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Condition Monitoring and Faults Diagnosis for Synchronous Generator Using Neural Networks

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Abstract

Early detection and diagnosis of incipient fault is desirable for on line condition assessment production quality assurance and improved operational efficiency of synchronous generator running of power supply. Artificial Intelligent techniques are increasly used for condition monitoring and fault diagnosis of machines. In this paper, Artificial Neural Network (ANNs) approach employed for fault diagnosis in the generator, based on monitoring generator currents to give indication of the winding faults. Feed-forward Network, error back propagation training algorithm are used to perform the generator faults diagnosis and their values. NN which has been trained for all possible operating condition of the machine used to classify the incoming data. The inputs of the NN are the stator and rotor currents, and the output represents the running condition of the generator. The training of the NN achieved by the data through a mathematical model based approach to simulate the generator faults at various degree of severity.This paper evaluates through simulation line currents magnitude of the generator .The final results have been represented on a monitoring unit, built using matlab program, to give early warning of the generator failure.

Keywords*: Multi-layer Feed-forward Network, Back Propagation algorithm, synchronous generator, condition monitoring, Fault diagnosis.*

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1. Introduction

Synchronous machines are the most important and valuable devices in power systems. These generators are generally well constructed and robust, but the possibilities of incipient faults are inherent due to stresses involved in the electromechanical energy conversion process. Fault diagnosis can produce significant cost saving by allowing for the scheduling of preventive maintenance, thereby preventing extensive downtime periods caused by extensive failure [1].In addition to bad performance, faults reduce the life span of the generators. Fault diagnosis of large and costly generators in power stations, oil refineries and petrochemical industries is thus required for preventive maintenance of the machines. Various fault diagnosis techniques have been proposed including expert system, fuzzy logic approaches [2], neural networks (NN) [3], and fuzzy neural networks [4]. The expert systems and fuzzy logic approaches have some intrinsic shortcomings, such as the difficulty of acquiring knowledge and maintaining fault databases.In NN approaches, the training data must be sufficient and compatible to ensure proper training. A synchronous generator fault not only damages the machine itself but may also cause an interruption in power and hence loss of revenue. In various diagnostic techniques, monitoring and measuring electrical, magnetic, chemical,acoustic and thermodynamic quantities as well as measuring partial discharge are required. About 60% of faults in electrical machines are caused by mechanical parts such as bearings, shaft and coupling. Nearly 80% of these faults result in the displacement of the axis of symmetry or the rotating axis of the rotor. Therefore, existing asymmetry between rotor and stator cause 50% of faults in these machines [5]. Furthermore, if these faults have not been diagnosed and prevented, the rotor may touch the stator and result in irreparable damage of the machine. In the case of static eccentricity, the rotating axis of the rotor coincides with its axis of symmetry, but these are displaced with respect to stator axis of symmetry. In the dynamic eccentricity condition, the stator axis of symmetry coincides with the rotating axis of the rotor, but the rotor

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axis symmetry is displaced with respect to the two former axes. Finally, in the mixed eccentricity condition, all three axes are displaced with respect to each other.

2. Modeling and Simulation of Synchronous Generator

A three phase synchronous generator employs two main windings, field winding supplied with direct current and three phase windings excited with derived alternating currents, it is assumed that both winding m.m.fs are space fundamental with respect to the winding of origin. A constant phase displacement of m.m.fs is achieved in practice using two alternative forms of machine construction with the three phase winding stationary, the field winding rotate at $\omega_r = 1$ electrical rad/s in synchronism with traveling wave of stator m.m.f alternatively, with the field winding stationary the three phase winding rotate at $\omega_r = \omega$ electrical rad/s in construction to its traveling wave of m.m.f. The speed of mechanical rotation is a unique value $(n_s = \omega / 2\pi \ polepairs)$ r.p.s called synchronous speed. [6]

2.1. Synchronous Generator Model for Condition Monitoring Purposes

Depending on the coupled circuit approach viewpoint the stator and rotor equation sets of a generator are each expressed in their respective physical circuits in which the machine will be regarded as a circuit element whose mutual inductances (between stator and rotor) depend on the angular positions of the rotor that runs at synchronous speed (n_s) as shown in Figure 1.

