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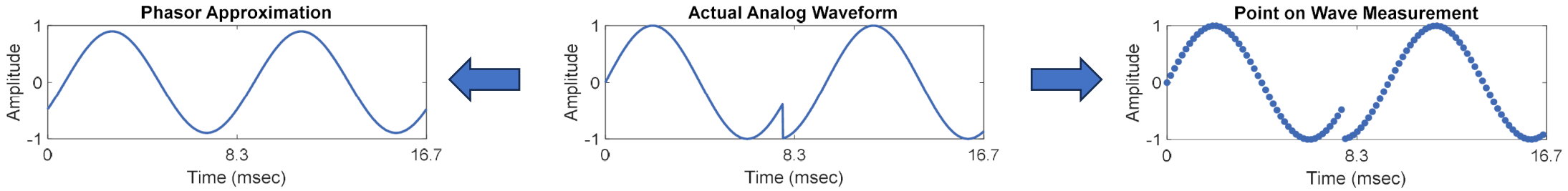
Advancing Grid Intelligence: Bridging PMU and PoW data for Enhanced Frequency Event Analysis

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Problems Plaguing Monitoring Systems in Modern Grids



Comparing PMU and PoW fidelity to actual waveform [1]

- Phasor Measurement Units (PMUs) are placed strategically and provide streaming estimated values of electrical quantities across the system thereby painting its snapshot, but may miss rapid transients
- Relays are ubiquitous in the grid and typically record more granular point-on-wave (PoW) data briefly around transients, thus may miss key pre- and post-transient behavior
- This study dives deeper into enhanced analysis of a critical event type in power systems, namely, **frequency events**, by trying to **bridge** this trade-off in grid monitoring



[1] Alison Silverstein, “Point on Wave Data, What and Why”, NASPI Work Group Meeting, Oct 2019.

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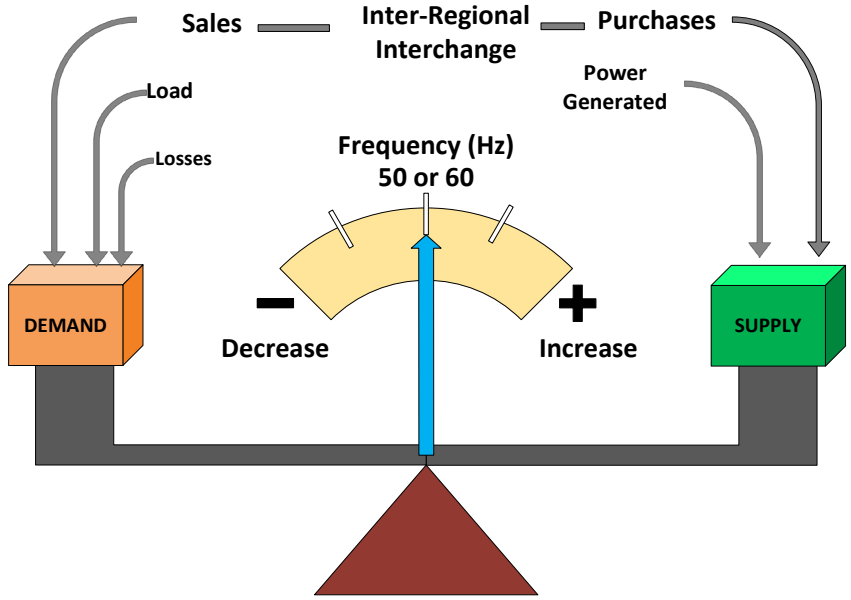
Introduction to Frequency Events and Motivation

- Sudden frequency excursions (events) can occur due to:
  - Load additions or drops
  - Generation additions or drops
  - Faults, trips, or switching

- Complex power system dynamics demand multiple type of sensors for accurate characterization of such events (relays and PMUs are usually readily available)

- The combination of PMU and PoW data gives observability during both fast transients and longer system responses

- **Final Goal:** Characterization of frequency events using automated analysis by employing machine learning/artificial intelligence (ML/AI) techniques

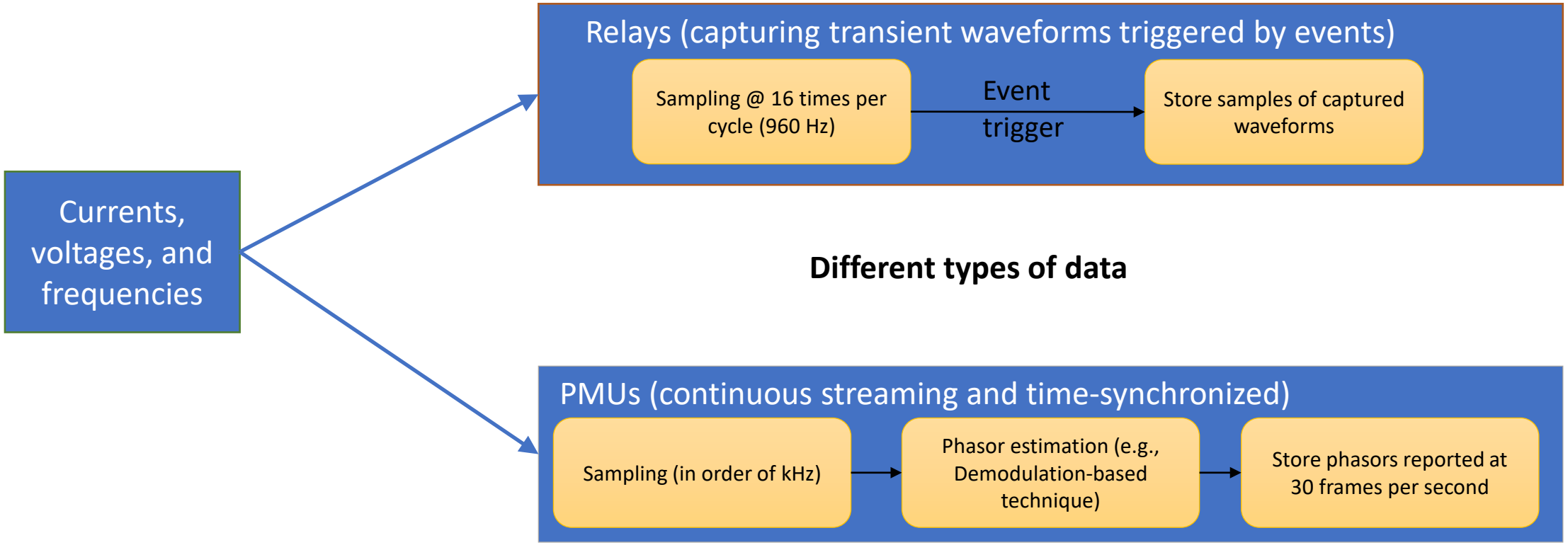


Power balance and nominal frequency [2]

[2] PJM Primary Frequency Response Senior Task Force, "Primary frequency response stakeholder education, part 1 of 2," tech. rep., PJM Interconnection, Sep. 2017. Presented September 1, 2017.

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Field Recorded Datasets Available



Different types of data

Description of available field recorded datasets from a utility in the Eastern Interconnection (EI)

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Description of Field Recorded Data

- The following information was obtained from the utility located in the EI:

➢ **PMU dataset:** Around 570 PMU locations; continuous streaming data was available for the years 2017-2021

➢ **Relay dataset:** PoW data from relays that got triggered in the EI utility system between the years 2016-2024

➢ **Network connectivity:** Raw file with lines, buses, and equipment information

➢ **PMU event log:** Event log with around 9500 events between the years 2009-2023 with a brief description of event location and cause (e.g., weather related or failed protection system)

- The given event log had the following structure (actual names hidden)

