Improved Time-Localization of Power System Forced Oscillations Using Changepoint Detection

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***Abstract*—This paper explores the use of changepoint detection (CPD) for an improved time-localization of forced oscillations (FOs) in measured power system data. In order for the autoregressive moving average plus sinusoids (ARMA+S) class of electromechanical mode meters to successfully estimate modal frequency and damping from data that contains a FO, accurate estimates of where the FO exists in time series are needed. Compared to the existing correlation-based method, the proposed CPD method is based on upon a maximum likelihood estimator (MLE) for the detection of an unknown number changes in signal mean to unknown levels at unknown times. Using the pruned exact linear time (PELT) dynamic programming algorithm along with a novel refinement technique, the proposed approach is shown to provide a dramatic improvement in FO start/stop time estimation accuracy while being robust to intermittent FOs. These findings were supported though simulations with the minniWECC model.**

I. Introduction

Power system forced oscillations can bias electromechanical mode meters toward ultra-low damping if not handled with proper care as seen in, e.g., [1]–[8]. This could cause false alarm scenarios where operators are led to believe that the system is nearly unstable, when in reality it is just a poorly behaving tool responding to a FO.

The least squares autoregressive moving average plus sinusoids (LS-ARMA+S) mode meter was shown in [4]–[8] to accurately estimate the electromechanical modes whether FOs are present or not. The algorithm does, however, require separately-estimated FO frequency and start/stop samples.

Estimating FO frequency is a classical signal processing problem. In contrast, the estimation of the start/stop samples has not been given the same attention. The authors of [4] proposed a correlation-based approach in [9] that performed reasonably well but cannot accommodate FOs with multiple start/stop times in an analysis window.

In this paper, a changepoint detection (CPD) approach to estimating FO start/stop times is presented. So far, CPD applications in power systems have been limited. For example, the work done in [10] focused on using a subspace approach to detect changes in power system operating point in a fast, online setting. Here it is seen that CPD provides start/stop estimates that are substantially more accurate than those found by [9] while also handling intermittent FOs with multiple start/stop times. The end results is an LS-ARMA+S mode meter that is more accurate and robust than before.

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In the next section, a review of the ARMA+S mode meter is provided. In Section III the proposed CPD-based method of FO start/stop time estimation is presented. The performance of the proposed method is explored using simulations with the minniWECC model in Section IV, and concluding remarks are given in Section V.

II. Background

It is well known that when a power system is linearized under small-signal stability analysis, measured system outputs such as voltage angle, frequency, active power, etc., may be modeled as an autoregressive moving average (ARMA) process under ambient conditions (e.g. [11]). In the presence of a FO, the ARMA plus sinusoids (ARMA+S) model may be used [4]

$$y[k] = x[k] + s[k] \tag{1}$$

where y is some measured output as a function of discrete sample $k \in [0, 1, \ldots, N-1]$, x is an ARMA process, and sinusoids s are defined as

$$s[k] = \sum_{i=1}^{p} A_i \cos(\omega_i k + \theta_i) I_{\epsilon_i,\eta_i}[k] \tag{2}$$

where A is the amplitude, ω is the frequency, θ is the phase angle, and indicator function I defines the FO starting sample ϵ and ending sample η by

$$I[k] = \begin{cases} 1, & \epsilon \le k \le \eta \\ 0, & \text{else} \end{cases} \tag{3}$$

Using the ARMA+S model has been shown in [4]–[8] to be a highly effective way of estimating the power system electromechanical modes in the presence of FOs that would otherwise bias the mode estimates toward zero damping and the FO frequency. The linear parameters of the model, i.e., the ARMA portion along with the FO amplitudes and phases, can be estimated using a least squares approach as detailed in [4]. Note that the LS algorithm uses estimates of the nonlinear model parameters, i.e., the frequency and start/stop samples, that must be estimated separately.

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The task of FO frequency estimation was addressed in [12], where a zero-padding periodgoram method was developed and subsequently used in the ARMA+S estimation contained in [5], [6]. In [8] it was shown that while optimized for FO *detection*, the methods in [12] were not necessarily the best choice for *estimation*. In particular, it was established that for FOs with high enough energy, the accuracy required to get good mode meter performance was impossible to achieve using zero-padding. Instead, the iterative approach from [13] was suggested for being both computationally and statistically efficient, and indeed a striking improvement in mode meter estimation accuracy was observed.

