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IDtools: An Automated Tool for Modal Identification from Time-domain Simulation Results for Establishing System Operating Limits

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SUMMARY

There is an increasing expectation from reliability coordinators in North America to ensure that electromechanical oscillations in power systems have a positive damping ratio above a certain threshold, commonly at least 3%. Damping ratio tests are typically conducted while establishing the system operating limits (SOLs) and interconnection reliability operating limits (IROLs). It is not uncommon for transient stability programs commonly used by system planners to lack automated means for determining if a given damping criterion is met. The work reported in this paper addresses this issue and aims at facilitating the assessment of system damping by integrating a time-domain modal identification method in a commercial transient stability program.

The modal identification approach advocated in the manuscript consists of two stages. First, the Eigensystem Realization Algorithm (ERA) is applied to compute the modes present in a given signal(s). The ERA is a well-known modal identification method based on the singular value decomposition (SVD) and has been documented in numerous publications [4], [5]. Following the application of the ERA, a set of simple rules is applied to the identified modes and the corresponding signals to determine the modal dampings. The selected modes are then checked to ensure that a pre-defined minimum damping ratio requirement is met. It will be shown that for nonlinear systems such as power systems, the demarcation between significant and insignificant/spurious modes, using either the magnitudes of the singular values or FFT results, is not always clear. This is because such linearization techniques can only approximate the underlying nonlinear system with a linear system. Consequently, the traditional application of modal identification methods to power systems relies on user interaction to estimate the number of oscillatory modes to be computed. In this paper, a metric is computed for each mode to determine the contribution of the given mode to a signal.

The proposed metric, used in conjunction with a simple threshold, is used to detect significant modes and to eliminate insignificant or spurious modes. The threshold is established based on the authors' experience with several signals of different types (power, angle, speed, current, voltage, etc.). This approach has been observed to work reliably in more than 95% of the cases. A modal identification tool, IDtools, has been implemented in GE's commercial transient stability program (PSLF) that achieves complete automation of modal identification using the above-mentioned approach. Additionally, checks are performed internally to ensure that the tool does not process signals with negligible oscillatory modal content. The application of the program to transient stability simulations is illustrated in the paper including detailed guidelines and recommendations for its use.

KEYWORDS

Damping ratio, modal identification, Eigensystem Realization Algorithm (ERA), Time-domain simulation, electromechanical oscillations.

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INTRODUCTION

Ensuring that the power system oscillations are well-damped is one of the important considerations of power system planners. One way to ascertain whether a system is well-damped is to linearize the underlying power system dynamic models and perform a small signal stability analysis to identify the dominant modes of the system and compute their damping ratios. However, the computational expense of this approach can be prohibitive for large systems. An alternative approach is to use time-domain signals obtained from either the results of transient simulations or from post-disturbance measured data, thus making the computation of system damping independent of the system size. This paper focuses on estimating the damping from the time-domain signals obtained as a result of transient stability studies. Since these studies are routinely performed for ascertaining acceptable system dynamic performance and typically involve the execution of a large number of time domain simulations; techniques that facilitate this process are needed today. IDtools, a modal identification tool implemented in GE's transient stability program, PSLF, was developed with this need in mind and is aimed at expediting the assessment of system damping.

Different methods have been introduced for computing system damping from time-domain signals following a system disturbance. A simple approach consists of computing the reduction in the magnitude of oscillations present in the signal over a given time period. A 53% reduction in the magnitude of oscillation amplitude over four periods of oscillation is typically considered acceptable, which translates to a 3% damping ratio. This approach yields reliable results if the signal has only one oscillatory mode. However, power system oscillations often include multiple oscillatory modes, such as inter-area modes (typically in the range of 0.1-0.9 Hz) and local modes (typically in the range of 1 to 3 Hz). For accurate analysis of such signals with multiple modes, more sophisticated modal identification methods have been developed, e.g., Prony, matrix-pencil, ERA, etc. [1], [7], [9], [10]. The Eigensystem Realization Algorithm (ERA) [2] – [6] is the method used in the work reported here. The method is based on the singular value decomposition of a matrix easily built from transient stability simulation results. The method is numerically stable and has been used in a variety of applications. A summary of the ERA is provided in the appendix. While several publications have explored different aspects of the ERA algorithm, of which [2] – [6] are a few, all such tools require a higher level of user involvement to identify the true modes. This paper advances the work done in [3], by computing a metric for each mode whose magnitude indicates the contribution of the given mode to the signal. The metric is used to detect the true and significant modes by comparing its value against a threshold. Results using Western Electricity Coordinating Council (WECC) cases representing the western interconnection in United States are provided that validate the proposed approach and illustrate the application of the program; guidelines for the use of such a modal identification tool are provided as well.

