# DETECTION, CLASSIFICATION LOCALISATION, AND CONTROLLING OF VOLTAGE SWELLS USING IUPQC THROUGH WAVELET BASED NEURAL NETWORKS

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**Abstract**

Vast spread of sensitive loads in power systems results in increasing susceptibility to power quality problems, which makes fast detection and classification and localization algorithms a necessity. A new approach for power quality event detection using Wavelet Multi Resolution analysis (MRA)is presented in this paper.

For Classification, Wavelet transform is utilized to extract feature vectors for various PQ disturbances based on the Multi Resolution Analysis (MRA). These feature vectors then are applied to the Neural Network system. For the compensation of the Voltage Swell an Interline Unified Power Quality Conditioner(IUPQC) was employed. The complete was carried out using MATLAB/ Simulink.

**Key words** : *Power Quality (PQ),Wavelet Transforms(WT), Multi Resolution Analysis(MRA), Interline Power Quality Conditioner(IPQC).*

## 1.INTRODUCTION

The recent proliferation of electronic equipment and microprocessor-based controls has caused electric utilities to redefine PQ in terms of the quality of voltage supply rather than availability of power. Recommended Practice for Monitoring Electric Power Quality, has defined a set of terminologies and their characteristics to describe the electrical environment in terms of voltage quality.

Voltage sag is a short-duration decrease of the Root Mean Square (RMS) voltage, lasting from 0.5 cycle to two minutes in duration (fig.1). These events are caused by faults on the power system or by the starting current of a relatively large motor or other large load. Typically for transmission faults, these voltage disturbances last for fractions of a second (≈ 1/10 second), which represents the total fault-clearing time for transmission faults. However, these momentary events can cause a complete shutdown of plant wise processes, which may take hours to return to normal operation(as stated by Dugan 2004).

A **voltage swell** may accompany voltage sag. A voltage swell occurs when a single line-to-ground fault on the system results in a temporary voltage rise on the unfaulted phases (fig.1). Removing a large load or adding a large capacitor bank can also cause voltage swells, but these events tend to cause longer duration changes in the voltage magnitude and will usually be classified as long-duration variations (fig1).

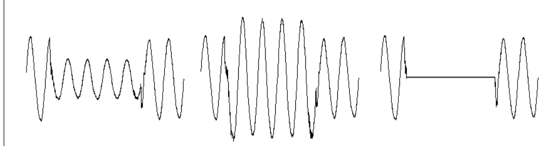



*Figure 1 Example waveforms for short-duration voltage variations*

Electric utilities must assess the present value of the power before taking any quality improvement actions. Therefore, detection of power quality disturbances has become a significant issue. Voltage variation caused by fault conditions and the energization of large loads, where high starting currents are involved. The faults can cause a 'drop', 'rise' and 'supply void' in the supply voltage, are also known as sag, swell and interruptions respectively.

## 2. WAVELET TRANSFORM

A signal can be represented in the frequency domain by its Fourier transform which is written as :

$$F[k] = \frac{1}{N}\sum_{n=0}^{N-1} f[n]\, e^{-j(2\pi kn/N)} \quad , \quad k=0,1,\ldots\ldots N-1 \qquad \ldots\ldots (1)$$

where $f[n]$ is the discrete-time signal. F[k] is its frequency domain representation.

The wavelet transform has such a zooming property. In contrast to the Fourier transform, the wavelet transform does not look for circular frequencies but rather for detail sizes 'a' at a certain time **t**. Instead of detail sizes, we will also speak of "***scale factors***", both notions will be used equivalently[10].

High frequencies correspond to small details and vice versa, thus, when comparing wavelet with Fourier transforms we have to take into account that frequencies and detail sizes are inversely proportional to each other: There exists a constant β such that

$$a = \frac{\beta}{\omega} \quad \text{-------------} \quad (2)$$

Wavelet tool provides a way of analyzing a signal both in time and frequency domains. If we denote $f$ as a function defined on the whole real line, then, for a suitably chosen mother wavelet function $\Psi$, $f$ can be expanded as

$$f(t) = \sum_{k=-\infty}^{\infty} c_k \varphi(t-k) + \sum_{k=-\infty}^{\infty} \sum_{j=0}^{\infty} d_{j,k} 2^{j/2} \psi(2^j t - k)$$

