Fault Classification in a DG Connected Power System using Artificial Neural Network

Anshuman Bhuyan[1], Basanta K. Panigrahi[2], Subhendu Pati[3]
[1,2,3]Department of Electrical Engineering, ITER, SOA Deemed to be University, Bhubaneswar

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ABSTRACT

Distributed generation is playing a major role in the power system to meet the growing load demand. Integration of Distributed Generator (DG) to grid leads to various issues of protection and control of power system structure. From the different fault issues that occur in a distributed generator integrated power system, classification of fault remains as one of the most vital issues even after years of in-depth research. Because researchers are attempting to detect and diagnose these faults as soon as possible in order to avoid financial losses, this work aims to investigate the sort of fault that happened in the hybrid system. This paper proposed artificial neural network-based approaches for fault disturbances in a microgrid made up of wind turbine generators, fuel cells and diesel generator. The voltage signal is retrieved at the point of common coupling (PCC). The extracted data are used for training and testing purposes. Artificial neural network technique is utilized for the classification of faults in the simulated model. Furthermore, performance indices (PIs) such as standard deviation and skewness are calculated for reduction of data size and better accuracy. Both the fault and parameters are varied to check the usefulness of the proposed method. Finally, the results are discussed and compared with different DG penetration.

Corresponding Author:

Basanta K. Panigrahi,
Department of Electrical Engineering,
ITER, SOA Deemed to be University, Bhubaneswar.
Email: basanta1983@gmail.com

1. INTRODUCTION

In this era, the demand for electrical power is rising. Traditional power systems, which depend on massive fossil-fuel-fired power stations, long-distance transmission lines, and centralized control centres, are modernizing [1]. A huge number of distributed generation units are being integrated into the power system at distribution level. Distributed generation (DG) is one of the most significant changes in the electrical sector and power grid in the last decade. The term "Distributed Generation" (DG) refers to energy generation near to the point of consumption [2]. The distributed generation resources are renewable energy such as wind, PV cell, tidal, geothermal heat, Biomass etc. one of the benefits of using DG is its close proximity to consumer’s load. Distributed generation is critical for enhancing grid dependability, lowering transmission line losses, offering better voltage stability, and enhancing power quality [3].

Apart from the benefits, the increased use of DGs in distributed power systems raises a number of safety and operational issues. When a large capacity DG is introduced into a power system, it has a more significant effect on the network voltage, real and reactive power flow, short circuit current and other characteristics [4]. The integration of DG transforms the radially passive distribution network into an active network of medium and small power sources, altering the amount and duration of fault currents, and current flow no longer flows unilaterally from the substation bus into the load. Additionally, the failure behaviour of the DG has an impact on system operation and protection and the most serious safety issue is the problem of fault in the system [5]. Short-circuit situations in the power grid system create considerable economic losses and impair power system efficiency. As a result, detecting and classifying the defect as soon as feasible is crucial in order to avoid inflicting harm [6].

Even though non-stationary power signals include all of the information in terms of current and voltage, intelligent approaches for interpreting potentially valuable information are highly challenging. Furthermore, the fault classification approach employs a feature extraction technique to obtain decreased dimensions and information data [7]. The fault detector and classifier modules utilize this module to extract numerous aspects that characterize the signal. In the protective relays of transmission lines and distribution systems, fault category classification is essential. To provide output as a fault category, the fault classifier must be effective and reliable [8]. An attempt was made in this study to suggest a convenient technique for fault classification of transmission lines.