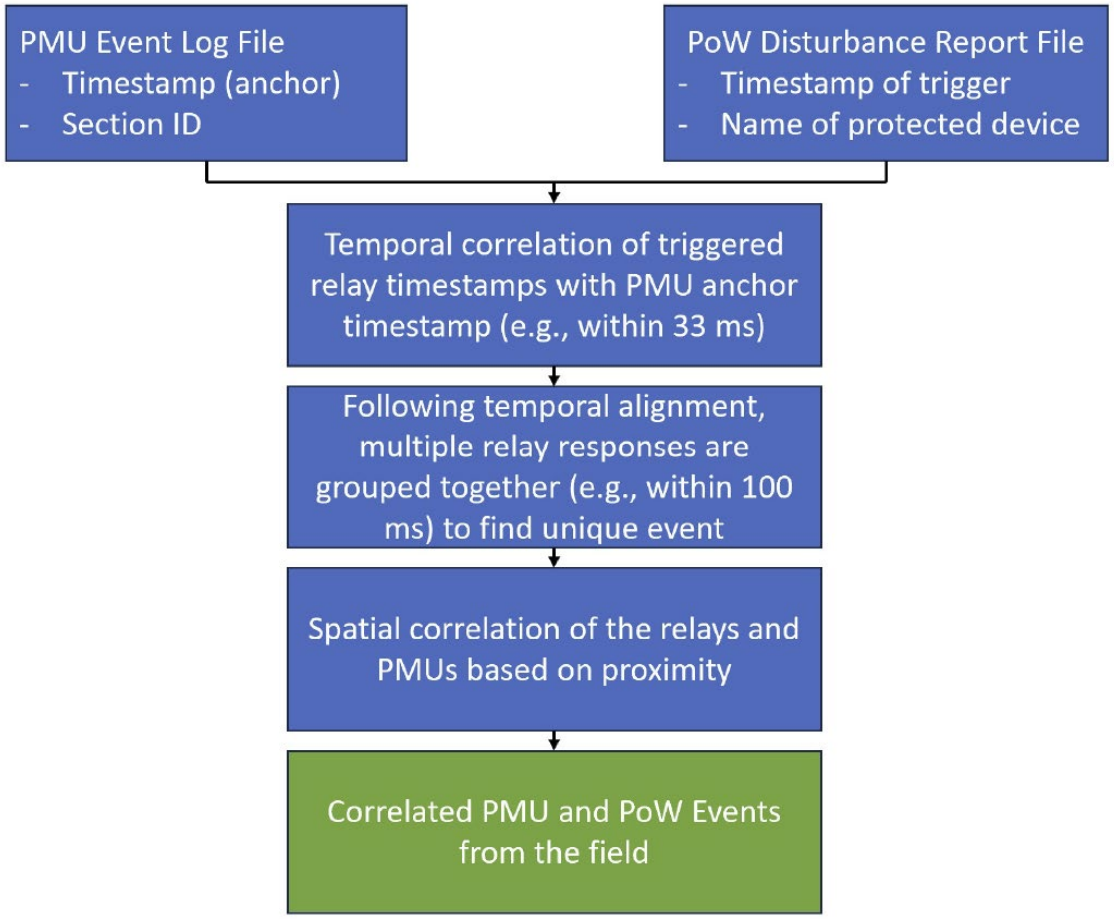
Timestamp	Event Location	Description	Number of Operations	Section ID
MM/DD/YYYY HH:mm:SS.fff	345 kV X Transformer	Failed AC Circuit Equipment- Transformer Bushing Exploded	say 2	say 1500

- We now present **a systematic procedure** to correlate events recorded in relay and PMU data

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Correlation of PoW and PMU Events for Combined Analysis

- Relay data uses local time (e.g., Central Time US) while the PMU data are recorded in UTC
- A critical step in the integration process is **time zone normalization**
- Next, all relay recordings within a defined temporal threshold (such as 100 milliseconds), with reference PMU event time, are grouped to identify relays that responded to the same event
- By matching the section ID from the PMU event with the relay identifier, it is possible to pinpoint the origin of the disturbance in terms of the bus or the transmission line
- We now present **three practical challenges** that were faced when correlating PMU and PoW data



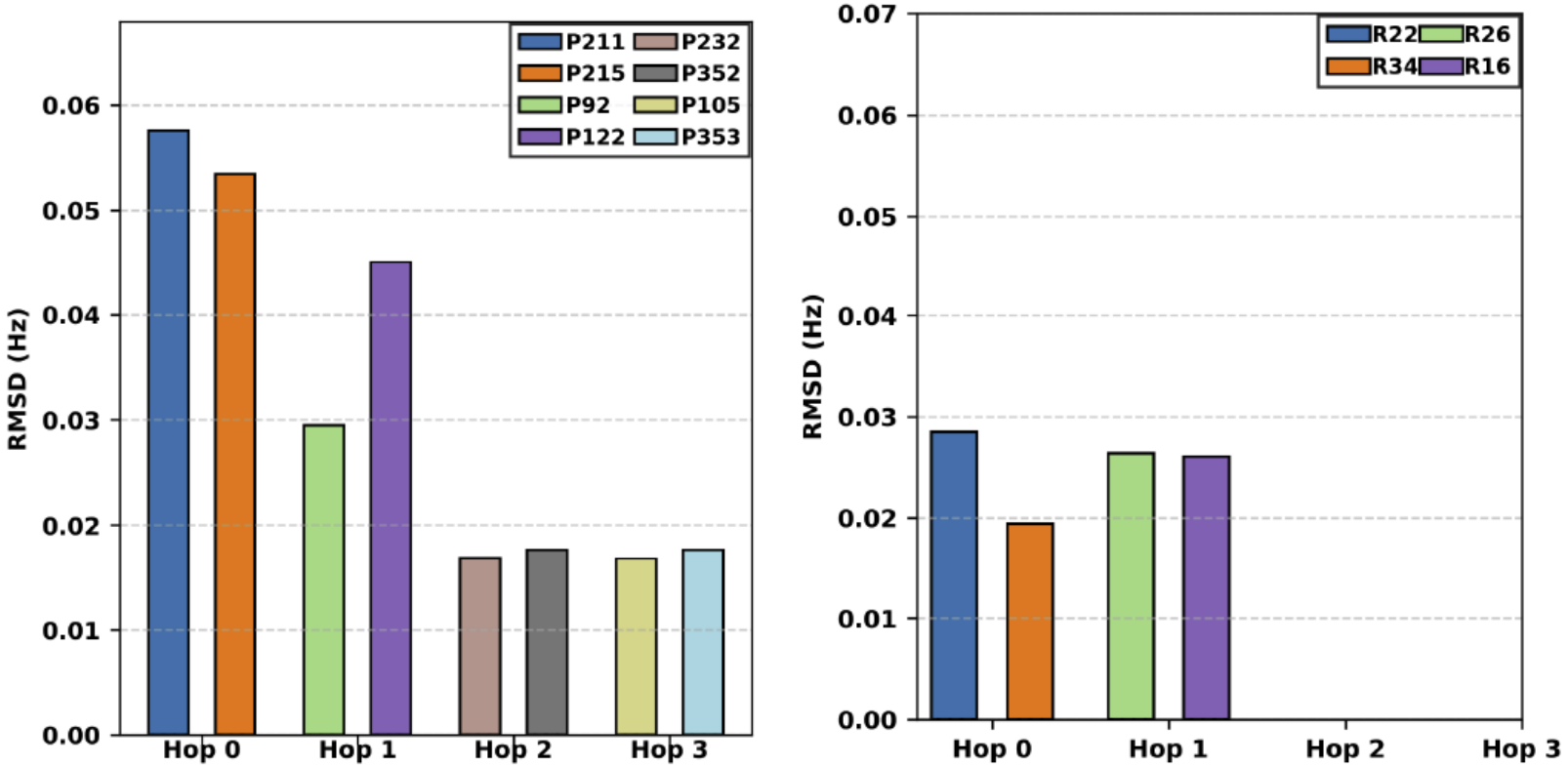
Process for correlating the PoW and PMU events for combined analysis

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Complementary Strengths and Integration Challenges of Field Recorded Data

- Complementary strengths:
  - Rapid dynamics observed (PoW)
  - System-wide behavior captured (PMU)

- Integration challenges:
  - **PoW data depend on the protection device activation and bus breaker operation**



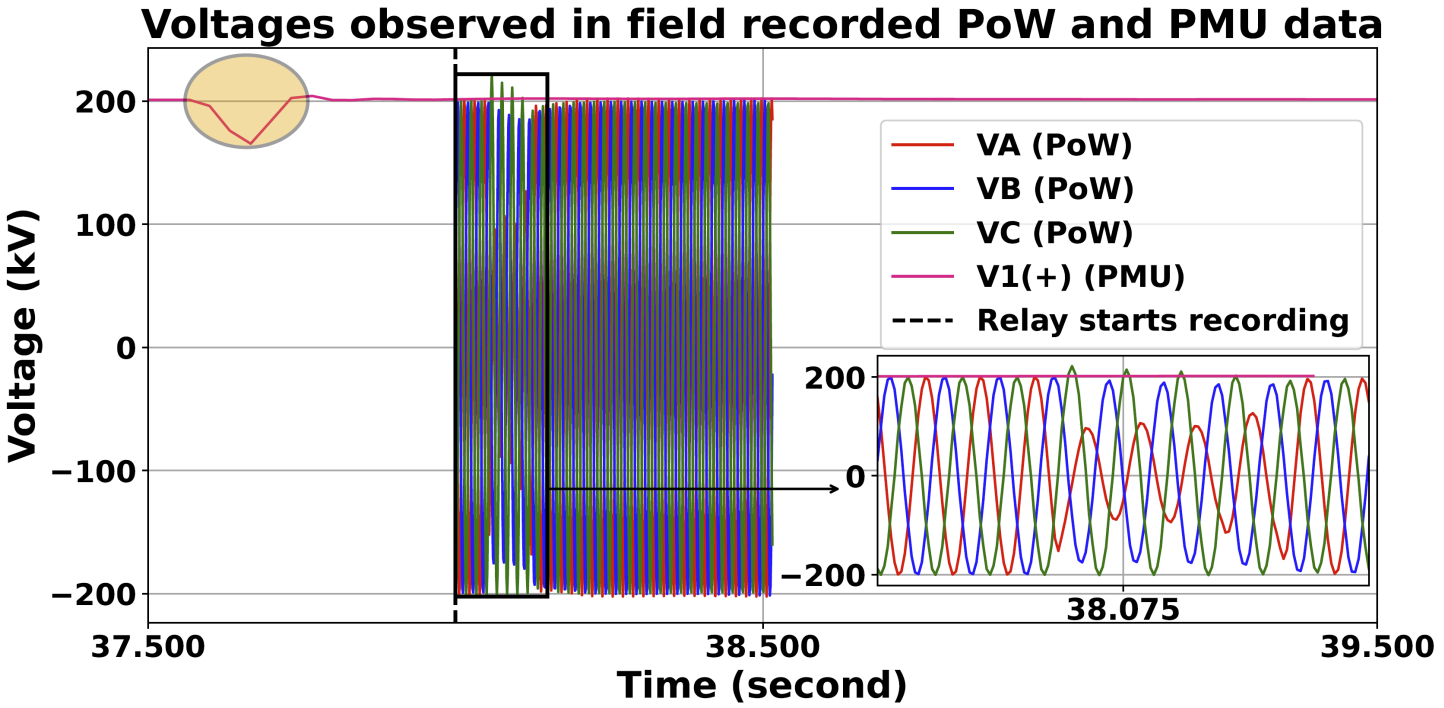
Estimated root mean square deviation (RMSD) in frequencies captured by PMUs and relays during a frequency event near an inverter-based resource (IBR) in the EI utility

