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Power Quality Disturbances Classification Using Signal Processing and Soft Computing Technique

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Abstract:. In recent years Power Quality has become an important issue for both utilities and customers. The increasing use of power quality sensitive equipment forced the distribution utilities to adopt a new method for continuously monitors the power quality of grid. Poor power quality may cause overheating of lines, inaccurate metering, and reduced efficiency of appliances. This dissertation proposes a new method to classify certain power quality disturbances. The power quality disturbances such as voltage sags, voltage swells, and voltage interruptions will be considered under study. In this dissertation work simulation of an electrical power system with power quality disturbances is done in MATLAB Simulink. Capturing of voltage signal is done for analyzing the power quality disturbances. The simulation results are further analyzed for the classification of power quality disturbances using MATLAB programming. The captured voltage signals are decomposed by using the signal processing techniques namely Wavelet transform. The estimation of statistical parameters is done from the decomposed signals for feature extraction. The extracted features are further used to classify the disturbances using soft computing techniques namely KNN. The proposed Wavelet-KNN approach classify these frequently occurring power quality disturbances accurately and with less computational complexity.

***Index Terms* – Machine Learning, KNN, SVM, MATLAB simulation , Wavelet etc**

I. INTRODUCTION

In recent years, the use of grid connected renewable energy (RE) based Distributed Generation (DG) is increasing in order to meet the energy demand. RE based DG in the utility grid requires power electronic converters which not only provide interfacing between the DG and the utility grid but also allow higher levels of penetration. The higher level of RE penetration largely affects the Power Quality (PQ). It may lead to various Power Quality Disturbances (PQDs) such as excess reactive power, transients, power factor collapse, large current and voltage fluctuations, sag, swell, notch, harmonics, and noise, etc. These PQDs are also generated in the utility grid due to sudden load changes, switching of lines, non-linear loads, faults, and strength of the ac grid. As mentioned above, PQDs are considered as the leading cause of deterioration of quality of power. These, result in the malfunctioning of digital equipment, unwanted tripping of protective relays and circuit breakers, damaging of computer, and microprocessor-based sensitive devices. Therefore, it is essential to diagnose these PQDs according to international standards, and suitable preventive techniques should be implemented. In this regard, detection and classification of PQDs becomes an essential task.

II. BLOCK DIAGRAM OF THE SYSTEM

The block diagram of the algorithm proposed in this dissertation is shown in figure 1. In the first stage the simulation of system under study will be done and different power quality disturbances are generated. In the second stage capturing of voltage signal is done at the sampling frequency of 10KHz. In the third stage the captured voltage signals are decomposed through the wavelet transform and the five statistical parameters are calculated from the decomposed signal. In the fourth stage the calculated statistical parameters are extracted as a features vector. In the fifth and final stage the above-mentioned features are used to classify different PQ disturbances using KNN classifier.

