Classification of Power Quality Events Using Radial Basis Function Neural Network

A Dissertation submitted in fulfillment of the requirements for the Degree

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in

Power Systems

Submitted by

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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, "**Classification of Power Quality Events Using Radial Basis Function Neural Network**", in partial fulfillment of the requirements for the award of the degree of **Master of Engineering in Power Systems**, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of **Ms. Manbir Kaur**. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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LIST OF ABBREVIATIONS

AC	Alternating Current
PQ	Power Quality
IEEE	Institute of Electrical and Electronics Engineers
IEC	International Electrochemical Commission
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
SLG	Single Line to Ground
LL	Line to Line
LLG	Line to Line to Ground
LLL	Line to Line to Line
LLLG	Line to Line to Line to Ground
SAIFI	System Average Interruption Frequency Index
CAIFI	Customer Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
CAIDI	Customer Average Interruption Duration Index
FACTS	Flexible AC Transmission System
BPL	Broadband Power Line
EMF	Electromagnetic Field
ANN	Artificial Neural Network
NN	Neural Network
SLP	Single Layer Perceptron
MLP	Multilayer Perceptron
RNN	Recurrent Neural Network
KNN	K-Nearest Neighbours
no.	Number
Time(s)	Time in second

ABSTRACT

Power quality is a measure issue in power system. This is the measure of system reliability, equipment security, and power availability in power system to the industry or end user. The power quality events/problems are caused at generation, transmission and distribution level due to generation to load mismatch, short circuit faults, equipment failure, etc. This dissertation is introducing the generation of power quality events and classification of these events using radial basis function neural network. The power quality events are generated by developing an electric power distribution model using SimPowersystem in MATLAB/Simulink. This creates power quality events such as sag, swell, interruption, harmonics, transient, noises etc. Classification of power quality signals is difficult task and neural network is a non-linear, data driven self adaptive method that is a promising tool for classification. Amongst the neural networks radial basis function neural network (RBFNN) suppose to be a good selection with respect to other neural networks because of its faster learning capability and more compact structure. RBFNN is a non linear parametric approximation model based on combination of Gaussian function is applied to classify PQ events in power system. This RBFNN is made more effective by using K-mean clustering algorithm, K nearest neighbour algorithm and pseudo inverse method. A gradient descent learning method is used for the model to increase the accuracy of classification of proposed RBFNN model.

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

Electrical power system is a network of electrical components that supply power to the customer such as industry, home, etc. Power system generally divided into the generators that supply the power, the transmission system that carries the power from generating center to load center and the distribution system that supply the power to nearby industries and homes. Majority of power system rely on alternating current (AC) power and this AC power increase complexity to move from the point of generation to point of consumption combined with variation in generation, load, weather and other factors. In order to transferring power from generation to consumption, an interconnection system is required which used to interconnect transmission line to neighbouring utilities or distribution system which used to transferring power to the costumer that may be connected through underground or overhead cables with equipments. Industrial, residential, commercial are the category of power system load which consist large number of sensitive equipments [1-3]. Power quality (PQ) is a set of electrical limitations that allow a piece of equipment to function in its proposed manner without significant loss of performances or life expectancy. In recent days PQ is very sensitive issue and Customers at different level (Industry, end user etc) have become very particular about power quality disturbances. Because of these disturbances the performances and efficiency of equipment decreases day by day. The use of electrical devices might be electrical motor, transformer, sensitive electronic equipments, communication equipments or failure or malfunctioning of power system exposed to one or more PQ disturbances [1-4].

PQ disturbances or PQ events generated in power system are sag, swell, interruption, transient, harmonics, voltage imbalance etc and they having very wide range of magnitude, time, frequency so to resolve these PQ events or action taken to mitigate these PQ events, firstly source and cause of disturbance must be specified and this requires monitoring, identification and classification of disturbances, in fact the most important issue is how to detect and classify PQ events. The identification of PQ events can be judged on the basis of information regarding typical magnitude, duration, spectral content for each category of the signal and specification and limitations of IEEE and IEC standards [5-9]. But effective detection based on fundamental inspection of waveform by human operators is laborious and time consuming and there are fewer chances to get effective important information from simple fundamental inspection, Hence it would be highly desirable to automate the process and intelligent. In recent year many researcher have presented an article based on rule based expert system, artificial neural network, fuzzy classification, kernel machines, support vector machines and others for the classification of PQ events.

Artificial neural network has been realized as a suitable tool for identification and classification of PQ events. The neural network recognizes a given pattern by learning or training with a set of examples and these set of examples consist of input patterns along with level of classes [12-14]. Amongst the neural networks radial basis function neural network (RBFNN) suppose to be a good selection with respect to other neural networks because of its faster learning capability and more compact structure. RBFNN is the most basic form of neural network which include three layers that is input, hidden and output layer with utterly different roles. The input layer is the source node, which connect the network with outer environment. Second layer that is the only hidden layer in the network, Apply a non linear transformation between input and hidden space. The third layer is the output layer is linear and this supply response of the network to the activation pattern applied to the input layer. RBFNN is a non linear parametric approximation model based on combination of Gaussian function or we can say approximation of a multivariate function. The objective of this thesis is to apply the RBFNN to classify PQ events in power system [11][16,17].

1.1 LITERATURE SERVEY

A. Collinson and J. Stones [5] have described about the power quality and its problem.They discussed source of power quality problems, its cause and their effect on customer, equipments etc..

D. Saxena et.al. [6] have investigated about the power quality issues and accurate techniques to identify and classify in last decade. The paper presented a comprehensive overview classification technique used for power quality issues. This paper also highlighted the major key issue challenges related to these advanced technique in automatic classification of power quality problems.

W. R. Anis Ibrahim and M. M. Morcos [13] have presented the recent trends of advanced artificial intelligence technique in power quality, application of mathematical tools like wavelets transform, application of fuzzy logic, expert system, neural network, genetic algorithm in power quality. In this paper they have given overview regarding wavelets in power quality analysis and data comparison.

C. C. Liao [14] has presented an enhanced radial basis function neural network. In this paper author approached with an enhanced clustering algorithm that is the combination of genetic algorithm and k-mean clustering algorithm which reduce overall time of recognition system. Newly propose algorithm overcome the problem of over sencitivity. To determine suitable number of center in RBF from the input data, Orthogonal least square algorithm is used.

C. C. Lee et.al. **[15]** have proposed this paper to show the better capability of approximation,fast learning speed, better size of network, high robustness to outliers of the RBFNN. This paper adopts fresh approach that is least square criterion as the objective function with conventional Gaussian function to get above advantages. This paper also introduced sequence of sigmoid function and robust objective function to rectify insurgency in approximation problem and training pattern interpolation problem.

A. P. Memon et.al [16] have presented a signal processing based automatic classifier. In this paper power quality disturbances are classified by combining discrete wavelets transform based time frequency analysis with multi resolution analysis algorithm (with different mother wavelets) and signal noise ratio for feature extraction in order to provide the vector input of feed forward neural network like RBF, multilayer perceptron (MLP) and probabilistic neural network(PNN).

J. Huilan et.al. [18] have presented this paper which is related to the diagnosis of fault in high voltage transmission line using radial basis function. In this paper RBF is used as pattern recognition. Self adaptive clustering algorithm approach is introduced for the cluster process of RBFNN to get quick and correct response of fault diagnosis.

S. Khokhar et.al. [19] have discussed the power quality disturbances and an attempt has been made to review the modeling and simulation of power quality disturbances due to utilization of various type of load. In this paper an effort has been made to generate real time power quality signals.

P. Chand et.al. [20] have presented the procedure to detect the responsible faults for power quality disturbance with the help of precise and faster feature extraction tool. Auther uses adaptive harmonic wavelet transform which provide better representation of power quality signals and try to compare with generalize harmonic wavelet transform to analyze all kind of disturbed signal with minimum human interaction.

T. Kanungo et.at. [22] have presented a simple and efficient implementation of Lloyed's k-mean clustering algorithm and competent application in colour quantization, data compression and image segmentation.

R. J. Almeida and J. M. C. Sousa [23] have presented a new feature selection for classification problem. In this paper author presented a comparison of fuzzy clustering algorithm like possibilistic c-means, fuzzy possibilistic c-means or possibilistic fuzzy c-means clustering algorithm in terms of computational efficiency and accuracy in classification problem.

R. J. Kuo [24] have described the original application of neural network. In this paper author presented the application of RBF neural network for short term system load forecasting becouse of the predictive capability and their ability to produce accurate measure.

1.2 OBJECTIVE OF DESERTATION

The main objective of the work is to generate power quality events and classify using RBF neural network. Events are generated by using different types of loads i.e. normal load, heavy load, non linear load and incorporating various faults such as single line to ground (SLG), line to line (LL), line to line to ground (LLG), triple line (LLL), triple line to ground (LLLG) in MATLAB environment and obtained data provided to the RBF neural network to classify. The work presented here is divided into two parts:

1. Generation of power quality events data
2. Classification of generated data using RBF neural network.

1.4 ORGINAZATION OF CHAPTER

The work is organized into five chapters and contents of each chapter are summarized as:

1. Chapter 1 includes the introduction of proposed work, literature review and objective of dissertation.
2. Chapter 2 includes detailed information about power quality and its events.
3. Chapter 3 includes the description of the RBF neural network.
4. Chapter 4 includes problem formulation and result.
5. Chapter 5 includes conclusion and future scope of the work.

CHAPTER 2

POWER QUALITY

2.1 INTRODUCTION

In the present scenario of the electrical power system the main concern is to provide power quality with reliable and uninterrupted supply of electricity to the customer. Therefore, the planning electric distribution system is based on keeping the electricity supply in service all the time. The reliability of electrical power distribution system depends upon indices such as system average interruption frequency index (SAIFI), customer average interruption frequency index (CAIFI), system average interruption duration index (SAIDI), customer average interruption duration index (CAIDI). By calculating these indices system engineer can determine system regulation to improve these scheduled maintenance process for better reliability [1]. The reliability concern can be fulfilled by solving the power quality issue in the power system. Definition of power quality according to IEEE standard is "Power quality is the concept of powering and grounding sensitive equipment in a matter that is suitable to the operation of the equipment" [8]. The quality of power is said to have distorted when the supply voltage fails to attend the pure sine wave of rated magnitude and frequency (50 or 60 Hz) with the variation of ±5%. Due to introduction of power electronics devices or non linear loads in power industries or devices as home utility, the power supplied to the customer is distorted in either the voltage signal or current or both. PQ disturbances which occur in power system is mainly sag, swell, interruption, transient, overvoltage, under voltage, harmonics, etc and the frequency of occurrence of these PQ disturbance is shown in Figure 2.1. PQ disturbances are mainly caused by exploitation of system which is summarized as [2][3]:

- Electric utility like point of generation, transmission system and distribution system are considered to be utility related problem. PQ problem are originated at generation point due to maintenance activity, planning, scheduling, load transfer from substation to substation. In the transmission system a small number of power quality problems are caused by lightning (occurrence of spike or transient overvoltage), insulator flash over, transformer energizing (result in inrush current), improper operation of voltage regulation devices, flexible AC transmission system (FACTS) devices, corona, power line carrier signals etc. In distribution system typical PQ problems are generated due to voltage regulation equipments, slow voltage variations, broadband power line (BPL), power line carrier and electromagnetic field (EMF) [2].

- Due to exploitation of various type of load such as switching of air condition, switching of heavy motors, switching of capacitor bank, sudden removal of heavy load etc. are cause of power quality problem.
- Due to different type of faults such as single line to ground (SLG), line to line (LL), double line to ground (LLG), triple line (LLL), triple line to ground (LLLG) and failure of conductors etc. are also considered as the cause of PQ problems.
- Equipment failure (home appliance or protection devices), lightning, storm, object (tree, cars, etc.) striking are the PQ problem creator [5].

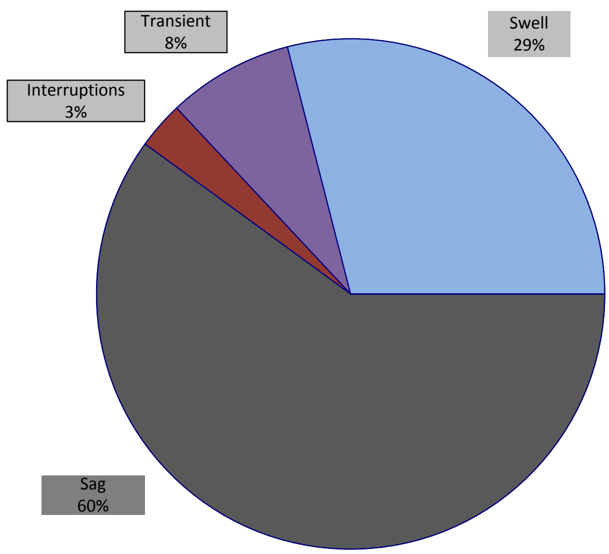

Figure 2.1 frequency of occurrence of power quality events

2.2 POWER QUALITY EVENTS

Power quality (PQ) events are generally identified in the system by a set of waveforms, these waveforms either observed, calculated or generated by test equipment. Power quality events are characterized by extracting information from various disturbances individually and generally classify according to voltage magnitude variation, time duration, frequency variation and transients. The magnitude and duration of event can be used to classify power quality events [2][3]. Various standards give a different name to these events. IEEE standards use numerous supplementary terms to classify these PQ events as compare to IEC terminology. IEEE -1159 provides information about categories and characteristics of electromagnetic phenomena as shown in Table 2.1 [8]

Table 2.1 Categorization of PQ events according to IEEE standard 1159-2009

Sr. No.	Category	Typical duration	Typical magnitude
1	Short duration magnitude		
	Sag		
	Instantaneous	0.5 - 30 cycle	0.1 – 0.9 pu
	Momentary	30cycle-3sec	0.1 – 0.9 pu
	Temporary	3sec – 1 min	0.1 – 0.9 pu
	Swell		
	Instantaneous	0.5 - 30 cycle	1.1-1.8 pu
	Momentary	30cycle-3sec	1.1-1.8 pu
	Temporary	3sec-1min	1.1-1.8 pu
	Interruption		
	Momentary	0.5-3sec	<0.1 pu
	Temporary	3sec-1min	<0.1 pu
2	Long duration magnitude		
	Interruption, sustained	>1min	0.0 pu
	Overvoltage	>1min	0.8-0.9 pu
	Under voltage	>1min	1.1-1.2 pu
3	Transient		
	Oscillatory		
	Low frequency	0.3-50ms	0-4 pu
	Medium frequency	20μs	0-8 pu
	High frequency	5μs	0-4 pu
	Impulsive		
	Nanosecond	<50ns	
	Microsecond	50ns-1ms	
	Milisecond	>1ms	
4	Voltage imbalance	Steady state	0.5-2%
5	Waveform distortion		
	Harmonics	Steady state	0-20%
	Notching	Steady state	
	Noise	Steady state	0-1%
6	Voltage fluctuation	Intermediate	0.1-7%
7	Power frequency variation	<10s	

.

2.2.1 Voltage Sag (dip)

In the power quality community the term sag is described as a short duration voltage decrease. Voltage sag is an event where the line voltage (rms) varies between 0.1 p.u. and 0.9 p.u. for time duration of 0.5cycle to 1 min as shown in Figure 2.2. The IEC definition for this phenomenon is dip. This is the most common type of power quality event which is generally associated with a short circuit type of fault such as single line to ground (SLG), Line to line (LL), line to line to ground (LLG), three phase (LLL) and three phase to ground (LLLG) faults in a system. Increased load demand and transitional events such as large motor starting also cause voltage sag [2][5][7][8].

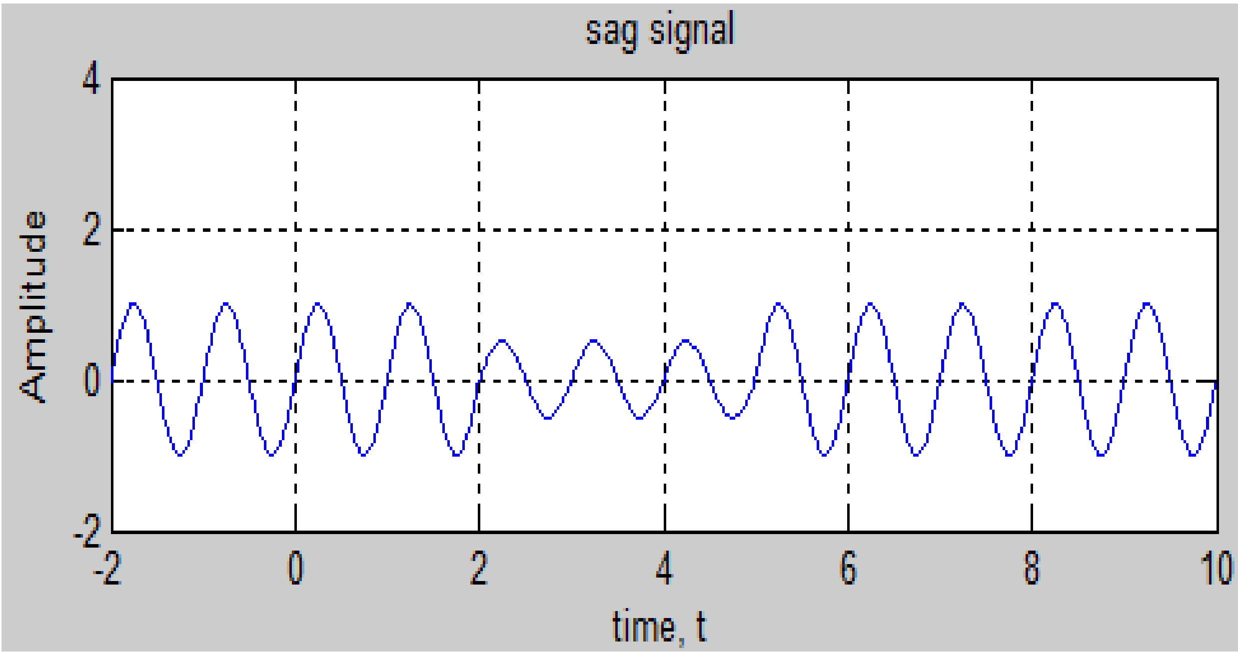

Figure 2.2 Voltage sag

2.2.2 Voltage Swell

Voltage swell is reverse of the sag and it is defined as an increase in line voltage (rms) to between 1.1 p.u. and 1.8 p.u. for the time duration of 0.5 cycles to 1 min as per IEEE standard as shown in Figure 2.3. This is also associated with the short circuit faults but this is much less common than voltage sag. The swell may be caused by SLG faults, in healthy phases. The swell is not common as sag and the main cause are switching off of heavy load, switching-on or energizing of a large capacitor bank and voltage increase of the healthy phase during single line to ground fault [2][5][7][8].

