

A Hilbert Transform Based Approach for Classification of Power Quality Disturbances

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Abstract: This study proposes an approach for classifying single stage Power Quality Disturbances (PQDs) that is based on the Hilbert Transform. These power quality disturbance signals are produced utilizing the MATLAB environment's simulation models and integral mathematical models of PQDs. Voltage sag, voltage swell, and voltage interruption are the power quality disturbances taken into account in this study. The Power Quality Index (PQI) curve is generated from these signals using the Hilbert transform, and features are then extracted from it. By changing the parameters, multiple instances of power quality disturbances are produced, and a dataset is produced. In order to train and test the Feed Forward Neural Network (FFNN) classifier, the dataset signals are transformed using the Hilbert transform to produce a feature vector. Calculating the efficiency of the proposed algorithm yields the effectiveness of the provided strategy. The single stage power quality disturbances are classified using a thresholding-based method as well.

Keywords: Power Quality Disturbances, Power Quality Index, Hilbert Transform, Feed Forward Neural Network

I INTRODUCTION

Power quality represents an equipment's capacity to use the power being supplied to it as well as the ability of a power grid to efficiently supply power to consumers. Technically speaking, sinusoidal waveform measurement, analysis, and improvement at the rated voltage and frequency constitute power quality.

A power system's efficiency and cost can be significantly impacted by power quality. Therefore, it is crucial to ensure that the system is compatible with the power given to it and that the power it consumes is of the appropriate quality. Consumer awareness of power quality has increased recently, which is why many governments have amended their regulations to require electric utilities to ensure that the power quality is up to design standards. Modern electrical utility equipment is also more susceptible to fluctuations in power quality. Power quality is a problem for utilities, manufacturers, and consumers, and this issue is growing daily.

Disturbances such voltage swell, voltage sag, notch, transients, harmonic distortions, and so on are the main culprits for power quality degradation. Due to the fact that electric motors consume more current while starting than when operating at rated speed. So voltage sag could be caused by an electric motor beginning. A huge capacitor bank being charged up can also increase voltage. Before taking the necessary mitigation measures, such disturbances should first be discovered in a practical distribution network to improve power quality.

II. POWER QUALITY

The term Power Quality is defined in various type, as per IEEE power quality is define as “the concept of powering and grounding sensitive electronics equipment in a manner that is suitable to the operation of that equipment”

IEC (International Electrotechnical Commission) power quality is a set of parameters defining the properties of power supply as delivered to the user in normal operating conditions in terms of continuity of supply and characteristics of voltage (magnitude, frequency, waveform).

[A] 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.

[B] Voltage Sag: A sag is decrease in rms value of voltage or current between 0.1 to 0.9 pu at the power frequency for duration from 0.5 cycle to 1 min.

[C] Voltage Swell: A swell is increase in rms value of voltage or current between 1.1 to 1.8 pu at the power frequency for duration from 0.5 cycle to 1 min.

III LITERATURE SURVEY

Rahul Saini et al. (2018) for the classification of power quality disturbances, describe an algorithm based on the Hilbert Transform and Rule base decision tree. In this instance, the power quality index curve is produced after processing the voltage signal using the Hilbert Transform. In order to classify data, features from the Hilbert Transform output are provided as input to the rule-based decision tree. The results of this investigation show that the suggested method is efficient at identifying and categorising complicated power quality issues.

T. Jayasree et al. (2009) the classification of power quality (PQ) disturbances using the Hilbert transform and an artificial neural network (ANN) is presented. In that the Hilbert transform (HT) is used to obtain the input features for the ANN from the envelope of the disturbance signals. The radial basis function (RBF) neural network receives these information after normalisation. According to the results of this study, the suggested approach is effective, low-sensitive to noise levels, and delivers improved classification accuracy even in noisy environments. Hilbert transform is also calculated more quickly than S-transform and Wavelet transform.

Vishakha Pandya et al. (2020) the combined characteristics of the Stockwell Transform and Hilbert Transform are presented for the detection and categorization of power quality issues. S- and H-transforms are applied to the resulting PQD signal in order to produce the S- and H-indices. To identify PQ disturbances, the ST-index, H-index, and PQ index are displayed and contrasted with reference plots pertaining to pure sine waves. The decision-supported rule uses the peak value of PQ disturbances as an input to effectively classify PQ disturbances. According to the results of this investigation, the proposed method has a high accuracy of better than 99% for both the detection and categorization of PQ disturbances.

R. Kaushik et al (2020) We offer a technique to identify single-stage and multiple (multi-stage) power quality disturbances (PQDs) utilising hybrid characteristics of the Hilbert transform (HT) and the Stockwell transform (ST). For the purpose of identifying PQDs, a power quality index (PI) and temporal location index (TLI), based on features derived from the voltage signal using HT and ST, are proposed. When classifying PQDs using a decision tree with rules, four features taken from the PI and TLI are taken into account. It is discovered that even in the presence of large levels of noise, an algorithm is effective in recognising both single stage and multiple PQD with an efficiency greater than 98%. The algorithm is scalable for use with voltages of all ranges and faster than several reported solution.

