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# Neural Network Based Fault Detector and Classifier for Synchronous Generator Stator Windings

## كاشف ومحدد أخطاء لملفات العضو الثابت للمولد المتزامن مؤسس على الشبكات العصبية

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**ملخص البحث:**

يقوم هذا البحث بتطبيق الشبكات العصبية ذات التغذية الامامية فى الحماية التفاضلية للمولدات التزامنية. حيث تختلف التيارات الخارجة عن الداخلة في الآلات المتزامنة وذلك طبقا لظروف الأخطاء من حيث نوعيتها ومكان حدوثها. ويقترح البحث استخدام الشبكات العصبية كوسيلة مناسبة لتحديد نوع الخطأ وكذا مكانه. ويقدم البحث تصميم شبكتين عصبيتين لتحقيق هذا الهدف. الشبكة الأولى تقوم بإكتشاف الأخطاء بالمولدات التزامنية. والثانية لتحديد نوع هذا الخطأ. وقد اثبت النظام المقترح فاعليته وسهولة تطبيقه في التعرف على نوع الأخطاء لإمكان استخدامه في أنظمة الحماية العملية.

## Abstract:--

This paper presents an application of multilayer feedforward neural network (MFNN) as a differential protection for synchronous generators. Two MFNN are designed, trained, and tested in this paper. The first one has two outputs which detect the internal and external fault state. The other neural network has four outputs to classify the faulty phases. The proposed neural fault detector and classifier were trained using various sets of data available from a selected synchronous model and simulating different fault scenarios (fault type, fault location, fault resistance and fault inception angle). The results show very good behavior of the MFNN and it was more reliable and accurate than conventional methods. It shows that MFNN offer the possibility to be used for on line synchronous generator protection and give satisfactory results.

**Keywords:** ***Differential protection, Generator protection, Multilayer feedforward neural networks, Fault detector and classification.***

## 1. Introduction

Synchronous generators are important devices in power system. Reliability and stability of the whole power system are the primary issues concerning generators. Any unscheduled repair work, especially replacement of faulty generator is very expensive and time consuming. So stator windings faults in synchronous generators need to be detected and classified as fast as possible.

Differential relay is normally used to detect the faults in stator windings. But detecting of ground fault depends on the generator grounding type. For high impedance grounding, the ground faults are not detectable by differential relay. Several protection techniques [1-7] have been introduced to provide protection against unbalanced fault conditions. A protection technique uses the double frequency current in the field windings [1] and the direction of negative sequence power flow at the generator's terminal for detecting and discrimination asymmetrical faults. Another digital technique for detecting faults in the stator windings [2] utilizes

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positive- and negative-sequence models of synchronous machine, and voltage and current measured at the generator terminal. Two power based protection algorithms have been introduced. The first algorithm [5,6] was introduced to provide protection for non utility generation units against islanding, the second power-based algorithm [7] was introduced for detecting pole-slipping conditions using three phase power measurements taken at the generator's terminal and the equal area criterion.

Due to the advantages of the artificial neural networks (ANN) techniques over conventional techniques which have parallel distributed architecture for information processing that allows it to lean any complex input/output mapping. A fault classification can be treated as a problem of input data pattern recognition which can be well handled by ANNs [8].

Many successful applications of ANNs to power system protection have covered fault detection and location in transmission lines [9-13], power transformer protection [14-16], induction motor protection [17], and generator protection. Two ANN based differential protection schemes [3], [4] have also been introduced to provide protection for generator stator windings. The first technique uses samples taken from the line-side, neutral-end and field currents of the generator. It can't be detect the phase faults. The second one uses the difference and average of the currents entering and leaving the generator windings. It proposed three different networks. Each network should be trained and implemented separately which may need a lot of calculations and efforts.

This paper presents a multilayer feedforward neural network based synchronous generator protection module. The proposed modules are trained using backpropagation algorithm and suitable training data. The neural network uses the three phase currents at the terminals of the synchronous generator as inputs. The current signals are sampled at 1kHz. A program was developed by the MATLAB /SIMULINK to generate simulation data for synchronous generator in normal state, internal fault state and external fault state at various conditions such as (fault type, fault location, fault resistance and fault inception angle) to train and test the networks. Finally the results showing the performance of the MFNN based detector and classifier are presented in the paper.

