Compressed DMD Based Power System Oscillation Detection Using PMU Data

Rajarshi Roychowdhury*, Balaji Guddanti †, Mahesh S. Illindala§
*Xcel Energy, Denver, CO, USA, Email: rajarshiroychowdhury@ieee.org
†General Electric Vernova, Schenectady, NY, USA, Email: balaji.guddanti@gevernova.com
§The Ohio State University, Columbus, OH, USA, Email: millindala@ieee.org

***Abstract*—Electro-mechanical oscillations in large interconnected power systems can threaten grid stability, if not studied carefully. Accurate, real-time mode identification from Phasor Measurement Unit (PMU) data is essential for wide-area monitoring and control. This paper introduces a Compressed Dynamic Mode Decomposition (cDMD) framework for efficient oscillation detection from high-dimensional PMU data. By projecting snapshots into a reduced subspace using random compression, cDMD estimates dynamic modes, eigenvalues, and damping ratios with minimal accuracy loss. The approach delivers significant computational gains and robust performance and was tested with real PMU data from the ISO-New England (ISO-NE) region of the United States.**

***Index Terms*—Phasor Measurement Units (PMUs), Power System Oscillations, Compressed Dynamic Mode Decomposition (cDMD), Modal Analysis, Low-Rank Approximation, Eigenvalue Decomposition, Data-Driven Stability Assessment**

I. Introduction

The deployment of Phasor Measurement Units (PMUs) has enabled unprecedented high-resolution monitoring of power system dynamics. PMUs provide synchronized measurements of voltages, currents, frequencies, and phase angles at a typical rate of 30–120 samples per second, capturing the dynamic evolution of the grid in near real time. However, the vast volume of streaming PMU data introduces significant challenges for traditional modal analysis techniques, such as Prony analysis, Matrix Pencil, and Eigensystem Realization Algorithm (ERA), which require high computational cost and are sensitive to measurement noise and model order selection. Prony analysis [1] has long served as a foundational technique for decomposing signals into a sum of exponential components, providing valuable insights in time-domain analysis. The Matrix Pencil (MP) method [2] was later introduced as a robust and numerically stable enhancement to Prony's approach. By constructing a "pencil" of matrices and evaluating their eigenvalues, the method directly estimates modal frequencies and damping ratios even under noisy measurement conditions. Its simplicity and numerical stability have made it a preferred choice in practical applications involving real-world data. Building on these developments, the Eigensystem Realization Algorithm (ERA) [3] advanced system identification methods by utilizing time-domain impulse response data to derive modal properties. ERA generates Hankel matrices from impulse sequences and employs singular value decomposition (SVD) to extract dominant modes and suppress measurement noise. A comparative assessment of ERA and Prony's performance is presented in [4], emphasizing their respective advantages in handling real and synthetic datasets. Some of the limitations of Prony, MP & ERA have motivated the adoption of data-driven approaches, such as Dynamic Mode Decomposition (DMD), which can extract modal information directly from measurement data without explicit system modeling. DMD was originally formulated to extract spatiotemporal patterns from fluid flow data, has recently gained significant traction in power system analysis due to its ability to perform real-time mode identification and stability assessment. Authors in [5] provided a novel DMD based framework to detect dominant modes from PMU data that is both corrupted and also has missing values. The work in [6] proposed a DMD-based multiscale framework capable of simultaneously extracting spatial and temporal patterns of transient processes from wide-area sensor data, enhancing the accuracy of monitoring and instability detection. A rapid DMD-based modal identification and monitoring framework for large-scale systems was presented in [7], addressing the need for scalable real-time analysis. The potential of DMD for wide-area monitoring and control applications was further explored in [8], highlighting its adaptability to diverse grid conditions. Hankel based Robust Mode Decomposition with Symmetric Operators was introduced in [9]. Finally, a comparative study between the Iterative Matrix Pencil method and DMD using synthetic grid data was carried out in [10], illustrating their complementary capabilities for modern modal analysis and stability evaluation in power systems. While our earlier work [5], focused primarily on robustness against noise, missing data, or improved modal extraction accuracy, scalability remains a major barrier for real-time deployment in modern wide-area monitoring systems (WAMS). As PMU deployment expands, the dimensionality of measurement data increases significantly, making conventional DMD computationally expensive due to repeated high-dimensional singular value decompositions.