The application of the program is straightforward; a user only needs to specify the file with the time-domain simulation results in PSLF and the list of signals that are to be processed. It then creates a summary report with a list of signals that failed to meet the minimum damping ratio requirement and a report with the details of modes present in each individual signal.

While in principle the ERA can be used to process a large number of signals obtained from transient stability simulations, the size of the matrix required by the algorithm would become too large and, perhaps more importantly, the task of correlating modes with individual signals would become too burdensome. Hence in the work reported in this paper, each signal was processed separately to identify the modes in it. Since the computations for different signals are independent of each other, parallel processing can be used to increase the execution speed.

PRE-PROCESSING OF SIGNALS IN THE PROGRAM

Before performing the modal identification, the initial value of the signal is removed, then the signal is normalized by dividing each data point by the magnitude of the largest data point. For example, if a signal has an initial value of 100, and a maximum absolute value of 105.7, 100 (initial value) will be subtracted from all data points in the signal and then all data points will be divided by 5.7. If the data point with the largest absolute value (after removing initial value) is smaller than 10^{-16}, normalizing is not done. These operations improve the condition number of the Hankel matrix while still retaining the necessary information about the signal shape and hence its modes.

Typically, the signals from time-domain simulations are sampled every quarter cycle (0.004s). However, identification of modes in the range 0.1 to 3Hz, does not require data with such granularity. Hence, internally the program further samples the signal. The required sampling rate for modal identification is automatically determined, to avoid picking too many data points.

Additionally, checks are performed internally to ensure that the tool does not process signals with very small variations. Such signals are not suitable for modal identification as they are often either linear (and hence have no oscillatory modes) or are very noisy. The noise or the “chatteriness” of such signals is often due to the convergence tolerance used in the simulations, since all digits beyond a desired tolerance have no physical meaning.

IMPACT OF INCLUSION OF SPURIOUS MODES

For truly linear systems, the magnitude of the singular values obtained by ERA or the results of an FFT of a signal are often good indicators of the contribution of a mode to a signal. As an example, the FFT outputs of two linear systems are shown in Figure 1, where clear peaks are seen. The plot on the left is the FFT of a system with a single mode at 2.0 Hz, while the plot on the right is for a system with two modes at 1.0 Hz and 1.5 Hz.

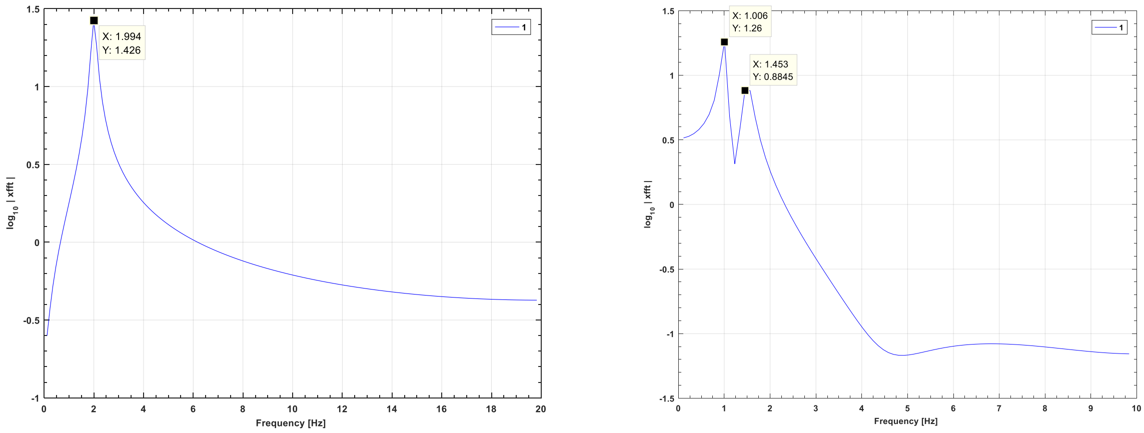

Figure 1. FFT outputs for purely linear systems

However, since power systems are inherently nonlinear, the FFT results or singular value magnitudes of the linearized approximations are not always clear indicators of the true modes which can be seen from Figure 2, where no clear peaks are displayed. Hence, in a case like this, it is difficult to differentiate between the true dominant modes of the system and spurious/insignificant modes. In some such cases, the spurious modes could be poorly damped, while the dominant modes are well-damped. In that case, a signal could be incorrectly flagged as being poorly damped. Such signals where FFT results, singular values etc. are not clear indicators of the true modes of the system, often do not exhibit a clear oscillatory behaviour. This will be discussed in detail in latter sections of the paper.

