Enhanced Event Clustering Using Real-world Harmonic Phasors and Intrinsic Mode Features

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***Abstract*—This paper introduces a data-driven framework for power system event analysis using harmonic phasor measurements and empirical mode decomposition (EMD). Unlike traditional methods that rely solely on fundamental phasors, we show that harmonic phasors provide additional, non-redundant insight—particularly for detecting subtle, high-frequency transients. We analyze two real-world datasets: a gapless harmonic phasor stream and an extensive event-triggered dataset. We extract features from EMD-applied harmonic phasor magnitude streams that capture dynamic event signatures more effectively than using raw phasor magnitudes alone. Leveraging a one-year dataset containing over 2400 events recorded by harmonic phasor measurement unite, we demonstrate that incorporating harmonic features improves event clustering. Unlike conventional harmonic analysis, our method focuses on transient phenomena, offering a more robust approach for monitoring and distinguishing power system disturbances in utility operations, with potential applications in situational awareness, event classification, and enhancing grid reliability.**

***Keywords*: Harmonic phasor measurement units (H-PMU), event signatures, power system situational awareness, emperical mode decomposition (EMD), intrinsic mode function (IMF).**

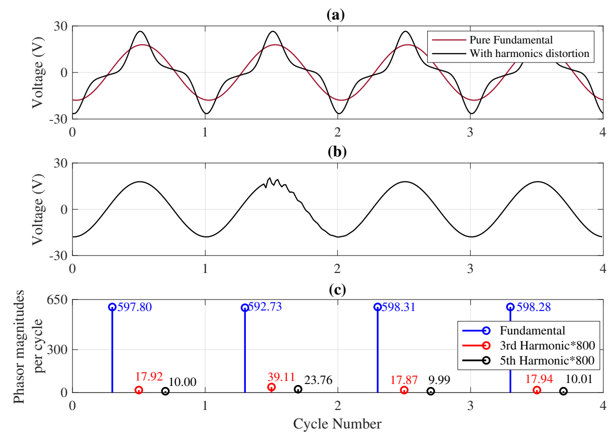

Fig. 1. (a) Voltage waveform with harmonic distortion; (b) Voltage waveform with transient high-frequency event; (c) per-cycle harmonics magnitude for (b), illustrating how harmonic analysis here targets transient events rather than conventional steady-state distortion studies.

I. Introduction

A. Background and Motivations

This paper focuses on analyzing transient events in power systems, which are often subtle, high-frequency deviations from nominal operating conditions but are critical for system reliability and protection. These event are often blurred in conventional phasor domain analysis. Typical approaches have mainly targeted these events using high-resolution waveform data [1], but such methods are resource-intensive and not widely available in real-world monitoring. Traditional phasor measurement units (PMUs) tend to analyze such events by primarily examining the fundamental frequency components of the voltage and/or current waveforms. However, the development of harmonic PMUs (H-PMUs) has introduced new opportunities to characterize transient events beyond the fundamental frequency [2, Section 4.5].

As shown in Fig. 1(b), the nature of transient events is different from those of steady-state harmonic distortion in Fig. 1(a). Fig. 1(c) further illustrates this by showing the per-cycle fundamental, 3^{rd}, 5^{th} harmonic voltage magnitudes for the transient in Fig. 1(b), which forms the basis of the analysis in this work. Rather than analyzing long-term harmonic distortion, this work leverages H-PMUs to capture the dynamic system behavior of voltage during transient events. In this context, harmonics are not merely distortive byproducts but informative signatures of underlying system dynamics. This shift in perspective highlights harmonics' potential to detect and characterize transient events, therby, supporting more resilient grid monitoring and faster operator response.

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B. Related Work

PMUs have long been used for analyzing events in modern power systems. A significant body of research has explored how fundamental phasor measurements can support applications such as event detection [3] and classification [4] and situational awareness [5].

In contrast, research on H-PMUs has followed a different trajectory. The bulk of prior work has focused on harmonic sources and assessing system-level harmonic propagation using methods such as harmonic state estimation [6], or developing algorithms for accurate extraction of harmonic phasors using advanced signal processing [7]. There are also some other applications including fault location identification [8], topology identification [9], etc. But, these efforts have primarily focused on steady-state harmonic behavior and have not directly addressed how harmonics respond to transient events. One notable exception is the study in [10], which uses H-PMU data and an information-theoretic framework to study power system events. While [10] offered initial evidence of the potential value of harmonic phasors, it primarily focused on establishing foundational metrics like mutual information.

