International Journal of Ethics in Engineering & Management Education
Website: www.ijeee.in (ISSN: 2348-4748, Volume 2, Issue 7, July 2015)

Fault Diagnosys of Synchronous Generator Using Neural Network Techniques

B. Vidya Sagar
Associate professor of EEE dept
Vivekananda Institute of Technology&Science
Karimnagar
Sagar.boorgula@gmail.com

Dr.S.S.Tulasiram
Professor of EEE dept
JNTU College of Engineering
Kukatpally, Hyderabad
ramsankara@gmail.com

Abstract: **Because of the development of electric power industry accurate analysis of incipient faults in generators becomes very important. This paper presents a method for simulating the internal faults in synchronous generators using artificial intelligence technique. The internal faults like single line to ground, double line to ground & triple line to ground of generator stator current, rotor speed, electromagnetic torque and field current etc.**

***Index Terms*—Synchronous Generator, d-q model, Internal faults, Artificial Neural networks.**

1. INTRODUCTION

The Synchronous Generator is described by a set of three stator circuits coupled through motion with two orthogonally placed damper windings and field winding. The stator and rotor circuits are magnetically coupled with each other.
The phase voltage equations of SG are

$$i_a R_s + v_a = -\frac{d\Psi_a}{dt}$$

$$i_b R_s + v_b = -\frac{d\Psi_b}{dt}$$

$$i_c R_s + v_c = -\frac{d\Psi_c}{dt}$$

$$i_D R_D = -\frac{d\Psi_D}{dt}$$

$$i_Q R_Q = -\frac{d\Psi_Q}{dt}$$

$$i_f R_f - V_f = -\frac{d\Psi_f}{dt}$$

The d-q model of synchronous generator should express both stator and rotor equations in rotor coordinates, aligned to rotor d and q aces because, at least in the absence of magnetic saturation, there is no coupling between the two axes. Stator voltages V_a, V_b, V_c, currents Ia, Ib, Ic and flux linkages Ψ_a, Ψ_b, Ψ_c have to be transformed into rotor orthogonal coordinates.

$$T(\theta_e) = \frac{2}{3}\begin{bmatrix} \cos(-\theta_e) & \cos\left(-\theta_e + \frac{2\pi}{3}\right) & \cos\left(-\theta_e - \frac{2\pi}{3}\right) \\ \sin(-\theta_e) & \sin\left(-\theta_e + \frac{2\pi}{3}\right) & \sin\left(-\theta_e - \frac{2\pi}{3}\right) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

$$V_{dqo} = T(\theta_e)V_{abc}$$
$$I_{dqo} = T(\theta_e)I_{abc}$$
$$\Psi_{dqo} = T(\theta_e)\Psi_{abc}$$

Expressions for Ψ_d, Ψ_q, Ψ_o are as follows

$$\Psi_d = L_d I_d + M_f I_f^r + M_D I_D^r$$
$$L_d = L_{sl} + L_{dm}$$
$$\Psi_q = L_q I_q + M_Q I_Q^r$$
$$L_q = L_{sl} + L_{qm}$$
$$\Psi_o = L_{sl} I_o$$

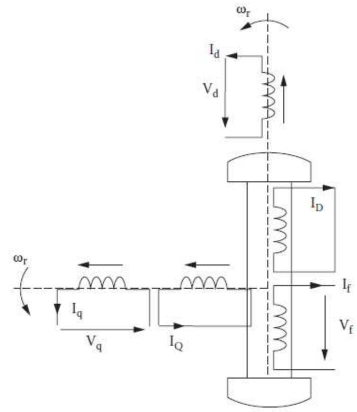


Fig.1 The d-q model of synchronous generators

For rotor

$$\Psi_f^r = (L_{fl}^r + L_{fm})I_f^r + \frac{3}{2}M_f I_d + M_{fD} I_D^r$$

$$\Psi_D^r = (L_{Dl}^r + L_{Dm})I_D^r + \frac{3}{2}M_D I_d + M_{fD} I_f^r$$

$$\Psi_Q^r = (L_{Ql}^r + L_{Qm})I_Q^r + \frac{3}{2}M_Q I_q$$

The magnetic field axes of the respective stator windings are fixed to the rotor d-q axes, but their conductors are at

Website: www.ijeee.in (ISSN: 2348-4748, Volume 2, Issue 7, July 2015)

standstill. The d-q model equations can be derived directly through the equivalent orthogonal axis machine as shown in fig.

