Classification of Multiple and Multistage Power Quality Disturbances Using S-Transform and Feed Forward Neural Network

Ravishankar S. Kankale
Department of Electrical Engineering
SSGMCE, Shegaon
India
rskankale@ssgmce.ac.in

Dr. Sudhir R. Paraskar
Department of Electrical Engineering
SSGMCE, Shegaon
India
srparaskar@ssgmce.ac.in

Dr. Saurabh S. Jadhao
Department of Electrical Engineering
SSGMCE, Shegaon
India
ssjadhao@ssgmce.ac.in

ABSTRACT

The reliable and uninterrupted supply of electrical power is fundamental to modern society's functioning. However, Power Quality Disturbances (PQDs), encompassing a diverse range of transient events such as voltage sags, swells, harmonics, and interruptions, can compromise the stability and effectiveness of power systems. Detecting and accurately classifying these disturbances, particularly those involving multiple and multistage events, is pivotal for mitigating their adverse effects. In response to this challenge, this research paper presents an in-depth investigation into the use of the S-Transform, a time-frequency analysis technique, for the detection and classification of multiple and multistage PQ disturbances. We propose a comprehensive methodology that integrates the S-Transform with advanced classification techniques, including Feed Forward Neural Network (FFNN). The effectiveness of the proposed methodology is demonstrated through the PQ disturbance datasets. The results showcase the S-Transform's aptitude in revealing fine-grained time-frequency structures inherent in multistage disturbances. Furthermore, the integration of advanced classification techniques yields robust and accurate identification of disturbance types, ensuring timely and appropriate responses to mitigate their impact.

Keywords— Power Quality Disturbances, Feed Forward Neural Network, S-Transform.

I. INTRODUCTION

In modern society, the uninterrupted supply of electric power has become an indispensable necessity for the operation of various critical infrastructures, industrial processes, and domestic activities. However, the reliability and quality of power supply are often challenged by a multitude of disturbances that can disrupt the normal functioning of electrical systems. Power Quality (PQ) disturbances encompass a wide array of transient and non-stationary events, such as voltage sags, swells, interruptions, harmonics, and flicker, among others. These disturbances can lead to severe economic losses, equipment damage, and operational disruptions, underscoring the significance of accurate and timely detection and classification.

To address these challenges, researchers and practitioners have focused their efforts on developing advanced techniques for the detection and classification of PQ disturbances. Traditional methods often rely on Fourier Transform-based techniques, which are suitable for stationary signals but fall short when analyzing non-stationery and time-varying disturbances. In response to this limitation, the S-Transform, also known as the Stockwell Transform, has emerged as a promising tool for the simultaneous analysis of signals in both the time and frequency domains. Its ability to provide enhanced time-frequency resolution makes it well-suited for the detection and classification of multistage PQ disturbances.

This research paper presents a comprehensive investigation into the application of the S-Transform for the detection and classification of multiple and multistage PQ disturbances. We delve into the underlying principles of the S-Transform and its advantages over conventional techniques in handling transient and non-stationary disturbances. Leveraging this transformative analysis method, our study aims to not only enhance the accuracy of detection but also enable the differentiation of complex PQ disturbance patterns that may involve multiple stages of events.

II. RELATED LITERATURE

The research conducted by Kuo et al. (2009) presented a novel approach for the detection and classification of multistage power quality disturbances using the S-Transform and probabilistic neural networks. The study highlighted the effectiveness of the S-Transform in capturing time-frequency features of PQ disturbances, enabling improved discrimination between different disturbance types. The integration of probabilistic neural networks provided accurate classification results, enhancing the overall reliability of the detection system.
Chandrasekaran and Sankaranarayanan (2010) proposed a method for PQ disturbance classification using the S-Transform and an adaptive network-based fuzzy inference system (ANFIS). The researchers showcased the ability of the S-Transform to capture transient and non-stationary features of PQ disturbances. The ANFIS-based classification demonstrated the system's adaptability to varying disturbance patterns, making it suitable for real-world applications.

Messina et al. (2011) contributed to the field by developing an automatic detection and classification framework for power quality disturbances using the S-Transform and fuzzy c-means clustering. The study emphasized the effectiveness of fuzzy clustering in identifying clusters of similar disturbance patterns, which facilitated accurate classification. The combination of the S-Transform and fuzzy clustering provided a robust solution for handling multistage disturbances.

In another study by Cheng et al. (2011), the authors investigated the automatic detection and classification of power quality disturbances using the S-Transform and a probabilistic neural network. The research highlighted the S-Transform's ability to reveal intricate time-frequency structures in disturbance signals. The probabilistic neural network demonstrated its proficiency in effectively distinguishing between various PQ disturbance types, enhancing the overall reliability of the classification process.

Yu et al. (2012) contributed to the field by presenting a power quality disturbance detection and classification methodology based on the S-Transform and probabilistic neural network. The research showcased the potential of the S-Transform in characterizing complex disturbances with multiple stages. The integration of a probabilistic neural network ensured accurate classification, underscoring the practicality of the approach for real-world power systems.

Collectively, these research papers highlight the significance of the S-Transform as a valuable tool for capturing time-frequency features of PQ disturbances, particularly those involving multiple and multistage events. The incorporation of advanced classification techniques, such as probabilistic neural networks and fuzzy clustering, further enhanced the accuracy and reliability of detecting and classifying these disturbances. The studies underscore the importance of these methodologies in ensuring the stability and reliability of power systems, particularly in the presence of intricate PQ events that can lead to significant operational and economic consequences.

III. S-TRANSFORM

The S-Transform, also known as the Stockwell Transform, is a time-frequency analysis technique used to analyze signals in both the time and frequency domains simultaneously. Unlike traditional Fourier-based techniques that provide a static frequency representation of a signal, the S-Transform captures the dynamic changes in frequency content over time, making it particularly useful for analyzing non-stationary and transient signals, such as those found in power quality disturbances, seismic signals, and biomedical data.
At its core, the S-Transform combines the concepts of the Short-Time Fourier Transform (STFT) and the windowed Fourier Transform. While the STFT uses a fixed window to analyze signal segments, the S-Transform employs an adaptive window that adjusts its length according to the local frequency characteristics of the signal. This adaptive window allows the S-Transform to provide higher time resolution in regions with fast frequency variations and higher frequency resolution in regions with slow variations.