------- (3)

where $\Psi(2^{j/2})$ & $\Psi(2^j\, t\text{-}k)$ are all orthogonal to each other. The coefficients $\boldsymbol{w_{jk}}$ gives information about the behavior of the function $f$ concentrating on the effects of scale around $2^{-j}$ near time $t \times 2^{-j}$. $j$ determines the scale or the frequency range of each wavelet basis function **ψ (t)** and ***k*** determines the time translation. $\mathbf{c_k}$ are called approximation coefficients and , $\boldsymbol{d_{j,k}}$ are called wavelet coefficients[11]. In the above expansion, the first summation gives a function that is a low-resolution or coarse approximation of $f(t)$. For each index $j$ in the second summation, a higher or finer resolution function is added, which adds new details. Generally, the wavelet transform can be represented by filter-bank operations where a series of linear low- and high-pass filters decompose the signals into successive details and approximations components. The filter operations are followed by dyadic down sampling the intermediate output signals, that is, at each level of decomposition every other sample is discarded. This wavelet decomposition of a function is closely related to a similar decomposition (the discrete wavelet transform, DWT) of signal observed in discrete time[14].

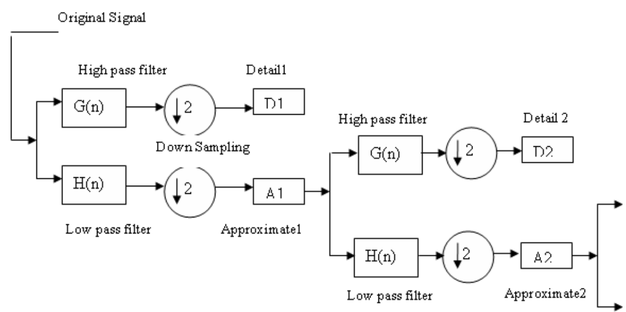



*Fig .2 Implementation of DWT using filter banks.*

Figure 2 shows the tree structure implementation of filter banks for one-dimensional DWT, where $g(n)$ stands for the high-pass filters and $h(n)$ for the low-pass filters and the arrows stand for the down sampling process.

There are some important properties of these filters

- $$\sum_n h(n)^2 = 1 \quad and \quad \sum_n g(n)^2 = 1$$ ............(4)
- $$\sum_n h(n) = \sqrt{2} \quad and \quad \sum_n g(n) = 0$$ ............(5)
- Filter g(n) is an alternating flip of the filter h(n) , which means there is an odd integer N such that,

$$g(n) = (-1)^n h(N - n)$$

..........(6)

Daubechies gives a detailed discussion about the characteristics of these filters and how to construct them. The decomposition procedure starts with passing a signal through these filters. The approximations are the low-frequency components of the time series and the details are the high-frequency components. Multi resolution analysis leads to a hierarchical and fast scheme. This can be implemented by a set of successive filter banks as shown in Fig.2, where h(n) and g(n) are the low-pass and high-pass filters as defined in (4)–(6)**.↓2** means the down sampling with a factor of 2,k is the coefficient index at each decomposition level.

## 3. MULTI RESOLUTION ANALYSIS (MRA)

Considering the filter bank implementation in Fig.3, the relationship of the approximation coefficients and detail coefficients between two adjacent levels are given as using the following equations[2]:

$$cA_j(k) = \sum_n h(2k-n)cA_{j-1}(n) \quad \text{……….(7)}$$

$$cD_j(k) = \sum_n g(2k-n)cA_{j-1}(n) \quad \text{……….(8)}$$

where $cA_j$ and $cD_j$ represent the approximation coefficients and detail coefficients of the signal at level j, respectively. In this way, the decomposition coefficients of MRA analysis can be expressed as,

$$\begin{aligned}[A_0] &\leftrightarrow [cA_1, cD_1] \\ &\leftrightarrow [cA_2, cD_2, cD_1] \\ &\leftrightarrow [cA_3, cD_3, cD_2, cD_1] \\ &\leftrightarrow \ldots\ldots\end{aligned}$$

which correspond to the decomposition of signal x(t) as,

$$\begin{aligned}x(t) &= A_1(t) + D_1(t) \\ &= A_2(t) + D_2(t) + D_1(t) \\ &= A_3(t) + D_3(t) + D_2(t) + D_1(t) \\ &= - - -\end{aligned}$$

where $A_i(t)$ is called the ***approximation*** at level i, and $D_i(t)$ is called the ***detail*** at level i.

Time–frequency analysis was applied to detect the presence of the transients added to voltage signals by any disturbance. These transients can be extracted from the wavelet detail components. The ability of the wavelet transform to detect particular transients in the voltage signals depends on the type of the wavelet family, its order and the level of decomposition, that is, the number of detail components extracted. In wavelet applications, different basis functions were proposed and selected. No single wavelet transform has a statistically significant advantage over other wavelets in performance of PQ classification. In the proposed scheme, the Db4 wavelets were selected as the wavelet basis function for the detection and classification of voltage disturbance. The wavelet analysis block transforms the distorted signal into different time-frequency scales detecting the disturbances present in the power signal. The wavelet transform (WT) uses the wavelet function Ψ and scaling function Φ to perform simultaneously the MRA decomposition and reconstruction of the measured signal. The wavelet function **Ψ** will generate the high frequency components (details) and scaling function Φ will generate the low frequency components (approximations) of the distorted signal.