Numerous signal processing algorithms, such as the Wavelet transform (WT), S-transform (ST) and Fourier transform (FT) are being used to evaluate the frequency characteristics of time domain data in order to identify associated properties [9]. When compared to the above approaches, high frequency transients are always associated with faults, and various studies have indicated that the wavelet transform is particularly successful in extracting vital information about current and voltage required for transmission line relaying. [10,11,12]. For extracting the individuality of fault signals., the WT has been a popular and effective approach. The WT is being utilized to calculate the maximum and minimum fault currents as well as the transmission line's different coefficients. In the literature [13], the three-level maximum and minimum values detail coefficients are discussed. The energy and standard deviation of the fault current are used as the input data for classification of fault [14]. It is vital to deploy an Artificial Neural Network as part of a protection plan to identify and categorise faults based on transient voltage and/or fault current signals. Biological neural networks are mathematical representations of ANN. According to [15], a strategy of the new technique of islanding detection using artificial neural networks was developed by which the results were more accurate. The output using ANN is very fast, accurate and reliable depending on the training process because it works on the cluster of inputs [16, 17]. The ANN is trained so as to produce desired, accurate output or response providing a particular pattern of inputs [18]. Wind and solar energy minimize reliance on fossil-fuel-based electricity generation; they also benefit greenhouse gas emissions, global health, and environmental sustainability. In this study, a hybrid system comprising a DG wind turbine and a PV cell was deployed. [19-22].

The reason for using the wind farm is that it uses less energy and releases less carbon dioxide. But the wind flow is not constant therefore the power generation is also not constant. The installation of a wind farm is very costly and it should be installed in a remote area. The reason for using the PV array is that if a wind farm fails to produce energy due to variation in the wind speed, to satisfy the load requirement, we can use solar energy as a backup. The maintenance cost of the PV array is less compared to the wind farm. It can be installed anywhere, even on the rooftop. During the operation of producing energy, the solar panel is silent whereas the wind turbines are noisy. But the solar irradiance is also variable so the production is also variable.

The framework of this paper is presented as follows. Section 2 presented the feature extraction and selection process. ANN is elaborately described in section 3. The proposed hybrid model gives in section 4 and results and discussion illustrate in section 5. Finally, Section 6 ends with the conclusion

2. FEATURE EXTRACTION AND SELECTION

The suggested approach pre-processes the signal and extracts the most effective features. The proper classification of fault accuracy depends upon responsive and meaningful features. Features of the signals contain vital information of the examined fault [23]. To reduce the size of the signal, the feature extraction method is generally implemented at the decomposition level for each of these coefficients. Incorrect features degrade the system's reliability and it fails to classify the fault correctly [24]. So correct feature selection is very important. For each time series variable$T_i = \{y_1, y_2 \dots . y_n\}$, where i varies from i =1...10. In this work, the following five different features are extracted from the decomposed coefficient.

a. *Arithmetic mean (AM)*

The arithmetic mean μ is located within a time window of average values $\{y_1, y_2 \dots . y_m\}$. It is calculated as:

$$\mu = \frac{1}{m}\sum_{i=1}^{m} y_i \quad (1)$$

b. *Standard Deviation (SD)*

The standard deviation is computed as expressed below to measure the value of $\{y_1, y_2 \dots . y_m\}$.

$$\sigma = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \mu)^2} \quad (2)$$

This feature is very much needed to differentiate between the high frequency and low frequency signal standard deviation.

c. ***Kurtosis***

Kurtosis is calculated to measure the spikiness of the probability distribution of the data as follows.

$$K_u = \frac{\mu_4}{\sigma^4} \tag{3}$$

Whereμ_4 is the 4th moment about the mean and can be represented as:

$$\mu_4 = \frac{1}{m}\sum_{i=1}^{m}(y_i - \mu)^4 \tag{4}$$

d. ***Skewness***

The asymmetry is measured by skewness of measurement data. It is calculated as:

$$S_k = \frac{\mu_3}{\sigma^3} \tag{5}$$

Whereμ_3 is the 3rd moment about the mean, and is given by:

$$\mu_3 = \frac{1}{m}\sum_{i=1}^{m}(y_i - \mu)^3 \tag{6}$$

e. ***Entropy***

Entropy is measure of random variables related impurities. The discrete variable set Y can be expressed with possible values $\{y_1, y_2 \ldots . y_m\}$ and the probability density function P (Y) in terms of entropy H is given as follows:

$$H(Y) = -\sum_{i=1}^{m} P(y_i) log_2 P(y_i) \tag{7}$$

These five different features are extracted from the output of transformation. The extracted features are fed to different classifiers ANN. The primary goal of feature extraction is to extract useful data from raw data that can be employed in the training and testing process to accurately classify different faults.

