International Journal of Electrical Engineering & Emerging Technology, Vol. 04, No. SI 01, Feb 2021, pp 01-07

Transmission Line Fault Detection and Identification Using Artificial Neural Network

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[**Received on:** 01-01-2021 **Accepted on**: 27-01-2021 **Published on:** 18-02-2021]

***Abstract*- Among subsystems of power system, transmission system faces high rate of severe faults. If these faults are not detected and eradicated quickly they can severely affect the continuity and reliability of the power supply. Many techniques have been put into effect for analysis of power system faults such as representing transmission lines by either first or second order and travelling wave techniques but these techniques lack in attaining the desired speed, selectivity and accuracy. For this purpose Artificial Neural Networks are highly efficient which after learning detect the fault quickly and accurately. In this research work Artificial Neural Network (ANN) using the back propagation technique is used to detect and identify the faults occurring on transmission system. The Network is trained with scaled conjugate gradient backpropagation.**

***Index Terms*—: Transmission line, faults, fault detection and identification, Artificial Neural Network (ANN).**

I. INTRODUCTION

Among different subsystems of the power system the transmission line has unique importance through which the generating station is linked with distribution system. As transmission line is exposed to the environment so probability of faults occurring on the transmission system is more than the rest of the components. Fault is the abnormal condition in electrical system due to which current does not follow the desired path. Different faults likely to occur on transmission system are; symmetrical (three phase short circuit) and unsymmetrical (double line to ground, line to line and single line to ground faults).

Whenever the fault occurs on transmission lines, one should expeditiously detect it and find its type so that it could be analyzed. Protection system will automatically detect and isolate the faulty portion provided that it is properly set. There must be an efficient method which can quickly detect and identify the faults on the transmission system. Many techniques have been put into effect for analysis of power system faults such as representing transmission lines by either first or second order and travelling wave techniques. These techniques lack in attaining the desired speed, selectivity and accuracy.

Regarding the transmission line fault classification and identification the Artificial Neural Network (ANN) is highly effective because it is a programming language and is able to solve nonlinear problems. ANNs are replica of biological neuron system. It consists of highly interconnected neural computing elements known as Neurons, having parallel distributed processing system. ANN has the ability to learn from the available data and act accordingly.

Eboule [1] Results are compared of concurrent neuro-fuzzy (CNF) technique which is applied to detect fault and location in different transmission lines. **AbdulKareem, A, et. al. [2]** Have investigated the effects of various asymmetrical faults on Nigerian grid. Load flow analysis has been done of existing 28-bus Nigerian Transmission grid by using Newton-Raphson algorithm done in run mode of Power World Simulator. In study it has been shown that the violations come at several buses and at some buses the voltage dips due to asymmetrical faults. **Gowrishanka et al. [3]** has used Daubechies as the mother wavelet using the discrete wavelet transform technique. The system is feed with differential energy, based on discrete wavelet transform, which is designed for the classification of all eleven fault types. **Bhattacharya [5]** with the help of Electro Magnetic Transients Program (AMT/EMTP) Software and Artificial Neural Network (ANN) faults are classified and their location is identified in non-radial power system network. **Yang et. al. [6]** in this piece of work the detailed ANN based fault detection and location, simulation is done by using PSCAD/EMTDC in which modeling of DC micro grid including wind turbine, battery energy storage system, load and AC grid is done. In the model, DC currents signals are implemented as input data. The simulation results show that any type of DC fault can be accurately and fast detected. **Samantaray SR [4]** has presented the new systematic fuzzy rule based approach for fault classification in transmission line. To identify the accurate phases involved in the fault process the classification of fault is important requirement of the distance relaying. For the initial classification the Decision Tree (DT) is used which is actually a knowledge representation method.

