Radial Basis Function Neural Network with Wavelet Transform for Fault Detection in Transmission Line

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Abstract Incipient faults which occur due to the electrical arc occurrence within the facility cables which have insulation problems are hard to detect by normal protective relays, and with passing time can become a permanent fault within the system. Employing Radial Basis Function Neural Network (RBFNN) method, the paper puts forward the method to detect the faults and finding out the efficiency and advantages of RBFNN method over other methods within the facility grid. The result proposed in this paper is based on the differentiation between the wavelet transform method and RBFNN method of the measured voltage and fundamental component of the measured voltage, evaluated by RBFNN computation within the sending end of the cable during the fault using which the incipient fault is detected. This method uses neurons to train the model and increase its accuracy so that with new data set, it can produce super accurate and faster results.

1 Introduction

The protection of power networks from unpredictable events as well as boosting their reliability in solid performance has always been a critical concern in the end-to-end delivery of energy [1]. In this situation, removing potential mistakes can go a long way toward preventing similar unpleasant incidents and so preserving the power system's reliability [2]. Electrical arcing in sections of electrical wires with closure abnormalities is most likely to blame for the first faults. Re-emerging with an

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equally elevated aspect of frequency occurring, initial errors over time can damage cable overhaul and can become a permanent flaw in the system. As a result, a precise system is crucial for rapid detection and detection of a recent fault in the system among comparable possible events [3]. Nascent defects are most noticeable in their short duration, as well as low electrical amplitude compared to other system defects, considering which conventional protective transmission can detect these errors [4]. The nascent flaw is recalled by a distorted waveform, similar to square surgery, rather than an error. With the detection of emerging errors, a permanent network error can be predicted [1]. Radial basis work networks are often used by the ANN type for performance measurement problems [5]. RBFNN is differentiated from other neural networks due to its better speculation and faster learning speed. The RBFNN-dependent model [1] uses the output data of the model simulated data as a target and then [6] trains the neural network using it [7]. In Sect. 2, the simulation behind the sensing and categorization in case of [8] wavelet-based transmission line fault is briefly discussed. Further, to overcome the constraints of this method, RBFNN has been proposed in Sect. 3. Its detailed methodology followed by experimental results has been briefly mentioned in Sect. 4. At last, in Sect. 5, the research has been concluded.

2   Wavelet-Based Transmission Line Fault Detection

Electromagnetic transients in energy systems are characterized by the most common short-term factors, such as errors, which are very important. These defects cause serious damage to the electrical system and the problem. Therefore, there is a need to find the error, its type, where it is formed in the line as well as to rectify the error at the earliest so as not to cause the same damage [9]. Wavelet modification is largely created by this strategy, which could be effectively implemented by using two filters HP and LP [10]. HPF was derived after applying the wavelet function while the measured details of the input with the LPF, which brings a smooth translation of the input signal and is taken from the mathematical function associated with the prominent mother wavelet. In this analysis, the results are controlled using db4 as the mother wavelet (prime wavelet) for signal analysis [1]. Basic electrical power and current phasors are calculated using an algorithm based on [11] discrete Fourier transform that minimizes the effects of DC decay significantly. The system is modeled on the MATLAB SimPowerSystems site. The results shown in the proposed system are secure, fast, and very accurate. The frequency has been set to 50 Hz with voltage of 220 V and transmission line of length 120 km. Making amplification of current signals using a threshold power level, the primary power of all current signals by keeping the balance without change to calculate the limit of the change in power, if any power exceeds this level, this means that there is an error condition at that section of the line [12]. The error is generated by selecting combination of different phases of lines from fault generation box (Fig. 1).
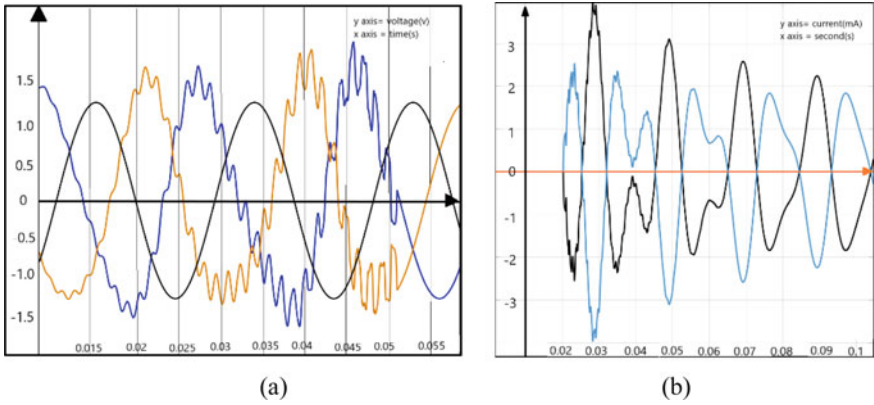
Fig. 1 a Voltage output waveform, **b** current output waveform

