

Radial Basis Function Neural Network with Wavelet Transform for Power System Fault Identification and Classification

N.Prashanth

Assistant Professor, GITAM Deemed to be University
Department of EEE & Research Scholar, JNTUH
Hyderabad, India
Prashanthkumar0228@gmail.com

Dr. K.Srinivas

Assistant Professor, Department of EEE
JNTUH University College of Engineering Jagityal,
Jagityal, Telangana, India
srinivask@jntuh.ac.in

Abstract

The three-phase fault detection and classification can be done by using radial basis function neural network with wavelet transform can be proposed in this paper. The Discrete Wavelet Transform (DWT) is used in implementation of wavelet approach and the radial basis function neural network (RBFNN) will be utilized to detect and classify different types of faults. This paper mainly focuses on identifying the faults and classification by obtaining detailed co-efficients of different types of faults. The RBFNN is used to overcome the drawback of wavelet transform for detecting and classification of faults. In this paper the concept of wavelet transforms and RBFNN with power system network is verified with MATLAB Simulink. The simulation results are obtained from wavelet transform technique and radial basis function neural network (RBFNN) for three phase fault detection and classification.

Keywords

Wavelet Transform (WT), Radial basis function neural network(RBFNN), Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), Artificial Neural Network (ANN).

1. Introduction

In today's world the continuous requirement of Electrical supply from Electrical power system network is increased with huge demand of various loads. Most of the interacting elements with power system network causes disturbances by creating different types of faults. It is required to identification and classification of different types of faults in three phase system accurately. The faults generally provide the damage to the system with carrying huge amount of current and breakdown of insulation (Stevenson 1982). For reducing breakdown maintenance and revenue losses of industry it is require for accurate measurement of fault identification. For multiclass fault identification sometimes the low cost bi-metal relay, electromagnetic relay, static relay is not suitable (Bhalja and Maheshwari 2006). The general type of faults which will occurring on the transmission lines are like single line to ground fault, double line to ground fault, three phase faults. The faults which are occurring on transmission lines not only damage the equipment and effect the power quality. So that it is required to identify the fault before the damage of equipment. The voltage and current signals associated with numerical relay are operated based on signal conditioning like filtering, sampling depends on the components available in the relay systems (Sybille et al.2000).

The three main parts of power system is generation, Transmission, and distribution of power to the various consumers. The major faults are generally existing in transmission lines. There is huge requirement for immediate fault detection for uninterruptable power transmission and distribution. For reliable power supply to the consumer, it is required to facilitate power system maintenance and protection against faults. The most practiced method is using

relay to detect the fault location and isolate the system. In recent research studies focusing on several fault detection methods to check the performance of speed at which the fault is detected and accurately locating the fault zone. The distance between fault location and relay should be determine in the fault zone. The importance is given to speed of operation for detecting fault location by using several methods of fault detection. When a fault exists in a power system, the variable of current, voltage, power, impedance, and frequency will change. Many of the fault detection methods comparing the post fault values with fault during the normal operation. Some of the methods using the Kalman filter, first derivative method, Fourier transform (FT) and least squares. Some other methods are based on differential equations, travelling waves, phasor measurement, Discrete wavelet transform (DWT), fuzzy logic, genetic algorithm, and artificial neural networks. In this paper, two methods are presented for identification and classification of three phase faults. A discrete wavelet transform approach and radial basis function neural network can be used to analyse three phase faults by considering suitable power system network.

2. Literature Review

The applications of artificial neural network in power system have been increasing during 1990. Many of the Artificial intelligence methods are identified for fault analysis (Kezunovic et al.1997). A new approach to the fault detection and classification for complex transmission lines can be analysed with help of fuzzy neuro techniques and different neural network models are presented in (Wang and Keerthipala 1998).However, there are still problems with implementation of hardware such as lack of good analog memories and limited interconnections. The traditional based signal analysis technique of Fourier transform not quite efficient because of fault signals has nature of non-stationary transient signals. The wavelet transform can investigate the transient based signals in power system(Jiang et al.2000). The wavelet transform method is effective in detecting transient nature of fault signals. The DWT integrated with fuzzy logic systems are utilized to detect the fault location and classification (Pradhan et al.2004).

