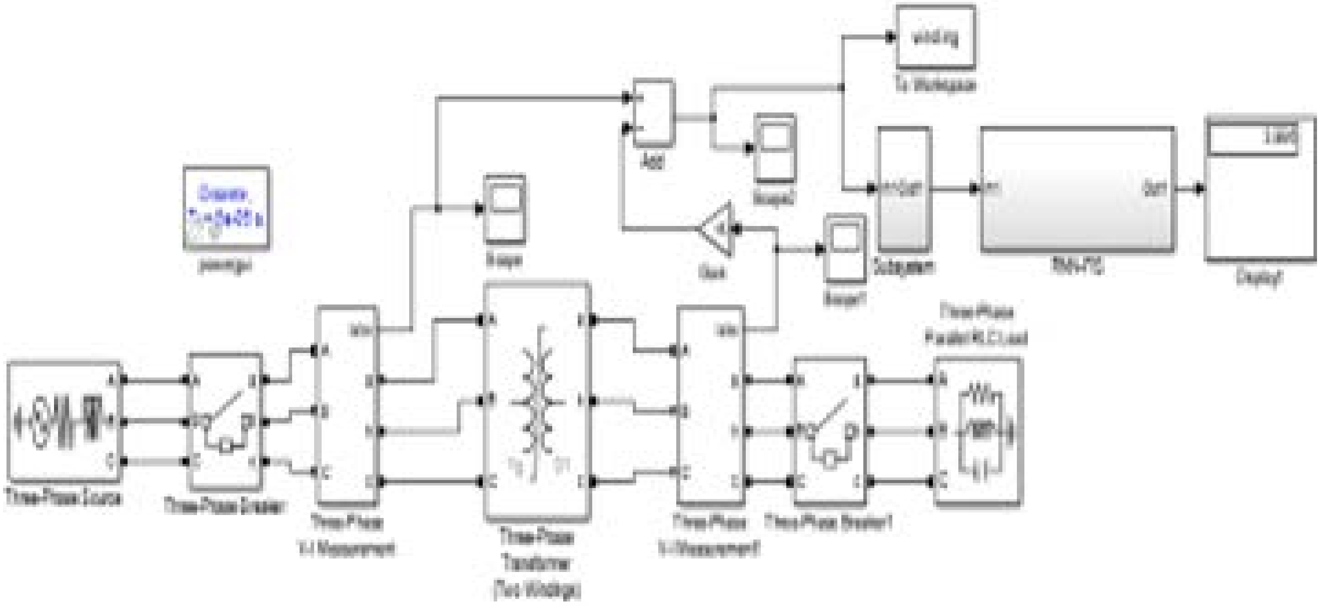

Figure 20: Winding fault occurrence in the transformer

The SIMULINK model of the transformer when the winding fault was initiated with the implementation of the RNN-FIS diagnostic model is shown in Figure 20. It can be seen that the diagnostic code displayed was 3.998 against 4.000 used in the modeling of the RNN-FIS model. Therefore, the error deviation of the model is 0.002 which is less than the error tolerance threshold of 0.5. As such, the diagnosis of the transformer can be said to be effectively carried out with the transformer having a winding fault. The graph of the current signal during the occurrence of the winding fault in the transformer is shown in Figure 21.