David Granados-Lieberman et al (2013) introduces a smart sensor for the identification, categorization, and measurement of PQD. The suggested smart sensor is built using FPGA technology, which offers high online compute performance as well as a cheap, portable, and effective SoC solution. A feed forward neural network (FFNN) classifies the envelope of a PQD while the Hilbert transform (HT) is employed as a detection technique. Last but not least, the indices derived from HT and Parseval's theorem for root mean square voltage (V_{rms}), peak voltage (V_{peak}), crest factor (CF), and total harmonic distortion (THD). This leads to the conclusion that smart sensor results acquired under simulated and actual operating settings demonstrate their accuracy, precision, and immunity to noisy surroundings, making their industrial usefulness clear. demonstrate a hybrid algorithm.

Eyad A. Feilat1a et al (2017) explains a method for quickly identifying and categorising short-lived voltage fluctuations, such as voltage sag, swell, and interruption. The detection method is based on classification using an artificial neural network and envelope generation using the Hilbert transform. The suggested envelope detection-ANN based classifier methodology offers a robust method for the quick and accurate categorization of voltage changes as well as the estimation of the voltage variation's beginning, ending, and length times.

R. S. Kankale et al (2022) explains research on a wavelet and machine learning approach for categorising PQDs in developing power systems. PQDs such voltage sag, swell, and interruptions are produced during the simulation of the new power system utilising a solar PV system and are then processed using a discrete wavelet transform. For the purpose of categorising PQDs, a machine learning-based classifier is created using the features extrapolated from DWT analysis. On a number of PQDs, the suggested approach has been evaluated. The simulation results demonstrate the effectiveness of the suggested technique for PQD classification.

Rahul et al (2018) introduces the Hilbert-Huang transform (HHT) and support vector machine-based hybrid recognition method and classification methodology to improve the accuracy of delivery and ensure effective recognition of power quality events. These power quality events split into intrinsic mode components and empirical mode decomposition Hilbert-Huang transform components. Empirical Mode Decomposition (EMD) is used to execute a decomposition

operation and feature separation for non-stationary power quality disturbances into intrinsic mode functions (IMFs). These factors are crucial in determining the frequency and amplitude of power quality events. Fuzzy rules are created based on these traits, and power quality problems are classified. From this, it is discovered that the suggested method has improved validity and accuracy for monitoring power quality disturbances.

IV METHODOLOGY

The following steps are used in the proposed algorithm for the classification of the single stage PQ disturbances.

- Generate the single stage power quality disturbances using the simulink model and integral mathematical model.
- Apply the Hilbert transform to voltage signal with power quality disturbance using the following command of the MATLAB.
A=Hilbert (v)
- Obtain the power quality index curve values using the following command and plot the curve.
B=abs (A)
- Obtain the features F1, F2, F3 and F4 from the power quality index curve using the following relations
F1=median (B) F2=kurtosis (B) F3=var (B) F4=std (B)
- These features are given as input to the thresholding-based algorithm for classification purpose and all the PQ disturbances are classified effectively.
- A feature vector is created by processing the dataset signals using Hilbert transform in order to train and test the ANN classifier.
- The effectiveness of the proposed approach is obtained by calculating the efficiency of proposed algorithm

V GENERATION OF POWER QUALITY DISTURBANCES

Power quality disturbances are generated by MATLAB Simulated model and integral mathematical equations in MATLAB Software system.

5.1 Generation of PQDs using MATLAB Simulink model

The single stage power quality disturbances such as voltage sag, voltage swell and voltage interruption are generated using MATLAB simulation model. Table I shows the configuration of Simulink models for generation of power quality disturbances.

Table I: Configuration of Simulink model used for generation of PQDs

Components	Parameters
3-Phase Voltage Source	11kV, 400V, 50Hz, 1MVA
3-Phase Programmable Source 11kV, 400V, 50Hz,	11kV, 400V, 50Hz, 1MVA
3-Phase Transformer	3-Phase Transformer 11kV/400V, 50Hz, 1MVA
3-Phase Active Load	500kW, 400V, 50Hz
3-Phase Reactive Load	100kVAR, 400V, 50Hz
Bus1	11 kV
Bus2	0.4 kV
Fault Resistance	1ohm, 1 MVA SC
Breaker Resistance	0.001ohm
Sampling Frequency	10 kHz

A. Generation of Voltage Sag

The voltage sag simulation model in MATLAB is depicted in Figure 2. The model is made up of a feeder representing a three-phase AC voltage source, a three-phase step-down transformer, a three-phase load, and a three-phase fault. Table 2 provides a full setup of each component. A three-phase ground fault is established at the 11 kV bus in order to produce the three-phase balanced voltage sag. A voltage sag is seen at both the 11 kV and 0.4 kV buses for 0.4 sec during the 0.3 second fault initiation and 0.7-second fault clearance. This voltage sag's magnitude can be altered by adjusting the fault resistance.

