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Research Paper

Identification of coherent trajectories by modal characteristics and hierarchical agglomerative clustering

Mario R. Arrieta Paternina[a,*], Alejandro Zamora-Mendez[b], José Ortiz-Bejar[b,c], Joe H. Chow[d], Juan M. Ramirez[e]

[a] National Autonomous University of Mexico (UNAM), Mexico City, Mex. 04510, Mexico
[b] Michoacan University of Saint Nicholas of Hidalgo (UMSNH), Morelia, Mich. 58030, Mexico
[c] Centro de Investigacion e Innovacion en Tecnologias de la Informacion y Comunicacion, Aguascalientes, Ags. 20313, Mexico
[d] Rensselaer Polytechnic Institute, Troy, NY 12180, USA
[e] CINVESTAV, Guadalajara, Jal. 45019, Mexico

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ABSTRACT

This paper introduces a novel method to identify coherent generators using the inter-area modal characteristics of power systems. The key idea is to extract the inter-area modes from the simulated data and then to apply a clustering strategy. Thus, the proposed method consists of extracting the phase of the oscillatory modes via a modal identification technique and applying a hierarchical agglomerative clustering technique together with the Elbow's method to gather the phases of each mode, enabling to provide coherent trajectories of generators. The proposed method uses a Taylor-Fourier filtering strategy to remove noises and nonlinearity in the time evolution of coherent generators. Simulated signals with noise added are used for assessing the proposition. Results corroborate the proposed strategy for identifying coherent trajectories in large-scale power systems.

1. Introduction

Coherent trajectories in power systems are useful for controlled islanding [1–3] and wide-area control [4,5]. They arise due to the synchronous rotating machines connected into the power network, because they behave as coupled swing dynamics. This concept is widely known as *coherency*.

There are two main types of methods for identifying coherent generators [6,7], classified as: (i) *model-based methods*; and (ii) *measurement-based methods*. The former is generally based on the linearized state-space model, where methods such as slow coherency grouping (using the singular perturbations technique to display the time-scale separation of the inter-area modes and local modes) [8], tight slow coherency grouping [8], Zaborszky's clustering technique [9], weak link, and Tolerance-Based Method (TBM) technique [10,11], are used to analize offline coherency studies. The TBM finds coherent generators using the right eigenvectors from a set of user-specified modes; where generators are considered coherent if the phase of their right eigenvector entries, relative to a common reference entry, are within a coherency threshold. Also, the chosen modes should be inter-area modes with large observability in the entire system. Meanwhile, the latter deals with the measured or simulated response of the power system taking advantage of Wide-Area Monitoring Systems (WAMS) composed of synchrophasors. Several methods have been proposed, including recent techniques based on Koopman modes [12,13], graph theory [1], hierarchical clustering [14], correlation coefficients [15], K-harmonic means clustering [16], independent component analysis (ICA) [17–19], support vector clustering [20,21], and frequency deviation signals (FDS) [22]. These techniques address the coherency problem using polluted signals, handling noise immunity between 20 and 50 dB for FDS and ICA [22]. This paper tackles the inter-area modes identification-based coherency from the simulated response of power systems, with the ability of identifying modal parameters even in presence of noise by the Taylor-Fourier

Abbreviations: WAMS, wide-area monitoring systems; TFF, Taylor Fourier filters; FT, Fourier transform; HHT, Hilbert-Huang transform; PA, Prony analysis; ERA, eigensystem realization algorithm; MP, matrix pencil; TKEO, Teager-Kaiser energy operator; TFT, Taylor-Fourier transform; HACA, hierarchical agglomerative clustering algorithm; NE, New England; NPCC, northeast power coordinating council; SC, slow coherency; MB, measurements-based; FLOPS, floating point operations; SSE, sum of squared errors; TBM, tolerance-based method.

