Measurement-Based Hybrid Approach for Ringdown Analysis of Power Systems

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***Abstract*—System identification methods have been widely used for the study of low frequency electromechanical oscillations and the development of low order dynamic models. This paper introduces a hybrid frequency/time-domain approach to estimate the dominant modes contained in ringdown responses of power systems. Practical issues and solutions encountered in the application of the hybrid method are discussed. The performance of the proposed technique is evaluated by applying the Monte Carlo method to synthetic signals and simulated responses from a large-scale power system, as well as to measurements recorded in a microgrid laboratory test facility. Results in all cases proved to be very accurate, verifying the robustness of the proposed method.**

***Index Terms*—Dynamic equivalencing, least-squares methods, mode estimation, ringdown analysis, system identification, system measurements.**

I. Introduction

THE identification of the oscillatory modes contained in a post-disturbance or "ringdown" response can provide vital information to assess the dynamic performance of the power system and plan measures to mitigate possible small-signal stability problems and reliability impacts [1].

Traditionally, power system modes are obtained by applying eigenanalysis on a detailed linearized model. However, this approach lacks of usability in cases of large power systems and real-time monitoring, due to the significant computational burden and the difficulties to keep the developed dynamic models updated over time and operating conditions. Other drawbacks also include the difficulty to limit the identification only to the modes of interest, neglecting possible surplus artificial modes, as well as limitations in cases of strongly nonlinear problems [2]-[4].

To overcome these weaknesses, measurement-based approaches have been proposed as supplementary solutions to directly estimate the dominant system modes from measured responses [5]. This technique gains significant interest considering the continuously increasing installation of phasor measurement units (PMUs), supported by global position system (GPS) and high-speed communication infrastructure in the form of wide-area measurement systems (WAMS) [4], [6]. In this context, real-time monitoring of power systems as well as the development of online dynamic equivalents [7] is possible using system identification techniques [4], [8]. The measurement-based approach also includes cases where model revalidation and calibration of power system components is required, providing a safer and more cost-effective alternative to staged tests [1]. Measurement-based methods can be generally classified into two main categories, in terms of the used type of data:

- Ambient-mode estimation methods that analyze responses excited by small load variations. Ambient data are continuously available through WAMS and intrude the least possible into power systems [9]-[11].
- Methods that perform analysis of ringdown responses occurred after a major disturbance, such as large load step-up, line-tripping, etc. The advantages of these methods are the high accuracy of the mode estimates and the fast convergence to the true values, since ringdown responses contain higher level of mode information density compared to ambient data [3], [12].

Several identification methods have been proposed to estimate the oscillatory modes from ringdown responses in power systems. The majority of them are based on the direct identification of model parameters from time-domain (TD) responses, with the most known being Prony method, originally proposed in [13], and later extended and improved to include transfer function applications and multiple output models [5], [14]-[17]. Other popular ringdown techniques include the minimal realization algorithm [18], the eigenvalue realization algorithm (ERA) [19], the matrix pencil method [20], the numerical algorithm for sub-space state-space system identification (N4SID) [21], and the prediction error method (PEM) [22]. Alternatively, in [23]-[25] the dominant modes are extracted in frequency-domain (FD) using the fast Fourier transform (FFT), combined also with the sliding window method for the estimation of the mode damping factor, while in [26] Hilbert-Huang transform is applied. Most of these methods use high-order models that contain additional artificial modes apart from the dominant ones. This is done to

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improve their estimation accuracy in noisy environments [5], however limiting their flexibility and applicability for automatic real-time monitoring and low-order modeling.

In this paper, a new hybrid FD/TD method is proposed to automatically identify the dominant modes contained in a power system ringdown and develop low-order models of the minimum required order. The basic idea of the proposed method is to obtain an initial estimate of the mode parameters and relocate them to more accurate values following an iterative procedure. Therefore, the hybrid method involves an initial step with the estimation of the mode parameters in FD. In the second step, the nonlinear least-squares (NLS) optimization procedure is applied to the TD ringdown. An iterative loop is used to find the best-fit model, containing the minimum required number of system modes. The advantages of the proposed method are:

1) It is a complete and compact identification technique, suitable for close to real-time monitoring and modeling;
2) The simultaneous estimation of all mode parameters, which ensures converging to optimal solution;
3) The automatic derivation of low-order models, excluding any surplus artificial modes in the estimate;
4) Its robustness, even in highly noisy environments, nonlinear responses and multimode signals or signals with very fast modes.

This paper is organized as follows: In Section II the background of ringdown analysis is presented and in Section III the proposed hybrid FD/TD approach is described. In Section IV sensitivity analysis is performed, while Sections V and VI verify the performance of the proposed method by means of Monte Carlo simulations using synthetic signals and responses from a large power systems model. In Section VII experimental results are used to test the applicability of the proposed method, while in Section VIII the paper conclusions are summarized.

II. Problem Formulation

A. Ringdown Response

Power systems are inherently nonlinear, complex and time-varying [3]. The ringdown response $y(t)$ of the nonlinear system following a perturbation can be approximated using system identification methods by function $\hat{y}(t)$, i.e. a sum of N damped sinusoids as follows [3]:

$$\hat{y}(t) = \sum_{i=1}^{N} A_i \cdot e^{\sigma_i t} \cdot \cos(\omega_i \cdot t + \varphi_i) \tag{1}$$

Essentially, system identification methods optimally fit a linear model to the actual response of the nonlinear system, where the subsequent calculated parameters $\lambda_i = \sigma_i \pm j\omega_i$ of (1) are the eigenvalues of a linear system. Specifically, $\omega_i = 2\pi f_i$ and σ_i are the angular frequency and the damping factor of the i-th mode, and A_i, φ_i are the corresponding amplitude and phase angle, respectively. Signal $y(t)$ can represent different system variables, such as the real and reactive power, bus voltage, etc. [22], [27]. By discretizing $\hat{y}(t)$, assuming $F_s = 1/T_s$ samples per second, N_w samples are generated and (1) can be written as:

$$\hat{y}[n] = \hat{y}(n \cdot T_s) = \sum_{i=1}^{N} A_i \cdot e^{\sigma_i n T_s} \cdot \cos(\omega_i \cdot n \cdot T_s + \varphi_i), \quad n = 0,1,\ldots,N_w - 1 \tag{2}$$

The unknown coefficients of (2) can be estimated in TD by means of NLS. In the NLS procedure, the response data are related to the predicted data by adjusting iteratively the nonlinear model parameters to minimize the summed square S of residuals (objective function) [28]:

$$S = \sum_{n=0}^{N_w-1} r_n^2 = \sum_{n=0}^{N_w-1} \left(y[n] - \hat{y}[n] \right)^2 \tag{3}$$

where r_n and $\hat{y}[n]$ are the residual and the predicted data of the n-th sample, respectively.

B. NLS Considerations

In the NLS procedure an initial estimation of the model parameters is required. It should be noted that during the optimization process local optimal solutions may occur, due to the inherent nonlinearity of the objective function [29]. The obtained local optimal solutions depend significantly on the guess of the initial values, thus their selection is critical for the accurate performance of the developed model. Although several approaches have been proposed [27], [28], only an initial estimation of the mode parameters close to the real ones can guarantee fast convergence to the real solution [22].

Moreover, the order of the model must be selected to include, if possible, only the dominant modes of interest in order to develop efficient low-order models which can be easily updated in real-time. This becomes a challenging task in highly noisy environments and especially when studying networks with distributed generation (DG), due to the higher frequency modes present in such systems and to the intermittent power of DGs, causing frequent changes in the network [22], [27].

