Detection of PQ Short Duration Variations using Stockwell Transform with LSTM

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Abstract

Within the electrical power system, classification, and detection of power quality disturbances (PQDs) are top priorities. We are utilizing feature extraction with artificial intelligence (AI) and deep learning to solve PQD problems utilizing a two-step technique: the feature extraction and categorization steps, with the Feature extraction step employing Stockwell Transform and the categorization step utilizing Long Short-Term Memory techniques. For the detection and classification of PQ disturbance occurrences, this study seeks to employ Stockwell Transform as a feature extraction method using the LSTM Deep Learning (DL) method.

Signal characteristics are extracted from time-frequency analysis data utilizing the Stockwell transform and Deep Learning in the long short-term memory (LSTM) network, which detects and classifies PQ disturbance events. Combining the S-transform with the long short-term memory (LSTM) network enables a high level of classification efficiency. Numerous PQ disorders are treated with single and combination disruptions. The results indicate that the proposed method is accurate and reliable for identifying and recognising single and combination PQ disruptions. Compared to numerous concise studies, the proposed strategy performs exceptionally well.

1. Introduction

Massive changes in electrical loads, such as heavy load powering up, large motor launching, capacitor recharging, cable line switching, and other phenomena, have occurred because of the growth of industry. Due to the non-linear and unbalanced characteristics, voltage, current, and frequency deviations occur, resulting in severe degradation of power supply quality. Such pollution would disrupt the normal operations of the sophisticated processing and computer industries, leading to irreparable losses.

Fast Fourier Transform (FFT) [1, 2], Short-Time Fourier Transform (STFT)[3, 4], Wavelet Transform (WT) [5, 6], Hilbert-Huang Transform (HHT) [7], and so on, are some of the most widely used techniques for extracting features from disturbance signals. FFT is only appropriate for stationary signals; it cannot discern transient signals (temporary fluctuations in amplitude or frequency)[8] . STFT overcomes the shortcomings of FFT by utilizing a sampling window with a fixed width in which the signal is considered approximately stable. Due to the constant breadth of the window, STFT lacks adaptability and has limited time and frequency resolution [9]. Wavelet transform overcomes the shortcomings of STFT and has excellent localization capability for mutation signals in the time-frequency domain. Due to spectrum leakage and the picket fence effect, however, computational costs increase. In addition, WT is susceptible to being affected by sounds and the employed algorithm [10, 11]. [12, 13] F. Z. Dekhandji devised a power quality monitoring system based on abc–0dq transformation and 90 phase shift algorithms. N. Mohan investigated the use of gated recurrent units (GRU) and the convolutional neural network-long short-term memory (CNN-LSTM) and proposed an optimal architecture for deep learning with specific network parameters and topologies [14]. H. Liu decomposes the signals utilizing singular spectrum analysis (SSA) and Fast discrete curvelet transform (FDCT) techniques, and then uses deep convolutional neural networks (DCNN) for classification [15].

S transform is a bidirectional time-frequency analysis technique proposed by Stockwel1 in 1996 [16] that is used between STFT and WT for non-stationary signals. By means of the time-frequency analysis of the signal, local characteristics, such as time-amplitude, frequency-amplitude, and time-frequency, are determined. Consequently, the S transform monitors the beginning and ending times of power quality disturbances, the fluctuation of the amplitude, and the change in frequency, which is employed progressively in the field of power quality disturbances. M. Jaya Bharata Reddy [17] presented a novel method for analyzing power quality based on an orthogonal time-frequency representation of the S transform. Two segments of the wolf sunspot series, seismic maps, and synthetic two-dimensional imagery are analyses using the generalized S transform in [18]. By introducing modifying parameters, the time-frequency resolution of the entire spectrum is enhanced. Milan Biswal proposed novel frequency partitioning schemes and band pass filtering, which substantially reduced the computational cost of the S transform[19]. N. Huang proposed a multiresolution generalized S transform in which the frequency domain is segmented into three frequency areas and the width factor of the window function that is used in the S transform is set to vary across frequency areas to satisfy the recognition requirements of various disturbances in each frequency area [20].

