International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 4 Issue 07, July-2015

Identification of Power System Faults based on Park's Transformation

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***Abstract* - The large-scale power system is always subjected to performance deterioration due to symmetrical and unsymmetrical faults. So fault identification is necessary for power system protection and the selection of suitable protective devices (i.e. relays). In this work, Park's Transformation Method is used for fault identification. Direct axis (d-axis), Quadrature axis (q-axis) and Zero axis (0-axis) sequence components are estimated. By identifying these components the fault type can be easily checked. MATLAB software is used as an analysis tool for this work with the help of Artificial Neural Network.**

Keywords - Park's Transformation, Direct axis sequence component, Quadrature axis sequence component, Artificial Neural Network.

1. INTRODUCTION

The monitoring, controlling, protecting and data recording are important task to the reliable operation of an electric power system. The performance of the power system requires the measurements of the system components, Direct, Quadrature and Zero sequence components [1]-[5], especially during the fault or abnormal operation of the system. Identification and diagnosis of the system faults are of great importance to the power engineers in the control center so that a correct action may be taken at the correct time, and a correct action to isolate this fault is taken by the correct relay in the system.

Power systems experiences different types of fault, almost eleven types. These include L-G faults for each phase (A-G, B-G, and C-G), L-L faults (A-B, B-C, and C-A), L-L-G faults (A-B-G, B-C-G, and C-A-G) and symmetrical faults either L-L-L (A-B-C) or L-L-L-G (A-B-C-G) fault. A method is needed to discriminate between the faults and utilize the characteristics of each type. Several techniques are developed in the past for classifying faults [1] on the transmission system. Most of these techniques [3] are based on the following:

1. Under-impedance Technique
2. Torque Technique
3. Over-current Technique

Reference [3] presents a method of classifying transmission line shunt faults. The algorithm developed in this reference is based on the measurement of phase angles between the positive and negative sequence components of the current phasor. It also uses the relative magnitudes of zero and negative sequence quantities present in the current waveforms to differentiate between grounded and ungrounded faults.

The proposed technique is based on the measurement of direct axis (d-axis) and quadrature axis (q-axis) sequence component of the current or voltage phasor and waveforms to differentiate between grounded and ungrounded faults. The technique was tested with MATLAB-generated data and the test results presented in this work reveal that the proposed technique can accurately identify transmission line shunt faults by using Artificial Neural Network [4].

2. METHODOLOGY

The some of the fault identification techniques were reviewed. Some shortfalls of these techniques were also presented. Although these techniques can identify most faults, they do not work under certain fault conditions. In addition, it was asserted that most of these techniques were developed for relaying purposes.

2.1 Proposed Technique

The technique proposed in this section uses magnitude of Direct Axis and Quadrature Axis components contained in the current phasor the relative magnitudes of these components from prefault to the fault stage to identify a fault. The technique operates favorably under most fault conditions. The technique is, therefore, suitable for use with any power system monitoring device as well as protective relays.

The technique that has been presented, we assume that m sample of the three phase voltage or currents are available at a preselected sampling frequency satisfying the sampling theorem. At healthy condition (prefault condition), the three phase voltage or current signals sampled at the same sampling frequency are obtained, which stored in the matrix form. If this three phase voltage or current signals in matrix form digitally multiplied by Park's Transformation matrix then a new set of three phase samples are obtained, known as dqo set. The equation of Park's transformation can be re-written as