3. ARTIFICIAL NEURAL NETWORK (ANN)

Machine learning (ML) techniques are widely used for fault classification in DG interconnected power systems because of its ability to process large sets of data [25]. In addition to this, machine learning techniques also remove the threshold calculations. The ML technique such as the Artificial Neural Network (ANN) which is employed for fault classification problems must be effective and simple [26]. The reason for using ANN is its learning capability and the nature of new problems. In this work the used ANN is having three layers i.e., input layer, hidden layer and output layer respectively. For getting the acceptable root mean square error value during the training process, determination of number of hidden neurons is required [27,28]. The architecture of a feed forward Artificial Neural Network Classifier is depicted in Figure 1.

The ANN is a widely used method in engineering and research for a variety of issues [29]. A computational model based on the design and functionalities of biological neural networks is known as an artificial neural network (ANN). An ANN's structure changes depending on the input and output. The complex correlation defined between input and output is simulated using ANN which is a nonlinear statistical data. [29]. ANN is a type of artificial neural network that is made up of a number of layers and nodes. An input layer, hidden (computational) layers, and an output layer are the three layers that make up a neural network. Through hidden layers, the input data is transmitted to the output layer. The error signals are then transmitted across the hidden and input layers through connections that connect the nodes in subsequent levels [30]. An activation function connects the output of any node in the hidden and output layers to the input node. The weight update and reduction processes are done using a learning method [31]. Supervised approaches are employed to train an ANN with the help of an instructor. This indicates that there is a training set (dataset) with instances of true values: tags, classes, and indicators. Unallocated sets are also utilised to train neural networks, and unsupervised techniques for doing so have been devised. Training is the process of choosing coefficients for each neuron in the layers so that we may receive the required set of output signals from a given set of input signals. Here a_1 ,a_2..a_n are the input parameters,β is the hidden layers of the architecture of artificial neural network classifier.

