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Transmission Line using Discrete Wavelet Transform and Backpropagation Neural Network based on Clarke's Transformation

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Keywords: Wavelet Transformation, back-propagation neural network, Fault Classification, Fault detection, Clarke's Transformation, PSCAD/EMTDC

Abstract. This paper proposes a new technique of using discrete wavelet transform (DWT) and back-propagation neural network (BPNN) based on Clarke's transformation for fault classification and detection on a single circuit transmission line. Simulation and training process for the neural network are done by using PSCAD / EMTDC and MATLAB. Daubechies4 mother wavelet (DB4) is used to decompose the high frequency components of these signals. The wavelet transform coefficients (WTC) and wavelet energy coefficients (WEC) for classification fault and detect patterns used as input for neural network training back-propagation (BPNN). This information is then fed into a neural network to classify the fault condition. A DWT with quasi optimal performance for preprocessing stage are presented. This study also includes a comparison of the results of training BPPN and DWT with and without Clarke's transformation, where the results show that using Clarke transformation in training will give in a smaller mean square error (MSE) and mean absolute error (MAE). The simulation also shows that the new algorithm is more reliable and accurate.

Introduction

The transmission line is vital elements in power system since this electrical energy can be transferred from are placed to another. However, this transmission line part of power system has often impaired. Most of the disturbances on the power system come from the interference on the transmission line. Therefore, speed and accuracy in the determination of fault detection and classification of disturbances in the transmission line have a very important role in electric power systems.

This paper proposes a method of using discrete wavelet transform (DWT) and back-propagation neural network (BPNN) based on Clarke's transformation to determine the fault detection and classification on single circuit transmission line. This study presents a different approach called alpha-beta transformation based on the Clarke's transformation, which is also a transformation of a three-phase system into a two-phase system [1, 2], where the result of the Clarke's transformation is transformed into discrete wavelets transform.

In recent years, several methods of fault classification have been proposed. Some of them are based on artificial neural network [3,4], wavelet transform [5,6] and also combination of these techniques [7-8].

This paper proposes a novel method for fault classification in transmission lines using discrete wavelet transform (DWT) and back-propagation neural network (BPNN). The key idea of the method is to use wavelet coefficient detail and the wavelet energy coefficient of the currents as the input patterns to create a simple multi-layer perception network (MLP). This paper presents the development of a new decision algorithm for use in the protective relay for fault detection and

classification. To validate this technique, the fault conditions had been simulated using EMTDC / PSCAD [9]

Overview of Wavelet transform and Artificial Neural Network (ANN)

Discrete Wavelet Transform (DWT). In general, the wavelet transform is the decomposition of a signal by a function $\Psi_{S,\tau}(t)$ which has been dilated and translated, known as the mother wavelet. In other words, the signal is represented as the sum of a collection of dilated-version and translated-version mother wavelet function. The set of functions is as defined in the following equations [10, 11]:

$$\Psi_{S,\tau}(t) = \frac{1}{\sqrt{S}}\varphi\left(\frac{t-\tau}{S}\right) \tag{1}$$

Where *S* is the dilation parameter (*S* ε real) and τ is the translation parameter ($\tau \varepsilon$ real). Parameter *S* indicates the width of the curve wavelet; so if the value of *S* is wider, the wavelet curve will be larger, and if the value of *s* is reduced, the wavelet curve will be smaller. Parameter τ indicates the localization of the wavelet curve centered on the space t = τ . Discrete data are required in fault classification and detection Discrete Wavelet Transform (DWT), so that Equation (1) becomes [12, 13]:

$$\Psi_{S,\tau}(t) = 2^{j/2} \Psi\left(2^{j}(S-\tau)\right), j, k \in \mathbb{Z}$$
⁽²⁾