Now a days most of the methods have been adopted to apply these signal conditioning process such as Neural networks, Fuzzy logic, Fourier transform, and wavelet transform for analysing the signal in both frequency and time domains. This will help in efficiently for determining the faults identifications and classifications with help of updated algorithms. The wavelet transform is the well-known developed tool for signal processing analysis in most of the applications. This wavelet theory is deals with processing of non-stationary signals by using set of small signals called wavelet signals (Isasare T.V. and MajumdarD. D. 2016). The DWT is used compared to the CWT because of computational burden with CWT. The wavelet transform will overcome the shortcomings of Fourier and window-based Fourier signals with association of non-stationary signals. The wavelet transform will analyse the signal at good time resolution at high frequency signals and having good frequency resolution at low frequency signals and the wavelet transform method is more suitable for analysing power signal analysis. An artificial neural network is described as the set of elementary neurons are connected biological inspired architecture which arranged in several layers. This paper is mainly focus on extraction of signal by using discrete wavelet analysis and apply one of the types of ANN based method to detect and classify the different types of faults(Ahmed Elnozahy et al.2019). This paper will explain about the radial basis function neural network can be used with wavelet transform to classify different types of faults.

ANN based methods have been used in power system network and the results are getting near to the desirable values. The wavelet analysis used to find detailed coefficients of signal and determine the classification of different faults. ANN can be considered as weighted directed graphs and it has artificial neurons are nodes and directed with weights are connected between neuron inputs and neuron outputs (Zhou et al.1994). The ANN Network can be grouped into two categories which are depends on network pattern. The first one is feed forward network generally this network graphs not having any loops and the second one is recurrent networks this network graphs generally having loops because of closed loop connections. In the understanding process, the ANN can be able to automatically understand from the examples makes its exciting and attractive. This learning capability is the advantage of ANN. The comparison with radial basis function network with established multilayer perceptron is the learning scheme of regular multilayer perceptron consists of the process of unrestrained nonlinear least squares optimization but whereas radial basis function network has single layer of adjustable to evaluate according to linear optimization techniques (Adnan Hamad et al.2010).

The neural networks-based methods have been developed and applied to several fields successfully. Back propagation neural network is one of the types of neural network which widely used for many applications because of its own effectiveness to solve different number of problems. The drawback of this Back propagation neural network partly limited by slow training performance. The radial basis function neural network is most used type feed-forward

network as well as back propagation neural network. The RBFNN is one of the best methods in neural networks which has special activation function such as Gaussian function or inverse multi quadratic function which makes it universal approximation and fast learning algorithm (Kumar et al. 2017). The RBFNN has quick concurrence and simple network structure, and it can adapt and adjust time varying functions successfully (Saravanan and Ramesh babu, 2016).

3. Methods

3.1 Wavelet Transform Analysis

The real-world signals in power system analysis are frequently exhibit slowly changing trends or oscillations with punctuated transients. The voltage and current waveforms are having nature of abrupt changes in terms of its time and frequency. To accurately analyze signals that have undefined changes, it required to use better class of functions that has clear identification of frequency and time. This requirement will introduce the knowledge of Wavelet analysis (Gaurav Kapoor 2018). A wavelet is a continuous changing wave like oscillation which has zero mean. Only in finite duration the wavelet will exist. Wavelets can have different sizes and shapes. The advantage of wavelet is it can be available with different pattern for suitable transients. The wavelet can be described as small wave, small in the sense of having short duration along with finite energy which integrates to zero, so that it is suitable for transient analysis. The wavelets can be able to focus on short time intervals for high frequency components whereas long term intervals for low frequency components to improve the analysis of signals with impulse oscillations. The Wavelets are more suitable for signals data having sharp discontinuities. The wavelet analysis can be applied by using mother wavelet for suitable application. The mother wavelet must be chosen in such a way to analyze the system in terms finding coefficients to get real time data. The following (see Figure 1) are different types of wavelets which can be used as mother wavelets (Kim and Aggarwal 2000).

