Journal of Theoretical and Applied Information Technology
30th November 2017. Vol.95. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DETECTION AND CLASSIFICATION OF POWER TRANSFORMER FAULTS USING FFA BASED RNN TECHNIQUE

[1]P.LAKSHMI SUPRIYA, [2]P.SUJATHA

[1]Assistant Professor, Department of EEE, M.G.I.T, Hyderabad, India

[2]Proffessor, Department of EEE, JNTUCEA, Ananthapuramu, India

E-mail: [1]plsupriya18@gmail.com, [2]psujatha1993@gmail.com

ABSTRACT

In this paper, proposed an intelligent technique for diagnosing the internal faults conditions in power transformers. The proposed intelligent technique is the composites of wavelet transform and RNN based FFA optimization technique. Initially, the normal signals are analyzed at the particular time instant. After that, investigate any faults occurred or not in the power transformer with the help of proposed technique. With the utilization of the proposed technique, the current signals of the power transformer is monitored and detected. Initially, the MWT is utilized to extract the features of the signal. In wavelet transform, the feature approximation of the signal is depends on the decompose levels of high and low frequency components. The extracted features are applied to the input of the FFA. The FFA is selected the optimized training dataset for training the RNN. After that the RNN testing process is evaluated the signal and classified the fault signal type. The effectiveness of the proposed technique is evaluated based on the statistical measures like accuracy, sensitivity and specificity qualities. The proposed method is implemented in MATLAB/Simulink platform and compared with the existing techniques.

Keywords: *Power Transformer, Fault Detection and Classification, Multi-Wavelet Transforms (MWT), Recurrent Neural Network (RNN) and Firefly Algorithm (FFA)*

1. INTRODUCTION

The power transformers are the most important key elements in any power system and are quite expensive and have no substitute for its major role [1]. The impacts of an in-service transformer failure can be catastrophic as it may cause extended outages, costly repairs and potentially serious injury or fatality. Furthermore, the continuous increase in load demand, nonlinear loads, smart appliances and plug-in electric vehicles that are considered as sizeable, unpredictable and source of harmonics loads along with the significant aged transformer population worldwide has increased the likelihood of transformer catastrophic failures. Failure of a transformer can cause extensive damage to equipment owned by consumers or the utility, under the influence of electrical, mechanical, thermal and environmental stresses which cause the degradation of insulation quality and ultimate failure of transformer leading to major breakdown of the power system itself [2]. Mechanical defects are probably the most common cause of problems in transformers. They include winding deformation in the axial or radial direction, hoop buckling, tilting, spiraling, displacements between high and low voltage windings, shorted or open-circuited turns, partial winding collapse, loosened clamping structures, core movement, faulty grounding of core or screens, broken clamping structures, and intermittent internal connections . They may be due to short-circuit currents, earthquakes, careless transportation between sites, and explosion of combustible gases accumulating in the transformer oil, and so on [3].

Diagnostic approaches can be divided into two groups: on-line and off-line. In Online Monitoring: have verified the technique in locating faults, attempts were made to test for automated monitoring when the transformer is operation. Generally, there are four main aspects of transformer condition monitoring and assessment, including thermal dynamics, dissolved gas analysis (DGA), partial discharge and Frequency Response Analysis, which should be monitored closely in order to determine power transformer conditions. The main function of mineral oil in transformer is as a cooler of transformer and provides insulation as well. When mineral oil is subjected to high thermal and electrical stresses, it decomposes and as a result, gases are generated. These gases are

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

considered as fault indicators and can be generated in certain patterns and amounts depending on the characteristics of the fault.

Within power systems, there are several quantities of interest with respect to monitoring the behavior and condition of items of plant and the power transformer as a whole. The diagnosis of equipment can be divided into two main parts: fault detection and fault identification [4]. These monitoring behaviors include: voltage and current, frequency, thermal measurement data, pressures of gas and liquid coolants and insulants, partial discharge activity, vibration data, etc. Within a large power generating station, the number of parameters measured may run into thousands. Transformer components including core, windings and insulation can be modeled as cascaded networks of capacitive, resistive and inductive elements whose value is changing due to winding or core deformation within the transformer. Frequency Response Analysis (FRA) is considered as a reliable tool to detect various winding deformations within power transformers. In addition, many techniques and tools are developed for power transformers internal faults detection; somehow many of these techniques rely on expert analysis. Dissolved Gas Analysis (DGA) is a usual method to diagnose the fault of power transformer [5]. With the growing demands for reliability, maintainability and survivability in large-scale power plants (PPs) and power systems (PSs), considerable attention has been focused on developing fault diagnosis systems, which includes the detection, isolation, identification or classification of faults respectively [6].