III. Hybrid FD/TD Method

The algorithm of the proposed hybrid FD/TD method is depicted in the flowchart of Fig. 1. The parameter estimation procedure involves two main stages: At the first stage of the algorithm an initial estimation of the mode parameters in FD is performed, while at the second step NLS optimization is applied to the TD ringdown, following an iterative loop to find the best-fit model. Additionally, data preprocessing is applied prior to parameter estimation, especially in the case of measured responses. The rest of this section describes each step in detail.

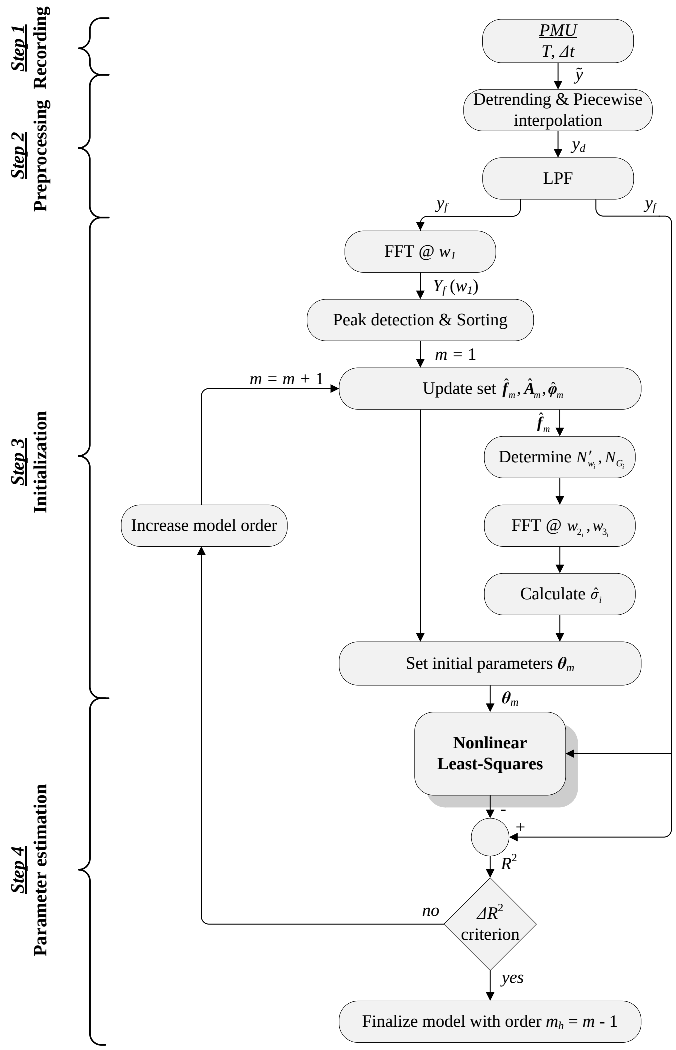

Fig. 1. Flowchart of the hybrid FD/TD algorithm.

A. *Signal Recording and Data Preprocessing*

The proposed hybrid FD/TD method can be applied for real-time automatic ringdown analysis and mode estimation using measurements. When a disturbance occurs, the resulting dynamic response is recorded using PMUs or ringdown analyzers [25]. In real-world conditions the measured ringdown response $\tilde{y}[n]$ contains, apart from the pure signal $y[n]$, the additive noise $\varepsilon[n]$ as described in (4).

$$\tilde{y}[n] = y[n] + \varepsilon[n] \tag{4}$$

Therefore, prior to parameter estimation, preprocessing is performed to focus on the low-frequency modes and improve the quality of the measured data by damping out the high-frequency components caused by noise and harmonics [22], [28], [29]. Preprocessing also increases the accuracy of the peak detection algorithm in the initialization step.

The dynamic response is first detrended and up-sampled by means of the shape-preserving piecewise interpolation technique. Signal detrending is used to remove the DC component and possible drifts in the response, as well as to improve the initial estimation of the damping factor [25]. Next, the signal is processed through a finite impulse response (FIR), zero-phase, low-pass filter (LPF) with an adjustable cut-off frequency f_c. The optimal choice of f_c depends on the range of the system time constants [28]. For a given network, f_c can be initially determined from historical data.

B. *Initialization*

In this paper the initial set of the mode parameters of (2) is estimated in the FD by means of the FFT and the sliding window method. Let us assume that the N_w samples of the signal response are recorded in the time period from t_1 to $t_1 + T_w$, corresponding to the wide window w_1. The observation time T_w is assumed large enough to contain most of the signal energy associated with the system oscillatory modes. The FFT of the signal calculated within this window is given by (5) using the efficient odd sampling scheme [30],

$$Y_{2k+1} = T_s \cdot \sum_{n=0}^{N_w-1} y_n \cdot e^{-j2\pi kn/N_w} \cdot e^{-j\pi n/N_w}, \quad k = 0,1,\ldots,N_w-1 \tag{5}$$

where:

$$y_n = y(n \cdot T_s) = \sum_{i=1}^{N} A_i \cdot e^{\sigma_i n T_s} \cdot \cos(\omega_i \cdot n \cdot T_s + \varphi_i) \tag{6}$$

To extract the dominant modes contained in the ringdown, a peak detection algorithm is applied to identify the peak power magnitudes associated with the resonant peaks in the resulted FD spectrum, according to the Nyquist - Shannon sampling theorem [23]. Each sample of (5) is compared to its neighboring values and a local peak is obtained when a sample element is larger than both of its neighbors. The detected frequency components are then sorted in descending order by means of their magnitude. In compliance with Parseval's theorem in (7), parameters f_i, A_i and φ_i of the i-th component are approximated by (8)-(10), respectively [23]-[25],

$$\sum_{n=0}^{N_w-1} |y[n]| = \frac{1}{N} \sum_{k=0}^{N_w-1} |Y_{2k+1}[k]| \tag{7}$$

$$\hat{f}_i = \arg\max_f \left(|Y_{2k+1}(\omega)| \right) \tag{8}$$

$$\hat{A}_i = \frac{2 |Y_{2k+1}(\hat{\omega}_i)| \Big|_0^{N_w-1}}{N_w \cdot T_s} \tag{9}$$

$$\hat{\varphi}_i = \operatorname{atan2}\left(\operatorname{Im}(Y_{2k+1}(\hat{\omega}_i)), \operatorname{Re}(Y_{2k+1}(\hat{\omega}_i)) \right) \tag{10}$$

where $\arg\max_f(\ )$ signifies the value of $\hat{f}_i$ which corresponds to a peak in $|Y_{2k+1}(\omega)|$. The large window w_1 is used to guarantee that most of the signal energy is included in the analysis, providing an accurate estimate of the mode parameters [25].

The corresponding mode damping factor σ_i is approximated using the sliding window technique. For each mode i, two additional smaller windows w_{2_i} and w_{3_i} of N'_{w_i} samples each are determined within window w_1 and are separated by a gap w_{G_i} of N_{G_i} samples. The size of N'_{w_i} corresponds to a window of $2/\hat{f}_i$ seconds in order to contain two periods of the i-th mode of interest, while N_{G_i} corresponds to a gap of $1/\hat{f}_i$ seconds [25]. Assuming that w_{2_i} starts at sample n_0 and ends at $n_0+N'_{w_i}$, whereas w_{3_i} starts at $n_0+N_{G_i}$ and ends at $n_0+N_{G_i}+N'_{w_i}$, the estimate $\hat{\sigma}_i$ of the i-th mode can be derived by:

$$\hat{\sigma}_i = \frac{\ln\left(\left|Y_{2k+1}\left(\hat{\omega}_i\right)\right|\Big|_{n_0+N_{G_i}}^{N'_{w_i}+n_0+N_{G_i}}\right)-\ln\left(\left|Y_{2k+1}\left(\hat{\omega}_i\right)\right|\Big|_{n_0}^{N'_{w_i}+n_0}\right)}{N_{G_i}\cdot T_s} \tag{11}$$

By calculating the mode damping factor, the initial set of parameters $\boldsymbol{\theta}_m = \left[\hat{\boldsymbol{f}}_m,\ \hat{\boldsymbol{A}}_m,\ \hat{\boldsymbol{\varphi}}_m\ \ \hat{\boldsymbol{\sigma}}_m\right]$ is defined, containing only the first m elements of the sorted mode parameters. Here, m denotes the m-th iteration of the algorithm, which is initially set equal to 1 and is updated by means of the parameter estimation criterion described in the next step.