An approach to estimating the FO start/stop samples was proposed in [9]. It is based upon the fact that the cross-correlation between one of the cosine elements in (2) and a complex exponential of the same frequency and record length is essentially a trapezoid, the vertices of which are directly related to the starting and stopping samples of the cosine. The algorithm from [9] fits a trapezoid to the cross-correlation between y and a complex exponential at the estimated FO frequency and assumes that the correlation only contains a single trapezoid. This approach was used in conjunction with the periodogram-based FO frequency estimation algorithm from [12] to successfully estimate mode frequency and damping in the presence of FOs using the ARMA+S model in [5], [6].

III. Changepoint Detection and FOs

The sudden appearance or disappearance of a FO in y can be viewed as a model change, the detection of which is heavily covered in [14]. In particular, the problem of detecting multiple jumps in signal mean where neither the values of the means nor the jump times are known is described. It is shown that the joint MLE for $m+1$ means and m jump times is the minimization of cost function

$$\begin{aligned} J(Y,n) &= \sum_{k=0}^{n_1-1} (y[k]-Y_0)^2 + \sum_{k=n_1}^{n_2-1} (y[k]-Y_1)^2 \\ &\quad + \ldots + \sum_{k=n_m}^{N-1} (y[k]-Y_m)^2 \end{aligned} \tag{4}$$

where $Y = \begin{bmatrix} Y_0 & Y_1 & \cdots & Y_m \end{bmatrix}^T$ are the means and $n = \begin{bmatrix} n_1 & n_2 & \cdots & n_m \end{bmatrix}^T$ are the changepoints. As illustrated in [14], the solution to (4) may be found using dynamic programming, which can be computationally burdensome.

The authors of [15]–[17] developed an approach to solving (4) that introduces a pruning step within the dynamic programming to lower the computational cost to $\mathcal{O}(n)$ from, e.g., $\mathcal{O}(n^2)$ or $\mathcal{O}(n \log n)$ in other methods. Named the pruned exact linear time (PELT) method, it has the ability to optimally select the number of changepoints m. Note that MATLAB function `ischange` uses PELT in its CPD algorithm to return estimates of both the means and the changepoints. Here it used with the `'MaxNumChanges'` option which places an upper limit on the optimal number of changepoints m to be found; a value that should be chosen to be larger than number of times a particular FO is expected to be appearing or disappearing throughout the data record.

A. Mode Meter Workflow

Before discussing how CPD is applied to the FO problem, its place in the overall mode meter algorithm must be explained. First, the presence of an FO is detected in the data analysis window using the periodogram-based method of [12]. Then, the frequency of the FO is estimated using the iterative method of [13]. Next, the FO frequency estimate is used by the CPD algorithm presented below to provide estimates of the FO start/stop samples. Finally, the LS-ARMA+S model is estimated with a two-stage least squares algorithm that uses the FO frequency and start/stop time estimates to produce modal frequency and damping estimates comparable to those observed in purely ambient conditions.

B. The CPD Algorithm

To apply the PELT-based CPD algorithm to FO start/stop sample estimation, the data is first preprocessed to produce a signal that has nonzero mean when a FO is present and zero mean otherwise. Note trigonometric identity

$$\begin{aligned} s_{cos}[k] &= A\cos(\omega k+\theta)\cos(\omega k+\phi) \\ &= \frac{A}{2}\cos(\theta-\phi)+\cos(2\omega k+\theta+\phi) \end{aligned} \tag{5}$$

where the mean of s_{cos} is maximized when $\phi = \theta$. Thus multiplying y by a cosine of the FO frequency and phase will result in a signal that has a mean of approximately $A/2$ when the FO is present and zero otherwise. Define

$$y_{cos}[k] = y[k]\cos\left(\hat{\omega}k+\hat{\theta}\right) \tag{6}$$

where $\hat{\omega}$ is the FO frequency estimated using [13] and phase $\hat{\theta}$ is estimated via the Discrete-Time Fourier Transform as