In this paper the proposed technique is the combination of wavelet transform and AI technique. Initially, the normal signals are analyzed at the particular time instant. After that, investigate any faults is occurred or not in the power transformer with the help of proposed AI technique. With the utilization of the proposed technique, the current signals of the power transformer is monitored and detected. Initially, the advanced MWT is utilized to extract the features of the signal. In wavelet transform, the feature approximation of the signal is depends on the decompose levels of high and low frequency components. After that, the extracted features are applied to the input of the AI technique. Different AI technique analysis is used to examine the performance of proposed hybrid method.

2. RECENT RESEARCH WORKS: A BRIEF REVIEW

Frequency response analysis (FRA) has been globally accepted as a reliable tool to detect mechanical deformation within power transformers. However, because of its reliance on graphical analysis, interpretation of FRA signature is still a challenging area that calls for skilled personnel, as so far, there is no widely accepted reliable standard code for FRA signature identification and quantification. While several papers investigating the impact of various mechanical winding deformations on the transformer FRA signature can be found in the literature, no attention was given to investigate the impact of various bushing faults and transformer oil degradation on the FRA signature. Dissolved gas analysis (DGA) of transformer oil is one of the most effective power transformer condition monitoring tools. There are many interpretation techniques for DGA results however all current techniques rely on personnel experience more than analytical formulation. As a result, the current techniques do not necessarily lead to the same conclusion for the same oil sample. A significant number of DGA results fall outside the proposed codes of the ratio-based interpretation techniques and cannot be diagnosed using these methods. Moreover, ratio methods fail to diagnose multiple fault conditions due to the mixing up of produced gases.

G. Rigatos *et al.* [7] have proposed a neural modeling and the local statistical approach to fault diagnosis for the detection of incipient faults in power transformers. The method can detect transformer failures at their early stages and consequently can deter critical conditions for the power grid. A neural-fuzzy network was used to model the thermal condition of the power transformer in fault-free operation. The output of the neural-fuzzy network was compared to measurements from the power transformer and the obtained residuals undergo statistical processing according to a fault detection and isolation algorithm. If a fault threshold was exceeded, then deviation from normal operation can be detected at its early stages and an alarm can be launched. In several cases fault isolation can be also performed, i.e. the sources of fault in the power transformer model can be also identified.

3. THE PROPOSED SYSTEM MODELING

In order to evaluate the robustness of the suggested method, the power system, shown in figure 1, is simulated using Matlab/Simulink platform. The simulated transformer is a three phase 100 kVA, 5500/410 V transformer. The primary winding has 1556 turns wound in eight layers and the secondary winding has 67 turns wound in two layers.

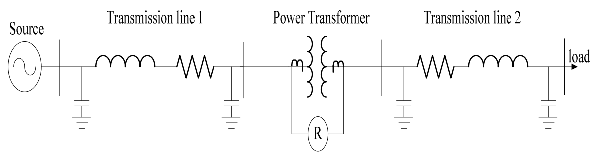


Figure 1: The proposed power transform system model

3.1 Internal Incipient Fault Model

The internal incipient fault can be modeled using a combination of aging and arcing models. The aging model consists of the losses and capacitive behavior of the winding dielectric, simulated by resistance r_{ag} and capacitance c_{ag}, respectively. So, a dissipation factor $\tan\delta$ is calculated and the degradation level can be defined as equation (1),

$$\tan\delta = \frac{1}{\omega r_{ag} c_{ag}} \qquad (1)$$

However, c_{ag} is almost constant during the insulation degradation process and degradation levels are determined by r_{ag}. The phase angle between the current and the voltage is 90°, in a perfect insulation. However, as the degradation level increases, the phase angle between the current and the voltage decreases. An arc can develop when sufficient voltage is across the degraded insulation. The arc voltage is generally flap-topped. So, the arcing process can be modeled as a random square voltage (E) and a time-variant high-value resistance R_t connected in parallel. Switches S_1 and S_2 are used to model non-arcing, extinction and burning periods. It models the non-arcing period, when switches are open.

The evaluation of the proposed method on classification problems is determined by computing the statistical parameters of sensitivity, specificity and classification accuracy.

3.2 Proposed Methodology for Classification

The main idea of the proposed work is to distinguish internal disturbance currents (i.e. internal incipient fault, inrush current and internal faults) from the external fault current considering CTs error, ratio mismatch and minor saturation. The MWT is employed to extract the features from the differential currents to discriminate the inrush current, internal and incipient faults. The proposed power transformer fault detection and classification process is described in followed figure 2.