C. Iterative Parameter Estimation

At this step the filtered TD signal response y_f is introduced into the NLS procedure with the initial set $\boldsymbol{\theta}_m$. The parameters of set $\boldsymbol{\theta}_m$ are adjusted successively to minimize (3) and the NLS process completes when either the change of the relative sum of squares is less than a specified tolerance, or when the maximum number of iterations is reached [28]. The NLS problem is simultaneously solved for all mode parameters of set $\boldsymbol{\theta}_m$, thus leading to an optimal solution, contrary to other two-step procedures, such as Prony analysis, matrix pencil and ERA [37]. The trust-region algorithm is adopted, since it is both fast and effective.

To find the best-fit model, including only the dominant modes contained in the ringdown and limiting any possible surplus modes due to noise, the parameter estimation process is performed through several iterations as shown in Fig. 1. In each iteration, the criterion $\mathit{\Delta} R^2 = R_m^2 - R_{m-1}^2$ between the last two successive steps is calculated, where R_m^2 is the coefficient of determination defined as:

$$R_m^2 = \left(1-\frac{\sum_{n=1}^{N}\left(y_f[n]-\hat{y}[n\,|\,\boldsymbol{\theta}_m]\right)^2}{\sum_{n=1}^{N}\left(y_f[n]-\bar{y}_f\right)^2}\right)\cdot 100\% \tag{12}$$

Note that R_0^2 is assumed equal to zero and that the algorithm completes when $\mathit{\Delta} R^2$ is less than the specified value. The resulting mode estimates by the hybrid FD/TD approach correspond to model order $m_h = m - 1$.

D. Multi-Signal Analysis

To analyze multiple signals using the proposed hybrid FD/TD method, the following procedure is adopted [11]: Let us assume a set of L signals, where $\ell = 1,2,\ldots,L$, that share a common set of modes. First, the hybrid FD/TD method is applied separately to each signal. Next, mode estimates are grouped, according to the corresponding mode frequency. For each group of modes, the final mode frequency and damping factor are calculated by means of the following weighted average functions:

$$\bar{f}_i = \sum_{\ell=1}^{L}\frac{E_\ell^i}{\sum_{\ell=1}^{L}E_\ell^i}\hat{f}_\ell^i \tag{13a}$$

$$\bar{\sigma}_i = \sum_{\ell=1}^{L}\frac{E_\ell^i}{\sum_{\ell=1}^{L}E_\ell^i}\hat{\sigma}_\ell^i \tag{13b}$$

where E_ℓ^i is the mode energy of the i-th mode of interest for the ℓ-th signal.

IV. Sensitivity Analysis

A sensitivity analysis is performed on testing signal 1 (TS1) to investigate the influence of the mode parameters on the ringdown and to indicate the required accuracy in the identification process [31]. TS1 contains one damped oscillatory mode with amplitude 1.0, damping factor -2.5 s^{-1}, mode frequency 3 Hz and angle $\pi/8$. The analysis is performed by introducing to each mode parameter of TS1 a 5 %, 10 % and 20 % error from its original value. The resulting R^2 between the estimated and the original signal is presented in Table I. Lower R^2 values show higher influence of the corresponding mode parameter. Results show that erroneous values of f_i result in the highest errors in the calculated dynamic responses, while the rest of the mode parameters do not have a significant effect. Based on the above analysis, it can be concluded that f_i is the most influential parameter and may significantly affect the simulated ringdown responses, thus must be identified with the highest possible accuracy.

TABLE I
COEFFICIENT OF DETERMINATION WITH VARIATION IN THE IDENTIFIED MODE PARAMETERS

Mode parameter	Error in mode parameters		
	5%	10%	20%
f	91.51	69.77	16.06
A	99.75	99.00	96.00
σ	99.88	99.55	98.4
φ	99.96	99.83	99.31

V. INTER-AREA MODE IDENTIFICATION WITH SYNTHETIC SIGNALS

A. *Mode Estimation with Noise*

The performance of the hybrid FD/TD method in the identification of dominant modes is evaluated using testing signal 2 (TS2), described by (14). The examined ringdown contains two modes to simulate inter-area oscillations in a transmission system [5]. The original pure signal of (14) is distorted by additive white Gaussian noise (AWGN) to simulate real measurement data. The variance of AWGN is adjusted to represent different levels of signal-to-noise ratio (SNR) from 3 to 30 dB [32]. For each noise level, 100 Monte Carlo (MC) simulations are performed to statistically evaluate the accuracy of the mode estimates.

$$y(t) = \underbrace{2e^{-0.1102t}\cos(2\pi\cdot 0.25\cdot t + 1.5\pi)}_{\text{mode \#1}} + \\ + \underbrace{2e^{-0.1596t}\cos(2\pi\cdot 0.39\cdot t + 0.5\pi)}_{\text{mode \#2}}, \tag{14}$$

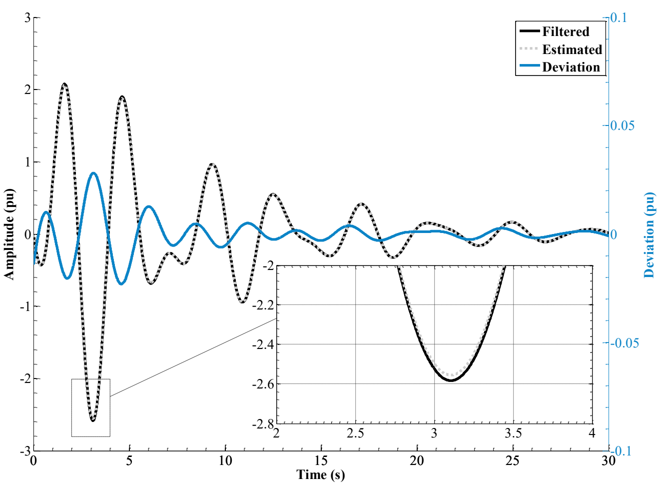

Fig. 2. Comparison of estimated and original ringdown responses.