However, the increased data complexity from H-PMUs necessitates advanced analytical methods to reliably interpret transient event signatures. Conventional signal processing approaches for time-frequency analysis, such as the Short-Time Fourier Transform (STFT), rely on fixed basis functions, which can limit their effectiveness for signals whose characteristics change over time. While the STFT provides simultaneous time and frequency localization, its resolution is fundamentally constrained by windowing effects. Wavelet transform techniques offer multi-resolution analysis and have proven successful for many nonstationary power system disturbances, but their performance can be sensitive to noise [11] and requiers choosing a mother wavelet which may not always match the underlying event patterns. Empirical mode decomposition (EMD) [12] is an adaptive method that decomposes nonstationary signals into a set of intrinsic mode functions (IMFs), each representing a specific frequency band. Unlike aforementioned methods, EMD does not rely on predefined basis functions. Instead, it adaptively derives them from the signal itself, which leads to more effective decomposition of nonstationary power quality (PQ) events [13]. This makes EMD a strong candidate for identifying transient disturbances and isolating harmonics in power system data [14], [15]. EMD has shown success in fault detection [16], PQ monitoring [13], and signal denoising [17], highlighting its robustness and versatility for power system applications.

C. Approach and Contributions

Building upon this foundation, the current work shifts focus toward demonstrating practical benefits: Using *real-world* H-PMU data, we show how incorporating harmonic phasors alongside fundamental phasors can enhance event characterization and clustering, especially for subtle events where fundamental-based analysis is insufficient. Additionally, although this work does *not* propose a new event detection algorithm, it demonstrates that the inclusion of harmonic phasor data provides valuable insight which might be beneficial even for enhancing event detection. Furthermore, in order to evaluate the practical utility of this theoretical findings, we apply them to real-world applications within power systems, potentially enhancing the way we understand and handle power system events.

The main contributions of this paper are as follows:

1) First *real-world* application of EMD to harmonic phasor magnitudes to extract features for identifying brief, transient events that are often missed by traditional methods.

2) Demonstration that EMD-based harmonic features provide both higher sensitivity and unique informational value compared to fundamental-only analysis, detecting transient events with minimal magnitude change while capturing distinctive event signatures that enhance characterization and clustering performance.

II. Empirical Mode Decomposition and Feature Extraction of H-PMU Measurements

Building on the motivations in Section I, in this section, we first formalize the problem, then review the EMD method, and finally, define the proposed EMD-based harmonic features.

A. Problem Statement

During an event, a conventional PMU records time-series of voltage and current phasors at the fundamental frequency:

$$\mathbf{X}_1 \angle \boldsymbol{\theta}_1, \tag{1}$$

where vector $\mathbf{X}_1 = [X_1[1], \ldots, X_1[n]]^T$ represents a sequence of n voltage or current phasor samples, and $\boldsymbol{\theta}_1 = [\theta_1[1], \ldots, \theta_1[n]]^T$ represents the corresponding phase angles.

With the emergence of H-PMUs, it is now possible to obtain synchronized phasor measurements not only for the fundamental frequency but also for higher-order harmonics. Specifically, an H-PMU may provide measurements for harmonic orders $i = 2, 3, \ldots, m$, where the available harmonic orders vary depending on the device and application [2, Section 4.5]. Suppose an H-PMU provides such measurements up to harmonic order m during an event. Then the sequence of the harmonic phasor data can be represented as:

$$\mathbf{X}_2 \angle \boldsymbol{\theta}_2, \mathbf{X}_3 \angle \boldsymbol{\theta}_3, \ldots, \mathbf{X}_m \angle \boldsymbol{\theta}_m. \tag{2}$$

In this paper, the focus is on voltage phasor magnitudes, $\mathbf{X}_i$, as they often show clearer transient signatures, while harmonic phase angles are more noise-prone and demand extra preprocessing. This scope enables a direct assessment of harmonic contributions to event analysis.

