ANALYSIS OF INTER-AREA OSCILLATIONS VIA NON-LINEAR TIME SERIES ANALYSIS TECHNIQUES

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Abstract – This paper compares the characteristics and information provided by different modal identification tools, in the analysis of a very complex forced inter-area oscillation problem recorded in the Mexican interconnected system.

These oscillations involved severe frequency and power changes throughout the system and resulted in load shedding and the disconnection of major equipment. This paper reports on the early analytical studies conducted to examine the onset of the dynamic phenomena.

Instances of variations in the amplitude and frequency of the excited inter-area modes are investigated and perspectives are provided regarding the nature of studies required to identify and characterize the underlying nonlinear process.

It is shown that nonlinear analysis tools are able to identify aspects of the dynamic behavior of the system that are needed in the validation and characterization of the observed phenomena, even in cases where power system dynamic characteristics change several times due to load shedding and generation tripping operations.

Keywords: Power system dynamic behavior, Inter-area oscillations, Modal identifications tools, Nonlinear modal identification tools.

1 INTRODUCTION

This document details the analytical studies conducted to examine the onset of major inter-area oscillations in the Mexican system during the winter of 2004. The study focuses on the use of time-frequency representations to extract the key features of interest directly from the actual system response.

Of primary interest here is the analysis of the time evolution of recorded signals, since this allows replicating the events leading to the onset of the observed oscillations, and analyzing the influence of particular operating conditions on system behavior.

The non-stationarity of the data following the triggering event makes reliable estimate of the frequency and damping characteristics of the observed oscillations difficult. Traditional methods of time series analysis do not address the problem of non-stationarity in power system signals, and often assume linearity of the process [1]. To circumvent these problems, time-frequency representations are used to give a quantitative measure of changes in modal behavior on different time scales.

Two main analytical approaches have been investigated to extract the underlying mechanism from the observed system oscillations. The first approach is based on the use of time-frequency representations of time series. These models are capable of explaining the nonlinear nature of the observed oscillations and permit the tracking of evolutionary characteristics in the signals and the development of measures like instantaneous characteristics to capture mode interaction. The second approach uses conventional analysis techniques currently used by the electric industry. Particular attention is paid to the suitability of these techniques as a detector of nonlinear modal interaction.

Analyses of observed measurement data via nonlinear spectral analysis techniques reveal the presence of complex dynamic characteristics in which the dynamic characteristics of the dominant modes of oscillation excited by the contingency change with time. The mechanism of interaction characterizing the transition of these modes involves strong nonlinear behavior arising from self –and mutual interaction of the system modes. This is a problem that has received limited attention in the power system community.

A challenging problem in studying this transition concerns the identification of the primary modes involved in the oscillation and the study of the nature of the coupling among interacting components giving rise to nonlinear, and non-stationary dynamics. The implications of such complex spatio-temporal behavior can throw much light on the dynamic patterns of the system and information about the local behavior in both the time and frequency domains can be extracted.

Numerical simulations with nonlinear spectral analysis techniques show good correlation with observed system behavior and also point to the importance of nonlinear effects arising from changing operating conditions. These predictions are the basis for additional studies currently being undertaken involving small-signal and large signal performance and are expected to improve modeling and analysis techniques used in power system dynamic analysis studies.

2 DESCRIPTION OF THE EVENT

2.1 General description of the system

The Mexican National Electric Power System is composed of 9 control areas. Six of these areas (namely

Northern, Northeast, Central, Oriental, Occidental and Peninsular) form an interconnected power system, and the remaining three areas operate as electrical islands.

The event of concern was registered during a temporary interconnection of the Northwest control area to the Mexican Interconnected System (MIS) through a 230 kV line, in January 2004 (see Figure 1). The equipment in charge of the automatic synchronization of both systems had a failure (a fusible blow) and the interconnection was performed with the systems out of phase.