$$\hat{A}\angle\hat{\theta} = \sum_{k=0}^{N-1} y[k]e^{-j\hat{\omega}k} \tag{7}$$

The main algorithm is shown in Fig. 1 with y_{cos} as the input. It must be initialized with N_{maxCP} the maximum number of changepoints passed to the `'MaxNumChanges'` option, N_{minSL} the minimum segment length to consider, and the estimate of the amplitude of the FO $\hat{A}$ from (7). Assuming CPs are detected, N_{short}, the number of segments shorter than N_{minSL}, is subtracted from N_{maxCP} and `ischange` is rerun. This eliminates any erroneously estimated FO segments that are a few samples long. N_{minSL} should be chosen such that it corresponds to an FO duration that would have negligible effect on mode meter performance. This loop runs until either no CPs are detected or all segments are long enough. Finally, the segments are categorized as either FO "on" or "off" based upon the segment mean relative to $\alpha\hat{A}$, where α is a scaling factor on the estimated FO amplitude. Note an extremely important area of future work is to study the sensitivity of the method to parameters N_{maxCP}, N_{minSL}, and $\alpha\hat{A}$.

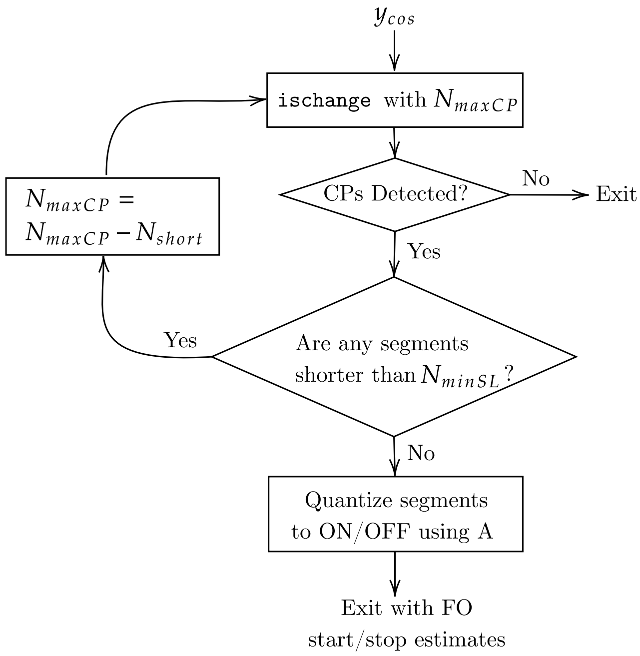

Fig. 1. The FO start/stop time CPD algorithm.

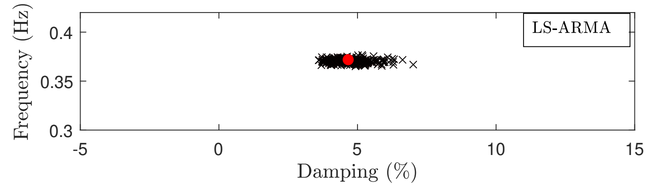

Fig. 2. Mode estimates from 300 Monte Carlo simulations of the minniWECC under ambient conditions. (True mode in red, estimates in black)

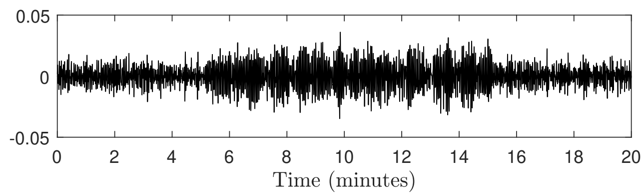

Fig. 3. Preprocessed minniWECC output with a 0.35-Hz 3-dB FO present from the 5- to 15-minute marks.

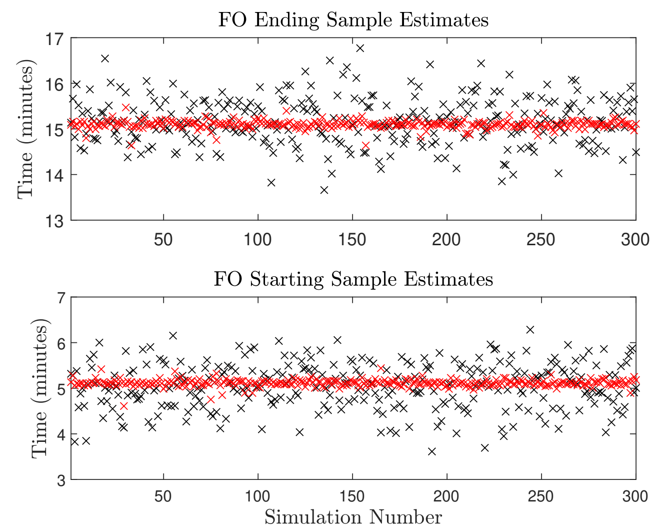

Fig. 4. Estimates of the FO start and stop times using the correlation method (black) and CPD (red) from simulations with a 0.35-Hz 3-dB FO present from the 5- to 15-minute marks.