While H-PMUs undoubtedly capture a richer set of measurements compared to PMUs, the key question is rather about the *value* of that data. Specifically, we investigate whether, and to what extent, having harmonic phasor measurements in (2) alongside the fundamental phasor in (1) offer *additional insight* beyond what is already conveyed by the fundamental phasor measurements for power system *event analysis*. Our findings presented in the Sections III and IV, show that they *do* offer non-redundant insight that improves the sensitivity and robustness of characterizing subtle, high-frequency events that are often missed by fundamental-only analysis.

B. Empirical Mode Decomposition

Let $X_i[n]$ for $i = 1, \ldots, m$ denote the time-series of voltage phasor magnitudes for harmonic order i (with $i = 1$ for the fundamental); and since the reporting resolution in our dataset one sample per cycle, the sample index n corresponds to the cycle number.

EMD decomposes the signal $X_i[n]$ into a set of IMFs i.e., $\{\mathrm{IMF}_{k,i}[n]\}_{k=1}^{K}$ and a residual component $r_i[n]$. The decomposition can be expressed as:

$$X_i[n] = \sum_{k=1}^{K_i} \mathrm{IMF}_{k,i}[n] + r_i[n] \tag{3}$$

where K_i is the number of IMFs. Each $\mathrm{IMF}_{k,i}$ satisfies two conditions: 1) the number of zero crossings and extrema can differ by at most one, 2) the envelope defined by its local maxima and minima must be zero mean. In the context of phasor magnitude signals, each IMF isolates a specific band of temporal variations: $\mathrm{IMF}_{1,i}$ captures the most rapid (i.e., high-frequency) transient oscillations, $\mathrm{IMF}_{2,i}$ captures slightly slower oscillations, and so on. In practice, only the first few IMFs are typically relevant for capturing the information from the signal [16].

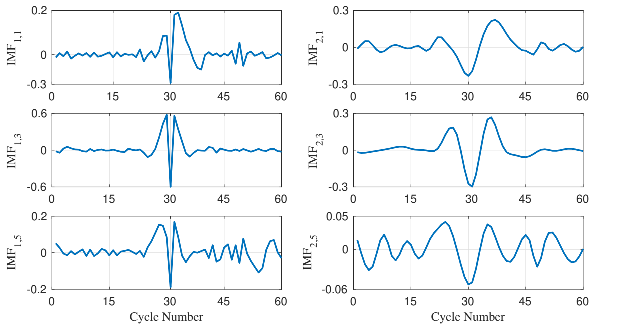

Fig. 2. First two IMFs extracted from a one-second of a gapless harmonic phasor magnitude stream of fundamental, 3^{rd} and 5^{th} harmonic order.

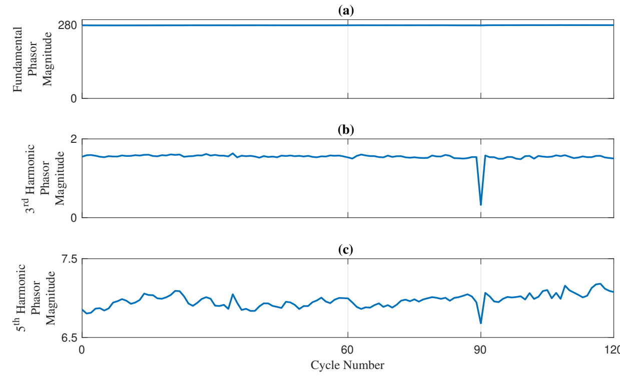

Fig. 3. Two one-second intervals of a gapless harmonic phasor magnitude stream with a transient event at cycle 90.

C. *Feature Extraction*

In this work, we focus on the first two IMFs ($k = 1, 2$), which capture the most rapid temporal variations. Accordingly, we define the following signed-peak features, for each harmonic order i:

$$f_{1i} = \max_{n} |\mathrm{IMF}_{1,i}[n]| \cdot s_{1i} \tag{4}$$

$$f_{2i} = \max_{n} |\mathrm{IMF}_{2,i}[n]| \cdot s_{2i} \tag{5}$$

where s_{1i} and $s_{2i} \in \{-1, +1\}$ are the signs of $\mathrm{IMF}_{1,i}$ and $\mathrm{IMF}_{2,i}$ at the cycles where they reach their absolute peaks respectively. The extremum in (4) and (5) is computed over all n within the analysis window. Here, we use non-overlapping windows; a sliding window could be used for continuous detection. We extract these features from the fundamental, 3^{rd}, and 5^{th} harmonic voltage magnitudes. For instance, Fig. 2 shows the extracted $\mathrm{IMF}_{1,i}$ on the left column and $\mathrm{IMF}_{2,i}$ on the right column. Here we can see the IMFs reach their extremum at cycle number 30. Also, for instant, f_{11} is -0.22, while f_{25} is -0.05.

