Application of Discrete wavelet transform and Back-propagation Neural Network for Internal and External Fault Classification in Transformer

Atthapol Ngaopitakkul, Chaiyan Jettanasen, Dimas Anton, and Asfani, Yulistya Negara

***Abstract*— This paper proposes an algorithm for internal and external fault discrimination in the three-phase two-winding power transformer based on a combination of discrete wavelet transform (DWT) and back-propagation neural network (BPNN). The maximum ratio obtained from division algorithm between DWT coefficient value of differential current and zero sequence component in post-fault condition differential current signals is employed as an input for the training pattern for BPNN in order to discriminate between internal fault and external short circuit. The proposed algorithm performance has been test using various cases studies based on Thailand electricity transmission and distribution systems data. Results show that the proposed technique can achieved satisfy accuracy for internal and external fault detection and discrimination in the considered system. This methodology and result can be used to further improve protection system of power transformer in the future.

***Keywords*— Back-propagation neural network, External Short Circuit, Internal Winding Fault, Power Transformer, Wavelet Transform.

I. Introduction

POWER transformer is a vital equipment in Electrical power system with it main features that can step up, step down and regulate voltage level without significant power loss in the equipment. With the increase complexity of the power system, the performance of conventional protection system might be affected. In order to guarantee safety and stability of electrical power grid, a precise protection scheme in power transformer is required.

literature for fault detection, several decision algorithms have been developed to be employed in the protective relay [1]-[18]. They (most of them) have different solutions and techniques. Wavelet Transform is a relatively popular method for transient analysis. There used wavelet to analyze the synchronously rotating reference frame (d-q) axis for discriminate inrush currents from the incipient fault currents [1]-[2], moreover there used energy of wavelet to separate inrush currents and internal fault [3]-[5]. The energy content of the second level approximation at different fault incidence angles is calculated. It is able to well discriminate the magnetizing inrush current with fault current [3]. There used dead angle of the Wavelet Energy Waveform to distinguish magnetizing inrush condition from internal fault condition, the dead angle of WEW is measured if the dead angle is less than the threshold value, it implies that the power transformer experiences an internal fault [4]. Then wavelet is used analysis by spectrum [6]-[7] Such as, this paper shows that the result can successfully detect the temporal and spectral interactions between the normal signal and one with partial discharge (PD) signal. The result can be used to conclude if a transformer passes the impulse test or not through visual interpretation of wavelet transform coherence spectrum [7].

In recent years, the classification algorithm based on the artificial intelligent techniques [9]-[13], Support Vector Machine (SVM) [9], Decision Tree (DT) [10], and Artificial Neural Networks (ANNs) [11]-[13] are often employed due to the precision results that its can achieved. The wavelet and SVM can be applied to discriminates between internal faults and other types of disturbances. The input feature is obtained with first-level wavelet decomposition of three-phase differential current samples of one-cycle duration. The proposed scheme gives an overall accuracy of 99.8%. There used wavelet and ANN for classification fault. Differential currents were decomposed by wavelet. The coefficients values on the scale 1 or 4 from wavelet are input the neural network for classify fault, inrush current, internal fault and external fault [11]-[13]. Although there are many types of neural networks, only a few of neuron-based structures have been used commercially. a back-propagation neural network (BPNN) is the most popular tool for applications such as pattern recognition, fault classification, and etc. As a result, back-propagation neural network is a kind of neural networks, which is widely applied today owing to its effectiveness to solve almost all types of problems. Normally, the algorithm uses BPNN to indicate the proper decision. It is interesting to investigate an appropriate neural network and implement it in

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newly-developed protection systems.

Hence, the objective of this paper is to study the decision algorithm of BPNN and applied its algorithm to discriminate between external fault and internal fault. The DWT is employed to extract high frequency component contained in the fault currents during fault disturbance, and the coefficients of the first scale from the DWT that can detect fault are investigated. The construction of the decision algorithm is detailed and implemented on various case studies based on Thailand electricity transmission and distribution systems.

II. Simulation

The power transformer under investigated is model after part of Electricity Generating Authority of Thailand (EGAT) transmission and distribution system. The simplified diagram of power transformer is shown in Fig. 1. and diagram from ATP/EMTP software is shown in Fig. 2. The technical specification is 50 MVA, 115/23 kV three-phase two-winding power transformer with its function as step down transformer is connected between two sub-transmission sections.