Prasad et. al. [9] in their survey they have found the different fault locations using ANN. **Saravanan et. al. [10]** in their work have presented the fault detection, fault classification and fault location of different faults such as LG, LLG, a nd LLLG which can possibly occur on double circuit overhead transmission lines. **Mahanty et. al. [16]** have presented the use of radial basis function (RBF) neural network for the purpose of classification and location of faults in transmission lines. Instantaneous current/voltage samples are considered as an input to the artificial neural network.

II. METHODLOGY

In this research paper the software used is MATLAB 2014b to simulate the power transmission system, different faults were created in transmission system and the data of current and voltage is used to train the Artificial Neural Network.

A. MATLAB SIMULATION MODEL

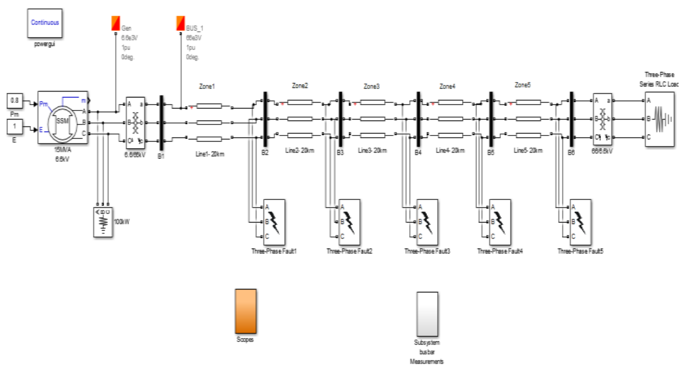

Fig 1: MATLAB Simulink model of transmission system

The model consists of a Simplified Synchronous Machine (SSM) which generates the Electrical power. Electrical Power is then transmitted using step-up transformer to the load through the transmission line. In transmission the distributed parameters line is used. Transmission line is divided into 5 sections each contains a three phase fault block to create different types of faults in that section.

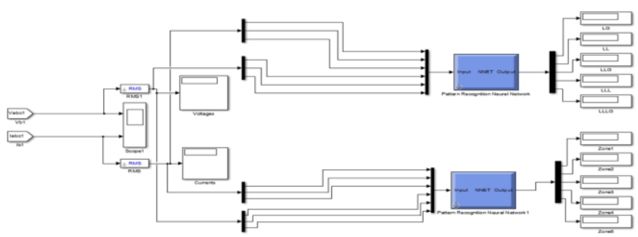

Fig 2: Parameters measurement subsystem at bus bar 1 with ANN

In figure using Goto and From block signals of current and voltage are fetched. Two pattern recognition neural network are used one to detect the fault and other to identify the zone in which fault is created. There are six inputs to each NNET block. Display blocks for voltage and current are used which show the magnitude of voltage and current during fault condition and no fault condition.

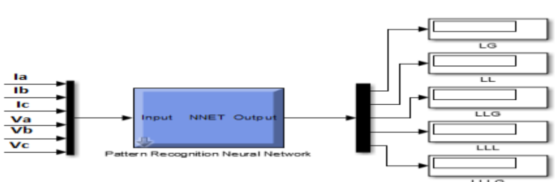

Fig 3: Matlab Simulink model of ANN for fault detection and identification

There are six inputs to this Simulink model of ANN three for each phase voltage and three for each phase current. By using mux six inputs are comprised and given to NNET. NNET has five outputs each dedicated to a type of fault. Each output is connected to a display. Each display block is given name of type of fault. If LG fault is created then LG block will show 1 and other blocks will show 0.

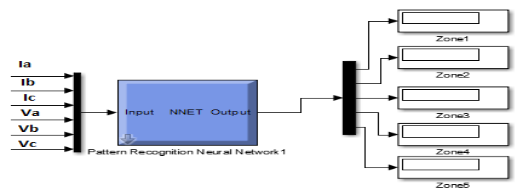

Fig 4: MATLAB Simulink model of ANN for fault zone identification

There are six inputs to this Simulink model of ANN (for zone identification) three for each phase voltage and three for each phase current. By using mux six inputs are comprised and given to NNET. NNET has five outputs each dedicated to a zone where fault will be created. Each output is connected to a display. Each display block is given name of zone. If fault is created in Zone1 then Zone1 block will show 1 and other blocks will show 0.