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Synchronization and Misalignment Constraints

- **Differing sampling rates, time bases (local vs. UTC), and recording lengths (triggered non-uniform length vs. continuous) complicate precise alignment**

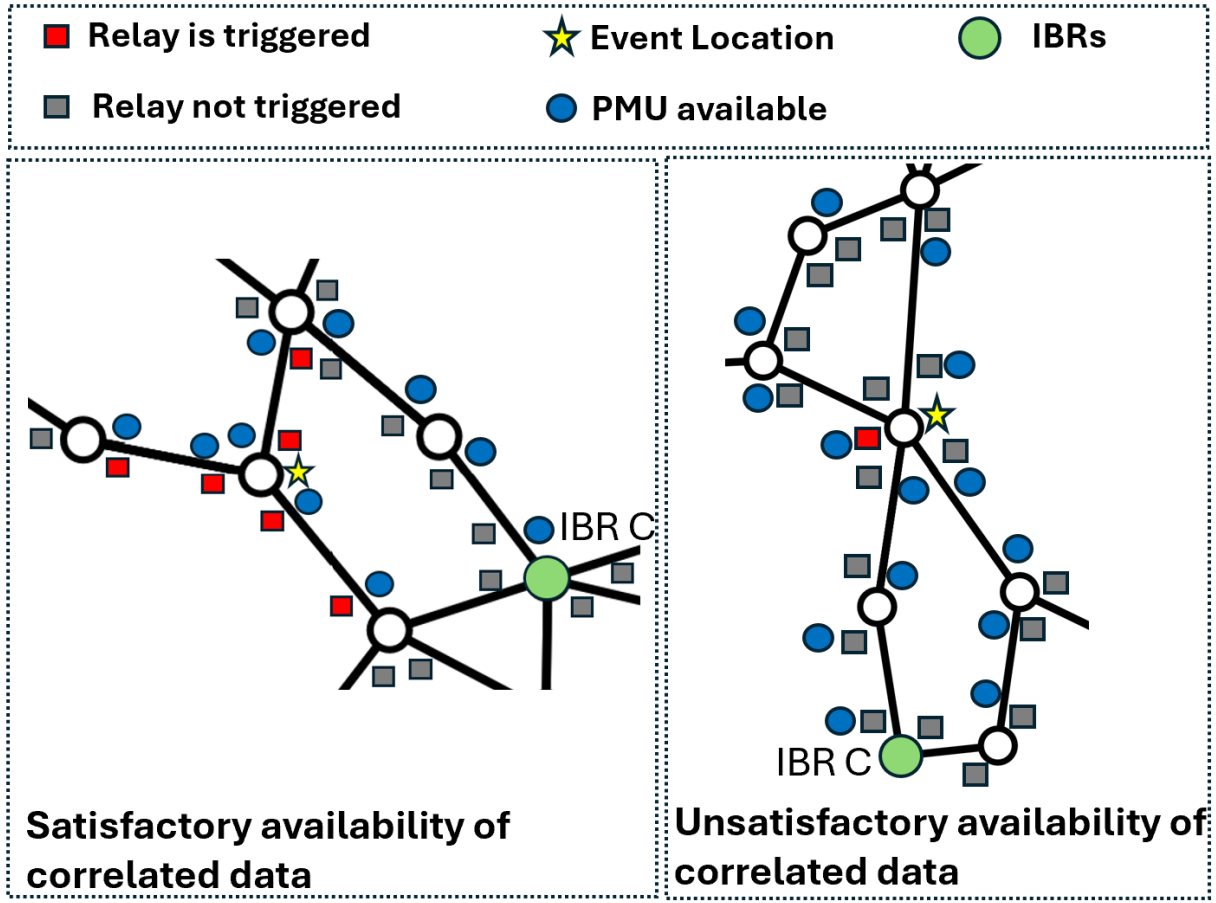
- Figure shows temporal separation for the same event signature by a neighboring relay and a PMU



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Uneven Spatial Coverage and Event Correlation Limitations

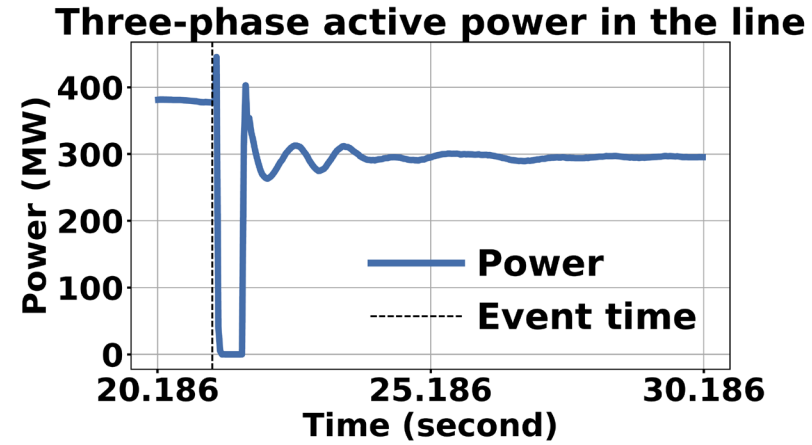
- **Limitations with capturing detailed activity by relays vs. system wide variation by PMUs**
- Two example cases showing satisfactory and unsatisfactory availability of correlated data
- PMU availability alone did not guarantee good quality data
- These inconsistencies made direct comparison of relay-triggered and non-relay triggered events difficult which in turn created gaps in comprehension
- We now look at **<u>two actual frequency events</u>** captured in field-recorded data

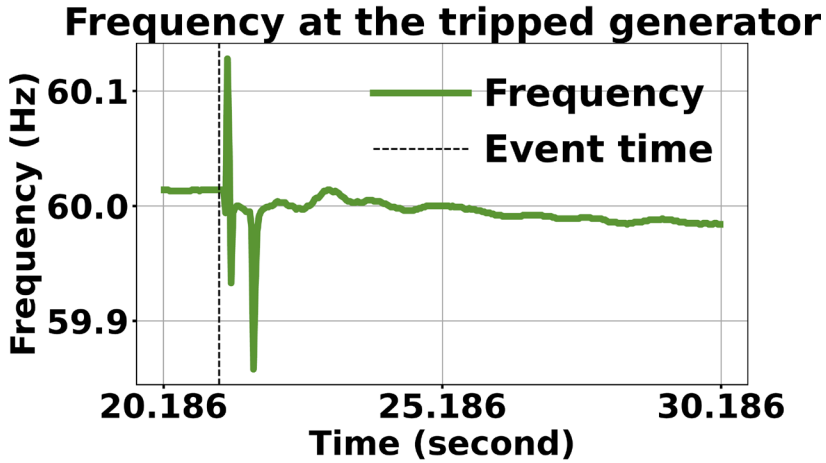


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Field Recorded Event 1: Simultaneous Line and Generator Trip Event

