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GRAPH-BASED REPRESENTATION LEARNING FOR RELIABLE EVENT CLUSTERING IN DISTRIBUTION NETWORKS WITH LIMITED D-PMU DEPLOYMENTS

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ABSTRACT

This paper addresses the challenging problem of identifying the type and cause of events captured by distribution-level phasor measurement units (D-PMUs) to enhance situational awareness in power distribution systems. Two key challenges are considered: (a) scarcity of measurement locations due to the high cost of procuring, installing, and streaming data from D-PMUs; and (b) limited prior knowledge of event signatures, as such events are diverse, infrequent, and inherently unscheduled. To overcome these issues, we propose an unsupervised graph-based representation learning framework, termed GraphPMU, designed to improve event clustering performance under locationally scarce data conditions. The proposed method introduces two innovations: (1) leveraging the topological information of the power distribution network to represent the relative positions of the limited D-PMUs; and (2) incorporating both conventional fundamental phasor measurements and the less explored harmonic phasor measurements for richer event signature analysis. A series of case studies, conducted on a standard distribution test system, demonstrate that GraphPMU significantly outperforms conventional methods in clustering accuracy and reliability. These results highlight the potential of topology-aware, multi-frequency phasor analysis in enabling robust event classification for modern, cost-constrained distribution networks.

Keywords: *Event Clustering, Distribution Networks, Measurement Units, Observability, Accuracy.*

I. INTRODUCTION

Keeping system reliability, operational efficiency, and resilience against faults or disruptions in today's power distribution networks requires the capacity to identify, categorize, and comprehend events as they happen in real time. One important factor that has allowed this possibility to become a reality is the implementation of distribution-level phasor measuring units (D-PMUs). Operators are able to record the grid's dynamic behavior with unprecedented granularity because to D-PMUs, which provide high-resolution, time-synchronized measurements of current and voltage phasors. The scarce adoption of D-PMUs is a real problem because of factors including cost, installation difficulty, and limits in communication infrastructure. Due to large data gaps caused by a lack of measurement sites, accurately grouping and interpreting network events is not a simple operation.

Such low-observability situations are not well-suited for traditional event clustering methods used in power systems, such those based on time-series similarity metrics or standard machine learning models. In the absence of enough data, these approaches, which often depend on extensive measurement coverage, fail to take advantage of the network's fundamental structural and topological linkages. Misclassification and delayed reaction may ensue because of the significant impairment in accurately differentiating between separate events like faults, switching processes, or transient disturbances. A potential answer in these cases may be found in graph-based techniques to advanced representation learning, which take use of both measurement data and the network's intrinsic connection.

Buses and D-PMUs are like nodes in a graph, and electrical connections are like edges, in a graph-based representation learning model of the distribution network. Incorporating both local measurement characteristics and relational dependencies among network nodes into the learning process is made possible by this concept. Even in situations when measurements are sparse or absent, the approach may infer valuable latent representations by incorporating the physical topology into the learning framework. Better event clustering is made possible by these representations, which capture the spatial-temporal patterns that appear during disruptions to the network.

New developments in GNNs and similar designs have shown tremendous promise in several fields, including social network analysis and chemical property prediction. These techniques may be modified to simulate electrical signal transmission and disturbance propagation in power system contexts. In low-measurement-density contexts, graph-based representation learning may be used in conjunction with unsupervised clustering approaches to efficiently group related events together. Because of financial limitations, utilities cannot afford to implement full-scale D-PMU coverage; hence, this capacity is of utmost importance to them.

Creating and testing a representation learning framework based on graphs for event clustering in distribution networks with few D-PMU installations is the main goal of this study. Using the measurement data provided by D-PMUs in conjunction with the physical connection of the network, we aim to achieve very accurate and reliable clustering. To further demonstrate the benefits of graph-based learning, the research will compare the suggested method to more traditional time-series clustering techniques. As a result of this study, smarter and more efficient monitoring systems will be developed, which will allow utilities to quickly react to occurrences even when measuring infrastructure is scarce.

