Oscillation Monitoring of the RTE Power System Using Synchrophasors

Final Project Report

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Power Systems Engineering Research Center
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Oscillation Monitoring of the RTE Power System Using Synchrophasors

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Executive Summary

Recent advances in design of fast oscillation monitoring algorithms have paved the way for real-time detection and analysis of electromechanical oscillations from wide-area synchrophasor measurements in large power interconnections. The oscillations if left unmitigated can lead to unwanted tripping of transmission lines and generators that could cascade into devastating blackouts. Oscillation monitoring algorithms developed at Washington State University have previously been implemented and tested in North American power grid and in India. In this project, we have studied oscillation phenomena in the RTE portion of the European power grid by using available synchrophasor data. Suitability of ambient versus ringdown analysis algorithms for analyzing recent oscillation events in RTE have been investigated. The effectiveness of the oscillation algorithms have been tested and improved by using simulated PMU data from dynamic models of the RTE system wherein the expected answers are known from small-signal analysis of the dynamic models.

Project Publications:

[1] Mohammadreza Maddipour Farrokhifard, Mohammadreza Hatami, Vaithianathan “Mani” Venkatasubramanian, Gilles Torresan, Patrick Panciatici, and Florent Xavier, “Clustering of Power System Oscillatory Modes Using DBSCAN Technique,” Proc. NAPS 2019 Conference, Wichita, USA, Oct. 2019, to appear.

[2] Mohammadreza Maddipour Farrokhifard, Vaithianathan “Mani” Venkatasubramanian, Gilles Torresan, Patrick Panciatici, and Florent Xavier, “PMU-based Modal Analysis of Two Major Events in RTE Power System”, submitted for review, PSCC 2020 Conference, Wichita, Porto, Portugal, June. 2020.

Student Theses: None completed (Mohammadreza Maddipour Farrokhifard and Yuan Zhi are pursuing research toward their PhDs)

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1. Introduction

1.1 Background

Power system oscillations have been a serious concern of operators for decades [1]. Oscillations with low or negative damping can lead to catastrophic blackouts or islanding of interconnected power systems [2]. Therefore, the monitoring and analysis of oscillations can help to enhance the operational reliability of the power system. Utilizing the linearized model of the system is the traditional way for the modal analysis of the system [1]. However, this approach suffers from some challenges such as the need for a detailed model of each system component and the inability to quickly update the model with system changes [3]. With the increased penetration of Phasor Measurement Units (PMUs) in power systems, measurement-based modal analysis methods have been received a lot of attention in recent years [4]. These methods are designed based on the type of PMU data which can be ambient [4-7], ringdown [8-11], or probing [12, 13]. A ringdown data is from the system response after a sudden disturbance in a power system such as outage of a generator or line tripping which results in a significant excitation of oscillatory modes. For ambient data, power system is assumed to be operating at its quasi-steady-state condition while the system input is from continuous small random fluctuations in loads and other related small variations which are assumed to be white noise. Since ambient data is always available through Wide Area Measurement Systems (WAMS) and they act as non-intrusive measurements, accurate oscillation analysis of ambient PMU data is of great importance. These analysis methods can provide operators with continuous estimates of system modes by monitoring routine system changes to random load fluctuations that are always present in any power system.

1.2 Literature Survey

There is an extensive literature on the different types of modal analysis methods. As mentioned earlier, ringdown data is a transient response which normally results from sudden disturbances, such as line tripping, adding or removing heavy loads, and tripping generators, and so on. One of the most prominent approaches for the analysis of this kind of data is the Prony method [8]. Authors of [14] proposed multi-channel Prony method to improve the performance of single-channel Prony method. Reference [15] proposed Matrix Pencil method as another tool for the modal analysis of ringdown data. Multi-Dimensional Fourier Ringdown Analysis was proposed in [9]. Authors of [11] proposed a non-stationary analysis method based on a refined Margenau-Hill distribution to extract the modal features from ringdown data. Modal analysis of PMU ambient data can be carried out by time- or frequency-domain methods. Another classification can be based on the number of PMU signals (channels) employed by the technique; some methods [16-18] use only one channel, whereas some others [4, 6, 19-21] utilize multiple channels for estimating modes. In [16], Yule-Walker (YW) method is applied to both simulated and real PMU data. [17] and [22] proposed Least Mean Square (LMS) and Recursive Least Squares (RLS) methods to extract the frequency and damping of inter-area modes by analysis of specific PMU signals respectively. In [18], Error–Feedback Lattice RLS filter is applied to the data of a single channel to estimate specific modes of the system, where it is assumed that the approximate value of mode frequencies are known a priori. All these mentioned single-channel methods analyze a signal with the highest observability of a mode for their estimation. On the other hand, there are multi-channel methods in which all the PMU signals can be analyzed together. Since a window of data from all the PMUs throughout the power system is analyzed in these methods, all the system modes as well as forced oscillations can be detected even if they are observable in any one signal or a few signals. In [20], Fast Frequency Domain Decomposition (FFDD) method is proposed to estimate modal properties of the system by all available PMU signals. Recursive Adaptive Stochastic Subspace Identification (RASSI) method was proposed in [9] as a time-domain multi-channel modal analysis method.

1.3 Scope of Work

The first part of this report presents two examples from RTE power system where critical situations arise, and the modal estimation is significantly important yet challenging. Critical situations refer to the conditions when there is a forced or sustained oscillation whose frequency is close to the system natural mode or even when two or more system natural modes have close frequencies. Fast SSI-Cov (FSSI-Cov) and fast FFD (FFDD) methods which are well-known, powerful, and suitable for real-time modal analysis of power systems are selected as the analysis tools. We will show that FSSI-Cov modal analysis method can handle these situations reasonably well, while the other method may have some limitations. Furthermore, the computational complexity of these methods is discussed. It will be explained that FSSI-Cov suffers from high computational burden, while FFDD enjoys the advantage of low computational burden. We will discuss strategies and improvements needed for implementing ambient modal engines such as FFDD and FSSI-Cov for real-time modal analysis.

In the next part of this report, the problem of clustering of estimates from an ambient oscillation monitoring algorithm into groupings representative of different system modes is addressed for the first time. The well-known DBSCAN method is applied for clustering the estimates. Archived results from three days of oscillation monitoring implementation in a real system, which were obtained from Fast Frequency Domain Decomposition (FFDD) modal analysis method in the RTE power system, are utilized for evaluation of the methodology.

1.4 Report Organization

The rest of the report is organized as follows. Section 2 presents the modal analysis for two recent major oscillation events in the RTE power system. In this section, first, the formulation of FFDD and FSSI as the measurement-based modal estimation tools utilized in this report are discussed. Afterward, these methods are applied to the RTE PMU data. Modal estimates are presented and discussed in this section. It is shown that how FSSI method can help in the precise interpretation of a phenomenon. Pros and cons of methods, implementation strategies, and improvements needed for the better performance of these methods are explained in the last part of this section. In Section 3, the problem of clustering of estimates is defined and the significant importance of clustering as a key step of data-based modal analysis techniques in small signal stability monitoring is clarified. Furthermore, DBSCAN formulation and the implementation process for clustering of power system modes is explained in this section. Results and discussions are presented in the last part of this section. Section 4 provides concluding remarks to this report.

2. PMU-based Modal Analysis of Two Major Events in RTE Power System

In this part, modal analysis is presented for two recent major oscillation events in the RTE power system. Data from Phasor Measurement Units (PMUs) collected during the events are analyzed by using Fast Frequency Domain Decomposition (FFDD) and Covariance-based Stochastic Subspace Identification (SSI-Cov) modal analysis methods. In the first event, we show that the frequency of an inter-area mode changes dramatically after a system topology change while the damping also decreases. The second event may be related to the emergence of an unknown sustained oscillation whose frequency is close to that of a system inter-area mode. Analysis of these two events shows the relative strengths and weaknesses of different oscillation monitoring algorithms and their usefulness in measurement-based modal analysis. Furthermore, the report will also discuss challenges in implementing the algorithms in real-time applications.

2.1 Overview

Ambient modal analysis methods are of great importance since they can provide operators with continuous estimates of system modes by monitoring routine system changes to random load fluctuations that are always present in any power system. Although the performance of the most of methods in the literature is acceptable in normal operating condition of the system, the estimation results of these algorithms should be carefully handled when there is a forced or sustained oscillation whose frequency is close to the system natural mode or even when two or more system natural modes have close frequencies.

In these critical situations, accurate estimation of all system modes and forced oscillation is significantly important for the correct understanding of system characteristics and subsequently triggering mitigatory actions. As is shown in the literature [23, 24], the interaction of system modes and forced oscillation can result in the emergence of resonance effects. The resonance can be intensified when the frequency of the forced oscillation is close to the frequency of the system poorly-damped inter-area mode. In this condition, accurate estimation of characteristics of both system mode and forced oscillation can help operators to prevent the system from catastrophic blackouts.

Authors of [25] provided some examples to show the erroneous modal estimation of methods such as Yule-Walker and Welch-Half-Power-Point method in the presence of forced oscillations. In the paper [24], it was shown that although Frequency Domain Decomposition (FDD) method can perfectly detect the forced oscillation, it is unable to simultaneously estimate system modes and forced oscillation when they have close frequencies. The event of November 2005 in the Western American power system was analyzed by covariance-based Stochastic Subspace Identification (SSI-Cov) in [23]. It was shown that this method can accurately estimate both system mode and forced oscillation when they have close frequencies. Authors of [26] evaluated the performance of SSI-Cov and SSI-data in the presence of forced oscillation whose frequency was close to that of system mode in Kundur test system. It was shown that although both methods can simultaneously detect forced oscillation and system mode with the lowest possible model order, SSI-data suffers from non-negligible bias.