2.2.3 Interruption

Interruption is defined as reduction in supply voltage, or load current to a level of 0.1 p.u. or complete loss of supply voltage for a period of time not exceeding 1 minute, as shown in Figure 2.4. Interruption is mainly measured by its duration. According to the IEEE standard 1250, an instantaneous interruption is between 0.5 and 30 cycles, a momentary interruption is between 30 cycles and 2 seconds, a temporary interruption is between 2 seconds and 2 minutes, a sustained interruption is 2 minutes. Interruption can be caused by system faults, control and protection malfunction or system equipment failure [2][5][8].

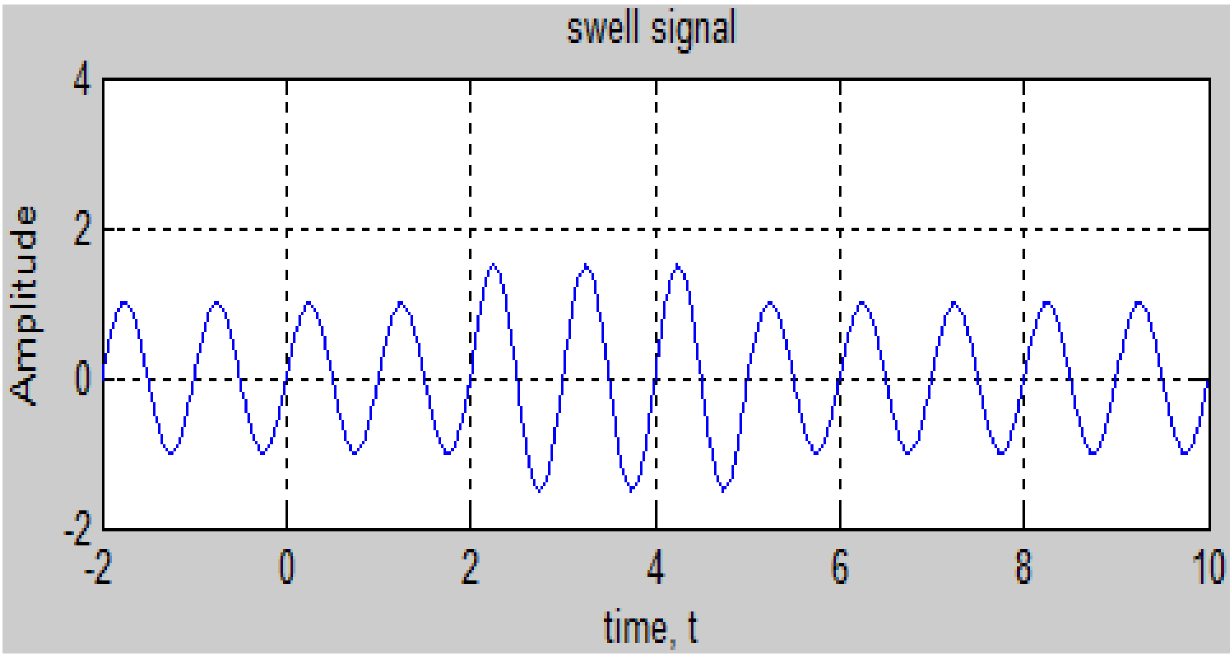

Figure 2.3 Voltage Swell

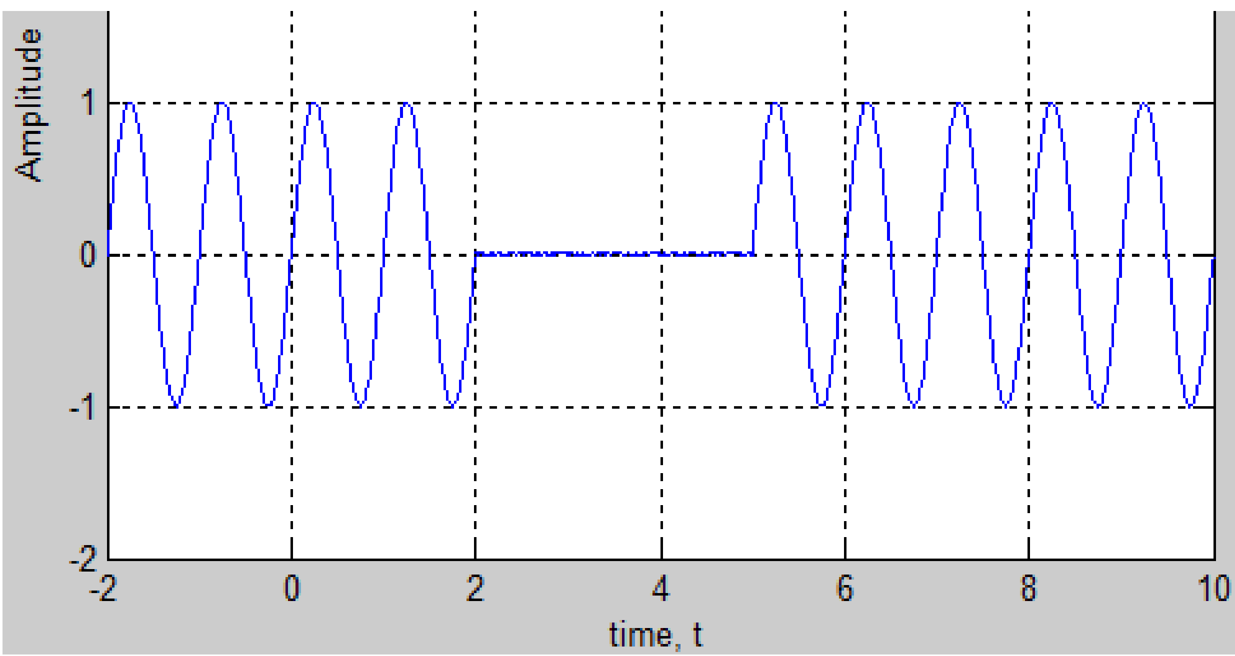

Figure 2.4 Interruption

2.2.4 Overvoltage and Under Voltage

A overvoltage a long duration swell as defined by IEEE, is an increase in ac rms voltage greater than 1.1 p.u. for a duration longer than 1 min as shown in Figure 2.5, typical values are 1,1 p.u. to 1.2 p.u. similarly an under voltage(long duration sag as defined by IEEE) is a decrease in AC rms voltage less than 0.9 p.u. for a duration longer than 1 min as shown in Figure 2.6, typical values are between 0.8 p.u to 0.9 p.u. Overvoltage caused by the load switching(switching off a heavy load) and under voltage are the result of disturbance that are the opposite of the disturbance that cause overvoltage [2][5][8].

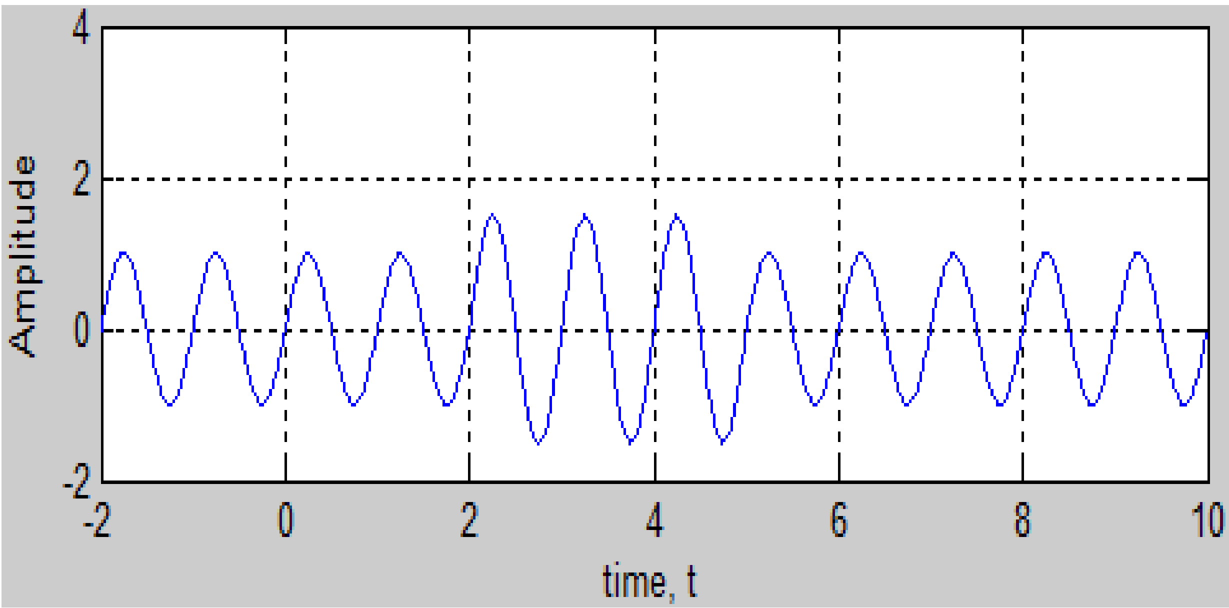

Figure 2.5 Overvoltage

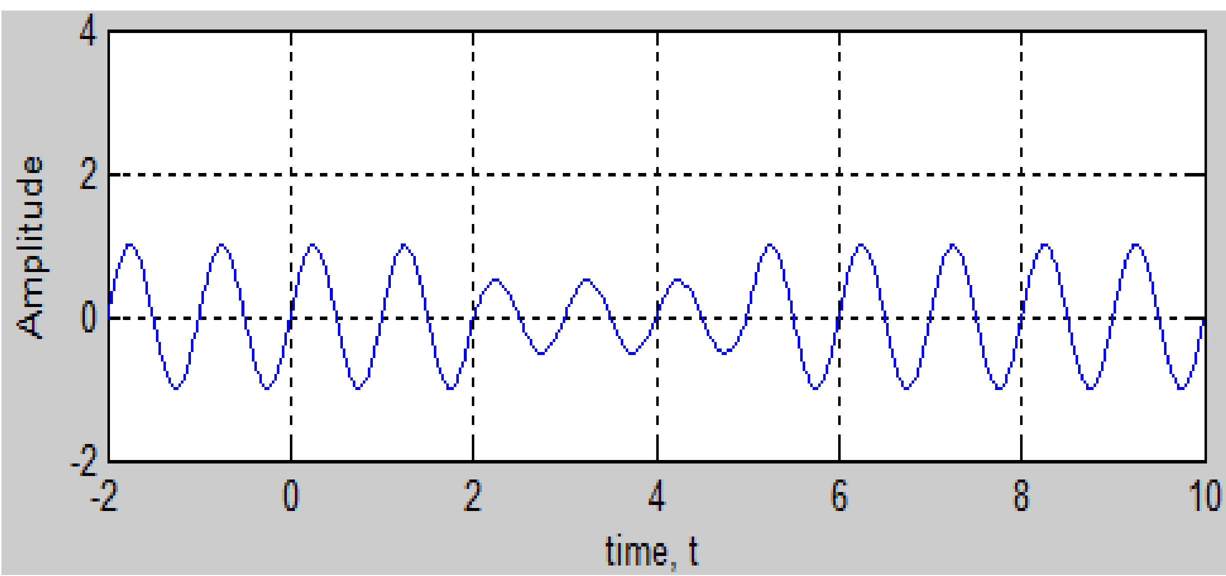

Figure 2.6 Under Voltage

2.2.5 Transients/surge

A transient is an undesirable and momentary type of events which usually initiated by some type of switching event such as energizing of capacitor bank or electric motor as shown in Figure 2.7. The duration of transient is much less than full cycle oftentimes a full second or less, these occur intermittently and may or may not impact on equipment. Transient can be classified based on characteristic features such as amplitude, duration, rise time, frequency of ringing, polarity, energy delivery capability and frequency of occurrence. Generally they are classified into two categories: oscillatory and impulsive.

An oscillatory transient is a sudden frequency change in steady state condition of voltage and/or current. It occurs for different reasons in power system such as switching on/off a heavy load, capacitor bank energization, fast active over current protective devices, and ferro-resonance.

An impulsive is a sudden frequency change in the steady state condition of the voltage and current or both that is unidirectional in polarity. An impulsive transient mainly occurs due to lightning strokes [2][5][8].

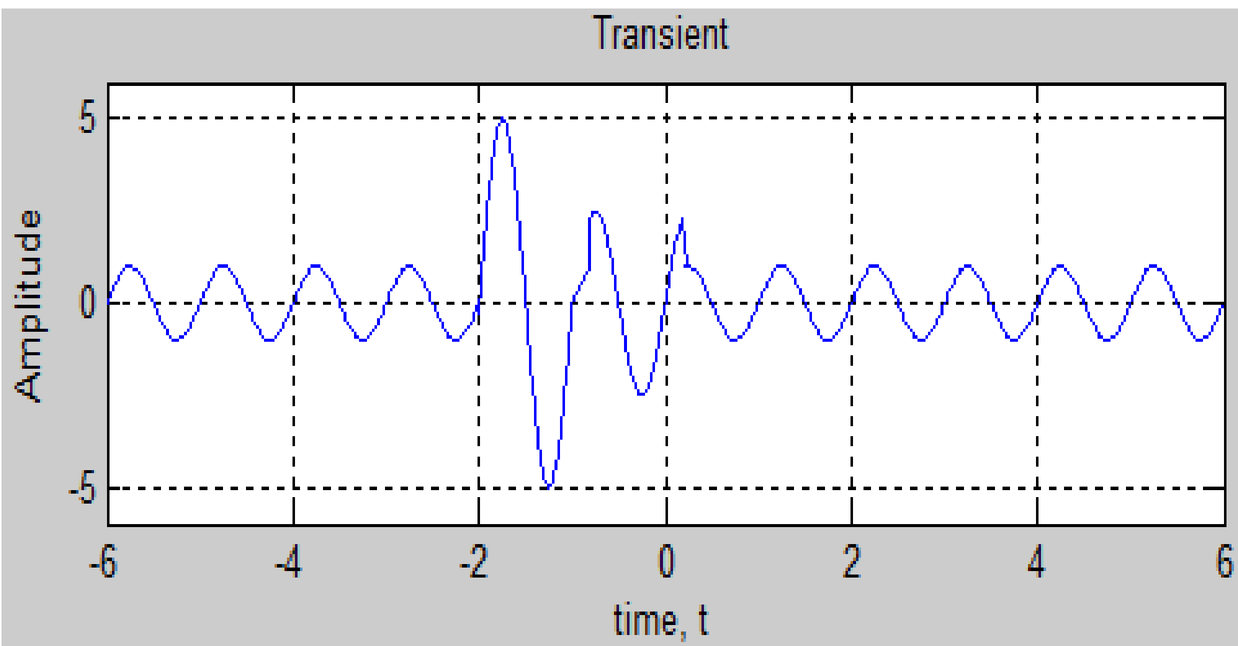

Figure 2.7 Transient

2.2.6 Voltage Imbalance

Voltage imbalance or unbalance is defined as the deviation in the magnitude of negative sequence component to the magnitude of positive sequence component in phase of one or more of the phase or/and magnitude of the three phase supply. Mathematically the percentage voltage imbalance is expressed as represented by equation 2.1 and is depicted in Figure 2.7. The main cause of voltage imbalance in power system is unbalanced single phase loading in three phase supply system, un-transposed overhead transmission lines, and blown fuse in one phase of three phase supply system [2][5][8].

$$\%\,Imbalance = \frac{|V_{neg}|}{|V_{pos}|} \times 100 \qquad \ldots \qquad (2.1)$$

2.2.7 Harmonics

Harmonics are periodic sinusoidal distortions in supply voltage and load current having frequencies those are integral multiples of the fundamental supply frequency at which system is designed to operate as shown in Figure 2.8. Harmonics are mainly caused by industrial non-linear loads such as rectifiers, inverters, static power converter, arc furnace, welding machines, and residential loads with switched mode power supply like television set, computers, fluorescent, and energy saver lamps [2][5][7][9].

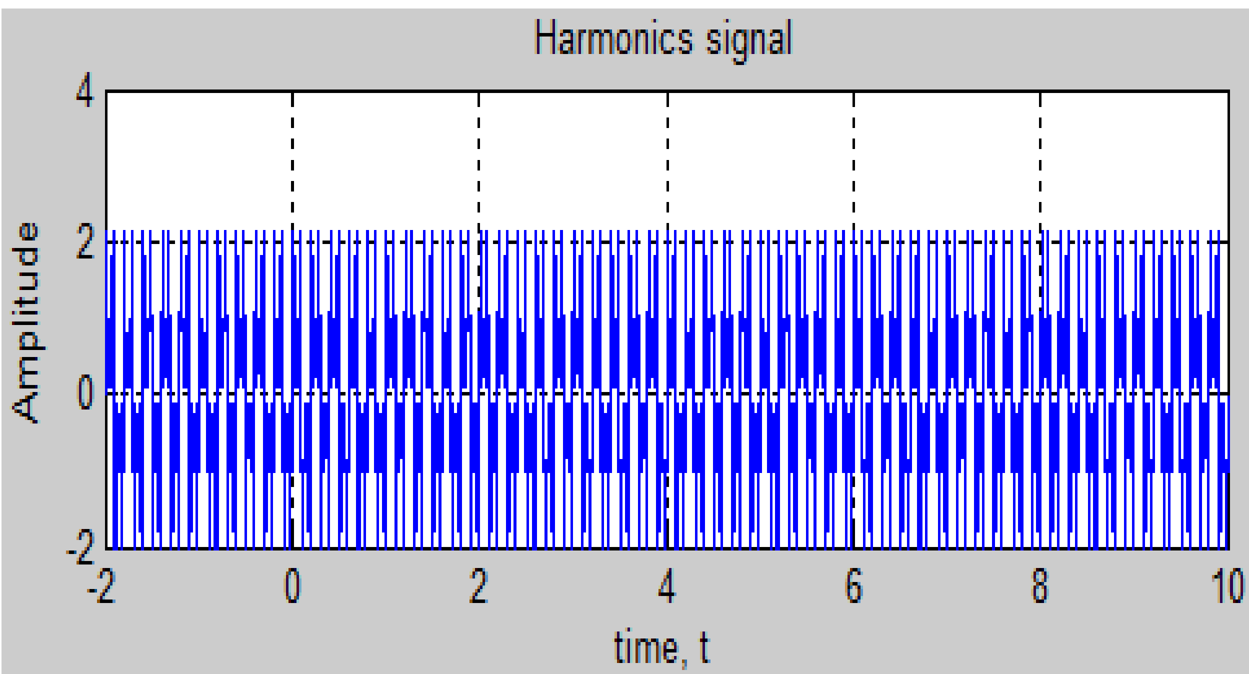

Figure 2.8 Harmonics

2.2.8 Notching

Notching is a type of voltage disturbance which is periodic in nature and contains both harmonics as well as transient distortion. Notching is repetitive and can be characterized by its frequency spectrum and usually not possible to measure with equipment used for harmonic analysis. Notch can be characterized by notch depth, notch width, notch area, and notch position.