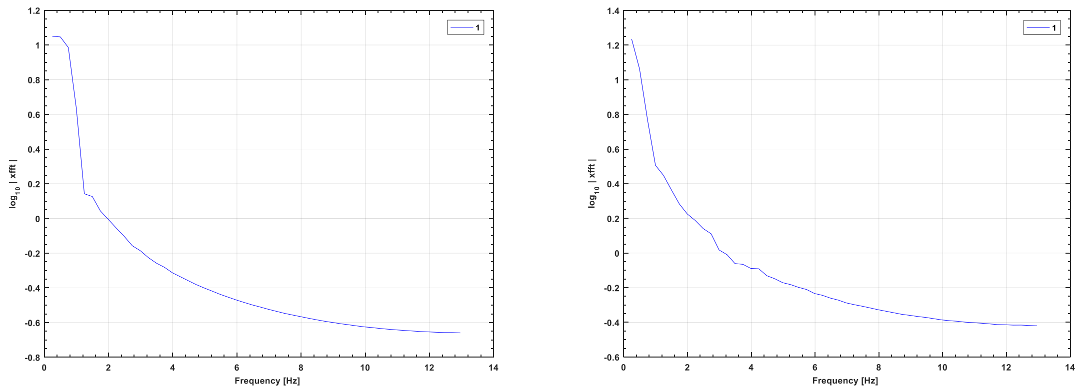

Figure 2. Sample FFT results for power systems

A good measure of the validity of the identified modes is whether a signal constructed using the identified modes approximates the signals from which the modes are derived. Examples of such comparison are shown in Figure 5, where the blue curves represent the impulse response of the linear system while the black curves are the true signals used for modal identification. Based on the excellent match between the two, it can be concluded that the modes identified for these two signals are very accurate.

Spurious modes do not contribute much to the signal shape. An example of this is shown in Figure 3, where the plot on the left has the signal reconstructed from a system with seven eigenvalues while the signal on the right has the same signal reconstructed from five eigenvalues. It can be seen that the spurious mode i.e. the last pair of eigenvalues does not contribute much to the shape. In some rare cases, the inclusion of a spurious mode can make the match between the actual signal and reconstructed signal worse. This is shown in Figure 4 where the plot on the left has a match with 13 modes, while the plot on the right has the results with 17 modes. It is clearly seen that the inclusion of the additional modes worsens the match between the actual signal and reconstructed signal.