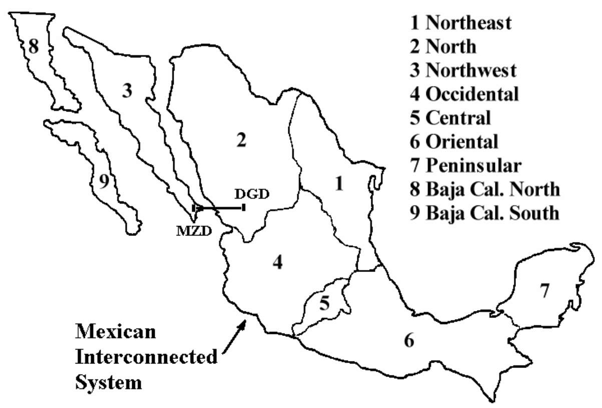


Figure 1: Pictorial representation of the MIS showing the location of the interconnecting line. The PMU is installed in MZD substation.

After the tie line was connected, undamped inter-area oscillations were observed throughout the system. These were on the order of ± 250 MW in the main interconnection, and continued for some minutes before damping out. As a consequence, protective relays operated, tripping about 140 MW of load and three generating units in order to compensate for the unbalanced caused by system oscillations. The line was finally disconnected.

2.2 Actual recorded response

The data used in this study was recorded on Phasor Measuring Units (PMUs) at several key locations in the system. Of special relevance, Fig. 2 shows the time behavior of the MZD-DGD 230 kV real power flow. This transmission line interconnects the North-Western control area and the Mexican Interconnected System and constitutes a crucial part of the system's backbone. On detailed examination, the records indicate the presence of nonlinear, non-stationary behavior which makes difficult the analysis and interpretation of the observed oscillations using conventional techniques.

In the following sections, we discuss in detail the theoretical studies conducted to analyze these oscillations and compare them with those found experimentally.

3 NONLINEAR SPECTRAL REPRESENTATION OF THE DATA

A distinct characteristic of the observed oscillations is the presence of nonlinear, non-stationary behavior

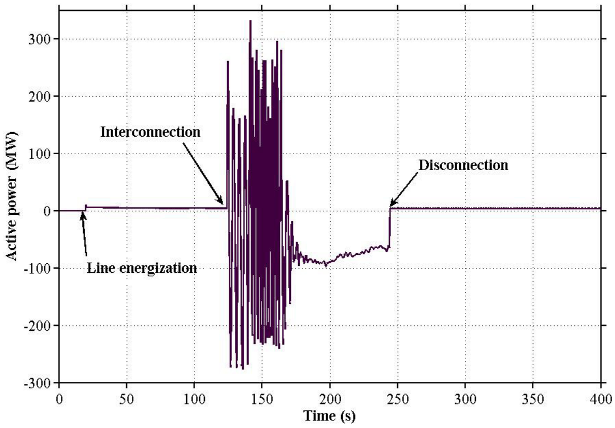


Figure 2: Active power flow oscillations in the transmission line interconnecting North-Western control area with the Mexican Interconnected System (MZD-DGD).

which precludes direct application of conventional analysis techniques. To address the shortcomings of conventional techniques and gain insight into the different time scales present in the oscillations, time windows have to be determined in which the oscillations are reasonable (locally) stationary with respect to these windows. We next examine the use of time-frequency (TF) techniques to extract the key features of the dynamic behavior of the system as well as to provide a comparison between nonlinear time series analysis and conventional Fourier analysis.

3.1 The wavelet transform

Wavelet spectral analysis provides a natural basis to estimate the time-frequency-energy characteristics of the observed data and is used in this work to identify dynamic trends in the observed system behavior.

Consider a time series x_n, with equal time spacing, Δt, and $n = 0...N-1$. Let $\psi_o(\eta)$ be a *wavelet function* that depends on a non-dimensional time parameter η. In the present analysis, a Morlet wavelet mother function has been used as a basis for the wavelet transform in the form [2],[3]

$$\psi_o(\eta) = \pi^{-1/4} e^{j\omega_o \eta} e^{-\eta^2/2} \tag{1}$$

where ω_o is the non-dimensional frequency to satisfy the admissibility condition.