$$I_d R_s + V_d = -\frac{d\Psi_d}{dt} + \omega_r \Psi_q$$

$$I_q R_s + V_q = -\frac{d\Psi_q}{dt} - \omega_r \Psi_d$$

The rotor equations are

$$I_f R_f - V_f = -\frac{d\Psi_f}{dt}$$

$$i_D R_D = -\frac{d\Psi_D}{dt}$$

$$i_Q R_Q = -\frac{d\Psi_Q}{dt}$$

The zero component equation is

$$I_o R_s + V_o = -\frac{d\Psi_o}{dt}$$

The motion equations are as follows

$$T_e = \frac{3}{2} p_1 (\Psi_d I_q - \Psi_q I_d)$$

$$\frac{J}{p1}\frac{d\omega_r}{dt} = T_{shaft} + \frac{3}{2} p_1 (\Psi_d I_q - \Psi_q I_d)$$

Consequently Per unit D-Q model equations can be written as

$$\frac{1}{\omega_b}\frac{d\Psi_d}{dt} = \omega_r \Psi_q - i_d r_s - v_d$$

$$\Psi_d = l_{sl} i_d + l_{dm}(i_d + i_D + i_f)$$

$$\frac{1}{\omega_b}\frac{d\Psi_q}{dt} = -\omega_r \Psi_d - i_q r_s - v_q$$

$$\Psi_q = l_{sl} i_q + l_{qm}(i_q + i_Q)$$

$$\frac{1}{\omega_b}\frac{d\Psi_o}{dt} = -i_o r_o - v_o$$

$$\frac{1}{\omega_b}\frac{d\Psi_f}{dt} = -i_f r_f + v_f$$

$$\Psi_d = l_{fl} i_f + l_{dm}(i_Q + i_D + i_f)$$

$$\frac{1}{\omega_b}\frac{d\Psi_D}{dt} = -i_D r_D$$

$$\Psi_D = l_{Dl} i_D + l_{dm}(i_d + i_D + i_f)$$

$$\frac{1}{\omega_b}\frac{d\Psi_Q}{dt} = -i_Q r_Q$$

$$\Psi_Q = l_{Ql} i_Q + l_{qm}(i_q + i_Q)$$

$$2H\frac{d\omega_r}{dt} = t_{shaft} - t_e;\ t_{shaft} = \frac{T_{shaft}}{T_{eb}};\ t_e = \frac{T_e}{T_{eb}}$$

$$t_e = -(\Psi_d i_q - \Psi_q i_d);$$

$$\frac{1}{\omega_b}\frac{d\theta_{er}}{dt} = \omega_r$$

Machine Parameters

$l_d = l_{sl} + l_{dm}$

$x_d = x_{sl} + x_{dm}$

$l_q = l_{sl} + l_{qm}$

$x_q = x_{sl} + x_{qm}$

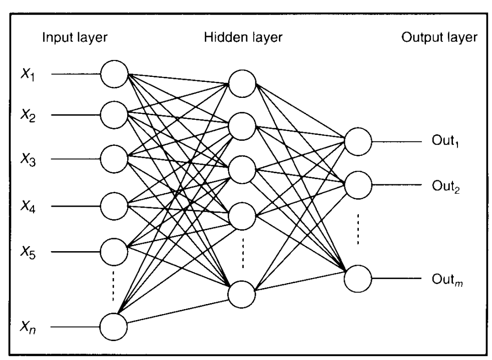
2. FAULT DETECTION

The main objective of fault detection system is to determine type of fault based on accessible data and knowledge about the behavior of the system using mathematical models. ANN provides a flexible mechanism for learning and recognizing system faults because of its ability to learn and generalize non linear functional relationships between input and output variables. ANNs are constructed with a certain number of single processing units which are called neurons. Neuron model is described by the equation

$$y = \sigma\left(\sum_{i=1}^{n} w_i u_i + b\right)$$

Where u_i denoted neuron inputs, b is the bias, w_i denotes weight coefficient, σ is the non linear activation function.

The multi layer perceptron is a network in which the neurons are grouped into layers. Such network has an input layer, one or more hidden layers and an output layer. Input units take the data process it and pass it onto the elements of hidden layer. Data processing includes scaling, filtering or signal normalization. The fundamental neural data processing is carried out in hidden and output layers. Neurons should be designed such that each element of previous layer connected with each element of next layer. Suitable weight coefficients can be determined for these connections depending on the task the network should solve. The training of neural network means the determination of these weight coefficients.



