

Diagnosis of Inter Turn Fault in the Stator of Synchronous Generator Using Wavelet Based ANFIS

R. Rajeswari and N. Kamaraj

Abstract— In this paper, Wavelet based ANFIS for finding inter turn fault of generator is proposed. The detector uniquely responds to the winding inter turn fault with remarkably high sensitivity. Discrimination of different percentage 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 generator phase winding. Training data for ANFIS are generated via a simulation of generator with inter turn fault using MATLAB. The proposed algorithm using ANFIS is giving satisfied performance than ANN with selected statistical data of decomposed levels of faulty current.

Keywords—Winding InterTurn fault, ANN, ANFIS, and DWT.

I. INTRODUCTION

At present the synchronous generators are protected against almost all kind of faults using differential methods of protection. All kind of faults develops into inter winding fault by damaging the inter winding insulation. So it is necessary to protect the synchronous generator from inter winding faults which represents the protection against all kind of faults. For inter winding protection differential method cannot be implemented as the current on both side of the fault will be the same. In this paper, 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 DWT Tool and features are extracted then normalized and used as input for ANN and ANFIS Synchronous generator can be protected within 0.01 seconds from the occurrence of the fault which will ensure maximum protection of the winding using this approach.

Stator winding faults of synchronous generator are considered serious problems because of the damage associated with high fault currents and high cost of maintenance. A high speed bias differential relay is normally used to detect three

phase, phase-phase and double phase to ground faults. In case of inter-turn winding fault the current on both side of the winding is 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 generation gets reduced. As the amount of winding under generating action is reduced the amount of current produced by induction principle also gets reduced. This reduces the power generated and affects the life time of the winding. When this problem is left undealt the inter winding insulation gets affected there by further reducing the amount of winding involved in generation. 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 proposed method is to protect the system within very short period in the range of milli seconds.

II. 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. 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

Manuscript received on October 26, 2007.

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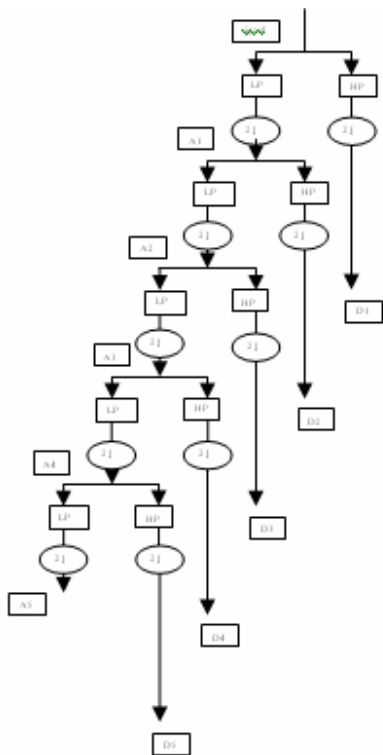


Fig. 1 DWT

$\Phi(t)$ and the wavelet function $\Psi(t)$

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

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

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 prototype of a class of orthonormal basis functions of the form

$$\phi_{j,k}(t) = 2^{j/2} \phi(2^j t - k) \quad j, k \in \mathbb{Z} \quad (3)$$

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k) \quad j, k \in \mathbb{Z} \quad (4)$$

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 \mathbb{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)

$$f(t) = \sum_{l \in \mathbb{Z}} c(l) \phi_l(t) + \sum_{j=0}^{\infty} \sum_{k \in \mathbb{Z}} d(j,k) \psi_{j,k}(t) \quad (5)$$

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

$$c(l) = \langle \phi_l | f \rangle = \int f(t) \phi_l(t) dt \quad (6)$$

$$d(j,k) = \langle \psi_{j,k} | f \rangle = \int f(t) \psi_{j,k}(t) dt \quad (7)$$

The expansion coefficients $c(l)$ 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 .