This part of the report presents two examples from RTE power system where the above-mentioned critical situations arise, and the modal estimation is significantly important yet challenging. Fast

SSI-Cov (FSSI-Cov) and fast FFD (FFDD) methods which are well-known, powerful, and suitable for real-time modal analysis of power systems are selected as the analysis tools. We will show that FSSI-Cov modal analysis method can handle these situations reasonably well, while the other method may have some limitations. Furthermore, the computational complexity of these methods is discussed. It will be explained that FSSI-Cov suffers from high computational burden, while FFDD enjoys the advantage of low computational burden. We will discuss strategies and improvements needed for implementing ambient modal engines such as FFDD and FSSI-Cov for real-time modal analysis.

2.2 Modal Analysis methods

In this report, fast FDD and fast SSI-Cov methods are utilized for the modal analysis of PMU data. In the following subsections, first, the foundation of these methods is explained. Afterward, the speedup procedure of FDD and SSI-Cov to make them applicable for real-time application is briefly discussed.

2.2.1 Fast Frequency Domain Decomposition (FFDD)

The key idea behind FDD is to apply Singular Value Decomposition (SVD) to the power spectrum matrix of measurements. After linearizing a high-order nonlinear power system model about its equilibrium point, the state-space equations can be written as follows,

$$\begin{aligned} \Delta\dot{x} &= A\Delta x + B\Delta u \\ \Delta y &= C\Delta x \end{aligned} \tag{1}$$

where $\Delta x, \Delta u,$ and Δy are the state, input, and output vectors, respectively. The Power Spectrum Density (PSD) matrix relating inputs and outputs in a multi-input multi-output system, can be written as follows,

$$S_{yy}(\omega) = H(\omega) S_{uu}(\omega) H^*(\omega) \tag{2}$$

in which $S_{yy}(\omega)$ and $S_{uu}(\omega)$ are the $n_y \times n_y$ and $n_u \times n_u$ output and input PSD matrices, respectively. If the inputs are white noise, $S_{uu}(\omega)$ will be a constant diagonal matrix. $H(\omega)$ is $n_y \times n_u$ frequency response matrix and $(\cdot)^*$ is the Hermitian transpose operation. Next step in FDD is to estimate $S_{yy}(\omega)$ matrix from PMU measurements and apply SVD to this matrix for each discrete frequency $\omega = \omega_i$. Decomposition of the estimated PSD matrix $\hat{S}_{yy}(\omega)$ is:

$$\begin{gathered} \hat{S}_{yy}(\omega_i) = W_i(\omega_i) S_i(\omega_i) W_i^*(\omega_i) = \begin{bmatrix} w_1(\omega_i) & \cdots & w_{n_y}(\omega_i) \end{bmatrix} \\ \begin{bmatrix} s_1(\omega_i) & & \\ & \ddots & \\ & & s_{n_y}(\omega_i) \end{bmatrix} \begin{bmatrix} w_1^*(\omega_i) \\ \vdots \\ w_{n_y}^*(\omega_i) \end{bmatrix} \end{gathered} \tag{3}$$

W_i is the matrix of singular vectors and S_i is the diagonal matrix of singular values. The rank of $\hat{S}_{yy}(\omega)$ indicates the number of contributing modes when $\hat{S}_{yy}(\omega)$ is evaluated near ω_r. If there is no significant contribution from other poorly-damped system modes or forced oscillations near the PSD peak frequency ω_r, $\hat{S}_{yy}(\omega)$ can be approximated by a rank-one matrix. In other words, S_i will have one dominant singular value $s_1(\omega_i)$ and $\hat{S}_{yy}(\omega_i) = s_1(\omega_i) w_1(\omega_i) w_1^*(\omega_i)$. The collection of the first singular values as the function of frequency makes the complex mode identification function (CMIF). By taking the inverse FFT of CMIF near the peak frequency of $\hat{S}_{yy}(\omega)$ a signal with the exponential sum model is obtained. Applying the Prony-type analysis to the obtained signal will result in the estimation of the frequency and damping ratio of the corresponding oscillation.
The process of making the FDD fast starts with the following theory for the calculation of the PSD matrix,

$$\hat{S}_{yy}(\omega_i) = F(\omega_i) F^*(\omega_i) \qquad (4)$$

where $F(\omega_i) = \left[F_1(\omega_i) \quad \ldots \quad F_{n_y}(\omega_i) \right]^T$ is the PMU measurements FFT matrix in frequency ω_i. The main simplification in FFDD is the procedure of CMIF calculation. Given $F(\omega_i) \neq 0$, it can be shown that the matrix $\hat{S}_{yy}(\omega_i)$ has only one nonzero singular value which can be calculated as follows,

$$s_1(\omega_i) = \sum_{j=1}^{n_y} F_j(\omega_i) F_j^*(\omega_i) \qquad (5)$$

and the corresponding singular vector is $F(\omega_i)$. Terms $F_j(\omega_i) F_j^*(\omega_i)$ are the auto spectrum estimates of the *j*th signal. Therefore, the CMIF, which is a function based on the dominant singular values of PSD matrix, can be directly calculated from the auto spectrum of signals. By doing so, the computational burden significantly decreases. In this simplification, the corresponding mode shape can be found from the right singular vector $F(\omega_i)$. Estimates obtained from FFDD are identical to the results of FDD if the PSD is calculated by a single windowing function. However, if higher-order windowing functions are used for the calculation of PSD, the results of FFDD will approximately match the estimates of FDD.

2.2.2 Fast Stochastic Subspace Identification (FSSI)

The stochastic state-space model of a system can be defined as follows,

$$\begin{aligned} x_{k+1} &= A x_k + w_k \\ y_k &= C x_k + v_k \end{aligned} \qquad (6)$$

where w_k is process noise due to the modeling inaccuracies and disturbances and v_k is the measurement noise. In this model, which is a pertinent design for ambient modal analysis, the input vector is implicitly modeled by w_k, v_k. The essential assumption for w_k, v_k is the whiteness which should not be violated. In general, there are two types of SSI methods: data-driven and covariance-driven. In the first method, the data matrix is the basis of analysis, while the second method operates on the covariance matrix. In this report, we focus on the covariance-based SSI method. Basically, the straightforward implementation of covariance-based stochastic subspace identification for modal analysis of PMU measurements can be summarized as the following steps. The proof of each step can be found in [27].

Collecting PMU data and make the measurements matrix as follows:

$$Y = \frac{1}{\sqrt{j}} \left(\begin{array}{cccc} y_0 & y_1 & \cdots & y_{j-1} \\ y_1 & y_2 & \cdots & y_j \\ \cdots & \cdots & \cdots & \cdots \\ y_{i-1} & y_i & \cdots & y_{i+j-2} \\ \hline y_i & y_{i+1} & \cdots & y_{i+j-1} \\ y_{i+1} & y_{i+2} & \cdots & y_{i+j} \\ \cdots & \cdots & \cdots & \cdots \\ y_{2i-1} & y_{2i} & \cdots & y_{2i+j-2} \end{array} \right) = \left(\frac{Y_{0|i-1}}{Y_{i|2i-1}} \right) = \left(\frac{Y_P}{Y_f} \right) \begin{array}{l} \} Li \\ \} Li \end{array} \tag{7}$$

where L is the number of PMU channels and i and j are the length of the internal analysis window and total analysis window. Y_p and Y_f denotes the past and future data blocks which are obtained from dividing Y into two block matrices. The covariance matrix H can be obtained as follows,

$$H = \begin{pmatrix} \Lambda_i & \Lambda_{i-1} & \cdots & \Lambda_1 \\ \Lambda_{i+1} & \Lambda_i & \cdots & \Lambda_2 \\ \vdots & \vdots & \vdots & \vdots \\ \Lambda_{2i-1} & \Lambda_{2i-2} & \cdots & \Lambda_i \end{pmatrix} \in \mathbb{R}^{Li \times Li} \tag{8}$$

where $\Lambda_i \equiv E\left[y_{k+i} y_k^T \right]$ and $\Lambda_i \equiv E[\cdot]$ denotes the expected value. Considering Eq. 8 and assuming ergodicity, the block Toeplitz matrix H can be calculated as follows:

$$H = Y_f Y_p^T \tag{9}$$

We can define the state-output covariance matrix as follows,

$$G \equiv E\left[x_{k+1} y_k^T \right] \tag{10}$$

Based on the definitions, the following property can be easily deduced,

$$\Lambda_i = CA^{i-1}G \tag{11}$$

therefore, the block Toeplitz matrix H can evidence as follows,

$$H=\begin{pmatrix} C \\ CA \\ \vdots \\ CA^{i-1} \end{pmatrix}\begin{pmatrix} A^{i-1}G & A^{i-2}G & \cdots & G \end{pmatrix}=O_iC_i \quad (12)$$

where O_i and C_i are the extended observability and controllability matrices. Both matrices can be obtained by applying SVD to H matrix:

$$H=USV^T=\begin{pmatrix} U_1 & U_2 \end{pmatrix}\begin{pmatrix} S_1 & 0 \\ 0 & 0 \end{pmatrix}\begin{pmatrix} V_1^T \\ V_2^T \end{pmatrix}=U_1S_1V_1^T \quad (13)$$

in which U and V are matrices of right and left eigenvectors, respectively. S is a diagonal matrix containing the singular values in descending order. It is assumed that S_1 contains n dominant singular values and the rest is considered to be zero. U_1 and V_1 are the corresponding right and left singular vectors. If the zero singular values and the corresponding singular vectors are deleted from the Eq. 13, the last equality of the Eq. 13 can be obtained. Based on the Eqs. 12 and 13, the extended controllability and observability matrices can be found as follows:

$$\begin{aligned} O_i &= U_1S_1^{1/2} \\ C_i &= S_1^{1/2}V_1^T \end{aligned} \quad (14)$$

from these matrices, A and C can be easily derived. According to the Eq. 12, C equals to the first l rows of O_i and A can be calculated by the following equation:

$$A=\underline{O}^{\dagger}\overline{O} \quad (15)$$

where $\underline{O}$ is the matrix O without the last l rows and $\overline{O}$ is the matrix O without the first l rows. The superscript $\bullet^{\dagger}$ denotes the Moor-Penrose pseudo-inverse. System modes and mode shapes can be obtained from the continuous-time matrices, which can be calculated as follows:

$$A_c = f_s.\log(A) \qquad C_c = C \quad (16)$$

in which f_s is the sampling frequency.

