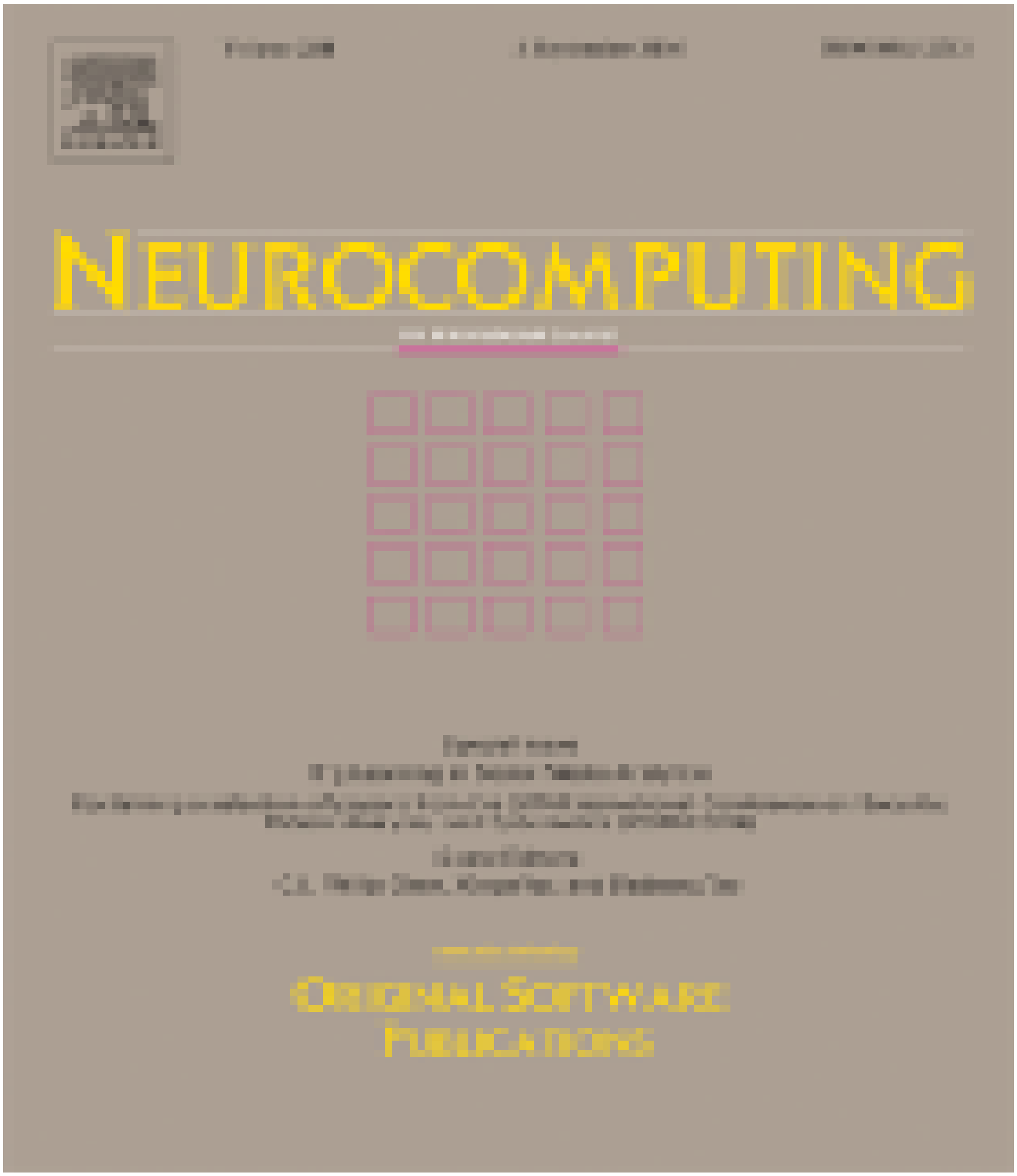
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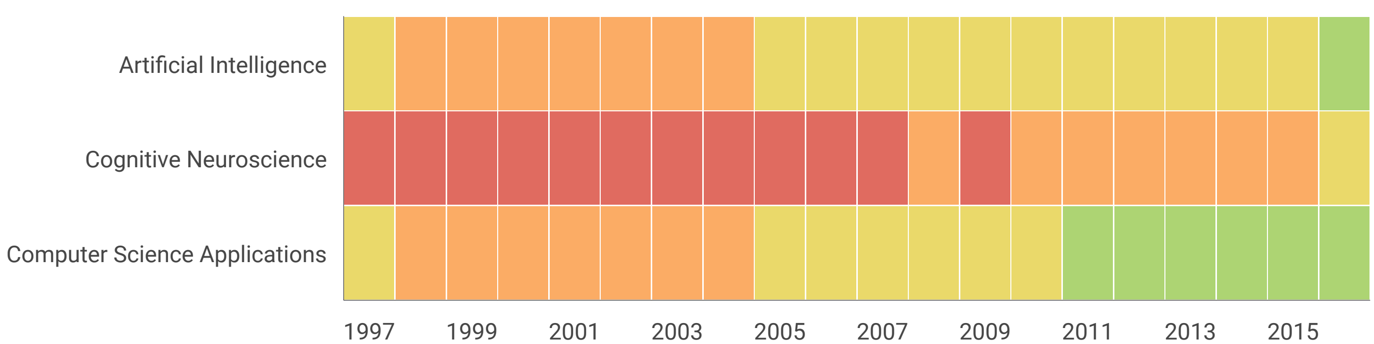

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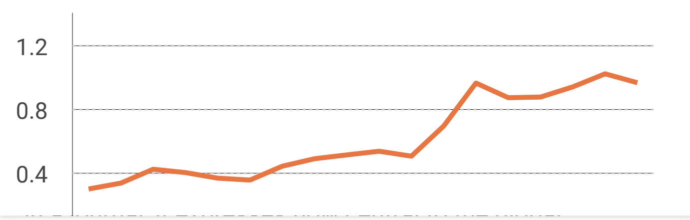