III. BASIC THEORY OF ANFIS

Adaptive neural fuzzy inference system (ANFIS) is a product by 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 don't 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 function. ANFIS fully makes use of the excellent characteristics of 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 nonlinear-system with less training data and quicker weakening speed and higher precision. ANFIS is a neural network in fact, which realize 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 as following:

If x_1 is A_{i11} and x_2 is $A_{2i2} \dots$, and x_n is A_{Nxn}
 Then $y_{i1i2 \dots iN} = \sum_{k=1}^N p_{i1i2 \dots iN}^{(k)} x_k + q_{i1i2 \dots iN}$
 $i1, i2, i3, \dots, iN \in \{1, 2, \dots, M\}$

The structure of ANFIS ($N=2, M=3$) is shown in fig.2, and the junction spot of same layer have same kind output function, the detail of whole network as following:

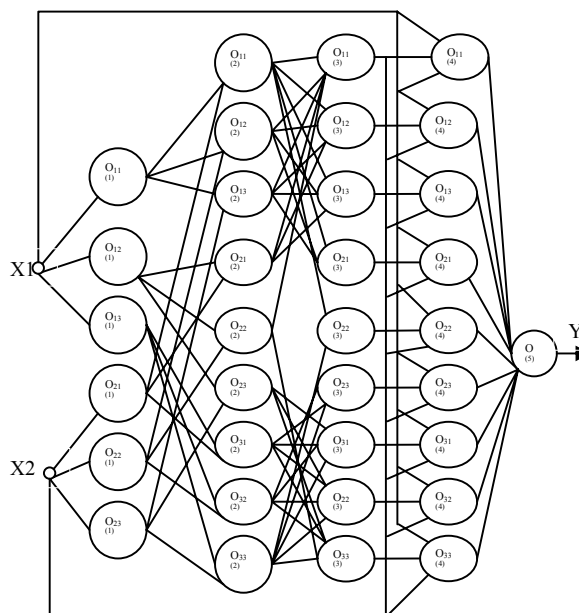


Fig. 2 Structure of ANFIS ($N=2, M=3$)

The first layer: the output function of each junction spot as following

$$O_{kik}^{(1)} = \mu_{kik}(x_k) \quad k = 1, 2 \dots N \quad i_k = 1, 2 \dots M$$

Where x_k is the input of the k, i_k junction spot, and is language *fuzzy* sets, and $O_{kik}^{(l)}$ is membership function of x_k , where membership function includes some parameter, taking an example, bell form function as following

$$\mu_{AN}(x) = (1 + \frac{(x - c_{kik})^2}{a_{kik}^2})^{-b_{kik}}$$

its form depends on three parameter $\{a_{kik}, b_{kik}, c_{kik}\}$

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

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

$i_1, i_2, \dots, i_N = 1, 2, \dots, M$

The third layer: this layer has the same junction spots as the second layer, the output of this layer as following

$$O_{i1i2...iN}^{(3)} = O_{i1i2...iN}^{(2)} / \prod_{k=1}^N O_{kik}^{(2)} = \prod_{k=1}^N \mu_{Akik}(x_k)$$

$i_1, i_2, \dots, i_N = 1, 2, \dots, M$

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 layer as following

$$O_{i1i2...iN}^{(4)} = O_{i1i2...iN}^{(3)} \cdot \prod_{k=1}^N \mu_{kik}(x_k)$$

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

The fifth layer: this layer has only one junction spot, the output of this layer as following

$$Y = O_{i1i2...iN=1}^{(5)} = O_{i1i2...iN}^{(4)}$$

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

IV. PROPOSED ALGORITHM

The algorithm depends on utilizing WT for its powerful analyzing and decomposing features. David.C.Robertson et al, Fernando H et al have been discussed about 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 of anything like maximum, mean, minimum, absolute mean deviation etc. Output vector of ANN & 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 generator will be tripped. In this proposed scheme, with I_c 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 3. If the system is considered with more number of statistical data the structure will take different number of neurons in three layers. In the example system one hidden layer is selected with five neurons. By trail and error, this number is selected optimally. Training Data for ANN are encoded as follows:

Ic Level 1 I- Max	Ic Level I- Range	Ic Level 1 II- Max	Ic Level II- Range	Ic Level 1 III- Max	Ic Level 1 III- Range	Ic Level 1 V- Max	Ic Level 1 IV- Range	Output t (% wdg of Fault)
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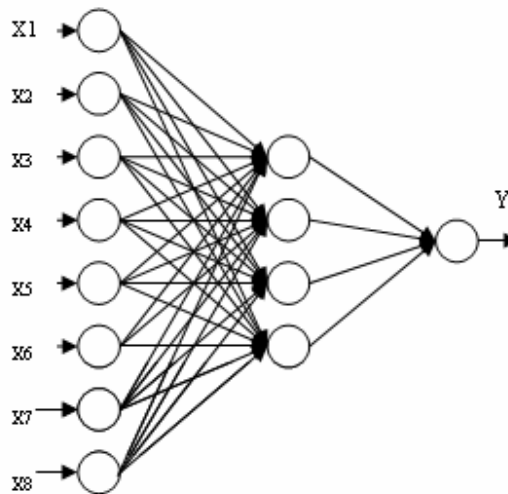


Fig. 3 Architecture of ANN

I_c phase current of generator is measured through Current Transformer. This signal is sampled at a sampling frequency of 2 KHZ. The algorithm starts by collecting $1/4$ 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 $1/4$ cycle. This quarter cycle data have to be checked for lying in I, II, III, IV quadrant of current signal. For healthy current signal, Fig. 4 show these quadrants.

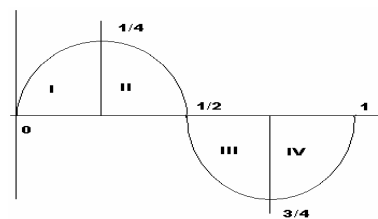


Fig. 4 Healthy current signal showing four quadrants

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 statistical data for current signal can be taken. Since all are giving satisfactory results, Results are given for simulated statistical data of maximum, range of level 1, 2, 3 & 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, IV quadrants of faulty currents respectively. ANFIS

gives decision about percentage of winding fault on the phase winding of generator. The same procedure can be adapted for other phase windings of generator for giving complete protection of the generator. So the 3 phase generator 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. The flowchart of this scheme is shown in Fig. 5.

TABLE I
 MEANING OF OUTPUT VECTOR OF ANN & GA-BPN

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

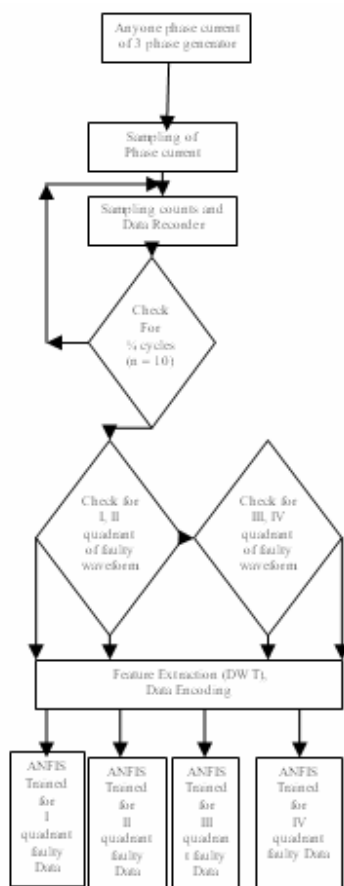


Fig. 5 Flowchart of proposed algorithm

V. SIMULATION RESULTS

The model network consists of one generator connected to 3 phase RLC load. The model network has been simulated using MATLAB. Rating of the generator is 1000MVA, 11KV, 50Hz.

Training data for the ANN are prepared by simulating various % of winding short circuit faults on the phase winding. The Interturn fault is generated by connecting a resistor across the winding which will reduce the resultant value of both resistance and reactance of the circuit. The above will be the actual case of the fault and simulated just by connecting a resistor across the winding [7]. The circuit (Fig: 6) is the modified circuit for fault simulation. A variable resistor is connected across the stator winding C. The percentage of the winding fault can be changed by varying the value of the resistor.

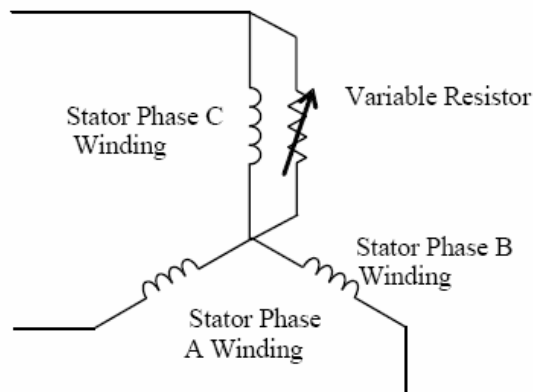


Fig. 6 Generator with fault simulating resistor

To increase the reliability of the system, the system should be trained for all the four quarter cycles of faulty current.