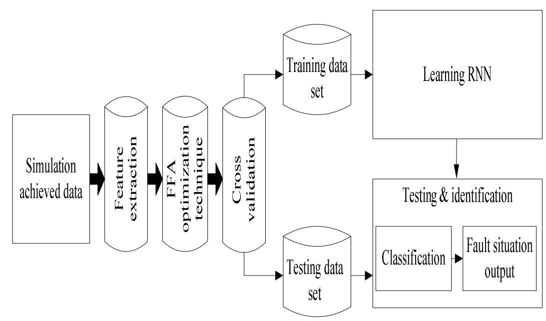


Figure 2: The proposed classification methodology

In this proposed methodology, the MWT is used for feature extraction of the measured signal. Then the FFA optimization technique is utilized for generating the optimal training dataset for training the RNN. Finally the classification process is carried out with the help of RNN of the proposed power transformer signal. To prove the effectiveness of the proposed technique is based on the statistical measures like accuracy, sensitivity and specificity qualities. Then the statistical measures of proposed technique is determined and compared with existing techniques like DWT-FLC, DWT-RBFN, DWT-ANFIS and MWT-ANN technique. The suggested method consists of the disturbance detection and disturbance discrimination steps.

3.2.1. Disturbance Detection

The differential protection principle is based on the assumption that under normal conditions and also during external fault, the differential currents have smaller amplitude than the case of the occurrence of the internal fault. However, high differential currents can exist in conditions (such as external faults or transformer tap changes) because of CTs ratio mismatch, accuracy difference and saturation. So, these abnormal conditions can cause mal-operation of the differential relay. Percentage differential relay can provide a solution to these problems. So, a detection step must be taken into account to prevent malfunctions caused by the above mentioned cases. Therefore a threshold current i_{thr} can be considered and when the differential current i_{diff} exceeds this threshold value, it will recognize as an internal disturbance current. Otherwise, it is identified as an external fault. The threshold value can be defined as equation (2),

$$i_{thr} = k\frac{i_{\sec T} + i_{pri T}}{2} \quad (2)$$

Where, k is the slope of the differential relay characteristic and can have values such as 0.1, 0.2 or 0.4. Lower values of k can provide more sensitive protection. Here, it is assumed that it equals to 0.25. $i_{pri T}$ and $i_{\sec T}$ are instantaneous currents of primary and secondary CTs, respectively, and if one of them exceeds i_{thr}, then the disturbance discrimination step should be started.

3.2.2. Disturbance Discrimination

In this step, the MWT is applied to differential currents of faulty phases, recognized in the disturbance detection step. The Multi-wavelets are the wavelets having various scaling functions and preferred ones over single wavelet/scalar wavelet in the areas like signal/image classification, compression and de-noising of non-stationary signal. In Multi-wavelets, multiple scaling and wavelet functions are used rather than single functions as in case of single wavelets. It yields the property of having more degree of freedom for generating multi-wavelets. The multi-wavelets have some unique characteristics that cannot be obtained with scalar wavelets. It motivates us to use multi-wavelet transform for classification of fault signals. The multi-wavelets are also based upon Multi Resolution Analyses (MRA), like wavelets. It gives sixteen sub bands after one level of decomposition as compared to four sub bands in wavelet decomposition. The standard MRA for scalar wavelet uses scaling function denoted as $\phi(t)$ and wavelet $\psi(t)$. The complementary subspaces of V_j are W_j, which are generated by the translations and dilations of multi-wavelet functions. The scaling space V_j is calculated as equation (3),

$$V_j = clos\{2^{j/2}\phi(2^j t - k); 1 \le i \le r, k \in Z\} \quad (3)$$

And the wavelet space W_j is given as equation (4),

$$W_j = clos\{2^{j/2}\psi(2^j t - k); 1 \le i \le r, k \in Z\} \quad (4)$$

Dilation equation in traditional scalar wavelet is obtained from the nesting condition $V_j \subset V_{j+1}$. Same is true for multi wavelets. The multi-wavelet is the extension of scalar wavelet where multiple scaling functions and associated multiple wavelets are used. In case of multi-wavelet, a basis for the subspace V_0 is formed by translating r scaling functions denoted by $\phi(t) = \phi_1(t-k), \phi_2(t-k), \ldots, \phi_r(t-k)$.