## 2. Simulated System

In order to adapt the neural networks to solve a problem, the training data set of an ANN should contain necessary information to generalize the problem. A suitable synchronous generator model is required to characterize the different operating and fault conditions such as (fault type, fault location, fault resistance and fault inception angle). For the purpose of this paper the authors develops dynamic model with MATLAB to simulate generator states [19]. Three phase sample power system was simulated and the input/output pair patterns were generated.

The power system consists of three phase synchronous generator connected to an infinite bus through a transmission line. The parameters of the power system are selected after [19] and are provided in appendix. The one line diagram of the modeled power system is shown in Fig.

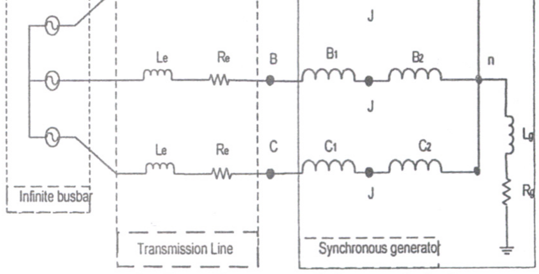


*Fig.1 Single line diagram of the modeled power system*

The measured devices are located at the two ends of the generator. The details of the transmission line and synchronous generator parameters are given in [19].

The simulated cases are divided into three groups. The first is the training group and it's patterns are selected randomly and normally distributed in order to make ANN to prevent skew learning. The second group is used to validate the ANN during the training process and the last one is the test group. Training set consists of about 3400 pattern representing different cases of the generator states, so that a wide range of possible cases is included.

## 4. A Multilayer Feedforward NN Based fault Detection Module

The function of neural network based fault detector module is to differentiate between the three generator states, the normal operation state, external fault state and internal fault state.

### 4.1 Input Selection of the NN

In differential protection it is essential to use both the line side and the neutral side currents as the input to the neural network. The sampled normalized current signals measured at the generator were considered as the input information to the neural network. The pre-processing is a useful method to reduce the dimensionality of the input data set. A simple wide second order Butterworth band pass filter was used to attenuate the DC component and high frequency noise.

It is common to use consecutive samples of all three currents on both sides of generator as inputs to the neural network. The currents waveforms were sampled at a rate of 20 sample/cycle in this paper. This sampling rate is compatible with the sampling rates commonly used in digital relays [18].

The appropriate data window length is also a major factor which should be considered. The authors were decided to cover the information of 1/4 of the cycle of the current inputs. Thus, each phase current was represented by its 5 consecutive samples. This data window length meets both requirements of speed and reliable operation.

A 30-input network with two neuron output layer was chosen as the fault direction identification network. The network needs two outputs to classify between three generator states. One output is assigned for instantaneous tripping for faults occurring in internal winding of the generator, while the other output give delayed tripping signals for faults occurring in the external system.

In reality, the values of the outputs during network performance will be analog between 0 and 1. Therefore one of the outputs of the ANN is mapped to a value of 1 and the other output is mapped to 0. For example, if internal fault occurs, then the ANN unit should develop [0 1] output and if external fault occurs then [1 0] output pattern is generated. Likewise, in normal state then [0 0] output pattern will appear.

### 4.2 The Structure and Training of NN

Many different neural network structures, having 30-inputs and two outputs but with different number of neurons in their hidden layers were considered and trained. Training and test patterns were generated by simulating different types of faults on different locations and phases regions of the simulated generator. Multilayer perceptron trained with the back propagation algorithm in general learns faster when the sigmoid activation function is asymmetric than when it is non symmetric. These networks were trained both with backpropagation (BP) and Marquardt-Levenberg (ML) algorithms. The criterion for determining the number of neurons in each hidden layers was based on a combined consideration of the training error (accuracy) and speed. In this study, several tests were performed to determine the optimum number of hidden neurons based on the mean square error (MSE) and number of training epochs. Moreover, different training functions were examined for convergence. It was found that the network trained with ML algorithm provides better results compared with the results of the networks trained with the Bp algorithm.

The network which showed satisfactory results, while not having a big size had 30 inputs, 20 neurons in first hidden layer, 15 neurons in second hidden layer and two out put neurons. The ANN structure of the fault detector is (30-20-15-2). The sigmoid transfer function is used for hidden and output layers.

$$\varphi(S) = \frac{1}{1+e^{-2s}} - 1 \qquad (1)$$

The ANN structure of the fault detector is shown in Fig. 2.

