Detrending and Characterizing System Frequency Oscillations Using an Adapted Zhou Algorithm

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***Abstract*—Electro-mechanical oscillations between interconnected synchronous generators and oscillations in system frequency are an inherent part of the operation of large power systems. Very Low Frequency (VLF) oscillations are usually classified as oscillations in the 0.01-0.1 Hz range. With the move towards variable renewable energy sources and low-inertia power systems, VLF oscillations are being observed with increasing regularity in many small and island grids. If left undamped, these can present a threat to system stability. However, finding the root cause and source(s) of VLF oscillations is an extremely challenging task for network operators. Recent work has identified a need for improved tools for identifying and characterising VLF oscillations, in order to determine the combination of system conditions that can be used as predictors for VLF events. A suitable small signal model is also required in order to enable verification of the root cause of VLF events and study of mitigation measures. Accordingly, this paper presents a new approach for detrending and characterizing system frequency oscillations using an adapted Zhou algorithm. The paper also describes a method for applying this algorithm for the detection/location of oscillations, and for their detrending and characterization. Finally, an approach for relating detected oscillation events to power system operating conditions for diagnostic purposes is described. The effectiveness of the proposed approach is demonstrated using a single frequency power system model, and using system frequency oscillations recorded from the Irish power system.**

***Index Terms*—power system oscillations, detrending, nonstationary, common mode oscillations, damping, low inertia systems, signal processing, wide area monitoring, power system monitoring, power system stability, very low frequency oscillations.**

I. Introduction

The phenomenon of electro-mechanical oscillations between interconnected synchronous generators and oscillations in system frequency are an inherent part of the operation of large power systems [1]. Such oscillations in system frequency can be a threat to system frequency stability, and present a danger to system operation [2], and if left undamped can contribute to the cause of system blackouts [3], [4].

Very Low Frequency (VLF) oscillations, also called common mode oscillations, are type of system frequency oscillation usually classified as having frequencies of between 0.01 and 0.1 Hz. It is a naturally occurring oscillation in a power system but is normally well damped [5], however unstable VLF oscillations are beginning to be observed more often, particularly in certain small or islanded systems [6], [8].

Studies carried out by the Irish Transmission System Operator (TSO), EirGrid, on such VLF oscillations occurring within the Irish transmission grid have identified the potential of type 3 wind turbines to mitigate the oscillations and provide frequency control [9]. However, the study found only limited correlation between the occurrence of VLF oscillations and system level measures such as the time of year, demand, and wind generation level, and concluded that a more sophisticated tool for identifying such VLF oscillations within recorded frequency data was required. Such a tool would enable grid operators to perform a more detailed assessment of VLF oscillations against system and machine level conditions in order to carry out detailed studies into the root cause of such oscillations [6].

Numerous existing operators and methods were examined for their potential in the development of such a tool. The potential of the Teager-Kaiser Energy Operator [10] for the detection and analysis of oscillations in particular was examined [11]. However it was found to provide insufficient distinction between low magnitude oscillations and background noise in the system and did not provide a sufficiently accurate measure on the frequency of VLF oscillations, particularly when data is gathered at a 1Hz sample rate.

Empirical mode decomposition [12] was also examined, and while it shares a number of similarities with the Zhou algorithm (in that it recursively detects local minima and maxima of a signal [13]), the Zhou algorithm also includes detrending capabilities and is designed for a power systems application. Similarly, Fast Frequency Domain Decomposition has been proposed as an oscillation monitoring method, but does not perform the detrending or characterisation functions necessary [14].

The Zhou algorithm, proposed by N. Zhou et. al. [15], is a detrending algorithm designed to detrend oscillations in power system frequency by locating maxima and minima points of oscillation, interpolating envelopes and finding a trend. It has proven to be very effective at detrending VLF oscillations in power system frequency [16], but does not inherently offer the characterisation of magnitude or frequency required.

Accordingly, this paper proposes an new approach for detrending and characterizing system frequency oscillations using an adapted Zhou algorithm. It also presents and demonstrates a methodology for applying this algorithm in the detection and location of oscillations, including detrending, characterization and relating found characteristics to power system operating conditions for diagnostic purposes. The potential of this approach for diagnosing the source of oscillations is verified via the use of a single frequency model, and the presented algorithm and method are applied to frequency oscillations recorded on the Irish power system.