The multi-wavelet can be considered as vector-valued wavelets which satisfy the condition of two-scale relationship with involvement of matrices rather than scalars. The scaling vector-valued function is represented as equation (5),

$$\Phi(t) = [\phi_1(t), \phi_2(t), \ldots, \phi_r(t)]^T \quad (5)$$

Here, T representing transpose and associated r-wavelets $\Psi(t) = [\psi_1(t), \psi_2(t), \ldots, \psi_r(t)]$ satisfies the following matrix dilation and matrix wavelet equations (6) and (7),

$$\Phi(t) = \sum_k^N G[k]\Phi(2t - k) \quad (6)$$

$$\Psi(t) = \sum_k^N H[k]\Phi(2t - k) \quad (7)$$

Where, H_k and G_k are low pass and high pass matrix filter banks respectively, $k = 0,1,\ldots,$ N is the number of filter banks. The multiplicity r is generally 2 for most of the multi-wavelets. The matrix elements in these filters provide more degrees of freedom than a scalar wavelet. This makes multi-wavelets have some significant properties, such as short support, orthogonality, symmetry, and vanishing moments. These properties are all important in signal processing. Similar to the scalar wavelet transform, the MWT is also based on the idea of MRA. During a single level decomposition using scalar wavelet transform, the input data is decomposed into two sub-bands, which represent the output of low-pass and high-pass filters individually. While, MWT decomposition produces two low-pass sub-bands and two high-pass sub-bands for each level decomposition. The decomposition and reconstruction process of MWT is illustrated in figure 3.

In MWT each multi filter bank contains two channels, so that there will two sets of scaling coefficients and two sets of wavelet coefficients for each level decomposition. Since multiple iterations

Journal of Theoretical and Applied Information Technology
30th November 2017. Vol.95. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

over the low-pass data are desired, the scaling coefficients for the two channels are stored together.

Likewise, the wavelet coefficients for the two channels are also stored together. Successive iterations are performed on the two sets of scaling coefficients from the previous stage. By the dilations of multi-wavelet functions, the following recursive relationship between the coefficients $\left[c_{1,j,k}, c_{2,j,k}\right]^T$ and $\left[d_{1,j,k}, c_{2,j,k}\right]^T$ can be obtained by equations (8) and (9).

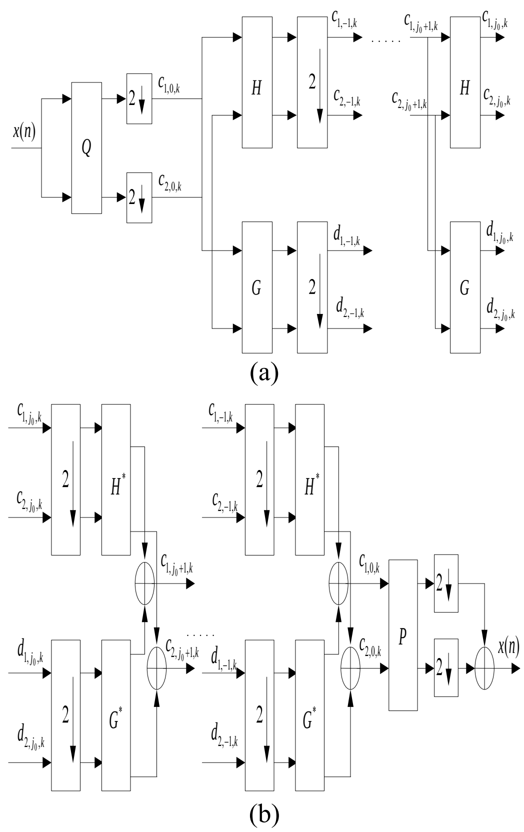


Figure 3: Multi-Wavelet Transforms (A) Decomposition And (B) Reconstruction

$$\begin{pmatrix} c_{1,j-1,k} \\ c_{2,j-1,k} \end{pmatrix} = \sqrt{2}\sum_{n=0}^{K} H_n \begin{pmatrix} c_{1,j,2k+n} \\ c_{2,j,2k+n} \end{pmatrix}; \quad j,k \in Z \qquad (8)$$

$$\begin{pmatrix} d_{1,j-1,k} \\ d_{2,j-1,k} \end{pmatrix} = \sqrt{2}\sum_{n=0}^{K} G_n \begin{pmatrix} c_{1,j,2k+n} \\ c_{2,j,2k+n} \end{pmatrix}; \quad j,k \in Z \qquad (9)$$

Similarly, multi-wavelet reconstruction can be obtained by equation (10),

$$\begin{pmatrix} c_{1,j,n} \\ c_{2,j,n} \end{pmatrix} = \sqrt{2}\sum_{n=0}^{K} \left(H_k^* \begin{pmatrix} c_{1,j-1,2k+n} \\ c_{2,j-1,2k+n} \end{pmatrix} + G_k^* \begin{pmatrix} d_{1,j-1,2k+n} \\ d_{2,j-1,2k+n} \end{pmatrix} \right) \qquad (10)$$

Where, H_k^* and G_k^* are dual matrices of H_k and G_k respectively. In MWT decomposition and reconstruction view of the matrix filter banks, preprocessing is necessary to translate one stream input signal into two streams. Correspondingly, a post-processing method is the inverse process of preprocessing. Q is represents the pre-filter for preprocessing and while P is the post-filter for post-processing. $\{H, G, H^*, G^*\}$ are represent low pass and high pass filter banks of multi-wavelets and their dual filter banks respectively [26]. $2\downarrow$ and $2\uparrow$ represent decimation and zero-padding respectively. Since preprocessing is a crucial step for the success of MWT in applications, various methods have been developed. The repeated-row method is the most commonly used, which is repeating the scalar input signal to get an input vector. This preprocessing method introduces oversampling of the original data by a factor of two. Since the repeated-row preprocessing has proved to be superior in feature extraction, it is also adopted in this work.