The phase current of one winding is passed through sampling circuits. These sampled signals perform as the inputs to the DWT based fault diagnosis algorithm. The described DWT-ANFIS algorithm is applied and tested on the sample generator. The fault current at phase C for 20% winding short circuit is shown in the Fig. 7

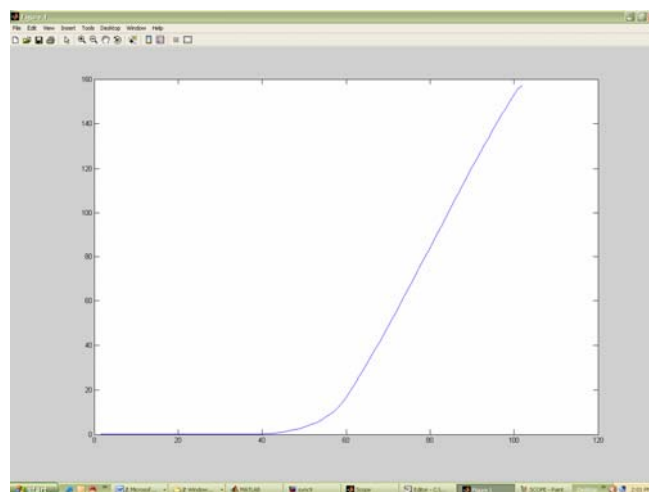
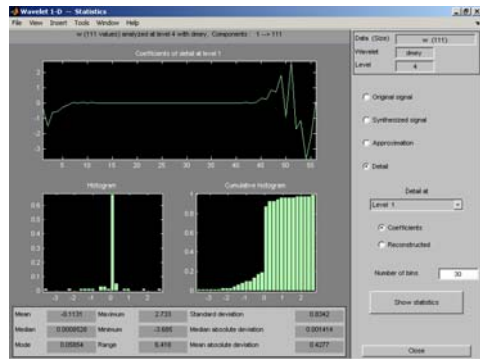


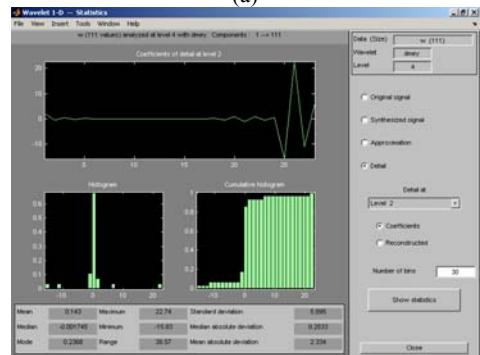
Fig. 7 Fault Current from Phase C of Synchronous Generator

This current is then loaded to Wavelet Tool of MATLAB and analyzed with dmey wavelet with four level decomposition. And statistics are recorded for each level of decomposition. Extracted features, statistical detail of maximum, range for four levels of phase current are arranged

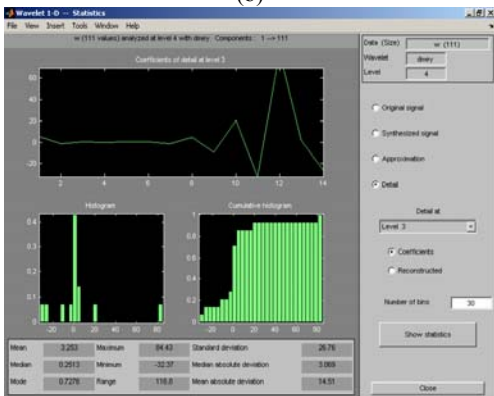
to form input vector for ANN& ANFIS for different % of winding short circuit fault. The four decomposed levels of faulty current with their statistical data are shown in Fig: 8a, 8b, 8c, and 8d.