Following Farge [2], the wavelet transformation of a discrete signal $x(t)$ is defined as

$$W_n(s) = \sum_{k=0}^{N-1} \hat{x}_k \hat{\psi}^*(s\omega_k) e^{i\omega_k n \Delta t} \tag{2}$$

where * denotes the complex conjugate, W_n is the transformation of the signal, and ω_k, is the angular frequency defined as

$$\omega_k = \begin{cases} \dfrac{2\pi k}{N\Delta t} : k \le \dfrac{N}{2} \\ -\dfrac{2\pi k}{N\Delta t} : k > \dfrac{N}{2} \end{cases} \tag{3}$$

We can then define the wavelet power spectrum, $|W_n(s)|^2$, at time point n and scale s. To ensure that that the wavelet transforms in (2) at each scale are directly comparable to each other, and to the transforms of other time series, the wavelet function at each scale s is normalized to have unit energy, namely [4]

$$\hat{\psi}(s\omega_k) = \left(\frac{2\pi s}{\Delta t}\right)^{1/2} \hat{\psi}_o(s\omega_k) \qquad (4)$$

Using the above normalization and referring to (2), the expectation value for $|W_n(s)|^2$ is equal to N times the expectation value for $|\hat{x}_k|^2$. For a white-noise time series, this expectation value is σ^2/N where σ^2 is the variance; the normalization by $1/\sigma^2$ gives a measure of the power relative to white noise. The details of this approach may be found in [4].

3.2 Wavelet analysis

The data used in the analysis is the actual oscillation time series extending from 0:43:00 through 0.45:00, with a sampling interval of 0.20 seconds. For the purpose of clarity, the analysis was restricted to an observation window between 120 second and 180 seconds which coincides with the period of concern. This allowed us as to concentrate on the onset and analysis of lightly damped inter-area modes.

The computed wavelet spectrum for the recorded signal is presented in Fig. 3. Also shown is the average variance of the signal and the normalized wavelet power spectrum. The power spectrum estimate in Fig. 3c) clearly reveals the presence of two dominant modes at about 0.22 Hz and 0.50 Hz. In addition, the analysis shows a higher frequency component at about 1.25 Hz.

One significant feature of the spectrum is the presence of time-varying, non-linear characteristics. Visual inspection of the response suggests, initially, the onset of two main periods of interest in the analysis of system response. In the first region, the analysis indicates the presence of a nearly constant frequency mode at about 0.22 Hz. The continuous nature of the spectrum, and the lack of harmonic frequencies, provides an indication that the dominant mode is essentially stationary.

For the second region, the analysis discloses harmonics superimposed on a slowly changing mode with an average frequency of 0.66 Hz. This implies that the periodic structure of the data is non-cosinusoidal involving frequency modulation; the presence of harmonics in the middle part of the wavelet spectrum indicates nonlinearity.

The analysis of this phenomenon, however, is not easy to interpret since wavelets introduce spurious harmonics to fit the data. It is also of interest to note that the energy distribution for the Wavelet spectrum is much more concentrated in the middle time period. This is the period of greatest interest to this analysis.

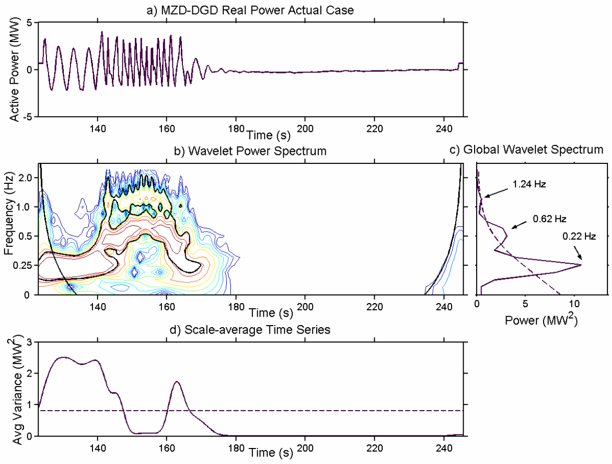


Figure 3: Wavelet time series analysis for the MZD-DGD power signal showing varying frequency characteristics

From wavelet analysis it is observed that:

- The spectrum can be divided into four distinct regions. In the first region, the behavior is essentially stationary and has a dominant modal component at about 0.22 Hz.
- The second region identified in the power spectrum (middle part of the plot) shows the transition of a low-frequency mode to a higher-frequency mode; the presence of higher order harmonics suggests the existence of nonlinear characteristics. Of primary interest here, the analysis identifies two main frequency components at about 0.42 Hz and 0.62 Hz.
- Subsequent to this period, the frequency of the modal component settles to about 0.25 Hz. The majority of the signal energy can be associated with region 2.

