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Diagnosis of Inter-turn Fault in the Transformer Winding Using Wavelet Based AI Approaches

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In this paper, Wavelet based ANFIS for finding the inter-turn fault of a transformer is proposed. The detector uniquely responds to the winding inter-turn fault with remarkably high sensitivity. Discrimination of different percentages of winding affected by inter-turn fault is provided via ANFIS having an eight dimensional input vector. This input vector is obtained from features extracted from DWT of inter-turn faulty current, leaving the transformer phase winding. Training data for ANFIS are generated via a simulation of transformer with inter-turn fault using MATLAB. The proposed algorithm using ANFIS gives more satisfactory performance than ANN and GABPN with selected statistical data of decomposed levels of faulty current.

Key words: *Winding inter-turn fault, ANN, ANFIS, DWT, GABPN*

1.0 INTRODUCTION

At present, transformers are protected against almost all kinds of faults using differential methods of protection. All kinds of faults develop into inter-winding fault by damaging the inter-winding insulation. So it is necessary to protect the transformer from inter-winding faults. For inter-winding protection, differential method cannot be implemented as the current on both sides of the fault will be the same. In this paper, the wavelet based ANFIS method for identifying the percentage of winding under fault is used. The faulty data are collected by simulating the fault by means of connecting a resistor in parallel with the winding. Faulty current data are given to the DWT Tool and features are extracted, normalised and used as input for ANN. Using this approach ANFIS Transformer can be protected within 0.01 seconds from the occurrence of the fault which will ensure maximum protection of the winding.

Secondary winding faults of transformers are considered serious problems because of the damage associated with high fault currents and the high cost of maintenance. A high speed bias differential relay is normally used to detect three phases, phase-phase and double phase to ground faults. In case of inter-turn winding fault, the current on both sides of the winding is the same. Due to this factor we cannot adapt the differential scheme of protection for inter-turn winding fault.

When there is an insulation failure in between the winding inter-turns, they get short circuited and the amount of winding involved in transformation gets reduced. As the amount of winding under transferring action is reduced, the amount of current in the secondary gets increased. When this problem is left undealt

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with, the inter-winding insulation gets affected there by further reducing the amount of winding involved in transformation. This fault will completely damage the winding at the extreme stage. The cost of winding is very high when compared to the protection methods which can adapt. The aim of the proposed method is to protect the system within a very short period in the range of microseconds.

2.0 WAVELET TRANSFORM

Wavelet transform was introduced at the beginning of the 1980s and has attracted much interest in the fields of speech and image processing since then. Its potential applications to power industry have been discussed recently by [1], [2], [3], [4], [5] and [6].

In this approach, any function f(t) can be expanded in terms of a class of orthogonal basis functions. In wavelet applications, different basis functions have been proposed and selected. Each basis function has its feasibility depending on the application requirements. In the proposed scheme, dmey wavelet was selected to serve as a wavelet basis function for extracting features from faulty currents. Fig. 1 shows the tree algorithm of a multiresolution WT for a signal.

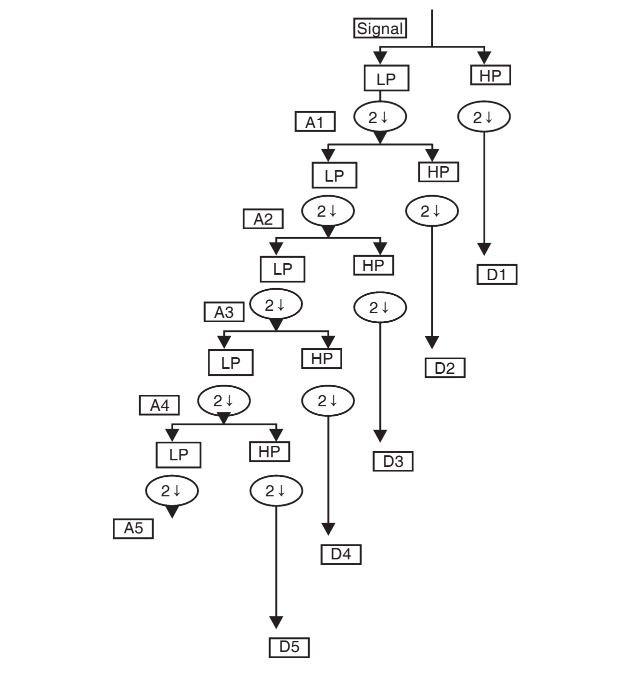

FIG. 1 DWT

The outputs of the LP filters are called the approximations (A), and the outputs of the HP filters are called the details (D). There are two fundamental equations upon which wavelet calculations are based; the scaling function: Φ (t)(1); and the wavelet function: Ψ(t)(2).

$$\phi(t) = \sqrt{2}\sum_k h_{k\phi}(2t - \qquad (1)$$

$$\psi(t) = \sqrt{2}\sum_k g_{k\phi}(2t - \qquad (2)$$

These functions are two-scale difference equations based on a chosen scaling function Φ, with properties that satisfy certain admission criteria. The discrete sequences h_k and g_k represent discrete filters that solve each equation. The scaling and wavelet functions are the prototypes of a class of orthonormal basis functions of the form:

$$j, k \ \varepsilon \ z \qquad (3)$$

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - \qquad j, k \ \varepsilon \ z \qquad (4)$$

Where the parameter j controls the dilation or compression of the function in time scale and amplitude, the parameter k controls the translation of the function in time, and z is a set of integers.