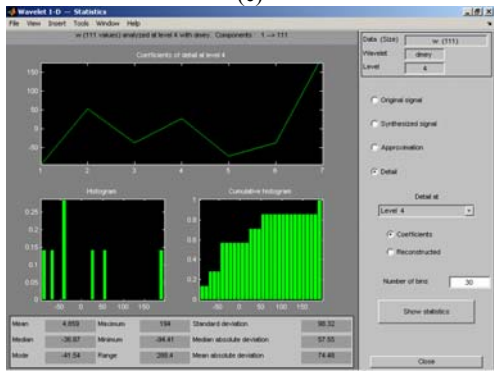
(a)



(b)



(c)



(d)

Fig. 8 4 decomposed levels of faulty current with their statistical data

With the proposed procedure, sample system having one generator has been tested and giving 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 generator. So CB will be operated according to the decision made by ANN or ANFIS. With ANN & ANFIS, system is tested with many data for the sample system. Four original testing data formulated as per the data format shown above are tested and outputs are given in Table IV. Inference made from output of the network is also given in the table. Total simulated data are hundred in number. But ten sample data are given in table: II (Unnormalized). Table III show corresponding normalized data.

ANFIS Structure used for this scheme is shown in Fig. 9. The ANFIS information are:

- Number of nodes: 1433
- Number of linear parameters: 711
- Number of nonlinear parameters: 1264
- Total number of parameters: 1975
- Number of training data pairs: 100
- Number of checking data pairs: 0
- Number of fuzzy rules: 79

ANFIS used for this purpose uses hybrid method as its optimization method. The error tolerance is taken as zero. The number of epochs for training the ANFIS is 10. Testing of ANFIS is performed for the following percentage of winding interturn faults of the generator: 3%, 15%, 25%, and 60%.

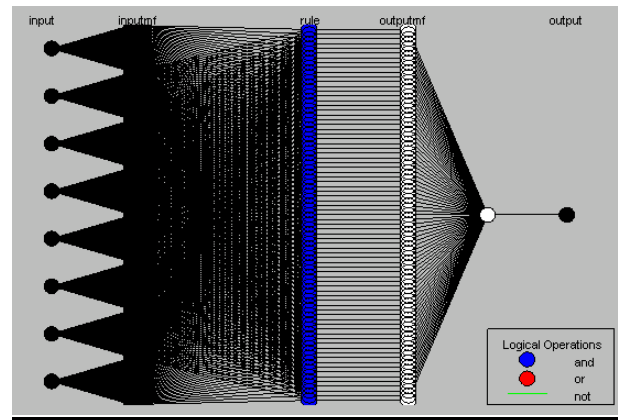


Fig: 9 Structure of ANFIS

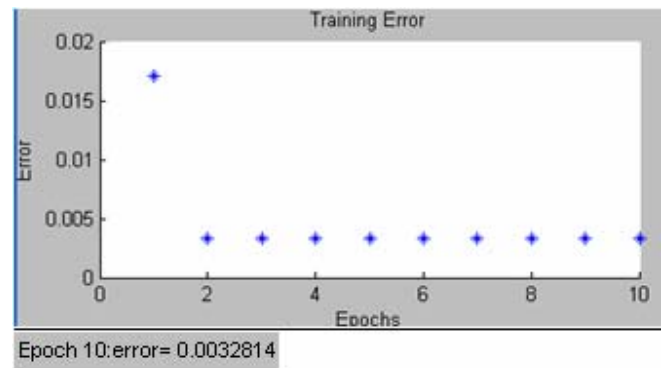


Fig. 10 Error Vs Epochs

Afer training of ANFIS the following Fig. 10 shows the training error for 10 epochs. Fig. 11 shows ANFIS output for 25% of winding interturn fault of the generator. Its average testing error is only 1.9298e-007

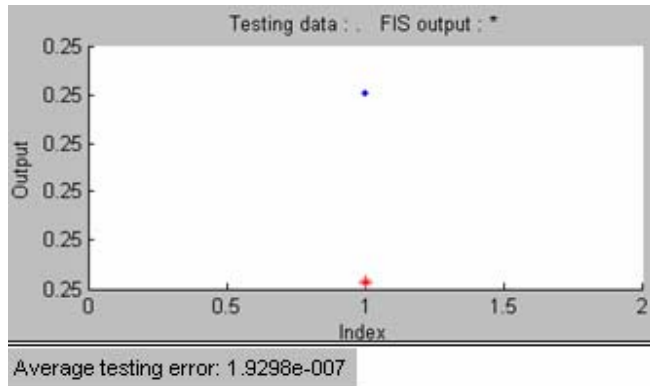


Fig. 11 ANFIS output for 25% of winding fault

Fig. 12 shows ANFIS output for 15% of winding interturn fault of the generator. Its average testing error is only 0.0057901.