A comparison of the power spectra for the MZD-DGD power signal in Fig. 4 shows that wavelet analysis accurately replicates the dynamic performance of the system. Wavelet analysis provides a good visual interpretation of the phenomenon but lacks the frequency resolution to capture the detailed time evolution of the observed oscillations. These observations prompt further investigation of the origin of mechanisms generating such nonlinear behavior.

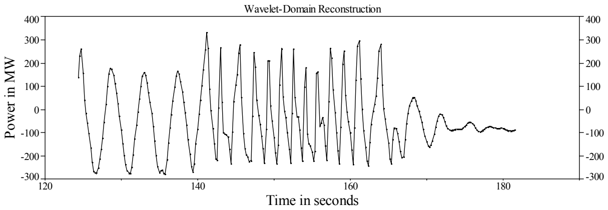


Figure 4: Comparison of the original system oscillations with the wavelet transform

3.3 Estimation of instantaneous attributes: The Hilbert-approach

In order to more accurately describe the event in both time and frequency, the Hilbert-Huang transform (HHT) method [5,6] was used to determine the nonlinear, non-stationary characteristics of the process. The HHT is a two-step data-analyzing method. In the first step, the time series $x(t)$ is decomposed into a finite number n of intrinsic mode functions (IMFs), which extract the energy associated with the intrinsic time scales using the empirical mode decomposition (EMD) technique. The original time series $x(t)$ is finally expressed as the sum of the IMFs and a residue:

$$\hat{x}(t) = \sum_{j=1}^{n} C_j(t) + r_n \qquad (5)$$

where r_n is the residue that can be the mean trend or a constant. Each IMF represents a simple oscillatory mode with both amplitude and frequency modulations.

Having decomposed the signal into n IMFs, the Hilbert transform of the kth component of the function c_k in the interval $-\infty < t < \infty$ can be written as

$$\hat{c}_k(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{c_k(t')}{t-t'} dt' \qquad (6)$$

From signal theory, a real signal c_k and its Hilbert transform define an analytic signal given by

$$C_k(t) = c_k(t) + j\hat{c}_k(t) = A_k(t)\exp(j\varphi_k(t)) \qquad (7)$$

Thus, the local amplitude A_k of the analytic function is

$$A_k(t) = \sqrt{c_k^2(t) + \hat{c}_k^2(t)} \qquad (8)$$

and its phase φ_k and instantaneous frequency ω_k are

$$\varphi_k(t) = arctg\left(\frac{\hat{c}_k(t)}{c_k(t)}\right); \quad \omega_k(t) = \frac{d\varphi_k(t)}{dt} \qquad (9)$$

It follows that the original signal $x(t)$ can then be expressed as the real part of the complex expansion

$$x(t,\omega) = \mathrm{Re}\left[\sum_{k=1}^{n} A_k(t)\exp\left(j\int \omega_k(t)dt\right)\right] \qquad (10)$$

where $A_k(t)$ and $\omega_k(t)$ are the instantaneous amplitude and frequency, respectively. Eq (10) represents a generalized form of the Fourier expansion with time variable amplitude and frequency; this allows to accommodate nonlinear, nonstationary data. For the sake of economy of space, details of the theory are omitted. A comprehensive account may be found in [5].

Fig. 5 shows the intrinsic mode functions (IMF) for the actual system response. Application of the HHT yields seven IMFs associated with different time scales of the data. The first IMF captures the higher-frequency modes whilst the subsequent IMFs give information about the lower frequency modes. The residue essentially gives the trend of the function.