The simulation of fault signal in the studies system were performed with various changes in parameters as follows:

- For simulations of internal winding fault, the positions of fault are designated on any phases of the transformer windings (both primary and secondary) at the position of voltage gap from 10% - 90% of transmission line with 10% interval. the fault inception angles are 0°-330° with 30° interval using voltage on phase A as reference.

- For simulations of external short circuit, types of faults (both side of transformer) are single line to ground, double lines to ground, line to line, and three-phase faults (AG, BG, CG, ABG, BCG, CAG, AB, BC, CA, ABC) with 5 Ω fault resistance. The fault locations on the transmission lines are varied from 10% - 90% of transmission line with 10% interval. The angles on phase A voltage waveform for the instants of fault inception are 0°-150° with 30° interval.

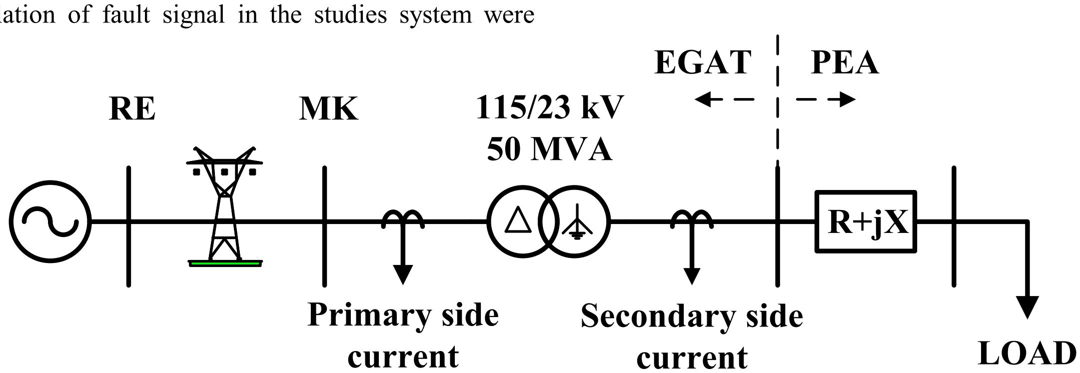
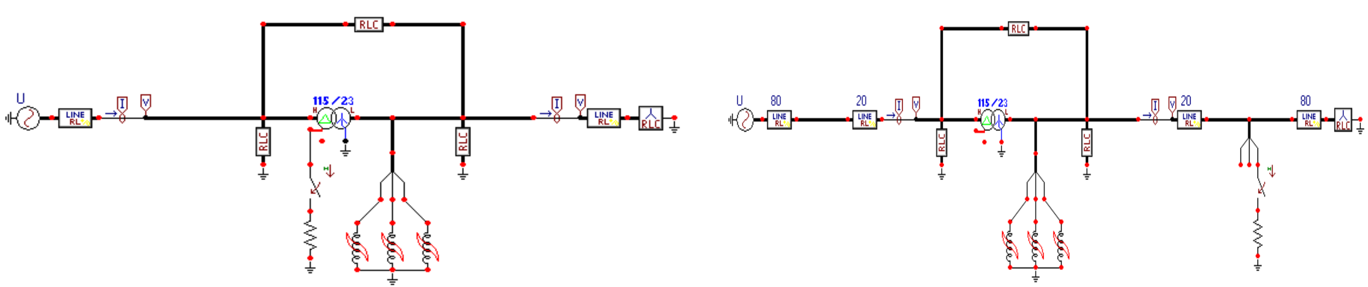


Fig. 1. The power transformer under studies [13].



(a) Internal fault

(b) External fault

Fig. 2. Simulation model using ATP/EMTP.

III. Proposed Algorithm

A. Fault Detection

From the simulated signals, the differential currents, which are a deduction between the primary current and the secondary current in all three phases as well as the zero sequence, are calculated, and the resulted current signals are extracted using the DWT. From the differential current of all three phases, coefficients from each scale of DWT are considered and employed in the fault detection with several trial and error processes.

DWT is applied to the quarter cycle of current waveforms after the fault inception. The mother wavelet daubechies4 (db4) [16-18] is employed to decompose high frequency components from the current signals. The coefficients of the signals obtained from the DWT are squared for a more explicit comparison. The comparison of the coefficients from each scale is investigated. The result is clearly seen that when fault occurs, the coefficients of high frequency components have a sudden change compared with those before an occurrence of the faults. This sudden change is used as an index for the occurrence of faults.

