Enhanced Time-Frequency analysis of Power Quality Disturbances using Fourier Synchro-Squeezing Transform

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***Abstract*—Power quality disturbances (PQD) critically impact the stability and performance of electrical equipment, necessitating their timely detection and thorough investigation. High resolution time-frequency analysis methods are essential for visualizing and recognizing non-stationary waveforms in power quality (PQ) disturbance signals. The Fourier Synchro-Squeezing Transform (FSST) is suggested as a better way to characterize and identify advanced time-frequency PQD techniques in this study. It is shown that FSST can provide accurate and detailed time-frequency representations of PQ disturbance signals, showing how well it works to improve the accuracy of PQD analysis and detection accuracy. In addition to presenting the merits of FSST, a comparative study with other state-of-the-art methods, such as the Stockwell Transform (ST) and Hilbert-Huang Transform (HHT), is conducted. This comparison shows that FSST is better in terms of resolution and ease of use, especially when dealing with complex, non-stationary signals common during power quality problems. The study examines various PQ disturbance signals, including voltage sags, swells, transients, and harmonic distortions, analyzed using FSST.**

***Index Terms*—Fourier Synchro-Squeezing Transform, Hilbert Huang Transform, Stockwell Transform, Power Quality Disturbance, Variational Mode Decomposition.**

I. Introduction

Power quality disturbances (PQD) have an impact on the stability and functionality of electrical equipment, making their detection and investigation crucial. Transients, harmonics, flickers, and voltage swells or sags are some examples of these disturbances. The Fourier Synchro-Squeezing Transform (FSST), Hilbert-Huang Transform (HHT), Stockwell Transform (ST), Variational Mode Decomposition (VMD) in conjunction with the Teager Energy Operator and Smooth Pseudo Wigner-Ville Distribution (SPWVD) are among the methods examined. Time-frequency analysis provides a localised perspective of frequency content with time, which is essential for analysing transient and non-stationary signals. This work assesses advanced time-frequency techniques to improve PQD characterization and identification. Every technique offers distinct perspectives on PQD frequency fluctuations, which are essential for averting equipment failure and guaranteeing effective power distribution.

By varying the coefficient's size or frequency, the synchro-squeezing post-processing technique reduces the uncertainty present in linear transformations [1]. This technique improves the quality of the time-frequency representation, hence lowering uncertainty and giving a more accurate picture of the signal frequency content that varies with time. The work on Time-Frequency Analysis of Non-Stationary Waveform in Power-Quality via SST in [2] explained that When it comes to characterizing PQ events, an SST-based method outperforms the conventional Continuous Wavelet Transform (CWT). This technique improves PQD analysis's precision and level of detail while providing deeper insights into the incidents. Power System Frequency and Amplitude Estimation Using Variational Mode Decomposition and Chebfun Approximation System is detailed in [3] and this paper shows a new way to estimate the frequency and amplitude of a power system. It uses the variational mode decomposition (VMD) algorithm and the Cheb-function (Chebfun) approximation system. The spectral information of power signals is extracted using VMD as sub-signals or modes. The HHT for evaluating the instantaneous frequency evolution of transient signals in non-linear systems is mentioned in [4]. This paper evaluated the validity of HHT results by examining signals from experimental circuits, in particular, the current flowing through an RLC circuit while it oscillates freely. David Looney et al. in [5] proposed to analyze multivariate data by introducing a multivariate extension of the synchro-squeezing transform.

In [6] signal processing techniques have been discussed with the further application of ML processing to it. Classification of Power Quality disturbances using the iterative Hilbert Huang Transform [7] explains the ability to analyze non-stationary complex waveforms with very good time resolution.The inability of the HHT to reliably separate signals whose frequency components are within a factor of two of one another is one of its limitations.The multi-disturbance complex power quality signal HHT detection technique [8] shows how the HHT method adaptively divides frequencies. This avoids the limitation of using harmonics as the baseline signal and makes signal analysis more flexible. Classification of power quality disturbance signals based on S-transform and HHT [9] Using HHT, the method extracts the signal's instantaneous amplitude before and following the disruption. PQDs are hence classified by combining the S-transform of the disturbance signals to obtain high-frequency and low-frequency properties. Early fault feature extraction of bearings based on Teager energy operator and optimal VMD is reported in [10]. Identification method for power system low-frequency oscillations based on improved VMD and Teager–Kaiser energy operator is discussed in [11]. The interplay between several modes in the system could create new modes, which would then affect the decomposition outcomes. In [12], the correlation coefficient criterion is used to improve VMD (IVMD) and estimate the number of decomposition components adaptively. IVMD-TEO is a time-frequency analysis method that combines the benefits of TEO and IVMD.