III. Feature Sensitivity Analysis and Illustrative Applications Using Continuous H-PMU Data

In this section, we use a gapless stream of real-world harmonic voltage phasor magnitude data to assess the sensitivity of the proposed EMD-based harmonic features under steady-state and event conditions. Two examples are presented: (i) their use in detecting short-duration transients; and (ii) qualitatively clustering events using fundamental versus harmonic features. The goal is not to design new detection or clustering methods, but to show that harmonic features provide complementary information to the fundamental phasor.

A. *Feature-Based Analysis of Harmonic Phasors*

We first examine event signatures in a continuous stream of harmonic voltage magnitudes under two operating conditions: steady state and event. The dataset comprises 16 hours of *real-world* harmonic phasor measurements at a substation in California. For analysis, we select two one-second segments: one captured during a transient event and another from one second prior, representing normal operation, as shown in Fig. 3. From each segment, we extract the features in (4) and (5) for the voltage harmonic magnitudes.

TABLE I
Voltage Features in (4) and (5) of Harmonic Phasor Magnitude: Normal vs. Event

Harmonic Order	**Non-Event** (f_{1i}, f_{2i})	**Event** (f_{1i}, f_{2i})
Fundamental	$0.09, -0.17$	$0.32, -0.25$
Percent change in (f_{1i}, f_{2i}): $259\%, -47\%$		
Percent change in phasor magnitude: 0.32%		
Third	$-0.05, -0.02$	$-0.60, -0.29$
Percent change in (f_{1i}, f_{2i}): $-1093\%, -1374\%$		
Percent change in phasor magnitude: 78.91%		
Fifth	$-0.01, -0.01$	$-0.11, -0.05$
Percent change in (f_{1i}, f_{2i}): $-955\%, -395\%$		
Percent change in phasor magnitude: 4.21%		

Table I shows the values for the features and their relative changes between the cases of no event and event. It also includes the percent changes in phasor magnitude, calculated as the percentage difference between the event cycle value and the average over one second of no-event data. As we can see, the fundamental phasor magnitude changes by only 0.32%, while the corresponding features changes by about 259% and 47%. This dramatic contrast highlights the feature's *robustness* even in fundamental phasor, as even subtle events yield strong, distinguishable signals in the defined feature space. Furthermore, *not only* is the difference in the fundamental phasor's *feature* level much more distinguishable compared to the *phasor magnitude itself* but, the difference in the *harmonics* magnitude (i.e., 79% for 3^{rd} and 4.2% for 5^{th} harmonic order) is even *more pronounced*. This again shows that harmonics contain *insight* that may not be captured by the fundamental phasor alone, and supports the features' *sensitivity* to subtle events.

This robustness is particularly valuable because event detection methods are often highly sensitive to *threshold settings*. As we illustrate in the next section, by incorporating harmonic phasors, we can enhance the robustness and accuracy of event detection, allowing for more *reliable* identification and distinction of event conditions.

B. *Harmonic-Based Features for Robust Event Detection*

We now exemplify that incorporating EMD-based harmonic features can enhance event detection, especially for transient events. We compute a weighted sum of the absolute-valued features to function as a scalar detection score. Using magnitudes prevents cancellation between harmonics whose