In order to speed up the SSI-Cov method, four efficient strategies are proposed in [28]. In this report, we have chosen the most efficient strategy to speed up the SSI-Cov. In this strategy, parallel computing is applied to the step of SVD decomposition. For SVD calculation, the partial Lanczos bidiagonalization technique is applied. Matrix computations are parallelized into the i independent tasks and distributed between available treads of the machine. More details of this procedure can be found in [28].

2.3 Analysis and Results

In this section, the modal analysis of two sets of data recorded by RTE PMUs is presented. These data sets contain ambient data as well as two major oscillatory events in the RTE system. It is noteworthy that because of specific characteristics of the oscillations in these two events, the accurate modal analysis is significantly important yet challenging. Voltage phase angles obtained from nine and twelve PMUs for the first and the second data sets are considered for the analysis by FFDD and FSSI methods implemented in the C# platform of Visual Studio 2017.

2.3.1 The First Case

Fig.2.1 is one of the voltage phase angle signals for the first event that occurred in the European interconnection on December 1, 2016 [32]. It can be seen that the event occurs at about 17th minute and it is cleared at about 24th minute. For the analysis of this event, the window length of 120s with the refresh rate of 5 seconds is chosen for the FFDD. Fig. 2.2 illustrates the estimated modes by FFDD. Evidently, there are 6 clusters of estimated modes. In this part, we focus on the modes with frequencies about 0.15Hz and 0.22Hz, since the main changes of the oscillatory behavior of the system during and after the event are related to these modes. Figs. 2.3 and 2.4 are the time plots of estimated frequencies about 0.15Hz and 0.22Hz and their corresponding damping ratios. As can be seen in Fig. 2.3, the damping ratio of mode with the frequency of 0.15Hz dropped to near-zero values once the event happened in the system. Meanwhile, estimates of the mode with frequency of 0.22Hz disappeared. In order to understand this phenomenon more deeply, we analyze PMU data with FSSI method. The window length for FSSI is selected as 240 seconds with the refresh rate of 5 seconds. The inner window length i is set to be 6 seconds. Results of FSSI discover the other side of this event which is indeed interesting. Fig. 2.5 shows the estimation of the well-damped mode with the frequency of 0.15Hz. As is evident, estimates are persistent before, during, and after the event. Based on these estimates, it can be concluded that the well-damped mode of the system with the frequency of 0.15Hz is not affected by this event. However, Fig. 2.6 shows the other set of estimates with the same frequency of 0.15Hz. These poorly-damped estimates appear once the event happens in the system. At the exact same time, estimates with the frequency of 0.22Hz shown in Fig. 2.7, which were persistent before the event, disappear. According to this analysis, the most possible scenario is that the system well-damped mode with the frequency of 0.22Hz has changed to the poorly-damped mode with the frequency of 0.15Hz. Furthermore, field evidence confirms this theory. This event is the result of tripping a significant tie line carrying a huge amount of power between two areas of the system. This tie line, which was connecting two large areas whose inter-area oscillatory mode was 0.22Hz, could not be recovered after the event. Therefore, the power flow had to be rerouted. Based on these observations and FSSI modal analysis, it seems that the change of the system topology as well as the operating point of the system result in the change of the well-damped mode 0.22Hz to the mode 0.15Hz. The abrupt change in mode frequency from 0.22 Hz to 0.15 Hz and the reduction in its damping ratio have been verified in model based simulations of the European interconnection [33]. As can be seen in Fig. 2.6, the damping ratio of the second mode with frequency of 0.15Hz is increasing after the clearance of the event.

In this case, although the FFDD analysis revealed that there is a poorly-damped oscillation in the system, the reason and characteristics of this oscillation were not quite clear. At first glance, one could think that the first system mode with frequency of 0.15Hz is getting poorly-damped after the event. However, FSSI results indicated that once the event happened in the system, another mode with the frequency of 0.15Hz appeared in the system and the first mode with this frequency was not affected. Since there are two modes with approximately same frequencies in the system after the event, FFDD couldn't detect both modes. The unique and significantly important capability of FSSI in the identification of both modes with close frequencies was the key in the more accurate analysis of this event.

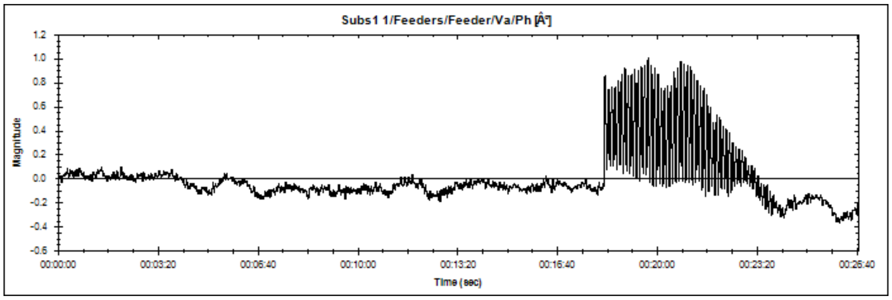

Fig. 2.1. Voltage phase angle before, during, and after the first event

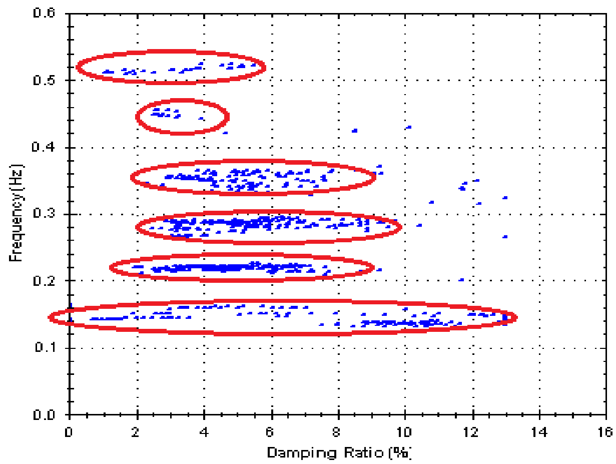

Fig. 2.2. Estimated modes by FFDD for the first set of PMU data

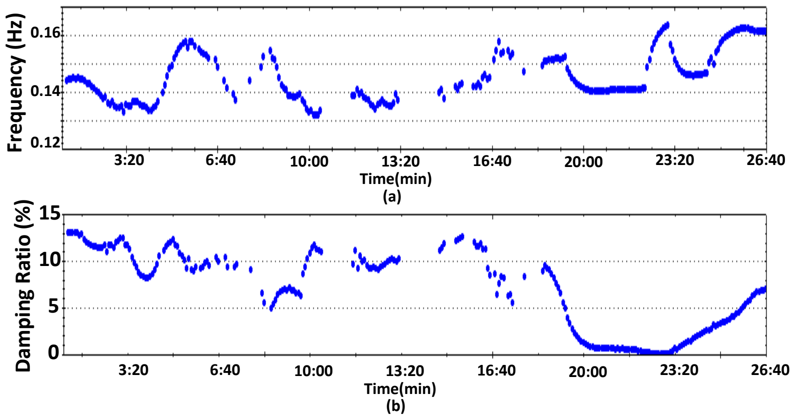

Fig. 2.3. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FFDD for mode with average frequency of 0.15Hz

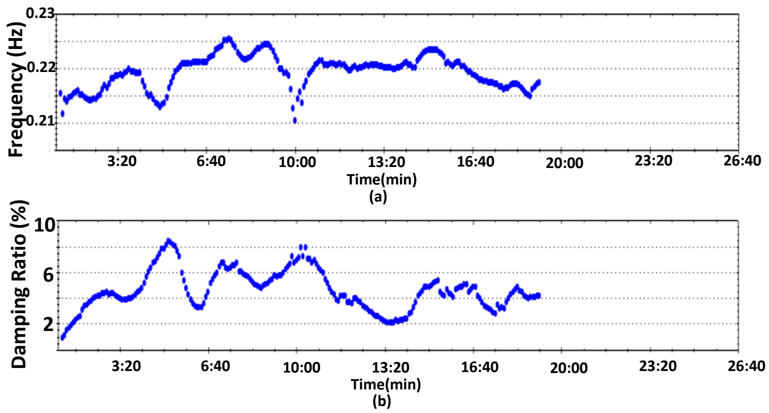

Fig. 2.4. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FFDD for mode with average frequency of 0.22Hz