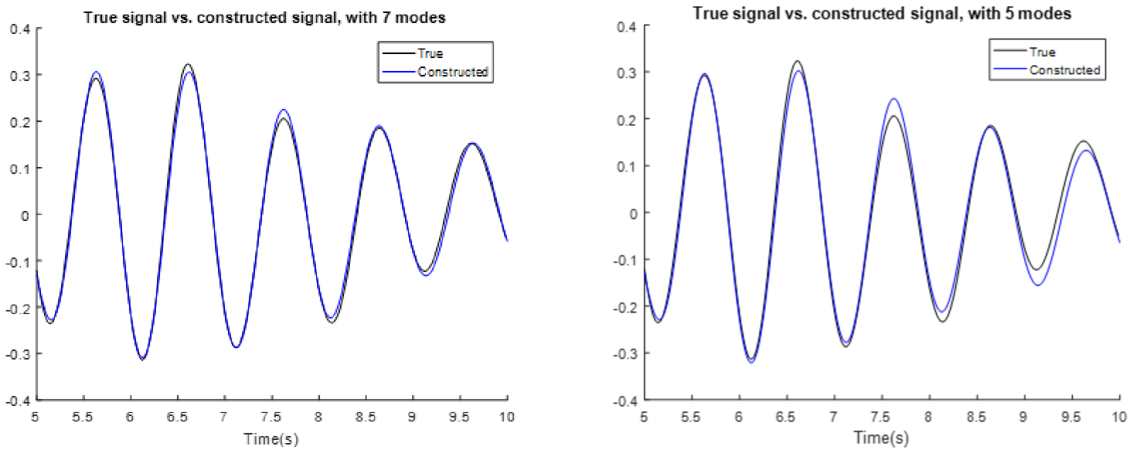

Figure 3 Example of lack of contribution from spurious modes

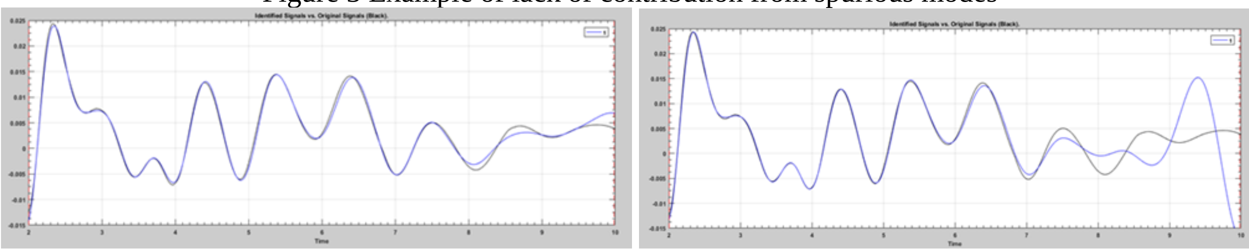

Figure 4 Example of detrimental effect of spurious modes

MODAL SCREENING METRIC AND NUMERICAL RESULTS

In order to differentiate between dominant modes and spurious/insignificant modes, a metric is computed using the signal residues for each mode. The left and right eigen vectors of the state matrix obtained as a by-product of the eigen analysis done in ERA, are used for this. Assuming the right eigenvector matrix of A_δ is given by V and left eigen vector matrix is given by W, two matrices are computed as:

$$Bjord = W * B \quad (1)$$

$$Cjord = C * V \quad (2)$$

Note that for a single input, single output system, B is a column vector while C is a row vector, hence *Bjord* and *Cjord* are also vectors. For the i^{th} mode, the magnitude of the signal residue is given by

$$Signal\_residue_i = |Cjord(i) * Bjord(i)| \quad (3)$$

The weight of each mode with eigen value λ_i is computed from the signal residues as:

$$Weight_i = Signal_{residue_i}^{\ 2} / |(1 - e^{2\lambda_i})| \quad (4)$$

The modes are ranked based on the weight for each mode. The relative weight of each mode is computed as:

$$Significance_i = Weight_i / \max(Weight) \quad (5)$$

Modes with significance less than 0.001 are ignored. This threshold was determined based on the results for several signals of different types for two WECC cases for different disturbance simulations.

In most cases, up to 7 eigenvalues (i.e. up to 3 oscillatory modes) suffice to replicate the behavior of a signal. This is illustrated in Figure 5 which shows six examples of a good match between actual signals and signals constructed using identified modes. In this figure, the actual signal (after removing initial value and normalizing) is plotted in black while the signal generated from the modes is plotted in blue. For most signals, the match was observed to be fairly accurate as shown below. However, in a few cases, the shape of the signal constructed from the modes did not match the true signal too well. However, such signals typically had very small variations and hence the difference between the actual quantity and the reconstructed quantity was fairly low despite the poor match in shape.

