

Classification of Power Quality Events Using Wavelet analysis and Probabilistic neural Network

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ABSTRACT

Power quality studies have become an important issue due to widespread use of sensitive electronic equipment in power system. The sources of power quality degradation must be investigated in order to improve the power quality. Switching transients in power systems is a concern in studies of equipment insulation coordination. In this paper a wavelet based neural network has been implemented to classify the transients due to capacitor switching, motor switching, faults, converter and transformer switching. The detail reactive powers for these five transients are determined and a model which uses the detail reactive power as the input to the Probabilistic neural network (PNN) is set up to classify the above mentioned transients. The simulation has been executed for an 11kv distribution system. With the help of neural network classifier, the transient signals are effectively classified.

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1. INTRODUCTION

Detection and classification of transient signals have recently become an active research topic in the area of power quality analysis [1-5]. In [6-7] the authors have proposed a method to classify the power system transients based on dual tree complex wavelet transform (DTCWT). But in this method computational complexity is very high. Power transients occur from variety of disturbances on the power system like, capacitor bank switching, different types of faults, converters and different apparatus switching. In order to improve the power quality, the location of such disturbances must be identified. Techniques like wavelet transforms, mathematical morphology etc have been used to identify them [5-7]. Wavelet analysis, can extract the essential features of transient signal effectively for its classification. With these features as inputs to the neural network, classification of the switching transients, short circuit fault, primary arc, lightning disturbance and lightning strike fault is possible [8]. Authors of paper [9] have proposed a discrete wavelet transform (DWT) based on multiresolution analysis technique and parseval's theorem which is employed to extract the energy distribution features of transient signal at different resolution levels. Probabilistic neural network (PNN) classifies the extracted features to identify the disturbance type. In paper [10] a discrete wavelet transform and multi fractal analysis based on a variance dimension trajectory technique have been used as tools to analyze the transients for feature extraction. A probabilistic neural network is used as a classifier for classification of transients associated with power system faults and switching. The authors of paper [11] presented DWT-FFT based integrated approach for detection and classification of various PQ disturbances with and without noisy environment. Ibrahim and Morcos [12] have given a survey of artificial intelligence technique for power quality, which includes fuzzy logic, artificial neural network (ANN) and genetic algorithm. Wavelet based on line disturbance detection for power quality applications have been discussed in [13]. Perunicic et al. [14] used wavelet coefficients of discrete wavelet transform (DWT) as

inputs of a self organizing mapping neural network to identify DC bias, harmonics, voltage sags and other transient disturbances. Elmitwally et al. [15] have proposed a method in which wavelet coefficients are used as inputs to the neuro-fuzzy systems for classifying voltage sag, swell, interruption, impulse, voltage flicker, harmonic and flat-topped waves. Chang and Wenquang [16] analyzed the effect of transients arising due to utility capacitor switching on mass rapid transit. Liu et al. [17] extracted features from the DWT coefficients of some typical power transients using scalogram. In [18] the authors have proposed a novel method for identifying, characterizing and tracking grounded capacitor banks connected to a power distribution line in a cost effective manner. Beg et al. [19] proposed a simple method based on DWT and a multi-layer feed forward artificial neural network for classification of capacitor, load switching and line to ground fault. In this method success rate is 97.47%.

To identify the type of transient the first step is to extract the feature of the transient signal. These features are used as input to a classifier for classification. The Probabilistic neural network (PNN) is used as a classifier in [20-29]. Probabilistic neural network combines some of the best attributes of statistical pattern recognition and feed-forward neural networks. Therefore, the PNN is chosen as a proper classifier of transients signals. In [30] have shown wavelet based reactive power computation resulting from 90° phase shift networks which gives the reactive power is shown. Wavelet transform has been used to reformulate the newly defined power components [31]. Wavelet analysis is able to extract the features of data, breakdown points and discontinuities very effectively.

The present paper attempts to classify the different types of transients such as capacitor switching, motor switching, different fault induced transients, converter and transformer inrush using a simple PNN based technique. To extract unique feature of each transients first discrete wavelet transform (DWT) has been performed to calculate the detail reactive power at level 1 and 3. As artificial neural network has the capability to simulate the learning process and work as a classifier, probabilistic neural network has been used to classify the mentioned transient disturbances and it has been shown that this single point strategy is very effective in classifying the different transient signals.

