

Wavelet and ANN based approach for Classification of Power Quality Disturbances using LabVIEW

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Abstract: In today's power system monitoring of power quality is critical. The ambition of the monitoring method is to discover the true source of Power Quality (PQ) problem. Classifying various forms of PQ disturbances is an important stage in the monitoring process. PQ is defined as the concept of powering and grounding electronic equipment in a manner suitable for the operation of that equipment and compatible with the premise wiring system and other connected equipment. There are several different sorts of power quality issues that might harm end-user devices. As a result, an examination of these power quality issues is required. All negative conditions would be encountered by the electrical user if the electric supply had low power quality. In this research paper, the PQ disturbances which are considered under study are voltage sag, voltage swell, and interruption. With the help of MATLAB Simulation three phase voltage signals are captured and given as an input to the algorithm develop in LabVIEW environment. The captured voltage signals are processed in LabVIEW using wavelet transform and math-script tool is used for feature extraction. Statistical parameters are calculated from the Wavelet Analysis as a features. A feature vector is created from the extracted features. This feature vector is further applied for training purpose & testing purpose of the ANN classifier to classify the type of PQ disturbance.

Keywords: Power Quality Disturbances, Discrete Wavelet Transform, Artificial Neural Network

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I. INTRODUCTION

Electronic equipment is now employed in almost all industries and commercial electrical consumers' regular operations. Power Quality has been disrupted as a result of the use of Power Electronics equipment in power systems, as well as the increased use of various time-varying and typical loads at the consumer end. Some of the examples of PQ disturbances are voltage sag, voltage swell, harmonics, inter-harmonics, voltage fluctuations, transient oscillations, transient over voltages, interruptions, and voltage imbalance. Problems regarding PQ can lead to equipment malfunctioning, failure, or disoperation, as well as financial issues. To prevent losing electricity and money, it is critical to reduce these disturbances. Only by precisely detecting and classifying the individual disturbance is it feasible to mitigate it. As a result, it is vital to regularly monitor power system data in order to properly mitigate the situation. As a result, developing an efficient PQ monitoring system will aid in better understanding and diagnosing the source of PQ problems. This study describes a approach based on wavelet and ANN for power quality disturbance categorization developed in the LabVIEW environment.

II. POWER QUALITY DISTURBANCES

The quality of energy is becoming increasingly important to both electric companies and end customers. The term "power quality" has been one of the most commonly used buzzwords in the power industry since the late 1980s.

Depending on one's point of view, there can be many distinct definitions for power quality. For example, a utility can define energy quality as reliability and claim that its system is 99.98 percent dependable. In this spirit, regulatory authorities routinely set criteria. Power quality is defined by a load equipment maker as the characteristics of the power supply that allow the equipment to function properly.

Any power problem manifested in voltage, current, or frequency deviations that results in failure or mis-operation of customer equipment.

Voltage Sag: A sag is a decrease to between 0.1 and 0.9 pu in rms voltage or current at the power frequency for durations from 0.5 cycle to 1 min." Some of the causes of voltage sag are Switching ON large loads in one instance, Direct online starting of large motors, Electrical short circuit, Energizing higher-capacity power transformer, Arcing fault in the system, Fault on the Transmission network. In general, sag causes end-user equipment to malfunction, such as PLCs, Process controllers, adjustable speed drives, illumination device flickering, and motor performance reduction.

Voltage Swell: "A swell is defined as an increase to between 1.1 and 1.8 pu in rms voltage or current at the power frequency for durations from 0.5 cycle to 1 min." Heavy load is turn off. Faulty condition at various point at A.C distribution system, energizing of large capacitor bank are some of the causes of voltage swell. Due to overheating, it can cause control problems and hardware failure in the equipment, which can lead to shutdowns. Electronics and other sensitive equipment are vulnerable to voltage swell damage.

Interruption: "An interruption occurs when the supply voltage or load current decreases to less than 0.1 pu for a period of time not exceeding 1 min." Equipment failures Control malfunction, power system faults, insulation failure, lightning insulator, and flashover are all examples of interruption causes.

Different characteristics and categories of Electromagnetic Phenomenon of Power System is shown in Table 2.1.

TABLE 2.1- Characteristics and Categories of Power System Electromagnetic Phenomena

| Categories | Typical spectral content | Typical duration | Typical voltage magnitude |
|--------------------------------|--------------------------|------------------|---------------------------|
| 1.0 Transients | | | |
| 1.1 Impulsive | | | |
| 1.1.1 Nanosecond | 5-ns rise | <50 ns | |
| 1.1.2 Microsecond | 1- μ s rise | 50 ns–1 ms | |
| 1.1.3 Millisecond | 0.1-ms rise | >1 ms | |
| 1.2 Oscillatory | | | |
| 1.2.1 Low frequency | <5 kHz | 0.3–50 ms | 0–4 pu |
| 1.2.2 Medium frequency | 5–500 kHz | 20 μ s | 0–8 pu |
| 1.2.3 High frequency | 0.5–5 MHz | 5 μ s | 0–4 pu |
| 2.0 Short-duration variations | | | |
| 2.1 Instantaneous | | | |
| 2.1.1 Interruption | | 0.5–30 cycles | <0.1 pu |
| 2.1.2 Sag (dip) | | 0.5–30 cycles | 0.1–0.9 pu |
| 2.1.3 Swell | | 0.5–30 cycles | 1.1–1.8 pu |
| 2.2 Momentary | | | |
| 2.2.1 Interruption | | 30 cycles–3 s | <0.1 pu |
| 2.2.2 Sag (dip) | | 30 cycles–3 s | 0.1–0.9 pu |
| 2.2.3 Swell | | 30 cycles–3 s | 1.1–1.4 pu |
| 2.3 Temporary | | | |
| 2.3.1 Interruption | | 3 s–1 min | <0.1 pu |
| 2.3.2 Sag (dip) | | 3 s–1 min | 0.1–0.9 pu |
| 2.3.3 Swell | | 3 s–1 min | 1.1–1.2 pu |
| 3.0 Long-duration variations | | | |
| 3.1 Interruption, sustained | | >1 min | 0.0 pu |
| 3.2 Undervoltages | | >1 min | 0.8–0.9 pu |
| 3.3 Overvoltages | | >1 min | 1.1–1.2 pu |
| 4.0 Voltage unbalance | | Steady state | 0.5–2% |
| 5.0 Waveform distortion | | | |
| 5.1 DC offset | | Steady state | 0–0.1% |
| 5.2 Harmonics | 0–100th harmonic | Steady state | 0–20% |
| 5.3 Interharmonics | 0–6 kHz | Steady state | 0–2% |
| 5.4 Notching | | Steady state | |
| 5.5 Noise | Broadband | Steady state | 0–1% |
| 6.0 Voltage fluctuations | <25 Hz | Intermittent | 0.1–7% 0.2–2 Pst |
| 7.0 Power frequency variations | | <10 s | |

