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A Comparison Study of Learning Algorithms for Estimating Fault Location

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Abstract

Fault location is one of the important schemes in power system protection to locate the exact location of disturbance. Nowadays, artificial neural networks (ANNs) are being used significantly to identify exact fault location on transmission lines. Selection of suitable training algorithm is important in analysis of ANN performance. This paper presents a comparative study of various ANN training algorithm to perform fault location scheme in transmission lines. The features selected into ANN is the time of first peak changes in discrete wavelet transform (DWT) signal by using faulted current signal acted as traveling wave fault location technique. Six types commonly used backpropagation training algorithm were selected including the Levenberg-Marquardt, Bayesian Regulation, Conjugate gradient backpropagation with Powell-Beale restarts, BFGS quasi-Newton, Conjugate gradient backpropagation with Polak-Ribiere updates and Conjugate gradient backpropagation with Fletcher-Reeves updates. The proposed fault location method is tested with varying fault location, fault types, fault resistance and inception angle. The performance of each training algorithm is evaluated by goodness-of-fit (R^2), mean square error (MSE) and Percentage prediction error (PPE). Simulation results show that the best of training algorithm for estimating fault location is Bayesian Regulation (R^2 = 1.0, MSE = 0.034557 and PPE = 0.014%).

Keywords: *fault location; discrete wavelet transform (DWT); artificial neural network (ANN)*

1. Introduction

Providing sufficient and uninterrupted power supply is the main focus in power system. The transmission lines has been primary concern due to it clearly exposed into fault that could happen randomly because of uncontrollable by human being such as tree falls, lightning strike and any abnormal flow of current in power system's component (1). Hence, it is important to have well-coordinated protection system by determine the location of fault occurs to have quick response for necessary repair. Once a fault is located, the circuit breaker could isolate the faulty part to maintain power system stability. At the mean time improve the reliability, service restoration; reduce outage time, operating cost and customer satisfaction.

Many researchers explored method for fault location either using conventional method or combination with other method to have better fault location scheme. In recent years, most researchers developed fault location scheme by combination of conventional method whether impedance-based or travelling wave method with ANN to achieve greater efficiency in fault location scheme. ANN did not only used in power system application since it has good prediction ability by learning process. An example Abdullah et al (2) used ANN to predict the potential pattern of soccer technical skills, Khan et al (3) used ANN to convert sign language into text and Tripathy et al. explored the body posture classification using ANN(4). For fault detection and classification also been explored using ANN by Sharna et al (5). This shows that ANN is a powerful machine learning which are inspired by biological nervous system where it learn the pattern given. Therefore, learning process is the most important process in ANN application and it have various types of training algorithm could be chosen.

In general, fault location method can be divided into two types which are impedance-based method and travelling wave method. Traveling wave is less dependency on system parameter compared to impedance-based. Transmission line is easily influenced by any changes of parameter value during fault occurs. This situation makes traveling wave is most

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suitable method for fault occurs in transmission lines during fault and thus determine accurate location of fault (6).

Estimating fault location using ANN typically include the following steps: (1) fault detection (2) feature extraction and (3) estimating fault location using ANN. Fault detection determines the presence or absence of a fault on transmission lines. Then feature extraction is performed to obtain informative features from the fault signal. Processing tools such as discrete wavelet transforms (DWT) is required for ANN for easily extract features before ANN estimate the location. DWT is signal processing tool to analyze the non-stationary transient signal. This technique able to analyze many kinds of transient signals in power system studies. According to wavelet transform theory, transient signal can be decomposed into a series of wavelet (7). Jamil et al explored the DWT for fault location estimation in transmission lines by using Daubechies4 (dB4) as a series wavelet (8). The features could be extracted from faulted current signal or faulted voltage signal. Many researcher for fault location in transmission line was extracted features from faulted current signal as in Raoofat et al. and Kale et al. using sample current signal features (6) (9).