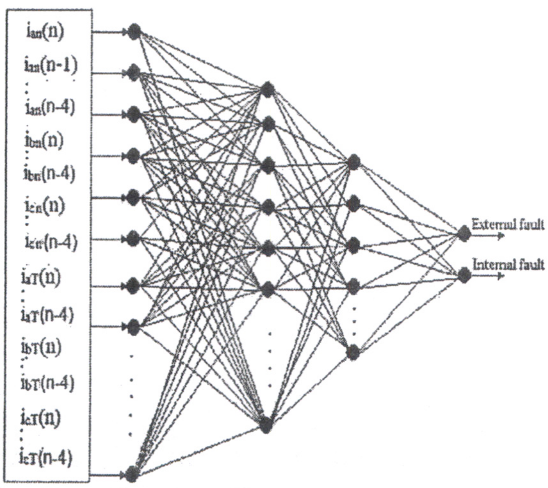


*Fig.2 Structure of ANN fault detector*

The program used for implementing the algorithm is developed by applying the MATLAB neural network toolbox. The output layer is capable to minimize the MSE of the ANN to a final value less than 6.06E-6 within 269 epochs. The MSE training error convergence diagrams for the ANN using "trainlm" training function is shown in Fig.3.

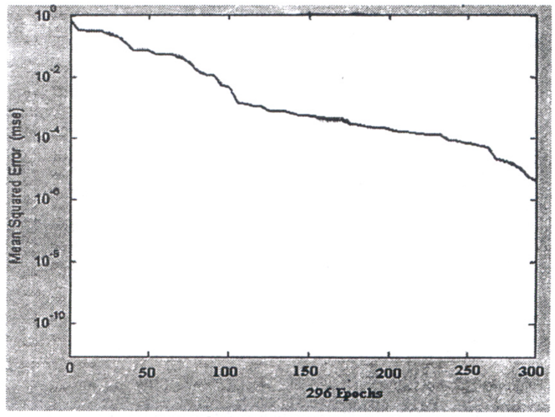


*Fig.3 MSE Training Convergence of the NN*

The training performance of the proposed ANN is depicted in Fig. 4. As can be seen from the plots, the results are very encouraging and accurate with target values.

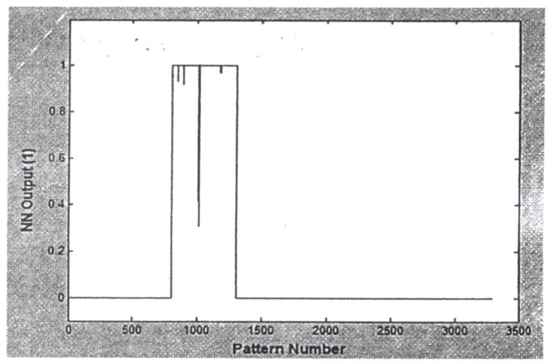


*Fig.4a Training Performance of Output 1*

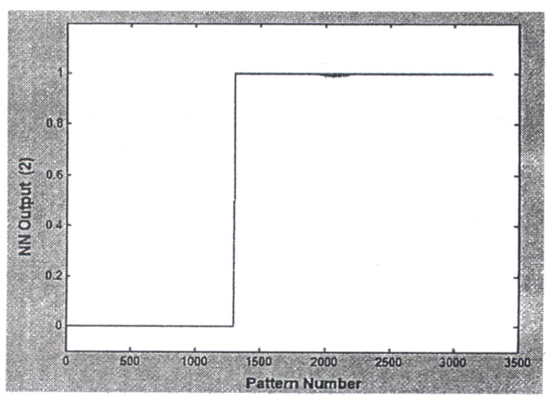


*Fig.5b Training Performance of Output 2*

### 4.3 Test Results

The proposed ANN operates in a static manner. The ANN was trained off-line. Once the desired performance was achieved, the weights of the ANN were frozen. The neural network was tested with different independent test patterns and promising results were obtained.

Determination of the fault is not affected by the type and the location of the fault, fault inception time, pre-fault power flow condition and the presence of fault resistance.

Table 1 shows the ANN results for external faults at different fault locations of the line, fault type, fault inception time, load power factor, and at 0.7 p.u. load.

The program is implemented for different load values (1, 0.9, 0.8 and0.7) the results shows that the network correctly detects the faults for all the studied cases except for one case (*) the output of NN has an error but it is correctly detected.

Table 2 gives the results for internal faults at 1 p.u. and different fault locations as a percentage of stator winding, different fault types and different fault inception time. The program is implemented for different load values and gives satisfactory results.