The paper is structured as follows: Section II covers the outline of the proposed method, Section III the characterising adaptations made to the Zhou algorithm and the relation of these characterisations to system conditions, Section IV covers the verification and application of this method in a case study where a a single frequency power system model is used to simulate a system with an oscillatory behaviour.

II. Outline Of Proposed Method

Single area power system frequency data is often measured and stored as a continuous sequence of frequency data samples, denoted $x(n)$, which forms the input to this algorithm. Initially this continuous string of samples is split into time windows, denoted $x_w(n)$,

$$x_w(n) = x(k), x(k+1)....x(k+T) \tag{1}$$

where k is a constant and the first sample of the window and T is the length of the window in number of samples. This windowing allows a rough location process to be carried out, identifying which time windows within the data contain oscillations. A Discrete Fourier Transform (DFT) of the form

$$X_w(f) = \sum_{n=-\infty}^{\infty} x_w(n) e^{-j2\pi f n} \tag{2}$$

is then applied to each time window where f is the sampling frequency of the data, and $X_w(f)$ is the frequency domain representation of the window of system frequency data. This frequency domain representation is used to identify if an oscillation in system frequency occurs during each window, by comparing the maximum value of the frequency domain representation of the time window to a predetermined value equivalent to a statistically significant oscillation. If the maximum value of the frequency domain exceeds what is required to be considered an oscillation, then the associated time window is categorised as containing an oscillation. Consecutive windows that are found to contain oscillations are adjoined to give a rough start and end time for individual frequency oscillation events.

With these rough start and end times established, the Zhou detrending algorithm is applied to the system frequency data between. This algorithm iteratively removes non-oscillatory trends from the data, through a process of forming envelopes around the oscillation, taking the average of these envelopes and subtracting it from the oscillatory data. After the detrending process has been complete, the process of forming the envelopes, and the envelopes themselves, are adapted to provide a measure of the magnitude and frequency of the oscillation over its course, allowing the characterisation of the oscillation. This characterisation includes the points in time at which the oscillation begins and ends, along with the points at which the nature of the oscillation change.

By carrying out this process of locating, detrending and characterising oscillations over an amount of data covering a significant period of time, a number of oscillations can be studied and characterised, and an indicative relationship between system conditions and the occurrence and nature of oscillations can be established. An assessment of what power system conditions changed at or near the same time an oscillation starts, ends or changes in nature is carried out. By studying a large number of oscillations in this manner, trends can be established as to what changes in system conditions tend to precede the occurrence of oscillations, or the changes that tend to change the nature of, or dampen oscillations. By analysing these trends, an indication of relationships between specific system conditions and oscillations can be developed, allowing further, more in depth, analysis to be targeted at specific components and conditions.

III. Adapted Zhou Algorithm

A. Zhou Algorithm

The Zhou algorithm for non-linear trend identification and detrending [15] follows five steps, four of which are repeated iteratively. The first, non-iterative, initialization step of the algorithm involves establishing the parameters for the trend identification, the upper and lower frequency values, f_h and f_l, between which the oscillation modes of interest lie.

With the parameters established, a sliding time window, whose content is denoted $y_i[t]$, is used to find local minimum and maximum values within the oscillation data. The width of the sliding window is the inverse of the upper frequency limit $\frac{1}{f_h}$. Local maximum and minimum points are defined as

$$\mathrm{y}_{min}[k] = \left\{ y_i[k] \middle| y_i[k] \leq y_i[t] \; for \; k - \tfrac{1}{2f_h} \leq t \leq k + \tfrac{1}{2f_h} \right\} \tag{3}$$

$$\mathrm{y}_{max}[k] = \left\{ y_i[k] \middle| y_i[k] \geq y_i[t] \; for \; k - \tfrac{1}{2f_h} \leq t \leq k + \tfrac{1}{2f_h} \right\} \tag{4}$$

In order to ensure that all local maxima and minima found using this sliding window are the result of the oscillatory signal, an additional constraint is added. If the slope of the signal is positive for 80% of the samples proceeding a potential maximum point, considering samples that are within half a window width of the point, it is considered a true maximum point. The same constraint is applied to the finding of local minimum, with the preceding slope required to be negative. With these constraints applied, the local maximum and minimum are defined as follows, where $y_i'[t]$ is the differential or slope of the signal $y_i[t]$

$$y_{min}[k] = \left\{ y_i[k] \middle| \begin{array}{ccc} y_i[k] \leq y_i[t] & for & k - \frac{1}{2f_h} \leq t \leq k + \frac{1}{2f_h} \\ y_i'[t] \leq 0 & 80\% of & k - \frac{1}{2f_h} \leq t \leq 0 \\ y_i'[t] \geq 0 & 80\% of & 0 \leq k + \frac{1}{2f_h} \end{array} \right\} \tag{5}$$