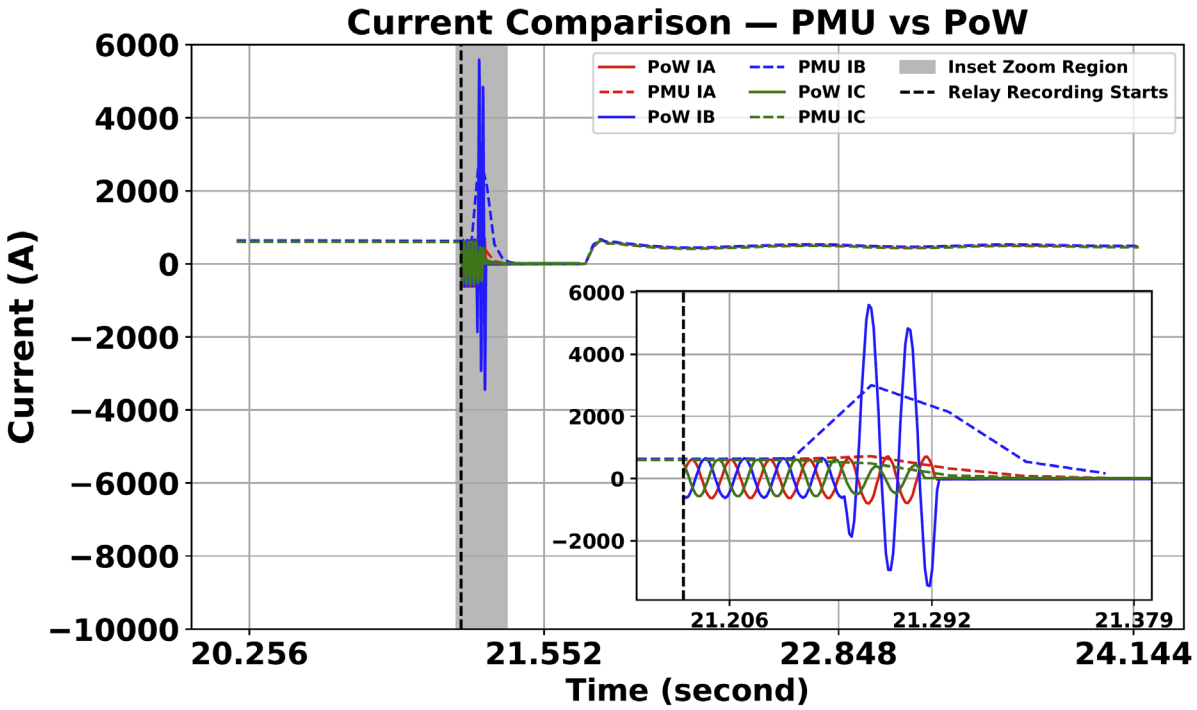
- The tripping of the generating unit caused an oscillatory response
- The power flow dropped sharply during the fault and, after reclosing, did not return to its pre-event level
- The frequency at the tripped generator exhibited short lived but massive frequency excursions at the same instant, indicating a strong dynamic response to the simultaneous line fault and unit trip

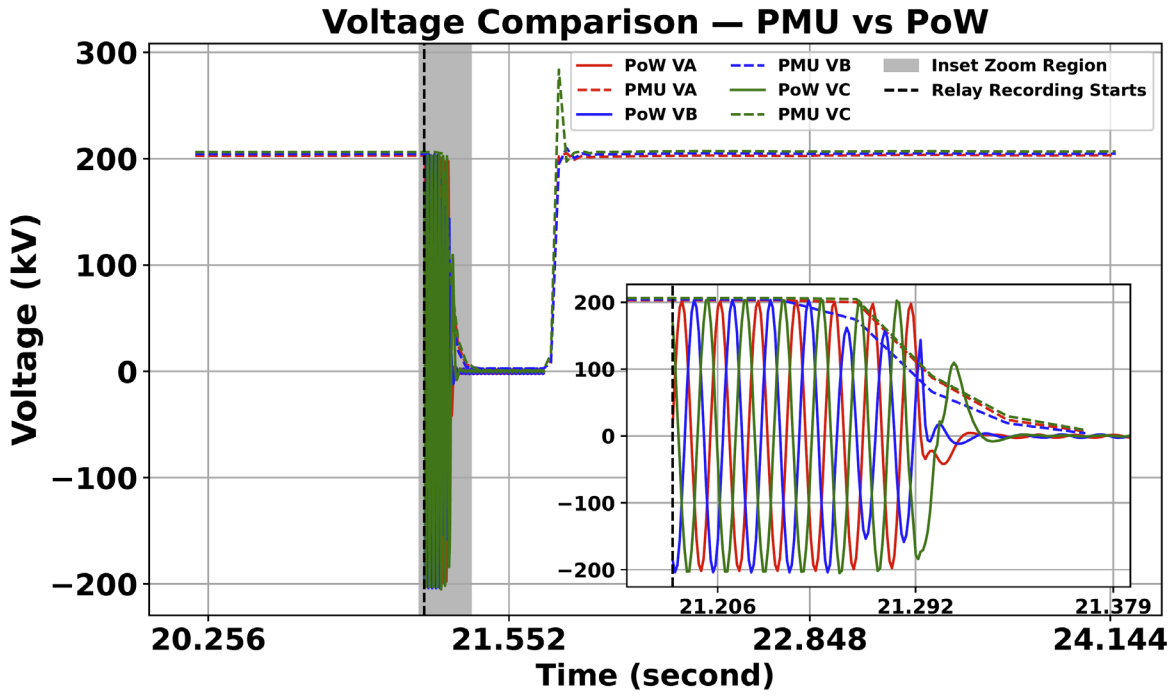




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Field Recorded Event 1: Simultaneous Line and Generator Trip Event





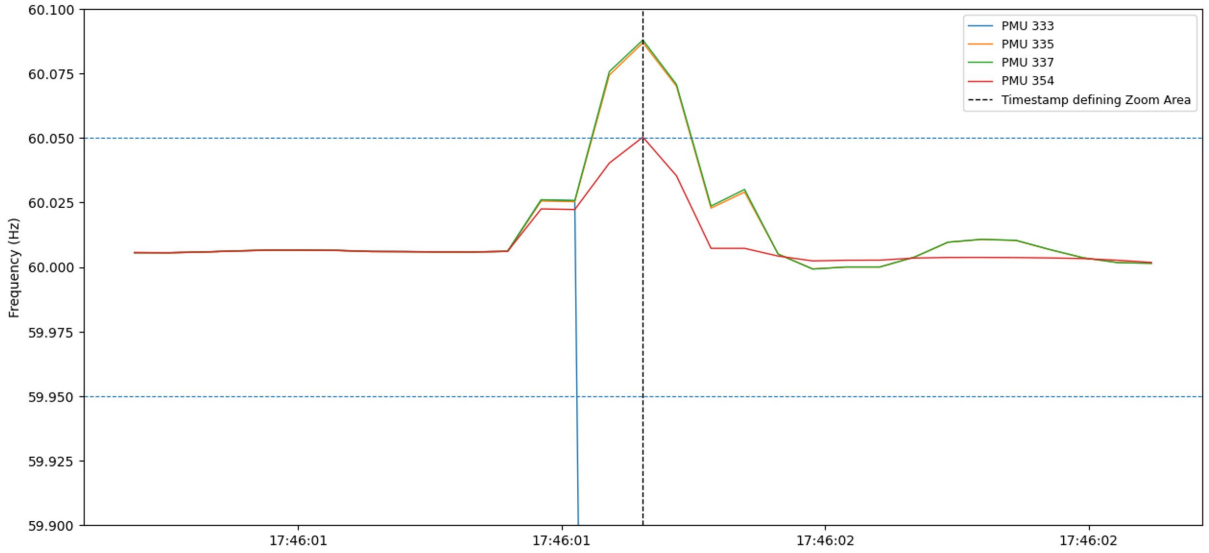
- The current waveforms from the relay and the PMU shows that only phase B current rises drastically during the fault, with PMU data estimating far from high values seen in PoW data. Supplementing PoW data with PMU data helps verify involvement of phase B in the fault and its actual severity

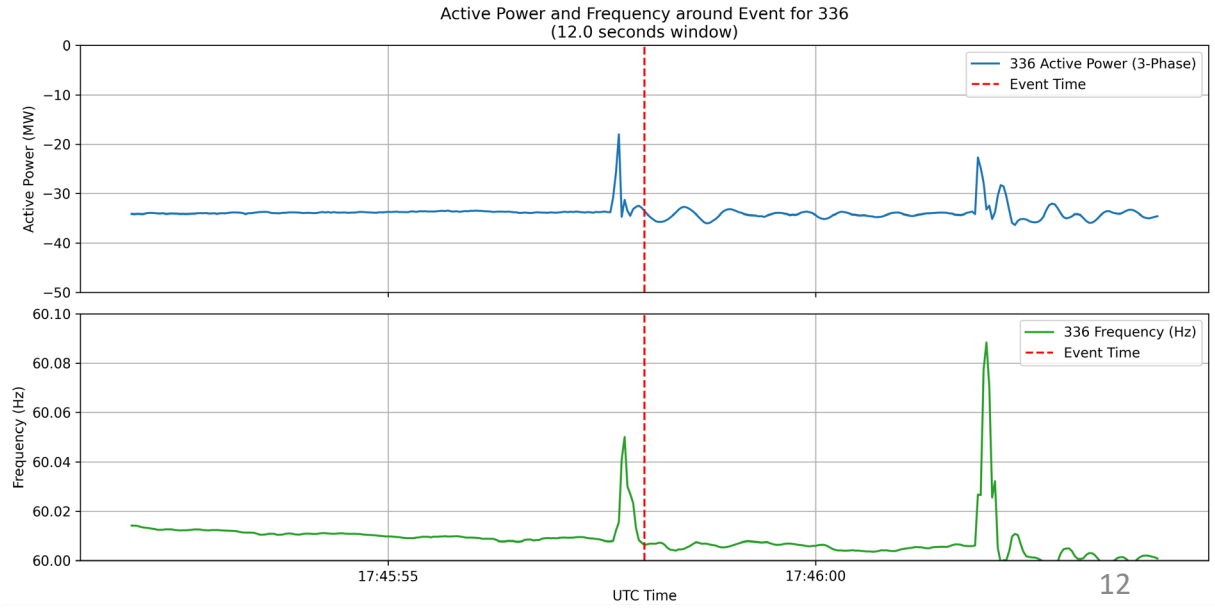
- The PMU data captures the post-event system response while the relay data does not