*Table.1 ANN results for external faults*

| Load | Fault point | Load P.F | Fault Type | Fault Time Occurrence | Target Output | ANN Output |
|---|---|---|---|---|---|---|
| 0.7 pu | End of Line | 0.9 | c-a-g | 0.2 (s) | [1 0] | [1.007 0.030] |
| | | 0.8 | a-b-g | | [1 0] | [0.952 0.088] |
| | | 0.7 | b-c-g | | [1 0] | [0.872 0.017] |
| | Half of Line | 0.9 | a-b-c-g | 0.204 (s) | [1 0] | [0.971 0.023] |
| | | 0.8 | a-b | | [1 0] | [1.036 0.132] |
| | | 0.7 | a-g | | [1 0] | [0.996 0.117] |
| | One Third of Line | 0.9 | c-g | 0.211 (s) | [1 0] | [0.783 0.279]* |
| | | 0.8 | b-c | | [1 0] | [0.972 0.117] |
| | | 0.7 | b-g | | [1 0] | [1.061 0.021] |

*Table 2 ANN results for internal faults at 1 p.u. load.*

| Fault point | Fault Type | Fault Time Occurrence | Target Output | ANN Output |
|---|---|---|---|---|
| 3% | b-c | 0.35(s) | [0 1] | [0.01460 1.005496] |
| | c-g | | [0 1] | [ 0.0006 1.005168] |
| | a-b-g | | [0 1] | [ 0.00051 1.002570] |
| | a-b-c-g | | [0 1] | [0.00025 1.000282] |
| 12% | b-g | 0.352(s) | [0 1] | [0.00047 0.995706] |
| | a-b | | [0 1] | [3.9E-05 0.987208] |
| | c-a-9 | | [0 1] | [0.00333 1.001646] |
| 27% | a-g | 0.355(s) | [0 1] | [ 0.0012 1.003633] |
| | a-b-g | | [0 1] | [0.01641 1.001880] |
| | b-c | | [0 1] | [0.00392 0.995925] |
| 39% | b-g | 0.358(s) | [0 1] | [ 0.00462 1.000642] |
| | b-c-g | | [0 1] | [0.0032 1.001144] |
| | c-a | | [0 1] | [0.0017 1.000222] |
| 58% | c-g | 0.36(s) | [0 1] | [ 0.00613 0.996748] |
| | b-c | | [0 1] | [0.03277 0.997766] |
| | c-a-g | | [0 1] | [ 0.00055 0.995670] |
| 74% | c-a | 0.366(s) | [0 1] | [0.00154 0.993026] |
| | b-c-g | | [0 1] | [0.00059 0.992070] |
| | b-c | | [0 1] | [0.00226 0.993676] |
| 85% | c-g | 0.369(s) | [0 1] | [0.01492 0.998514] |
| | a-b-g | | [0 1] | [0.00904 0.995236] |
| | c-a | | [0 1] | [0.0060 1.002873] |

The results show the stability of the MFNN outputs under all fault states conditions and rapid convergence of the output variables to the expected values under fault conditions. This clearly confirms the effectiveness of the proposed fault detector.

## 5. Multilayer Feedforward NN Based Classifier Module

The fault classifier (FC) is designed to estimate the faulty phases and the fault type in the synchronous generator stator windings. The (FC) is activated after a fault is detected by the fault detector.

### 5.1 Structure of the ANN Fault Classifier Module

In this module the three phase currents at the two ends of the generator windings are used as inputs to NN as shown in Fig.5.

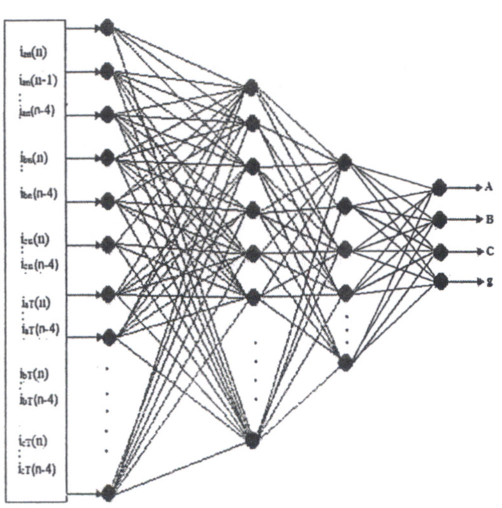


*Fig.5 Structure of ANN fault classifier*

The inputs to the FC are 6-currents each current is represented by 5 samples, making a total of 30 inputs. The FC has three layers with activation function tan-sigmoid for the hidden layers, and log-sigmoid for the output layer. The output layer has 4 neurons to represent the faulty phases and the ground for example a single phase to ground fault has an output equal to [1 0 0 1].

