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New algorithm for detection and fault classi ? cation on parallel transmission line using DW T and BPNN based on Clarke □s transformation Abdullah Asuhaimi Mohd Zin a , Makmur Saini a ,c , n , Mohd Wazir Mustafa a , Ahmad Rizal Sultan a, c , Rahimuddin b a Faculty of Electrical Engineering, Universiti Teknologi Malaysia (UTM), Johor Bahru 81310, Malaysia b Faculty of Engineering, Universitas Hasanuddin, Makassar 90245, South Sulawesi, Indonesia c Politeknik Negeri Ujung Pandang, Makassar 90245, South Sulawesi, Indonesia art ic l e i nf o Article history: Received 2 July 2014 Received in revised form 23 February 2015 Accepted 10 May 2015 Communicated by Hongli Dong Available online 19 May 2015 Keywords: Wavelet transformation Back-propagation neural network Fault location Fault detection Clarke□ s transformation Transmission parallel line abstract This paper presents a new algorithm for fault detection and classi? cation using discrete wavelet transform (DW T) 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 (DW T) to get the wavelet transform coef ? cients (W TC) and the wavelet energy coef? cient (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 classi ? cation faults. The results

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show that the best Clarke transformation occurred on the con? guration 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 Pa ra ll el transmissi on li nes have b een w id ely u sed in m od ern powe r sys te ms to improve p ower transfer, reliability and s ecurity for the tra nsmiss ion of electri cal energy. The possibility of different con?gu ra tions o f p aral lel l ines, combi ned w ith m utu al coup li ng e ff- ects, makes their p rote ction a challenging p roblem, therefore a f ast and rel iable p rotection i s needed for rapid fault detection and a ccura te estimation of fault loc ation e r rors.

This is vital to s upport the mai nte na nce and restora tion s ervi ces to improve the con tinuity an d re l i a bi l i t y o f su p p ly. T h e ref o re , a p a ra l l e l t ra n s m i s si o n l i n e re qu i res special consi deration in comparison with the single tra nsmission line, due to th e effect of mut ual coupling on the parallel tran smission line. It must also c o mp ly with the s tandards of IEEE.ST D.114 2 0 0 4[1]. One major adva n tage of p aral lel transmissi on i s avai la bi lity o f t ransmission network during and af te r t he fault.

This paper applies discrete wavelet transform (DW T) and back- propagation neural network (BPNN) using Clarke□s transformation to determine the fault detection and classi ? cation 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 transfor- mation 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 monitor- ing. Among all, the power system protection continues to be a major application area of wavelet transform in power systems [4] , while Arti ? cial Neural Network (ANN) continues as an ef? cient pattern recognition, classi ? cation and generalization tool that motivates many algorithms based on ANN to be used for fault detection and classi ? cation [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 classi ? cation [9] , state estimation and control system [10,11] . Contents lists available at ScienceDirect jo u r n al h o m e p a g e : w w w . e l s e vi e r . c o m / l o c a t e / n e u c o m Neurocomputing htt p ://dx.doi.org/10.1016/j.neucom.2015.05.026 0925-2312/ n Corresponding author. E-mail addresses: abdullah@fke.utm.my (A . Asuhaimi M ohd Zin),

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(M. Saini). Neurocomputing 168 (2015) 983 □ 993 Thi s p ap e r pre sents t he d e ve lop m ent o f a new d ecision a lgorithm for use in the protective relay for fault detection and classi ?ca tion. I n this met h od, f au lt cond iti o ns a re si m ul ated using E MT DC /PSCAD[12]. Current waveforms obtained from the simulation a re then ex tracted u s i n g C l a rk e t ra n s f o r m a t i o n a n d wavelet t ra nsformation .

Deci si on algorithm, therefore, is built b ased on back-propagation neural net- wo rk . I n this s tudy, the val idity of the p ro posed al gori thm had been te sted u si n g va r iou s ini t ial e rror angl es, l oca t ion and brok en p h ase erro rs. I n addition, the results of the p ro posed algorith ms were compared with and without wavelet transform ba sed 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]: a □ 0 2 64 3 75 □ 2 3 1 ┐ 1 2 ┐ 1 2 0 v 3 2 ┐ v 3 2 1 2 1 2 1 2 2 664 3 775 X a b c 2 64 3 75 □ 1 □ where a , b, c represent the current values of the phase A , B, C respectively; and a , □ , 0 represent the modal values.