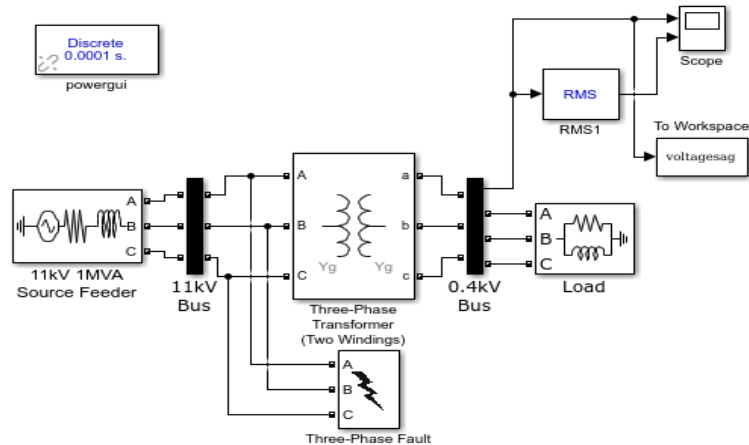


Fig 2. MATLAB Simulink model for Voltage Sag

B. Generation of Voltage Swell

The MATLAB simulation model for voltage swell is shown in Figure 3. A three-phase programmable voltage source that represents a feeder and a three-phase load makes up this model. Table 2 lists every component's precise configuration. Three phase voltage sources with variable amplitudes are used to produce a three-phase balanced voltage swell at 0.4 kV bus. At 0.3 seconds, a voltage swell is initiated and maintained for 0.7 seconds. The size of this voltage swell is adjustable by changing the amplitude in a programmable source.

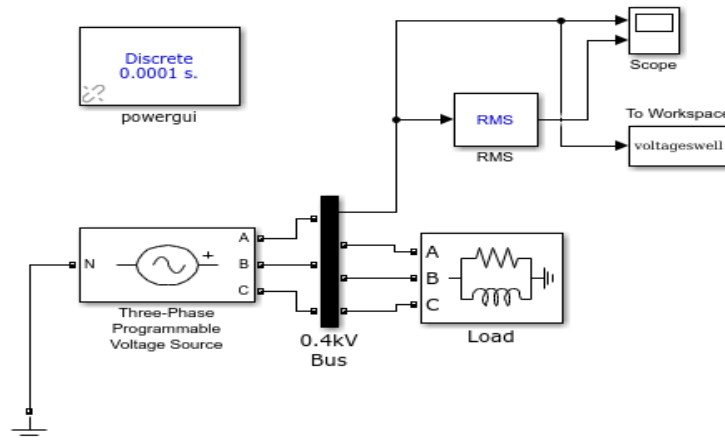


Fig 3 MATLAB Simulink model for Voltage Swell

C. Generation of Voltage Interruption

The MATLAB Simulation model for voltage interruption is displayed in Figure 4. A three-phase circuit breaker, a three-phase step-down transformer, a three-phase load, and a three-phase AC voltage supply (representing a feeder) are all included in this model. Table 2 lists every component's precise configuration. A three-phase circuit breaker in an 11 kV feeder is activated to cut off the supply to the three-phase transformer in order to produce the three-phase voltage interruption. A voltage interruption is seen at 0.4 kV buses during a circuit breaker's OPEN and CLOSED phases of 0.3 and 0.7 seconds, respectively.

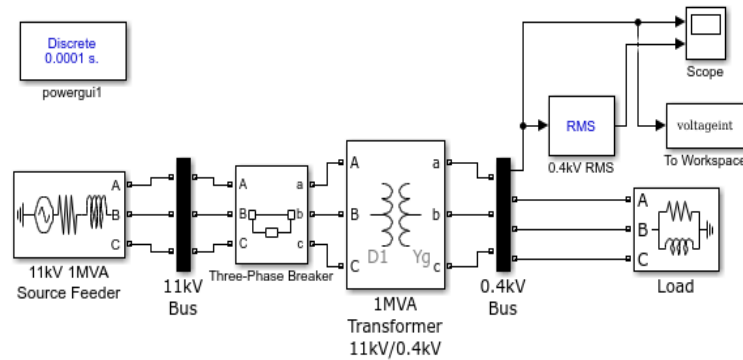


Fig 4 MATLAB Simulink model for Voltage Interruption

5.2 Generation of PQDs using mathematical modelling

PQDs	Equations	Parameters
Voltage sag	$x(t) = A (1 - \alpha(u(t - t_1) - u(t - t_2))) \sin(\omega t)$	$0.1 \leq \alpha \leq 0.8, T \leq (t_2 - t_1) \leq 9T$
Voltage swell	$x(t) = A (1 + \alpha(u(t - t_1) - u(t - t_2))) \sin(\omega t)$	$0.1 \leq \alpha \leq 0.8, T \leq (t_2 - t_1) \leq 9T$
Voltage interruption	$x(t) = A (1 - \alpha(u(t - t_1) - u(t - t_2))) \sin(\omega t)$	$0.9 \leq \alpha \leq 1, T \leq (t_2 - t_1) \leq 9T$