2. WAVELET TRANSFORM BASED DETAIL REACTIVE POWER

This section redefines power components definitions contained in IEEE Standard 1459-2000 [31] for single phase system under nonsinusoidal situations. Consider the following sinusoidal and nonsinusoidal voltage and current waveforms: Tables and Figures are presented center, as shown below and cited in the manuscript.

$$v_1 = \sqrt{2} V_1 \sin(\omega t - \alpha_1), i_1 = \sqrt{2} I_1 \sin(\omega t - \alpha_1), \quad (1)$$

$$v_H = \frac{\sqrt{2}}{h \neq 1} \sum V_h \sin(h\omega t - \alpha_h) \quad (2)$$

$$i_H = \frac{\sqrt{2}}{h \neq 1} \sum I_h \sin(h\omega t - \beta_h) \quad (3)$$

Where, v_1, i_1 represent power system frequency components ($\omega = 2\pi f = 100\pi$ rad/sec) while v_H, i_H represent the total harmonic voltage and current components, α_1 and β_1 represent the fundamental voltage and current phase angle, respectively, while α_h and β_h represent individual harmonic voltage and current phase angle respectively.

The RMS values of voltage and current are

$$V_t = \sqrt{\int_0^T v_t^2 dt} \quad V_t^2 = V_1^2 + V_H^2 \quad V_H^2 = \sum_{h \neq 1} v_h^2 \quad (4)$$

$$I_t = \sqrt{\int_0^T i_t^2 dt} \quad I_t^2 = I_1^2 + I_H^2 \quad I_H^2 = \sum_{h \neq 1} i_h^2 \quad (5)$$

Where T is the time period. The reactive power as proposed in [30] is measured where v_{t-90° and i_t are the voltage and current signals. v_{t-90° is obtained by introducing a 90° phase lag at each frequency over its range. If v_{t-90° and i_t are periodic signals with time period T , then reactive power Q is given as

$$Q = \frac{1}{T} \int_0^T i_t v_{t-90^\circ} dt \quad (6)$$

In wavelet domain the total reactive power (Q) is defined as

$$Q = Q_{app} + Q_{det} \quad [24] \quad (7)$$

Where Q_{app} is the approximation reactive power and Q_{det} is the details reactive power. Q_{det} is defined as

$$Q_{det} = \sum_{j \geq j_0}^{P-1} \frac{1}{2^P} \sum_{k=0}^{2^j-1} d_{j,k} d''_{j,k} \quad [23] \quad (8)$$

Where, j_0 is scaling level, the voltage and current signals are digitized with $n=0, 1, \dots, 2^P-1$, $d_{j,k}$ is wavelet coefficient of current and $d''_{j,k}$ is the coefficient of voltage with 90° phase shift at wavelet level j and time k .

3. CALCULATION OF DETAIL REACTIVE POWER IN A RADIAL DISTRIBUTION SYSTEM

A radial distribution network is shown in Fig. 1. The fundamental frequency internal impedance of the voltage source ZS is considered to be $(0.5+j0.5) \Omega$ and the line impedance is $(1+j1) \Omega$ for each section. The fundamental frequency impedance of each load viz. $Z1, Z2, Z3, Z4$ and $Z5$ is $(300+j300) \Omega$ when all the loads are linear. Transformer, capacitor, motor and converter have been connected with time controlled switch to each bus to get detail reactive power under different transient conditions. EMTP simulation package has been used to capture instantaneous voltage and current signals. The voltage and current signal have been processed and analyzed using discrete wavelet transform (DWT) in MATLAB.

An 11 kv distribution system is studied in this paper and its EMTP model is set up as shown in Fig.1. All the input signals are generated with 128 samples per cycle. Its recording time is 0.1 second and hence sampling frequency of the signal is 6.4 kHz. Reference frequency is 50 Hz. There are various types of mother wavelets for signal processing but one of the most popular mother wavelet is Daubechies [36] which has been used to detect and characterize power transients. So the authors have used daubechies wavelet with four filter coefficients (db4) for transient analysis. Simulation of five types of transients is carried out in this network. They are capacitor switching, converter switching, motor switching, fault and transformer switching. The switching transients are classified by probabilistic neural network (PNN). The original signal is decomposed up to level 5 using DWT and after considering all the parameter the authors of this paper have chosen the detail reactive power at level 1 and level 3 i.e. Q_{det1} and Q_{det3} as inputs to the classifier. The proposed method is a single point strategy because in this method all the voltage and current signals are captured from the sending end side only.

4. WAVELET TRANSFORM BASED FEATURE EXTRACTION

a. Capacitor switching

Figure. 2.1 and Figure. 2 show the capacitor switching transients in the above mentioned radial network. In this paper the authors have used capacitors of different ratings ($50\mu F$ to $550\mu F$) and they varied the switching time to capture the detail reactive power to distinguish the capacitor switching transients from other transients. Table 1 shows the values of Q_{det} from level 1 to level 5 at different buses when $150\mu F$ capacitor is switched on.

b. Motor switching

Figure. 3 shows the motor switching transients of the above mentioned radial network. To perform the simulation, induction motor with different rating (5 KW to 10 KW) has been considered and their switching time is also varied to collect sufficient number of data.

