POWER SYSTEM FAULT DETECTION CLASSIFICATION BASED ON PCA AND PNN

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***Abstract*— This paper presents a new approach for power system fault classification based on principal component analysis (PCA) and probabilistic neural network (PNN).the work presented in this paper is focused on identification of simple power system faults. The new model mainly includes three steps. Firstly wavelet transform is used to analyze power system fault signals, and distinguishing features are extracted from the result of wavelet transform. Secondly, principal-component analysis (PCA) is used to reduce the dimensionality of data set, mean while extract principal-components to describe nonstationary signals of the power system. Finally, use the principal-components as the input vectors of probabilistic neural network and classify the power system faults. The simulation results show the validity and efficiency of the proposed model.** .

***Keywords* — Power System Faults, Principal-Component Analysis (PCA), Probabilistic Neural Network (PNN), Wavelets.**

I. INTRODUCTION

Determination of fault classification in electric power lines is vital for economic operation of power systems. Accurate fault classification will facilitate quicker repair, improve system availability, reduce operating costs, and save time. A conventional approach classifies the fault based on fundamental frequency only [2]. Wavelets have been used for several years in areas like seismic, image compression, acoustics, and mechanical vibrations. Recently, several papers have been presented proposing the use of wavelets for power system analysis [3] , fault detection [4], data compression [5], analysis for power quality problem solution [6], power quality assessment [7], protection [8], transient analysis, and fault classification [9]. In [10], the authors have suggested to classify the fault with the assumption that the line is ideally transposed and hence, it may have difficulty in classifying a double line to ground fault. In [11], the authors used a set of coefficients based on sequence current and voltage phasors. The relay system failure causes large area disturbances and cascading blackouts [12]. A synchronized sampling based fault analysis is introduced in [13].

Fore mentioned pattern recognition approaches use the features extracted from the results of signal processing as the inputs of classifier without the process of future reduction. The numerous features will affect classification effectiveness.

In this paper, an approach based on wavelet transform, principal –component analysis (PCA) and probabilistic neural network (PNN) is proposed to classify the different power system faults .We use wavelet transform for time frequency analysis of non-stationary power system fault signals. Then 45/1 matrix is obtained for each fault. In order to simplify the structure of the neural net work and increase the classification effectiveness, PCA is used for future reduction, here the matrix size is reduced to 9/1. At the last the principal components are chosen as the inputs of PNN network. Compared with fore mentioned pattern recognition approaches, the new approach has advantages of fast classification and simple logical structure.

2. WAVELET TRANSFORM

Wavelet theory is the mathematics, which deals with building a model for non-stationary signals, using a set of components those look like small waves, called wavelets. It has become a well known useful tool since its introduction, especially in signal and image processing [14][15].

2.1Continuous Wavelet Transform

Considering a time series, Xn, with equal time spacing Δt and $n = 0 \ldots N-1$. Considering a *wavelet function,* $\psi_0(\eta)$, that depends on a non dimensional time parameter η. This function must have zero mean and be localized in both time and frequency domain. The wavelets are generated from a single basic wavelet $\psi(t)$, namely, *mother wavelet*, by scaling and translation:

$$\psi_{s,\tau(t)} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \qquad (1)$$

In (1) s is the scale factor, τ is the translation factor and the factor $s^{\frac{-1}{2}}$ is the energy normalization across the different scales.

2.2Discrete Wavelet Transform (DWT)

To obtain the DWT the parameters a and b need to discretized. Discretizing a= 2^j and b= 2^jk will yield orthogonal basis functions for certain choices of ψ

$$\psi_{(j,k)}(t) = 2^{-j/2}\psi\left(2^{-j}t - k\right) \quad (2)$$

Mallat showed that Multi Resolution Analysis can be used to obtain the DWT of a discrete signal by applying lowpass and highpass filters, iteratively, and subsequently down sampling them by two. Fig 1 illustrates this process, where g[n] and h[n] are the highpass and lowpass filters, respectively [16]. At each level, this procedure computes.

$$y_{high}[k] = \sum_n x[n] \cdot g[2k-n] \quad (3)$$

$$y_{low}[k] = \sum_n x[n] \cdot h[2k-n] \quad (4)$$

where

$$h[N-1-n] = (-1)^n g[n] \quad (5)$$

With N being the total number of samples in x[n] and y_{high} and y_{low} are the outputs of highpass and lowpass filters, respectively, at each level. The number of levels in this process is repeated depends on the choice of the user. At the last level the $y_{low}[k]$ obtained is called as Approximation. The $y_{high}[k]$ computed at each level is called as the detail coefficient at that level.