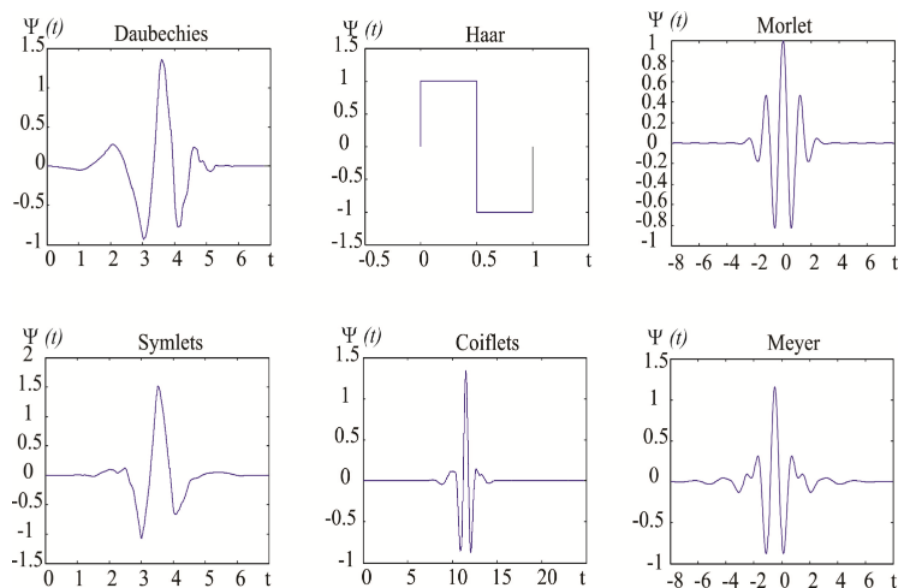


Figure 1. Different types of Mother wavelets

For identification and classification of fault analysis the Daubechies wavelet used as mother wavelet where it can be more suitable for analyzing different types of fault analysis in power system.

For the signal $f(t)$ the continuous wavelet transform with mother wavelet of $\psi(t)$ can be represented as

$$F(a, T) = \frac{1}{\sqrt{a}} \int f(t) \psi * \left(\frac{t-T}{a} \right) dt$$

In the above equation of CWT, a is the scale of the wavelet in frequency axis. In case of wavelet transform analysis, the mother wavelet needs to choose for most of the applications unlike Fourier transform. Most of the engineering applications are preferred to use Discrete wavelet transform can able compared with Continuous wavelet transform because CWT has more computational burden and required more memory. The discrete wavelet transform (DWT) of signal can be represented as

$$DWT[m, k] = \frac{1}{\sqrt{a_0^j}} \sum_{n=0}^{N-1} f[n] \varphi\left(\frac{k - na_0^j}{a_0^j}\right)$$

In the above equation $\varphi(n)$ is called as mother wavelet and DWT can be implemented in multiresolution analysis. In multiresolution analysis the signal can be decomposed into several levels by using high pass \bar{g} and low pass \bar{h} filters. The final output of low pass filter will generate approximation coefficients and high pass filter will generate detailed coefficients. The frequency of the signal will change after crossing different levels of decomposition and same signal will be reconstructed by using the filters (Saurabh kamble and Ishita dupare 2014). The following (see figure 2) will show the example of multiresolution analysis.