To address this gap, this work introduces a compressed Dynamic Mode Decomposition (cDMD) framework that shifts the design focus from robustness to scalability. By leveraging randomized compression and subspace embedding properties, the proposed method reduces computational and memory complexity while preserving spectral accuracy. Thus, unlike

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prior robust DMD variants, the proposed approach targets near real-time feasibility for large-scale interconnected grids.

The proposed *Compressed Dynamic Mode Decomposition (cDMD)* approach employs random projections or structured compression operators to reduce the dimensionality of PMU measurements while preserving the essential modal subspace. By performing DMD on compressed data matrices, cDMD significantly reduces memory and computation requirements without sacrificing modal accuracy. This enables scalable real-time implementation for large interconnected grids and facilitates online oscillation tracking through a sliding-window formulation. The key contributions of this paper are as follows. First, a rigorous mathematical proof is established demonstrating the spectral equivalence between the compressed Dynamic Mode Decomposition (cDMD) operator and the standard DMD reduced operator under a subspace-injective compression condition. This theoretical result guarantees that cDMD preserves the exact eigenvalue spectrum of the full-state dynamics and converges to the true system modes as the number of snapshots increase. Second, a computationally efficient cDMD-based framework is developed for real-time extraction of inter-area and local oscillatory modes from compressed PMU measurements. The proposed formulation considerably reduces the dimensionality and computational burden while maintaining high modal accuracy, thereby enabling scalable and practical implementation for wide-area stability monitoring in large interconnected power systems.

The remaining sections of the paper are organized as follows. Section II explains the mathematical preliminaries of DMD, introduces cDMD, the algorithm and how its used for oscillation detection in power systems. Section III validated the proposed algorithm on real-world PMU data. Finally, the conclusions are summarized in Section IV.

II. Mathematical Preliminaries

Dynamic Mode Decomposition (DMD) provides a data-driven approach to extract coherent spatiotemporal modes from high-dimensional time-series data, such as phasor measurement unit (PMU) recordings in wide-area power systems. The compressed variant (cDMD) enables the same modal information to be obtained from a reduced set of measurements or compressed snapshots, thereby improving computational efficiency and scalability for real-time oscillation monitoring.

A. PMU Data Representation

Consider n synchronized PMU channels, each measuring a system state variable (e.g., voltage magnitude, angle, frequency, or active power) at a uniform sampling interval Δt. The measurements over m successive time instants can be represented as a sequence of snapshot vectors:

$$x_i = \begin{bmatrix} x_i^{(1)} & x_i^{(2)} & \cdots & x_i^{(n)} \end{bmatrix}^\top \in \mathbb{R}^n, \quad i = 1, 2, \ldots, m. \tag{1}$$

Assuming the underlying dynamics evolve approximately linearly between snapshots, there exists an unknown linear operator $A \in \mathbb{R}^{n \times n}$ such that

$$x_{i+1} \approx A x_i. \tag{2}$$

B. Snapshot Matrices and System Evolution

Defining the data matrices

$$X = \begin{bmatrix} x_1 & x_2 & \cdots & x_{m-1} \end{bmatrix}, \qquad X' = \begin{bmatrix} x_2 & x_3 & \cdots & x_m \end{bmatrix}, \tag{3}$$

the system evolution in (2) can be written compactly as

$$X' \approx AX. \tag{4}$$

The goal of DMD is to approximate the dominant eigenvalues and eigenvectors of the high-dimensional operator A using only the data matrices (X, X') without explicitly forming A.