NOTE: s = second, ns = nanosecond, μ s = microsecond, ms = millisecond, kHz = kilohertz, MHz = megahertz, min = minute, pu = per unit.

III. WAVELET TRANSFORM

A wavelet transform is the breakdown of a signal into a series of fundamental functions consisting of contractions, expansions, and translations of a mother function (t) (WT).

One of the mathematical functions that divides a continuous-time signal or function into scale components is the wavelet transform. Each scale component is usually given a frequency range. Each scale component's resolution can then be matched to its scale.

Discrete Wavelet Transform:

The DWT assessment is split into two parts. The wavelet coefficients $hd(n)$ and $gd(n)$ are calculated initially (n). These coefficients represent the supplied signal X in the wavelet domain (n). The second stage entails using these coefficients to calculate both the approximated and detailed versions of the original signal, which are referred to as $cA1(n)$ and $cD1(n)$, respectively.

$$cA_1(n) = \sum_k S(n).h_d(-k + 2n) \quad 1$$

$$cD_1(n) = \sum_k S(n).g_d(-k + 2n) \quad 2$$

Where $hd[n]$ is the low pass filter's impulse response, $gd[n]$ is the high pass filter's impulse response, $X(n)$ is the discretized original signal, and $cA1(n)$ is the approximate coefficient of level 1 decomposition/output of the first LPF.

$cD1(n)$ = Level 1 decomposition detail coefficient/first HPF output

We may find the nth decomposition level coefficient in this fashion, starting with the first stage approximation and detailed coefficient.

TABLE 3.1- Frequency Bands of DWT Coefficients at different levels

| Decomposition Level | Frequency Band (Hz) |
|---------------------|---------------------|
| d1 | 10000-5000 |
| d2 | 5000-2500 |
| d3 | 2500-1250 |
| d4 | 1250-625 |
| d5 | 625-312.5 |
| d6 | 312.5-156.25 |
| a5 | 156.25-0 |

IV. LabVIEW

Full form of LabVIEW is “Laboratory Virtual Instrumentation Engineering Workbench”. It is a National Instruments development software that allows you to interact with measurement and control gear, do data analyses, discuss results, and distribute systems quickly and cost-effectively. It is built on graphical programming approaches, which allow for visual expressions, text spatial layouts, and graphic symbols. The software is built around a block diagram (a graphical programme development tool) and a front panel (a user-interactive visual interface made up of switches and panels).

In this research work, we have used LabVIEW Software for Signal Processing and Feature Extraction purpose. We have used Discrete Wavelet transform for signal processing with the help of Multiresolution Block present in Electrical Tool Kit of LabVIEW. And we have used Math-script block for extracting the features.

V. ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network is a network created using artificial neurons (ANN). These neurons are connected in the same way that biological neurons are. The neural network can be used to create an adaptable system that can change its behaviour in response to data coming in and out of the network. An ANN can be used for specialised applications like data classification and pattern recognition via learning. In our research work, we have utilised ANN to distinguish voltage sag and swell waveforms and classify them accordingly. A training algorithm is a set of learning principles that can be used to train a neural network. Basic back-propagation is a training algorithm with several drawbacks, such as the longer training time. However, because to its popularity,

this algorithm is undergoing significant development in order to converge the training as quickly as feasible. The back-propagation algorithm was made faster by using optimization techniques such as the Levenberg–Marquardt algorithm, conjugate gradient method, and effective back-propagation algorithm. Some networks can be trained using data generated for training, and samples can be used as an input vector for the network. The network's number of neurons can be gradually raised while training it to produce the desired output. Some neurons and 2 hidden layers will make up the network. The remaining samples can then be utilised for validation and testing. The average squared difference between the output and the target can be used to characterise training performance. 80% of data for training purpose and 20% data for testing purpose is used. The training procedure will be completed when the error value is sufficiently small. A trained network will be built after the training procedure is completed. The accuracy which we have obtained after building a network is 100%.

VI. PROPOSED METHODOLOGY

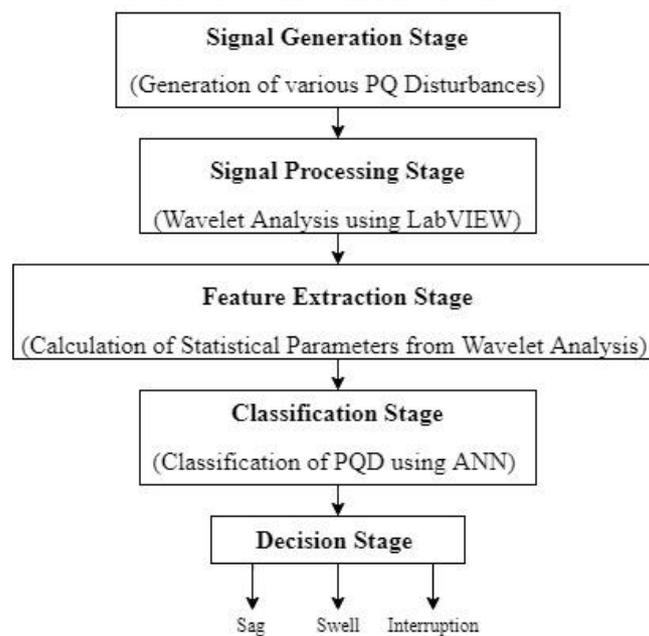


FIG 6.1- Proposed Methodology

Explanation of all the stages of block diagram shown in fig 6.1 is given below

Signal Generation Stage

In this stage with the help of various MATLAB Simulink Models, Power Quality Disturbances such as Sag, Swell, and Interruption are generated.