Table 2 shows different values of Q_{det} from level 1 to level 5 at different buses when a 9KW induction motor is switched on when voltage was at its peak value.

c. Fault induced events

In Figure. 4 the faults induced transients are shown and Table 3 shows different values of Q_{det} from level 1 to level 5 when unsymmetrical fault occurs at different buses.

d. Converter

Figure. 5 shows the transients which are generated by the converters. In this paper the authors have used both 6 pulse and 12 pulse converters with varying firing angles. Table 4 shows the different values of Q_{det} from level 1 to level 5 at different buses.

e. Transformer switching

Figure. 6 shows transformer generated transient. Transformers with different KVA ratings have been chosen to distinguish the transformer inrush with the other transients. Table 5 shows the different values of Q_{det} from level 1 to level 5 when a 100 KVA transformer is switched on.

5. PROBABILISTIC NEURAL NETWORK (PNN)

After calculating the DWT based detail reactive power at level 1 and 3, the authors have classified the different transient signals in the network. The problem of multi-class classification has been considered in this paper. A set of data points are given from each class and objective is to classify any new data sample into one of the classes. Hence the authors used the probabilistic Neural Network (PNN) as a classifier because it can learn the complex nonlinear mapping from the input space to output space.) The base of PNN is the Bayes classification rule and Parzen's method of probability density function (PDF) estimation [10].

An unknown sample $X=(x_1, \dots, x_p)$ is classified into class k if

$$u_k l_k f_k(X) > u_j l_j f_j(X) \text{ for all classes } j \text{ not equal to } k.$$

Bayes classification rule improves the classification rate by minimizing the expected cost of misclassification. In this rule first PDF has to be estimated based on a training set. A method of determining a univariate PDF from random samples has been presented by Parzen [10]. With the increase of number of samples the univariate PDF converges asymptotically to the true PDF. Assuming there are n_k number of training cases for a given class k and the estimated univariate PDF for that class, $v_k(x)$, is

$$v_k = \frac{1}{n_k \sigma} \sum_{r=1}^{n_k} w\left(\frac{x - x_r}{\sigma}\right)$$

Where $W(x)$ is a weight function (kernel) and the σ is scaling parameter which defines the width of the kernel. $W(x)$ is the Gaussian Function. Since the PNN processes p inputs variables, the PDF estimator must consider multivariate inputs [10]. Fig. 7 shows the PNN architecture which consists the four layer organization.

The input neurons distribute input variables in the input layer to the next layer. One neuron consists with one training case and it computes distance between the unknown input x and training case represented by that neuron. An activation function, known as the Parzen estimator, is applied to the distance measured. In the summation layer, the neurons sum the values of the neurons corresponding to the class who's estimated PDF has to be determined in the pattern layer by the Bayes discriminate criterion. In the output layer, which is simple threshold discriminator a single neuron has been activated to represent a projected class of the unknown sample.

6. CLASSIFICATION OF TRANSIENTS USING PNN

To check the validity of the proposed method simulation work has been conducted to classify the different transients in power system. Each type of transient is treated as an individual class and assigned the classification number from 1 to 5. MATLAB code is used to calculate the DWT based detail reactive power i.e. Q_{det1} and Q_{det3} . These detail reactive powers are used as input to the ANN model. For each transient 75 sets of features are extracted, in which 25 sets are used as training purpose i.e. 125 features are taken as training samples and another 50 sets i.e. 250 features are used for testing purpose. To obtain the training and testing data for ANN model for each transient, the authors have varied value of the capacitance of the capacitor, KW rating of the induction motor, converter firing angle, KVA rating of transformer, fault resistance and time of occurrence of fault.

The simulations produced 375 sets of detail reactive power (Q_{det}) up to level 5 individually for the above mentioned five transients. Table 6 shows the assigned classes of transient samples.

Applying this method it is noticed that success rate for identifying the different classes of transients depends on the decomposition level also. Table 7 shows the variation of success rate by varying decomposition level. From this table it is observed that if the original signal is decomposed up to level 5 instead of level 3, the success rate remains same. It is also observed that the success rate at 1st, 3rd and 6th row is same. But in remaining rows the success rate is quite low. So considering all the results the authors have chosen only level 1 and 3 i.e. row 6th to reduce the computational burden.