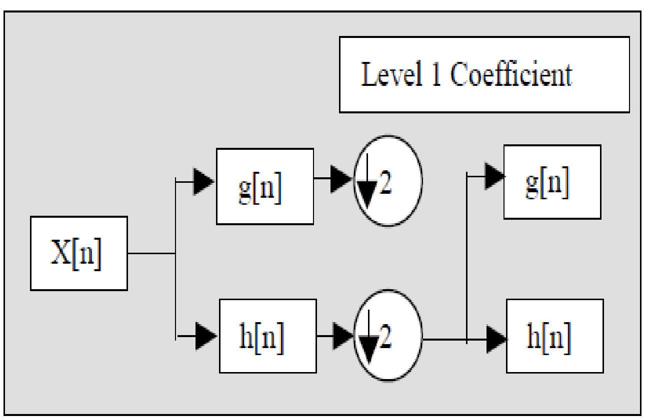


Figure 1.Computation of DWT by MRA

3. A GENERAL FRAMEWORK

Line fault currents Ia, Ib, Ic are measured to classify the types of the fault among LG, LL, LLG, LLL and LLLG. These signals decomposed by wavelet transform into several detail coefficients and Approximations. The decomposition of the signal into these detail coefficients and approximations are carried out until the fundamental frequency signal (60Hz) is obtained as the approximation at that level. The fundamental frequency of the system is 60Hz and sampling rate is 6.4 kHz i.e. 108 samples per cycle are taken after the decomposition the matrix contains 45 samples per cycle.

The classification precision is improved by the number of features increase, but the classifier has more complicated structure and low efficiency with too much inputs. The new method resolves the problem by future reduction using PCA.

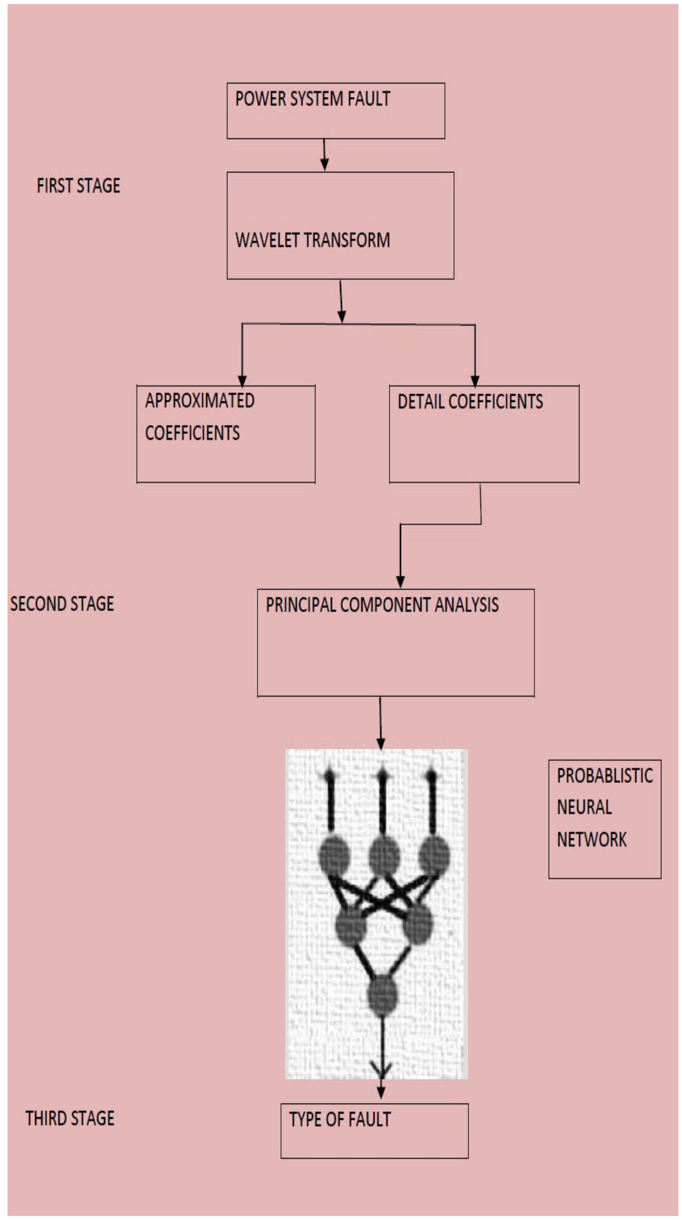


Figure 2.