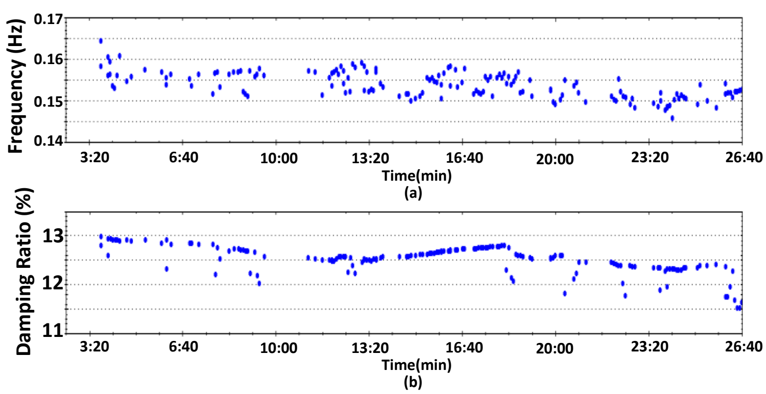

Fig. 2.5. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FSSI for the well-damped mode with average frequency of 0.15Hz

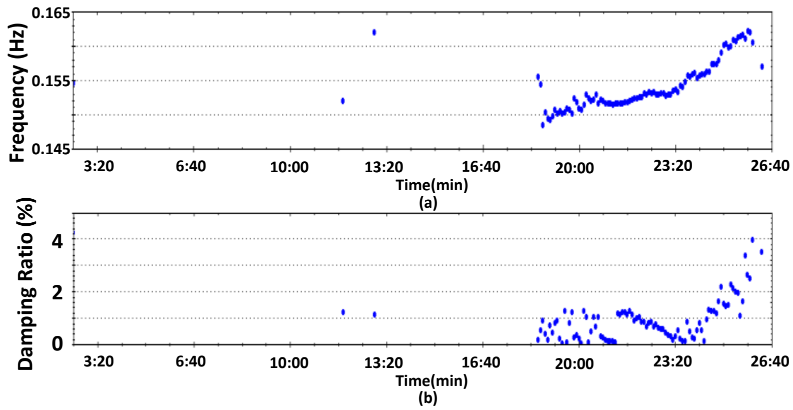

Fig. 2.6. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FSSI for the poorly-damped mode with average frequency of 0.15Hz

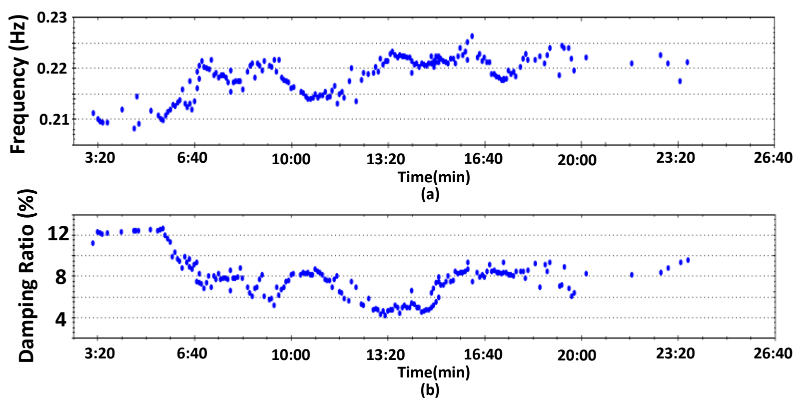

Fig. 2.7. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FSSI for the mode with average frequency of 0.22Hz

2.3.2 The Second Case

Next an oscillation event that occurred in the European interconnection on December 3, 2017 is analyzed [34]. Fig. 2.8 illustrates one of the voltage phase angle signals utilized for the analysis of this case. As can be seen, the event occurs from 49th to 57th minutes. For the modal analysis of this case, the same settings as the previous case are selected for FFDD. Fig. 2.9 shows the estimates obtained by FFDD. In this case, we keep the focus of the study on the estimates with frequencies about 0.2Hz. Fig. 2.10 demonstrates time plots of the estimated frequency and damping ratio by FFDD. Evidently, before occurring the event, the frequency of estimates is about 0.22Hz and the damping ratio is high, which exactly matches the characteristics of the system mode. Once the event occurs, the frequency of estimates drops from 0.22Hz to 0.19Hz and the damping ratio drops from about 10% to near-zero values. For a better understanding of this event, data is also analyzed by FSSI. Initial window length of 120s, inner window length of 6s, refresh rate of 5s, and system order of 20 are the selected parameters for this analysis. Figs. 2.11 and 2.12 both are estimates with frequencies about 0.2Hz. In Fig. 2.11, estimates with the average frequency of 0.22Hz and damping ratio of 9% persistently exist in the entire analysis time period. As can be seen in Fig. 2.12, once the event begins, a new set of estimates with the frequency of 0.19Hz and near-zero damping ratio appears in the system.

In the modal analysis of this case, although FFDD shows estimates with near-zero damping ratios once the event happens, it is not clear whether the frequency and damping of the system mode decreased due to the event or a new oscillation appeared in the system. Results of FSSI confirm that the cause of the event is the appearance of a new sustained oscillation, not the dropping of the frequency and damping ratio of the system natural mode.

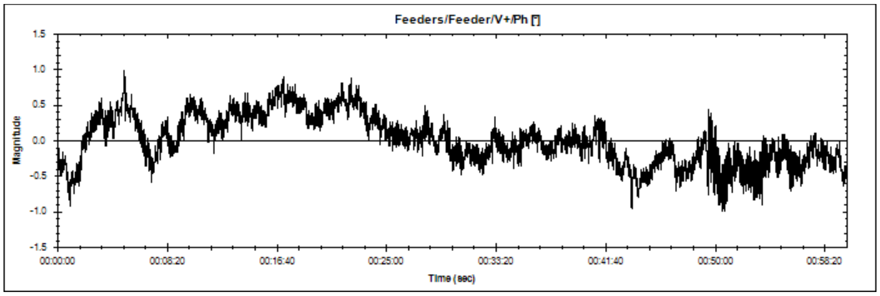

Fig. 2.8. Voltage phase angle before, during, and after the second event

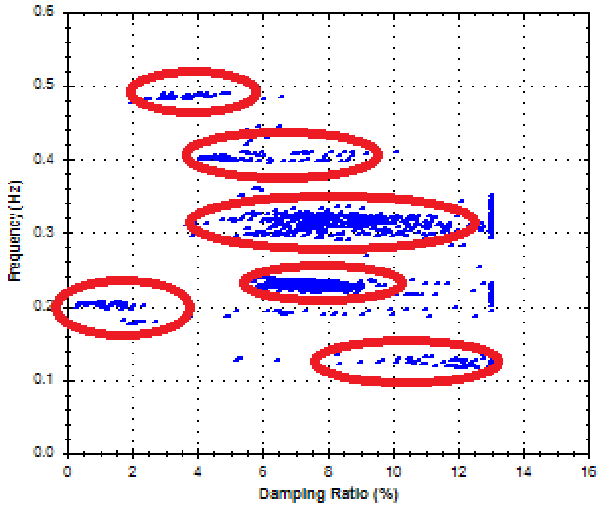

Fig. 2.9. Estimated modes by FFDD for the first set of PMU data

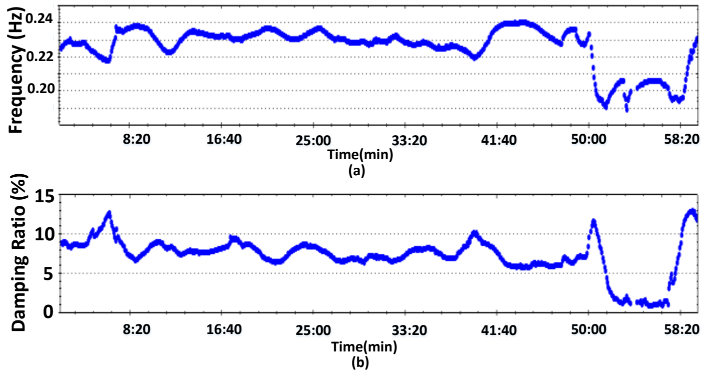

Fig. 2.10. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FFDD

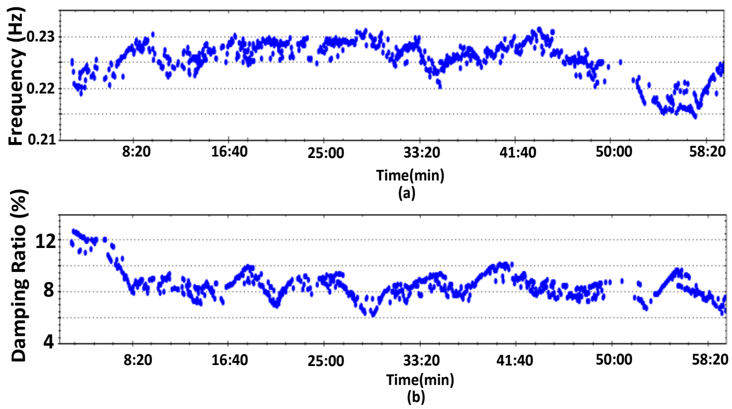

Fig. 2.11. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FSSI for the well-damped mode with average frequency of 0.22Hz

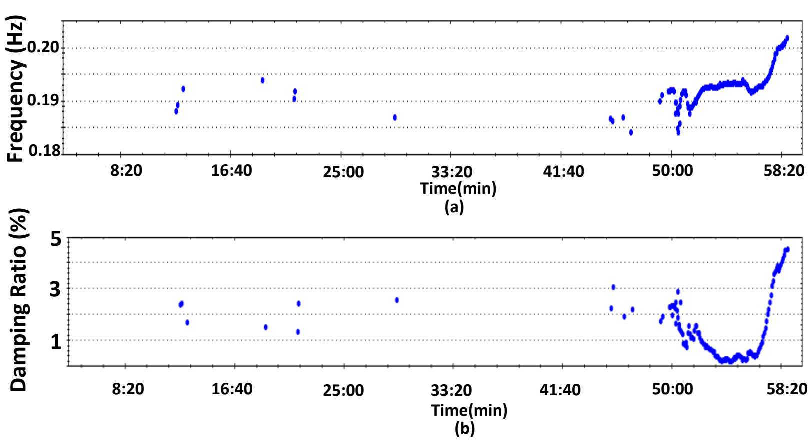

Fig. 2.12. Time plots of (a) estimated frequency (b) estimated damping ratio obtained from FSSI for the poorly-damped oscillation with average frequency of 0.19Hz

2.4 Discussion

In both mentioned cases, it was shown that although FFDD can accurately detect the poorly-damped estimates which are of great importance for operators, it is not capable of tracking both system modes, or a system mode and sustained oscillations if they have close frequencies. In these situations, there are two dominant singular values in S_1 matrix in Eq.3. Therefore, considering only the largest singular value and discarding the second one brings about missing the second estimate. It is noteworthy that most of the modal analysis methods have difficulties in the handling of these challenging situations [25]. Although FFDD cannot detect both estimates simultaneously, the following significant advantages of this method make it universally applicable in the modal analysis of power systems:

- Short analysis window and fast update about new events and changes in modal properties of the system.
- Very fast and near-real-time calculations even for a large number of signals (more than a thousand signals).
- Giving the correct estimates of the low-damped (i.e. the mode with higher energy) or a forced oscillation when there are system modes with close frequencies.