2. The Proposed PQ Categorizations Methodology

In the initial phase of this project, code written in MATLAB was employed to generate simulated voltage time signals. This section provides strategies for identifying PQ disruptions (LSTM) depending on the S-transform and long-short-term memory. Based on the S-transform as an extracted signal feature, these algorithms identify, classify, and localize PQ disturbances. MATLAB equations are used to generate signals (at 50 Hz) with power quality disturbances in accordance with IEEE-1159. These signals provide data in real-time that is used to assess the generalizability of the classifier. ST was employed to extract features from these signals, followed by the training and evaluation of deep learning identification algorithms (LSTM).

This data set contains simulations of numerous power quality disturbance (PQD) signals, including Interruption, Normal, Sag, and Swell, as well as complex power quality disturbances, including Sag plus Harmonics and Swell plus Harmonics.

The deep learning algorithms were then evaluated using data obtained from experiments of voltage signal measurements that included the previously mentioned perturbations. In MATLAB/Code, Deep Learning Algorithms were implemented to generate the power quality disturbances dataset.

2.1 Stockwell transform.

As a signal processing transform, R. G. Stockwell introduced the Stockwell transform, also known as the (S-transform) in 1996. It combines elements of both short-time Fourier analysis and wavelet analysis, but it is a distinct category [16]. Using MRA, the S-transform decomposes a time-varying waveform (PQ disturbance signals) while preserving the absolute phase of each constituent frequency [21]. Therefore, the S-transform can be used to effectively extract features from non-stationary Power Quality disturbance waveforms. When ST is employed to identify power signals as described in [18], it becomes a component of power quality detection methods. ST, like STFT, uses a window to localize the complex sinusoidal Fourier signal, but the window's width and maximal value scale with frequency, as do wavelets. Such a description can be found in [22] regarding detecting voltage sag and surge. The authors proposed using ST and a probabilistic neural network to identify and classify single and complex power quality issues with an overall accuracy of 89%[23] .In addition, a real-time method for detecting and classifying distorted power waveforms was published recently [24].According to [25], an ST-derivative technique known as Discrete Orthogonal S-Transform is applied to five distinct disturbances. The output of an S-transform-based signal decomposition is a n*m-dimensional complex matrix. This matrix is known as an S-matrix and is mathematically represented by the following formula [26].

$$S_x(\tau, f) = \int_{-\infty}^{\infty} x(t)\, w(t-\tau, f) e^{-2\pi jft} dt \tag{1}$$

$$w(\tau, f) = \frac{1}{\sigma(f)\sqrt{2\pi}} e^{\frac{-t^2}{2\sigma(f)^2}} \tag{2}$$

$$\sigma(f) = \frac{1}{|f|} \tag{3}$$

$$S_x(\tau, f) = A(\tau, f) e^{(-i\varphi(\tau, f))} \tag{4}$$

where $w(\tau, f)$ represents the Gaussian window and $\sigma(f)$ represents the window standard deviation, which controls the window width of the Gaussian in the time domain as a percentage of the analysis’s frequency.

Where $\varphi(\tau, f)$ stands for phase and $A(\tau, f)$stands for amplitude. The rows and columns of the S-matrix represent frequency and time, respectively. Each row represents the magnitude corresponding to a particular frequency regarding time in terms of zero to N -1 samples. Each column depicts the frequency components associated with the signal at a particular instant in time. From the S-matrix, the frequency, phase, and magnitude containing valuable information are obtained. At a specific instant in time, the magnitude contour corresponds to the location of the maximal S-matrix value. The phase of the S-matrix corresponds to the regions of maximum amplitude. The frequency contour depicts the signal's frequency content, as determined by the S-matrix.