The classification results can be described in terms of confusion matrix which is a standard tool for testing classifier. From Table 8 one can see that a confusion matrix has one row and one column for each class. The row represents the original class and the column represents the predicted class by the PNN classification. The number in the matrix shows the various pattern of misclassification that is obtained from the testing set. For instance, in Table 8, we can observe that out of 50 cases of motor switching only one has been misclassified as fault. In this table network classification error rate for each type of transients are mentioned. From the above result it can be concluded that using this method the network classifies correctly 249 data out of 250. That means the correct classification rate is 99.6%. In Table 3 it can be seen that most of the classification error occurs in between class 2 and 3, because characteristic harmonics of these two switching are nearly similar.

7. COMPARATIVE STUDY WITH OTHER METHODS

In Table 9 a comparative study with the other existing method is presented. These methods are somewhat similar with the methodology proposed in this paper i.e. they extracted the features of distorted signal using wavelet transform and then classified those signal by using artificial intelligence technique. The results presented in Table 9 have shown that the proposed method gives better performance compared to the existing methods because in this method success rate is 99.6% and computational complexity is lower than the method proposed in [6].

8. CONCLUSIONS

In a monitoring system the indicators that contain the unique features of power systems are acquired for distinguishing disturbances. But for effective classification of the disturbances, storage of a large number of data should be avoided.

In this paper a novel and simple method has been proposed based on DWT and PNN for classification of capacitor switching, converter switching, motor switching, transformer switching and fault induced events. An accurate and reliable power transient classifier has been developed to distinguish these transient signals. DWT has been used to calculate the detail reactive power at level 1 (Q_{det1}) and 3 (Q_{det3}) which are used as the input to the ANN model. Here Probabilistic Neural network has been used as a classifier. To check its validity and reliability different case studies are considered which show that this technique is well suited for classification of transients in power system network.

Table 1. Capacitor Switching Data At Different Bus

BUS	Q_{det1}	Q_{det2}	Q_{det3}	Q_{det4}	Q_{det5}	Class
A	1.64×10^8	1.67×10^6	3.87×10^7	2.2×10^6	4.3×10^7	1
B	1.07×10^7	1.87×10^6	2.78×10^7	2.4×10^6	$3.24.3 \times 10^7$	(C=150 μ F Switching angle 60°)
C	4.07×10^6	1.9×10^6	2.78×10^7	2.01×10^6	$3.34.3 \times 10^7$	
D	1.98×10^6	2.1×10^6	2.78×10^7	1.97×10^6	$3.34.3 \times 10^7$	
Y	1.05×10^6	2.44×10^6	2.78×10^7	2.3×10^6	$3.34.3 \times 10^7$	

Table 2. Motor Switching Data

BUS	Q_{det1}	Q_{det2}	Q_{det3}	Q_{det4}	Q_{det5}	Class
A	2.1×10^8	6.1×10^8	2.9×10^7	5.5×10^8	2.4×10^7	2
B	6.1×10^7	4.21×10^8	6.76×10^6	3.75×10^8	6.2×10^6	(9 kw Switching angle 90°)
C	4.6×10^7	3.3×10^8	4.05×10^6	2.56×10^8	3.67×10^6	
D	3.3×10^7	2.4×10^8	3.45×10^6	1.87×10^8	2.78×10^6	
Y	2.7×10^7	9.7×10^7	2.56×10^6	9.1×10^7	1.97×10^6	

Table 3. Fault Induced Transient Data At Different Bus

BUS	Q_{det1}	Q_{det2}	Q_{det3}	Q_{det4}	Q_{det5}	Class
A	2.5×10^5	1.2×10^6	2.3×10^6	1.1×10^6	6.8×10^5	3
B	1.1×10^5	1.2×10^6	7.2×10^6	4.2×10^5	3.2×10^5	(R _f =20 Ω Switching angle 90°)
C	4.2×10^4	5.67×10^5	4.2×10^6	2.1×10^5	2.1×10^5	
D	3.98×10^4	2.95×10^5	3.1×10^6	1.1×10^5	1.06×10^5	
Y	2.44×10^4	1.48×10^5	2.1×10^6	6.7×10^4	2.08×10^4	

Table 4. Converter Switching Data At Different Bus

BUS	Q_{det1}	Q_{det2}	Q_{det3}	Q_{det4}	Q_{det5}	Class
A	5.21×10^3	4.9×10^4	1.68×10^6	4.49×10^4	5.45×10^7	4
B	3.61×10^3	4.77×10^4	1.68×10^6	4.51×10^4	4.56×10^7	(α=60° firing angle)
C	1.53×10^3	4.58×10^4	1.68×10^6	4.74×10^4	3.45×10^7	
D	1.25×10^3	4.55×10^4	1.68×10^6	4.77×10^4	2.34×10^7	
Y	1.2×10^3	4.54×10^4	1.69×10^6	4.61×10^4	1.12×10^7	