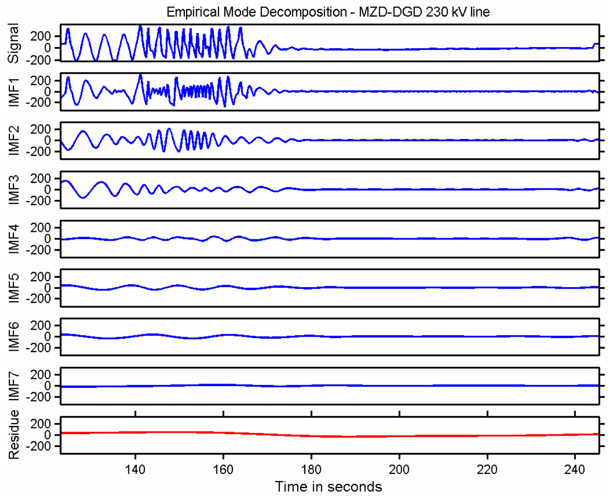


Figure 5: The intrinsic mode function (IMF) components for the MZD-DGD power signal

Once the IMFs are computed, the instantaneous characteristics were determined using the approach in [6]. This is illustrated in Fig. 6 that shows the instantaneous amplitude and frequency of each IMF. We con fine our discussion on the analysis of the first four IMFs, since they have the largest contribution to system behavior and are of relevance to the inter-area mode phenomenon. It should be noted in analyzing these results that the relative significance of each mode is determined by its peak (amplitude) values compared to those of the original data.

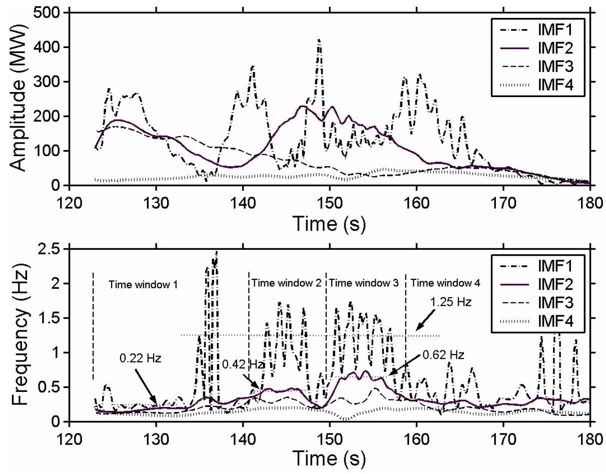


Figure 6: Instantaneous amplitude and frequency of the first four intrinsic mode functions (IMFs) showing selected time windows for linear spectral analysis

The fluctuating nature of the IMFs and the variation of the amplitude provides and indication of nonlinear, non-stationary effects in the driving mechanism. In particular, the varying frequency characteristics suggest frequency modulation, and therefore nonlinear behavior especially for IMFs 1 and 2. On the basis of this representation, the recorded signal was divided into four main observation (time) windows. Each time window was then segmented into sub-intervals to investigate specific characteristics of interests. These are:

Time window 1. A window in which the system response is initially dominated by two main modes; an essentially constant amplitude, nearly stationary mode at 0.18 Hz, and a oscillation mode about 0.22 Hz (IMF 2). A third IMF is also observed with a frequency slightly higher that the second IMF whose amplitude decreases slowly.

Time window 2. A window in which, the analysis of the instantaneous frequency shows that the frequency of the 0.28 Hz mode increases to about 0.42 Hz. It is also of interest to observe that the frequency of the second and third IMFs increase slightly.

Time window 3. A window in which the frequency of the second IMF increases to about 0.65 Hz and strong nonlinear frequency modulation is observed at about 1.25 Hz, suggesting the presence of a second harmonic.

Time window 4. A windows in which the frequency of second IMF decreases to about 0.25 Hz and instances of nonlinear behavior are barely observed.

These results agree very well with wavelet analysis, but in this approach, the time evolution of the observed oscillations is more closely captured.

By dividing the time series into several periods which are nearly stationary and linear, it is possible to apply conventional analysis techniques to the study of the phenomena of concern and obtain results which are meaningful. In the sequel, we concentrate on the analysis of system behavior in each of these observation windows in an effort to identify modal characteristics.

4 LINEAR SPECTRAL REPRESENTATION OF THE DATA

On the basis of the pervious results, conventional analysis techniques were used to assess system dynamic behavior over a range of time scales. Fourier spectral analysis and Prony analysis were performed over the observation windows selected in previous studies and to ensure stationarity, the average value within each window was substracted; this enables to focus on specific features of interest in the data. The selected periods of time for Fourier and Prony analyses are clearly indicated in Fig. 7.