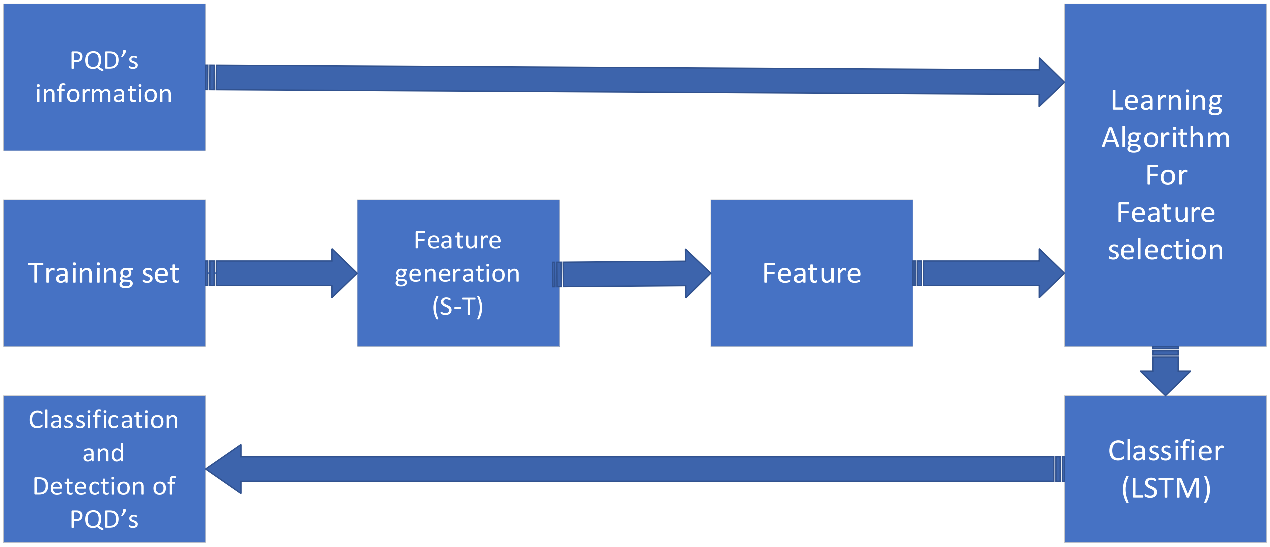

Figure 1. The steps to implement this algorithm.

2.2 Long-Short Term Memory (LSTM)

A Recurrent Neural Network (RNN) is a deep learning technique that represents a discrete dynamic periodic system with input Xt and output ht, where A is the current state's hidden layer. RNNs are utilised for sequence data processing. It can process sequential data changes, unlike typical neural networks [27]. The displayed loop enables the transfer of data between layers. Standard RNN repeating module topology consists of only one tanh layer. Internally, LSTM is more complex than RNN, with four neural network layers: input gate, neglect gate, cell state, and output gate[28] . As shown in Figure 3, these three gates precisely regulate the LSTM to skip or add information to the cell state. Consequently, by employing constant error flow via constant error carousels within special units, LSTM can learn to bridge minimum time gaps exceeding 1000 discrete time steps [29]. Back-propagation over time is the most prevalent training method for RNNs. However, due to the difficulty in isolating gradients, parameters typically capture short-term dependence while information from earlier time decays. Exploding gradients, the opposite phenomena, may happen as well and cause the error to grow rapidly with every time step [28]. LSTM is a novel neural network that employs repetition to solve this problem. LSTMs use additional gates to control the information in the output of the hidden cell and its subsequent concealed state. This allows the network to discover longer-term data connections more efficiently.