Signal Processing Stage

Signal processing algorithm is developed in LabVIEW environment. Signals generated in MATLAB are used as input to Wavelet Analysis. The Discrete Wavelet Transform is a prominent signal processing technique that we have utilised to extract features.

Feature Extraction Stage

Features extracted for classification of PQ Disturbances are max, mean, median, variance, standard deviation, skewness, kurtosis and Energy. Discrete Multi Resolution Wavelet Transform is used for feature extraction.

Classification Stage

The classification result accuracy is produced using Artificial Intelligence (AI). Extracted features from signal processing techniques are given to the AI classifier. AI classifiers that we are going to use as a decision-making mechanism is Artificial Neural Network. Training and testing process of ANN classifier is done for accurate classification ANN classified the three PQD

Decision Stage

The three PQ disturbances like sag, swell, interruption are classified successfully

VII. SYSTEM UNDER STUDY

In this research paper, PQ Disturbances such as sag, swell and interruption are generated using different MATLAB Simulink Models

Models and their configuration for respective PQ Disturbance generation are given below:

Table 7.1- Configuration of system under study

| BLOCK NAME | PARAMETERS |
|---------------------|-----------------------|
| 3-Phase Source | 11kV, 400V, 50Hz |
| 3-Phase Transformer | 11kV/400V, 50Hz, 1MVA |
| RL Load | 100 var, 400V, 50Hz |
| Fault Resistance | 1ohm |
| Breaker Resistance | 0.001ohm |
| Sampling Frequency | 10000 Hz |

Generation of Voltage Sag

The system under study is simulated in MATLAB Simulink environment. A three phase to ground fault is created at 11kV bus in order to generate the three-phase balance voltage sag. A three phase to ground fault is applied at 0.3 sec and the fault is cleared at 0.7 sec during this duration a voltage sag is obtained at 11kV and 0.4kV buses. The magnitude of this voltage sag is varied by varying the fault resistance and in order to generate different cases the fault inception angle is varied by varying the fault creation instant. The voltage sag propagates downstream from the 1 MVA transformer to the load through the 11 kV/0.4 kV. Figure 7.1 shows the voltage sag model developed in MATLAB. Voltage sag waveform magnitude often provided in RMS waveform and instantaneous for better visualisation in power quality investigations, as shown in fig 8.1.

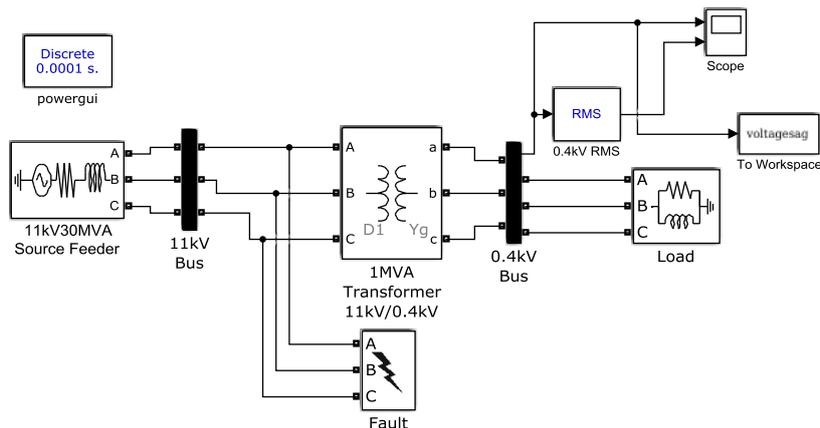


FIG 7.1- Sag Model

Generation of Voltage Swell

The system under study is simulated in MATLAB Simulink environment. Programmable voltage source is used to create three phase voltage swells. In this block we can program the time variation for the amplitude, phase of the fundamental component of the source. Swell is created at 0.3 sec and cleared at 0.7 sec during this duration voltage sag is obtained at 0.4kV bus. The magnitude of this voltage is varied with the help of programmable voltage source. Here the voltage swell propagates downstream through the 0.4 kV feeder to the load. Figure 7.2 shows the voltage swell model developed in MATLAB. Voltage swell waveform magnitude is often provided in RMS waveform and instantaneous for better visualization in power quality investigations, as shown in fig 8.2.

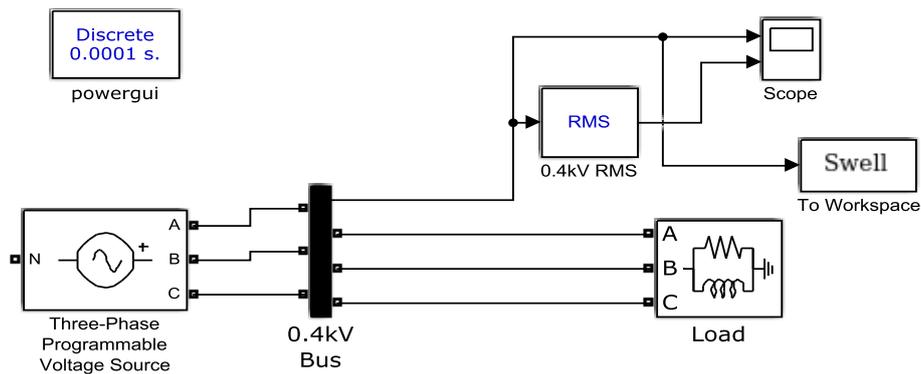


FIG 7.2- Swell Model

Generation of Interruption

The interruption with the opening of switchgear at 11kV/0.4 kV feeder lines between 0.3 and 0.7 seconds is generated using the Simulink model depicted in figure 7.3. The 11kV/0.4 kV bus is seen to be interrupted at all phases. The low breaker resistance of 0.001 between the three lines is the reason for this. The interruption waveform is frequently given as RMS waveform and instantaneous for improved visualisation in power quality investigations (fig 8.3).

