Higher Order Dynamic Mode Decomposition for Robust Parameter Estimation in Power Grids

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***Abstract*—To ensure the stability, control and quality performance of the electrical system, it is important to monitor the fundamental parameters such as frequency and amplitude. The current research provides a data-driven hybrid technique for the extraction of fundamental parameters using the Higher-order dynamic mode decomposition (HODMD) algorithm in smart grid. HODMD's capacity to account for non-linearities enables it to produce accurate representations of the underlying dynamics, resulting in better model estimation. Thus HODMD is an appropriate method for power quality analysis due to its capacity to analyze multidimensional data and non-uniformly sampled data. In this work, the potential of HODMD is examined for the estimation of fundamental frequency, amplitude, and the existence of disturbance components, such as harmonics. In the proposed methodology, HODMD modes are computed using the low-rank approximation and then extracted the amplitude and frequency information from the data. The hyper parameters of the proposed methodology are properly tuned to get an accurate estimate of the underlying parameters. The optimistic results on various synthetic and real-time scenarios indicate that the proposed methodology can be used to estimate the power system frequency and amplitude in general periodic and quasi-periodic dynamics.**

***Index Terms*—Power quality, power system stability, higher order dynamic mode decomposition, Hankel matrix, singular value decomposition.**

I. Introduction

In the dynamic and ever-changing landscape of modern energy distribution, power grids play a critical role in guaranteeing the uninterrupted flow of electricity to fulfill our daily needs. The massive networks of generators, transformers, and transmission lines are the invisible arteries that supply power to our homes, industries, and technologies. Microgrid (MG) coupled with renewable energy sources, cutting-edge flexible AC transmission devices, high-voltage DC transmission lines, and adaptable load management, are ushering in a new era [1]. These innovations do not just meet the surging power demands, they transform the way we think about transmission capabilities and cater to an array of consumer needs [2]. As we continue to expand our generation capacity to accommodate the ever-growing load demand, the grid finds itself at the crossroads of vulnerability, grappling with issues related to quality, reliability, stability, control, and protection [3]–[5].

The frequencies and amplitudes serve as fine-tuned conductors in the symphony of electrical currents pouring across power networks, orchestrating the harmony of a stable and reliable energy supply [6] [7]. Amplitudes describe the strength of these harmonies, whereas frequencies represent the melodic cadence of generators and loads. These characteristics act as a compass, directing power engineers and grid operators through the flow of energy. Accurate frequency evaluation ensures synchronized energy exchange while also detecting abnormalities and minimizing potential instabilities. Similarly, amplitude estimation provides information on the strength of these oscillations, revealing possible stress areas that must be carefully monitored and managed [8]–[11].

Power system complexity along with noise, nonlinearities, and transient events, presents tremendous hurdles to accurate frequency and amplitude estimation [12]. Traditional methodologies frequently fail in the face of such complexities, leaving a gap in our understanding of grid behavior. HODMD is a mathematical tool that investigates system multi-frequency dynamics [13]. Unlike traditional approaches, which sometimes ignore entangled frequency components, HODMD has the unique ability to extract various frequency modes, and thus provide a complete picture of the system's behavior. This new innovation makes use of the capacity of data-driven analysis to reveal insights that not only improve our understanding of complex systems but also give us the skills to forecast their behavior with unparalleled accuracy.

II. Related Works

Numerous techniques have been suggested for the estimation of amplitude and frequency within power systems. Detecting zero-crossings is a straightforward and fundamental approach for estimating frequency and amplitude. However, in real-time circumstances, harmonic and noise contamination causes errors in zero-crossing recognition [14]. Although Fourier-based techniques are frequently utilized for estimating power system parameters, their effectiveness on time-varying, non-stationary power data is inadequate. Spectral leakage, the picket-fence effect, and prior knowledge of system frequency are a few of the issues that restrict the performance of Fourier-based techniques [15]. Additionally, Fourier techniques often struggle to accurately detect the inter and sub-harmonics existing in power data [5]. Prony examination can be utilized to assess recurrence and abundance. Nonetheless, it experiences issues in assessing complex signals. Weighted least-squares and least-squares-based approaches can be utilized to assess signal boundaries. The incorporation of inverses builds the computational intricacy of least-squares and weighted least-squares calculations [16].