Ambient oscillatory mode assessment in power system using time-varying filter-based Empirical Mode Decomposition (TVF-EMD) in [13]. This paper suggests a new approach to detect oscillatory modes in the power system and extract the modal properties. The Teager-Kaiser energy operator (TKEO) method is utilised for parameter estimation, and the technique is based on the sophisticated signal processing approach known as TVF-EMD. In many situations, such one-dimension frequency analysis is adequate. Nonetheless, it is essential to represent the studied signal on the time-frequency plane in order to more fully depict the signal's properties. Time-frequency representations (TFR) for displayed measured signals are widely available. The most often used ones are the Gabor Transform (GT) and Spectrogram (SPEC), which are based on direct DFT findings [14]. A new improved synchrosqueezing transform based on an adaptive short-time Fourier transform is proposed by Guo Y et al. in citeb15. The effective variation of the width of the Gaussian window is discussed in [16] and it demonstrates that the Gaussian window has more control over the S-Transform's energy concentration. This has been made possible by adding a new parameter (δ) to the window, which changes in frequency and effectively modulates the S-Transform kernel as frequency increases.

Time–frequency analysis of seismic data using an S transform (ST) in [17]. Through this paper, thin beds and channel detection are made more difficult by the reduced temporal resolution of the TF spectrum acquired by the ST at low frequencies. A nonlinear time-frequency analysis method is discussed in [18]. This study contrasts conventional discrete Fourier transform (DFT)–based techniques with an alternative method for time-frequency signal analysis.

Despite these advancements, comprehensive comparative studies of different methods. Challenges in generating the dataset for all the 15 classes and achieving high accuracy in critical methods still persist. This report aims to address these gaps by providing a detailed comparison of FSST with HHT, ST, SPWVD, VMD with Teager. This will contribute to a better understanding of the relative strengths and weaknesses of each method.

II. Dataset

A synthetic dataset with 15 PQD classes is generated in MATLAB to analyze various Power Quality Disturbances (PQD) as per Table:I. Swell, Flicker, Notch, Harmonics, Interruption, Oscillation Transients, Impulse Transient, Sag with Harmonics, Sag with Oscillations, Sag with Harmonics and Oscillations, Swell with Harmonics, Swell with Oscillations, and Swell with Harmonics and Oscillations are all included in the dataset. Matlab programs were used to mimic each class correctly, and the waveform data were stored as .txt files. Then, these separate datasets were merged to create a comprehensive dataset that was saved in a .txt file format for easy access and additional processing.

A. Simulation Parameters

The MATLAB signal generating parameters were carefully selected to simulate power quality disruptions in the real world. The subsequent set of fixed parameters were utilized: There are 622 cycles, 1 amplitude (A), 50 Hz frequency (f) and 3200 Hz sampling rate. The selection of 622 cycles guarantees that every generated signal has enough data points to appropriately depict the disturbance's features. A high-resolution time series signal is produced by combining this number of cycles with a sampling rate of 3200 Hz, which makes it easier to create precise and in-depth disturbance images. The ability to discriminate between various forms of disruptions depends on the high sample rate's ability to capture fleeting events and minute fluctuations in the signal.

B. Disturbance classes

- Sine Wave: The baseline waveform representing normal operation without disturbances.
- Sag: A temporary reduction in voltage.
- Flicker: Rapid variations in voltage causing light flickering.
- Notch: A brief drop in voltage due to load switching or fault conditions.
- Harmonics: Distorted waveform caused by the presence of multiple frequencies.
- Interruption: A complete loss of voltage for a brief period.
- Oscillation Transients: High-frequency oscillations superimposed on the normal waveform.