All the above-mentioned advantages of FFDD are what really required for reliable estimation and source location of problematic oscillations. Fast estimation of the second largest singular value is the future research question for improving the performance of this method.

On the other hand, FSSI can provide a clear insight about what is really happening in the mentioned challenging situations. Beside this distinctive and significantly important advantage of this method, this method has the following disadvantages:

- The higher computational burden in the case of the large number of signals in comparison with FFDD.
- More spurious estimates (outliers, noise) in comparison with FFDD.

Decreasing the computational burden of FSSI and identification of real modes versus spurious modes are indicted for future researches. Considering the pros and cons of each method, it is suggested to use both methods simultaneously, assuming enough computer resources are available. Otherwise, operators can select which method is more suitable for their purposes based on the mentioned features of each method and their available resources.

3. Clustering of Power System Oscillatory Modes Using DBSCAN Technique

Measurement-based power system modal analysis is useful to operators in that alarms can be issued when the damping of some natural oscillatory modes becomes unacceptably low or when forced oscillations suddenly appear in a power system. Considering the fact that mitigating the mechanism of each mode or forced oscillation requires a specific remedial action, the mode estimates should be properly clustered and identified before such corrective actions can be decided. In this part of the report, the problem of clustering of estimates from an ambient oscillation monitoring algorithm into groupings representative of different system modes is addressed for the first time. The well-known DBSCAN method is applied for clustering the estimates. Archived results from three days of oscillation monitoring implementation in a real system, which were obtained from Fast Frequency Domain Decomposition (FFDD) modal analysis method in the RTE power system, are utilized for evaluation of the methodology.

3.1 Overview

Measurement-based modal analysis of power systems is one of the most important Phasor Measurement Unit (PMU)-based applications [11, 29-31]. PMU-based real-time modal analysis of power systems can be used to send alarms to the control room for triggering mitigatory actions when the damping of a mode drops below a certain level or when a problematic forced oscillation appears in the system. Among all modal estimation methods, ambient data analysis techniques are of great importance [4, 6, 16, 17],[8-10]. These methods can provide the operator with early warnings of the system getting close to the small signal instability. Modal analysis of PMU ambient data can be carried out by time- or frequency-domain methods. Another classification can be based on the number of PMU signals (channels) employed by the technique; some methods [16-18] use only one channel, whereas some others [4, 6, 19-21] utilize multiple channels for estimating modes. In [16], Yule-Walker (YW) method is applied to both simulated and real PMU data. [17] and [22] proposed Least Mean Square (LMS) and Recursive Least Squares (RLS) methods to extract the frequency and damping of inter-area modes by analysis of specific PMU signals respectively. In [18], Error–Feedback Lattice RLS filter is applied to the data of a single channel to estimate specific modes of the system, where it is assumed that the approximate value of mode frequencies are known a priori. In general, single-channel methods analyze a signal with the highest observability of a mode for its estimation. These methods are capable of estimating a limited number of modes from a single channel, since each channel contains the information of few system modes. The advantage of these methods is that the operator exactly knows which mode is being tracked by analyzing a specific PMU channel; then, remedial actions can be taken directly for the problematic mode based on the results of these methods. The main disadvantage of these techniques is their inability to track previously unknown modes and forced oscillations in the system. Furthermore, if the selected PMU signal encounters any significant issue, the estimation process may be interrupted.

On the other hand, there are multi-channel methods in which all the PMU signals can be analyzed together. Since a window of data from all the PMUs throughout the power system is analyzed in these methods, all the system modes as well as forced oscillations can be detected even if they are observable in any one signal or a few signals. In [20], Fast Frequency Domain Decomposition (FFDD) method is proposed to estimate modal properties of the system by all available PMU signals. Recursive Adaptive Stochastic Subspace Identification (RASSI) method was proposed in [9] as a time-domain multi-channel modal analysis method.

Generally, ambient oscillation monitoring methods discussed above utilize a moving window approach to provide continuous modal estimation from ambient data. However, some issues such as changes in mode frequencies and their damping levels during the day, intermmitent observability of modes, forced oscillations, or existence of modes with close frequencies make the tracking of modes or forced oscillations from the estimates available from the moving window analysis challenging.

In this report, Density-based spatial clustering of applications with noise (DBSCAN) which is a well-known clustering method is utilized to classify the estimated modes. DBSCAN is extensively used in power system studies such as PMU calibration [35] and anomaly detection [36, 37]. The procedure of implementation of DBSCAN for clustering of the system estimated modes is comprehensively discussed in Section III. Archived modal analysis results from RTE power system over three different days are used as test cases to evaluate the performance of the proposed method. In the first two days of these datasets, the power system is operating in a normal operating condition. On the third day, there is a sustained oscillation with its frequency close to that of a system mode for a period of time where proper clustering of estimates is especially important yet challenging. It is shown that with reasonable settings of the method, clusters obtained from this method for all three days are acceptable.

3.2 Problem definition

Fig. 3.1 illustrates the procedure of implementing single-channel modal analysis techniques in control rooms. An appropriate signal is selected based on the prior studies on the system dynamic model and features of the signals to monitor specific modes. After estimating the mode damping, they can set up an automatic alarm and remedial actions for the times when the damping of the mode becomes low. In multi-channel methods, since all the measurements throughout the system are analyzed together, all observable system modes and forced oscillations can be identified. The implementation procedure of these methods in control rooms is demonstrated in Fig. 3.2.

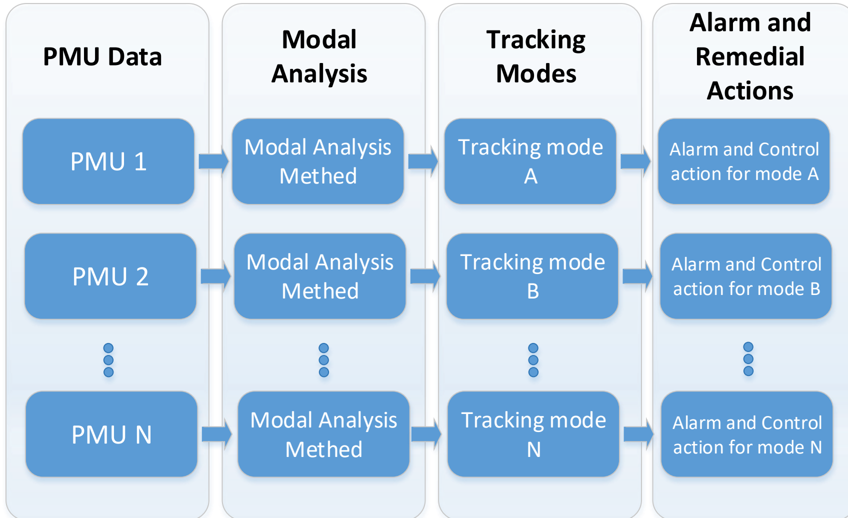

Fig. 3.1. The implementation process of the single-channel modal analysis methods

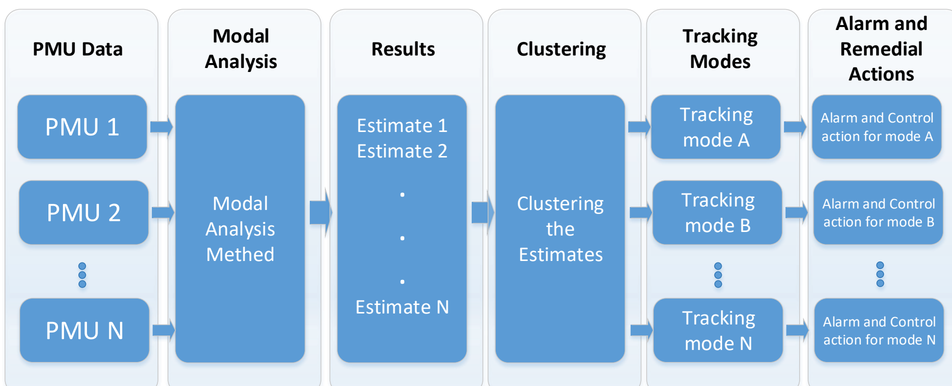

Fig. 3.2. The implementation process of the multi-channel modal analysis methods

As can be seen in this figure, setting up an alarm and automatic triggering of control actions for problematic oscillations in the system needs an efficient way of clustering of estimated modes in each window. For the following reasons, real-time clustering of the results is a challenging problem:

- Existence of spurious modes: time-domain approaches, deployed for modal analysis of synchrophasor data, try to fit mathematical models which emulate the small-signal behavior of power systems. A large model order introduces some spurious modes which are presented to satisfy the mathematical equations. In addition, numerical issues in frequency-domain methods or signal quality problems may introduce spurious modes as well. Spurious modes should be identified and discarded to prevent issuing any false alarm.
- Changes of the characteristics of system modes: not only can the damping of a mode vary during the time by system changes, the frequency of a mode can vary as well. Therefore, tracking a mode by considering a constant value or even a range for its frequency might lead to an erroneous conclusion.

