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Faults Detection and Classification on Parallel Transmission Lines using MoieClar's Trnsfomao -ANN Approach Abstract. This paper introduces a comparative study for fault detection and classification on parallel transmission line using cascade forward and feed forward back propagation. Both calculations were based on discrete wavelet transform transforms coefficients (WTC) and wavelet energy coefficients (WEC) of high frequency signals.

The coefficients were inputs for training of neural network back-propagation (BPNN). The results showed that the feed forward back propagation algorithm of Artificial Neural Network (ANN) models responded better than Cascade forward back propagation algorithm models, particularly in fault detection and classification on parallel transmission.

The results showed that the proposed method for fault analysis was able to classify all the faults on the parallel transmission line rapidly and correctly. Streszczenie. In this place the editor of journal inserts Polish version of the abstract. Please leave three lines for this abstract. Of course Polish language Authors are requested to prepare also Polish "Streszczenie". All papers should have two sets: title, abstract, keywords - Polish and English.

(- - Polish tittle at the end). Keywords: Cascade and Feed forward back- praginr etor arks rsormi aul etton;FtClsici nd Wavelet Slo kloe: in the case of foreign Authors in this line the Editor inserts Polish translation of keywords.

Introduction Power transmission line is an essential element in power system as it can dispatch electrical energy from one place to another. However, faults are often occurred on the transmission lines due to the interferences. Moreover, short circuit at the transmission line that connected to the wind turbine for example, could damage the wind turbine generator and its power electronics device [1].

Therefore, a quick and accurate analysis is necessarily required to detect and classify the transmission lines faults to guarantee the high reliability of the power system. a parallel transmission line needs more special consideration in comparison with the single transmission line, due to the effect of mutual coupling on the parallel transmission line including a parallel transmission line that is connected with wind turbine [2].

The most advantage of the parallel transmission compared to the single line is the probability of parallel system to transmit power continuously during and after fault is better than the single line. This paper proposed a discrete wavelet transform and back-transformation to detect and classify the faults on the parallel transmission line.

This study proposes a new method called alpha-beta transformation that is based on three-phase system into a two-phase system [3-6]. Clke's transformation result is then transformed into discrete wavelets transform. Wavelet transforms have been applied in several applications of in power systems; for example on partial discharge, power system protection, power system transients, condition monitoring and transformer protection.

Among aforementioned above, the power system protection become the major application area of wavelet transform in power systems [7], while the Artificial Neural Network has been widely used in power system protection [8]. In this study, a novel approach is proposed for some reliable fault detection, classification, and location. The proposed approach applied based on ANN scheme. Various types of faults were applied for classification of the faults and location [9].

There are some papers recently discussed the hybrid application of wavelet and ANN that have been applied on the variety of power system planning and power quality disturbances [10-13], estimating fault location [16], classification using Oscillographic data [14, 15], control system and state estimation [16, 17]. This study introduces a new approach for classifying faults in transmission lines using discrete wavelet transform and back-propagation neural network.

The main idea of the approach is to employ wavelet coefficient detail and the wavelet energy coefficient of the currents as the input patterns to generate a simple multi-layer perception network (MLP). In addition, this study proposes the development of a new decision algorithm to be used in the protective relay for fault classification and detection.

To validate this method, the applied faults were simulated using EMTDC / PSCAD software package [18]. Moreover, to obtain the significant of the study, the results of the proposed method were compared with and without wavelet transform based Clarke transformation. Research Methodology In this section Figure 1 shows the procedure of main steps for fault detection on transmission line using DWT and based Clke's rormitalsh ows some tools like PSCAD/EMTDC, wavelet transform (WT) and back propagation neural network (BPNN) is used to detect and classify the faults. Fig. 1.

Flow chart for the proposed methodology The design process of the proposed fault detection and classification algorithm for transmission line goes through the following steps: 1) wavelet transform. The signal flow of PSCAD is then converted into m. Files (*. M) 2) Determining the data stream interference, where the transformation to convert the transient signals into the 3) Input signals are analyzed by DWT for extracting the information of the transient signal in the time and the frequency domain [19]. 4) Selection of a suitable BPNN topology & structure for a given application.

5) Training of BPNN and validation of the trained BPNN to check its correctness in generalization. Results and Discussion In this study, the system under study is consisted of two identical transmission lines of 200 Km length which both end side are connected to Bus A and Bus B respectively. Each bus is connected to identical generator. The system was built on a 230 kV, conducted and simulated using PSCAD/EMTD.

The system under study is shown in Fig. 2. In this study faults are applied at 0.22s and last for 0.15s and system under study parameters are provided in Table 1. Table 1. Parameters used in the model of System under Study System Part Sequence Impedance ohm/km Transmission Lines 0.03574 + j 0.5776 0.36315 j 1.32.647 Generator A and B 9.1859 j 52.093 Ohm Fig. 2.