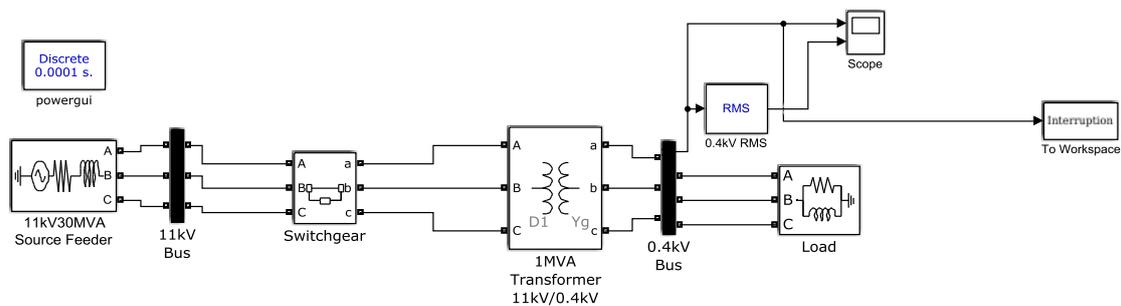


FIG 7.3- Interruption Model

VIII. SIMULATION RESULTS

Sag

PQDs such as voltage sag, voltage swell, and voltage interruptions can be modelled by simulating the system in the MATLAB Simulink environment. A three-phase symmetrical fault is injected into the system to cause the voltage sag. During the fault duration of 0.3 seconds, a voltage sag is obtained and cleared at 0.7 seconds. For one second, the simulation is executed. The amplitude of voltage sag should be modified by changing the fault resistance to provide the data needed for training and testing the classifier. The voltage sag waveform caused by a three-phase failure with a 90% sag is shown in Figure 8.1.

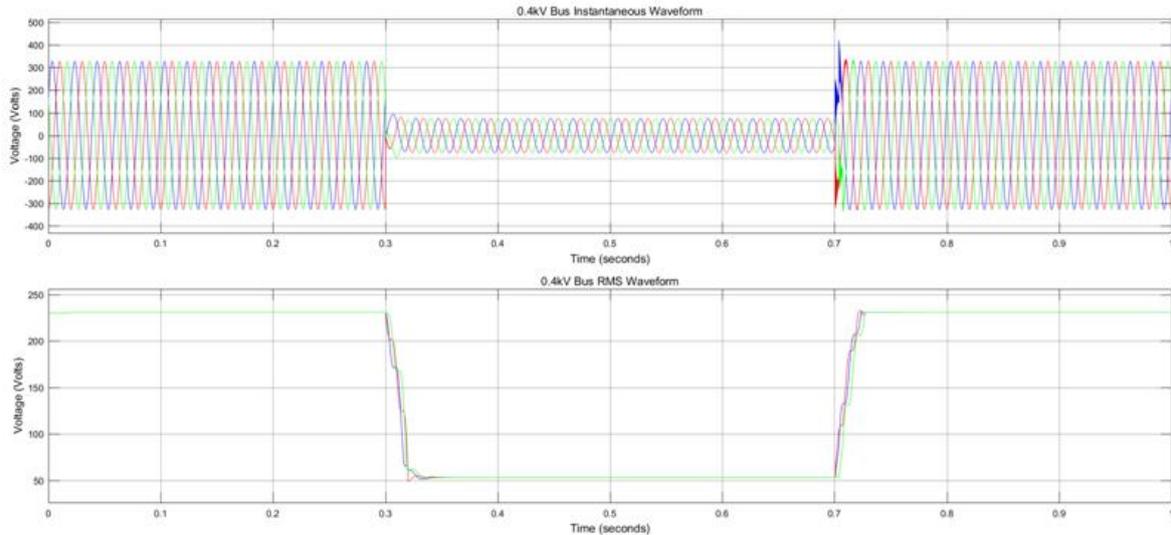


FIG 8.1- Voltage Sag Waveform developed in MATLAB

Swell

The voltage swell is achieved by programmable source. The voltage swell lasts 0.3 seconds and terminates at 0.7 seconds. For 1 second, the simulation is run. The magnitude of voltage swell is adjusted by adjusting the programmable block parameters to supply the data needed to train and assess the classifier. Figure 8.2 depicts the voltage swell waveform produced which has 20 percent swell.