Standard IEEE-519 set limit for notch depth and duration with respect to the system impedance and load current. The cause of notching is the three phase converter which produces continuous dc current, in this when current transfers from one phase to another, there is a momentary short circuit, this phase change for the momentary time cause notching[2][8].

2.2.9 Noise

Noise is an unwanted electrical signal with frequency spectrum lower than 200 kHz. Noise in power system is due to the superimposing of high frequency signal in voltage and current in phase conductor. The typical magnitude of noise is about less than 1% of the voltage magnitude as shown in Figure 2.9. Noise may result from faulty connection in distribution system, power electronics devices, arcing equipment, control circuit, loads with solid state rectifier, switching power supply, improper grounding, turning off capacitor bank, adjustable-speed drives, corona, and broadband power line communication circuit [2][7][8].

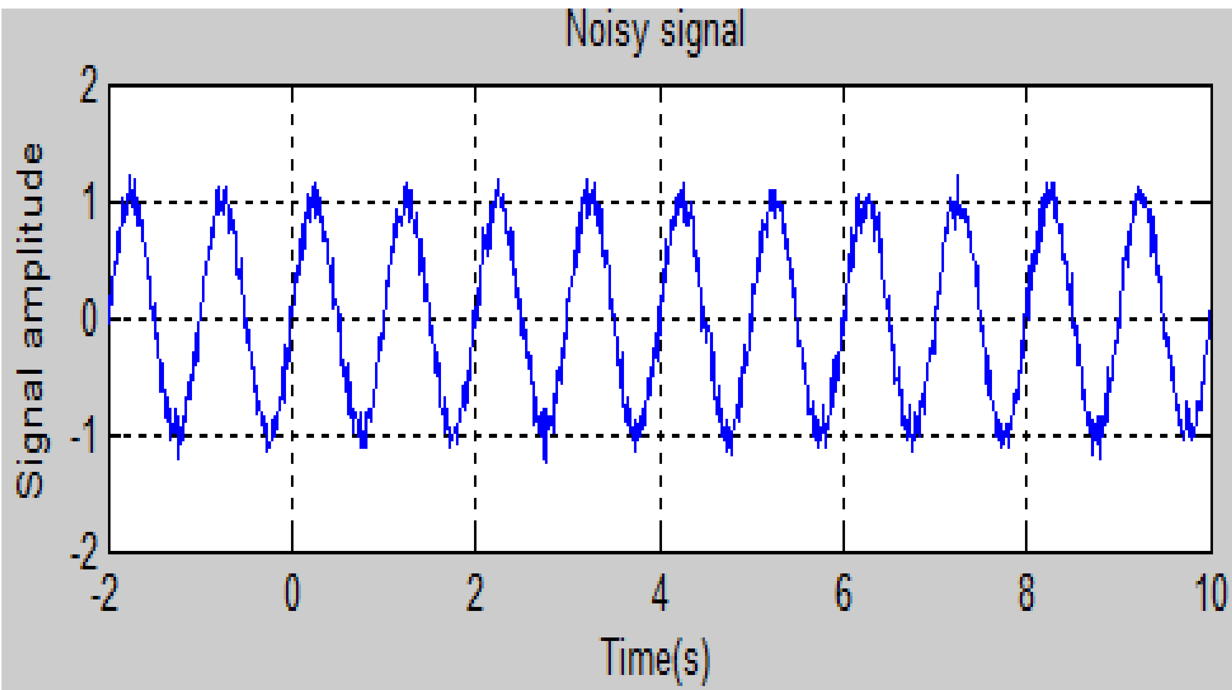

Figure 2.9 Noise

2.2.10 Voltage Fluctuation

Voltage fluctuation is fluctuation in voltage means due to the loads like incandescent lamp or discharge lightning source, the sudden reduction in voltage less than 0.5% can cause a noticeable reduction in light output. So the voltage fluctuation is about the fluctuation of voltage amplitude modulated by a signal with frequency of 0-25 Hz.

2.2.11 Power Frequency Variation

Frequency deviation to its precise nominal value of 50 Hz and is defined as frequency variation or power frequency variation. Due to the unbalance or mismatch between load and generator these types of disturbances occur. A sudden shedding of load, fault on heavy power transmission system or a large source of generation going off line are the cause of power frequency variation

2.3 POWER QUALITY STANDARDS

Many papers for supervision and control purpose of power quality have been generated by various organizations and institutes. These papers come in application with applicability and authority that is guidelines, recommendations, and standards.

- **Power quality guidelines** are illustration and excellent procedures that holds typical parameters and delegate solutions to commonly encounter power quality problems.
- **Power quality recommended practices** recommend specific solution over many other solutions. Any working limits that are indicated by approval are not necessary but should be the parameters to be achieved for design.
- **Power quality standards** set proper agreement between industry, user, and the government as to the suitable procedure to generate, measure, examin, manufacture and devour electric power.

The basic reason of setting guideline, recommendation, and standard in power system to keep disturbances to customer equipment within permissible limit to provide consistent as well as reliable technology and test procedure for PQ event, and to provide a regular platform on which a variety of engineering is referenced. There are many standards that deal during PQ event reorganization are summarized:

2.3.1 IEC 61000 SERIES of Standards

The IEC 61000 or EN 61000 series is commonly used in Europe as a reference for PQ. It consist six parts which illustrate standards and technical reports.

- Part 1(General): This section cover application and interruption aspect of EMC.
- Part 2(Environment): This section gives classification of electromagnetic environment and capability levels for environments.
- Part 3(Limits): This section cover emission limit for harmonics and other disturbances.

- Part 4(Testing and measurement technique): This section describe standard methods for testing equipment of emission and immunity to different disturbances
- Part 5(Installation and mitigation guideline): This section cover earthling, cabling, improvement, and degree of security against electromagnetic events.
- Part 6(Generic standard): This section cover immunity and emission standard for entire industrial, residential, commercial, and power plant environment

2.3.2 IEEE-1159 Standard

The IEEE-1159 is United States based reference document for PQ disturbances. It is recommended practice for standard definition and monitoring of power quality disturbances. It includes a consistent description of conducted electric phenomenon occurring on power system. This recommended practice presents definitions of nominal condition and deviation from normal condition.

2.3.3 IEEE-519 Standard

IT is also United States based standard documents but very useful reference document, even outside of the United States. IEEE-519 recommended practices and requirements for harmonic control in electric power system. It is also well known document for PQ limits. It contain thirteen sections, every describe standards and technical report. IEEE-519 set limits on the voltage and current harmonics distortion at the point of common coupling.

CHAPTER 3

RADIAL BASIS FUNCTION NETWORK

3.1 INTRODUCTION

Artificial neural network(ANN) is an information based machine that is designed to model in a way that the brain perform. It has the capability to perform certain computations like perception, pattern recognition, control etc. Artificial neural network is the function of visual system to provide a representation of the environment around us and more important to supply the information we need to interact with the environment. Neural network (NN) is a extremely parallel distributed processor made up of simple processing units which has a natural tendency to store pragmatic knowledge and making it existing for use. It resembles the brain in two respects.

1. Knowledge is acquired by the network from its environment through a learning process
2. Interneuron connection strengths, known as synaptic weight are used to store the acquired knowledge

The design and architecture of neural network is motivated by the fact that neuron in human brain can die and that new synaptic connections can grow and the modification in synaptic weight is performed by learning process which called learning algorithm**.**

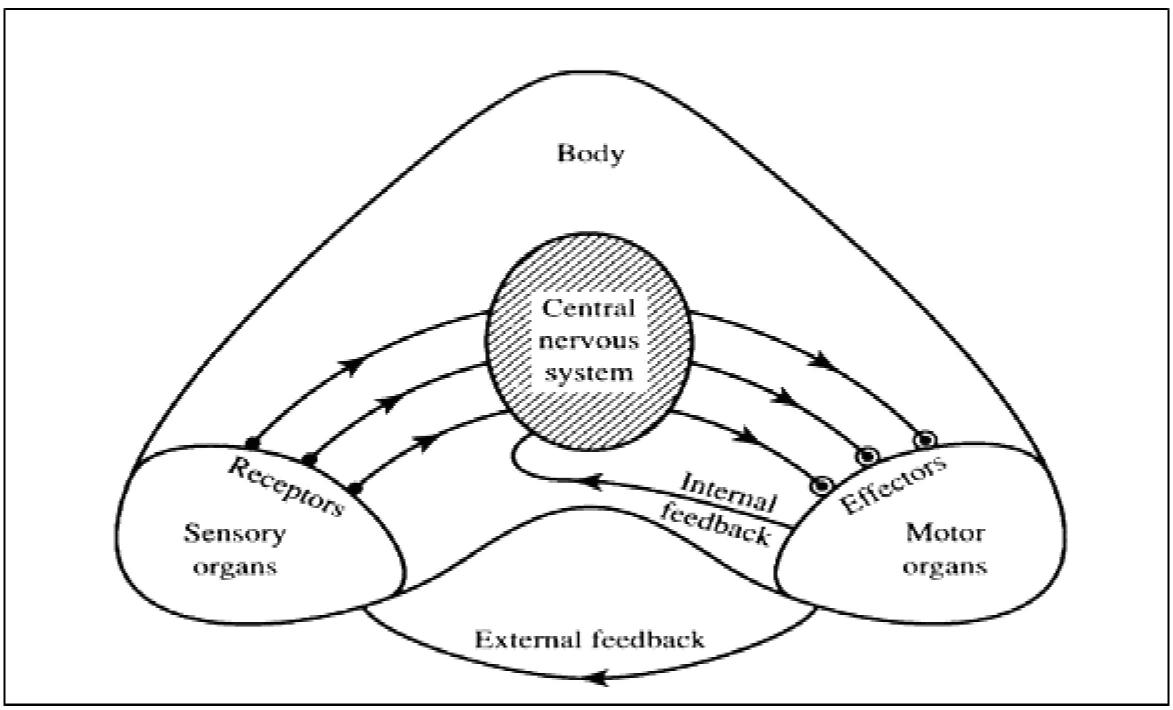

Figure 3.1 Information flow in nervous system

The neural network is a complex interconnection in which neurons communicate with each other by means of electric impulses. The input in the network is delivered through sense organ and sensory receptors in the form of electrical impulses that communicate the information to the network of neurons. Figure 3.1 represent a closed loop control system in which commands are generated, these and transmitted to the motor organs, these motor organs are monitored in control nervous system by both internal and external feedback links that verify their action [11][12].

3.1.1 Model of Neuron

Neural network are mean to be artificial neural network consisting of neuron models. In this area first neuron model is suggested by McCulloch and Pitts in 1943 and they describe the behavior of neuron in very simple manner. The model suggested by McCulloch and Pitts is known as McCulloch-Pitts neuron model [11].

- **McCulloch-Pitt neuron model**

The neuron model consist a set of synapses or connecting links each of which characterized by a weight or strength of its own as shown in Figure 3.2. A signal x_j at the input of synapse j connected to network multiplied by the synaptic weight w_{kj}.The synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive value. The input signals are summing with their respective synapses of the neuron through adder, operation described here constitute a linear combiner and an activation function for limiting the amplitude of the output of a neuron. Figure 3.2 also includes an externally applied bias denoted by b_k .The bias b_k has the effect of lowering and increasing the net input of activation function which depend upon the nature of net value whether it is negative or positive respectively

$$u_{k=} \sum_{j=1}^{m} w_{kj x_j} \qquad \ldots \qquad (3.1)$$

$$y_k = \varphi(u_k + b_k) \qquad \ldots \qquad (3.2)$$

$$v_k = u_k + b_k$$

Where $x_1, x_2, \ldots\ldots. x_m$ are the input signals; $w_{k1}, w_{k2}, \ldots\ldots. w_{km}$ are the synaptic weights of neuron k; u_k is the linear combiner output due to input signals; b_k is the bias; $\varphi(.)$ is the activation function; and y_k is the output signal of the neuron.

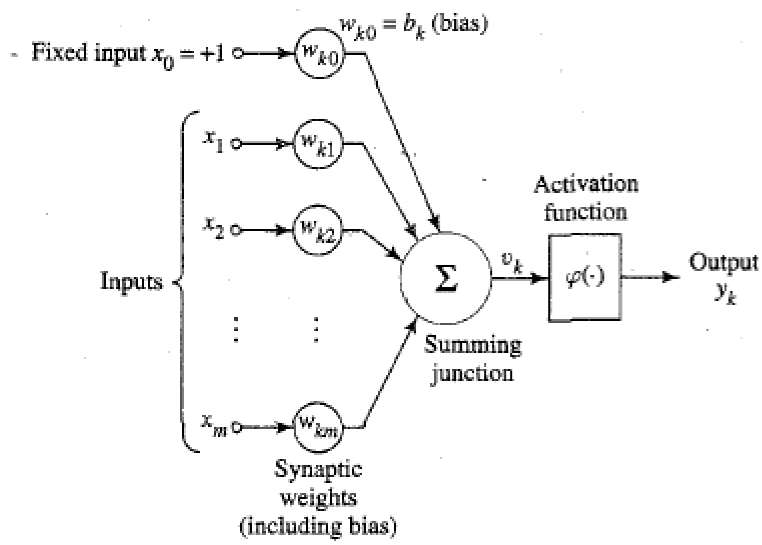

Figure 3.2 Non linear model of neuron

The bias b_k is an external parameter of artificial neuron k. By combining equation 3.1 and 3.3 as follows

$$v_{k}=\sum_{j=0}^{m} w_{kj}x_j \qquad \ldots \qquad (3.4)$$

$$y_k=\varphi(v_k) \qquad \ldots \qquad (3.5)$$

3.1.2 Type of Activation Function

The activation function denoted by $\varphi(v)$, defines the output of a neuron in terms of the induced local field v.There are three types of activation functions

- **Threshold function**:-In this type of activation function we have

$$\varphi(v)=\begin{cases}1 & if\ v \geq 0\\ 0 & if\ v < 0\end{cases} \qquad \ldots \qquad (3.6)$$

This form of threshold function is also called Heaviside function equally the output of neuron k employing such threshold function is shows in Figure 3.3 and expressed as

$$y_k=\begin{cases}1, & if\quad v \geq 0\\ 0, & if\quad v < 0\end{cases} \qquad \ldots \qquad (3.7)$$

- **Piece wise linear function**:-For a piece wise linear function describe in Figure 3.4

$$\varphi(v)=\begin{cases}1 & if\ v \geq +\frac{1}{2}\\ v & if\quad \frac{1}{2} > v > -\frac{1}{2}\\ 0 & if\quad v \leq 0\end{cases} \qquad \ldots \qquad (3.8)$$

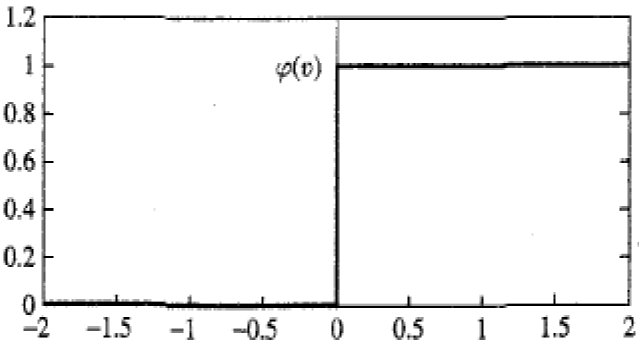

Figure 3.3 Threshold function

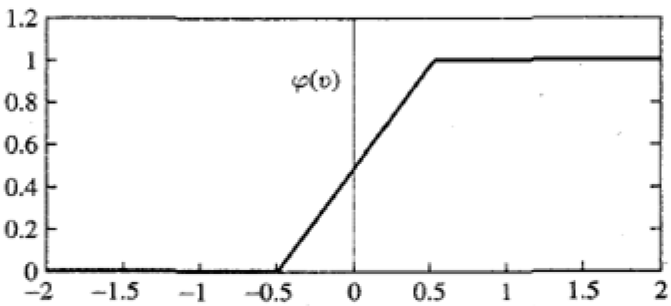

Figure 3.4 Piece wise linear function

- **Sigmoid function**

  A s-shaped rigorously increasing function which demonstrate a refined equilibrium between linear and non linear behavior and it is expressed as

$$\varphi(v) = \frac{1}{1+exp^{(-av)}} \qquad \ldots \qquad (3.9)$$

Where a is the slope parameter and varying this we obtain sigmoid function of different slope as shows in Figure 3.5.If it approaches infinitely the sigmoid function become simply a threshold function. Sigmoid functions assume a continuous range of value from 0 to 1 and It is differentiable.

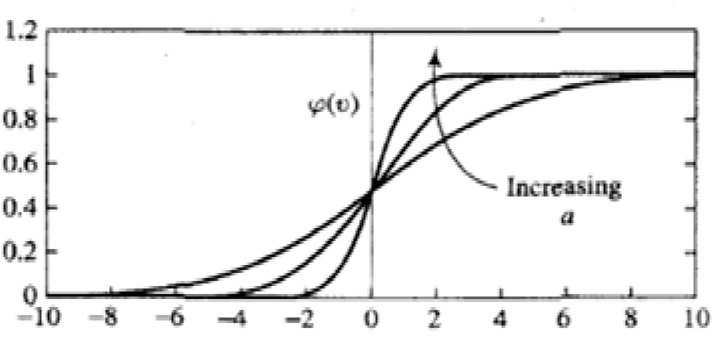

Figure-3.5 Sigmoid function

3.1.3 Neural Network Architecture

The model of neuron provides a functional description of various elements. The signal in neural network is directly associated with the input layer or we can say these are interconnected at certain point called nodes and it has linked transfer function or transmittance that specify the mode in which the output signals at that particular node depends upon the input signal of that node. The flow of signals depends upon these three basic rules [11][12].

1. A signal flows along a connection which defined by the arrow on the link those are synaptic and activation links.
2. The algebraic sum of all signals entering the relevant node via the incoming connections is equal to the node signal.
3. The signal at a node is transmitted to each outgoing connection originating from that node with the transmission being totally independent of the transmission being totally independent of the transfer function of the outgoing connection.

These three basic rules not describe only the signal flow from neuron to neuron but also the signal flow inside each neuron.

To sum up all these rules the neural network further classify in in many networks those are:

3.1.3.1 Feed forward Network

A feed forward network which is defined as the network which involves no time delay between input and output as shown in Figure 3.6 (b). There is no feedback. In this network the input is mapped into output as instructed by a teacher or on the basis of information provided. In this type of network the desired output can be evaluated by introducing error signal. Feed forward network further classified in two different types of structures [11][12].