4. PCA

Principal-component analysis[17] is used in many engineering and scientific fields such as data compression, pattern recognition and image processing.PCA projects the input data from the original n-dimensional vector space onto an m-dimensional output space(m<<n). That means PCA can transform a very large amount of correlated input data to asset of statically decorrelated componenets.

Let x as the n-dimensional input vector and y as the m-dimensional vector.

$$x = \sum_{i=0}^{N-1} y(i) a_i \text{ and } y(i) = a_i^T x. \qquad (6)$$

Then define a new vector in the m-dimensional subspace as

$$\hat{x} = \sum_{i=0}^{m-1} y(i) a_i \qquad (7)$$

Where a_i is the column of chosen matrix. i=0,1,…….N-1.

$\hat{x}$ is the projection of x onto the subspace spanned by the m eigenvectors. If we try to approximate x by its projection $\hat{x}$, the resulting mean square error is given by

$$E\left[\|x-\hat{x}\|\right] = E\left[\left\|\sum_{i=m}^{N-1} y(i) a_i\right\|^2\right] \qquad (8)$$

Aim to minimum MSE, we have

$$E\left[\left\|\sum_{i=m}^{N-1} y(i) a_i\right\|^2\right] = E[\sum_i \sum_j (y(i) a_i^T (y(j) a_j)] = \sum_{i=m}^{N-1} a_i^T E[xx^T] a_i \qquad (9)$$

Finally we have

$$E\left[\|x-\hat{x}\|\right] = \sum_{i=m}^{N-1} a_i^T \lambda_i a_i = \sum_{i=m}^{N-1} \lambda_i \qquad (10)$$

λ_i is the respective eigenvalues of chosen matrix correspond and the error in above equation is minimized.

5. PROBABILISTIC NEURAL NETWORK

PNN has an input layer, an exemplar layer, a summation layer and an output layer as shown in Fig.3. The activation function of a neuron in the case of the PNN is statistically derived from estimates of probability density functions (PDFs) based on training patterns [1][18]. The principal components (vector **X**) are fed to the input layer consisting of 54 neurons of the Probabilistic Neural Network. The exemplar layer, having 9 neurons (3 faults x 3 sets of data for each fault), consists of the activation functions corresponding to each of the training sets. Estimator for the PDF is,

$$p(x \mid s_i) = \frac{1}{(2\pi)^{m/2} \sigma_i^m \mid s_i \mid} \sum_{j=1}^{n_i} \exp\left[\frac{-(x-x_j^{(i)})^T (x-x_j^{(i)})}{2\sigma_i^2}\right] \qquad (11)$$

Where $p(x \mid s_i)$ is the probability of vector x occurring in set S_i corresponding to the type of fault.

$x_j^{(i)} = j^{th}$ exemplar pattern or training pattern or training pattern belonging to class S_i type of fault.

n_i = is the cardinality of the set of patterns in class S_i .

σ_i =Smoothing parameter.

The summation layer consisting of one summation unit corresponding to each class has a total of 3 neurons. Each unit is used to compute the sum in(11) from the outputs of the previous layer. The output layer is the decision layer governed by Winner-take-all mechanism selects the maximum posterior Probability $p_r(S_i \mid x)$, from the outputs of the previous summation layer for each i. Graphical model is shown in fig 3. Posterior probability $p_r(S_i \mid x)$,that the test input data ,principal components is from class S_i, is given by Bayer's rule.

$$p_r(s_i \mid x) = \frac{p(x \mid s_i) p_r(s_i)}{p(x)} \qquad (12)$$

Where $p_r(x \mid S_i)$, i=1, 2,..K is the priori PDF of the pattern in classes to be separated $p_r(s_i)$, prior probabilities of the classes are equal (assumed equally likely).P(X) is assumed to be constant. The decision rule is to select class S_i of the fault type, for which $p_r(S_i \mid x)$ is maximum.

