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Identification of Power System Oscillation Modes Using Empirical Wavelet Transform and Yoshida-Bertecco Algorithm

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ABSTRACT Oscillations occurring in the power system are one of the biggest threats to its secure operation. Although they occur rarely, these oscillations can cause severe damage to the power system if they are not detected at the earliest. Hence, this work focuses on identifying the parameters of oscillations in the power system using a combination of Empirical Wavelet Transform and Yoshida-Bertecco algorithm. As these oscillations occur rarely, a preprocessing method based on Teager Kaiser Energy Operator is used to check whether the signal under consideration contains any oscillation modes. The effectiveness of the proposed method is tested using a test signal, simulated power system signal, and PMU data from an actual power system under various levels of noise contamination. Further, the performance of the proposed method is compared with a VMD-Hilbert transform-based, Prony-based, and SSI-based methods in the literature. Results reveal the superiority of the proposed method irrespective of the parameters of the signal under consideration.

INDEX TERMS Empirical wavelet transform, power system oscillations, Prony's method, stochastic subspace identification, Teager Kaiser energy operator, variational mode decomposition.

I. INTRODUCTION

Oscillations occurring in power systems can be broadly classified into low-frequency, sub-synchronous, and super-synchronous oscillations. Low-frequency oscillations occur owing to gradual changes in the load or generation of the power system and have frequencies between 0.1 - 2 Hz. On the other hand, sub-synchronous oscillations (SSO) are abnormal electro-mechanical phenomena that occur in conventional power systems owing to the resonance between the electrical system and the generator. These oscillations are highly dangerous and can cause system separation events and blackouts in the power system. For instance, the shaft system of the Mohave power plant in Nevada, USA, was damaged by SSO in 1970 and 1971 [1]–[3]. Similarly, low-frequency inter-area oscillations were observed during the WSCC system outage in August 1996 [4]. However, similar

incidents can be prevented by developing suitable mitigation strategies based on the analysis of these oscillations.

Modern power systems use phasor measurement units (PMU) for monitoring, primarily because they provide synchronized data measurements at high reporting rates. Since the introduction of PMUs, signal processing methods using PMU data have been proposed for detecting and analyzing power system oscillations. More specifically, Prony's method [5]–[7], ARMA [8], [9], Wavelet Transform [10], [11], ESPRIT [12], [13], Matrix Pencil [14], [15], Eigen Realization Algorithm (ERA) [16], Stochastic Subspace Identification (SSI) [17], Dynamic Mode Decomposition (DMD) [18], Variational Mode Decomposition (VMD) [19], and Hilbert Huang Transform [20] are some of the popular signal processing techniques used for analyzing power system oscillations.

Prony's method [5]–[7] is one of the most commonly used signal processing techniques for the analysis of power system oscillations. It provides accurate estimates of the frequency and damping factor of the power system oscillating modes at medium to high signal-to-noise ratios (SNR). However, its

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performance deteriorates significantly when the SNR of the power system signal is low. The ARMA-based techniques proposed in [8], [9] use a time series model to fit power system oscillations. However, they are also highly sensitive to noise. Analysis of power system oscillations using wavelet transform-based methods is proposed in [10], [11]. Unlike model-based methods, such as Prony and ESPRIT, wavelet transform-based methods can effectively analyze non-stationary power system oscillations. However, the accuracy of the analysis depends on the mother wavelet used, which is a drawback. The identification of power system oscillations using model-based methods, such as ESPRIT, Matrix Pencil, SSI, and ERA are proposed in [12]–[17]. The methods mentioned above provide accurate estimates of the frequency and damping factor of the power system oscillations even under low signal-to-noise ratios. However, these methods are computationally intensive. Moreover, they require an accurate model order estimate for their proper operation. If the model order estimate is overestimated or underestimated, it will lead to the presence of fictitious modes or the non-identification of one or more true modes present in the power system oscillations.

Analysis of the power system oscillations using mode decomposition methods are proposed in [19], [20]. In [19], the power system oscillation is decomposed into single-frequency components using VMD and the parameters of these single-frequency components are estimated using Hilbert's transform. Similarly, in [20], Empirical Mode Decomposition (EMD) is used to decompose the power system oscillations and the modal parameters are estimated using Hilbert transform.

From the literature, it is evident that the analysis of power system oscillation is a research topic in which extensive work has been carried out. However, it is observed that a pre-processing algorithm for the early detection of power system oscillations is not included in any of the previous studies. The inclusion of a pre-processing algorithm will help separate the signals with oscillating modes for analysis using signal processing-based algorithms. Meanwhile, the signals without oscillating modes will be detected and not be analyzed, thereby reducing the computational complexity of the signal processing-based algorithms. It is also observed that model-based methods are primarily employed for the analysis of power system oscillations. These methods provide accurate estimates of modal parameters; however, they require an accurate model order estimate for this purpose. Furthermore, these methods are computationally intensive. However, this drawback is not present in wavelet-based methods, in which the wavelet transform acts as a filter bank to decompose the signal into its monocomponents. But, as explained earlier, the accuracy of the wavelet transform-based methods depends on the mother wavelet used for decomposing the signal. This drawback is absent in Empirical Wavelet Transform (EWT) which uses an adaptive wavelet filtering technique. In other words, the EWT develops wavelets based on the information present in the signal, thereby enabling the decomposition

much more efficiently than other wavelet transform methods. Hence, this study proposes an algorithm for analyzing power system oscillations based on the Empirical Wavelet Transform [21], [22] and Yoshida-Bertecco algorithm [23]. In the proposed method, the EWT acts as a filter bank and decomposes the waveform into its mono components. The parameters of these mono components are then identified using the Yoshida-Bertecco algorithm. The novelties of the proposed method are listed below.