The variables *j* and *k* represent an integer for scaling and shifting the mother wavelet function to produce a kind of wavelet known as Haar wavelet. The width of the wavelet is indicated by scale s and while its position is indicated by τ . Discrete wavelet transformation aims to reduce the redundancy in continuous transformation by taking the discrete values of the parameters s and τ . Wavelet function in Equation (1) was first introduced by Grossman and Morlet, while Equation (2) was pioneered by Daubechies. In Grossman Morlet function, s is the dilation parameter and τ is the translation parameter. In Daubechies function, the dilation parameter is indicated by 2^{j} , and translation parameters by τ . Both functions of Ψ can be regarded as the mother wavelet. In the context of wavelet transform, signal processing is a method to decompose the desired input signal into another wave called wavelet and also to analyze the signal by giving treatment of the wavelet coefficients. The decomposition process involves two filters, namely low pass filter and high pass filter. The results obtained in the form of cA approximation signal and detail signal cD are shown in Fig. 1, as equations [14]:

$$\delta_{high}\left[k\right] = \sum_{n} X[n] \cdot g[2k-n] \,. \tag{3}$$

$$\delta_{low}[k] = \sum_{n} X[n] \, . \, h[2k-n] \, . \tag{4}$$

Where $\delta_{high}[k] = \text{Output of high-pass filter and } \delta_{low}[k] = \text{Output of low-pass filter.}$



Figure 1. The process decomposition of Discrete Wavelet Transform

Back-Propagation Neural Network (BPNN). In general, the neural network is divided into two parts: training and testing. Training is a learning process of the neural network system that governs how the input values and the output are mapped to obtain the appropriate model, while testing is a process of testing the accuracy of the model obtained from the training process. Back-propagation neural network (BPPN) is a trained network to obtain a balance between the ability of the network to recognize the patterns used for training, as well as the network's ability to provide the correct response to the input pattern similar to the style employed during training. Back-propagation training includes the following 3 steps:

1. Step I: Feed Forward

During the forward propagation, the value of the input (x_i) and the output of each unit of the hidden layer (z_j) will be propagated to the hidden layer is defined using activation function, and so on to generate the output value of the network (y_k) . Next, the output value of the network (y_k) will be compared with the target to be achieved (t_k) . Difference of $t_k - y_k$ is the error that occurs. If this error is smaller than the tolerance limit, the iteration is stopped. However, if the error is greater than the tolerance limit, the weight of each line in the network will be modified to reduce the errors.

2. Step II: Back-propagation Based on the error $t_k - y_k$, calculated factor δ_k (k = 1, 2, ..., m) which is used to distribute

the error in the unit y_k to all hidden units will be connected directly with y_k . δ_k is also used to change the line weight, directly related to the output unit. In a similar way, the δ_j factor is calculated in each unit in the hidden layer as a basis weight of all the changes in the layer below, until all the factors δ in hidden units directly related to the input units have been computed.

3. Step III: Changes in Weight

After all δ factors have been calculated, the weights of all the lines will be simultaneously modified, according to changes in weight of a line based on the factor δ in the upper layer neurons. For selecting models of fault detection and classification, Mean Absolute Error (MAE) and Mean Squared Error (MSE) are used. The best model is the model that has the smallest value of MAE and MSE.

$$MAE = \frac{\sum_{i=1}^{n} |e_{k}|}{n}$$
(5)
$$MSE = \frac{\sum_{i=1}^{n} e_{k}^{2}}{n}$$
(6)

n Where: MAE = Mean Absolute Error, MSE = Mean Squared Error $e_k = t_k - y_k$, $t_k =$ Target, $y_k =$ Output and n = number of data

Proposed Algorithm. The design process of the proposed fault detection and classification algorithm for on single circuit transmission lines are as shown in Figure 2:



Figure 2. Architecture of Proposed DWT-BPNN based on Clarke's Transformation

- Simulation of various types of disturbances on single circuit transmission line by using PSCAD / EMTDC.
- 2) Determining the data stream interference, where the signal is transformed by using the Clarke's transformation to convert the transient signals into the signal's basic current (Mode), formulated as follows [15,16]:

$$\begin{bmatrix} i_{\alpha} \\ i_{\beta} \\ i_{0} \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} X \begin{bmatrix} i_{a} \\ i_{b} \\ i_{c} \end{bmatrix}$$
(7)