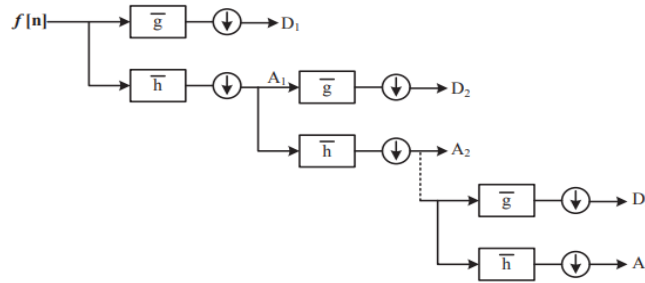


Figure 2. Multiresolution Analysis

3.1.1 Implementation Of Wavelet Transform in Power System Network

The wavelet transform can be used in simple power system network for classification of different types of faults. Initially simple power system network can be implemented in MATLAB Simulink and the fault currents will be detected by using wavelet transform. The MATLAB Simulink diagram for power system network as shown below.

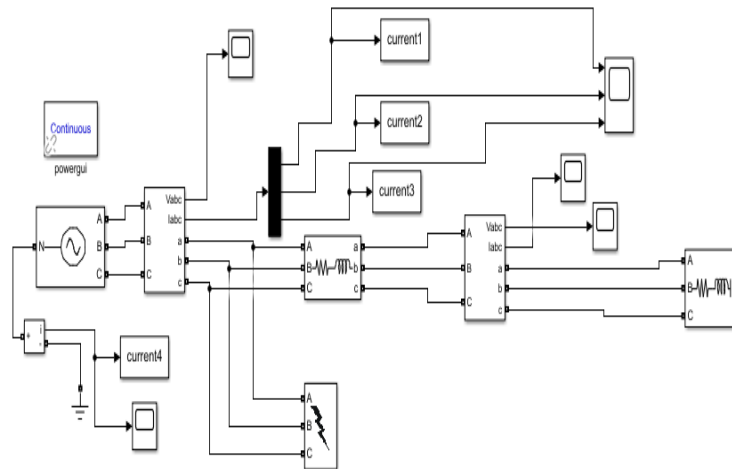


Figure 3. MATLAB Simulation diagram of power system network

In the above MATLAB Simulation (Figure 3), all the three phase currents are represented separately with help of demultiplexer. In addition to neutral current, all the three phase currents are connected to the workspace block and these currents can easily Applied with wavelet transform in workspace. The Daubechies wavelet 4 is used in this MATLAB programming. This wavelet transform can be applied to this power system network by writing programme on the workspace with following steps:

Step1: Assign the command to load the simulation

Step2: Simulate the respective simulation block

Step3: Load the phase currents and neutral current

Step4: Apply the following command of wavelet decomposition for each phase and neutral current

[c, l] = wavedec (x, n, wname);

Where, wavedec =function which decompose the signal

X= signal

N= wavelet layer (default =1)

wname= name of the wavelet type

c = output wavelet decomposition vector

l = number of coefficients by level

Step 5: obtain the detailed coefficients of the phase currents and neutral current by using following syntax

D = detcoef (C, L, N);

Where C = output wavelet decomposition vector

L = Number of coefficients by level

N = Wavelet layer

D = Extracts the detail coefficients at the coarsest scale from the wavelet decomposition structure [C, L]

Step 6:Obtain the maximum value of each coefficient

After obtaining maximum value of each coefficient will indicate the value of each phase currents and neutral currents. The main strategy of this concept is when the fault is applied any one of the phases that fault current should have maximum value of current and other non-fault currents having minimum or zero value. The maximum value of detailed coefficients of all phases and ground current for different faults are shown (see Table 1).

Table 1. detailed coefficients of all phases and ground current for different faults

