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A NOVEL APPROACH FOR CLASSIFICATION OF POWER QUALITY DISTURBANCES USING S-TRANSFORM

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Abstract: Classification of Power Quality Disturbances (PQDs) becomes a key issue for end-users in order to enhance the Power Quality (PQ). To improve the electric power quality, sources and causes of disturbances must be known and controlled. It is necessary to classify these events in order to provide proper mitigation action as power quality disturbance waveform recognition is difficult because it involves a broad range of disturbance categories or classes. This dissertation presents S-transform (ST) based feature extraction method in which by visual inspection one can classify the power quality disturbances. S-transform can be effectively used for the analysis of power quality (PQ) disturbances and has the ability to detect the disturbance correctly. In this dissertation work three types of PQ disturbances namely voltage sag, swell and interruption are generated using the integral mathematical models of power quality disturbances implemented in MATLAB. The voltage signals obtained from integral models are further processed using ST and appropriate features are extracted. The extracted features are further used for classification of power quality disturbances using ANN.

I. INTRODUCTION

In the early days of development of the power system, electrical engineers were mainly concerned about ‘keeping the lights on’. They designed the power system to withstand outages. The main concern was to prevent the frequency of power system from deviating from 50Hz after outages. With the development in technology, use of gadgets like computers, arc furnaces, xerox machine etc. increased. Due to the wide spread use of power electronics in every place in the power industry, the power supplied to the customers gets distorted in either the voltage signal or current signal or both of them. This distortion has a great effect on the sensitive equipment’s and may cause interruption, rise or decay of supply voltage, harmonics etc., to the equipment’s that result in very expensive consequence. For instance, at any moment it can crash the computer or data loss and other such problems. So, it becomes necessary to know the cause and category of these disturbances so that they can be suppressed. Hence, unique features that characterizes such power quality events and methodologies in order to extract them from recorded waveforms is a great solution for this. Power quaity events are characterized by their maximum amplitudes, crest voltages, RMS, frequency, statistics of wavelet transform coefficients, instantaneous voltage drops, number of notches, duration of transients, etc. These characteristics are different for each power quality event; thus, they are unique identifying most important mathematical transforms in power engineering. A power quality problem can best be described as any variations in the electrical power service, such as voltage dips and fluctuations, momentary interruptions, harmonics and transients, resulting in maloperation or failure of end-use equipment. With the advent of computers, it becomes easier to simulate a power system in simulation software’s available for simulation such as PSCAD, ATP and MATLAB/SIMULINK.

II. Problem Statements

In early days utility customers were concern about getting the electrical power for the operation of their equipment’s, but nowadays they are concern about the quality of power they are getting from the utility. Because the power quality disturbances arising in power system due to various causes degrade the power quality which may lead to failure or maloperation of end user equipment’s causing millions of damages. In order to overcome this problem, the utility needs power quality monitoring system which can detect and classify the PQDs. Further the cause of the disturbance is identified and mitigation of the disturbance is done. In the power quality monitoring system, the detection and classification of PQDs along with its cause is an important task. This research problem mainly addresses the detection and classification of various PQDs.

III. Aim and Objectives of Dissertation Work

Aim:

The aim of this dissertation work is to classify the power quality disturbances using S-Transform.

Objectives:

The objectives of this dissertation work are to

1. Generate power quality disturbances namely voltage sag, voltage swell and voltage interruption using integral mathematical model.
2. Analyze the power quality disturbances using Stockwell transform for feature extraction.
3. Classify the power quality disturbances using ANN.

IV. Algorithm

- Generation of Power Quality Disturbances using Integral Mathematical Models of Power Quality Disturbances.
- Capturing of voltage signals
- Importing captured voltage signals in MATLAB environment for signal processing using S- Transform.
- Extraction of features from ST matrix.
- Classification of Power Quality Disturbances using ANN.

V. Generation of Power Quality Disturbances using MATLAB

In this dissertation the implementation of integral mathematical models of three power quality disturbances in the form of parametric equation is done using the software program develop in MATLAB software. Three power quality disturbances are generated namely voltage sag, voltage swell, voltage interruption. Figure 1 shows the voltage signal with a sag of 50% for time duration 0.08sec generated by controlling the parameters of the parametric equation.