The mathematical representation of the S-Transform of a signal x(t) at a specific time t and frequency f is given by:

$$S_x(t,f) = \int_{-\infty}^{\infty} x(\tau) g(t-\tau) e^{-2\pi i f(t-\tau) d\tau} \tag{1}$$

Here
$x(t)$ is the input signal
$g(t)$ is the analyzing window function
f represents frequency
t denotes time
i is the imaginary unit

The result of the S-Transform is a complex-valued matrix where the magnitude represents the amplitude of the frequency component at a specific time and frequency, and the phase represents the phase information.

IV. FEED FORWARD NEURAL NETWORK (FFNN)

A feedforward neural network is a fundamental architecture in artificial neural networks that models the relationship between input data and corresponding output predictions. It is a form of supervised learning where the network learns to map input features to desired output labels through a series of interconnected layers. Feedforward neural networks are widely used for various tasks, including pattern recognition, classification, regression, and function approximation.

A feedforward neural network consists of layers of interconnected nodes, commonly referred to as neurons. These neurons are organized into three main types of layers: input layer, hidden layers, and output layer. Information flows from the input layer through the hidden layers to the output layer without any feedback loops, hence the term "feedforward."

Each neuron in a layer is connected to all neurons in the previous layer and to all neurons in the subsequent layer. These connections are associated with weights that determine the strength of the connection. The process of learning in a feedforward neural network involves adjusting these weights to minimize the difference between the network's predictions and the actual target values, typically using optimization algorithms like gradient descent.

The output of each neuron is determined by an activation function. Common activation functions include the sigmoid function, rectified linear unit (ReLU), and hyperbolic tangent (tanh). These functions introduce non-linearity to the network, enabling it to model complex relationships within the data.

The operation of a feedforward neural network occurs in two main steps: forward propagation and backpropagation. During forward propagation, input data is fed into the input layer. The input is multiplied by the weights and passed through the activation functions in each subsequent layer, ultimately producing an output prediction in the output layer.

Mathematically, the output O_j of a neuron j in a layer can be expressed as:

$$O_j = f\left(\sum_i \omega_{ij} . o_i + b_j\right) \tag{2}$$

Here:

ω_{ij} is the weight of the connection between neuron *i* in the previous layer and neuron *j* in the current layer.

o_i is the output of neuron *i* in the previous layer.

b_j is the bias term associated with neuron *j*.

f is the activation function.

Feedforward neural networks provide a powerful framework for learning complex relationships in data. By organizing neurons into layers and using activation functions, they can model intricate patterns within input data and generate meaningful predictions. The training process, involving forward propagation and backpropagation, enables these networks to adapt their weights and biases to optimize their performance on specific tasks. As a foundational concept in artificial intelligence and machine learning, feedforward neural networks continue to drive advancements in various fields by enabling computers to learn from data and make informed decisions.

V. PROPOSED METHODOLOGY

In this algorithm the PQ disturbance signal is processed using S-Transform. The resultant S-Transform complex matrix is obtained. To obtain the maximum voltage amplitude versus time contour, the maximum of the absolute value of S-Transform matrix has been taken for analysis. It provides the absolute value of the fundamental frequency element present in the PQ disturbance signal. Figure 1 shows the flowchart of the proposed methodology adopted in this research work.

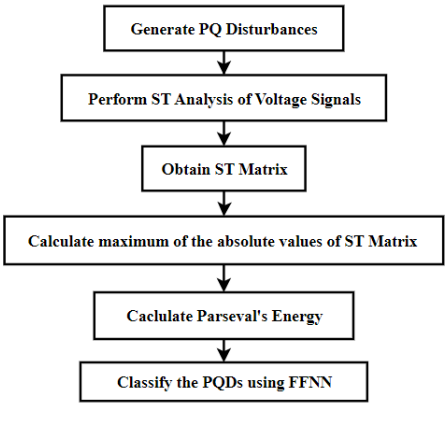

Figure 1: Flowchart of proposed methodology

VI. GENERATION OF POWER QUALITY DISTURBANCES

The Power Quality Disturbances required for the evaluation of the performance of proposed algorithm are generated by using the integral mathematical models of PQDs as per the standards. By varying the parameters of the models, we obtained different dataset of PQDs. The details of the multiple and multistage PQDs considered under study is given below.

A. Multiple Power Quality Disturbances

The superimposition of more than one type of PQ disturbances during the same periodcorresponds to multiple PQ disturbances e.g., voltage sag with flicker, voltage swell with harmonics, transient with harmonics, flicker with harmonics, interruption with harmonics, voltage sag with harmonics, etc. These disturbances are generated by theaddition/multiplication of single-stage PQ disturbances. PQ variation such as harmonics which always exists in a power distribution network, when multiplied with single-stage PQ disturbances, produces multiple PQ disturbances. The multiple PQ disturbances have been generated as shown in Figure 2-4. The selection of parameter values of these disturbances has been performed as per Table 1.

Table 1: Mathematical Modelling of Multiple PQ Disturbances

PQ disturbance	Mathematical model	Parameter range
Sag with harmonics	$V(t)=\left(1-\beta\left(u\left(t-t^*\right)-u\left(t-t^{**}\right)\right)\right)$ $\left(\beta_1\sin(\omega t)+\beta_3\sin(3\omega t)+\beta_5\sin(5\omega t)+\beta_7\sin(7\omega t)\right)$	$0.1\le\beta\le 0.9, T\le t^{**}-t^*\le 9T$ $0.05\le\beta_3,\beta_5,\beta_7\le 0.15,$ $\sum\beta_i^2=1$
Swell with harmonics	$V(t)=\left(1+\beta\left(u\left(t-t^*\right)-u\left(t-t^{**}\right)\right)\right)$ $\left(\beta_1\sin(\omega t)+\beta_3\sin(3\omega t)+\beta_5\sin(5\omega t)+\beta_7\sin(7\omega t)\right)$	$0.1\le\beta\le 0.8, T\le t^{**}-t^*\le 9T$ $0.05\le\beta_3,\beta_5,\beta_7\le 0.15,$ $\sum\beta_i^2=1$
Interruption with harmonics	$V(t)=\left(1-\beta\left(u\left(t-t^*\right)-u\left(t-t^{**}\right)\right)\right)$ $\left(\beta_1\sin(\omega t)+\beta_3\sin(3\omega t)+\beta_5\sin(5\omega t)+\beta_7\sin(7\omega t)\right)$	$0.9\le\beta\le 1.0, T\le t^{**}-t^*\le 9T$ $0.05\le\beta_3,\beta_5,\beta_7\le 0.15,$ $\sum\beta_i^2=1$