$$y_{max}[k] = \left\{ y_i[k] \middle| \begin{array}{ccc} y_i[k] \geq y_i[t] & for & k - \frac{1}{2f_h} \leq t \leq k + \frac{1}{2f_h} \\ y_i'[t] \geq 0 & 80\% of & k - \frac{1}{2f_h} \leq t \leq 0 \\ y_i'[t] \leq 0 & 80\% of & 0 \leq k + \frac{1}{2f_h} \end{array} \right\} \quad (6)$$

With y_{min} and y_{max} established, the third step of the Zhou algorithm is to form upper and lower envelopes of the signal. These envelopes, denoted $X_{upper}[t]$ and $X_{lower}[t]$ are found by interpolating $y_{max}[k]$ and $y_{min}[k]$ respectively, using the Piecewise Cubic Hermite Interpolation Polynomial (PCHIP) [17]. To ensure these envelopes fully encompass the signal, any samples that lie outside the two envelopes are considered outliers, and are added to either $y_{max}[k]$ or $y_{min}[k]$ appropriately. The interpolation process is then repeated with the outliers included in $y_{max}[k]$ and $y_{min}[k]$, forming new envelopes. This process is repeated until the entirety of the signal is contained within the envelopes.

With the upper and lower envelopes established, the trend of the signal can be found as

$$X_{trend}[t] = \frac{X_{upper}[t] + X_{lower}[t]}{2} \quad (7)$$

With $X_{trend}[t]$ found, the oscillation signal can be detrended by subtracting the trend from the original signal. This detrending process of finding local maxima and minima, forming envelopes, trend identification and subtraction is repeated iteratively, until the trend found to be present can be considered insignificant, and the signal is completely detrended.

B. Adaptations to Zhou Algorithm

The second and third stages of the Zhou algorithm were utilized and adapted to provide a measure of oscillation frequency and magnitude in addition the detrending process, allowing for characterization of the oscillation. As part of the last iteration of the Zhou algorithm for detrending process, the local maxima and minima of the now detrended oscillation, denoted $y_{max,dt}[k]$ amd $y_{min,dt}[k]$ respectively, along with the upper and lower envelopes encompassing the oscillation, denoted $X_{upper,dt}[t]$ and $X_{lower,dt}[t]$ respectively, will have been found for the detrended oscillation. As the trend of the oscillation is now negligible and the oscillation is centered around zero, the magnitude of the oscillation is found by summing the absolute value of the two envelopes for there entire length,

$$A[t] = |X_{upperdt}[t]| + |X_{lowerdt}[t]| \quad (8)$$

where $A[t]$ is the amplitude of the oscillation with time. The Rate of Change of Magnitude (RoCoM) of the oscillation, denoted $A'[t]$ is also found by differentiating the amplitude with respect to time

$$A'[t] = \frac{d}{dt}A[t] \quad (9)$$

The frequency of the oscillation can also be found over its course by considering the maximum and minimum points found by the Zhou algorithm. The frequency of the oscillation is measured at each zero crossing of the oscillation by finding the time difference between the maxima or minima point preceding the zero crossing and the maxima or minima point proceeding the zero crossing, with double this time difference to be equivalent of one full oscillation, denoted $T[i]$.

$$T[i] = 2S(n_2 - n_1) \quad (10)$$

where S is the sample rate of the data in seconds, n_1 is the sample number for the preceding maxima or minima point and n_2 is the sample number of the proceeding maxima or minima point. The inverse of this time difference is then taken to form the measurement of frequency for that zero crossing, $F[i] = \frac{1}{T[i]}$.

This allows for the frequency of the oscillation to be measured every half cycle of the oscillation, where i denotes the half cycles of the oscillation.

By performing these additional steps after the detrending process of the Zhou algorithm, the magnitude and frequency of the oscillation can be found over its course, which allows for the characterisation of said oscillation.

C. Relation of Oscillation Characteristics to System Conditions

By examining the characterization provided by the adaptations to the Zhou algorithm, instances, or points of interest, at which the nature of the oscillation changes to be identified. This includes determining accurate start and end times for the oscillation, points at which the RoCoM changes abruptly and where there is a change in the frequency of oscillation. By identifying these instances, a profile for an oscillation can be built, consisting of its start and end time, along with the instances its nature changes.