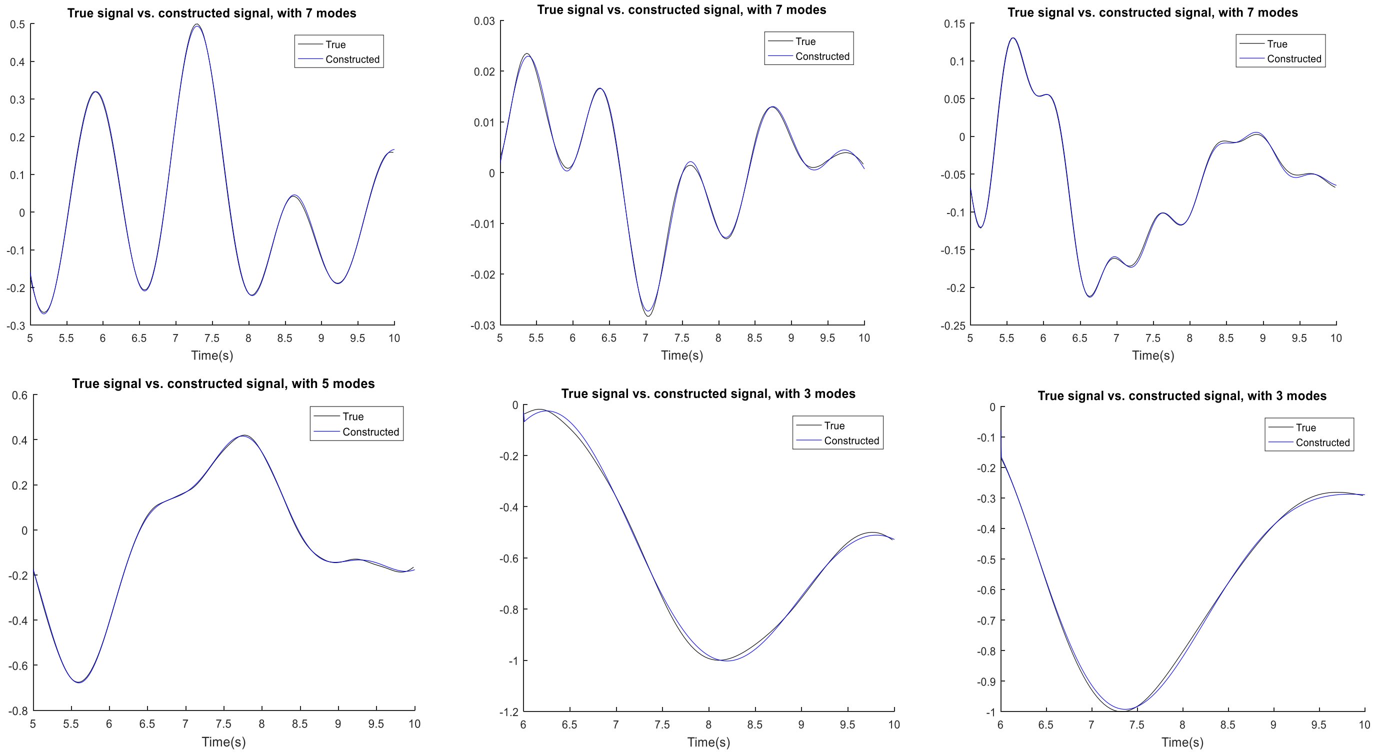

Figure 5 Examples of cases where the signals constructed using the modes match the true signal accurately

In order to validate the threshold, two WECC cases were used to run 10 simulations, using different disturbances at different locations in the system. For each case, the signals to be assessed were chosen by picking three to 10 signals from each area that had the worst spread. The statistics are provided in Table 1. A total of 968 signals were inspected of different types (voltage magnitude, angle, active and reactive power, field voltage,, speed etc.), of which 70 signals were poorly identified despite using the above-described metric. The poorly identified signals either contained spurious modes selected, or did not provide an accurate match between the true signal and the reconstructed signal. Of these 70 signals, 58 signals fell in one of the following categories:

1. Variations in the signal are too small, with the relative spread ((Max_value – Min_value)*100/Initial_value) being less than 2% of the initial value.
2. Signal is too noisy/non-linear to be used for modal identification.
3. The magnitude of the original signal is too small.

For signals that are small in magnitude, the probability of falsely flagging a signal as poorly damped due to a spurious mode was found to be higher. From a system stability perspective, the output of larger generating units and branches with heavier flows are typically more critical and are expected to be assessed using this tool, along with p.u. terminal voltages, currents and speeds. Of the larger signals looked at (output of the larger generating units and branches with heavier flows, along with p.u. terminal voltages, currents and speeds), less than 2% of the signals that were flagged as being poorly damped were due to spurious modes.

The quality of the match can be determined by looking at the RMS error between the actual signal and the reconstructed signal. For a few cases, the signal shape is not captured very accurately by modal identification as shown in Figure 6. However, note that in such cases, it was observed that the signal variations were typically so small, that the difference between the actual electromechanical signal and the re-constructed signal was still quite low. Note that in the example shown in Figure 6, the relative spread of the signals over the time-frame chosen is less than 2%. In such cases, more than 7 eigen values are needed to accurately identify the system. For the example shown in Figure 6, a good match can be obtained with 17 eigen values as shown in Figure 7. It has been observed that if the time frame for modal identification is chosen to be smaller, the accuracy of the match improves. Moreover, the signals with higher errors are observed to be signals that are too nonlinear; or are signals that are very small in magnitude and are not expected to be critical from a system stability perspective (for example reactive power/flow of <5 MVAr).

