Neural Networks for Synchronous Generator Fault Diagnosis

Asaad F Nashee¹ and Ateer H Herez¹
¹Department of Information and communications technology, Institute of Technology, Middle Technical University, Baghdad, Iraq
Email. assadfngin@yahoo.com

Abstract: Fault Diagnosis is play vital rule in the industrial applications and machine drives for the fault analysis (FA) and predicting the level of severity to optimise maintenance and improve reliability. Early detection of faults in the supervised process renders it possible to perform important preventative actions. In this paper, fault diagnosis of stator and rotor windings using field current as fault indicator. Static neural network (NN) has been implemented as fault classifier under different operating conditions. The results obtained from the real time simulation demonstrates the effectiveness and reliability of the proposed methodology. The detection and identification of faults in accurately way ensure the importance of the neural networks in the fault diagnosis field.

1. Introduction
The importance of companies dealing with electrical appliances more condition monitoring and diagnosis. Electric drive system by using a non-invasive state monitoring method of supervision, improve the reliability of the electric drive of many branches of the industry-leading method. The distinguish between the physical amount of symmetry and a typical question about the fault get the reliable detection of obstacles. The deteriorated process is an indication of start of fault, which is need to measure and detect the input signal in the early stage of operation. To allow the reconstruction of the action more effectively, hence increase the efficiency of plant operations and scheduled maintenance. This will lead to reduce the effect on the costs of monitoring and factory.Focused on examining fixed armature current of electric generators can provide symptoms without having access to a generator current do detect the faults [1]. Allow scheduling repairs before actual failure diagnosis of developmental disorders, personal maintenance during the last decade has been much interest in early fault detection and diagnosis techniques for use in condition based maintenance (CBM) [2]. The fault diagnostics based artificial neural networks use stator current spectrum as fault indicator, extract the data present in the sample frequency. These frequency components, are classified into four categories with decreasing the level of important based on these rule. Operating machine with the trained neural network is introduced in [3], also implementation artificial neural network (ANN) observations in estimating and tracking synchronous generator parameter from time domain online disturbance measurements data for training the NN observers are obtained through off-line simulation of a synchronous generators operating in a one-machine infinite bus environment [4]. The fault is an unexpected change of system functionality, which causes deviation of a plants behaviour from that which is specified for it. This is distinct from the definition of a failure, which implies a complete breakdown of a system component. The system
under consider will be simulated first and then implemented in real time with artificial neural network (NN) in order to make the system more robust and stable is introduced in [5]. Fault detection and isolation (FDI) have received great deal of attention in the last 20 years. As a control subject, the diagnosis is based on the model of the system under study. The model-based FDI approach involves two main steps: residual generation and decision-making. This model usually represents the normal behavior of the system, in the absence of any fault [6]. The generalized system with all possible faults acting can be shown in Figure 1.

![Figure 1. General system with faults.](image)

Where: Uc, UR, YR, Ym, fa, fc, f is the desired control input, actuation to plant, actual plant output, measured plant output, actuator faults, component faults, sensor faults respectively.

Fault identification is the knowledge of size and nature of the fault.

The process of fault diagnosis have been often broken down into two steps:

1. Residual generation: This is the generation of signals, which carry information about the faults.
2. Residual analysis: Analysis or the decision making to determine the location of the fault.[7]

2. Internal Faults in Electrical Machines

The electrical machine faults may be implicitly included in some kinds of the faults such as the external faults of the electrical machine, unbalance voltages, vibrations take place, one or more phase unbalanced, torque oscillation or any kind of the faults, rotor and stator faults, series and shunt winding faults[8]. Include the path without coming in contact with ground or other phases or other failure does not intend in the same phase between two points (turn-to-turn faults). Ground fault of electric machine-phase fault resistance that is associated with the early failure. Internal faults the fault that occur at an arbitrary location, x-along the winding including the neutral (x=0) and the phase terminal, (x=1) the current-in- the fault and the fault current depend on the method for grounding the neural point of the electrical machine. For evaluation of damage caused by the fault and the fault current knowledge are very important. This knowledge is also important in planning and the electromechanical relay protection system design and performance analysis [7].

3. Diagnostic improvement through neural network

The identification and tuning of physical systems of weights of NN, parallel distributed processing different connection architecture and processor operation mechanism (neurons) to minimize errors by purpose error back propagation algorithm grade rules. One hidden layer architecture that is configured with a value greater than the sum of the inputs and outputs is used as usual in [9]. The NN used in this work is shown in Figure 2.
Thus, it was used 3-layer feed-forward (ANN) and error back propagation algorithm. It was taken a monotone increasing sigmoid function in equation (1) classic algorithms

\[ F(x) = \frac{1}{1+e^{-x}} \]  

(1)

The output \( o_j \) for each unit in the ANN

\[ o_j = f(\text{net}_{ij}) = \sum_i w_{ij} o_i + \theta_j \]  

(2)

Where the output of \( i \) unit is \( o_j \), \( w_{ij} \) is the weight from \( i \) unit to \( j \) unit and \( \theta_j \) is threshold of \( j \) unit.