IV. Simulation Study

To assess the effectiveness of the proposed approach, a simulation study was conducted using the minniWECC model of the Western Electricity Coordinating Council (WECC) power system (see [18] for technical details). In each of the studies below, 300 Monte Carlo simulations of 20-minutes in duration were conducted. Ambient system conditions were created by modeling 0.125% of each load as random using $1/f$ filtered Gaussian White Noise (GWN). The system output was chosen as the difference between voltage angles at buses from the northern and southern edges of the grid, chosen for the high observability of the mode under study, i.e., the 0.37 Hz and 4.67% damping mode often referred to as the "North-South B" (NSB) mode. Gaussian white measurement noise was added to the output to achieve an SNR of 80 dB.

The simulations were conducted at the common PMU reporting rate of 120 samples per second, and the system outputs were preprocessed by lowpass filtering and downsampling to 5 samples per second and then detrended with a high pass filter. The LS-ARMA+S mode meter was implemented with model orders of AR-32, MA-6, and high-order AR of 50 (stage 1 in the Two-Stage Least Squares process). In each Monte Carlo trial, the mode estimates from LS-ARMA+S were sifted such that only those between 0.3 and 0.42 Hz and below 25% damping were kept. To establish a baseline, ambient-only data was analyzed, and the resulting mode estimates are shown in Fig. 2. The CPD altorighm was implemented with $N_{maxCP} = 10$, $N_{minSL} = 2$ minutes, and $\alpha = 0.7$.

A. Contiguous Forced Oscillations

A FO was introduced by applying a square wave to the mechanical power input of a particular generator beginning 5 minutes into the simulation and ending at the 15-minute mark of 20 minutes of otherwise ambient data. First consider a 0.35-Hz FO with a 3 dB SNR, defined with the FO as the signal and the ambient data as the noise. An example realization of the system output is shown in Fig. 3.

As can be seen in Fig. 4, the estimates of the FO start and stop times are vastly improved using the CPD approach. The mode frequency and damping estimates are, however, far less dramatic. Shown in Fig. 5, the FO is bothersome enough that the classic LS-ARMA mode meter is severely biased, while the correlation-based LS-ARMA+S mode meter has a small bias. The new CPD-based LS-ARMA+S mode meter provided nearly identical results to the purely ambient case.

Next, the amplitude of the FO was increased to 13 dB and the simulation study was repeated. See Fig. 6 for an example simulation output. The increased observability of the FO in the data greatly improved the estimation accuracy of both

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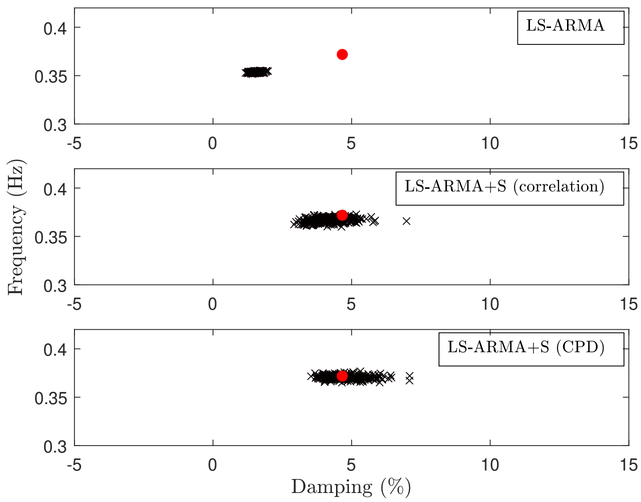

Fig. 5. Estimates of mode frequency and damping from simulations with a 0.35-Hz 3-dB FO present from the 5- to 15-minute marks. (True mode in red, estimates in black).

approaches as seen in Fig. 7. As with the 3-dB case, the standard deviations of the correlation-based approach were about 6 times those of the CPD-based method. The mode estimates, shown in Fig. 8, reveal that the increased FO energy had a catastrophic effect on the LS-ARMA mode meter; virtually every estimate is at the FO frequency with nearly 0% damping. Despite the improved FO start/stop estimation accuracy, the correlation-based LS-ARMA+S mode meter demonstrated a performance degradation as compared to the 3-dB case, while the CPD approach maintained its accuracy. These simulation cases demonstrate the trend discussed in [8] that the more severe the FO, the greater the accuracy needed when passing values of the nonlinear FO parameters to the LS-ARMA+S algorithm.