III. ARTIFICIAL NEURAL NETWORK TRAINING

A. ANN Training for fault detection and identification

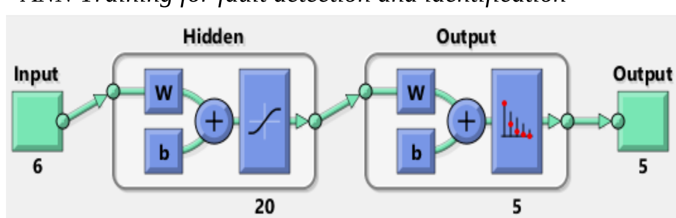

Fig 5: Neural Network configuration for fault detection and identification

Figure shows that there are six inputs (three of currents and three of voltages) to the Neural Network. There are 20 hidden layers and 5 output layers, and there are five outputs from the Neural Network.

Table I: Results after training of Neural Network which shows the % Error

Results	Samples	CE	%E
Training	39	1.73973e-0	10.25641e-0
Validation	8	5.28493e-0	25.00000e-0
Testing	8	5.28704e-0	25.00000e-0

Table I: shows that Out of the total 55 fault sample data set, 39 data samples has been used for the training of Neural Network for fault detection and identification. It means that 70% of the data is used for training purpose, and for validation and testing 15% data is used.

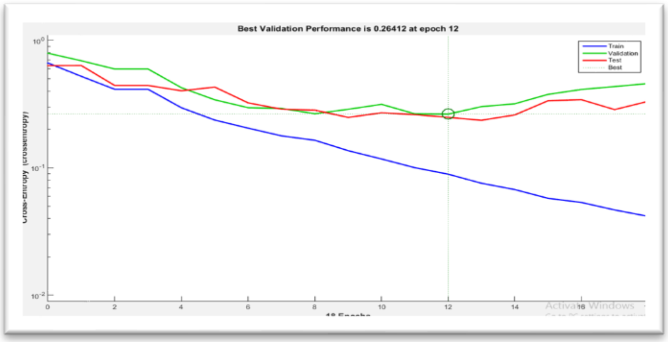

Fig 6: Neural Network training performance for fault detection and identification

Training performance plot shows that during the training process of the Neural Network for fault detection and identification neural network takes 12 epochs and the green line showing the mean square error has become minimum of 0.26412.

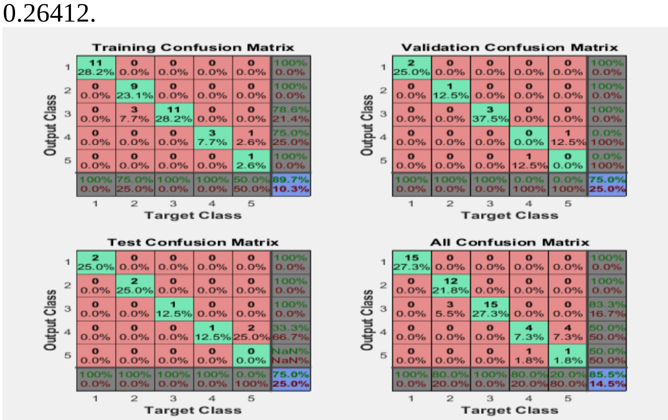

Fig 7: Confusion Matrix for training of neural network for fault detection and identification

Confusion Matrix shows that how much given data has correctly been classified and for how much data ANN was in confusion state. Fig: shows that from the total fault cases 85.5% of the fault cases has been correctly classified and the remaining 14.5% has not been classified correctly. For the incorrectly classified data the Neural Network was in confusion state.