Table 5. Transformer Switching Data At Different Bus

BUS	Q_{det1}	Q_{det2}	Q_{det3}	Q_{det4}	Q_{det5}	Class
A	1.05×10^3	5.98×10^3	1.83×10^7	6.07×10^7	6.2×10^5	5
B	1.04×10^5	5.97×10^5	1.78×10^7	5.99×10^7	6.01×10^5	(10 KVA Switching angle 60°)
C	8.9×10^4	5.85×10^5	1.78×10^7	5.2×10^7	5.9×10^5	
D	1.09×10^5	5.2×10^5	1.79×10^7	3.45×10^7	5.28×10^5	
Y	1.17×10^5	5.15×10^5	1.78×10^7	2.3×10^7	5.6×10^5	

Table 6. Classes of transient samples and simulated data set for training and testing of PNN network

Type of transient	Assigned Class	Training data (Set)	Testing data (Set)
Capacitor switching	1	25	50
Motor switching	2	25	50
Fault	3	25	50
Converter	4	25	50
Transformer switching	5	25	50

Table 7. Decomposition Level And % Of Success Rate

SL. No	Decomposition level	Features selected	% of success rate
1	Decomposed up to Level 5	Q_{det1} to Q_{det5}	99.6
2	Decomposed up to Level 4	Q_{det1} to Q_{det4}	99.6
3	Decomposed up to Level 3	Q_{det1} to Q_{det3}	99.6
4	Decomposed up to Level 2	Q_{det1} to Q_{det2}	92.1
5	Decomposed at Level 1	Q_{det1} only	21.4
6	Decomposed at level 1 and 3	Q_{det1} and Q_{det3} only	99.6
7	Decomposed at level 1 and 2	Q_{det1} and Q_{det2} only	97.6

Table 8. Confusion Matrix

Class	1	2	3	4	5
1	50				
2		49	1		
3			50		
4				50	
5					50

Sl. No.	Method for identification of Power system transients	% of success rate	Other disadvantage
1	Wavelet-transform+ANN based classifier[33]	95	
2	Wavelet-transform based classifier [34]	95	
3	S-transform +competitive neural network based classifier [35]	97.5	
4	DTCWT+ ANN based classifier [6]	100	Computational Complexity high [32]
5	Proposed method	99.6	Computational Complexity less [32]

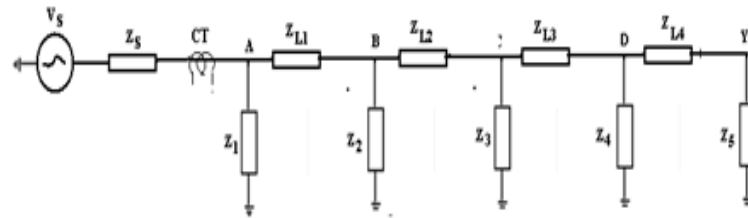


Figure 1. The Example Network

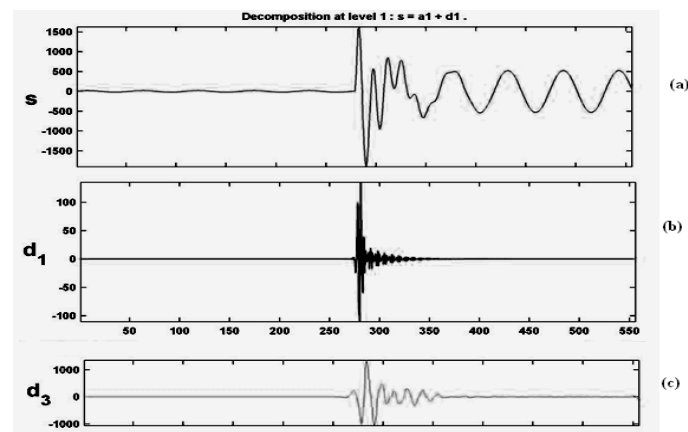


Figure 2.1. (a) simulated current transient during capacitor switching, (b) current signal decomposed at level 1, (c) current signal decomposed at level 3.