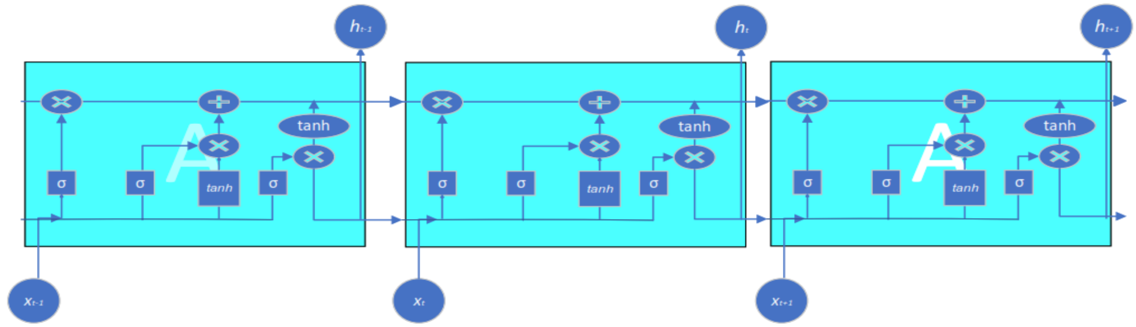

Figure.2 Block chart of an LSTM cell

Three LSTM parameters reduce the network's dependence on long-term data. The Forgotten State eliminates irrelevant or superfluous data. The Input State processes the new data, while the Output State completes the processing of the input data. The illustration in Figure 2 depicts a block diagram of an LSTM cell.

3. SIMULATION RESULTS

MATLAB is used to generate synthetic PQ disturbance signals using parametric formulas which involve signal distortions and voltage variations. As shown in Table I, these signals include simple PQ disturbances such as sag, swell, interruption, and harmonics in addition to complex PQ disturbances such as sag with harmonics and swell with harmonics.

Each disturbance generates one hundred random event signals. The sampling frequency is set to 6,400 Hz. There were 700 PQD disruptions in total. 70% of the data was selected at random for training, while the remaining 30% was utilised for testing. Thus, it will satisfy the required quantity of training data. These signals and their respective labels were layered on the cell array. PQ disturbance signals are subjected to Stockwell transform feature extraction using these inputs. After gathering signal sets of data in MATLAB code being used, it is necessary to implement Stockwell Transformer feature extraction in.

100 concealed layers receive the unprocessed PQ signals. 100 concealed units, or 100 LSTM blocks, were employed to identify time series results for the under-evaluation scheme. To complete the architecture, an entirely connected layer, a SoftMax layer, and a classification layer are added. The activation function in any hidden layer enables the division of signals into distinct categories.

The features obtained in each layer are passed to the succeeding layer, with the final layer's activation values ultimately classifying the data into distinct groups.

TABLE 1 Parametric equations for the simulation of PQ problems [30, 31]

PQ problem	Simulation equation	Parameters
Normal wave	$V(t) = a * sin(\omega t)$	$\omega = 2\pi f$
Sag	$V(t)=(1 - \alpha(u(t - t1) - u(t - t2))) * sin(\omega t)$	$0.1 \le \alpha \le 0.9,\ T \le t2 - t1 \le 9T$
Swell	$V(t) = (1 + \alpha(u(t - t1) - u(t - t2))) * sin(\omega t)$	$0.1 \le \alpha \le 0.8,\ T \le t2 - t1 \le 9T$
Interruption	$V(t) = (1 - \alpha(u(t - t1) - u(t - t2))) * sin(\omega t)$	$0.9 \le \alpha \le 0.1,\ T \le t2 - t1 \le 9T$
Harmonics	$V(t) = \alpha 1 sin(\omega t) + \alpha 3 sin(3 \omega t) + \alpha 5 sin(5 \omega t) + \alpha 7 sin(7 \omega t)$	$0.05 \le \alpha 3,\ \alpha 5,\ \alpha 7 \le 0.15,$
Sag with harmonics	$V(t) = (1 - \alpha(u(t - t1) - u(t - t2))) *(\alpha 1\ sin(\omega t) + \alpha 3 sin(3 \omega t) + \alpha 5\ sin(5 \omega t) + \alpha 7\ sin(7 \omega t))$	$0.1 \le \alpha \le 0.9,\ T \le t2 - t1 \le 9T$ $0.1 \le \alpha 3,\ \alpha 5,\ \alpha 7 \le 0.15$
Swell with harmonics	$V(t) = (1 + \alpha(u(t - t1) - u(t - t2))) * (\alpha 1\ sin(\omega t) + \alpha 3 sin(3 \omega t) + \alpha 5\ sin(5 \omega t) + \alpha 7\ sin(7 \omega t))$	$0.1 \le \alpha \le 0.9,\ T \le t2 - t1 \le 9T$ $0.1 \le \alpha 3,\ \alpha 5,\ \alpha 7 \le 0.15$