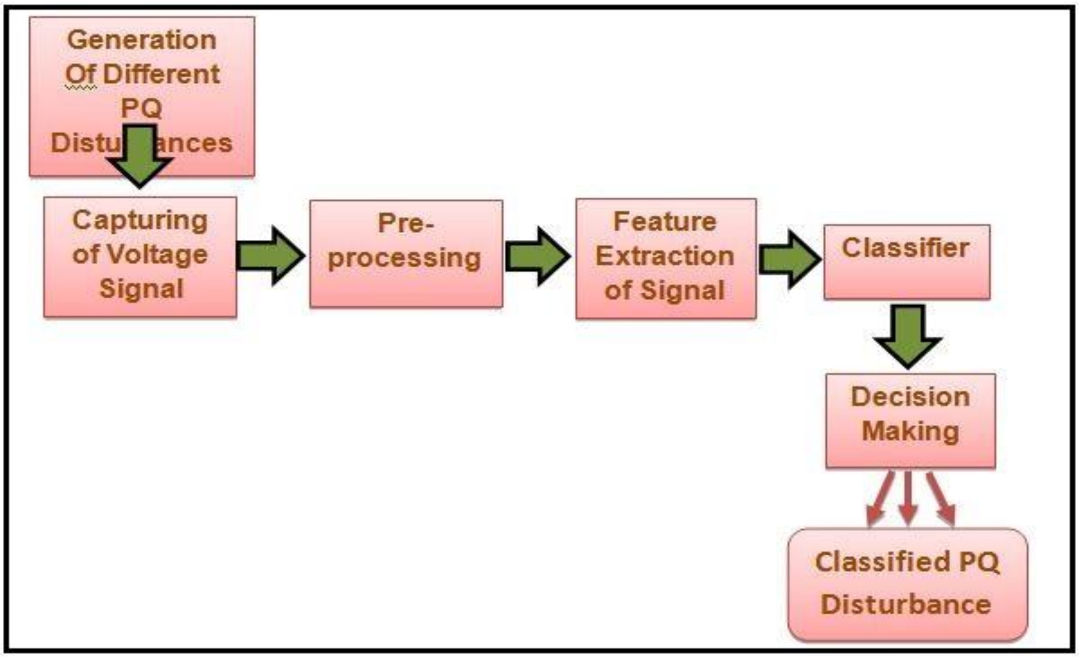

Figure 1:- Block diagram of proposed algorithm

- **Simulation Model**

The grid connected distributed generation system is simulated using MATLAB Simulink Environment. Different Power Quality Disturbances are generated such as voltage sag, voltage swell and voltage interruption.

- **Pre-Processing**

1. This block represents the Power Quality Disturbances performs normalization and segmentation in different stage.
2. Normalization process is used to divide the instant voltage values by the maximum voltage values so that all PQ disturbance data are scaled to the per unit (p.u.)
3. In Segmentation, the data sequence is divided into
   1) Transition Segments: With large and sudden change in signal.
   2) Event Segments: From which features can be extracted.

- **Feature Extraction of Signal**

1. It is the transformation of row signal from its original form to a new form, from which suitable information can be extracted.
2. Wavelet Transform is used for the feature extraction in the proposed methodology.
3. Extracted features by the signal processing are used as input to the classifier in the classification stage.

- **Classifier**

1. The intelligent classifiers are used to classify various power quality disturbances.
2. AI based classifier is used as it is suitable when large amount of data for the training of classifier is available.
3. It recognises a given pattern by experience which is acquired during the learning and training of the network.

III. METHODOLOGY OF PROPOSED ALGORITHM

In this dissertation work the Wavelet-KNN approach is used for the detection and classification of power quality disturbances. The steps involved in this approach are given below.

Step 1 – simulation of system under study in matlab simulink.
Step 2 – various power quality disturbances are generated – voltage sag, voltage swell, voltage interruption.
Step 3 – capturing of voltage waveforms.
Step 4 – capturing of waveforms at a sampling frequency of 10khz is done.
Step 5 – data sets are created for 10 cases of each power quality disturbance.
Step 6 – decomposition of data sets is done with the help of wavelet transform up to level 6 using db4 wavelet.
Step 7 – five features – mean, variance, standard deviation, rms and entropy are extracted from the decomposed signal.
Step 8 – feature matrix is created.
Step 9 – Training of KNN classifier is done with the Feature Matrix as an input.
Step 10 – KNN classifier is used to classify all the 30 training cases of Sag, Swell and Interruption.
Step 11 – Confusion matrix is plotted and accuracy is calculated.
Step 12 – Testing of algorithm is done by using the test cases.

IV. SYSTEM UNDER STUDY

The system under study comprises grid connected distributed generation system. The configuration of system under study is taken from the experimental facilities available in the laboratory. It consists of 11kV main grid of 630KVA power rating and 5kW Solar PV system supplying power to the 10KW, 400V load 1 and 5KW, 400V load 2. A step-down transformer of 630KVA 11kV/400V transformer is feeding power to the system through the 20KVA 400V/400V isolation transformer. A 5kW Solar PV system is acting as a renewable energy based distributed generation source connected at point of interconnection through circuit breaker. The bus at which grid, DG sources and load are connected is called as point of interconnection (POI). The system under study is simulated in MATLAB Simulink environment in order to generate the power quality disturbances. Figure 2 shows the simulation of grid connected distributed generation system. The detailed configuration of system under study is given in table 1.