Discrete Wavelet Transform (DWT) is the basic tool for feature extraction[12]. DWT is the discrete counterpart of the Continuous Wavelet Transform (CWT). The CWT of a continuous time signal x *(t)* is defined as

$$CWT_\psi x(a,b) = \int_{-\alpha}^{\alpha} x(t)\psi^*_{a,b}(t)dt, \qquad a,b \in R, a \neq 0, \quad \text{……….(9)}$$

where,

$$\psi^*_{a,b}(t) = \frac{1}{\sqrt{a}}\psi^*\left[\frac{t-b}{a}\right]. \quad \text{……….(10)}$$

The function $\Psi$ (t) is the mother wavelet, and the asterisk denotes a complex conjugate. ‘a’ and ‘b’ are the scaling and translating parameters respectively. The sampled signal $x_k$ is used to replace the CWT of $x_t$ such that

$$DWT_\psi x(m,n) = \sum_k x_k \psi^*_{m,n}(k), \quad \text{……….(11)}$$

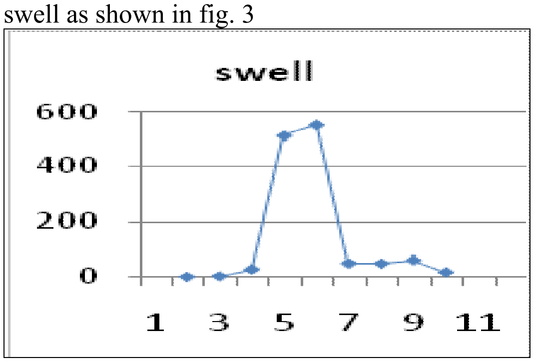
where,

$$\psi^*_{m,n}(k) = \frac{1}{\sqrt{a_0^m}}\psi^*\left[\frac{k - nb_0a_0^m}{a_0^m}\right]. \quad \text{……….(12)}$$

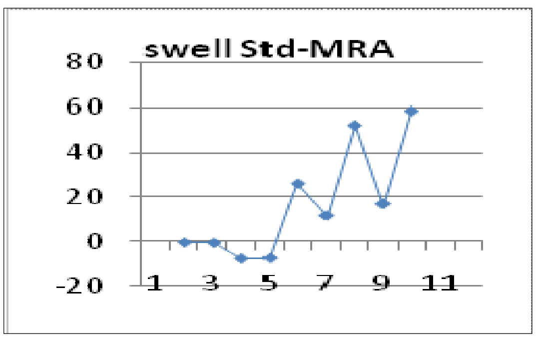
Both the *scaling factor* $a_0^m$ and the *shifting factor* $nb_0a_0^m$ are functions of the integer parameter *m*, where *m* and *n* are scaling and sampling numbers respectively and *m* = 0,1, 2, … By selecting $a_0$ = 2 and $b_0$ = 1 , a representation of any signal $\boldsymbol{x_k}$ at various resolution levels can be developed by using the MRA.

## 4 FEATURE EXTRACTION

Standard deviation multi resolution analysis curve (StdΔMRA) has the ability to quantify the magnitude of variation within the signal. The extracted features help to distinguish one disturbance event from another. MRA can detect and diagnose defects and provide early warning of power quality problems. In power quality problem, the graph of standard deviation of multi resolution analysis is very similar in some cases such as swell, notching, interruption and voltage swell as shown in fig. 3




(a)




(b)

*Fig.3(a),(b)Standard deviation MRA (Std Δ_MRA) Of Voltage Swell*

4.1. WAVELET BASED FEATURE EXTRACTION

In order to reduce the feature dimension, we will not directly use the detail $D_i(t)$ and approximate $A_i(t)$ information for future training and testing[3][7]. Instead, we propose to use the energy at each decomposition level as a new input variable for Back propagation classification. The energy at each decomposition level is calculated using the following equations:

$$ED_{x} = \sum_{j=1}^{N} | D_{ij} |^2 , i = 1 --- l \text{ .......(13)}$$

$$EA_l = \sum_{j=1}^{N} | A_{ij} |^2 \text{ ..........(14)}$$

where i=1,2,.........$l$ is the wavelet decomposition level from level1 to level $l$. N is the number of the coefficients of detail or approximate at each decomposition level. $ED_i$ is the energy of the detail at decomposition level i and $EA_l$ is the energy of the approximate at decomposition level l . In this way, for an $l$ level wavelet decomposition, we construct a ($l$+1) dimensional feature vector for future analysis. Fig.4 shows data flow in the proposed wavelet feature extraction.