3.1 Analysis of PQ disturbances using Stockwell Transform (ST)

In this section, we present an analysis of Power Quality (PQ) disturbances through the utilization of the Stockwell Transform (ST). The ST is a mathematical technique that employs a windowed Fourier Transform to provide time-frequency localization of signals. Our approach involves the generation of diverse plots using the ST-matrix, aimed at identifying and classifying PQ issues. Specifically, we employ the waveform curve, frequency contour, amplitude-time plot, Total Harmonic indicator, and Long Short-Term Memory (LSTM) output to conduct the analysis. Moreover, the ST-based plots of pure sine waves serve as a benchmark for identifying PQ disturbances. Through this scientific investigation, we aim to enhance our understanding of PQ disturbances and their impact on power systems.

3.1.1 Case I: Normal sine wave

In Case I, we look at a regular sine wave signal and use several Stockwell Transform (ST)-based displays to assist identify PQ problems. Figure 3 shows a variety of ST-based graphs of the normal sine wave that can be used to identify PQ disturbances. The amplitude-frequency curve of a normal sine wave has a peak at 50 Hz, suggesting a pure sinusoidal waveform. Any variations from these charts might point to the presence of a PQ disturbance in the signal. We can properly identify and characterize PQ disturbances using the ST-based analytical technique, thereby improving our understanding of power system behavior.

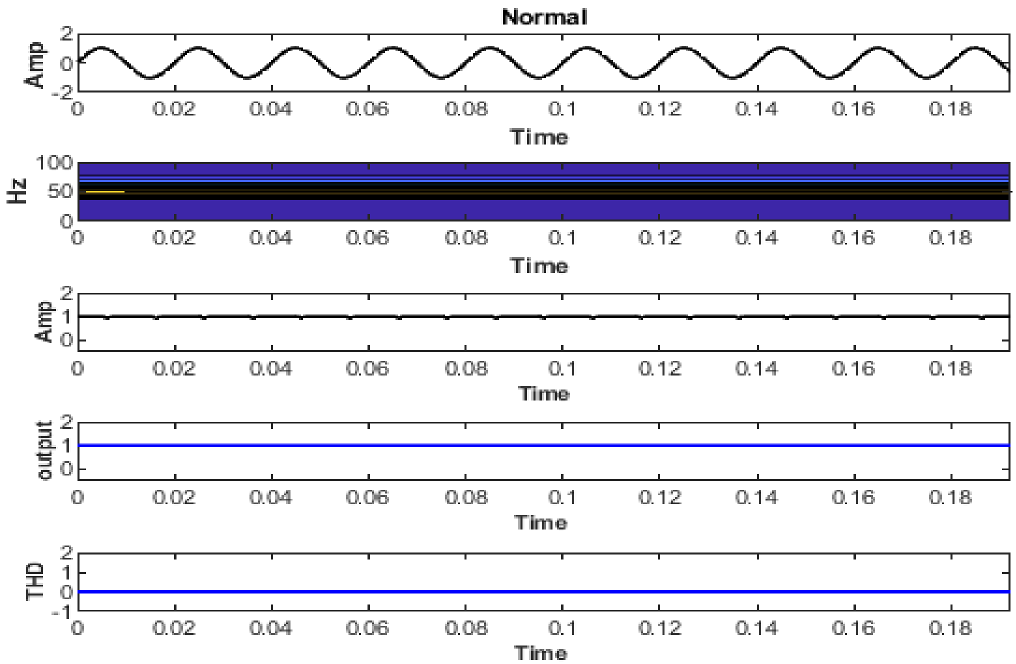

Figure 3: Case I (a) Normal waveform (b) Frequency contour(c) amplitude, (d) LSTM output, and (e) THD

3.1.2 Case II: Voltage Transients

Case II evaluates voltage transients, and Figure 4 depicts Stockwell Transform (ST) transform-based visualizations of these transients. Figures 4(b) to (d) show the produced surge or transient waveform, as well as the amplitude and output values from the Long Short-Term Memory (LSTM) network. Notably, at 0.017 s, the LSTM output equals 0.6, indicating the presence of a spike. In addition, the Total Harmonic Distortion (THD) value for this waveform is 0, indicating that no harmonic distortions exist. We can effectively recognise and categories voltage transients using the ST-based analytic technique and the LSTM network, offering significant insights into power system behaviors.

