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Modal analysis of active distribution networks using system identification techniques

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ABSTRACT

Mode identification from post-disturbance "ringdown" responses can provide vital information concerning the dynamic performance and the stability margins of power systems. Therefore, several measurement-based identification techniques have been proposed in the literature to analyze ringdown responses of transmission systems and provide close to real-time estimation of the modal content. However, the applicability of these methods has not been thoroughly investigated for the analysis of active distribution networks (ADNs). Scope of this paper is to evaluate the applicability and the performance of eight measurement-based system identification techniques for the modal analysis of ADNs. The examined methods are used to identify the dominant oscillatory modes contained in ringdown responses of different types of signals. The Monte Carlo method is applied to investigate the influence of several parameters on the accuracy and efficiency of the identification procedure, while laboratory measurements are used to further demonstrate the accuracy of the examined methods. Practical issues encountered in the application of the identification techniques for the analysis of ADNs are discussed and potential solutions are proposed. Results reveal that although most of the examined techniques perform satisfactorily enough and thus can be readily employed for the modal analysis of ADNs, the Vector Fitting and the Hybrid FD/TD seem to be the most effective methods in terms of accuracy, robustness and computational efficiency.

1. Introduction

Traditionally, modal analysis of transmission power systems is performed by applying eigenanalysis on detailed linearized power system models [1–3]. However, this approach lacks of usability in cases of real-time applications and large power system configurations, due to its inherent computational burden [3]. Additionally, the implementation of model-based, eigenvalue analysis methods is rather limited in distribution grids, since it is practically impossible to keep updated over time detailed linearized distribution system models, due to the intermittent operation of renewable energy sources which causes frequent changes in the network topology and operational state.

To overcome these issues, the application of measurement-based system identification techniques has been proposed as supplementary solution to perform modal analysis and to predict stability margins of power systems [1,4]. Nowadays, system identification techniques gain significant interest due to the increased installation of phasor measurement units (PMUs) at transmission networks [5] and of frequency disturbance recorders (FDRs) [6] and micro-PMUs (μ-PMUs) [7] at distribution grids. Compared to traditional offline eigenvalue analysis methods, measurement-based identification techniques allow the close to real-time estimation of oscillatory modes, enhancing drastically the dynamic analysis and control of power systems [4]. In this context, real-time monitoring, transient stability assessment, online development of dynamic equivalents and fine-tuning of power system model components as well as wide-area control are some of the newly introduced applications deployed nowadays in distribution networks [8,9].

Most of the above applications can be performed by analyzing measured signals acquired either from operational ambient or ringdown responses [1,4,10]. In the former, modal parameters are identified using responses excited by small load variations [11,12], containing high levels of noise and low mode information density [2,12,13]. On the other hand, ringdown responses, obtained during or

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after major disturbance events (short circuits, line tripping, large load step-up, etc.) [4], contain higher levels of mode information compared to ambient data, facilitating the accurate identification of modal parameters [1].

Over the past decades, several system identification techniques have been proposed to perform modal analysis of power systems using ringdown responses. Considering the form of data they use, measurement-based system identification techniques can be classified into time-domain (TD) and frequency-domain (FD) [10]. The former operate directly on the measurement time series [4,10], i.e. on instantaneous [14] and/or phasor signals, while the latter are applied to the spectrum of the measured signals [10]. The most known measurement-based identification technique is the Prony method, originally proposed in [15]. Other popular identification techniques include the matrix pencil (MP) method [16], the eigenvalue realization algorithm (ERA) [17], the subspace state-space system identification (N4SID) [18], the prediction error method (PEM) [19], and the application of the fast Fourier transform (FFT) combined with the sliding window technique [20,21]. In [22], the use of the dynamic mode decomposition is discussed for the analysis of oscillatory modes in transmission systems, while in [23,24] the application of Kalman filter is investigated. The use of Teager-Kaiser energy operator is analyzed in [25], while in [26], autoregressive moving average exogenous (ARMAX) models are employed to identify oscillatory modes. Additionally, in [27], mode identification is performed using Zolotarev polynomials, while in [28] the digital Taylor-Fourier transform is introduced as a method for the identification of low-frequency electromechanical modes. In [29,30], the Vector Fitting (VF) algorithm is introduced as a technique for the modal analysis of power systems, while in [2] a hybrid TD/FD method is proposed.

Most of the above-mentioned identification techniques use high-order models that contain additional artificial modes apart from the dominant ones, in order to supress noise and signal offsets and to improve the estimation accuracy [2,31]. However, this approach limits the applicability and flexibility of the methods regarding automatic real-time monitoring [2,31]. Therefore, new methodologies are required to automatically identify the dominant system modes, ensuring the development of low-order models.