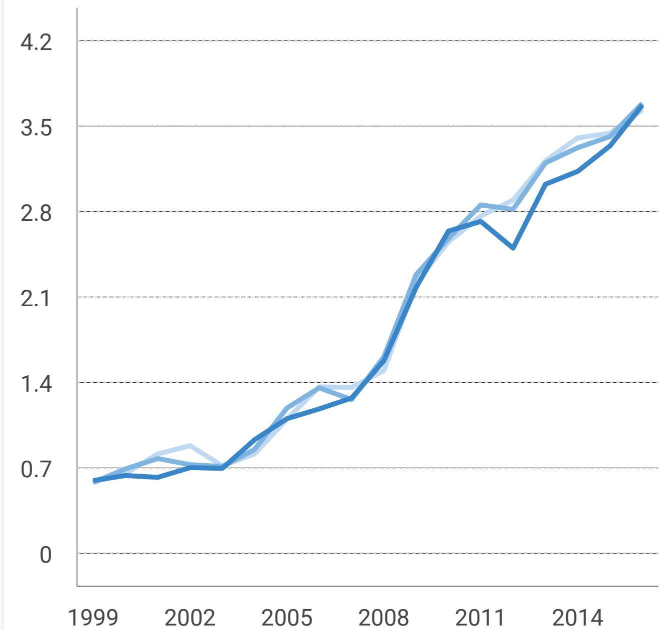

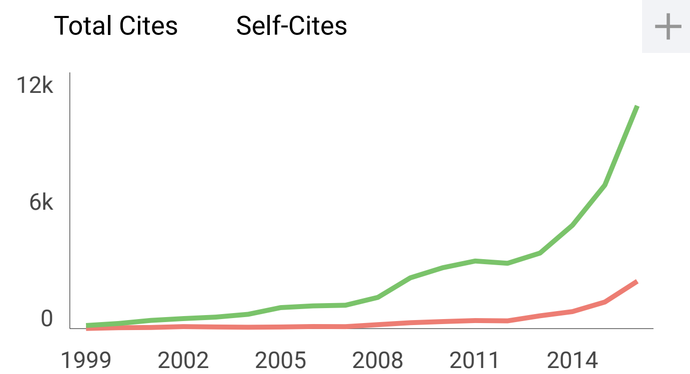

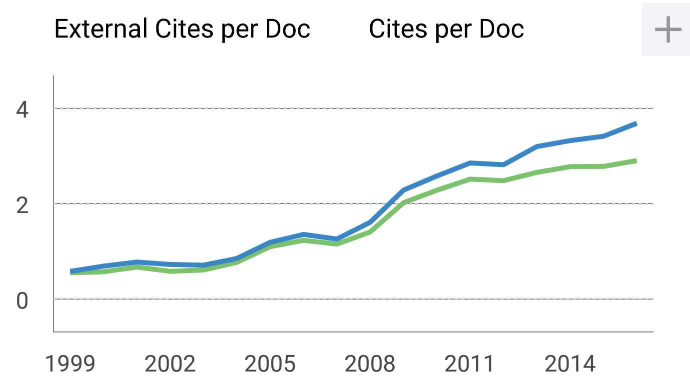

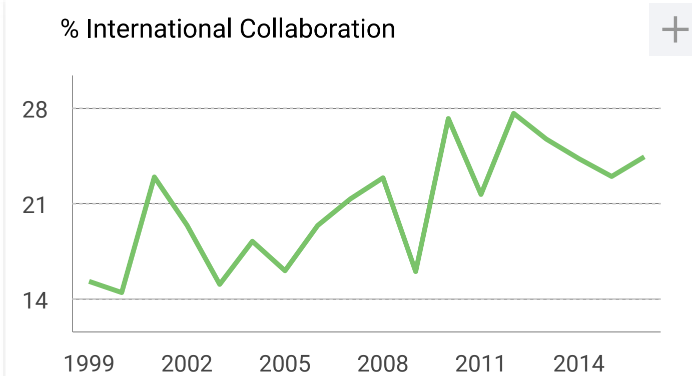

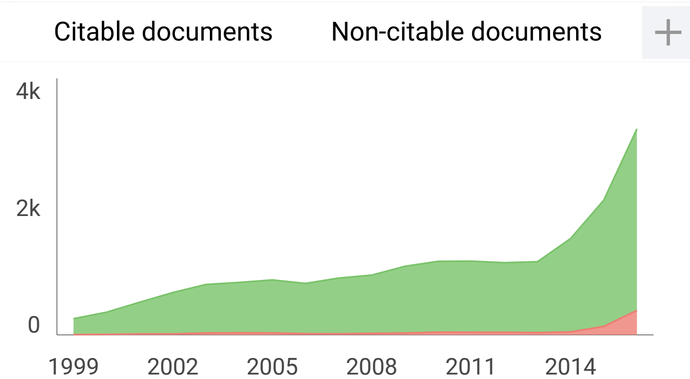

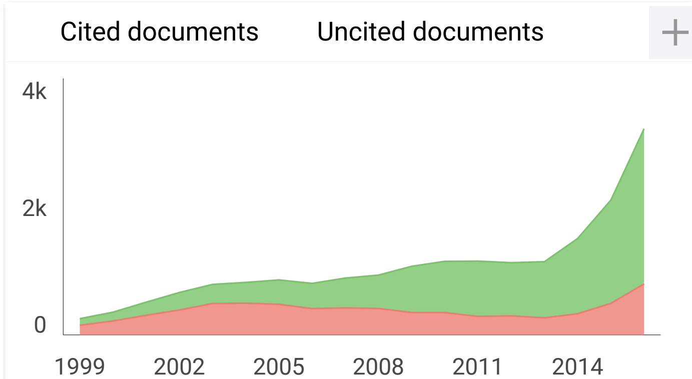

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Title: A new algorithm for detection and fault classification on parallel transmission line using DWT and BPNN based on Clarke's transformation
Authors: Abdullah Asuhaimi, Prof; Makmur Saini, M.D; Mohd Wasir Mustafa, Prof; Ahmad Rizal Sultan, M.D

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NEUCOM-D-14-01258

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Ref.: Ms. No. NEUCOM-D-14-01258
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Dear Mr. Saini,

Please find below the referee reports. Based on these and the corresponding recommendation of the associate editor, I have to inform you that your paper

A new algorithm for detection and fault classification on parallel transmission line using DWT and BPNN based on Clarke's transformation with manuscript number: NEUCOM-D-14-01258

in its present form cannot be accepted for publication in Neurocomputing.

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Sincerely,

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Neurocomputing

Editor's and Reviewers' comments:

Associate Editor: Two independent review reports have been collected. They raise quite a few issues, from both technical and writing aspects. The authors are suggested to carry out a thorough revision, addressing each reviewer's concerns adequately.

Reviewer #1: This paper presents a method for fault type classification and fault location based on wavelet transform and intelligent techniques. In general, the work is meaningful. To further improve the qulity of the paper, the following points need to be clarified or addressed:
- The title of Fig. 1 should be changed to "Fault type classification flowchart", since it does not include fault location.
- Grammar may be improved.
- In fig. 2, the numbering for different layers needs to be improved. For example, for the input layer, it reads '1 2 12', which should be changed to '1, 2, ..., 12'.
- Section 5.1 is confusing. The title says 'fault location and classification'. But the content only has fault classification, and does not contain fault location". Please clarify.
- The following reference is relevant. Please add it.
Thai Nguyen and Yuan Liao, "Transmission line fault type classification based on novel features and neuro-fuzzy system," Electric Power Components and Systems, vol. 38, no. 6, pp. 695-709, April 2010.

Reviewer #3: This manuscript 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. There are several concerns should be revised in this manuscript.
1. The Abstract should be revised. In Abstract, this manuscript should describe the role of the BPNN.
2. The title of Section 2 should be revised as "Related works" or "Literature review". Section 3 "Overview of Wavelet Transform" and Section 4 "Overview of Artificial Neural Networks" should be merged into Section 2. Moreover, the introduction of BPNN is well known, it should be simplified.
3. This manuscript should survey more related literature in the past five years.
4. This manuscript should carefully check mathematical symbols. Mathematical variables should be Italic font.
5. The title of Section 5 should be revised as "The proposed algorithm".
6. This manuscript uses a BPNN to perform classification task. The performance index "classification error" should be considered. Meanwhile, the statistical test should be performed for experimental results.
7. This manuscript should compare the experimental results obtained using the proposed algorithm with those obtained using other alternative neural computing approaches.