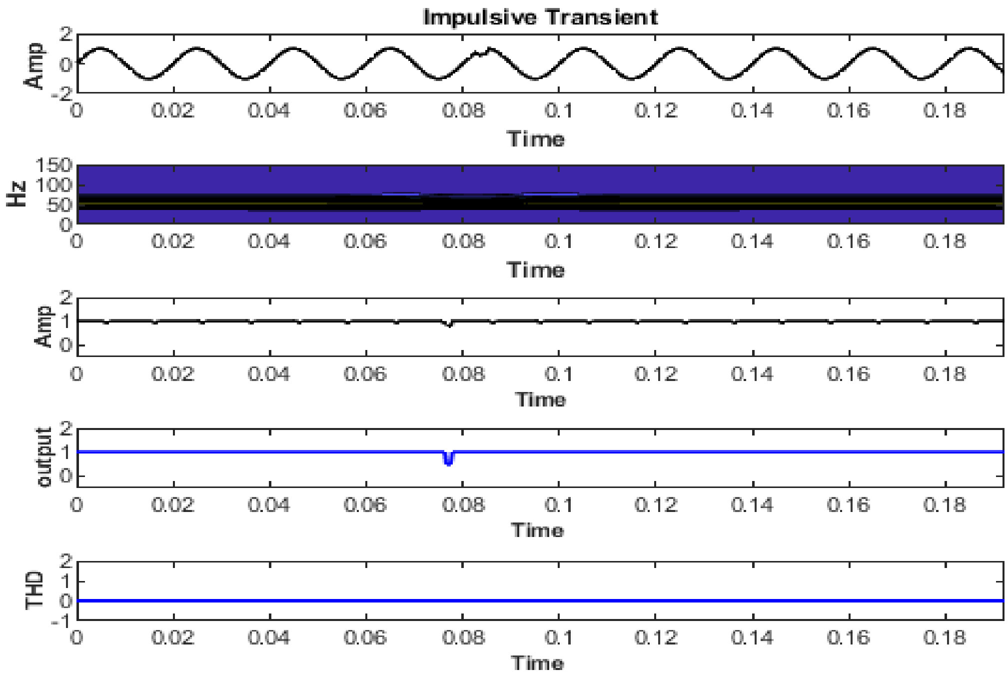

Figure 4 Case II (a) Transient waveform (b) Frequency contour(c) amplitude, (d) LSTM output, and (e) THD

3.1.3 Case III: Voltage sag with harmonics

Case III involves the analysis of a voltage sag event contaminated with harmonic distortions. Figure 5 displays the Stockwell Transform (ST)-based plots of the distorted signal mixed with the sag event. Specifically, Figure 5(b) presents the frequency contour plot, while Figure 5(c) showcases the amplitude-time curve. Additionally, Figure 5(d) illustrates the Long Short-Term Memory (LSTM) output plot. The ST-based plots and their associated values indicate that the signal is complex, containing both harmonic distortions and sag events. Notably, the LSTM output equals 1 for the time periods from 0 to 0.078 s and 0.13 s to the end of the captured time period, indicating that the waveform is normal during these intervals. However, the output equals 0.5 from 0.78 to 0.13 s, indicating the presence of a sag event, as depicted in Figure 5(d). Furthermore, the Total Harmonic Distortion (THD) value for this waveform is 1, confirming the existence of a distortion in the captured signal, as shown in Figure 5(e). By utilizing the ST-based analysis approach, we can accurately identify and classify voltage sag events, even in the presence of harmonic distortions, providing valuable insights into power system behavior.