- Impulse Transient: A sudden, short-duration disturbance with high amplitude.
- Sag with Harmonics: A voltage sag combined with harmonic distortions.
- Sag with Oscillations: A voltage sag accompanied by oscillatory transients.
- Sag with Harmonics and Oscillations: A complex disturbance involving sag, harmonics, and oscillations.
- Swell with Harmonics: A voltage swell combined with harmonic distortions.
- Swell with Oscillations: A voltage swell accompanied by oscillatory transients.
- Swell with Harmonics and Oscillations: A complex disturbance involving swell, harmonics, and oscillations.

C. Disturbance Parameters

Various parameters are defined to simulate several types of PQDs:

- Magnitude of sag/swell/interruption
- Magnitude of interruption
- Flicker modulation depth

  ω : Angular frequency of the fundamental component (50 Hz)

  γ: Angular frequency of the flicker

  $\beta 3$: Coefficient for the 3rd harmonic

  $\beta 5$: Coefficient for the 5th harmonic

  t1 and t2: Start and end times of disturbances

  u: Unit step function

III. Methodology

Fig.1 represent the whole process of FSST. In FSST, an input signal is first divided into brief segments. During this segmentation process, the signal is divided into overlapping windows, and each window is then multiplied by a windowing function. Each window is subjected to the Fourier Transform (FT) after segmentation, which transforms the signal from the time domain to the frequency domain. In order to create an accurate time-frequency representation, these segments are finally stacked together and the data is arranged along the time and frequency axes.

The Fourier Synchro-Squeezing Transform (FSST), Hilbert-Huang Transform (HHT), Stockwell Transform (ST), Smooth Pseudo Wigner-Ville Distribution (SPWVD), and Variational Mode Decomposition (VMD) with Teager Energy Operator analysis are the five sophisticated signal processing techniques that are introduced in this study. These techniques are used to generate a comprehensive dataset for analysis by modeling fifteen different types of PQDs. High-resolution data is ensured by simulating real-world situations in MATLAB with a sampling frequency of 1000 Hz and a time vector of one second. Predetermined characteristics, such as frequency, magnitude, and common disturbances including flicker, sags, swells, harmonics, interruptions, and their combinations, are used to construct each PQD. This FSST modification improves the performance of non-stationary signal analysis [19]. There is an energy change in the time-frequency plane. The first step is converting a signal into an STFT.

The STFT is given as S(m, k)

$$S(m,k) = \sum_{i=0}^{A-1} x(i)B(i-p)e^{-j\frac{2\pi}{N}k(i-p)} \tag{1}$$

where the number of samples is A and B is the window function and the number of points in the frequency domain can be represented as k.

The range of values for these parameters is as follows:

i, p = 0, 1, . . . , (N-1)

k = 0, 2, . . . , (N-1)

$$w[m,k] = \text{Round off}\left[\text{Real}\left(\frac{N}{2\pi j}S(m+1,k)\right)\right] \tag{2}$$

The resulting matrix can be compressed and the energy can be further focused by non-linearly mapping the frequency domain. Synchronized pinching may require instantaneous frequency, which can be produced by,

$$\text{FSST}(m,\hat{k})_n = \sum_{k=0}^{N-1} S(m,k)\delta\left[\hat{k}-\hat{\omega}(m,k)\right] \tag{3}$$