C. Low-Rank Projection and Reduced Operator

Applying the singular value decomposition (SVD) to X,

$$X = U \Sigma V^*, \tag{5}$$

where $U \in \mathbb{C}^{n \times r}$, $\Sigma \in \mathbb{R}^{r \times r}$, and $V \in \mathbb{C}^{(m-1) \times r}$ with $r = \operatorname{rank}(X)$, enables the projection of the dynamics onto an r-dimensional subspace spanned by the columns of U. The reduced operator $\tilde{A}$ is then given by

$$\tilde{A} = U^* X' V \Sigma^{-1}. \tag{6}$$

The eigen-decomposition of $\tilde{A}$,

$$\tilde{A} W = W \Lambda, \tag{7}$$

yields the discrete-time eigenvalues $\Lambda = \operatorname{diag}(\lambda_1, \ldots, \lambda_r)$ and corresponding eigenvectors W in the reduced subspace.
The full-state DMD modes are reconstructed as

$$\Phi = X' V \Sigma^{-1} W \in \mathbb{C}^{n \times r}. \tag{8}$$

D. Modal Quantities

Each DMD mode ϕ_i describes a spatial pattern across PMU locations associated with a temporal evolution governed by λ_i. Continuous-time eigenvalues are obtained by

$$\omega_i = \frac{\log(\lambda_i)}{\Delta t}. \tag{9}$$

From $\omega_i = \alpha_i + j\beta_i$, the oscillation frequency and damping ratio are

$$f_i = \frac{\beta_i}{2\pi}, \qquad \zeta_i = -\frac{\alpha_i}{\sqrt{\alpha_i^2 + \beta_i^2}}. \tag{10}$$

The amplitude of each mode is estimated by least squares as

$$b = \Phi^+ x_1, \tag{11}$$

where Φ^+ denotes the Moore–Penrose pseudoinverse. The reconstructed signal is then

$$\hat{x}(t) = \sum_{i=1}^{r} b_i \phi_i e^{\omega_i t}, \tag{12}$$

which can be used to identify dominant inter-area or local oscillatory modes in the system.

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E. Compressed DMD Formulation

In large interconnected systems, n (the number of PMU channels) may be very high, making the direct SVD of X computationally expensive. The proposed cDMD algorithm addresses this limitation by projecting the data into a lower-dimensional subspace using a measurement matrix $C \in \mathbb{R}^{p\times n}$ ($p \ll n$):

$$Y = CX, \qquad Y' = CX'. \tag{13}$$

The compressed SVD,

$$Y = U_Y S_Y V_Y^*, \tag{14}$$

is used to construct a low-dimensional approximation of the operator:

$$\tilde{A}_Y = U_Y^* Y' V_Y S_Y^{-1}. \tag{15}$$

Eigen-decomposition in the compressed space,

$$\tilde{A}_Y W = W\Lambda, \tag{16}$$

produces the same eigenvalues λ_i as the full DMD under suitable conditions on C (e.g., satisfying a subspace embedding property). The full-state DMD modes can then be recovered as

$$\Phi = X' V_Y S_Y^{-1} W. \tag{17}$$

Thus, cDMD efficiently reveals the dynamic modal content of the grid from compressed PMU data, providing a foundation for real-time oscillation detection and stability assessment.

F. Spectral Equivalence and Convergence of cDMD

The compressed Dynamic Mode Decomposition (cDMD) operator in (15) is mathematically shown to be *similar* to the standard DMD reduced operator in (6). As a result, cDMD yields identical eigenvalues and converges to the true system modes whenever the original DMD formulation does.

Setup.