- 3) Input signals are analyzed by DWT for extracting the information of the transient signal in the time and the frequency domain [17]. In the proposed algorithm, 'Db4' mother wavelet is used to get the DWT coefficients for the classification of different types of fault. It will then be calculated S_0 , S_{α} , S_{β} , S_{γ} , Q_0 , Q_{α} , Q_{β} , Q_{γ} , E_0 , E_{α} , E_{β} and E_{γ} where S_0 , S_{α} , S_{β} and S_{γ} represent the sum of the four levels of detail coefficients of mode currents I_0 , I_{α} , I_{β} and I_{γ} , respectively, while Q_0 , Q_{α} , Q_{β} and Q_{γ} represent the sum of the absolute value of the coefficient of the fourth-level detail mode currents I_0 , I_{α} , I_{β} and I_{γ} , respectively, and wavelet energy of coefficients E_0 , E_{α} , E_{β} and E_{γ} represent the sum of the four levels of wavelet energy of coefficients of mode currents I_0 , I_{α} , I_{β} and I_{γ} , respectively.
- 4) The input of BPNN training consists of detail coefficients wavelet and wavelet energy. Combination of different fault conditions must be considered and training patterns are required to be generated by simulating various types of faults on single circuit transmission line. Therefore, the type of fault, fault location, fault resistance and fault inception can be determined.
- 5) Selection of a suitable BPNN topology & structure for a given application. In this proposed scheme, different architectures had been considered. In this study, the set of inputs used were 12 samples of output current signals of on single circuit transmission lines. Two hidden layers were taken and the number of neurons was varied as hidden (1) is 6 and 10, hidden (2) is 12 and 20 results and set output 4, as shown in Fig. 2.
- 6) Training of BPNN and validation of the trained BPNN is required to check the correctness in generalization, to get back propagation neural network model of the good, and to do experiments on some kind of network architecture in order to generate the value of the smallest

MSE and MAE with the learning process of the training data, test data, as well as the training data. The learning process is done by using the back-propagation gradient descent with adaptive learning rate with 12 input variables, two hidden layer, and 4 outputs, Mean Square Error (MSE) and Mean Absolute Error (MAE)

Simulation Result and Discussion

For the case study, the simulation was modeled on a 150 kV single circuit transmission line, 100 km in length, and connected with the sources at each end, as shown in Fig 3. This system was simulated using PSCAD/EMTD.



Figure 3. The single line of the system under study using PSCAD/EMTDC

Transmission data:

Sequence Impedance ohm/km

Positive and negative = 0.03574 + j 0.5776 Zero = 0.36315 + j 1.32647Fault Starting = 0.22 seconds Duration in fault = 0.15 Seconds Fault Location (distance) for training and testing = 10, 25, 50, 75 and 90 km Fault Resistance (R_f) for training and testing: = 2 ohm

Fault Inception Angle for training and testing = 30 degrees

The proposed DWT and BPNN were able to precisely differentiate between the ten categories of faults, as shown in Table 1, with preference to the faults and the ideal output for each of the faults.

			· · · · · · · · · · · · · · · · · · ·	
Fault Type	Phase A	Phase B	Phase C	Ground G
	Output 1	Output 2	Output 3	Output 4
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
ABG	1	1	0	1
ACG	1	0	1	1
BCG	0	1	1	1
AB	1	1	0	0
AC	1	0	1	0
BC	0	1	1	0
ABC	1	1	1	0

Table 1 Neural network desired output.