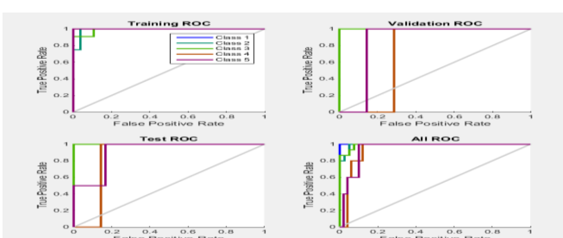

Fig 8: Neural network training Receiver operating characteristic (ROC) for fault detection and identification.

ROC is used to check the quality of a classifier. The more the lines touch left and upper side, better is the classification.

B. Neural Network Training for zone identification

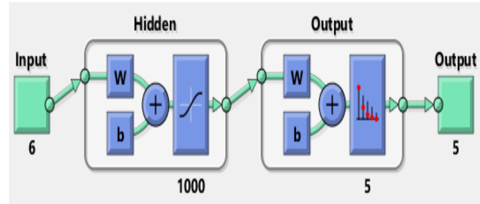

Fig 9: Neural Network configuration for Zone identification

Figure shows that there are six inputs (three of currents and three of voltages) to the Neural Network. There are 1000 hidden layers and 5 output layers, and there are five outputs from the Neural Network.

Table II: Results after training of Neural Network which shows the % Error

Results	Samples	CE	%E
Training	39	2.16650e-0	10.25641e-0
Validation	8	6.29959e-0	50.00000e-0
Testing	8	6.37094e-0	50.00000e-0

Table II: shows that Out of the total 55 sample data set, 39 data samples has been used for the training of Neural Network for zone identification. It means that 70% of the data is used for training purpose, and for validation and testing 15% data is used.

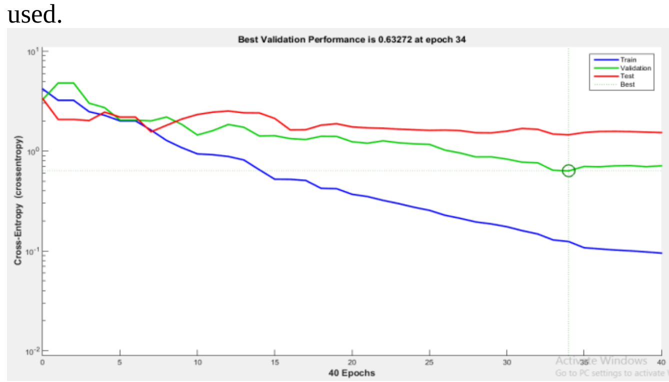

Fig 10: Neural Network training performance for fault Zone identification.

Training performance plot shows that during the training process of the Neural Network for fault detection and identification neural network takes 34 epochs and the green line showing the mean square error has become minimum of 0.63272.

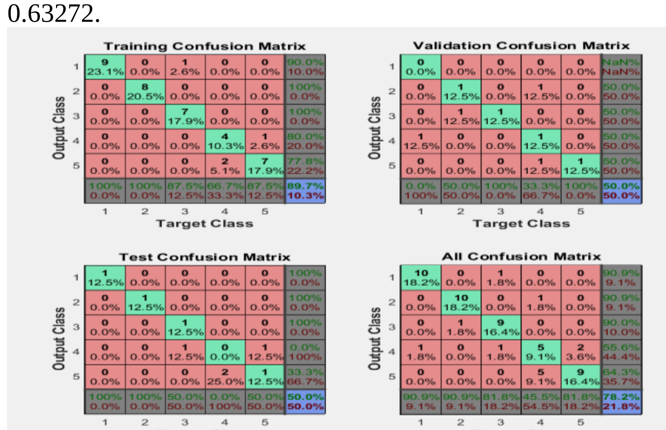

Fig 11: Confusion Matrix for training of neural network for fault zone identification

Confusion Matrix shows that how much given data has correctly been classified and for how much data ANN was in confusion state. Fig: shows that from the total given data 78.2% of the cases (faulty zone) has been correctly classified and the remaining 21.8% has not been classified correctly. For the incorrectly classified data the Neural Network was in confusion state.