Let $X, X' \in \mathbb{C}^{n\times(m-1)}$ satisfy the exact linear evolution

$$X' = AX, \qquad A \in \mathbb{C}^{n\times n}. \tag{18}$$

The thin singular value decomposition (SVD) of X is expressed as $X = U\Sigma V^*$ with $\operatorname{rank}(X) = r$. The standard reduced operator is given by $\tilde{A} = U^* X' V \Sigma^{-1}$.

A measurement matrix $C \in \mathbb{R}^{p\times n}$ ($p \ll n$) is used to compress the data:

$$Y = CX, \qquad Y' = CX', \qquad Y = U_Y S_Y V_Y^*.$$

The corresponding cDMD operator is defined as $\tilde{A}_Y = U_Y^* Y' V_Y S_Y^{-1}$.

Assumption (Subspace Injectivity).

Let $\mathcal{S} = \operatorname{range}(X) = \operatorname{range}(U)$ denote the r-dimensional snapshot subspace. It is assumed that the restriction $C|_{\mathcal{S}}$ is injective, i.e.,

$$\operatorname{rank}(CU) = r. \tag{19}$$

This assumption holds with high probability when C is constructed as a random projection, a sparse random matrix, or a subsampled randomized Hadamard transform (SRHT) with $p \gtrsim r$, following the Johnson–Lindenstrauss subspace embedding property.

Algorithm 1 Compressed DMD (cDMD) for PMU-Based Oscillation Detection

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Input: PMU snapshots $\{x_i\}_{i=1}^m$, $x_i \in \mathbb{R}^n$; sampling step Δt; rank k; measurements p
Input: (Optional) sliding window length m and hop h

Input: Compression matrix $C \in \mathbb{R}^{p\times n}$ (row-sampling / sparse RP / SRHT)
Output: DMD modes Φ, eigenvalues $\{\lambda_i\}$, frequencies f_i, damping ratios ζ_i, amplitudes b

1: **Form snapshots:**
2: $X = [x_1 \ \cdots \ x_{m-1}], \quad X' = [x_2 \ \cdots \ x_m]$
3: ▷ De-mean, synchronize, and (optionally) band-limit channels beforehand
4: **Compress:**
5: $Y = CX, \quad Y' = CX'$
6: **Truncated SVD on Y:**
7: $Y = U_Y S_Y V_Y^*$ with $U_Y \in \mathbb{C}^{p\times k}$, $S_Y \in \mathbb{R}^{k\times k}$, $V_Y \in \mathbb{C}^{(m-1)\times k}$
8: ▷ Choose k from energy threshold or expected *a priori* modal count
9: **Projected evolution:**
10: $\tilde{A}_Y = U_Y^* \ Y' \ V_Y \ S_Y^{-1}$
11: **Eigen-decomposition (compressed space):**
12: $\tilde{A}_Y W = W\Lambda, \quad \Lambda = \operatorname{diag}(\lambda_1, \ldots, \lambda_k)$
13: **Full-state mode reconstruction:**
14: $\Phi = X' \ V_Y \ S_Y^{-1} \ W \in \mathbb{C}^{n\times k}$
15: **Continuous-time parameters:**
16: $\omega_i = \log(\lambda_i)/\Delta t; \quad f_i = \operatorname{Im}(\omega_i)/(2\pi); \quad \zeta_i = -\operatorname{Re}(\omega_i)/|\omega_i|$
17: **Mode amplitudes:**
18: $b = \Phi^+ x_1$
19: ▷ Least-squares using first snapshot
20: *(Optional, sparse selection)*: solve $\min_b \|x_1 - \Phi b\|_2^2 + \gamma\|b\|_1$
21: **(Streaming) Slide window and repeat:**
22: advance by h samples, update X, X', recompute Steps 2–12
23: **Ranking/filtering (practical):**
24: retain modes with (i) f_i in expected bands (e.g., inter-area/local), (ii) small ζ_i (lightly damped), and (iii) large $|b_i|$ (energy)

Lemma (Structure of the Compressed SVD).

