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CLASSIFICATION OF TRANSMISSION LINE FAULTS BY USING WAVELET TRANSFORM AND PROBABILISTIC NEURAL NETWORKS

ABSTRACT

In this paper, an alternative method which uses discrete wavelet transform (DWT) and probabilistic neural networks (PNN) is presented for classification of transmission line faults. DWT is used to extract distinctive features of fault transients. Detail coefficients of DWT are feed the PNN. A comparison study with other classification methods such as Back Propagation Algorithm (BPA) and Bayes classifiers is also performed to confirm the feasibility of the proposed method. It has been shown that the proposed method classify all fault types with %98.61 accuracy rate.
Keywords: Transmission Line Faults, Discrete Wavelet Transform, Probabilistic Neural Networks

DALGACIK DÖNÜŞÜMÜ VE OLASILIKSAL SİNİR AĞLARI KULLANARAK İLETİM HATTI ARIZALARININ SINIFLANDIRILMASI

ÖZET

Bu makalede, iletim hattı arızalarını sınıflandırmak için ayrık dalgacık dönüşümünü (ADD) ve olasılıksal sinir ağlarını (OSA) kullanan altenatif bir yöntem sunulmuştur. Arıza geçici durumlarının ayırt edici özelliklerini çıkarmak için ADD kullanılmıştır. ADD'nin detay katsayıları OSA'nın girişine uygulanmıştır. Önerilen yöntemin uygunluğunu doğrulamak için geri yayılım algoritması (GYA) ve Bayes sınıflandırıcıları gibi yöntemlerin sonuçları karşılaştırılmıştır. Önerilen yöntemin tüm arıza tiplerini %98.61'lik bir doğruluk oranıyla sınıflandırdığı görülmüştür.
Anahtar Kelimeler: İletim Hattı Arızaları, Ayrık Dalgacık Dönüşümü, Olasılıksal Sinir Ağları

1. INTRODUCTION (GİRİŞ)

Recently, electric power networks have become more complicated due to the high demand of electric energy. It is important to ensure the reliability of the systems for both manufacturer and customer. Therefore, power engineers and researchers have worked on the protection schemes, particularly on fault location and fault identification.

There are several methods such as using the variation of line impedance, measuring of faulted current and voltage signals and a lot of study has been continued with advance in computer technology. When fault location is estimated by using current and voltage wave information, methods based on traveling waves, faulty line impedance calculations, neural network and wavelet transform (WT) are used widely [1]. In traveling wave method, fault location is determined by using time difference between incidents and reflecting waves [2-4].

This method has been restricted because of the difficulty in analyzing. Traveling waves requires a very high sampling rate as well. Calculating characteristic reactance is another method which is used for estimating fault distance [5]. This method calculates reactance between relay point and fault represents an accurate estimation of fault distance when the fault resistance is very small at line ends. One of the other techniques is employed Fourier transform (FT) which obtains line impedance in the frequency domain [6]. In spite of FT, WT has been used to obtain the best information of current and voltage signals. The main advantage of WT is that the band of analysis can be fine adjusted and the results obtained from WT are shown on both the time and frequency domain.

Application of digital technology allows modifications to be made on line to improve the network protection and control in the presence of the controllable and non-controllable devices [7]. Artificial intelligence (AI) techniques naturally become the best choice to improve the performance of the present system used. AI possesses powerful characteristics such as fast learning, fault tolerance and ability to produce correct output when fed with partial input. It can adapt to recognize learned patterns of behavior in electric power systems where exact functional relationships are neither well defined nor easily computable [8]. Recently, the most used AI technique in the applications of power system protection is Artificial Neural Networks (ANN) [9].

2. RESEARCH SIGNIFICANCE (ARAŞTIRMANIN ÖNEMI)

In this paper, a WT and PNN based fault detection method is proposed. PNN is a method that has high performance level especially in classification problems [10]. Different types of faults (single-line to ground, line to line, double-line to ground and three-phase symmetrical) are simulated by ATP/EMTP [11]. Faults are occurred at different locations and inception angles. WT is implemented to all fault current and voltage curves. This gives distinctive information about the fault cases. Features obtained from WT are used as inputs to PNN which uses less training data and time compared with back propagation neural networks.