B. Intermittent Forced Oscillations

While the previous subsection demonstrated mild to moderate improvement in mode meter performance using the CPD approach, here we consider a case where the correlation-based method necessarily fails. If a FO suddenly turns off and on again any number of times within an analysis window, perhaps due to a malfunctioning controller tripping briefly or an oscillatory load going offline temporarily, the cross correlation waveform used in the correlation-based approach will be comprised of several trapezoids - one for each segment of data where the FO is “on.” Because the correlation-based approach operates by fitting the cross-correlation data to a single trapezoid, it will fail. Granted, if the number of “on” segments of the FO are known, the correlation method could be adapted. The CPD approach, due to its dynamic programming, does not require prior knowledge of the number of segments.

To demonstrate, a simulation was conducted with the 0.35-Hz 3-dB FO from above, but with opposite on/off states. The FO was present from the start through the 5-minute mark, and then again from the 15-minute mark through the end. Figure 9 provides an example realization of the system output under

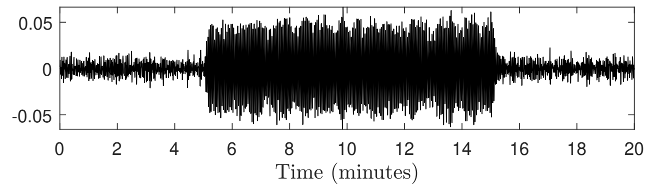

Fig. 6. Preprocessed minniWECC output with a 0.35-Hz 13-dB FO present from the 5- to 15-minute marks.

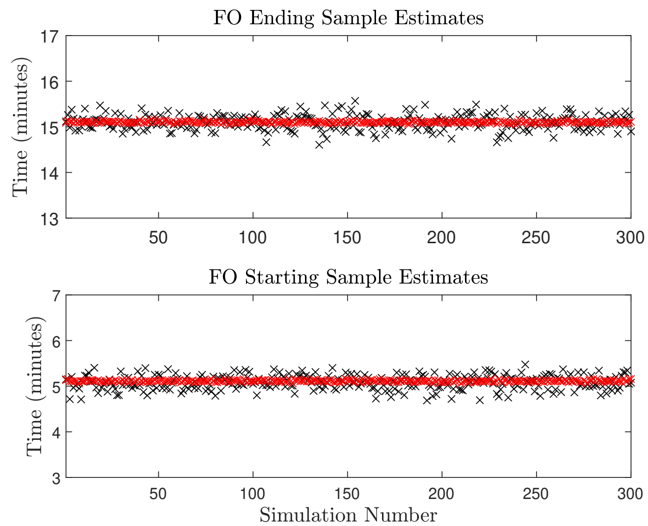

Fig. 7. Estimates of the FO start and stop times using the correlation method (black) and CPD (red) from simulations with a 0.35-Hz 13-dB FO present from the 5- to 15-minute marks.

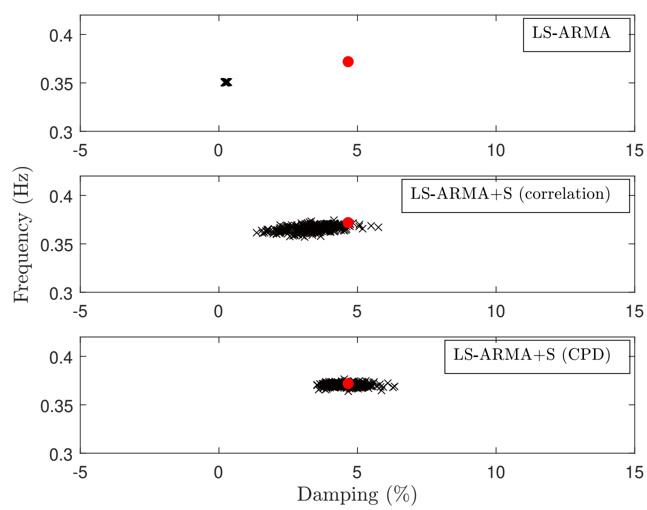

Fig. 8. Estimates of mode frequency and damping from simulations with a 0.35-Hz 13-dB FO present from the 5- to 15-minute marks. (True mode in red, estimates in black).

these conditions. The cross correlation is shown in Fig. 10 where one trapezoid from each “on” period is clearly visible.