3. Neural network

Fundamental training algorithm for feed forward multilayer networks is the back propagation algorithm. This algorithm is of an iterative type and it is based on the minimization of a sum squared error utilizing the optimization gradient descent method.

$$w(k+1) = w(k) - \eta \nabla J(w(k))$$

Where w(k) denotes the weight vector at the discrete time k, η is the learning rate

The Levenberg-Marquardt (LM) algorithm is another nonlinear optimization algorithm based on the use of second order derivatives. The LM algorithm is a combination of the features of gradient descent found in back propagation and the Newton method. This algorithm assumes that the system modeled is linear and the minimum error can be found in one step. For this single step it calculates weight change. With this new weight network can be tested whether error is lower or not. If the error is decreased change weight is accepted and the linear assumption is reinforced by decreasing a control parameter, μ. If the error is increased, the weight is rejected and control parameter can be increased to emphasize the linear assumption. The process is repeated until the desired error or maximum number of iterations is reached.

3. ANN FOR FAULT IDENTIFICATION

To design neural network for internal fault identification of synchronous generator several parametric studies are carried out on the system with different scenarios. In these some measurement patterns are corresponding to normal operation, some patterns are corresponding to faulty operations. The parameters used as inputs for ANN are stator current, voltage and rotational speed as these are the main parameters affected during faulty conditions. MATLAB/SIMULINK is used for detailed modeling of synchronous generator and power system. The system was simulated with each fault in normal circumstances. Each fault is simulated with different fault resistances. 104 patterns are collected for each fault. 50 patterns are collected for normal condition with different loads. Total 8 faults are simulated which includes LLLG, LLG and LG. i.e. total 882 patterns of stator current , voltage and rotational

speed(882x7) are taken by simulating modeled synchronous generator and power system. As shown in table 1. A value is associated with each fault, during detection of fault the output of the network should be this associated value for each fault condition. Hence these values of every faulty condition can be taken as target data for network training.

Table 1.

S.No.	fault	Value
1	ABCG	15
2	ABC	14
3	ABG	13
4	BCG	7
5	ACG	11
6	AG	9
7	BG	5
8	CG	3

Neural networks presented were designed in MATLAB environmental using Neural Network Toolbox.

Quantities selected for forming the patterns are filtered using ant initializing filters. These filters are second order low pass Butterworth filters with the cut off frequency 1 KHz. The patterns are normalized by scaling their features to have zero mean, and be in the range [-1,1]. Identical scaling ration is used latter on for normalization of test patterns. The networks are examined with the test data sets, when the proposed networks have trained to the desired goal. Testing the network involves presenting the test set to the network and calculating the error. If the error goal is met, the training is complete.

The Levnberg Marquadrt training is used to train the data because it is fast and it has inherent regularization properties. Regularization is a technique which adds constraints so that the results are more consistent. The 5% misclassification and 5% input data error is chosen to calculate a sum of square error goal (SSE). The training process will be finished when the SSE goal is met

$$SSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{L}\left(y_{ij} - d_{ij}\right)^2}$$

Where y_{ij} -------output value of neural network
d_{ij} -------output of training data.
N---------Number of training data
L---------Number of units in the output layer

4. FAULT DETECTION RESULTS

The performance of the proposed network tested on the system shown in fig 3.

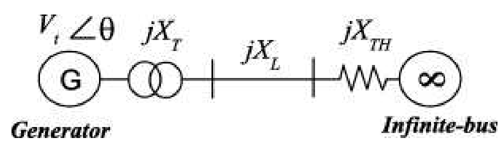


Fig 3. power system

Synchronous generator is modeling in MATLAB and connected to an infinite bus system through the power transformer and transmission line. Different faults are placed in generator to collect the data patterns for training the neural network. Total 882X7 patterns are collected for different faults. Variation of system voltages and currents are shown in fig for different faults. Fault is occurred in the generator at 6 seconds. And fault resistance is 0.001 ohms. Fig 4 is showing variation of different machine parameters for single line to ground fault. Fig 5 is showing for double line ground fault and fig 6 is for triple line ground fault.

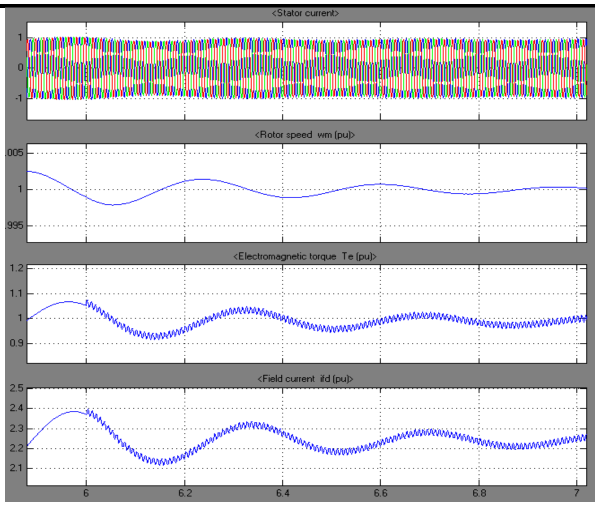


Fig 4. Stator current, rotor speed, electromagnetic torque and field current for single line to ground fault