Makmur Saini <makmur.saini@fkegraduate.utm.my> Sat, Feb 14, 2015 at 6:56 AM
To: jasrul jamian <jasrul@fke.utm.my>

Assalamu Alaikum

Yth Bapak DR. Jasrul

Maaf sebelumnya inci , bila ada masa saya mau jumpa dengan inci, diskusi tentang paper ini, saya disuruh revisi sampai 27 -3-2014, inci sudah ada pengalaman di journal Neurocompuiting , mudah-mudahan bileh juga ikut jejak pak doktor di terima di jounal neurocompuiting . terima kasih

Best Regards

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Neurocomputing

Dear Mr. Saini,

Please find below the referee reports. Considering these comments and the corresponding recommendation of the associate editor, I am very pleased to inform you that your paper

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Reviewer #1: Reviewer's comments have been addressed.

Reviewer #3: This revised manuscript can be accepted.

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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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0925-2312/

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]:

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

where a, b, c represent the current values of the phase A, B, C respectively; and α, β, 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 α represents the line-modal between phase A and phase B, while modal β represents the line-modal between phase A and phase C. In order to represent the line-modal between phase B and phase C, modal γ is proposed.

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

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:

$$I_b=I_c = 0 \text{ and } V_a = 0 \tag{3}$$

Then, the boundary condition instantaneous will be:

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

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:

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

Then the boundary condition instantaneous will be:

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

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:

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

Then, the boundary condition instantaneous will be:

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

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:

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

Then, the boundary condition instantaneous will be:

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

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]:

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

where a is the dilation parameter ($a\ \varepsilon$ Real) and b is a translation parameter ($b\ \varepsilon$ 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];

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

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:

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

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

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

Table 1
Characteristics of various different faults based on Clarke's transformation.

Type fault	α-Modal	β-Modal	0-Modal	γ-Modal
AG	$2/3\ I_a$	0	$1/3 I_a$	$-2/3\ I_a$
BG	$-\ 1/3\ I_b$	$1/3\sqrt{3}\ I_b$	$1/3\ I_b$	$1/3\ I_b\ (1+\sqrt{3})$
CG	$-\ 1/3\ I_c$	$-\ 1/3\sqrt{3}\ I_b$	$1/3\ I_c$	$1/3\ I_c\ (1-\sqrt{3})$
AB	I_a	$-\ 1/3\sqrt{3}\ I_b$	0	$-I_a-\ 1/3\sqrt{3}\ I_b$
BC	0	$2/3\sqrt{3}\ I_b$	0	$-\ 2/3\sqrt{3}\ I_b$
AC	$-I_c$	$-\ 1/3\sqrt{3}\ I_c$	0	$I_c-\ 1/3\sqrt{3}\ I_c$
ABG	$2/3\ I_a-\ 1/3\ I_b$	$1/3\sqrt{3}\ I_b$	$1/3 I_a+1/3\ I_b$	$-2/3\ I_a+1/3\ I_b\ +\ 1/3\sqrt{3}\ I_b$
BCG	$-1/3 I_a-1/3\ I_b$	$1/3\sqrt{3}\ I_b-1/3\sqrt{3}\ I_c$	$1/3 I_b+1/3\ I_c$	$1/3 I_a+1/3\ I_b+1/3\sqrt{3}\ I_b-1/3\sqrt{3}\ I_c$
CAG	$2/3\ I_a-\ 1/3\ I_c$	$-\ 1/3\sqrt{3}\ I_c$	$1/3 I_a+1/3\ I_c$	$-2/3\ I_a+1/3\ I_c\ -\ 1/3\sqrt{3}\ I_c$
ABC	$\frac{2}{3} I_a-\frac{1}{3} I_b-\frac{1}{3} I_c$	$1/3\sqrt{3}\ I_b-1/3\sqrt{3}\ I_c$	0	$-\frac{2}{3} I_a+\frac{1}{3} I_b-\frac{1}{3}\sqrt{3}\ I_b+\frac{1}{3} I_c+\frac{1}{3}\sqrt{3}\ I_c$

2.2.2. Wavelet energy

The wavelet energy coefficient is obtained from the sum of square of detailed wavelet transform coefficients [20]. The wavelet energy coefficient varies over different scales depending on the input signals. The wavelet energy coefficient can be defined as follows:

$$E(s(t)) = \sum_{j=1}^{N} a_j c_j^2 \tag{15}$$

with suitable scaling coefficients, a_j, for the coefficient, c_j, obtained from the equivalent signals (t). The energy of the signal is limited mostly in the estimation part and a little in the detail part [21]. For example, the estimated coefficient at the first-level contains much more energy than the other coefficients at the same level of the decomposition tree. Because the faulty signals have high frequency components, it is more typical to use wavelet energy coefficient [22].

2.3. Artificial neural network (ANN)

The concept of ANNs has been around since the 1950s, which biologically inspires the view of the human brain as a processor using interconnected neurons. ANN represents a connection to the brain, such as artificial neurons that are interconnected and adaptive to the output of other connected nodes that have modified parameters [23]. ANN is widely used in engineering fields such as telecommunications, medical, control and power systems [24]. ANN training is necessary to associate the correct output response to a particular input pattern. Once properly trained, an ANN has the ability to generalize the similar moment, but not identical pattern introduced to the network [25]. One of the most popular neural networks is Back Propagation Neural Network (BPNN) method, commonly used to solve many nonlinear problems, but the original BP network used to suffer primarily from a lack of convergence, because they used to get stuck in a local minimum. Over the years, different variations of BPNN improvement have been proposed to specifically address several important issues, namely reducing the convergence time, ease the computational burden, reducing memory requirements and so on [26].

2.3.1. Architecture of BPNN

Feed-forward neural network architecture layers are shown in Fig. 2. This architecture consists of one input layer, two hidden layer and one output layer. It may have one or more hidden layers. All layers are fully connected and feed-forward type. The output is a nonlinear function of the input, and is controlled by the weights calculated during the learning process. The learning process uses supervised learning paradigm which is back propagation. In Back-Propagation (BP) training process, the activation function is restricted and differentiated. The most common function is the sigmoid. It is bound between the minimum (0) and maximum (1). Before the signal is passed to the next layer of neurons, each neuron summed output is scaled by this function [27].

2.3.2. BPNN algorithm

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 [27]. Back-propagation neural network (BPNN) 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), Mean Squared Error (MSE), Standard Error (SE) and Variance Error (VE) are used. The best model is the model that has the smallest value of MAE, MS, SE and VE.