A detailed survey of different strategies for harmonic and inter-harmonic scenarios is presented in [14]. For the investigation of parameter estimation in power grid scenarios various techniques such as fuzzy adaptive filtering [17], band-pass second-degree computerized integrator [18], empirical mode decomposition (EMD) [19], empirical wavelet transform (EWT) [20], sparse signal decomposition (SSD) [21], variational mode decomposition [22], are proposed. The afore-mentioned methods are less effective due to various factors, including their ineffectiveness in noisy conditions, limited frequency range, the requirement for prior knowledge of the system frequency, inaccurate estimation in the presence of harmonics, and spectral leakage. Accordingly, an exact and trustworthy methodology that is impervious to symphonious contamination and other abnormal changes in power signals is required.

The goal of this paper aims to propose an accurate approach for robust frequency and amplitude estimation in dynamic systems utilizing HODMD algorithm. This study includes the construction of snapshot matrices by Hankelization, the use of singular value decomposition (SVD), singular value truncation for low-rank approximation, the computation of dynamic mode matrices, and the extraction of pertinent features to estimate fundamental parameters. This enhances the potent and effective framework for the analysis of intricate power systems. This will contribute to the enhancement of our comprehension and management of dynamic processes in various domains of research.

III. Higher Order Dynamic Mode Decomposition

Higher order dynamic mode decomposition (HODMD) is a data-driven technique that relies on observational data to extract hidden patterns [13], [23]. It is an extended version of normal DMD and has gained huge attention in recent years, for its ability to accurately estimate power system signals. By decomposing signals into orthogonal modes, this approach extracts key features and underlying patterns. These modes enable the estimation of system dynamics and the identification of unknown parameters. It is effective for a broad range of scenarios, including generic periodic and quasi-periodic dynamics, transient processes transitioning to periodic or quasi-periodic attractors, and cases with low spatial complexity but significant frequency involvement [4].

Nonlinear systems frequently exhibit complicated behavior that is not accurately described by linear models. HODMD excels at capturing the intrinsic non-linearity in complex systems. In contrast to linear approaches, which pre-suppose linearity [12], HODMD can represent nonlinear relationships in data, making it more accurate for nonlinear systems. It distinguishes between distinct modes or patterns in data, even when they contain nonlinear relationships. This separation allows for a more complete knowledge of the system's constituent behaviors and can aid in the identification of essential aspects.

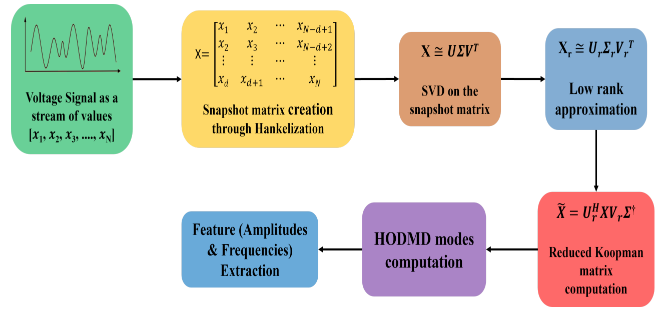


Fig. 1: Overview of the proposed methodology

IV. Proposed Methodology

This section outlines the sequential procedure as illustrated in Fig. 1 of the proposed methodology for analyzing the power signals along with its mathematical foundation. In general, the proposed method consists of the following stages:

- Data generation
- Snapshot matrix creation through Hankelization
- SVD truncation for low-rank approximation
- Computation of dynamic mode matrix
- Feature extraction for parameter estimation

A. Data Generation

The current study uses two categories of data for evaluation. The first category is the synthetic signals which are generated by a combination of cosine waves with varying amplitudes and frequencies. A specified reference frequency (f_1) and sampling frequency (f_s) are used in each case to generate the synthetic power system scenarios. A sample signal which is considered in this study is shown in Fig. 2(a). A real-time signal used in this study is shown in Fig. 2(b).