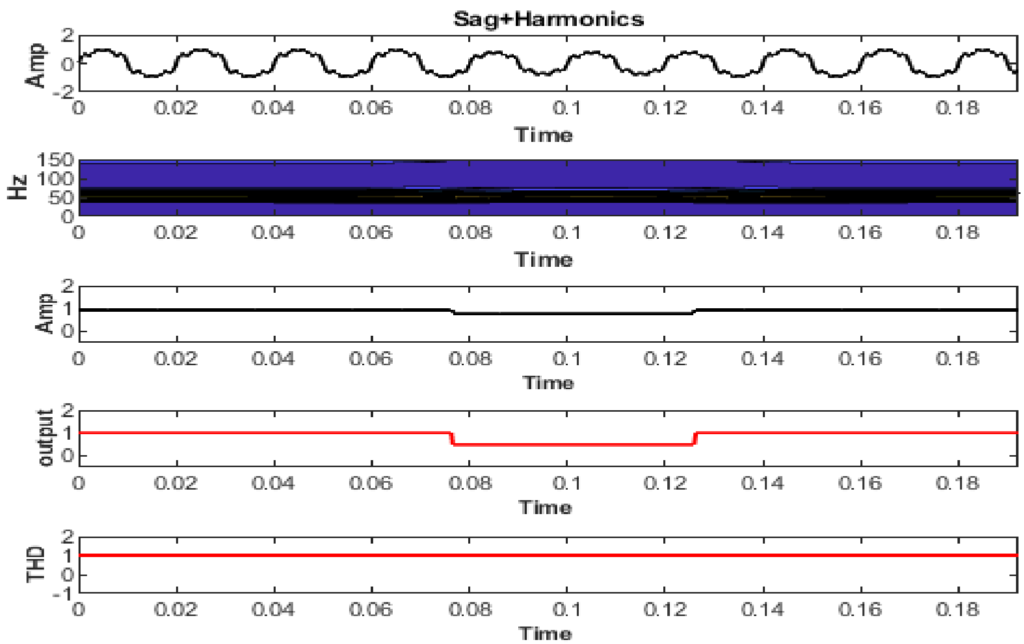

Figure 5 Case III (a) Sag with Harmonics waveform (b) Frequency contour(c) amplitude, (d) LSTM output, and (e) THD

3.1.4 Case Ⅳ: Voltage swell with harmonics.

Case VI involves the analysis of a voltage swell event contaminated with harmonic distortions. Figure 6 displays the Stockwell Transform (ST)-based plots of the distorted signal mixed with the swell event. Specifically, Figure 6(b) presents the frequency contour plot, while Figure 6(c) showcases the amplitude-time curve. Additionally, Figure 6(d) illustrates the Long Short-Term Memory (LSTM) output plot. The ST-based plots and their associated values indicate that the signal is complex, containing both harmonic distortions and swell events. Notably, the LSTM output equals 1 during the normal part of the waveform and equals 1.5 during the swell event, as depicted in Figure 6(d). Furthermore, the Total Harmonic Distortion (THD) value for this waveform is 1, confirming the existence of a distortion in the captured signal, as shown in Figure 6(e). By utilizing the ST-based analysis approach, we can accurately identify and classify voltage swell events, even in the presence of harmonic distortions, providing valuable insights into power system behavior.