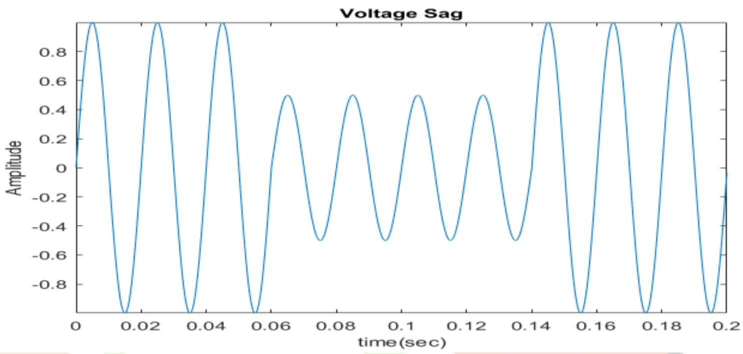


Figure 1:- Voltage Sag waveform generated using the parametric equation.

Figure 2 shows the voltage signal with a swell of 150% for time duration 0.08sec generated by controlling the parameters of the parametric equation.

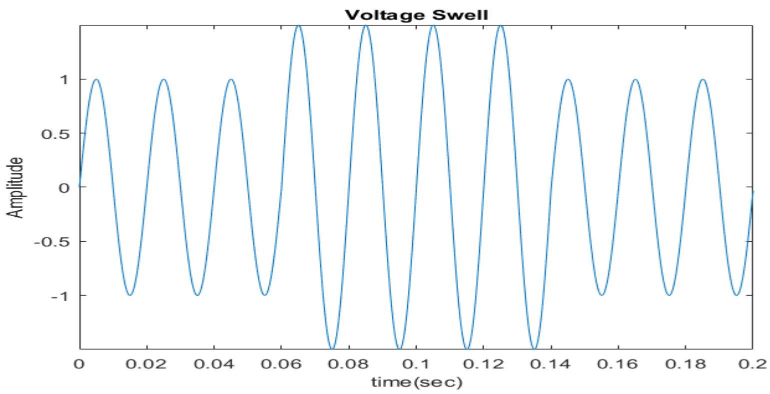


Figure 2:- Voltage Swell waveform generated using the parametric equation.

Figure 3 shows the voltage signal with interruption for time duration 0.08sec generated by controlling the parameters of the parametric equation.

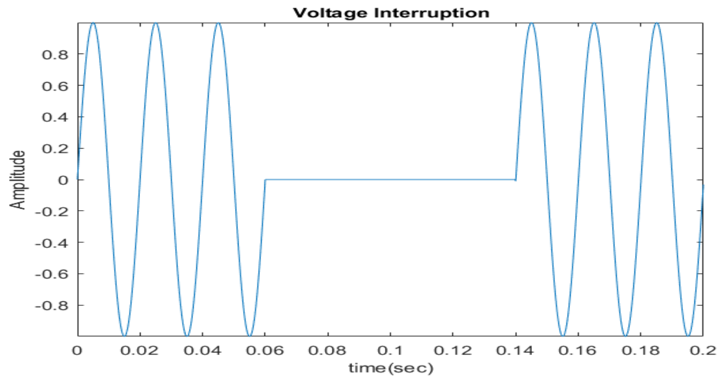


Figure 3:- Voltage Interruption waveform generated using the parametric equation.

VI. STOCKWELL TRANSFORM

A new tool for monitoring power quality problems is introduced by scientist Stockwell in 1996i.e., S Transform. This transformation has ability to analyze different power quality problems simultaneously in both time and frequency domains. The detection and extraction of disturbance features from various types of electric power quality disturbances is important as-

- Feature extraction is the key for pattern recognition so it is the most important component of designing the system.
- Pattern recognition is important since even the best classifier will perform poorly if the features are not chosen well.