Indeed, the correlation-based algorithm failed on each of the Monte Carlo trials, leading to mode meter estimates no better than the LS-ARMA cases as seen in Fig. 11. The CPD algorithm correctly identified both “on” segments in all Monte Carlo trials, and estimated the start/stop times with accuracy

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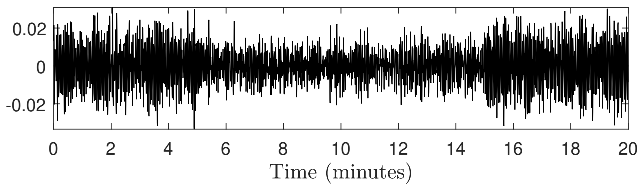

Fig. 9. Preprocessed minniWECC output with a 0.35-Hz 3-dB FO present from the 0- to 5-minute marks, and then again from the 15- to 20-minute marks.

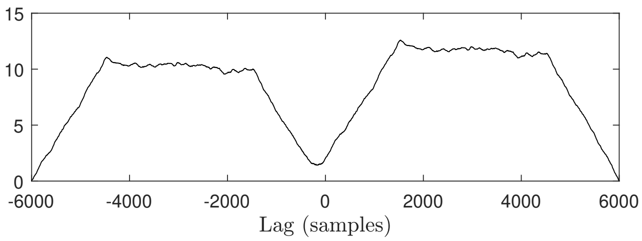

Fig. 10. Cross correlation of the data from Fig 9 with a 0.35-Hz complex exponential.

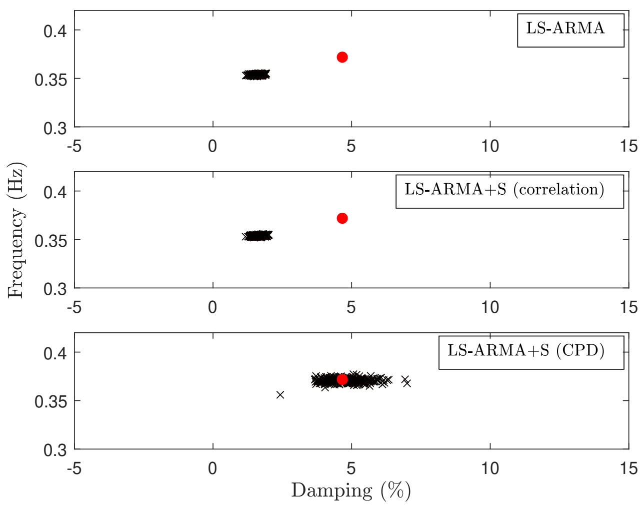

Fig. 11. Estimates of mode frequency and damping from simulations with a 00.35-Hz 3-dB FO present from the 0- to 5-minute marks, and then again from the 15- to 20-minute marks. (True mode in red, estimates in black)

comparable to that of Fig. 4, leading once again to mode estimates that nearly match the purely ambient case.

V. Conclusions

This paper explores the use of changepoint detection for estimating the start/stop samples of forced oscillations in otherwise ambient data. Compared to the correlation-based method, it provides estimates with lower variance and has the ability to handle multiple changepoints, allowing for the analysis of intermittent FOs. These improvements make the LS-ARMA+S mode meter both more accurate and robust.

Ongoing work includes an investigation into alternative CPD methods, e.g., [10], [14]. A battery of tests is being conducted under a variety of difficult simulation conditions including multiple FOs of closely spaced frequency, and power system conditions that include ringdowns or low-damping system modes. Additionally, these methods must be validated with data measured from actual power systems. Finally, it must be noted that these approaches so far assume stationary FOs. An extremely important area of future work is the task of dealing with FOs with amplitude and frequency that drift over time.

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