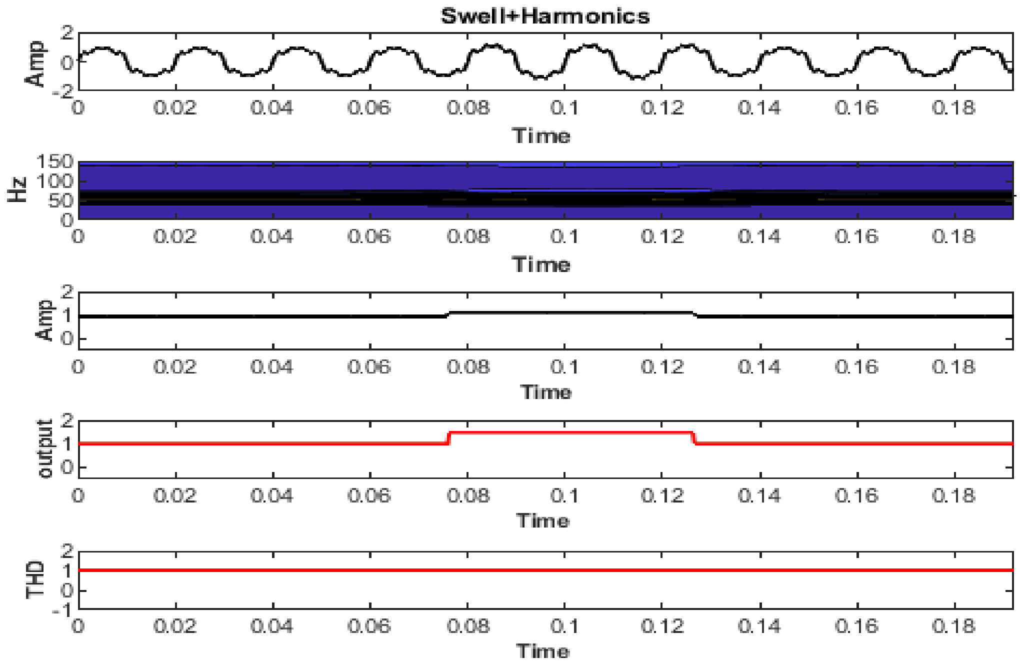

Figure 6 Case Ⅳ (a) Swell with Harmonics waveform (b) Frequency contour(c) amplitude, (d) LSTM output, and (e) THD

3.1.5 Comparisons with other PQ detection techniques

Comparisons are made between the proposed method and several other state-of-the-art methods for making predictions, including the Kalman filter technique with fuzzy-expert method (KF-FES) [32], the Sparse signal decomposition on hybrid dictionaries (SSD) [33], the Long Short-Term Memory (LSTM) [34], the convolutional neural network (CNN)[35], and the double resolution ST (DRST) with directed acyclic graph (DAG) [36]. Tables II's comparison findings show that the suggested method detects all PQDs with an average accuracy of 99.7% and detects simple PQDs with 100% accuracy. These findings demonstrate the effectiveness of the suggested technique in complicated PQ settings, where it recognizes and identifies signals from a wide range of PQ disturbance occurrences. The absence of noise in the predictions demonstrates that the proposed method is robust and accurate, outperforming competing methods. The classification time is successfully shortened while keeping high accuracy with the suggested technique because the computation complexity of classification is reduced.

TABLE 2 **Accuracy based comparison of the WS with LSTM with other classification techniques for no noise PQ problems.**

PQ disturbance	ADALINE and FFNN [37]	DRST, DAG [32]	SSD on hybrid dict. [[33]	LSTM [38]	CNN [39]	CNN-LSTM [34]	Adjusted CNN-LSTM [34]	Proposed ST-LSTM
Normal	100	100	100	100	11.4	100	49.7	100
Interruption	100	97.0	100	100	100	100	100	100
Sag	100	99.5	100	89.8	92	90.3	98.4	100
Swell	100	99.0	100	89.2	99.8	97.7	95.7	100
Flicker	94.0	99.5	100	----	---	---	---	100
Harmonics	98.0	100	100	85.4	100	98.2	97.8	100
Transient	98.86	99.3	96.33	0	88.4	0	49.8	100
Sag with Harmonics	98.0	100	84.67	---	---	---	----	96.6
Swell with Harmonics	97.0	99.5	86.0	----	----	----	----	98
Mean%	98.38	99.31	96.33	62.4	66.9	81.03	89.4	99.8

4. CONCLUSION

This study proposes a novel method for detecting and classifying PQD using ST and LSTM. The proposed method extracts features from PQD signals using ST before classifying simple and complex PQD problems using LSTM. This strategy reduces differences between distinct classes while preserving their distinction. For obvious visualization, rather than the original electrical power quality perturbation signal, frequency contour plot, amplitude, and THD are used as inputs. To evaluate the performance of the proposed method, various simple PQD events, including transient, as well as complex PQD events, including sag with harmonics and swell with harmonics. The results demonstrate that the proposed method outperforms other approaches for classifying PQD problems while reducing the classification's calculation complexity. The proposed algorithm reduces classification time while maintaining classification precision. Overall, the ST with LSTM method is an efficient and effective technique for detecting and classifying PQD issues.

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