V. SIMULATION RESULT AND DISCUSSION

5.1 Results of PQDs Generated using MATLAB Simulink Models

To acquire PQDs voltage sag on an 11kV bus, a three-phase symmetrical fault is given to the system and causes voltage sag using the simulation model of voltage sag in MATLAB Simulink. A three phase to ground fault occurs on an 11 Kv bus in 0.3 seconds and is repaired in 0.7 seconds. During the period of the problem, there is a voltage drop on the 11 kV and 0.4 Kv bus V buses. One second is chosen as the simulation time. The fault resistance amplitude can be altered. The instantaneous and RMS voltage waveform with a sag of 50% is shown in Fig. 5 and was generated by the MATLAB Simulink model.

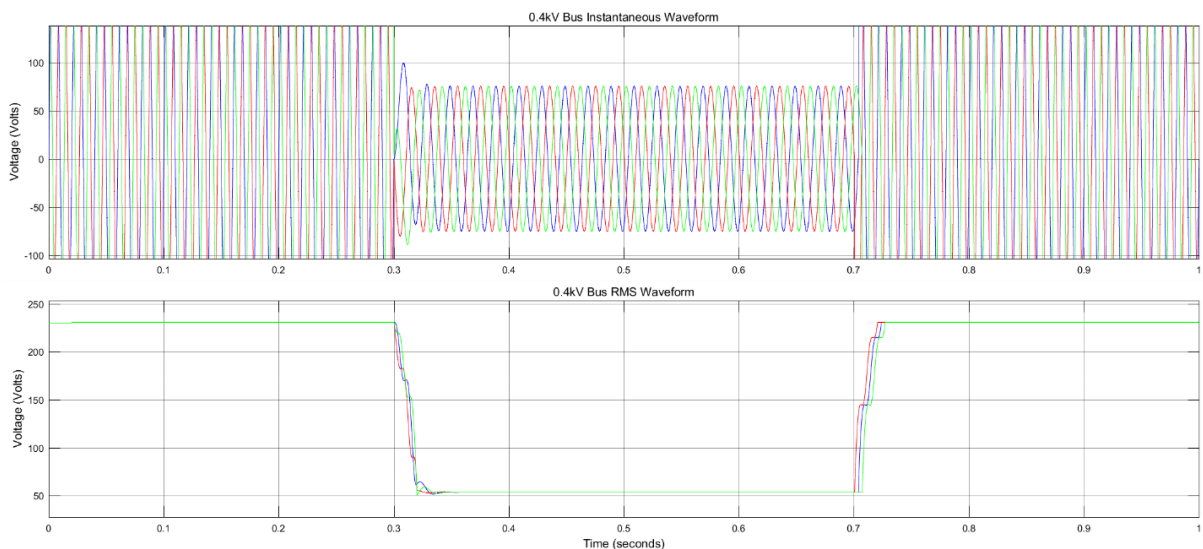


Fig 5 Waveform for Voltage Sag

In MATLAB Simulink, the voltage swell simulation model is run to produce the voltage swell. The characteristics of the programmable source can be altered to alter the amplitude of the voltage swell. The duration of the event is 0.3 and 0.7

seconds. The instantaneous and RMS voltage waveform with a swell of 20% is shown in Fig. 6 after the simulation time is adjusted to 1 sec. using the MATLAB Simulink model.