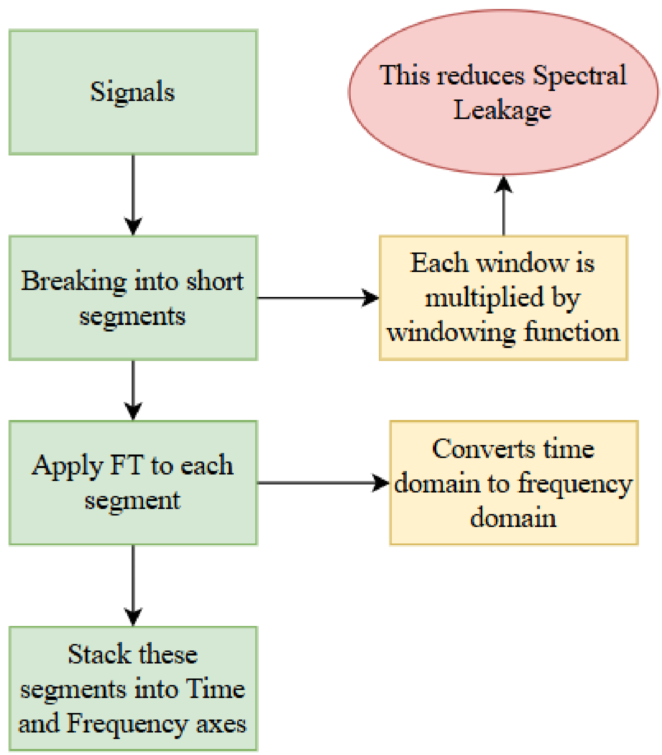

Fig. 1: FSST Flowchart

FSST is an enhancement of the traditional Short-Time Fourier Transform (STFT) [20] that sharpens the time-frequency representation by reallocating frequency components. Spectral leakage, in which signal energy overflows into neighboring frequencies during this windowing stage, may cause the frequency representation to become hazy.By

TABLE I: Numerical modeling of the simulated PQ disturbances

S.No.	Disturbance Class	Mathematical Expression	Parameters
1	Sine Wave	$x(t) = A\sin(\omega t)$	A=1,$\omega = 2\pi \times 50$ rad/s
2	Sag	$x(t) = (1-A(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1 \leq A \leq 0.8, T \leq (t_2 - t_1) \leq 9T$
3	Swell	$x(t) = (1+A(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1 \leq A \leq 0.8, T \leq (t_2 - t_1) \leq 9T$
4	Flicker	$x(t) = (1 + C\sin(\gamma t))\sin(\omega t)$	$C = 0.1, \gamma = 2\pi \times 10$ rad/s
5	Notch	$x(t) = \sin(\omega t) - \sin(\sin(\omega t))$	$\omega = 2\pi \times 50$ rad/s
6	Harmonics	$x(t) = A(\sin(\omega t) + \beta_3\sin(3\omega t) + \beta_5\sin(5\omega t))$	$A = 0.5, \beta_3 = 0.1, \beta_5 = 0.05$
7	Interruption	$x(t) = (1-B(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$B = 1, T \leq (t_2 - t_1) \leq 9T$
8	Oscillation Transients	$x(t) = \sin(\omega t) + \left(\sum_{k=1}^{n} a_k e^{-\alpha_k(t-t_1)}\sin(\omega_k t)\right)\cdot u(t-t_1)$	$0.05 \leq \alpha_k, \omega_k \leq 0.015, t_1 = 0.2$ s
9	Impulse Transient	$x(t) = \sin(\omega t) + \delta(t - t_1)$	$\delta(t - t_1), t_1 = 0.2$ s
10	Sag with Harmonics	$x(t) = (1 - A(u(t-t_1) - u(t-t_2)))(\sin(\omega t) + \beta_3\sin(3\omega t) + \beta_5\sin(5\omega t))$	$A = 0.5, \beta_3 = 0.1, \beta_5 = 0.05, T \leq (t_2 - t_1) \leq 9T$
11	Sag with Oscillations	$x(t) = (1 - A(u(t-t_1) - u(t-t_2)))\sin(\omega t) + \left(\sum_{k=1}^{n} a_k e^{-\alpha_k(t-t_1)}\sin(\omega_k t)\right)\cdot u(t-t_1)$	$A = 0.5, 0.05 \leq \alpha_k, \omega_k \leq 0.015, T \leq (t_2 - t_1) \leq 9T$
12	Sag with Harmonics and Oscillations	$x(t) = (1 - A(u(t-t_1) - u(t-t_2)))(\sin(\omega t) + \beta_3\sin(3\omega t) + \beta_5\sin(5\omega t)) + \left(\sum_{k=1}^{n} a_k e^{-\alpha_k(t-t_1)}\sin(\omega_k t)\right)\cdot u(t-t_1)$	$A = 0.5, \beta_3 = 0.1, \beta_5 = 0.05, 0.05 \leq \alpha_k, \omega_k \leq 0.015, T \leq (t_2 - t_1) \leq 9T$
13	Swell with Harmonics	$x(t) = (1 + A(u(t-t_1) - u(t-t_2)))(\sin(\omega t) + \beta_3\sin(3\omega t) + \beta_5\sin(5\omega t))$	$A = 0.5, \beta_3 = 0.1, \beta_5 = 0.05, T \leq (t_2 - t_1) \leq 9T$
14	Swell with Oscillations	$x(t) = (1 + A(u(t-t_1) - u(t-t_2)))\sin(\omega t) + \left(\sum_{k=1}^{n} a_k e^{-\alpha_k(t-t_1)}\sin(\omega_k t)\right)\cdot u(t-t_1)$	$A = 0.5, 0.05 \leq \alpha_k, \omega_k \leq 0.015, T \leq (t_2 - t_1) \leq 9T$
15	Swell with Harmonics and Oscillations	$x(t) = (1 + A(u(t-t_1) - u(t-t_2)))(\sin(\omega t) + \beta_3\sin(3\omega t) + \beta_5\sin(5\omega t)) + \left(\sum_{k=1}^{n} a_k e^{-\alpha_k(t-t_1)}\sin(\omega_k t)\right)\cdot u(t-t_1)$	$A = 0.5, \beta_3 = 0.1, \beta_5 = 0.05, 0.05 \leq \alpha_k, \omega_k \leq 0.015, T \leq (t_2 - t_1) \leq 9T$