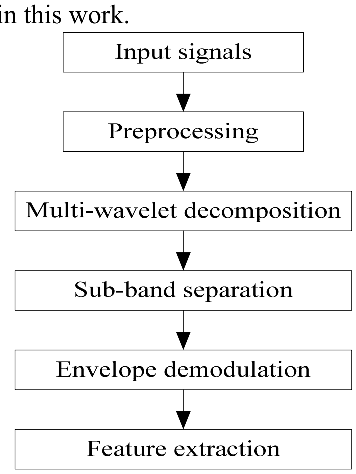


Figure 4: The Implementation Steps For Multi-Wavelets

The steps of multi-wavelets are shown in figure 4. The steps are as follows:

i. Preprocessing method is performed to translate the one-stream input signal into two streams.
ii. The two stream signals are decomposed into two branches, each branch consists of an approximation signal and several detail signals in different scales.
iii. The decomposed signals are separated into different sub-bands.
iv. The envelope demodulation methods are applied to extract the modulation

components in signals of different sub-bands.

v. The fault features are finally extracted for accurate fault diagnosis.

3.3. The Proposed Algorithm for Classification

In this section, we first introduce the architecture of the proposed RNN model. And then, we give the FFA based learning algorithms for training the RNN of this proposed model. Finally, we analyze the computational complexity of the learning algorithms.

3.3.1. The RNN for Signal Classification

The architecture of RNN model is shown in figure 5. The input layer consists of vectors $u, v(t), a(t)$ and $s(t-1)$ representing the current user, item, feedback activity and the last hidden layer state, respectively. In the model, user i is represented by an $m \times 1$ vector, in which the i^{th} element is 1 and other elements are 0. Each item (or each kind of feedback activity) is represented by an $n \times 1$ or 1×1 vector in the same way. h and s are the hidden layers for user and item, respectively. The vector $s(t)$ represents the output of hidden layer s at the time step t. o is the output layer [9].

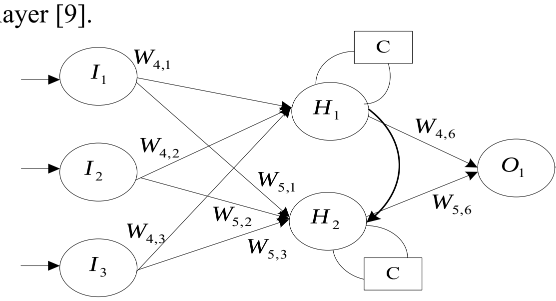


Figure 5: The architecture of RNN model

The user vector u in input layer is connected to the hidden layer h through the weight matrix Q. This part is non-recurrent and the output of the hidden layer his computed as equation (11),

$$h = f(Qu) \tag{11}$$

Here, h is a $D \times 1$ vector, which is the dimension of hidden layer. Q is a $D \times m$ matrix, in which each column represents a user's preference. Function f is the sigma function, which is given as equation (12)

$$f(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

3.3.2. FFA based Optimized Learning Model

In this section, it is proposed to the proposed model. Usually, ANN is trained by back propagation (BP) algorithm. Because the proposed model is a RNN, it can also be trained by FFA optimization algorithm. Fireflies use flash signals to attract other fireflies for potential mates. Based on this behavior, a meta-heuristic algorithm was developed by Xin-She Yang [10]. All the fireflies are considered unisexual and their attraction is directly proportional to the intensity of their flash. Therefore, if a firefly particle had the choice of moving toward either of two fireflies, it will more attracted toward the firefly with higher brightness and moves in that direction. If there are no fireflies nearby, the firefly will move in a random direction.. In firefly algorithm, there are three idealized rules:

i. A firefly is attracted by other fireflies regardless of their sex.

ii. Attractiveness is proportional to their brightness and decreases as the distance among them increases.

iii. The landscape of the objective function determines the brightness of a firefly.