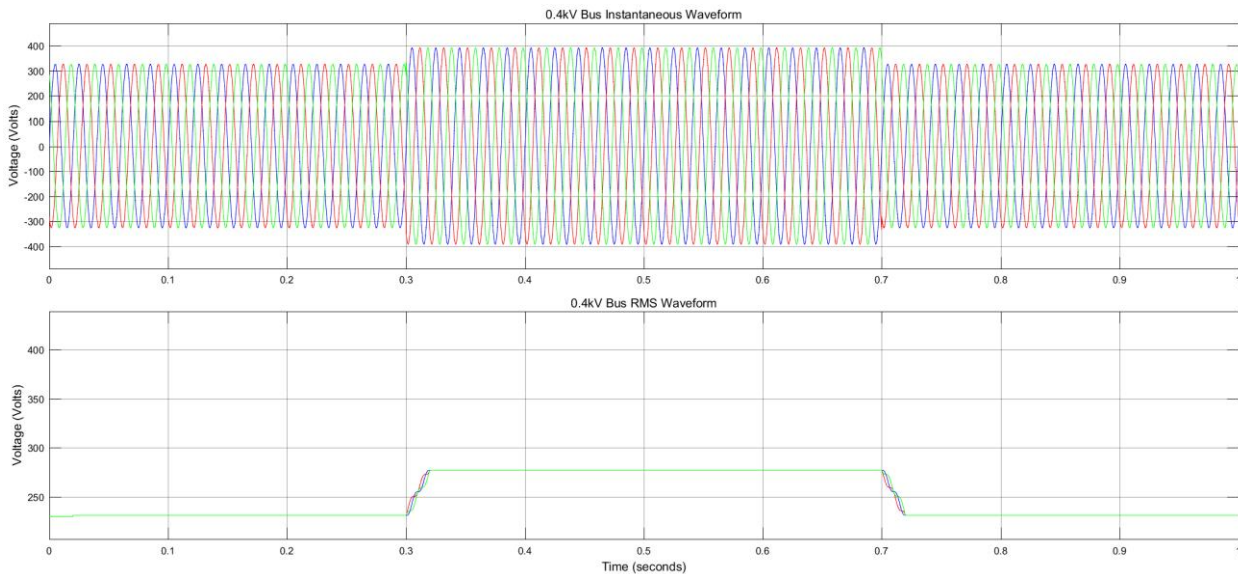


Fig 6 Waveform for Voltage Swell

In MATLAB Simulink, the voltage interruption simulation model is simulated to obtain the voltage interruption. A voltage interruption is observed at the 0.4 kV bus when the circuit breaker at the 11 kV feeder opens at 0.3 seconds and shuts off at 0.7 seconds. One second is chosen as the simulation time. The instantaneous and RMS voltage waveform with an interruption from the MATLAB Simulink model is displayed in fig. 7.

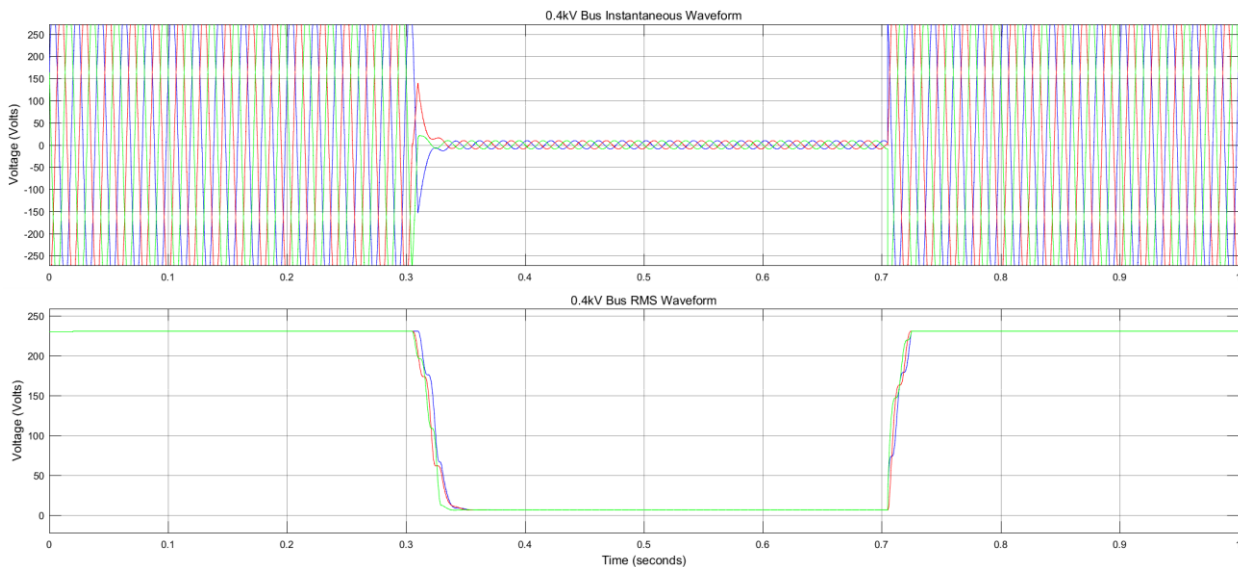


Fig 7 Waveform for Voltage Interruption

5.2 Results of PQDs Generated using integral mathematical modelling

The parametric equations are programmed in MATLAB programming to produce the single stage PQDs. The parameter A controls the PQDs' amplitudes, while the temporal constants t_1 and t_2 govern their durations. In this study, the value of $A=326$ represents the highest value of the three-phase instantaneous waveform, and the RMS value was determined to be 400 V. Figure 7 displays the voltage signal with a 50% sag for 0.4 seconds that was produced by altering the parameters $=0.6$, $t_1=0.3$, and t_2 . The waveform's complete duration is one second.

