Non-Stationary Power System Forced Oscillation Analysis using Synchrosqueezing Transform

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Abstract—Non-stationary forced oscillations (FOs) have been observed in power system operations. However, most detection methods assume that the frequency of FOs is stationary. This assumption could lead to errors in the estimation. In this paper, we present a methodology for the analysis of non-stationary FOs. Firstly, synchrosqueezing transform (SST) is used to provide a concentrated time-frequency representation of the signals. Then, retrieval of non-stationary modes is performed using a ridge extraction method. To continue, the Dissipating Energy Flow (DEF) method is applied to the extracted modes to locate the source of forced oscillations. The methodology is tested using simulated as well as real PMU data. The results show that the proposed SST-based mode decomposition enhances the performance of the DEF Method.

Index Terms—Forced oscillations, non-stationary signal, phasor measurement unit (PMU), time-frequency analysis, synchrosqueezing, multicomponent signals.

I. INTRODUCTION

Unlike modal oscillations, which mainly depend on the dynamic characteristics of the system, forced oscillations (FOs) are determined by inputs and disturbances that drive the system [1] [2]. FOs can occur in power systems due to different causes, such as equipment failure, inadequate control designs, and abnormal generator operating conditions [3]. The sustained presence of significant forced oscillations on the power system could lead to long-term adverse effects. For example, equipment fatigue and possible damage to rotor shafts or power quality reduction. It is clear that monitoring these oscillations, understanding how they act on power systems, and implementing mitigation strategies are relevant matters to be considered [3].

The most efficient way for mitigating sustained oscillations is to locate the source and to disconnect it from the network. This action requires locating the system component causing the oscillations [4]. Many methods for locating the source have been proposed in the past few years, and each of them has advantages and disadvantages and can be successfully used only for specific circumstances [5]. Among these methods, the Dissipating Energy Flow (DEF) method [4] has shown the best performance, and it was recently applied to data obtained from a practical experience [6]. Most methods for analyzing FOs assume that the frequency of the oscillation source is stationary [1], [3], [4], [6]–[10]. However, past events have shown that FO fundamental frequency could be non-stationary (for example, in the October 3, 2017 event in ISO-NE) [11].

Synchrosqueezing Transform (SST) is a time-frequency (TF) analysis technique that was designed to decompose signals into constituent components with time-varying oscillatory characteristics [12]. SST is an alternative to the Empirical Mode Decomposition (EMD) method [13] with a stronger analytical foundation [14]. SST was originally introduced in the context of Continuous Wavelet Transform (CWT) [12]. The univariate CWT-based SST (WSST) reassigns the wavelet coefficients in scale or frequency by combining the coefficients that contain the same instantaneous frequencies, such that the resulting energy is concentrated around the instantaneous frequency curves of the modulated oscillations. A natural extension of WSST was proposed in [15] by using the short-time Fourier transform (STFT). This technique was referred as STFT-based SST (FSST) [14].

Traditional methods like STFT or CWT are restricted by the Heisenberg uncertainty principle, namely, high resolution on both time and frequency domains cannot be achieved simultaneously. Thus, classical linear TF analysis methods generate a blurred TF representation, failing to characterize TF features of non-stationary signals accurately [16]. SST is related to the class of time-frequency reassignment (TFR) post-processing algorithms that are used for instantaneous frequencies (IF) estimation from the modulus of a TF representation. TFR methods apply a reassignment map that concentrates and sharpens the spectrogram energy around the IF curves, resulting in a pointed TF plot [17]. Unlike classical TFR techniques, SST allows for the reconstruction of the components [14]. Hence, SST has been successfully applied to analyze non-stationary signals in several applications, such as medical electrocardiography (ECG) reading [18], atomic crystal images in physics [19], [20], mechanical engineering [21]–[23], art investigation [24], [25], geology [26], etc. Previously, SST has been applied in the field of power systems for parameter identification of low frequency natural oscillations [27], and subsynchronous oscillation detection [28]. In both cases, the method was applied to simulated data of reduced power system models. Nevertheless, the SST has not been applied yet to analyze FOs in electrical power systems using PMU data.

In this paper, we propose a novel methodology by using the FSST to extract the modes of a power system non-stationary FOs. This technique is applied to simulated as well as real PMU data. Then we apply the DEF Method to the extracted modes to trace the source of the FO. The purpose is to improve the application of the DEF method in the case of non-stationary FOs, mostly when the usual assumption of stationary FOs lead to inaccurate results.