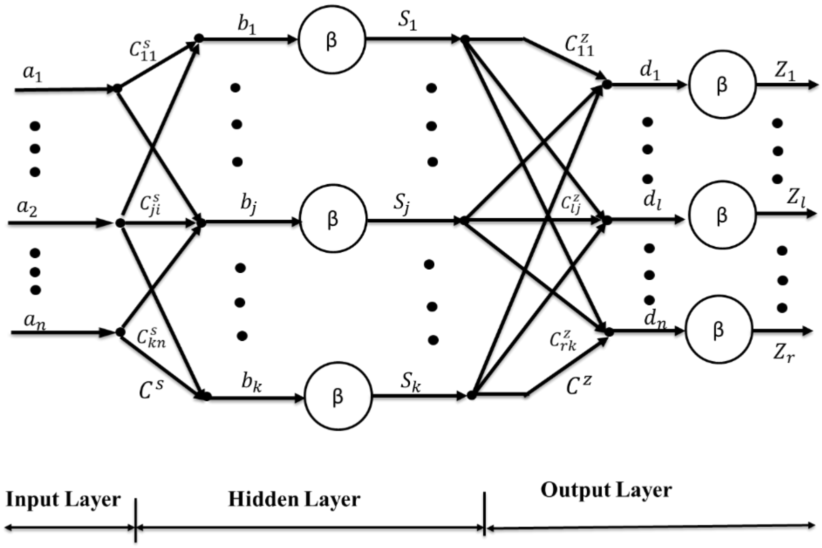

Figure 1. Architecture of Artificial Neural Network Classifier

There are 11 different types of faults that may occur in the DG connected power system and the neural network is capable of classifying all the faults correctly [34-35]. The 11 different faults are unsymmetrical faults (R-G, Y-G, B-G, R-Y-G, Y-B-G, B-R-G, R-Y, Y-B, B-R, and R-Y-B-G) and symmetrical faults (R-Y-B). Back propagation algorithm is employed for the neural network architecture. In general, the number of hidden layers to be used is decided by heuristics. There is no formula for determining how many hidden layers are required. In many circumstances, one hidden layer is sufficient, but we must use a heuristic method such as cross validation to justify this for a specific problem. It achieves an excellent fit if the number of hidden layers is more, but at the same time it may also be over fitting. This suggests that the training set of ANN fits well but the performance is bad for testing data sets. This means that comparable inputs produce diverse outputs. The error was found by starting from the last step at each point and iteration and sending the error backwards [32,33]. The optimal weight value (w_{ij}) of the node is computed using the algorithm. In this algorithm the expected output is deducted from the known output value for determining the error value. After getting the error values weights are rearranged. This process is continued on all the neurons till the error value among calculated value and target value is less than tolerable limit.

4. PROPOSED MODEL

The proposed solar, wind and diesel generator integration scheme is modelled and simulated in the MATLAB/Simulink environment. The system under investigation is depicted in Figure 2, that comprises two distributed generators (DGs) with different power outputs that are synchronized with the grid. The two DG sources connected in this proposed model are wind turbines and solar panels. MATLAB is the software tool that was employed to develop and analyse the model. The model consists of one source of 30KV,50Hz to which a star connected step-up transformer and two steps down transformer are connected through 100km long transmission line where the circuit breaker is also installed after the step-up transformer which will trip during the fault in the given range of switching time. At the PCC, PV array and wind farms are connected. As the wind turbine source and PV source completely depends upon the climatic condition, the proposed model incorporates a diesel engine generator to enhance the hybrid system's efficiency.

The system model, illustrated in figure 3, shows the proposed (PV-wind-diesel engine) connected hybrid power system. The generation of diesel engine generators does not depend upon climatic conditions. The ratings of proposed model are line length of 100km, voltage of 25kv and frequency of 50 Hz at the sending end of the transmission line.

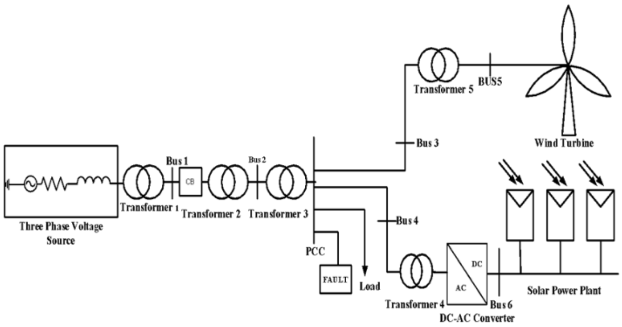

Figure 2. Single line diagram of the proposed DG(PV-wind) connected hybrid power system

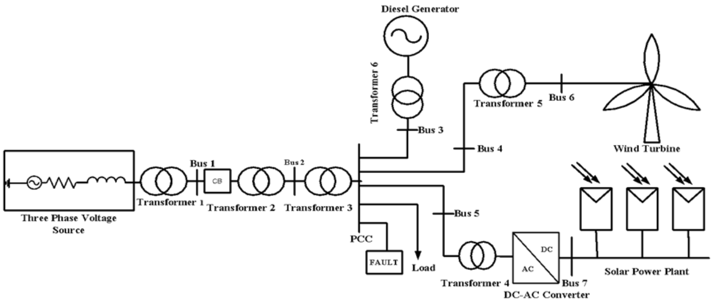

Figure 3. Single line diagram of the proposed DG (PV-wind-diesel engine) connected hybrid power system

5. SIMULATION RESULT AND ANALYSIS

A fine dataset of fault features is the foundation of the majority of classification approaches. The list of relevant features should be compact and minimal in computing complexity. In most real-world applications, relevant characteristics are suppressed due to redundancy and noise, so it's important to extract this information in a cost-effective manner without losing the vital data.