To get a good general performance, the fault classification module was tested with a set of independent test patterns to cover all types of faults. The training set consists of about 2000 patterns representing different types of internal faults. These patterns were the internal fault patterns used previously for training the fault detector module.

The output layer is capable to minimize the MSE of the ANN to a final value less than 4.69E-4 within 158 epochs. The MSE training error convergence diagrams for the ANN using "trainlm" training function is shown in Fig.6.

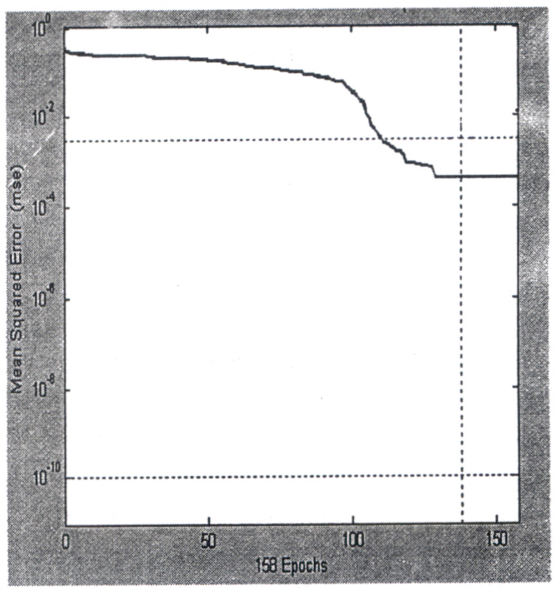


*Fig.6 MSE Training Convergence of the MFNN*

Various networks with different number of neurons in their hidden layer were studied. The number of neurons for the two hidden layers of the network were finally chosen to be 10 and 15 neurons. The training performance of the proposed MFNN is depicted in Fig 7. The figure illustrates the four output of the fault classifier module. The results are very encouraging with target values and no misclassification has occurred.