In the implementation of the algorithm, the flashing light is formulated in such a way that it gets associated with the objective function to be optimized. Fireflies are characterized by their flashing light produced by biochemical process bio-luminescence. For proper design of FFA, two important issues need to be defined: the variation of light intensity (I) and the formulation of attractiveness (β). Initial population of fireflies in the attractiveness of a firefly is determined by equation (13) its light intensity or brightness and the brightness is associated with the objective function.

$$X_i = [X_1, X_2, X_3, \ldots, X_n] \tag{13}$$

4. RESULTS AND DISCUSSION

The performance analysis of the proposed technique with some power transformer parameters. The proposed technique is applied with Intel(R) core(TM) i5 processor, 4GB RAM and MATLAB/Simulink 7.10.0 (R2015a) platform. The Simulink model of the proposed system is illustrated in the figure 6, which shows the power system connected with the transformer power system and the proposed control methodology. The proposed technique is estimates the fault signal and detect the error and categorizes the signal depend on the reference signal. Initially, the proposed technique is estimate the normal signal and then extracting the features based on the MWT. The extracted features are making the group of data for the measured signal and identify the faults and categorizing the dissimilar error and dissimilar positions.

The winding faults are classified and evaluated based on the proposed hybrid technique. The proposed hybrid technique is the composite of RNN and FFA, which investigates the error signal from the reference signal and the instantly measured signal.

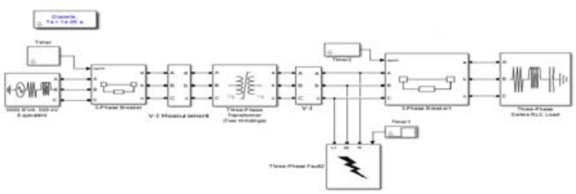
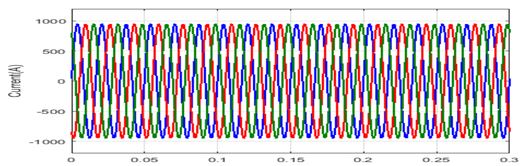
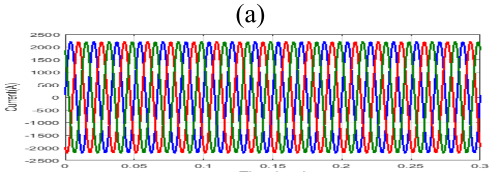


Figure 6: Simulink Diagram Of Proposed Power System Model

The FFA is utilized to train the RNN and testing performance is improved the back propagation algorithm. The detection and classification of the fault signal are executed and examined in different winding location and different fault conditions. Finally, the presentation of the projected technique is examined and contrasted with the presentation of existing techniques like DWT-FLC, DWT-RBFN, DWT-ANFIS and MWT-ANN.



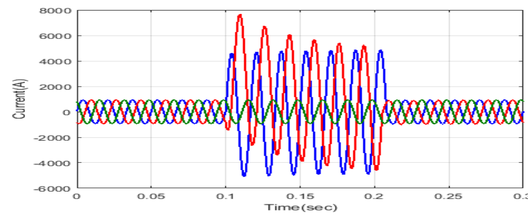
(a)



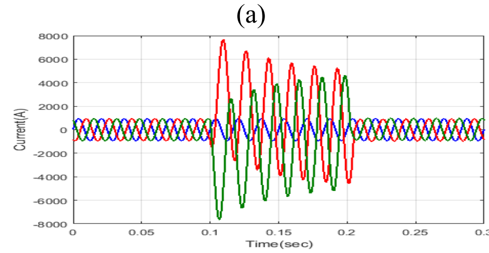
(b)

Figure 7: The Inrush Current Of (A) Primary And (B) Secondary In Normal Condition

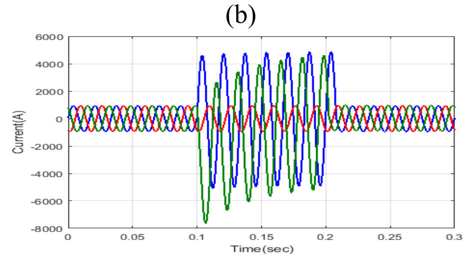
Initially the primary and secondary current of the power transformer is measured in a normal condition, which is illustrated in figure 7. In this current is taken as the reference for the fault signal. To analyze the proposed system with the proposed technique is evaluated based on the primary and secondary current value of the transformer. So the classification process is evaluated separate measured signal and classified the faults. The primary winding classified signal is illustrated in the figure 8. In this figure contains the line to line faults such as AB-G, BC-G, CA-G and ABC-G.