The coef ? - cients 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 a represents the line-modal between phase A and phase B, while modal □ represents the line-modal between phase A and phase C. In order to represent the line-modal between phase B and phase C, modal ? is proposed.

a □ 0 ┐ ? 2 666 6664 3 777 7775 □ 2 3 1 ┐ 1 2 ┐ 1 2 0 ?? 3 p 2 ┐ ?? 3 p 2 1 2 1 2 1 2 _ __ ___ _ _ __ ___ _ _ __ _ _ __ ___ _ _ __ _ _ _ __ ___ ┐ 2 3 1 3 □ 1 □ ??? 3 p □ 1 3 □ 1 ┐ ??? 3 p □ 2 66666664 3 77777775 X a b c 2 64 3 75 □ 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) , assumin g the g ro undi ng resi sta nce i s z e ro , t hen t he instantaneous boundary con ditions w ill be: I b □ I c □ 0 and V a □ 0 □ 3 □ Then, the boundary condition instantaneous will be: I a □ 2 3 I a ; I □ □ 0; I ? □┐ 2 3 I a and I 0 □ 1 =3 I a □ 4 □ 2.1.2.2. Line to line fault.

Suppose the line to line fault (AB), assuming the grounding resistance is zero, then the instant- aneous boundary conditions will be: I c □ 0; I a □┐ I b and V a □ V b □ 5 □ Then the boundary condition instantaneous will be: I a □ I a ; I □ □┐ 1 3 ??? 3 p I b ; I ? □┐ I a ┐ 1 =3 ??? 3 p I b and I 0 □ 0 □ 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 ; I b □ I c and V b □ V c □ 0 □7

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 Then, the boundary condition instantaneous will be: I a ┐ 1 3 I b ┐ 1 3 I c ; I   1 3 ??? 3 p I b ┐ 1 3 ??? 3 p I c ; I ? 1 =3 I a 1 =3 I b 1 =3 ??? 3 p I b ┐ 1 =3 ??? 3 p I c and I 0 1 3I b 1 3 I c 8 2.1.2.4. Three phase fault.

Su pp ose t hree ph ase f au lt (AB C) , assumi ng the g ro unding re sistanc e is zero , t hen t he instan taneous b ounda ry cond ition s wi ll be: I a I b I c 0 and V a V b V c 0 9 Then, the boundary condition instantaneous will be: I a 2 3 I a ┐ 1 3 I b ┐ 1 3 I c ; I   1 3 ??? 3 p I b ┐ 1 3 ??? 3 p I c ; I ? ┐ 2 3 I a 1 3I b ┐ 1 3 ??? 3 p I b 1 3 I c 1 3 ??? 3 p I c and I 0 0 10 Ta b l e 1summarizes the chara cteristics of va rious d iffere nt faults ba sed o n C la rk es transformati o n, based o n the above e qu ations. 2.2. Wavelet transform 2.2.1.

Discrete wavelet transform Wavelet transformation is de ? ned as the decomposition of a signal by a function, f 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] : f ab t   1???ap f t ┐ b a ↨ ‼ 11 where a is the dilation parameter (a e Real) and b is a translation parameter (b e Real).

Parameter a indicates the width of the wavelet curve when the value of a wider magni? ed 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 (DW T) is required so that the equation becomes [17,18] ; f ab t   2 j =2 f 2 j a ┐ b ┼◄ ; j :k A Z 12 Variables j and k are integers that scale the shift s 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 (DW T) is a method used to decompose the input signal, and the signal is analyzed by giving treatment to the wavelet coef ? cients. The decomposition process involves two ? lters, which are low-pass ? lter and a high-pass ? lter [19] . The results, obtained in the form of cA approximation signal and detail signal cD, as equations: d hig h k┐ └ X n Xn? :g 2 k ┐ n┐ └ : 13 d low k┐ └ X n Xn? :h 2 k ┐ n┐ └ : 14 where d hig h k┐ └ Output of high-pass ? lter and d low k┐ └ Output of low-pass ? lter. A . Asuhaimi Mohd Zin et al.

/ Neurocomputing 168 (2015) 983 993984 2.2.2. Wavelet energy The wavelet energy coef ? cient is obtained from the sum of square of detailed wavelet transform coef ?cients [20] . The wavelet energy coef ? cient varies over different scales depending on the input signals. The wavelet energy coef ? cient can be de ? ned as follows: E st ☐ X N j 1 a j c 2 j 15 with suitable scaling coef ? cients, a j , for the coef ? cient, 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].

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For example, the estimated coef ? cient at the ? rst-level contains much more energy than the other coef ? cients at the same level of the decomposition tree. Because the faulty signals have high fre- quency components, it is more typical to use wavelet energy coef ? cient [22] . 2.3. Arti? cial neural network (ANN) The con cept of ANNs ha s b een a round si nc e the 1950s, w hi ch biologically inspires the view of the hu man b rain as a processor u si ng i nte rc onnec ted neuro ns.

ANN re pre sent s a conn ecti on to th e b rai n, su ch as ar ti?c ia l neurons tha t a re i nte rcon nected a nd a dapt ive to the output o f ot her co nnec ted no des t hat have m odi?ed parameters[23]. ANN is w idely u sed in engineering?elds such as teleco mmunications, medic al , cont ro l a nd powe r s ys te ms[24]. A NN tra in ing is necessa ry to associate the correct o utput response to a particular input pattern. On ce properly trained, an ANN has the ability to generalize the similar moment , b ut n ot i denti ca l pat ter n in tro duc e d to t he network[25].