WTC and WEC based fault detection and classification. Fault detection can be achieved by using mathematical tools of Discrete wavelet transform (DWT). In this method, each of the derived current fault signal is decomposed into its constituent wavelet sub-bands or levels by the mother wavelet (Db4). The 4 levels of frequency bands are named as dl, d2, d3 and d4. The high frequency components will be increased from d4 to d1. The wavelet coefficients detail of the currents is filtered using Clarke transformation, as shown in Fig. 4, while Fig. 5 shows filtering without using Clarke transformation. By using the rules above mentioned, the first and last faulted samples were found at 10⁵ respectively, for a sampling frequency of 200 kHz.



Figure 4. Level 4 DWT coefficients detail of the fault (AG) 75 km, signalled with Clarke's transformation.



Figure 5. Level 4 DWT coefficients detail of the fault (AG) 75 km, signalled without Clarke's transformation.

The Wavelet energy coefficients (WEC) are obtained from the sum of square of detailed wavelet transform coefficients (WTC) [18]. The wavelet energy coefficient varies over different scales depending on the input signals. The wavelet energy coefficients E(s(t)) can be defined as follows. $E(s(t)) = \sum_{j=1}^{N} a_j c_j^2$ (15)

With suitable scaling coefficients, a_j , for the coefficient c_j , is obtained from equivalent signals. Wavelet energy coefficients E_0 , E_α , E_β and E_γ represent the sum of the four levels of wavelet energy coefficients of mode currents I_0 , I_α , I_β and I_γ with Clarke's transformation, as shown in Table 2, while E_0 , E_a , E_b and E_c represent the sum of the four levels of wavelet energy coefficients of line currents I_0 , I_α , I_b and I_c without Clarke's transformation as shown in Table 3.

TYPE S_o S_{α} S_{β} S_{γ} E_o E_{α} E_{β} E_{γ} AG 0.018988 0.045331 0.093813 0.048482 0.002453 0.011291 0.241902 0.047061 BG 0.123914 -0.02885 0.150221 0.179081 0.006076 0.005560 0.136218 0.088392 CG -0.04495-0.06826 0.002109 0.070369 0.011168 0.046384 0.030233 0.102816 AB 0.000184 0.402218 -0.15201 -0.55423 90.723575 0.082800 0.040877 0.016681 -0.01499 0.151428 94.395346 0.204705 0.083398 AC -0.00357 -0.16642 0.002808 0.052911 BC -0.38468 87.329198 0.002600 -0.00460 0.021685 -0.36300 0.035734 ABG -0.00729 -0.20360 -0.62208 0.099141 0.042845 0.418471 0.007414 0.012927 ACG 0.030388 -0.23095 -0.10108 0.129875 0.015425 0.021610 0.033333 0.055919

Table 2. Wavelet coefficient detail and wavelet energy coefficient in fault location 75 km, fault resistance = 2 ohm and fault inception at angle 30 degrees with Clarke's transformation.

With the use of these wavelet coefficient details, various parameters S_0 , S_{α} , S_{β} , S_{γ} and S_0 , S_a , S_b and S_c are calculated as Sum of 4th level detailed coefficients of mode current I_0 , I_{α} , I_{β} and I_{γ} with Clarke's transformation as shown in Table 2, and of line currents I_0 , I_a , I_b and I_c without Clarke's transformation as shown in Table 3.