3. TRANSMISSION LINE MODEL (İLETİM HATTI MODELİ)

The online diagram of 750 kV, 50 Hz power transmission line connecting two systems is shown in Figure 1. Shunt reactors are connected to both end of the line to reduce re-closing arc current [11].Different types of the faults are considered such as; single line to ground (SLG), double line to ground (LLG), double line (LL) and three phase to ground which are occurred at different locations with fault resistance. The power transmission line system which has been modeled by using ATP-EMTP is shown in Figure 2.

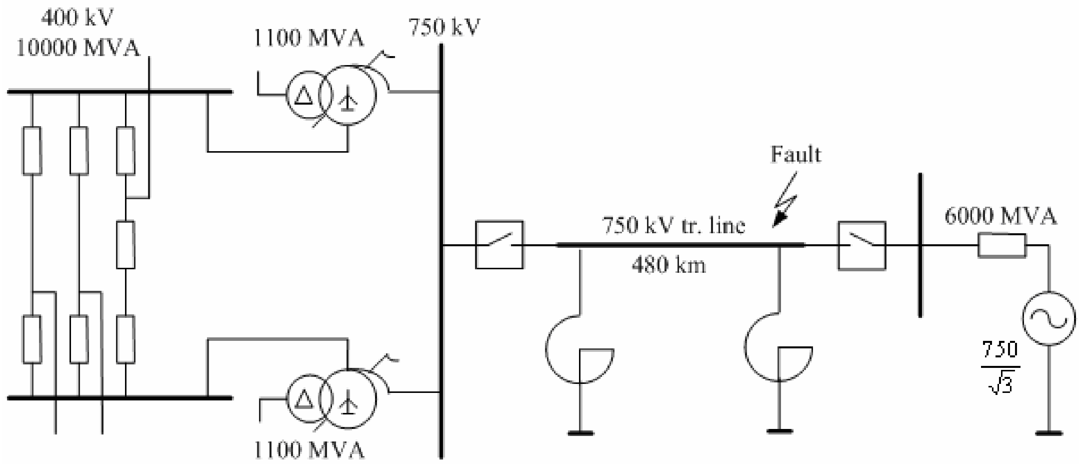

Figure 1. One-line diagram of 750 kV transmission line
(Şekil 1. 750 kV'luk iletim hattının tek-hat diyagramı)

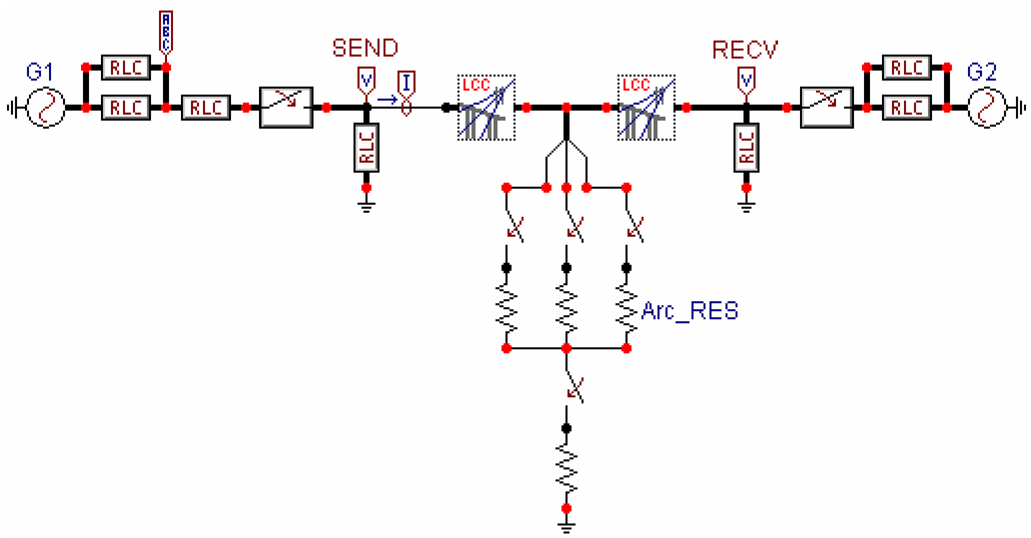

Figure 2. ATP/EMTP model of 750 kV power transmission line
(Şekil 2. 750 kV'luk güç iletim hattının ATP/EMTP modeli)

Each LCC object represents a part of the transposed transmission line. Any fault occurring on the line causes transient state distorting the sinusoidal waveforms of voltages and currents. These distortions have diagnostic features about the fault types. All current and voltage signals which are used in the classification have been recorded at the sending end of the line. The voltage and current signals of a SLG fault occurred at the receiving end of the line are shown in Figure 3.