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Field Recorded Event 2: Severe Weather Event

- During this event, the utility's event log recorded multiple entries clustered around a transmission line
- The transmission line originated from a bus connected to an IBR
- The large frequency swings suggest a highly stressed system condition, likely driven by the combined effects of adverse weather on infrastructure performance and system dynamics



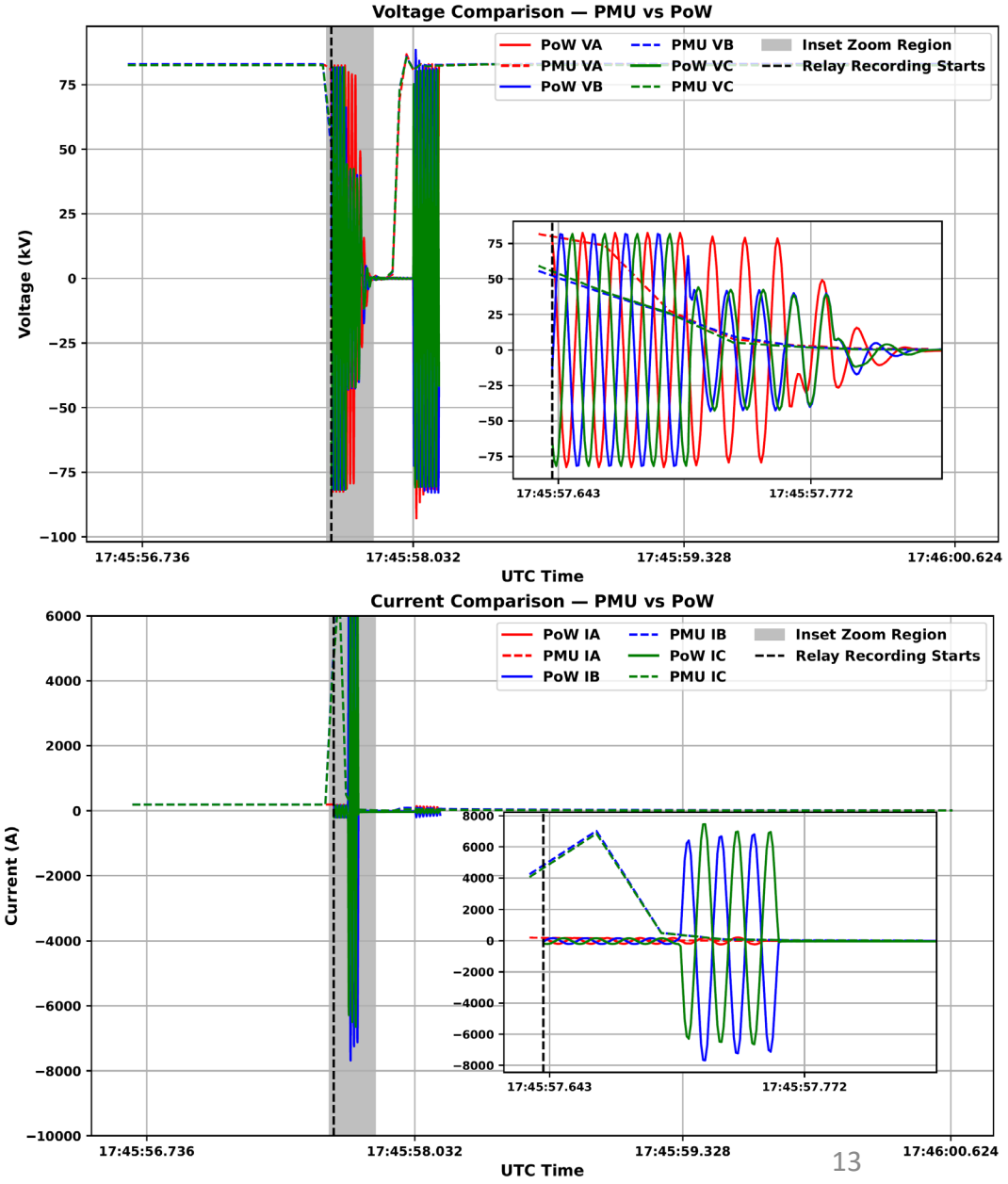


Active power and frequency during a frequency event near a windfarm (IBR) in an EI utility

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Field Recorded Event 2: Severe Weather Event

- Severe weather event led to conductor galloping in the affected area
- Due to galloping of the conductors, a line-to-line fault (phases B and C) is seen to occur
- The temporal alignment between the event log entries and the PMU measurements further indicates that the disturbances were not isolated incidents, but rather part of a broader, weather-induced system response affecting grid stability in the area



Reconstruction of voltages, and currents (merged PoW-PMU data) during a frequency event near a windfarm (IBR) in an EI utility

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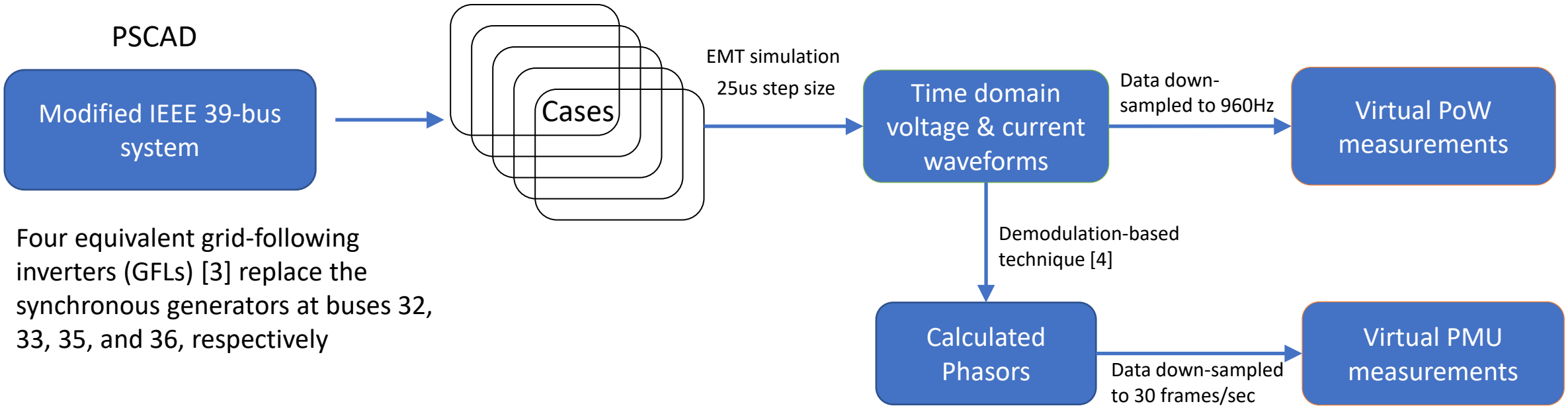
Limitations of Event Tracking Using Solely Field Recorded Datasets

- Examination of all significant frequency events recorded between the years 2017-2021 show us that event tracking in the presented manner is limited due to:
  - Paucity in the frequency of event occurrence
  - Data availability (PMUs being strategically located hence sparse; all relays do not get triggered for neighboring events; thus, the combination does not warrant correlated PMU and PoW data for analysis at a bus/line of interest)

- The above-mentioned limitations in field recorded data in addition to data quality issues do not present us with suitable data to train a ML/AI tool for frequency event characterization, necessitating the creation of simulated data

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Simulated Data



[3] Kenyon, Rick Wallace, Sajadi, Amirhossein, Hoke, Andy, & Hodge, Bri-Mathias, "Open-Source PSCAD Grid-Following and Grid-Forming Inverters and a Benchmark for Zero-Inertia Power System Simulations", 2021.
[4] R. Razo-Hernandez, A. Mejia-Barron, D. Granados-Lieberman, M. Valtierra-Rodriguez, and J. F. Gomez-Aguilar, "A new phasor estimator for PMU applications: P class and M class," Journal of Modern Power Systems and Clean Energy, vol. 8, no. 1, pp. 55–66, 2020.