II. REVIEW OF LITERATURE

Kumar, Nidarshan et al., (2023) for distribution grids monitored by Phasor Measurement Units (PMUs), this work builds, tests, and verifies a platform for real-time state estimation utilizing Real Time Digital Simulator (RTDS). The medium voltage distribution grid in the southwest (Zeeland area) of the Netherlands, which is part of the Dutch distribution utility Stedin, has this platform created as a proof-of-concept. Here, 50 kV is the voltage used by the ring network. Keeping up with the fast sampling rates of PMUs requires the platform to use computationally efficient algorithms for state estimation and detection, discrimination, and identification of anomalies such as inaccurate data and rapid load variations. Quick anomaly detection, classification, and identification are now possible because to measurement advancements made possible by Forecasting Aided State Estimation. To provide fast state forecasting and filtering, the Extended Kalman Filter (EKF) approach has been used. In our evaluation, we took into account both typical and non-standard operating conditions, such as those characterized by measurement noise, insufficient data, and sudden changes in load, among other variables. We look at the computational efficiency, compatibility with the anomaly detection, discrimination, and identification module, and estimate accuracy of EKF compared to Unscented Kalman Filter (UKF) to demonstrate the merits and downsides of incorporating EKF into the platform. According to the results of the simulations, the Stedin distribution grid might work for PMU-based real-time state estimation.

Ibrahim, Abdul et al., (2023) the processes for tracking, securing, and managing DERs are become more complex as they are integrated into distribution networks (DNs). This is because power DNs are fundamentally designed to let current to flow in both directions, from various sources to loads. It is possible to enhance the system's situational awareness by carefully monitoring the grid dynamics of the whole DER integration processes using synchronized high-resolution real-time measurement data from physical sensors placed in the DN. For this reason, vPMUs are now part of the DN. Power measurement units (PMUs) may measure more than just voltage, current, and associated phasors; they can also measure frequency and the rate of change of frequency (ROCOF). Using strategically positioned μPMUs, this study proposes a way to generate precise event data for a practical utility DN. This method employs an imbalanced DN in conjunction with an IEEE 34 test feeder that contains 12 μPMUs that are deliberately positioned to provide accurate μPMU data derived from real-time events for various situational awareness applications. The currents in the lines and the voltages at the nodes were used to examine the various fault and no-fault events. The author utilized his experience running real-time utility grids to gather data for his PhD thesis. He then ran many experiments on situational awareness and problem diagnosis in a real unbalanced DN. A DN simulator was developed using the DIgSILENT PowerFactory (DP) software. The data-driven algorithms may be constructed using the generated realistic vPMU data in several research on event-detection, classification, and section-identification.

Aligholian, Armin et al., (2022) In order to improve power distribution system situational awareness, this work focuses on the difficult but necessary job of classifying and determining the origin of events recorded by distribution-level phasor measurement units (D-PMUs). Our objective is to tackle two primary problems plaguing this area: a) the limited availability of measurement sites caused by the high expense of buying, setting up, and transmitting data from D-PMUs; and b) the lack of background information regarding event signatures because events are varied, rare, and characterized by unknown factors. In order to address these issues, we present GraphPMU, an unsupervised graph-representation learning method, which can greatly enhance event clustering performance even when data is scarce in terms of physical location. GraphPMU takes two novel approaches: 1) it makes use of topological information regarding the relative placement of the few phasor measurement units on the power distribution network graph; and 2) it analyzes event signatures using both the widely-used fundamental phasor measurements and the less-explored harmonic phasor measurements. We demonstrate that GraphPMU can significantly surpass the widely used approaches in the literature by doing a thorough examination of many case studies.

Zhao, Tianqiao et al., (2022) with the continued growth of renewable output, online transient analysis becomes more crucial for dynamic power systems. Online applications are not a good fit for traditional numerical approaches for transient analysis since they are computationally costly and need exact contingency information as input. The current literature on online transient evaluation mostly aims to establish a stability margin or post-contingency system stability. Using initial system responses captured by phasor measurement units (PMUs), this research provides a new graph-learning framework called Deep-learning Neural Representation (DNR) for live prediction of the time-series trajectories of the system states. A Network Constructor records the interdependencies of the generators in the network, while a Dynamics Predictor foretells the future of the system.