After applying the DWT, an example of an extraction using DWT for the differential currents and zero sequence current from scale 1 to scale 5 for a case of internal fault at 20% in length of the winding. The proposed fault detection algorithm on power transformer can be illustrated in Fig. 3. The mother wavelet daubechies4 (db4) is employed to decompose high frequency components from the current signals.

B. Fault Classification

The proposed internal and external fault discrimination algorithm.A training process is performed using neural network toolboxes in MATLAB [21]. Before carrying out the training process, input data sets are normalized and divided into 252 sets for training and 168 sets for validation. A structure of the BPNN consists of 3 neurons inputs, two hidden layers, and 1 neuron output. Hyperbolic tangent sigmoid functions are used as an activation function in all hidden layers while linear function is used as an activation function in output layers. The input patterns are the maximum ratio obtained from division algorithm between coefficient from DWT of differential current and zero sequence for post-fault differential current waveforms. The output variables of the neural networks are designated as either 0 or 1, corresponding to external fault and internal fault. If output value of BPNN is less than 0.5, external fault does occur; conversely, if this output value of BPNN is more than 0.5, internal fault does occur. In addition, there are many adjustment weights and biases in the neural network toolbox such as quasi-Newton algorithm, Levenberg-Maquardt algorithm, Resilient Backpropagation, Conjugate Gradient algorithm, and etc. Each method has different efficiency and training time. A comparison of the various training algorithms has been mentioned, and it is shown that Levenberg-Marquardt algorithm has the fastest convergence [21]. As a result, Levenberg-Marquardt algorithm is selected as adjustment weight and bias in this paper.

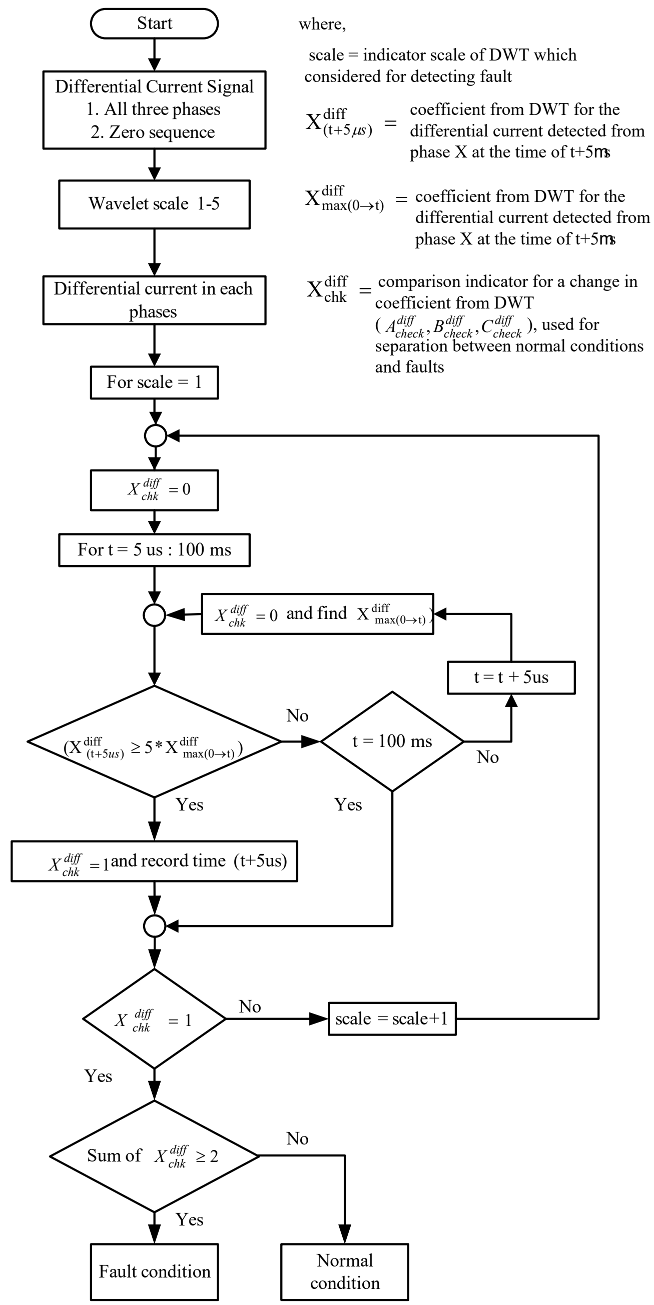


Fig. 3. Flowchart for detecting the fault condition

TABLE I. NUMBER OF DATA FOR BPNN.