Application in ANN has three important steps for any purposes which are training, testing and validation. ANN had been used to estimate the fault location. The technique is useful for power system applications because they can be trained with off-line data. Ramamoorthy (10) explored the application of neural networks to locate fault distance by using Levenberg-Marquardt (LM) training algorithm and Bayesian Regulation training algorithm. The author claimed that performance of proposed system is obtained once the data is trained sufficiently and suitably, thus it can perform correctly when different system situation. Most of researchers using LM as training algorithm for fault location proposed such as (11–14) since many researchers claimed that the algorithm gives accurate result and fastest convergence compared to others learning technique. Gowrishankar et al (1) performed transmission line fault detection and classification using DWT and ANN by using training algorithm of scaled conjugate Gradient backpropagation. In other application, there have a research in fault classification in transmission lines on training algorithm selection by Mahmud et al (15) that compared eight different training algorithm of MLP network which are trainlm, trainscg, resilient back-propagation (trainrp), BFGS Quasi-Newton Backpropagation (trainbfg), Conjugate Gradient Backpropogation With PolakRibiere Updates (traincgp), Conjugate Gradient Backpropogation With Powell Beale Restars (traincgb), Conjugate Gradient Backpropogation With Fletcher Reeves Updates (traincgf) and One Step Secant Backpropogation (trainoss). The authors claimed that traincgb was the best training algorithm for the studies.

This paper aims to explore the comparative study of fault location scheme on transmission line using travelling wave technique and various types of learning algorithm of ANN. The simulated faults are limited to 10 types of fault and single-ended method of travelling wave technique. The 10 types of fault are single line to ground fault (AG, BG, and CG), double line fault (AB, AC and BC), double line to ground fault (ABG, ACG and BCG) and three phase fault. The length of transmission line is limited to 500km with voltage of 500KV, 50Hz.

2. Research Method

This study conducted fault simulation where it varies the fault types which are three types of single line to ground fault, three types of double line fault, three types of double line to ground fault and lastly a three phase fault. Fault location, fault resistance and fault inception angle also varies some range value to ensure the robustness of scheme develop. The fault location scheme was used fault current signal as reference to analyze. Overall of the research works follows the sequential in Figure 1.

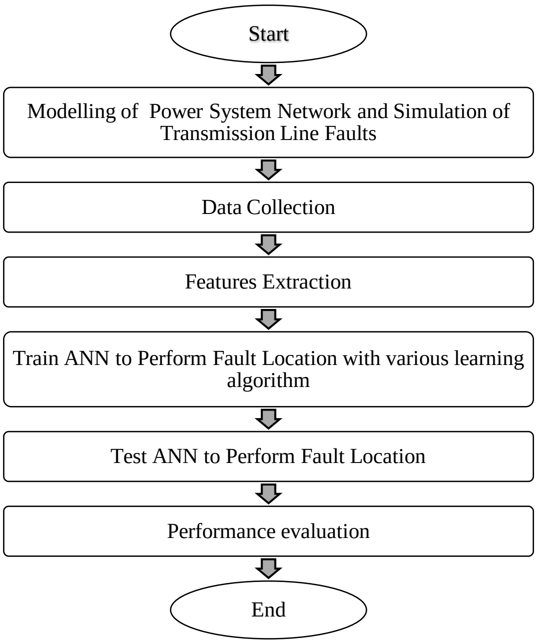

Figure 1. Overview of Research studies

2.1. Modeling and Simulation of Power System Network

Various techniques could be implementing for fault simulation but this paper perform single-ended line measured of travelling wave method. The transmission line model considered for this paper has been shown in Figure 2. The model was developed using MATLAB/Simulink to run fault simulation for data generation.

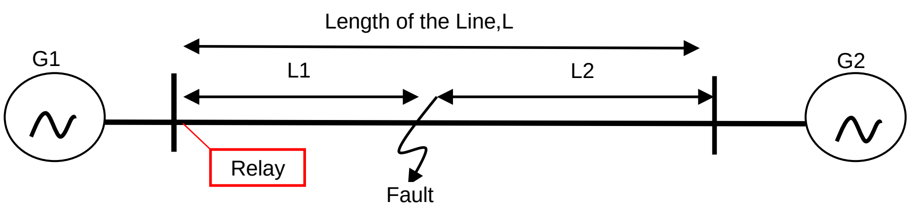

Figure 2. Single Transmission Line Model

The fault is created at 0.002s with sampling frequency of 1.25 MHz and the parameter setting for transmission line is:

R1 = 0.01273 Ω/km; R0 = 0.3864 Ω/km;
L1 = 0.9337e-3 H/km; L0 = 4.1264e-3 H/km;
C1 = 12.74e-9 F/km; C0 = 7.751e-9 F/km

The value of varies parameter for fault location, fault resistance and fault inception angle was tabulated in Table 1.