3. The proposed algorithm

3.1. Fault classification using wavelet principle

As mentioned earlier, this paper proposes a new algorithm for fault classification using wavelet based on Clarke's transformation to obtain the fault current. By considering the frequency band of the fault-induced discrete wavelet transformed (DWT), on the transmission lines, the current signals are sampled at the sampling rate of 200 kHz. The Clarke's modal transformation will then be used to decouple the three-phase currents. The current modal components are shown in Eq. (1). The signal is first passed through the high-pass filter and low-pass filters, and then half of each output is taken as sampling, down through the sampling operation. This is called decomposition first level process, done in the frequency range of 100–200 kHz. Considering these factors, DWT under second, third, and fourth scales are then adopted. When the highest frequency that could be obtained is 50–100 kHz, 25–50 kHz and 12.5–50 kHz can be used in the algorithm.

The features used to distinguish between internal and external disturbances of the parallel transmission lines are protected. Proposed algorithm fault discrimination, the α and β modal components covers all of the possible fault types in each of the parallel circuit. To cover the inter-circuit faults as well, the γ-modal component of the current signals is defined as follows:

$$I_\gamma = -2/3\, I_a + 1/3(1+\sqrt{3})I_b + 1/3(1-\sqrt{3})\, I_c \tag{16}$$

The magnitude of the current gamma of each different type of fault can be seen in Table 1.

The fault discrimination criteria are defined as follows:

$$\left|\frac{I_{\alpha1}}{I_{\alpha2}}\right| > 1 \text{ or } \left|\frac{I_{\beta1}}{I_{\beta2}}\right| > 1 \text{ Fault Internal Circuit 1} \tag{17}$$

$$\left|\frac{I_{\alpha2}}{I_{\alpha1}}\right| > 1 \text{ or } \left|\frac{I_{\beta2}}{I_{\beta1}}\right| > 1 \text{ Fault Internal Circuit 2} \tag{18}$$

$$\left|\frac{I_{\alpha1}}{I_{\alpha2}}\right| = 1 \text{ or } \left|\frac{I_{\beta1}}{I_{\beta2}}\right| = 1 \text{ Fault External} \tag{19}$$

where $I_{\alpha1}$ and $I_{\beta1}$ denote the modulus maxima of the modal components for the first circuit currents, and $I_{\alpha2}$ and $I_{\beta2}$ denote those of the second circuit.

The protection technique should be able to classify the faulted phase for single-phase-to-ground faults [28]. Fig. 1 illustrates the proposed fault-type classification algorithm that uses the modal components of the current signals. In the case of single-phase-to-ground faults, two of the modal components that include the faulted phase should have almost the same amplitude and the other modal component should be zero, as follows:

$$\frac{S_\alpha}{S_\gamma}+1 < \in \text{ and } Q_\alpha - Q_\gamma \le \in \;\Rightarrow \text{AG fault} \tag{20}$$

$$\frac{S_\gamma}{S_\beta - S_\alpha}-1 < \in \text{ and } Q_\gamma\text{–}(Q_\alpha + Q_\beta) \le \in \;\Rightarrow \text{BG fault} \tag{21}$$

$$\frac{S_\beta}{S_\alpha + S_\gamma}-1 < \in \text{ and } Q_\beta\text{–}(Q_\alpha + Q_\gamma) \le \in \;\Rightarrow \text{CG fault} \tag{22}$$

The algorithm will continue to determine the faulted phases involved in a multiple-phase fault. In the case of line of line faults, the criteria are as given in (25)–(26):

$$\frac{S_\gamma}{S_\alpha - S_\beta}+1 < \vartheta \text{ and } Q_\gamma\text{–}(Q_\alpha + Q_\beta) \le \vartheta \;\Rightarrow \text{AB fault} \tag{23}$$

$$\frac{S_\alpha}{S_\gamma - S_\beta}+1 < \vartheta \text{ and } Q_\alpha\text{–}(Q_\beta + Q_\delta) \le \vartheta \;\Rightarrow \text{AC fault} \tag{24}$$

$$\frac{S_\beta}{S_\gamma}-1 < \vartheta \text{ and } Q_\beta - Q_\gamma \le \vartheta \;\Rightarrow \text{BC fault} \tag{25}$$

where S_α, S_β, S_γ represent the sums of fourth level detail coefficients wavelet of line currents I_α, I_β and I_γ, respectively. Similarly, Q_α, Q_β and Q_γ represent the sums of absolute values of fourth level detail coefficients wavelet of line currents I_α, I_β and I_γ, respectively.

By determining the fault classification, as shown in Fig. 1, the fault classification will be divided into 2 categories, which are ground and unground. If the current is near zero at the threshold of interference, it would be unground fault, otherwise if the current S_0 is greater than the specified threshold limit, it would be the ground fault. The unground fault is the line to line fault, while the threshold limit is given for termination criteria σ=0.02, while the ground is divided into 2, which are lined to ground fault with the given threshold ε=0.03, and the line to line to ground fault with the given threshold δ=0.05 for termination criteria [29].

3.2. Fault detection and classification using DWT and BPNN principle

The design process of the proposed fault detection and classification algorithm for parallel transmission lines goes through the following steps:

(1) Finding the input to the Clarke transformation and wavelet transform. The signal flow of PSCAD is then converted into *m.* files (*. M)
(2) Determining the data stream interference, where the signal is transformed by using Clarke's transformation to convert the transient signals into the signal's basic current by means of Eq. (2)
(3) Input signals are analyzed by DWT for extracting the information of the transient signal in the time and the frequency domain [30].
(4) Selection of a suitable BPNN topology and structure for a given application.
(5) Training of BPNN and validation of the trained BPNN to check its correctness in generalization.

Line currents I_a, I_b and I_c at a frequency of 50 Hz measured simultaneously by PSCAD delivery at the end of the line are then used to classify the type of errors between LG, LL, LLG, LLL and healthy (normal) condition after using Clarke's transformation to get the current modes I_α and I_β. As indicated in previous studies, the Daubechies mother wavelet has a good ability to capture the transient and time-frequency feature extraction for power system fault [29]. In the proposed algorithm, 'Db4' mother wavelet is used to get the DWT coefficients for the classification of different types of fault. By using the detail coefficients wavelet of various parameters, namely S_0, S_α, S_β, S_γ,Q_0, Q_α, Q_β and Q_γ will then be calculated 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 E_0, E_α, E_β and E_γ represent the sum of the four levels of energy wavelet of mode currents I_0, I_α, I_β and I_γ.

The input of BPNN training consists of detail coefficients wavelet and wavelet energy. The combination of different fault conditions that must be considered and training patterns are required to be generated by simulating various types of faults on parallel transmission. Therefore, the type of fault, fault location, fault resistance and fault inception can be determined.