Once a wavelet system is created, it can be used to expand a function f(t) in terms of the basis functions(5):

$$(5)$$

Where the coefficients c(l) and d(j, k) are calculated by inner product as (6) and (7):

$$c(l) = \langle \phi_l \mid f \rangle = \int f(t \qquad (6)$$

$$d(j,k) = \langle \psi_{j,k} \mid f \rangle = \qquad (7)$$

The expansion coefficient c(l) represents the approximation of the original signal f(t) with a resolution of one point per every 2^J points of the original signal. The expansion coefficients d (j, k) represent details of the original signal at different levels of resolution. c (l) and d (j, k) terms can be calculated by direct convolution of f(t) samples with the coefficients h_k and g_k.

3.0 BASIC THEORY OF ANFIS

Adaptive Neural Fuzzy Inference System (ANFIS) is a product of combining the fuzzy inference system with neural network. The fuzzy inference system is used widely to fuzzy control; it can number rules by leading into a new ideal of membership function to deal with structural knowledge. Neural network usually does not deal with structure knowledge, but it has the function of self-adapting and self-learning. By learning a lot of data, it can estimate the relations between the data of input and output, and has strong inundate functions. ANFIS fully makes use of the excellent characteristics of the neural network and fuzzy inference system and is widely applied in fuzzy control and model discerning fields. As a special neural network, ANFIS can approach all non-linear systems with less training data and quicker weakening speed and higher precision. ANFIS is a neural network in fact, which realises Sugeno system using network. Thinking of a system with N input and 1 output, each input is divided into M fuzzy sets, fuzzy of Sugeno model is as following:

If, x_1 is A_{1i1} and x_2 is A_{2i2}…., and x_n is A_{Nxn}

Then, $y_{i1i2...,iN} = {}_{k=1}{}^{N}\ p_{i1i2...iN}{}^{(k)}\ x_{k} + q_{i1i2...iN}$,

i1, i2, i3.., iN $\in$ {1, 2….M}

The structure of ANFIS (N=2, M=3) is shown in Fig. 2, and the junction spot of the same layer has the same kind of output function.

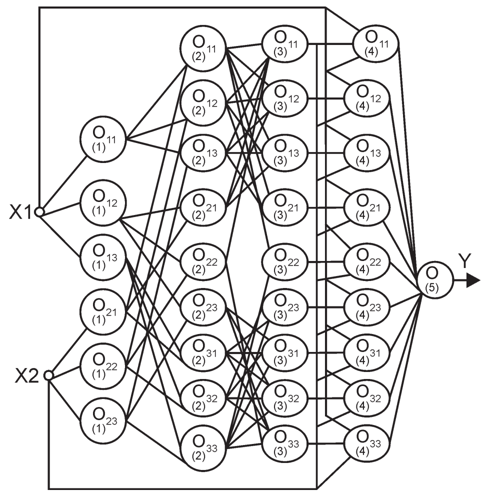

FIG. 2 STRUCTURE OF ANFIS (N=2, M=3)

The detail of the whole network is as follows:

The first layer: The output function of each junction spot is as follows:

$$O^{(l)}_{kik} = \mu_{kik}(x_k)$$

$$k = 1, 2... N\ i_k = 1, 2 ...M$$

Where x_k is the input of the k, i_k junction spot, and is language *fuzzy* sets, and $O^{(l)}_{kik}$ is membership function of x_k, where membership function includes some parameter. Taking an example, bell form function as follows:

$$\mu_{A\,N}(x) = (1+|(x - c_{ik}) / a_{kik}|^{2bkk})^{-1}$$

Its form depends on three parameters {a_{kik}, b_{kik}, c_{kik}}.