Set	Number of data set	Internal fault		External fault	
		HV	*LV*	*HV*	*LV*
Training	252	81	81	45	45
Validation	168	54	54	30	30
Case Studies	84	27	27	15	15

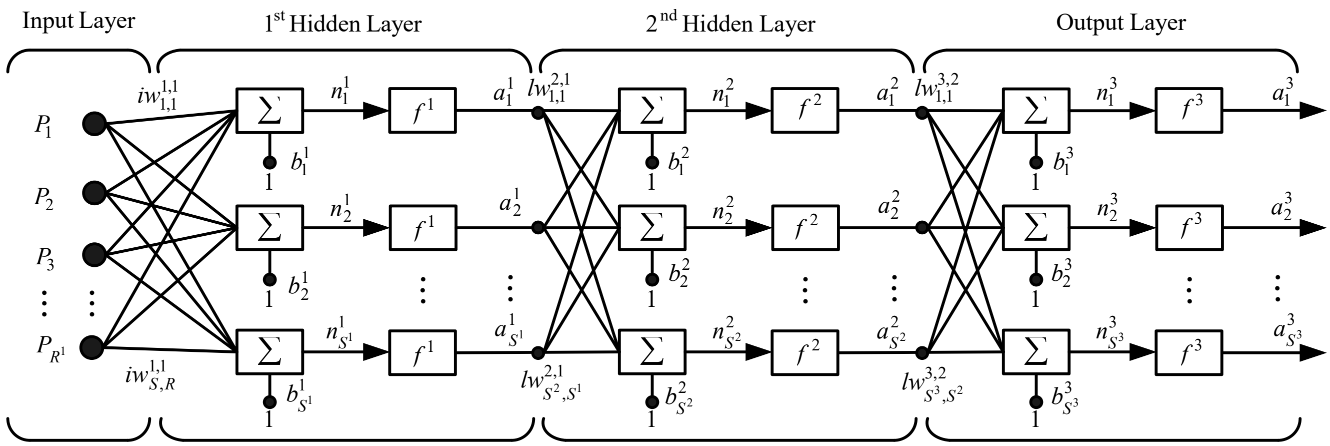


Fig. 4. Back propagation with two hidden layers

IV. Result

After the training process, the decision algorithm is employed in order to discriminate between internal fault and external fault in the power transformer. Case studies are varied so that the decision algorithm capability can be verified. The total numbers of the case studies are 84 as shown in Table 3. There are 54 sets for internal winding fault and 30 sets for external short circuit. The comparison of average accuracy between decision algorithm using BPNN and the comparison of the coefficients DWT, which is developed by previous research works [14-15]. From Table II, the result can be seen that the BPNN decision algorithm can give a better performance in discriminating between internal fault and external fault, so BPNN is selected in the decision algorithm. The results obtained from the algorithm proposed in this paper are shown in Table III and Table IV. It can be seen that BPNN decision algorithm is tested with various lengths of the winding. The results are shown that the average accuracy of fault detection from the decision algorithm proposed in this paper is highly satisfactory.

The comparative studies on proposed algorithm (DWT and BPNN) compare with previous methodology (Trial & error and Spectrum comparison) in term of fault classification accuracy can be summarized in Fig. 5.