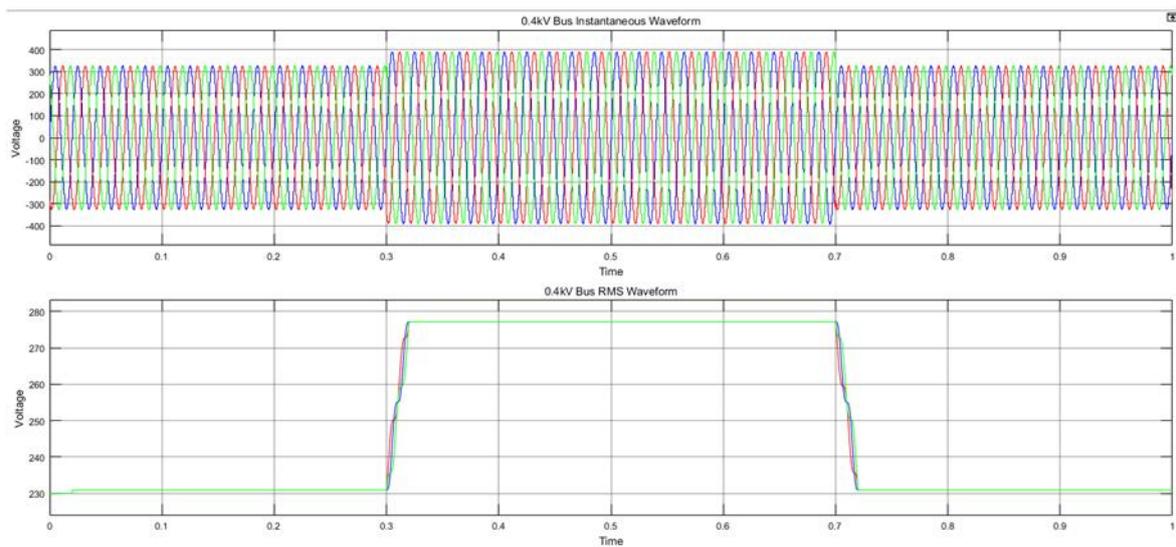


FIG 8.2- Voltage Swell Waveform developed in MATLAB

Interruption

The voltage interruption is achieved by briefly interrupting the supply with three-phase circuit breakers. We experience a voltage interruption when the circuit breaker is turned off for 0.3 seconds and then turned back on for 0.7 seconds. The simulation takes 1 second to complete. Different voltage interruption scenarios are constructed by changing the instance of the event in order to obtain the data needed to train and test the classifier. Figure 8.3 shows the voltage interruption waveform caused by breaker action.

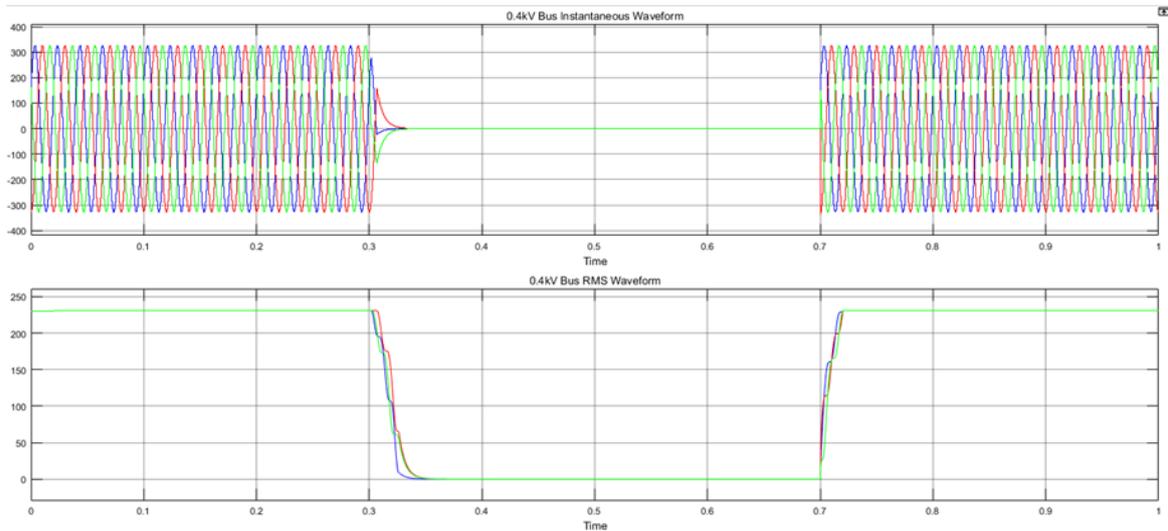


FIG 8.3- Interruption Waveform developed in MATLAB

Wavelet Analysis Algorithm Developed in Lab VIEW

Data Generated in MATLAB Simulink is given as input one by one for Sag, Swell and Interruption to Wavelet Analysis Algorithm and we have obtained respective output

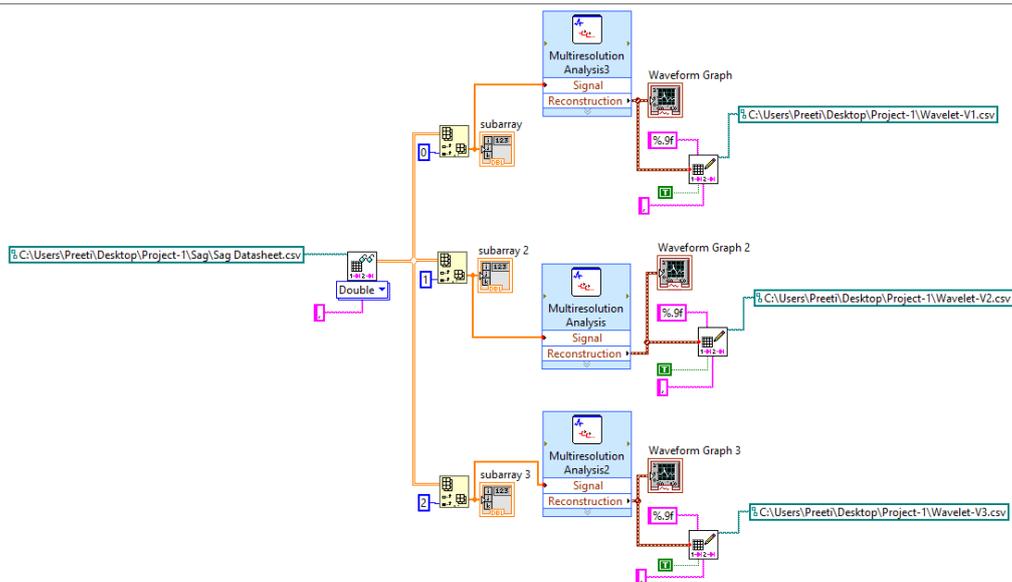


FIG 8.4- Wavelet Analysis Algorithm developed in LabVIEW

In the algorithm shown in Fig 8.4, sampling frequency of voltage signal in 10kHz in the wavelet analysis we have decomposed the signal using db4 mother wavelet upto 6th level. The output from this block is plotted on waveform graph. The waveform graph data is written on excel sheet. This Algorithm is common for sag, swell and interruption. In further procedure we only need to change the input excel sheet data.