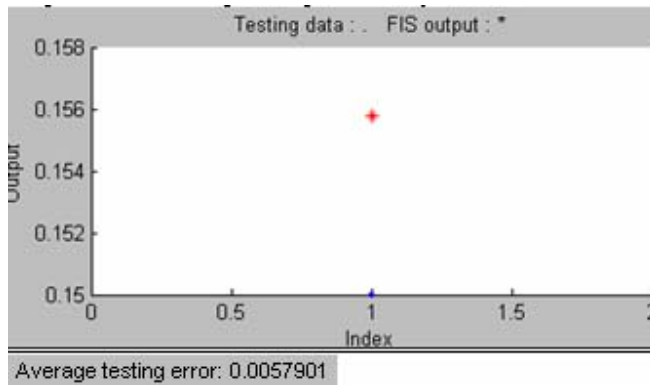


Fig. 12 ANFIS output for 15% of winding fault

Fig. 13 shows ANFIS output for 3% of winding interturn fault of the generator. Its average testing error is only 8.1805e-009

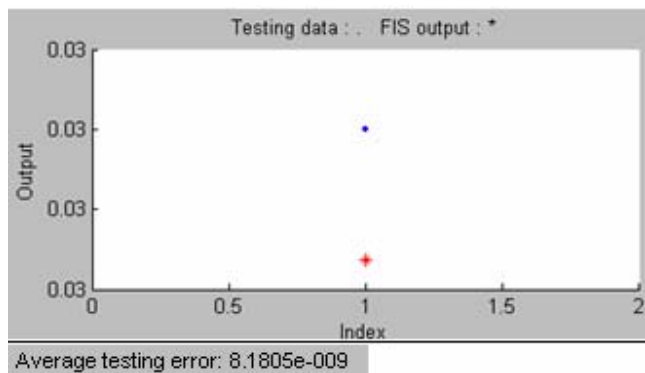


Fig. 13 ANFIS output for 3% of winding fault

Fig. 14 shows ANFIS output for 60% of winding interturn fault of the generator. Its average testing error is only 9.798e-005.

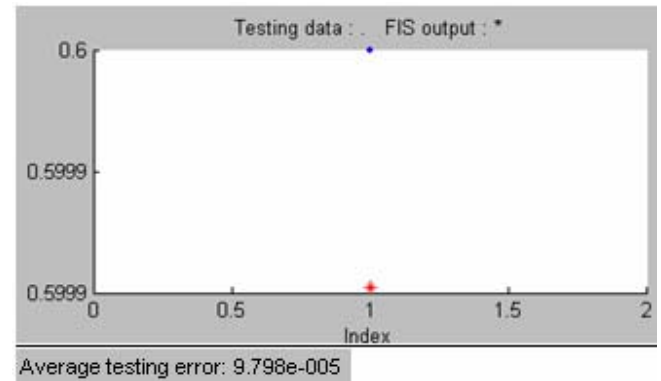


Fig. 14 ANFIS output for 60% of winding fault

ANN used for this application is feed forward propagation network. Network was trained for the training data for 500 epochs and simulated with same testing data of ANFIS, giving satisfactory results. But comparison is made between these two systems. The following table shows the average testing error of ANN and ANFIS for various percentages of winding faults. Fig. 15 shows the ANN used for this purpose. Fig. 16 shows performance curve of ANN after training the network.