Figure 4, 5 and 6 explain the standard deviation, mean and skewness for symmetrical and unsymmetrical faults. It is clearly visible from the extracted features that the LLL fault is the most severe fault followed by LL fault and LG fault. The severity of fault also depends upon the location of data extraction. LLL fault occurs rarely in a power system network but when it occurs the fault currents are balanced in nature but the magnitude of the fault current is more in comparison to unsymmetrical fault.

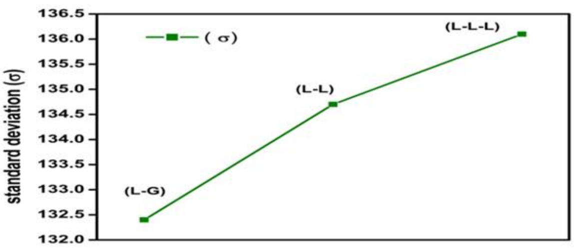

Figure 4. Standard deviation value for symmetrical and unsymmetrical fault

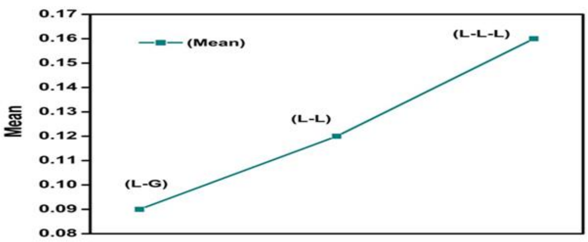

Figure 5. Mean value for symmetrical and unsymmetrical fault

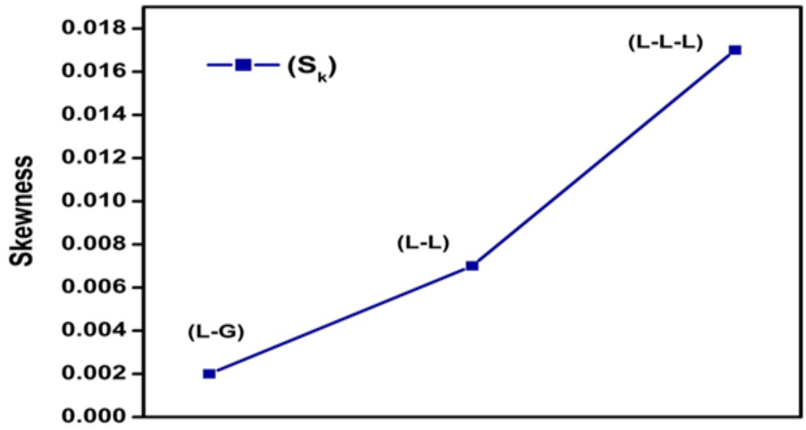

Figure 6. Skewness for symmetrical and unsymmetrical fault

Model performance is heavily influenced by the data features used to train the ANN classifiers. Model performance can be harmed by features that are unrelated or just partially relevant. The best feature selection might assist you improve your learning accuracy. If the suitable feature is chosen, it reduces training time and computational complexity.

5.1. Case.1: Wind- PV Cell Distributed Generators Connected to Grid

The Wind-PV cell distributed generator connected to the grid model is studied in this section to confirm the efficacy of the proposed technique for fault classification. The performance is assessed using the mean square error and gradient. The suggested technique's practicality is demonstrated using fault data, demonstrating its suitability for real-time applications. Data sets are formed with different faults and then collecting the data for training and testing purposes. The plots indicate that the system is working properly. The training signal is employed to train the fault classifying signal, that is taken at fault distances of 20 kilometres, 30 kilometres, 40 kilometres, and 50 kilometres for various fault types (i.e.single phase to ground, phase to phase, double phase to ground or three-phase fault) Figure 7 depicts the gradient function, as well as the training and validation functions employing ANN.