These two modules are sequential in the DNR architecture that has been suggested. Integrating spatial-temporal message-passing procedures into structurally-aware graph neural networks is crucial for enhancing prediction performance. By comparing its performance under various contingency situations for systems of varying sizes, comparative studies prove its efficacy and scalability. This framework offers a way to forecast the dynamics of a system after a defect has occurred using real-time PMU data. It may also be used to simulate offline transients rather than whole trajectories, which is useful for other applications.

Yuan, Yuxuan et al., (2021) Power system functioning may be better understood with the help of a widespread installation of phasor measuring units (PMUs), which, when seen through the lens of data, expose the underlying physical principles of power systems. On the other hand, real-time system event detection may face significant technological hurdles due to the impure data quality, high granularity, and non-stationary characteristics of PMU time series. A two-stage learning-based methodology is suggested in this research to tackle these difficulties. The first step involves using a Markov transition field (MTF) technique to encode the transition statistics and temporal dependencies of PMU data in graphs, and then extracting the latent data characteristics. In order to swiftly and effectively recognize operation events, a convolutional neural network (CNN) is set up with the help of spatial pyramid pooling (SPP). The suggested approach is both grounded in and tested on a substantial real-world dataset consisting of tens of thousands of PMU sources (together with their associated event logs) distributed throughout the United States over the course of two consecutive years. Our technique has excellent identification accuracy and shows strong resilience against low data quality, as shown by the numerical findings.

III. GRAPHPMU WITH FUNDAMENTAL AND HARMONIC FREQUENCY DATA

We have been assuming up until now that the fundamental frequency is the point at which all phasor measurements are taken. Indeed, this is the average PMU's current level of experience in this area. Nevertheless, as discussed in Section, it is anticipated that conventional DPMUs will eventually double as H-PMUs, enabling them to provide phasor measurements at both the fundamental and chosen harmonic frequencies.

Consequently, we will extend the GraphPMU model in this part to account for this new development in the available data in this area.

More Distinctive Event Signatures

Without limiting ourselves, let's say that every D-PMU not only measures the fundamental frequency but also the third and fifth harmonics in a coordinated fashion. While it would not be essential, it would be beneficial to expand the study to include higher harmonic orders. This is because the majority of occurrences appropriately manifest in either the third or fifth harmonics, or both. For every bus j in M, we take measurements of V_{φ}, I_{φ}, and PF_{φ}; however, we record them not only for the fundamental frequency but also for the third and fifth harmonics.

When it comes to grouping events, it might be quite helpful to consider the harmonic phasors since they show more unique fingerprints. Contributing to the overall success of the proposed GraphPMU technique, this may assist compensate for some of the issues caused by locationally-scarce data.

The input to the suggested graph encoder consists of these vectors in addition to the positive and negative graphs. The positive and negative samples are shaped by pairing the graph encoder's output with representations at the node and graph levels. After then, in order to maximize MI, the discriminator learns to distinguish between these samples.

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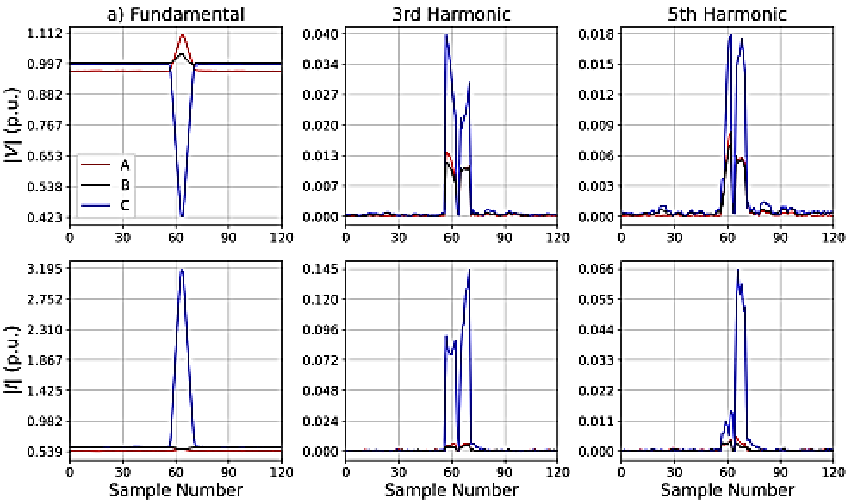

Figure 1: Comparing the signatures during the same event at the fundamental phasor measurements vs. at the 3rd and 5th harmonic phasor measurements.