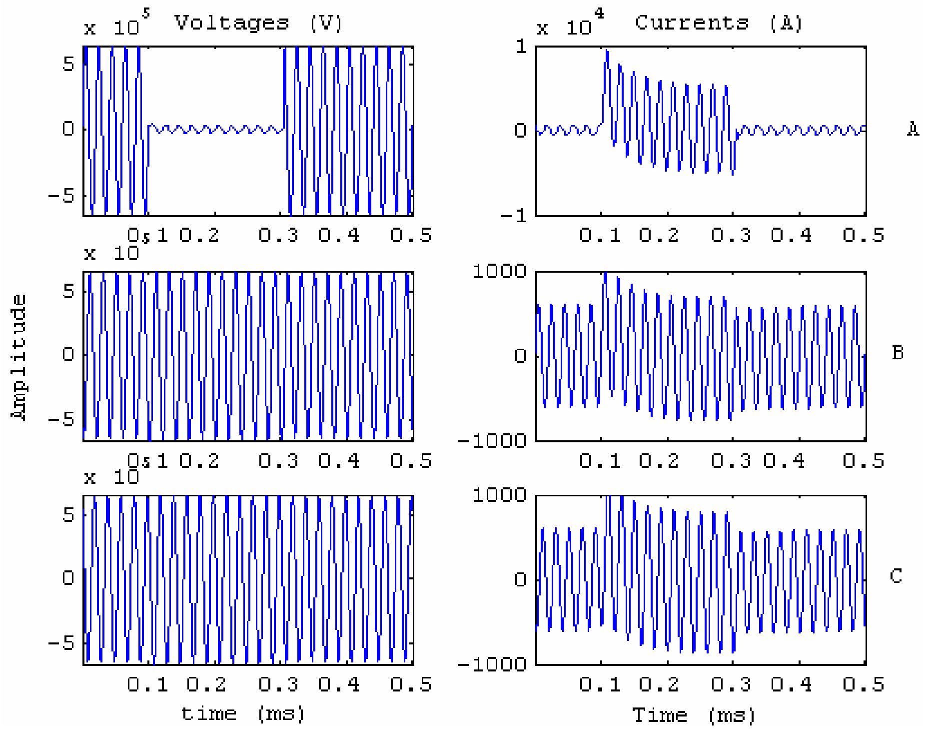

Figure 3. Voltage and current transients for a SLG fault.
(Şekil 3. Bir SLG arızası için gerilim ve akım geçici durumları)

4. REVIEW OF WAVELET TRANSFORM (DALGACIK DÖNÜŞÜMÜNÜN İNCELENMESİ)

Wavelet transform (WT) is a mathematical technique used for many application of signal processing [5, 12]. Wavelet is much more powerful than conventional methods in processing the stochastic signals because of analyzing the waveform time-scale region. In wavelet transform, the band of analysis can be adjusted so that low frequency and high frequency components can be windowing by different scale factor. Recently WT is widely used in signal processing applications, such as de-noising, filtering, and image compression [13]. Many pattern recognition algorithms have been developed based on the wavelet transforms. It also has been used widely by the power system researchers. According to scale factor, wavelet categorized different section. The wavelet transform of $f(t)$ is defined as;

$$CWT_{\psi} f(a,b) = W_f(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \tag{1}$$

where

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

In this paper, instead of continuous dilation and translation the mother wavelet dilated and translated discretely by selecting $a = a_0^{\,m}$ and $b = nb_0 a_0^{\,m}$, where a_0 and b_0 are fixed constant with $a_0 > 1,\ b_0 > 0,\ m,n \in Z$ and Z is the set of positive integers. Then ψ defined as;

$$\psi_{m,n}(t) = a_0^{\frac{-m}{2}}\psi\left(\frac{t-nb_0\, a_0^{\,m}}{a_0^{\,m}}\right) \tag{3}$$

For any function $f(t)$, discrete wavelet transform (DWT) is written as

$$DWT_{\psi} f(m,n) = \int_{-\infty}^{\infty} f(t)\psi_{m,n}(t)dt \qquad (4)$$

where, ψ is mother wavelet [5, 12]. The decomposition for two-level is shown Figure 4.