O n e o f t h e m o s t p o p u l a r n e u ra l n e t wo rk s i s B a ck P ro p a g a t i o n Ne ura l Ne twork (BPNN) m etho d, c o mmonly u sed to s olve ma ny n o nl inea r problems, b ut the original B P netwo rk used to suffer primarily from a lack of converge nce, be cause they u sed to ge t stuck i n a lo cal minimum. Over the years, differe nt variations of BP NN improvement have been proposed to speci?cally a ddress several important issues, na mely re duc in g the conve r gen cetime, ease t he computational burd en, reducing m emory requirements and so on[26]. 2.3.1.

Architecture of BPNN Fe e d - f o r wa rd n e u r a l n e t wo r k a rc h i te c t u re l aye r s a re s h ow n i n Fig. 2. T hi s a rchi tecture consists o f one input layer, two hidden l ayer a nd one output laye r. It may have one or more hidden layers. Al l l ayers a re f ul ly con necte d and feed-fo rward type. T he output is a n onl inea r func tion of th e i np ut , a nd is co ntrolled by the weigh ts calculated during the l earning p ro cess.

Th e l earnin g p rocess uses supervised learning para digm which i s b ack p ropagation. In Back-Propag ation (BP) training process, t he ac tivat ion f un ction i s restricte d an d di fferentia ted. The m ost common function is the si gmoid. It is bound bet ween the m inimum (0) and maximum (1). Bef ore the signal is pa ssed to the next layer of neuro ns, eac h neuro n s ummed output is scaled by this fun ction[27]. 2.3.2.

BPNN algorithm In ge neral , the neura l network i s divi ded i nto two pa rts: trai ni ng and testi ng. Trai ni ng i s a le arn ing proc ess o f t h e neural netwo rk system that governs how the i np ut values and the output are mapped to obtain the a pp ropriate model, while testing is a p rocess of testing the a cc ura cy o f t he model o btai ned f ro m t he tra in ing proc ess[27]. Ba ck-propagation neural network (BPNN) i s a trained netwo rk to obtain a b alance between the a bility of the n etwork to recognize the pa tterns u s ed for t ra in ing , as well

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as th e n etwork□s ability to provide the cor rect response to the input patter n similar to the style employed du ri ng trai ni ng.

B ack- prop ag ati o n t rai n i n g i nc lu d e s t h e fol l ow i n g 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 de ? ned 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 modi ?ed to reduce the errors. 2. Step II: Back-propagation Based on the error t k □ y k , calculated factor d 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 . d k is also used to change the line weight, directly related to the output unit.

In a similar way, the d 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 d in hidden units directly related to the input units have been computed. 3. Step III: Changes in weight After all d factors have been calculated, the weights of all the lines will be simultaneously modi? ed, according to changes in weight of a line based on the factor d in the upper layer neurons.

For selecting models of fault detection and classi ? ca- tion, 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. Table 1 Characteristics of various different faults based on Clarke□ s transformation. Type fault a -Modal □ -Modal 0-Modal ? -Modal AG 2 = 3 I a 0 1/3 I a ┐ 2 =3 I a BG ┐ 1 = 3 I b 1/3 ??? 3 p I b 1 = 3 I b 1 =3 I b □ 1 □ ??? 3 p □ CG ┐ 1 = 3 I c ┐ 1/3 ??? 3 p I b 1 = 3 I c 1 =3 I c □ 1 ┐ ??? 3 p □ AB I a ┐ 1/3 ??? 3 p I b 0 ┐ I a ┐ 1/3 ??? 3 p I b BC 0 2/3 ??? 3 p I b 0 ┐ 2/3 ??? 3 p I b AC ┐ I c ┐ 1/3 ??? 3 p I c 0 I c ┐ 1/3 ??? 3 p I c ABG 2 = 3 I a ┐ 1 =3 I b 1/3 ??? 3 p I b 1/3 I a □ 1 = 3 I b ┐ 2 =3 I a □ 1 =3 I b □ 1/3 ??? 3 p I b BCG ┐ 1/3 I a ┐ 1 = 3 I b 1/3 ??? 3 p I b ┐ 1/3 ??? 3 p I c 1/3 I b □ 1 = 3 I c 1/3 I a □ 1 = 3 I b □ 1/3 ??? 3 p I b ┐ 1/3 ??? 3 p I c CAG 2 = 3 I a ┐ 1 =3 I c ┐ 1/3 ??? 3 p I c 1/3 I a □ 1 = 3 I c ┐ 2 =3 I a □ 1 =3 I c ┐ 1/3 ??? 3 p I c ABC 2 3 I a ┐ 1 3 I b ┐ 1 3 I c 1/3 ??? 3 p I b ┐ 1/3 ??? 3 p I c 0 ┐ 2 3 I a □ 1 3 I b ┐ 1 3 ??? 3 p I b □ 1 3 I c □ 1 3 ??? 3 p I c A . Asuhaimi Mohd Zin et al. / Neurocomputing 168 (2015) 983 □ 993 985 3. The proposed algorithm 3.1.