$$x_{odq} = P\, x_{abc} \tag{1}$$

Where,

$\mathbf{X}$ = An arbitrary quantity, like voltage or current,

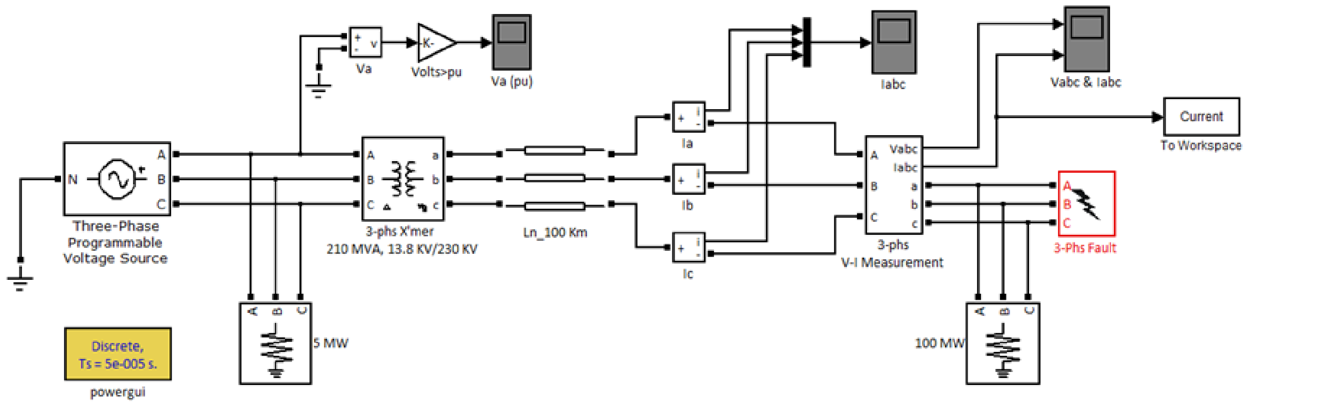

Fig. 3.1:Matlab System Simulated

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

From new set of dqo sequence components in the form of voltage or current, we obtained statistical parameters like minimum value, maximum value, mean value, median value, standard value, var value, add value, skewness value, kurtosis value, rms value, Energy value, absum value, sf value cf value, etc. These statistical parameters are obtained at healthy condition or prefault condition. The system are subjected to the different types of fault which include L-G faults for each phase (A-G, B-G, and C-G), L-L faults (A-B, B-C, and C-A), L-L-G faults (A-B-G, B-C-G, and C-A-G) and symmetrical faults either L-L-L (A-B-C) or L-L-L-G (A-B-C-G) fault. For different fault conditions, obtained statistical parameters of voltage or current in terms of dqo set. Use Neuro Solution, Identify the type of fault according to the results obtained for the Direct, Quadrature and Zero sequence components of the three-phase voltage or current signals sampled.

2.2 Technique Implementation

A power system was simulated using a sample model of a regulated voltage source with associated loads in MATLAB.

The following steps summarize the proposed technique:

Step 1. Assume that we are given m digital samples of a three-phase voltage or current samples, sampled at a specified sampling frequency Fs.

Step 2. From the simulation of a Power System sample model in MATLAB, the samples of the three-phase voltage or current signals sampled at the same sampling frequency are obtained.

Step 3. If this matrix is multiplied digitally by the samples of the three-phase voltage or current signals sampled at the same sampling frequency of matrix (20), a new set of three –phase samples are obtained, we call this set a d-q set.

Step 4. Find out the statistical parameters of this new d-q set, i.e. min value, max value, mean value, median value, std value, var value, add value, skewness value, kurtosis value, rms value, Energy value, absum value, etc.

Step 5. Use Neuro Solution, Identify the type of fault according to the results obtained for the Direct, Quadrature and Zero sequence components of the three-phase voltage or current signals sampled.

