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Grid Operator Analytics and Assessment Tools for Inverter-Based Resources Dominated Grid (GOAAT-IBR)



PingThings



QUANTA
TECHNOLOGY



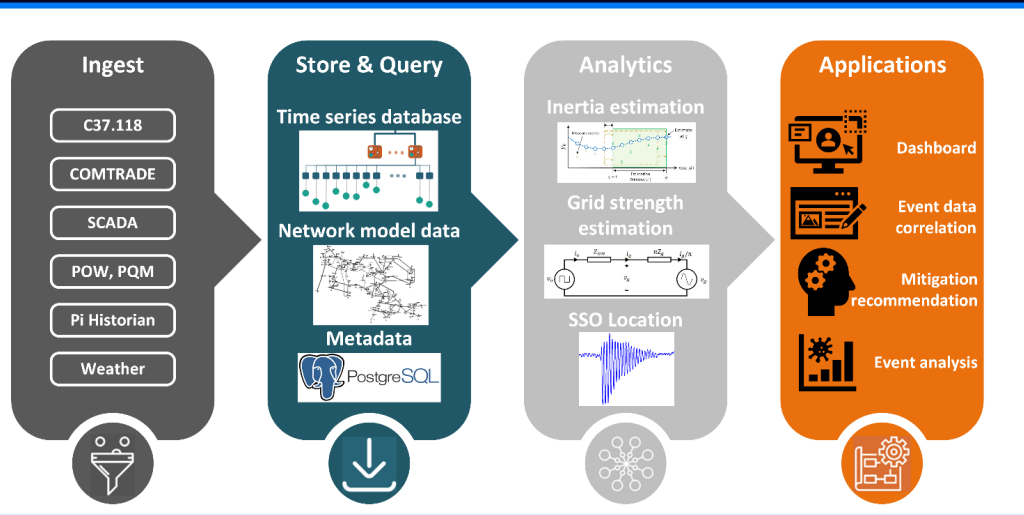
Required DOE Disclosures



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Grid Operator Analytics and Assessment Tools for Inverter-Based Resources Dominated Grid (GOAAT-IBR)



Key technical goals:

- Interactive dashboard visualizing system health in real time, e.g., grid inertia, IBR related sub-synchronous oscillations, and grid strength.
- Disturbance event dataset correlation and curation for post-event analysis.
- Real-time mitigation recommendation.
- Automated event analysis and report generation.

Key technical approaches:

- Use cloud-based time-series platform to ingest diverse sensor streams and perform data analytics.
- Rigorous lab sensor hardware-in-the-loop prototyping and validation.
- Field demonstration in Entergy's system.

Unique perspectives:

- Practical yet innovative real-time solutions with a clear path to commercialization.
- Diverse team.
- Leveraging extensive existing PMU data from Entergy's system.

Budget:

- Total budget: \$5,280,184.
 - Federal funds: \$3,826,341.
 - Cost-share: \$1,453,843.

Overall Project Plan (BP-1/2/3)

BP-1 objective

1. Complete developing all software modules.
2. Determine if data analytic algorithms meet expected performance using simulated data or historical data.
3. Set up 43 live sensor streams in RTDS lab.
4. Set up PingThings and cloud environment in the test lab.
5. Plan field sensor deployment.

BP-2 objective

1. Complete GOAAT prototype that works with real-time simulation and lab hardware sensors (meets performance targets).
2. Compose detailed plan for BP-3 demonstration and deploy any additional hardware sensors at the demonstration utility.
3. Deploy field sensors.