In Figure 1, we can see the event signatures in several phasor measurements taken during a single-line-to-ground fault. A basic voltage drop and an inrush current provide the event signature at the fundamental frequency shown in Figure 1(a). However, the event signatures in the harmonic phasor Measurements at the 3rd harmonic in Figure. 1b) and at the 5th harmonic in Figure. 1(c) are considerably more distinctive.

Extended Temporal-Based Learning

In the same way that we use AED to learn fundamental phasor data, we also use it to learn harmonic phasor time series representations. So, in order to use them during clustering, we get the embedding vectors. Crucially, we need to train separate AEDs for each fundamental or harmonic order because the general nature and intensity of the time series of harmonic phasors varies from those of fundamental phasors. Compared to employing a single AED for all of these time series, time domain representation learning is now more precise and dependable. We use Algorithm 2 to conduct the training. We join all the embedding vectors together to create

$$Em_i^j = [Em_i^{j,1}\ Em_i^{j,3}\ Em_i^{j,5}]^T.$$

Extended Topology-Based Learning

Using Algorithm 1, we next feed the newly obtained vectors Em_i^j into the GNN to finish the event clustering operation. Because the input vector is not the same size or type. The new feature vector requires a re-training of the GraphPMU. Lastly, we utilize zero padding concatenation to the basic embedding vectors that were previously for any bus j ∈ B\M that does not contain a sensor. This occurs because, by default, it is presumed that the steady-state values at areas that have not been measured do not include any harmonics.

IV. EVENT SIMULATION AND ANALYSIS ON IEEE 34-BUS TEST SYSTEM

Figure 2 shows the three-phase power distribution test system based on the IEEE 34-bus. In this part, we do many case studies using this system. To guarantee capturing the event's transitory signatures, the PSCAD network simulation model is built. There are nine distinct kinds of occurrences that are replicated:

1) Three-Phase Capacitor Bank switching at bus 840

2) Three-Phase Capacitor Bank switching at bus 849
3) Single-phase load switching at bus 858
4) Three-phase load switching at bus 836
5) Three-phase motor-load switching at bus 812
6) Three-phase motor load switching at bus 828
7) Single-phase-to-ground fault at bus 852
8) Two-phase-to-ground fault at bus 862
9) Three-phase-to-ground fault at bus 816.

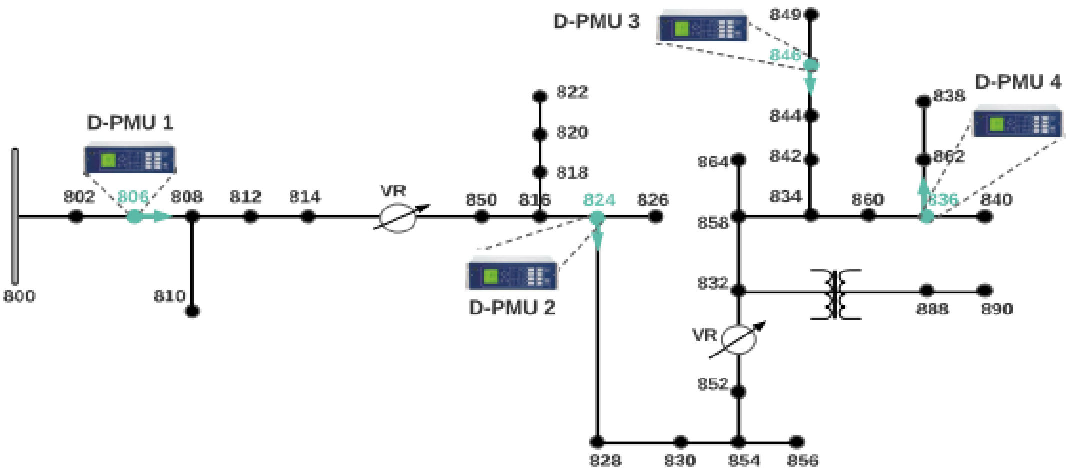

Figure 2: The IEEE 34-bus test system with locationally-scarce phasor measurements.