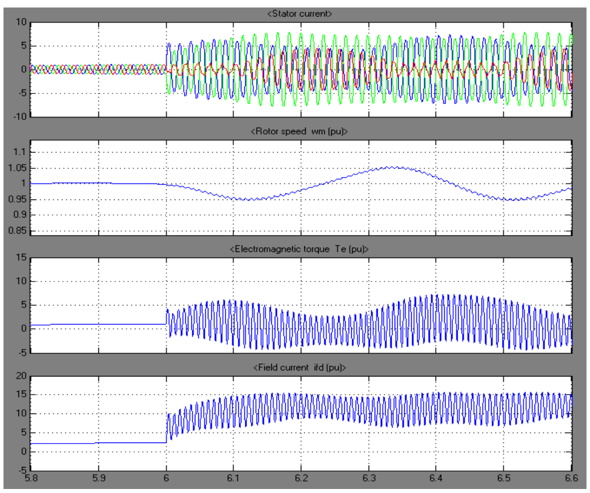


Fig 5. Stator current, rotor speed, electromagnetic torque and field current for double line to ground fault

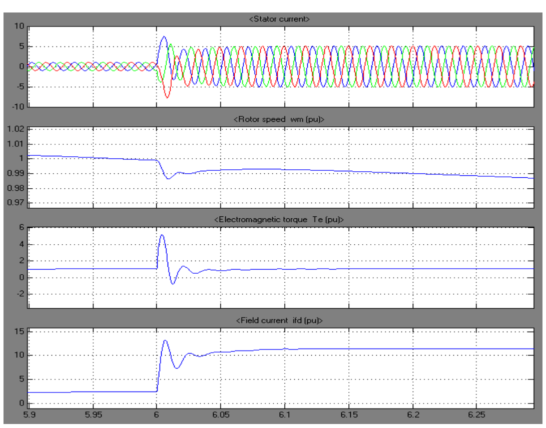


Fig 6. Stator current, rotor speed, electromagnetic torque and field current for triple line to ground fault

CONCLUSION

The proposed networks are tested on two categories. First the networks are tested with the test set at the same operating points that means with same fault resistances. The tested results are illustrated in table II. Error between actual and target output data is less than SSE goal (0.0623). Hence proposed network is working satisfactorily for test data.
In second category new testing data simulated for different operating conditions that is change in fault resistance and change in load. These results are illustrated in table III.

Table II.

S.No.	Fault Type	Output	Error
1	ABCG	14.9568	0.0432
2	ABC	14.02253	0.02253
3	ABG	12.9614	0.0386
4	BCG	6.9857	0.0143
5	ACG	11.0365	0.0365
6	AG	8.9936	0.0064
7	BG	4.9465	0.0535
8	CG	2.9588	0.0412

Table III.

S.No.	Fault Type	Output	Error
1	ABCG	14.2369	0.7631
2	ABC	13.58	0.42
3	ABG	12.6895	0.3105
4	BCG	6.51	0.49
5	ACG	10.896	0.104
6	AG	8.54	0.46
7	BG	4.26982	0.7302
8	CG	2.3569	0.6431

REFERENCES

[1]. A. I. Megahed and O. P. Malik, “Simulation of internal faults in synchronous generators,” IEEE Trans. Energy Convers., vol. 14, no. 4, pp. 1306–1311, Dec. 1999.
[2]. D.Muthumuni, P. G.Mclaren, E. Dirks, and V. Pathirana, “A synchronous Machine model to analyze internal faults,” in Conf. Rec. 2001 IEEE Ind. Appl. Conf., Chicago, IL, Sep. 30–Oct. 4, vol. 3, pp. 1595–1600.
[3]. P. P. Reichmeider, C. A. Gross, D. Querrey, D. Novosel, and S. Salon, “Internal faults in synchronous machines part I: The machine model,” IEEE Trans. Energy Convers., vol. 15, no. 4, pp. 376–379, Dec. 2000.
[4]. P. P. Reichmeider, D. Querrey, C. A. Gross, D. Novosel, and S. Salon, “Internal faults in synchronous machines part II: Model performance,” IEEE Trans. Ind. Electron., vol. 15, no. 4, pp. 380–383, Dec. 2000.
[5]. P. P. Reichmeider, D. Querrey, C. A. Gross, D. Novosel, and S. Salon,“Partitioning of synchronous machine windings for internal fault analysis,” IEEE Trans. Energy Convers., vol. 15, no. 4, pp. 372–375, Dec.2000.