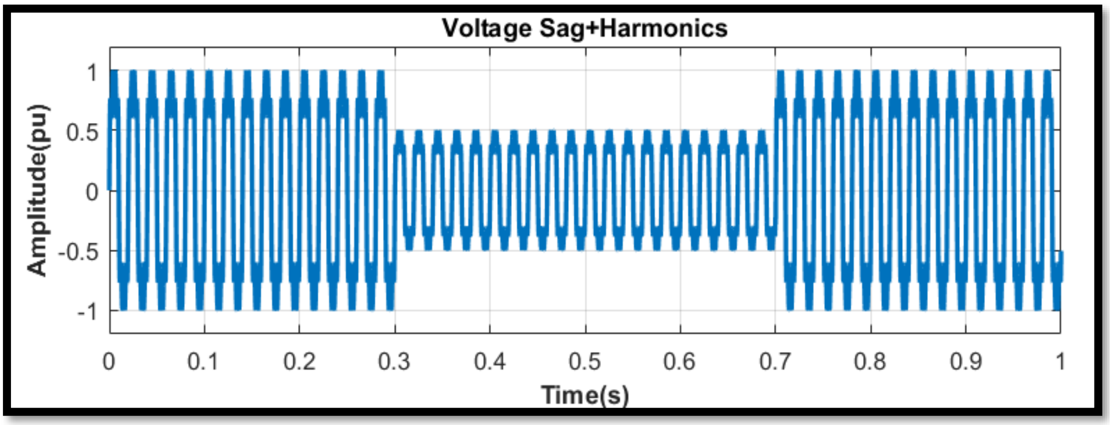

Figure 2: Simulated sag with harmonic signal

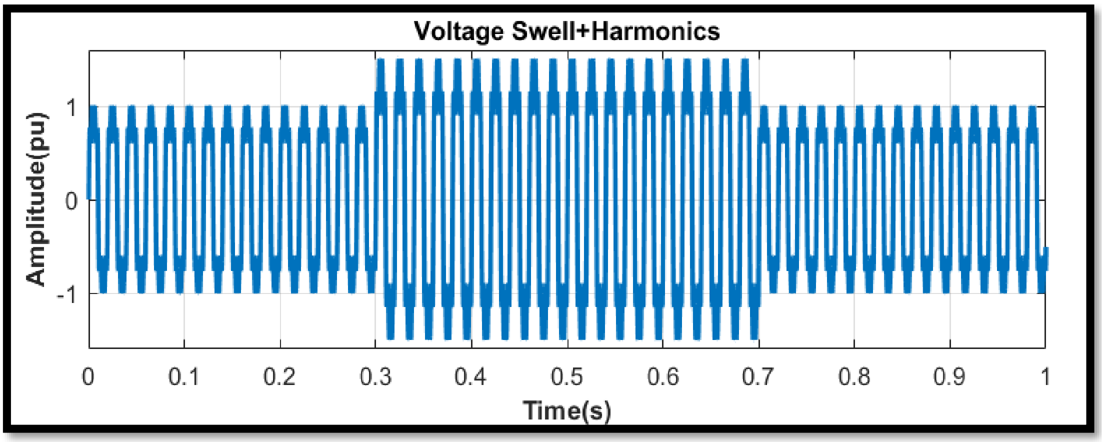

Figure 3: Simulated swell with harmonic signal

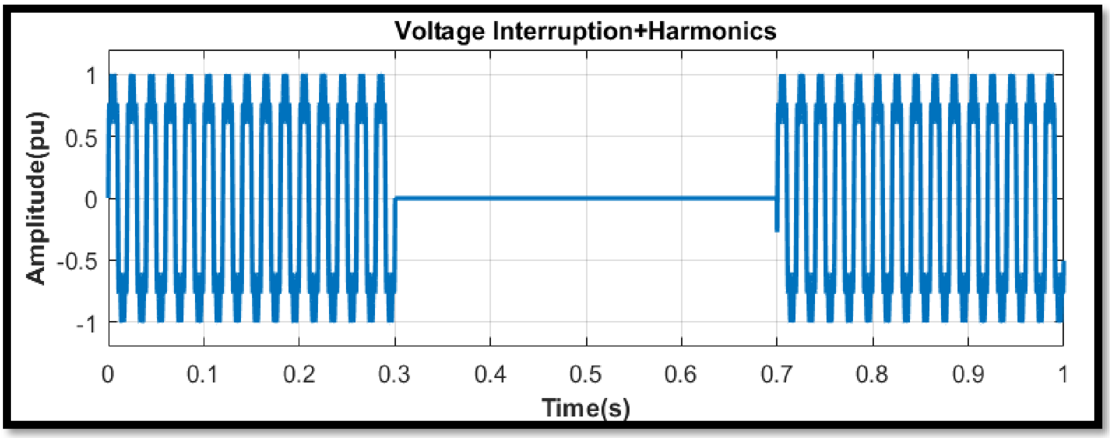

Figure 4: Simulated interruption with harmonic signal

B. **Multi Stage PQ Disturbances**

Multi-stage PQ disturbances are defined as the single-stage PQ disturbance followedby some other PQ disturbance before the recovery of the former disturbance e.g., voltage sag followed by swell, voltage swell followed by sag, transient followed by sag, transient followedby swell, etc. These disturbances change their parameters before recovery. It is formedusing the addition of single-stage PQ disturbances. Several generated multi-stage PQ disturbances (two stages) are shown in figure 5-7. The parameters of these disturbancesare selected as per Table 2. Likewise, the multi-stage PQ disturbances having more than twostages which may be possible due to the complexity of the power system, can be synthetically generated.

Table 2: Mathematical Modelling of Multi-Stage PQ Disturbances

PQ disturbance	Mathematical model	Parameter range
Multi-stage sag	$V(t)=\begin{pmatrix} 1-\beta_1\left(u\left(t-t^*\right)-u\left(t-t^{**}\right)\right)+ \\ 1-\beta_2\left(u\left(t-t^{**}\right)-u\left(t-t^{***}\right)\right) \end{pmatrix}\sin\omega t$	$0.1\le\beta_1,\beta_2\le0.9,\ T\le t^{**}-t^*\le9T,$ $T\le t^{***}-t^{**}\le9T,$
Multi-stage Swell	$V(t)=\begin{pmatrix} 1+\beta_1\left(u\left(t-t^*\right)-u\left(t-t^{**}\right)\right)+ \\ 1-\beta_2\left(u\left(t-t^{**}\right)-u\left(t-t^{***}\right)\right) \end{pmatrix}\sin\omega t$	$0.1\le\beta_1,\beta_2\le0.8,$ $T\le t^{**}-t^*\le9T,$ $T\le t^{***}-t^{**}\le9T$
Multi-stage sag with swell	$V(t)=\begin{pmatrix} 1-\beta_1\left(u\left(t-t^*\right)-u\left(t-t^{**}\right)\right)+ \\ 1+\beta_2\left(u\left(t-t^{**}\right)-u\left(t-t^{***}\right)\right) \end{pmatrix}\sin\omega t$	$0.1\le\beta_1\le0.9,$ $0.1\le\beta_2\le0.8,$ $T\le t^{**}-t^*\le9T,$ $T\le t^{***}-t^{**}\le9T$