Fault classi? cation using wavelet principle As menti o ned e a rli er, t his pa p er proposes a new al go rit hm f or fa ul t classi?cat ion using wavelet based on C lark e□s transformation to obtain the f a u lt c u rrent. By c o

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nsi der ing t he frequency b a nd o f t he faul t- induced discrete wavelet transf ormed (DW T), on t he t ransmission lines, the c urrent signals a re sampl e d a t the sampli ng rate of 20 0 kHz . The Clark e□s m odal transfor mation will then be used to dec ouple the three-ph as e currents.

Th e c urrent modal components are shown i n Eq. (1). The signal is ?rst p assed through t he hi g h-pa ss?lter and l ow- pass ?lters, and then half of each output i s taken as sampling, down through t he samp ling operat ion. This is called deco mp osition?rst l e ve l p ro c e s s , d o n e i n t h e f re qu e n c y ra n ge o f 10 0□20 0 kH z. C ons id e r- ing t hese factors, DW T u nder second, t hird , and fourth scales are t hen ad opte d .

When the h igh e st frequ e ncy t ha t c ou ld b e ob ta ine d is 5 0□ 10 0 k H z , 2 5□50 kHz an d 12 .5□50 kHz ca n b e u s ed in the al gor ith m . The features used to distinguish between internal and external disturbances of the parallel transmission lines are protected. Proposed algorithm fault discrimination, the a and □ modal components covers all of the possible fault types in each of the parallel circuit. To cover the inter-circuit faults as well, the ? -modal component of the current signals is de ?ned as follows: I ? □┐ 2 =3 I a □ 1 =3 □1 □ ??? 3 p □ I b □ 1=3 □ 1 ┐ ??? 3 p □ I c □ 16 □ The magnitude of the current gamma of each different type of fault can be seen in Table 1 .

The fault discrimination criteria are de? ned as follows: I a 1 I a 2 4 1 or I □ 1 I □ 2 4 1 Fault Internal Circuit 1 □ 17 □ I a 2 I a 1 4 1 or I □ 2 I □ 1 4 1 Fault Internal Circuit 2 □ 18 □ I a 1 I a 2 □ 1 or I □ 1 I □ 2 □ 1 Fault External □ 19 □ where I a 1 and I □ 1 denote the modulus maxima of the modal components for the ? rst circuit currents, and I a 2 and I □ 2 denote those of the second circuit. Th e p rotect ion techn ique should be able to classify the fau lted phase f or si ngl e -pha se- to -ground fa ul ts[28]. Fig.

1 illustrates the proposed fault-type classi?c ation algo rithm t hat u ses th e modal compon ents of the cur re n t sign als. In th e case o f single-phase-to- ground faults, t wo of th e m o dal co mpon ents that inc lude the faulte d phase shoul d have almost the sa me amplitude an d t he other modal component s ho uld be zero, as fo llows: S a S ? □ 1 o A and Q a ┐ Q ? r A) AG f ault □ 20□ S ? S □ ┐ S a ┐ 1 o A and Q ? □□ Q a □ Q □ □ r A) BG fault □ 21□ S □ S a □ S ? ┐ 1 o A and Q □ □□ Q a □ Q ? □ r A) CG fa ul t □ 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): S ? S a ┐ S □ □ 1 o ? and Q ? □□ Q a □ Q □ □ r ?) AB fault □ 23 □ S a S ? ┐ S □ □ 1 o ? and Q a □□ Q □ □ Q d □ r ?) AC fault □ 24 □ S □ S ? ┐ 1 o ? and Q □ ┐ Q ? r ?) BC fault □ 25□ where S a , S □ , S ? represent the sums of fourth level detail coef ? cients wavelet of line currents I a , I □ and I ? ; respectively. Similarly, Q a , Q □ and Q ? represent the sums of absolute values of fourth level detail coef ? cients wavelet of line currents I a , I □ and I ? , respectively.

By determining the fault classi ? cation, as shown in Fig. 1 , the fault classi ?cation 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 speci ?ed 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 s 0.02, while the ground is divided into 2, which are lined to ground fault with the given threshold e 0.03, and the line to line to ground fault with the given threshold d 0.05 for termination criteria [29] . 3.2.

Fault detection and classi ?cation using DW T and BPNN principle The design process of the proposed fault detection and classi- ?cation algorithm for parallel transmission lines goes through the following steps: (1) Finding the input to the Clarke transformation and wavelet transform. The signal ? ow of PSCAD is then converted into m . ? les (n . 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 DW T for extracting the informa- tion 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 cu rrents I a , I b and I c at a frequ ency of 50 Hz measured si multaneously by PSCAD delive ry at the end of the line are then used to classi fy the type of errors b etween LG, LL, LLG, LLL a nd heal thy (norma l) cond ition a f ter usin g C lark es transformation to getthe current m odes I a and I .