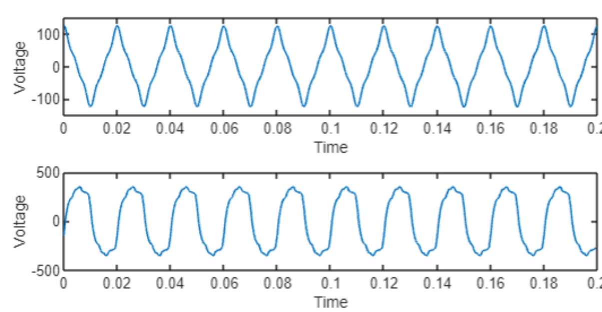


Fig. 2: Illustration of voltage signals. (a) Voltage vs Time plot of a synthetic signal. (b) Voltage vs Time plot of the live signal for 0.2 seconds.

B. Snapshot matrix creation through Hankelization

To capture the nonlinear dynamics and underlying characteristics of the signal, the generated stream of voltage-time series data is converted into a snapshot matrix through a process called Hankelization. This involves stacking of the time-delayed snapshots of the data into a matrix. Consider the voltage waveform X, where x_i signifies the voltage values of the power signal at each temporal instance i. By successively appending time-shifted snapshots of this temporal data, two modified Hankel (snapshot) matrices are generated as below.

$$X = [x_1, x_2, x_3, x_4, \ldots, x_N] \tag{1}$$

$$H_1 = \begin{bmatrix} x_1 & x_2 & \cdots & x_{N-d} \\ x_2 & x_3 & \cdots & x_{N-d+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_d & x_{d+1} & \cdots & x_{N-1} \end{bmatrix}_{d\times\,(N-d+1)} \tag{2}$$

$$H_2 = \begin{bmatrix} x_2 & x_3 & \cdots & x_{N-d+1} \\ x_3 & x_4 & \cdots & x_{N-d+2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{d+1} & x_{d+2} & \cdots & x_N \end{bmatrix}_{d\times\,(N-d+1)} \tag{3}$$

The count of delays (or) temporally shifted columns within the Hankel matrix depends upon the HODMD parameter d. Each column of the Hankel matrix corresponds to a snapshot captured at a specific temporal moment. The influence of d parameter on the method's performance is thoughtfully examined in Section VI.

C. SVD truncation for low-rank approximation

Given our focus on capturing the inherent spatio-temporal nature of the data, our approach involves applying the SVD on the snapshot matrix. The application of SVD on the matrix H_1 is formalized in Eq. (4).

$$H_1 \approx U\Sigma V^T \tag{4}$$

To preserve the dominant features, insignificant features that do not contribute to the total energy captured by a subset of significant singular values are eliminated. Truncation of singular values is done to reduce the dimensionality of the snapshot matrix [24].

$$\hat{H}_1 \approx U_r \Sigma_r V_r^T \tag{5}$$

The rank reduced matrix is constructed from Eq. (4) and (5) as shown in Eq. (7).

$$r = \min_{k\in\mathbb{N}} \left\{ k : \frac{\sum_{i=1}^{n} \sigma_i^2}{\sum_{i=k+1}^{n} \sigma_i^2} \leq \epsilon \right\} \tag{6}$$

$$\tilde{H} = U_r^H H_2 V_r \Sigma_r^{\dagger} \tag{7}$$

D. Computation of dynamic mode matrix

The dynamic mode matrix is computed by performing the eigen decomposition on the reduced snapshot matrix $\tilde{H}$ as shown in Eq. (8).

$$\tilde{H} = W \wedge W^{-1} \tag{8}$$

The eigenvalues derived from the eigen decomposition serve as the basis for feature extraction within the data. Furthermore, they play a vital role in monitoring the growth rate of individual dynamic modes. This step facilitates better visualization of the dynamic modes corresponding to dominant behaviors. Further, the dynamic mode matrix is computed as follows,

$$\Phi = H_2 V_r \Sigma_r^{\dagger} W \tag{9}$$

E. Feature extraction for parameter estimation

This phase constitutes the core part the proposed methodology as it encompasses the interpretation of dynamic modes extracted from the dynamic mode matrix. The analysis of these modes, along with their associated eigenvalues that reveal frequencies or growth rates, provides insights into the dominant behaviors of the system and their temporal evolution.