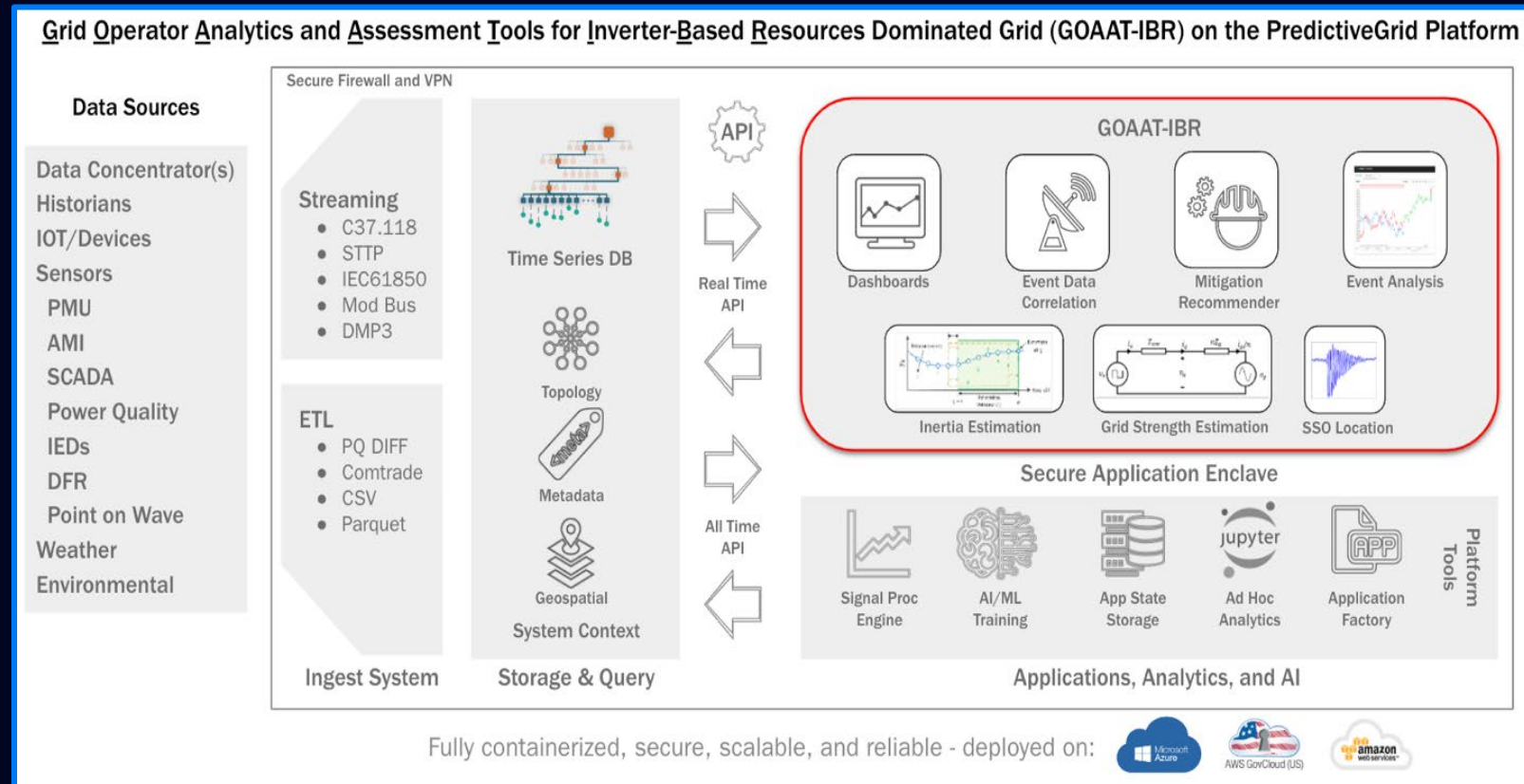
BP-3 objective

1. Deploy GOAAT at demo utility.
2. Work GOAAT with live sensor streams.
3. Show evidence GOAAT meets all performance targets.
4. Complete techno-economic analysis for commercialization.

Main Objectives in BP-1

BP-1 objectives:

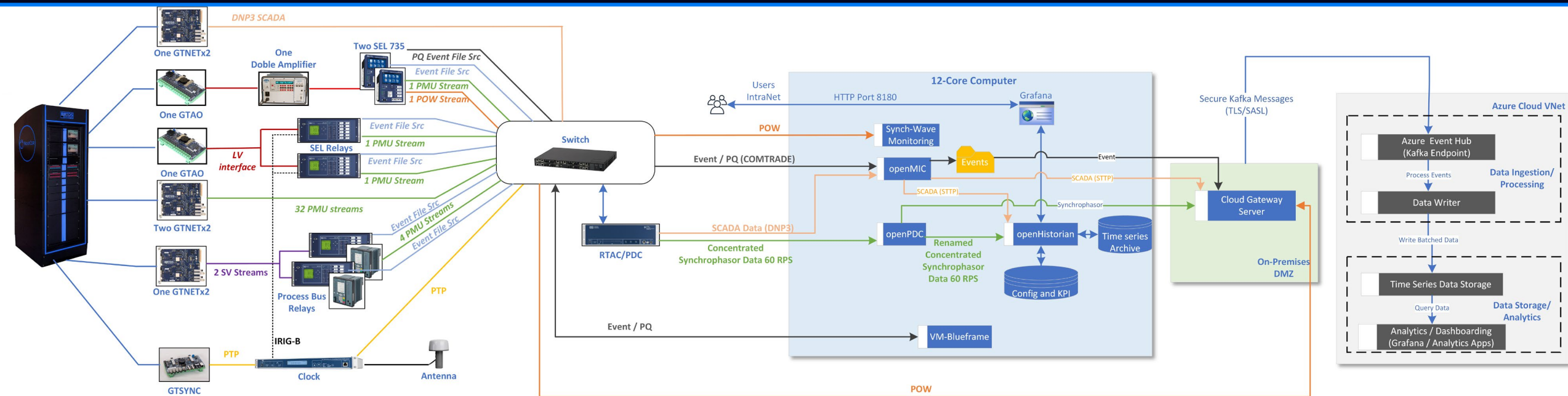
- Develop data analytic algorithms using simulated data or historical data.
- Set up 43 live sensor streams in the RTDS lab.
- PredictiveGrid cloud-based time-series platform to ingest and time-align real-time and historical data from diverse sensors.
- Set up NDAs and sub-contracts.



Sensor Hardware Lab Setup

Sensor hardware-in-the-loop simulation of the IEEE 14 bus system:

- One generator, three synchronous condensers
- Three IBR plants modeled (one black-box GTSOC model, two generic models).



Data Ingestion – Example Dashboard

Ingested streaming PMU, point-on-wave (POW), and Event data.

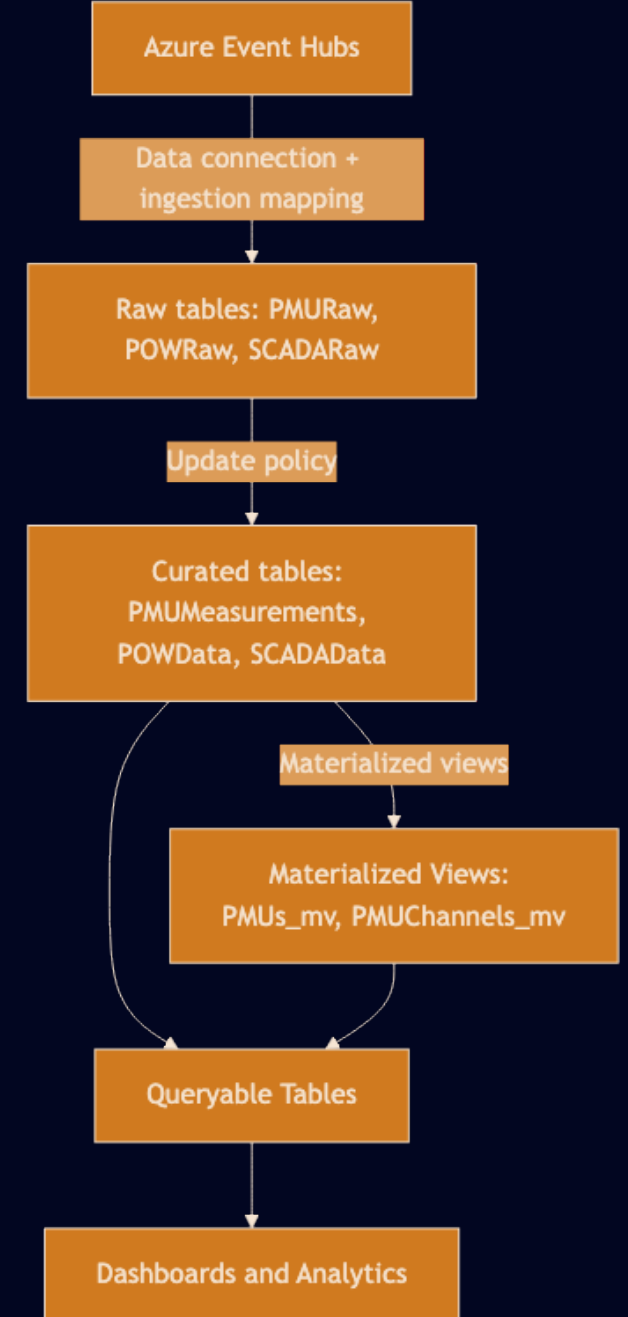


Data Ingestion, Visualization, and Analytics

Ingestion:

- 39 PMUs (60 fps):
 - Total data per day (39 PMUs):
 $8.35 \text{ GB} \times 39 = 325.6 \text{ GB/day}$.
- 1 POW (3 kSPS):
 - Data per day: 12.07 GB/day.
- 7 COMTRADE event file data sources.
- SCADA:
 - 39 status points.
 - 139 analog points.