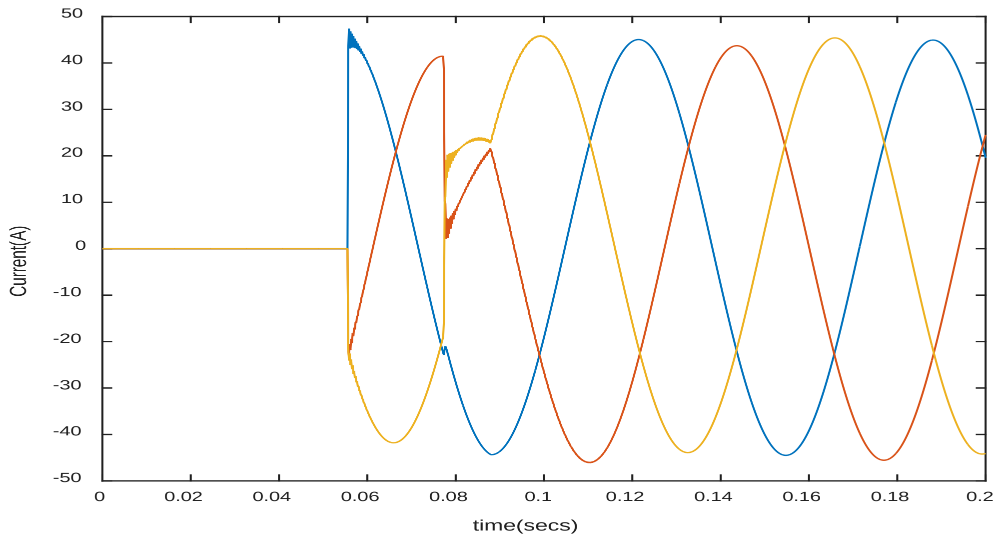

Figure 21: Current signal of the transformer winding fault

The system with the current signal indicating winding fault in the transformer is shown in Figure 21. The current signal for the entire simulation results showed low current values with some glitches in the trend of the plot. Hence the RNN-FIS implored diagnosed the system accurately as winding fault occurrence in the transformer. The SIMULINK model of the transformer showing the occurrence of incipient fault with the diagnostic model is shown in Figure 22.

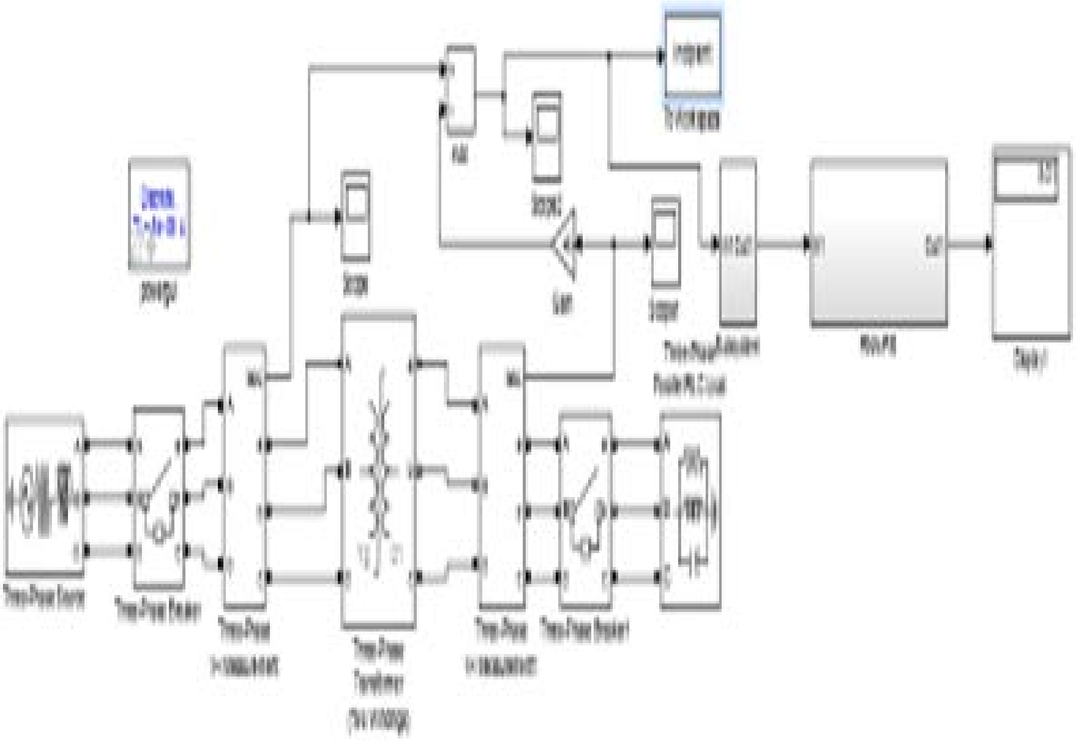

Figure 22: Incipient fault occurrence.

Figure 22 shows the occurrence of incipient fault on the transformer with the presence of the RNN-FIS model. The diagnostic code displayed by the RNN-FIS model is 5.01 as against 5.00 code used in the development of the model. The error deviation is 0.01 (5.01 – 5.00). Error deviation value is less than the error threshold of 0.01 which implies that the proposed intelligent diagnostic model adequate diagnose the transformer as operating with incipient fault. The current signal trend of the occurrence of incipient fault is shown in Figure 23.