Under the injectivity condition (19), let the thin QR factorization of CU be $CU = QR$ with $Q^*Q = I_r$ and R invertible. The compressed data matrix $Y = CX$ then admits the thin SVD

$$Y = U_Y S_Y V_Y^*, \qquad U_Y = Q, \ \ S_Y = R\Sigma, \ \ V_Y = V. \tag{20}$$

Proof. Substituting $X = U\Sigma V^*$ and $CU = QR$ yields

$$Y = CX = (CU)\Sigma V^* = Q(R\Sigma)V^*,$$

which satisfies the definition of a thin SVD with the stated factors. □

Theorem (Spectral Equivalence of DMD and cDMD).

Under (18) and (19), there exists an invertible matrix $R \in \mathbb{C}^{r\times r}$ such that

$$\tilde{A}_Y = R\,\tilde{A}\,R^{-1}. \tag{21}$$

Consequently,

$$\operatorname{spec}(\tilde{A}_Y) = \operatorname{spec}(\tilde{A}),$$

implying that the compressed and full DMD operators share identical eigenvalues.

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Proof. From Lemma (20), the identities $U_Y = Q$, $S_Y = R\Sigma$, and $V_Y = V$ hold. Using $X' = AX$ and $X = U\Sigma V^*$ gives

$$\tilde{A}_Y = U_Y^* Y' V_Y S_Y^{-1} = Q^* C A U \Sigma (R\Sigma)^{-1}.$$

Since $\Sigma(R\Sigma)^{-1} = R^{-1}$ and $Q^* C U = R$, the expression simplifies to

$$\tilde{A}_Y = R(U^* A U) R^{-1} = R\,\tilde{A}\,R^{-1},$$

which proves (21). □

Convergence to the True Modes.
If the snapshot subspace $\mathcal{S}$ is invariant under A and spanned by eigenvectors of A with eigenvalues $\{\mu_i\}_{i=1}^{r}$, then $\tilde{A}$ recovers these eigenvalues exactly, i.e., $\lambda_i = \mu_i$. By Theorem II-F, the same equality holds for $\tilde{A}_Y$. In more general cases where DMD eigenvalues $\lambda_i^{(\mathrm{DMD})}$ converge to the eigenvalues of A as the number of snapshots m increases, the cDMD eigenvalues satisfy

$$\lambda_i^{(\mathrm{cDMD})} = \lambda_i^{(\mathrm{DMD})} \Rightarrow \lim_{m\to\infty} \lambda_i^{(\mathrm{cDMD})} = \mu_i.$$

Remark.
When random projection matrices are employed for compression, the probability that $\mathrm{rank}(CU) = r$ approaches unity once $p \geq c\,r\log r$ for some constant c. Therefore, the cDMD formulation preserves the spectral accuracy of standard DMD while significantly reducing the dimensionality of the measurement space and computational effort.

III. Case Study With Real PMU Data : ISO-NE Event I

This section illustrates the practical implementation of the proposed cDMD algorithm using real Phasor Measurement Unit (PMU) dataset [11]. This data was obtained from the ISO-New England (ISO-NE) system. ISO-NE operates within the northeastern region of the Eastern Interconnection in the United States and manages a peak load of around 26,000 MW. The PMU data used in this study feature high temporal resolution, recorded at 30 samples per second (sampling interval $\Delta t = 0.034$ seconds). The case study highlight the capability and effectiveness of the proposed algorithm in analyzing real-world small signal dynamics within large-scale power systems. The Event I dataset [11] represents Phasor Measurement Unit (PMU) recordings from a near-resonant oscillation event in the ISO-New England (ISO-NE) system on June 17, 2016. The incident involved a 0.27 Hz forced oscillation that excited a natural mode of the Eastern Interconnection (EI), leading to sustained system-wide oscillations across a large portion of the EI. Subsequent analysis identified a malfunctioning control valve at the Grand Gulf Nuclear Station as the root cause. The corresponding voltage magnitude signals from multiple substations, covering a 0–180 s time frame, are presented in Fig. 1.