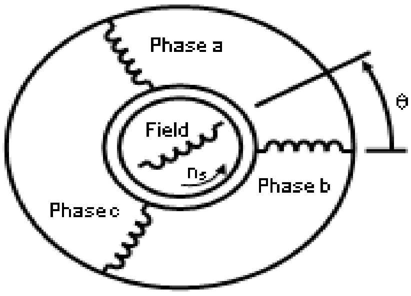

Figure 1. Schematic Representation of a Generator

For the 3-phase winding, the vector of stator and rotor voltages, V, is related to the vector of stator and rotor winding currents, I, and the machine flux linkages λ which will be expressed in terms of the currents and inductances. The result will be a set of nonlinear differential equations describing the dynamic performance of the machine as shown below [6]:

$$[V] = [R][I] + [p\lambda] \tag{1}$$

Where $p = \frac{d}{dt}$ is the differential operator. In terms of the instantaneous winding quantities, the vectors of equation (1) are:

$$v = \begin{bmatrix} v_a \\ v_b \\ v_c \\ v_{fd} \end{bmatrix}, \ i = \begin{bmatrix} i_a \\ i_b \\ i_c \\ i_{fd} \end{bmatrix}, \ \lambda = \begin{bmatrix} \lambda_a \\ \lambda_b \\ \lambda_c \\ \lambda_{fd} \end{bmatrix} \tag{2}$$

The matrix of winding resistance has the diagonal form:

$$R = \begin{bmatrix} R_a & 0 & 0 & 0 \\ 0 & R_b & 0 & 0 \\ 0 & 0 & R_c & 0 \\ 0 & 0 & 0 & R_{fd} \end{bmatrix} \quad (3)$$

In equations (2) and (3) a, b and c represent the three phase winding of the stator and f_d represent the field winding. The damper windings are not seen in the equations because the monitoring system is at steady state. If L is a matrix of winding inductances and the inter-winding mutual inductances, then the machine flux linkages in the vector $[\lambda]$, used in equation (1) may be formed from:

$$[\lambda] = [L][I] \quad (4)$$

Using the vector $[\lambda]$ from equation (4) in equation (1) then gives:

$$[V] = [R][I] + [p(LI)] \quad (5)$$

On expanding the differential of the matrix-vector product $[LI]$:

$$[V] = [R][I] + \left[\frac{\partial L}{\partial \theta}\right] \cdot \frac{\partial \theta}{\partial t} \cdot [I] + [L][pI] \quad \text{Or} \quad [V] = [R][I] + [G]\omega[I] + [L][pI] \quad (6)$$

In which

$$[G] = \left[\partial L / \partial \theta\right] \;;\theta = \omega.t \quad \text{and} \quad \omega = \partial \theta / \partial t \quad (7)$$

2.2. Machine Voltage Equation Matrix

Since there is 120° degree phases difference between the three phases, so the voltage and current matrices can be substituted with [7]:

$$\begin{bmatrix} V_a \\ V_b \\ V_c \\ V_{fd} \end{bmatrix} = \begin{bmatrix} V\sin(\omega t) \\ V\sin(\omega t - 120^\circ) \\ V\sin(\omega t - 240^\circ) \\ V_{fd} \end{bmatrix}, \quad \begin{bmatrix} I_a \\ I_b \\ I_c \\ I_{fd} \end{bmatrix} = \begin{bmatrix} I\sin(\omega t) \\ I\sin(\omega t - 120^\circ) \\ I\sin(\omega t - 240^\circ) \\ I_{fd} \end{bmatrix}$$

After substituting the above equations of L and G matrices in equation (6), yields:

$$\begin{bmatrix} V\sin(\omega t) \\ V\sin(\omega t - 120^\circ) \\ V\sin(\omega t - 240^\circ) \\ V_{fd} \end{bmatrix} = \begin{bmatrix} R_a & 0 & 0 & 0 \\ 0 & R_b & 0 & 0 \\ 0 & 0 & R_c & 0 \\ 0 & 0 & 0 & R_{fd} \end{bmatrix} \begin{bmatrix} I\sin(\omega t) \\ I\sin(\omega t - 120^\circ) \\ I\sin(\omega t - 240^\circ) \\ I_{fd} \end{bmatrix} +$$

$$\begin{bmatrix} 0 & 0 & 0 & L_{afd}\sin(\omega t) \\ 0 & 0 & 0 & L_{bfd}\sin(\omega t - 120^\circ) \\ 0 & 0 & 0 & L_{cfd}\sin(\omega t - 240^\circ) \\ L_{afd}\sin(\omega t) & L_{bfd}\sin(\omega t - 120^\circ) & L_{cfd}\sin(\omega t - 240^\circ) & 0 \end{bmatrix}$$