The second layer: The layer has M^N junction spot, and the output of each junction spot is the product of all inputs multiplied, but the multiplication may be instead of all kinds of T-model plan egg. The output of this layer is as follows:

$$O^{(2)}_{i1i2...iN} = {}^{N}_{k=1}\ O^{(1)}_{kik} = {}^{N}_{k=1}\ \mu_{kik}(x_k)$$

$$i_1, i_2, .. i_N = 1, 2, ..M$$

The third layer: This layer has the same junction spots as the second layer. The output of this layer is as follows:

$$O^{(3)}_{i1i2...iN} = O^{(2)}_{i1i2...iN} / {}_{i1i2...iN=1}O^{(2)}_{i1i2...iN}$$

$$= ({}^{N}_{k=1}\ \mu_{Akik}(x_k)) / {}_{i1i2...iN}\ {}^{N}_{k=1}\ \mu_{kik}(x_k)$$

$$i_1, i_2, .. i_N = 1, 2, ..M$$

The fourth layer: The layer has the same junction spots as the third layer, and each junction spot has auto-adapting function. The output of this layer is as follows:

$$O^{(4)}_{i1i2...iN} = O^{(3)}_{i1i2...iN}\, y_{i1i2...,iN} \quad i_1, i_2, ..i_N = 1, 2, ..M$$

Where $p_{i1i2...iN}^{(k)}$ and $q_{i1i2...iN}$, are adjustable parameters.

The fifth layer: This layer has only one junction spot. The output of this layer is as follows:

$$Y = O^{(5)} = {}_{i1i2...iN=1}^{M} O^{(4)}_{i1i2...iN}$$

ANFIS is a special neural network, if input variables are divided into enough *fuzzy* sets, the network can accurately approach all kinds of non-linear functions by adjusting parameters of the membership function in the first layer and adjusting the output function parameter $p_{i1i2...iN}^{(k)}$ and $q_{i1i2...iN}$, in the fourth layer (4) (5).

4.0 BASIC THEORY OF GABPN

Genetic Algorithm is used for finding weights of Artificial Neural Network which reduces the training time of the neural network. Fitness function computation for BPN using GA is shown in Fig. 3.

The algorithm for finding weights of ANN is divided into two sections. The first part is to compute the fitness function and the second part is to generate weights of ANN using back propagation algorithm.

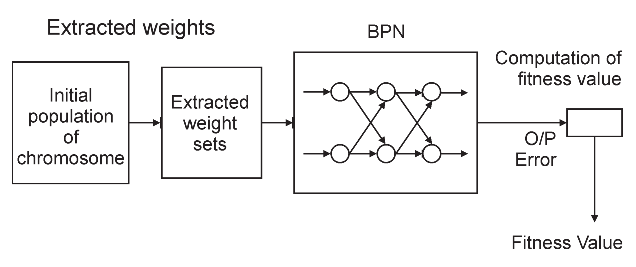

FIG. 3 FITNESS FUNCTION COMPUTATION FOR BPN USING GA

ALGORITHM FOR GABPN

{

i = 0;

Generate the initial population Pi of real-coded chromosomes Cji each representing a weight set for the BPN;

While the current population Pi has not converged

{

Generate fitness values Fji for each Cji ∈ Pi using the algorithm FITGEN ();

Get the mating pool ready by terminating worst fit individuals and duplicating high

Fit individuals;

Using the crossover mechanism, reproduce offspring from the parents

Chromosomes;

i++;

Call the current population Pi

Calculate fitness values Fji for each Cji ∈ Pi;

}

Extract weights from Pi to be used by the BPN;

}

ALGORITHM FOR FITGEN

{

Let (Ii, Ti), i = 1, 2, …, N where $Ii=(I_{1i}, I_{2i}, …, I_{li})$ and $Ti = (T_{1i}, T_{2i}, …, T_{ni})$ represent the input-output pairs of the problem to be solved by BPN with a configuration l-m-n.

For each chromosome Ci, i = 1, 2, …, p belonging to the current population Pi whose size is p

{

Extract weights Wi from Ci with the help of equation (8) and (9).

$$W_k = +(x_{kd+2} * 10^{d-2} + x_{kd+3} \qquad (8)$$

$$W_k = -(x_{kd+2} * 10^{d-2} + x_{kd+3} \tag{9}$$

Keeping Wi as fixed weight setting, train the BPN for the N input instances;

Calculate error Ei for each of the input instances using formula (10),

$$E_i = j\sum (T_{ji} - O_{ji} \tag{10}$$

Where, O_{ji} is the output vector calculated by BPN;

Find the root mean square E of the errors Ei, i = 1, 2… N

i.e., $$E_i = \sqrt{\left(\sum_i E_i \div N\right)} \tag{11}$$

Calculate the fitness value F_i for each of the individual string of the population as

$$F_i = 1/E \quad ; \tag{12}$$

}

Output F_i for each Ci, i=1,2…….pi

}

5.0 PROPOSED ALGORITHM

The algorithm depends on utilising WT for its powerful analysing and decomposing features. David C Robertson et al, Fernando H et al have discussed the use of wavelets for signal transients. For four decomposition levels of the phase current, maximum range values are taken as featured input vector under faulty condition. Extracted features may be anything like maximum, mean, minimum, absolute mean deviation, etc. Output vector of ANN, GABPN and ANFIS reveals the percentage of winding affected by fault. If the disturbance is classified as a fault on the winding, the circuit breaker of the transformer will be tripped. In this proposed scheme, with Ia fault current data taken with different percentage of winding short circuit, fault current data is considered for 0.25 cycles from the instant of fault. The structure for ANN is taken as 8-5-1 for the model system. The architecture of ANN used for this application is shown in Fig. 4.