1. It uses Teager-Kaiser Energy Operator [24], [25] (TKEO) based pre-processing algorithm for detecting the presence of oscillation modes in the signal. Accordingly, the signals with oscillating modes are only analyzed by the EWT-based algorithm thereby reducing the computational complexity of the proposed method.
2. It uses EWT to decompose the power system signal and the Yoshida-Bertecco algorithm to estimate its modal parameters. To the best of our knowledge, EWT is not used for analyzing the modal parameters of power system oscillations.
3. EWT-based filters are designed based on the Fourier spectrum of the signal. Hence, prior information about the signal is not required, unlike in model-based methods.

The effectiveness of the proposed method is compared with that of SSI-based [17], Prony-based [6] and VMD-based methods [19] in the literature using synthetic signals and simulated and actual PMU data from the WECC system. The results reveal the robustness of the proposed model, irrespective of the noise contamination and modal parameters.

II. METHODOLOGY

The schematic representation of the proposed method is shown in fig. 1. It comprises three major blocks: pre-processing, EWT, and Yoshida-Bertecco algorithms. First, the signal from the PMU is fed into the preprocessing algorithm, which checks whether it has any oscillating modes. If the presence of one or more oscillating modes in the signal is confirmed, the signal is passed to the EWT algorithm where it is decomposed into its monocomponents. The modal parameters of these monocomponents are estimated by using the Yoshida-Bertecco algorithm. A detailed explanation of each component of the proposed method is provided in the following subsections.

A. PREPROCESSING ALGORITHM

In the proposed method, the signal obtained from the PMU is first analyzed using the pre-processing algorithm to check for the presence of any oscillating modes. The use of a preprocessing algorithm is crucial as it helps to analyze only those signals with oscillating modes through the proposed EWT-based method, thereby reducing its computational complexity. The proposed preprocessing algorithm is based on TKEO [24], [25]. TKEO calculates the instantaneous energy of the signal and is highly responsive even to small changes

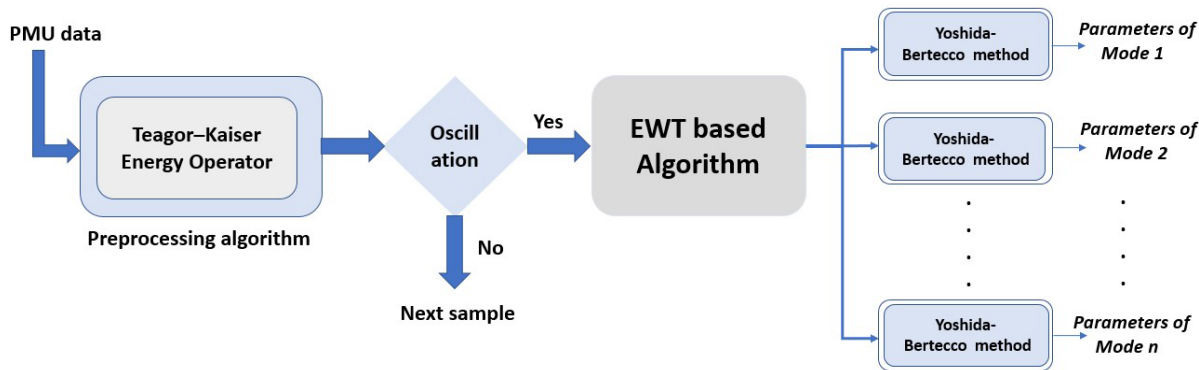


FIGURE 1. Schematic representation of the proposed EWT-based method.

in it. Hence, this property is utilized to detect the oscillating modes in the signal.

The major steps of TKEO based preprocessing algorithm are given below.

Step 1: Calculate the instantaneous energy of the signal ($\Psi\{x[n]\}$) using TKEO

$$\Psi\{x[n]\} = x[n]^2 - x[n+1]x[n-1]$$

Step 2: Plot $\Psi\{x[n]\}$ and check for peaks. The presence of a peak indicates an oscillatory event. Obtain the location of the peaks.

Step 3: Select two sets of data points around the peak of the TKEO plot. The first set consists of 20 data points before the peak, whereas the second set consists of 20 data points after the peak.

Step 4: Calculate Shannon’s entropy of these two data sets using the following equation.

$$SH = - \sum_{i=1}^{20} X_i^2 * \log(X_i^2);$$

Here, X_i denotes the i^{th} data point of the data set.

If they are dissimilar, the presence of oscillation is confirmed.