more accurately concentrating the signal's energy.FSST, as illustrated in Fig.1, minimizes spectral leakage, or the loss of frequency resolution caused by signal energy spreading onto neighboring frequencies. The final output of the FSST is a time-frequency representation of the signal processing-provides valuable insights into the signal's behavior and characteristics, particularly for non-stationary signals with time-varying frequency components. By incorporating the CWT as a preprocessing step, it can leverage the advantages of wavelet-based time-frequency analysis to better capture the characteristics of non-stationary signals and provide more informative representations for further analysis and interpretation.

Precise localisation of signal components is ensured by the synchrosqueezing process (FSST), which excels at creating finer time-frequency signal representations. Power quality studies benefit greatly from this, especially when signals show abrupt frequency overlaps or variations. Lets discuss more in detail in the next section,Results and Discussions.

IV. Results and Discussions

With empirical mode decomposition (EMD), HHT is an excellent tool for capturing non-stationary features and local oscillations typical of nonlinear data. On the other hand, it employs preset wavelet functions to provide accurate time-frequency views. Although HHT offers localized frequency representation, the computing efficiency of FSST typically outperforms that of HHT. Similar to FSST, the S-Transform looks for time-varying frequency components by analyzing the energy distribution in the time-frequency plane. However, unlike the S-Transform, the FSST uses specified wavelet functions to improve frequency localization and computational efficiency.

While both FSST and SPWVD provide localized views of signal components, FSST uses wavelet analysis to achieve superior frequency localization. While SPWVD offers a better time-frequency representation by smoothing the Wigner-Ville Distribution to reduce cross-term interference, its frequency localization precision is not as precise as that of FSST. Comparably, localized perspectives in the time-frequency domain are offered by Variational Mode Decomposition (VMD) in conjunction with the Teager-Kaiser Energy Operator (TKEO) and FSST. VMD's flexibility in signal representation enhances FSST's accurate depiction.

When it comes to PQD analysis, FSST surpasses other techniques such as SPWVD, HHT, ST, and VMD. Specifically, FSST shows better accuracy in capturing oscillatory transients' time-frequency characteristics. By offering a more precise representation of harmonic components, FSST guarantees enhanced detection. Moreover, FSST performs exceptionally well in flicker detection, providing improved time-frequency resolution to accurately record flicker modulation depth.

These results highlight the benefits of FSST over alternative methods. The efficacy of FSST for PQD analysis is demonstrated by its capacity to provide precise and in-depth capture of intricate transient events, harmonic distortions, and flicker occurrences. As a result, by offering a thorough and precise analysis, FSST distinguishes itself as a great instrument for guaranteeing effective power distribution, avoiding equipment damage, and maintaining system reliability.