Waveforms of 6th level from Wavelet Analysis for Sag, Swell and Interruption are given below

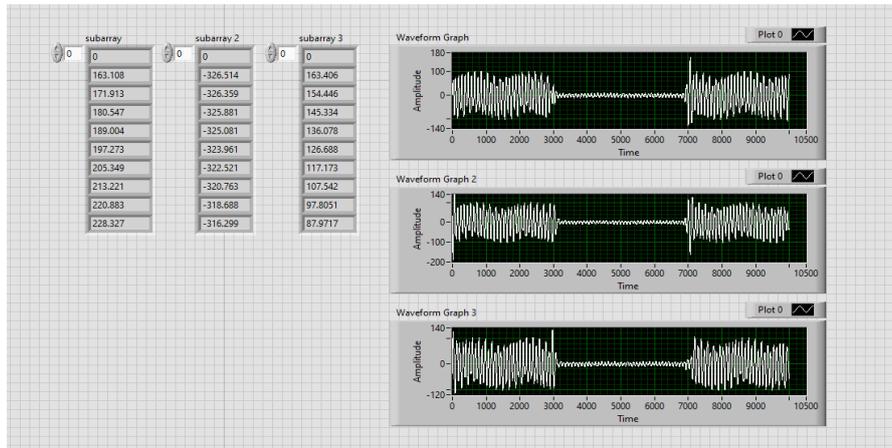


FIG 8.5- Detailed coefficient waveform of 6th level obtained from the Wavelet Analysis of voltage sag signal in Lab VIEW

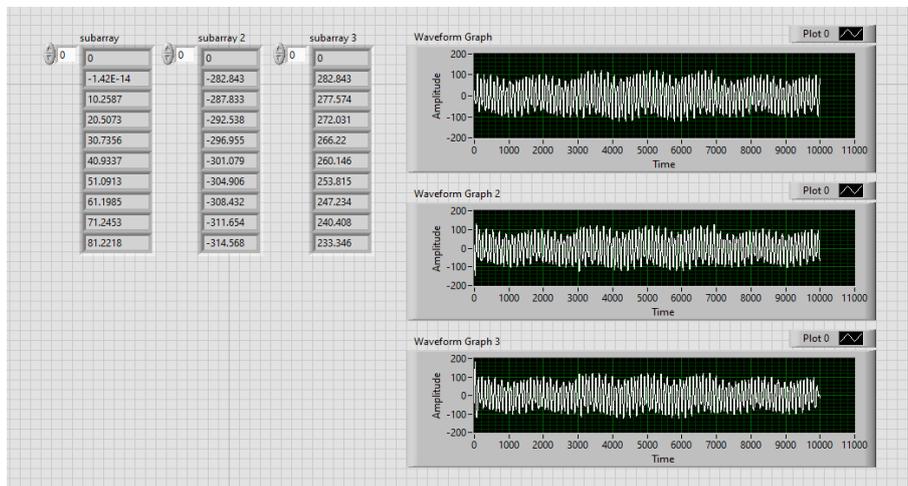


FIG 8.6- Detailed coefficient waveform of 6th level obtained from the Wavelet Analysis of voltage swell signal in Lab VIEW

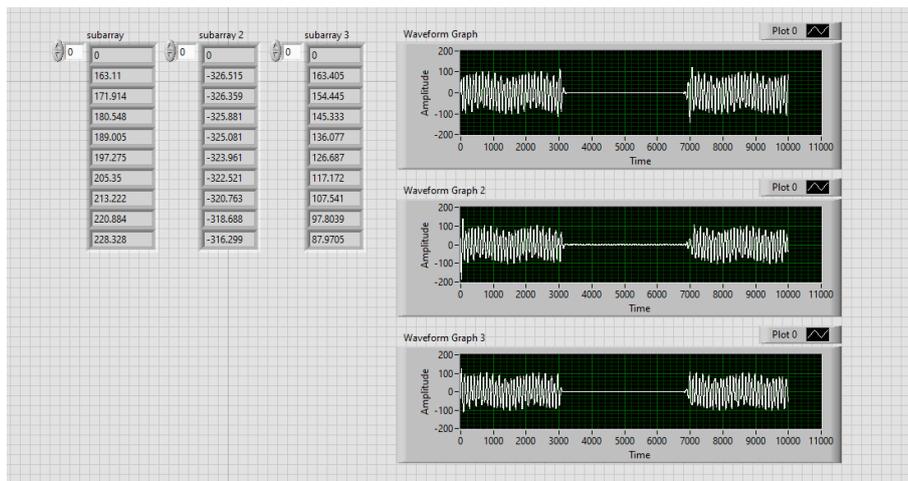


FIG 8.7- Detailed coefficient waveform of 6th level obtained from the Wavelet Analysis of voltage interruption signal in Lab VIEW

This wavelet decomposed signals are used for feature extraction. The frequency that corresponds to voltage sag, voltage swell, and voltage interruption occurrences is in the fifth and sixth decomposition levels, according to the wavelet analysis. Hence, the data corresponding to d5 & d6 detailed coefficient is used for feature extraction.

Data Generated in form of excel sheet from Wavelet Analysis is given as input one by one for Sag, Swell and Interruption to Feature Extraction Algorithm and we have obtained respective output. This output is further used for classifying PQD's.