The effectiveness of the pre-processing algorithm is evaluated using the two-mode signal $p(t)$ given below.

$$p(t) = \begin{cases} 20, & \text{if } t \leq 6 \\ 20 + (2 * e^{-0.02} \sin(2\pi * 1.6t) \\ + (2 * e^{-0.07} \sin(2\pi * 0.6t)), & \text{if } t > 6 \end{cases}$$

Fig. 2(a) illustrates a plot of $p(t)$. It is observed that the $p(t)$ has a constant amplitude of 20 units until 6 seconds after which it starts oscillating. The TKEO plot of the signal shows that the instantaneous energy of the $p(t)$ is zero till 6 seconds after which there is a spike in its value owing to the oscillations. The Shannon’s entropy of the two datasets around this peak (generated according to Step 3 of the algorithm) is found to be different. This confirms the presence of oscillation in $p(t)$ after 6 seconds. It is also observed that the

TKEO-based pre-processing algorithm detects the oscillation even when the SNR value of $p(t)$ is 15 dB. This proves that the TKEO-based preprocessing algorithm is effective even when the signal is noisy.

B. EMPIRICAL WAVELET TRANSFORM

Empirical Wavelet Transform [21], [22] was proposed by Jerome Gilles in 2013 for decomposing the signal into its monocomponents by building adaptive wavelets. The EWT of the signal under consideration can be determined using the following steps.

Step 1: Let $x(t)$ denote the power system signal obtained from the PMUs and $X(f)$ correspond to its Fourier transform.

Step 2: Identify the highest peak of $X(f)$. The peaks of $X(f)$ that are at least 10% of the highest peak is selected. These peaks ($f_1, f_2 \dots f_M$) represent the dominant frequencies of the signal.

Step 3: Identify the local minima between consecutive peaks. They form the boundaries to split the Fourier spectrum $X(f)$.

Step 4: Design the empirical wavelets $\phi_1(f)$ and $\psi_i(f)$ using the following equations

$$\phi_1(f) = \begin{cases} 1, & \text{if } |f| \leq (1-\gamma)\rho_1 \\ \cos(\frac{\pi}{2}\beta(\gamma, f, \rho_1)), & \text{if } (1-\gamma)\rho_1 \leq |f| \leq (1+\gamma)\rho_1 \\ 0, & \text{otherwise} \end{cases}$$

$$\psi_i(f) = \begin{cases} 1, & \text{if } (1+\gamma)\rho_i \leq |f| \leq (1+\gamma)\rho_{i+1} \\ \cos(\frac{\pi}{2}\beta(\gamma, f, \rho_{i+1})), & \text{if } (1-\gamma)\rho_{i+1} \leq |f| \leq (1+\gamma)\rho_{i+1} \\ \sin(\frac{\pi}{2}\beta(\gamma, f, \rho_i)), & \text{if } (1-\gamma)\rho_i \leq |f| \leq (1+\gamma)\rho_i \\ 0, & \text{otherwise} \end{cases}$$

$$\beta(\gamma, f, \rho_i) = \beta(\frac{1}{2\gamma\rho_i}(|f| - (1-\gamma)\rho_i)) \tag{1}$$