2.3 Flowchart

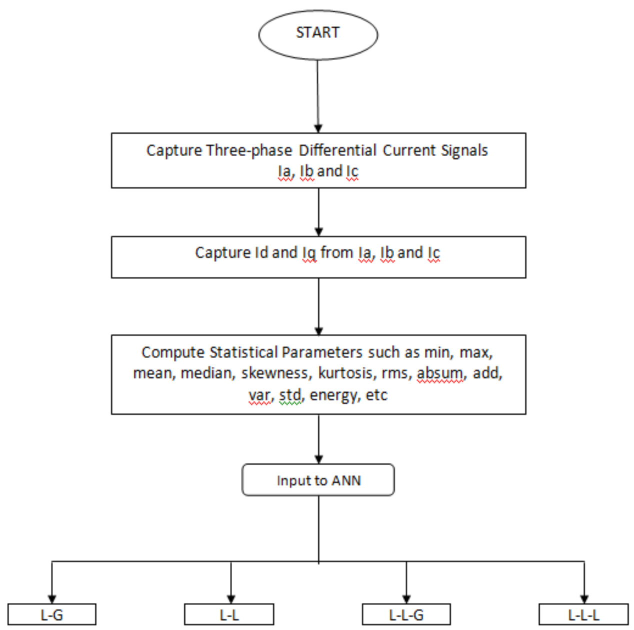

Fig. 2.1: Flowchart of proposed technique

3. Case Study

In order to test the method, a power system was simulated using a sample model of a regulated voltage source with associated loads in MATLAB. As shown in Fig. 3.1, the system consists of a 13.8 KV, 60 Hz Three Phase Programmable Voltage Source connected to the transmission lines via delta-wye 13.8-230 KV transformers. The overall system and controls parameters are given in power system block set provided by MATLAB SIMULINK and have not been modified. The original demo system included a voltage behind reactance model for an infinite bus or grid, which was omitted here for simplicity. The simulation solver was chosen to be ODE45 subsequent simulations. For each run the system was allowed to start from the same initial state, continue steady state operation for 0.01667 s, and then a fault was applied for 0.11667 s. At healthy condition, the three-phase waveform shown in figure. This block allows the selection of any fault and 3-Phase Fault automatically configures the system to respond accordingly.

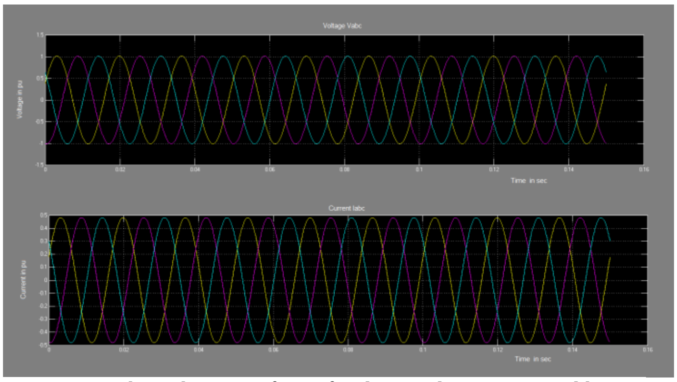

Fig. 4.1: Three phase waveform of Voltage and Current at Healthy Condition

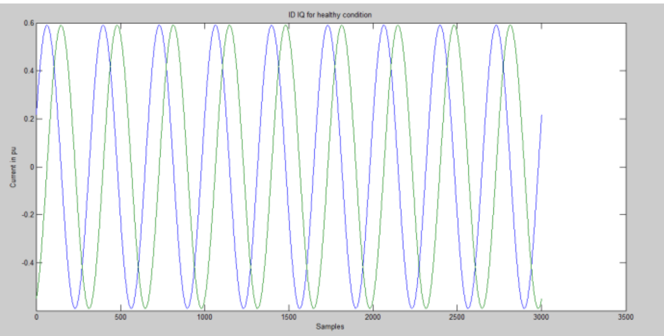

Fig. 4.2: Three phase waveform of Id and Iq Current at Healthy Condition

Most of the failures on the power system lead to short-circuit fault and cause heavy current to flow in the system. A fault occurs when two or more conductors that normally operate with a potential difference come in contact with each other. These faults may be caused by sudden failure of a piece of equipment, accidental damage or short-circuit to overhead lines or by insulation failure resulting from lightning surges. Irrespective of the causes, the faults in a 3-phase system can be classified into two main categories *viz.*

(Dormand-Prince) with a variable time step with a maximum of 1 ms.

The system was lightly loaded then faulted for few cycles. The data was then transferred to the workspace via the scope blocks in SIMULINK. A MATLAB script including the park transformation and all the technique steps listed previously was written to operate on the fault data files.