$$\omega\begin{bmatrix} I\sin(\omega t) \\ I\sin(\omega t-120^\circ) \\ I\sin(\omega t-240^\circ) \\ I_{fd} \end{bmatrix} + \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} & L_{af} \\ L_{ba} & L_{bb} & L_{bc} & L_{bf} \\ L_{ca} & L_{cb} & L_{cc} & L_{cf} \\ L_{fa} & L_{fb} & L_{fc} & L_{ff} \end{bmatrix} \begin{bmatrix} \frac{\partial I_a}{\partial t} \\ \frac{\partial I_b}{\partial t} \\ \frac{\partial I_c}{\partial t} \\ \frac{\partial I_{fd}}{\partial t} \end{bmatrix} \qquad (8)$$

Where: L_{aa} is the self inductance of phase "a", L_{bb} is the self inductance of phase "b", L_{cc} is the self inductance of phase "c", and L_{ab} is the mutual inductance between phases "a" and "b", L_{bc} is the mutual inductance between phases "b" and "c", L_{ca} is the mutual inductance between phases "c" and "a". This work depends on the rate of change of current in the detection, so the rate of change of current for the three phases and the field current can be deduced from the last equation, as follows:

$$\begin{bmatrix} \frac{\partial I_a}{\partial t} \\ \frac{\partial I_b}{\partial t} \\ \frac{\partial I_c}{\partial t} \\ \frac{\partial I_{fd}}{\partial t} \end{bmatrix} = \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} & L_{af} \\ L_{ba} & L_{bb} & L_{bc} & L_{bf} \\ L_{ca} & L_{cb} & L_{cc} & L_{cf} \\ L_{fa} & L_{fb} & L_{fc} & L_{ff} \end{bmatrix}^{-1} \begin{bmatrix} V\sin(\omega t) \\ V\sin(\omega t-120^\circ) \\ V\sin(\omega t-240^\circ) \\ V_{fd} \end{bmatrix} - \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} & L_{af} \\ L_{ba} & L_{bb} & L_{bc} & L_{bf} \\ L_{ca} & L_{cb} & L_{cc} & L_{cf} \\ L_{fa} & L_{fb} & L_{fc} & L_{ff} \end{bmatrix}^{-1} \begin{bmatrix} R_a & 0 & 0 & 0 \\ 0 & R_b & 0 & 0 \\ 0 & 0 & R_c & 0 \\ 0 & 0 & 0 & R_{fd} \end{bmatrix} \begin{bmatrix} I\sin(\omega t) \\ I\sin(\omega t-120^\circ) \\ I\sin(\omega t-240^\circ) \\ I_{fd} \end{bmatrix}$$

$$- \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} & L_{af} \\ L_{ba} & L_{bb} & L_{bc} & L_{bf} \\ L_{ca} & L_{cb} & L_{cc} & L_{cf} \\ L_{fa} & L_{fb} & L_{fc} & L_{ff} \end{bmatrix}^{-1} \begin{bmatrix} 0 & 0 & 0 & L_{afd}\sin(\omega t) \\ 0 & 0 & 0 & L_{bfd}\sin(\omega t-120^\circ) \\ 0 & 0 & 0 & L_{cfd}\sin(\omega t-240^\circ) \\ L_{afd}\sin(\omega t) & L_{bfd}\sin(\omega t-120^\circ) & L_{cfd}\sin(\omega t-240^\circ) & 0 \end{bmatrix} \omega \begin{bmatrix} I\sin(\omega t) \\ I\sin(\omega t-120^\circ) \\ I\sin(\omega t-240^\circ) \\ I_{fd} \end{bmatrix} \qquad (9)$$

This equation means that the rate of change of current in the three phases and the field are dependent on the inductances and resistances of each part, and it will be used, as basis for monitoring since any fault will be reflected on current as will be seen later.