Table 1. Summary of the performance of the screening metric

WECC case	Disturbance	Time-frame of study	Total number of signals studied	A: Number of signals where spurious mode was selected	B: Number of signals where chosen number modes are insufficient for accurate match	Comments regarding poorly identified cases (both categories A and B)
Case1	3ph bus fault	8-10s	220	0	1	Spread less than 0.1 MVAr
Case1	Step voltage reference of a large nuclear generator	8-10s	220	2	2	Very flat/small
Case1	3ph bus fault	5-10s	66	7	2	Very flat/small
Case2	Trip large generator	6-15s	66	13	11	11/13 signals with spurious mode: signal very small. 8/11 with poor match are signals that are very small
Case2	Trip large generator	10-15s	66	8	0	Very flat/small
Case2	Trip load	6-10s	66	9	5	All too “chattery”/nonlinear with low-magnitude variations
Case2	3ph linear fault	6-10s	66	5	0	2 signals have significance metric close to threshold, all signals less than 10 MW/MVArs
Case2	LLG bus fault	6-10s	66	2	0	
Case2	LG line fault	6-10s	66	1	1	
Case2	3ph bus fault	10-13s	66	1	0	Signal almost linear, no oscillations

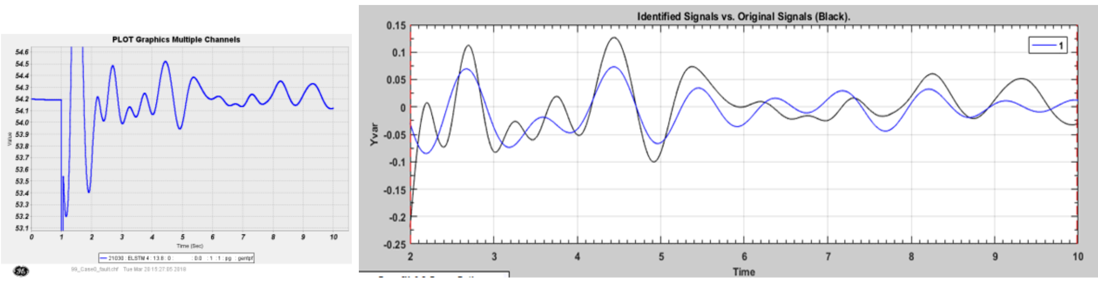

Figure 6 Example of case where the signal shape is not captured too accurately by modal identification

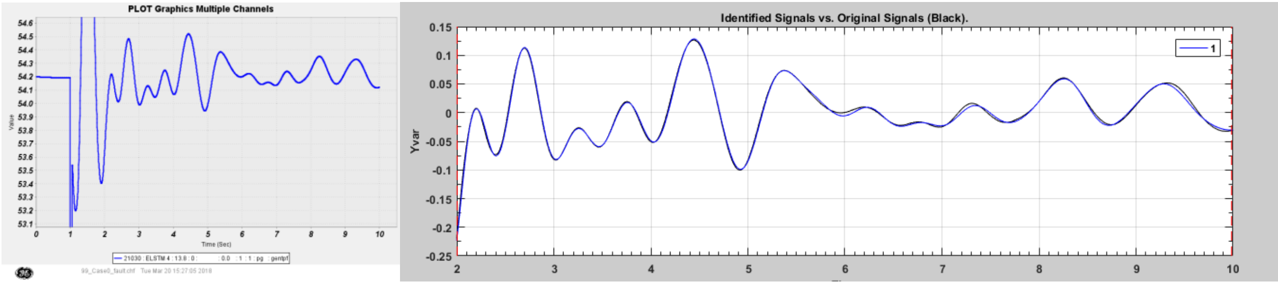

Figure 7 Example where higher number of modes are needed for accurate modal identification

RECOMMENDATIONS FOR USE OF AUTOMATED MODAL IDENTIFICATION TOOLS

Modal identification tools are meant to compute lightly damped electromechanical modes from one or several signals within a given time frame. Examples of such signals are shown in Figures 5 and 7. These signals clearly show an oscillatory behaviour in the frequency range typically associated with electromechanical oscillations ~0.1-3 Hz.

Such algorithms should not be used to process signals where there are no discernible electromechanical oscillations in the time frame selected for modal identification. Based on the authors' experience, it is recommended that this program *not* be used for signals that have less than 2% relative spread within the time frame used for modal identification as they may be flagged as being poorly damped due to spurious or insignificant modes. In some cases, especially if the time frame used for the modal identification is towards the end of the simulation, the signals do not have any oscillatory modes present (as the dominant oscillatory modes may have already died down by then). For example, see Figure 8 (the left image shows the signal over the entire simulation duration while the right image shows the zoomed in image focusing on the last 2 seconds of simulation); the plot of the signal in the last two seconds of the simulation show what is essentially a straight line from which it is not possible to extract oscillatory modes. Note that the range of variations for the signal (bus voltage angle) is less than 0.001 degrees which is essentially constant from a practical standpoint. The program assumes that the signals have at least one oscillatory mode and hence, if such near-linear curves are processed, it will inevitably compute some spurious oscillatory modes that may be poorly damped.