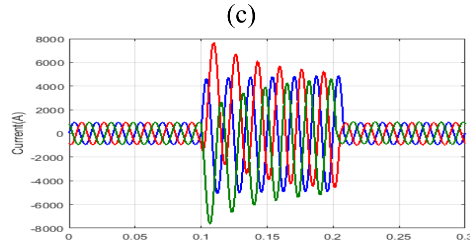
(a)



(b)



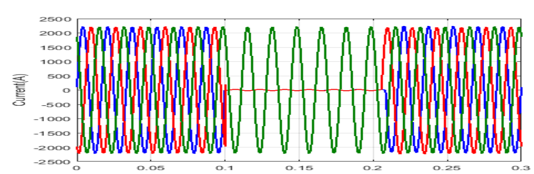
(c)



(d)

Figure 8: Primary Winding Faults In (A) AB-G (B) BC-G (C) CA-G And (D) ABC-G Phases

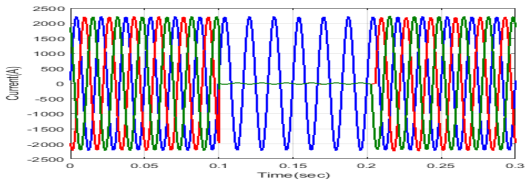
In this proposed technique is used to classify the faulty signal is measured from the transformer primary and secondary windings. The fault current of the secondary winding is illustrated in figure 9, which shows the different phase faults. Each and every phase should be classified for evaluating the performance of the proposed technique.



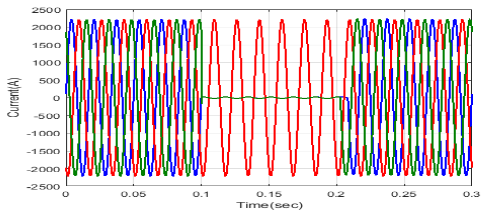
(a)

Journal of Theoretical and Applied Information Technology
30th November 2017. Vol.95. No 22

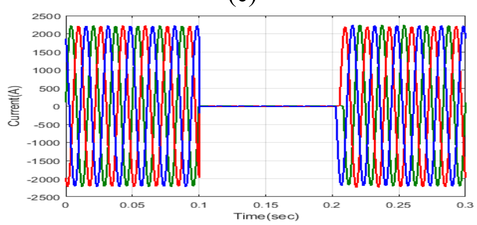
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(b)



(c)



(d)

Figure 9: The Secondary Winding Faults In (A) AB-G (B) BC-G (C) CA-G And (D) ABC-G Phases

Moreover the analysis of the comparison with the some different techniques and its performance is specified in the following. Here, the statistical measures such as accuracy, sensitivity and specificity are analyzed. By using the proposed controller, the fault types are correctly classified. After that, the performance of the proposed method is compared with the existing techniques. Then the accuracy, sensitivity and specificity of the proposed technique is analyzed from the True positive (TP), False positive **(**FP), True negative **(**TN) and False negative (FN) values.

Table 1: Description Of TP, TN, FP And FN

Descriptions of signals		Testing results	
		Faulty signal	Normal signal
Input Conditions	Faulty signal	TP	FN
	Normal signal	FP	TN

From the above table 1, the TP, FP, TN and FN are described as the AB fault is correctly identified as a faulty signal, Normal signal is incorrectly identified as fault signal, Normal signal is correctly identified as normal and AB fault signal incorrectly identified as normal respectively. Likewise, the other types of faults are described and the accuracy, sensitivity and specificity values are calculated.

From the output of proposed method, the fault is detected and classified their types. Then, the TP, TN, FP and FN are evaluated from the testing output of adaptive technique. Then the performance of proposed technique is determined and compared with existing techniques. The evaluated output of proposed technique is tabulated in Table 2. In this table is presented the statistical measures average values from different algorithm. Based on this analysis the proposed method has high accuracy also the Sensitivity.

Table 2: Accuracy, Sensitivity And Specificity For Proposed Method

Signal analysis	Internal faults						
	TP	FP	FN	TN	Accuracy	Sensitivity	Specificity
AB	9	3	0	8	0.85	1	0.73
BC	9	1	1	9	0.9	0.9	0.9
CA	8	1	2	9	0.85	0.8	0.9
ABC	8	2	1	9	0.85	0.89	0.82
Normal	10	1	0	9	0.95	1	0.9

From the above figures the proposed system is much effectiveness in a nonlinear condition and also good performance of the transformer power system. A classifier was utilized to identify the error situations and no-fault situations using the RMS values of the current signal in a variety of frequency groups. The comparison of classifier presentation is exposed in table 3. From the table, the examination of the presentation of the categorization for dissimilar method is prepared.