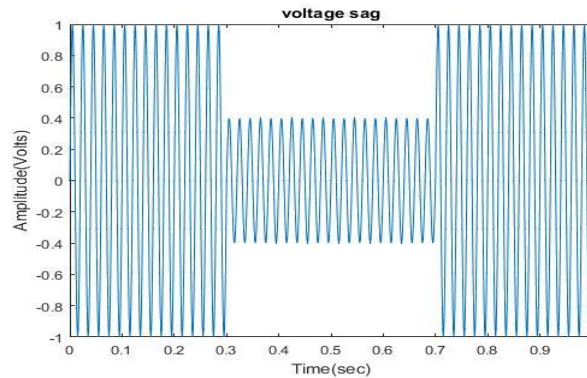


Fig 8 Waveform for Voltage Sag

Figure 8 illustrates the voltage signal that results from altering the parameters $\phi=0.5$, $t_1=0.3$, and $t_2=0.7$. The voltage signal has a swell that lasts for 0.4 seconds. The waveform's complete duration is one second.

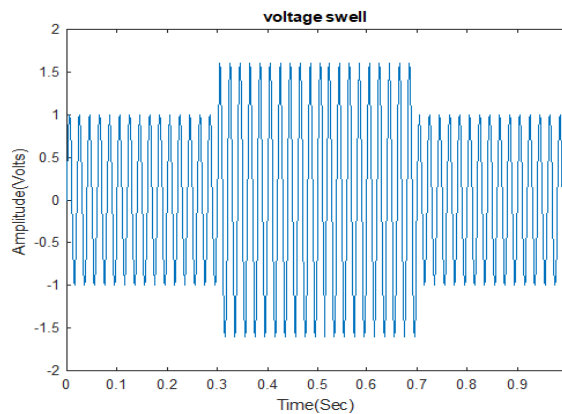


Fig 9 Waveform for Voltage Swell

Figure 10 illustrates the voltage signal with a 0.4-second interruption that is produced by varying the values of $\phi=0.95$, $t_1=0.3$, and $t_2=0.7$. The waveform's complete duration is one second.

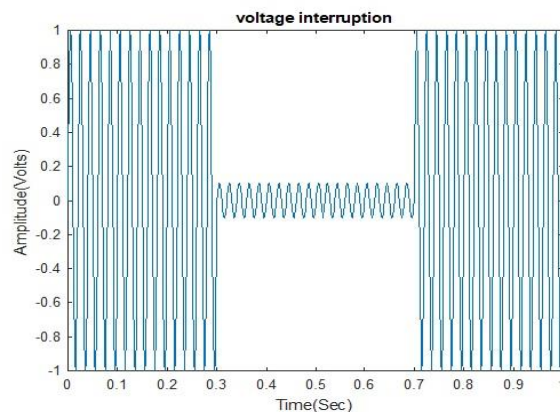


Fig 10 Waveform for Voltage Interruption

5.3 Power Quality Index Curve

The Hilbert transform is used to deconstruct the voltage signal with sag that was produced by simulating the mathematical equations in MATLAB. Calculating the output of the Hilbert transform's absolute value yields the power quality index curve. Figure 11 displays the waveform of a signal with a voltage sag and a power quality index curve. Figure 11 shows that values of the power quality index curve drop from 0.3 seconds to 0.7 seconds.

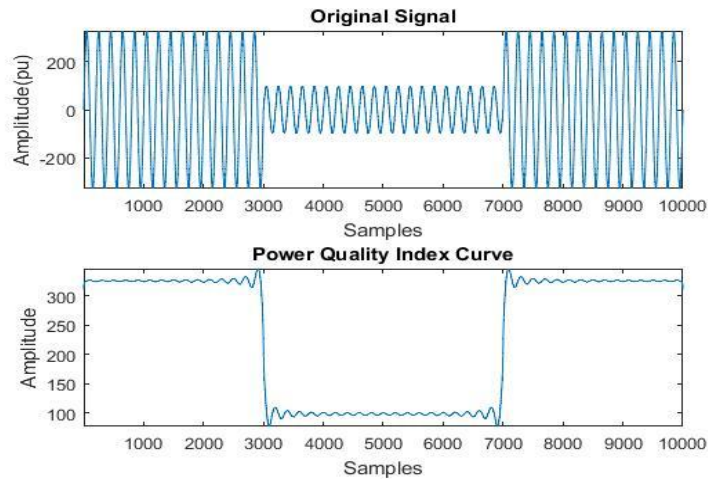


Fig 11 Power Quality Index Curve of Voltage Sag

The Hilbert Transform is used to decompose the signal with voltage swell that was produced by simulating the mathematical relationship. Calculating the absolute values of the output of the Hilbert transform yields the power quality index curve. Figure 12 provides the voltage signal waveforms with swell and the proposed power quality index curve for the voltage swell. This can be seen in Fig. 12, where the values of the power quality index curve increase at 0.3 and 0.7 s, respectively, indicating the occurrence of voltage swells between those times.