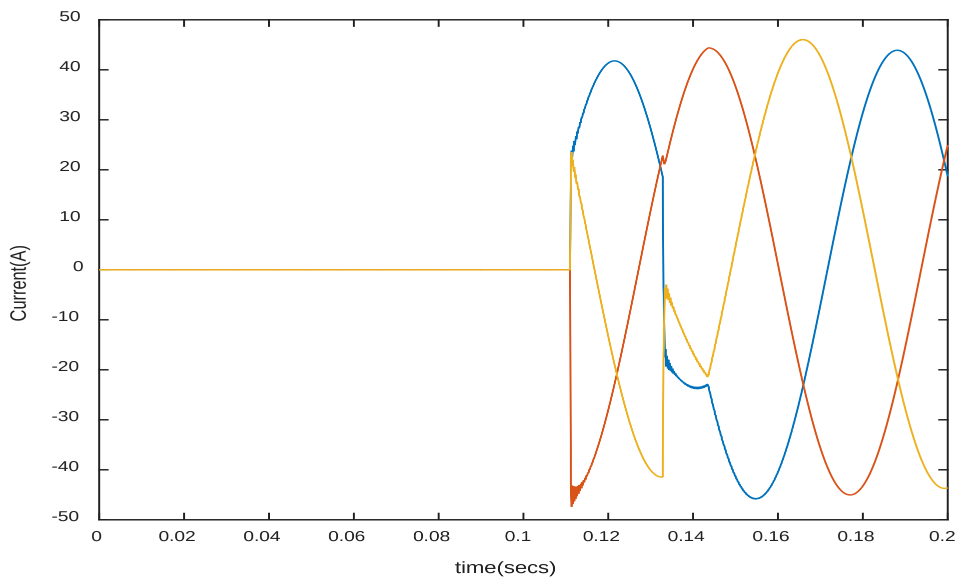

Figure 23: Current signal during incipient fault in the transformer

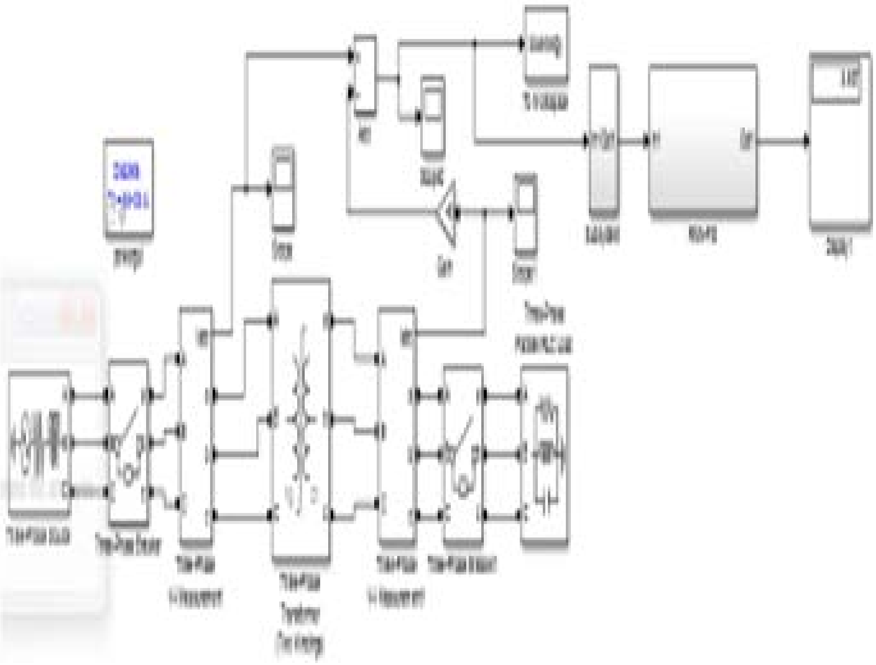

Figure 24: Fault Diagnostics for low energy fault.

The diagnostics code value displayed by the model is 5.987 as shown in Figure 24 as against 6.00 meant for low energy fault of the transformer. The error value is 0.013.
The simulated current signal at low energy fault occurrence in the transformer is shown in Figure 25.

The model for the high energy fault is shown in Figure 26. The current signal values for the high energy occurrence in the transformer is shown in Figure 27.