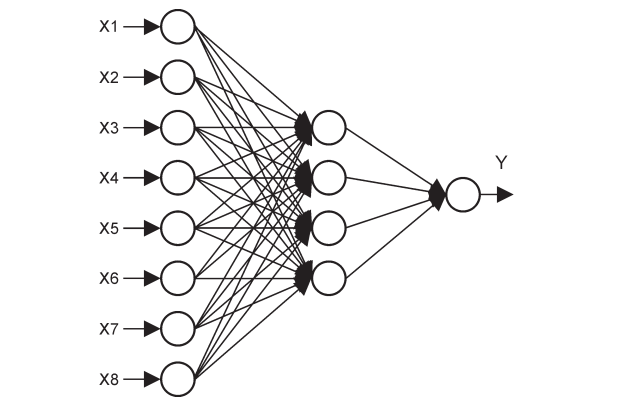

FIG. 4 ARCHITECTURE OF ANN

If the system is considered with more statistical data, the structure will take a different number of neurons in three layers. In the sample system one hidden layer is selected with four neurons. By trial and error, this number is selected optimally. Training Data for ANN, GABPN and ANFIS are encoded as follows:

Ia Level I-Max	Ia Level I-Range	Ia Level II-Max	Ia Level II-Range	Ia Level III-Max	Ia Level III-Range	Ia Level IV-Max	Ia Level IV-Range	Output (% wdg of Fault)

Ia phase current of the transformer is measured through Current Transformer. This signal is sampled at a sampling frequency of 2 KHz. The algorithm starts by collecting ¼ cycle sampled data window of the signal. Based on a sampling frequency of 2 KHz, one cycle contains 40 samples (frequency of operation is 50 Hz). So with sample count of 10, after finishing quarter cycle of current signal, values are recorded for this ¼ cycle. This quarter cycle data have to be checked for lying in I, II, III, IV quadrants of the current signal. For healthy current signal, Fig. 5 shows these quadrants.

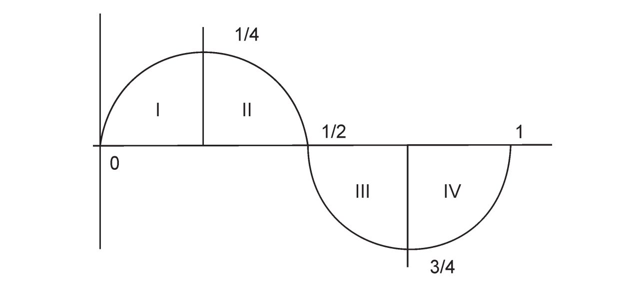

FIG. 5 HEALTHY CURRENT SIGNAL SHOWING FOUR QUADRANTS

This checking will be possible by just comparing two successive samples. If difference between two samples is positive, positively rising i.e., lying in I quadrant. If difference is negative, negatively falling i.e. lying in II quadrant. Similarly for negative half cycle. After determining the quadrant of current signal, DWT is applied to extract statistical data for its 4 decomposition levels. For this algorithm, any of the statistical data for current signal can be taken as all give satisfactory results. Results are given for simulated statistical data of maximum range of level 1, 2, 3 and level 4 of faulty signal. After extracting statistical features, data is encoded as per the format shown above. Then it is given to the corresponding ANFIS which are trained for I, II, III and IV quadrants of faulty currents respectively. ANFIS gives decision about percentage of winding fault on the phase winding of the transformer. The same procedure can be adapted for other phase windings of the transformer for giving complete protection to the transformer. So the 3 phase transformer can be protected from faulty condition by classifying the percentage of winding fault. No fault case is also taken into account for training the ANFIS, GABPN and ANN. The flowchart of this scheme is shown in Fig. 6.