4. Result and Discussion

In order to obtain a valid steady state initial point for the simulation, the system was run for 1.5 sec, and then the final state was used as an initial state for all

(i) Unsymmetrical faults ***(ii)*** Symmetrical faults

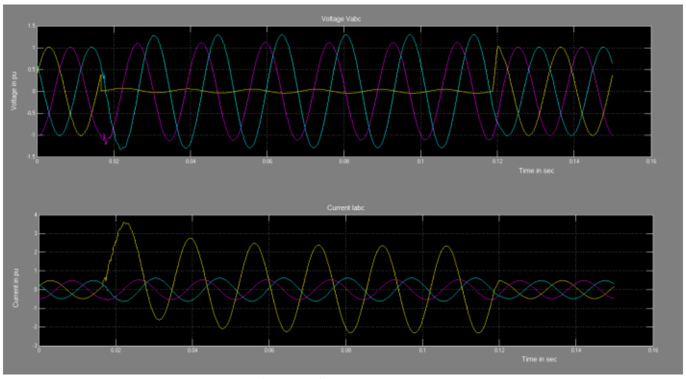

Fig. 4.3: Three phase waveform of Voltage and Current at AG Faulty Condition

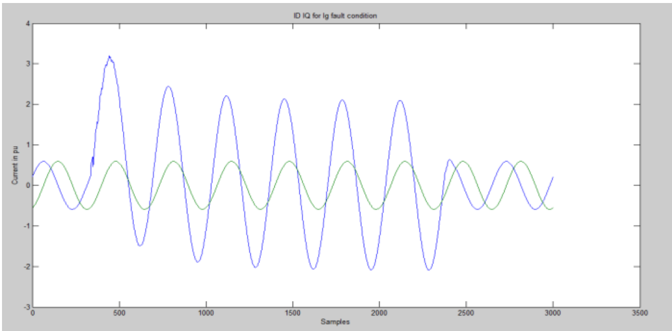

Fig. 4.4: Three phase waveform of Id and Iq Current at AG Faulty Condition

The Multilayer Perceptron (MLP) is most widely used neural network for General Classification or Regression. A Multilayer Perceptron (MLP) is a feedforward artificial neural network model that maps set of input data onto a set of appropriate outputs. A MLP consist of multiple layer of nodes in a directed graph, with each fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilize a supervised learning technique called backpropogation for training the network.

4.2.1 Training in ANN

We trained fault type neural net with more than 1000 training patterns simulating all relevant fault types, fault start times and faultless situations. It has been found out, that a net with 28 inputs, 1 node in hidden layer, 2 processing elements and 5 outputs (28-1-2-5) is capable to minimize the error E.

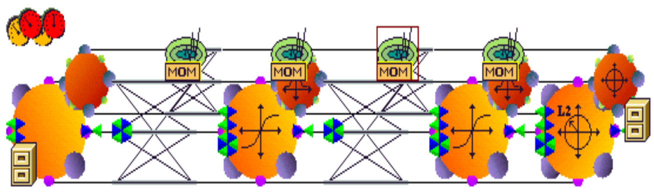

Fig. 4.5: Multilayer Perceptron (MLP) Architecture for a given power system

We used the Backpropagation Training Algorithm with dynamic learning rate. Therefore, the possibility of weight changing decreases cycle by cycle until training is stopped. This learning strategy converges quickly. Fig. 4.6 shows Average MSE with Standard Deviation Boundaries for 3 Runs. The table-4.1 and table-4.2 gives the training data from the graph as shown in fig. 4.7.

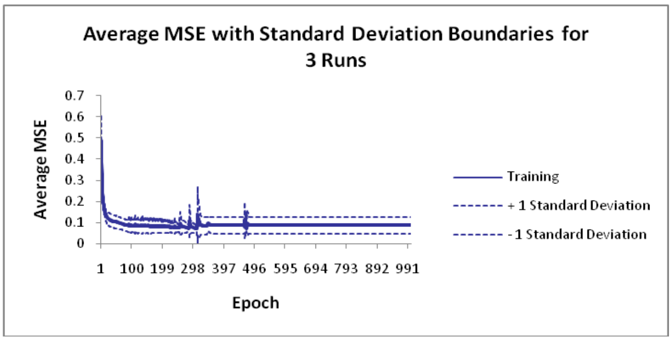

Fig. 4.6: Average MSE with Standard Deviation

Table: 4.1
Average training standard deviation

All Runs	Training Minimum	Training Deviation	Standard
Average of Minimum MSEs	0.069646193	0.015831302	
Average of Final MSEs	0.086472833	0.039158312	