As indicated in previous studies, the Daubechies mother wave let has a good ability to c apt ure the tra nsient and time-frequency fe ature extraction for p ower system fault[29]. In the proposed a lgorithm,Db 4 mother wave let i s u sed to get the DW T coef?cients for the classi?cation of differe nt types of f ault. B y u sing t he det ai l coef?cients wave let of vario us paramete rs, n amelyS 0 ; S a , S , S ? ,Q 0 , Q a , Q and Q ? will then be calculated wh ereS 0 , S a , S and S ? represent t he sum o f the four levels of detail coef?cients of mode currents I 0 , I a , I and I ? , respectively, while Q 0 , Q a , Q and Q ? re present t he sum of the a bsol u te va lue of the c oef?ci ent o f t he fourth-level detail mode currentsI 0 , I a , I an d I ? , respectively,and wa v e l e t e n e r g yE 0 , E a , E and E ? represent the su m of the four levels of energy wave let of mo de curre ntsI 0 , I a , I and I ? .

The input of BPNN training consists of detail coef?ci ents wavel e t and wave let energy. T he combination of d iffere nt fault co nditions that m u s t be c o n s i d e re d a n d t ra i n i n g p a t te r n s a re re qu i re d to b e ge n e ra te d by simulatin g var ious types of fault son para llel transmission. There- fore , the type of fault , fault l ocation,fa ult resista nc e a nd fault i nc epti on can b e d etermined.

ANNarchitecture is used sothat it will be able to recognizeand classif y all the possible operating co nditions of parallel transmission, A . Asuhaimi Mohd Zin et al. / Neurocomputing 168 (2015) 983 993986 a nd then p rovide a tri p s igna l wh e neve r th e faul t i s identi?ed. I n t his propo sed scheme, d iff e re nt architecture s h ave been considered[30]. The s et of inputs u sed were 12 s ampl es of output current s ignals of para llel transmissio n.

T wo hidden laye rs we re taken an d th e n umber of n e uron s was var ied as hidden 1 from 6 to 24 , h idden 2 from 12 from 4 8 re sults and th e s et output 4, as sh ow n inFig. 2. 4. Simulation result and analysis 4.1. Data simulation In this study, t he system was c onnected with t he s ources at each end, as show n i n Fig. 3. T h i s s ys te m wa s s i m u l a te d u s i n g P S CA D / Start Clarke□s Transformation Wavelet Transformation Coefficients Detail Mode So = Ground Fault type Unground Fault Type and and and and and and and and and AB AC BC AG BG CG ABG ACG BCG ABC NO Yes Yes Yes Yes Yes Yes Yes Yes Yes NO NO Yes NO NO NO NO NO Fig. 1.

Fault classi ? cation ? owchart. A . Asuhaimi Mohd Zin et al. / Neurocomputing 168 (2015) 983 □ 993 987 EMTD. For the case s tudy, the simulation was m odeled on a 2 30 kV doub le circuit transmi ssion li ne, w hich wa s 20 0 km in length. 4.1.1. Transmission data Sequence impedance ohm/km. Transmission line Z 1 □ Z 2 □ 0.03574 □ j 0.5776 O/km Z 0 □ 0.36315 □ j 1.32.647 O/km Source A and B Z 1 □ Z 2 □ Z 0 □ 9.1859 □ j52.093 O Fault starting □ 0.22 s duration in fault □ 0.15

s After calculating the parameters, the training sample of the detail coef ? cients wavelet various parameters, namely S 0 ; S a , S □ , S ? , Q 0 , Q a , Q □ , Q ? and wavelet energy E 0 , E a , E □ and E ? 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 20 0 O and different fault distances from 0 to 20 0 km.

Fault Type: AG, BG, CG, ABG, BCG, ACG, AB, BC, AC, and ABC Fault Location (distance) for training and testing: 25, 50, 75, 10 0, 125, 150 and 175 km Fault Resistance □ R f □ for training and testing: 0.0 01,25, 50, 75, 10 0, 125, 150, 175 and 20 0 O Fault Inception Angle for training and testing: 0, 15, 30, 45, 60, 90, 120, 150 and 180 degrees The proposed DW T and BPNN were able to accurately distin- guish 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 ? ltered wavelet coef ? cients detail of the currents is shown in Fig. 4. By using the rules aforementioned, the ? rst and last faulted samples were 10 5 , respectively, for a sampling frequency of 20 0 kHz. 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 O and 10 0 O 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 O and fault inception angle 60 degrees were d □ 0.0 0 0 07; this was greater than the threshold set on the fault line to line to ground of d 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 10 0 O and fault inception angle of 90 degrees obtained a threshold of s 0.0 0 0 012, smaller than the threshold set of s 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 a 1 /I a 2 and I 1 /I 2 , between 1.2 and 3, indicating that the fault was an internal fault circuit 1. The fault classi ? cation algorithms signi? ed that the proposed algorithm is accurate and precise PSCAD SIMULATION CLARKES TRANSFORMATION DISCRETE WAVELET TRANSFORMATION 1 2 12 1 2 3 24 48 3 2 1 1 2 4 INPUT LAYER HIDDEN LAYER 1 HIDDEN LAYER 2 OUTPUT LAYER ; :: . . ; Fig. 2.