TABLE 1

MEANING OF OUTPUT VECTOR OF ANN, GABPN AND ANFIS

Output	**% of winding affected by the short circuit**
0.1	1%
0.2	2%
0.3	3%
0.4	4%
0.5 ….	5% ….
1	100%

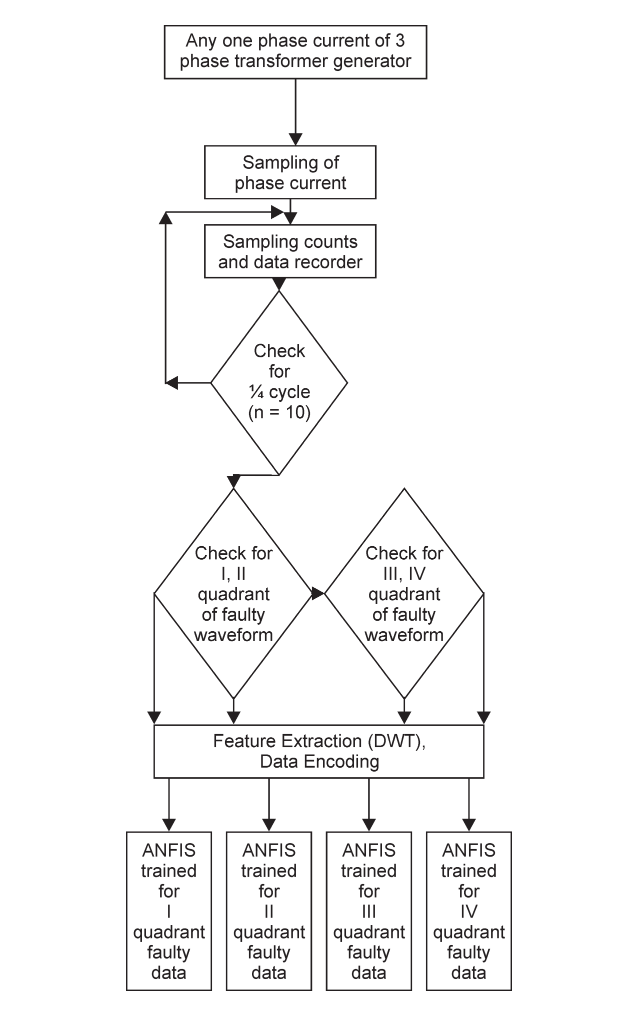

FIG. 6 FLOWCHART OF PROPOSED ALGORITHM

6.0 SIMULATION RESULTS

The sample network consists of one generator connected to 3 phase RL load through two transformers and one transmission line. The model network has been simulated using MATLAB and is shown in Fig. 7. Rating of the generator is 1000MVA, 11KV, 50Hz.

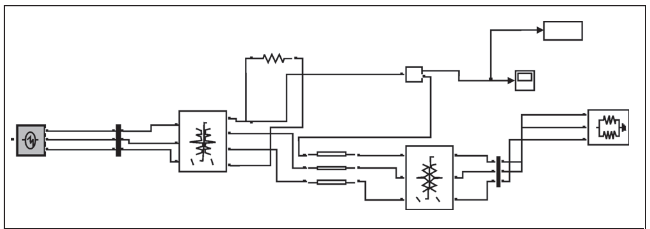

FIG. 7 TRANSFORMER WITH FAULT SIMULATING RESISTOR

Training data for the ANN, GABPN and ANFIS are prepared by simulating various %

of winding short circuit faults on the phase winding. The inter-turn fault is generated by connecting a resistor across the winding which will reduce the resultant value of both resistance and reactance of the phase winding. The above will be the actual case of the fault and simulated just by connecting a resistor across the winding [7]. A variable resistor is connected across the secondary winding A. The percentage of the winding fault can be changed by varying the value of the resistor.

To increase the reliability of the system, the protection system should be trained for all the four quarter cycles of faulty current. The phase current of one winding is passed through sampling circuit. These sampled signals perform as the input to the DWT based fault diagnosis algorithm. The described DWT-ANFIS algorithm is applied and tested on the sample transformer. The fault current at phase A for 20% winding short circuit is shown in Fig. 8.

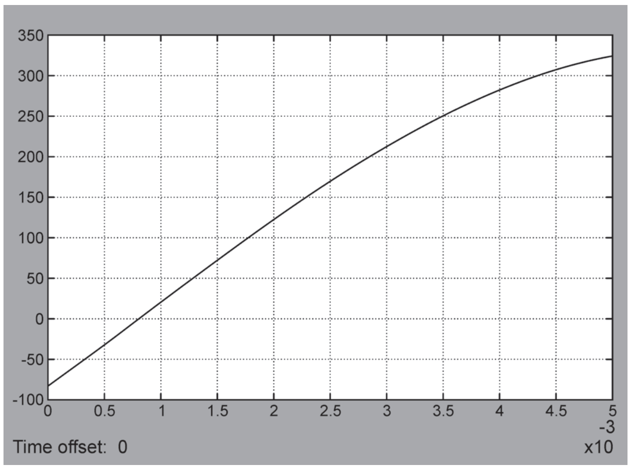

FIG. 8 FAULT CURRENT FROM PHASE A OF TRANSFORMER PRIMARY

This current is then loaded to the Wavelet Tool of MATLAB and analysed with dmey wavelet with four level decomposition. Statistics are recorded for each level of decomposition. Extracted features are statistical details of maximum range for four levels of phase current. They are arranged to form input vector for ANN, GABPN and ANFIS for different % of winding short circuit fault. The four decomposed levels of faulty current with their statistical data are shown in Figs. 9A, 9B, 9C and 9D.