-0.64417

-0.59167

0.002075

14.807200

0.005211

0.018472

0.074346

0.059018

0.103031

0.042369

BCG

ABC

-0.00816

-0.06323

-0.00854

0.091704

-0.65272

-0.49996

TYPE	S ₀	S _a	S_b	S _c	Eo	Ea	E _b	E _c
AG	0.018988	0.064319	0.077567	-0.08492	0.002453	0.006306	0.202030	0.188700
BG	0.123914	0.103078	-0.05106	0.017892	0.006076	0.121018	0.019778	0.161645
CG	-0.04495	-0.11321	-0.00899	-0.01265	0.011168	0.096478	0.078739	0.010235
AB	0.000184	0.402402	-0.33257	-0.06927	90.723575	0.016663	0.051274	0.144141
AC	-0.00357	-0.16999	0.066654	0.092623	94.395346	0.002819	0.217860	0.045663
BC	-0.00460	0.017077	-0.32982	0.298920	87.329198	0.002580	0.046332	0.026386
ABG	-0.00729	0.411173	-0.39286	-0.04020	0.007414	0.010510	0.054248	0.190577
ACG	0.030388	-0.20057	0.058327	0.233409	0.015425	0.018716	0.111303	0.011746
BCG	-0.00816	-0.01671	-0.56917	0.561383	0.002075	0.007826	0.078249	0.046000
ABC	-0.06323	0.028474	-0.54206	0.323901	14.807200	0.019092	0.051526	0.044710

Table 3. Wavelet coefficient detail and wavelet energy coefficient in fault location 75 km, fault resistance = 2 ohm and fault inception angle 30 degrees without Clarke's transformation

Training the fault classifier using DWT and BPPN With/Without Clarke's Transformation. The designed network takes in sets of 12 inputs (wavelet coefficient detail, wavelet coefficient absolute detail and wavelet energy coefficient. The network has four outputs, each of them corresponding to the fault condition of each of the three phases and one output for the ground line. Hence, the outputs are either 0 or 1, denoting the absence or presence of a fault on the corresponding line A, B, C or G, where A, B and C denote the three phases of the transmission line and G denotes the ground. Hence, various possible permutations can represent each of various faults accordingly. The proposed neural network should be able to accurately distinguish between the ten possible categories of faults. The truth table representing the faults and the ideal output for each of the faults is illustrated in Table 1.

Table 4 The obtained result of different fault using DWT and BPNN, with configuration (12.6, 12.4)

	(12-0-12-4)											
Туре	Distance	Rf	Fault	Clarke's Transformation				Without Clarke's Transformation				
Fault			Inception	MSE = 0.139410 and MAE = 0.169911				MSE = 0.159702 and MAE = 0.30657				
	km	Ohm	Degree	Α	В	С	G	Α	В	С	G	
AG	10	2	30	1.21624	0.15817	0.19468	0.95641	0.94019	0.10155	0.24147	0.79446	
BG	25	2	30	0.07674	0.95209	0.04316	1.03655	0.04391	1.18475	0.36251	0.92219	
CG	50	2	30	0.06927	0.25132	0.88855	0.98963	0.28549	0.00518	0.86619	1.09217	
AB	75	2	30	1.03169	1.03222	0.10546	0.06769	0.78983	1.23393	0.01507	-0.1476	
AC	90	2	30	1.00565	0.22939	0.81288	0.04103	0.86270	0.22158	0.77180	-0.0329	
BC	10	2	30	0.14976	1.01003	1.14211	0.05596	0.23484	0.86584	0.75078	0.01245	
ABG	25	2	30	1.38861	0.78583	0.12909	0.83006	0.86929	0.76989	0.04391	1.05712	
ACG	50	2	30	1.03445	0.01978	1.04523	0.95785	0.77904	-0.0231	0.80246	1.09085	
BCG	75	2	30	0.21671	1.05015	0.87383	0.86315	0.12607	0.76167	1.03733	1.19104	
ABC	90	2	30	1.01254	0.98616	0.93193	0.04276	0.72034	0.70374	0.85015	0.07266	

Table 4 shows the results of fault classification and detection on single circuit transmission lines with fault resistance 2 ohm and the fault inception at angle of 30 degrees at various distances, as well as the training, performance plot of the neural network 12 - 6 - 12 - 4 (12 neurons in the input layer, 2 hidden layers with 12 and 6 neurons in them, respectively, and 4 neurons in the output layer). Table 4 shows the results of DWT and BPNN training without Clarke's transformation, where the Mean Square Error (MSE) was 0.159702 and the mean absolute error (MAE) was 0.30657. For the results of DWT and BPNN training obtained with Clarke's transformation, the MSE was 0.139410 and MAE was 0.169911. The results above show that using the Clarke's transformation had lesser error than without using Clarke's transformation.