Table 3: Comparison Of The Proposed Method With The Other Traditional Techniques

Methods	No. of cases	Correct classification	Misclassification	Classification	Error rate
Proposed techniqu	20	18	2	90	10
MWT-ANN	18	15	3	83.33	16.67
DWT-ANFIS Techniq	16	12	4	75	25
DWT-RBFNN	14	9	5	64.28	35.72
DWT-FLC	12	6	6	50	50

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

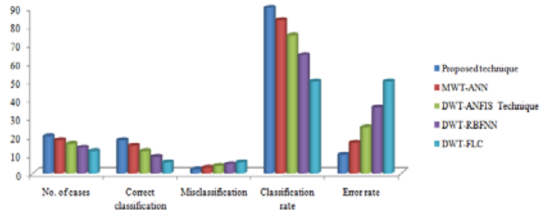


Figure 10: The Comparison Analyses With Proposed Technique

The points out methods are approved for 20 numbers of experiment situations and then, the accurate categorization, misclassification and the categorization rate are intended. From the comparison, the existing methods are some misclassifications and the classification and error rate is presented in this table. The comparison analysis is performed and described in figure 10. The proposed technique is high classification rate and less error rate from the evaluated power system better than the existing methods such as DWT-ANFIS, DWT-RBFNN, MWT-ANFIS and MWT-FLC based GA. For develops the presentation of the projected technique can enhance the number of the situations. In the projected technique can obtain the 20 situations and the categorization rate is 90 and the fault rate is 10, which is competent more the other recognized methods.

5. CONCLUSION

This paper proposed FFA based RNN algorithm was utilized for diagnosing the internal faults conditions in power transformers. The proposed technique was worked with MWT and RNN based FFA optimization technique. Initially, the normal signals were analyzed at the particular time instant. After that, the faults were investigated in the power transformer with the help of proposed technique. The proposed technique was utilized for detection and classification the current signals of the power transformer. The MWT was utilized to extract the features of the measured signal. In MWT feature approximation of the signal was depends on the decompose levels of high and low frequency components. The extracted features of the current signal were given to the FFA. The FFA was selected the optimized training dataset for training the RNN. After that the RNN testing process was evaluated the signal and classified the fault signal type. The proposed method was implemented and compared with the existing techniques. Finally the statistical measures like accuracy, sensitivity and specificity qualities were evaluated and established the effectiveness of the proposed technique.

REFERENCES

[1] M. R. Ahmed, M. A. Geliel and A. Khalil, "Power transformer fault diagnosis using fuzzy logic technique based on dissolved gas analysis", *In proceedings of IEEE conference on Control & Automation*, pp. 584-589, 2013

[2] Hameed, Z., Y. S. Hong, Y. M. Cho, S. H. Ahn and C. K. Song, "Condition monitoring and fault detection of wind turbines and related algorithms: A review", *An International Journal of Renewable and Sustainable energy reviews*, Vol. 13, No. 1, pp. 1-39, 2009

[3] Haroldo de Faria.Jr, Joao Gabriel Spir Costa and Jose Luis Mejia Olivas, "A review of monitoring methods for predictive maintenance of electric power transformers based on dissolved gas analysis", *An International Journal of Renewable and Sustainable Energy Reviews*, Vol. 46, pp. 201-209, 2015

[4] Mortada, Mohamad-Ali, Soumaya Yacout, and Aouni Lakis, "Fault diagnosis in power transformers using multi-class logical analysis of data", *An International Journal of Intelligent Manufacturing,* Vol. 25, No. 6, pp. 1429-1439, 2014

[5] Naveen Kumar Sharma, Prashant Kumar Tiwari and Yog Raj Sood, "Review of Artificial Intelligence Techniques Application to Dissolved Gas Analysis on Power Transformer", *An International Journal of Computer and Electrical Engineering*, Vol. 3, No. 4, pp. 577-582, 2011

[6] Jashandeep Singh, Yog Raj Sood and Raj Kumar Jarial, "Condition monitoring of power transformers-bibliography survey", *IEEE Electrical Insulation Magazine*, Vol. 24, No. 3, pp. 11-25, 2008

[7] G. Rigatos and P. Siano, "Power transformers' condition monitoring using neural modeling and the local statistical approach to fault diagnosis", *An International Journal of Electrical Power and Energy Systems*, Vol. 80, pp. 150-159, 2016

[8] Hailiang Sun, Zhengjia He, Yanyang Zi, Jing Yuan, Xiaodong Wang, Jinglong Chen and Shuilong He, "Multiwavelet transform and its applications in mechanical fault diagnosis –A review", *An International Journal of Mechanical Systems and Signal Processing*, Vol.43, pp.1–24, 2014

[9] CaihuaWu, Junwei Wang, Juntao Liu and WenyuLiu, "Recurrent neural network based recommendation for time heterogeneous feedback", *An International Journal of*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Knowledge-Based Systems, Vol.109, pp.90–103, 2016

[10] Iztok Fister, Iztok Fister, Xin-She Yang and Janez Brest, "A comprehensive review offirefly algorithms", *Swarm and Evolutionary Computation,* Vol.13, pp.34–46, 2013