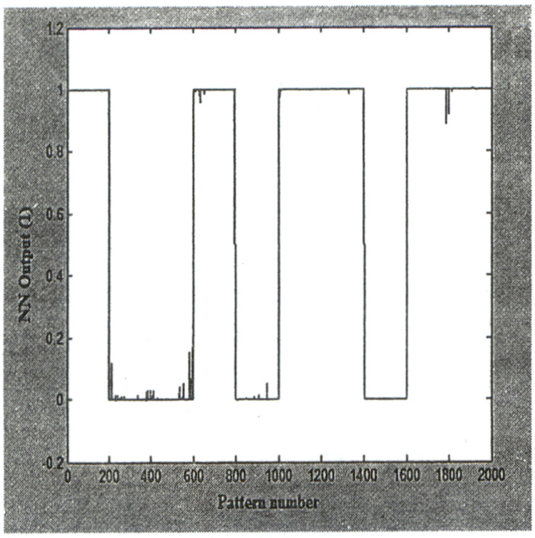


*Fig.7a training performance of output (1)*

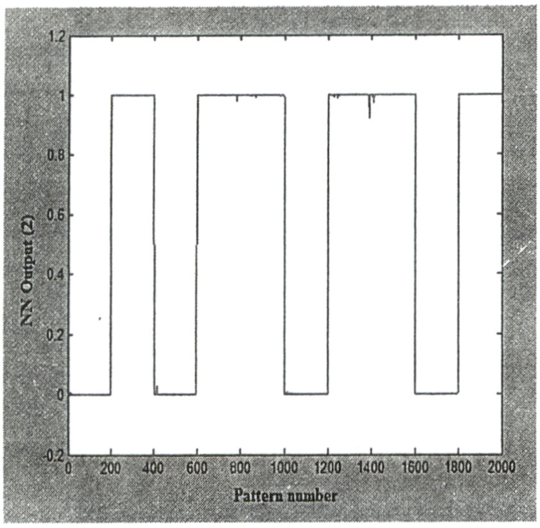


*Fig.7b training performance of output (2)*

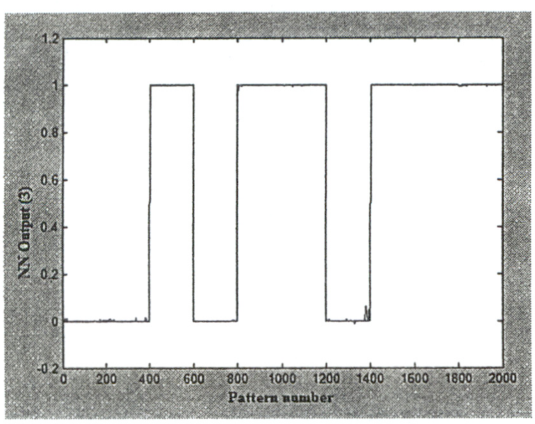


*Fig.7c training performance of output (3)*

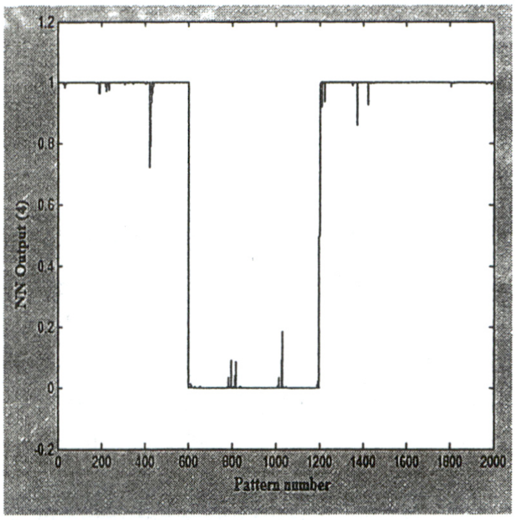


*Fig.7d training performance of output (4)*

### 5.2 Test results of FC module

The internal (FC) module is activated by the fault detector module only in the event of an internal fault. The FC was subjected to different types of internal faults at different percentages of the windings, and different inception angles of fault to check its performance. The network was tested with different independent test patterns and promising results were obtained.

Table 3 shows the results of the FC module for different internal fault types at different loading and different power factor conditions.

Table 4 gives the results for internal faults at 1 p.u. and different fault locations as a percentage of stator winding, different fault types and different fault inception time. The program is implemented for different load values and gives satisfactory results.

The results indicate that the FC is accurate robust and is not affected by the different pre-fault loading conditions, fault types, fault locations and inception angle. It can reliably and correctly respond to the faults very near to the neutral point.

*Table 3 Results of ANN FC module at 1p.u.*

| Fault point % | Load | Fault Type | Load PF | Fault Time Occurrence | Target Output | ANN Output |
|---|---|---|---|---|---|---|
| 58% | 0.9p.u | b-g | 0.95 | 0.360(s) | [0 1 0 1] | [0.000860 1.000356 0.000593 1.002739] |
| | | c-a | 0.90 | | [1 0 1 0] | [1.000326 0.000458 0.999938 0.004041] |
| | | b-c-g | 0.80 | | [0 1 1 1] | [0.000238 0.992793 1.000252 0.999711] |
| | 0.8p.u | a-b-c-g | 0.85 | | [1 1 1 1] | [0.999355 1.000733 0.000790 0.997982] |
| | | c-g | 0.75 | | [0 0 1 1] | [0.000541 0.001664 1.000007 1.004504] |
| | | a-b | 0.70 | | [1 1 0 0] | [1.000404 1.001172 0.000296 0.001610] |
| | 0.7p.u | c-a-g | 0.95 | | [1 0 1 1] | [1.000438 0.000965 1.000153 1.001788] |
| | | a-b-c-g | 0.80 | | [1 1 1 1] | [1.000806 1.001189 1.000812 1.001832] |
| | | a-g | 0.75 | | [1 0 0 1] | [0.97992 0.005120 0.001454 1.003640] |