Table 1. Transmission Line Model Parameter

Parameters	Value
Fault Location, L (km)	0-500
Fault Resistance, Rf (Ω)	0.01, 1, 10, 50, 100, 200
Fault inception angle, Ft(degree)	0, 90

The conventional mathematical equation for traveling wave technique for single-ended method as in Equation (2).

$$V = \frac{1}{\sqrt{LC}}, t_d = t_2 - t_1 \tag{1}$$

$$FL = V \times t_d \tag{2}$$

where V, L, C, t_d, t_1, t_2 and FL are the velocity of propagation, inductance value, capacitance value, difference in time, time of fault occurs, time of fault appears and fault location (in km), respectively.

2.2. Feature Extraction using Time Information

ANN development have several process before estimate the location as in Figure 3. The current fault signal is used because of the sensitivity to any changes to the system.

Figure 3. Fault location scheme

Although the current and voltage signal contain all the information of system but it is difficult to fit raw signal data into ANN since ANN only capable into some set of rules and criterion. Selection of data input into ANN influence the performance of the whole system proposed. Therefore, for this paper choose features extracted by considering the time of first peak using DWT signal. The DWT is applied into current signal to extract time as a features. The DWT decomposed into details and approximations as in Equation 3 that have lower frequency parts are called approximation of the signal and lower scales are called signal details.

$$\psi_{j,k} = 2^{\frac{-j}{2}} \psi(2^{-j} t - k) \tag{3}$$

Where, j and k are scale and translation parameters, respectively. Parameter j changes the amount of signal compression and k displaces the wavelet in time domain

In this paper, dB4 from Daubechies family was chosen as series wavelet since most of researchers claimed that dB4 is the best for fault location scheme (16, 17). The sample point of first peak change in DWT signal is extracted. Then the sample point is convert to time by multiple by sample time set.

2.3. Artificial Neural Network

Multilayer perceptron (MLP) network is the most commonly used type of ANN configurations. It is a feedforward network and consists of three layer which are input layer, hidden layer and output layer, as illustrated in Figure 4. The MLP network was selected for this study because the model displays an efficient learning environment where each layer is connected with weight and bias for minimizing error between target and obtained value. The process of training, validation and testing are performed using neural network toolboxes in MATLAB with suitable number of hidden layer.

The ANN architecture includes the number of inputs and outputs to the network, number of hidden layer between input and output layer and the number of neuron in hidden layer.

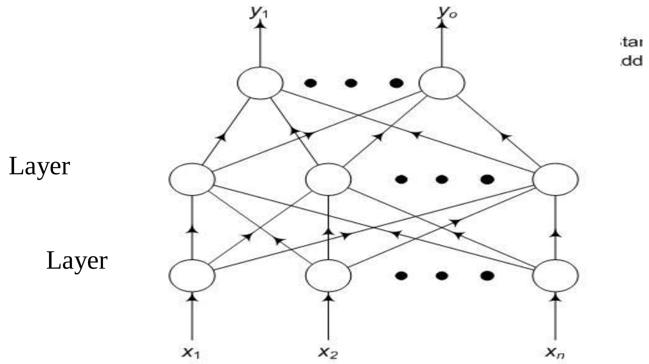

Figure 4. Structure of MLP network

The hidden layer and output layer transfer function are respectively sigmoid and linear function. The number of hidden layer are important due to it will influence the performance of system develop.Once it was decided how many input and output network required, the number of hidden layer is selected by choosing the hidden nodes which have minimum value of Mean square error (MSE) and performance of R^2.