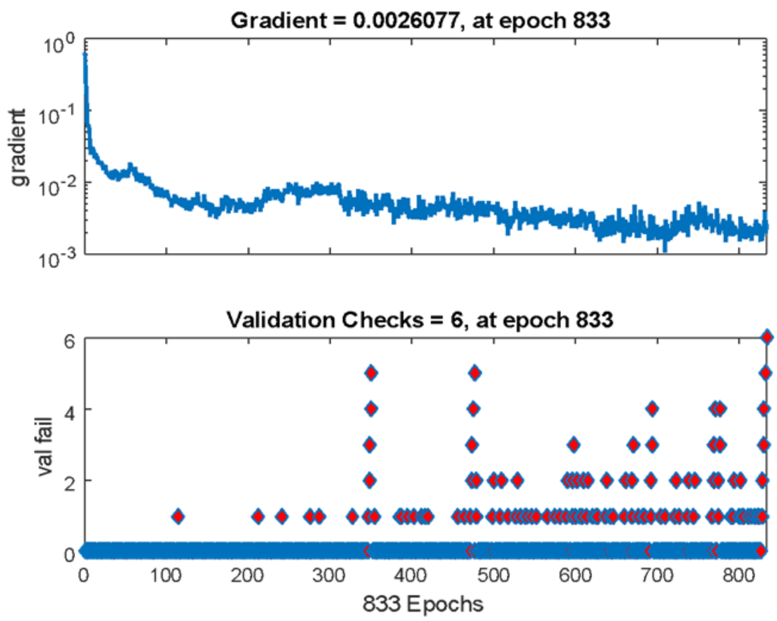

Figure 7. Graph of gradient and Val fail with respect to Epochs (ANN)

For different fault resistances similar to the above, simulations have been performed for all different types of faults (LG, LLG, LL and LLL). Data sets having 16,000 data in total out of which 8,000 data are used as training data and 8,000 data as testing data for ANN classification for this system model. Figure 8 depicts the ANN classifier's total mean square error. The correct percentage of fault classification in the system is 99.43 % in this procedure. The proposed neural network classifier is capable of classifying different faults effectively.

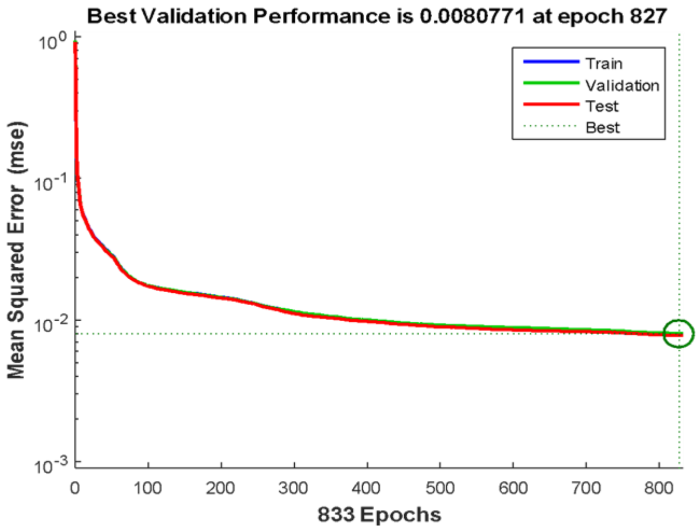

Figure 8. Error value at different epochs (ANN)

5.2. Case.2: Wind-PV-Diesel engine Distributed generators Connected to Grid

One more DG (Diesel Generator) is connected in this subsection to test the adequacy of the suggested model and to improve the system's reliability. The proposed model was simulated and the simulation results of accurate classification of faults using artificial neural networks were discussed here. The simulation is carried out for both symmetrical and asymmetrical faults at different fault resistance i.e. at 0.001, 0.01, 0.1,1,10,100 ohm. The raw data are taken out from the PCC and used to extract the closely associated features that characterized the signal and severity of the fault. The extracted datas are fed as the input to the classifier. This process is done for reducing the computational burden as well as to analyze the characteristics of the data signal in a simplified way.

The data set is collected by extracting the voltage signal of the 3 phase system out of which 668 data were trained and 668 were tested for this system model. Figure 9, demonstrates the graph of gradient and valfail with respect to epochs. Figure 10, explains the error value at different epochs using ANN. The size of data can enhance the accuracy of fault classification, while at the same time, it increases the time and complexity of the system. The accurate percentage of fault categorization in the system is 98.94 % in this procedure.