Table 1:- Configuration of system under study

Component	Configuration
3-Phase Source (Main Grid)	630KVA, 11kV, 50Hz
3-Phase Step-down Transformer	630KVA, 11kV/400V, 50Hz
3-Phase Isolation Transformer	20KVA, 400V/400V, 50Hz
Load 1	10kW, 400V, 50Hz
Load 2	5kW, 400V, 50Hz
Solar PV Array	5kW, 400V, 50Hz

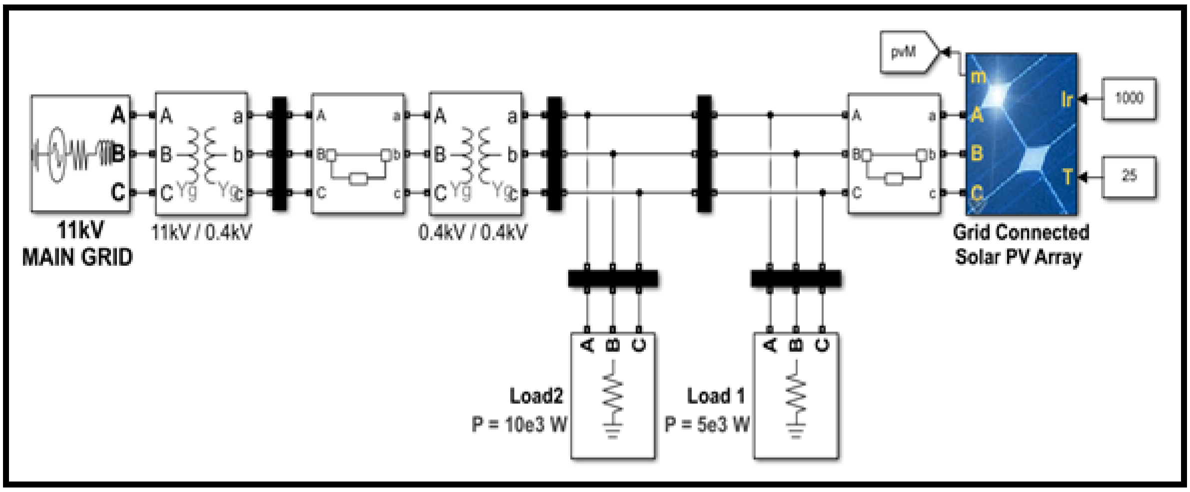

Figure 2:- MATLAB simulation of system under study

V. SIMULATION CASES

The system under study is simulated using MATLAB Simulink Environment. The generation of three power quality disturbances namely voltage sag, voltage swell and voltage interruption and the capturing of voltage signal is done at the sampling frequency of 10KHz. The voltage sag event is generated by creating a three-phase fault in the system for duration of 0.4sec with different fault resistance in order to get different magnitude of sag. The voltage swell event is generated by creating a LG fault, by switching off the heavy load and by energization of capacitor bank in the system for duration of 0.4sec in order to obtain different magnitude of swell. The voltage interruption event is generated by switching off three-phase breaker in the system for duration of 0.4sec.

- **Generation of Voltage Sag**

In this case, the voltage sag is generated by creating a three-phase symmetrical fault in the system. The fault is applied at 0.3 sec and it is cleared at 0.7 sec during the fault duration we get voltage sag. The simulation run time is 1 sec. Voltage sag of different magnitude are obtained by varying the value of fault resistance in order to create the datasets for training and testing of classifier. Figure 3 shows the voltage sag waveform generated by three phase fault having 50% sag.