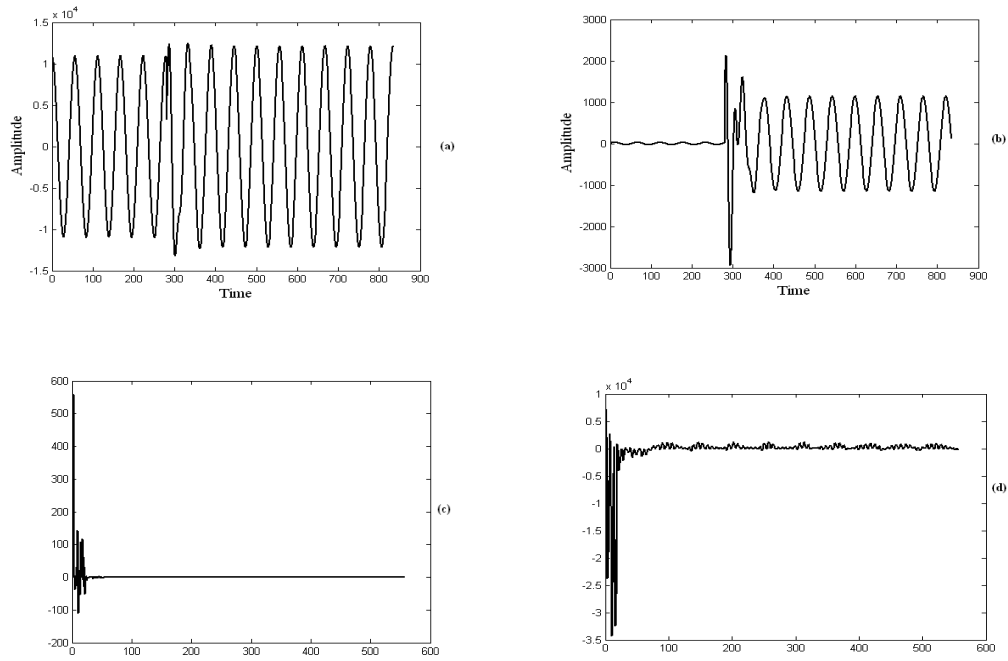


Figure 2.2. (a) Voltage profile during Capacitor switching transient, (b) Current profile during Capacitor switching transient (c) detail reactive power profile at level 1, (d) detail reactive power profile at level 3.

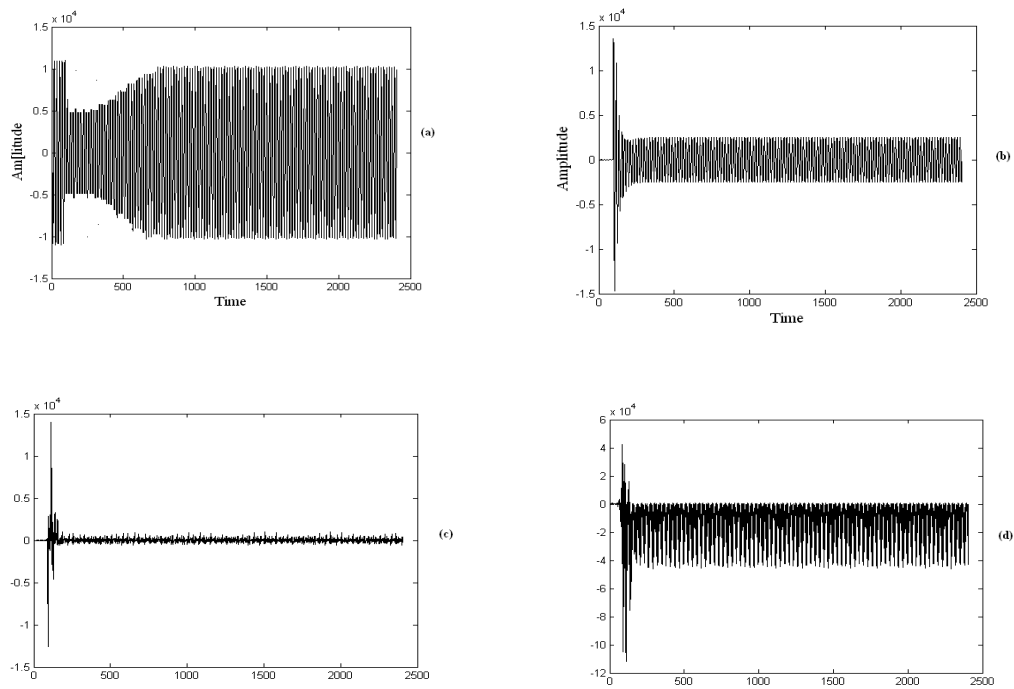


Figure 3. (a) Voltage profile during Motor switching transient, (b) Current profile during Motor switching transient (c) detail reactive power profile at level 1, (d) detail reactive power profile at level 3.