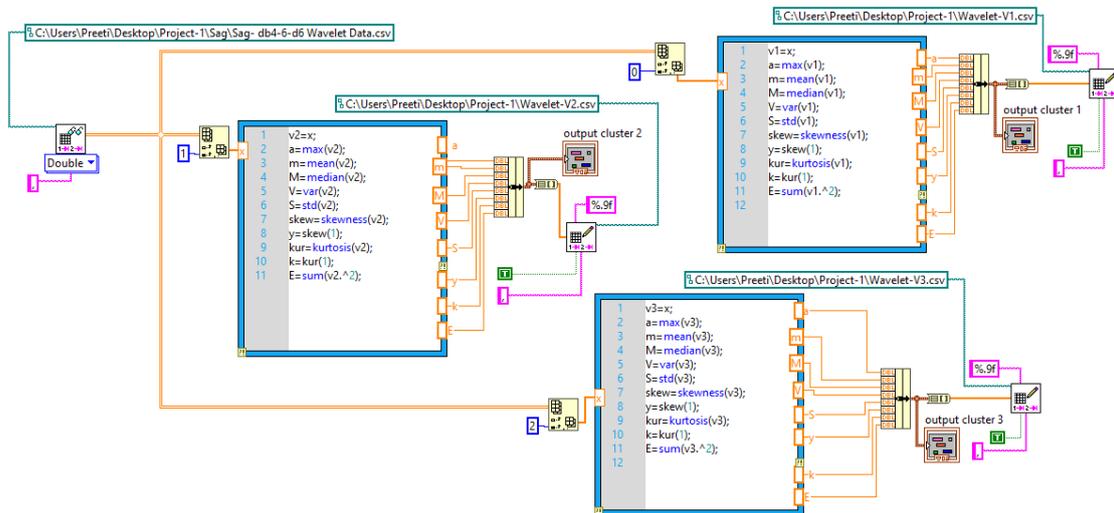


FIG 8.8- Feature Extraction Algorithm developed in Lab VIEW

| output cluster 1 | output cluster 2 | output cluster 3 |
|------------------|------------------|------------------|
| a | a | a |
| 161.674 | 126.083 | 131.939 |
| m | m | m |
| -0.155424 | 0.168508 | -0.0130846 |
| M | M | M |
| 0.0408068 | 0.0965842 | 0.118571 |
| V | V | V |
| 1742.2 | 1839.97 | 1674.38 |
| S | S | S |
| 41.7397 | 42.8949 | 40.9192 |
| y | y | y |
| 0.0586869 | -0.0124993 | 0.0559961 |
| k | k | k |
| 3.47477 | 3.39077 | 3.30145 |
| E | E | E |
| 1.568E+7 | 1.656E+7 | 1.50694E+7 |

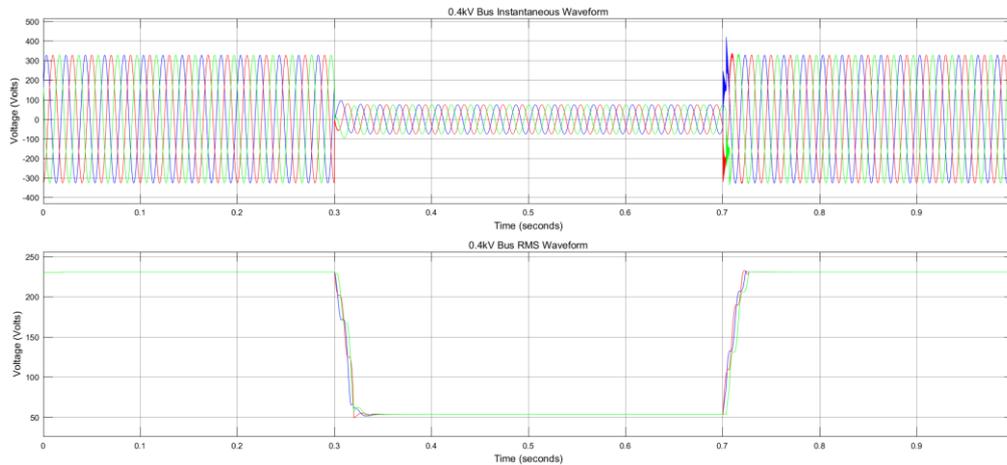
FIG 8.9- Output for Feature Extraction Algorithm developed in Lab VIEW

The statistical parameters max, mean, median, variance, standard deviation, Skewness, kurtosis, and energy, these eight features are extracted from the decomposed signal. These characteristics are fed into an ANN classifier for training and testing.

The details of statistical parameters are given in table 8.1

TABLE 8.1- Details of Statistical Parameters

| Statistical Parameter | Mathematical Formula | Variables |
|-----------------------|--|---|
| Mean | $\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$ | where, \bar{X} is mean, X_i is set of values & n is number of values |
| Median | $m = L + \left(\frac{\frac{N}{2} - F}{f}\right) c$ | N= number of sample |
| Variance | $\sigma^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1}$ | where, σ^2 is variance, \bar{X} is mean, X_i is set of values & n is number of values |
| Standard Deviation | $\sigma = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1}}$ | where, σ is standard deviation, \bar{X} is mean, X_i is set of values & n is number of values |
| Kurtosis | $K = \frac{\frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^4}{\left(\frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^2\right)^2}$ | Where, \bar{X} = mean of the given data S= Standard Deviation of the data n= total number of observations |
| Energy | Energy = $\sum_{i=1}^n (X_i)^2$ | where, X_i is set of values & n is number of values |
| Skewness | $S = \frac{\frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^3}{\left(\frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^2\right)^{\frac{3}{2}}}$ | \bar{X} = mean of the given data S= Standard Deviation of the data N= number of samples |



ANN Algorithm Parameters

- No of Inputs: 8
- No of Output: 3
- No of Hidden Layer: 2
- Train Ratio: 80/100
- Test Ratio: 20/100
- Performance Goals: 0.001
- Epochs Between Displays: 15
- Maximum number of Epochs to train: 1000
- Maximum Validation Failures (used to avoid over-fitting): 5

Classification of Power Quality Disturbances using the features extracted from the d6 level

