Chapter 7
Detection and Classification of Fault in Distributed Generation System Using Neuro-Fuzzy Technique

Saurabh Singh, Kishora Sasamal, and Santi Behera

Abstract The inclusion of distributed generation in usual distribution system has several advantages and technical harms. This inclusion has been done for fulfillment of several challenges such as fast growing population, world's growing economy, improvement of life's quality, and sustainability of resources. However, with this, several harms have also been seen which are yet to be solved and one such harm is fault detection in distributed generation (DG) system. The existing protecting equipment and fault detecting techniques cannot perform the same as in usual distribution system. This paper deals with a DG system consisting of two wind farms connected to a regular distribution network which is simulated using MATLAB for data collection and on the basis of the data of current and voltage samples various features are extracted. The features are trained and tested using the Neuro-Fuzzy classifier which identifies the type of fault during testing with a error very close to zero having RMSE of 0.031.

Keywords Distributed generation (DG) · Neuro-Fuzzy (NF) · Neuro-Fuzzy classifier (NFC) · Neural network (NN) · Root mean square error (RMSE) · Doubly fed induction generator (DFIG)

1 Introduction

With regular improvement in the quality of lives of people, fast increase in population, fast growing economy, and sustainability of resources, various technological advancements are happening and this has led to the encroachment in the complexity of power system. Nowadays, much emphasis is taken on green technology for making the world sustainable and for resources to last long and also it is very important for us human creature as well as for nature to survive. Electricity is in much demand and has become one of the most important obsession without which life cannot be imagined. The conservative way of generating electricity is based on the usage of

S. Singh (✉) · K. Sasamal · S. Behera
Department of Electrical Engineering, VSSUT, Burla, Odisha, India
e-mail: saurabh1697singh@gmail.com

S. Mahapatra et al. (eds.), *Advances in Energy Technology*, Advances in Sustainability Science and Technology, https://doi.org/10.1007/978-981-15-8700-9_7

usual fossil fuel like coal, natural gas, etc. However, the use of these has led to degradation of nature, scarcity of resources, and affecting the health of humans. One such step in solving this setback is being done in power system by using non-conventional sources like solar, wind, geothermal, etc., the development in this field is called Green Technology Development. The use of non-conservative sources such as wind, solar in form of wind farm, photovoltaic arrays in the distribution side is called Distributed Generation System [1, 2]. Despite of several advantages such as no greenhouse gas emission, sustainable, no use of fossil fuel, reduction in Tx, and distribution cost, can be installed in remote places where there is scarcity of electricity and installation capability is easy there are several harms to it as well.

Mostly, the power system has a unidirectional flow of power, however, with the inclusion of DG this concept converts to bidirectional flow. Thus, most of the protective equipment connected and various protection schemes applied for detection purpose will not be able to deliver the same results as earlier when power flow was unidirectional. The several negative forces of connecting a DG [1] to the usual distribution side are:

- Fault detection becomes a main concern after the connection of DG as due to its presence short circuit level of current increases and can cause mal-operation of breaker.
- There is a reduction in the reach of impedance relay and this happens due to extra supply of voltage by DG thus causing to increase the actual measured impedance by the relay.
- Islanding is another critical fact which occurs when grid is disconnected due to some abnormal condition however DG is still supplying and can huge voltage and frequency instability.
- Distribution system generally uses radial feeder due to unidirectional flow of power however with DG connection power flow direction is bidirectional and also sets up a reverse gradient of voltage which must be taken care of.

From the various problems faced due to the DG in distribution network, fault plays a significant role in bringing a normal power system network to abnormal condition. The effect of faults leads to imbalance in the system, equipment failures, and hampers the insulation of equipment. The part of the power system which is most frequently affected by the faults is the overhead transmission lines. Thus, it is very incumbent to distinguish the fault as fast as feasible and hence classify its type so to reduce the down time of the power failure. Classification of fault is a vital process in distance relaying depending upon which the distance estimation is attained and overall assessment is acquired. This work deals with a hybrid intelligence technique called Neuro-Fuzzy implementation for "Fault detection and classification" in a system consisting of two DFIG. The layout of this paper is as follows. In Sect. II, problem formulation has been done; in Sect. III Neuro-Fuzzy is described separately as well as in combination. The simulation and results are discussed in Sect. IV and finally, Sect. V concludes this paper with conclusion.