- **Single layer Feed forward Network**

A neural network organized in the form of layers. The simplest form of neural network contains an input layer of source node and that is projected onto output layer called computation node. This network is strictly a feed forward or acyclic type. Such a network is called single layer network or single layer perceptron (SLP) [11][12].

An architecture of m neurons receiving n inputs as shown in Figure 3.6(a).Its input and output vector are respectively

$$O = [o_1, o_2, \dots \dots . . o_m]^t \quad \dots \quad (3.10)$$

$$V = [v_1 , v_2, \dots \dots . . v_n]^t \quad \dots \quad (3.11)$$

Weight w_{ij} connects the i^{th} neuron with j^{th} input. The activation value for each i^{th} neuron is called net_i so,

$$net_i = \sum_{j=1}^{n} w_{ij} x_j \qquad for\ i = 1,2,\dots,m \qquad \dots \quad (3.12)$$

the transformation performed by the activation function by each m neuron in the network is expressed as

$$o_i = f(w_i^t x) \qquad for\ i = 1,2,\dots,m$$

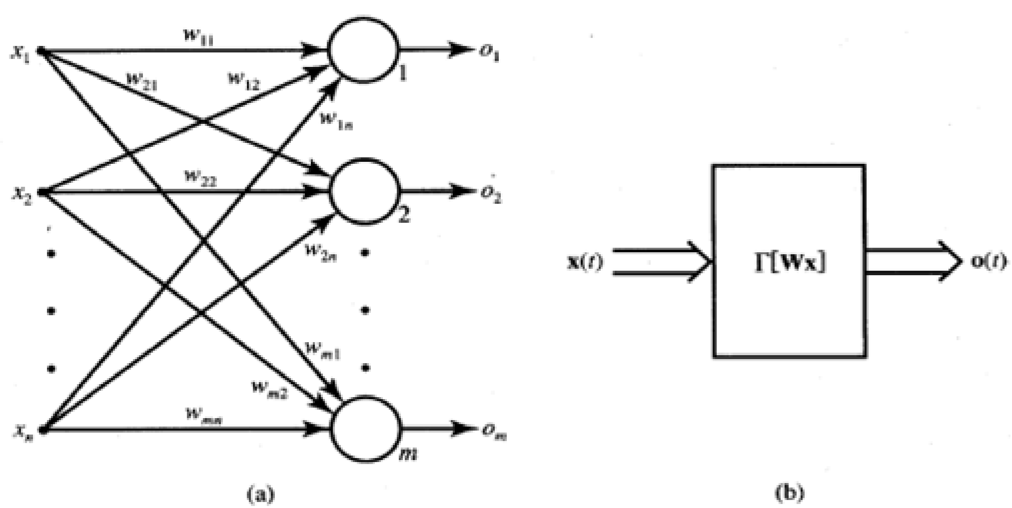

Figure 3.6 Single layer feed forward network: (a) interconnection scheme; (b) block diagram

- **Multilayer Feed forward Network**

This is the second class of layer feed forward network. Which contain input layer, hidden layer and output layer these are also called **multilayer perceptron (MLP)**. The hidden layers are incorporated between input and output layer. By adding one or more hidden layers, the network is enabled to extract high order statics. The input layer of source node supply respective elements of the activation pattern. It constitutes an input signal applied to the second layer or first hidden layer further its output is applies to the input of second hidden layer. Final layer or output layer constitutes the overall response. This type of neural network are called multilayer network. A network is said to be a fully connected if every node in each layer of the network is connected to every other node in the adjacent forward layer, otherwise it is partially connected [11][12].

This is further classified in different type of structure:

- **Multilayer feed forward network with one hidden layer**

  This type of multilayer feed forward network contains one input layer, one hidden layer and one output layer. Radial basis function network (RBFN) is the example of this type of network as shown in Figure 3.7.

- **Multilayer feed forward network with many hidden layers**

  This type of multilayer feed forward network contain one input layer, many hidden layer and one output layer as shown in Figure 3.8. This type of network is trained by back propagation algorithm.

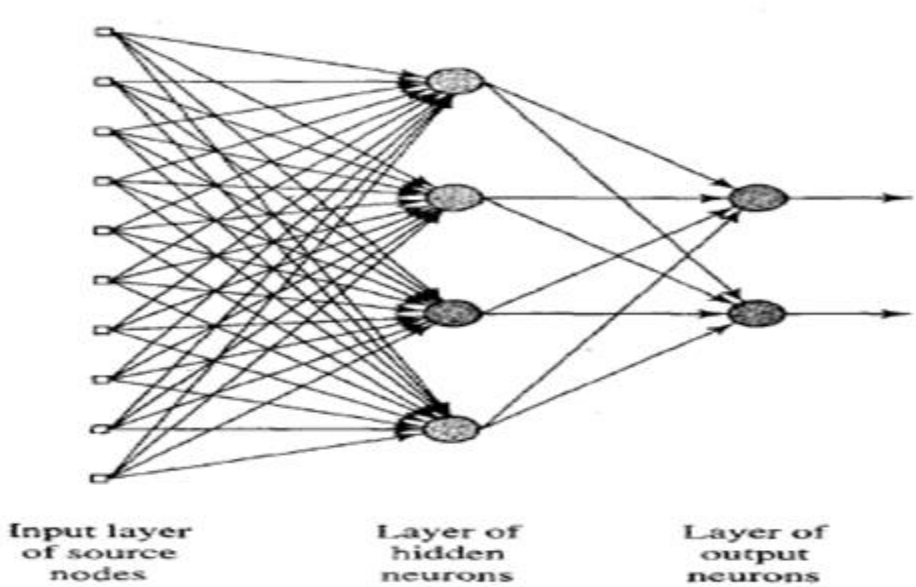

Figure 3.7 Fully connected fed forward with one hidden and one output layer

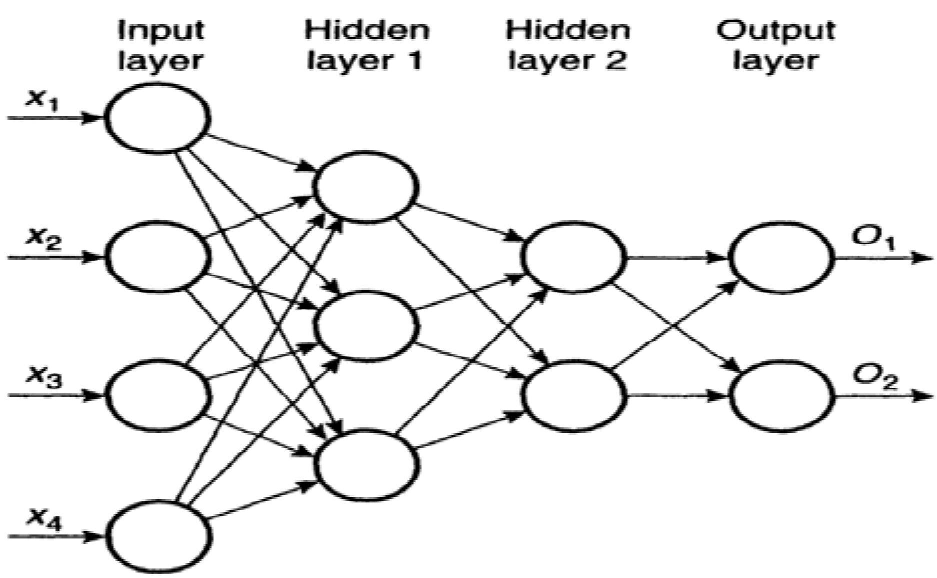

Figure 3.8 Multilayer feed forward network with more than layers

3.1.3.2 Feedback Network

A feedback network is the close loop representation of feed forward network as shown in Figure 3.9.By connecting neuron output to their inputs the output controlled through feedback. At the following instant, $o(t+\Delta)$ represents output where Δ represents the delay time which apology to provide refractory period of an elementary biological neuron model the mapping of $o(t)$ into $o(t+\Delta)$ can be written as [12]

$$o(t+\Delta)=\Gamma[wo(t)] \quad \ldots \quad (3.14)$$

Feedback network further classified as

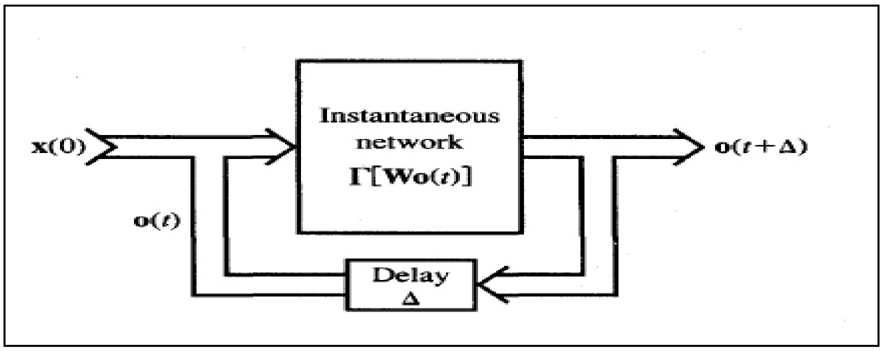

Figure 3.9 Feedback network block diagram

- **Single layer feedback network**

  Single layer feedback network have an input layer and an output layer. Hopfield network represents a single layer feedback neural network. In this network a feedback is provided from output to the input neurons as shown in Figure 3.10. Here i represent the input neurons and j represents output neurons. Feedback input to the i^{th} neuron which is equal to the weighted sum of j^{th} output neuron. Every neuron consist a threshold value T_i and weight w_{ij} denotes the weight value of j^{th} output neuron connected to the i^{th} input neuron so net_i can be expressed as

$$net_i = \sum_{\substack{j=1 \\ j\neq i}}^{n} w_{ij}v_j + i_i - T_i \quad \ldots \quad (3.15)$$

for i =1,2,….

and the output of node is expressed as

$$v_i^{k+1}=sgn(net_i) \quad \text{for i=1,2,…n} \quad \ldots \quad (3.16)$$

- **Multilayer feedback network**

  A multilayer feed forward network with feedback connections are represented as multilayer feedback network. Recurrent Neural Network (RNN) represent multilayer feedback neural network. RNN is a feed forward network with at least on feedback loop as shown in Figure 3.11. A RNN define as the network which can learn algorithm to map input sequence to output sequence with or without teacher [12].

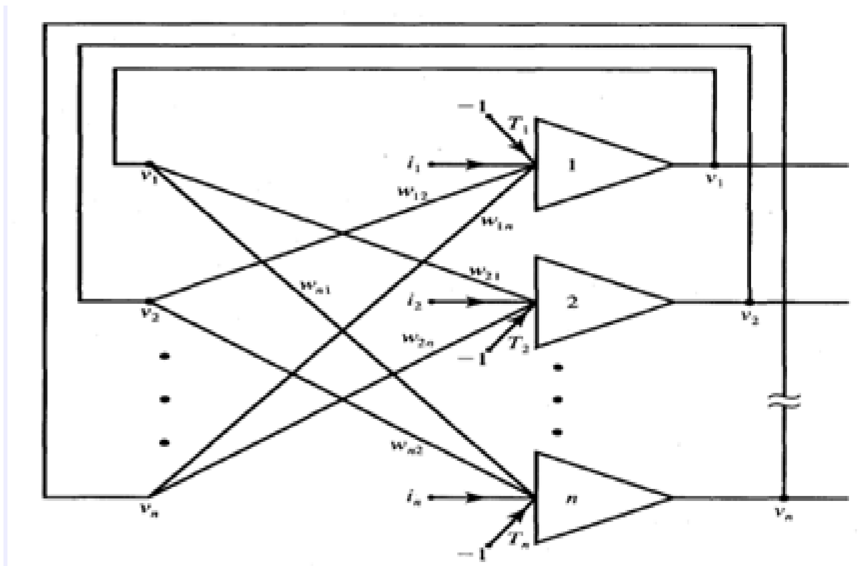

Figure 3.10 Single layer feedback neural network

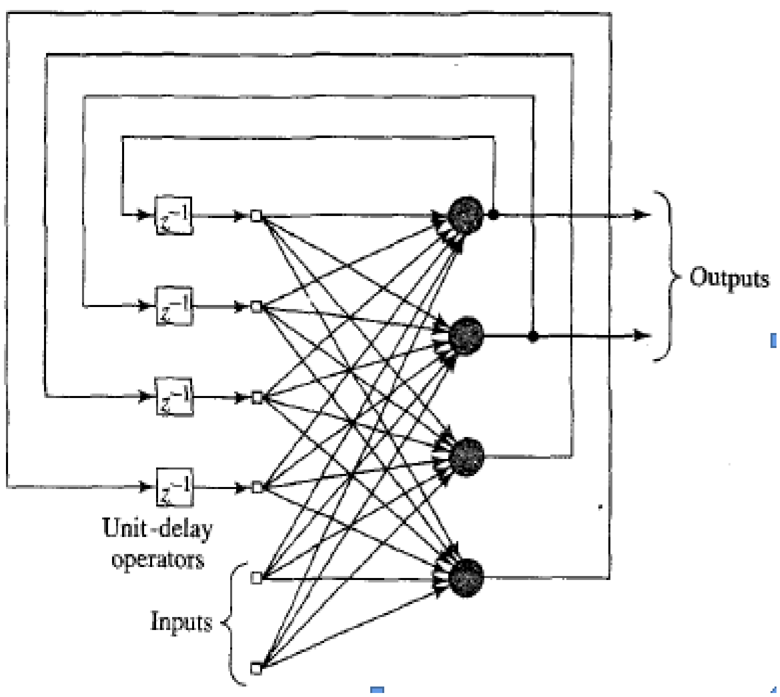

Figure 3.11 Recurrent network with input, hidden and output layer

3.1.4 Learning

Learning in a network defines the training process without information about the input/output. Neural networks are trained by supervised and unsupervised learning. Learning with feedback either from the teacher or environment is supervised learning. The concepts of feedback play a central role in learning [11][12]. Two different type of learning are distinguished as:

Learning with supervision or supervised learning

Learning without supervision or unsupervised learning

The learning type block diagram are illustrated in Figure 3.12

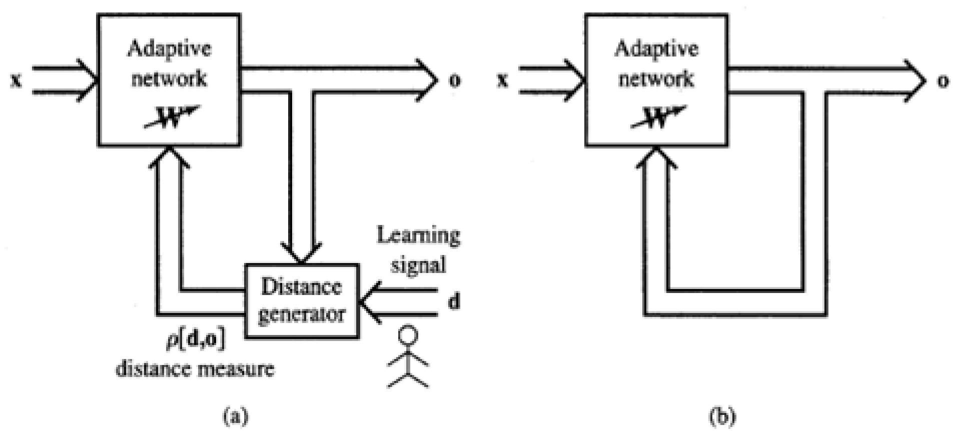

Figure 3.12 Block diagram for: (a) supervised learning (b) unsupervised learning

- **Supervised learning**:-In supervised learning we assume that a set of input and output pattern which is supervised by a teacher. When the input is applied, the desired response **d** of the system can be achieved by correcting error through adjustable weight. A training set is required for this learning mode. In this mode of learning the teacher estimate the negative error gradient direction and reduce the error accordingly. The error minimization process is overall its random realization. Most supervised learning reduced to stochastic minimization of error in multi dimensional weight space [11][12].
- **Unsupervised learning:-**In learning without supervised desired response is not known so explicit error information can't help to improve the network behavior. In this mode of learning the network must learn for itself any possibly existing pattern, regularities, separating properties etc. In this type of learning network undergo change of its parameter, which is called self-organization. The unsupervised learning is often used to

perform clustering as the unsupervised classification of objects without providing information about the actual class. This kind of learning corresponds to minimal a priori information available [11][12].

3.2 RADIAL BASIS FUNCTION NEURAL NETWORK

There is a verity of way to pursue the design of supervised neural network, one of them which are approaches by viewing the design of neural network as a curve fitting (approximation) problem in a high dimensional space. Search in multi dimension surface by interpolate the test data which provide best fit for any function. Such, a viewpoint behind the method of radial basis function. According to the neural network, the hidden unit provide a set of "function" that constitute an arbitrary "basis" for the input pattern (vector) when they are expanded into the hidden space, these functions are called Radial Basis Function. The radial basis function neural network has the universal approximation ability; therefore the radial basis function neural network can be used for the interpolation problem. In addition to many applications and improvements several theoretical results have also been obtained. Radial basis function utilizes a combination of supervised and unsupervised learning technique [12-15]. A RBF network is a multilayer feed forward structure with an input layer, only one hidden layer of RBF pattern units and an output layer of linear units as shown in Figure 3.13 Figure 3.13, shows n input source node that is x_i, i =1,2,3…..m. The activation function is in the form of radial basis function which is denoted as $\varphi_j(x)$, taken in the hidden layer consider as a node [12][21]. Each node contain a center and its response that increase or decrease monotonically with distance from center c_j , j = 1,2,3……n with respect to input vector of RBF network. Output layer contains output node represented as y, is linearly connected to hidden layer with synaptic weights which is denoted by w_j and the response of the RBF network can be express as

$$y \triangleq f(x) = w_j \varphi_j(x) \quad \ldots \quad (3.17)$$

Where, $\varphi_j(x) = \varphi\left(\|x - c_j\|\right)$ … (3.18)

For the case of multiple output node y_i where i= 1, 2, 3 …. m. of RBF network is express as

$$y_i \triangleq f_i(x)$$

$$y_i \triangleq f_i(x) = \sum_{i=0}^{m} w_{ij} \varphi_j(x) \quad \ldots \quad (3.19)$$

Where, $\varphi_j(x) = \varphi_j\left(\|x_i - c_j\|\right)$

Where i = 1, 2, 3….. m ; j = 1,2,3…..n

Where, $\varphi_j(\|x_i - c_j\|)$ stands for radial basis function which maximum value at the center at x=c_j and approach towards zero monotonically.