As seen in the image, this network only has four accessible D-PMUs (H-PMUs). Nonetheless, any place may host the activities. Unless otherwise specified, we will assume that the power distribution network contains a total of four phasor measuring units. On Figure 2, you can see where the D-PMUs (H-PMUs) are located. Please take note that:

$$\mathcal{M} = \{806, 824, 836, 846\}.$$

Based on the case study, we infer that every D-PMU either gives us phasor readings for the fundamental component alone or for the fundamental component plus the third and fifth harmonics. Since we want GraphPMU to be as accurate as possible, we train it using the assumption that events are infrequent and that there are only a limited number of each sort of event. By applying noises and time shifting to the raw data, we were able to enhance the data from the limited number of occurrences that were available. All sensors and event types undergo this process. We took into account 50,000 occurrences of different kinds for training, 5000 for assessment, and 5000 for testing.

Parameters of GraphPMU

There are two GCN layers in the graph encoder, with 128 and 64 sized hidden layer vectors, respectively. A total of 192 and 32 neurons, respectively, make up the discriminator's two fully-connected layers. Because we combine the characteristics of the hidden layer with those of the global graph, the total input size of the discriminator is 192 (128 + 64 = 192). We drive the GNN encoder to learn more discriminative features by deliberately selecting a naïve discriminator with just two fully-connected NNs. For event clustering, this may be useful.

The AED's encoder part consists of a 32-unit fullyconnected layer, two layers of LSTM modules (32 and 64 units, respectively), and so forth. Following a fully-connected 64 × 125 layer, the decoder section consists of two Long Short-Term Memory (LSTM) layers with 64 and 32 units, essentially reversing the encoder.

With a leak slope of 0.2, all activation functions are LeakyReLU. We used the coarse-to-fine technique for hyper-parameter tweaking. In order to achieve greater stability during training, β1 is set to 0.5 and the learning rate α to $1e^{-3}$. Adam optimizer is used. Using Pytorch, we build all of our models.

These GNN models are Constructed using the Nvidia GTX 1050 ti GPU, an Intel Core i-7 2.2GHz CPU, and 32 GB of RAM, all with the help of the Deep Graph Library.

In the basic phasor, the mean squared errors (MSEs) for the training and testing phases are 0.04425 and 0.04522, correspondingly. For the decoder to accurately recreate the time series, it is necessary that the encoder compress the high-resolution data to a low-dimensional format. This validates the AED sub-system's performance for the remainder of our investigation.

To measure clustering accuracy, this article use the Adjusted Rand Index (ARI) score. ARI may take on values between zero and one. Better clustering is indicated by a higher ARI.

Comparison with Temporal-Based Benchmarks

The ARI for the suggested event clustering approach is shown in the final row of Table 1, while other benchmark methods are compared in the first nine rows. Here, we'll go over the first five approaches, which make up the upper portion of Table 1. These are the approaches that don't take the network topology into account in any way. The five approaches in question are k-means clustering, k-Shape clustering, AED, DEC, and kernel k-means. Time Series (TS) in this context indicates that the approach makes use of unencoded, raw time series data.

Table 1 Ari Score for Different Methods under Locationally-Scare Phasor Measurements at Four Buses

Graph Model Usage	Method	ARI
Without Graph Model	AED	0.473
	DEC	0.520
	Kernel TS	0.237
	k-shape TS	0.418
	k-means TS	0.343
With Graph Model	TS + N/G + NL	0.487
	AED + N/G	0.423
	AED + N/G + RL	0.533
	AED + G + NL	0.585
	GraphPMU = AED + N/G + NL	**0.720**

Table 1 shows that among the five non-graph model techniques, DEC and AED are the most accurate. All 10 of the approaches in Table 1 are assumed to have the same steady-state constants at the sensor-free buses in order to make a fair comparison.