The power signal with disturbance when subjected to DWT will generate a discontinuous state at the start and end points of the disturbance duration. For each of the disturbance, the DWT coefficients generated have variations which are used to recognize the various power signal disturbance and thereby classifying the different power quality problems(Fig.4)[7].

By applying DWT, the distorted signal can be mapped into the wavelet domain and represented by a set of wavelet coefficients. There are different wavelets that can be used to decompose the distorted signal and extract the feature vector. Here the Daubechies "**Db4**" wavelet function is used to decompose the signal by DWT. Since maximum energy localization is obtained using db4 and db8 when compared to the other type of wavelets db4 is used. The parameters of the voltage waveforms during Power Quality (PQ) events are statistically different from those that are calculated during an event free time period. This statistical difference is used for effective detection of the PQ events like sag/swell, momentary interruption, harmonics etc… The statistical behavior of the feature vectors is obtained. Local statistical properties of the waveform vary with the PQ events.

Table .1

| PQ disturbances | Class Symbol | Model | Parameters |
|---|---|---|---|
| Pure Sinusoidal | C1 | x(t) = sin(ωt) | |
| Momentary Swell | C2 | x(t) = A(1+α(u(t-$t_1$)-u(t-$t_2$)))sin(ωt) | 0.1≤α≤0.4 |
| Temporary Swell | C3 | x(t) = A(1+α(u(t-$t_1$)-u(t-$t_2$)))sin(ωt) | 0.1≤α≤0.4 |
| Long-term Swell (Over voltage) | C4 | x(t) = A(1+α(u(t-$t_1$)-u(t-$t_2$)))sin(ωt) | 0.1≤α≤0.2 |

VOLTAGE SWELLS

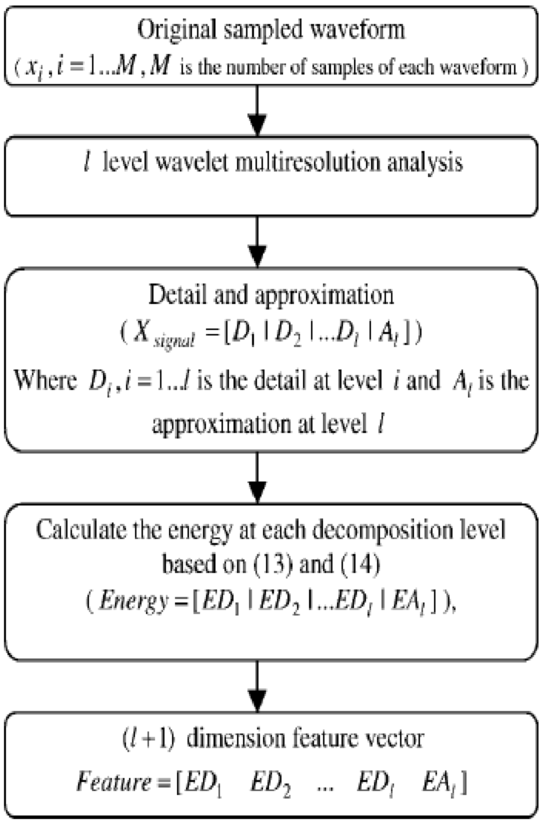



Fig. 4. Wavelet based feature extraction.

## 5. VOLTAGE SWELL CONDITIONS OF POWER QUALITY EVENTS:

Several typical PQ disturbances, especially voltage swells are taken into consideration in this paper. Using MATLAB 7.0.1, the most commonly occurring disturbances are initially simulated. The categories that are simulated are normal sinusoid, voltage swell, further categorized as Momentary, Temporary and long term swell.

## 6 . GENERATION OF VOLTAGE SWELL SIGNALS

These signals generated are sampled at a frequency of 4 kHz. The unique attributes for each disturbance type are used(Table.1) and allowed to change randomly, within specified limits, in order to create different disturbances.

### 6.1. PURE SINUSOIDAL

It is the ideal voltage waveform generated by pure sinusoidal signal. The signal is generated (fig 5) at 50 Hz having 1 p.u magnitude as shown in fig.(5).