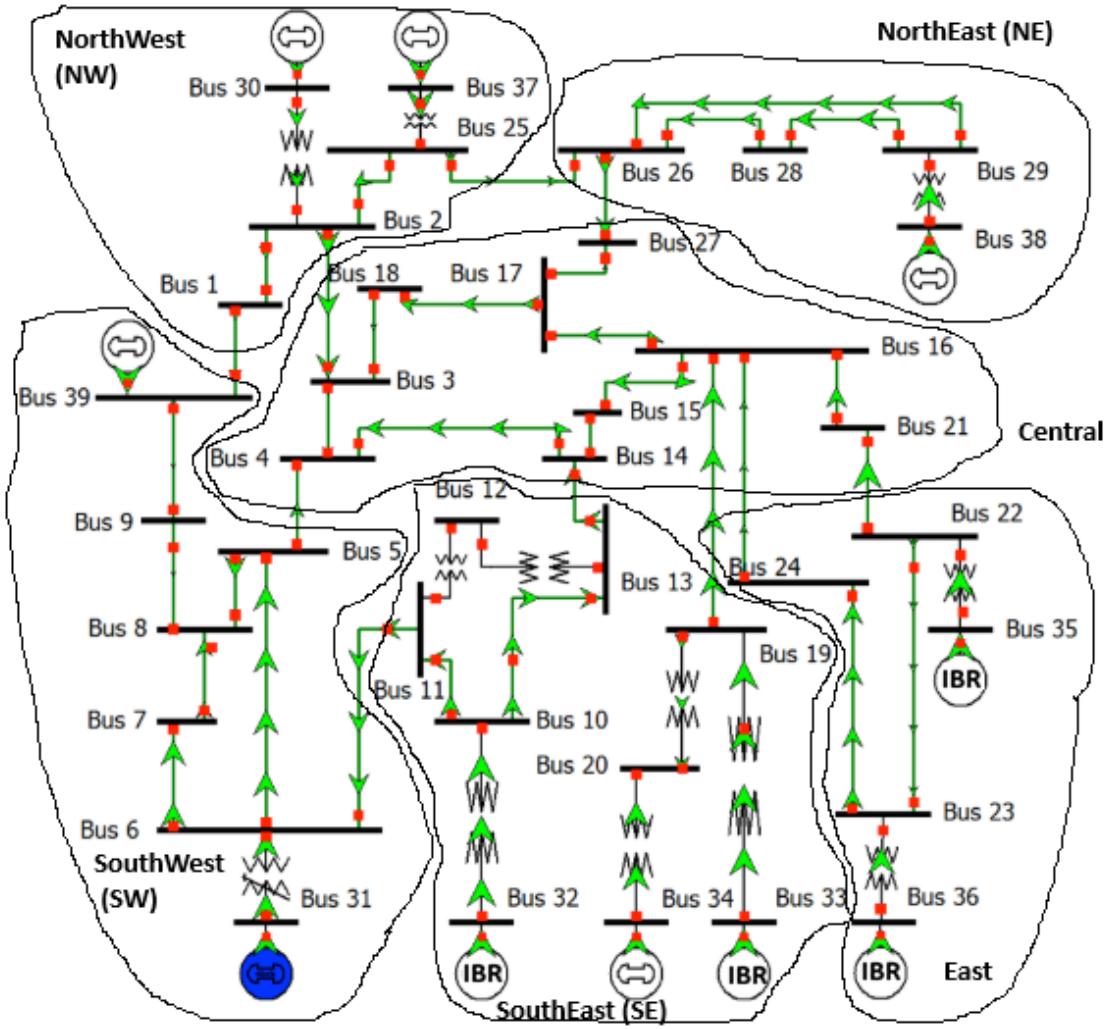
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Number of Frequency Events in the Simulated Data

- Number:
  - ➢Normal Scenarios: 325 samples (Label 0) (59.95 to 60.05 Hz in the PMU data)
  - ➢Generator Loss: 500 samples (Label 1)
  - ➢Load Loss: 500 samples (Label 2)
  - ➢Load Addition: 500 samples (Label 3)
  - ➢Line Fault: 500 samples (Label 4)

- Imbalance Ratio (IR) = 500/325 = 1.54 (Mild class imbalance)

- Such imbalance is generally acceptable in ML/AI applications as it presents very minimal risk of introducing significant training bias



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Measurement Error Modeling

- To enhance realism of simulated dataset, measurement errors consistent with practical standards were introduced into PMU and PoW signals (assuming Gaussian error model)

- PMU measurement errors were modeled for M-class devices (used for monitoring) [5], where it specifies a maximum error for frequency and ROCOF as 0.005 Hz and 0.1 Hz/s, respectively

$$\sigma_F = \frac{0.005}{3} \approx 0.0017 \text{ Hz}, \qquad \sigma_{\text{ROCOF}} = \frac{0.1}{3} \approx 0.033 \text{ Hz/s}$$

- Voltage magnitude and angle errors were modeled in accordance with total vector error (TVE) limits (≤ 1%)

$$\sigma_V \approx 0.33\%, \qquad \sigma_\theta \approx 0.33^\circ$$

- PoW recordings exhibit device-dependent noise and transients, and lack strict performance requirements unlike PMUs, hence relatively larger errors were introduced into voltage and current signals

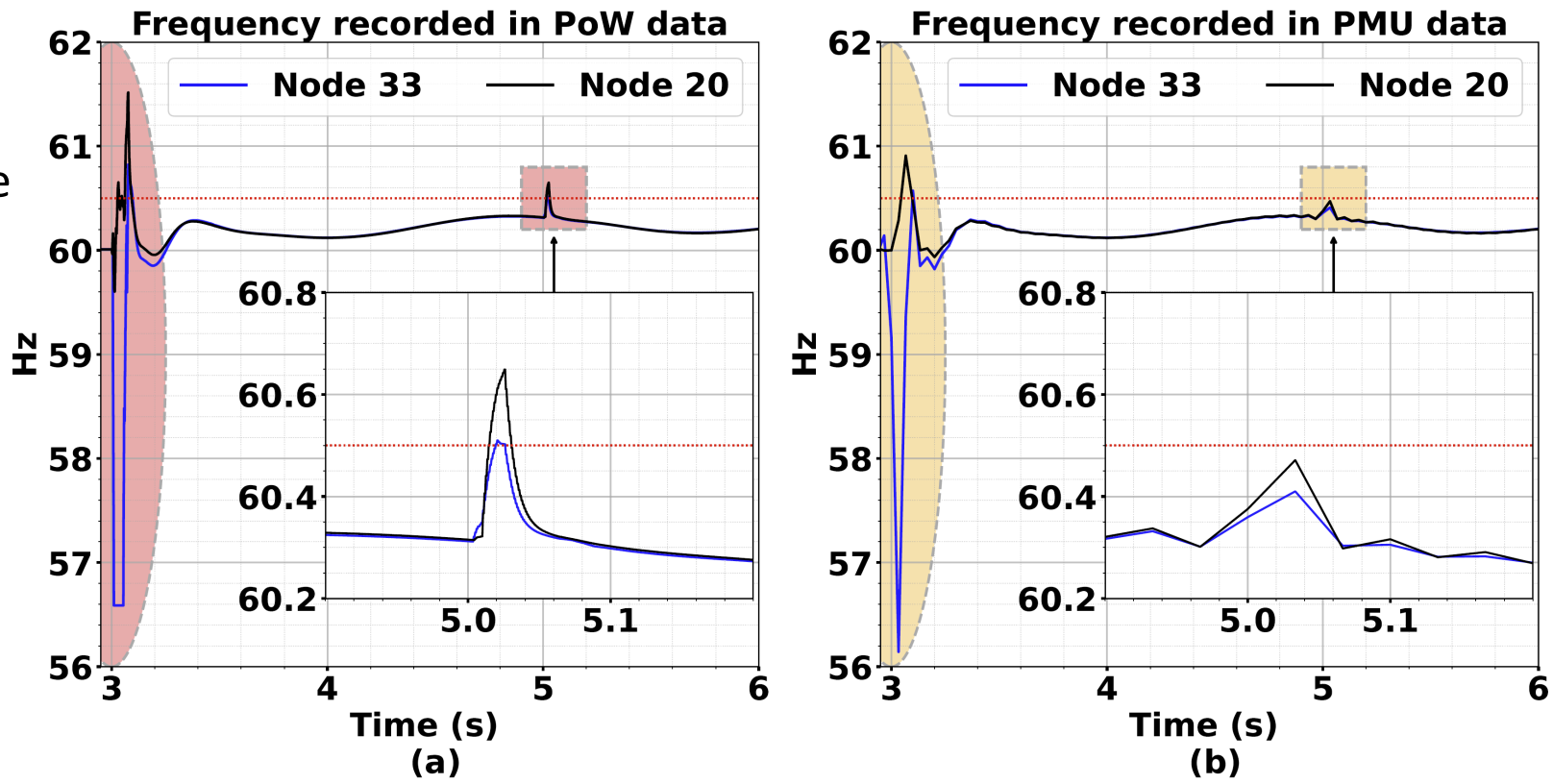
$$\sigma_{v^{\text{PoW}}} = 2\%, \qquad \sigma_{i^{\text{PoW}}} = 3\%$$

[5] IEEE/IEC, "IEEE/IEC international standard—measuring relays and protection equipment—part 118-1: Synchrophasor for power systems- measurements," IEC/IEEE 60255-118-1:2018, pp. 1–78, Dec. 2018.