- Existence of close modes: power systems may have modes with close frequencies and damping levels.
- The appearance of forced oscillation or new modes: It is always possible in a power system that unknown modes or forced oscillations may suddenly appear because of topological changes or accidents respectively.

The above-mentioned reasons clearly justify the necessity of proper clustering of estimated modes. Furthermore, they show why only considering bands for frequency cannot address the problem of tracking different modes of the system.

Application of the DBSCAN method for clustering the estimated modes is proposed in this report. In the next part, the proposed clustering methodology is explained.

3.3 DBSCAN and system mode clustering

3.3.1 DBSCAN Basics

DBSCAN is an unsupervised data mining method which aims to discover clusters and noise in a spatial database [38]. Among different proposed clustering algorithms, DBSCAN offers the following advantages:

- Discovering clusters of the arbitrary shapes
- Not sensitive to the order of points
- No need to the number of clusters as input
- Capable of finding outliers

However, this method needs two inputs from the user:

- MinPts: the minimum number of points in a cluster
- Epsilon (ε): the neighborhood criteria.

Suppose *D* is a set of points which should be clustered, and *p* and *q* are two points in this set. The $\varepsilon-$neighborhood of point *p* is defined as follows:

$$N_{\varepsilon}(p) = \{q \in D \mid dist(p,q) \le \varepsilon\}$$

where $dist(p,q)$ is Euclidean distance between *p* and *q*. Based on (ε) and MinPts, all data points are classified into three types:

- Core Point: The $\varepsilon-$neighborhood of core points contains at least MinPts data points.
- Boundary Point: A point which has at least one core point in the $\varepsilon-$neighborhood but does not have MinPts data points as neighbors.
- Outlier: The rest of the data points which are not core or boundary points are outliers. In other words, the points from the dataset which are not classified in any of the clusters are known as outliers.

Before starting the explanation of the process of DBSCAN method, the following two definitions should be expressed:

- Directly density-reachable: An object *q* is directly density-reachable from object *p* if *p* is a core object and *q* is in the $\varepsilon-$neighborhood of *p*.
- Density-reachable: A point *p* is density-reachable from a point *q* wrt. ε and MinPts if there is a chain of points $p_1, p_2, \ldots, p_n$, $p_1 = q$, $p_n = p$ such that p_{i+1} is directly density-reachable from p_i .

The summary of the algorithm is as follows:

- Select an arbitrary object *p* in the dataset *D*;
- If it is unvisited, mark it as visited, and retrieve all objects in the $\varepsilon-$neighborhood of *p*;
- If *p* is a core point wrt. ε and MinPts, a cluster is formed. The density-reachable points from *p* should be retrieved and put in this cluster;
- If *p* is a boundary point, according to definitions, no objects are density-reachable from *p*, then DBSCAN visit the next object of the dataset;
- After algorithm visits all the points in the dataset, points are classified in different clusters. Points which are not in any clusters are outliers.

3.3.2 Clustering of the mode estimates

In order to efficiently apply the algorithm for the clustering of power system modes, some considerations should be taken into account. There are some common features in the estimated modes by modal analysis methods which should be used in the modification of the clustering:

1- In the estimation of electromechanical modes, the range of frequency is usually 0.05Hz - 2Hz, while the estimated damping ratio can be from 0% -20% or even higher.
2- The standard deviation of damping ratio estimates is significantly higher than frequency estimates. In other words, the estimation of frequency is usually more accurate than the damping ratio.
3- The range of change of a mode frequency due to system changes is usually less than that of the mode damping ratio.

Therefore, instead of using (f_i, ζ_i) which are the estimated frequency and damping ratio of the *i*th system mode, weighted frequency is used and clustering algorithm is applied on $(\alpha.f_i, \zeta_i)$. α is the weighting coefficient of frequency and is determined by the user based on the features of the system estimated modes.

3.4 Implementation and Results

In this section, two different cases are examined to evaluate the performance of DBSCAN method in the clustering of estimated modes. The first case includes the estimated modes of two days of PMU data from RTE when the power system is in normal condition, while in the second case, there is a sustained oscillation whose frequency is close to the system mode frequency. In both cases, system estimated modes are obtained by FFDD with the window length of 90s and refresh rate of 10 seconds. The last part of this section is designated to a discussion about the limitations of this method.

3.4.1 Case 1: Clustering of estimated modes in normal operating condition

In this case, estimated modes, which are obtained from 3.5 and 4.5 hours of RTE power system PMU data, are clustered by DBSCAN. For the first day, α and ε are chosen as 200 and 1.6, respectively. MinPts is selected to be 12. Results are shown in Fig. 3.3. It can be seen that 10 clusters as well as outliers (noise) are precisely discovered. Time plots of modes estimated frequencies for the different clusters of the first day are shown in Fig. 3.4. The range of frequency change of the second cluster with the frequency mean value of 0.32Hz is from 0.3Hz to 0.34Hz. Therefore, if the clustering process is done simply by defining band frequencies, a frequency band of 0.04Hz should be defined to capture all the estimates of this mode in one cluster. If this frequency band was selected as the measure of clustering of the estimated modes, clusters of 0.057Hz and 0.082Hz would be mixed together. On the other hand, if the frequency band is set as low as 0.025Hz (or less) for the proper clustering of these two modes, quite a few number of estimates for the mode 0.32Hz would be classified in a wrong cluster. Therefore, defining a fixed frequency band as the measure of clustering can result in a misleading interpretation of modes. Fig. 3.5 illustrates the clustering of the second day estimated modes with parameters of $\alpha = 400$, $\varepsilon = 1.07$, and MinPts=10. Evidently, 8 clusters as well as outliers are detected. Fig. 3.6 is the time plots of the estimated frequency of different clusters. Owing to the random nature of ambient load fluctuations, some modes get excited only for a short period of time, while some others persistent for long periods during the day. DBSCAN can easily designate new clusters for modes appearing only for a short time. Similar to the first day, there is no single frequency band which results in a correct clustering of modes. Tiny frequency bands can cluster one mode into two or more clusters, while a broad frequency band can combine two or more separate modes into one cluster. Therefore, clustering of modes using frequency bands might result in incorrect classification of estimates into modes.

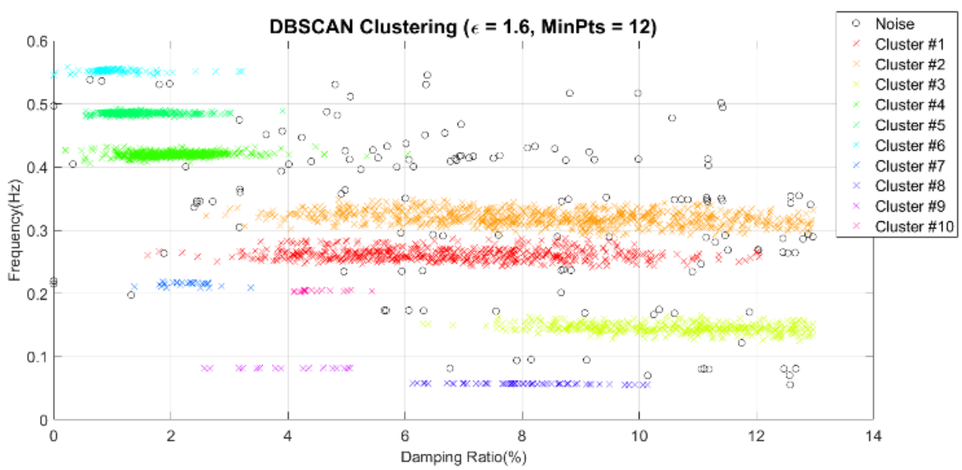

Fig. 3.3. Frequency vs. damping ratio of different clusters of the first day modes