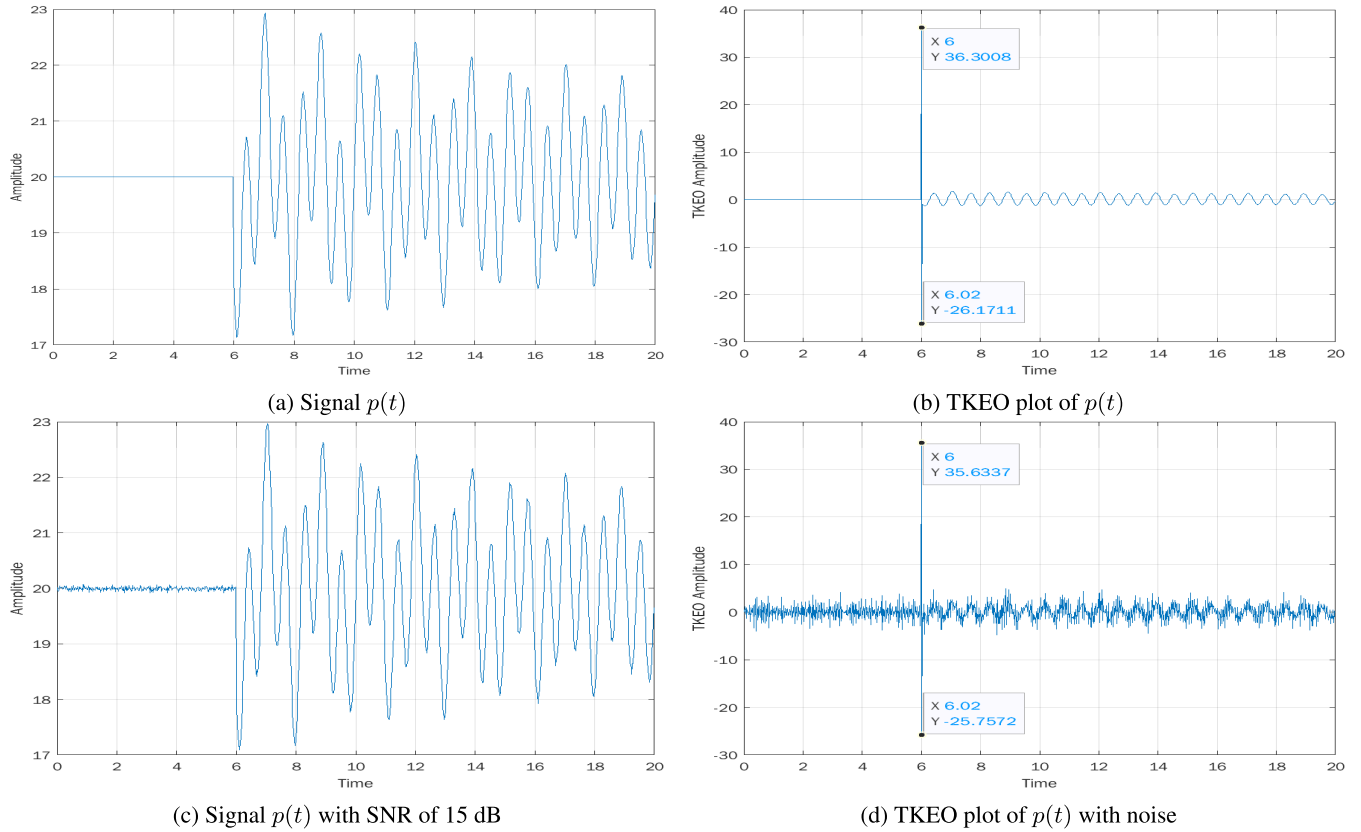


FIGURE 2. Signal $p(t)$ and corresponding TKEO plots.

TABLE 1. Estimated parameters of x_i with proposed, VMD-Hilbert, SSI and Prony based methods.

SNR	Proposed Method				VMD-Hilberts method [19]				SSI method [17]				Prony method [6]			
	f_i	D_i	Error in f_i (%)	Error in D_i (%)	f_i	D_i	Error in f_i (%)	Error in D_i (%)	f_i	D_i	Error in f_i (%)	Error in D_i (%)	f_i	D_i	Error in f_i (%)	Error in D_i (%)
15	5.6193	0.0664	0.0126	5.14	5.6161	0.0749	0.0700	7	5.6218	0.0770	0.03	10	5.6201	0.0684	0.0018	2.29
	1.0989	0.0738	0.1001	7.75	1.0989	0.0633	0.1004	20.875	1.0986	0.0685	0.13	14.37	1.1002	0.0703	0.0182	12.12
	0.3990	0.0842	0.25	6.44	0.3995	0.0781	0.1142	13.888	0.4019	0.0916	0.47	1.78	0.3990	0.0853	0.25	5.22
20	5.6196	0.0681	0.0072	2.71	5.6178	0.0666	0.0392	4.857	5.6196	0.0679	0.0071	3.00	5.6204	0.0727	0.0072	3.86
	1.0996	0.0769	0.0364	3.875	1.0971	0.0730	0.2602	8.750	1.1008	0.0900	0.0721	12.50	1.1005	0.0776	0.0455	3.00
	0.3994	0.0870	0.15	3.33	0.3991	0.0775	0.2341	13.88	0.3999	0.0912	0.025	1.33	0.3999	0.0956	0.025	6.22
25	5.6198	0.0690	0.0036	1.42	5.6190	0.0646	0.0172	7.7737	5.6199	0.0670	0.0018	4.29	5.6199	0.0731	0.0018	4.43
	1.0997	0.0781	0.0273	2.375	1.0992	0.0751	0.0693	6.125	1.1004	0.0823	0.0363	2.87	1.1003	0.0770	0.0273	3.75
	0.3997	0.0878	0.075	2.444	0.3999	0.0862	0.0240	4.222	0.4002	0.0898	0.0500	0.22	0.3997	0.0875	0.075	2.78
30	5.6199	0.0694	0.0018	0.857	5.6192	0.0690	0.0146	1.4280	5.6199	0.0706	0.0018	0.86	5.6201	0.0709	0.0018	1.29
	1.0999	0.0790	0.0091	1.25	1.0996	0.0790	0.0398	1.25	1.1001	0.0803	0.0091	0.37	1.0998	0.0813	0.0182	1.62
	0.3998	0.0889	0.05	1.22	0.3996	0.0803	0.1069	10.778	0.4002	0.0909	0.0500	1.00	0.4000	0.0887	0	1.44

here, ρ_i represents the boundary between peaks corresponding to f_i and f_{i+1} . γ is a parameter that prevents overlap between two consecutive transition areas.

Step 5: Calculate the approximate and detail coefficients of the signal as follows.

$$EWT(1, n) = IFFT(X(f) * \phi_1(f)) \quad (2)$$

$$EWT(i, n) = IFFT(X(f) * \psi_i(f)) \quad (3)$$

Here, IFFT denotes the inverse Fast Fourier Transform.

The decomposed mono-component signals are present in $EWT(1, n)$ and $EWT(i, n)$.

More details about the EWT transform can be found in [21], [22]

C. YOSHIDA-BERTECCO ALGORITHM

After the signal is decomposed into single-frequency components using the EWT algorithm, its frequency and damping factor is estimated using the Yoshida-Bertecco algorithm [23]. The major steps of this algorithm are as follows.

Step 1: Let $y(t)$ denote the single-frequency component extracted from the power system signal using the EWT algorithm and $Y(w)$ be its Fast Fourier Transform (FFT).

TABLE 2. Estimated modal parameters of reduced WECC 179-bus system.