2 Problem Formulation

The problem is formulated by considering a system consisting of two numbers of WIND energy systems (9 MW each), conventional system (100 MVA), Neuro-Fuzzy controller, Faults (11 nos.), transformers (three), feeders (20 km), loads (two numbers each of 500 KW rated value) as shown in Fig. 1.

Wind energy system [3] which is a DFIG [4, 5] based 9 MW wind farm connected to a 11 kV distribution system transmits power to a 220 kV grid through a 20 km, 11 kV feeder. Wind farm using DFIG consists of wound rotor induction generator and Ac/Dc/Ac-IGBT-based PWM converter. The DFIG equipment allows extracting maximum energy from wind for low wind speeds by optimizing the turbine speed, while minimizing mechanical stresses on the turbine during gusts of wind. The conventional system consists of a 100 MVA, 220 kV grid, a 20 km length feeder which is again steeped down to 400 V for supplying load. The Neuro-Fuzzy controller used is a hybrid fault classifier which is based on two types, namely Mamdani approach and Takagi-Sugeno approach. However, in this paper, Takagi-Sugeno approach has been used which is called ANFIS [6, 7] (Adaptive Neuro-Fuzzy Inference System). Fault plays a significant role in the power system. Short circuiting of conductors due to branches falling on transmission line, wind, and storm comprises the natural happenings. The effects of faults lead to unbalance in the system, equipment failures, and hampers the insulation of equipment. Faults are segregated into two category: series and shunt faults. Series faults mainly represent the broken conductors or if any one or two phases are opened and the other remains in the circuit. These are signalized by increase in voltage and frequency but decrease in current. The shunt faults are commonly known as short-circuit fault and are signalized by increase in current. These are further categorized into symmetrical and unsymmetrical faults. The triple line faults are known as balance or symmetrical faults and all other remaining faults come under asymmetrical faults. 11 cases of short-circuit faults [8, 9] (LG, LL,

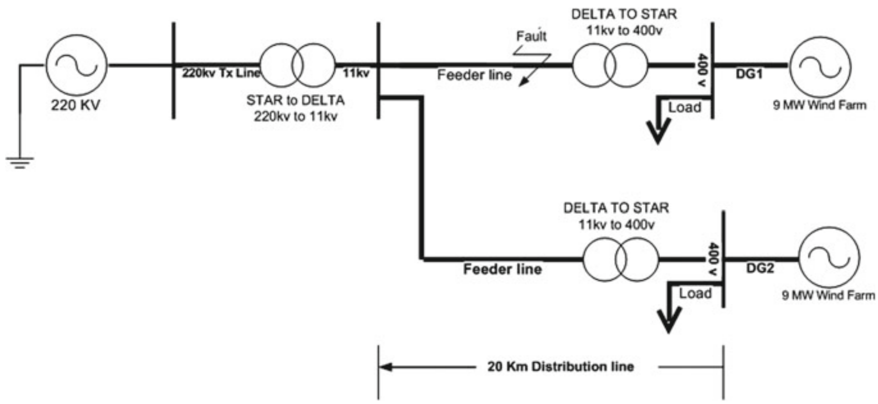

Fig. 1 Single-line diagram of the system

LLG, LLL, and LLG) are applied to the simulated system and results are observed. Three transformers are used which can be seen from Fig. 1 one is star-to-delta-type transformer which has been used to step down the grid voltage of 220 to 11 kV feeding the feeder. Other two are delta-to-star-type transformer which is used to step down the 11 kV feeder voltage to 400 V. The feeder is a 20 km long pi network consisting of inductance (L) and capacitance (C) where C is divided into two parts that is C/2 and C/2 forming the Pi network. Two loads are connected to each branch which can be seen from the single-line diagram in Fig. 1. Each load is 500 KW rated value. Each load is a series-type load consisting of only resistive part.

3 Neuro-Fuzzy Technique

Fault classification technique is generally done using three methods and these are prominent method, hybrid method and modern method.