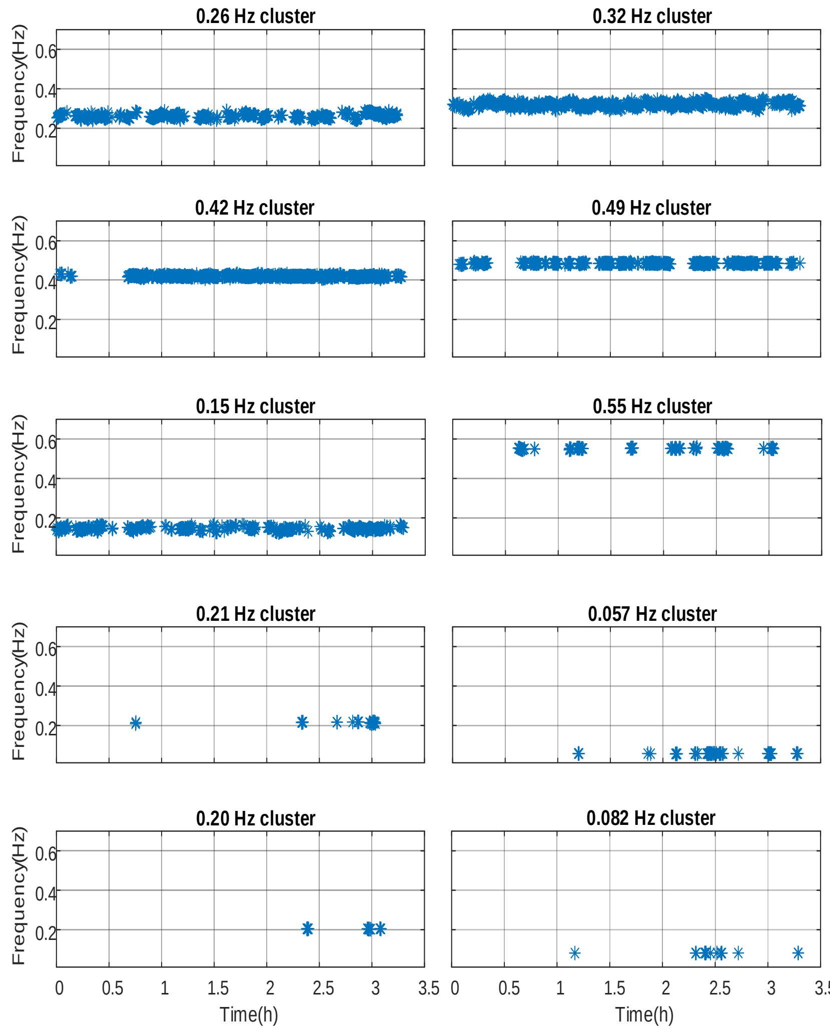

Fig. 3.4. Time plots of modes estimated frequencies for different clusters of the first day

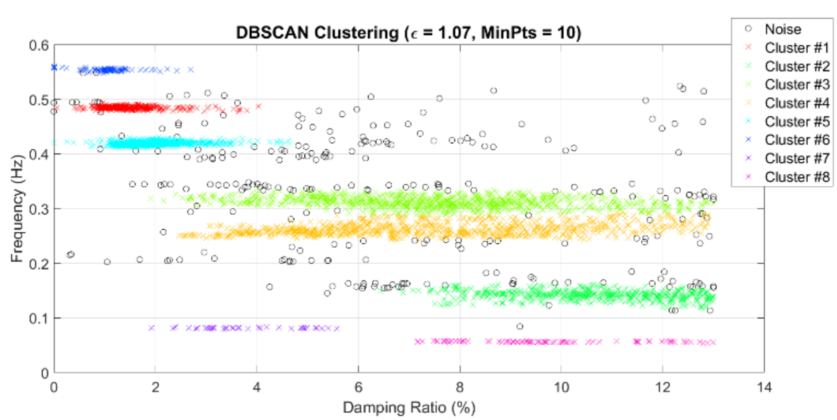

Fig. 3.5. Frequency vs. damping ratio of different clusters of the second day modes

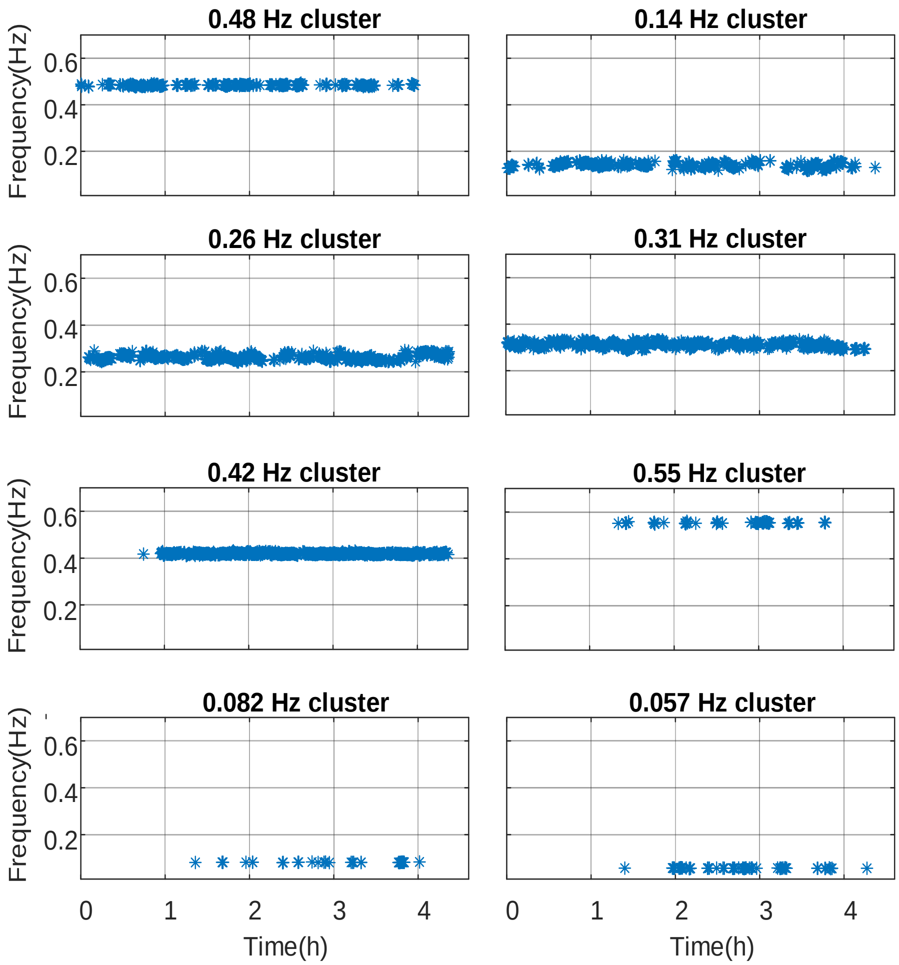

Fig. 3.6. Time plots of modes estimated frequencies for different clusters of the second day

3.4.2 Case 2: Presence of sustained oscillation close to a system mode

In this case, a sustained oscillation of unknown origin, whose frequency was close to the frequency of the system mode, happened in the RTE system and FFDD method could detect the undamped oscillation with damping estimates near zero. However, it is important to distinguish whether indeed the damping of the system mode was becoming low or an unrelated sustained oscillation (possibly a forced oscillation) was present in the system. Fig. 3.7 shows the results of clustering with parameters $\alpha = 400$, $\varepsilon = 2$, and MinPts = 12. Estimated frequency time plots for different clusters are shown in Fig. 3.8. It can be seen that 7 clusters as well as outliers are discovered. Among clusters, there are three clusters with the average frequency of 0.23Hz, 0.19Hz, and 0.20Hz. In order to clarify the interpretation of each of these clusters in the real system, time plots of frequency and damping ratio of these clusters are brought in Figs. 3.9-3.11. Mode with the frequency of 0.23Hz and average damping ratio of 7.34% persistently exists in the system before time 1.6h. Afterward, estimates with the frequency of 0.19 Hz appears and damping of this cluster is changing from 10% to 5%. These estimates associate with the transition period when the sustained oscillation appears in the system and the analysis window has the sustained oscillation as part of it. As time goes on and more data of the sustained oscillation comes through the analysis window, the estimated damping drops more and more. Eventually, the transition period is finished and the entire analysis window contains only the sustained oscillation data. Fig. 3.11 illustrates the cluster for frequency and damping estimates of the sustained oscillation. As is evident, the frequency of sustained oscillation is about 0.20 Hz and the average damping ratio is about 1.12%. The sustained oscillation observed in PMU data is detected with small positive damping ratio estimates by FFDD because of the nonlinear nature of the oscillations observed and from estimation bias. After disappearance of the sustained oscillation, there is another transition period which is shown in the right-hand side estimates of Fig. 3.10. Therefore, the clustering method with the mentioned parameters could successfully distinguish the system mode, transition of estimates, and the sustained oscillation. For this case, if a frequency band with specific bandwidth was chosen for the clustering of modes, results would be completely misleading. Clusters with the average frequency of 0.23Hz and 0.31Hz have the frequency deviation of 0.035Hz - 0.04Hz. Hence, the frequency band of at least 0.04Hz is suitable for capturing these estimates in one cluster. Selecting this band would combine all the estimates associated with the system mode and sustained oscillation into one cluster which may be problematic.

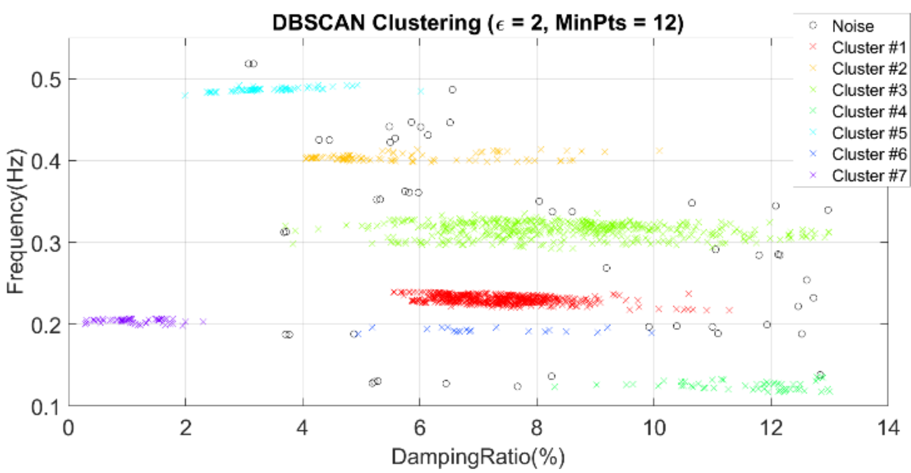

Fig. 3.7. Frequency vs. damping ratio of different clusters of the system modes in the presence of sustained oscillation with frequency close to the system mode