Feature extraction from S-transform

- The Power Quality Disturbances generated using the integral mathematical model are further analyze using S-transform for feature extraction in MATLAB environment. Feature extraction is done by calculating the statistical parameters from the ST matrix. These features are useful for classification of power quality disturbances. The power network signal is normalized with respect to a base value, which is the normal value without any disturbance. In this dissertation seven features are extracted from S-transform analysis which are used to classify the PQDs using the ANN based algorithm. In addition to the seven features the energy of ST matrix is calculated to classify the PQDs on the basis of energy of ST matrix. Following features are extracted from the S- transform output:

F1: Mean of the fundamental frequency contour divided by 2
F2: Minimum value of the fundamental frequency peak values
F3: Maximum value of the fundamental frequency peak values
F4: Mean of the third harmonic (150 Hz)
F5: Mean of the 5th harmonic (250 Hz)
F6: Mean of the 7th harmonic (350 Hz)
F7: Sum of values from 700 to 1600 Hz contours

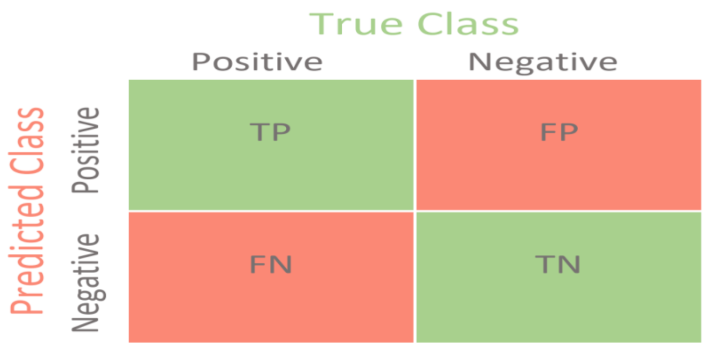
Additional Feature:

The Parseval's energy of ST matrix is calculated as an additional feature for classification of PQDs using energy threshold algorithm

VII. Confusion matrix

A confusion matrix is a tabular way of visualizing the performance of your prediction model. Each entry in a confusion matrix denotes the number of predictions made by the model where it classified the classes correctly or incorrectly. In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class. The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e., commonly mislabeling one as another). It is a special kind of contingency table, with two dimensions ("actual" and "predicted"), and identical sets of "classes" in both dimensions (each combination of dimension and class is a variable in the contingency table).

CONFUSION MATRIX FOR BINARY CLASSIFICATION



- Figure 4:- Confusion Matrix

As you can see, a binary classification problem has only two classes to classify, preferably a positive and a negative class. Now let's look at the metrics of the Confusion Matrix.

True Positive (TP): It refers to the number of predictions where the classifier correctly predicts the positive class as positive.

True Negative (TN): It refers to the number of predictions where the classifier correctly predicts the negative class as negative.

False Positive (FP): It refers to the number of predictions where the classifier incorrectly predicts the negative class as positive.

False Negative (FN): It refers to the number of predictions where the classifier incorrectly predicts the positive class as negative. It's always better to use confusion matrix as your evaluation criteria for your machine learning model. It gives you a very simple, yet efficient performance measures for your model. Here are some of the most common performance measures you can use from the confusion matrix.

Accuracy: It gives you the overall accuracy of the model, meaning the fraction of the total samples that were correctly classified by the classifier. To calculate accuracy, use the following formula: ***(TP+TN)/(TP+TN+FP+FN)***.

Precision: It tells you what fraction of predictions as a positive class were actually positive. To calculate precision, use the following formula: ***TP/(TP+FP)***.

Recall: It tells you what fraction of all positive samples were correctly predicted as positive by the classifier. It is also known as True Positive Rate (TPR), Sensitivity, Probability of Detection. To calculate Recall, use the following formula: ***TP/(TP+FN)***.

VIII. ANN Classification Results for Parseval's Energy Feature Based Algorithm

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 90 datasets are used 30 datasets of each disturbance. This dataset is given as an input to the ANN 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 5 shows the training confusion matrix, figure 6 shows the testing confusion matrix and figure 7 shows the all-confusion matrix of ANN classifier showing 100% accuracy.