Each column of the matrix Φ, represents an individual mode Φ_i, and their corresponding eigenvalues are denoted as λ_i. These eigenvalues are utilized to compute the frequencies and growth rates of the modes, as demonstrated in Eq. (10).

$$\delta_i + i\omega_i = \frac{\log \lambda_i}{\Delta t} \tag{10}$$

For the computation of the amplitudes, SVD is performed on the observation matrix P, assembled from the matrix Q housing the eigenvectors and the diagonal matrix M containing the eigenvalues.

$$P = \begin{bmatrix} Q \\ QM \\ \vdots \\ QM^{\text{r-1}} \end{bmatrix} \quad a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_M \end{bmatrix} \quad x = \begin{bmatrix} \hat{x_1} \\ \hat{x_2} \\ \vdots \\ \hat{x_r} \end{bmatrix} \tag{11}$$

$$P \approx U_1 \Sigma_1 V_1^T \tag{12}$$

$$a = V_1 {\Sigma_1}^{-1} {U_1}^{\mathrm{T}} x \tag{13}$$

As a concluding step, the insignificant amplitudes that do not contribute to the data are eliminated by employing a threshold value. This threshold value acts as a trade off between extracting potential information and simplifying the model which depends on the signal. In a scenario, where the data is clean or with a low SNR value, a small value may work well. However, in noisy or complex data, a larger value may be preferred to ensure robust results.

V. Analysis of Experimental Findings

The efficacy of the proposed methodology is evaluated through experimentation on synthetic and real-time signals, along with a comparative analysis against alternative approaches for conducting PQ analysis. The experiments are carried out under the following cases:

- Signal with integer harmonics
- Signal with off-nominal frequencies and noise
- Signal with integer harmonics and noise
- Signal with integer, inter and sub-harmonics
- Real-time voltage signal

The performance is verified using the error percentage (given in Eq. 14) as a metric that denotes the proportion between the absolute difference of estimated values and the corresponding actual values, divided by the actual value.

$$\text{Error } \% = \left(\frac{|E - A|}{A}\right) \times 100 \tag{14}$$

The method's greater performance is emphasized by the lowest error in the estimation of signal parameters.

A. Signal with integer harmonics

The first test case deals with the synthetic signals with integer harmonics. The signal considered has a 10KHz sampling frequency. The fundamental frequency, f_1 = 50Hz and harmonics 150Hz and 250Hz are considered. The results obtained by the proposed method alongside other methods are tabulated in Table I. It can be inferred that the proposed method outperforms other approaches in accurately estimating signal parameters.

TABLE I: Signal with integer harmonics

Methods	Error% for f1(50Hz)	Error% for f2(150Hz)	Error% for $f_3(250Hz)$
DFT [25]	0.0000	0.0000	0.0000
Freq.inter (Rectangular) [10]	0.0000	0.0000	0.0000
Freq.inter (Hanning) [10]	0.0000	0.001	8*e-4
DMD [26]	0.0000	0.0000	0.0000
HODMD	**0.0000**	**0.0000**	**0.0000**

B. Signal with off-nominal frequencies and noise

In general, off-nominal frequencies imply fluctuations from the standard frequency. Analyzing these kinds of signals helps in studying more generalized data. This test signal exhibits harmonics at frequencies of 49.5Hz, 148.5Hz, and 468.27Hz with a sampling frequency of 3.2KHz. Furthermore, the signal is corrupted with 55dB Gaussian noise. The results are tabulated in Table II.