Dataset elements of TS2 are generated at a rate of 100 samples/s (sps), to simulate a realistic PMU data stream, assuming total observation time of 30 s. The signal record is detrended, up-sampled to 1000 sps and low-pass filtered with a cut-off frequency at 3 Hz. From the Fourier spectrum of the signal for the window *T*, the corresponding initial mode parameters are estimated with windows $w_{2_i}(=w_{3_i})$ equal to 8.573 s and 5.454 s, while the gap windows w_{G_i} are equal to 4.286 s and 2.727 s for modes #1 and #2, respectively. The modal estimation process is carried out assuming tolerance of ΔR^2 = 1 %. This value is selected as default to guarantee high accuracy. The proposed algorithm performs three iterations, resulting in a model order of m_h = 2 i.e. equal to the number of the dominant modes. The identified mode parameters are used to simulate the TD response. In Fig. 2 one instance of the estimated ringdown responses is compared to the filtered signal $y_f[n]$ of (14). Negligible differences are observed, since the deviation curve in the same figure indicates the high accuracy of the estimated results. The deviation curve between the filtered and the estimated response is defined in (15).

$$dev[n] = \hat{y}[n] - y_f[n] \tag{15}$$

B. *Effect of ΔR^2 Criterion*

An important user-defined model property is the ΔR^2 criterion, which determines the resulting model order. To investigate the effect of ΔR^2 on the performance of the hybrid technique, the identification process of the previous case is performed again assuming different number of iterations *m*. In Figs. 3a and 3b the average values of ΔR^2 and the resulting R^2 are illustrated, respectively, using the MC method for different SNR levels. Note that the *x*-axis in Fig. 3a corresponds to the number of iterations *m*, while in Fig. 3b to the corresponding model order m_h, i.e. $m_h = m - 1$.

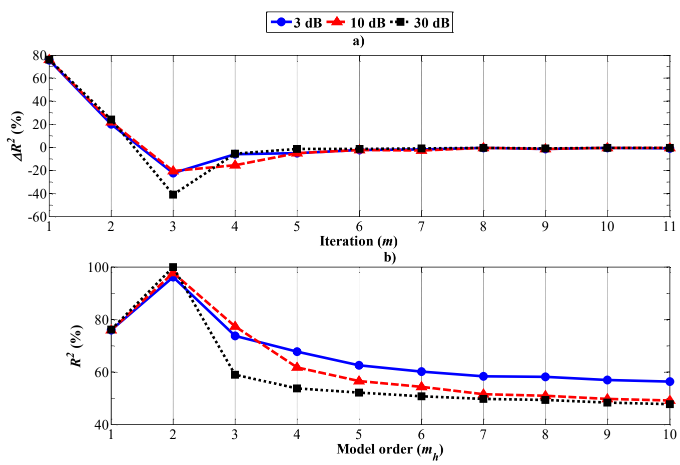

Fig. 3. Influence of model order, a) ΔR^2, b) R^2.

It is evident that at the 3-rd iteration (*m* = 3), i.e. for m_h = 2, results are very accurate for all SNR levels, since R^2 is over 99 % and ΔR^2 is lower than 1 %. In this case only the dominant oscillatory modes contained in the ringdown are identified and no surplus modes are included. A further increase in the model order leads to significant model performance degradation, since the surplus modes result in over-fitting of the model data. The analysis indicates that the proposed algorithm presents a fast convergence using iteration steps and ensures the accurate identification of the minimum number of dominant modes contained in the ringdown, by choosing a relatively small value for ΔR^2, such as 1 % - 5 %.

C. *Effect of the Initial Estimation*

The significance of the initial modal parameter estimation is investigated considering test cases (TC) TC1, TC2 and TC3. In TC1 the proposed initialization procedure is followed, in TC2 only the mode frequency components as initial parameters are considered, i.e. the most influential mode parameters, and in TC3 random initial mode parameters are used. In all TCs, m_h is equal to 2 for consistency in the comparisons. In Tables II and III the initial mode parameters and the calculated R^2 values with the hybrid method are presented respectively for the three TCs, using one instance of the ringdown responses. Results verify the significance of the mode frequency component estimation close to the original values as indicated by the sensitivity analysis. Moreover, results reveal that an initial mode estimation diverging greatly from the original values may lead to poor results in the parameter estimation of Step 4 in Fig. 1 and cannot guarantee algorithm convergence without the inclusion of surplus modes.

Note that in TC1 the FD method of [23]-[25] is used for the initial mode estimates in the first step of the hybrid method. In this step, the calculated R^2 is 43.74 %, while significant differences are observed in the mode damping factor and amplitude, compared to the original mode values of (14). It is evident that the second step of the hybrid method (iterative NLS optimization) significantly improves the mode estimates. On the other hand, the algorithm complexity and computational burden is increased in the hybrid method. The computational burden in an Intel Core i7-4770, 3.4 GHz, RAM 8 GB personal computer using MATLAB implementation is 4859 ms using the hybrid method, while for the FD method is 96.97 ms.

TABLE II
INITIAL MODE PARAMETERS FOR DIFFERENT INITIALIZATION CASES

Mode Parameter	TC1		TC2		TC3	
	mode1	mode2	mode1	mode2	mode1	mode2
σ (1/s)	-0.008	-0.279	-	-	-0.075	-0.240
f (Hz)	0.233	0.323	0.233	0.323	0.091	0.608
A (pu)	0.913	0.158	-	-	0.69	0.606
φ (rad)	0.965	0.632	-	-	0.713	0.637

TABLE III
RESULTING R^2 VALUES

	TC1	TC2	TC3
R^2 (%)	99.96	99.90	56.38

D. Effect of Sampling Rate

In this section the effect of the sampling rate on mode estimation is analyzed. The proposed method is applied to identify the modes of TS2, assuming different sampling rates for the SNR levels 30 dB, 10 dB and 3 dB. The R^2 curve of the simulated dynamic responses is plotted against the sampling rate in sps in Fig. 4a.

In general, significant increase of R^2 is observed for increasing sampling rates up to 100, where R^2 exceeds 95 %. Further increase of the sps improves the simulated responses for cases of low SNR levels, while for high SNR levels results are practically unaffected. This is also analyzed in Fig. 4b where the %PE is plotted for SNR = 3 dB. It is shown that for all mode parameters the %PE is significantly lower than 1 % when sps is higher than 100. The analysis indicates that signal up-sampling can generally improve the estimation accuracy. All results presented in the previous analysis correspond to the average values obtained from the MC simulations.

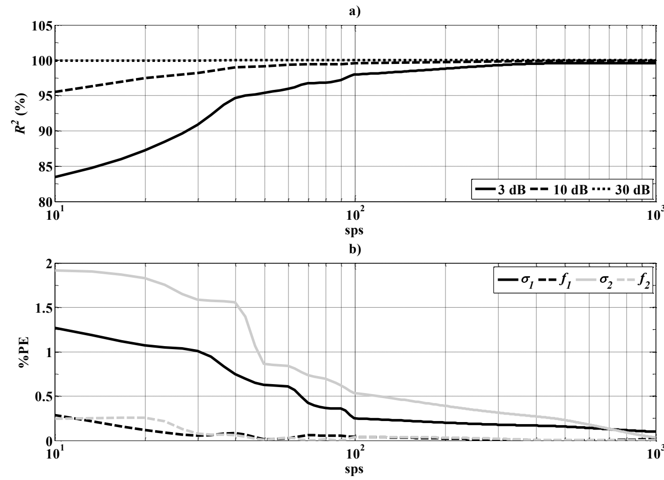

Fig. 4. Effect of sampling rate: a) R^2 against sps, b) mode %PE against sps for SNR = 3 dB.

E. Comparison with Other Methods

The performance of the proposed hybrid FD/TD method is evaluated and compared with three other mode estimation algorithms, namely the Prony method, N4SID and PEM of the MATLAB system identification toolbox.

Prony method has been widely used to estimate oscillatory modes from ringdown responses in power systems [13]. Briefly, a ringdown response is transformed to z-domain to construct a discrete time prediction model that fits the response. The roots of the characteristic polynomial of the prediction model are determined and are associated with the system eigenvalues and the complex residues [13].

N4SID belongs to the general class of sub-space methods and has been recently used to identify power system modes [21]. The system matrices of a linear state-space model are estimated using input/output data from measurements, by properly separating them into signals and noise sub-spaces. As a nonlinear optimization algorithm, N4SID is fast but also non-iterative [33].