Single line diagram of the system under study After calculating the parameters, the training sample of the detail coefficients wavelet of , , , , , , and wavelet energy of , , and for various types of faults were set as input variables to create neural network. The data sets were generated by considering different operating conditions, for examples, the different values of initiation angles ranging between 0 and 180 degrees, different values of fault resistances are set between 0 and 200 ohm and different fault distances from 0 to 200 km.

The fault types are AG, BG, CG, ABG, BCG, ACG, AB, BC, AC, and ABC, where fault locations for training and testing are assumed occurs at 25, 50, 75, 100, 125, 150 and 175 km. For training and testing of Fault Resistance ( ) are determined as: 0.001,25, 50, 75, 100, 125, 150, 175 and 200 ohm, whilst Fault Inception Angle for training and testing are set at: 0, 15, 30, 45, 60, 90, 120, 150 and 180 degrees.

From the simulation results, it can be stated that the proposed DWT and BPNN were able to accurately distinguish among 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. WTC and WEC Based Fault Classification and Detection DWT is one of mathematical tools that can be used to detect fault.

In this approach, each of the derived current fault signals was decomposed into its constituent wavelet sub-bands or levels by the mother wavelet (Db4). The 4 levels of frequency bands are mentioned as dl, d2, d3 and d4. The high frequency components will be increased from d4 to d1. The wavelet coefficients detail of the currents was filtered using Clarke transformation, as exhibit in Fig. 3, while Fig.

4 shows the filtering response without using Clarke transformation. By applying aforementioned rules above, the first and last faulted samples were found at respectively, for a sampling frequency of 200 kHz. Table 2. The truth table representing the faults and the ideal output for each of the faults 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 From the sum of square of detailed WTC, we can obtain the WEC [25]. The wavelet energy coefficient varies over different scales depending on the input signals.

Wavelet energy coefficients , , and correspond to the sum of the four levels of wavelet energy coefficients of mode currents , , and , , and correspond to the sum of the four levels of wavelet energy coefficients of line currents , , and without Results of using DWT and Feed Forward Back Propagation Network A fter calculating the parameter s, the training sample of the detail coefficients wavelet var ious pa rameter s of , , , , , , and wavelet energy of , , and for various types of faults were set as input variables to create neural network.

The data sets were generated by considering different operating conditions, for instant, the different values of inception angles ranging between 0 and 180 degrees, different values of fault resistances between 0 and 200 ohm and different fault distances from 0 to 200 km. Discreet combination (A-B-C-G) of faults classification obtained by defining 1 for the value more than 0.6 and 0 for the value less than 0.4.

The simulation results are shown in Table 3. Error percentage of combination using preprocessing transformation calculated as follows: Percentage of MSE Validity = (2)

Percentage of MAE Validity = (3) Transformation and MSE (WiTC) is Mean Square Error (MSE) TC) is Simulation result of fault classification and detection using DWT and Feed-forward BPPN performing better results when architecture combination of 12-12-24-4 (12 neurons in the input layer, 2 hidden layer with 12 and 12 neurons in them, respectively and 4 neurons in the output layer). The results of the training performance plot of the neural network are shown in Fig. 3 and Fig. 4.

G A A G 1 A a a 1 A a a 2 2 Bus A Bus B 200 KM TYPE AG 0.068989 -0.3704 -0.00055 0.369859 0.001663 0.001836 9.14E-08 0.000631 BG -0.03712 -0.0998 0.171581 0.271431 0.000482 0.00012 0.000294 0.000534 CG -0.03166 -0.0861 -0.14941 -0.06323 0.000364 6.63E-05 0.000331 2.16E-05 AB -0.00016 -0.6434 0.372936 1.016395 0.000459 0.002611 0.000626 0.001788 AC -3.1E-05 -0.6144 -0.35366 0.260785 0.000679 0.001273 0.001437 0.0002 BC -0.05344 -0.1426 0.027444 0.170052 0.000541 6.57E-07 4.27E-06 4.99E-06 ABG 0.02478 -0.552 0.242529 0.794534 0.000282 0.003453 0.000445 0.002407 ACG 0.028348 -0.5327 -0.22018 0.312529 0.000378 0.002169 0.000585 0.000531 BCG -0.05344 -0.1426 0.027444 0.170052 0.001348 0.000407 5.83E-06 0.000294 ABC -0.00028 -0.9140 0.038158 0.95217 0.000198 0.002261 3.61E-06 0.001233 TYPE AG -0.47442 0.39492 0.39557 2.427159 1.397726 1.402985 0.000813 0.000934 BG -0.21173 0.255042 -0.21078 0.784318 1.324211 0.782586 0.000288 0.00021 CG -0.18215 -0.18289 0.223225 0.683062 0.676059 1.170582 0.000202 0.000219 AB -0.87854 0.87947 -0.00104 7.960639 7.955942 0.038965 0.002489 0.001513 AC -0.83959 0.00068 0.839376 7.59872 0.022613 7.597116 0.001393 1.52E-07 BC 0.000603 0.042871 -0.04201 0.033349 0.474973 0.475698 0.006368 1.83E-08 ABG -0.89047 0.868212 0.131157 8.170009 7.762025 0.677111 0.00196 0.001467 ACG -0.85188 0.151946 0.822367 7.834709 0.755132 7.377227 0.00175 0.000187 BCG -0.28832 0.065931 -0.01845 1.337943 1.159071 1.062607 0.00065 8.59E-05 ABC -1.1443 0.615456 0.530183 10.35624 5.594105 4.86936 0.0026 0.000678 Fig. 3 . Lvel DW cfidaiofhaul)at25 m, sgall h Care’sansoraton Fig. 4.