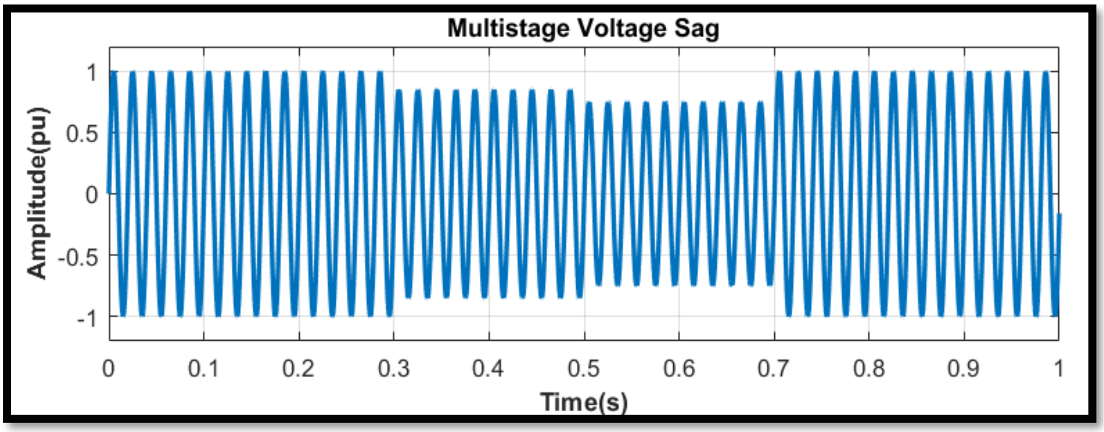

Figure 5: Simulated multi-stage sag signal

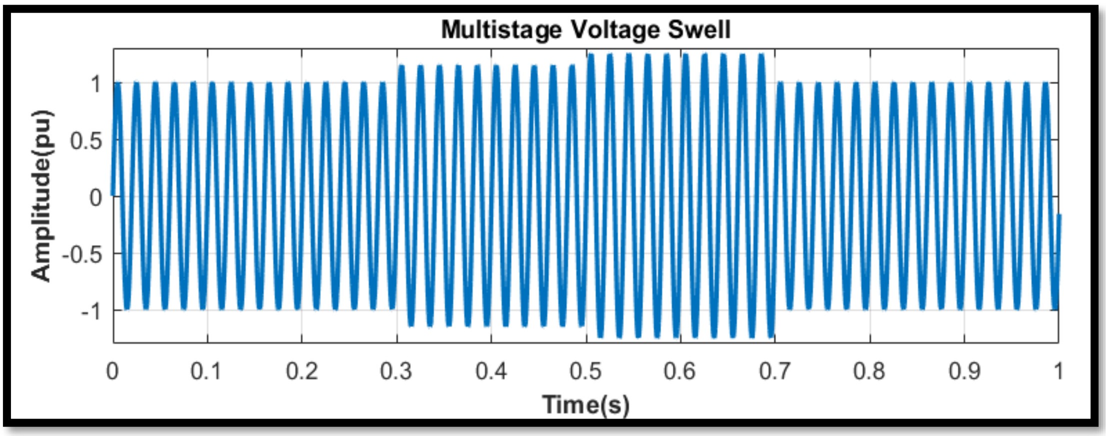

Figure 6: Simulated multi-stage swell signal

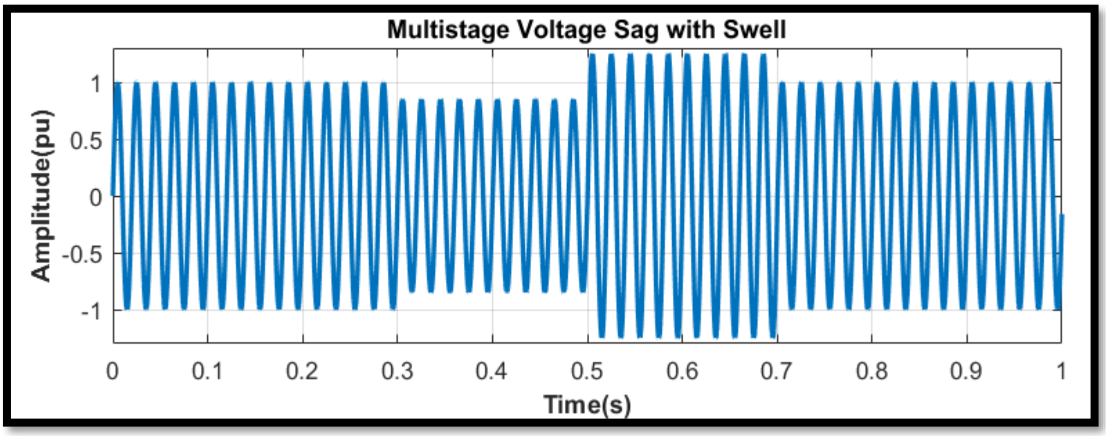

Figure 7: Simulated multi-stage sag with swell signal

VII. S-TRANSFORM ANALYSIS RESULTS

The voltage signals corresponding to multiple and multistage Power Quality Disturbances are processed using S-Transform. The results of the ST analysis is discussed in this section. Figure 8 (a) – 10 (a) show the three types of multiple PQ disturbances and Figure 8 (b) – 10 (b) show their voltage amplitude versus time vectors respectively. Three cases of multistage PQdisturbance have been shown in Figure 11 (a) – 13 (a) with their voltage amplitude versus time vectors as shown in Figure 11 (b) – 13 (b). From the figures obtained from ST analysis it is cleared that the time versus normalized amplitude plot obtained from the maximum of the absolute value of S-Transform matrix forms an important aspect for the classification of both multiple and multistage PQDs. These characteristics found to be distinct for different PQDs.