* Corresponding author.
E-mail addresses: mrarrieta@gdl.cinvestav.mx (M.R. Arrieta Paternina), azamoram@umich.mx (A. Zamora-Mendez), jortiz@umich.mx (J. Ortiz-Bejar), chowj@rpi.edu (J.H. Chow), jramirez@gdl.cinvestav.mx (J.M. Ramirez).

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filters (TFF) introduced in power systems in [23,24] and in phasor estimation in [25]; which allow to extract the inter-area modes, as exhibits in [23,24]. Likewise, measurement-based methods allow coherency identification under changes in system operating condition and network configuration, because the grouping of coherent generators may vary. Thus, transient conditions imply that one coherent group may be split into smaller groups, or on the contrary, multiple groups may be joined into a bigger coherent group.

The proposed approach is motivated by the coherency concept defined by Podmore in [26], where a clustering algorithm is used to process the approximate swing curves obtained by linear simulation and thereby determine the coherent generators, so that the coherency is based on similar dynamic behavior between two machines. The approach here is driven by the advance in modal extraction techniques based on the power system measured response, which are assumed reliable in [27–30]. Other approaches have been proposed for identifying oscillatory modes based on measurements. Some relevant techniques are discussed in [31,32]. Among these, the following are highlighted: Fourier transform (FT); Hilbert-Huang transform (HHT); Prony analysis (PA); eigensystem realization algorithm (ERA); matrix pencil (MP); and Teager-Kaiser energy operator (TKEO). In reference [33], comparisons are accomplished exhibiting the Taylor-Fourier transform (TFT) performance with respect to PA, ERA, and MP, unveiling a suitable performance on its applicability for identifying electromechanical modes.

In order to get the coherent groups, the modal characteristics estimated by TFF and a clustering technique are used. As stated, previous works use the topological information of the grid for grouping the coherent trajectories. In this paper, the modal information is used for identifying the coherent groups, i.e., no information about the network structure is needed. The hypothesis is validated using an exhaustive clustering technique known as the hierarchical agglomerative clustering algorithm (HACA) [34,35], selecting the optimal number of clusters by the Elbow's method presented in [36]. The applicability of this proposition has been assessed in two large-scale power systems: New England (NE) power system [37] and the Northeast Power Coordinating Council (NPCC) system [8]. Comparisons with the classical slow-coherency method are provided in order to corroborate the proposition.

According to the above-mentioned, the major contributions of the paper are summarized as follows:

1. A novel strategy for determining inter-area-mode-based coherent trajectories including high noise tolerance is proposed by a filtering approach.
2. This paper introduces the coherent trajectory grouping based on modal characteristics from the Taylor-Fourier filters estimates.
3. A hierarchical agglomerative clustering technique and the Elbow's method are used to identify coherency.

The paper is organized as follows. Section 2 presents the technique of identifying oscillatory modes based on Taylor-Fourier filters. Then, the hierarchical agglomerative clustering algorithm and Elbow's method are discussed in Section 3. In Section 4, the computational complexity is presented. Finally, the method is applied to two large-scale power systems in Section 5.

2. Identification of modal characteristics

The Taylor-Fourier transform (TFT) for extracting modal information from oscillating signals in power systems is described here. The TFT is integrated by Taylor and Fourier subspaces (for more details, see [24,33]), allowing a choice on the number of non-zero Taylor terms used for the continuous-time signal defined by

$$s(t) = \mathrm{Re}\{p(t)e^{j2\pi f_1 t}\} = a(t)\cos(2\pi f_1 t + \varphi(t)) \tag{1}$$

where $p(t) = a(t)e^{j\varphi(t)}$ is known as a dynamic phasor and f_1 is the fundamental frequency, so that the phasor can be approximated by the Kth Taylor polynomial centered at t_0 as

$$\begin{aligned} p_K(t) = \quad & p(t_0) + \dot{p}(t_0)(t-t_0) + \cdots + p^K(t_0)\frac{(t-t_0)^K}{K!} \\ & t_0 - T/2 \le t \le t_0 + T/2 \end{aligned} \tag{2}$$