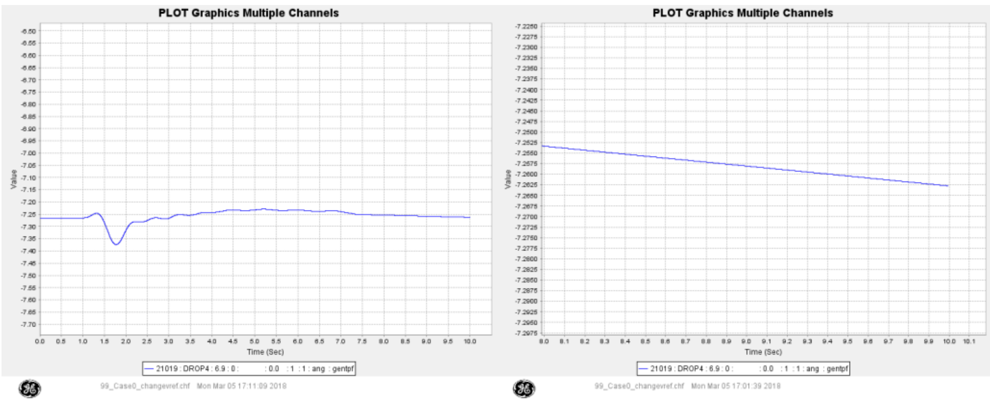

Figure 8 Signal with very small variations

Other problematic situation occurs when the variations are so small that the signal appears to be noisy, for example see Figure 9 (The left image shows the signal over the entire simulation duration while the zoomed in image focusing on the last 2 seconds of simulation is shown on the right, variations in the last 2 seconds are of the order of 0.0001 MVAr). The program should *not* be used to process signals that are noisy and/or exhibit "chatter", as the signal constructed from the modes will not match the true signal well due to the presence of sudden variations in the signal (which are physically meaningless). Such signals can be detected by metrics such as signal to noise ratio. The program should *not* be used for signals that exhibit discrete and/or abrupt changes such as those encircled in Figure 10, since the signal constructed from the identified modes cannot capture the abrupt changes in the signal. This is an indication that the identified modes might be in error and the RMS errors between the actual signal and the reconstructed signal will consequently be higher.