The squared error function \( E_p \) for a pattern \( p \) is defined by (3).

\[ E_p = \frac{1}{2} \sum_{j \in \text{output}} (t_{pj} - o_{pj})^2 \]  

(3)

The purpose is to make \( E_p \) by choosing appropriate small enough to \( w_{ij} \) and \( \theta_j \).

The internal illustration of the proposed NN is shown in Figure 3.

The back propagation steps to train the NN will be as follows:

1. Initializes the value of the weights of the network.
2- Repeat these steps until it reaches the standards of some: (for each training pair).

3- Sum Apply the weighted inputs, calculating the output of the hidden layer activation functions.

\[ h_i = f \left( \sum x_i w_{ij} \right) \]  
(4)

4- Amount weighted output's hidden layers to calculate the output of the output layer and activation functions.

\[ Y_k = f \left( \sum h_i w_{jk} \right) \]  
(5)

5- Calculate back propagation error

\[ \delta_k = (d_k - Y_k) f' \left( \sum \delta_i w_{jk} \right) \]  
(6)

6- Calculate weight correction term

\[ \Delta w_{jk}(n) = \eta \delta_k h_i + M \Delta w_{jk}(n-1) \]

7. Sums delta input for each hidden unit and calculate error term.

\[ \delta_k = \sum \delta_k w_{jk} f' \left( \sum x_i w_{ij} \right) \]  
(7)

8. Determine weight correction term.

\[ \Delta w_{ij}(n) = \eta \delta_i x_i + \mu \Delta w_{ij}(n-1) \]  
(8)

9. Update weights

\[ w_{jk}^{\text{new}} = w_{jk}^{\text{old}} + \Delta w_{jk} \]  
(9)

\[ w_{ij}^{\text{new}} = w_{ij}^{\text{old}} + \Delta w_{ij} \]  
(10)

10. Calculate the error

\[ SSE = \sum_p \sum_k (d_k^p - o_k^p)^2 \]  
(11)

P = no of input patterns, K = no of output neurons, SSE = sum square error

11. If SSE ≤ 10^-4

12. END

4. Dynamic model of the synchronous generator

The problem is not good approach for the machine according to deterioration in the magnetic circuits. The synchronous motor magnetic field modelling approach in many cases is a simplified. Approach to coupled system of magnetic flux crossed number of rotating magnetic field into account when create the geometry of the basic machine, the rotating magnetic field yet and physical layout of the winding line to use to find the inductance of the winding machine [10, 11]

Stator flux linkage

\[ \psi_s = L_s I_s + M_{sr} I_r \]  
(12)

Rotor flux linkage

\[ \psi_r = L_r I_r + M_{sr} I_s \]  
(13)

Instantaneous applied coil voltages

\[ V_s = I_s R_s + P \psi_s \]  
(14)

\[ V_r = I_r R_r + P \psi_r \]  
(15)

Where \( p = d / dt \)

\[ V_s = [V_a V_b V_c]' \]  
(16)

Also
\[
R_s = \begin{bmatrix}
Ra & 0 & 0 \\
0 & Rb & 0 \\
0 & 0 & Rc
\end{bmatrix}
I_s = [I_a, I_b, I_c]
\]

(17)

\[
L_s = \begin{bmatrix}
L_{aa} & L_{ab} & L_{ac} \\
L_{ba} & L_{bb} & L_{bc} \\
L_{ca} & L_{cb} & L_{cc}
\end{bmatrix},
M_{sr} = \begin{bmatrix}
\mu_{af} \\
\mu_{bf} \\
\mu_{cf}
\end{bmatrix}
\]

(18)

Also
\[v_r = v_f, \quad \psi_r = \psi_f\]

\[I_r = I_f, \quad R_r = R_f\]

Where I_{aa}, I_{bb}, I_{cc} are the stator phases self-inductance’s, In summation of the magnetizing inductance and leakage inductance, and rap is the mutual inductance of the stator phase (a) due to the current in phase (b), \(\mu L_{fa}\) is the mutual inductance of the stator phase a due to the excitation current in rotor field winding. (\(R_f\)) is the rotor field resistance, (\(L_f\)) is the rotor field inductance [12, 13].

5. Simulation Results

The value of the current parameter of the dynamic behaviour of a generator of electric power system investigated. This fault is effected by magnetic saturation, machine internal temperature and machine gain. The proposed technique of a fault diagnosis system depends on the fact that the effective change in the behaviour of the local electric and magnetic circuits, fault level or performance degradation, so identify the effects of electric current generator produces any such change. Diagnostic improvement through ANN is a suitable for normalization leads to a diagnostic system fit not only for a single machine but for a range of different size machine. The condition monitoring system in this work consist of three parts. The first part, represent the modelling of the synchronous generator has been programmed using [MATLABver 6]. The relation between the generator currents and internal of their parameters such as resistances inductance introduce in the next section.