3. Artificial Neural Networks (ANNs)

The Artificial Neural Networks (ANNs) are highly connected network of elementary processors running in parallel. Each elementary processor computes a single output based on information it receives. Two main elements constitute an ANNs: the neuron model used to build the network and then the network architecture. Each artificial neuron is an elementary processor that receives a number of neural inputs upstream. At each of these inputs has an associated weight representing the strength of connections between neurons corresponding. This puts forward two specific characteristics of each neuron: a "potential" equal to the weights sum of the inputs and an "activation function" which gives the output of the neuron according to its "potential" [8-9]. The neural network is an effective method of fault diagnosis based on its input and output nonlinear mapping, parallel processing and a high degree of self-organization and selflearning ability [10]. In a feedforward back propagation neural networks structure, the only appropriate connections are between the outputs of each layer and the input of the next layer [11]. Neural Network with back propagation algorithm is one of the famous methods to make a learned machine or system that can provide a final decision of classification with a number of learning process. It can be developed by NN tool provided in MATLAB, although sometimes it would result in different accuracies in object detecting and recognition for every experiment [12-13].

4. Backpropagation Neural Network Structure

The backpropagation algorithm is an extension of perceptions to multilayered neural networks. Thus, the backpropagation algorithm employs three or more layers of processing units (neurons).Figure 2 shows an architecture of a typical three layered network for the backpropagation algrithm. The leftmost layer of units is the input layer to which the input data is supplied. The later after it is the hidden layer where the processing units are interconnected to the layers before and after it. The rightmost layer is the output layer. The layers in Figure 2 are fully interconnected, which means that each processing unit is connected to every unit in the previous layer and in the succeeding layer. However, units are not connected to other units in the same layer. Note that the backpropagation networks do not have to be fully interconnected, that means any number of hidden layer may be used. [14]. For simplicity, we consider three layered neural networks given by Figure 2.

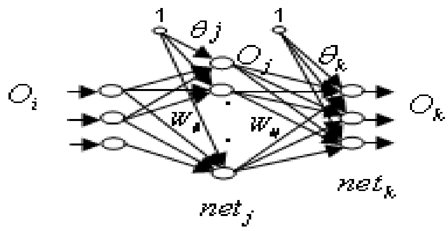

Figure 2. Multilayered neural networks

Where O_k, O_j and O_i are the output values at the output, hidden, and input layer, respectively. A connection weight from a unit j at the hidden layer to a unit k at the output layer is denoted by W_{kj} .Also, W_{ji} is a connection weight from a unit i at the input to a unit j at the hidden layer.

4.1. Backpropgation Algorithm Steps

The backpropagation algorithm can be summarized as in the following steps:

Step 1: set the initial values of W_{kj} ,W_{ji} ,θ_j ,θ_i and α .

Step 2: apply the input to neural network, specifiy the corresponding desired output τ_k , and calculate O_j ,O_k and δ_k by the formula:

$$\partial_k = O_k(1-O_k)(\tau_k - O_k) \quad (10)$$

Step 3: change the connection weights by:

$$\Delta W_{kj}(t+1) = \eta\delta_k O_j + \alpha\Delta W_{kj}(t) \quad (11)$$

Step 4: calculate δ_j by:

$$\delta_j = O_j(1-O_j)\sum_k \delta_k W_{kj} \quad (12)$$

Step 5: change the connection weights by:

$$\Delta W_{ji}(t+1) = \eta\delta_j O_i + \alpha\Delta W_{ji}(t) \quad (13)$$

Step 6: if $t \rightarrow t+1$ go to step2.

Where, η is the learning rate, and α is a constant which determine the effect of the past connection weight changes on the current direction of movement in connection weight space.

5. System Identification

Let us consider the I/O behavior of a plant. In order to train an ANN of given topology to identify the plant; we send to the plant and the ANN the same set of input signals. The corresponding outputs of the plant represent the target network output as indicated in Figure 3, Provide that the training patterns have significantly covered the input volume of interest and that the ANN has been properly trained. The ANN represents a plant model which is used for the plant behavior of fault diagnosis and even for control purposes if the plant can be controlled [12].

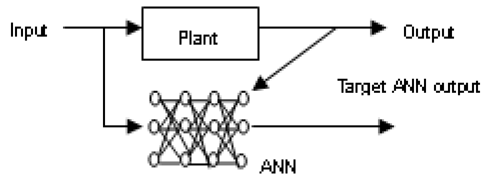

Figure 3. Use of an ANN for lant identification

5.1. Implementation of the Neural Network Fault Diagnosis Classifier

In this work the monitoring cycle is divided into three parts as shown in Figure 4. The first part represents the machine modeling of the synchronous generator, which has been discussed fully in section 3. The model used to represent the relation between the generator currents and their internal parameters such as resistance and inductance. The second part of the condition monitoring system is to let the neural net work learn this relation. The third part use the neural network to recognition criteria, by making comparison between the received data and give indication for early warning of the machine failure. The output forms which represent the final decision is given to the operator (diagnostic).In this section part two and three will be discussed in details.