The important process in ANN is how the network learn the pattern of system. Therefore, Table 2 shows the types of training algorithm would be tested in this paper to perform fault location and thus could find the best algorithm for this fault location proposed.

Table 2. Types of Training Algorithm Selected

Training Algorithm	MATLAB function
Levenberg-Marquardt (LM) backpropagation	*trainlm*
Bayesian Regulation (BR) backpropagation	*trainbr*
Conjugate gradient (CG) backpropagation with Powell-Beale restarts	*traincgb*
BFGS quasi-Newton backpropagation	*trainbfg*
Conjugate gradient (CG) backpropagation with Polak-Ribiere updates	*traincgp*
Conjugate gradient (CG) backpropagation with Fletcher-Reeves updates	*traincgf*

2.4. Performance Evaluation

The performance of system are evaluated by calculating performance indicator. Performance indicator chosen is R^2, PPE and MSE. R^2 is an indication the relationship between the outputs and targets. The linear regression model shows the fitness of data from output and target by checking the goodness-of-fit via the coefficient of determination, R^2. If the predictions are close to the actual values, R^2 would to be close to 1. On the other hand, if the predictions are unrelated to the actual values, then R^2 would be close to 0. In all cases, R^2 lies between 0 and 1.

The Mean Square Error, MSE is an indicator for quality of the estimated data from targeted output. Best results of MSE is 0.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(OutputANN_i - OutputT\arg et_i\right)^2 \tag{4}$$

Where n represents the number of data.

The Percentage Prediction Error, PPE is indication of ability the network to locate fault. Less error indicates the high performance system.

$$PPE = \frac{OutputANN - OutputT\arg et}{OutputT\arg et} \times 100 \tag{5}$$

3. Results and Analysis

In this section explained the findings of research and at the same time is given the comprehensive discussion.

3.1. System Model and Fault Simulation

The Figure 5 shows the single line diagram of three phase transmission line model using MATLAB/Simulink. This model were designed for 10 types of fault simulation.

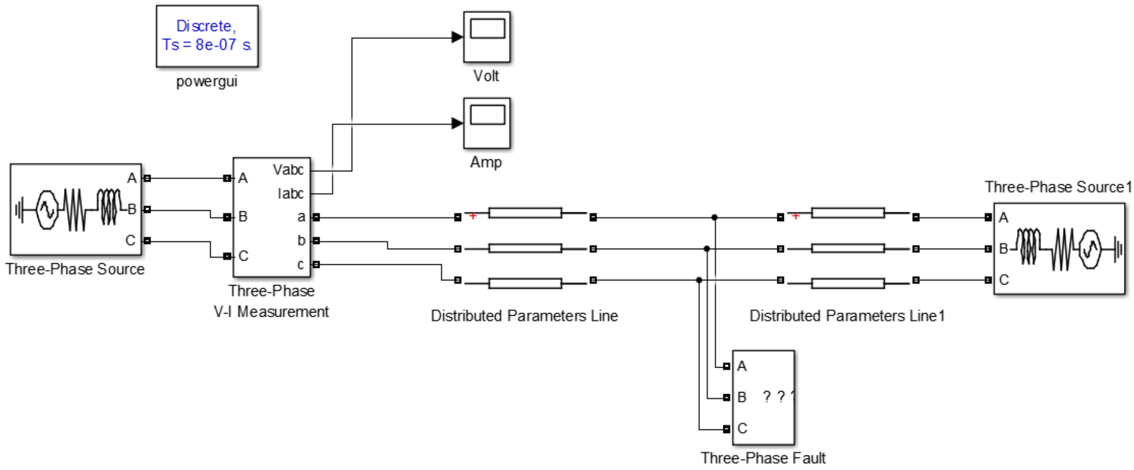

Figure 5. Transmission line model in MATLAB/SIMULINK

The transmission line model generated 150 data for each fault types and the total of 6000 data for all varies parameter value. The data collected by using first level details of dB4. Figure 6 shows an example of faulted signal in time domain, sample signal and DWT signal. The data was taken from the first peak change of time in DWT as shown in First Level Detail signal on Figure 6. The data collected is used as input into ANN.