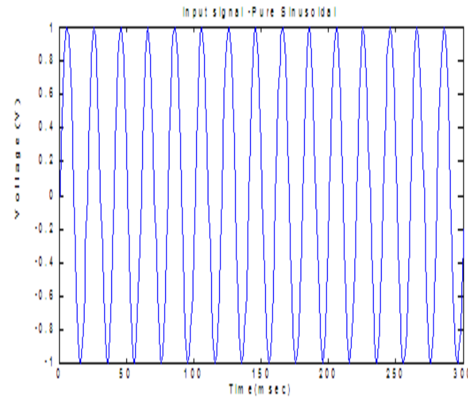


*Fig.5 Pure Sinusoidal Wave form*

### 6.2. VOLTAGE SWELL

Voltage swell is described as a drop of 10-90% of the rated system voltage lasting for half a cycle to one minute. The causes of voltage swell are :

1. Voltage swell are caused by system faults
2. It can also be caused by energisation of heavy loads.

This signal generated in fig.6 (a), (b) are from the model equation

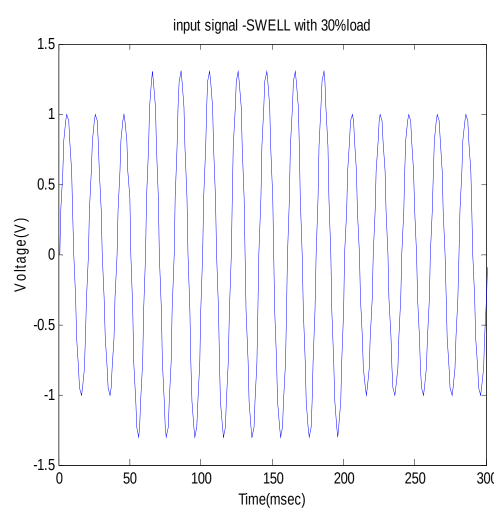
$$\mathbf{x(t) = A(1+\alpha(u(t-t_1)-u(t-t_2)))sin(\omega t)}$$

where, $t_1<t_2$, $u(t) = 1, t \geq 0$

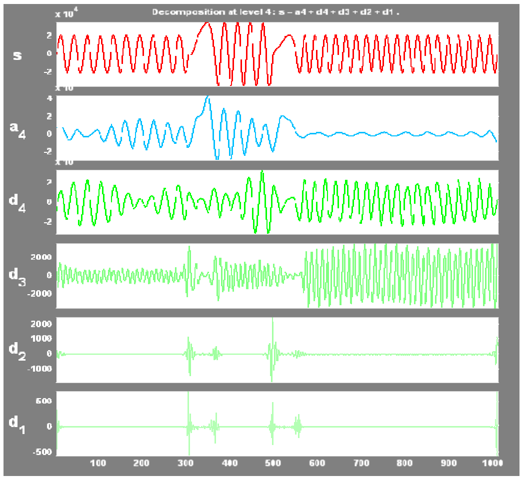
$0.1\leq\alpha\leq0.9; T\leq t_2-t_1\leq 9T$

$= 0, t < 0.$

and the decomposition up to four levels ($a_4$, $d_4$) using Db4.



(a)




(b)

Fig 6. (a) Voltage Swell Signal (b) Decomposed Signal using Wavelet (Db4)

Voltage swell is again classified as Momentaneous, Temporary and long term over voltages depending upon the time duration of the event[4]. The standards of limitations as per IEEE are given in table 2 as follows:

Table 2.
Categories of power quality variation (Voltage Swells) – Institute of Electrical and Electronics Engineers (IEEE) 1159-1995

| Type of Swell | Time duration | Typical amplitude |
|---|---|---|
| Momentaneous swell | 30 cycles to 3 sec | 1.1 p.u to 1.4 p.u |
| Temporary swell | 3 sec to 1 min | 1.1 p.u to 1.4 p.u |
| Long-term Over Voltage | > 1min | 1.1 p.u to 1.2 p.u |

The 10%, 20%, 30% swell disturbance lasting for 15cycles are shown in Fig 7(a),(b),(c) .

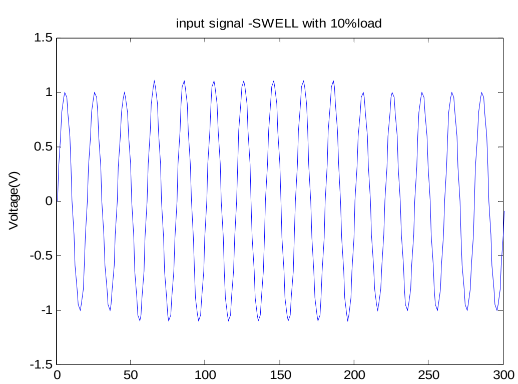



Fig.7.a

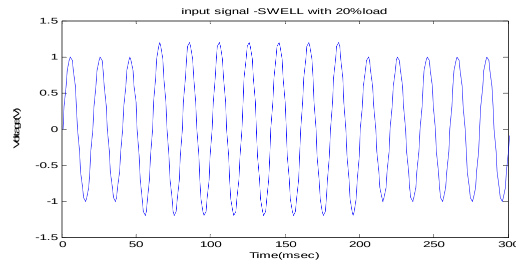



Fig.7.b

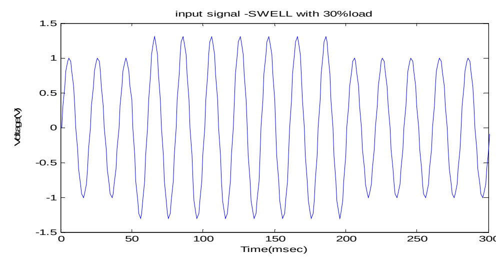



Fig.7.c

*Fig 7 (a),(b),(c) Voltage Swells*

Table .1 VOLTAGE SWELLS (on next page)