Signal	Estimated value from [26]		Proposed method		VMD method [19]		SSI method [17]		Prony method [6]	
	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)
ND 1	1.41	0.01	1.4163	0.01	1.4211	0.02	1.426	0.024	1.3442	0.04
ND 8	1.27	1.06	1.2753	1.08	1.2785	1.08	1.2946	1.33	1.2813	0.02
	1.41	-0.22	1.4084	-0.21	1.3946	-0.36	1.3972	-0.27	1.43	-0.02

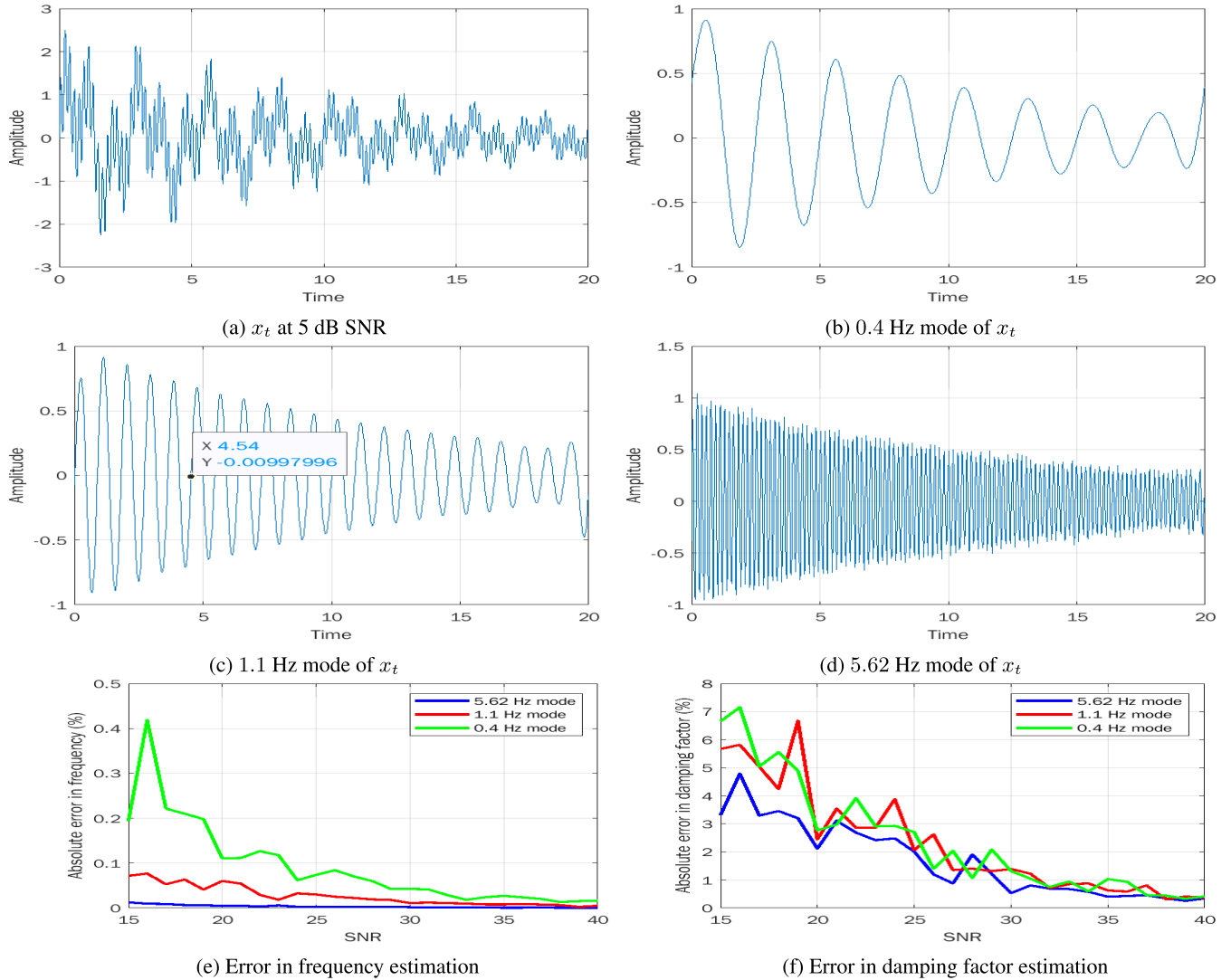


FIGURE 3. Three mode signal $x(t)$ and its modes with the error in parameter estimation.

Step 2: Calculate R , r and w_i using the following equations.

$$R = \frac{Y(k-1) - Y(k)}{Y(k) - Y(k+1)} \quad (4)$$

$$w_k = k * \frac{2\pi}{N}; \quad (5)$$

$$r = \frac{-e^{jw_k} + e^{jw_{k-1}}}{-e^{jw_{k+1}} + e^{jw_k}} \quad (6)$$

Here, k is the peak of the $Y(w)$ and N denotes the length of the single-frequency signal.