This identification of points of interest is carried out by the examining of the amplitude, RoCoM and frequency characteristics ($A[t]$, $A'[t]$ and $F[i]$) of an oscillation, and involves assessing the values of these three characteristics both at the point being examined and in comparison to the characteristics of the whole oscillation.

These oscillation profiles can then be related to changes in the operation of the power system or its components. Changes in system conditions & operation that occur simultaneous to, or proceeding, a found change in oscillation nature are recorded, along with the nature of the change. By applying this process over extended periods of time to a power system that experiences sporadic or regular frequency oscillations, trends can be established, wherein a change in system operation or conditions repeatedly precedes a change in the nature of an oscillation. The identification of such a trend provides a statistical indication of how said system condition or operation interacts with system frequency oscillations. This statistical indication can then be used to enable and guide more in-depth, targeted studies.

This principle of relating characteristic changes in oscillation nature to changes in system conditions, along with the adaptations to the Zhou Algorithm, are explored in more detail via two case studies in Section IV below.

IV. Verification Through Case Study

To verify the potential of the adapted algorithm and relation method for aiding in the analysis of system frequency oscillations it will be applied to power system experiencing system frequency oscillations simulated using a single frequency model. For this case study, the proposed detrending, characterising and relation method were implemented in Python 3.7 [18].

1) Power System Model: For the purpose of testing the developed algorithm a simple power system Single Frequency Model (SFM) was built in the Matlab Simulink program. It consists of eight generators of varying properties connected to a load, which is represented at a single point, forming a power system with a single frequency that varies in response to changes in the system. Each generator is under a frequency feedback droop control.

2) System Model: This power system model first finds the net system power difference in MW as

$$\Delta P_{MW} = G_{MW} - D_{MW} \tag{11}$$

where G_{MW} is the total generation in the power system and D_{MW} is the total demand for power in the system. This is used to calculate the net torque of the system

$$T_{net} = \frac{\Delta P_{MW}}{f_{rad}} \tag{12}$$

where f_{rad} is the frequency of the power system during the previous timestep in $rads^{-1}$. The angular acceleration of the system turbines is calculated using the total system inertia provided by active turbines, denoted I_{total},

$$\alpha = \frac{T_{net}}{I_{total}} \tag{13}$$

and the current system frequency is found by integrating this value of angular acceleration, and converted into Hz.

$$f_{Hz} = \frac{f_{rad}}{2 \cdot \pi} = \frac{\int \alpha dt}{2 \cdot \pi} \tag{14}$$

The integrator used to perform this function has an initial value of $314.16 rads^{-1}$, the equivalent of $50Hz$. Despite this initial condition there is a transient on starting the simulation, however issues are avoided by allowing enough time to pass for the transient to clear before starting any testing. With the system frequency value calculated, it is used as an input to the control of generators within the model and exported as an output of the model. The system demand varies with time, and is created by summing a number of ramping values and white noise.

3) Generator Model: Each of the eight generators within the Single Frequency Model (SFM) use the same generator model, which consists of three parts, the governor, turbine and frequency response droop control. The maximum generation, provided inertia and time constants vary between generators to represent typical real world generators, Table I.

The governor and turbine are modeled as a delay transfer function system in a model proposed by M. Gupta [19],

$$G_{gov}(s) = \frac{1}{J_g \cdot s + 1} \tag{15}$$

$$G_{turbine}(s) = \frac{1}{J_t \cdot s + 1} \tag{16}$$

wherein J_g and J_t are the time constants of the governor and turbine respectively.

The set-point of each generator governor is set by a series of functions so as the total generation roughly matches the total demand,

Each generator has a defined power output set point which is subject to a droop frequency control system, where the set-point is adjusted based on the system frequency, before forming the input to the governor. The droop constant and dead-band are those used in the Irish power system [20].

The power output of the turbine transfer function is subjected to a saturation function to ensure that it does not exceed the maximum or minimum generation limits, and is then considered the power output of the generator. The power generated by each generator, and the inertia they provide, are summed to provide the system totals for the calculations of system conditions. A generator is only considered to be providing inertia if it is generating power.

Generators 5-8 have a constant power set-point, and generators 1-4 vary their set-points in a planned manner to roughly mirror the large, expected, changes in system demand, with the droop control of the system correcting any imbalances.