TypeofFault	Max.coefficient of Phase ACurrent	Max.coefficient of Phase BCurrent	Max.coefficient of Phase C Current	Max.coefficient of GroundCurrent
ThreephasetogroundFault	1.6097e+07	4.0725e+07	1.6097e+07	7.1824e+05
ThreephaseFault	1.6097e+07	4.0725e+07	1.6097e+07	0.0081
DoubleLinetoGroundFault(AB-G)	1.0796e+07	2.1332e+07	103.9772	7.7574e+05
DoubleLinetoGroundFault(AC-G)	1.9807e+07	103.9772	8.6730e+06	1.9393e+06
DoubleLinetoGroundFault(BC-G)	103.9784	4.0725e+07	8.1478e+06	9.7619e+05
LinetoLine(A-B)Fault	1.0794e+07	2.0363e+07	103.9772	0.0087
LinetoLine(A-C)Fault	2.0363e+07	103.9772	8.6153e+06	0.0204
LinetoLine(B-C)Fault	103.9784	4.0725e+07	7.2573e+06	0.0100
SingleLinetoGroundFault(A-G)	1.3523e+06	103.9772	103.9772	1.6087e+06
SingleLinetoGroundFault(B-G)	103.9784	3.7024e+06	134.3960	1.1253e+06
SingleLinetoGroundFault(C-G)	103.9784	103.9772	1.4099e+06	3.7023e+06
SystemwithoutFault	103.9784	103.9772	103.9772	7.1737e-10

From the Table 1 it is observed that all the types of faults in phases will have higher coefficient values whereas the phase currents which not having any fault will have very small value. The maximum value of phase current which not having any fault is equal to 134.39 A. It is observed that the faults can be distinguished with the help of standard reference value of current can be compared with all phase currents. If the value of phase currents greater than 200 A then the fault exists in those phases and can easily distinguish the faults. From the above condition can be implemented in the MATLAB programme which can identify and classification of different types of faults.

The wavelet transform based classification depends on the threshold value of the power system. In this paper the power system threshold value is chosen as 200. But this value is not generalized and not applicable for same power system network which having different voltages, distance of transmission line, power capacities and fault resistance. It means that for every new power system network, this threshold value will be determined again in order successful classification and identification of faults. This limitation can be overcome by using computational intelligent

techniques such as artificial intelligent techniques and its types. In this paper it is focusing on one of the types of artificial intelligence technique is Radial basis function neural network (RBFNN) for identification and classification of faults. This RBFNN method is not depends on various threshold value for identification of different types of faults.

3.2 Fault Detection with RBFNN

The radial basis function networks are having different architecture than most neural network architectures. Most of the neural network architectures are having many layers and introduce nonlinearity by repetitively applying nonlinear activation functions. The RBF networks on other hand consists of only an input layer, a single hidden layer, and an output layer. The input layer simply feeds the data to the hidden layers and the hidden layer takes the input in which the pattern might not be linearly separable and transform it into a new space that is more linearly separable. The output layer uses a linear activation function for both classification or regression tasks.

3.2.1 Radial Basis Function Neural Network

The radial basis Neural networks are more suitable for identifying and classification of faults in power system (Giveki et al.2018). The RBFNN is mainly focused and depends on theory of function approximation (Sadeghkhanian et al. 2012). The Radial basis network has two-layer feed forward networks (Figure 4). The radial basis functions in the hidden networks are used as Gaussian Function (Dash et al.2001). The network training can be divided in to two stages. The weights can determine from layers of input to hidden in primary stage and secondary stage will have weights in the layers of hidden to output side (Karayiannis 1997).

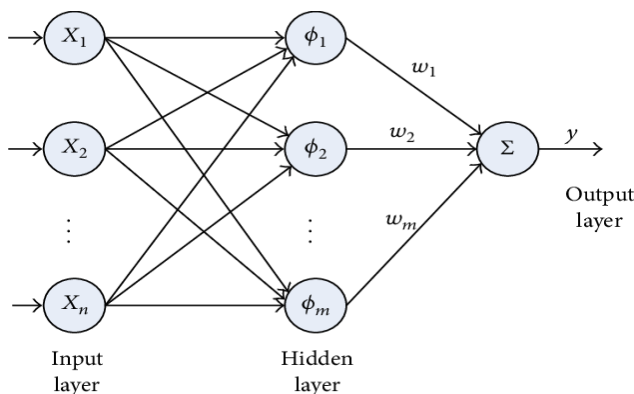


Figure 4. Architecture of RBF Network

3.2.2 Fault Analysis with Radial Basis Function Neural Network

Accuracy of the artificial intelligence will be depending on Input and Output data and noted that larger the data will give larger the accuracy. To apply this RBFNN for any power system network it is required determine coefficients of all the phase currents and neutral currents by using wavelet transform method. The coefficients of all the phase and neutral currents are the input data for this method. For getting better accuracy it is required take more data from different cases in power system network. The more input data can be determined by changing fault ground resistance and changing the condition of applying fault at before the transmission line and after the transmission line.