TABLE II: Signal with off-nominal frequency with 55dB noise

Methods	Error% for f1(49.5 Hz)	Error% for f2(148.5 Hz)	Error% for f3(468.27 Hz)
DFT [25]	1.0100	1.0100	0.6340
Freq.inter (Rectangular) [10]	0.0440	0.0040	0.6790
Freq.inter (Hanning) [10]	0.0040	0.1970	0.4230
DMD [26]	0.0000	0.0040	0.0010
HODMD	**0.0000**	**.0000**	**0.0064**

C. Signal with integer harmonics and noise

This test case deals with the synthetic signals having integer harmonics with additive noise. The signal considered here has 10KHz as the sampling frequency. The fundamental frequency 50Hz and its harmonics 250Hz and 350Hz are considered. Table III depicts the results obtained under different noisy scenarios. From the table, it can be seen that the proposed methodology performs well even in highly noisy scenarios.

TABLE III: Signal with integer harmonics under multiple noisy scenarios

Noise	Freq-1 / Amp - 1	Freq - 2 / Amp -2	Freq - 3 / Amp - 3
15 dB	50.0000 / 100.1060	249.9000 / 17.9240	349.9000 / 11.9899
25dB	50.0000 / 100.3720	250.0000 / 18.0459	350.0000 / 11.9941
35 dB	50.0000 / 100.0860	250.0000 / 17.9818	350.0000 / 12.0300
45 dB	50.0000 / 100.0210	250.0000 / 18.0434	350.0000 / 11.9912
50 dB	50.0000 / 100.0120	250.0000 / 18.0244	350.0000 / 11.9950

D. Signal with integer, inter and sub harmonics

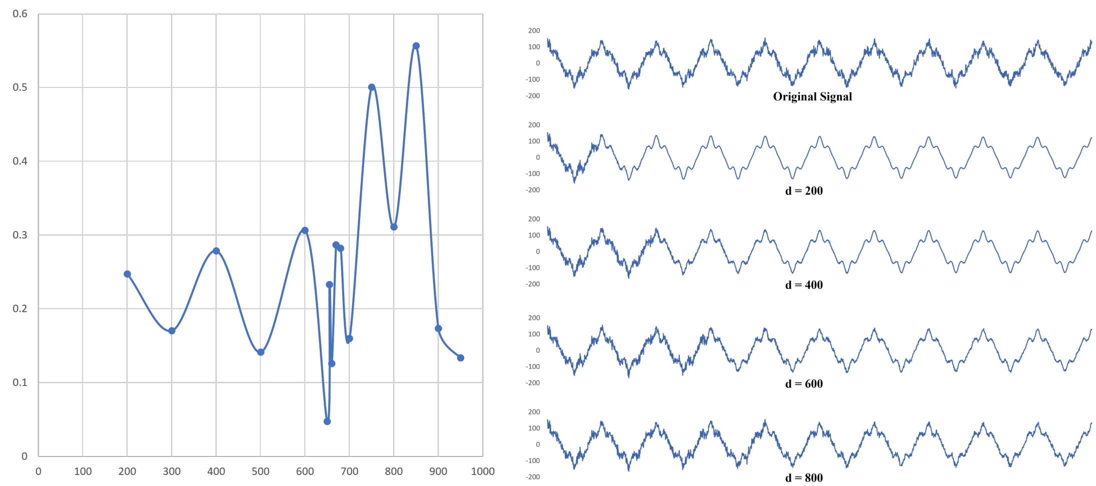
Inter-harmonics are those frequency components that do not precisely align with integer multiples of the fundamental frequency while sub-harmonics are less than the fundamental frequency. The signal is sampled under 10kHz whose fundamental frequency 50Hz and harmonics 150Hz, 250Hz, 350Hz, 450Hz, 26Hz, 180Hz, 230Hz are considered. The results are tabulated in Table IV which depicts the comparison of the proposed method alongside other methods. Analyzing signals of this nature enables a comprehensive estimation, a task accomplished by the proposed method.