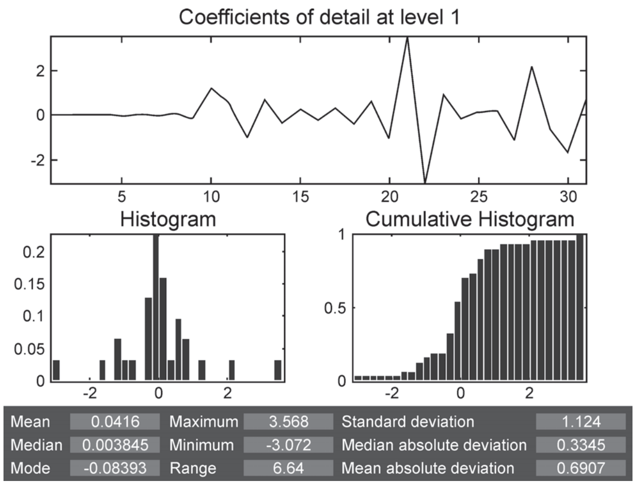

FIG. 9A DECOMPOSED LEVELS OF FAULTY CURRENT

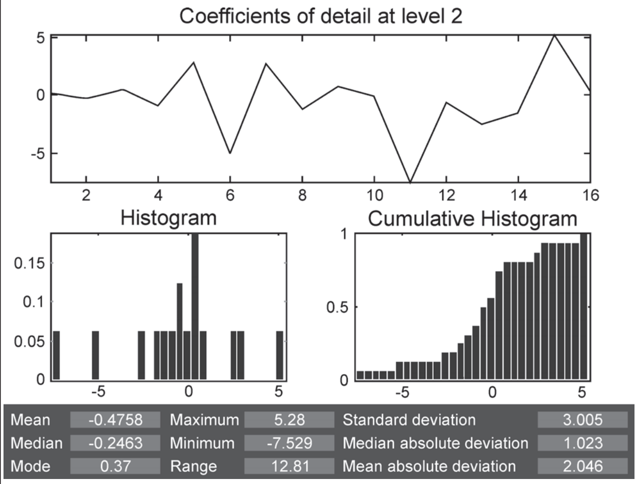

FIG. 9B DECOMPOSED LEVELS OF FAULTY CURRENT

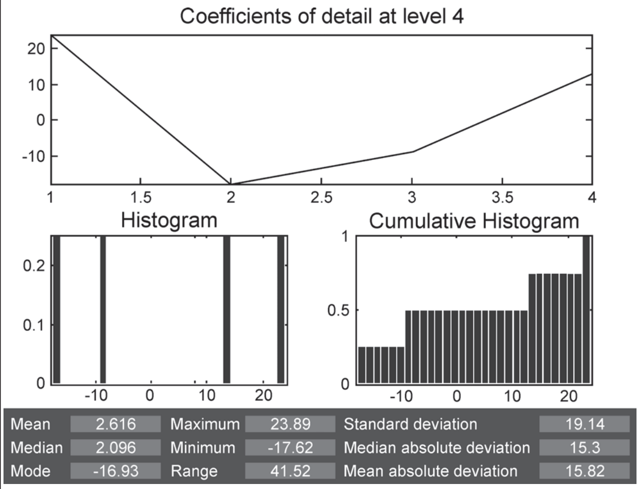

FIG. 9C DECOMPOSED LEVELS OF FAULTY CURRENT

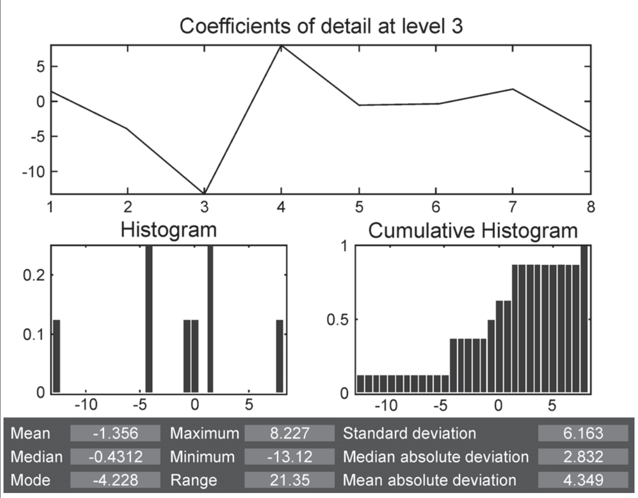

FIG. 9D DECOMPOSED LEVELS OF FAULTY CURRENT

With the proposed procedure, a sample system having two transformers has been tested which gives 100% performance with only two features of maximum and range of four levels of one phase current. Therefore input vector will have eight components. Similar procedure can be followed for other phase currents of the transformer. So CB will be operated according to the decision made by ANFIS. With ANN, GABPN and ANFIS, the system is tested with many data for the sample system. For normalised four original testing data formulated as per the data format shown above, average testing errors for ANN, GABPN and ANFIS are given in Table 4.