Level 4 DWT coefficient detail of the fault (AG) at 125 km, signalled without Cark tansorati Tabel 3. Detail of Wavelet Coeficient and Wavelet Energy Coeficient in Fault Locatio at 125 Km, Flt Risanc00hannctiat gl30 Drwile’s Transformation Tabel 4. Detail of Wavelet Coeficient and Wavelet Energy Coeficient in Fault Locatio at 125 Km, Flt Risanc00hannctiat gl30 Drwioule’srfmon Fig. 5.

Fit Regression of the Outputs vs. Targets of Feed-forward BPPN with configuration (12-12-24-4) Fig. 6. Fit Regression of the Outputs vs. Targets of Feed-forward BPPN with configuration (12-12-24-4) with Fig. 7 Fit Regression of the Outputs vs. Targets of Cascade-forward with configuration (12- 12-24-4) with using Care’sansormi Tru Tand PN aig tht lk transformation shown that MSE is 0.056214 and MAE is 0.154754, and with

Clarke's transformation show that MSE is 0.053876 and MAE is 0.150301. Percentage of MSE Validity obtains about 4.159 % and MAE obtains about 2.877 % compare to without procsngCark ansorati pl ing of the best linear regression that relates the targets to the outputs are shown in Fig.5 and Fig. 6.

Results of using DWT and Cascade Forward Back Propagation Network. Similar to the feed Forward Back propagation Network, the parameters of the training of the detail coefficients of wavelet has various parameters, namely , , , , , , and wavelet energy , , and for various types of faults were set as input variables of the neural network.

The data sets were generated by considering the different operating conditions, for example, the different values of inception angles are ranging between 0 and 180 degrees, different values of fault resistances are varied between 0 and 200 ohm and different fault distances take places from 0 to 200 km. Discreet combination (A-B-C-G) of faults classification obtained by defining 1 for the value more than 0.6 and 0 for the value less than 0.4. Fig. 9 and Fig.

10 show the training performance plot of the neural network. The results of DW dBPN aing itoutCark ansorati, fd that MSE is 0.073929 and MAE is 0.1421057. Meanwhile, with Clarke's transformation, where the MSE is found to be 0.062201 and MAE is 0.129653, Percentage of MSE Validity achieves about 15.863 % and MAE for about 8.763 % compare to without procsngCare’strfmi hpotngofte es linear regression that relates the targets to the outputs are shown in Fig.

11 and Fig. 12. The simulation results for various neural network combination / architecture were presented in Table 5. The feed forward back propagation network shows better performance with the MSE and MAE have lesser error compared to the performance of Cascade forward back propagation network. It is shown that the MSE and MAE of FFBPPN have a smaller value than CPBPPN.

By adopting Clarke's transformation, it was yielded that MSE and MAE have smaller value compared to the network without Clarke's transformation on FFBPPN and CPBPPN. Among all the architectures, the best architect was 12-24-48-4. Conclusion This paper is aimed to compare and explore the practicability of Feed forward back propagation and Cascade forward back propagation network in ANN models in order to recognize fault classification and detection on parallel transmission lines. This approach applies Daubechies4 (db4) as a mother wavelet.

Various circumstances have been investigated, including variation on distance, fault resistance and the initial angle.This study also compare the results of training BPPN and

DWT with and houtCltansfati e he esult exhis tusihe arke's rormon ir aining will create smaller MSE and MAE, compared to training without Cltansfaton. Among the three structures, the best architects result is 12-24-48-4.

The Feed forward back propagation algorithm of Artificial Neural Network (ANN) models performed better results than Cascade forward back propagation algorithm models, particularly in fault classification and detection on parallel transmission lines. Acknowledgment The authors would like to thank Research, Technology and Higher Education Ministry of Indonesia for supporting the Research.

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