In this paper larger input data has been generated which is nearly equal to 138 different cases of data. To classify all the type of faults it is required to have output signal for each phase current and neutral current. The four output variables are chosen at the output. The zero (0) value is assigned for the currents does not have any fault and value one (1) is assigned for currents which are subjected to the faults to distinguish between faults. The following (Table 2) will show the input and output data of RBFNN.

Table 2. Input And Output Data Of RBFNN

SI.No	Type of Fault	Max. coefficient of Phase A Current	Max. coefficient of Phase B Current	Max. coefficient of Phase C Current	Max. coefficient of Ground Current	Output Value for Phase A	Output Value for Phase B	Output Value for Phase C	Output Value for Ground Current
1	ABC-G Fault	1.6097e+07	4.0725e+07	1.6097e+07	7.1824e+05	1	1	1	1
2	ABC Fault	1.6097e+07	4.0725e+07	1.6097e+07	0.0081	1	1	1	0
3	AB-G Fault	1.0796e+07	2.1332e+07	103.9772	7.7574e+05	1	1	0	1
4	AC-G Fault	1.9807e+07	103.9772	8.6730e+06	1.9393e+06	1	0	1	1
5	BC-G Fault	103.9784	4.0725e+07	8.1478e+06	9.7619e+05	0	1	1	1
6	A-B Fault	1.0794e+07	2.0363e+07	103.9772	0.0087	1	1	0	0
7	No Fault	103.9784	103.9772	103.9772	7.1737e-10	0	0	0	0
8	B-C Fault	103.9784	4.0725e+07	7.2573e+06	0.0100	0	1	1	0

The total input and output data can be used to divide into the two categories. One is training data and another one testing data and most of the cases 70 % data can be used for training data and 30 % will be used for testing data. When arranging the training and testing data for any application it is required to have both training and testing data has some close relation then only the accuracy will be increases. The 108 cases of data randomly chosen for training purpose and 30 cases of data chosen for testing purpose. Initially load the input and output, testing data into the workspace. To apply radial basis function neural network for training the data MATLAB program is developed by following steps:

Step 1: Assign the input command

Step 2: Assign the output command

Step 3: set the goal

Step 4: Set the value of spread factor

Step 5: use the following command to apply radial basis Function

net = newrb (input, output, goal, spread) ;

After following the above steps and implemented in program the data has been trained for chosen cases. The testing data can also be done using Radial basis function neural network with following steps:

Step 1:load the testing data

Step 2: simulate the data testing command

Step 3: Arrange the data in required order

After completing testing procedure, the testing data will provide result which almost like the training data and matching with input and output data. The following table will show the comparison of RBFNN output results with actual output values. The following (Table 3) will show that RBFNN output is almost similar results of actual output.