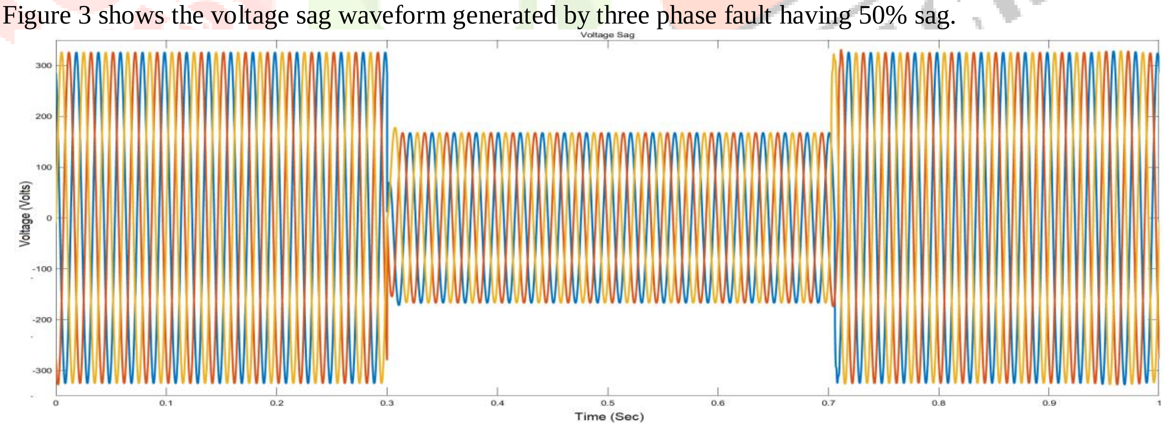

Figure 3:- Voltage sag waveform

- **Generation of Voltage Swell**

In this case, the voltage swell is generated by creating a L-G fault, by release of heavy load for short duration and by capacitor bank energization for short duration in the system. The voltage swell event starts at 0.3 sec and ends at 0.7 sec. The simulation run time is 1 sec. Voltage swell of different magnitude are obtained by varying the value of fault resistance, by varying the load and by varying the capacitor bank rating in order to create the datasets for training and testing of classifier. Figure 4 shows the voltage swell waveform generated by energizing the capacitor bank having 120% swell.

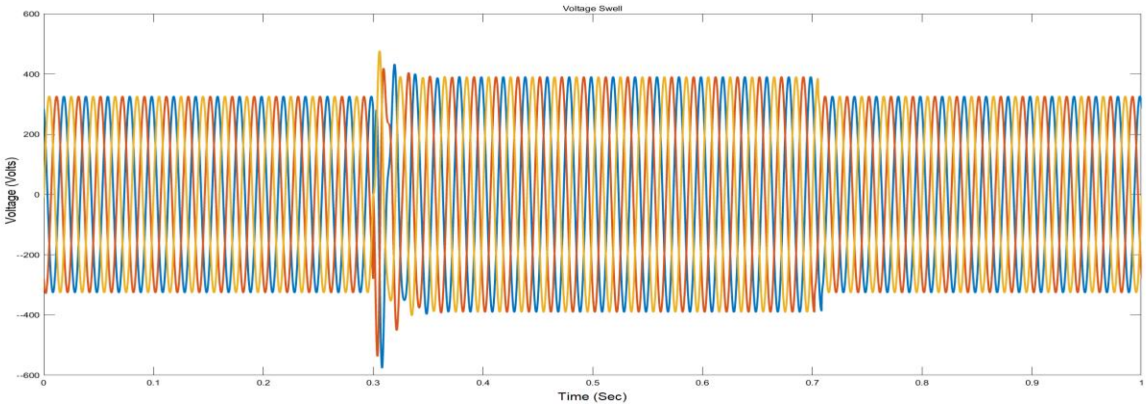

Figure 4:- Voltage sag waveform

- **Generation of Voltage Interruption**

In this case, the voltage interruption is generated by switching off the supply with the help of three-phase circuit breakers for short duration. The circuit breaker is switch off at 0.3 sec and it is switch on at 0.7 sec during the off period we get a voltage interruption. The simulation run time is 1 sec. Number of cases of voltage interruption are created to obtain the datasets for training and testing the classifier. Figure 5 shows the voltage interruption waveform generated by breaker operation.