PEMs are iterative methods and use a sequence of past input-output data to predict the next one-step system output. The system parameters are estimated by minimizing the distance between the predicted and the measured outputs. The PEM algorithm in MATLAB starts the identification process using an initial estimation obtained by N4SID [28].

All algorithms are tested to identify the dominant modes contained in TS2 for different noise levels using the MC method. The resulting mean (μ) and standard deviation (std) of the estimated damping factor and mode frequency for the two modes across the four algorithms are compared in Tables IV and V for SNR equal to 30 dB and 10 dB, respectively.

TABLE IV
COMPARISON OF THE IDENTIFIED EIGENVALUES FOR SNR 30 dB

	σ_1	f_1	σ_2	f_2	Order
Hybrid FD/TD					
μ	0.1102	0.2500	0.1596	0.3899	2
std	8.61E-5	0.0000	0.0001	1.83E-5	0
Prony					
μ	0.1113	0.2500	0.1612	0.3900	3
std	0.0035	0.0000	0.0045	0.000	1
PEM					
μ	0.1104	0.2494	0.15304	0.3895	3
std	0.0033	0.0006	0.0054	0.0014	0
N4SID					
μ	0.1009	0.2502	0.1606	0.3865	10
std	0.0061	0.0009	0.0088	0.0011	0

From Tables IV and V as well as by comparison to the original mode parameters of (14) it can be noticed that the proposed method provides very accurate results for both signal levels, since the mean %PE is lower than 1 % for all mode parameters. Similar accuracy to the mode estimates is also obtained with Prony and PEM for SNR = 30 dB. However, for lower SNR levels noticeable performance degradation is observed for both of these methods and especially for Prony. N4SID generally shows inferior performance, both in terms of accuracy of the estimate and the model order. The hybrid FD/TD method presents also high performance in terms of variance for both noise levels and most significantly ensures the inclusion of only the dominant modes of interest, compared to all other methods.

TABLE V
COMPARISON OF THE IDENTIFIED EIGENVALUES FOR SNR 10 dB

	σ_1	f_1	σ_2	f_2	Order
Hybrid FD/TD					
μ	0.1103	0.2499	0.1606	0.3902	2
std	0.0007	8.98E-5	0.0013	0.0014	0
Prony					
μ	0.1022	0.2507	0.1613	0.3903	18
std	0.0395	0.0025	0.0413	0.0032	1
PEM					
μ	0.1093	0.2501	0.1475	0.3888	4
std	0.0061	0.0014	0.0128	0.0018	1
N4SID					
μ	0.0907	0.2488	0.1584	0.3832	20
std	0.0253	0.0023	0.0363	0.0051	3

To further assess the robustness of the proposed hybrid method under different noise conditions, the μ and *std* of the damping factor and mode frequency estimates are plotted in Fig. 5 as a function of SNR. The colored range represents the standard deviation of the estimation, while the central lines the mean value. The variance of the mode estimate increases slightly as the SNR decreases, while the mean value remains practically unaffected. For the frequency estimation the *std* is of order 10^{-7} to 10^{-3}, while for the damping factor the *std* is lower than 10^{-3} in all cases. Therefore, it is important to conclude that the accuracy of the frequency and damping factor estimates of both modes is adequately high, even for cases of low SNR levels.

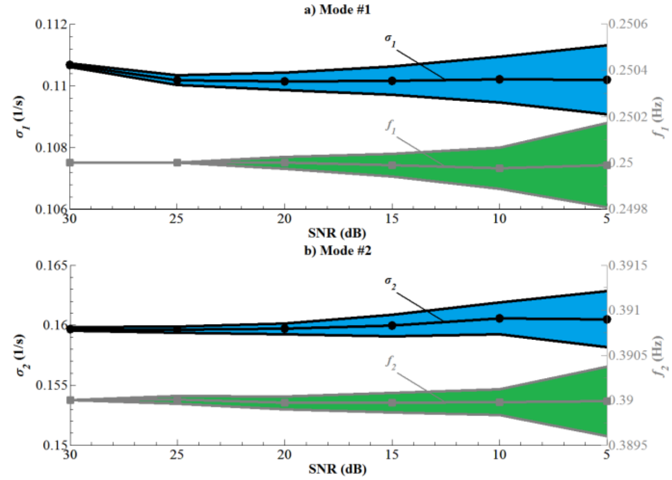

Fig. 5. Effect of noise on mode parameter estimation, a) mode #1, b) mode #2.

The average processing time using the same PC as previously is 860 ms, 2570 ms and 4960 ms, considering 3000, 15000 and 30000 samples, respectively. Although a large PMU data stream of 30 s is analyzed, the CPU process time remains relatively small, allowing the online application of the hybrid algorithm.

VI. SIMULATION STUDY IN AN EXTENDED MULTI-MODAL SYSTEM

The scalability of the hybrid FD/TD method is tested in a complex multi-machine power system. The system used is the IEEE 39 New England power grid model [34], consisting of 39 buses and 10 generators. The power system, including all dynamics of the generators and the associated controls, is implemented in the NEPLAN software [35]. The proposed method performance is evaluated for small and also severe disturbance cases. Additionally, in order to investigate the true small-signal dynamics of the system and calculate the corresponding system modes [36], the simulation model is linearized into a linear model represented by 100 states, using the eigenvalue analysis module of the NEPLAN software. The resulted dominant oscillatory modes are at 0.582 Hz, 1.129 Hz, 1.36 Hz and 1.595 Hz with damping factor -0.511 s^{-1}, -1.36 s^{-1}, -1.62 s^{-1} and -1.91 s^{-1}, respectively.

Initially, ringdown responses are generated by increasing 30 % the load power at Bus 21 for 1.5 s. In order to investigate real-world conditions, ambient data caused by small load variations are added to the simulated pure ringdown response according to (4) with SNR = 10 dB. Ambient data are generated by low-pass filtering Gaussian noise at a cut-off frequency of 2.5 Hz [12]. To simulate the random behavior of load variations a set of 100 random responses is used by means of the MC method. In Fig. 6 one instance of the simulated transferred real power response from Bus 05 to Bus 06 is illustrated. In the same figure the corresponding deviation curve calculated by means of (15) is also presented.

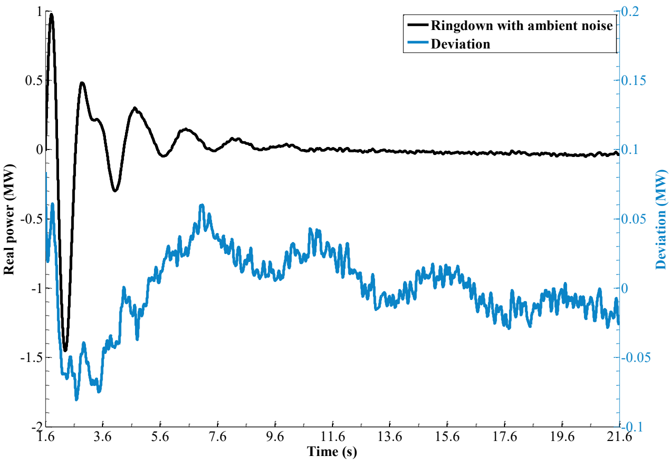

Fig. 6. Instance of ringdown response with ambient data and deviation curve.