Comparison with Topology-Based Benchmarks

The data about the network's architecture is really used by the following five procedures in the lower part of Table 1. Our goal may have been accomplished with any of these permutations. But you can only see our final GraphPMU design in the last row. Benchmarks are provided by the remaining procedures. According to the new acronyms in Table 1, GNN stands for "graph level representation only," N/G for "node level representation and graph level representation both," NL for "nominal load flow model to obtain constants at the buses without sensors," and RL for "random loading data" in place of nominal loading data.

1) Advantage of Using Data Compression: In Table 1, we can see that the only distinction between GraphPMU and TS+N/G+NL is the latter's use of AED as opposed to TS. Crucially, compared to TS+N/G+NL, which uses the raw time series as input, GraphPMU uses compressed data, making it more unique for the GNN. So, in general, GraphPMU performs much better in event clustering. However, even without a graph model, the majority of the benchmark techniques in the top section of Table 1 can still be outperformed by TS+N/G+NL thanks to its use of topological information.
2) Advantage of Pairing Node-Level and Graph-Level Vectors: You can see that the only difference between AED+G+NL and GraphPMU is the use of G as opposed to N/G by comparing the two in Table 1. Instead of employing the node-level/graph-level pairings, the AED+G+LN technique maximizes MI by using just the final layer of the graph learning model for the positive and negative graphs. Having said that, for GraphPMU to correctly extract the common structure between the graph-level representations and the node-level representations, which in turn allows for more distinct clusters, such a pair is required.
3) Advantage of Using Nominal Load Data: Table 1 shows that the sole difference between AED+N/G and GraphPMU is the use of N/L. The buses lacking sensors are excluded from the graph-based learning process in AED+N/G. Consequently, the method's accuracy plummets. The four sensor buses constitute the sole nodes on the graph, which is the reason for this. This is because there aren't enough sensors in the right places. You won't get much use out of topology-based learning on such a little network. The performance of this approach is much worse than that of AED+N/G+RL. The findings show that using the nominal loading data for a basic power flow study does help.