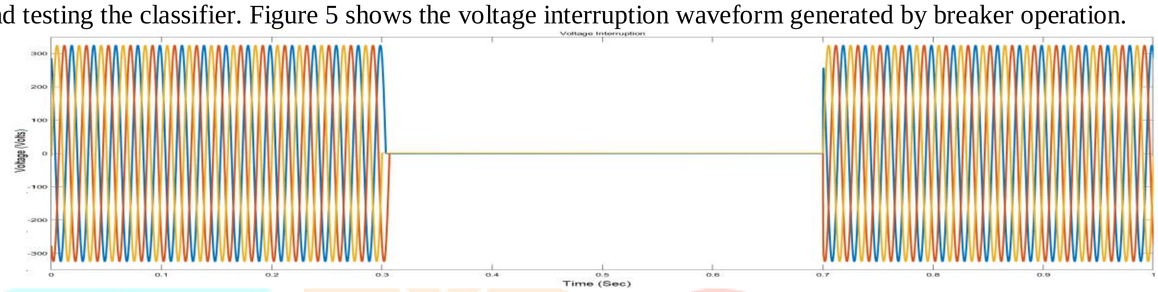

Figure 5:- Voltage interruption waveform

- **Wavelet Analysis of voltage signals**

A wavelet transform (WT) is the decomposition of a signal into a set of basic functions consisting of contractions, expansions, and translations of a mother function ψ(t), called the wavelet.

A wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually, one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale.

A Wavelet is a wave-like oscillation that is localized in time, an example is given below. Wavelets have two basic properties: scale and location. Scale (or dilation) defines how "stretched" or "squished" a wavelet is. This property is related to frequency as defined for waves. Location defines where the wavelet is positioned in time (or space).

In DWT analysis decomposition of voltage wave is carried out upto six levels using db4 wavelet. The sub band frequency ranges in each decomposition level are shown in table 2.

Table 2:- Frequency levels of Wavelet Functions Coefficients

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

Figure 6 shows the wavelet analysis of voltage signal with voltage sag using the db4 wavelet upto sixth level. The voltage signal is decomposed in different frequency bands. The frequency of voltage sag generated by three-phase fault is found to be more prominent in fifth and sixth level.

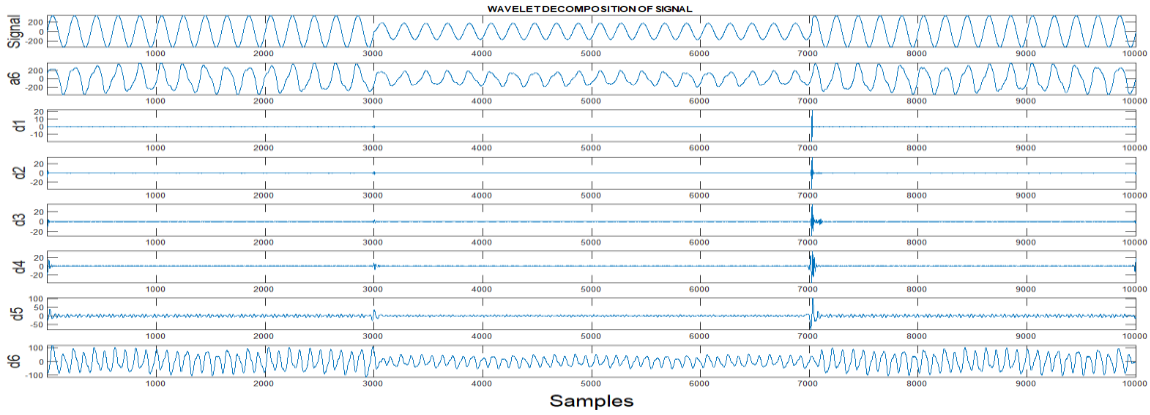

Figure 6:- Wavelet analysis of voltage signal with voltage sagevent

Figure 7 shows the wavelet analysis of voltage signal with voltage swell using the db4 wavelet upto sixth level. The voltage signal is decomposed in different frequency bands. The frequency of voltage swell generated by capacitor bank energization is found to be more prominent in fifth and sixth level.