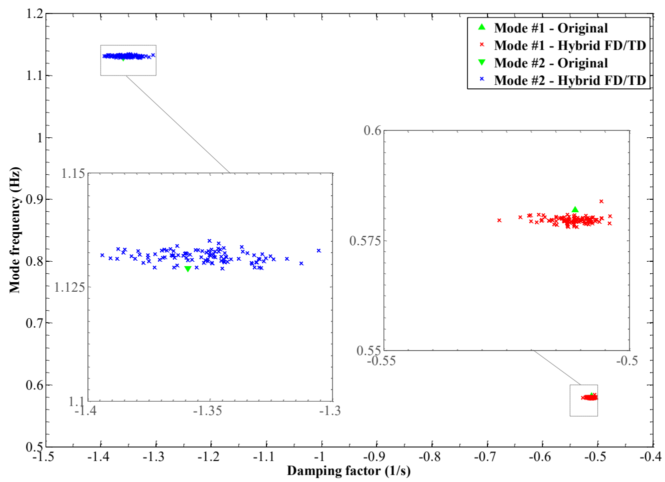

Fig. 7. Identified modes from ringdown responses using 100 MC simulations.

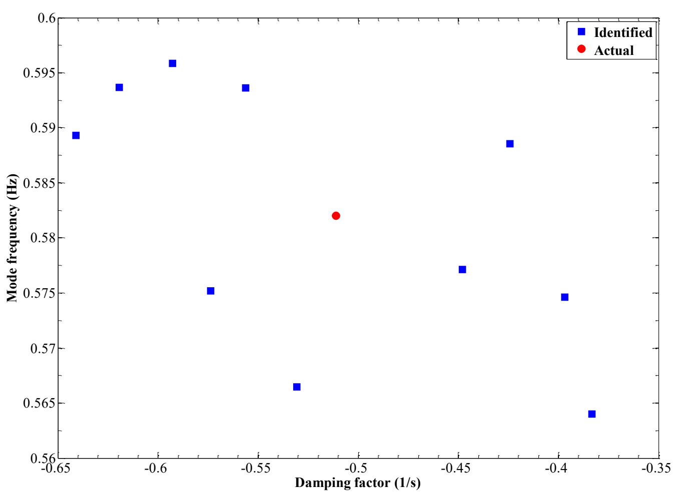

Fig. 8. Identified inter-area mode from different ringdown responses.

In all MC simulations the hybrid FD/TD algorithm converges into three iterations, assuming tolerance $\Delta R^2 = 1$ %. Therefore, the number of the most significant modes contained in the ringdown, describing sufficiently enough the examined response is two, as summarized in Fig. 7. The parameters of the identified modes are in the vicinity of the eigensolution oscillatory modes at 0.582 Hz and 1.129 Hz, whereas the range of the estimated R^2 is from 99.05 % to 99.89 %, indicating the accuracy of the method. The μ and *std* of the estimated damping factor and frequency of the two identified modes are shown in Table VI.

The multi-signal approach of the proposed method is evaluated using 10 sets of noisy ringdowns, recorded at different positions in the system. The mode estimates of the common dominant mode among the responses as well as the corresponding actual value are shown in Fig. 8. The mode frequency and damping factor estimates for the combined multi-signal analysis are 0.583 Hz and -0.514 s^{-1}, respectively, showing that the added information in the multi-signal analysis improves slightly the calculated results.

Next, the performance of the hybrid FD/TD method is investigated for the case of ringdown responses caused by a severe disturbance. For this purpose a solid three-phase fault is applied at t = 0.5 s at Bus 21 of the power system and is cleared at t = 0.7 s. The time-frame used in the analysis is from t = 1.2 s to t = 20 s.

TABLE VI
DOMINANT IDENTIFIED MODES

	Mode #1		Mode #2	
	σ_1	f_1	σ_2	f_2
μ	-0.512	0.580	-1.353	1.132
std	0.0039	7.6e-04	0.0181	0.0012

In Fig. 9 the simulated real power responses transferred from different buses are compared to the corresponding estimated by the hybrid FD/TD. In Fig. 9a the transferred real power response is described by a single mode, while in Figs. 9b and 9c by two and three dominant modes, respectively. Further details on the examined buses are given in Fig. 9. The SNR is 30 dB, since high SNR levels are typically observed in case of large disturbances [37]. It can be seen that the original simulated responses and the estimated by the hybrid FD/TD match almost perfectly in all cases, while R^2 is higher than 99 %, verifying the applicability of the proposed method even for highly nonlinear responses. In this test case, the average identification time for the ringdown responses of Figs. 9a, 9b and 9c is calculated at 1027 ms, 1266 ms and 4399 ms, respectively, considering 10000 samples. It is shown that the processing time is increasing in a nonlinear way with the number of the dominant modes contained in the ringdown, due to the increased number of iterations.

In Table VII the damping ratio and frequency estimates of the common dominant mode among the three responses throughout the event are summarized. Also in this Table, the corresponding results obtained by Prony, PEM and N4SID methods are presented. In general, the proposed method yields results with similar accuracy compared to the three identification techniques. However, the model order required for Prony, PEM and N4SID is in all cases higher compared to the hybrid FD/TD. Note that the inherent system nonlinearities have changed the oscillation characteristics and especially the mode damping factor from the corresponding of the small-signal dynamics case [36].

TABLE VII
ESTIMATED DOMINANT MODE DAMPING RATIO (%) AND FREQUENCY (HZ)

Response	Hybrid FD/TD	Prony	PEM	N4SID
Bus 01 - Bus 02	27.03 % @ 0.59 Hz	26.97 % @ 0.59 Hz	28.45 % @ 0.56 Hz	28.41 % @ 0.56 Hz
Bus 16 - Bus 19	26.49 % @ 0.58 Hz	28.42 % @ 0.56 Hz	27.04 % @ 0.57 Hz	27.07 % @ 0.57 Hz
Bus 05 - Bus 06	27.60 % @ 0.58 Hz	26.98 % @ 0.59 Hz	27.93 % @ 0.57 Hz	27.93 % @ 0.57 Hz

To further demonstrate the influence of the model order on the performance of the proposed method, the identification process for the case of the ringdown response of Fig. 9c, is analyzed in Table VIII and in Fig. 10. Different numbers of iterations are considered, resulting to different number of identified oscillatory modes and model order. The six dominant modes identified for seven iterations are listed in Table VIII. Assuming ΔR^2 = 1 % the proposed method can converge into four iterations, thus the resulting number of the identified modes is three (m_h = 3). A further decrease of ΔR^2 results in the inclusion of the additional modes #4, #5 and #6. However, it is evident that results are not practically improved, since the estimated responses for m_h = 3 and m_h = 4 overlap, as shown in Fig. 10. Therefore, in the plots for the case of the 5th and 6th model are not presented.

TABLE VIII
DOMINANT MODES FOR REAL POWER RESPONSE FROM BUS 05 TO BUS 06

Mode parameters	Modes					
	#1	#2	#3	#4	#5	#6
σ (1/s)	-0.775	-0.844	-3.865	-1.689	-0.292	-27.04
f (Hz)	0.5766	1.1587	1.1463	2.227	3.6447	0.0002
A (pu)	0.7041	0.7319	0.9026	0.0242	1.1E-5	3.72
φ (rad)	-0.799	-0.979	2.8894	13.724	-3.614	7.849

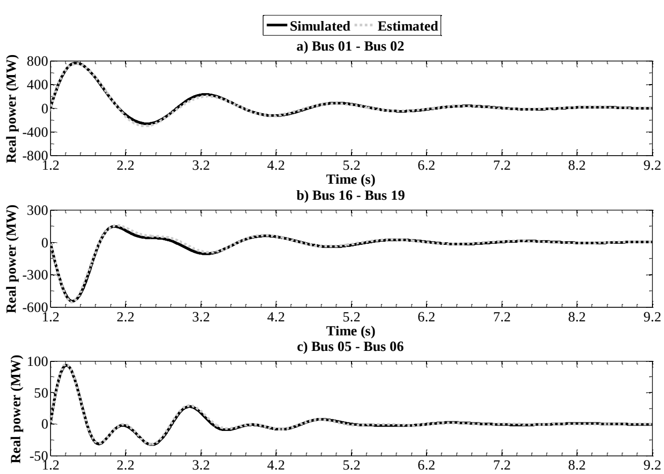

Fig. 9. Comparison of simulated by NEPLAN and fitted ringdown responses.