IV. MATLAB SIMULATION RESULTS

A. *Fault Cases*

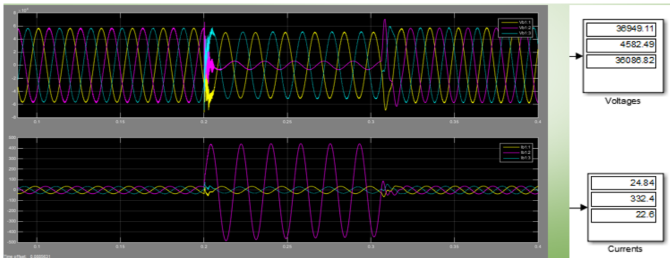

Fig 12: Three Phase Current and Voltage waveforms for BG (LG) fault applied in Zone1, which is 20km away from reference bus bar 1.

In fig: the waveforms of single line to ground fault (BG) are shown , the voltage waveform of phase B is disturbed and its magnitude has decreased which is shown in display block and the current waveform of phase B is also disturbed and its value has increased which is shown in display block.

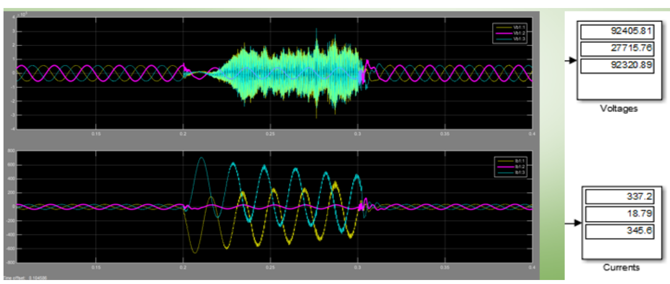

Fig 13: Three Phase Current and Voltage waveforms for ACG (LLG) fault applied in Zone2, which is 40km away from reference bus bar1.

In fig: the waveforms of double line to ground fault (ACG) are shown , the voltage waveforms of phase A and C are disturbed and their magnitudes have decreased which is shown in display block and the current waveforms of phases A and C are also disturbed and their value has increased which is shown in display block.

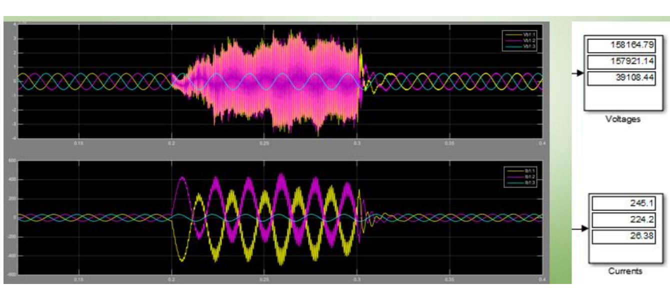

Fig 14: Three Phase Current and Voltage waveforms for AB (LL) fault applied in Zone3, which is 60km away from reference bus bar1.

In fig: the waveforms of line to line fault (AB) are shown , the voltage waveforms of phase A and B are disturbed and their magnitudes have decreased which is shown in display block and the current waveforms of phases A and B are also disturbed and their value has increased which is shown in display block.

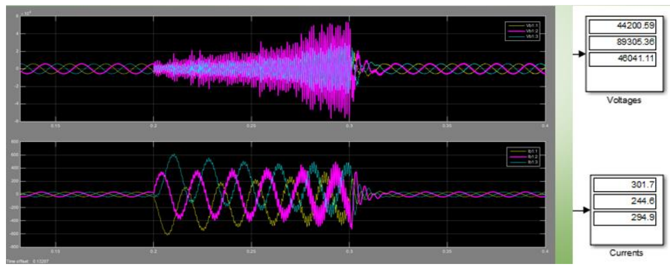

Fig 15: Three Phase Current and Voltage waveforms for ABC (LLL) fault applied in Zone4, which is 80km away from reference bus bar1.