The rest of this paper is organized as follows. Background on DEF Method and SST is presented in Section II. Section
III presents the proposed methodology. In Section IV the methodology is validated by applying it to measured and simulated power system data, and also it is compared with the usual application of the DEF Method. Concluding remarks and expectations for future work are outlined in Section V.

II. BACKGROUND ON DISSIPATION ENERGY FLOW METHOD AND SYNCHROSQUEEZING TRANSFORM

A. Conventional Application of The Dissipation Energy Flow Method

The first steps of the DEF method are [6]:

- **Frequency identification** Use the Discrete Fourier Transformation (DFT) to identify \( f_s \), the frequency of the mode of interest of the sustained oscillation.
- **Filtering the mode of interest.** Filtering is applied to the variables of interest for DEF calculation (i.e. active and reactive power, voltage magnitude, angle, and frequency). The filtering process must satisfy the following conditions: (a) preserves phases among all quantities, (b) preserves magnitudes for all filtered quantities.

Then, the flow of dissipating transient energy is calculated in the branches of the systems for the identified mode. The rate of change of the dissipating energy flow allows tracing the source of sustained oscillations. The flow of dissipating energy, for a specific mode in a branch \( ij \), is expressed by integrating over the system trajectory as follows [5]:

\[
W_{ij} \approx \int \Delta P_{ij} d\Delta \theta_i + \int \Delta Q_{ij} \frac{d\Delta V_i}{V_i},
\]

where \( P_{ij} \) and \( Q_{ij} \) are the active and reactive power flows in branch \( ij \), \( \theta_i \) is the bus voltage angle, and \( V_i \) is the bus voltage magnitude. \( \Delta \) indicates that the magnitudes are filtered components for a mode. For discrete PMU signals, a discrete-time approximation has the form:

\[
W_{ij,t+1}^{D} = W_{ij,t}^{D} + \Delta P_{ij,t} (\Delta \theta_{i,t+1} - \Delta \theta_{i,t}) + \Delta Q_{ij,t} \frac{d\Delta V_i}{V_i},
\]

where \( t \) represents the time instant. The integration limits are determined from the transient when sustained oscillations have significant magnitude larger than noise.

B. Multicomponent Signal Decomposition with Synchrosqueezing

We denote by \( \hat{s} \) the Fourier transform of function \( s \) with the following normalization:

\[
\hat{s}(\eta) = \int_{\mathbb{R}} s(x) e^{-j2\pi \eta x} dx.
\]

The STFT is a local version of the Fourier transform obtained by means of a sliding window \( g \) [15]:

\[
V_s^g (\eta, t) = \int_{\mathbb{R}} s(\tau) g(\tau - t) e^{-j2\pi \eta (\tau - t)} d\tau
\]

Non-stationary oscillatory data \( s(t) \) is represented by a superposition of oscillatory modes as follows [17]:

\[
s(t) = \sum_{k=1}^{K} s_k(t) + r(t)
\]

\[
s_k(t) = A_k(t) e^{j2\pi \varphi_k(t)},
\]

where each component \( s_k(t) \) is an oscillatory mode, with time-varying amplitude \( A_k(t) \) and instantaneous frequency (IF) \( \varphi'_k(t) \). The signal \( r(t) \) is a noise signal or measurement error plus low frequency trend. If we assume slow variations of \( A_k(t) \) and on the IF \( \varphi'_k(t) \), we can write the following approximation in the vicinity of a fixed time \( t_0 \):

\[
s(t) \approx \sum_{k=1}^{K} A_k(t_0) e^{j2\pi [\varphi_k(t_0) + \varphi'_k(t)(t-t_0)]}
\]

The corresponding approximation for the STFT then results (changing \( t_0 \) by a generic \( t \)):

\[
V_s^g (\eta, t) \approx \sum_{k=1}^{K} s_k(t) \hat{g}(\eta - \varphi'_k(t))
\]

The representation of this multicomponent signal by \( V_s^g (\eta, t) \) in the TF plane shows that the peaks are concentrated around so-called ridges, defined by \( \eta = \varphi'_k(t) \). The frequency width around each ridge is related to the frequency bandwidth of \( \hat{g} \). If frequencies \( \varphi'_k(t) \) are separated enough for different \( k \), each mode has a distinct domain in the TF plane, allowing for their detection, separation and reconstruction [15]. The aim of the SST is twofold. On one hand, it provides a concentrated representation of multicomponent signals in the TF plane. On the other hand, it is a decomposition method that enables the separation and demodulation of the different modes. Starting from STFT, the FSST moves the coefficients around a small frequency band \( \hat{g} \). The operator defined in [9] is the instantaneous frequency of the signal at time \( t \), filtered at frequency \( \eta \) and it results a local approximation for \( \varphi'_k(t) \). Then, the short-time Fourier transform-based synchrosqueezing transform (FSST) coefficients are given by [13]:

\[
T_s^g (f, t) = \frac{1}{g(0)} \int_{\mathbb{R}} V_s^g (\eta, t) \delta[f - \hat{f} (\eta, t)] d\eta
\]

where \( \delta \) denotes the Dirac distribution. The FSST sharpens the information relative to modes in the TF plane around the ridges associated to \( \varphi'_k(t) \). Each component \( s_k(t) \) can be recovered by integrating \( T_s^g (f, t) \) around a small frequency band \( d \) around the curve of \( \varphi'_k(t) \) associated to the \( k \)th component [15]:

\[
s_k(t) = \int_{|f - \varphi'_k(t)| < d} T_s^g (f, t) df
\]
Practical implementation of the SST algorithm is described in [17]. Theoretical foundation of SST for mode extraction can be found in [12], [15]. Theoretical results are obtained assuming the window $g$ is Gaussian and the following assumptions on the signal $s(t)$ [29]:

A1) \( s_k \) has weak frequency modulation, implying the existence of small $\epsilon$ such that for each $t$, one has $\sigma^2 |\phi_k(t)| \leq \epsilon$ and $|A_k(t)| \leq \epsilon |\phi_k(t)|$, where $\sigma$ is the standard deviation of the Gaussian window.

A2) The modes are well separated in frequency. If the frequency bandwidth of $g$ (in rad/s) is $[\Delta - \Delta, \Delta]$ ($\Delta = \sqrt{2 \log(2)/\sigma}$ since $g$ is the Gaussian window), this assumption corresponds to the inequality $|\phi_k(t) - \phi_k'(t)| \leq 2 \Delta$ for each $t$ and $k \neq l$.

### III. PROPOSED METHODOLOGY

Fig. 1 shows the scheme of the proposed novel methodology, which consists of four steps. The first step is high frequency filtering and elimination of the low frequency trend. Several methods can be used in this step. In particular, in this paper noise-assisted multivariate empirical mode decomposition (NA-MEMD) [30] is used as data-driven band-pass filter to subtract low frequency trend and high frequency content. It is an extension of the empirical mode decomposition (EMD) [10] to multivariate cases, with the assistance of noise in order to enforce the dyadic filterbank property [30]. Code for implementing NA-MEMD is available in [31]. Due to the dyadic filter bank property of NA-MEMD, this method was not useful to separate non-stationary modes, and mode mixing occurs. However, NA-MEMD is useful as an initial band-pass filter over the range of frequencies of interest [14].

In the second step, FSST is applied using (4), (9) and (10) to each signal to generate multiple univariate multicomponent TF planes with high localization in both time and frequency. In the third place, ridge identification and mode reconstruction using (11) is performed. A standard ridge identification method is used, where a penalized forward-backward greedy algorithm is used to extract the maximum-energy ridges from a time-frequency matrix. The algorithm finds the maximum time-frequency ridge by minimizing $-\ln |T^g_\eta(\eta, t)|$ at each time point. Minimizing $-\ln |T^g_\eta(\eta, t)|$ is equivalent to maximizing the value of $|T^g_\eta(\eta, t)|$. The algorithm optionally constrains jumps in frequency with a penalty that is proportional to the distance between frequency bins [32] [33]. The description of the functions used for FSST can be found in [34] and for ridge extraction in [33]. Finally, DEF Method is applied using [4] locally in each substation over each non-stationary oscillating mode for oscillation source tracing.

### IV. FO ANALYSIS

In this section, we present the analysis of two different examples. First, the proposed methodology is applied to simulated data obtained from the WECC179 model, where a non-stationary disturbance is applied to the mechanical power of a generator. Secondly, the proposed methodology is applied to real PMU measurements obtained from an event occurred in ISO-NE [11]. This case shows that non-stationary FOs may exist in real power system operation and it motivates the development of the methodology presented here. In both cases, the performance of the proposed methodology is compared with the application of the DEF method according to [6].

#### A. Simulated Case

Fig. 2 shows the WECC 179 test system. Data for simulation were obtained from [11].