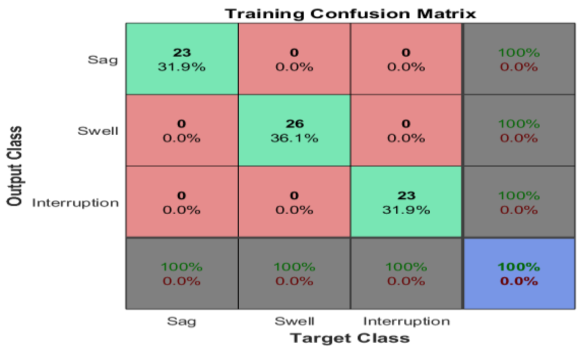


Figure 5:- Training confusion matrix

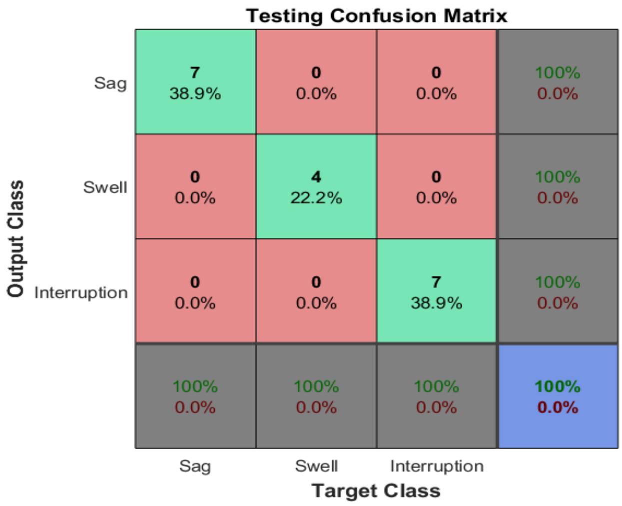


Figure 6:- Testing confusion matrix

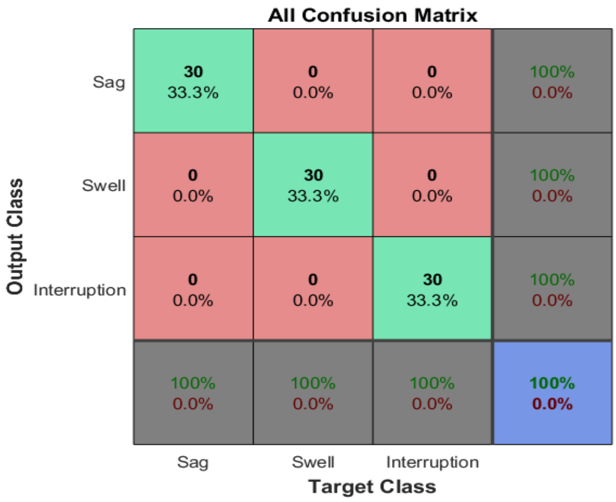


Figure 7:- All confusion matrix

IX. ANN Classification Results for Seven Features Based Algorithm

The feature vector of 90 datasets is created by computing the Parseval's energy of different PQDs. The training of SVM classifier is done using the feature vector of 90 data samples (30 samples of each class). Table 1 shows the training results of the SVM classifier represented in the form of confusion matrix. In the confusion matrix the diagonal elements denote correctly classified PQDs, while the non-diagonal elements denote misclassification. All diagonal elements are averaged to calculate overall accuracy.

Table 1:- Confusion Matrix of ANN Classifier Training Results

Class	**Voltage Sag**	**Voltage Swell**	**Voltage Interruption**	**Accuracy %**
Voltage Sag	50 33.33%	0 0.0%	0 0.0%	100% 0.0%
Voltage Swell	0 0.0%	50 33.33%	0 0.0%	100% 0.0%
Voltage Interruption	0 0.0%	0 0.0%	50 33.33%	100% 0.0%
Accuracy %	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%

The SVM classifier is tested with 30 different datasets (10 samples for each class). Table 2 shows the testing results of the SVM classifier in terms of the confusion matrix.