ANN architecture is used so that it will be able to recognize and classify all the possible operating conditions of parallel transmission,

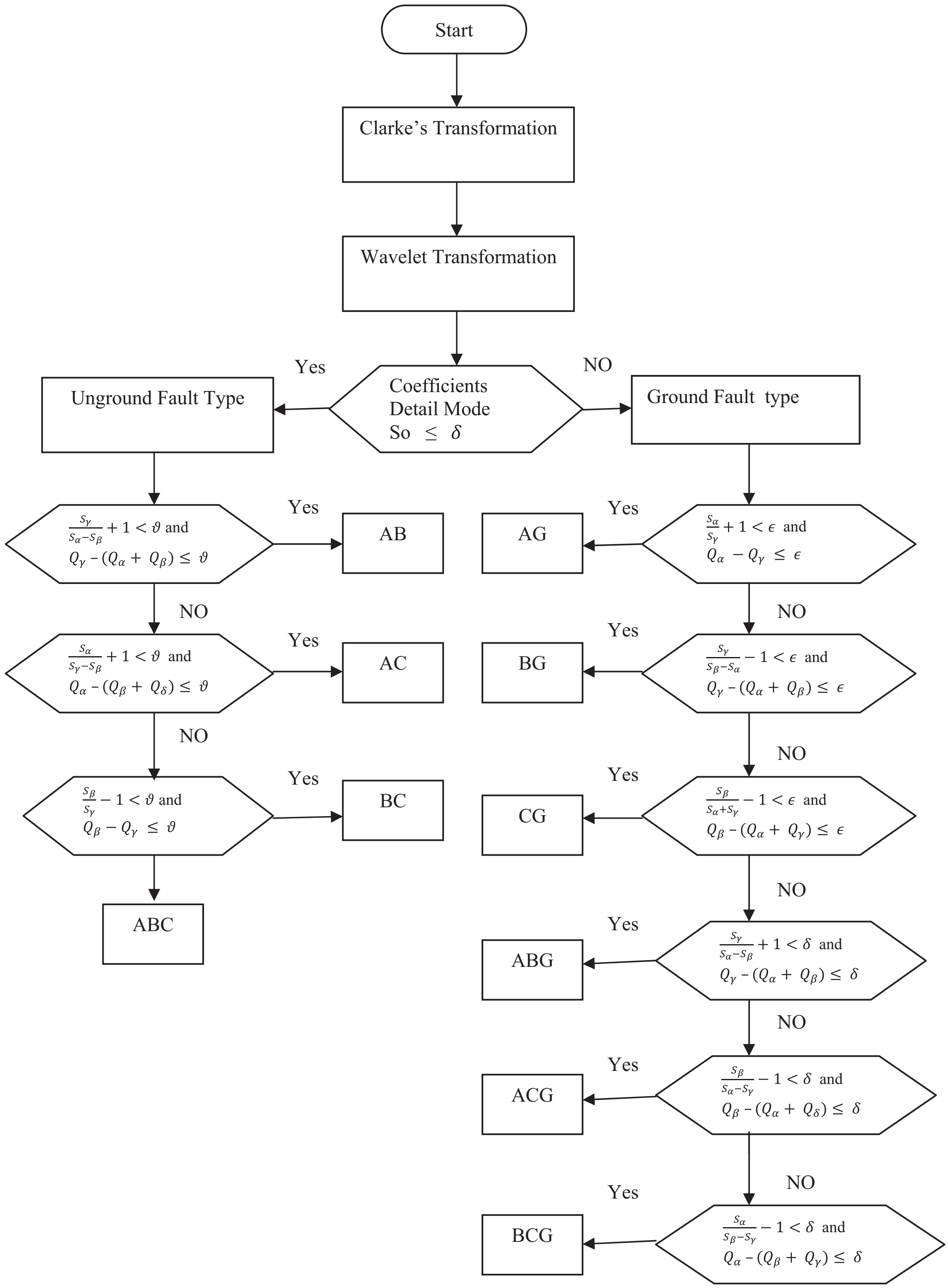

Fig. 1. Fault classification flowchart.

and then provide a trip signal whenever the fault is identified. In this proposed scheme, different architectures have been considered [30]. The set of inputs used were 12 samples of output current signals of parallel transmission. Two hidden layers were taken and the number of neurons was varied as hidden 1 from 6 to 24, hidden 2 from 12 from 48 results and the set output 4, as shown in Fig. 2.

4. Simulation result and analysis

4.1. Data simulation

In this study, the system was connected with the sources at each end, as shown in Fig. 3. This system was simulated using PSCAD/

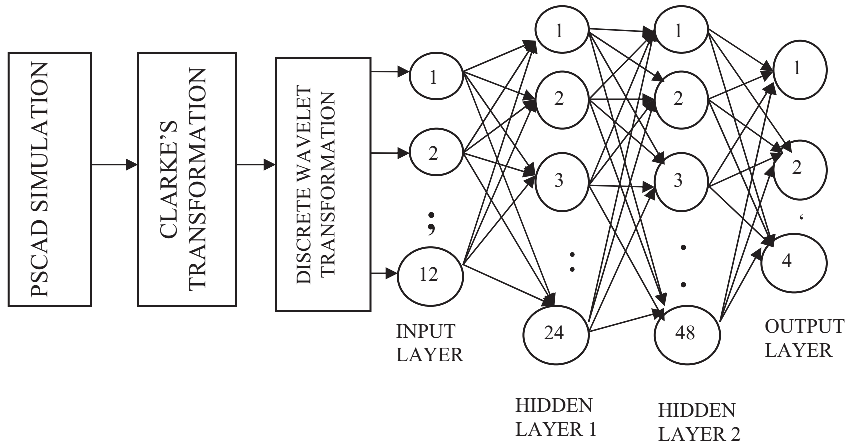

Fig. 2. Architecture of proposed DWT-BPNN based on Clarke's transformation.

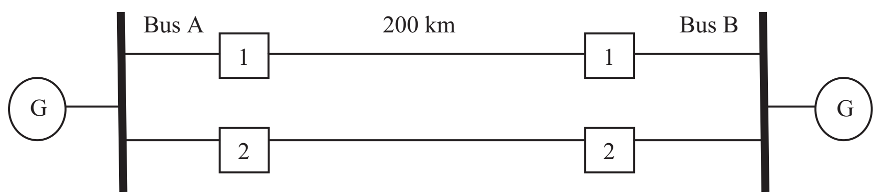

Fig. 3. One line diagram of the simulated transmission system.

EMTD. For the case study, the simulation was modeled on a 230 kV double circuit transmission line, which was 200 km in length.

4.1.1. Transmission data

Sequence impedance ohm/km.
Transmission line $Z_1 = Z_2 = 0.03574 + j\ 0.5776\ \Omega/\text{km}$
$Z_0 = 0.36315 + j\ 1.32.647\ \Omega/\text{km}$
Source A and B $Z_1 = Z_2 = Z_0 = 9.1859 + j52.093\ \Omega$
Fault starting = 0.22 s duration in fault = 0.15 s

After calculating the parameters, the training sample of the detail coefficients wavelet various parameters, namely S_0, S_α, S_β, S_γ, Q_0, Q_α, Q_β, Q_γ and wavelet energy E_0, E_α, E_β and E_γ for various types of faults were set as input variables to build neural network. The data sets were created by considering different operating conditions, i.e. the different values of inception angles ranging between 0 and 180 degrees, different values of fault resistances between 0 and 200 Ω and different fault distances from 0 to 200 km.