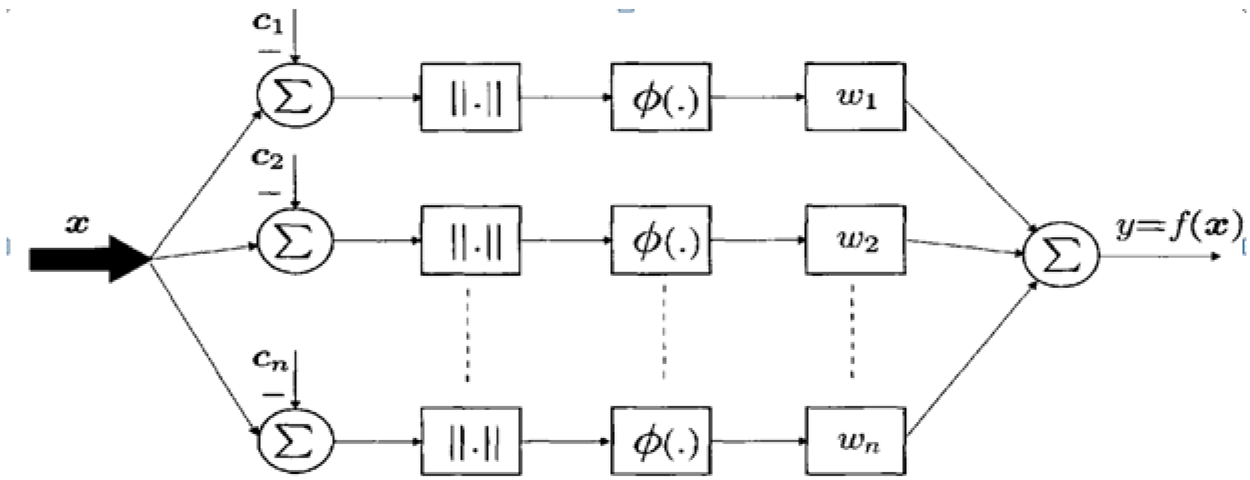

Figure 3.13   Block diagram representation of radial basis function network

$$y_i \triangleq f_i(x) = \sum_{i=0}^{m} w_{ij}\varphi_j(\|x_i - c_j\|) \qquad \ldots \qquad (3.20)$$

Where, $w_{ij} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{12} & w_{22} & \cdots & w_{2m} \\ \vdots & & & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nm} \end{bmatrix}$; and $\varphi_j = \begin{bmatrix} \|x - c_1\| \\ \|x - c_2\| \\ \vdots \\ \|x - c_n\| \end{bmatrix}$.

3.2.1 Interpolation Theory

The practical benefit of separable pattern classification is to map input space into a high dimension or we can say non linear mapping is used to transform a non linear early separable one. RBFs were first introduced to the problem of multivariable interpolation as an approach to dealing with irregularly positioned data points. The RBF network is one of the possible solution to the real multivariable interpolation problem for data that are non uniformly sampled, so for a n different points $x_i \in R^p$ for i=1,2,…n

and $y_i \in R$ for i=1,2,…n

following interpolation conditions are satisfied as

$$f(x_i) = y_i \qquad \ldots \qquad (3.21)$$

Equation 3.21 can be expressed as

$$y = f(x) = \sum_{i=1}^{n} w_i \varphi(\|x - x_i\|) \qquad \dots \qquad (3.22)$$

Inserting the interpolation condition equation 3.22

$$\begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\ \varphi_{12} & \varphi_{22} & \cdots & \varphi_{2n} \\ \vdots & & & \vdots \\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \qquad \dots \qquad (3.23)$$

Where $[w]$ denotes the weight vector, $[\varphi]$ denotes the radial basis function $\varphi(.)$ vector and $[y]$ denotes desired value vector.

$$\varphi_{ij} \triangleq \varphi\big(\|x_i - x_j\|\big) \quad \text{for,} \quad i\ , j = 1,2,\ldots..n \qquad \dots \qquad (3.24)$$

equation 3.23 can also written as

$$w\varphi = y \qquad \dots \qquad (3.25)$$

The necessary and sufficient condition to solve the interpolation problem is the inevitability of $[\varphi]$ that means $[\varphi]$ must be nonsingular, so

$$w = \varphi^{-1} y \qquad \dots \qquad (3.26)$$

from equation 3.26 we can find weight matrix. The value of interpolation function totally depends upon the radial basis function $\varphi(.)$ it also written as $\varphi(x)$. There are the many type of radial basis function:

(1) Gaussian radial basis function:

$$\varphi(x) = e^{-(x/\sigma)^2} \qquad \dots \qquad (3.27)$$

(2) Multi quadratic radial basis function:

$$\varphi(x) = (c^2 + x^2)^{\beta} \quad ;\ 0 < \beta < 1 \qquad \dots \qquad (3.28)$$

(3) Inverse multi quadratic radial basis function:

$$\varphi(x) = \frac{1}{(c^2 + x^2)^{\alpha}} \quad ;\ \alpha > 0 \qquad \dots \qquad (3.29)$$

(4) Thin plate splines radial basis function :

$$\varphi(x) = r^2 \log(x)$$

(5) Cubic splines radial basis function

$$\varphi(x) = x^3 \qquad \dots \qquad (3.30)$$

(6) Linear splines radial basis function:

$$\varphi(r) = r \qquad \dots \qquad (3.31)$$

All above functions are used in practice for data interpolation by using equation 3.23. From given radial basis functions, Gaussian radial basis function and inverse multi quadrant commonly used [12].

3.2.2 Gaussian Radial Basis Function Neural Network

A Gaussian radial function neural network, or simply the Gaussian neural network, which consist of a normalized form of Gaussian density function given by equation (3.27)

$$\varphi(x) = e^{-(x/\sigma)^2}$$

It is most important radial basic function of RBFNN, which is bounded and strictly positive and continuous on R^n, has peak at the center and decreases monotonically as moving from the centre increases as shown in Figure 3.14

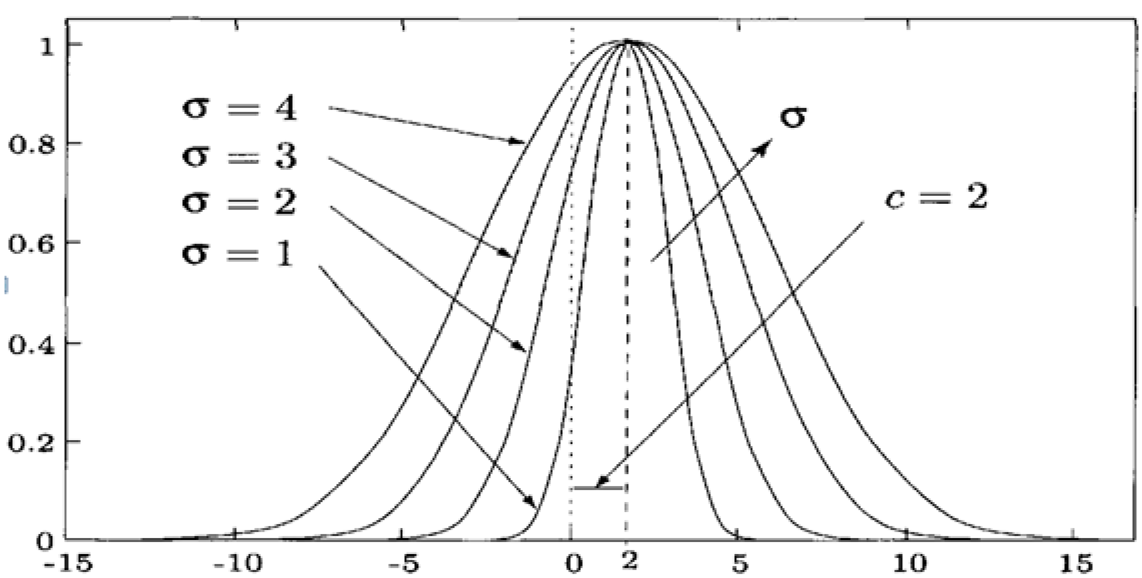

Figure 3.14 A Gaussian radial basis function

It also shows the separable non-linearity property, i.e.

$$\varphi_j(x) = \varphi_j(\|x_i - c_j\|) = \varphi(x_1 - c_1)\,\varphi(x_2 - c_2) \dots \dots .\,\varphi(x_m - c_n) \qquad \dots \qquad (3.33)$$

$$= \prod_{i=1}^{m} \varphi(x_i - c_j) \qquad \dots \qquad (3.34)$$

So, for x_i input with n number of hidden nodes the Gaussian radial function is expressed as

$$\varphi_j(x) = e\left(-\frac{\|x_i - c_j\|^2}{2\sigma_i^2}\right) \qquad \dots \qquad (3.35)$$

Gaussian network are highly non-linear and provide a better environment for incremental learning. It is used to control and learning of non-linear dynamic system and has some powerful schemes for modeling complex input-output mapping [12].

3.2.3 Learning Strategies of Gaussian RBFNN Parameters

A radial basis function neural network is based on the combination of nonlinear and linear activation function strategy. There are linear weights associated with the output units and the hidden layer's activation function includes non linear-optimization strategy. There are different parts of RBF network which perform different task so it is reasonable to separate the optimization of different type of layers with different techniques that is,

- Hidden layer of RBFNN is trained with unsupervised learning algorithm.
- Output layer of RBFNN is trained with supervised learning algorithm.
- Apply supervised learning algorithm between hidden layer and output layer for weight.

Learning strategy applied for the hidden layer of the RBFNN is center selection and width/variance calculation. Most of the techniques started by breaking the problem into two parts, one is learning in intermediate stage, which typically performs the clustering algorithm and other one is the adjusting of the center and variance parameters by supervised learning.

Clustering means the classification of same type of data into classes which called as clusters. The items of the same class are separated into one class and different item belongs to other class as possible. Clustering is basically the comparison of same type of data, where a bunch of data converges into a particular type of samples or clusters, so we can definition the clustering could be “the procedure of selecting data into same type of groups whose companions are similar in some way”. A cluster is therefore define as set of items which are “similar” between them and are “dissimilar” to the items belonging to other cluster [17][18].some algorithms are listed below which are

- **K-Mean clustering**

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. This is very suitable for data classification or data mining. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) which is summarized in following steps:

- Step 1: Fixed a priori, means k no. of centroid depute for every cluster. The better choice is to place centroid as much as possible far away from each other.

- Step 2: Select every point belonging to a given data set and calculate distance by equation 3.36 to the nearest centroid. When no point is remain, the second step is finished and an early group age is done.

$$d = |x - c| = \sqrt{\sum_{i=1}^{m} \left|x_i - c_j\right|^2} \qquad \ldots \qquad (3.36)$$

- Step 3: Now recalculate the centroid of same group age which is calculated in the previous step.
- Step 4: New centroid of each cluster is calculated now and these centroids are varying until the location of the center is not going to change further. In other words centroids do not move any more [18][22][23].

Finally, this algorithm aims at minimizing an objective function in this case a squared error function. The objective function, is

$$\varphi_j = \sum_{j=1}^{\mathrm{k}} \sum_{i=1}^{\mathrm{m}} \|x_i - c_j\|^2 \qquad \ldots \qquad (3.37)$$

Where $\|x_i - c_j\|^2$ is a chosen distance measure between a data point x_i and the cluster centre c_j, is an indicator of the distance of the *n* data points from their respective cluster centers.

The algorithm is composed of the following steps:

1. Place K points into the data space represented by the set of data that are being clustered. These points represent initial set of group centroids.
2. Assign each data set to the group that has the minimum distance to the centroid.
3. When all data set have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids resist to move. The process to separation the data set into groups from which the metric to be minimized can be calculated.

- **Fuzzy clustering**

Fuzzy clustering is similar to k-mean clustering in which data is categorized into crisp data cluster. Data of the data set formulated on clustering method in which each data belongs to a particular cluster. In fuzzy clustering, all data belongs to the membership function of the fuzzy cluster and membership function belongs to a particular cluster. This also belongs to other clusters simultaneously. Fuzzy clustering is categorized as soft clustering, means data can belongs to more than one cluster at a time. The degree of fulfillment of these membership functions lies between zero to one. The discreet nature of the fuzzy clustering partitioning also causes difficulties with algorithms based on regular functional, since these functional are not differentiable [13][23][24].

The algorithm is composed on following steps:

1. Collect and process the data to the system.
2. Establish the structure of the system according to the feature of problem.
3. Select clustering algorithm and specify the parametric value for the clustering model.
4. Implement clustering algorithm on the data with appropriate number of cluster.
5. Obtain membership function from clusters
6. Apply membership function with fuzzy rules for each cluster.
7. Certify model for appropriate problem.

- **K nearest neighbours (KNN)**

K nearest neighbour is a supervised learning strategy. This is a non parametric decision procedure which stores all available cases and classifies a new class on the basis of similarity measure that is distance functions like Euclidean distance, Manhattan, etc. In KNN case is classified by a majority vote of its neighbour. Its training is very fast and it learns complex target function easily. This method is slow at query time means if more data is present than its implementation is not justified [12][24].

The algorithm is composed on following steps:

1. Select the integer k
2. Find k nearest training point
3. Measure distance between test point and training point using distance function

$$D = \sqrt{\sum_{i=1}^{k}\left(x_i - c_i\right)^2} \qquad \ldots \qquad (3.38)$$

4. Calculate mean of k nearest outcome

- **Weight calculation method**

Hidden to output layer is connected by linear weights similar to multilayer perceptions. The output weight can be obtained by either supervised or unsupervised methods.

(1) Pseudo inverse learning

Second stage consist a single layer of weight, they can easily be found analytically by solving a set of linear equations. This can be done quickly, without need for a set of iterative weight updates as un supervised method of learning [12][17][24]. Pseudo inverse method is one of those method where need of iteration is not required. From equation 3.25

$$w\varphi = y$$

Or, $$\varphi^T \varphi w = \varphi^T y$$

Or, $$w = (\varphi^T \varphi)^{-1} \varphi^T y \qquad \ldots \qquad (3.39)$$

Or, $$w = \varphi^* y \qquad \ldots \qquad (3.40)$$

Where, $$\varphi^* = (\varphi^T \varphi)^{-1} \varphi^T \qquad \ldots \qquad (3.41)$$

This is called pseudo inverse learning.

(2) Gradient descent learning

The weight of second layer can be trained by supervised learning method like back propagation algorithm or orthogonal least square method etc. Method is to employ supervised learning by adaptive updating the linear weights w_i,i=1,2,3…. Using gradient descent learning. It is a combined measure of error which is defined as G[12]. Where

$$G = \frac{\partial E(n)}{\partial w_i(n)}$$

and weight is updated as

$$w_i(n+1) = w_i(n) - \gamma \frac{\partial E(n)}{\partial w_i(n)} \qquad \ldots \qquad (3.42)$$

Where, γ is the learning rate

$$\frac{\partial E(n)}{\partial w_i(n)} = \sum_{j=1}^{N} e_j \ \varphi_i(\|x - c_i\|)$$

e_j =target - actual output

In this proposed work, the classification model to classify the PQ events is including the RBFNN and the parameters of the radial basis function such as center of the basis function of hidden units, width of the hidden units and weight between hidden units and output units is calculated or trained by k-mean clustering algorithm, KNN algorithm, and pseudo inverse method respectively. Further the weight between hidden units to output units is updated using gradient descent learning rule which helps to increase the classification accuracy of the proposed model.

CHAPTER 4

PROBLEM FORMULATION AND RESULT

4.1 PROBLEM FORMULATION

The proposed work in this dissertation is implemented in two parts,

Firstly, the generation of power quality events data in MATLAB environment by using different type of loads (normal load, heavy load, non linear load) with various type of faults (SLG, LL, LLG, LLL, LLLG) and

secondly the classification of the generated data by using RBF neural network model.

4.1.1 Power Quality Event Generation

Power quality event is generated by real time electrical distribution test model is designed in MATLAB/Simulink by using SimPower System toolbox. The sampling frequency and fundamental frequency are considered as 10 kHz and 50 Hz respectively which is basically 200 points for each cycle to implement practically. This test model represent a three phase distribution network which consist 50MVA, 25kV generator with source impedance of Z_s , Z_s= 5+j0.314, connected with 20km, distribution line and π-equivalent model,

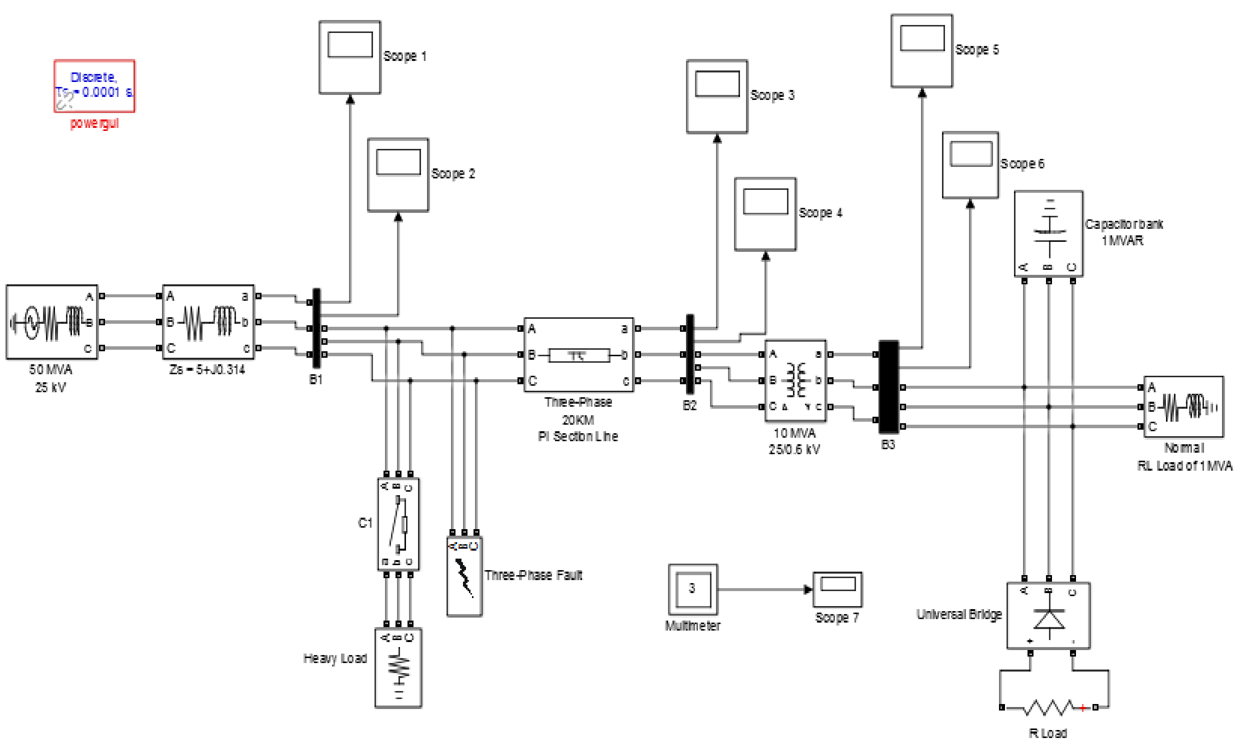

Figure 4.1 SIMULINK diagram of electrical power distribution model

A delta/star step down transformer which steps down the voltage level to 0.6 kV is connected with normal RL load of 1MVA as shown in Figure 4.1. There are three buses which are connected to get voltage and current values when different type of loads such as heavy load, non-linear load and various faults like SLG, LL, LLG, LLL, LLLG are created. At bus 3, a capacitor bank of 0.8 MVA is connected for reactive power compensation in order to simulate a fixed switching of a bank of capacitor which cause oscillatory transient. At bus one a single line to ground fault is created for few cycles which cause sag and interruption in faulty phase and swell in healthy phase after that the voltage in all phase is normal. Sag and swell can also be caused by line to line fault created on phase A and phase B. Therefore sag is produced in phase A and B where as swell in phase C. Due to heavy load on phase A for 5 cycles where as interruption in phase A for those cycles and swell in phase B and C. Due to switching of non-linear load (Three phase bridge rectifier) harmonics are caused. These disturbances are created in per unit, time duration for various instants to get various kinds of data to classify [19][20].