To investigate the dynamic variability of the dominant modes in a power system, the hybrid FD/TD method is applied at different time positions of a recorded signal by sliding the wide window w_1 [13] and applying successively the identification procedure. In Table IX the identified dominant modes for a sliding-window analysis are presented assuming a wide window length equal to 10 s and tolerance ΔR^2 = 1 %. Results for the ringdown response of Fig. 9c show that the inter-area mode at 0.58 Hz is strongly involved in all cases and the mode damping factor gradually tends to the original value with the window time position, as generators return to their normal operation.

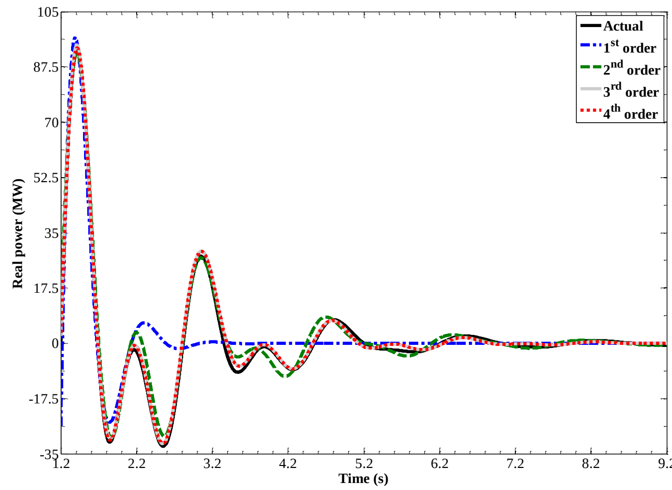

Fig. 10. Estimated ringdown responses for different number of modes.

TABLE IX
DOMINANT MODES FOR REAL POWER RESPONSE FROM BUS 05 TO BUS 06

Window time position	Modes					
	#1		#2		#3	
	σ	f	σ	f	σ	f
1.2 s	-0.775	0.5766	-0.844	1.1587	-3.865	1.1463
1.957 s	-0.817	0.5824	-0.821	1.167	-	-
3.086 s	-0.470	0.5709	-1.010	1.1513	-	-
3.625 s	-0.564	0.5759	-1.234	1.1275	-	-
4.815 s	-0.500	0.5800	-1.143	1.1877	-	-
5.472 s	-0.526	0.5805	-1.210	1.1710	-	-

VII. APPLICATION TO REAL MEASUREMENTS

To test the applicability of the hybrid FD/TD method, it is used to analyze measured responses obtained from a 400 V, 50 Hz, laboratory-scale microgrid (MG). The MG can operate either interconnected to a weak distribution system or in islanded mode. It consists of a 2 kVA synchronous generator, a 10 kVA inverter, a 5 kW/3.75 kVAr static load bank (SL) and a 2.2 kW, 0.87 lagging asynchronous machine. In islanded mode an additional 80 kVA synchronous generator is connected to the MG in order to provide voltage and frequency support. Both the rotating and the inverter-interfaced units follow an *f-P*, *V-Q* droop control scheme. Signals of different system variables, e.g. real and reactive power, frequency, etc., are recorded with a rate of 500 sps. Further details on the MG system and the experimental setup can be found in [22], [27].

The mode parameters of the real and reactive power responses are identified for different disturbance levels, caused by step-ups on the SL, ranging from 5 % to 50 %. All laboratory tests are repeated 20 times for each disturbance level, both for the grid-connected and the islanded mode of operation. Therefore, a total number of 120 responses comprise the data set for each system response. The hybrid method is applied to the measured data, considering observation time of 1.5 s and 5 s for the grid-connected and the islanded mode respectively. The measured real and reactive power responses are passed through the corresponding LPFs, each of order 100 with cut-off frequencies at 5 Hz and 20 Hz, respectively.

In Figs. 11 and 12 one instance of the real and reactive power response is shown for the 40 % increase in the SL, for the islanded and the grid-connected modes of operation, respectively. Specifically for the islanded case, in all disturbances two dominant modal components are required to describe accurately both the real and reactive power responses. In the grid-connected case, the real power response is described by a single complex modal component, while the reactive power by two.

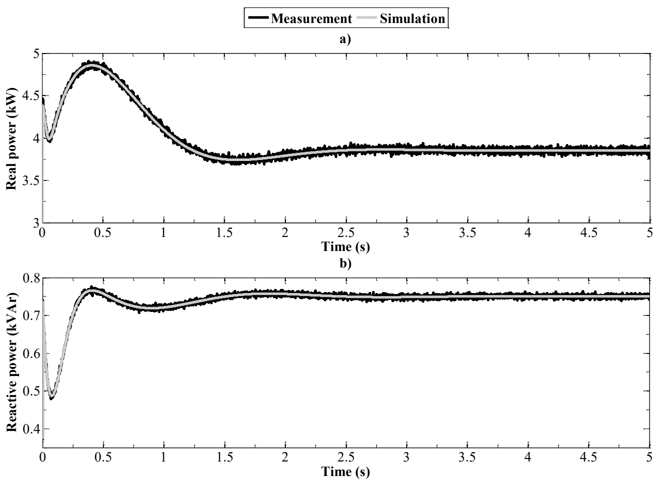

Fig. 11. Measured and estimated dynamic responses of a) real and b) reactive power. Islanded mode of operation.

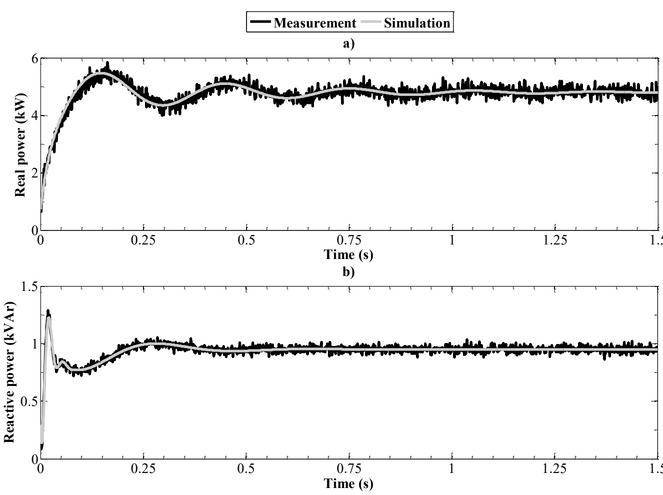

Fig. 12. Measured and estimated dynamic responses of a) real and b) reactive power. Grid-connected mode of operation.

The dominant modes of the real and reactive power identified for the set of the 120 responses for the islanded case are summarized in Fig. 13. For the grid-connected case, the estimation results for the damping factor and frequency of the three modes are analyzed in the boxplots of Figs. 14 and 15, respectively. In all cases the drift of the mode parameter values is due to the changes of the loading condition and generation unit operating points during the disturbance [23]. Additionally, in Table X the range of the resulting R^2 is presented for each disturbance level.