Step 3: Calculate λ using the following equation.

$$\lambda = \frac{r - R}{re^{-2\pi/N} - Re^{2\pi/N}} \quad (7)$$

Step 4: Estimate the frequency (f_i) and damping factor (ζ_i) of the single-frequency component from λ .

$$f_i = \frac{f_s}{2\pi} * \text{Im}(\log(\lambda)) \quad (8)$$

$$D_i = f_s * \text{Re}(\log(\lambda)) \quad (9)$$

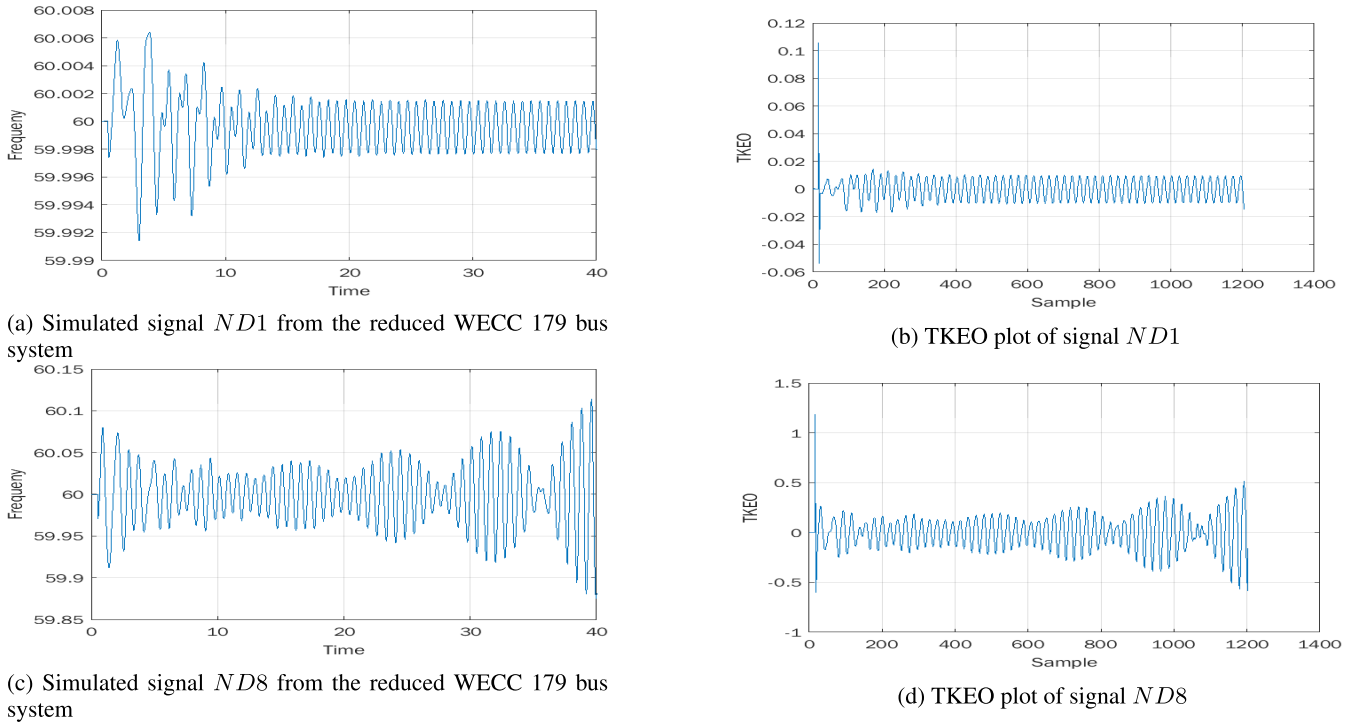


FIGURE 4. Simulated signals ND1 and ND8 from the reduced WECC 179 bus and the corresponding TKEO plots.

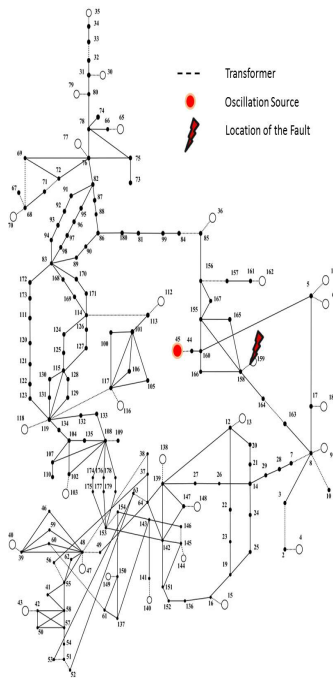


FIGURE 5. Reduced WECC 179 bus 29-machine system.

$$\zeta_i = -\frac{D_i}{\sqrt{(2\pi * f_i)^2 + (D_i)^2}} \quad (10)$$

Here, f_s is the sampling frequency of the signal under consideration.

Steps 1-4 are repeated for all single-frequency components to find their frequency and damping factor.

III. SIMULATION RESULTS

The effectiveness of the proposed EWT-based method is tested using synthetic signals and simulated and actual PMU data from the Western Electricity Coordinating Council (WECC) system. The details of the tests are described in the following subsections.