TABLE IV
 PERFORMANCE COMPARISONS BETWEEN ANN & ANFIS

Percentage of Winding Fault	Average testing Error	
	ANN	ANFIS
15	0	0.0057901
3	8e-6	8.1805e-9
25	8e-5	1.9298e-7
60	2.5e-4	9.798e-5

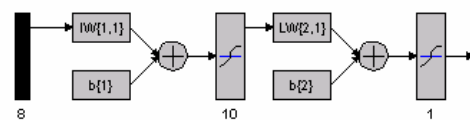


Fig. 15 Structure of ANN

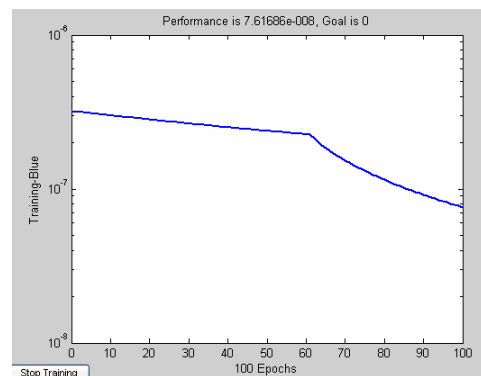


Fig. 16 Performance (MSE) curve after training

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

Data Number	Level I		Level II		Level III		Level IV		Output % of fault
	Max	Range	Max	Range	Max	Range	Max	Range	
1	2.73	6.42	22.74	38.57	84.43	116.8	194	288.4	1
2	3.06	4.66	14.65	25.3	66.86	94.52	165.4	229.9	2
3	2.13	3.22	14.2	23.7	53.08	75.88	135.5	191.9	3
4	1.36	2.75	12.79	21.36	48.44	69.34	127.1	175.4	4
5	1.97	4.42	8.9	15.13	41.85	60.99	115.3	159	5
6	1.83	4.22	8.34	14.19	39.29	57.26	107.7	148.6	6
7	1.72	2.35	7.83	13.32	36.68	53.45	100.6	138.9	7
8	0.88	1.47	7.39	12.55	34.3	50.01	94.42	138.3	8
9	0.88	1.4	7.14	12.1	7.14	12.1	89.14	123.2	9
10	0.83	1.33	6.8	11.52	30.66	44.68	84.58	116.9	10

TABLE III
NORMALIZED SIMULATED TRAINING SAMPLE DATA FOR DIFFERENT % OF
WINDING SHORT CIRCUIT FAULT OF MODEL SYSTEM

Data Number	Level I		Level II		Level III		Level IV		Output % of fault
	Max	Range	Max	Range	Max	Range	Max	Range	
1	0.892157	1	1	0.27854	0.635782	1	1	1	0.01
2	1	0.725857	0.644239	0.182708	0.503475	0.809247	0.852577	0.797157	0.02
3	0.696078	0.501568	0.62445	0.171154	0.399708	0.649658	0.698454	0.665395	0.03
4	0.444444	0.428349	0.562445	0.154255	0.364767	0.593864	0.655155	0.608183	0.04
5	0.643791	0.688474	0.391381	0.109264	0.315143	0.522175	0.59433	0.551318	0.05
6	0.590039	0.657321	0.366755	0.102476	0.295665	0.49024	0.555155	0.515257	0.06
7	0.562092	0.366044	0.344327	0.096193	0.276211	0.45762	0.518557	0.481623	0.07
8	0.287582	0.228972	0.324978	0.090632	0.268289	0.428168	0.486701	0.479542	0.08
9	0.287582	0.218069	0.313984	0.087382	0.063766	0.103596	0.459485	0.427184	0.09
10	0.271242	0.207165	0.299033	0.083194	0.290879	0.382534	0.435979	0.40534	0.1

From the Table IV shown above, ANFIS is giving better performance than ANN.

VI. CONCLUSION

A new scheme for diagnosing inter turn fault of synchronous generator is presented in this paper. The scheme depends on measuring three phase currents of the synchronous generator. 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 is working with efficiency of 100% if limited no of statistical data are considered for making input vector. Limitation for selecting statistical data by trail and error is four. In the sample system, selected only two data for forming input vector. All faults at different loading can be identified in less than half cycle after the fault inception.

ACKNOWLEDGMENT

I owe my thanks to the Principal of A.C.College of Engg. & Tech., Karaikudi, for providing me with all necessary facilities for completing this work. I feel honored Dr.N.Kamaraj who is working as Associate Professor in Electrical & Electronics Dept. of Thiagarajar College of Engg., Madurai, TamilNadu, India, for getting immense help rendered right from the beginning of my work I acknowledge the Management, Principal of Thiagarajar College of Engg., Madurai, Tamilnadu, India.

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