3   Radial Basis Function Neural Network (RBFNN)

RBFNNs are used to compare advanced functions straight from output data to a simple topology [1]. They have a better overall performance compared to most neural feed-forward networks. The most widely used basic function is the Gaussian exp function. In successional learning, the neural network is trained to measure activity while a sequence of training sample dice is randomly drawn, introduced into a network and are read by each network [13]. RBFNN has a special two-layered structure one hidden layer and one output. The input layer does not process the information; it only works to distribute input data between nodes. Each node in the hidden layer is an RBF [1]. The output from jth Gaussian node of the x_i input object is calculated, where the vector x_i captures the ith input data, and vector c_j represents the central point of the jth Gaussian function. $\|x_i - c_j\|$ is the calculated [6] Euclidean distance, and width σ is a criterion that controls the smoothness of the function. The output is calculated by a combination of linear radial functions and bias w_0 [7].

4   Experiment and Result

Accuracy of artificial neural network depends upon the input and output data. Larger the data, higher will be the accuracy and vice-versa. The simulation is run for 138 times. The maximum coefficient of all simulations is stored in form of a table. In order to classify all types of faults, we need output signal for each phase current as well as for ground current. There are 4 variables which represents phase A, B, C, and ground. In normal condition, the output is encountered as "0" and during fault it is "1" (Table 1).

Table 1 Maximum coefficient of different phases in different types of faults

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
ABC-G	1.6097e+07	4.0725e+07	1.6097e+07	7.1824e+05
ABC	1.6097e+07	4.0725e+07	1.6097e+07	0.0081
AB-G	1.0796e+07	2.1332e+07	103.9772	7.7574e+05
AC-G	1.9807e+07	103.9772	8.6730e+06	1.9393e+06
BC-G	103.9784	4.0725e+07	8.1478e+06	9.7619e+05

We have obtained 138 cases by applying all 12 fault conditions before the transmission line as well as after the transmission line position and by changing the fault ground resistance in the form of a table as shown here (Table 2).

Normal output condition is represented by assigning "0" and that of fault condition is represented by "1". At this stage, we have defined the input and output data for the RBFNN. We have a total of 138 cases. The normal proportion for division of data into training and testing is 70% and 30%, respectively. However, as a rough estimate, we have chosen 30 cases for testing purpose and remaining 108 cases for training purpose. After successful training, the performance of the RBFNN is tested for these unseen 30 cases. If neural network classifies correctly, its efficiency will be 100% (Table 3).

Table 2 Output values of different phases in different types of faults

Type of fault	Output value for phase A	Output value for phase B	Output value for phase C	Output value for ground current
ABC-G fault	1	1	1	1
ABC fault	1	1	1	0
AB-G fault	1	1	0	1
AC-G fault	1	0	1	1
BC-G fault	0	1	1	1

Table 3 Comparison of RBFNN output with actual output

Type of fault	Actual output value for phase A	Actual output value for phase B	Actual output value for phase C	RBFNN output for phase A	RBFNN output for phase B	RBFNN output for phase C
ABC-G	1	1	1	1.0000	1.0000	1.0000
ABC	1	1	1	1.0000	1.0000	1.0000
AB-G	1	1	0	1.0000	1.0000	−0.0000
AC-G	1	0	1	1.0000	−0.0000	1.0000
BC-G	0	1	1	−0.0000	1.0000	1.0000