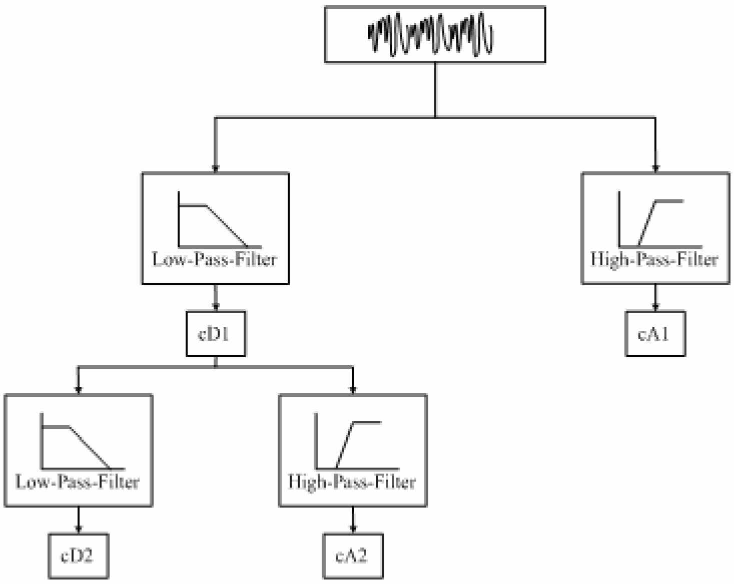

Figure 4. Two-level signal decomposition diagram
(Şekil 4. İki seviyeli sinyal ayrıştırma diyagramı)

The $cA_i,\ i=1,2,...,n$, represents approximation coefficients and $cD_i,\ i=1,2,...,n$, denotes detail coefficients of n-level decomposition.

5. GENERATION OF FEATURES (ÖZELLİKLERİN ÜRETİLMESİ)

The feature extraction is very important in signal processing operations because the rough and large data sets cause difficulties, when a network is trained. DWT is an excellent method which enhances the disturbance and reduces the data to coefficients, corresponding to the similarity of the signal to the wavelet at a particular location and time scale [14]. Before the feature extraction stage, different faults occurred at different locations on the power transmission line have been simulated by ATP/EMTP program. Time step of the simulation is selected as 0.00002 second and simulation runs 0.5 second. 25000 data are obtained for each faulty phase. It is considered, that faults occur 48 different locations. It is impossible to use such a big amount of data in the classification task. Half cycle of pre-fault and half cycle of post-fault are considered to reduce the data set in size. Therefore 1000 samples are obtained for each faulty voltage or current signal. Then, DWT has been employed for obtaining high frequency detail component which gives distinctive features about the curves. Daubechies-4 (db4) was selected as a mother wavelet [15]. Wavelet coefficients are shown in Figure 5 and 6 respectively, for three-level decomposition of voltage and current signals belonging to SLG fault at 10th km.