*Table 4 Results of ANN FC module at 1 p.u and PF 0.8*

| Fault point % | Fault Type | Fault Time Occurrence | Target Output | ANN Output |
|---|---|---|---|---|
| 3% | a-g | 0.350(s) | [1 0 0 1] | [0.99992 0.004120 0.000454 1.000640] |
| | a-b | | [1 1 0 0] | [0.998387 1.000950 0.000400 0.000650] |
| | b-c-g | | [10 1 1] | [0.000246 1.000986 1.000212 0.999602] |
| | a-b-c-g | | [1 1 1 1] | [1.000776 0.999035 1.000196 0.997246] |
| 12% | b-g | 0.352(s) | [0 1 0 1] | [0.000808 1.000356 0.000593 1.002732] |
| | b-c | | [0 1 1 0] | [0.000583 0.998339 1.000213 0.003644] |
| | a-b-g | | [1 1 0 1] | [0.998582 1.001368 0.000183 0.993525] |
| | a-b-c-g | | [1 1 1 1] | [1.000797 1.001337 1.000646 0.991966] |
| 27% | c-g | 0.354(s) | [0 0 1 1] | [0.000604 0.000727 0.999752 1.005340] |
| | c-a | | [1 0 1 0] | [1.000260 0.000000 1.000093 0.008464] |
| | c-a-g | | [1 0 1 1] | [1.000265 0.000573 1.000216 1.002921] |
| | a-b-c-g | | [1 1 1 1] | [1.000711 1.001549 1.000563 0.994051] |
| 39% | a-g | 0.356(s) | [1 0 0 1] | [0.999965 0.004070 0.000466 0.993600] |
| | b-c | | [0 1 1 0] | [0.000035 1.002000 1.000260 0.002818] |
| | a-b-g | | [1 1 0 1] | [1.000266 1.000553 0.000279 0.994626] |
| | a-b-c-g | | [1 1 1 1] | [1.000739 1.000825 0.999355 0.997786] |
| 74% | a-g | 0.362(s) | [1 0 0 1] | [1.000018 0.010600 0.000601 0.993000] |
| | b-c | | [0 1 1 0] | [0.000171 0.994549 1.000275 0.003901] |
| | a-b-g | | [1 1 0 1] | [1.000296 1.001209 0.000292 0.993869] |
| | a-b-c-g | | [1 1 1 1] | [0.997840 1.000566 1.000678 0.991808] |
| 96% | c-g | 0.369(s) | [0 0 1 1] | [0.000604 0.002146 0.999699 1.001145] |
| | a-b | | [1 1 0 0] | [0.996317 1.001221 0.000169 0.003829] |
| | c-a-g | | [1 0 1 1] | [1.000384 0.008661 1.000108 0.999727] |
| | a-b-c-g | | [1 1 1 1] | [1.000740 1.000493 1.000760 0.996066] |

## 6. Conclusion

This paper presents a scheme for synchronous generator relaying using artificial neural network. An efficient neural network based fault detector for internal faults in generator and fault classifier have been proposed. The results demonstrate the ability of ANN to generalize the situation from the provided patterns and to accurately indicate the presence of fault and identify the faulty phases. The presented test results demonstrate the effectiveness of the detector module under a variety of fault conditions including fault types, fault locations, fault inception angles, and different power system data. The proposed MFNNs have the possibility to be used for on-line fault detection and classification in stator windings of synchronous generators. It is planned to develop a prototype to test the proposed networks.

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# Appendix A

- Parameters of synchronous machine.

Rating 100 MVA
Frequency 50 Hz
$I_{fag}$ 313.2 A
Line voltage 13.8 kV

***Table A.1 Generator data***

| **Manufacturer's parameters** | **Data** |
|---|---|
| $X_d$ | 2.03900 (p.u.) |
| $X_q$ | 1.94400 (p.u.) |
| $X_l$ | 0.12800 (p.u.) |
| $X_o$ | 0.09600 (p.u.) |
| $X_2$ | 0.14850 (p.u.) |
| $X_{d'}$ | 0.21700 (p.u.) |
| $X_{q'}$ | 0.44600 (p.u.) |
| $X_{d'}'$ | 0.15000 (p.u.) |
| $X_{q''}$ | 0.14700 (p.u.) |
| $R_a$ | 0.00400 (p.u.) |
| $T_a$ | 0.09846 (p.u.) |
| $T_{d'}$ | 0.59757 (Sec) |
| $T_{q'}$ | 0.10485 (Sec) |
| $T_{d''}$ | 0.01521 (Sec) |
| $T_{do'}$ | 5.61500 (Sec) |
| $T_{do''}$ | 0.02200 (Sec) |
| $T_{qo'}$ | 0.45700 (Sec) |
| $T_{qo''}$ | 0.04600 (Sec) |
| $T_{q''}$ | 0.01507 (Sec) |

- The external resistance Re and inductance Le are 0.19044 Ω and 0.35364 mH