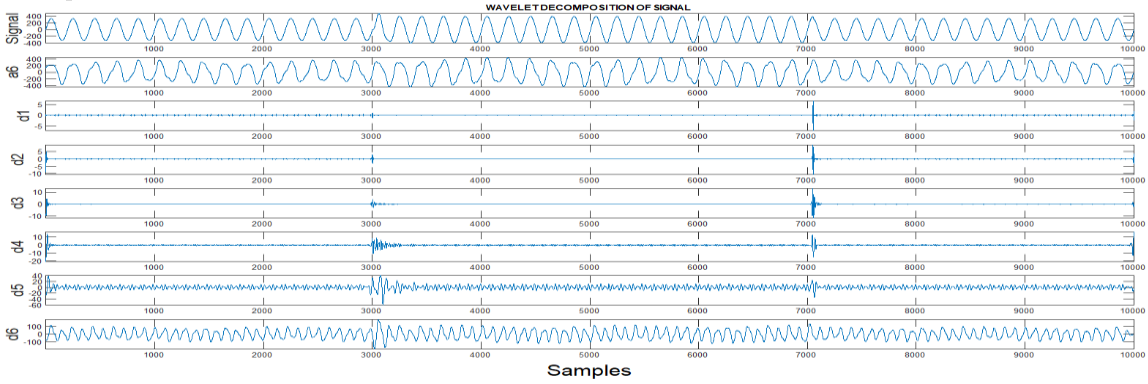

Figure 7:- Wavelet analysis of voltage signal with voltage swell event

Figure 8 shows the wavelet analysis of voltage signal with voltage interruption using the db4 wavelet upto sixth level. The voltage signal is decomposed in different frequency bands. The frequency of voltage interruption generated by capacitor bank energization is found to be more prominent in fifth and sixth level.

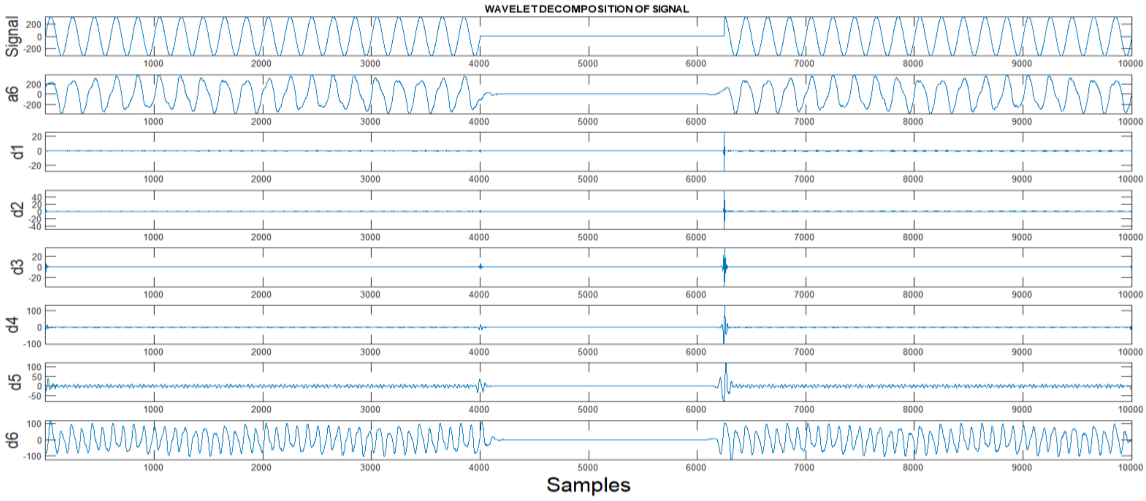

Figure 8:- Wavelet analysis of voltage signal with voltage interruption event

VI. FEATURE EXTRACTION

The wavelet decomposed signals are used for feature extraction. From the wavelet analysis it is clear that the frequency corresponds to voltage sag, voltage swell and voltage interruption events lies in fifth and sixth decomposition level. Hence, the data corresponding to d5 & d6 detailed coefficient is used for feature extraction. Five features are extracted from the decomposed signal by calculating the statistical parameters namely mean, variance, standard deviation, entropy and rms value. These features are given as an input to KNN classifier for training and testing purpose. The details of statistical parameters are given in table 3