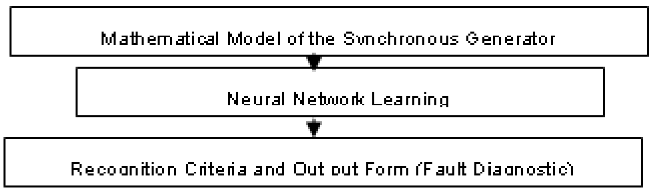

Figure 4. Monitoring cycle

6. Artificial Neural Network Learning

The mathematical model, which represents the synchronous generator, has been programmed using matlab program. The neural network training using data achieved from the model. Neural network three layer feed-forward with bipolar tangent activation function is used. Supervised back-propagation training algorithm has been used to train the NN for all possible operating conditions.to minimize the sum squared error. The network topology is shown in Figure 5.

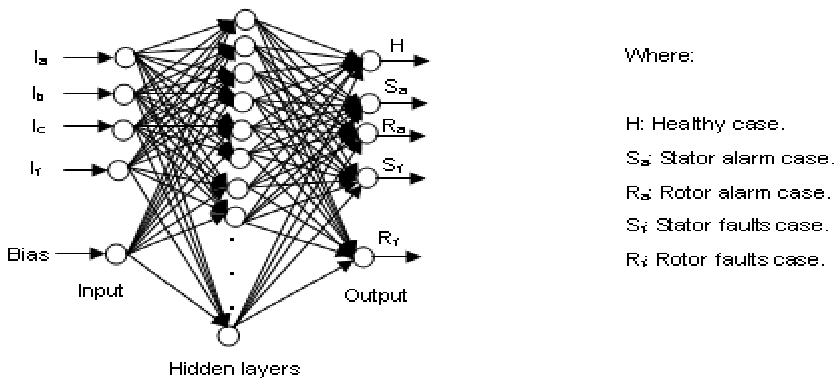

Figure 5. Multi layer neural network according to 4 inputs, 20 hidden layers, 5 outputs.

The trainable weights are initialized at small random value (-0.05, 0.05). The input layer consists of four unit's representation the stator currents (I_a, I_b, I_c) and the rotor current (I_f). A choice of twenty hidden layer units gives the best work performance. The output layer representing four different classes of the running conditions (healthy, alarms, stator faults, rotor faults), the target output will be (-1, 1). Based on these rules the neural network has been trained for all possible operating condition of the machine.

7. Research Method

7.1. Monitoring and Faults Detection Methods (Short Circuit in the Stator Windings)

The stator winding in the generator is very highly stressed, electrically, thermally and mechanically. If severe mechanical movements of the windings occur during its daily operation, then the windings conductors' insulation may fail due to this movement leading to arcing because of conductors shorting. For many years the occurrence of a short – circuited turn in the stator windings was considered acceptable until it resulted in an operational problem such as a change in vibration level due to thermal unbalance. The progression of faults may produce very high temperatures and since the insulation (between the windings in the weakest components of any electrical machine) may be defected.

Table 1. Rated data and output

Parameter	Values
Appearance power & Active power	200MVA , 160MW
Current & Voltage	11kA, 10.5kV
Speed & Frequency	3000 rpm, 50Hz
Power factor	0.8
Rated field current for rated output	2520A
Field voltage	220V

Table 2. Resistance in ohms at $75C^{\circ}$

Parameter	Values
Stator winding (phase a)	$0.0064005234*10^4$ ohms
Stator winding (phase b)	$0.0064722617*10^4$ ohms
Stator winding (phase c)	$0.0064114665*10^4$ ohms
Rotor windings	$0.01574*10^4$ ohms

Table 3. Inductances in henry at $75C^{\circ}$

Parameter	Values
Self inductance for (phase a)	0.007541099 henry
Self inductance for (phase b)	0.007541073 henry
Self inductance for (phase c)	0.007541095 henry
Mutual inductances between stator phases	0.000009 henry
Mutual inductances between stator and rotor	0.0001 henry
Self inductances for rotor field winding	0.045 henry

The value of the resistance can be taken as a measure to determine the severity of the fault. The levels below are chosen to indicate this severity of fault and we take phase current "a" as an example. The indications and comments about the above graph are:

a) The above graphs represent the current in phase "a".

b) The amplitude of the first curve (healthy case) is about $14x10^5$ Ampere, which represent the rate of change for the generator in its healthy condition. This amplitude increases as shown in above graphs with short circuit until it reaches to about $21x10^5$ Ampere in case of fault.

c) The above graph is taken for one cycle (i.e. 0.02 second) since the generation frequency is 50 Hz.