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Simulated Data Event: Frequencies in PoW and PMU Data for a Cascade Event

- PMU data is unable to give a complete picture of frequency transients: **frequency at bus 20 only rises suddenly, in contrast, it falls and then rises** (red vs. orange semi-ovals)
- **Frequency deviation of 0.5 Hz from the nominal value is an important violation** (red vs. orange square); not seen in PMU data
- Frequency events can be underestimated by using PMU data alone, hence integration of PMU and PoW data gives a richer picture of grid dynamics



A three-phase-to-ground fault (at 3s timestamp for 0.05s duration) on bus 33, where an IBR generating 632 MW and 103 MVAR is connected, followed by a load loss at bus 20 two hops away (136 MW and 20.6 MVAR at 5 s); the lost load represented 20% of the original load

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ML/AI Model for Frequency Event Characterization

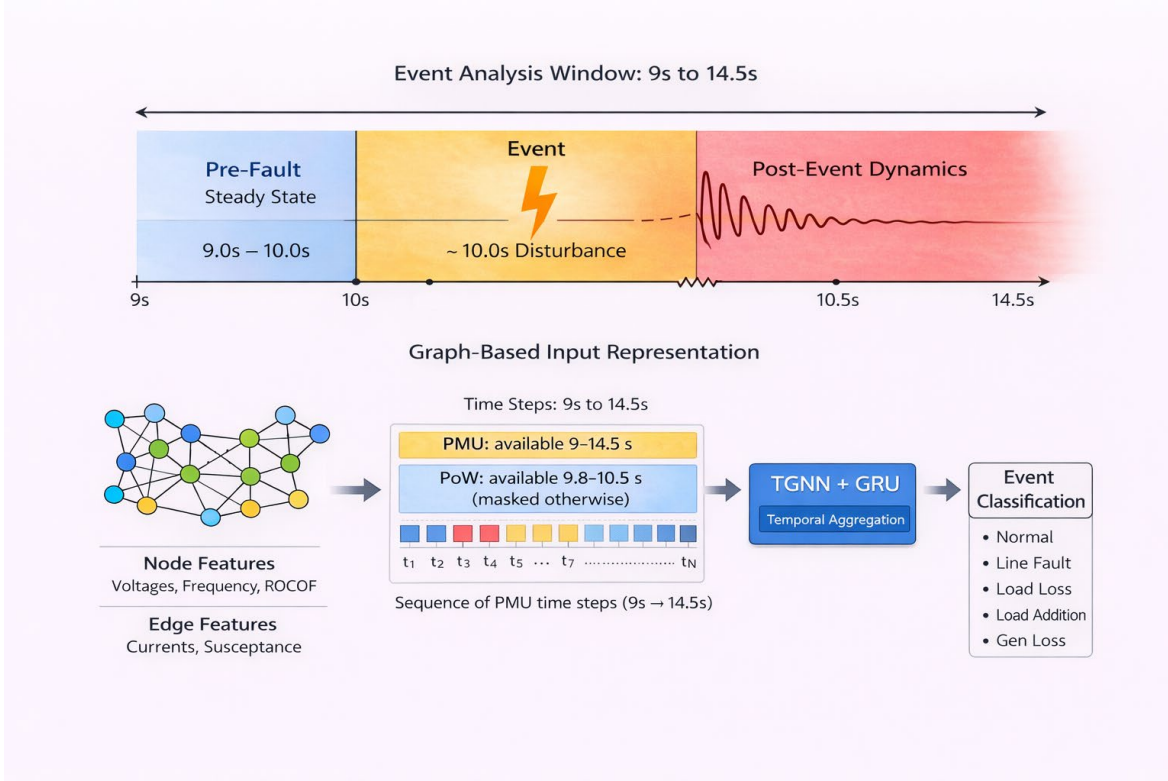
- Temporal graph neural networks (TGNNs) preserve spatial relationship and infer from temporal dynamics

- **Spatial learning at each time step:**
  - Operates on the graph at each time t
  - Captures how buses influence each other through network connectivity
  - Uses node + edge features (voltages, currents, susceptance)
  - Produces a graph embedding z(t) representing system state at time t

- **Sequence formation:**
  - Over the window 9s→14.5s: {z(1),z(2),…,z(T)}

- **Gated Recurrent Unit (GRU) for temporal learning:**
  - Takes the sequence of graph embeddings
  - Learns temporal patterns and transient responses
  - Maintains a hidden state to remember past dynamics

- **Final representation:**
  - The last hidden state (s_T) summarizes the full event
  - Used for classification (Normal, Fault, Load Loss, etc.)



Node and Edge Features

$$x_i(t) = [V_{i,1}^{\text{mag}}, V_{i,2}^{\text{mag}}, V_{i,3}^{\text{mag}}, V_{i,\text{pos}}^{\text{mag}}, \sin\theta_{i,1}, \cos\theta_{i,1}, \sin\theta_{i,2}, \cos\theta_{i,2}, \sin\theta_{i,3}, \cos\theta_{i,3}, \sin\theta_{i,\text{pos}}, \cos\theta_{i,\text{pos}}, f_i, \text{ROCOF}_i, v_{i,1}, v_{i,2}, v_{i,3}, f_i^{\text{PoW}}]$$

$$e_{ij}(t) = [b_{ij}(t), |I_{ij,1}(t)|, |I_{ij,2}(t)|, |I_{ij,3}(t)|, |I_{ij,\text{pos}}(t)|, \sin\angle I_{ij,1}(t), \cos\angle I_{ij,1}(t), \sin\angle I_{ij,2}(t), \cos\angle I_{ij,2}(t), \sin\angle I_{ij,3}(t), \cos\angle I_{ij,3}(t), \sin\angle I_{ij,\text{pos}}(t), \cos\angle I_{ij,\text{pos}}(t), i_{ij,1}^{\text{PoW}}(t), i_{ij,2}^{\text{PoW}}(t), i_{ij,3}^{\text{PoW}}(t)]$$

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Graph Structure and Missing Feature Handling

- The power system is modeled as a fixed undirected graph: G = (V, E). The graph connectivity is represented using an edge index matrix, as seen to the right

$$\text{edge_index} \in \mathbb{N}^{2\times|E|} \qquad \text{edge_index}[:,k] = \begin{bmatrix} i \\ j \end{bmatrix} \quad \Rightarrow \quad \text{edge } (i,j)$$

- For a single simulation sample, the node and edge feature tensors are defined as seen to the right

$$X \in \mathbb{R}^{T\times N\times F}, \qquad E \in \mathbb{R}^{T\times|E|\times F_e}$$

$$X^{(b)} \in \mathbb{R}^{B\times T\times N\times F}, \qquad E^{(b)} \in \mathbb{R}^{B\times T\times|E|\times F_e}$$

- The corresponding binary masks for node and edge features are defined as seen to the right

$$M_n \in \{0,1\}^{B\times T\times N\times F}, \qquad M_e \in \{0,1\}^{B\times T\times|E|\times F_e},$$

- The effective inputs for the TGNN model are constructed via element-wise multiplication (denoted by $\odot$) of the features with masks as seen below