4.1 Fourier spectral analysis of data

To confirm the non-stationary nature of the observed oscillations, and estimate local characteristics of the system response, we computed the Fourier spectra for each of the time windows described above. Fig. 8 shows the discrete Fourier spectra of the actual power data for each of these windows. From this analysis, several trends can be identified:

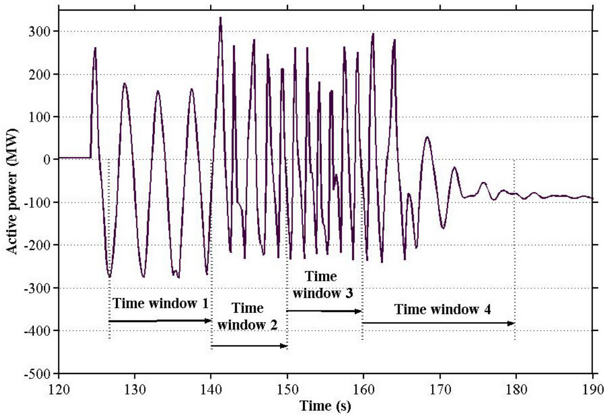


Figure 7: Selected time windows for linear spectral analysis.

- For the first observation window, the analysis reveals a major dominant mode at about 0.22 Hz.
  As the windows moves through the second period, Fourier spectral analysis identifies the presence of three major modes: a mode at about 0.42 Hz, a mode at about at about 1.25 Hz and a third mode at 0.90 Hz. These results are in good agreement with the results in Fig. 6.
- In turn, the analysis of the time window 3 shows that the frequency of the slowest mode increases to about 0.62 Hz whilst the frequency of the 1.25 Hz remains practically constant. An interesting observation should be noted; the higher frequency mode appears to be harmonically related to the 0.62 Hz (second harmonic) mode, indicating the presence of nonlinear behavior. These results are in good agreement with mid-term behavior of the wavelet spectrum in Fig. 4.
- Finally, the analysis of time window 4 shows that the frequency of the modes decreases to 0.22 Hz and 0.40 Hz as suggested from the HHT method.

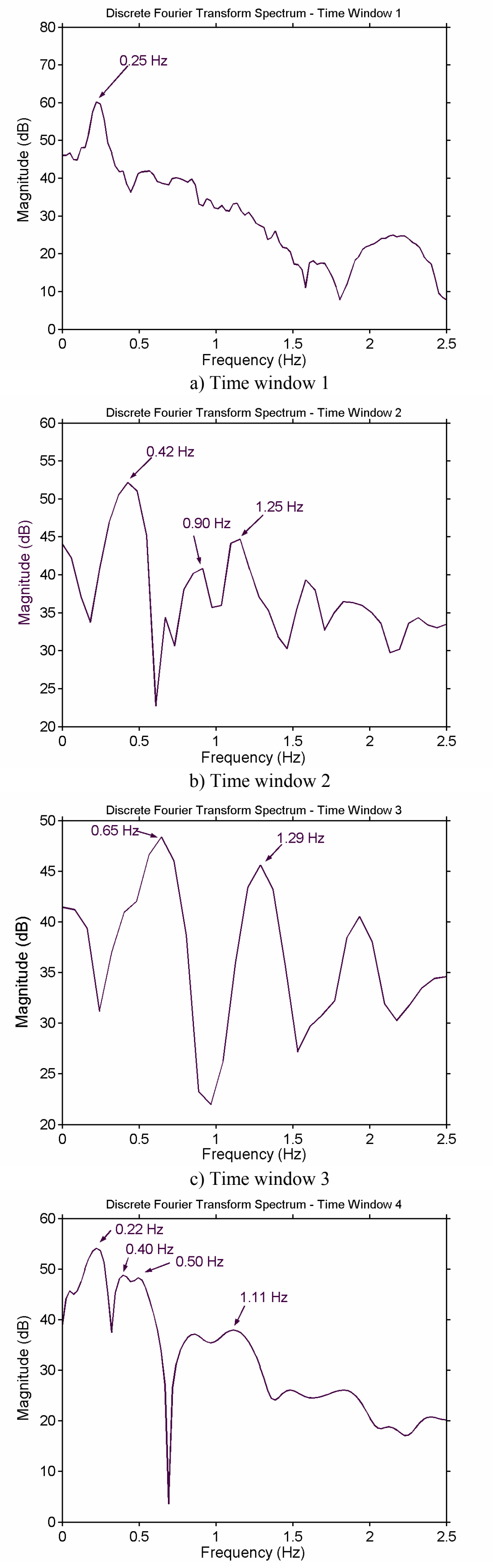
Simulation results are in good agreement with previous findings, but the combined use of Fourier spectral analysis and Hilbert spectral analysis enables to characterize the spatio-temporal dynamic behavior of the system.