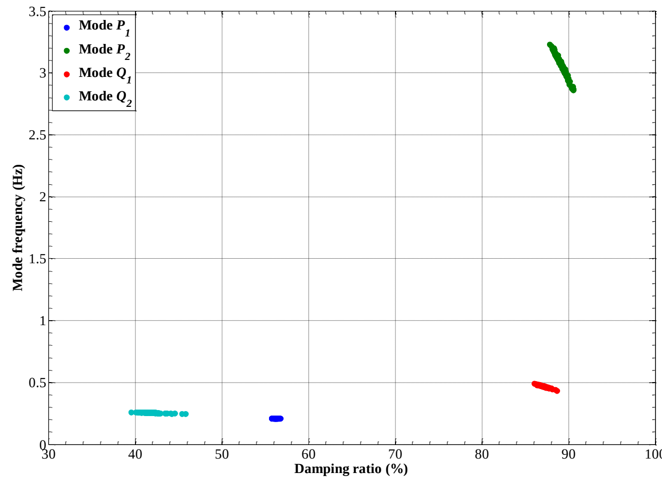

Fig. 13. Identified dominant modes from real and reactive power responses of the islanded mode of operation.

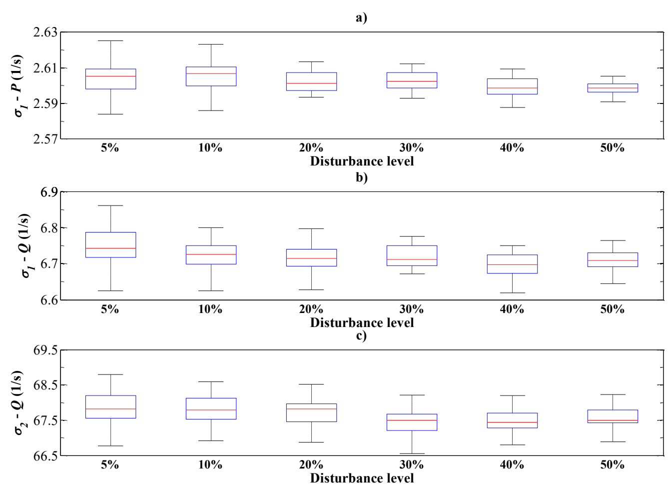

Fig. 14. Boxplots of damping factor estimation for the grid-connected mode of operation.

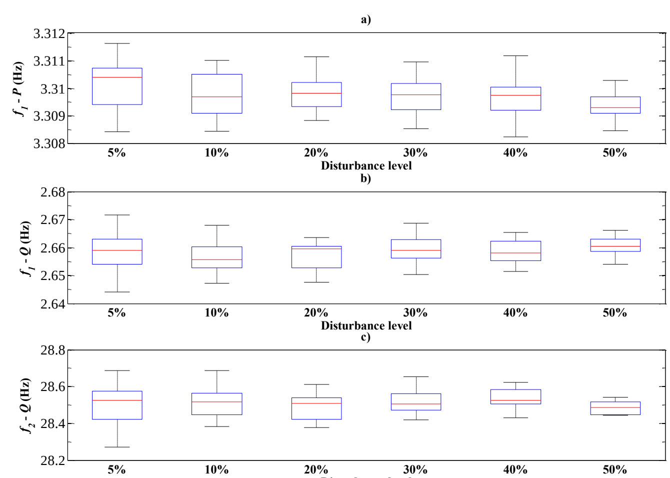

Fig. 15. Boxplots of frequency estimation for the grid-connected mode of operation.

All above results show that the hybrid FD/TD method can be successfully applied for mode estimation of different signal types and operating conditions of the MG. This is a much more complex task compared to conventional transmission systems, due to the significant high damping ratio of the system modes. Therefore, the proposed method can be used either for mode estimation or to facilitate the development of online black- and grey-box models [22], [27]. Generally, the estimation accuracy increases with the disturbance level, as indicated by the R^2 results. The performance of the hybrid method is satisfactory even for small disturbance levels, i.e. for the 5 % and 10 % cases, thus its application can possibly be extended to ambient data responses. The boxplot analysis reveals that the variance of the mode damping factor and frequency decreases with the disturbance level. Therefore, the accuracy of the mode estimates increases with the disturbance level. Specifically the mode frequency estimates are more accurate than the damping factor, while their accuracy decreases with the mode frequency.

TABLE X
RANGE OF ESTIMATED R^2

	Islanded		Grid-connected	
Disturb.	**Real power**	**Reactive power**	**Real power**	**Reactive power**
5 %	99.33 - 99.72	99.11 - 99.54	99.70 - 99.93	97.61 - 97.78
10 %	99.72 - 99.87	99.74 - 99.98	99.77 - 99.93	97.58 - 97.85
20 %	99.05 - 99.72	99.82 - 99.99	99.79 - 99.94	97.61 - 97.82
30 %	99.02 - 99.73	99.16 - 99.91	99.84 - 99.94	97.58 - 97.76
40 %	99.68 - 99.73	99.36 - 99.84	99.83 - 99.94	97.61 - 97.77
50 %	99.59 - 99.72	99.85 - 99.99	99.85 - 99.93	97.64 - 97.81

VIII. CONCLUSIONS

In this paper a new hybrid FD/TD method is proposed and formulated to automatically identify the dominant modes contained in ringdown responses, obtained from either synchrophasors or simulation results. The proposed method is applied to multiple case studies, including synthetic signals as well as multimodal nonlinear systems, and is compared with other mode identification algorithms. The performed sensitivity analysis shows that the initial estimate of the mode frequencies mostly affects the performance of the NLS identification procedure and must be estimated with the highest possible accuracy, as guaranteed by the proposed scheme. The proposed method is also extended for multi-signal analysis to accommodate and handle the increasing number of PMU measurements. The major advantages of the proposed hybrid FD/TD method are:

1) The hybrid method involves both FD and TD methods. It implements a close to the real values initial estimation of the mode parameters in FD, especially for the mode frequency, which is the most significant parameter for mode identification. At the second step, all mode parameters are calculated simultaneously by means of NLS optimization. The combination of the above techniques guarantees convergence to the optimal solution. Although the second step increases the algorithm complexity, it significantly improves the estimation of the mode parameters compared to the mode estimates extracted only in the FD.
2) Low-order models, containing the dominant modes of the ringdown, are automatically derived by combining dominant mode identification in the FD and NLS optimization through iterations. Additionally, a preprocessing step is introduced to improve the quality of the measured dataset and enable the proposed method to be applied in real-world conditions. Apart from an initial set up of the used LPFs, no other user interaction is required for the application of the method.
3) It provides very accurate results with small variance in the mode estimates, as shown via Monte Carlo simulations. This advantage of the method becomes more significant as the SNR decreases.
4) The method is very robust considering the noisy conditions, the type and the level of the examined ringdown response. The accuracy of the method has been verified for different SNR levels and for signals related to different system variables, such as real and reactive power, different power system configurations from large power systems to MGs operating in grid-connected or islanded mode, as well as to linear and nonlinear responses.
5) The method is numerically stable and efficient, converging fast with relatively small execution times.

Therefore, the proposed method combined with the preprocessing procedure create a new reliable tool, suitable for the online monitoring of power system characteristics and the automatic analysis of ringdown responses to accurately estimate the system modes under real-world operating conditions.

Further work will be carried out to investigate the applicability of the proposed method to ambient data analysis. A possible combination of the results obtained from both ambient and ringdown data analysis into an integrated algorithm may lead to improved accuracy and efficiency on the mode estimates, and also enhance the performance of WAMS under different operating conditions.

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