Fault Type: AG, BG, CG, ABG, BCG, ACG, AB, BC, AC, and ABC

Fault Location (distance) for training and testing: 25, 50, 75, 100, 125, 150 and 175 km

Fault Resistance (R_f) for training and testing: 0.001,25, 50, 75, 100, 125, 150, 175 and 200 Ω

Fault Inception Angle for training and testing: 0, 15, 30, 45, 60, 90, 120, 150 and 180 degrees

The proposed DWT and BPNN were 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 2.

The filtered wavelet coefficients detail of the currents is shown in Fig. 4. By using the rules aforementioned, the first and last faulted samples were 10^5, respectively, for a sampling frequency of 200 kHz.

Table 2
Binary coding of ANN output.

Fault type	Phase A output 1	Phase B output 2	Phase C output 3	Ground G 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

4.2. Simulation results for type of fault, distance, resistance and inception angle using mother wavelet Db4

As shown in Table 3, the simulations showed the effect of the variation of fault inception angle, ranging from 30 degrees to 150 degrees, with variations in fault resistance of 75 Ω and 100 Ω in various types of fault and fault distance. Meanwhile, the threshold obtained in line to ground disturbance (AG) at a fault distance of 150 km, fault resistance 75 Ω and fault inception angle 60 degrees were $\delta = 0.00007$; this was greater than the threshold set on the fault line to line to ground of $\delta = 0.05$, as it was connected to the ground. The double line to ground fault (BCG) at a fault distance of 75 km, fault resistance 100 Ω and fault inception angle of 90 degrees obtained a threshold of $\sigma = 0.000012$, smaller than the threshold set of $\sigma = 0.02$. Table 4 shows that if the fault inception angle was enlarged, then the fault current would increase, except for fault three-phase (ABC), which had results of $I_{\alpha1}/I_{\alpha2}$ and $I_{\beta1}/I_{\beta2}$, between 1.2 and 3, indicating that the fault was an internal fault circuit 1. The fault classification algorithms signified that the proposed algorithm is accurate and precise

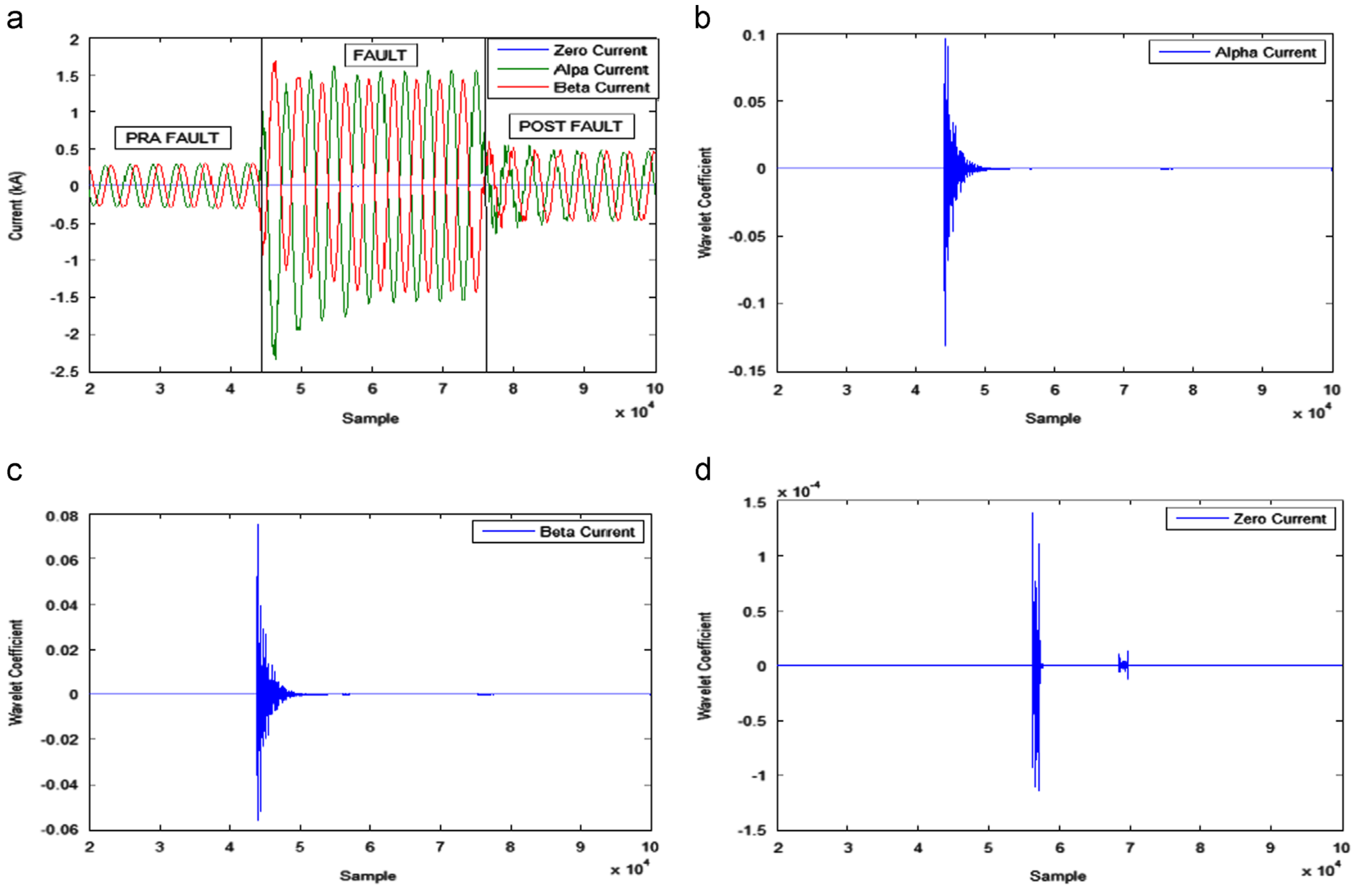

Fig. 4. Level 4 DWT coefficients of the fault currents (AB): (a) Clarke's signal current (a) α; (b) β; and (d) zero-sequence component.

4.3. Simulation results of using DWT and BPPN with/without Clarke's transformation

Discreet combination (A–B–C–G) of faults classification obtained by defining 1 for values greater than 0.6 and 0 for values less than 0.4. The simulation results are shown in Tables 4–6. Error percentage of combination using pre-processing Clarke's transformation compared to without Clarke's transformation calculated as follows;

$$\text{Percentage of MSE Validity} = \frac{\text{MSE(WoTC)} - \text{MSE(WiTC)}}{\text{MSE(WoTC)} \times 100\%} \tag{26}$$

$$\text{Percentage of MAE Validity} = \text{MAE}\left(\frac{\text{(WoTC)} - \text{MAE(WITC)}}{\text{MAE(WoTC)} \times 100\%}\right. \tag{27}$$

where MSE (WoTC) is mean square error (MSE) without transformation Clarke's, MSE (WiTC) is mean square error (MSE) with transformation Clarke's, MAE (WoTC) is mean absolute error (MSE) without transformation Clarke's, MAE (WiTC) is mean absolute error (MSE) With Transformation Clarke's.