Architecture of proposed DW T-BPNN based on Clarke s transformation. Bus A 200 km Bus B G G 1 1 2 2 Fig. 3. One line diagram of the simulated transmission system. 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 AC G 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 A . Asuhaimi Mohd Zin et al. / Neurocomputing 168 (2015) 983 993988 4.3.

Simulation results of using DW T and BPPN with/without Clarke s transformation Discreet combination (A B C G) of faults classi ? cation obtained by de? ning 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 transfor- mation compared to without Clarkes transformation calculated as follows; Percentage of MSE Validity MSE WoTC MSE WiTC MSE WoTC ┐ 100 % 26 Percentage of MAE Validity MAE WoTC   MAE WITC MAE WoTC┐ 100 % ↕ 27 where MSE (WoTC) is mean square error (MSE) without transfor- mation Clarkes, 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 classi ? cation using DW T and BPPN deliver good results when analyzed with pre- processing using Clarkes transformation and architecture combi- nation 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 trans- formation, the mean square error (MSE) was 0.0776 6 and the mean absolute error (MAE) was 0.171058, and with Clarkes 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 Clarkes trans- formation as shown in Table 4 .

Table 5 shows the effects of variations in the resistance of 25 O and 50 O 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 DW T 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 classi ?cation using DW T and BPPN deliver good results when analyzed with pre- processing using Clarke □s transformation and architecture combi- nation of 12-24-4 8-4 (12 neurons in the input layer, 2 hidden layers with 24 and 4 8 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 trans- formation will produce better result. 4.4. Comparison with the BPNN and pattern recognition network (PRN} based fault classi ?cation The comparison of BPNN and PRN based classi ? er for type of fault is veri? ed and classi ? cation result are summarised as shown in Table 7 . Fig. 4. Level 4 DW T coef ? cients of the fault currents (AB): (a) Clarke□ s signal current (a) a ; (b) □ ; and (d) zero-sequence component. A . Asuhaimi Mohd Zin et al.

/ Neurocomputing 168 (2015) 983 □ 993 989 Table 4 The obtained result of different fault using DW T and BPNN, with con ? guration (12-6-12-4). Type fault Distance R f Fault inception Clarke□ s transformation Without Clarke□s transformation MSE □ 0.072245 and MAE □ 0.150773 MSE □ 0.07766 and MAE □ 0.171058 km Ohm Degree A B C G A B C G AG 25 0.0 01 0 0.95142 0.10 052 ¬ 0.1282 1.0 6332 1.07509 ¬ 0.1591 ¬ 0.0 460 1.02017 BG 50 0.0 01 0 0.27148 1.014 47 0.0 4518 0.98523 0.29988 0.77232 0.24082 1.03434 AB 75 0.0 01 0 0.98479 1.02404 0.03225 0.010 04 1.07188 0.93337 0.03655 0.0 06 8 AC 10 0 0.0 01 0 1.03366 0.0 0918 0.96 656 ¬ 0.0766 0.90738 0.10155 1.0590 6 0.29056 ABG 125 0.0 01 0 1.02768 0.85509 ¬ 0.0 628 1.01392 1.12254 1.0 0395 ¬ 0.1871 0.7094 4 ACG 150 0.0 01 0 1.03969 0.0 0339 0.94

847 0.89650 0.90 037 0.0 4 411 1.0 0111 0.7316 4 ABC 175 0.0 01 0 0.83261 1.09872 0.90557 0.02879 0.91583 1.0 6532 1.17350 0.02907 Table 5 The obtained result for different resistance fault using DW T and BPNN, with con ? guration (12-12-24-4). Type fault Distance R f Fault inception Clarke□s transformation Without Clarke□ s transformation MSE □ 0.053876 and MAE □ 0.150301 M SE □ 0.056214 and MAE □ 0.154754 km Ohm Degree A B C G A B C G BG 50 25 15 ¬ 0.2601 0.8120 0 0.19912 1.0 0950 0.27056 0.97048 ¬ 0.0520 0.96 410 BG 50 50 15 ¬ 0.20 60 0.88430 0.20585 1.0 0 64 4 0.20

411 1.08331 ¬ 0.0347 0.95417 AB 75 25 15 0.92614 1.0 6886 0.16 452 ¬ 0.0137 1.0250 6 0.75573 0.24930 0.02225 AB 75 50 15 0.940 4 9 1.03467 0.12603 ¬ 0.0 054 0.980 41 0.77873 0.27164 0.0 4101 ACG 125 25 45 0.940 42 0.30193 0.72921 1.10 056 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 0.950 41 0.95152 0.86122 0.0284 8 1.0 4392 1.21587 1.3274 8 ┐ 0.1776 ABC 150 50 45 0.91256 0.86101 1.0 0 063 0.02601 1.0 0739 1.23383 1.14222 ┐ 0.1332 Table 6 The obtained result for different inception fault using DW T and BPNN with con ? guration (12-24-48-4).