Additionally, it is worth noticing that all the above-mentioned identification techniques have been extensively evaluated only for the analysis of conventional transmission systems. However, the dynamic behavior of modern power systems has been altered drastically, due to the constant shift from traditional passive power systems to active networks, especially at the distribution level, where the concepts of active distribution networks (ADNs) and micro-grids (MGs) have been introduced. According to the CIGRE WP C4.605, ADNs are "*distribution networks with a significant amount of distributed generation (DG) which at specific periods of time (e.g. at minimum loading conditions) is a net exporter of active power, but at other times (e.g. at maximum loading conditions) may be a net importer of active power*" [32]. Accordingly, Micro Grids (MGs) can be defined as "*a type of a low voltage ADNs being comprised of an aggregation of loads and micro-generation systems (including local storage devices), typically operated in a two-level hierarchical management and control scheme supported by communication infrastructure assuring its operation as a controlled entity (aggregated load or generator) either connected to the main distribution network, or autonomously when isolated from it*" [32].

Consequently, the application of conventional identification methods for the analysis of ADNs and MGs constitutes a challenging task, due the intermittent nature of renewable energy sources as well as due to the high frequency modes and the significant noise levels present in such systems [33,34]. In fact, in the literature there are only few publications discussing the application of specific measurement-based identification techniques for the modal analysis of ADNs [8,33]. Therefore, a systematic evaluation and comparison of the most known identifications methods is required to investigate their performance and applicability under the new operating conditions arising from the advent of ADNs and MGs.

Scope of this paper is to evaluate the performance of eight system identification techniques already proposed in the literature to analyze the modal content of ringdown responses in ADNs as well as to propose an iterative procedure to automatically identify the dominant modes contained in measured ringdown responses. Specifically, the most widely used TD and FD methods are considered and evaluated. The examined TD techniques include the Prony, the ERA, the MP, the N4SID and the PEM methods. On the other hand, the FD methods include the conventional FFT, the VF algorithm as well as a hybrid FD/TD method.

The algorithmic details and distinct characteristics of each method are briefly discussed. The performance of the identification techniques is evaluated by applying the Monte Carlo (MC) method to artificially distorted data of simulated responses on a medium-voltage ADN that includes different types of DG units and loads. A comparative analysis is conducted, investigating the effect of the type of signal used in the identification procedure, the impact of noise and sampling rate on the accuracy of the estimates as well as the effect of the disturbance level on the performance of the examined identification methods. Finally, the accuracy of the most effective identification methods is further evaluated using measurements, acquired from a laboratory-scale MG.

The paper is organized as follows: In Sections 2 and 3, the theoretical background of dynamic system analysis and the formulation of the examined identification techniques are briefly described, respectively. The methodology for the automatic determination of the optimal model order is presented in Section 4, while in Section 5, the impact of several parameters on the accuracy of the examined identification methods is investigated using dynamic responses acquired through detailed RMS simulations conducted in the NEPLAN software. In Section 6, the performance of the most effective methods is further evaluated using laboratory measurements. The findings of the paper are summarized and discussed in Section 7.

2. Background

2.1. Linear systems

The dynamic performance of a multiple-input multiple-output (MIMO) system, subject to small perturbations, can be analyzed using the state-space representation of (1) in continuous-time form by assuming that the system is linear time-invariant (LTI) [1]. The set of equations in (1) is evaluated at the operating point, around which the perturbation is considered [35].

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{w}(t) \tag{1a}$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) + \mathbf{v}(t) \tag{1b}$$

Vectors $\mathbf{y} \in R^{m\times1}$ and $\mathbf{u} \in R^{r\times1}$ are the output and input system responses, respectively, while $\mathbf{x} \in R^{n\times1}$ is the state vector. $\mathbf{A} \in R^{n\times n}$, $\mathbf{B} \in R^{n\times r}$, $\mathbf{C} \in R^{m\times n}$ and $\mathbf{D} \in R^{m\times r}$ are the system matrices, while $\mathbf{w} \in R^{n\times1}$ and $\mathbf{v} \in R^{m\times1}$ are the measurement and process noise vectors, respectively. The homogeneous response of each system state can be described as the sum of the influence of the n system modes [1]:

$$x_i(t) = \sum_{i=1}^{n} c_i e^{\lambda_i t} = \sum_{i=1}^{n} a_i e^{\sigma_i t}\cos(\omega_i t + \varphi_i) \tag{2}$$

where $\lambda_i = \sigma_i \pm j\omega_i$ denote the eigenvalues of $\mathbf{A}$, while $\omega_i = 2\pi f_i$ and σ_i are the angular frequency and damping factor, respectively. Moreover, $c_i = a_i \cdot e^{\pm j\varphi_i}/2$ is the residue of the i-th mode, while a_i and φ_i are the corresponding amplitude and phase angle.

Let us assume that (1) is discretized, with $F_s = 1/T_s$ samples per second and N generated samples. The discrete-time state-space representation of the system at time instant k is:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}u_k + \mathbf{w}_k \tag{3a}$$

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k + \mathbf{v}_k \tag{3b}$$