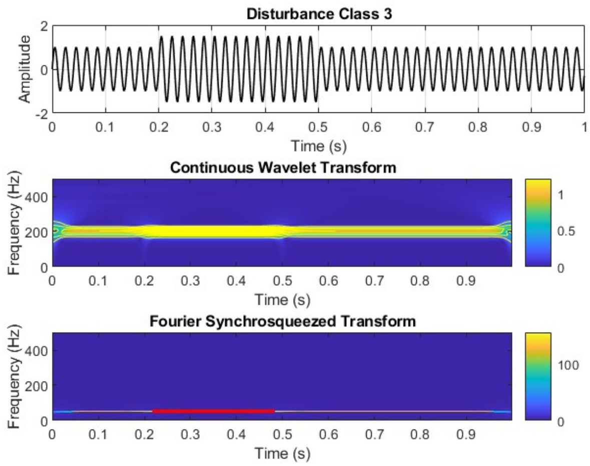

Fig. 2: Swell Disturbance class under FSST

As per Fig.2, three assessments of a disturbance signal characterized as a swell are shown. The top plot depicts a time-domain signal that increases in frequency from 200 Hz at $t = 0$ seconds to 400 Hz at $t = 1$ second. The center graphic, employing the CWT, shows a time-frequency representation with frequencies gradually increasing from 200 Hz to 400 Hz. FSST, in the bottom plot, provides higher resolution, capturing frequency increases and presenting more precise energy concentrations, particularly between $t = 0.3$ and $t = 0.45$ seconds, indicating a voltage swell.

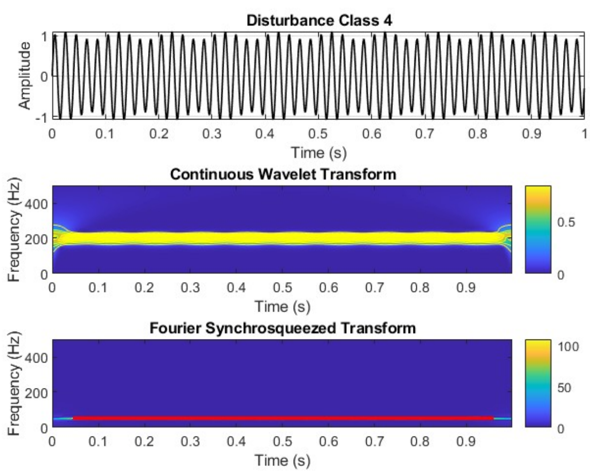

Fig. 3: Flicker Disturbance class under FSST

In Fig.3, the amplitude vs. time plot of the raw data reveals periodicity over 0–1 seconds. CWT highlights a dominant frequency at 200 Hz, with scattered energy suggesting noise. FSST improves frequency resolution, localizing the dominant frequency at 200 Hz with minimal noise. This precise characterization validates the signal's periodicity and dominant frequency, useful for vibration analysis and signal processing applications.

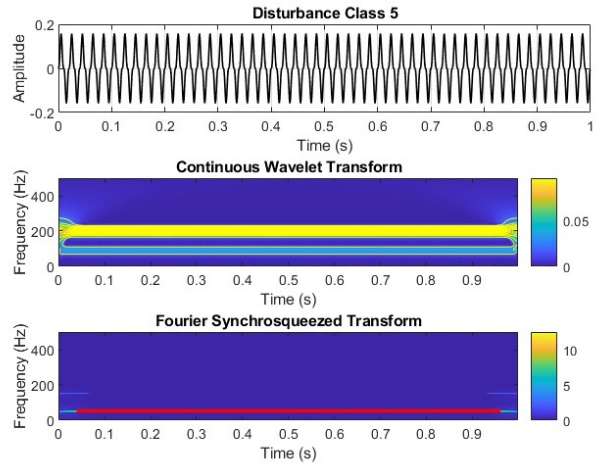

Fig. 4: Notch Disturbance class under FSST

Fig.4 illustrates periodic amplitude oscillations over one second in its time-domain plot. CWT highlights prominent components, such as a 200 Hz band, while FSST reduces noise and improves frequency localization. This comparison showcases FSST's superior accuracy for signal processing applications.