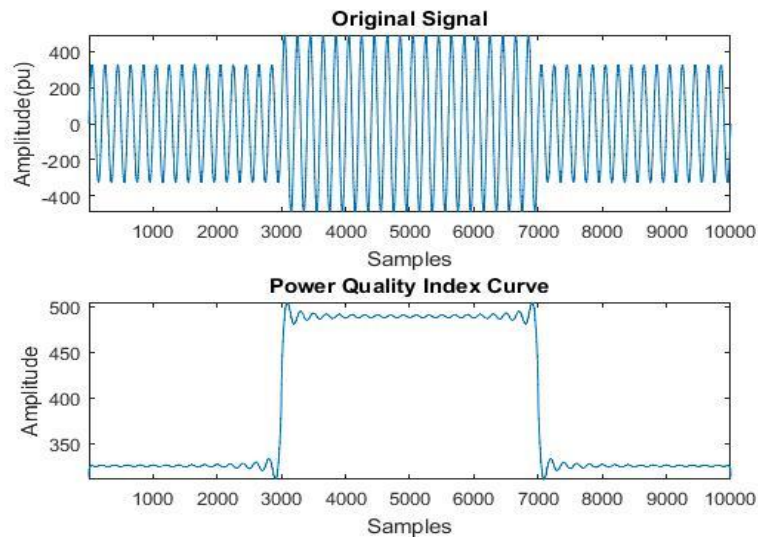


Fig 12 Power Quality Index Curve of Voltage Swell

The Hilbert Transform is used to breakdown the voltage-interrupted signal that was produced by simulating the mathematical relationship. Calculating the absolute values of the output of the Hilbert transform yields the power quality index curve. Figure 13 provides the voltage signal waveforms with interruptions and the proposed power quality index curve for the voltage interruption. This can be seen in Fig. 13, where the values of the power quality index curve increase at intervals of 0.3 to 0.7 seconds, suggesting the presence of voltage interruptions.

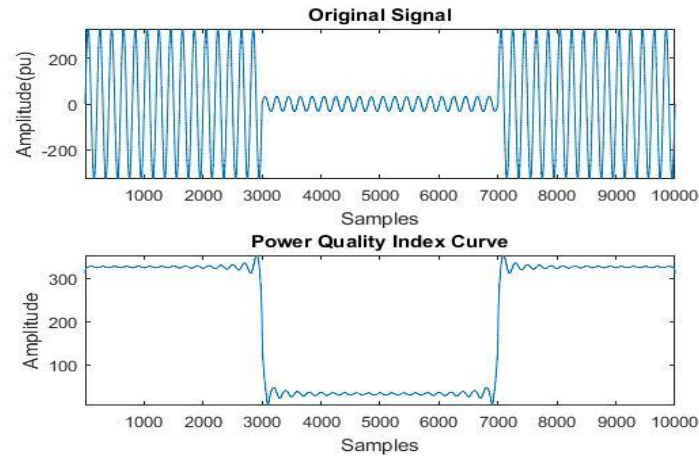


Fig 13 Power Quality Index Curve of Voltage Interruption

Table II Features of Power Quality Disturbances

PQ disturbances	F1	F2	F3	F4
Voltage Sag	324.4901375	1.181264408	12439.33053	111.5317467
Voltage Swell	327.2457379	1.180576302	9157.608646	95.69539512
Voltage Interruption	324.0777875	1.181669005	20471.08924	143.0772143

VI CLASSIFICATION OF POWER QUALITY DISTURBANCES

6.1 Classification of Single Stage PQD using mathematical modelling

The values of features F1, F2, F3, F4 provided in the Table II. These features are given as input to the thresholding-based algorithm for the classification of the single stage power quality disturbances. The detailed classification of the power quality disturbances using the thresholding based algorithm is provided in fig.14. The classification is initialized using the feature F4. The first group consists of voltage interruption whereas the second group consists of the voltage sag, voltage swell.