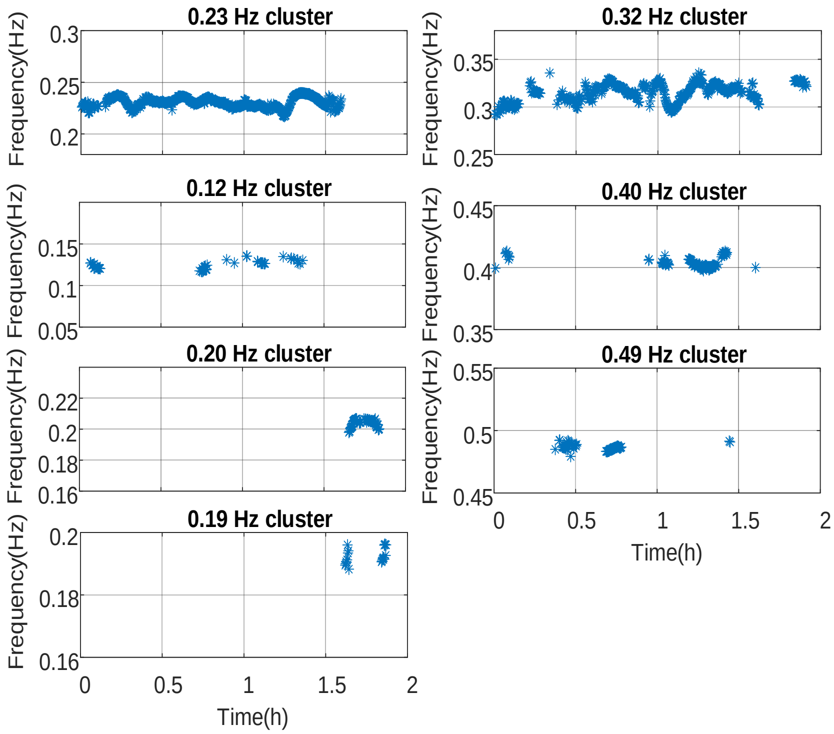

Fig. 3.8. Time plots of modes estimated frequencies for different clusters of the day with sustained oscillation

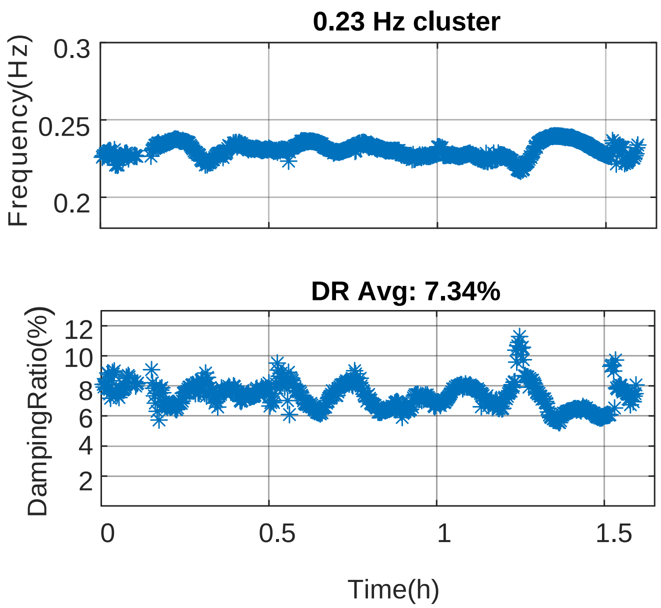

Fig. 3.9. Time plots of estimated frequency and damping ratio of system mode before the appearance of sustained oscillation

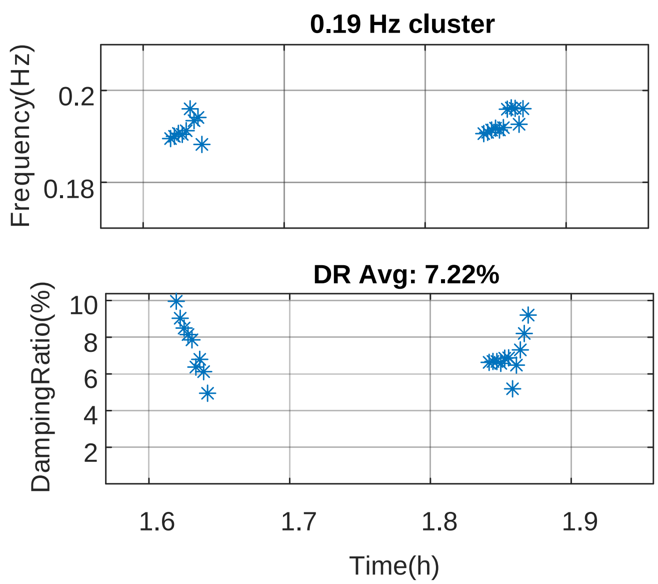

Fig. 3.10. Time plots of estimated frequency and damping ratio in the transition period exactly after the appearance of sustained oscillation

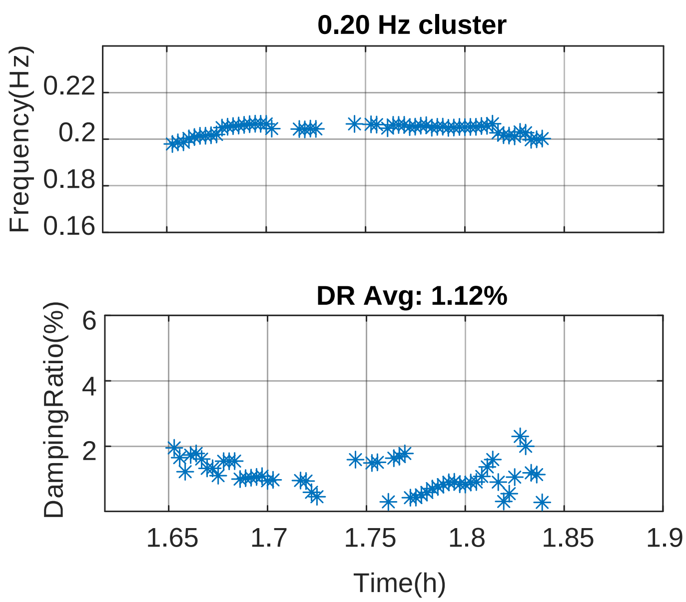

Fig. 3.11. Time plots of estimated frequency and damping ratio of sustained oscillation

3.5 Discussions

In the previous two cases, it was shown that DBSCAN can efficiently cluster estimated modes in different system operating conditions. Although DBSCAN with the mentioned implementation process and tuned parameters could successfully classify the estimated modes, there are some limitations on this clustering process:

- The performance of the method is sensitive to the clustering parameter values. In other words, one set of parameters might not work for other datasets and proper tuning of parameters should be separately done for each set of data which may be unrealistic.
- When there are multiple modes with close frequencies and damping ratios, the clouds of estimates might overlap with each other by the passage of time. Therefore, clustering these estimates would be more challenging and the proposed method is not able to correctly classify them.
- When there is a sustained or possible forced oscillation in the system whose frequency is close to the frequency of a poorly damped system mode, the proposed method cannot distinguish the system mode estimates from the estimates of the sustained oscillation.

Considering these limitations, it is noted that the problem of clustering of estimated modes obtained by multi-channel modal analysis methods requires further research.

4. Conclusion

In the first part of this report, the modal analysis of two challenging events of RTE system was presented. For each event, data of PMUs before, during, and after the events were recorded and analyzed by two ambient modal analysis methods, FFDD and FSSI. Although the model of the system was not available and only a few number of PMUs installed in the system, the cause of these events could be guesstimated thanks to the distinctive and significantly important capability of FSSI in the estimation of oscillations with close frequencies. By the analysis of these two events, it was shown that FFDD, similar to the most of other modal analysis methods, encounter difficulties when there are two or more system modes with close frequencies, or a forced or sustained oscillation whose frequency is close to that of the system mode. However, FSSI could perfectly estimate both system modes with close frequencies in the first event and both system mode and sustained oscillation with close frequencies in the second event. As well as the demonstration of this outstanding and unique characteristic of FSSI in the modal analysis of challenging events, other advantages and disadvantages of FSSI and FFDD were comprehensively discussed. Although FSSI can simultaneously calculate estimates with close frequencies, it has a higher computational burden and more spurious estimates in comparison with FFDD. Besides low computational burden and capability of handling a large number of PMUs, FFDD can result in acceptable estimates with even small analysis windows, which is a crucially important feature for tracking the changes of system modal characteristics.

In the second part of the report, the problem of clustering of estimated modes by multi-channel modal analysis methods was discussed. A well-known clustering method called DBSCAN was utilized for classifying estimated modes. The proposed clustering methodology was applied to the modal analysis results obtained by the real-time FFDD modal analysis tool installed in the RTE company. Two cases were examined to evaluate the performance of the clustering method. In the first case, the clustering process was applied to the estimated modes of two days when the system was operating in a normal condition. In the second case, a sustained oscillation whose frequency was close to the frequency of a system mode appeared in the system. In this condition, distinguishing system mode and sustained oscillation is of great significance for the operator. The clustering technique could successfully distinguish and classify not only all system modes in normal condition, but also the sustained oscillation when its frequency is close to the frequency of a system mode. It was shown that choosing a frequency band for clustering estimated modes cannot result in correct clusters. It was pointed out that the performance of this method is significantly dependent on the choice of parameters. Furthermore, specific situations were discussed where the proposed clustering method is not capable of yielding suitable results. In these cases, the clouds of estimates in the frequency-damping plane get mingled up, and this clustering method cannot correctly cluster the estimates. Future research is indicated for addressing these concerns.

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