Table 3. RBFNN output results with actual output values

S. No.	Type of Fault	Actual Output Value for Phase A	Actual Output Value for Phase B	Actual Output Value for Phase C	Actual Output Value for Ground Current	RBFNN Output for Phase A	RBFNN Output for Phase B	RBFNN Output for Phase C	RBFNN Output for Ground Current
1	ABC-G Fault	1.6097e+07	4.0725e+07	1.6097e+07	7.1824e+05	1	1	1	1
2	ABC Fault	1.6097e+07	4.0725e+07	1.6097e+07	0.0081	1	1	1	0
3	AB-G Fault	1.0796e+07	2.1332e+07	103.9772	7.7574e+05	1	1	0	1
4	AC-G Fault	1.9807e+07	103.9772	8.6730e+06	1.9393e+06	1	0	1	1
5	BC-G Fault	103.9784	4.0725e+07	8.1478e+06	9.7619e+05	0	1	1	1
6	A-B Fault	1.0794e+07	2.0363e+07	103.9772	0.0087	1	1	0	0
7	No Fault	103.9784	103.9772	103.9772	7.1737e-10	0	0	0	0
8	B-C Fault	103.9784	4.0725e+07	7.2573e+06	0.0100	0	1	1	0

1	ABC-G Fault	1	1	1	1	1.0000	1.0000	1.0000	1.0000
2	ABC Fault	1	1	1	0	1.0000	1.0000	1.0000	-0.0000
3	AB-G Fault	1	1	0	1	1.0000	1.0000	-0.0000	1.0000
4	AC-G Fault	1	0	1	1	1.0000	-0.0000	1.0000	1.0000
5	BC-G Fault	0	1	1	1	-0.0000	1.0000	1.0000	1.0000
6	A-B Fault	1	1	0	0	1.0000	1.0000	-0.0000	-0.0000
7	A-C Fault	1	0	1	0	1.0000	0	1.0000	-0.0000
8	B-C Fault	0	1	1	0	-0.0000	1.0000	1.0000	0
9	A-G Fault	1	0	0	1	1.0000	-0.0000	-0.0000	1.0000
10	B-G Fault	0	1	0	1	-0.0000	1.0000	-0.0000	1.0000
11	C-G Fault	0	0	1	1	-0.0000	-0.0000	1.0000	1.0000

4. Conclusion

The implementation of wavelet transform for classification and identification of faults in power systems has been discussed in this paper. The performance of wavelet transform with fault analysis mainly depends on its threshold value, but this value is not same for different power system networks, and it is required to determine separate threshold value for respective power system network. This drawback can be overcome by using Radial Basis Function neural network. The analysis of RBFNN also presented in this paper. The RBFNN will not depend on any threshold value for classification and identification of faults in the power system. The RBFNN requires a large amount of input and output data for training and testing to get better accuracy.

References

- Bhalja B. and Maheshwari R. P., Wavelet transform based differential protection scheme for tapped transmission line, *Proceeding of the IEEE International Conference on Industrial Technology*, pp. 1004-1008, 2006.
- Adnan Hamad, Dingli Yu1, J. B. Gomm and Mahavir S. Sangha, Radial basis function neural network in fault detection of automotive engines, *International Journal of Engineering, Science and Technology* Vol. 2, No. 10, pp. 1-8, 2010.
- Gaurav Kapoor, Wavelet transform based fault detector for protection of series capacitor compensated three phase transmission line, *International Journal of Engineering, Science and Technology*, Vol. 10, No. 4, pp. 29-49, 2018.
- Gholam Ali Montazer Davar Giveki, Maryam Karami and Homayon Rastegar, Radial Basis Function Neural Networks: A Review, *Computer Reviews Journal* Vol 1, No 1, ISSN: 2581-6640, 2018.
- Ahmed Elnozahy, Khairy Sayed and Mohamed Bahyeldin, Artificial Neural Network Based Fault Classification and Location for Transmission Lines, *IEEE Conference on Power Electronics and Renewable Energy (CPERE)*, 2019.
- Saurabh Kamble, Ishita Dupare, Detection of Power Quality Disturbances Using Wavelet Transform And Artificial Neural Network, *International Conference on Magnetics, Machines & Drives*, 2014.
- Isasare T.V., Majumdar D. D., Application of Wavelet Transform in Power System, *International Journal of Engineering Research & Technology (IJERT)*, ISSN: 2278-0181, IC-QUEST, 2016.
- Sadeghkhani I., Yazdekhashti A., Mortazavian A., and Haratian N., Radial basis function neural network based approach to estimate transformer harmonic overvoltages, *Advances in Computer Science and its Applications*, vol. 1, no. 1, pp. 38-44, 2012.