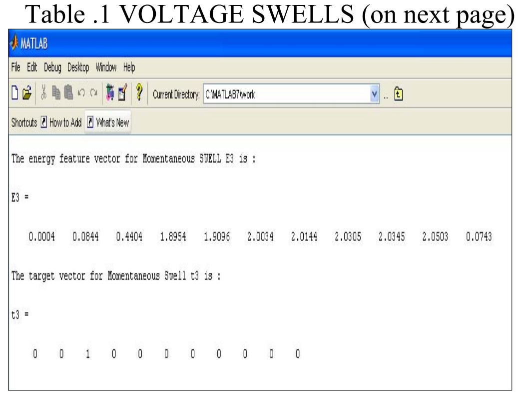



**Fig 8. Feature Extraction & Target vector for the Neural Network.**

## 7.Detection of Voltage Swell :

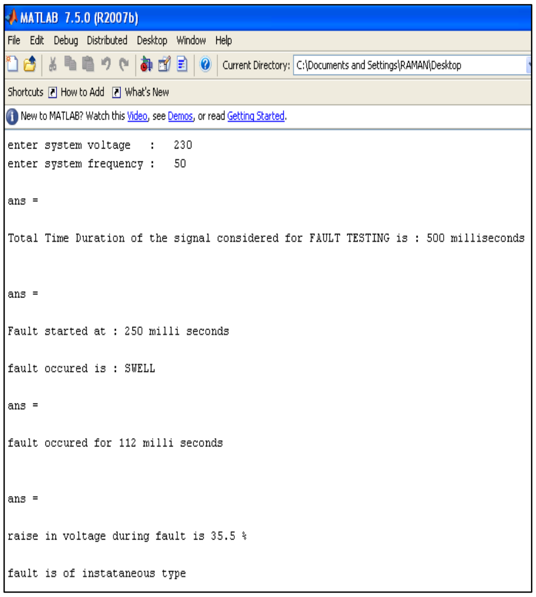



*Fig 9 Detection of Instantaneous Swell*

In fig 9. the detection of Instantaneous type swell was shown, where the fall in voltage is 35.5% and the duration of the fault id 112 msec.

| CLA--SS | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| C1 | 100 | 0 | 0 | 0 |
| C2 | 0 | 80 | 7 | 0 |
| C3 | 0 | 5 | 93 | 1 |
| C4 | 0 | 5 | 2 | 93 |

## 8. ARTIFICIAL NEURAL NETWORK:

ANN's can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges are connections between neuron outputs and neuron inputs. Based on the connection pattern (architecture), ANN's can be grouped into two categories:

* Feed-forward networks, in which graphs have no loops
* Recurrent (or feedback) networks, in which loops occur because of feedback connections.

Generally speaking, feed-forward networks are static, that is, they produce only one set of output values rather than a sequence of values from a given input. Feed- forward networks are memory-less in the sense that their response to an input is independent of the previous network state. Recurrent or feedback networks, on the other hand, are dynamic systems. When a new input pattern is presented, the neuron outputs are computed. Because of the feedback paths, the inputs to each neuron are then modified, which leads the network to enter a new state. Different network architectures require appropriate learning algorithms.

### 8.1. CLASSIFICATION USING BACK PROPAGATION:

A single-layer network of S **logsig** neurons having R inputs is shown below in figure 10. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons[1]. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range –1 to +1. On the other hand, if you want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as logsig).