Table 3:- 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
Variance	$\sigma^2 = \frac{\Sigma_{i=1}^{n}(X_i - \bar{X})}{n-1}$	where, σ^2 is variance, $\bar{X}$ is mean, X_i is set of values & n is number of values
Standard Deviation	$\sigma. = \sqrt{\frac{\Sigma_{i=1}^{n}(X_i - \bar{X})}{n-1}}$	where, σ is standard deviation, $\bar{X}$ is mean, X_i is set of values & n is number of values
Entropy	$H(x) = -\int_{-\infty}^{\infty} P(x).log_a P(x)dx$ *info. entropy* $H(x) = -\sum_{i=-\infty}^{\infty} P(X_i) log_a P(X_i)$ *spect. entropy*	Where, P(x) is probability density
RMS Value	$RMS = \sqrt{\frac{\Sigma_{i=1}^{n}(X_i)^2}{n}}$	where, X_i is set of values & n is number of values

VII. KNN TRAINING RESULTS

The dataset created by using the features extracted from wavelet analysis of voltage signals corresponding to different cases of voltage sag, voltage swell and voltage interruption are used for training purpose. Total 30 datasets are used 10 datasets of each disturbance. This dataset is given as an input to the KNN classifier for training purpose. After training the classifier a confusion matrix is plotted to evaluate the performance of the model. The obtained confusion matrix is a 3x3 matrix with '3' class labels in our problem. The training confusion matrix shows 100% accuracy. Figure 9 shows the confusion matrix of KNN classifier showing 100% training accuracy.

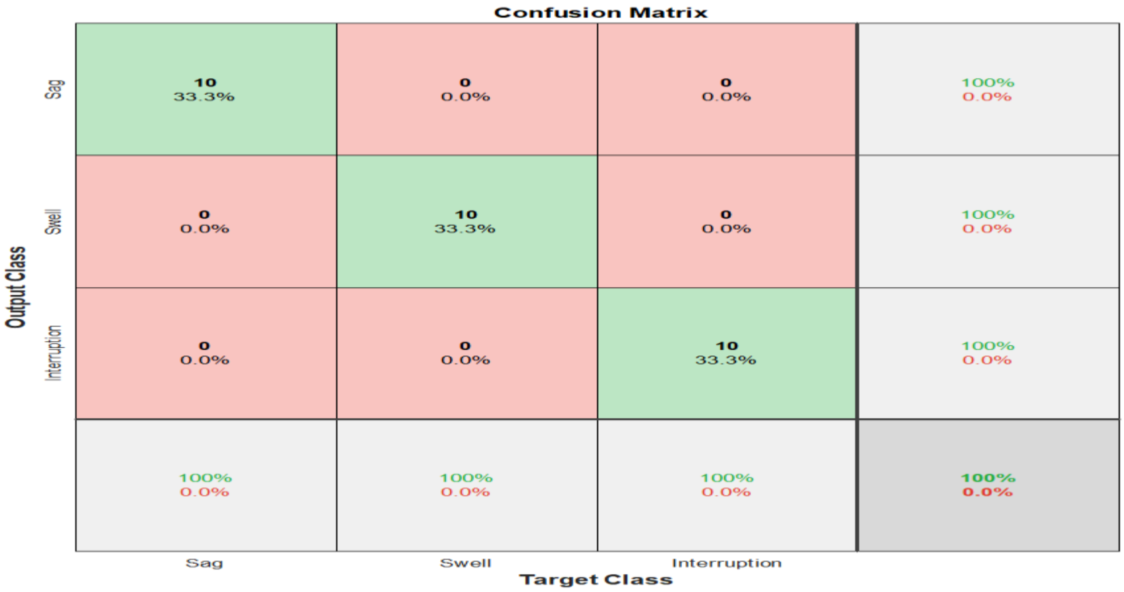

Figure 9:- Confusion Matrix KNN Classifier

VIII. KNN TESTING RESULTS

In the testing case separate dataset is created by running the simulation and the algorithm is applied to the captured voltage signal. The captured voltage signal is decomposed using Wavelet transform and features are extracted. The extracted features are used for testing the KNN classifier. The KNN classifier accurately detects the class of event and the evaluation time of the algorithm is estimated. Figure 10 shows the detection of voltage sag event using KNN along with the evaluation time of the algorithm.