Simulation result of fault detection and classification using DWT and BPPN deliver good results when analyzed with pre-processing using Clarke's transformation and architecture combination of 12-6-12-4 (12 neurons in the input layer, 2 hidden layer with 12 and 6 neurons in them, respectively and 4 neurons in the output layer). The results are as follows: without Clarke's transformation, the mean square error (MSE) was 0.07766 and the mean absolute error (MAE) was 0.171058, and with Clarke's transformation, the MSE was 0.072245 and MAE was 0.150773. Percentage of MSE Validity shows less about 6.972% and MAE less about 11.883% compared to without pre-processing Clarke's transformation as shown in Table 4.

Table 5 shows the effects of variations in the resistance of 25 Ω and 50 Ω with fault inception angle at 15 and 45 degrees with varying distances, training performance plot of the neural network 12-12-24-4 (12 neurons in the input layer, 2 hidden layer with 12 and 24 neurons in them, respectively, and 4 neurons in the output layer).

The results of DWT and BPNN training are as follows: without Clarke's transformation, MSE was 0.056214 and MAE was 0.154754, with Clarke's transformation, the MSE was 0.053876 and MAE 0.150301. Percentage of MSE Validity shows less about 4.159% and MAE less about 2.877% compared to without pre-processing Clarke's transformation.

Simulation result of fault detection and classification using DWT and BPPN deliver good results when analyzed with pre-processing using Clarke's transformation and architecture combination of 12-24-48-4 (12 neurons in the input layer, 2 hidden layers with 24 and 48 neurons in each and 4 neurons in the output layer). Table 6 shows the result without Clarke's transformation, where MSE was 0.055139 and MAE was 0.121617, whereas with Clarke's transformation, the MSE was 0.037218 and MAE was 0.119521. Percentage of MSE Validity shows less about 32% and MAE less about 1.7% compared to without pre-processing Clarke's transformation. The results above show that using Clarke's transformation will produce better result.

4.4. Comparison with the BPNN and pattern recognition network (PRN} based fault classification

The comparison of BPNN and PRN based classifier for type of fault is verified and classification result are summarised as shown in Table 7.

Table 3
The obtained results for type of fault, distance, resistance and inception angle using mother wavelet Db4.

Fault	*AG*		*AC*		*BCG*		*ABC*	
Distance (km)	150		125		75		50	
Fault resistance (Ohm)	75		100		75		100	
Fault inception angle (θ)	60	75	30	45	75	90	120	150
s_{o1}	0.04299	0.03966	0.00000	8.30e−11	0.03873	0.03138	0.00000	0.00000
$S_{\alpha1}$	−0.33810	−0.30690	−0.71065	−0.72874	−0.09405	−0.07683	−0.09242	−0.00608
$s_{\beta1}$	−7.45e−05	−0.00011	−0.41032	−0.42077	−0.32223	−0.36301	−0.19696	−0.14961
$s_{\gamma1}$	0.33803	0.30679	0.30033	0.307970	−0.22817	−0.28618	−0.10454	−0.14353
Q_{o1}	0.33760	0.30611	0.00000	1.44e−08	0.36216	0.29997	0.00000	0.00000
$Q_{\alpha1}$	1.57459	1.44100	3.07181	3.142558	0.91795	0.77506	1.52386	0.24135
$Q_{\beta1}$	0.01012	0.01504	1.77449	1.818559	1.68581	1.85502	3.23387	2.54802
$Q_{\gamma1}$	1.57474	1.443868	1.300907	1.330685	1.453591	1.635708	2.54802	2.512856
$I_{\alpha1}$ (kA)	0.6723	0.8005	0.8963	0.9292	0.7293	−0.8503	2.2589	2.0813
$I_{\alpha2}$ (kA)	0.4196	0.5677	0.2908	0.3547	0.4812	0.6391	0.9405	1.0646
$I_{\alpha1}/I_{\alpha2}$	1.6002	1.4100	3.0822	2.6197	1.5165	−1.3305	2.4018	1.9555
$I_{\beta1}/I_{\beta2}$	1.4187	1.2849	2.4276	1.9144	2.4631	2.2247	2.2517	1.7363

Table 4
The obtained result of different fault using DWT and BPNN, with configuration (12-6-12-4).

Type fault	Distance	R_f	Fault inception	Clarke's transformation MSE=0.072245 and MAE=0.150773				Without Clarke's transformation MSE=0.07766 and MAE=0.171058			
	km	Ohm	Degree	A	B	C	G	A	B	C	G
AG	25	0.001	0	0.95142	0.10052	−0.1282	1.06332	1.07509	−0.1591	−0.0460	1.02017
BG	50	0.001	0	0.27148	1.01447	0.04518	0.98523	0.29988	0.77232	0.24082	1.03434
AB	75	0.001	0	0.98479	1.02404	0.03225	0.01004	1.07188	0.93337	0.03655	0.0068
AC	100	0.001	0	1.03366	0.00918	0.96656	−0.0766	0.90738	0.10155	1.05906	0.29056
ABG	125	0.001	0	1.02768	0.85509	−0.0628	1.01392	1.12254	1.00395	−0.1871	0.70944
ACG	150	0.001	0	1.03969	0.00339	0.94847	0.89650	0.90037	0.04411	1.00111	0.73164
ABC	175	0.001	0	0.83261	1.09872	0.90557	0.02879	0.91583	1.06532	1.17350	0.02907

Table 5
The obtained result for different resistance fault using DWT and BPNN, with configuration (12-12-24-4).

Type fault	Distance	R_f	Fault inception	Clarke's transformation MSE=0.053876 and MAE=0.150301				Without Clarke's transformation MSE=0.056214 and MAE=0.154754			
	km	Ohm	Degree	A	B	C	G	A	B	C	G
BG	50	25	15	−0.2601	0.81200	0.19912	1.00950	0.27056	0.97048	−0.0520	0.96410
BG	50	50	15	−0.2060	0.88430	0.20585	1.00644	0.20411	1.08331	−0.0347	0.95417
AB	75	25	15	0.92614	1.06886	0.16452	−0.0137	1.02506	0.75573	0.24930	0.02225
AB	75	50	15	0.94049	1.03467	0.12603	−0.0054	0.98041	0.77873	0.27164	0.04101
ACG	125	25	45	0.94042	0.30193	0.72921	1.10056	1.27393	−0.0218	1.02932	1.03103
ACG	125	50	45	1.02505	0.25839	0.87277	1.05164	1.24756	−0.0894	1.0371	0.99745
ABC	150	25	45	0.95041	0.95152	0.86122	0.02848	1.04392	1.21587	1.32748	−0.1776
ABC	150	50	45	0.91256	0.86101	1.00063	0.02601	1.00739	1.23383	1.14222	−0.1332

Table 6
The obtained result for different inception fault using DWT and BPNN with configuration (12-24-48-4).