4.1.2 Data Collection

PQ events are classified on the basis of magnitude of various PQ events which is generated by electrical power distribution test model. PQ events are generated at different time duration for various events of PQ and these data is used as a row data or training pattern for the proposed RBF neural network model.

4.1.3 RBFNN Model Architecture

The proposed RBF neural network architecture in this study consist of three layered feed forward network as shown in Figure 4.2. Its first layer is input layer which connect the network to the power quality event data training pattern data. Second layer is the only one hidden layer which consist Gaussian radial basis function and its basic parameters that are center and width are trained by K-mean clustering algorithm and KNN algorithm. Third layer is the output layer and it is linearly connected to the hidden layer with synaptic weight which is calculated by pseudo inverse method. Steps followed for the training of RBF neural network model is summarized:

Assumptions

x_i = Input nodes (i= 1,2,3…..m

c_j=center of Gaussian radial basis function of hidden layer node (j=1,2,3…n)

σ_j=width of the node of Gaussian radial basis function of hidden layer

w_{rj}= connecting weight from j^{th} node of hidden layer to r^{th} node of output layer

Input and output data set: $\{x^i, d^r\}$

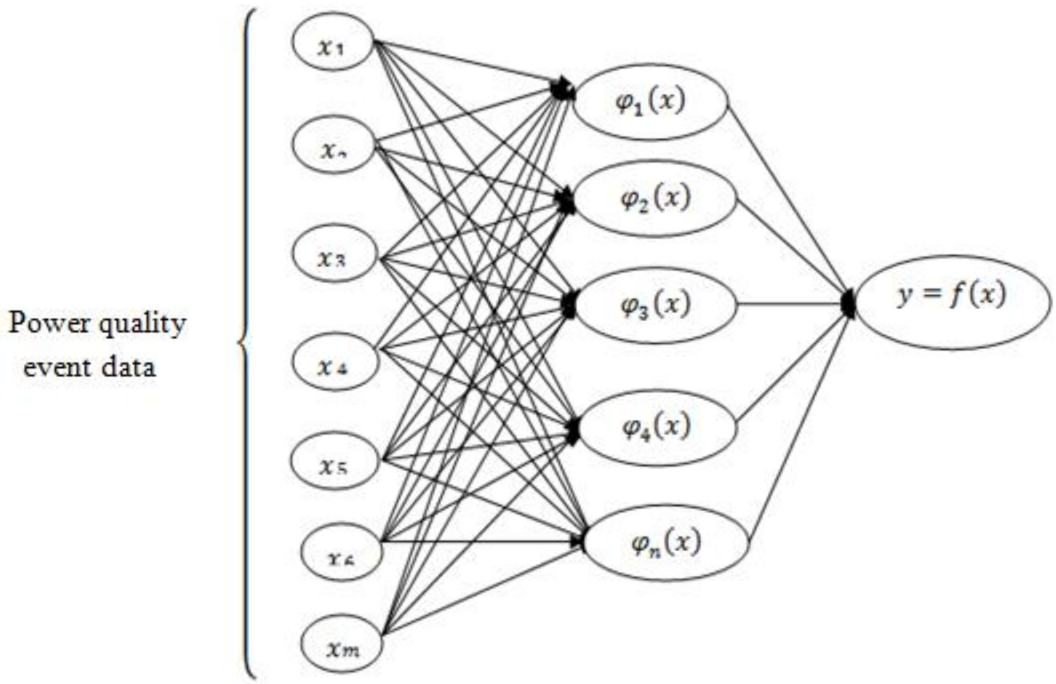

Figure 4.2 RBF neural network architecture

Step 1: Apply x_i pattern of input to the input nodes of network.

Step 2: Assume j number nodes in hidden layer which contain j number of centers and width.

Step 3: Randomly select K number of centers from input data set.

Step 4: Train the selected centers using K-mean clustering algorithm.

Step 5: Calculate width of the node using root mean square distance and train with KNN algorithm.

Step 6: Calculate Gaussian radial basis function $\varphi_j(x)$ by

$$\varphi_j(x) = e\left(-\frac{\|x_i - c_j\|^2}{2\sigma_i^2}\right)$$

Step 7: Calculate weight between hidden layer to output layer by using pseudo inverse method that is

$$w = (\varphi^T \varphi)^{-1} \varphi^T y$$

Step 8: Update the weight using gradient descent learning method.

Step 9: Calculate output of the network by

$$y_i = \sum_{i=0}^{m} w_{ij}\varphi_j(\|x_i - c_j\|)$$

For each power quality event data there is a set logic to get the final result such as for sag event the output should be less than 1, for swell output should be more than 1, for interruption it is between 0 to 0.9 and many others. The classification of PQ events data depends upon the typical measure of magnitude of every PQ event. The flowchart for classification of data using RBF neural network model is in Figure 4.3.

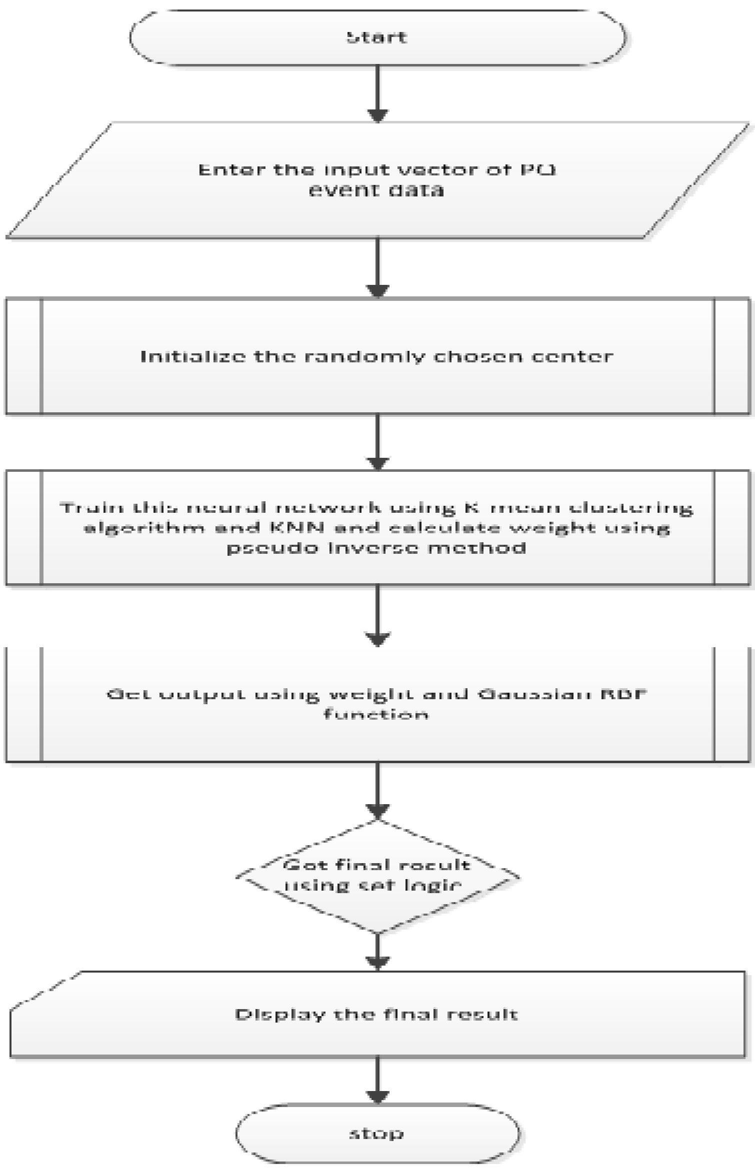

Figure 4.3 Flowchart of RBF neural network model training

4.1.4 Accuracy of Classification

Accuracy of classification is defined by the number of samples detected by the RBF neural network with respect to the number of samples considered.

$$(\%)\ \text{Accuracy of Classification} = \frac{l}{h} * 100 \qquad \dots \qquad (4.1)$$

Where, l = Number of samples correctly detected

h = Total number of samples considered

4.2 RESULT

The objective of dissertation work is the generation of power quality events and performance of RBF neural network model to classify these power quality events. Data generated by using electrical power distribution model, compared with the typical magnitude of the power quality events according to IEEE standard 1159-2009 and the generated data is classified using proposed methodology of RBF neural network. To insure the effectiveness of the RBF neural network model classification accuracy is measured, which is the ratio of the number of sampled data detected with respect to total number of sampled data.

4.2.1 Simulation Model

For simulation purpose electrical power distribution model is designed as shown in Figure 4.1 using SimPower System Simulink model by applying various type of loads and faults like short circuit fault, heavy load, normal load, non linear load, capacitor bank switching off/on.

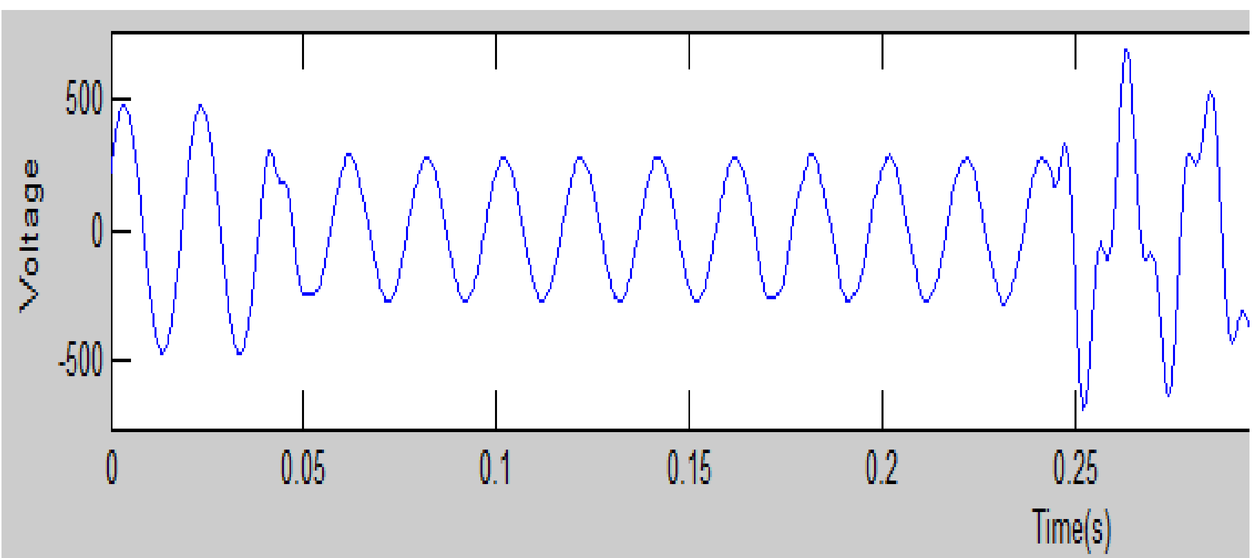

Figure 4.4 Voltage sag caused by single line to ground fault

The electrical power distribution model consist 25 kV voltage source and 50 Hz fundamental frequency. Each power quality events simulate for 10 cycles and a sampling frequency of 10 kHz. When single line to ground fault is applied at bus 1 then, voltage sag and interruption cause on faulty phase and voltage swell caused on healthy phase. Voltage sag swell and interruption also caused due to switching on a heavy load as shown in Figure 4.4, 4.5, 4.6 respectively.

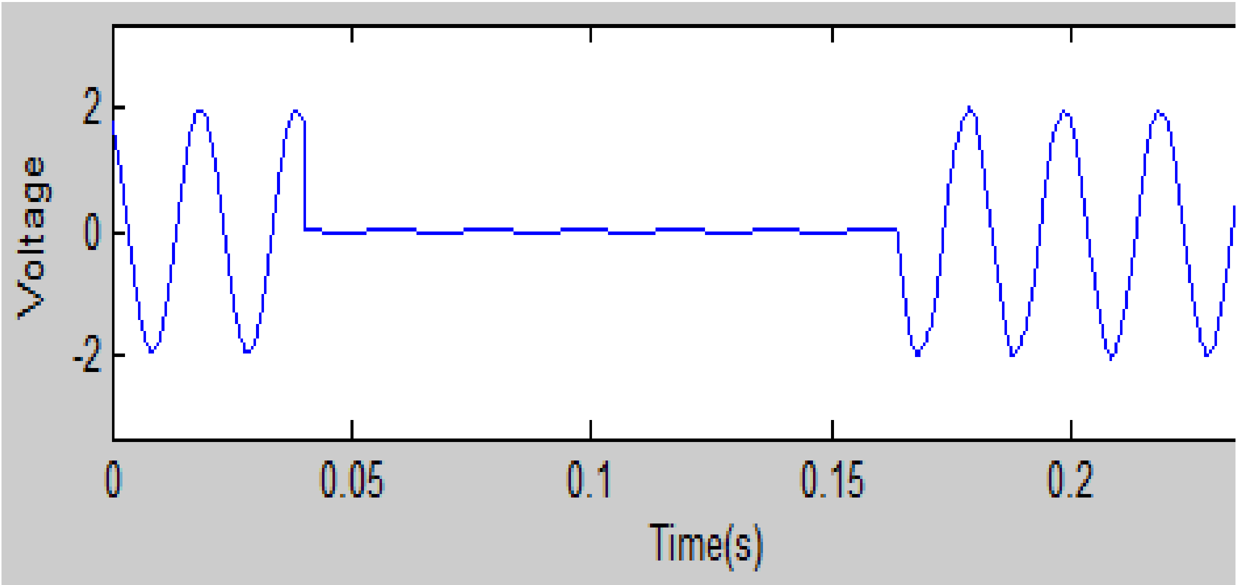

Figure 4.5 Interruption caused by single line to ground fault

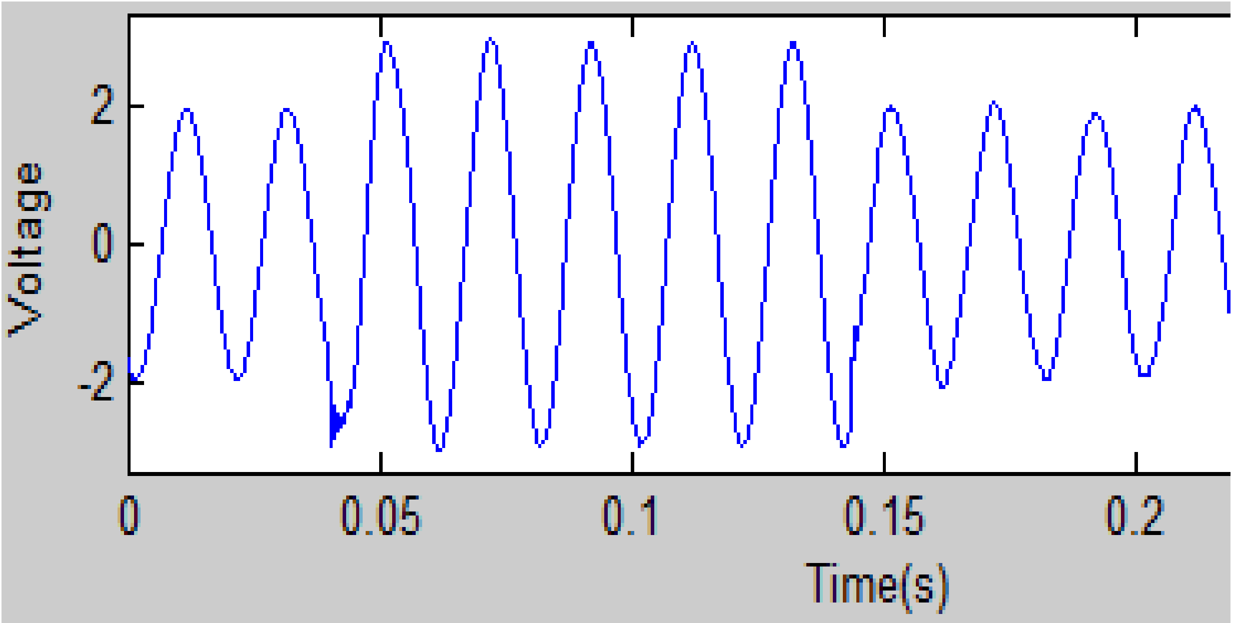

Figure 4.6 Voltage swell caused by single line to ground fault

When capacitor bank is applied to the Simulink model, an oscillatory transient is produced in supply voltage due to the operation of a capacitor bank as shown in Figure 4.7. The frequency of the oscillatory transient depends upon the size of capacitor bank.