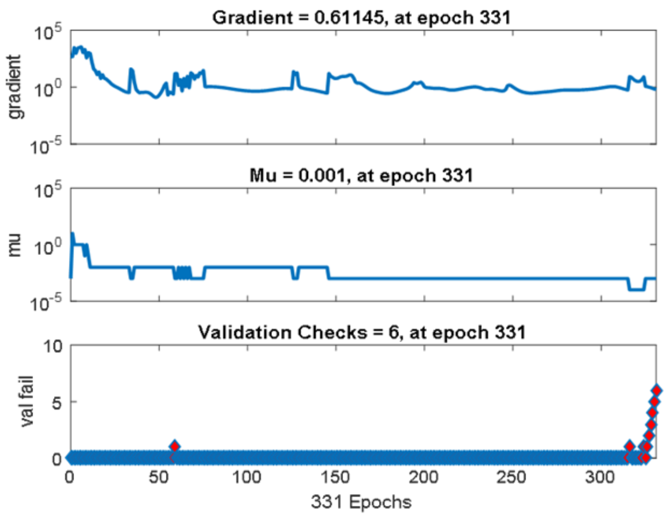

Figure 9. Graph of Gradient and Val-fail w.r.t Epochs

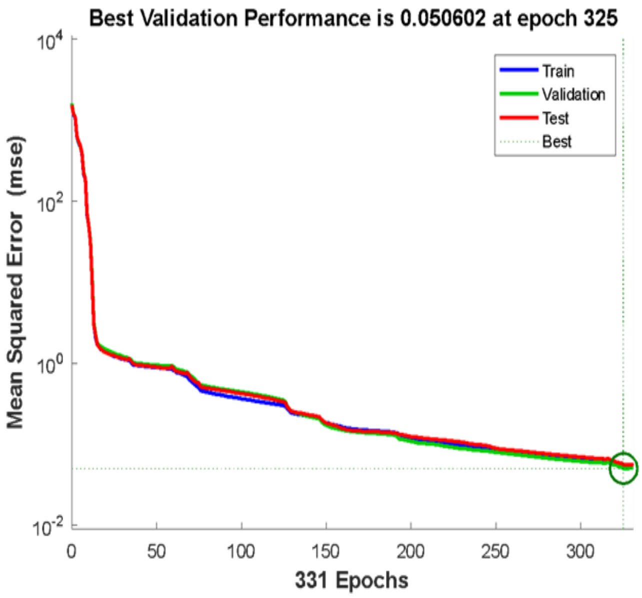

Figure 10. Error value at different epochs (ANN)

The proposed method's fault classification accuracy is compared to that of [34]. The test results are listed in the table below. The comparative table-1 shows that in the same operating state, the proposed method has a higher correct percentage of classification.

Table-1. Comparative result of the proposed method with [34]

	Wavelet Neural Network(WNN)[34]	Artificial Neural Network(ANN)[34]	Proposed Method Using ANN (Case-1)
Correct percentage of classification	96.5%	92.06%	99.43%

6. CONCLUSION

Artificial neural networks are used to classify faults in DG-connected power systems in this work. Because researchers are attempting to detect and diagnose these faults as soon as possible in order to avoid financial losses, this work aims to investigate the sort of fault that happened in the hybrid system. The three-phase voltages and phase currents are extracted from the PCC. The outcomes of the comparison simulations are shown, as well as feature extractions such as standard deviation, mean and skewness. From the features the severity of fault is checked and then the extracted data are used as the inputs to the neural network classifier. Half of the fault data in the whole data set is utilized as training data, while the other half is used for testing. In Wind-PV Hybrid combination, the correct percentage of fault classification in the microgrid is 99.43% where as in Wind-PV-Diesel hybrid combination the correct percentage of classification accuracy is 98.94% using the proposed method. The simulation results were found to prove that adequate performance has been achieved by the proposed method.

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