$$\widetilde{X} = X \odot M_n, \qquad \widetilde{E} = E \odot M_e$$

$$M_n(b,t,i,f) = 1 \Rightarrow \text{node feature is available},$$

$$M_n(b,t,i,f) = 0 \Rightarrow \text{node feature is missing},$$

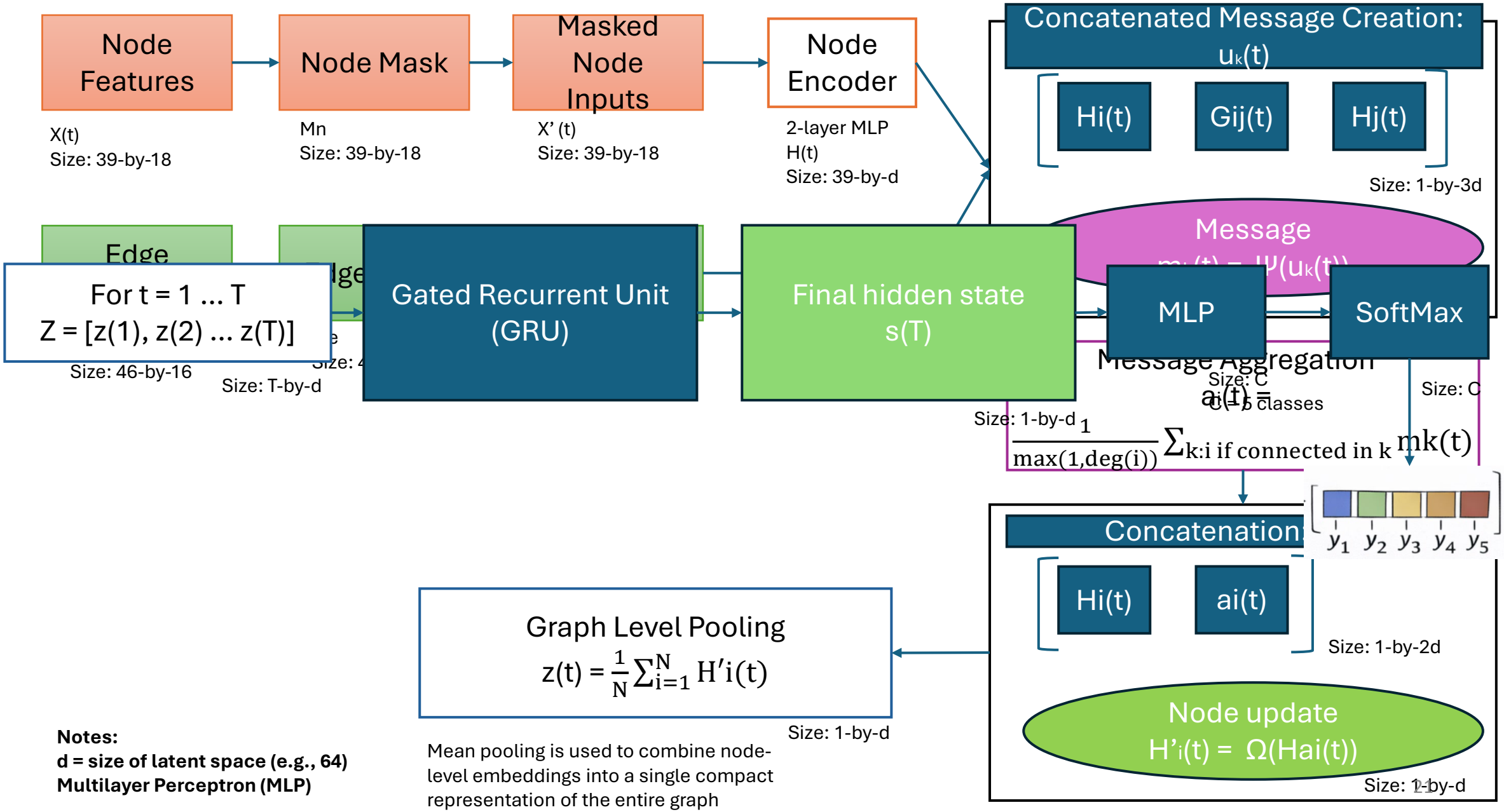
$$M_e(b,t,k,f) = 1 \Rightarrow \text{edge feature is available},$$

$$M_e(b,t,k,f) = 0 \Rightarrow \text{edge feature is missing}.$$

Arizona State University

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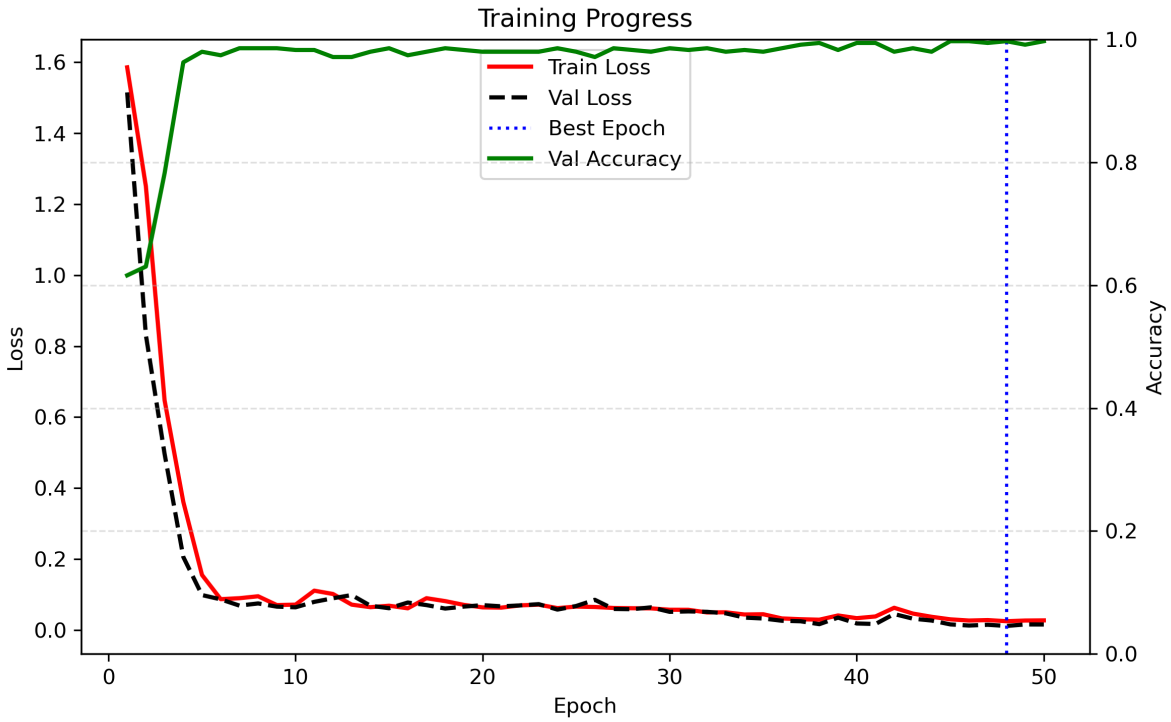
TGNN Flow and Final Classification

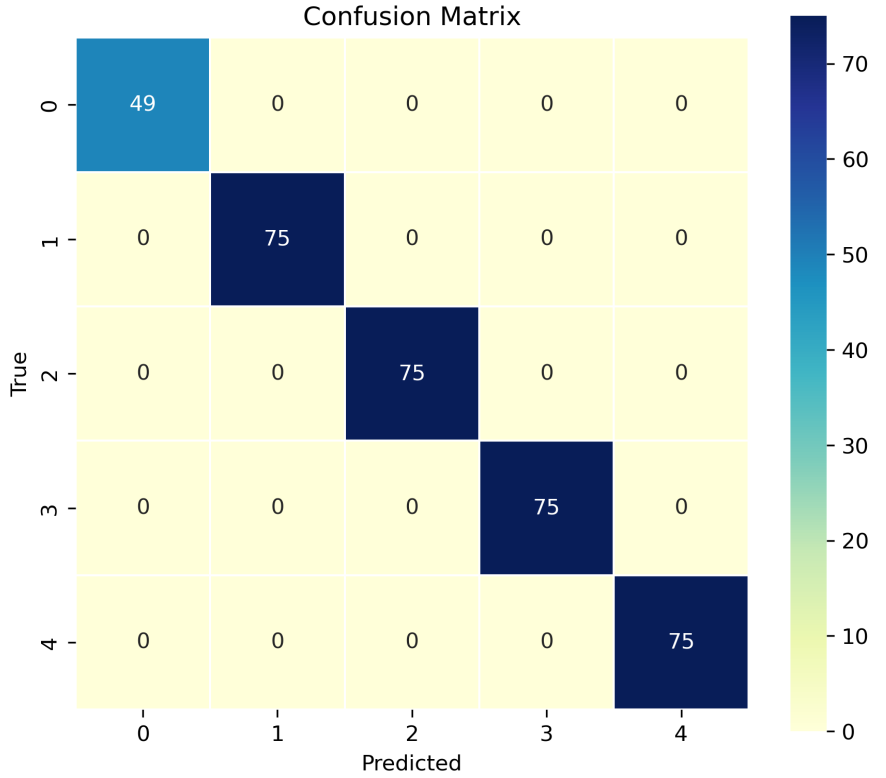


Notes:
d = size of latent space (e.g., 64)
Multilayer Perceptron (MLP)

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Classification Results Obtained Using TGNN





Train/Validation/Test Split: 70/15/15 on a 2325 case dataset

Trained for 50 epochs

Validation accuracy: 99.71%

Test accuracy: 100%

[Labels: Normal(0), GenLoss(1), LoadLoss(2), LoadAdd(3), and LineFault(4)]

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Recommendations

- Verify relay settings and align the disturbance capture window across devices wherever possible. If uniform recording cannot be enforced, the record length variation should be documented as part of data quality notes
- Utility should review and document the configuration of relays with respect to frequency measurement capabilities, and where feasible, standardize settings to ensure consistent recording across devices
- Utility should standardize and consistently record ROCOF in PMU data using a well-defined methodology
- Correct relay timestamp offsets by accounting for DST (i.e., use –(A-1) hours during DST). Additionally, utilities should ensure vendor tools properly handle time conversions or provide corrected timestamps

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Conclusion

- Gaps in grid comprehension due to limitations arising from trade-off between PMU and PoW data characteristics can be bridged by combining use of both sources
- Frequency behavior captured by PMUs and relays can be leveraged to identify frequency events, but huge volumes of granular PMU and PoW data require automated methods for event detection and characterization
- TGNN was employed to characterize frequency events accurately in the merged and correlated PoW and PMU data obtained from simulation in PSCAD
- This work can inform stakeholders and support the development of real-world tools for efficient and timely characterization of frequency events, which is essential for mitigating the impacts of disruptive frequency disturbances and ensuring power system stability



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Yadu Paudel



Diving Deeper

- Enhanced Analysis of Critical Power System Events Using Merged and Correlated PoW and PMU data, SGSMA 2026, Chile https://doi.org/10.1109/SGSMA65955.2026.11618875