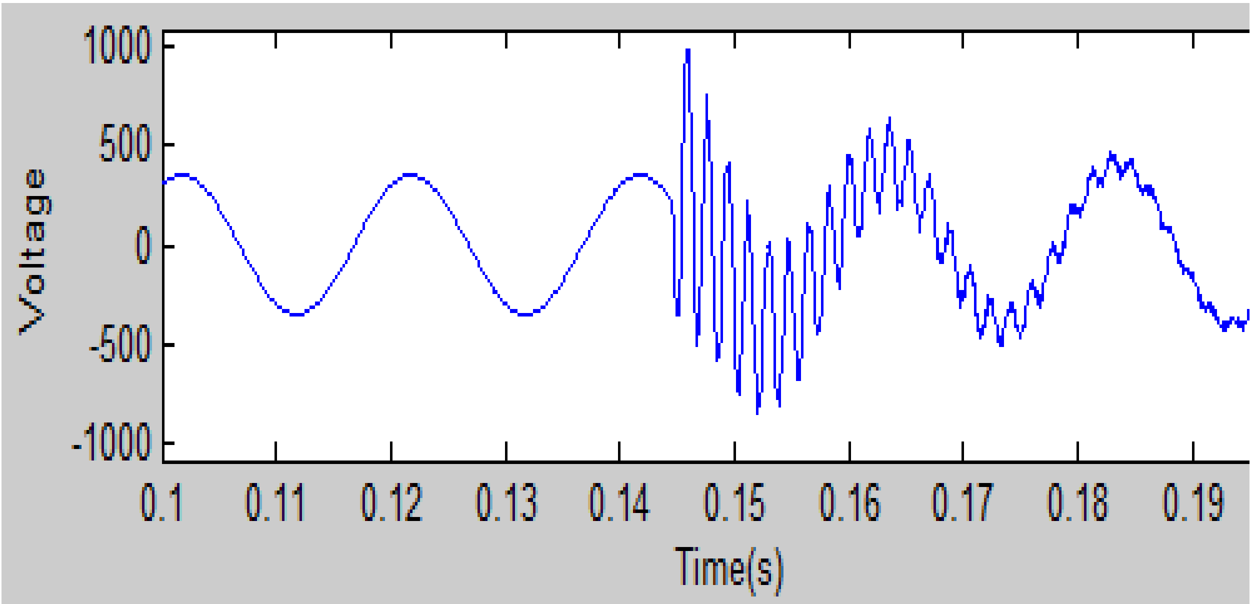

Figure 4.7 Oscillatory transient caused by capacitor switching

When a three phase bridge rectifier i.e. non- linear load is connected at bus 3 as shown in Figure 4.1 than, harmonics are produced due to switching on the three phase bridge rectifier as shown in Figure 4.8.

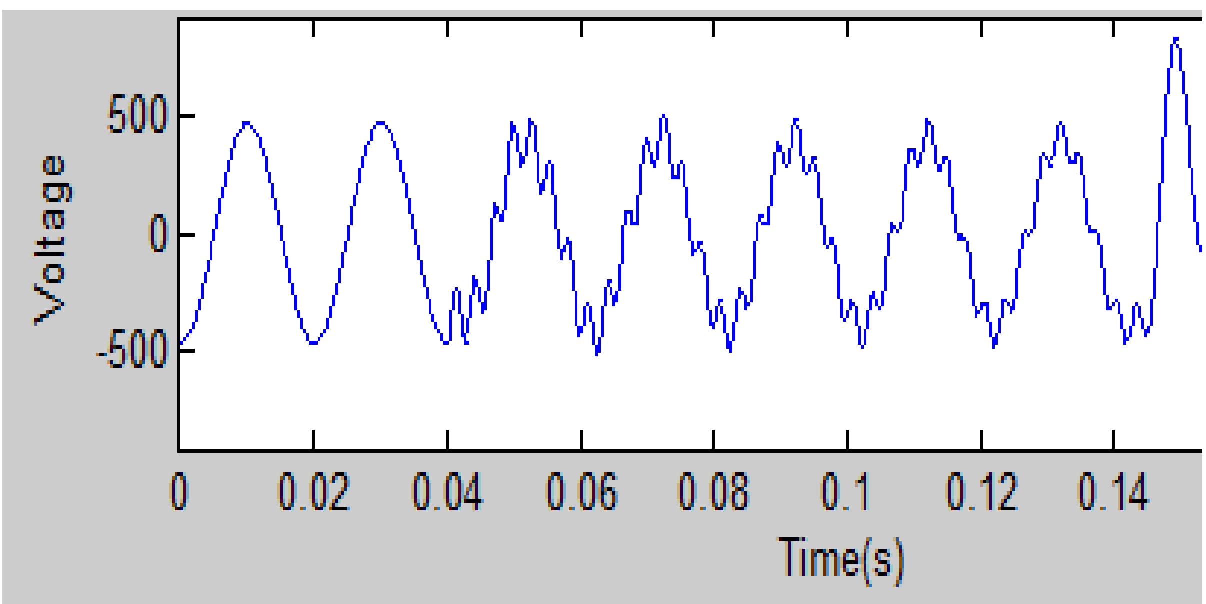

Figure 4.8 Harmonics caused by three phase bridge rectifier

4.2.2 Classification of Power Quality Events using RBF Neural Network

RBF neural network model is proposed to classify PQ event data. This model consist of input layer, only one hidden layer and a output layer which already discussed in previous chapter. The implementation of classification procedure is proposed in following manner.

1. Select the proposed RBF neural network architecture as shown in Figure 4.2.
2. Apply training pattern for the input of RBF neural network to classify PQ events data which is collect the voltage magnitude data for different cycles at different time instant.
3. Initialized the centers of hidden layer and trained them using proposed clustering algorithm.
4. Calculate the width of each hidden node and output of the hidden nodes using center and width.
5. Calculate linear weights connected between hidden layer and output layer and update the weight using gradient descent method.
6. Compute the output of the network.
7. The result obtained is further categorized according to the specified typical value of IEEE standard 1159-2009.
8. The accuracy of classification of the model is calculated by the ratio of number of samples detected with respect to total number of samples taken as tabulated in Table 4.1.

The training pattern for the input of RBF neural network is taken on the basis of number of cycles for which faults occurred and point of instant of time. For this RBF neural network model we are considering 10 numbers of training patterns for each class and the classes of PQ events are categorized as:

E_1= Sinusoidal signal

E_2= Voltage sag signal

E_3= Voltage swell signal

E_4= Interruption signal

Sinusoidal signal (E_1) that is the original signal generated by the voltage source to energize an electrical network without any disturbances. The magnitudes of sinusoidal signals for training pattern of E_1 class are shown in Table 4.1.

Table 4.1 Training pattern data for sinusoidal signal

Time / Cycles	0.05	0.1	0.15	0.2	0.25	0.3	0.35
2-7	0.0000	0.3090	0.5878	0.8090	0.9511	1.0000	0.9511
2-10	0.9511	1.0000	0.9511	0.8090	0.5878	0.3090	0.0000
1-12	0.9511	0.8090	0.5878	0.3090	0.0000	0.3090	0.5878
3-14	0.3090	0.5878	0.8090	0.9511	1.0000	0.9511	0.8090
5-16	0.5878	0.3090	0.0000	0.3090	0.5878	0.8090	0.9511
8-18	0.3090	0.5878	0.8090	0.9511	1.0000	0.9511	0.8090
10-20	1.0000	0.9511	0.8090	0.5878	0.3090	0.0000	0.3090
5-20	0.9511	1.0000	0.9511	0.8090	0.5878	0.3090	0.0000
3-20	0.8090	0.9511	1.0000	0.9511	0.8090	0.5878	0.3090
2-22	0.9511	1.0000	0.9511	0.8090	0.5878	0.3090	0.0000

For the training pattern of RBF neural network for voltage sag signal (E_2), voltage swell signal (E_3), and interruption signal (E_4) is tabulated in table 4.2, 4.3, and 4.4 respectively. These training pattern data are the voltage magnitude of the voltage sag, swell and interruption signal for different cycles at different time instant, samples of few data are included in APPENDIX with relative waveforms.

Table 4.2 Training pattern data for voltage sag signal

Time / Cycles	0.05	0.1	0.15	0.2	0.25	0.3	0.35
2-7	0.00018	0.000052	0.1619	0.1132	0.1212	0.1173	0.1207
2-10	0.00018	0.000052	0.00012	0.00008	0.1090	0.1167	0.1211
1-12	0.00016	0.000062	0.00011	0.00008	0.2869	0.1145	0.1212
3-14	0.1191	0.000038	0.00012	0.000078	0.00011	0.2728	0.1232
5-16	0.1191	0.1191	0.00014	0.000069	0.00011	0.000084	0.1547
8-18	0.1191	0.1191	0.1191	0.000038	0.00012	0.000078	0.00011
10-20	0.1191	0.1191	0.1191	0.1191	0.00014	0.000069	0.00011
5-20	0.1191	0.1191	0.00014	0.000069	0.00011	0.000084	0.0001
3-20	0.1191	0.000038	0.00012	0.000078	0.00011	0.000086	0.0001

2-22	0.00018	0.000052	0.00012	0.000081	0.00011	0.000087	0.0001

Table 4.3 Training pattern data for voltage swell signal

Time / Cycles	0.05	0.1	0.15	0.2	0.25	0.3	0.35
2-7	1.18	0.1141	1.8821	1.2339	1.0338	0.7754	0.7332
2-10	1.4281	1.0909	0.9609	0.9603	0.8443	0.8376	0.8424
1-12	1.1121	1.1686	1.168	1.1686	1.1686	1.1686	1.1686
3-14	0.77298	1.15939	1.1594	1.1594	1.1594	0.773	0.77298
5-16	0.77298	0.77298	1.15939	1.1594	1.1594	1.1594	0.77298
8-18	0.77298	0.77298	0.77298	1.15939	1.1594	1.1594	1.1594
10-20	0.77298	0.77298	0.77298	0.77298	1.15939	1.1594	1.1594
5-20	0.77298	0.77298	1.15939	1.1594	1.1594	1.1594	1.1594
3-20	0.77298	1.15939	1.1594	1.1594	1.1594	1.1594	1.1594
2-22	0.77298	1.15939	1.1594	1.1594	1.1594	1.1594	1.1594]

Table 4.4 Training pattern data for interruption signal

Time / Cycles	0.05	0.1	0.15	0.2	0.25	0.3	0.35
2-7	0.4818	0.5358	0.5878	0.6374	0.6845	0.7290	0.7705
2-10	0.8090	0.8443	0.8763	0.9048	0.9298	0.9511	0.9686
1-12	0.9980	1.0000	0.9980	0.9921	0.9823	0.9686	0.9511
3-14	0.9298	0.9048	0.8763	0.8443	0.8090	0.7705	0.7290
5-16	1.0000	0.9980	0.9921	0.9823	0.9686	0.9511	0.9298
8-18	0.5878	0.5358	0.4818	0.4258	0.3681	0.3090	0.2487
10-20	0.0628	0.1253	0.1874	0.2487	0.3090	0.3681	0.4258
5-20	0.6845	0.7290	0.7705	0.8090	0.8443	0.8763	0.9048
3-20	0.7290	0.6845	0.6374	0.5878	0.5358	0.4818	0.4258
2-22	0.0628	0.1253	0.1874	0.2487	0.3090	0.3681	0.4258

For example, interruption is classified by the proposed RBFNN is summarized in following steps:

Step 1: Select RBFNN model of 7 inputs with 10 patterns, 4 hidden units and 1 output units. Training patterns for interruption is tabulated in Table 4.4, where inputs data are indicated as x, centers and width of hidden units are presented as c and σ respectively. Output of the network is denoted as y and weight between hidden and output unit is w.

Step 2: Initialize the cluster k = 4, and select the data from training pattern as shown below.

$$c_{pre} = \begin{bmatrix} 0.8090 & 0.8443 & 0.8763 & 0.9048 & 0.9298 & 0.9511 & 0.9686 \\ 0.9298 & 0.9048 & 0.8763 & 0.8443 & 0.8090 & 0.7705 & 0.7290 \\ 0.5878 & 0.5358 & 0.4818 & 0.4258 & 0.3681 & 0.3090 & 0.2487 \\ 0.6845 & 0.7290 & 0.7705 & 0.8090 & 0.8443 & 0.8763 & 0.9048 \end{bmatrix}$$

and calculate Euclidean distance of each data (x) to selected center of clusters by equation 3.36.

$$d = |x - c| = \sqrt{\sum_{i=1}^{m} \left|x_i - c_j\right|^2}$$

Step 3: Select minimum distance for each pattern and select the cluster. Now take mean of all points of one cluster. This provides a non movable center.

$$c_{new} = \begin{bmatrix} 0.9357 & 0.9474 & 0.9555 & 0.9597 & 0.9602 & 0.9569 & 0.9498 \\ 0.8377 & 0.8377 & 0.8377 & 0.8377 & 0.8377 & 0.8377 & 0.8377 \\ 0.3606 & 0.3677 & 0.3735 & 0.3777 & 0.3805 & 0.3818 & 0.3815 \\ 0.5832 & 0.6324 & 0.6791 & 0.7232 & 0.7644 & 0.8026 & 0.8377 \end{bmatrix}$$

Step 4: Calculate the width (σ) of hidden neuron by k nearest neighbour algorithm for k=1,in this formulation k= p = 1 and the width calculated by equation 3.38

$$\sigma_j = \sqrt{\sum_{i=1}^{k} \left(x_i - c_j\right)^2}$$

σ_j=[0.9048 1.0000 0.8443 0.5358]

Step 5: Calculate Gaussian radial basis function by equation 3.35

$$\varphi_j(x) = e\left(-\frac{\|x_i - c_j\|^2}{2\sigma_i^2}\right)$$

$$\varphi_j(x) = \begin{bmatrix} 0.3468 & 0.3562 & 0.3073 & 0.3594 \\ 0.3606 & 0.3554 & 0.2577 & 0.3530 \\ 0.3618 & 0.3554 & 0.2643 & 0.3532 \\ 0.3431 & 0.3562 & 0.3191 & 0.3518 \\ 0.3616 & 0.3570 & 0.2701 & 0.3546 \\ 0.2257 & 0.2551 & 0.3515 & 0.2542 \\ 0.2792 & 0.3061 & 0.3569 & 0.3040 \\ 0.3582 & 0.3584 & 0.2739 & 0.3594 \\ 0.2729 & 0.3012 & 0.3569 & 0.2999 \\ 0.2792 & 0.3061 & 0.3569 & 0.3040 \end{bmatrix}$$

Step 6: Calculate the weight between hidden to output unit by pseudo inverse method by equation 3.39

$$w = (\varphi^T \varphi)^{-1} \varphi^T y$$

$$w = \begin{bmatrix} 12.4011 \\ -15.3585 \\ 4.1561 \\ 2.5193 \end{bmatrix}$$

Step 7: Update these weight by gradient descent learning. Firstly calculate error of final result and target i.e $\frac{\partial E(n)}{\partial w_i(n)}$,where $E(n)$ is error and weight updated as equation 3.42 for epoch 1, 10 and 100. i.e

$$w_i(n+1) = w_i(n) - \gamma \frac{\partial E(n)}{\partial w_i(n)}$$

γ=learning rate= 0.5

Step 8: Output of these calculations are calculated by equation 3.20,and result is shown below for epoch 1

$$y_i = \sum_{i=0}^{m} w_{ij}\varphi_j(\|x_i - c_j\|)$$

y_i = [1.0131 0.9725 1.0168 0.9975 1.0169 0.9825 1.0110 0.9803 0.9959 1.0110]

Step 9: Now the output of the network is now compared with the specific value of interruption i.e below 0.8 p.u, if value of y is less than 0.8 p.u than y=1, otherwise y= -1.

Step 10: If the generated pattern is equal to the target pattern than stop the iteration otherwise go to step 7 until defined no of iterations.

Step 11: Now calculate the accuracy of the network by taking total number of pattern and detected pattern by equation 4.1. here total number of patterns (h) is 10 and l depends upon the number of iteration which is shown in tables 4.5, 4.6, 4.7 and analysis based on iterations in table 4.8.

$$(\%)\ \text{Accuracy of classification} = \frac{l}{h} * 100$$

Where, l = Number of samples correctly detected

h = Total number of samples considered

step 12: similarly for sag and swell is also calculated and summarized in table 4.5,4.6,4.7 and 4.8.

Table 4.5 (%) Accuracy of classification for epoch 1

Events	E_1	E_2	E_3	E_4
E_1	100	0	0	0
E_2	0	90	10	0
E_3	0	0	100	0
E_4	0	50	0	50
	Overall accuracy = 85%			

Table 4.6 (%) Accuracy of classification for epoch 10

Events	E_1	E_2	E_3	E_4
E_1	100	0	0	0

E_2	0	90	10	0
E_3	0	0	100	0
E_4	0	0	0	100
Overall accuracy = 97.5%				

Table 4.7 (%) Accuracy of classification for epoch 100

Events	E_1	E_2	E_3	E_4
E_1	100	0	0	0
E_2	0	100	0	0
E_3	0	0	100	0
E_4	0	0	0	100
Overall accuracy = 100%				

Table 4.6 (%) Comparative analysis performance of RBF neural network for epoch 1,10 and 100

Events	No. of Epoch= 1	No. of Epoch =10	No. of Epoch= 100	Avg. accuracy (%)
E_1	100	100	100	100
E_2	90	90	100	93.33
E_3	100	100	100	100
E_4	50	100	100	83.33
Overall accuracy = 94.16%				

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

A power quality problem in power system keeps very high concern as well as other power system problem for the sake of reliability of system, security of equipments, and availability of power for the customer or end user. The generation of PQ events using Simulink in MATLAB is quite similar to the actual PQ events as documented in IEEE standard documents. The result of proposed work that is classification of power quality events using RBFNN gives a reasonable accuracy to achieve this goal. The accuracy of classification of the proposed model gives higher accuracy result by increasing number of epochs and the average of (%) accuracy of classification for 1, 10 and 100 epoch gives a comparative analysis performance of the proposed model.

5.2 FUTURE SCOPE OF WORK

The clustering of data is a very big problem in data classification and K-mean clustering is the simplest method to do this. Researchers getting problem to select the center position of radial basis function and number of centers, this can be improved by using genetic algorithm, orthogonal least square algorithm, fuzzy logic, cross validation and etc. Most of the classifier uses to classify same type of events or one type of events, so to classify other type of events from the same classifier need to be search and implement. There is also need of improvement to investigate the cause of the PQ events simultaneously with classification of the PQ events.

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APPENDIX

The sample data for training pattern which is generated by electric power distributed model is tabulated in table AT 1, AT 2.AT 3 and related waveforms are presented in Figure AF 1, AF 2, AF 3 for different cycles for different PQ events.