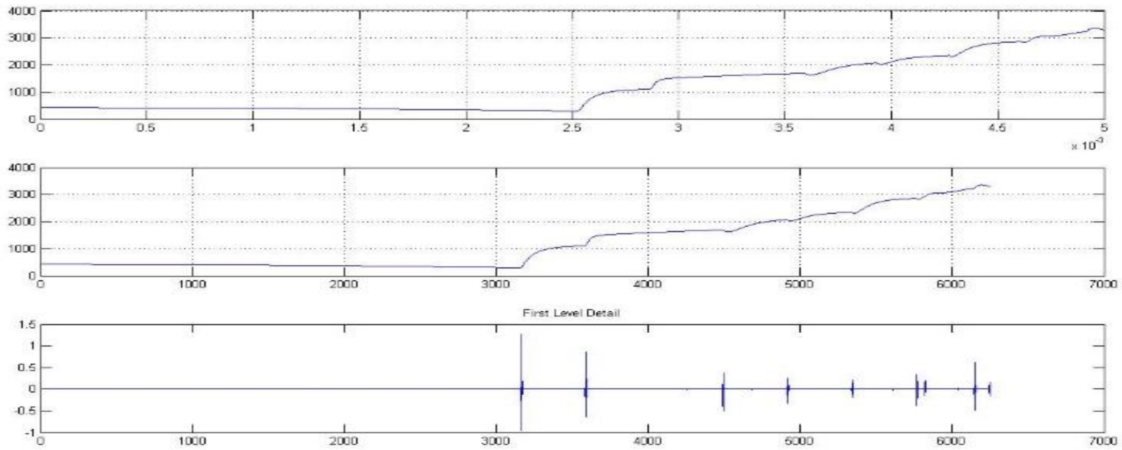

Figure 6. Fault at 64km

3.2. Performance Varying Fault Resistance

The scheme proposed is tested by varying fault resistances between 0.01Ω to 200Ω. Figure 7 clearly shows that all varying values of fault resistance do not influence the data generated. This indicates the all cases have the same results of PPE.

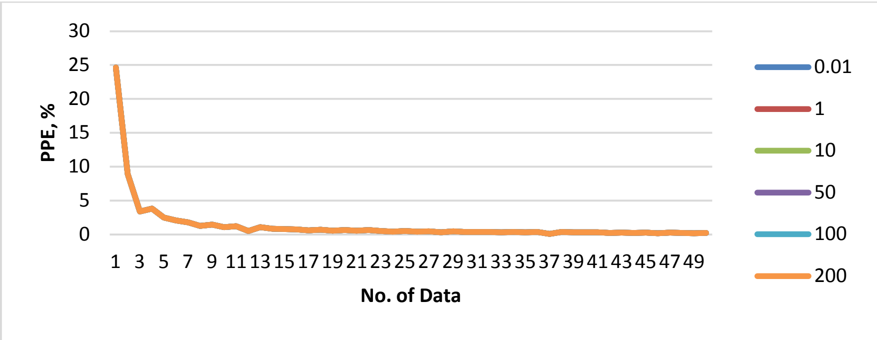

Figure 7. Performance data by varying fault resistance

3.3. Performance Varying Fault Inception Angle

The fault location scheme proposed is checked by varying inception angle of 0° and 90° respectively. From Figure 8, it could be seen that both inception angle have approximately the same results. As all the task are performed in time domain, inception angle variation do not affected the proposed scheme.

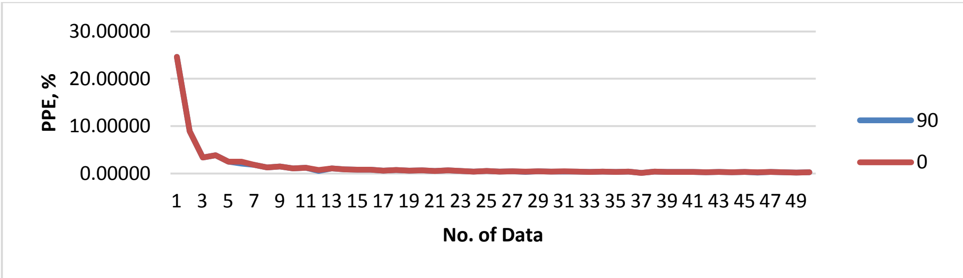

Figure 8. Performance data by varying inception angle

3.4. Comparison of Learning Algorithm

From the total data generated, only 150 data chosen as input into ANN due to have same results of all varies cases. 50 data used for training, 50 data for testing and 50 data for validation. The input chosen was valid for all types of cases to perform fault location using ANN algorithm.