TABLE I
Generator Time Constants, Inertia and Generation Limits

Generator	Value			
	J_g	J_t	$MaxGen(MW)$	$Inertia(MWs)$
$Gen1$	10.556	10.89	800	2.0
$Gen2$	1.556	0.0089	700	0.0
$Gen3$	20.556	0.0089	700	1.0
$Gen4$	20.556	5.089	600	1.5
$Gen5$	20.556	0.0089	400	1.0
$Gen6$	20.556	5.089	400	0.7
$Gen7$	20.556	0.0089	400	0.3
$Gen8$	20.556	5.089	400	1

4) Simulating system frequency oscillations: To use this model to test the developed algorithm, system frequency oscillations were introduced through Generator "Gen1". When the governor set-point of the generator increased above 400 MW, the generator entered a "rough running" region [21] and an oscillation is added to the governor output. It is sinusoidal in nature and has a magnitude proportional to how much greater than 400 MW the Governor set point currently is. This causes an oscillation in generator output which grows as the generator output gets further into the rough running region of operation and is limited by the saturation function to not exceed the limits of the generator. This oscillation in generator power output then drives an oscillation in system frequency.

The outputs of the single frequency model are the system frequency and the set-points of the generator governors, before the droop control is applied, both taken as a continuous string of measurements

The resulting system frequency output of the model is shown in figure 1 with the plot starting after the model startup transient has cleared, 1000s into the full simulation.

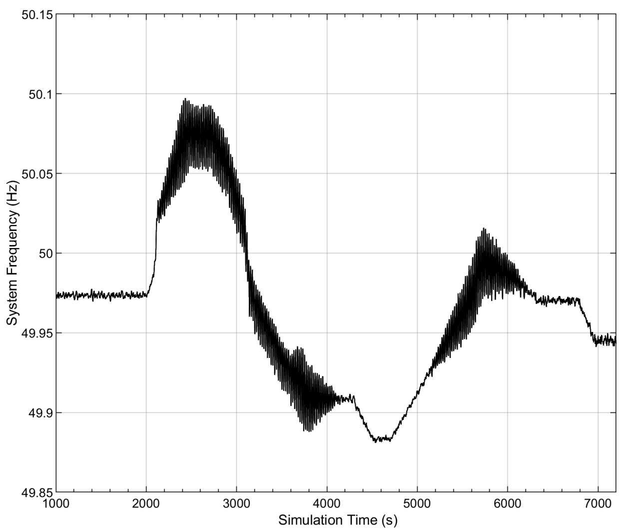

Fig. 1. Simulated system frequency from SFM.

5) Testing & verification of method: To test the method proposed in this paper the system frequency output of the single frequency model is used as the input to the developed method. The Fourier transform process windows the simulated system frequency data into 600s windows, and identified which windows contained oscillations in system frequency and combines sequential windows. Seven windows were found to have a FFT magnitude greater than the set limit, which were separated into two continuous oscillations, the first shown in figure 2. This provided the initial identification and rough location of the oscillations within the frequency data.

The detrending process is then carried out with the Zhou detrending algorithm shown in Section III.A applied to the oscillations, followed by the proposed characterisation methods. Local maxima and minima of the oscillation are found, upper and lower envelopes interpolated from them and the trend of the oscillation found by averaging the two envelopes. This trend is then subtracted from the oscillation and the process is repeated iteratively.

The first of the identified oscillations, with the first iteration of maxima, minima, envelopes and trends is shown in Fig. 2, and the detrended oscillation can be seen in Fig. 3.

With the oscillation detrended, the magnitude and frequency of the oscillation is characterised using the methods outlined in Section III.B. From the resulting magnitude and frequency characteristics, points of interest are found in the manner described in Section III.C. These consist of when the oscillation starts, ends and when the nature of the oscillation changes.

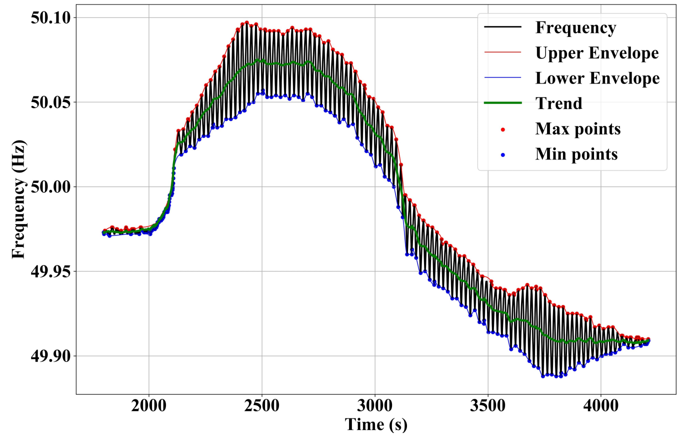

Fig. 2. First Continuous oscillations identified in SFM frequency.