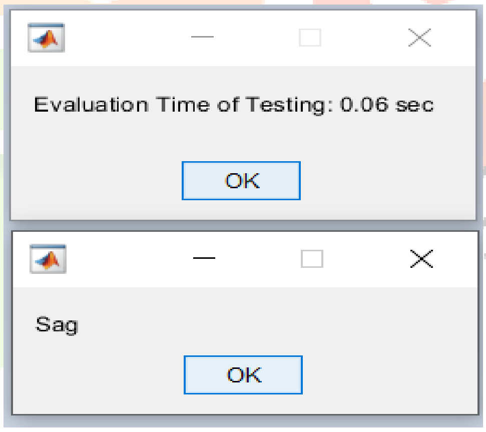

Figure 10:- Detection of voltage sag using KNN along with evaluation time

Figure 11 shows the detection of voltage swell event using KNN along with the evaluation time of the algorithm.

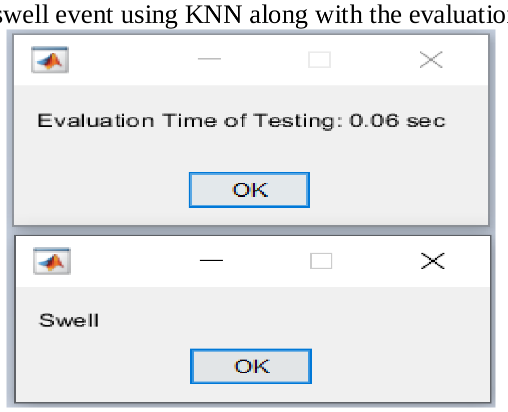

Figure 11:- Detection of voltage swell using KNN along with evaluation time

Figure 12 shows the detection of voltage interruption event using KNN along with the evaluation time of the algorithm.

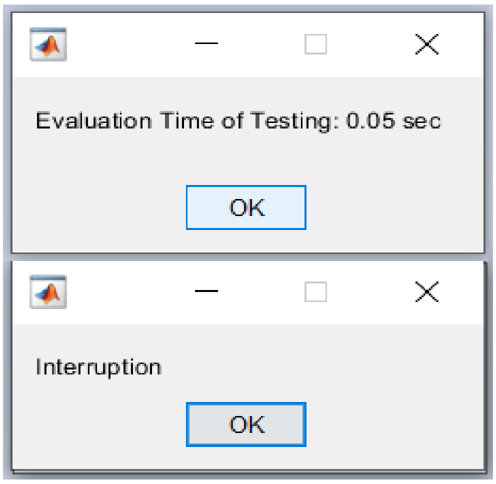

Figure 12:- Detection of voltage interruption using KNN along with evaluation time

IX. CONCLUSION

This dissertation has explored an approach for detection and classification of power quality disturbances using discrete wavelet transform & machine learning classification. Three PQ disturbances namely voltage sag, voltage swell and voltage interruptions are simulated based on different running states of distributed energy sources. The discrete wavelet transform has been used for the detection of various voltage disturbances in power systems. The DWT detects the disturbance after decomposition the signal into levels, the level decomposition gives detail coefficients and the type of the disturbance is identified through the approximation signal. Features extracted from the decomposed waveform are capable to classify the power quality disturbances.The KNN classifier is trained 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 is 100%.The KNN classifier is tested with number of test cases of Sag, Swell and Interruption and gives 100% accuracy. Performance of proposed algorithm is tested on 10 data sets of each PQ disturbance obtained by varying parameters.It can be concluded from the results that the proposed algorithm accurately detects and classifies the power quality disturbances.From the analysis, we can conclude that proposed methodology outperforms existing methods. The implementation of these techniques, on a large scale, could improve the disturbance detection and in consequence the power system's quality. This dissertation focuses on the algorithm innovation, but lacks the design of online real-time detection system. In the future, the embedded system based on the algorithm will be studied to effectively detect PQ disturbances in real-time applications.

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