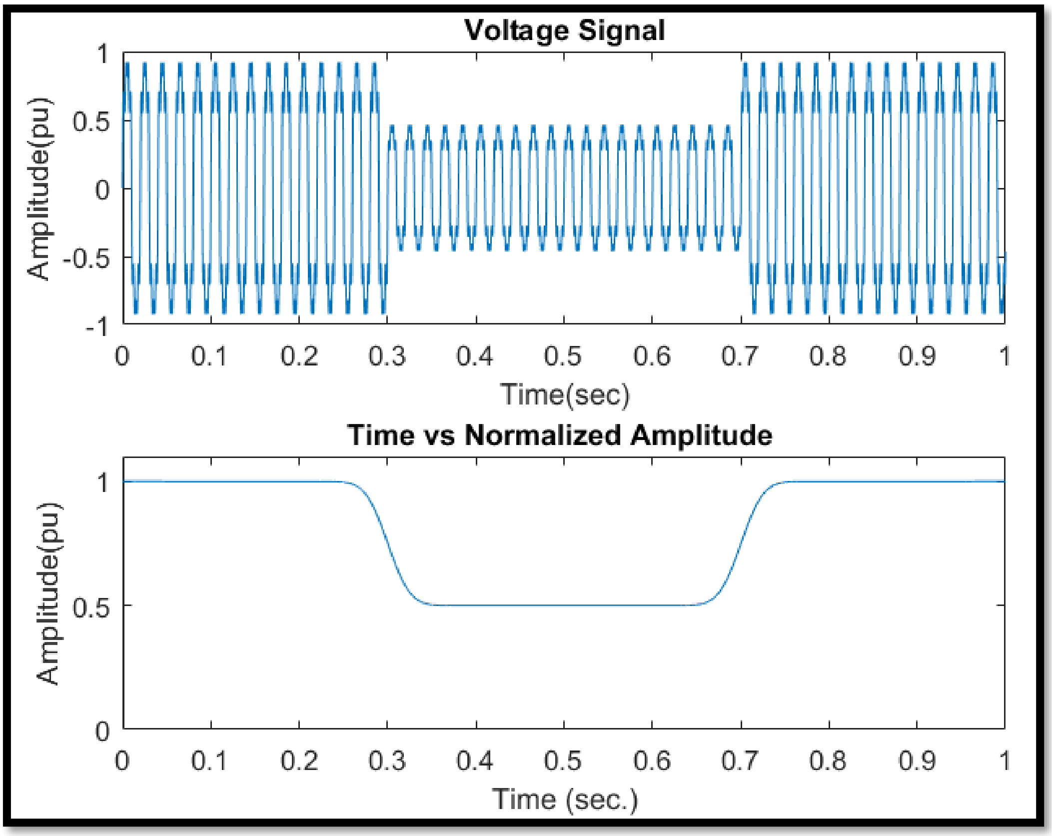

Figure 8: (a) Sag with harmonics (b) Voltage amplitude vs time vector

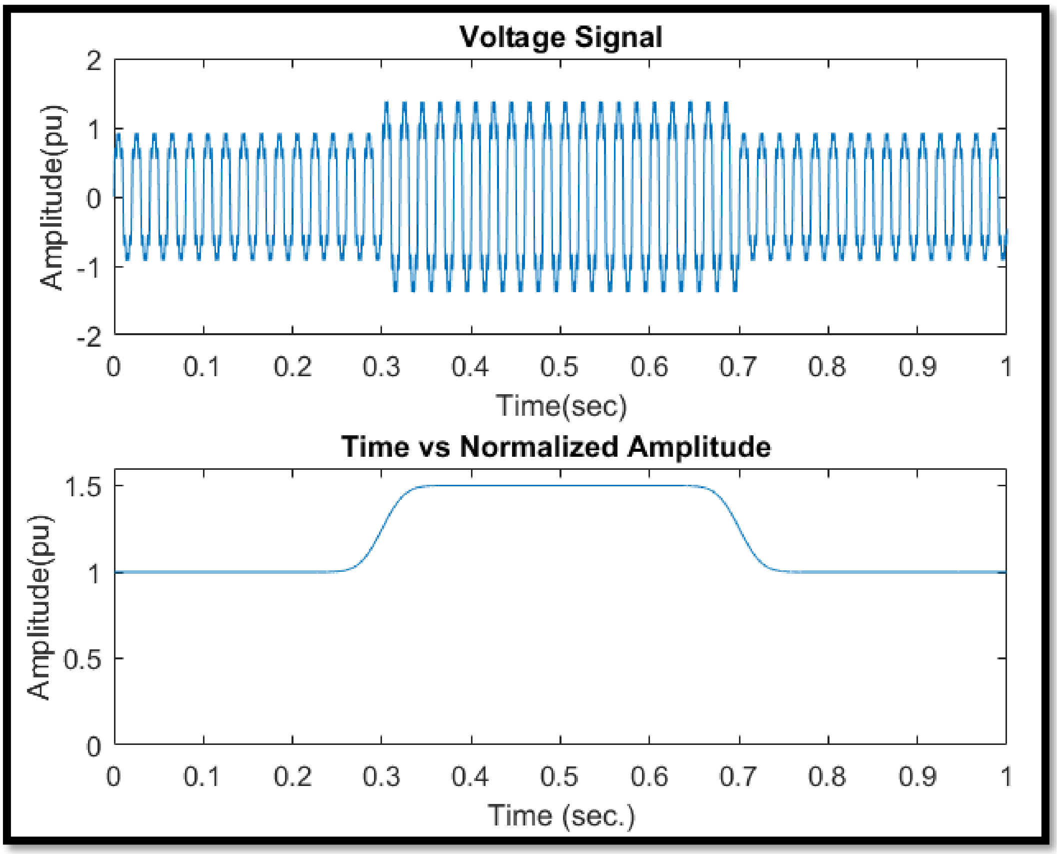

Figure 9: (a) Swell with harmonics (b) Voltage amplitude vs time vector

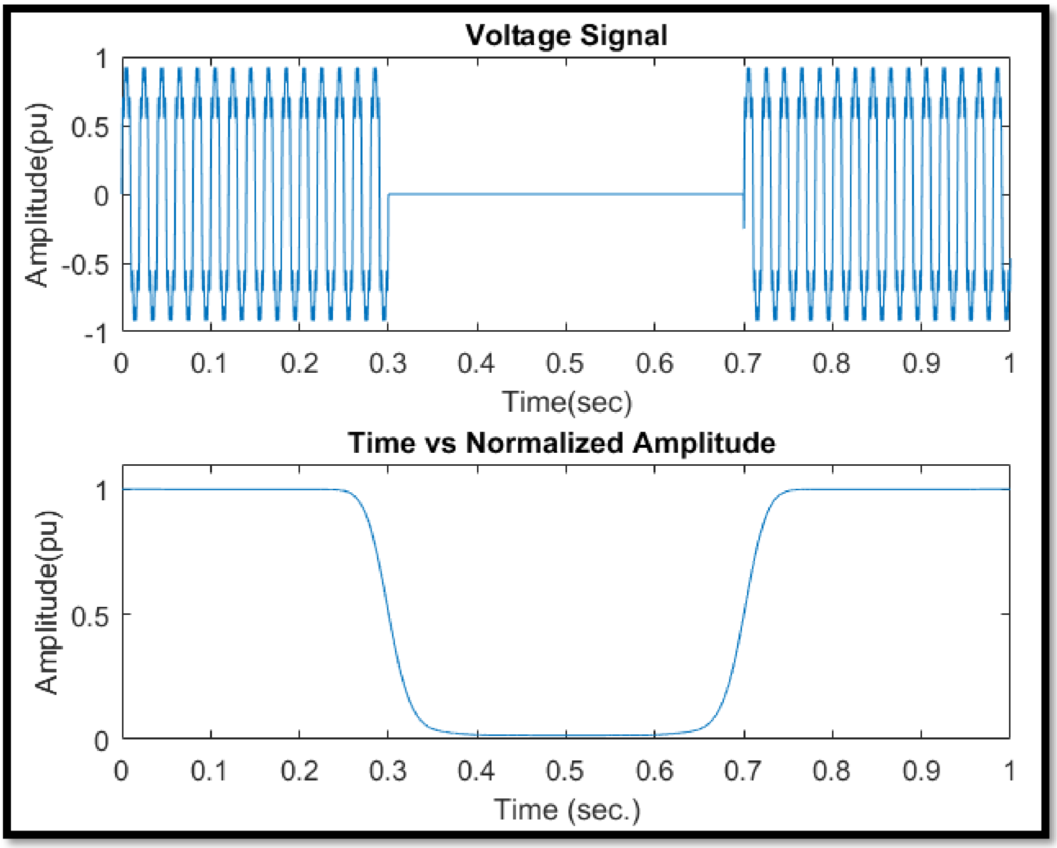

Figure 10: (a) Interruption with harmonics (b) Voltage amplitude vs time vector

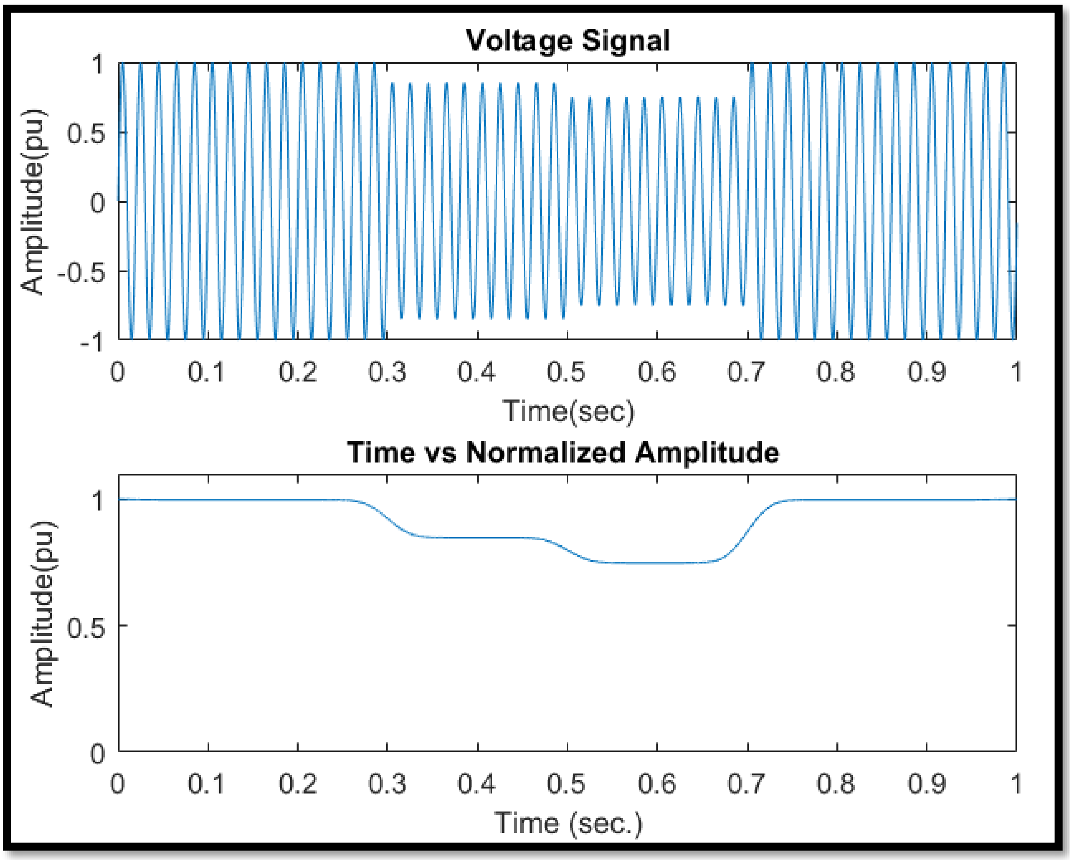

Figure 11: (a) Multistage sag (b) Voltage amplitude vs time vector

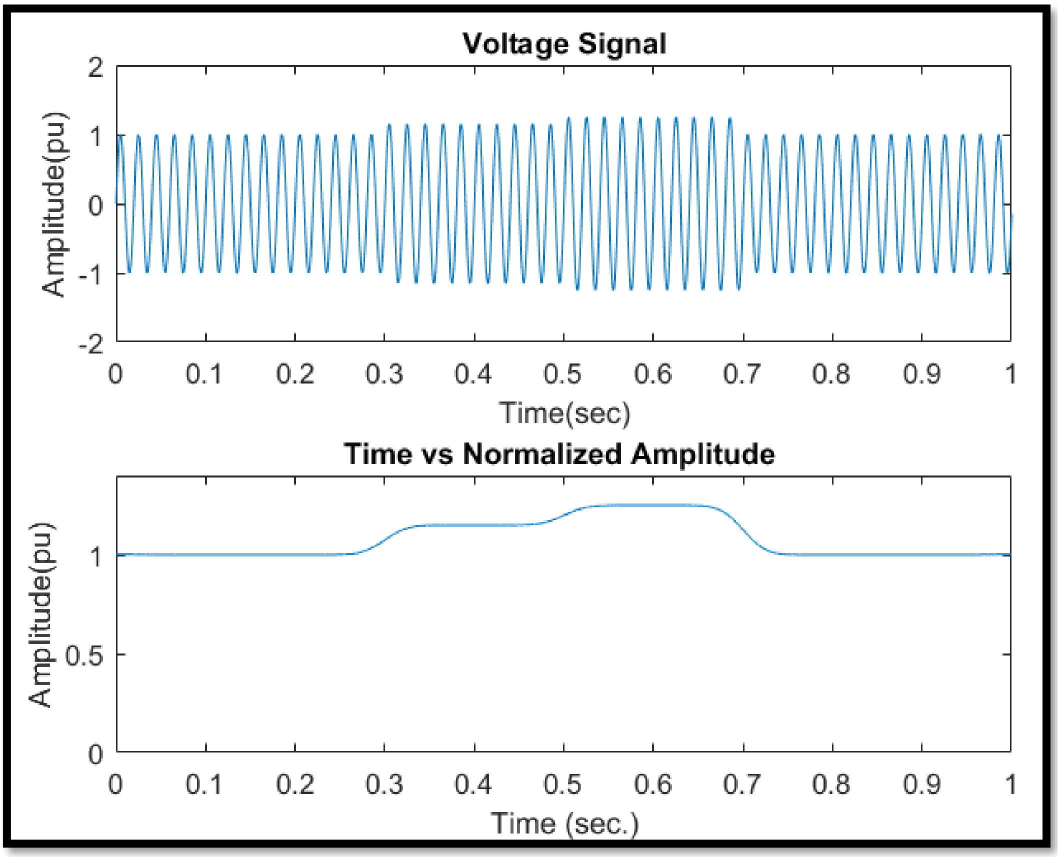

Figure 12: (a) Multistage swell (b) Voltage amplitude vs time vector