The summary of the error deviations for fault diagnostics of the various fault occurrence in the transformer are shown in Table 3.

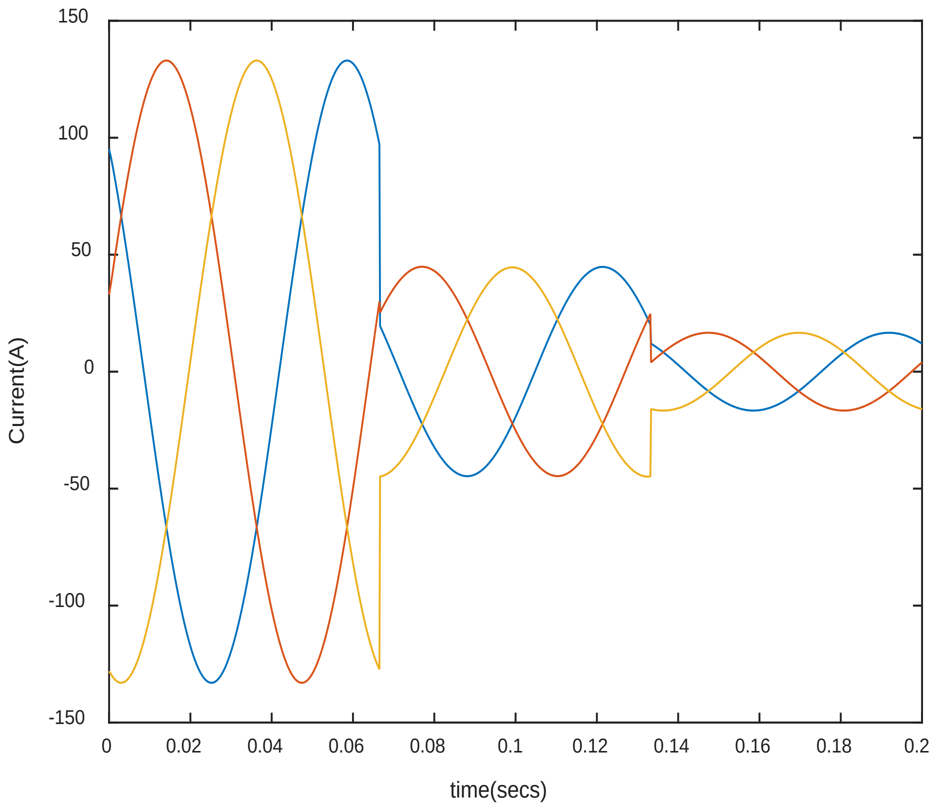

Figure 25: Current for low energy fault occurrence in the transformer.