In fig: the waveforms of three phase fault (ABC) are shown , the voltage waveforms of phase A,B and C are disturbed and their magnitudes have decreased which is shown in display block and the current waveforms of phases A,B and C are also disturbed and their value has increased which is shown in display block.

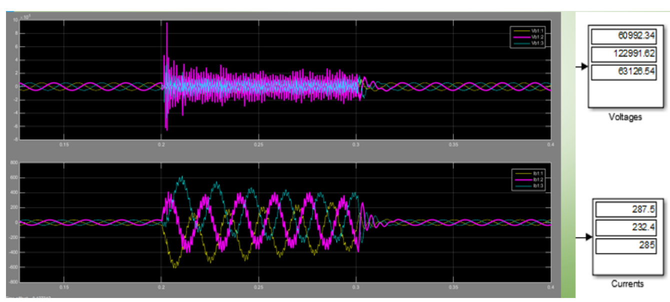

Fig 16: Three Phase Current and Voltage waveforms for ABCG (LLLG) fault applied in Zone5, which is 100km away from reference bus bar1.

In fig: the waveforms of three phase to ground fault (ABCG) are shown , the voltage waveforms of phase A,B and C are disturbed and their magnitudes have decreased which is shown in display block and the current waveforms of phases A,B and C are also disturbed and their value has increased which is shown in display block.

B. Neural Network Results for Fault detection and identification

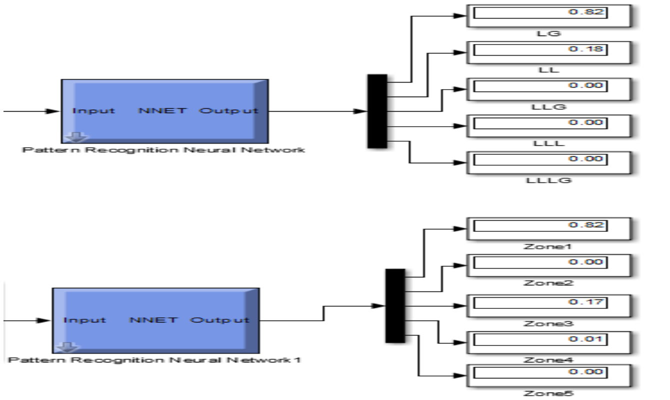

Fig 17: Fault detection and identification for BG (LG) fault applied in Zone1, which is 20km away from reference bus bar 1.

In fig the value of the LG display block is approximately equal to 1 it means the fault which was created is single line to ground fault, and the value of zone1 display block is approximately equal to 1 it means the fault which was created is in zone1.

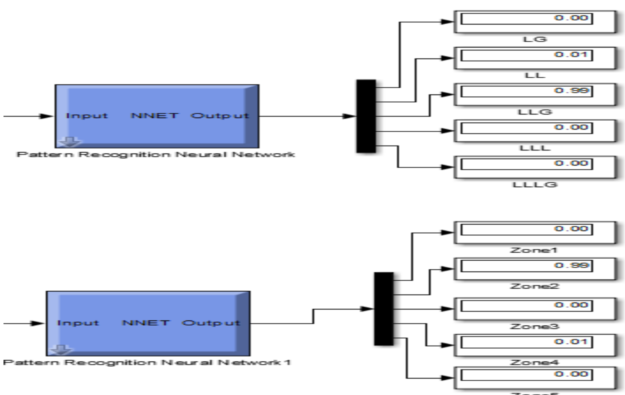

Fig 18: Fault detection and identification for ACG (LLG) fault applied in Zone2, which is 40km away from reference bus bar1.

In fig the value of the LLG display block is approximately equal to 1 it means the fault which was created is double line to ground fault, and the value of zone2 display block is approximately equal to 1 it means the fault which was created is in zone2.