TABLE II
EVENT DETECTION RESULTS FOR DIFFERENT WEIGHT COEFFICIENTS

$(\omega_{11}, \omega_{12}, \omega_{13}, \omega_{23}, \omega_{15}, \omega_{25})$	**Detection Accuracy**	**False Positives**
(0.35, 0.05, 0.25, 0.05, 0.25, 0.05)	73.08%	29
(0.2, 0.1, 0.3, 0.1, 0.2, 0.1)	57.69%	9
(0.25, 0.05, 0.35, 0.05, 0.25, 0.05)	76.92%	11
(0.25, 0.05, 0.25, 0.05, 0.35, 0.05)	65.38%	12
(0.15, 0.05, 0.35, 0.05, 0.35, 0.05)	46.15%	0
(0.95, 0.05, 0.0, 0.0, 0.0, 0.0)	65.38%	67

deviations have opposite signs, allowing all disturbance contributions to be reflected in the final score:

$$\begin{aligned} &\omega_{11} \times |f_{11}| + \omega_{12} \times |f_{12}| \\ &+ \omega_{13} \times |f_{13}| + \omega_{23} \times |f_{23}| \\ &+ \omega_{15} \times |f_{15}| + \omega_{25} \times |f_{25}|. \end{aligned} \tag{6}$$

where, ω_{ki} is the weight assigned to the feature f_{ki} from (4) and (5). An event is flagged if (6) exceeds a predefined threshold. For this illustrative application, the threshold was set heuristically to balance missed detections and false positives. The intent here is not to optimize this value, but to use a reasonable setting that demonstrates the effect of including harmonic features. Such tuning could be pursued in a dedicated event-detection study.

We tested this method using different sets of weights $w_k i$ on 16 hours of harmonic phasor data from a substation, where 26 transient events (each lasting less than a couple of cycles) were identified using methods similar to [18]. The weight sets shown in Table II span a spectrum of patterns: from those dominated by the fundamental frequency, to ones emphasizing the 3rd or 5th harmonics, and to balanced contributions across harmonic orders. These weights are not optimized but meant to show that adding harmonic-based features can enhance detection. In a full event-detection study, weights could be selected systematically to maximize accuracy and minimize false positives. Table II also shows the detection accuracy and false positives when using the different weights in (6). These results suggest that emphasizing the 3^{rd} harmonic's feature (i.e., f_{k3}) improves accuracy, while over-reliance on the fundamental phasor feature, (i.e., f_{k1}) increases false positives. These findings show that harmonic features help identify short-duration disturbances even with *limited-resolution* data (1 sample/cycle), underscoring harmonics' *practical value* for situational awareness.

It is worth noting that waveform-based event detection, typically sampled at 64–512 samples per cycle, indeed offers superior temporal resolution for capturing *transients*. However, it generates large volumes of data. The proposed H-PMU-based approach may offer a reliable and *resource-efficient* alternative for *utilities* seeking to monitor transient events.

C. Event Clustering via Fundamental vs. Harmonic Features

After analyzing feature sensitivity and demonstrating the value of the extracted features, clustering events based on the extracted features can be applied to group similar or recurring patterns to enhance situational awareness. For this purpose, a qualitative clustering of the 26 events from Section III-A is shown in Fig. 4. In Fig. 4(a), three clusters are obtained from the feature space of the fundamental phasor using k-means. Fig. 4(b) and (c) show the feature spaces of the 3^{rd} and 5^{th} harmonic phasors, respectively, with the same color labels from Fig. 4(a) applied. The key observation is that the cluster separation visible in Fig. 4(a) is no longer present in the harmonic feature spaces. This confirms that harmonic phasors capture event-specific insight not present in the fundamental alone.

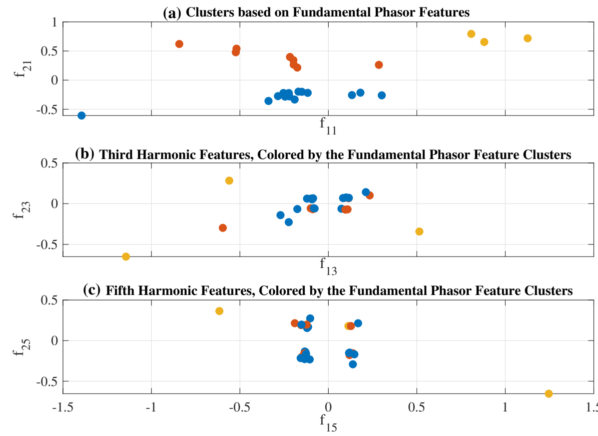

Fig. 4. Clustering of the 26 transient events in the gapless harmonic magnitude dataset using features from fundamental phasors. Colors represent clusters formed in the fundamental phasor feature space, which do not hold when applied to harmonic features.