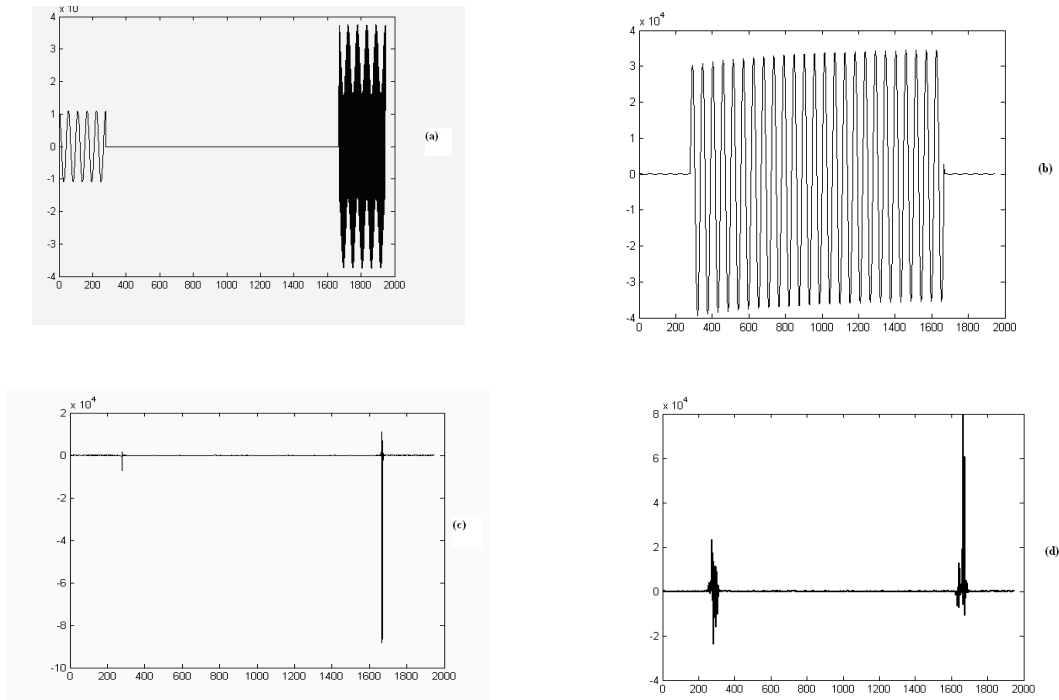


Figure 4. (a) Voltage profile during Fault induced transient, (b) Current profile during Fault induced transient (c) detail reactive power profile at level 1, (d) detail reactive power profile at level 3.