Analysis Based on Different Types of Events

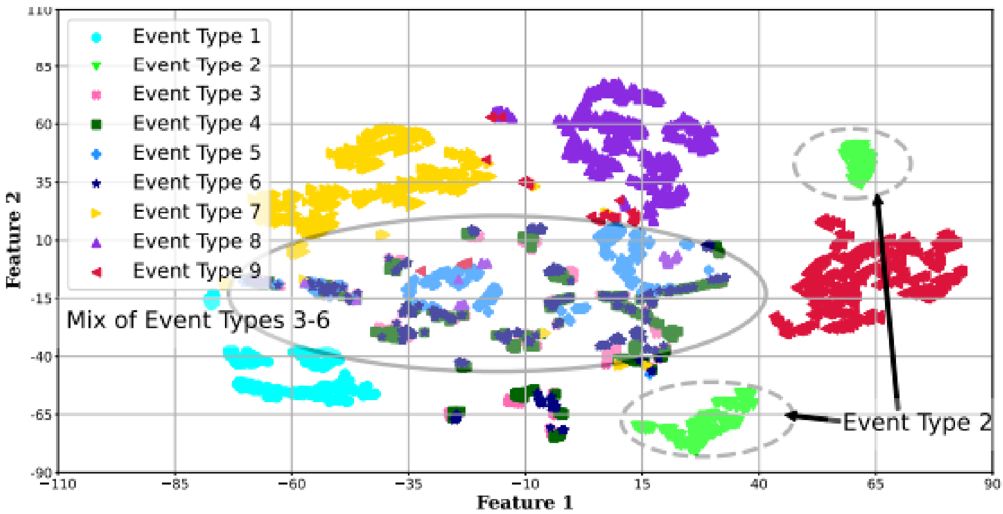

Figure 3: t-SNE scatter plots for the test events for DEC, ARI = 0.524 methods

The t-SNE scatter plot of all test events for the three approaches is shown in Figure. GraphPMU, AED+G+NL, and DEC are the three options shown. Every dot represents a distinct occurrence. Each of the nine event kinds has a form and color that corresponds to its correct name. Methods devoid of graph models suffer greatly from an issue with correctly clustering "smaller" occurrences (event types 3, 4, 5, and 6). Figure 3 shows an example of such a region, delineated by an oval and a solid line. All four of these event kinds are muddled together here. Therefore, event kinds 3-6 cannot be distinguished using the DEC approach.

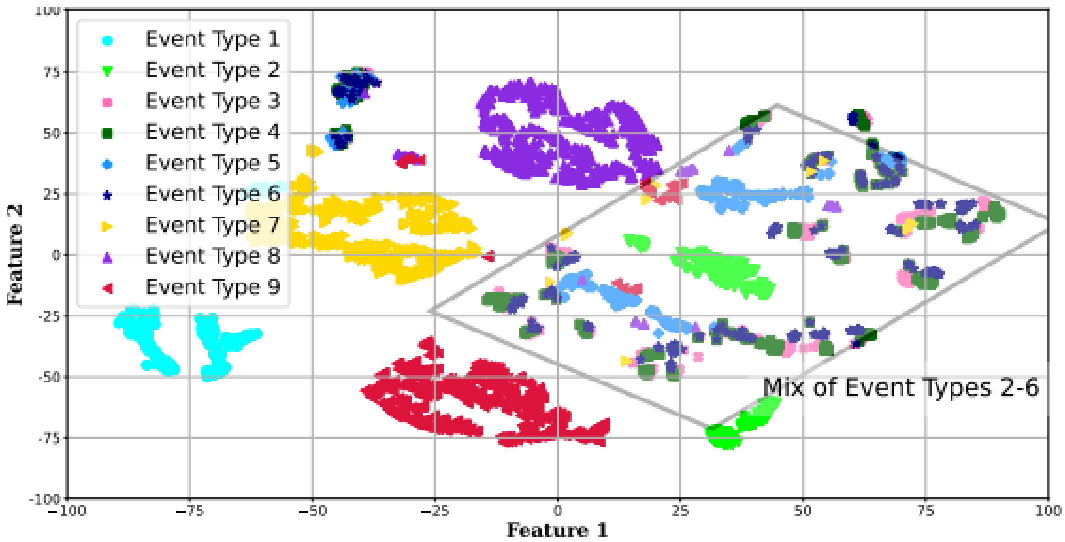

Figure 4: t-SNE scatter plots for the test events for AED+G+NL, ARI = 0.585

After that, look at Figure 4 for the AED+G+NL findings. Even AED+G+NL can't separate the "small" occurrences, as seen by the diamond-marked region. The more distinct clusters for the "major" event categories 1, 7, 8, and 9 cause its ARI to be somewhat higher than DEC's. Figure 4 shows that the DEC technique wrongly divided event type 2 into two sets of points, as shown by the two circles with dashed lines. With only 8 H-PMUs in a network with 34 buses, GraphPMU obtains a very high ARI score of 0.92 Figure 4.