Type fault	Distance	R_f	Fault inception	Clarke's transformation MSE=0.037218, MAE=0.119521				Without Clarke's transformation MSE=0.055139, MAE=0.121617			
	km	Ohm	Degree	A	B	C	G	A	B	C	G
AG	150	75	60	0.96366	0.02287	−0.0790	0.99251	0.99819	0.35599	0.05123	1.04945
AG	150	75	75	1.04744	0.11159	0.13258	1.04361	0.98178	0.35063	0.10977	1.03948
AC	125	100	30	1.02566	0.02795	1.00082	0.03517	0.91547	0.05778	0.96419	−0.07465
AC	125	100	45	1.04593	0.15348	0.74610	0.11221	0.89002	−0.03641	1.16882	−0.04335
BCG	75	75	75	0.01242	0.72528	0.89684	1.07555	−0.15165	0.99650	0.98279	0.99787
BCG	75	75	90	−0.0289	0.83212	0.97222	1.05126	−0.02451	1.11924	1.00483	1.04200
ABC	50	100	120	0.83261	1.09872	0.90557	0.02879	0.70757	0.90057	1.20523	0.00774
ABC	50	100	150	0.82418	1.16831	0.85983	0.03543	0.67534	0.81013	0.95471	0.07862

Table 7
The comparison result for model BPNN and PRN based on Clarke's transformation with configuration (12-24-48-4).

Type fault	Distance	R_f	Fault inception	Back-propagation neural network MSE=0.037218, MAE=0.119521				Pattern recognition network MSE=0.13115, MAE=0.26489			
	km	Ohm	Degree	A	B	C	G	A	B	C	G
AG	150	75	60	0.96366	0.02287	−0.0790	0.99251	0.90539	0.32014	0.11389	0.99892
AG	150	75	75	1.04744	0.11159	0.13258	1.04361	0.75950	0.27251	0.19157	0.99786
AC	125	100	30	1.02566	0.02795	1.00082	0.03517	0.99935	0.34371	0.71337	0.00208
AC	125	100	45	1.04593	0.15348	0.74610	0.11221	0.92150	0.00003	0.99957	0.00146
BCG	75	75	75	0.01242	0.72528	0.89684	1.07555	0.22582	0.70012	0.70752	0.99869
BCG	75	75	90	−0.0289	0.83212	0.97222	1.05126	0.21743	0.79599	0.73602	0.99689
ABC	50	100	120	0.83261	1.09872	0.90557	0.02879	0.75951	0.79234	0.80087	0.00014
ABC	50	100	150	0.82418	1.16831	0.85983	0.03543	0.78047	0.82732	0.76302	0.00015

Table 8
the comparison SE for model BPNN and PRN based on Clarke's transformation.

Configuration	Standard error (SE)							
	Back-propagation neural network				Pattern recognition network			
	Output A	Output B	Output C	Output G	Output A	Output B	Output C	Output G
12-6-12-4	0.24666	0.31006	0.23211	0.07275	0.40700	0.44677	0.40645	0.23975
12-12-24-4	0.25194	0.26869	0.22829	0.09127	0.40836	0.36352	0.43509	0.27885
12-24-48-4	0.22979	0.25438	0.20463	0.08553	0.42236	0.43000	0.43078	0.16211

Table 9
VE comparison for model BPNN and PRN based on Clarke's transformation.

Configuration	Variance error (VE)							
	Back-propagation neural network				Pattern recognition network			
	Output A	Output B	Output C	Output G	Output A	Output B	Output C	Output G
12-6-12-4	0.06084	0.09614	0.05388	0.00529	0.16565	0.19961	0.16520	0.05748
12-12-24-4	0.06347	0.07219	0.05212	0.00833	0.17839	0.18491	0.18558	0.02628
12-24-48-4	0.05280	0.06471	0.04187	0.00732	0.16378	0.18001	0.15227	0.02422

Table 7 show the results of Clarke's transformation. With training DWT and BPNN, MSE was 0.037218 and MAE was 0.119521, and for DWT and PRN, the MSE was 0.13115 and MAE 0.26489. Simulation result of fault detection and classification using Clarke's transformation deliver good results when analyzed with pre-processing using training DWT and BPNN and architecture combination of 12-24-48-4.

Table 8 shows a comparison of the statistical test by using the standard error (SE), BPPN with PRN. Standard Error (SE) is the standard deviation of the sampling distribution of a statistic. The term may also be used to refer to an estimate of that standard deviation, derived from a particular sample used to compute the estimated [31].

Table 8 shows the comparison between BPNN with PRN. If the results of the standard error is smaller for BPNN than PRN, BPNN is better than PRN. Table 8 also shows the output phase G of BPNN and PRN are the smallest compared to other phases.

Table 9 shows a comparison of the statistical test by using the Variance Error (VE), BPPN with PRN. Variance Error is a result of systematic differences between samples, with is the data set that describes the actual probability distribution of an observed population of numbers [32,33].

Table 9 shows the comparison between BPNN and PRN. If the variance error is smaller for BPNN than PRN, BPNN is better than PRN. Table 9 also shows the output phase B of BPNN and PRN was the largest compared with other phases.

Table 10 shows the comparison performance for model for Back Propagation Neural Network, Fit Network and Pattern Recognition Network Algorithm based on Clarke's transformation.

The results show that the best Clarke's transformation occurred on the 12-24-48-4 configuration. For instance, using MSE method, the errors of Back Propagation Neural Network, Pattern Recognition Network and Fit Network are 0.03721, 0.13115 and 0.03728, respectively, and the errors using MAE method, are 0.11952, 0.26489 and 0.11953, respectively. This suggests that the Back propagation Neural Network results in the lowest error thus it is most best compared Pattern Recognition Network and Fit Network.

5. Conclusion

This paper proposes a technique of using a combination of discrete wavelet transform (DWT) and back-propagation neural networks (BPPN) with and without Clarke's transformation, in order to identify fault classification and detection on parallel circuit transmission lines. This technique applies Daubechies4 (Db4) as a mother wavelet. Various case studies have been studied, including variation distance, the initial angle and fault resistance. This study also includes comparison of the results of training BPPN and DWT with and without Clarke's transformation, where the results show that using Clarke's transformation will produce smaller MSE and MAE, compared to without Clarke's transformation. Among the three structures, the

Table 10
Comparison of MSE and MAE for Back propagation neural network, Pattern recognition network and fit network algorithm.

Configuration	Back propagation neural network Clarke's transformation		Pattern recognition network Clarke's transformation		Fit network Clarke's transformation	
	MSE	MAE	MSE	MAE	MSE	MAE
12-6-12-4	0.07224	0.15077	0.14704	0.30409	0.073897	0.15052
12-12-24-4	0.05387	0.15030	0.13225	0.28122	0.056055	0.15225
12-24-48-4	0.03721	0.11952	0.11135	0.26489	0.037281	0.11953

Architects result was the best, which was 12-24-48-12. Four statistical methods are utilized in the present study to determine the accuracy of detection and classification faults, suggesting that the Back Propagation Neural Network results in the lowest error thus it is the best compared with Pattern Recognition Network and Fit Network.

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