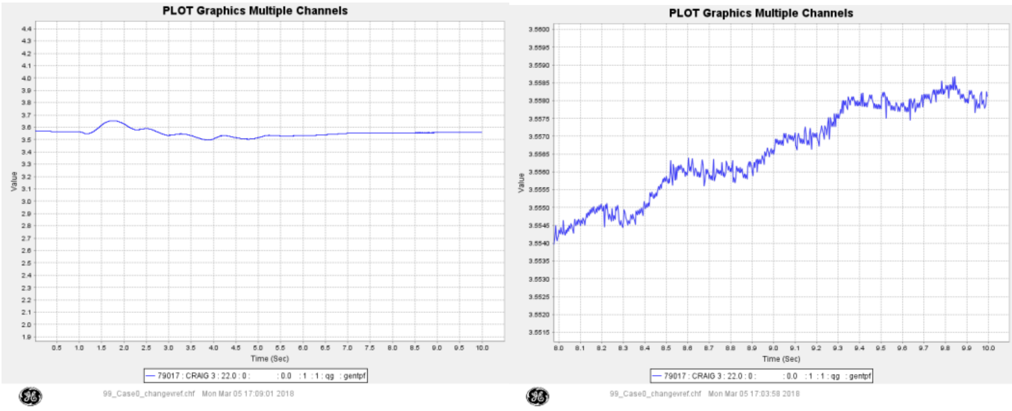

Figure 9 Signal with small variations and chattery behavior

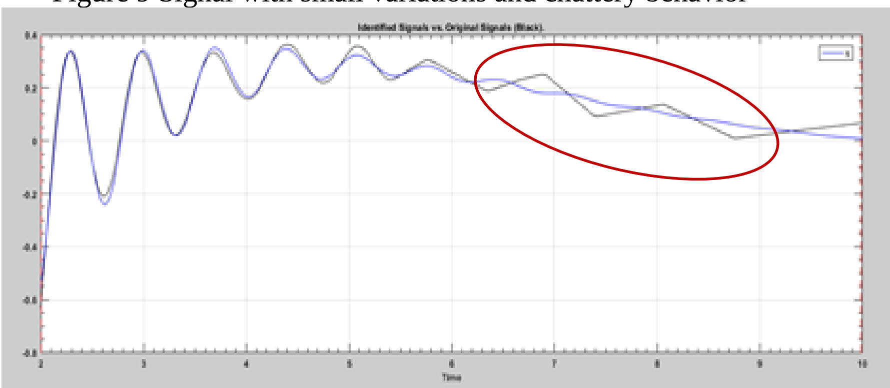

Figure 10 Example of a case where the signal exhibits abrupt changes

CONCLUSIONS

This work is the latest effort toward merging modal damping identification from time domain simulations in a commercial product. Using the described screening approach, the automated modal identification tool described in the paper, IDtools has been integrated in GE-PSLF. For each signal being processed, it identifies up to three oscillatory modes, out of a total of 7 eigenvalues (including purely real eigenvalues as well as complex-conjugate pairs). If appropriate signals with sufficient signal variations were used, it appropriately identified approximately 98% of nearly 900 signals inspected. With a C implementation, it takes on average 0.12 s to process each signal, with a major portion of the time spent in reading and pre-processing the data. Since all signals are processed independent of each other, the process can easily be parallelized for speed. This is the first step towards a complete automation of modal identification from time-domain signals. These computations are strongly recommended to be done after all automatic discrete adjustments in the system have already been made following a fault clearance or other major switching event, in order to ensure that the signals do not have any sharp changes. The process of filtering out unnecessary modes is a key step which will continue to be refined. While the screening is not 100% accurate, users can look at the predominant modes for several signals in a given area since they are expected to have the same true modes. One future approach to further refine the screening process, could be to check for the consistent presence of a given mode as the linearized system size is increased [3].

APPENDIX A: SUMMARY OF ERA ALGORITHM

The first step of ERA involves obtaining a discrete system is such that the input signal is its free-state impulse response (i.e. system output when all initial states are at zero and an impulse input is applied to the system):

$$X[k+1] = AX[k] + B\delta[0] \qquad (6)$$

$$Y[k] = CX[k] + B\delta[0] \qquad (7)$$

Given that for zero-state impulse response, $X[0] = 0$, one can easily obtain that:

$$X[1] = B, Y[1] = CB \quad (8)$$
$$X[2] = AX[1] = AB; X[3] = AX[2] = A^2B \quad (9)$$
$$X[k+1] = A^kB; Y[k] = CA^{k-1}B \quad (10)$$

ERA uses (10) to obtain the A,B,C matrices from the sampled data points [3] – [6]. The first step in ERA algorithm involves constructing two Hankel Matrices H_0 and H_1 from the data points in the signal.

$$H_0 = \begin{bmatrix} Y(1) & Y(2) & \dots & Y(m) \\ Y(2) & Y(3) & \dots & Y(m+1) \\ \vdots & \vdots & \ddots & \vdots \\ Y(n) & Y(n+1) & \dots & Y(m+n-1) \end{bmatrix} \quad (11)$$
$$H_1 = \begin{bmatrix} Y(2) & Y(3) & \dots & Y(m+1) \\ Y(3) & Y(4) & \dots & Y(m+2) \\ \vdots & \vdots & \ddots & \vdots \\ Y(n+1) & Y(n+2) & \dots & Y(m+n) \end{bmatrix} \quad (12)$$

The dimensions of the above matrices are *no* x *ni* where *no* is number of outputs (i.e. number of modes to be computed) and *ni* is the number of inputs (i.e. number of signals being processed). The most important part of ERA involves performing an SVD of H_0.

$$H_0 = PSQ^T \quad (13)$$

It has been shown that the state matrix *A*, input matrix *B* and output matrix *C* for this linear system are given by (14) – (16) [4].

$$A = S^{-1/2}P^TH_1QS^{-1/2} \quad (14)$$
$$B = S^{1/2}Q^T \quad (15)$$
$$C = PS^{1/2} \quad (16)$$

The discrete system can then be converted to a continuous system as:

$$A_\delta = \ln(A/h) \quad (17)$$
$$B_\delta = [\int_0^h e^{A_\delta t} dt]^{-1} \quad (18)$$
$$C_\delta = \mathrm{C} \quad (19)$$

Once the state matrix of the continuous system is obtained, its eigen values λ, are the modes of the system. The damping ratio of each mode can be computed as:

$$\zeta_i = -Re(\lambda_i)/|\lambda_i| \quad (20)$$

Since each signal is processed separately in the program, the value of *ni* is 1. For each signal, a single-input, single-output system is identified, with the input being an impulse and the output being the original signal.

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