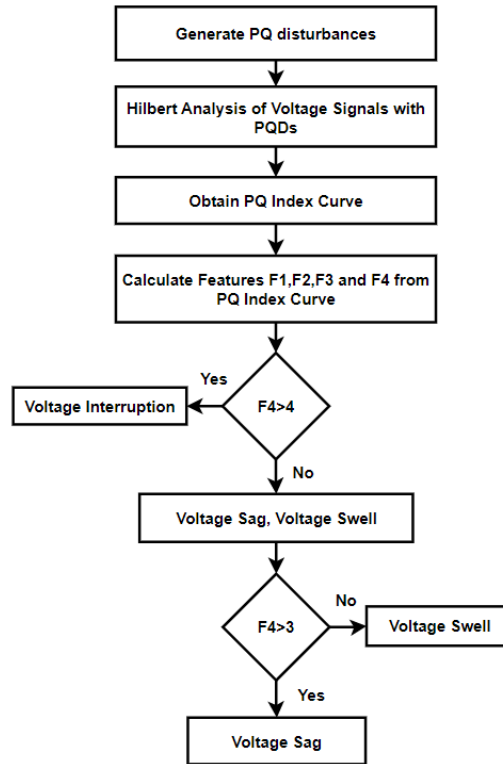


Fig 14 Classification of Single Stage PQD Using Thresholding Based Algorithm

6.2 Classification of Single Stage PQD using Simulink Model

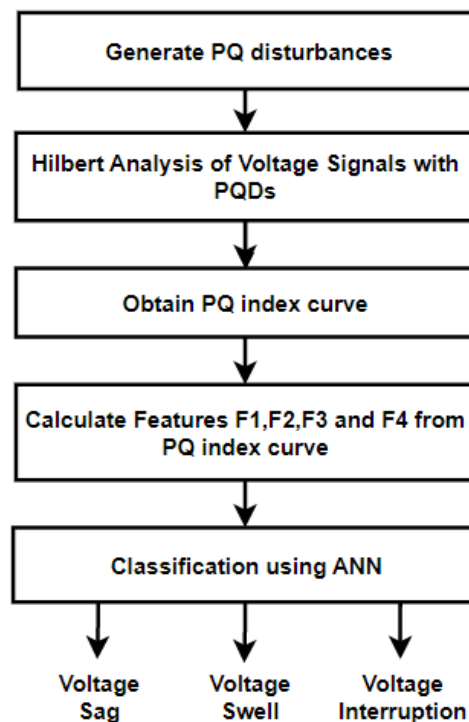


Fig 16 Classification of Single Stage PQD using ANN

The feature vector with 48 datasets of each disturbance (48x3=144) are fed to ANN classifier. 80% of the data (115 datasets out of which 39 datasets are of sag, 41 datasets are of swell and 35 datasets are of interruptions) are used for training purpose and 20% data (29 datasets out of which 7 datasets are of sag, 7 datasets are of swell and 13 datasets are

of interruptions) are used for testing purpose. Fig 17 shows all confusion matrix, from this matrix it is found that voltage sag is classified with an accuracy of 93.8%, voltage swell is classified with 100% and voltage interruption is classified with 95.8% accuracy. The overall accuracy of classifier is 96.5%.

All Confusion Matrix

Output Class	Sag	45 31.2%	0 0.0%	2 1.4%	95.7% 4.3%
	Swell	0 0.0%	48 33.3%	0 0.0%	100% 0.0%
	Interruption	3 2.1%	0 0.0%	46 31.9%	93.9% 6.1%
		93.8% 6.2%	100% 0.0%	95.8% 4.2%	96.5% 3.5%
		Sag	Swell	Interruption	

Target Class

Fig 17 All Confusion Matrix

The ANN classifier's training results are displayed in the form of confusion matrix in fig 18, from this matrix it is found that voltage sag is classified with an accuracy of 92.3%, voltage swell is classified with 100% and voltage interruption is classified with 97.1% accuracy. The overall accuracy of training is 96.5%.

Training Confusion Matrix

Output Class	Sag	36 31.3%	0 0.0%	1 0.9%	97.3% 2.7%
	Swell	0 0.0%	41 35.7%	0 0.0%	100% 0.0%
	Interruption	3 2.6%	0 0.0%	34 29.6%	91.9% 8.1%
		92.3% 7.7%	100% 0.0%	97.1% 2.9%	96.5% 3.5%
		Sag	Swell	Interruption	

Target Class

Fig 18 Training Confusion Matrix

The ANN classifier's testing results are displayed in the form of confusion matrix in 19, from this matrix it is found that voltage sag is classified with an accuracy of 100%, voltage swell is classified with 100% and voltage interruption is classified with 92.3% accuracy. The overall accuracy of training is 96.6%.

Testing Confusion Matrix

		Target Class			
		Sag	Swell	Interruption	
Output Class	Sag	9 31.0%	0 0.0%	1 3.4%	90.0% 10.0%
	Swell	0 0.0%	7 24.1%	0 0.0%	100% 0.0%
	Interruption	0 0.0%	0 0.0%	12 41.4%	100% 0.0%
		100% 0.0%	100% 0.0%	92.3% 7.7%	96.6% 3.4%
		Target Class			
		Sag	Swell	Interruption	

Fig 19 Testing Confusion Matrix

VII CONCLUSION

This research work presents an algorithm using Hilbert transform and thresholding-based algorithm for classification of PQ disturbances. It has been concluded that the proposed algorithm is effective in the classification of the various single stage PQ disturbances with efficiency greater than 96%. The features extracted from the Hilbert transform are very simple and yet very effective. It found sufficient to accurately classify the single stage PQ disturbances with ease. The proposed approach gives satisfactory results. Overall, the algorithms developed are less complex. The ANN classifier takes less time for training and the classification accuracy is very high. The proposed technique has been found to be successful in classifying the various complex PQ disturbances. Compared to the Wavelet transform and S-transform, the Hilbert transform can be quickly calculated, so that the proposed method is efficient, making the suggested method more efficient.

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