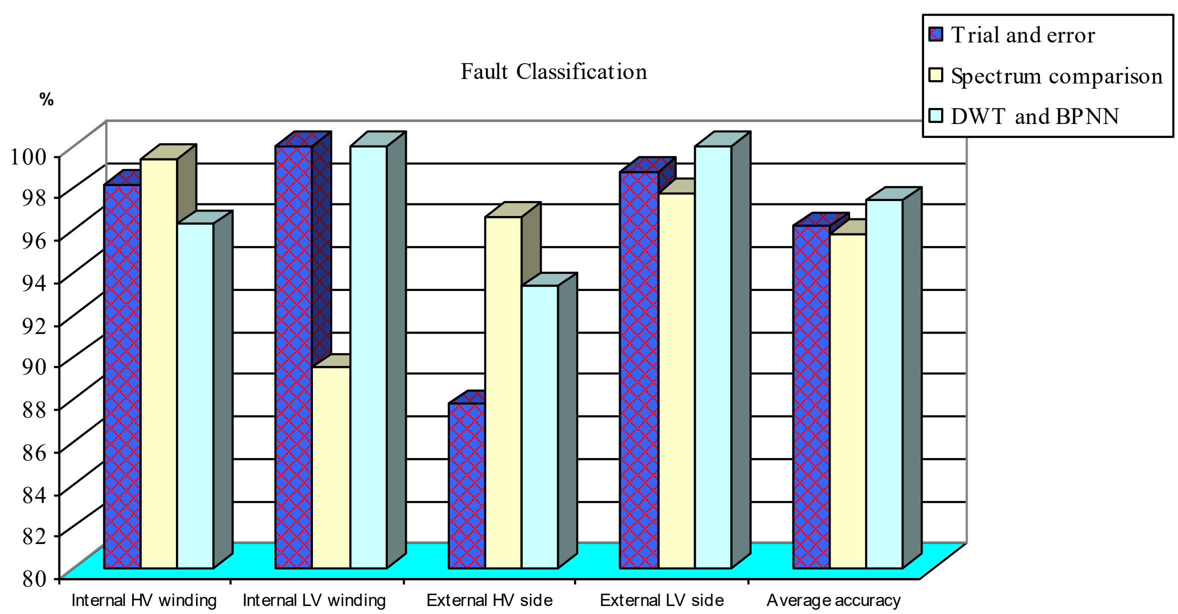


Fig. 5. Comparison of average accuracy for fault detection.

TABLE II. SUMMARY OF RESULTS FROM ALL SIMULATIONS

Fault Types	Location of faults	Number of case studies	Average accuracy (%)		
			Trial and error method [13]	*Spectrum comparison technique [14]*	*DWT and BPNN*
Internal	HV winding	27	98.15%	99.4%	96.30%
	LV winding	27	100%	89.5%	100%
External	HV side	15	87.77%	96.67%	93.33%
	LV side	15	98.76%	97.77%	100%
Average		87	96.17%	95.83%	97.41%

TABLE III. PERCENTAGE OF AVERAGE ACCURACY IN CASE OF INTERNAL WINDING FAULT

Coil	DWT and BPNN decision algorithm					
	High Voltage Winding			*Low Voltage Winding*		
	AC	*BA*	*CB*	*A*	*B*	*C*
10%	100%	100%	100%	100%	100%	100%
20%	100%	100%	100%	100%	100%	100%
30%	100%	100%	100%	100%	100%	100%
40%	100%	100%	100%	100%	100%	100%
50%	0%	100%	100%	100%	100%	100%
60%	100%	100%	100%	100%	100%	100%
70%	100%	100%	100%	100%	100%	100%
80%	100%	100%	100%	100%	100%	100%
90%	100%	100%	100%	100%	100%	1000%
Average	96.30%			100%		

TABLE IV. PERCENTAGE OF AVERAGE ACCURACY IN CASE OF EXTERNAL WINDING FAULT

Distance	DWT and BPNN decision algorithm					
	High Voltage Side			*Low Voltage Side*		
	A	*B*	*C*	*A*	*B*	*C*
20%	100%	0%	100%	100%	100%	100%
40%	100%	100%	100%	100%	100%	100%
50%	100%	100%	100%	100%	100%	100%
60%	100%	100%	100%	100%	100%	100%
80%	100%	100%	100%	100%	100%	100%
Average	93.33%			100%		

V. CONCLUSION

This paper proposed a technique for detecting and discriminating between external fault and internal fault of the power transformer. The simulations, analysis and diagnosis were performed using ATP/EMTP and MATLAB/Simulink. The DWT has been employed to decompose high frequency components from fault signals. The maximum ratio obtained from division algorithm between coefficient of differential current and zero sequence for post-fault differential current signals obtained by the DWT has been used as an input for the training process of the BPNN in a decision algorithm. It is shown that combination of DWT and BPNN is a powerful tool owing to its satisfactory results as shown in Table II-IV. This technique would be useful in the differential protection scheme for the transformer and can be applied to actual protection system in the future.

VI. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

APPENDIX

Appendixes, if needed, appear before the acknowledgment.

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