A non-stationary mechanical power was applied in generator 79 (indicated as the oscillation source in Fig. 2) using a square signal whose fundamental frequency is linearly increased from 0.1 Hz to 0.3 Hz in 100s. Fig. 3 shows the mechanical power $P_{mech}$, electric power $P$, terminal voltage magnitude $V$, reactive power $Q$ of generator 79 and the sliding window $g$. In this simulated case, the first step of the proposed methodology (elimination of low frequency trend) consists in extracting the mean value of the signals. For the second step, STFT is first calculated with [4]. Fig. 4 shows amplitude of STFT over TF plane for $P$, $V$, $Q$ and terminal voltage angle $angV$ of generator 79. It can be seen that STFT concentrates the
information around the ridges that correspond to the time-varying fundamental frequency and harmonics frequencies of the forced oscillation. Then, FSST is calculated using (10). Fig. 5 shows that FSST improves the definition of each mode and allows better identification of the components in the time-frequency plane. Fig. 6 shows the results of the ridge identification algorithm applied to the FSST amplitude of the active power flow of generator 79. The obtained curves representing the different modes on the TF plane from FSST are used for decomposing the other three variables \(V, Q,\) and \(\text{ang}V\) of the respective generator. For example, Fig. 7 shows the extracted modes applying the reconstruction formula (11) around each ridge, for the electric power of generator 79. The same procedure is performed on all the 29 generators of the WECC179 test system.

After performing the decomposition for all the variables of the generators, we calculate the associated DEF for all modes and generators. Fig. 8 shows the DEF of modes with higher energy for the generators with greater participation in the oscillation process. Looking at the different modes, we see that the rate of change of DEF is positive only in generator 79. Thus, it is concluded that generator 79 is the source of oscillations in every mode. In particular, modes 1 and 2 present significant monotonously increasing DEF values. On the other hand, modes 3 and 4 only show DEF increments during certain instants, where the amplitude of the corresponding components is sufficiently large (see Fig. 6 and Fig. 8 together).

To compare the proposed methodology with the conventional application of DEF method, the DFT of the full time series of the electric active power of generator 79 is calculated. Fig. 9 shows that the fundamental frequency cannot be identified as a sharp peak due to the nonstationary behavior. For the application of band-pass filtering, we assume that this wide peak is classified as a frequency component of FO of \(f_{s1}=0.2\text{Hz}\). On the other hand, a second peak in \(f_{s2}=0.83\text{Hz}\) is identified.
Filter design specifications used for mode extraction bandpass filtering approach are as in [3]: Butterworth filter with the pass frequencies $f_{pi} = (1 \pm \varepsilon)f_{si}$ where $\varepsilon=0.05$; cutoff frequencies $f_{ci} = (1\pm2\varepsilon)f_{si}$; 1 dB of ripple allowed and 1015 dB attenuation at both sides of the passband. Matlab function designfilt is used for known each of the frequencies of interest $f_{si}$, $i = 1$, 2. Zero-phase distortion is achieved by applying filtering in both forward and reverse directions for all signals by using the Matlab function filtfilt [6]. At the bottom of Fig. 10, the DEF is shown using a bandpass filter with $f_{s1}=0.2$ Hz. Here, for comparative purposes, the corresponding mode 1 of the FSST-based decomposition is included. It can be observed that the DEF calculated using the bandpass filtering approach has significant variations only between 40 and 60 seconds. This shows that by using bandpass filtering in this case, DEF can only be accurately calculated in the region of the time series where the instantaneous frequency of the non-stationary mode overlaps with the frequency band of the filter, as shown in the center of Fig. 10. Thus, it is unable to capture the complete non-stationary signal component. On the other hand, the calculated DEF for mode 1 of the SST-based decomposition reflects significant variations over all the time, providing a more accurate estimate.

At the top of Fig. 10 DEF calculated with the filtered components using the frequency $f_{s2}=0.83$Hz is also shown. It only presents significant values when the filtering band intersects with the non-stationary frequency components. For example, in the interval from 80 to 90 seconds, the frequency band intersects with the instantaneous frequency ridge of mode 2 obtained by SST. Only in that time interval, the variations of DEF are similar to those of mode 2. On the other hand, between 30 and 40 seconds, the DEF variations are similar to those of mode 3, where the filter frequency band overlaps with the instantaneous frequency of mode 3. In the same way, this happens with mode 4. However, in the instants where the filter band does not intercept any instantaneous frequency ridges, the DEF calculated with the bandpass filter approach does not suffer variations, resulting in inaccurate results. On the other hand, evaluating DEF on non-stationary modes allows obtaining DEF variations at all times.
B. Event ISO New England System

ISO New England is a North-East part of the Eastern Interconnection in the USA (Peak load is about 26,000 MW). PMU data from real events is available in the Test Cases Library of the IEEE PES Task Force on Oscillation Source Location [11]. Fig. 11 shows the available PMU data and their links to external areas. On October 3, 2017, an issue in the governor of a large generator outside of the ISO-NE system created a multi-frequency process for 5 minutes. Oscillations of significant MW magnitude were observed in multiple locations of the New England power system (Case 2 of [11]). Fig. 12 shows active power flows through three selected lines indicated in Fig. 11. The non-stationary nature of the oscillation is clear, exhibiting a growing fundamental frequency and amplitude.