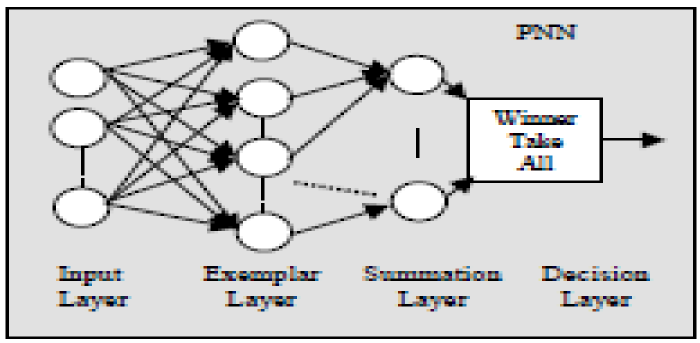


Figure 3. Model of a Probabilistic Neural Network. Principal components are fed to the input layer and the type of the is obtained as the output.

6. SYSEM STUDY.

A simple power system network shown in fig 4. consisting of generator a load two buses and a transmission line was used for the simulation purpose.

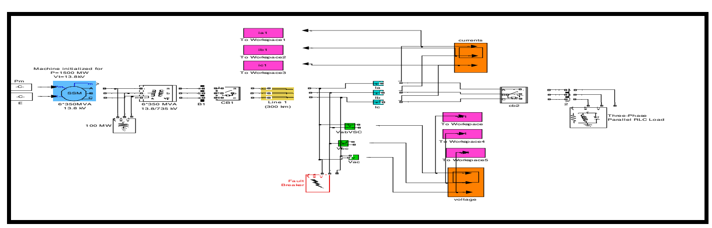


Figure 4

Faults were created at different locations on the transmission line. Simulation is carried out for LG, LL, LLG and three phase symmetric faults. Data sets for each type of fault were obtained by varying the inception angle.

7. Application of Wavelets

Mayer wavelet shown in figure is used as the mother wavelet. The fault signal obtained is decomposed to the 4th level of decomposition, the approximation obtained a4, is the fundamental frequency component of 60Hz uncorrupted by noise. The 4th level detail coefficients obtained are used to get principal components; these principal components are fed to PNN.

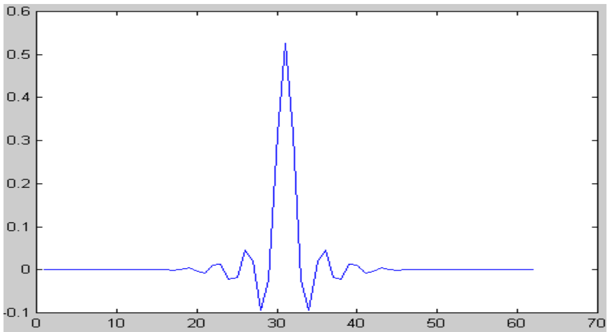
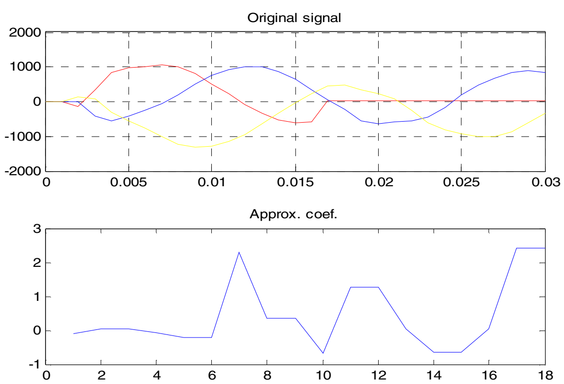
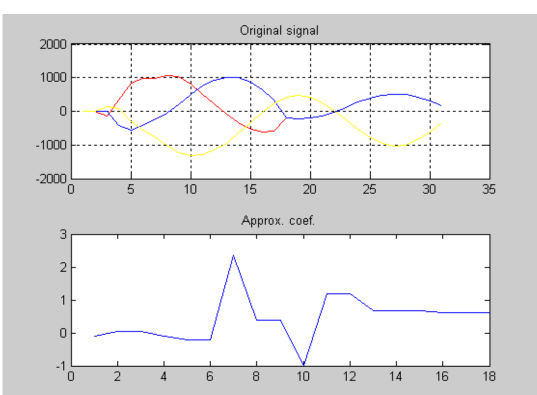


Figure 5 Meyer Wavelet used for the analysis.