For the analysis using the proposed cDMD algorithm, a 20-second segment (40–60 s) of the voltage data was extracted to capture the primary oscillatory behavior. The cDMD framework utilizes randomized compression before Singular Value

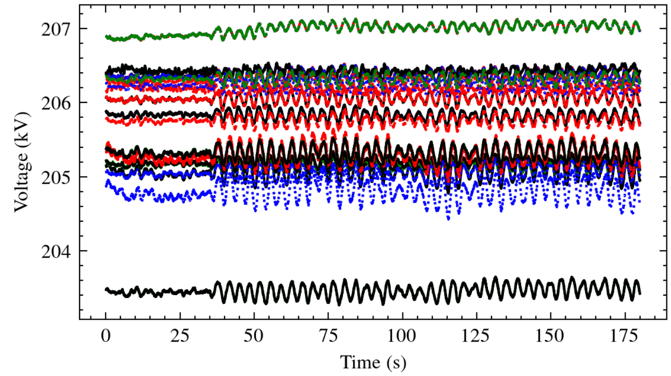

Fig. 1: ISO-NE Event I PMU Voltage Signals

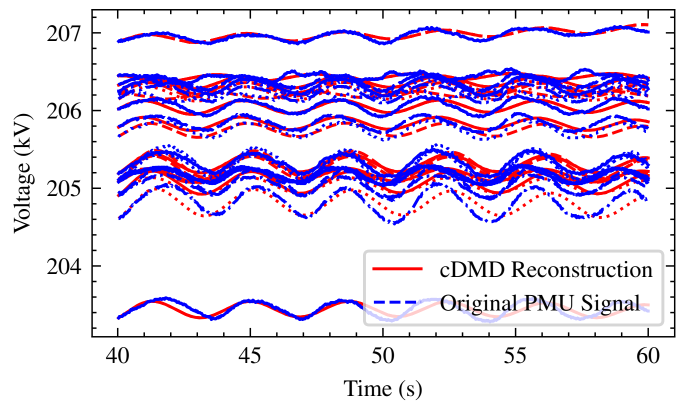

Fig. 2: ISO-NE Event I PMU Signal Reconstruction

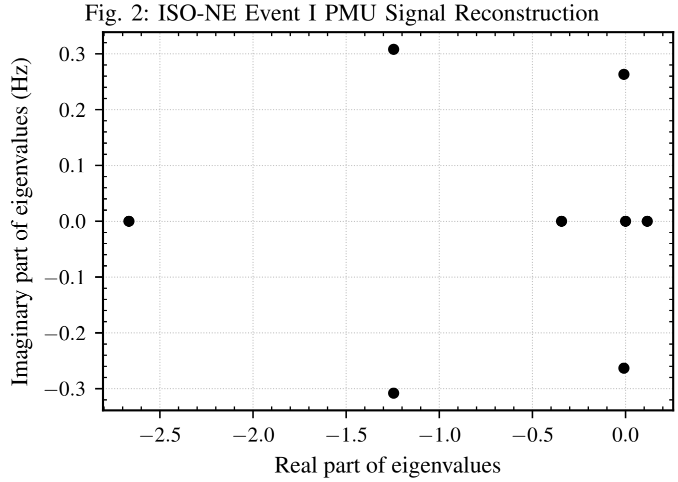

Fig. 3: ISO-NE Event I Eigen Decomposition

Decomposition (SVD) to achieve computational efficiency while maintaining high accuracy. In practical implementation (32 GB RAM laptop with an AMD Ryzen 7 processor), the cDMD algorithm completed execution in less than one second, compared to approximately five seconds for our previous delay-structured robust DMD method [5]. The number of retained modes (r) was determined using hard thresholding on the singular values obtained from the compressed data. A r value of 8 was selected, preserving over 98% of the system's dynamic information.