From Fig. 2, it is clear that prominent technique has three sub-methods, namely wavelet method, ANN method, and fuzzy logic method for classification of fault. The prominent techniques nowadays are not in much use because each one has its own advantages and disadvantages and also results obtained are not highly accurate. Hence, in order to overcome each other's disadvantages, hybrid methods were introduced which comprises of Neuro-Fuzzy, Wavelet and ANN, Wavelet and fuzzy logic and wavelet and Neuro-Fuzzy. Modern techniques comprise of nature inspired algorithm such as genetic algorithm (GA), particle swarm, and space vector machine (SVM).

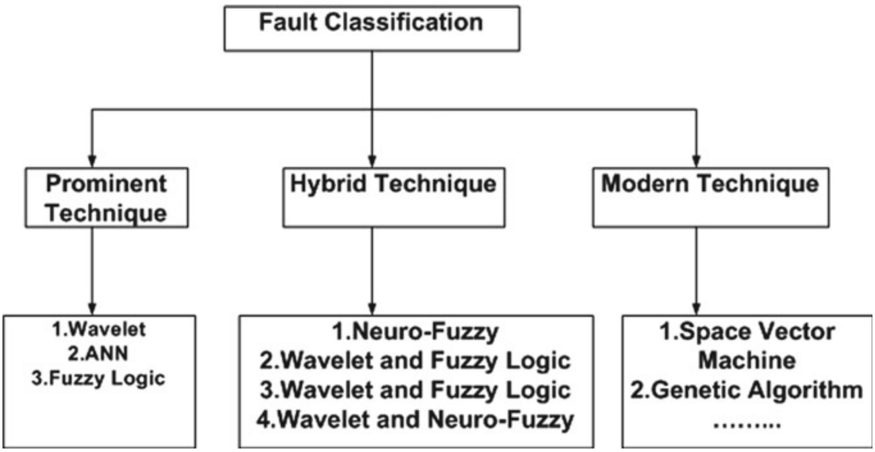

Fig. 2 Tree diagram of fault classification techniques [8]

A. Artificial Neural Network

Neural network can be defined in the specific group of neurons which are connected in bio-inspired structures and assembled in different layers. ANN [10–12] serves many problems, out of which the pattern recognition is of our interest. It is one of the ingenious algorithms which are used for identification and control. The neural networks can assimilate the system behavior. These networks can be used to recognize the relevant system behavior in nonlinear system. In ANN, the data gathered from the faulted set of current and voltage is applied and neural network then tries to follow the hidden pattern in the data and then according to it learns the pattern. After learning, during testing, it applies whatever it has learned and produces the output. ANN uses various algorithms like back propagation, feed forward propagation, etc., and a large number of neurons can be used by it upon which the accuracy of results depends. The main drawback with ANN is that it is good at recognizing pattern but not good at explaining how to reach their decision (Fig. 3).

B. Fuzzy Logic

Fuzzy logic system is inflected in three basic elements that are fuzzification, fuzzy inference, and defuzzifiction. Here, several inputs in form of crisp value are given to it and then membership function is defined in terms of linguistic variables such as low as L, medium as M, and high as H. The membership function can be a triangle, sigmoid, Gaussian, etc., depending upon output desired. The degree of membership is calculated in the fuzzifier layer. The output of this layer is sent to fuzzy inference system which is actually an intelligence layer which receives membership values as input and depending upon the fuzzy rule base produces an output. The output of this layer is sent to defuzzification layer which produces the crisp output.