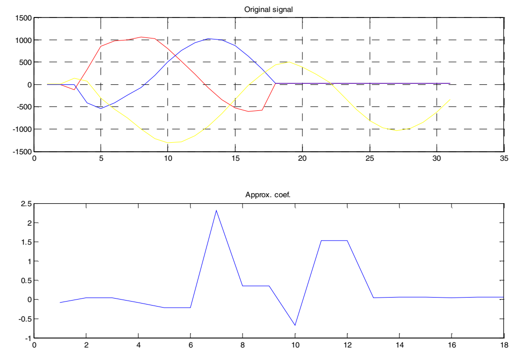
8. Results.



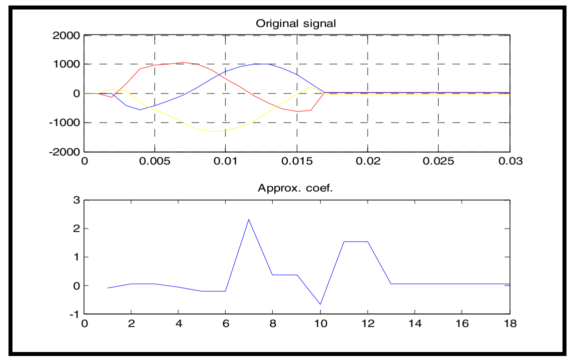
Waveforms for LG fault and its pattern



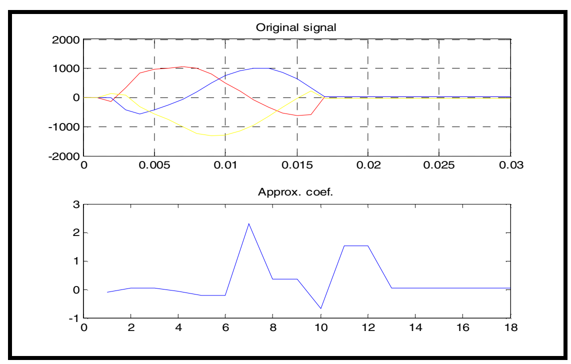
Waveforms for LL fault and its pattern



Waveforms for LLG fault and its pattern



Waveforms for LLL fault and its pattern



Waveforms for LLLG fault and its pattern

9. THE NEW APPROACHE DESCRIPTION

The process of classification is described as follows.

1) The non-stationary power system faults are processed by Wavelet transform.

2) Extract [45/1] matrix from the result of Wavelet transform.

3) Future reduction by PCA. After principal-component analysis, it shows that almost 99% of the variance is accounted for by the first 9 principal components.

4) Use the vector with 9 principal components instead of feature vector with [45/1] features as the input of PNN.

5) Train the PNN and classify power system faults by the trained neural network.

10. SIMULATION

In order to test the proposed method, 500 simulated events of each fault are generated to train the PNN and 100 simulated events of each fault are generated to test the accuracy of new method. Some unique parameters for each different fault type, such as the ground resistance, transition time are changed randomly.

Type of fault	Classification Accuracy (in percentage)	
	PNN	PCA-PNN
LG Fault	100	100
LL Fault	99	98
LLG Fault	100	100
LLL Fault	100	100
LLLG Fault	100	99

TABLE 1. SIMULATIVE RESULT

The result of the new method compare with the PNN without Future reduction shows in table 1. According to the simulation results, the new approach with less feature number is nearly the same rate of accuracy to the traditional PNN method.

11. CONCLUSIONS

This paper proposes an effective method for classification of Power system faults. The input vector of PNN with 45 features is reduced to the modified vector with 9 principal components. The PNN with principal component vector input has simple structure and better classification effectiveness. The simulation results show the method has high precision and its precision is similar to the method with 45 features input. New method is feasibility and validity.

The further research will focus on classification of faults on complex system.

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