The reconstructed voltage signals from the cDMD closely

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TABLE I: Summary of Modal Estimation Results for Different Methods (only positive frequencies are listed)

Method	Frequency (Hz)	Damping Ratio
Compressed DMD (cDMD)	0, 0.27, 0.31	1, −0.0054, 0.5865
Prony's Method	0.19, 0.27, 0.43, 0.55, 0.75, 1, 1.2	0.003, −0.001, 0.027, 0.02, 0.022, 0.03, 0.03
Matrix Pencil (MP)	0.20, 0.27, 0.38, 0.52, 0.63, 0.78, 0.91	−0.02, −0.0058, 0.0038, 0.0106, 0.0028, −0.0235, −0.0078
Eigensystem Realization Algorithm (ERA)	0.19, 0.27, 0.37, 0.51, 0.62, 0.76, 0.89	0.0108, 0.0009, 0.0541, 0.0350, 0.0278, 0.0096, 0.0127

aligned with the original PMU data, as illustrated in Fig. 2, confirming the method's ability to accurately capture temporal dynamics with reduced computational cost. The eigendecomposition results in Fig. 3 show the extracted eigenvalues, whose imaginary parts represent the modal frequencies. The 0.27Hz dominant mode was identified along with other modes. For benchmarking, traditional modal estimation techniques such as Prony analysis, Matrix Pencil (MP), and Eigensystem Realization Algorithm (ERA) were applied using a 15th-order model. Although these methods detected the same dominant mode (Fig. 4), their accuracy and stability were highly dependent on model order selection. In contrast, the proposed cDMD approach demonstrated robustness, efficiency, and consistency, making it a superior choice for large-scale oscillation analysis in modern power systems.

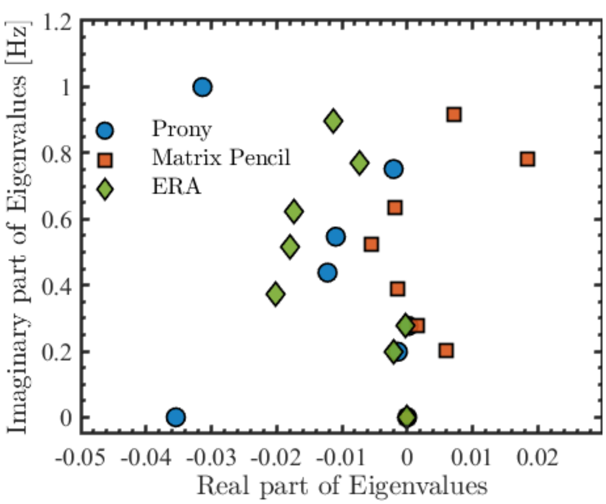

Fig. 4: ISO-NE Event I Prony, MP and ERA Eigen Decomposition

IV. Conclusion

The Compressed Dynamic Mode Decomposition (cDMD) algorithm demonstrated strong effectiveness in identifying dominant oscillatory modes from real Phasor Measurement Unit (PMU) data. By integrating randomized compression with the DMD framework, the proposed approach significantly reduces computational cost while maintaining high accuracy and robustness. The algorithm successfully extracts meaningful spatiotemporal patterns and reveals the underlying dynamic behavior of large-scale power systems. Its resilience to noise and reduced sensitivity to parameter selection make it particularly suitable for real-world PMU applications, where data may be incomplete or irregular. Future work will focus on extending the proposed cDMD framework toward adaptive and real-time operational deployment. In particular, adaptive compression strategies that dynamically adjust the projection dimension based on system dynamics will be investigated to improve efficiency under varying grid conditions. In summary, the cDMD method provides a powerful and efficient alternative to traditional modal estimation techniques such as Prony, Matrix Pencil, and ERA, enabling faster, more reliable mode detection and offering strong potential for real-time grid monitoring and stability assessment.

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