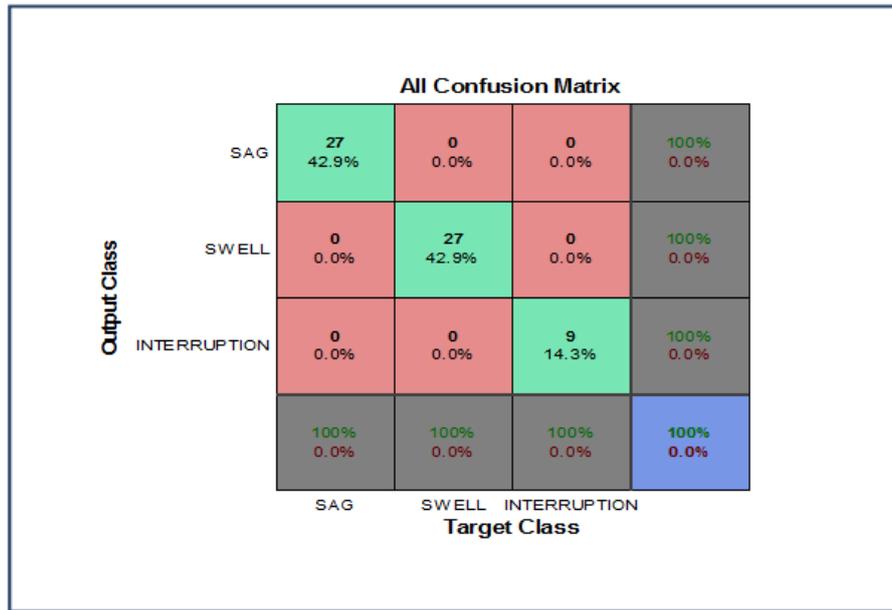


FIG- 8.10

In each cell, the total number of observations is displayed in the “All Confusion Matrix”. Total 63 samples are taken into account. The rows of the confusion matrix indicate the true class, whereas the column represents the predicted class. The diagonal and off-diagonal cells, respectively, reflect correctly and incorrectly classified observations. Row wise, column wise and over all accuracy obtained is 100%.

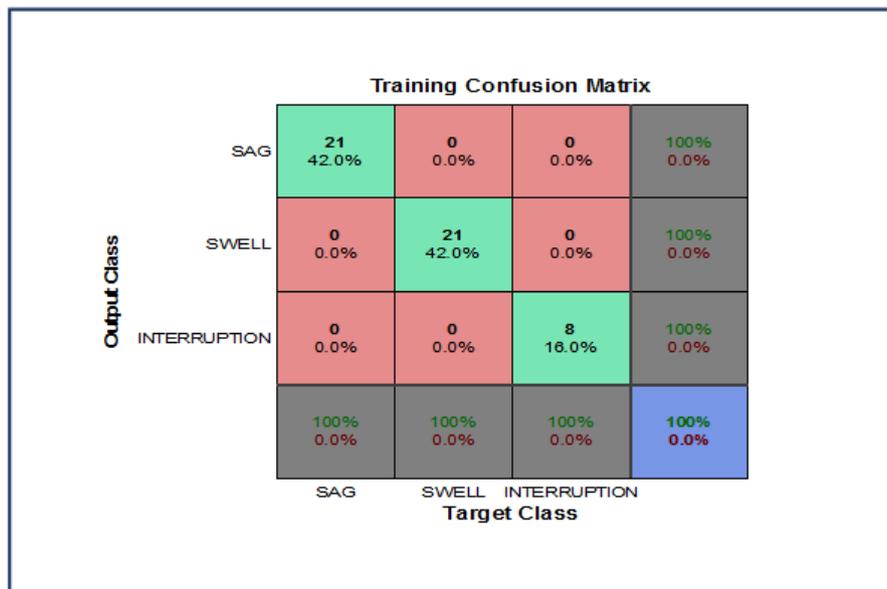


FIG- 8.11

The "Training Confusion Matrix" shows the number of observations used for training in each cell. The rows of the training confusion matrix reflect the true class, whereas the column represents the predicted class. The diagonal and off-diagonal cells, respectively, reflect correctly and incorrectly classified observations. 80 % data is used for training purpose (out of 63 samples 50 samples are used). Row wise, column wise and over all accuracy obtained is 100%.

| Output Class | Target Class | | | |
|--------------|--------------|--------------|--------------|--------------|
| | SAG | SWELL | INTERRUPTION | |
| SAG | 6 46.2% | 0 0.0% | 0 0.0% | 100% 0.0% |
| SWELL | 0 0.0% | 6 46.2% | 0 0.0% | 100% 0.0% |
| INTERRUPTION | 0 0.0% | 0 0.0% | 1 7.7% | 100% 0.0% |
| | 100% 0.0% | 100% 0.0% | 100% 0.0% | 100% 0.0% |

FIG-8.12

The Testing Confusion Matrix shows the amount of observations in each cell that were used for testing. The rows of the testing confusion matrix indicate the true class, whereas the column represents the predicted class. The diagonal and off-diagonal cells, respectively, reflect correctly and incorrectly classified observations. A total of 20% of the data is used for testing purposes (out of 63 samples 13 samples are used). Row wise, column wise and over all accuracy obtained is 100%.

IX. CONCLUSION AND FUTURE SCOPE

We have used Wavelet and ANN-based technique for categorization of power quality disturbances in this research work. In MATLAB Simulink, three PQ disturbances are simulated: voltage sag, voltage swell, and voltage interruptions. The signal processing tool discrete wavelet transform is used for the analysis of voltage signals obtained from MATLAB simulation. In DWT analysis the voltage signal is decomposition upto 6th level. The detailed coefficients of the 6th level are used for extraction of eight features. The extracted features found to be capable of classifying the power quality disturbances. The ANN classifier is trained using the extracted features and the confusion matrix is plotted with the training cases of Sag, Swell and Interruption. From the confusion matrix it is found that the training accuracy for d6 decomposition level is 100%. The ANN classifier has been tested with a variety of Sag, Swell, and Interruption situations and has 100% accuracy. It can be concluded from the results that the proposed algorithm accurately classifies the power quality disturbances. From the analysis, we can conclude that proposed methodology outperforms existing methods. The widespread application of these strategies could improve the power quality monitoring system. This project work focuses on the algorithm innovation, but lacks the design of online real-time detection system. In the future, the embedded system-based algorithm will be developed to classify the PQ disturbances effectively in real-time.

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