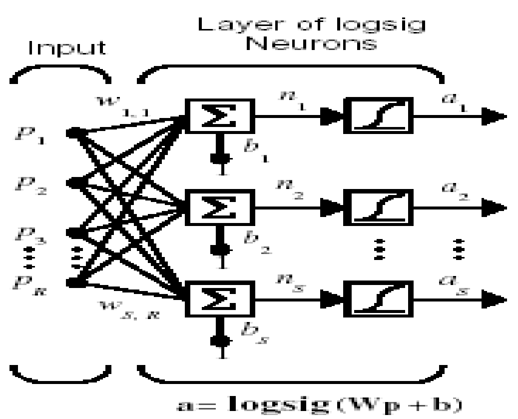



*Fig. 10 Single layer network*

## 9. SIMULATION AND ANALYSIS:

The simulation data was generated in MATLAB based on the model in table 1. All the four classes (C1–C4) of different PQ (Voltage Sag type) disturbances, named undisturbed sinusoid (normal), sag and its different categories. Table I gives the signal generation models and their control parameters. Seventy five cases of each class with different parameters were generated for training and another 25 cases were generated for testing. Both the training and testing signals are sampled at 200 points/cycle and the normal frequency is 50 Hz. Fifteen power frequency cycles which contain the disturbance are used for a total of 300 points. Daubechies4 (Db4) wavelets with four levels of decomposition were used for analysis (*l*=4). Based on the feature extraction shown above, 4-dimensional feature sets for training and testing data were constructed. The dimensions here describe different features resulting from the wavelet transform, that is to say, the total size of the training data or testing data set is 100x4, where 400 comes from 100 cases per class multiplied by 4 classes and 4 is the dimension of the feature size of each case. All data sets were scaled to the range of (1–200) before being applied to Feed-forward back propagation network for training and testing[13].

The results are tabulated for all the 4 events in table 4.

C1 → Pure Sinusoidal
C3 → Temporary Swell
C2 → Momentaneous Swell
C4→ Long-term Swell (over voltage).

Table 3
Simulation results

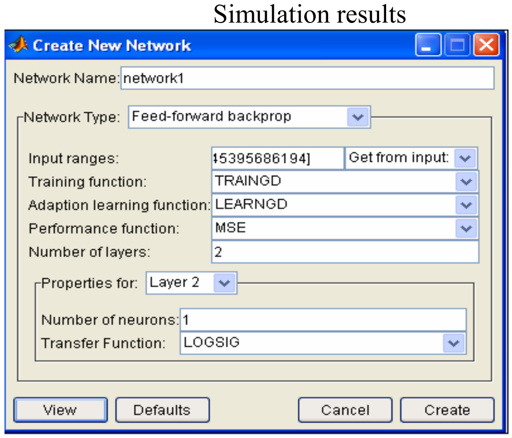



*Fig. 11 Training the BPNN*

## 10. LOCALIZATION OF THE EVENTS USING WAVELET MODULUS MAXIMA (WMM):

Generally speaking, fault location methods can be classified into two basic groups, traveling wave-based schemes and impedance measurement-based ones. Travelling wave schemes can be used either with injecting a certain travelling wave from the locator position or with analyzing the generated transients due to the fault occurrence. Impedance measurement schemes are classified whether they depend on the data from one or both line ends. Each category can be then classified according to the considered line model during the derivation method using either simpler (lumped) models or detailed (distributed parameters) ones. According to travelling wave theory, voltage and current travelling waves appear on the line when fault occurs. The fault generated travelling waves contain sufficient fault information that can be used for high-speed fault identification and line protection[14]. In AC transmission lines, the amplitude of fault generated travelling waves changes with the voltage angles. The pure frequency domain

based methods are not suitable for the time-varying transients and the pure time domain based methods are very easily influenced by noise. The wavelet transform provides a new approach for analyzing time-varying transients. It has the capability of analyzing signals simultaneously in time and frequency domain. Moreover, it can adjust analysis windows automatically according to frequency, namely, shorter windows for higher frequency and vice visa. Hence it is suitable for characteristic identification and travelling wave protection. The results show that the wavelet techniques lead to a new way for the fault identification and the protection.

**10.1. Wavelet Modulus Maxima (WMM):** It can be seen that during fault period, the WMM undergoes sudden changes and it rises to a large value during the fault period and is of low value in absence of fault. By observing the amplitude of WMM, ac fault can be known[15]. In normal operation, WMM is of low value and there are no sudden changes which indicate there is no fault.

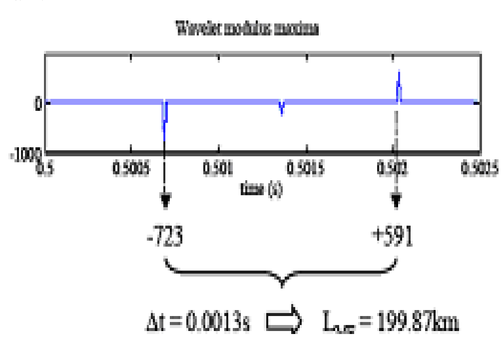
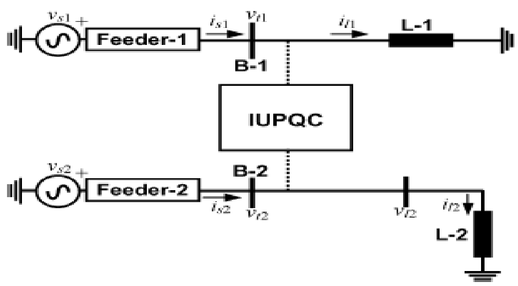