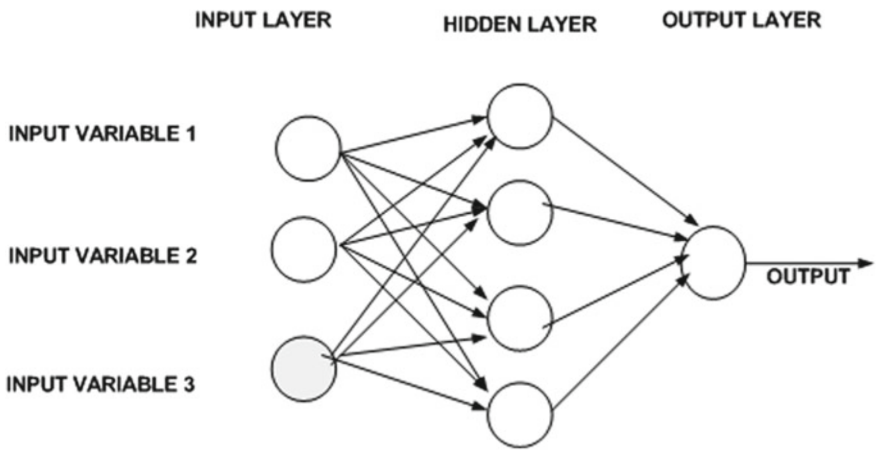

Fig. 3 Artificial neural network

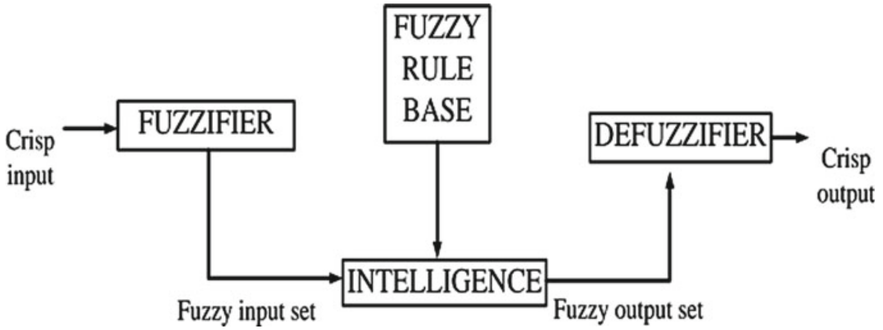

Fig. 4 Fuzzy logic model

The negative aspect of this approach is that number of fuzzy rules increases exponentially with respect to input. Also the Fuzzy logic [13–15] has the capability to take decision but is not capable of adapting to the changes (Fig. 4).

C. Neuro-Fuzzy

Incorporation of fuzzy logic in artificial neural network leads to fruitful and valuable output. Artificial neural network can be trained but no such training is possible in fuzzy logic. By integrating these two techniques, creates a new hybrid technique known as Neuro-Fuzzy [16–20] inference system which helps in memorizing the data set by providing a learning procedure. This technique is based upon data processing. It produces a felicitous input/output mapping with membership function which is based upon "fuzzy IF-THEN rules to procreate the input/output match up." The back propagation technique can be used to adjust these control parameters. Therefore, the input/output data must be operated on a wide range so that the control performance of this method will be guaranteed; otherwise, the previous designed controller will not yield the accurate output or result. In Fig. 5, P to Q are the inputs; in this paper, these are extracted features, the 1st and 4th layers nodes are adaptive and other nodes are fixed. It can use the feed forward back propagation network which has a very simple procedure for the learning process that comprises of providing the data having patterns of inputs and the target outputs, accessing the network performance, adaption of connection strength to produce better output. In neural network, the input/output behavior of the system can be determined by the use of weights between the input and output layers. The parameters obtained in the fuzzification and defuzzification process of the fuzzy logic system can thus be trained using the updated weights of neural network. This hybrid approach has been considered in many applications successfully and also few works have been done on fault classification purpose of the power system in transmission and distribution lines but not in distributed generation system. Looking to the extensive use and higher performance, in this work, the Neuro-Fuzzy (NF) classifier also considered as one of the approach. The neural network has the edge over other techniques in terms of robustness, work efficiently

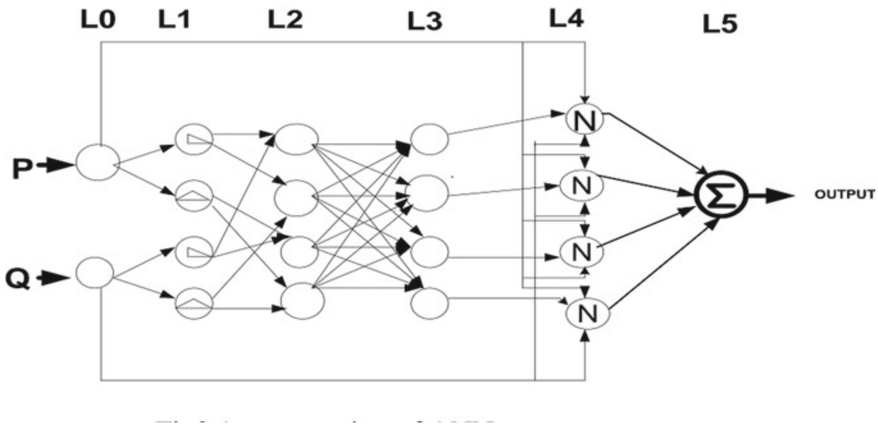

Fig. 5 Neuro-Fuzzy system

with both quantitative and qualitative data, computational burden and do not need exact mathematical modeling of the system.