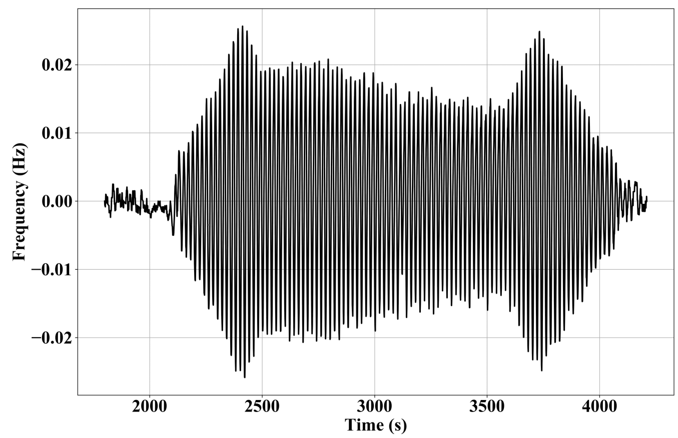

Fig. 3. First Detrended SFM oscillation.

The magnitude characteristics of the oscillation with these identified points of interest are shown in Fig. 4.

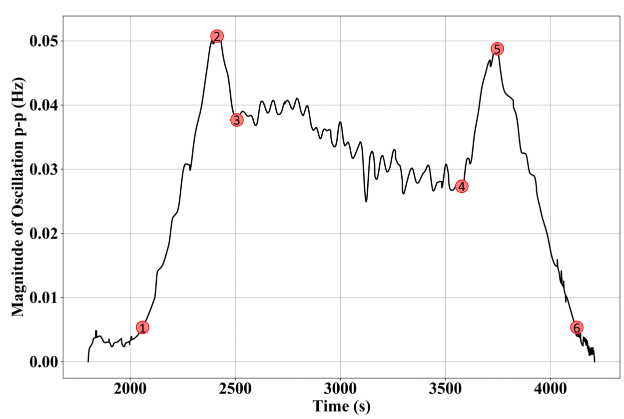

Fig. 4. Magnitude characteristic and identified points of interest

Six points of interest are identified: where the oscillation begins, four points where the RoCoM of the oscillation changes suddenly, and where the oscillation ends.

With the points of interest of the oscillations established, a python script was created to relate these points to changes in system conditions, as described in Section III.C. The only considered system condition is the governor set-points, pre droop, as it is the only controlled system condition.

With this method of characterisation and relation applied to the frequency output of the SFM, Generator 1 was correctly identified as the generator driving oscillations. Also identified was an approximate range of set-point values for which the Generator 1 drives oscillations, above 476.49 MW. While this is not exactly the value for which Generator 1 does drive oscillations, a larger sample size would likely further refine the estimate.

V. Conclusion

This paper presents an approach for identification and characterisation of VLF oscillations, based on an adapted Zhou algorithm. It can be used to aid diagnosis of VLF oscillations, by identifying instants when the nature of the oscillation changes and correlating them with changes to component operation. By applying this process to a large number of oscillations an indicative profile can be built, providing insights in to the influence system components have over VLF oscillations.

The effectiveness of this approach was demonstrated using a Single Frequency Model of a power system, consisting of a group of eight generators and a load. It was shown that the generator causing system frequency oscillations and the responsible operating conditions could be successfully identified.

One limitation of the presented approach is that it does not verify the accuracy of the method when estimating frequency, and the maximum/minimum could be distorted by noise or oscillation interaction. This will be addressed in further work by comparing the running estimated VLF oscillation frequency with expected values. In addition, the model used in Section IV-1 was specifically developed for this work. Future work will apply the method using an open model, such as the IEEE 10-machine 39-bus system, in order to better allow others to duplicate results.

Evidence to date has indicated VLF oscillations in the Irish system are not directly linked to simple measure such as time of year, demand, wind, or inertia, but are instead driven by unit commitment and dispatch of synchronous generators [6]. At the time of writing, the approach developed in this paper is being integrated with existing system frequency analysis tools used within EirGrid, the Irish national transmission grid operator, in order to aid in diagnostics and ongoing studies of VLF oscillations [6].

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