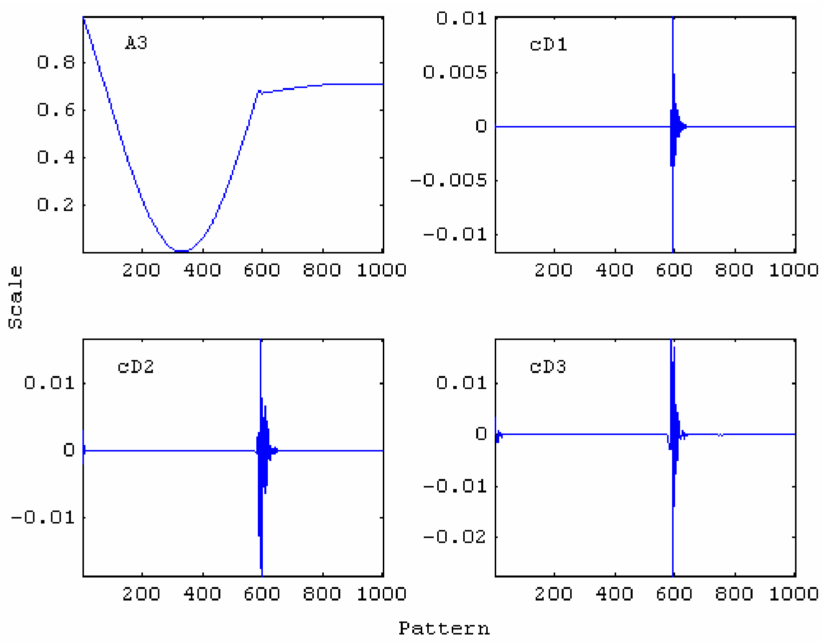

Figure 5. Voltage coefficients of DWT
(Şekil 5. Gerilim katsayılarının ADD'si)

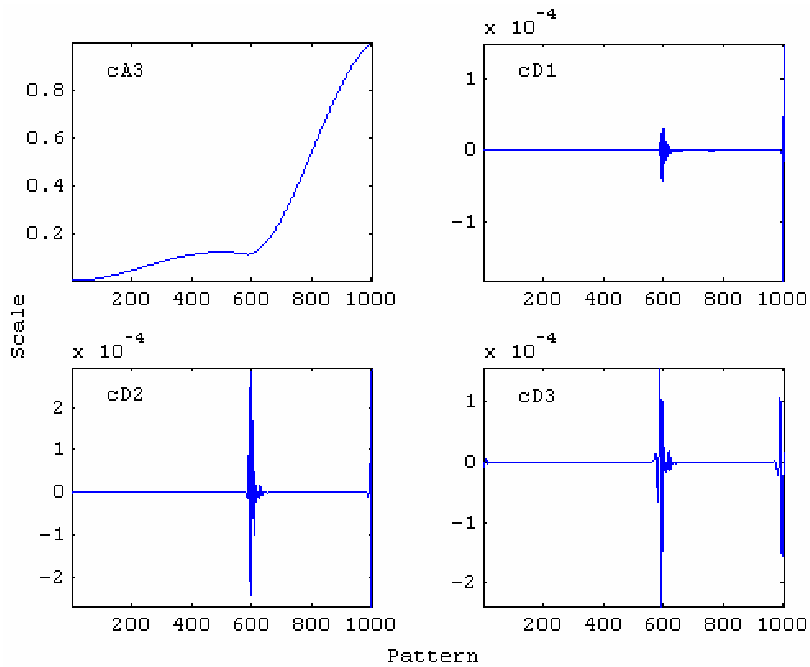

Figure 6. Current coefficients of DWT
(Şekil 6. Akım katsayılarının ADD'si)

One approximation and three details coefficients have been obtained with three-level decomposition for each curve. Wavelet energy criterion is applied to WP coefficients to reduce the data sets. The first feature which has the highest energy value belongs to the approximation and hence is ignored. Thus, 3 features are chosen for only one faulty current or voltage waveform. Therefore, total 6 distinctive features which belong to one terminal current and voltage signals have been obtained for each fault case. These features will be used for classification.

6. PROBABILISTIC NEURAL NETWORKS (OLASILIKSAL SİNİR AĞLARI)

Probabilistic Neural Network (PNN) is a network formulation of 'probability density estimation'. It is a model based on competitive learning with a 'winner takes all attitude' and the core concept based on multivariate probability estimation. The development of PNN relies on the Parzen window concept of multivariate probabilities. The PNN is a classifier version, which combines the Bayes' strategy for decision-making with a non-parametric estimator for obtaining the probability density function [16]. In 1990, D. Specht proposed a four-layered feed-forward network topology that implements Bayes' decision criterion and Parzen's method for density estimation. The PNN network described in Figure 7 consists of an input layer, two hidden layers (one each for exemplar/pattern and a class/summation layers) and an output/decision layer. This model can compute nonlinear decision boundaries that asymptotically approach the Bayes' optimal. Bayesian strategies are decision strategies that minimize the expected risk of a classification [17].

PNNs are a kind of radial basis function (RBF) neural networks which are suitable for many classification problems [18]. The most distinctive feature of PNN which differentiates from RBF is that PNN works on estimation of probability density function while RBF works on iterative function approximation. The training of RBF is noticeably faster than BPA feed forward neural networks.