4 Simulation and Results

A distribution network is being considered and modeled in MATLAB Simulink, the wind farm considered here is of DFIG type that is doubly fed induction generator because of increased power quality, energy efficiency, and controllability. Several Go-to are used to detect the current and voltage of the entire system under normal and faulty condition. A monitor is also being modeled so that each output voltage and current can be observed at once which is shown in Fig. 6.

Different short circuit faults were created at different locations of feeder that is at a distance of 4 km from 11 kV feeder end. Similarly, other faults were created at a distance of 8, 12, and 16 km from feeder end, respectively. With variation in fault distance, fault resistances were also changed varying from 0.001 to 10 Ω. Thus, in this way, a total of (5 × 4) 20 cases were observed for each short circuit fault.

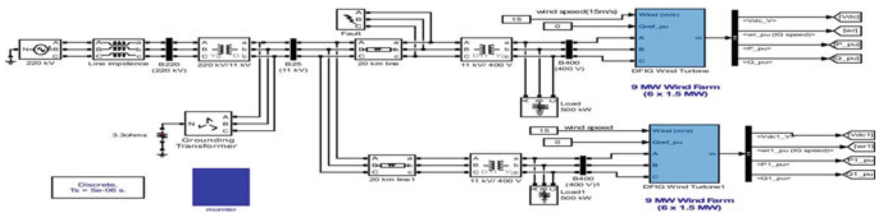

Fig. 6 Distributed generation system on Simulink

Thus, a total of (20 × 9) 180 cases for whole nine short circuit faults was taken into consideration. The results of faulted current and voltage for a fault distance of 4 km and fault resistance of 0.01 Ω are shown as in Figs. 7, 8 and 9.