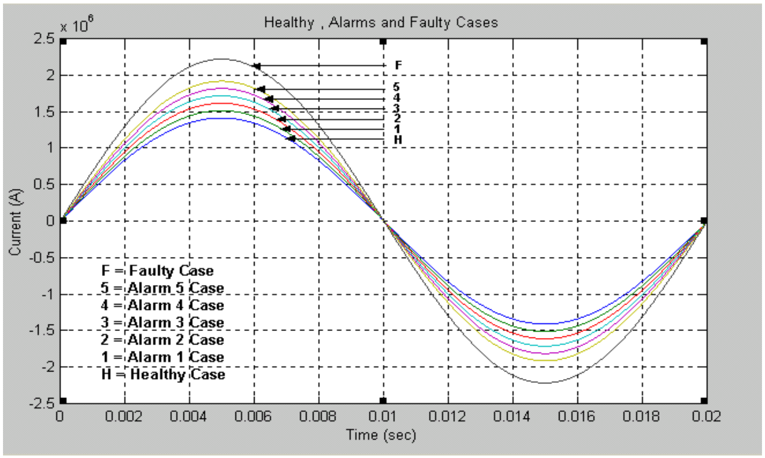

Figure 6. Stator current levels (healthy, alarms, and faulty).

7.2. Recognition Criteria and Output Form (Fault Diagnostic)

The third part of the condition monitoring cycle, is the of artificial neural network to classify the incoming data. The final results have been represented and interface, built using matlab program, to give early warning of the machine failure**.** For Operating the condition monitoring system, If a short circuit occurs in one the stator winding. The first step, we solve the differential equation when mathematical model used**.** The second step, learning the neural network**.** The third step, give decision to the operator (diagnostic)**.** The sum squared error with respect to the number of iteration shown in Figure 7.

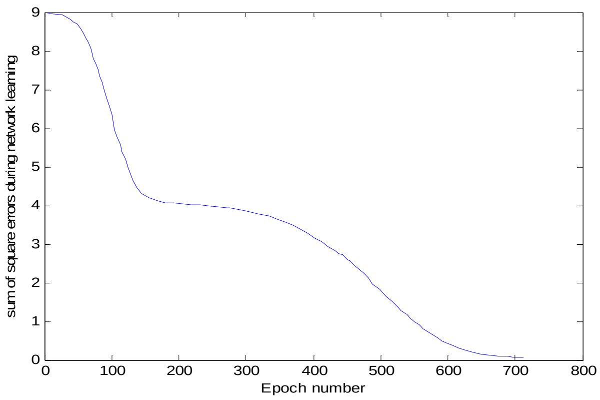

Figure 7.the sum squared error with respect to the number of itetations

The indications and comments about the above graph are:

Neural network toolbox used with matlab was employed to train the artificial neural networks for this investigation. A three layers feed forward neural network with back propagation algorithm was used to perform the desired analysis. The network topology is shown in Figure.5. There are 5 input nodes, 20 hidden nodes and 5 output nodes. After employing trail and error based computation, it was found that the networks with 20 hidden neurons yielded the optimum result. It is depicted training sum square error related to the number of iterations as shown in Figure 7.

8. Conclusion and Recommendations

This paper is used condition monitoring system to detect the stator and rotor winding faults. The generator currents (stator, rotor) can be used to give early warning of synchronous generator failure. The results show that current monitoring can provide more accurate indications to detect the fault and its value. The work can be extended to apply stator current monitoring to detect mechanical failure related to rotor, bearing, and air gap eccentricity. Also apply Artificial Neural Network (ANNs)**,** fuzzy and genetic algorithm to diagnosis the system for rotating machines, or apply the same approach which used in this paper with monitoring flux diagnosis faults in the synchronous generator. Also it possible to use the monitoring system as a teaching program for the new operators and engineers, with insertion of some useful ideas to be helpful, such as some figures or some video clips, showing the repair of some important parts of the generator.

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