- Sybille, G., Brunelle, P., Hoang, L., Dessaint, L.A., and K. Al-Haddad, Theory and applications of power system blockset, a MATLAB/Simulink-based simulation tool for power systems, in *Proceedings of the IEEE Power Engineering Society Winter Meeting*, vol. 1, pp. 774–779, 2000.
- Dash, P.K., Pradhan, A.K., and Panda, G., Application of minimal radial basis function neural network to distance protection, *IEEE Transactions on Power Delivery*, vol. 16, no. 1, pp. 68–74, 2001.
- Zhou, Q., Davidson, J. and Fouad, A.A., Application of artificial neural networks in power system security and vulnerability assessment. *IEEE Transactions Power Systems*, 1994.
- Stevenson, W.D., Elements of power system analysis. 4th edition. McGraw-Hill, 1982.
- Karayiannis, N.B., Growing radial basis neural networks: merging supervised and unsupervised learning with network Growth techniques. *IEEE Trans Neural Networks*, 1997.
- Kumar, K., Ramesh Babu, N., and Prabhu, K.R., Design and Analysis of RBFN-Based Single MPPT Controller for Hybrid Solar and Wind Energy System, *IEEE Access*, Volume-5, pp. 15308-15315, 2017.
- Saravanan, S., Ramesh Babu, N., RBFN based MPPT algorithm for PV system with high step-up converter, *Energy Conversion and Management*, Volume-122, pp.239-251, 2016.
- Kezunovic, M., Rikalo, I. and Sobajic, D.J., High-speed fault detection and classification with neural network, *Electric Power System Research*, vol.34, pp.109-116, 1995.
- Wang, H., Keerthipala, W.W.L., Fuzzy-neuro approach to fault classification for transmission line protection. *IEEE Transaction on power system protection*, Volume-3, Issue-4, pp.1093-1104, 1998.
- Jiang, Z.Q., Bo, F., Chen, v., Dong, X.Z., Weller, G., and Redfern, M.A., Transient based protection for power transmission systems, *Proceedings of the IEEE Power Engineering Society Winter Meeting*, PP. 1832-1837, 2000.
- Pradhan, A.K., Routray, A., Pati, S. and Pradhan, D.K., Wavelet fuzzy combined approach for fault classification of a series compensated transmission line, *IEEE Trans. On Power Delivery*, vol.19, no.4, pp.1612-1618, 2004.
- Kim, C.H., and Aggarwal, R., Wavelet transforms in power systems part 1: General introduction to the wavelet transforms, *Power Engineering Journal*, volume-14, Issue-2, pp. 81-88, 2000.

Biographies

N. Prashanth received his B-Tech degree in Electrical and Electronics Engineering from Jyothishmathi Institute of Technology and Science, Karimnagar, Jawaharlal Nehru Technological University, Hyderabad in 2008. Obtained M-Tech Degree from Kalinga Institute of Industrial Technology (KIIT) University, Odisha, India in 2010. Currently working as Assistant professor in Department of Electrical and Electronics Engineering, GITAM Deemed to be University, Hyderabad and research scholar in Jawaharlal Nehru Technological University, Hyderabad. His field of interest include Multilevel Inverters, Power Quality and Power electronics control in power systems.

Dr K. Srinivas received the B.E. degree in Electrical and Electronics Engineering from Chaitanya Bharathi Institute of Technology and Science, Hyderabad, Osmania University, Hyderabad, India, in 2002, M.Tech. Degree in power systems and Power Electronics from Indian Institute of Technology, Madras, Chennai, in 2005, Ph.D. from Jawaharlal Nehru Technological University Hyderabad. Currently working as an Assistant Professor and Head Department of Electrical and Electronics Engineering, Jawaharlal Nehru Technological University Hyderabad University College of Engineering Jagityal. His fields of interest include power quality and power-electronics control in power systems.