*Fig.12. Application of WMM to Travelling wave of Voltage sag*

## 11. CONTROLLING THE VOLTAGE SWELL USING INTERLINE UNIFIED POWER QUALITY CONDITIONER(IPQC) :

An UPQC consists of a series voltage-source converter (VSC) and a shunt VSC both joined together by a common dc bus. It is demonstrated how this device is connected between two independent feeders to regulate the bus voltage of one of the feeders while regulating the voltage across a sensitive load in the other feeder(fig13). Since the UPQC is connected between two different feeders (lines), this connection of the UPQC will be called an interline UPQC (IPQC)[16]. The structure, control and capability of the IPQC are discussed in this paper.



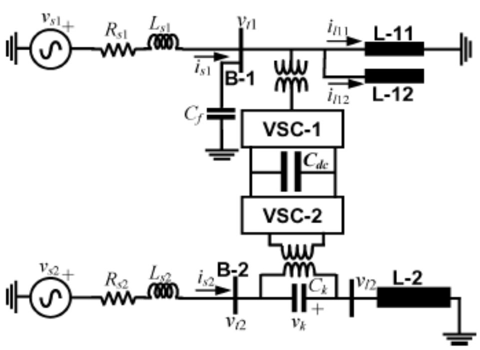




*Fig 13 Single line diagram of an IPQC*
*Fig. 14 Typical IUPQC connected in a distributed System in a distribution System*

The performance of the IPQC has been evaluated under various disturbance conditions such as voltage swell in either feeder, fault in one of the feeders and load change. It has been shown in fig.14 that in case of a voltage swell, the phase angle of the bus voltage in which the series connected VSC plays an important role as it gives the measure of the reactive power required by the load. The IPQC can mitigate a voltage swell of about 0.35 p.u. (9 kV to 12.5 kV) in Feeder-1(fig 16) and 0.6 p.u. (i.e.,9 kV to 11 kV) in Feeder-2 for long duration(fig. 16). In the IPQC configuration discussed in this paper, the sensitive load is fully protected against sag/swell and interruption. The sensitive load is usually a part of a process industry where interruptions result in severe economic loss . Therefore, the cost of the series part of IPQC must be balanced against cost of interruptions based on past reliability indices (e.g., CAIFI,CAIDI). It is expected that a part of IPQC cost can be recovered in 5–10 years by charging higher tariff for the protected line. Furthermore, the regulated bus B-1 can supply several customers who are also protected against sag and swell. The remaining part of the IPQC cost can be recovered by charging higher tariff to this class of customers. Such detailed analysis is required for each IPQC installation.

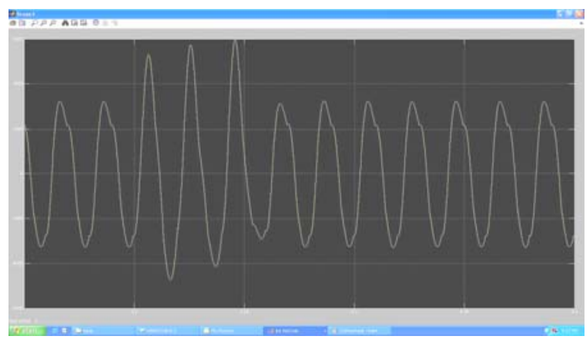


*Fig 15 Voltage swell applied at feeder 1 without IPQC*


*Fig 16 Compensated Voltage Signals at feeder1 &2 with IPQC*

## 12. CONCLUSIONS:

In this paper one type of voltage signal disturbance, called voltage swell was detected using wavelet decomposition technique. For different types of voltage swell conditions like momentary swell, temporary swell and long term over voltage swell, the classification was done with the help of feature extraction using Multi Resolution Analysis (MRA) and Feed Forward Back Propagation Neural Network Training Algorithm. The most important part of the work is to locate the fault being accurately done using Travelling Wave method and Wavelet Modulus Maxima (WMM). After the process of detection, classification and localization, it is essential to control or compensate the voltage signal disturbance using a proper controlling device called Unified Power Quality Conditioner (UPQC). On the distribution side two feeders F1 & F2 were considered. In feeder1, Voltage Swell has been generated. The controlling has been observed in both the feeders using Interline Unified Power Quality Conditioner (IPQC). All the work was carried out using MATLAB/Simulink (Wavelet and Neural Network Toolboxes). The lines are protected satisfactorily from swell disturbances by using IPQC.

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