4.2 Prony analysis

Prony analyses are applied to the recorded power of the line for each one of the selected time windows of Figs. 6 and 7. The results of Prony analysis are reported in Table 1. In order to filter out spurious modes from the results, the sliding windows technique and other techniques like de-trending the signal were used [7].

In Table 1, column 1 indicates the time window of concern in seconds; columns 2 and 3 present the frequency and damping ratio of the identified dominant modes. Finally, column 4 shows the "signal to noise ratio", which is a measure of the accuracy of Prony analysis. Good accuracy is achieved for SNR values around 40 dB [8].

It can be seen in the results of Table 1 that the information provided by Prony analysis also shows that the signal behavior is non-stationary. The mode frequencies



d) Time window 4

Figure 8: Fourier spectra of the actual system oscillations for the different selected time windows

Table 1: Results of Prony analysis of each one of the selected time windows of Figs. 6 and 7.

1	2	3	4
Period (s)	***f*** **(Hz)**	ζ **(%)**	***SNR*** **(dB)**
128-137	0.234037	1.04	55.921
140-149	0.455560	-2.39	49.446
	0.883367	0.69	
	1.126563	0.67	
149-158	0.621214	0.92	50.719
	1.233446	-0.10	
162-175	0.218626	8.277	71.724
	0.365159	4.762	
	0.518301	9.563	
	1.288916	8.883	

determined for each time window are very similar to the ones found using Fourier analysis, but Prony is able to complement this information by providing the damping of the identified modes. It is interesting to note that in some time windows some changing modes become unstable (have negative damping) and then go back to stable as a consequence of the different switching operations.

5 CONCLUSIONS

This paper reports on the experience in the use of nonlinear, non-stationary analysis techniques to characterize forced inter-area oscillations in power systems. The study of this problem has received limited attention in the power system community owing to the complexity of the mechanism of interaction giving rise to the oscillations and the lack of appropriate analysis techniques with the ability to extract the key features of system behavior.

The analysis of actual system recordings shows that forced inter-area oscillations may exhibit a complex behavior in which the characteristics of the fundamental modes excited by a given contingency vary with time. Simulation results support the inference that the mechanism of interaction characterizing the transition of these modes involves strong nonlinear behavior arising from self –and mutual interaction of the system modes. These interactions may play an important role in the dynamics of the system and contribute significantly to the variability of the observed oscillations.

Time-frequency spectral analysis methods for time series are able to extract some characteristics of power system behavior, which might not be exposed effectively and efficiently by conventional linear modal identification methods and provide insight into the nature of coupling among nonlinearly interacting modes.

Of particular concern, our investigation demonstrate that under certain operating conditions, two (or more) major inter-area modes in the Mexican interconnected system may interact nonlinearly, and identifies them.

This also suggests that system controllers should be coordinated to enable better control of the observed composite oscillations, especially under heavy stress conditions.

Since the poorly damped oscillations problems are usually very complex, a complete set of additional studies, using complimentary techniques (like modal analysis) is needed in order to determine the underlying causes leading to the onset of nonlinear mode coupling, as well as to determine conditions under which mode interaction might lead to system instability. The modal identification techniques presented in this paper constitute, however, a very important step in that direction which allows adjusting the power system model response to the actual dynamic behavior contained in the recorded signals.

This research should also lead to better understanding of the nonlinear nonstationary nature of system behavior, and to further development of analytical techniques able to identify and quantify complex nonlinear dynamics.

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