A. SYNTHETIC SIGNAL

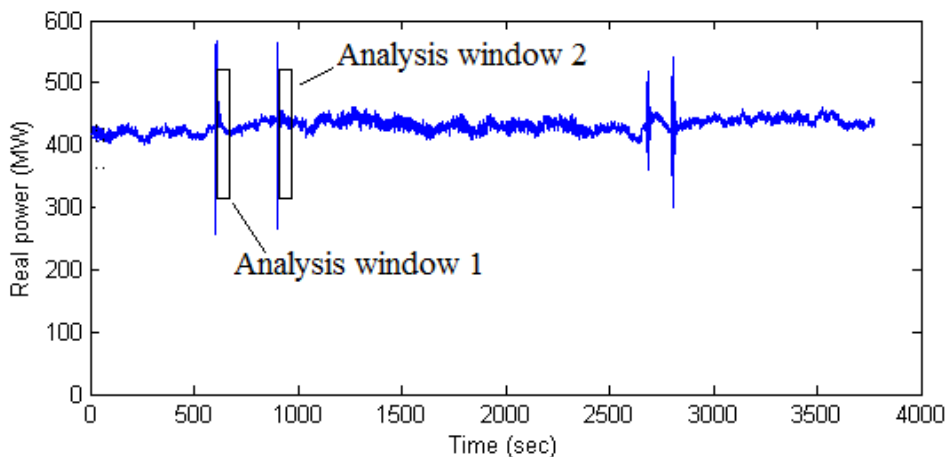
In this section, the effectiveness of the proposed method is tested using synthetic signal x_t . The following signal is used for this purpose:

$$x_t = e^{-0.09t} * \sin(2\pi * 0.4t) + e^{-0.08t} * \sin(2\pi * 1.1t) + e^{-0.07t} * \sin(2\pi * 5.62t) + s_t$$

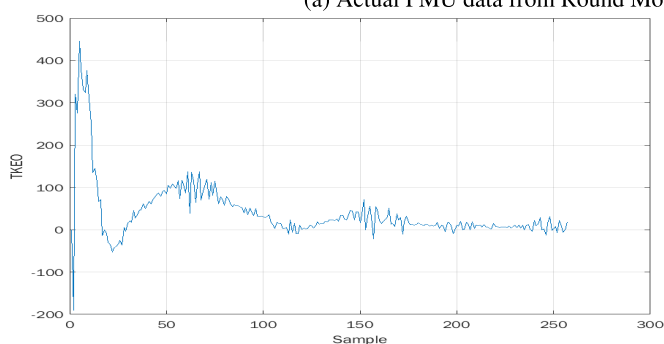
Here, s_t denotes the white Gaussian noise added into the signal x_t .

x_t has three modes with frequencies of 5.620 Hz, 1.1 Hz, and 0.4 Hz. The signal is sampled at a frequency of 50 Hz. These modes are extracted from $x(t)$ using the EWT algorithm and are shown in figs. 3(b), 3(c) and 3(d).

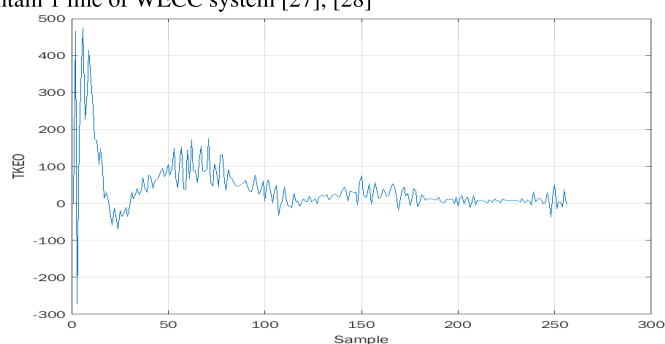
The robustness of the proposed method against measurement noise is tested by estimating the parameters of the x_t for different levels of noise contamination. Accordingly, figs. 3(e) and 3(f) present the percentage error in the estimation of the frequencies and damping factor of different modes of x_t when its SNR is varied from 15 dB to 40 dB.



(a) Actual PMU data from Round Mountain 1 line of WECC system [27], [28]



(b) TKEO plot of signal corresponding to Analysis window 1



(c) TKEO plot of signal corresponding to Analysis window 2

FIGURE 6. Actual PMU data from WECC system and its TKEO plots.

It is observed that the estimated values of the damping factor have the highest error, whereas the frequency estimation is almost perfectly accurate. It is also observed that percentage error is highest at SNR = 15 dB and gradually decreases with an increase in the value of SNR. The maximum error of the frequency and damping estimation is found to be around 0.4% and 7% respectively.

Furthermore, the effectiveness of the proposed EWT-based method is proved by comparing the estimated values of x_t with that of the VMD-Hilberts [19], Prony-based [6] and SSI-based methods [17] in the literature. Table 1 lists the estimated values of the frequency and damping factor of x_t using the proposed method, VMD-Hilbert transform-based, SSI-based, and Prony-based methods respectively. The values reported in this table are obtained by calculating the mean of 50 consecutive simulations. It is observed from Table 1 that, all methods under consideration estimate the frequencies of the modes of x_t with considerable accuracy. However, it is noted that, while estimating the damping factor, the accuracy of the proposed method is much higher than that of the VMD-based, Prony-based, and SSI-based methods. For instance, the maximum estimation errors of x_t at 15 dB SNR are approximately 20.875%, 12.12%, and 14.37% for the VMD, Prony and SSI-based methods, respectively, whereas

that of the proposed method is only 7.71%. Therefore, it is safe to infer that the proposed method estimates the modal parameters with higher accuracy than VMD, Prony, and SSI-based methods.

B. SIMULATED DATA OF REDUCED WECC 179-BUS SYSTEM [29]

In this subsection, the effectiveness of the proposed method is tested using simulated data from a reduced WECC 179-bus 29-machine system. This system is simulated in TSAT software by Power Tech labs, where the generators are modeled using the second-order differential model and the loads are modeled using the constant MVA model. The PMU measurements were obtained from the outputs of these time-domain simulations. The PMU data has a length of 40 seconds and a sampling frequency of 30 Hz [26].