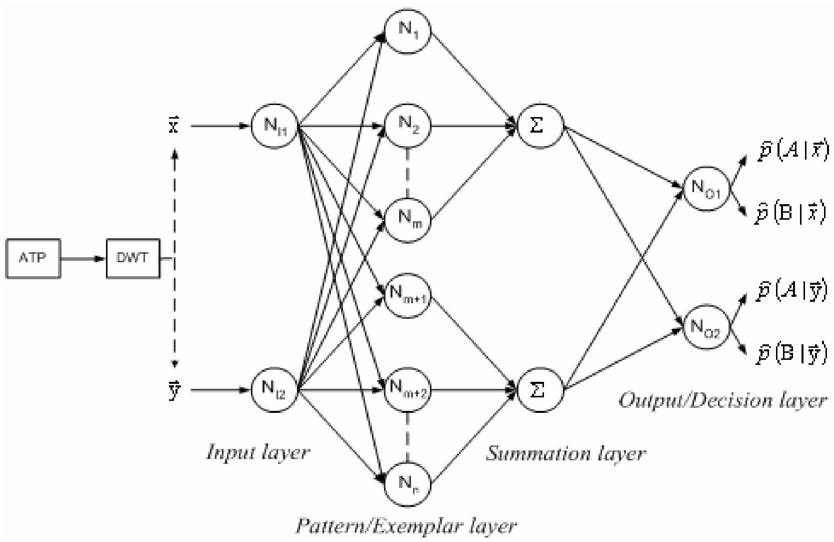

Figure 7. Architecture of PNN for two classes
(Şekil 7. İki sınıf için OSA mimarisi)

In order to classify a feature vector which belongs to different predefined classes, the conditional probability of each class is estimated. Then these estimates are combined by the rule of Bayes to yield a-posteriori class probabilities that allow in making optimal decisions [16]. The input layer of the PNN in Figure 7 contains two input neurons, N_{I1} and N_{I2}, for the two test cases, $\vec{x}$ and $\vec{y}$. There is one pattern or exemplar node for each training example. Each pattern node forms a product of the weight vector and the given example for classification, where the weights entering a node are from a particular example. After that this product passes through an exponential activation function defined as;

$$exp\left(\left(x^T w_{ki} - 1\right)/\sigma^2\right) \quad (5)$$

where k represents the predefined classes, w_{ki} is the weight vector and σ is the variance or smoothing parameter. The second hidden layer contains one summation unit for each class. Each neuron of summation layer receives the outputs from the pattern neurons associated with a given class. In the PNN of Figure 7, the training set comprises cases belonging to two classes, A and B. In total, m training cases belong to class A. The associated pattern neurons are $N_1 \ldots N_m$. Class B contains n−m training cases; the associated pattern neurons are $N_{m+1} \ldots N_n$. Since we have two classes in this example, the PNN has two summation neurons. The summation neuron for class A sums the output of the pattern neurons that contain the training cases of class A. The summation neuron for class B sums the output of the pattern neurons that contain the training cases of class B.

$$\sum_{i=1}^{N_k} exp\left[\left(x^T w_{ki} - 1\right)/\sigma^2\right] \quad (6)$$

The activation of the summation neuron for a class is equivalent to the estimated density function value of this class. The summation neurons feed their result to the output nodes in the output layer. These nodes are binary neurons that produce a decision based on

$$\sum_{i=1}^{N_k} exp\left[\left(x^T w_{ki} - 1\right)/\sigma^2\right] > \sigma_{i=1}^{N_k}\left[\left(x^T w_{ki} - 1\right)/\sigma^2\right] \quad (7)$$

The output neuron NO1 generates two outputs which contain the estimated conditional probabilities that belong to class A and B for test case $\vec{x}$. The output neuron N_{O2} generates the respective estimated probabilities for the test case $\vec{y}$. Unlike other feed-forward neural networks, e.g., multi-layer perceptrons (MLP), all hidden-to-output weights are equal to 1 and do not vary during processing.

7. COMPARISON STUDY (KARŞILAŞTIRMA ÇALIŞMASI)

In this section, a comparison study has been performed to evaluate the performance of PNN as a classifier. The most widely used methods in classification problems such as Bayesian classifiers and BPA are tested for performance evaluation. Wavelet transform is employed to extract the deterministic features of the faulty signals before the classification phase. Wavelet transform is used in many applications especially in signal processing because of its localization properties in the time-frequency plane.