Fig. 11. ISO-NE Network Scheme and PMU data available [8].

Fig. 12. Active Power Flow in MW during oscillation.

To start the analysis, the proposed methodology is applied to the active power flow from line Ln21. Fig. 13 shows the active power after performing low frequency trend extraction and high frequency filtering. The selected window is also shown on this figure.

Fig. 13. Filtered Active Power Flow through Ln21 in p.u. without trend and selected window.

Fig. 14 shows the STFT of the active power flow through Ln21 and the corresponding FSST, as well as the results of ridge identification algorithm.

Fig. 14. Results for the first steps of the proposed methodology applied to the Active Power Flow through Ln21 in pu. Top: STFT; middle: FSST; bottom: Ridge identification.

Fig. 15 shows the extracted components resulting from integration around each ridge. The red curve in Fig. 15 is the sum of all the extracted modes. The residue contains mainly higher frequencies, associated to high order harmonics that were not included. The same procedure is applied to the active power $P$, voltage magnitude $V$, voltage angle $\theta$, and reactive power flow $Q$ in each of the lines. Once the decomposition of each signal is performed, the DEF method is applied to each non-stationary mode using (2).

Fig. 15 shows the extracted components resulting from integration around each ridge. The red curve in Fig. 15 is the sum of all the extracted modes. The residue contains mainly higher frequencies, associated to high order harmonics that were not included. The same procedure is applied to the active power $P$, voltage magnitude $V$, voltage angle $\theta$, and reactive power flow $Q$ in each of the lines. Once the decomposition of each signal is performed, the DEF method is applied to each non-stationary mode using (2).

Fig. 16 shows DEF in the lines Sub9-Ln21, Sub3-Ln7 and Sub2-Ln3 with the convention indicated in Fig. 11. It can be seen that apart from the fundamental frequency of the oscillation (mode 1), the fifth harmonic (mode 5) has a considerable DEF because it is close to a natural system mode. Negative rate of change of DEF in Sub9-Ln21 confirms that the source of oscillation is in Area 3, as indicated in [11].
To compare the performance with the conventional DEF method described in Section II, the DFT of the active power flow from Sub9-Ln21 is shown in Fig. 17. The DFT does not show the non-stationary nature of the signal and only three clear peaks are identified at 0.077 Hz, 0.15 Hz, and 0.31 Hz.

Fig. 18 shows the filter frequency band for the fundamental component $f_{s1}$ and the corresponding ridge of mode 1. Note that part of the frequency ridge is out of the filter band. Fig. 18 compares the DEF of the fundamental mode obtained with bandpass filtering and with the FSST-based decomposition. It can be seen that, in the case of bandpass filtering, DEF can be accurately calculated only when the instantaneous frequency of the non-stationary mode overlaps with the frequency band of the filter. On the other hand, the FSST based methodology allows tracking the variations of the instantaneous frequency and provides a more precise calculation of DEF.

Fig. 15. Extracted components of Active Power Flow of Sub9-Ln21.

Fig. 16. DEF applied over non-stationary modes. Sign and magnitude of the rate of change of DEF allow tracing the source of oscillations.

Fig. 17. DFT of Active Power Flow of Sub9-Ln21.

Fig. 18. Top: scheme of band pass filtering over plot of FSST coefficients of Active Power Flow of Ln21. Bottom: Comparison of DEF of fundamental mode obtained with band pass filtering and FSST decomposition.
This paper presents a methodology based on the FSST and the DEF method to analyze, decompose, and locate the source of nonstationary FOs. The results, on simulated as well as on real PMU data, show that the proposed nonstationary mode decomposition framework is more efficient than conventional methodology based on bandpass filtering. Specifically, when using bandpass filtering, DEF can be accurately calculated only when the instantaneous frequency of the non-stationary mode overlaps with the frequency band of the filter. It could also happen that more than one component of the signal is in the frequency band of a bandpass filter, but at different times. During the time instants where the filter band does not intercept any instantaneous frequency ridges, the DEF calculated using the bandpass filtering approach does not show variations, resulting in inaccurate results. On the other hand, the methodology based on FSST follows the variations of the instantaneous frequency and it provides a more precise calculation of DEF at all times. Taking advantage that the modes are present in different variables, the multivariable decomposition of the available signals in each substation is proposed as a future work.

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