Table 3. Comparison performance of ANN training algorithm

Training Algorithm	ANN architecture	R^2	MSE	Time(s)
trainlm	1-2-1	1.0000	0.036736	2.2650
trainbr	1-14-1	1.0000	0.034557	5.8289
traincgb	1-16-1	0.9996	5.775518	0.1570
trainbfg	1-14-1	0.9996	5.606493	5.3480
traincgp	1-17-1	0.9824	4.950366	0.2340
traincgf	1-16-1	0.9998	3.48648	0.2660

The comparison performance of ANN influenced by training algorithm was tabulated in Table III. From the table, trainbr was found to achieve the best training algorithm where it has the lowest MSE and good results of R^2 then followed by trainlm. On the contrary, trainbr takes longer training time than the LM algorithms. The best ANN architecture for trainbr is 1 input, 14 hidden layer and 1 output. On the other hand, traincgb has the lowest performance (the highest MSE and lowest R^2) and not suitable for this fault location scheme.

3.5. Analysis of Percentage Prediction Error, PPE

The test result shows the suitability of the scheme to locate 10 types of fault under wide varieties of the operating and fault condition as in Figure 9.

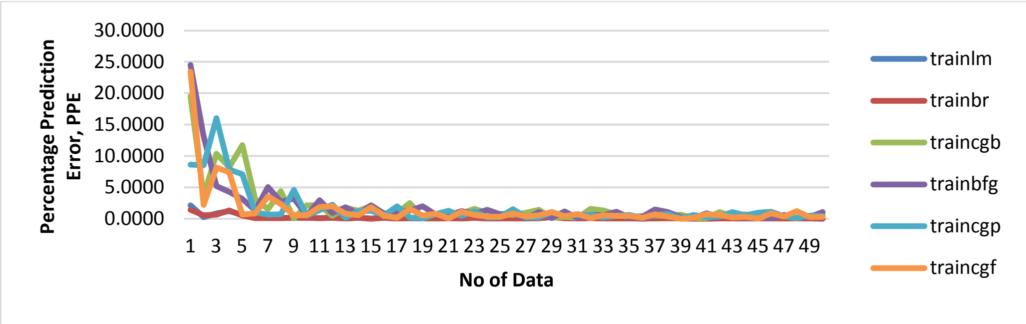

Figure 9. PPE for all types of training algorithm

Fault location checked the ability of 6 types of training algorithm to locate fault as in Figure 9. From Figure 9, it shows that the fault occurs at short distance from measured point has a problem to locate exact fault location. The figure also shown that the best approach is either trainbr or trainlm which have maximum PPE of 1.4% and 2.1%, respectively. Meanwhile, trainbfg was found to be insufficient to estimate the fault location as it achieved the maximum PPE of 25%.

4. Conclusion

In short, fault location in transmission line using combination of ANN and DWT is the best way to predict fault location. The DWT is the best processing tools since it decomposed into details and approximation in time domain. The features selection plays a vital roles as input into system thus it learn the pattern of scheme proposed. This paper used features extracted from DWT where it measured a time of first changes of first level details. Next, the selection of hidden nodes also take parts influenced the system performance. Therefore the best hidden nodes for each types of training algorithm is chosen by the lowest MSE and the goodness-of-fit. From the studies, the best training algorithm for fault location in transmission line using travelling wave technique and ANN is BR backpropagation which have 1.4% of PPE but it takes time to converge and estimate the location of fault. LM backpropagation could also be chosen since the result still below than 2.5% of PPE and have fastest time to converge compared to BR backpropagation.

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