Type fault Distance R f Fault inception Clarke s transformation Without Clarke s transformation MSE 0.037218, M AE 0.119521 MSE 0.055139, MAE 0 .1216 17 km Ohm Degree A B C G A B C G AG 150 75 60 0.9636 6 0.02287 ┐ 0.0790 0.99251 0.99819 0.35599 0.05123 1.0 4945 AG 150 75 75 1.0 474 4 0.11159 0.13258 1.0 4361 0.98178 0.35063 0.10977 1.0394 8 AC 125 10 0 30 1.0256 6 0.02795 1.0 0 082 0.03517 0.91547 0.05778 0.96 419 ┐ 0.07465 AC 125 10 0 45 1.0 4593 0.15348 0.74610 0.11221 0.890 02 ┐ 0.036 41 1.16882 ┐ 0.0 4335 BCG 75 75 75 0.01242 0.72528 0.896 84 1.07555 ┐ 0 .1516 5 0.99650 0.98279 0.99787 BCG 75 75 90 ┐ 0.0289 0.83212 0.97222 1.05126 ┐ 0.02451 1.11924 1.0 04 83 1.0 420 0 ABC 50 10 0 120 0.83261 1.09872 0.90557 0.02879 0.70757 0.90 057 1.20523 0.0 0774 ABC 50 10 0 150 0.82418 1.16831 0.85983 0.03543 0.67534 0.81013 0.95471 0.07862 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 10 0 75 10 0 Fault inception angle (?) 60 75 30 45 75 90 120 150 s o 1 0.0 4299 0.0396 6 0.0 0 0 0 0 8.30e ┐ 11 0.03873 0.03138 0.0 0 0 0 0 0.0 0 0 0 0 S a 1 ┐ 0.33810 ┐ 0.30 690 ┐ 0.71065 ┐ 0.72874 ┐ 0.09405 ┐ 0.076 83 ┐ 0.09242 ┐ 0.0 0 608 s 1 ┐ 7.45e ┐ 05 ┐ 0.0 0 011 ┐ 0.41032 ┐ 0.42077 ┐ 0.32223 ┐ 0.36301 ┐ 0.19696 ┐ 0.14961 s ? 1 0.33803 0.30 679 0.30 033 0.307970 ┐ 0.22817 ┐ 0.28618 ┐ 0.10454 ┐ 0.14353 Q o 1 0.33760 0.30 611 0.0 0 0 0 0 1.4 4e ┐ 08 0.36216 0.29997 0.0 0 0 0 0 0.0 0 0 0 0 Q a 1 1.57459 1.4 410 0 3.07181 3.142558 0.91795 0.77506 1.52386 0.24135 Q 1 0.01012 0.01504 1.774 4 9 1.818559 1.6 8581 1.85502 3.23387 2.54 802 Q ? 1 1.57474 1.4 43868 1.30 0907 1.3306 85 1.453591 1.635708 2.54 802 2.512856 I a 1 (kA) 0.6723 0.80 05 0.8963 0.9292 0.7293 ┐ 0.8503 2.2589 2.0813 I a 2 (kA) 0.4196 0.5677 0.2908 0.3547 0.4 812 0.6391 0.9405 1.0 646 I a 1 /I a 2 1.60 02 1.410 0 3.0822 2.6197 1.5165 ┐ 1.3305 2.4018 1.9555 I 1 /I 2 1.4187 1.284 9 2.4276 1.914 4 2.4631 2.2247 2.2517 1.7363 A . Asuhaimi Mohd Zin et al.

/ Neurocomputing 168 (2015) 983 993990 Table 7 show the results of Clarke s transformation. With training DW T and BPNN, MSE was 0.037218 and MAE was 0.119521, and for DW T and PRN, the MSE was 0.13115 and MAE 0.26 4 89. Simulation result of fault detection and classi ? cation using Clarke s transformation deliver good results when analyzed with pre-processing using training DW T and BPNN and architec- ture combination of 12-24-4 8-4. 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] . Ta b l e 8 shows the c omparison between BPNN with PRN. If the re sults of the standa rd error is smaller for B PNN than PRN, B PNN is better tha n PRN.Ta b l e 8a lso shows t he ou tput phas e G of BPNN a n d PRN are the smalles t compare d 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 popu- lation of numbers [32,33]. Ta b l e 9 shows t he compari son b e tween B P NN and P RN. I f t he varianc e er ro r is s maller for BPNN than PRN, BPNN is better than PRN.