Fig. 2 Performance of
RBFNN training data
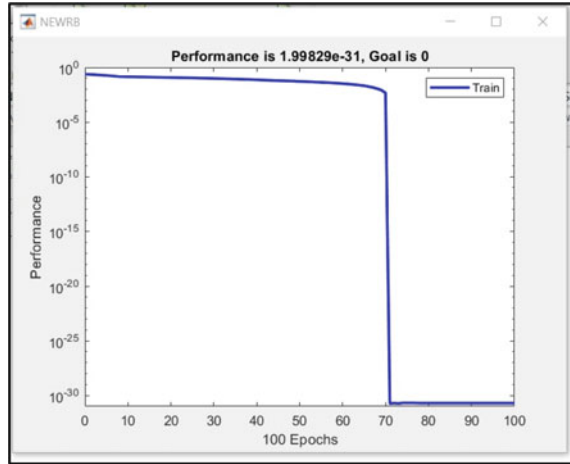
RBFNN has provided the output of all 30 cases, which was compared with the actual output of all the 30 cases (Fig. 2).

Radial basis function neural network is very fast and has completed its training within short period of time. With 100 neurons, it has provided highest successful training with error equal to 1.99829e−31.

5 Conclusion

RBFNN has successfully and accurately detected the output of all the 30 cases. This shows that it has accuracy of 99.16%. RBFNN is much faster from the traditional wavelet method. Wavelet transform depends on the threshold value to classify the different types of faults in power system, which is not generalized and cannot be used for all types of power system, leading to lack of directional selectivity. Therefore, to overcome this limitation, RBFNN method has been used. We can see this from the graph where 108 cases have been trained in very short period of time.

References

1. Ray P, Mishra DP, Budumuru GK (2016) Hybrid technique for underground cable to locate the fault. In: 2016 International conference on information technology (ICIT), pp 235–240. https://doi.org/10.1109/ICIT.2016.055
2. Sudhir KS (2013) Wavelet based fault detection & ANN based fault classification in transmission line protection scheme. Int J Eng Res Technol 2(5):1492–1500
3. Kirubadevi S, Sutha S (2017) Wavelet based transmission line fault identification and classification. In: 2017 International conference on computation of power, energy information and communication (ICCPEIC). IEEE

4. Rao YS, Kumar GR, Rao GK (2017) A new approach for classification of fault in transmission line with combination of wavelet multi resolution analysis and neural networks. Int J Power Electron Drive Syst 8(1):505
5. Jin N, Liu D (2008) Wavelet basis function neural networks for sequential learning. IEEE Trans Neural Netw 19(3):523–528
6. Ray P, Mishra DP, Dey K, Mishra P (2017) Fault detection and classification of a transmission line using discrete wavelet transform & artificial neural network. In: 2017 International conference on information technology (ICIT), Bhubaneswar, pp 178–183. https://doi.org/10.1109/ICIT.2017.24
7. Ray P, Mishra DP, Panda DD (2015) Hybrid technique for fault location of a distribution line. In: 2015 Annual IEEE India conference (INDICON), New Delhi, pp 1–6. https://doi.org/10.1109/INDICON.2015.7443134
8. Ren S, Gao L (2009) Linking direct orthogonal signal correction and wavelet transform with radial basis function neural network to analyze overlapping spectra. In: 2009 Second international workshop on knowledge discovery and data mining. IEEE
9. Mishra DP, Ray P (2018) Fault detection, location and classification of a transmission line. Neural Comput Appl 30:1377–1424
10. Sidhu TS, Xu Z (2010) Detection of incipient faults in distribution underground cables. IEEE Trans Power Deliv 25(3):1363–1371
11. Borghetti A, et al (2008) Continuous-wavelet transform for fault location in distribution power networks: definition of mother wavelets inferred from fault originated transients. IEEE Trans Power Syst 23(2):380–388
12. Baqui I et al (2011) High impedance fault detection methodology using wavelet transform and artificial neural networks. Electr Power Syst Res 81(7):1325–1333
13. Lin Y, Wang FY (2005) Modular structure of fuzzy system modeling using wavelet networks. In: Proceedings. 2005 IEEE networking, sensing and control. IEEE