Туре	Distance	Rf	Fault	Clarke's Transformation				Without Clarke's Transformation			
Fault			Inception	MSE = 0.105410 and MAE = 0.166937				MSE = 0.139810 and MAE = 0.265709			
	km	Ohm	Degree	А	В	С	G	А	В	С	G
AG	10	2	30	0.94185	0.03077	0.09673	1.00708	0.76445	0.24719	0.11148	0.76598
BG	25	2	30	0.28048	0.88582	0.12022	0.93869	-0.1600	1.21815	0.26640	0.77413
CG	50	2	30	0.03435	0.10865	0.84605	1.08524	0.28508	0.33793	1.23327	0.85946
AB	75	2	30	1.05979	1.00515	-0.0288	0.08248	0.98452	1.25075	0.11031	0.05437
AC	90	2	30	1.02225	0.23159	0.89008	0.01478	0.86991	0.33681	0.93814	-0.0756
BC	10	2	30	0.28696	0.80149	1.06486	-0.1357	0.38817	0.76029	0.78835	0.12609
ABG	25	2	30	1.02164	1.02468	0.24852	0.78830	0.78765	0.63582	0.32030	0.64403
ACG	50	2	30	0.98279	0.21340	0.88670	0.93152	0.91280	-0.0387	0.88481	0.89238
BCG	75	2	30	-0.0611	0.95990	0.93043	0.83307	0.20744	1.26780	0.70490	0.83165
ABC	90	2	30	1.15583	0.65050	0.92697	-0.2799	0.84551	0.73034	0.89146	0.13683

Table 5 The obtained result of different fault using DWT and BPNN ,with configuration(12-10-20-4)

Table 5 shows the results of fault classification and detection on single circuit transmission lines with fault resistance 2 ohm and the fault inception at angle of 30 degrees at various distances of errors, as well as the training, performance plot of the neural network 12-10-20 -4 (12 neurons in the input layer, 2 hidden layers with 10 and 20 neurons in them, respectively, and 4 neurons in the output layer). Table 5 shows the results of DWT and BPNN training without Clarke's transformation, where the mean Square Error (MSE) was 0.139810 and the mean absolute error (MAE) was 0.265709. For the results of DWT and BPNN training with Clarke's transformation, the MSE was 0.105410 and MAE was 0.166937. The results above show that the outcome obtained using Clarke transformation became smaller.



with Clarke's transformation

Figure 6. shows the training performance plot of the neural network 12 - 10 - 20 - 4 neurons in the input layer, 2 hidden layers with 10 and 20 neurons in them respectively and four neurons in the output layer with Clarke transformation. It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process is 0.105410 and MAE is 0.166937.



Figure 7. Mean-square error performance of the network configuration (12-10-20-4) without Clarke's transformation

Figure 7 shows the training performance plot of the neural network 12 - 10 - 20 - 4 neurons in the input layer, 2 hidden layers with 10 and 20 neurons in them, respectively, and four neurons in the output layer without Clarke's transformation. The best validation performance in term of the Mean Square Error (MSE) by the end of the training process was 0.139810, while the MAE is 0.265709.

Conclusion

This paper developed the technique which is the linking discrete wavelet transform (DWT) and back-propagation neural network (BPNN) based on the Clarke transformation for fault classification and detect on single circuit transmission lines. This study also includes comparison on the results of training BPPN and DWT with and without Clarke's transformation, where the results show that using the Clarke's transformation in training will produce smaller MSE and MAE, compared with without transformation Clarke's, among the three structures, the Architecture result was the best, which was 12 - 10 - 20 - 4. This technique applies Daubechies4 (db4) as a mother wavelet using in this paper, the performance shows that the proposed technique gives good accuracy of transient classification.

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