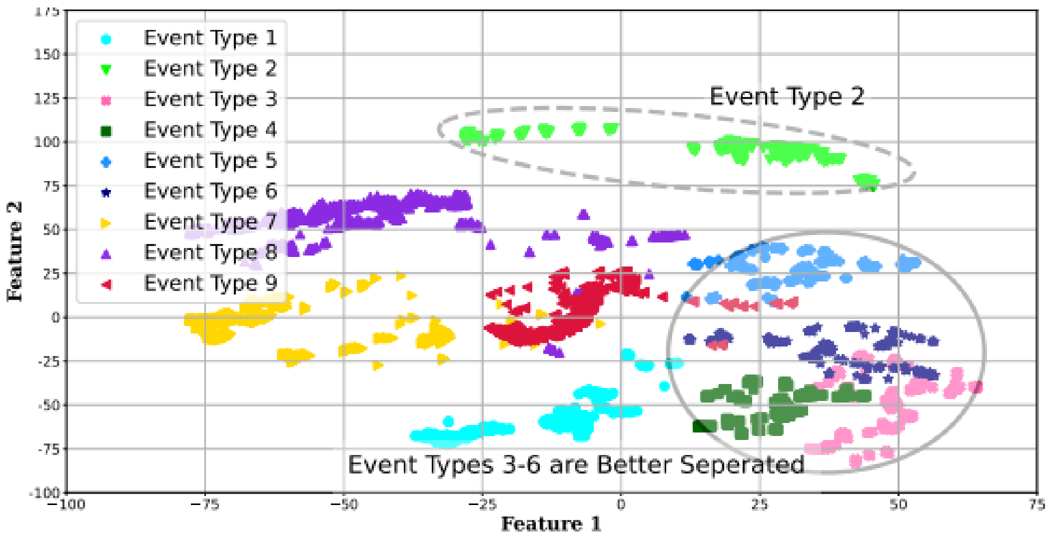

Figure 5: t-SNE scatter plots for the test events for GraphPMU, ARI = 0.720

Figure 5 shows that GraphPMU fixes all of these problems. One the one hand, GraphPMU strives for maximum separation of the "major" event kinds. The points for event type 2 are clustered together in the dashed oval region of Figure 5, for instance, and they are not far from any of the other occurrences. As a result, clustering event type 2 accuracy is significantly enhanced.

The "smaller" event kinds are kept decently apart by GraphPMU as well. The points for event types 3, 4, 5, and 6 are much better isolated from each other in the circular region shown with a solid line in Figure 5 compared to the other figure.

Impact of Adding Harmonic Phasor Measurements

Table 2 displays the event clustering outcomes for AED, DEC, and GraphPMU when both the fundamental and harmonic phasor measures are used. All three approaches significantly enhance event clustering performance, as shown in Table 2 as compared to Table 1. This is because, as we saw in Section, certain event kinds have more unique transitory characteristics.

Out of the nine event categories, the most significant gains in accuracy are shown with imbalanced events, namely types 3, 7, and 8. If we look at Table 2 and only look at the basic phasor measurements, or if we look at both tables, we can see that GraphPMU is much superior than the other approaches.

Table 2 Ari Score for Graphpmu and the Top Two Methods without Graph Models When Adding Harmonic Phasor Measurements

Method	ARI
AED (Fundamental + Harmonics)	0.666
DEC (Fundamental + Harmonics)	0.694
GraphPMU (Fundamental + Harmonics)	**0.814**

Phasor measurements, both fundamental and harmonic, as seen in Table 2. With sensors installed in only 12% of the buses—4 out of 34—an ARI of 0.814 is quite high.

Impact of the Number of D-PMUs

There are three distinct patterns that emerge from these figures. First of all, compared to other approaches, GraphPMU consistently performs better. Under locational-scarcity situations, when the number of sensors is low, its relative better performance is at its peak. Second, the overall clustering accuracy for all of these approaches improves as the number of available sensors increases. Finally, when there is a high level of locational scarcity, AED+N/G performs worse than AED. However, as the number of sensors increases, it starts to outperform AED. This is because only with a number of sensors at our disposal can AED+N/G make use of data pertaining to the network architecture. Fortunately, GraphPMU takes care of this issue.

V. CONCLUSION

Reliable event clustering in distribution networks, especially with limited D-PMU installations, may be achieved by graph-based representation learning, a powerful and unique technique. To overcome the limitations of conventional clustering methods that depend only on dense data availability, this approach incorporates the network's physical architecture and accessible measurement data into the learning process. Improved situational awareness and operational decision-making are possible outcomes of the capacity to derive significant spatial-temporal patterns from sparse data. The study's anticipated results will show that utilities may use graph-based learning frameworks to improve event categorization reliability with little instrumentation. In the grand scheme of things, these developments bode well for efficient and resilient electricity distribution systems, smart grid development, and cost-effective grid monitoring methods.

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