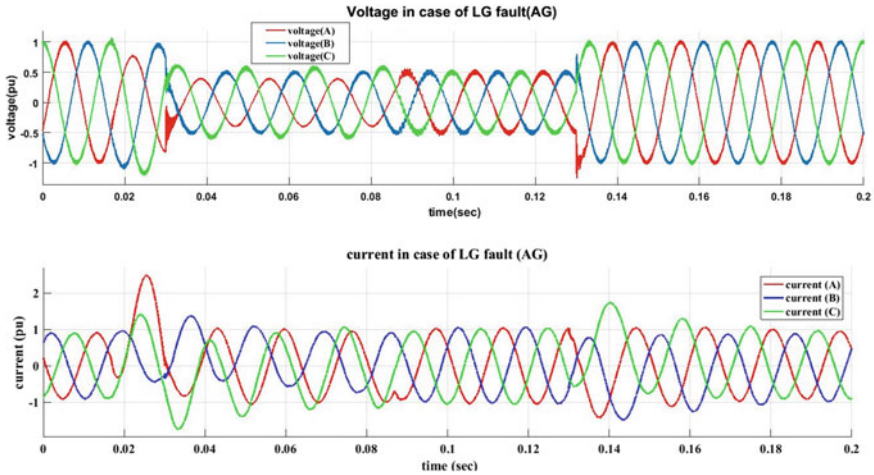

Fig. 7 Voltage and current sample in case of L-G fault

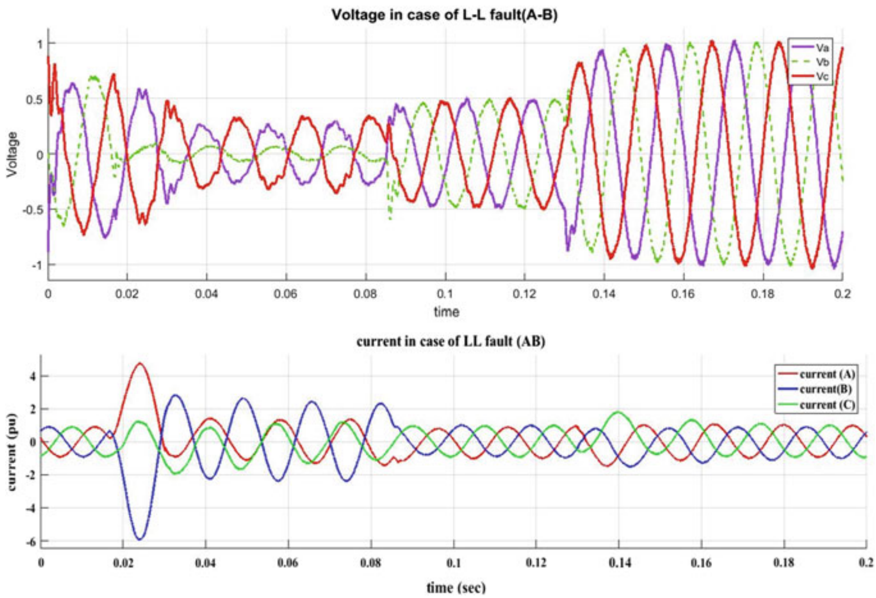

Fig. 8 Voltage and current sample in case of L-L fault

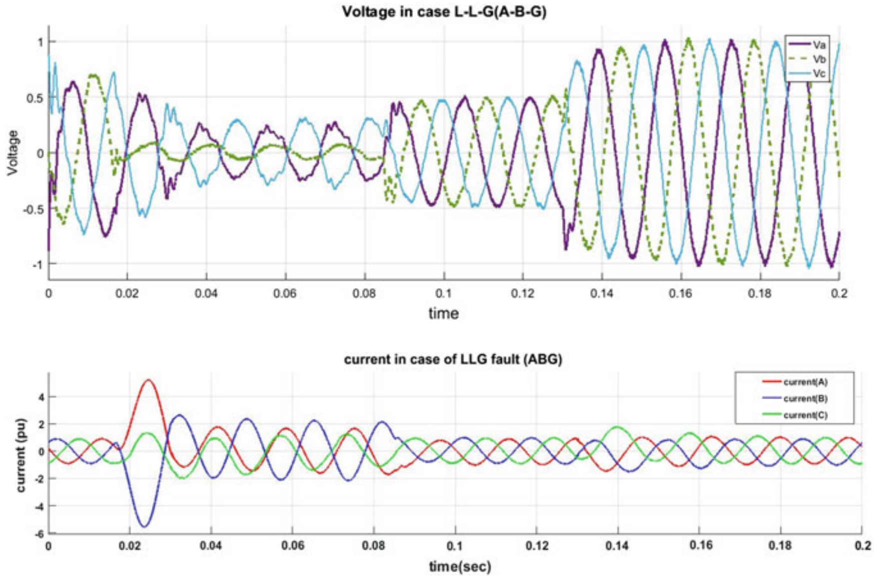

Fig. 9 Voltage and current sample in case of L-L-G fault

From above faulted current and voltage signals, we can calculate several features [21] such as total harmonic distortion (THD), signal-to-noise ratio (SNR), kurtosis, entropy, standard deviation, skewness, and mean. These features were selected on the basis of accuracy of results for classification and also provide improved results in case of noise factor. Thus, for 180 cases as discussed, seven features are calculated for each forming an input data matrix of 180 × 7. A sample data set has been in Table 1. The output (target) matrix consists of values from 1 to 11 representing each

Table 1 Sample data

Faults	Features						
	STD.	Skewness	Entropy	Mean	Kurtosis	THD	SNR
AG	0.6943	−8.935e−05	4.8491	−4.385e−04	1.5424	−42.2042	27.4420
BG	0.6945	−0.001189	4.8442	0.0011	1.5344	−41.9154	28.1674
CG	0.6925	1.6781e−4	4.8453	−7.126e−04	1.5464	−41.4045	28.6244
AB	0.6852	0.0030	4.8613	−4.598e−04	1.5386	−44.5682	27.6362
BC	0.6855	−0.0024	4.8603	0.0012	1.5339	−44.8153	27.6435
AC	0.6946	−15.910e−4	4.8400	6.6820e−04	1.5620	−41.6923	28.2300
ABG	0.6731	−0.0010	4.8530	0.0012	1.6017	−45.5898	27.5616
BCG	0.6737	0.0010	4.8575	−7.453e−04	1.6125	−39.2755	27.4535
ACG	0.6708	0.0018	4.8572	−7.1984e−04	1.6448	−42.0662	27.2386

