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# New algorithm for detection and fault classification on parallel transmission line using DWT and BPNN based on Clarke's transformation

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ABSTRACT

This paper presents a new algorithm for fault detection and classification using discrete wavelet transform (DWT) and back-propagation neural network (BPNN) based on Clarke's transformation on parallel transmission. Alpha and beta (mode) currents generated by Clarke's transformation were used to convert the signal of discrete wavelet transform (DWT) to get the wavelet transform coefficients (WTC) and the wavelet energy coefficient (WEC). Daubechies4 (Db4) was used as a mother wavelet to decompose the high frequency components of the signal error. The simulation was performed using PSCAD/EMTDC for transmission system modeling. Simulation was performed at different locations along the transmission line with different types of fault and fault resistance, fault location and fault initial angle on a given power system model. Four statistic methods utilized are in the present study to determine the accuracy of detection and classification faults. The results show that the best Clarke transformation occurred on the configuration of 12-24-48-4, respectively. For instance, the errors using mean square error method, the errors of BPNN, Pattern Recognition Network and Fit Network are 0.03721, 0.13115 and 0.03728, respectively. This indicates that the BPNN results are the lowest error.


## 1. Introduction

Parallel transmission lines have been widely used in modern power systems to improve power transfer, reliability and security for the transmission of electrical energy. The possibility of different configurations of parallel lines, combined with mutual coupling effects, makes their protection a challenging problem, therefore a fast and reliable protection is needed for rapid fault detection and accurate estimation of fault location errors. This is vital to support the maintenance and restoration services to improve the continuity and reliability of supply. Therefore, a parallel transmission line requires special consideration in comparison with the single transmission line, due to the effect of mutual coupling on the parallel transmission line. It must also comply with the standards of IEEE.STD.114 2004 [1]. One major advantage of parallel transmission is availability of transmission network during and after the fault.

This paper applies discrete wavelet transform (DWT) and back-propagation neural network (BPNN) using Clarke's transformation to determine the fault detection and classification on the parallel transmission line. This study presents a different approach called alpha-beta transformation based on Clarke's transformation; which is also a transformation of a three-phase system into a two-phase system [2,3], where the result of the Clarke's transformation is changed into discrete wavelets transform.

Recently, some applications of wavelet transforms in power systems are power system protection, power system transients, partial discharge, transformer protection and condition monitoring. Among all, the power system protection continues to be a major application area of wavelet transform in power systems [4], while Artificial Neural Network (ANN) continues as an efficient pattern recognition, classification and generalization tool that motivates many algorithms based on ANN to be used for fault detection and classification [5]. In recent years, the combination of ANN and wavelet has been applied on researches regarding various power system planning and operation problems [6,7], as well as power quality [8], fault classification [9], state estimation and control system [10,11].

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This paper presents the development of a new decision algorithm for use in the protective relay for fault detection and classification. In this method, fault conditions are simulated using EMTDC/PSCAD [12]. Current waveforms obtained from the simulation are then extracted using Clarke transformation and wavelet transformation. Decision algorithm, therefore, is built based on back-propagation neural network. In this study, the validity of the proposed algorithm had been tested using various initial error angles, location and broken phase errors. In addition, the results of the proposed algorithms were compared with and without wavelet transform based Clarke transformation.

## 2. Related works

### 2.1. Clarke's transformation

#### 2.1.1. A phase to modal transformation

The phase-modal transforms is usually applied to decouple three phase systems, relative to the Clarke's transform-based phase-modal transformation adopted in this study. The Clarke's transform is formulated as follows [13,14]:

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

where $a$, $b$, $c$ represent the current values of the phase A, B, C respectively; and $\alpha$, $\beta$, 0 represent the modal values. The coefficients of the above matrix are real numbers, so the values of the modal can be deduced from the instantaneous sampling values of the three phases. The matrix of the Clarke's transformation is a full-order matrix. Modal $\alpha$ represents the line-modal between phase A and phase B, while modal $\beta$ represents the line-modal between phase A and phase C. In order to represent the line-modal between phase B and phase C, modal $\gamma$ is proposed.