Table AT 1 sample data of sag, swell and interruption for 2-7 cycles

Cycles / Time(s)	2-7 cycles		
	sag	swell	Interruption
0.046	0.036824	1.005379	0.000151234
0.0461	0.064539	1.016328	0.000154697
0.0462	0.091536	1.02474	0.000150928
0.0463	0.119287	1.035501	0.000154102
0.0464	0.150093	1.037107	0.000150245
0.0465	0.179709	1.033692	0.000153241
0.0466	0.204825	1.03535	0.000149096
0.0467	0.230633	1.032515	0.000151873
0.0468	0.260191	1.023916	0.000147497
0.0469	0.28866	1.02229	0.00015
0.047	0.313977	1.022326	0.000145487
0.0471	0.339063	1.016908	0.000147878
0.0472	0.363988	1.016791	0.000143041
0.0473	0.388341	1.021221	0.0001451
0.0474	0.414466	1.019789	0.000140166
0.0475	0.440626	1.019427	0.000142122
0.0476	0.46269	1.023201	0.000136912
0.0477	0.483845	1.019815	0.000138626
0.0478	0.50898	1.012593	0.000133247
0.0479	0.534611	1.008835	0.000134736
0.048	0.556536	0.998764	0.000129192
0.0481	0.577396	0.981566	0.000130603
0.0482	0.599051	0.967897	0.000124829
0.0483	0.619924	0.952176	0.000125918
0.0484	0.640895	0.929384	0.00012003
0.0485	0.662102	0.910193	0.000121094
0.0486	0.679792	0.893812	0.000114999
0.0487	0.694716	0.872254	0.000115814
0.0488	0.7123	0.853346	0.000109596
0.0489	0.731386	0.839873	0.000110274
0.049	0.746615	0.822195	0.000103902

0.0491	0.759327	0.804138	0.000104519
0.0492	0.773312	0.791464	9.80E-05
0.0493	0.787409	0.774706	9.84E-05
0.0494	0.800714	0.753278	9.18E-05
0.0495	0.814318	0.735482	9.22E-05
0.0496	0.825984	0.714794	8.54E-05
0.0497	0.834501	0.686807	8.56E-05
0.0498	0.844325	0.660675	7.88E-05
0.0499	0.856495	0.634515	7.89E-05
0.05	0.865509	0.601619	7.20E-05
0.0501	0.870439	0.569849	7.21E-05
0.0502	0.875901	0.541529	6.52E-05
0.0503	0.882148	0.508811	6.51E-05
0.0504	0.886727	0.476543	5.81E-05
0.0505	0.890442	0.450069	5.81E-05
0.0506	0.893089	0.421344	5.11E-05
0.0507	0.892849	0.390989	5.09E-05
0.0508	0.892523	0.366199	4.38E-05
0.0509	0.894914	0.340477	4.38E-05

Table AT 2 sample data of sag, swell and interruption for 5-15 cycles

Cycles / Time(s)	5-15 cycles		
	sag	Swell	Interruption
0.1015	0.011612	0.90304	-2.53E-06
0.1016	0.002084	0.921665	1.27E-06
0.1017	0.00611	0.939566	-8.64E-07
0.1018	0.023773	0.965127	3.33E-06
0.1019	0.036085	0.984654	-5.88E-07
0.102	0.056285	0.99693	3.01E-06
0.1021	0.077111	1.012955	-1.26E-07
0.1022	0.072529	1.02351	4.69E-06
0.1023	0.071133	1.023658	2.85E-06
0.1024	0.105669	1.026438	7.24E-06
0.1025	0.135636	1.028106	3.31E-06
0.1026	0.129483	1.019948	7.82E-06
0.1027	0.126145	1.014578	6.76E-06
0.1028	0.145308	1.014787	1.23E-05
0.1029	0.159877	1.008777	9.34E-06

0.103	0.169746	1.003989	1.39E-05
0.1031	0.184924	1.008104	1.19E-05
0.1032	0.184362	1.009237	1.77E-05
0.1033	0.175774	1.008005	1.66E-05
0.1034	0.197647	1.013963	2.22E-05
0.1035	0.230333	1.017502	1.95E-05
0.1036	0.229085	1.014027	2.46E-05
0.1037	0.218483	1.014022	2.43E-05
0.1038	0.235988	1.012065	3.11E-05
0.1039	0.258486	0.999874	2.91E-05
0.104	0.267094	0.988016	3.43E-05
0.1041	0.278091	0.977286	3.33E-05
0.1042	0.284383	0.957421	4.00E-05
0.1043	0.277182	0.93627	3.95E-05
0.1044	0.287433	0.92038	4.60E-05
0.1045	0.316824	0.899817	4.43E-05
0.1046	0.319632	0.877389	5.00E-05
0.1047	0.299901	0.862412	5.01E-05
0.1048	0.30483	0.846629	5.77E-05
0.1049	0.326845	0.827479	5.66E-05
0.105	0.332342	0.814695	6.22E-05
0.1051	0.332573	0.802672	6.18E-05
0.1052	0.338212	0.784259	6.92E-05
0.1053	0.334975	0.768399	6.91E-05
0.1054	0.337709	0.75393	7.60E-05
0.1055	0.362506	0.731092	7.51E-05
0.1056	0.373808	0.706638	8.12E-05
0.1057	0.355255	0.684736	8.14E-05
0.1058	0.350869	0.655886	8.95E-05
0.1059	0.372624	0.623407	8.90E-05
0.106	0.380837	0.595361	9.48E-05
0.1061	0.371921	0.564358	9.44E-05
0.1062	0.36993	0.529683	0.000102173
0.1063	0.367065	0.50085	0.000102328
0.1064	0.361061	0.473102	0.00010921

Table AT 3 sample data of sag, swell and interruption for 8-18 cycles

Cycle / Time(s)	8-18 cycles		
	sag	swell	nterruption
0.1797	0.845639631	1.004178	0.000151158
0.1798	0.858709287	1.012092	0.000146752
0.1799	0.868863641	1.02023	0.000145108
0.18	0.873182606	1.028946	0.000140538
0.1801	0.877134277	1.036806	0.000138277
0.1802	0.882252844	1.042387	0.000133453
0.1803	0.885865067	1.045711	0.000131292
0.1804	0.88901089	1.046895	0.000126658
0.1805	0.891626329	1.045499	0.000124619
0.1806	0.890658421	1.041241	0.000119659
0.1807	0.889138598	1.034408	0.000117029
0.1808	0.892041626	1.026087	0.000112116
0.1809	0.894955399	1.017444	0.000110096
0.181	0.892496929	1.008478	0.00010524
0.1811	0.888882768	0.999086	0.000102639
0.1812	0.887857826	0.990484	9.75E-05
0.1813	0.88601464	0.983379	9.52E-05
0.1814	0.88195225	0.976608	9.03E-05
0.1815	0.876978189	0.969213	8.81E-05
0.1816	0.868973069	0.961395	8.31E-05
0.1817	0.858292894	0.952832	8.04E-05
0.1818	0.849974274	0.94238	7.54E-05
0.1819	0.842648589	0.929225	7.33E-05
0.182	0.830164521	0.913253	6.85E-05
0.1821	0.814783625	0.894982	6.60E-05
0.1822	0.802523055	0.874925	6.09E-05
0.1823	0.791522999	0.852895	5.87E-05
0.1824	0.778372274	0.829207	5.39E-05
0.1825	0.764704014	0.805525	5.18E-05
0.1826	0.750457204	0.78282	4.70E-05
0.1827	0.734234881	0.760477	4.47E-05
0.1828	0.719319219	0.738466	3.99E-05
0.1829	0.706513013	0.717649	3.81E-05
0.183	0.689841319	0.697818	3.37E-05
0.1831	0.668474343	0.677767	3.16E-05
0.1832	0.648730049	0.656677	2.69E-05

0.1833	0.630953438	0.63422	2.51E-05
0.1834	0.610294526	0.610241	2.09E-05
0.1835	0.587296999	0.584377	1.93E-05
0.1836	0.564262251	0.555891	1.51E-05
0.1837	0.54004459	0.524911	1.33E-05
0.1838	0.516058929	0.492831	9.12E-06
0.1839	0.494803081	0.46032	7.86E-06
0.184	0.472389427	0.427019	4.19E-06
0.1841	0.445863851	0.393662	2.82E-06
0.1842	0.420531185	0.36175	-1.23E-06
0.1843	0.399133463	0.331459	-2.32E-06
0.1844	0.376485118	0.302101	-5.70E-06
0.1845	0.350649544	0.27349	-6.53E-06
0.1846	0.324789077	0.245615	-9.98E-06

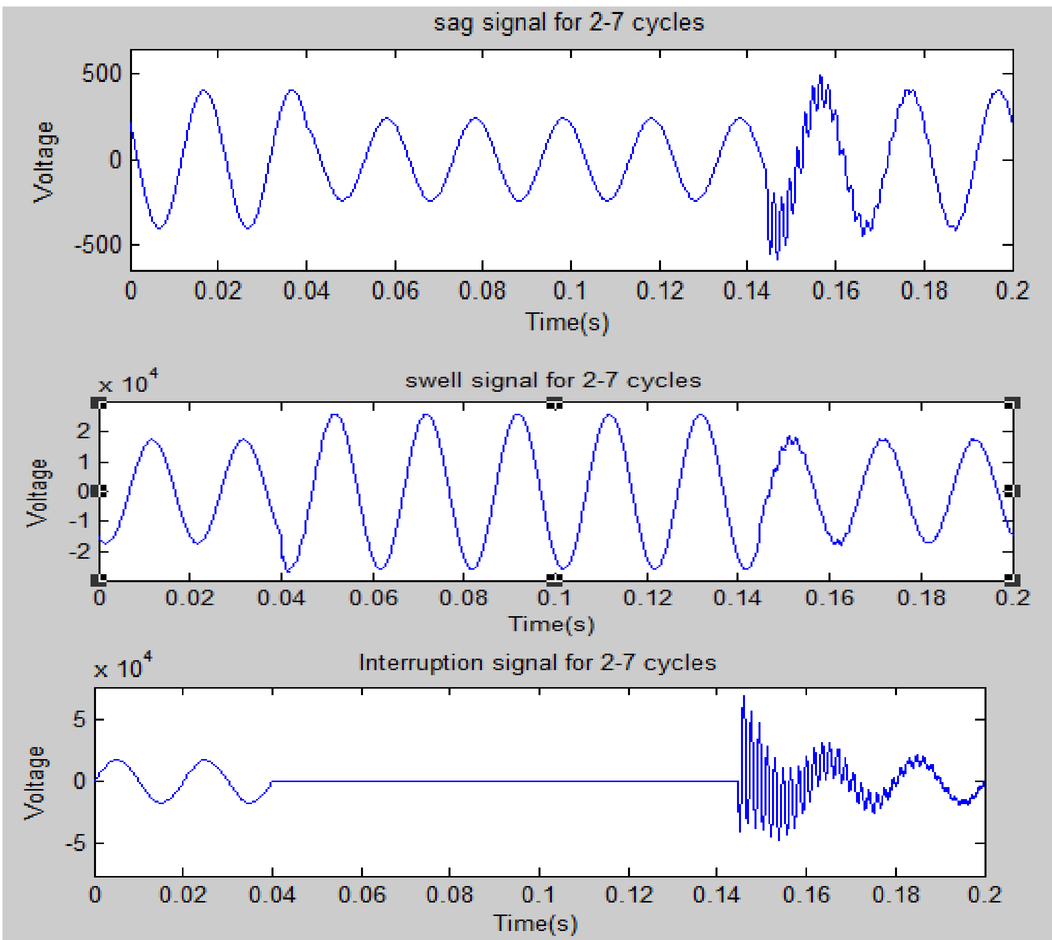

Figure AF 1 Waveform of sag, swell and Interruption for 2-7 cycles

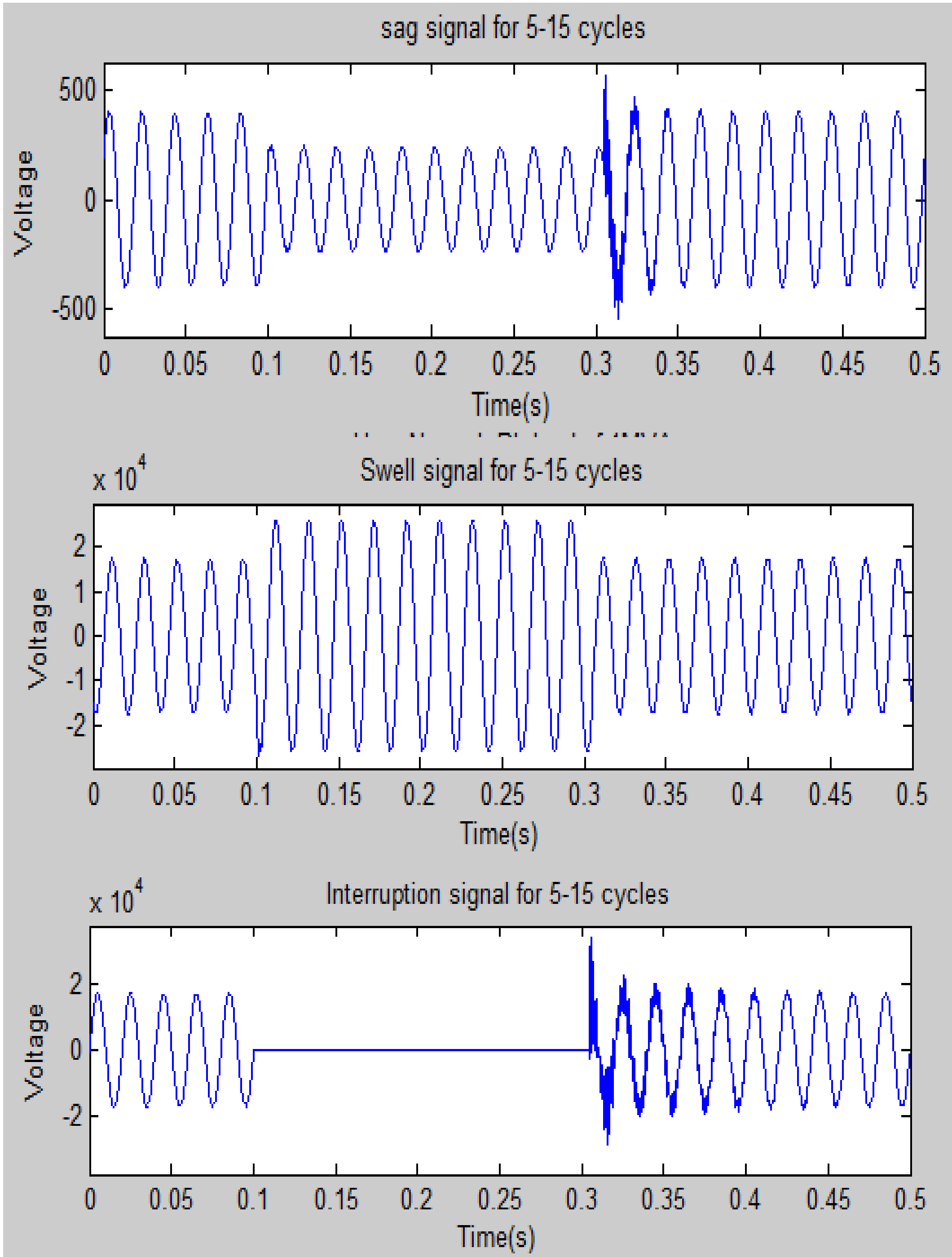

Figure AF 2 Waveform of sag, swell and Interruption for 5-15 cycles

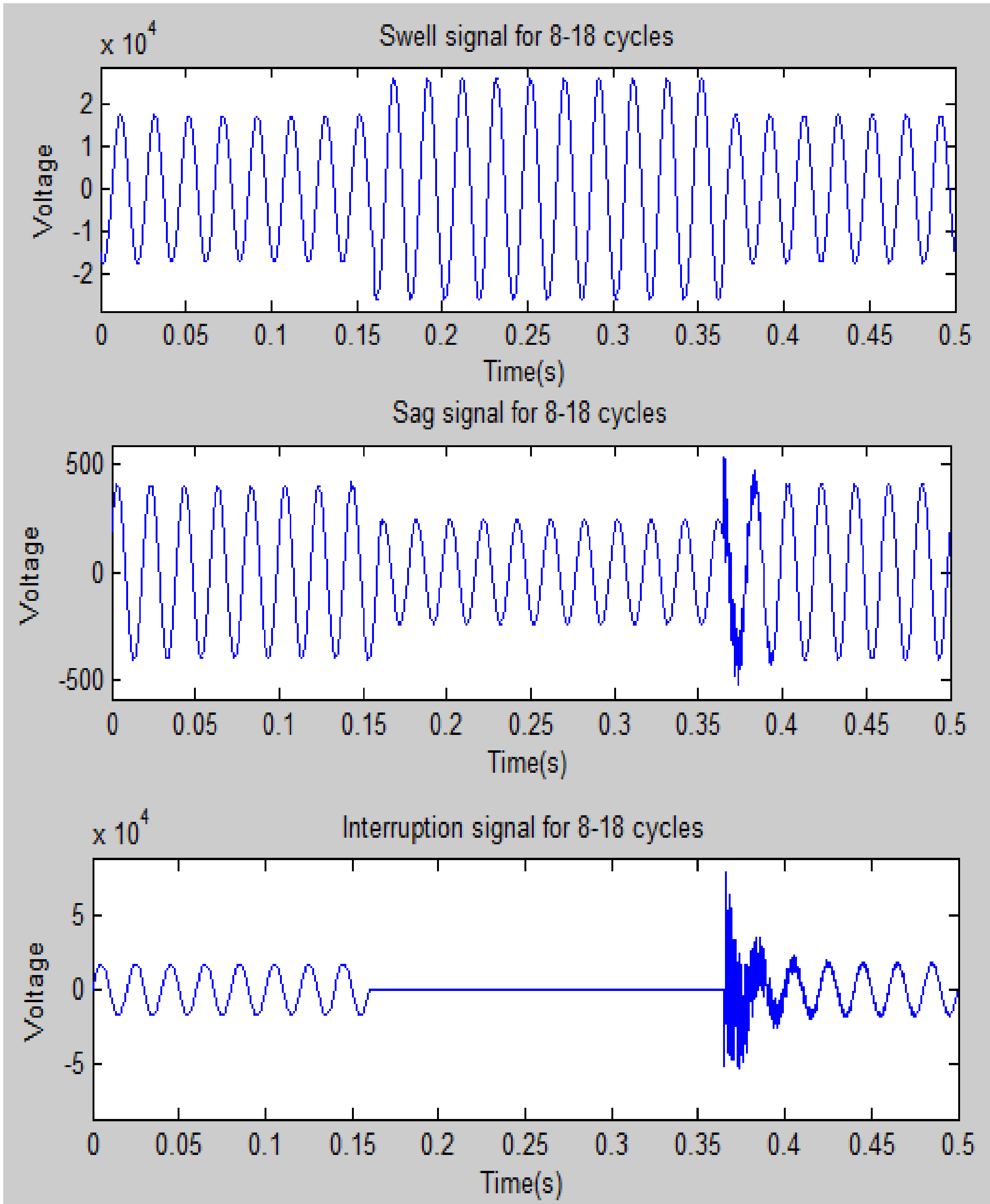

Figure AF 3 Waveform of sag, swell and Interruption for 8-18 cycles