Two poorly damped oscillations, ND1 and ND8, shown in figs. 4 (a) and 4(c) respectively, generated from the above system are used to evaluate the proposed EWT-based method. The TKEO plots of these signals are shown in figs. 4(b) and 4(d). The peaks in the TKEO plots confirm the presence of oscillating modes in these signals. The modal parameters of these poorly damped oscillations are listed in Table 2.

TABLE 3. Dominant modes and its parameters of WECC system probe data.

Signal	Estimated value from [27]		Proposed method		VMD method [19]		SSI method [17]		Prony method [6]	
	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)
Analysis window 1	0.32	8.3	0.3252	8.24	0.3142	8.46	0.3302	8.65	0.3422	13.40
			0.6765	5.06	0.6242	13.42	0.6998	17.23	0.6815	5.25
Analysis window 2			0.3202	7.53	0.3081	8.35	0.03227	9.27	0.3190	8.97
			0.6641	5.78	0.6228	12.24	0.6767	15.11	0.6615	14.55

TABLE 4. Dominant modes and its parameters of WECC system probe data at different SNRs.

Signal	SNR = 15 dB		SNR = 20 dB		SNR = 25dB		SNR = 30 dB	
	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)	Frequency (Hz)	ζ (%)
Analysis window 1	0.3224	7.98	0.3211	8.01	0.3201	8.04	0.3201	8.04
	0.6920	12.81	0.6918	12.82	0.6919	12.80	0.6919	12.80
Analysis window 2	0.3197	7.67	0.3191	7.71	0.3194	7.73	0.3194	7.73
	0.6892	12.33	0.6892	12.33	0.6892	12.33	0.6892	12.33

It is observed that the poorly damped oscillation ND1 has a dominant mode of 1.4163 Hz at a damping ratio of 0.01%. Similarly, the modal parameters of ND8 are estimated to be 1.2753 Hz and 1.4084 Hz at damping ratios of 1.08% and -0.21% respectively. These values are consistent with those reported in [26] which are obtained from TSAT. It is also observed that the estimated values of VMD-Hilberts, SSI, and Prony-based methods are not as accurate as those of the proposed method. Hence, it can be inferred that, in comparison to the VMD-Hilberts, SSI, and Prony-based methods, the proposed method is found to be superior in performance.

C. ACTUAL PMU DATA FROM WECC SYSTEM

To verify the ability of the proposed method to estimate the modal parameters of real-time power system data successfully, it is tested using the data obtained from the PMUs of the WECC system. The active power flow data obtained from the PMUs placed on the Round Mountain 1 line of the WECC system on 14th September 2005 was utilized for this purpose [27], [28]. Two signals with a length of 8.6 seconds and sampled at 30 Hz, as depicted in fig. 6(a), generated from this data, is used to compare the proposed method with the VMD Hilberts-based, SSI-based, and Prony-based methods. The TKEO plots of the signals corresponding to these analysis windows are shown in figs. 6(b) and 6(c). The peaks in the TKEO plot confirm the presence of oscillating modes in these signals.

As shown in Table 3, all the methods under consideration have identified both modes present in the signals corresponding to Analysis windows 1 and 2. However, it is noticed that, while analyzing the signal corresponding to analysis window 1, the proposed method estimates the two modes having frequencies of 0.3252 Hz and 0.6765 Hz with

a damping ratio of 8.24% and 5.06% respectively. This estimate is similar to the reported values of the signal corresponding to analysis window 1 in [27], i.e. 0.32 Hz with 8.3% damping. Meanwhile, the damping factor estimates of the VMD-Hilberts, SSI, and Prony-based methods are 8.46%, 8.65%, and 8.97% respectively, which are slightly erroneous compared to the proposed EWT-based method. The results in Table 4 indicate that the variation in the estimated modal parameters is negligible for the proposed method even at high levels of noise. Hence, as evident from Tables 3 and 4, in comparison with the other three methods, the proposed method is a better choice for the identification of poorly damped modes present in real-time signals.

IV. CONCLUSION

This work proposed an accurate method based on a combination of the EWT and Yoshida-Bertecco algorithm to analyze the oscillations occurring in the power system. As oscillations rarely occur in the power system, a preprocessing algorithm based on Teager Kaiser energy operator is developed to identify whether the signal contains oscillations, which in turn helps to reduce the computational complexity of the system. If the signal has oscillation modes, it is passed into the EWT-based algorithm for decomposition, and the signal parameters are estimated using the Yoshida-Bertecco algorithm. The robustness of the proposed method is tested using test signals with varying levels of noise contamination, simulated signals, and PMU data from an actual power system. Furthermore, the performance of the proposed method is tested by comparing it with a VMD-Hilberts transform-based method, an SSI-based method, and a Prony-based method in the literature. Comparisons revealed the superior performance of the proposed method, irrespective of the values of signal parameters and the noise contamination. The proposed

method can be further improved by adding an intelligent classifier to the TKEO based preprocessing algorithm such that events like generator loss, line trip and load loss are detected and classified before the analysis by the proposed EWT algorithm.

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