Inference made from output of the network is also given in the Table.

TABLE 2

SIMULATED SAMPLE DATA FOR DIFFERENT % OF WINDING SHORT CIRCUIT FAULT OF MODEL SYSTEM

Data	Level I		Level II		Level III		Level IV		Output
Number	Max	Range	Max	Range	Max	Range	Max	Range	% of fault
1	3.175	6.412	6.905	11.1	14.2	34.78	17.69	28.34	11
2	2.875	5.559	3.636	9.914	20.21	39.55	34.01	37.46	12
3	2.604	5.407	7.241	13.87	17.7	37.09	23.51	40.41	13
4	1.969	5.069	5.844	12.03	20.01	39.48	29.99	51.1	14
5	3.466	6.294	8.396	15.04	19.68	39.4	40.26	62.11	15
6	2.481	4.757	8.606	15.4	12.93	32.8	51.96	78.24	16
7	2.543	4.442	3.936	11.53	8.739	28.53	64.24	91.88	17
8	2.026	4.495	4.923	12.03	13.32	33.71	71.35	100.8	18
9	3.426	5.695	3.169	10.32	10.29	31.56	75.75	118.4	19
10	1.343	2.842	4.188	10.32	9.142	17.37	32.89	59.21	20

TABLE 3

NORMALISED SIMULATED TRAINING SAMPLE DATA FOR DIFFERENT % OF WINDING SHORT CIRCUIT FAULT OF MODEL SYSTEM

Data	Level I		Level II		Level III		Level IV		Output
Number	Max	Range	Max	Range	Max	Range	Max	Range	% of fault
1	0.3913	0.4338	0.2302	0.1854	0.111	0.1517	0.0458	0.0369	0.11
2	0.3543	0.3761	0.1212	0.1656	0.158	0.1726	0.088	0.0487	0.12
3	0.3209	0.3658	0.2414	0.2316	0.1384	0.1618	0.0608	0.0526	0.13
4	0.2426	0.343	0.1948	0.2009	0.1565	0.1723	0.0776	0.0665	0.14
5	0.4271	0.4258	0.2799	0.2512	0.1539	0.1719	0.1041	0.0808	0.15
6	0.3057	0.3219	0.2869	0.2572	0.1011	0.1431	0.1344	0.1018	0.16
7	0.3134	0.3005	0.1312	0.1926	0.0683	0.1245	0.1662	0.1196	0.17
8	0.2497	0.3041	0.1641	0.2009	0.1041	0.1471	0.1846	0.1312	0.18
9	0.4222	0.3853	0.1056	0.1723	0.0805	0.1377	0.1959	0.1541	0.19
10	0.1655	0.1923	0.1396	0.1723	0.0715	0.0758	0.0851	0.077	0.2

TABLE 4

PERFORMANCE COMPARISONS BETWEEN ANN, GABPN AND ANFIS

Percentage of Winding Fault	Average Testing Error		
	ANN	GABPN	ANFIS
35	0.01021	0.010413	0.0002577
3	0.05437	0.030011	0.0183202
25	0.01468	0.027607	0.0046316
60	0.00199	0.048634	0.0028127

Total simulated data are hundred in number. But ten sample data are given in Table 2 (Unnormalised). Table 3 shows corresponding normalised data.

ANFIS Structure used for this scheme is shown in Fig. 10. The ANFIS information is:

Number of nodes	:	155
Number of linear parameters	:	72
Number of non-linear parameters	:	128
Total number of parameters	:	200
Number of training data pairs	:	99
Number of checking data pairs	:	0
Number of fuzzy rules	:	8

ANFIS used for this purpose uses the hybrid method as its optimisation method. The error tolerance is taken as zero. The number of epochs for training the ANFIS is 300. Testing of ANFIS is performed for the following percentage of winding inter-turn faults of the transformer: 3%, 35%, 25% and 60%.