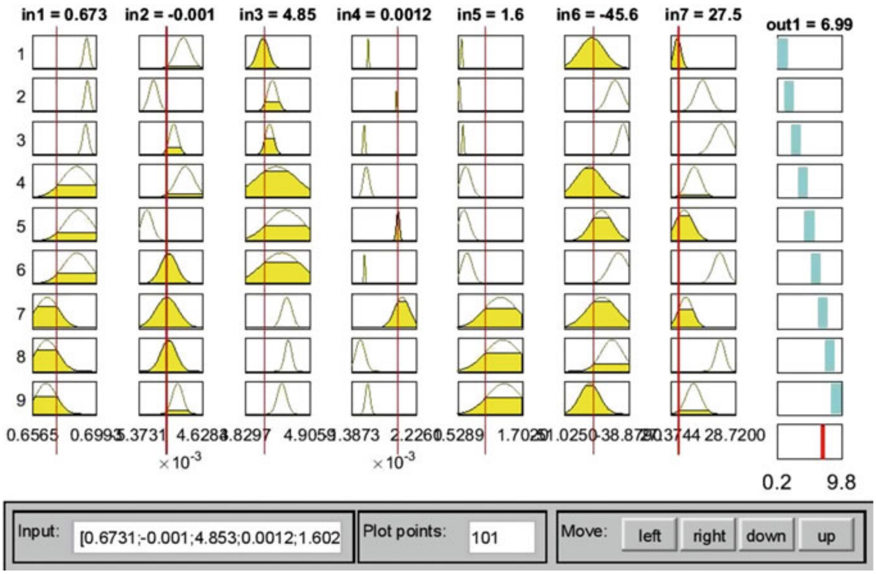

Fig. 11 Neuro-Fuzzy viewer

short circuit fault (AG-1, BG-2, CG-3, AB-4, BC-5, AC-6, ABG-7, BCG-8, and ACG-9).

The dataset so prepared is given as input to Neuro-Fuzzy classifier for training and half of the prepared data set is used for testing purpose. The Neuro-Fuzzy classifier output is a crisp output varying from 1 to 9 and performance evaluation is done by plotting RMSE VS EPOACH plot which is shown below.

From Fig. 11, we can see that there are seven inputs which are actually the seven features which were extracted from the faulted current and voltage. We can vary the input and depending upon this, the classifier output changes. Here, as in Fig. 11, for a particular set of input, the output which is crisp value is seen to be seven that means ABG fault has occurred in this way the different short circuit faults are classified.

Also in Fig. 12, we can see this classification is done with a higher accuracy having RMSE of only 0.031 which almost close to zero.

5 Conclusion

The problem was formulated to detect and classify the different types of faults. Nine cases of different fault types were simulated over a range of fault resistances from 0.001 to 10 Ω and fault distance of 4 to 16 km. The current and voltage samples were recorded. Through this process, different faulted data samples were collected. By using the voltage and current samplesm the different features of power system

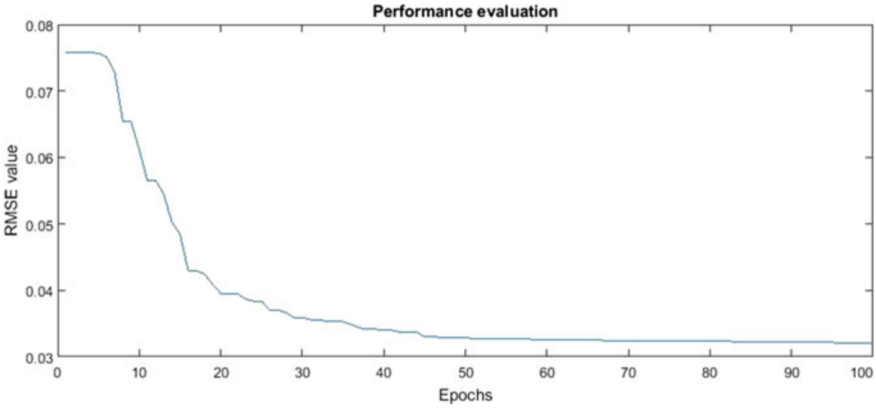

Fig. 12 Performance plot

were extracted. A data set was prepared from the extracted features. The prepared data set is then acts as the input to the Neuro-Fuzzy classifier.