To build the Taylor subspace, the signal model in (1) is discretized by $t = n_s T_s$, where $T_s = 1/(Nf_1)$ is the sampling period, and N represents the samples per fundamental cycle. Thus, the Taylor subspace is constructed by

$$\mathbf{T} = [\mathbf{t}_n^0 \quad \mathbf{t}_n \quad \mathbf{t}_n^2/2! \quad \cdots \quad \mathbf{t}_n^K/K!] \tag{3}$$

where t_n is a diagonal matrix whose components are given by $\mathbf{t}_n = -(K+1)T_s(n_s/2)$ to $(K+1)T_s(n_s/2)$, n_s corresponding to each sample of the Taylor's interpolating polynomial at each sampling time (T_s).

The Taylor-Fourier (TF) subspace in [33] is shaped as

$$\mathbf{B} = \begin{bmatrix} \mathbf{t}_{n1}^0 & \mathbf{t}_{n1}^1 & \cdots & \mathbf{t}_{n1}^K \\ \mathbf{t}_{n2}^0 & \mathbf{t}_{n2}^1 & \cdots & \mathbf{t}_{n2}^K \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{t}_{nC}^0 & \mathbf{t}_{nC}^1 & \cdots & \mathbf{t}_{nC}^K \end{bmatrix} \begin{bmatrix} \mathbf{W}_N & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{W}_N & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{W}_N \end{bmatrix} \tag{4}$$

where $C = K + 1$ is the number of cycles, which corresponds to the slower swing modes into the oscillating signal, and $\mathbf{W}_N$ is the Fourier matrix with harmonic phase factors $\omega_N^h = e^{j2\pi h/N}$ in each vector $h = 0, \ldots, N-1$. Thus, the Fourier matrix is

$$\mathbf{W}_N = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \omega_N & \omega_N^2 & \cdots & \omega_N^{(N-1)} \\ 1 & \omega_N^2 & \omega_N^4 & \cdots & \omega_N^{2(N-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega_N^{(N-1)} & \omega_N^{2(N-1)} & \cdots & \omega_N^{(N-1)^2} \end{bmatrix} \tag{5}$$

Note that in (4), the vectors of the Fourier matrix are harmonic modulators of the Taylor terms included in a Kth Taylor polynomial, $K > 0$.

Once the Taylor-Fourier subspace is defined, the synthesis equation is established by

$$\hat{\mathbf{s}} = \mathbf{B}\hat{\boldsymbol{\xi}}, \tag{6}$$

where matrix $\mathbf{B}$ is known as the Taylor-Fourier matrix, $\hat{\mathbf{s}}$ is the estimated signal, and vector $\hat{\boldsymbol{\xi}}$ contains the estimated TF coefficients and their derivatives according to the signal model (1) proposed in [23,38].

By taking the least-squares technique as the Taylor-Fourier coefficients in [39,40]. The error between the input signal $\mathbf{s}$ and its approximated Kth Taylor interpolating polynomial $\mathbf{B}\hat{\boldsymbol{\xi}}$ is defined as

$$\mathbf{e} = \mathbf{s} - \mathbf{B}\hat{\boldsymbol{\xi}}. \tag{7}$$

Then, the best estimates of $\hat{\boldsymbol{\xi}}$ are those obtained by solving the normal equations in (8).

$$\mathbf{B}^H\mathbf{B}\hat{\boldsymbol{\xi}} = \mathbf{B}^H\mathbf{s}. \tag{8}$$

By solving (8), the best parameters are attained, in the sense that they minimize the sum of the squared errors in (7). Thus, no iterative procedure is required. Then, the TF estimates are given by

$$\hat{\boldsymbol{\xi}} = [\mathbf{B}^H\mathbf{B}]^{-1}\mathbf{B}^H\mathbf{s} = \mathbf{B}^{\dagger}\mathbf{s}, \tag{9}$$