Ta b l e 9 also shows the output phase B of BPNN and PRN was the la rgest compa re d w ith other p h ases. 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 b es t Clarke□s transformation o ccurred on the 12-24-4 8-4 con?gurati on. For insta nc e, using MSE m ethod, the erro rs of Back Propagation Neural Netwo rk , Pattern Rec ognition Net- wo rk and F it Ne twork a re 0. 03721, 0 .13115 a nd 0.03728, res p ective ly, and the errors us ing MAE method, a re 0.11952 , 0.264 89 and 0 .119 53 , re spective ly.

T his sugge sts t hat t he Ba ck propagati on Neural Netwo rk results in the lowesterror thus it is most best compared Pattern Re cognition Netwo rk a n d F it Ne twork . 5. Conclusion This paper p ro poses a te chnique of using a combinati on of di scre te wavel et t ransfo rm (DW T) and back-propagation neural network s (BPPN) w ith and without Clark e□s t ransformati on, in order to identify fault c lassi?cation and detection on parallel circuit transmi ss ion lines.

This te chni qu e ap plies Dau bechies4 (Db 4) a s a mother wavelet. Va rious c a se stu dies have been stud ied, incl ud ing varia tion d is ta n ce, the ini ti al angle and fault resi stance. Thi s study also i ncludes compar- ison of the results of training BPPN and DW T with and without Cla rke□s t ransfo rmation, where t he re sults show t hat using Clarke□s trans f ormati on wil l produc e s ma ller M SE and M A E , c omp are d to withou t Cl ark e□s t ransformation.

Among t he thre e s tructure s, the Table 7 The comparison result for model BPNN and PRN based on Clarke□ s transformation with con? guration (12-24-48-4). Type fault Distance R f Fault inception Back-propagation neural network Pattern recognition network MSE □ 0.037218, MAE □ 0.119521 M SE □ 0.13115, MAE □ 0.26 489 km Ohm Degree A B C G A B C G AG 150 75 60 0.9636 6 0.02287 ┐ 0.0790 0.99251 0.90539 0.32014 0.11389 0.99892 AG 150 75 75 1.0 474 4 0.11159 0.13258 1.0 4361 0.75950 0.27251 0.19157 0.99786 AC 125 10 0 30 1.0256 6 0.02795 1.0 0 082 0.03517 0.99935 0.34371 0.71337 0.0 0208 AC 125 10 0 45 1.0 4593 0.15348 0.74610 0.11221 0.92150 0.0 0 0 03 0.99957 0.0 0146 BCG 75 75 75 0.01242 0.72528 0.896 84 1.07555 0.22582 0.70 012 0.70752 0.99869 BCG 75 75 90 ┐ 0.0289 0.83212 0.97222 1.05126 0.21743 0.79599 0.73602 0.996 89 ABC 50 10 0 120 0.83261 1.09872 0.90557 0.02879 0.75951 0.79234 0.80 087 0.0 0 014 ABC 50 10 0 150 0.82418 1.16831 0.85983 0.03543 0.780 47 0.82732 0.76302

0.0 0 015 Table 8 the comparison SE for model BPNN and PRN based on Clarke s transformation.

Con ? guration 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 0.2466 6 0.310 06 0.23211 0.07275 0.4070 0 0.4 4677 0.40 645 0.23975 12-12-24-4 0.25194 0.26 869 0.22829 0.09127 0.40836 0.36352 0.43509 0.27885 12-24-4 8-4 0.22979 0.25438 0.20 463 0.08553 0.42236 0.430 0 0 0.43078 0.16211 Table 9 VE comparison for model BPNN and PRN based on Clarke s transformation. Con ? guration 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 0.0 6084 0.09614 0.05388 0.0 0529 0.16565 0.19961 0.16520 0.05748 12-12-24-4 0.0 6347 0.07219 0.05212 0.0 0833 0.17839 0.184 91 0.18558 0.02628 12-24-4 8-4 0.05280 0.0 6471 0.0 4187 0.0 0732 0.16378 0.180 01 0.15227 0.02422 A . Asuhaimi Mohd Zin et al.

/ Neurocomputing 168 (2015) 983 993 991 Architec ts re sult was t he best, which was 12-24-4 8-12. Four statistical methods are utilized in the present study to d etermine the a ccuracy of dete cti on and cl assi? cation faults , sugge sting t hat t he Back Propaga- tion Ne ural Ne twork results in th e l owest e rror th us it is the b es t compared with Pattern Recognition Ne twork a nd Fit Network . Acknowledgments The authors would like to express their gratitude to Universiti Teknologi Malaysia, the State Polytechnic of Ujung Pandang, PT.

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Con ? guration Back propagation neural network Pattern recognition network Fit network Clarke□ s transformation Clarke□ s transformation Clarke□s transformation MSE MAE MSE M AE MSE MAE 12-6-12-4 0.07224 0.15077 0.14704 0.30 409 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 0.26 489 0.037281 0.11953 A . Asuhaimi Mohd Zin et al. / Neurocomputing 168 (2015) 983 □ 993992 Mohd Wazir Mustafa received his B. Eng Degree (1988), M. Sc. (1993) and PhD (1997) from University of Strathclyde, United Kingdom.

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