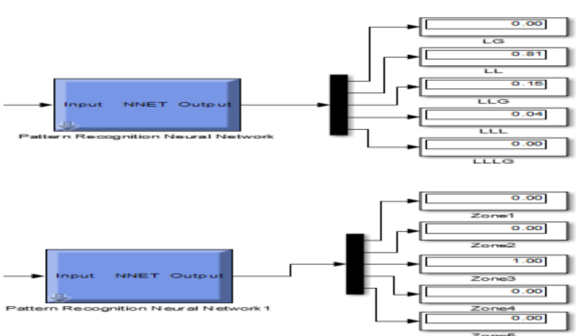

Fig 19: Fault detection and identification for AB (LL) fault applied in Zone3, which is 60km away from reference bus bar1.

In fig the value of the LL display block is approximately equal to 1 it means the fault which was created is line to line fault, and the value of zone3 display block is equal to 1 it means the fault which was created is in zone3.

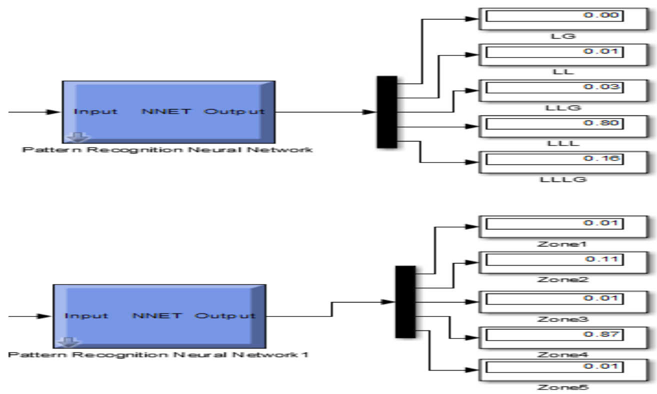

Fig 20: Fault detection and identification for ABC (LLL) fault applied in Zone4, which is 80km away from reference bus bar1.

In fig the value of the LLL display block is approximately equal to 1 it means the fault which was created is three phase fault, and the value of zone4 display block is approximately equal to 1 it means the fault which was created is in zone4.

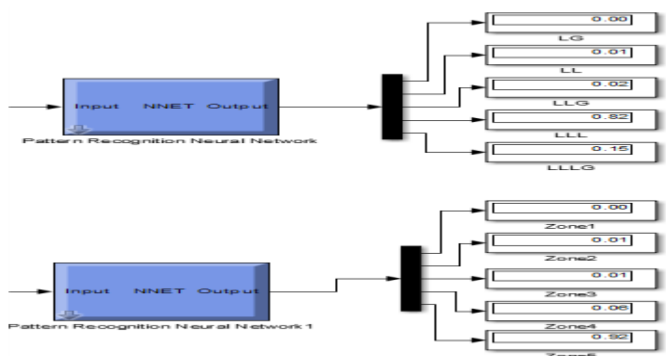

Fig 21: Fault detection and identification for ABCG (LLLG) fault applied in Zone5, which is 100km away from reference bus bar1.

In fig the value of the LLLG display block is approximately equal to 1 it means the fault which was created is three phase to ground fault, and the value of zone5 display block is approximately equal to 1 it means the fault is created in zone5.

V. CONCLUSION

In this research paper different faults on the transmission system has been detected and identified by utilization of Back Propagation (BP) neural network. Transmission line system has been designed in the MATLAB 2014b software. Artificial Neural Network (ANN) has been trained by current and voltage data taken during faults created on the transmission system.

The unsymmetrical faults; single line to ground fault (LG), double line fault (LL), and double line to ground fault (LLG) along with symmetrical faults has been taken into consideration. It is shown that network could correctly detected and identified faults on the transmission system. From results it is clear that this method can be used for designing a protective scheme for transmission line implementing Artificial Neural Network.

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