The complete data set is again split into two halves for the training and testing purposes. The training data set is given as input to the fuzzy neural network and the fuzzy neural network attempts to learn from these training data and provides the fuzzy if then rules in output. With the help of this, fault classification was performed and output performance was evaluated.

References

1. Kumar R, Saxena D (2016) Fault location in distribution network with distributed generation: an overview and key issues. IEEE
2. Singh SN, Ostergaard J, Jain N (2014) Distributed generation in power system: an overview and key issues. In: Proceedings of IEC, May 2014
3. Baroudi JA, Dinavahi V, Knight AM (2007) A review of power converter topologies for wind generators. Renewable Energy 32:2369–2385
4. Lei Y, Mullane A, Lightbody G, Yacamini R (2006) Modeling of the wind turbine with a doubly fed induction generator for grid integration studies. IEEE Trans Energy Convers 21(1):257–264
5. Musab Bayat M, Torun Y (2017) Modeling and linearization of DFIG based wind turbine. Euro Sci J 158–168
6. Kamel TS, Moustafa Hassan MA. Adaptive neuro fuzzy inference system (ANFIS) for fault classification in the transmission lines. Online J Electron Electr Eng (OJEEE) 2(1):164–169
7. Elbaset AA, Hiyama T (2009) Fault detection and classification in transmission lines using ANFIS. Institute of Electrical Engineers of Japan, pp 705–713
8. Prasad A, Belwin Edward J, Ravi K (2017) A review on fault classification methodologies part II
9. Prasad A, Belwin Edward J, Ravi K (2016) A review on fault classification methodologies part I
10. Padhy SK, Panigrahy BK, Ray PK, Satpathy AK, Nanda RP, Nayak A (2018) Classification of faults in a transmission line using artificial neural network. In: 2018 International conference on information technology (ICIT), pp 239–243. IEEE

11. Perera WPDR, Danawardana UATI, Thamel WAL, Ireshika MAST (2017) Fault detection in distribution lines using artificial neural network. Research gate on 27 October 2017
12. Awasthi Saurabh, Singh Ranjay (2016) Identification of type and location of fault in a distributed generation system using neural network. Int J Sci Res (IJSR) 5:2059–2065
13. Joseph Lekie A, Idoniboyeobu DC, Braide SL (2018) Fault detection on distributed line using Fuzzy logic. Int J Sci Eng Res (IJSER) 9:490–503
14. Vimal M, Vaghamshi AL, Matang D (2017) Simulation and analysis of transmission line fault detection and location using Fuzzy Logic. Int J Technol Res Eng 4:1463–1470
15. Prasad A, Belwin Edward J, Shashank Roy C, Divyansh G, Kumar A (2015) Classification of falts in power transmission lines using Fuzzy Logic Technique. Ind J Sci Technol (IJST) 8
16. Wang H, Keerthipala WWL (1998) Fuzzy-Neuro approach to fault classification for transmission line protection. IEEE Trans Power Del 13(4)
17. Babayomi O, Keku G, Ofodile NA (2017) Neuro-Fuzzy based fault detection identification and location in a distribution network, 2017 IEEE PES-IAS Power Africa
18. Keerthipala WWL, Wang H, Wai CT (2000) On-line testing of a fuzzy-neuro based protective relay using a real-time digital simulator. IEEE Conf Publ 3:1917–1922
19. Rashidi F (2004) Sensorless speed control of induction motor derives using a robust and adaptive neuro-fuzzy based intelligent controller. IEEE international conference an industrial technology (ICIT), pp 617–627
20. Dash PK, Pradhan AK, Panda G (2000) A novel fuzzy neural network based distance relaying scheme. IEEE Trans Power Deliv 15(3):902–907
21. Mahmud MN, Ibrahim MN, Osman MK, Hussain Z (2015) Selection of suitable features for fault classification in transmission line. 2015 IEEE international conference on control system, computing and engineering, pp 591–596, 27–29 Nov 2015