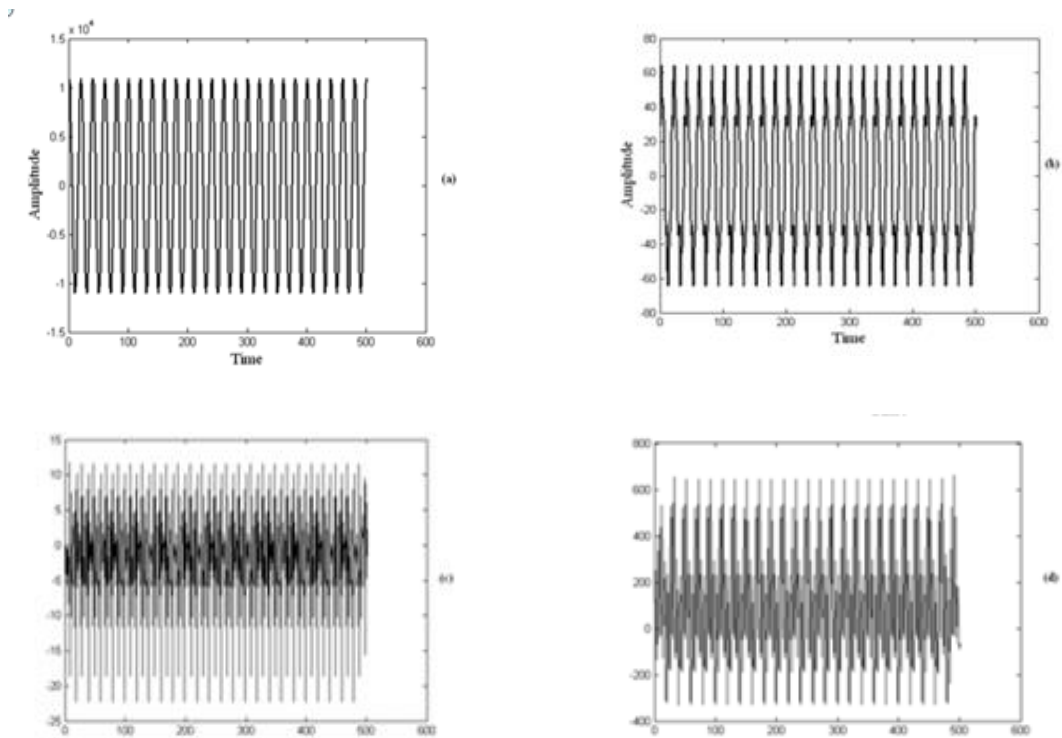


Figure 5. (a) Voltage profile during Converter Switching, (b) Current profile during Converter Switching transient, (c) detail reactive power profile at level 1, (d) Detail reactive power profile at level 3.

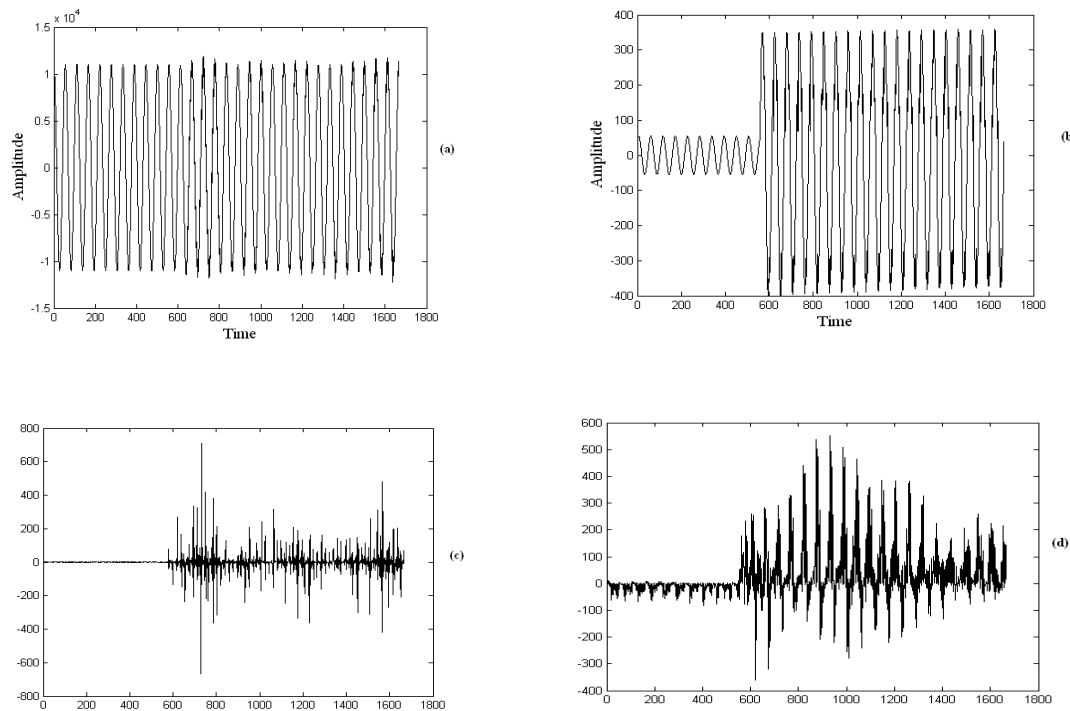


Figure 6. (a) voltage profile during Transformer switching transient, (b) Current profile during Transformer switching transient (c) detail reactive power profile at level 1, (d) detail reactive power profile at level 3.

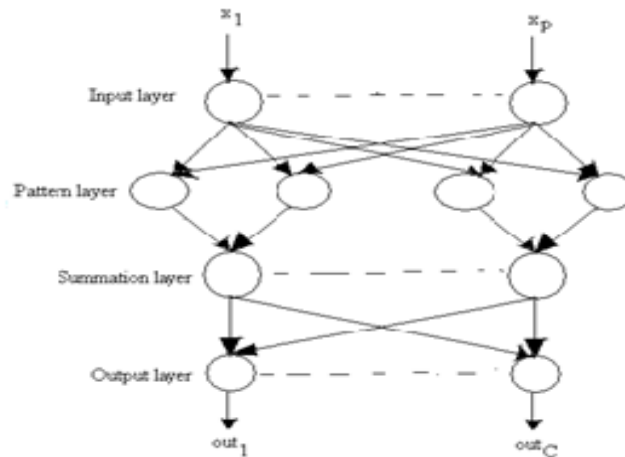


Figure 7. PNN Architecture

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