E. Estimation of real-time signals

The signal shown in Fig. 2 is taken into study to prove the robustness and potential of the proposed methodology in a real-time scenario. This voltage signal is extracted from a distribution system spanning 5 seconds with a sampling frequency of 6.4KHz. Table V depicts the estimation of frequency components using our proposed methodology alongside other methods.

TABLE IV: Signal containing integer harmonics, inter and sub harmonics

Methods	Error% of f1 (50Hz)	Error% of f2 (150Hz)	Error% of f3 (250Hz)	Error% of f4 (350Hz)	Error% of f5 (450Hz)	Error% of f6 (26Hz)	Error% of f7 (180Hz)	Error% of f8 (230Hz)
DFT [25]	0.0000	0.0000	0.0000	0.0000	0.0000	3.8460	0.0000	0.0000
Freq.inter (rectangular) [10]	0.1840	0.0080	0.9090	0.0020	0.0020	-	0.0120	20.6430
Freq.inter (Hanning) [10]	0.0000	0.0000	0.7280	0.0000	0.0000	-	0.4280	20.5610
DMD [26]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HODMD	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**



(a) (b)

Fig. 3: (a) Illustration of error % vs the value of HODMD parameter d for the synthetic signal with integer harmonics having 50dB Noise, (b) Illustration of the re-construction of the signal having integer harmonics with 15dB noise under different d values.

TABLE V: Real-time voltage signal analysis using Total DMD (TDMD), Non-stationary Fourier Mode Decomposition (NFMD) and the proposed method (HODMD).

Methods	Freq -1 (50Hz)	Freq - 2 (150Hz)	Freq - 3 (250Hz)	Freq - 4 (350Hz)	Freq - 5 (450Hz)	Freq - 6 (550Hz)
TDMD [5]	49.99	149.98	249.98	349.97	-	549.97
NFMD [15]	49.99	149.98	249.98	349.97	-	549.97
HODMD	**49.9900**	**148.98**	**249.98**	**349.97**	**-**	**549.96**

VI. Influence of HODMD parameter

The value of d represents the number of time-delayed snapshots of the signal used to construct the Hankel matrix as in Eq. 2. Hence the selection of parameter d significantly influences the capability of HODMD in capturing and accurately representing the important characteristics of power signal. A lower value signifies capturing a limited amount of temporal information about the signal thereby making it difficult for prediction. On the other hand, a higher value allows for a more intricate representation that captures all the signal features, but it may lead to overestimation if the signal is noisy.

Through our experiments, the proposed methodology yields smoother estimations for noise-free signals under lower d values, while relatively higher d values result in smoother estimations and reconstruction for noisy signals. However, the optimal value of d was determined by careful consideration of the experiment's outcomes, selecting the value that exhibits the lowest error rate. Figure 3(a) demonstrates the impact of different d values on the estimation of amplitudes of the signals considered. Figure 3(b) shows the importance of choosing an optimal DMD parameter for better reconstruction of the original signal.

VII. Conclusion and Future Prospects

In this study, we proposed the use of the HODMD for power quality analysis in electric grid scenario. In the proposed methodology, the amplitude and frequency for specific features in the data are extracted by utilizing the computation of HODMD modes through the low-rank approximation. The proposed analysis indicated that HODMD is quite efficient in the detection and description of voltage waveform distortions, specifically harmonics and inter-harmonics. The technique successfully pinpointed the prominent frequencies and amplitudes of these distortions, with the resulting HODMD modes presenting distinct graphical depictions of the spatio-temporal patterns linked to each distortion. In contrast to alternative techniques, HODMD boasts numerous benefits including its ability to handle high-dimensional data, robustness against disturbances and outliers, and capability to detect nonlinear dynamics.. The approach is highly efficient from a computational standpoint and can be readily implemented on extensive data sets. This study emphasizes the capability of HODMD as a means of analyzing power quality and indicates its potential as a beneficial resource for engineers and scholars working in this area. Future directions may investigate how HODMD can be utilized for analyzing various forms of power system information, and also delve into creating automated methods for extracting and categorizing features based on DMD modes.

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