IV. VALIDATING HARMONIC-BASED INSIGHTS USING REAL-WORLD EVENT-TRIGGERED DATASET

Complementing the analysis from the previous section, we now shift to a large-scale, *real-world event-triggered* dataset to further investigate the role of harmonics. The data was collected over one year (March 2022–February 2023) from the secondary side of a 69 kV/12.47 kV transformer, capturing 2400 three-phase events. Each event includes voltage phasor magnitudes of both fundamental and harmonics. The gapless harmonic phasor magnitude dataset in Section III allowed us to compare feature behavior under both event and non-event conditions and to assess their event-detection sensitivity. In contrast, the large event-triggered dataset used here contains thousands of events but no continuous baseline data. This make it suitable for quantitative analyses such as clustering to evaluate the added value of 3^{rd} and 5^{th} harmonic order features alongside the fundamental.

A. Clustering Analysis Using Proposed Harmonic Feature Set

To assess whether harmonics help differentiate between events more effectively, we perform an unsupervised clustering analysis using features derived from our analysis in both fundamental and harmonic phasor measurements. Given that real-world event datasets are often unlabeled, we rely on silhouette values to evaluate clustering quality. The silhouette score, ranging from -1 to 1, indicates how well a data point fits within its cluster compared to others, where higher values reflect better cohesion and separation [19].

We apply k-means clustering for $k = 2$ to 10 clusters to examine performance across different grouping granularities.

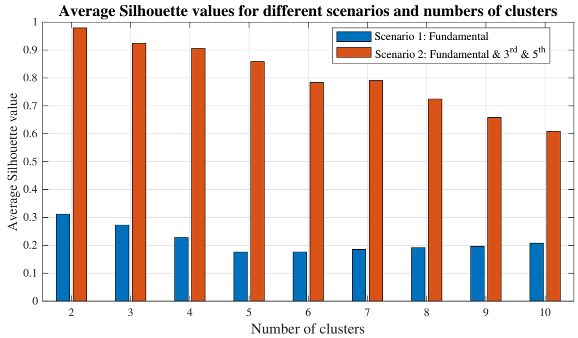

Fig. 5. Silhouette values for different scenarios and different number of clusters in the event-triggered data set.

Fig. 5 illustrates the clustering performance for two scenarios: in the first scenario, only the features of the fundamental phasor magnitudes are used, while in the second scenario, the features for the 3^{rd} and 5^{th} harmonics are also incorporated. As shown, incorporating harmonic features consistently yields higher silhouette values for all k. Although the gain varies with the chosen number of clusters, the overall result is a notably improved separation between event types.

B. Performance Comparison with Prior Work

To distinguish this study from our prior work in [10], we compare clustering performance on the same event-triggered dataset using the same number of four clusters. In [10], each event was characterized using two heuristic features, i.e., transient and steady-state signatures, yielding a silhouette value of 0.22 using only fundamental phasors, and 0.68 when harmonic phasors were included. In contrast, the features in this work are extracted according to (4) and (5). In this regards, using only features f_{11} and f_{21} from the fundamental phasor, the silhouette score improves to 0.28. When harmonic-based features f_{12}, f_{22}, f_{13}, and f_{23} are also incorporated, the score rises significantly to 0.91. This highlights the improved expressiveness of the proposed EMD-based feature set and its effectiveness in revealing structure in real-world event data.

V. Conclusions

This paper introduced a data-driven framework for enhancing power system event analysis using harmonic phasor measurements. By applying EMD to the voltage phasor magnitude streams, we extracted features from the first two IMFs that captured high-frequency transients more effectively than traditional fundamental-only analysis. Our results, based on two distinct sets of *real-world* H-PMU data, confirm that harmonic phasors at the 3^{rd} and 5^{th} orders offer non-redundant and insightful information not captured by the fundamental component alone. Including harmonic features improved event detection accuracy and enhanced clustering quality, as quantified by silhouette scores. These findings highlight a practical opportunity: utilities can leverage existing H-PMU infrastructure not only for harmonic distortion monitoring, but also for improved situational awareness and faster response to subtle disturbances.

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