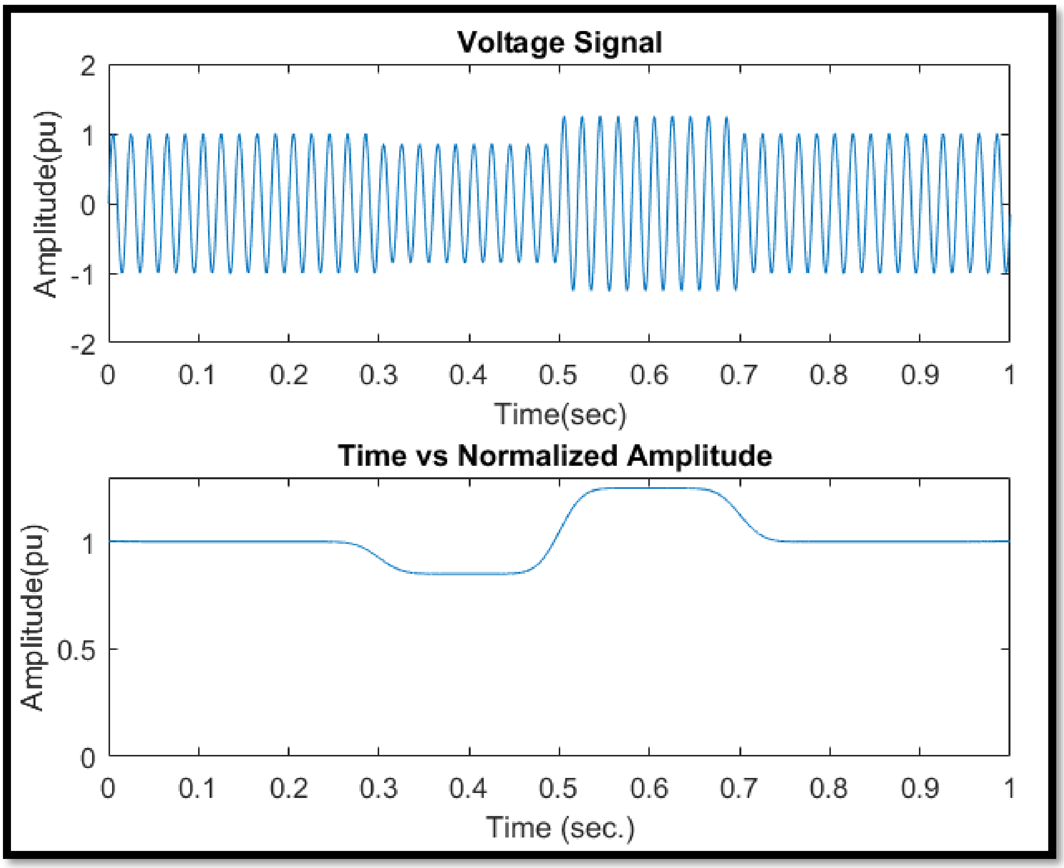

Figure 13: (a) Multistage sag with swell (b) Voltage amplitude vs time vector

VIII.FEATURE EXTRACTION FROM S-TRANSFORM ANALYSIS

The existing literature focuses on detection and recognition of single-stage PQ disturbances. So, this work emphases on the detection and classification of multiple and multistage PQ disturbances using S-Transform. Voltage amplitude versus time vector obtained from S-Transform complex matrix clearly depicts the PQ disturbance behavior. Further, features extracted from the transformed signals are used for automatic identification of multiple and multistage PQ disturbances. The Parseval's energy calculated from the magnitude of time vs normalized amplitude plot is used to classify the multiple and multistage power quality disturbances. Figure 14 shows the Parseval's energy plot of both multiple and multistage PQ disturbances. By calculating the values of energy corresponding to different PQ disturbances a dataset is created for the classification of disturbances.