The coefficients of WT contain very large data sets. It is impossible to give this data to classifiers as input. Therefore, wavelet energy criterion is implemented to wavelet coefficients and thus, the sizes of data sets are decreased relatively. In spite of data reduction, it is difficult to train such a big amount of data due to the computation load. For example, the size of input vector used in this study has 18 features for each fault case. 192 fault cases are considered in this study containing 4 fault types. Thus, a matrix which has 18 rows and 192 columns are obtained. The patterns which are used for testing of PNN classifier are shown in Figure 8.

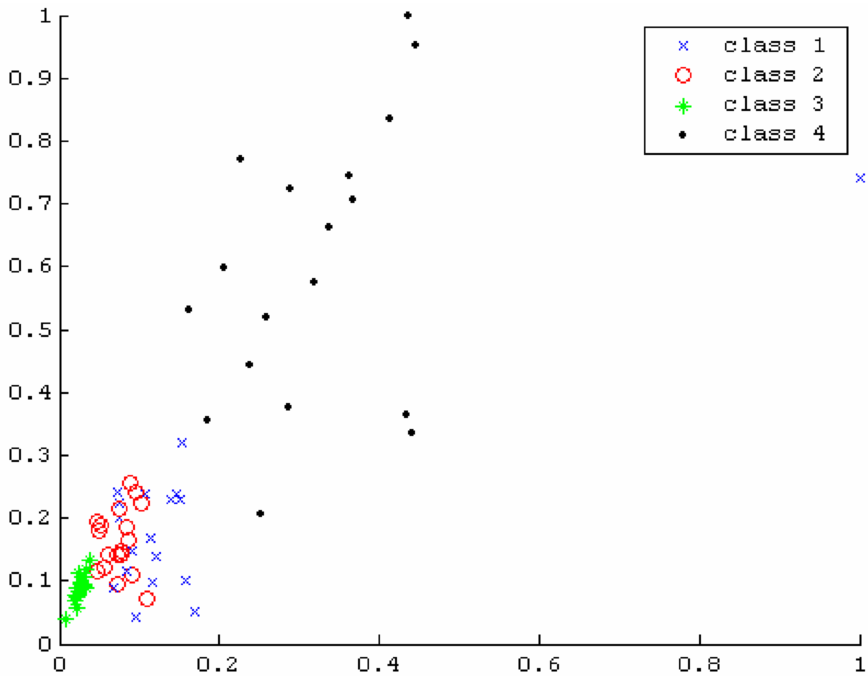

Figure 8. Demonstration patterns in feature space.
(Şekil 8. Örüntülerin özellik uzayında gösterimi)

The proposed technique uses a combination of WT and PNN. The application of WT combining PNN to determine fault type is a novel technique with a very high accuracy of 98.61%. The PNN was found to improve the accuracy as well as the speed compared to the conventional BPA [19]. On the other hand, Bayesian classifier is trained quickly but its classification error is higher than PNNs. The comparison results of these methods are shown in Table 1.

Table 1. Comparison of classifiers
(Tablo 1. Sınıflandırıcıların karşılaştırılması)

Type of classifiers	Number of trained pattern	Number of tested pattern	Elapsed-time (sec)	Testing performance %
PNN	120	72	0.5150	98.61
Bayesian	120	72	0.0470	85.00
BPA	120	72	74.125	88.88

8. CONCLUSION (SONUÇ)

In this paper, a technique using discrete wavelet transform combined with probabilistic neural networks in order to identify fault types on a 750 kV power transmission line has been proposed. The discrete wavelet transform has been employed to extract deterministic features of fault signals. After feature extraction phase, wavelet energy criterion has been applied to coefficients of wavelet transform to reduce data sets in size. Because of its high energy level, the first approximation coefficients were neglected. Probabilistic neural network has been used to classify the type of faults. Different fault cases including different inception angles and fault types have been investigated in this study. Bayesian classifier and back propagation algorithm have been trained and tested to evaluate the performance of proposed method and it has been observed that PNN is an effective technique in classifying transmission line faults with less training time and testing error. The results have illustrated that the proposed algorithm can identify the fault types on transmission line with the accuracy of 98.61%.

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