Table 2:- Confusion Matrix of ANN Classifier Testing Results

Class	**Voltage Sag**	**Voltage Swell**	**Voltage Interruption**	**Accuracy %**
Voltage Sag	30 33.33%	0 0.0%	0 0.0%	100% 0.0%
Voltage Swell	0 0.0%	30 33.33%	0 0.0%	100% 0.0%
Voltage Interruption	0 0.0%	0 0.0%	30 33.33%	100% 0.0%
Accuracy %	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%

X. Classification of PQDs using Parseval's Energy

The Parseval's energy of the ST matrix is calculated by squaring the maximum values of the ST matrix and taking the sum. Figure 8 shows the Parseval's energy corresponding to voltage sag, swell, and interruption. It is found that the Parseval's energy corresponding to voltage swell is greater than 2×10^{32}, voltage sag is less than 2×10^{32} and greater than 1×10^{32}, and voltage interruption is less than 1×10^{32} for all cases of PQDs. The classification algorithm developed based on threshold values of Parseval's energy gives accurate results for all cases of PQDs.

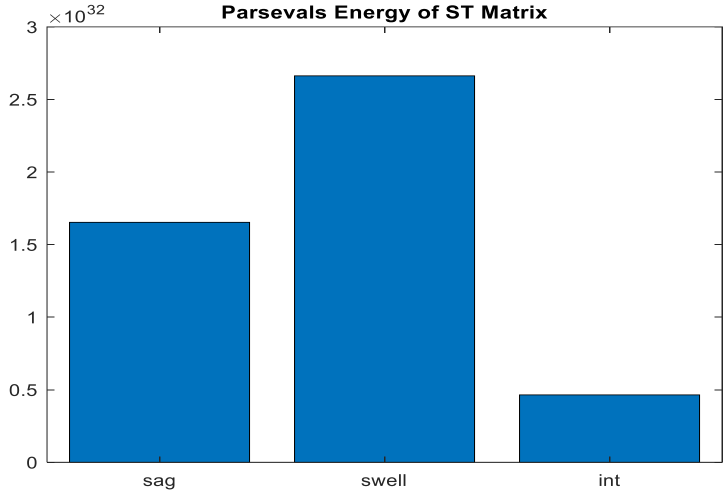


Figure 8:- Parseval's Energy corresponding to Sag, Swell and Interruption

XI. Conclusion

In this dissertation work, three power quality disturbances are classified using the combine approach of S-Transform and Artificial neural network. This work shows that the S-Transform is a perfect tool used to extract the features for classification purpose. It gives 100% accuracy for classifying the disturbances.

Time – frequency contour representation of ST matrix gives the clear idea about the type of disturbance. Thus, ST can also detect the disturbances by visual inspection of contour.

It also reduces computation time as compared to other transforms like wavelet where one needs to choose mother wavelet for better accuracy.

ST is a powerful analysis tool for detection, localization and classification of power quality problems. Various features can be extracted using ST matrix. Frequency dependent resolution of the S- Transform allows the detection of high frequency bursts and shows good frequency resolution on the long period signal.

In the first algorithm proposed in this dissertation a single feature extracted by computing the Parseval's energy from the ST matrix was found to be sufficient for the classification of PQDs. The classification algorithm developed based on threshold values of Parseval's energy gives accurate results for all cases of PQDs. A dataset is generated from the feature vector by computing the Parseval's energy for different cases of PQDs for training and testing the ANN classifier. The classification results show that the ANN classifier accurately classifies the type of PQDs with 100% training and testing accuracy.

In the second algorithm proposed in this dissertation seven features (F1-F7) were extracted by computing them from the ST matrix. These extracted features were found to be sufficient for the classification of PQDs. The classification algorithm developed based on seven features gives accurate results for all cases of PQDs. A dataset is generated from the feature vector by computing the seven features for different cases of PQDs for training and testing the ANN classifier. The classification results show that the ANN classifier accurately classifies the type of PQDs with 100% training and testing accuracy.

The proposed approach was validated using the synthetic data. The results reported in this dissertation effectively demonstrate the ability of the proposed algorithm to correctly classify the PQDs. We can conclude from the analysis that the suggested methodology outperforms existing methods. The proposed approach was found to be much faster and simpler than other WT-based approaches. The use of this technique on a broad scale could improve the power quality monitoring system and finally the quality of the power.

XII. Future Scope

In this dissertation work, only three power quality disturbances are considered for study. This work can further be extended to-

- Detect and classify more power quality disturbances.
- Detect and classify both single and multiple power quality disturbances.
- Detect and classify the power quality disturbances in Realtime.

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