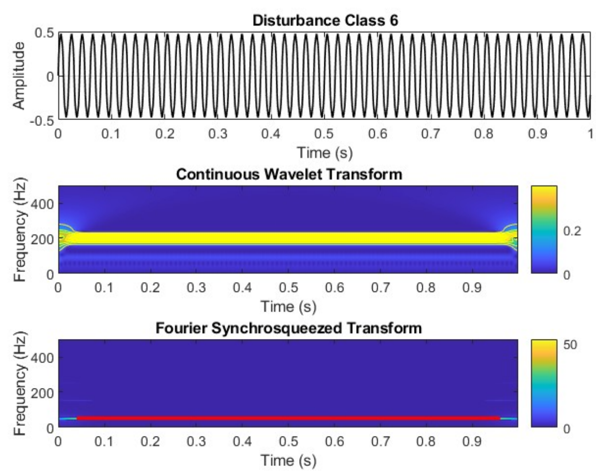

Fig. 5: Oscillation Transient Disturbance class under FSST

Fig.5 highlights FSST's accuracy in representing frequency content over time for oscillatory transients. Between $t = 0.3$ and $t = 0.45$ seconds, FSST captures higher energy concentrations, indicating a voltage oscillation transient, with superior resolution compared to CWT.

In Fig.6, the amplitude oscillations of Class 6 signals are shown. FSST provides clearer frequency localization around

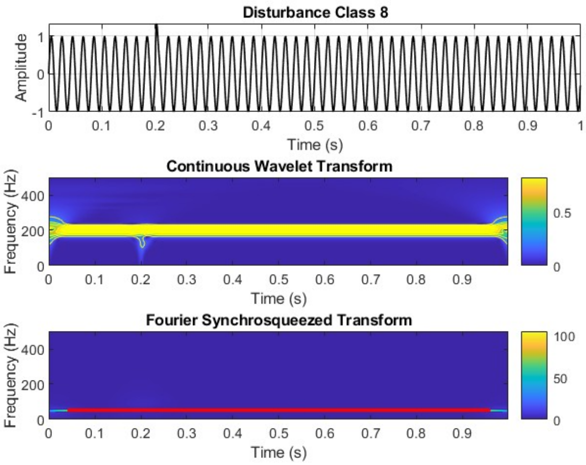

Fig. 6: Harmonics Disturbance class under FSST

200 Hz compared to CWT.Therefore,FSST is for giving precise time-frequency representations of different types of power quality disruptions.For identifying and addressing power quality problems ,it provides useful information by precisely localizing frequency components and emphasizing transient events.

High-resolution time-frequency analysis and processing efficiency are balanced via the Fourier Synchro-Squeezing Transform (FSST). It is appropriate for real-time applications, but its complexity stems from three steps: $O(N \log N)$ for the Short-Time Fourier Transform (STFT), $O(MN)$ for synchrosqueezing, and additional overhead for reconstruction. FSST is computationally lighter than Hilbert-Huang Transform (HHT), which has $O(N^2)$ because of iterative Empirical Mode Decomposition. Similarly, in terms of efficiency, FSST outperforms the Smoothed Pseudo Wigner-Ville Distribution (SPWVD), which uses $O(N^2)$ for cross-term smoothing. FSST efficiently combines speed and accuracy for accurate power quality disturbance analysis due to its faster processing speed and minimal memory requirements.

V. Conclusion

Ultimately, the exploration of time-frequency analysis approaches in MATLAB reveals a variety of strategies, each with specific advantages and disadvantages. FSST provides high accuracy and clarity in the analysis of PQDs analysis, even though SPWVD, S-Transform, HHT, and VMD with the Teager Energy Operator all offer insightful methods.

FSST is a constant companion that helps us traverse the always changing world of power systems and steers us towards a future where efficiency, stability, and dependability are paramount. FSST is the industry leader in PQD analysis, shedding light on the intricate details of electrical phenomena and enabling us to create a more robust and brighter future.As discussed, FSST excels at catching oscillatory transients, harmonic distortions, and flicker events. Prospective investigations may examine the combination of FSST with machine learning techniques to augment automated PQD identification and classification.

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