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

#### 2.1.2. Fault characterization under Clarke's transformation

*2.1.2.1. Single line of ground fault.* Suppose a line to ground fault (AG), assuming the grounding resistance is zero, then the instantaneous boundary conditions will be:

$$I_b=I_c = 0 \text{ and } V_a = 0 \quad (3)$$

Then, the boundary condition instantaneous will be:

$$I_\alpha=\frac{2}{3}I_a\ ; \quad I_\beta = 0; \quad I_\gamma = -\frac{2}{3}\ I_a \text{ and } I_0= 1/3I_a \quad (4)$$

*2.1.2.2. Line to line fault.* Suppose the line to line fault (AB), assuming the grounding resistance is zero, then the instantaneous boundary conditions will be:

$$I_c=0, \quad I_a=-I_b \text{ and } V_a=V_b \quad (5)$$

Then the boundary condition instantaneous will be:

$$I_\alpha=I_a; \quad I_\beta=-\frac{1}{3}\sqrt{3}\ I_b; \quad I_\gamma= -I_a-1/3\sqrt{3}I_b \text{ and } I_0=0 \quad (6)$$

*2.1.2.3. Line to line to ground fault.* Suppose line to line to ground fault (BCG), assuming the grounding resistance is zero, then the instantaneous boundary conditions will be:

$$I_a=0, \quad I_b=I_c \text{ and } V_b=V_c=0 \quad (7)$$

Then, the boundary condition instantaneous will be:

$$I_\alpha=-\frac{1}{3}I_b-\frac{1}{3}I_c; \quad I_\beta=\frac{1}{3}\sqrt{3}I_b-\frac{1}{3}\sqrt{3}I_c; \quad I_\gamma=1/3I_a+1/3I_b+1/3\sqrt{3}I_b -1/3\sqrt{3}I_c \text{ and } I_0=\frac{1}{3}I_b+\frac{1}{3}I_c \quad (8)$$

*2.1.2.4. Three phase fault.* Suppose three phase fault (ABC), assuming the grounding resistance is zero, then the instantaneous boundary conditions will be:

$$I_a+I_b+I_c=0 \text{ and } V_a+V_b+V_c=0 \quad (9)$$

Then, the boundary condition instantaneous will be:

$$I_\alpha=\frac{2}{3}I_a-\frac{1}{3}I_b-\frac{1}{3}I_c; \quad I_\beta=\frac{1}{3}\sqrt{3}I_b-\frac{1}{3}\sqrt{3}I_c; \quad I_\gamma=-\frac{2}{3}I_a+\frac{1}{3}I_b-\frac{1}{3}\sqrt{3}I_b +\frac{1}{3}I_c+\frac{1}{3}\sqrt{3}I_c \text{ and } I_0=0 \quad (10)$$

Table 1 summarizes the characteristics of various different faults based on Clarke's transformation, based on the above equations.

### 2.2. Wavelet transform

#### 2.2.1. Discrete wavelet transform

Wavelet transformation is defined as the decomposition of a signal by a function, $\varphi_{a\,(t)}$ which is deleted and translated by the so-called mother wavelet. The mother wavelet's function can be written as follows [15,16]:

$$\varphi_{ab(t)}=\frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right) \quad (11)$$

where $a$ is the dilation parameter ($a$ ε Real) and $b$ is a translation parameter ($b$ ε Real). Parameter $a$ indicates the width of the wavelet curve when the value of a wider magnified wavelet curve is diminished as the curve gets smaller, while parameter curve $b$ shows the localization of wavelet centered at $t=b$. The detection of fault of discrete wavelet transformed (DWT) is required so that the equation becomes [17,18];

$$\varphi_{ab(t)}=2^{j/2}\ \varphi\left(2^j(\ a-b)\right), \quad j.k\in Z \quad (12)$$

Variables $j$ and $k$ are integers that scale the shifts of the mother wavelet function, to produce the types of mother wavelet as Syms and Haar wavelet. The width of a wavelet is shown by scale $a$, and the position is indicated by wavelet scale $b$.

Discrete Wavelet Transformation (DWT) is a method used to decompose the input signal, and the signal is analyzed by giving treatment to the wavelet coefficients. The decomposition process involves two filters, which are low-pass filter and a high-pass filter [19]. The results, obtained in the form of cA approximation signal and detail signal cD, as equations:

$$\delta_{high}\ [k]=\sum\nolimits_n X[n].g[2k-n]. \quad (13)$$

$$\delta_{low}\ [k]=\sum\nolimits_n X[n].h[2k-n]. \quad (14)$$

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