Monitoring second part uses 2 layers of feed-forward NN error back propagation algorithm in artificial neural network learning, analysing, ran a four-input node, twenty hidden nodes and five output nodes. The trainable weights are initialized at small random value between (-0.05, 0.05) the network has been tasted by many signals when the training cycles has been accomplished. The input to the neural network represent stator currents (I_a, I_b, I_c) and the output represent the running condition cases (stator fault, rotator fault, alarm healthy cases). The third part using identification by neural network to recognize the abnormal situation by compare between the healthy case with other cases and give indication for early warning. The generator stator current at healthy case is shown in Figure 4.

When fault occurs in stator windings due to change their parameter (R, L) current change in levels. Figure 5 represent stator current (phase B) at 1/3 from its original value (Fault) With 0.8 of its original, value (ALARM) as shown in Figre 6.
Figure 4. Stator and rotor currents at healthy case.

Figure 5. Rotor and Stator Current For (Rb, Lbb) 0.3 of original value

Figure 6. Stator 0.8 of the original value alarm
At rotor winding faults when field winding parameters value change 0.3 as shown in Figure 7 or 0.8 from the original value to give alarm indication as shown in Figure 8.

**Figure 7. Rotor And Stator Current For (Rf ,Lff ) 0.3 From Original Value**

**Figure 8. Rotor and Stator Current for (Rf ,Lff) 0.8 From Original Value [Alarm Case]**

Figure 9. Represent the sum square error with respect to the number of iteration.
The data of the electrical machine used in this paper are shown in table 1.

**Table 1.** Parameter values used in this work

| Parameters                                    | Value   | Unit   |
|-----------------------------------------------|---------|--------|
| Apparent power                                | 2       | KVA    |
| Active Power                                  | 1.6     | KW     |
| Current                                       | 3.05    | A      |
| Voltage                                       | 380     | V      |
| Speed                                         | 1500    | r/min  |
| Frequency                                     | 50      | HZ     |
| Power Factor                                  | 0.8     |        |
| Connection                                    | STAR    |        |
| Rated field current for rated output          | 0.7     | A      |
| Field voltage                                 | 110     | V      |
| Stator winding resistance                     | 57.55   | ohm    |
| Rotator winding resistance                    | 157     | ohm    |
| Self inductance for stator winding            | 0.3738  | henry  |
| Self inductance for rotor winding             | 0.045   | henry  |
| Mutual inductances between stator phases      | 0.015   | henry  |
| Mutual inductances between stator rotor       | 0.00396 | henry  |

6. **Conclusions**

In this paper, a NN is presented to diagnosis synchronous generator electrical faults by monitoring generator currents (stator, rotor). A new intelligent fault diagnosis technique for stator and filed winding faults is proposed. A set of fault scenarios were designed and tested under different operating conditions, including different motor speeds and loads. Three-phase synchronous generator mathematical model was implemented to collect the required data to develop and train the static neural network that have been implemented to recognized between healthy and abnormal situation.
References

[1] Chetouani Y, Process Safety and Environmental Protection 92 215–223.
[2] Misiti M, Misiti Y, Oppenheim G and Poggi J 2014 Wavelet Toolbox User’s Guide.
[3] Howard D, Mark B and Martin H 2006 Neural Network Toolbox Use with MATLAB The Mathowrks User's Guide, Version 5.
[4] Harmouche J, Delpha C and Diallo D 2015 Energy Conversion, IEEE Transactions on 30 376–383.
[5] Khalaf S Gaeid, HW Ping (2010). Induction motor fault detection and isolation through unknown input observer. Scientific Research and Essays 5 (20), 3152–3159.
[6] Khalaf S Gaeid, HW Ping, HAF Mohamed 2009 Indirect vector control of a variable frequency induction motor drive (VCIMD). IEEE conference on Instrumentation, Communications, Information Technology, and Biomedical 1-9.
[7] Gritli Y, Filippetti F and Casadei D 2014 Diagnosis and Fault Detection in Electrical Machines and Drives based on Advanced Signal Processing Techniques Ph.D thesis in Electrical Engineering, University of Bologna, Italy.
[8] Khalaf S Gaeid, HW Ping, HAF Mohamed (2010). Diagnosis and Fault Tolerant Control of the Induction Motors Techniques a Review. Australian Journal of Basic and Applied Sciences, vol.4,no.2,pp. 227-246.
[9] Spyropoulos D and Mitronikas E 2013 A Review on the Faults of Electric Machines Used in Electric Ships, Advances in Power Electronics 8 10.1155-216870
[10] Valéria L, Jonas S, Giscard V, Luiz S, Erik Leandro B and Levy O 2015 IEEE Transaction on Industrial Electronics 62 1855-1865.
[11] Jiang j, Yin k, Li j and Tang w 2014 Journal of Shock and Vibration doi:418178.
[12] Abed W, Sharma S and Sutton R 2013 Fault diagnosis of brushless DC motor for an airc- raft actuator using a neural wavelet network IET conference doi: 10.1049 002
[13] Salam J Hammadi, Ahmed R Ajel 2015 IJSCE 4 139-142.