Table: 4.2
Best network training result

Best Network	Training
Run #	3
Epoch #	341
Minimum MSE	0.057693128
Final MSE	0.064085565

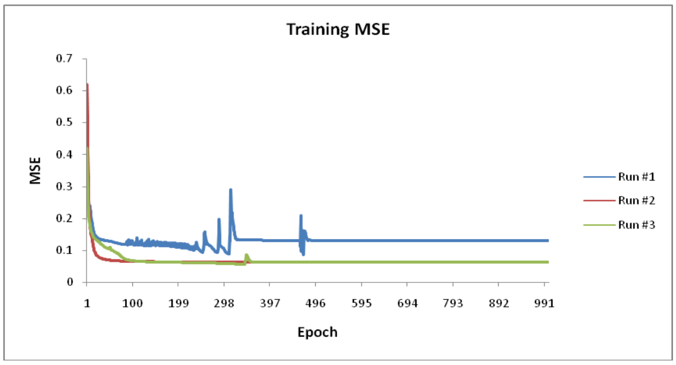

Fig. 4.7: Training MSE

4.2.2 Testing in ANN

The testing is done after training of given system with the help of Multilayer Perceptron (MLP) Architecture as shown in fig. 4.5. Trained fault type neural net was tested with a set of independent test patterns. We illustrate a typical fault situation and four fault type classifications as shown in Table-4.3 and Table-4.4.

Table: 4.3
Fault Type Classification Desired

Output / Desired	H	AG	AB	ABG	ABC
H	1	0	0	0	0
AG	0	2	0	0	0
AB	0	0	5	0	0
ABG	0	0	0	2	0
ABC	0	0	0	0	4

Table: 4.4
Fault Type Classification Performance of a Given Network

Performance	H	AG	AB	ABG	ABC
MSE	0.001775475	0.006176197	0.169594483	0.068098401	0.000936908
NMSE	0.0267687	0.050438941	0.738678193	0.556136941	0.00459085
MAE	0.038584159	0.065807927	0.307613633	0.207177972	0.024096706
Min Abs Error	0.007625468	0.000293857	0.001800413	0.046999741	0.000343953
Max Abs Error	0.054252789	0.176713677	0.65384121	0.500073541	0.054795212
r	0.988998212	0.97668393	0.661725865	0.693796069	0.999457385
Percent Correct	100	100	100	100	100

5. Conclusion

Most fault identification techniques that are currently available have been reviewed in the paper. These techniques were basically developed for relaying purposes. In electrical power systems, the prerequisite of protection devices accurate, fast and reliable performance is its corresponding fault type discriminated quickly and defined exactly. An algorithm was proposed for the estimation of direct, quadrature and zero sequence components after faults. These components are used in fault type identification as shown here. A new algorithm that overcomes the constraints of the existing techniques has been proposed. To ascertain the effectiveness of the technique, it was tested with model-based power system was used in MATLAB to conduct a series of faults and then identify the type of fault given a minimum number of fault current cycles. The technique is based on the simple use of the park transform and Artificial Neural Network. Result of the proposed technique was able to classify all of the faults that were presented to it.

This paper presented a multi-neural network based approach to fault classification of high speed protective relaying systems. Basically, neural network computing and implementation of digital signal processing concepts are used. The new method is suggested an approach to fault type classification of 1-phase, 2-phase and 3-phase faults. Classification of fault type is fast and reliable. Obtained results were encouraging and indicated that this approach can be used to support conventional protective relaying systems. It can also be used as a part of a new generation of high speed protective relaying systems.

The test results, therefore, suggest that the proposed technique operates reliably for faults within different power systems operating under different conditions.

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