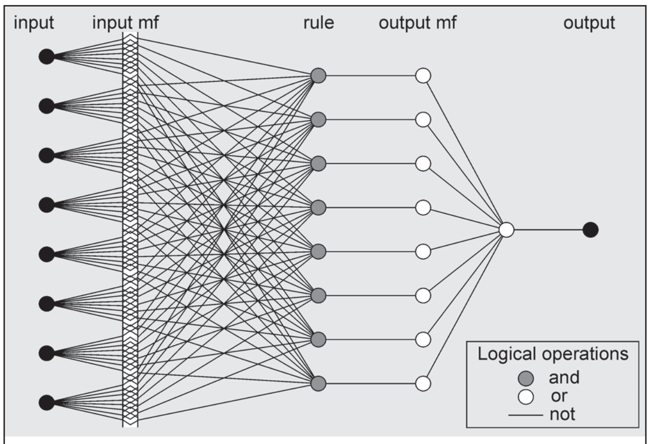

FIG. 10 STRUCTURE OF ANFIS

Fig. 11 shows the training error for 300 epochs after training of ANFIS.

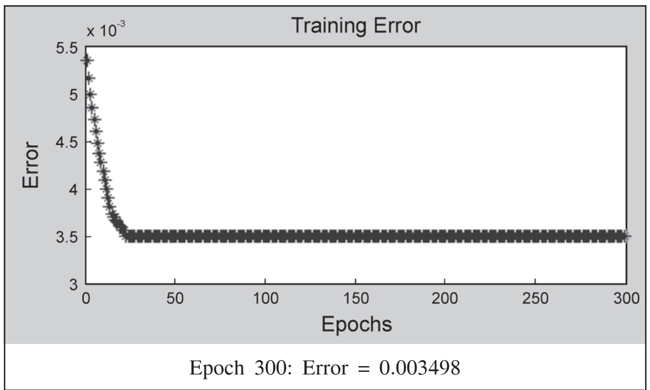

FIG. 11 ERROR Vs EPOCHS

The ANN used for this application is feed forward propagation network. Network was trained for the training data for 300 epochs. For the neural network, weights are determined using Genetic Algorithm. ANN is again tested with same testing data, giving satisfactory results. Comparison is made among these three systems. From the results, the proposed wavelet based ANFIS gives better performance than ANN and GABPN. Table 4 shows the average testing error of ANN, GABPN and ANFIS for various percentages of winding faults. Fig. 12 shows the ANN used for this purpose. Fig. 13 shows the performance curve of ANN after training the network.

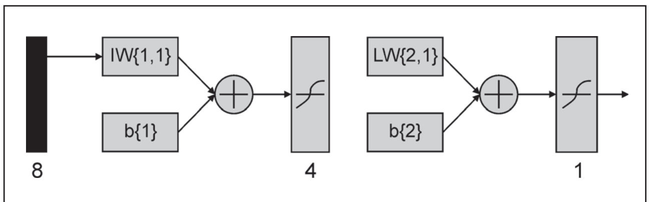

FIG. 12 STRUCTURE OF ANN

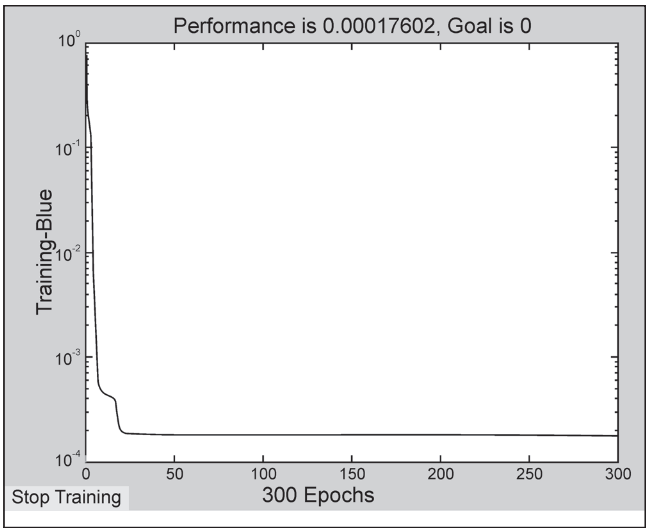

FIG. 13 PERFORMANCE (MSE) CURVE OF ANN AFTER TRAINING

From Table 4, it is concluded that ANFIS gives better performance than ANN and GABPN.

7.0 CONCLUSION

A new scheme for diagnosing inter-turn fault of the transformer is presented in this paper. The scheme depends on measuring three phase currents of the transformer. The DWT with its magnificent characteristics is employed to detect the disturbances in the current signals. The proposed algorithm has been applied for the sample system. This algorithm works with an efficiency of 100% if limited no. of statistical data of decomposition levels of faulty current are considered for making input vector. Limitation for selecting statistical data by trial and error is four. In the sample system, only two data are selected for forming input vector. All faults at different loading can be identified in less than half cycle time after the fault inception. For training ANN, GABPN and ANFIS, no fault case is considered with loading.

8.0 ACKNOWLEDGEMENT

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