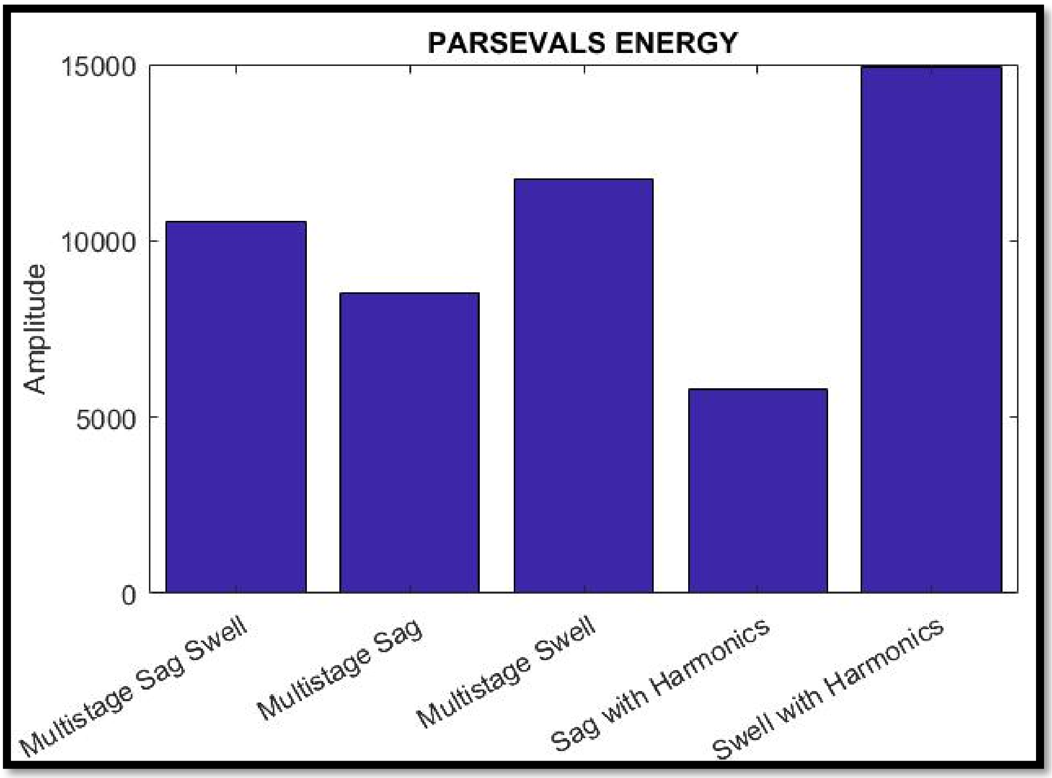

Figure 14: Parseval's Energy calculated for multiple and multistage PQ disturbances

IX. FEED FORWARD NEURAL NETWORK CLASSIFIER RESULTS

The feature vector of 20 datasets of each disturbance is created by computing the Parseval's energy of different PQDs from the ST analysis. The training and testing of Feed Forward Neural Network (FFNN) are done using the extracted feature vector. Table 3 shows the results of the FFNN 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 3: Confusion Matrix of FFNN Classifier

Class	C1	C2	C3	C4	C5	C6
C1	20	-	-	-	-	-
C2	-	20	-	-	-	-
C3	-	-	20	-	-	-
C4	-	-	-	20	-	-
C5	-	-	-	-	19	1
C6	-	-	-	-	-	20

In order to evaluate and examine the performance of the detecting algorithm, a classification system technique is needed. In this research work Feed Forward Neural Network (FFNN) is used as a classifier. Table 4 shows the results of FFNN.

Table 4: Classification accuracy of FFNN with hidden layers

Class	PQDs	1 hiddenlayer	2 hiddenlayers
C1	Sag with Harmonics	100.00 %	100.00 %
C2	Swell with Harmonics	100.00 %	100.00 %
C3	Interruption with Harmonics	95.00 %	100.00 %
C4	Multistage Sag	100.00 %	100.00 %
C5	Multistage Swell	95.00 %	95.00 %
C6	Multistage Sag and Swell	100.00 %	100.00 %
	Overall Accuracy	**98.33 %**	**99.17** %

X. CONCLUSION

In the S-Transform based multiple and multistage PQ disturbances detection and classification approach the normalized amplitude versus time vector is obtained from the S-Transform matrix clearly shows the behavior of PQ disturbance. The features extracted from the transformed signals are used for automatic classification of multiple and multistage PQ disturbances. The Parseval's Energy computed using the normalized amplitude found sufficient to categorize the PQ disturbances based on threshold values. The computational complexity and time of S-Transform is high which limits its application in real-time detection of PQ disturbances. The FFNN trained and tested using the Parseval's energy gives accuracy of 95% and above for individual disturbance and overall accuracy is more than 98%.

REFERENCES

[1] C. L. Kuo, C. W. Liu, Y. C. Cheng, T. H. Huang, "Detection and Classification of Multistage Power Quality Disturbances Using S-Transform and Probabilistic Neural Networks", IEEE Transactions on Power Delivery, Vol. 24, Issue 1, pp. 292-301, Jan 2009.

[2] S. Chandrasekaran, V. Sankaranarayanan, "Power Quality Disturbance Classification Using S-Transform and Adaptive Network-based Fuzzy Inference System (ANFIS)", IEEE Transactions on Power Delivery, Vol. 25, Issue 2, pp. 905-912, April 2010.

[3] G. G. Messina, J. I. Yuz, L. A. N. Lorena, D. A. A. M. G. Monteiro, "Automatic Detection and Classification of Power Quality Disturbances Using S-Transform and Fuzzy C-Means Clustering", IEEE Transactions on Power Delivery, Vol. 26, Issue 4, pp. 2634-2641, Oct 2011.

[4] Y. C. Cheng, C. L. Kuo, J. C. Wang, C. M. Huang, "Automatic Detection and Classification of Power Quality Disturbances Using S-Transform and Probabilistic Neural Network", IEEE Transactions on Power Delivery, Vol. 26, Issue 1, pp. 197-205, Jan 2011.

[5] Y. J. Yu, J. S. Hsu, T. F. Wu, C. T. Su, "Power Quality Disturbance Detection and Classification Using S-Transform and Probabilistic Neural Network", IEEE Transactions on Power Delivery, Vol. 27, Issue 1, pp. 56-63, Jan 2012.

[6] R. Kankale, S. Paraskar and S. Jadhao, "Classification of Power Quality Disturbances in Emerging Power System using S-transform and Support Vector Machine," 2021 IEEE 2nd International Conference on Electrical Power and Energy Systems (ICEPES), 2021, pp. 1-6, doi: 10.1109/ICEPES52894.2021.9699673.

[7] R. Kumar, R. Kumar, S. Marwaha and B. Singh, "S-Transform Based Detection of Multiple and Multistage Power Quality Disturbances," 2020 IEEE 9th Power India International Conference (PIICON), Sonepat, India, 2020, pp. 1-5, doi: 10.1109/PIICON49524.2020.9112945.

[8] Umamani Subudhi, Sambit Dash, "Detection and classification of power quality disturbances using GWO ELM", Journal of Industrial Information Integration, Volume 22, 2021, 100204, ISSN 2452-414X,

[9] Dash, Sambit Supriya and Umamani Subudhi. "Multiple power quality event detection and classification using modified S-transform and WOA tuned SVM classifier." International Journal of Power and Energy Conversion (2019): n. pag.

[10] Minh Khoa, Ngo, and Le Van Dai. 2020. "Detection and Classification of Power Quality Disturbances in Power System Using Modified-Combination between the Stockwell Transform and Decision Tree Methods" *Energies* 13, no. 14: 3623. https://doi.org/10.3390/en13143623