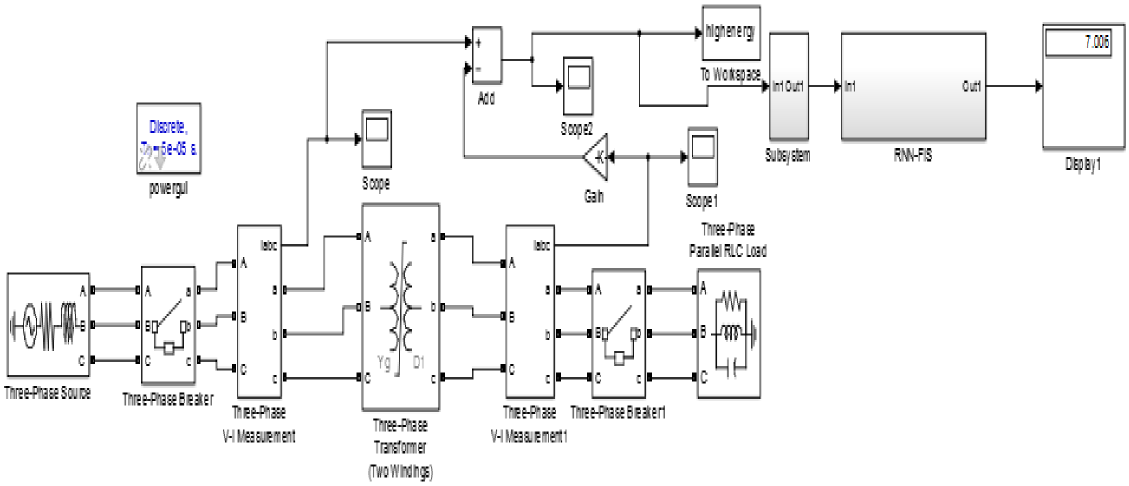

Figure 26: Fault diagnostics for high energy transformer fault

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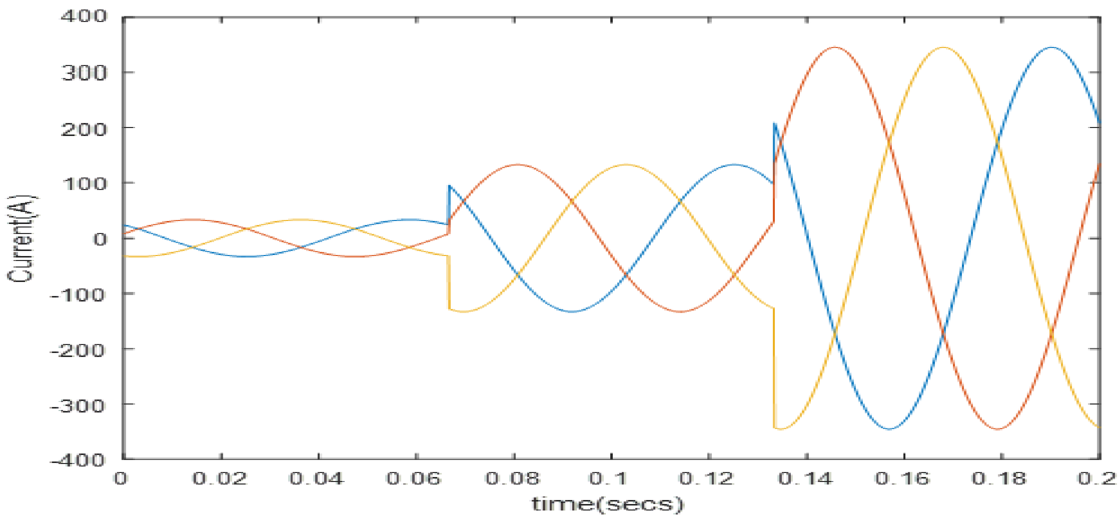

Figure 27: Current signal of high energy fault in the transformer

Table 3: Summary of the Error Deviations for Fault Diagnostics of the Various Fault Occurrence in the Transformer

Transformer faults	Actual Fault diagnostic code	Predicted Fault diagnostic code	Error deviation
Normal condition	1	1.004	0.004
Over current	2	21.99	0.01
Terminal	3	33.007	0.007
Winding	4	43.996	0.004
Incipient	5	5.01	0.01
Low energy	6	5.987	0.013
High energy	7	7.006	0.006

From the error deviation values of the diagnostic codes shown in Table 3, it can be seen that the highest error deviation value was 0.013 (1.3%) for low energy fault occurrence. At error deviation of 1.3% means it is at a tolerable value, this implies that the RNN-FIS model introduced can be utilized in the diagnosis of the various transformer fault occurrence. The average prediction accuracy achieved with RNN-FIS was 98.7%. The comparative analysis of this study with previous ones is shown in Table 4.

Table 4: Comparative Study with Related Literature

	Author	Diagnostic Detection Accuracy (%)
1	This Study	98.7
2	Haikun (2005)	96.2
3	Mohammed (2007)	72
4	Chauban (2015)	93.35
5	Chao (2009)	82.2

From the results presented in Table 4, it can be seen that the RNN-FIS model for transformer fault diagnostic had a higher detection accuracy when compared related studies. Hence, this model should be implemented to aid in prompt and accurate report of fault occurrence in a power transformer.

V CONCLUSION

RNN-FIS was used in the diagnosis of fault in the transformer. The current signal of each of the faults of the transformer was used as the input parameter to the diagnostic model with the diagnostic code utilized as the output data. The intelligent model utilized was as the diagnostic model was inserted in the SIMULINK model of the transformer to obtain the performance of the model in fault diagnostic of the transformer. Since the highest error deviation was 0.013 (at the occurrence of low energy fault in the transformer), it can be concluded that the intelligent hybrid of RNN-FIS diagnostic model can be utilized in the diagnosis of the selected transformer faults done in this study.

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