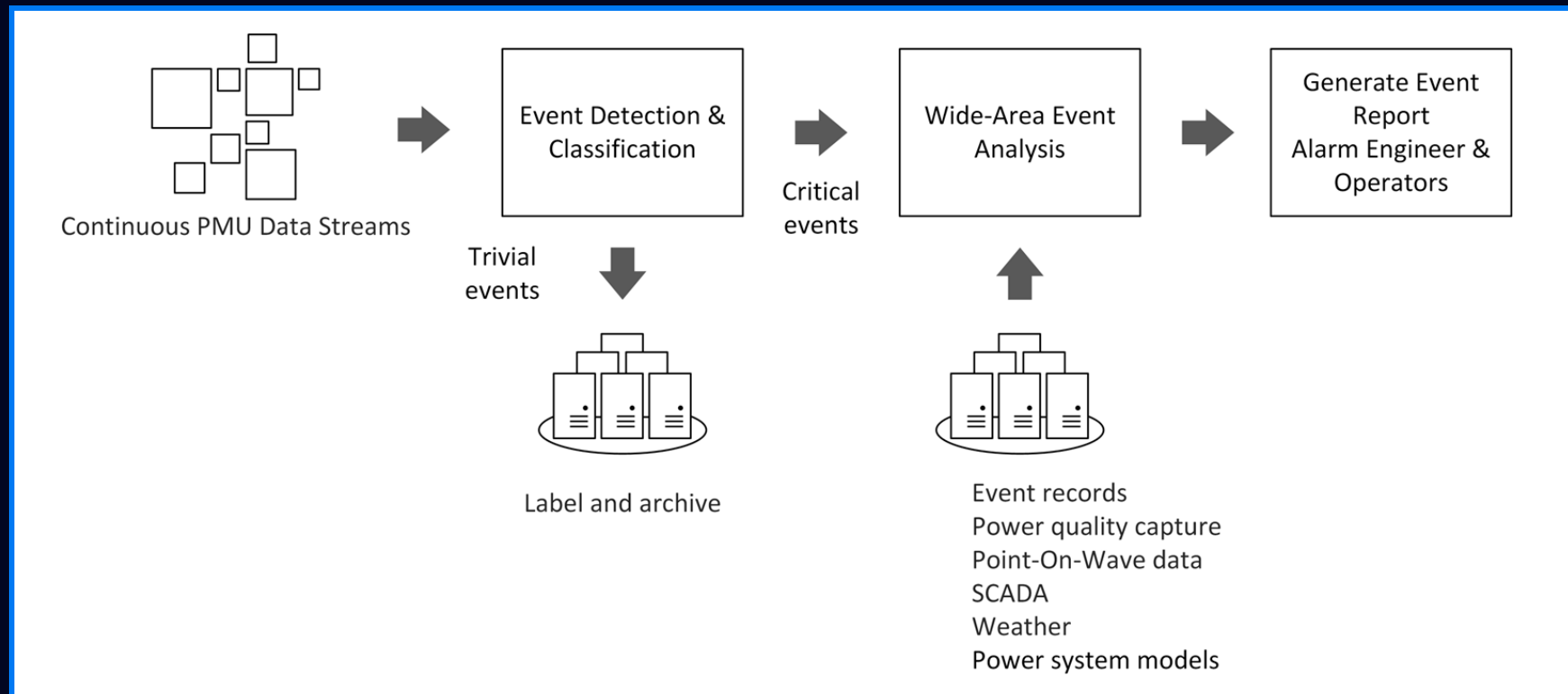
Workflow:



Monitoring and Analytics Architecture

Rely on streaming PMU data
for event detection

Sensor fusion for
deep event analysis



- Fault analysis (location, relay performance, etc.)
- Oscillation detection and location
- Voltage and frequency disturbance analysis
- Grid health assessments (inertia and strength)
- IBR standards/compliance verification

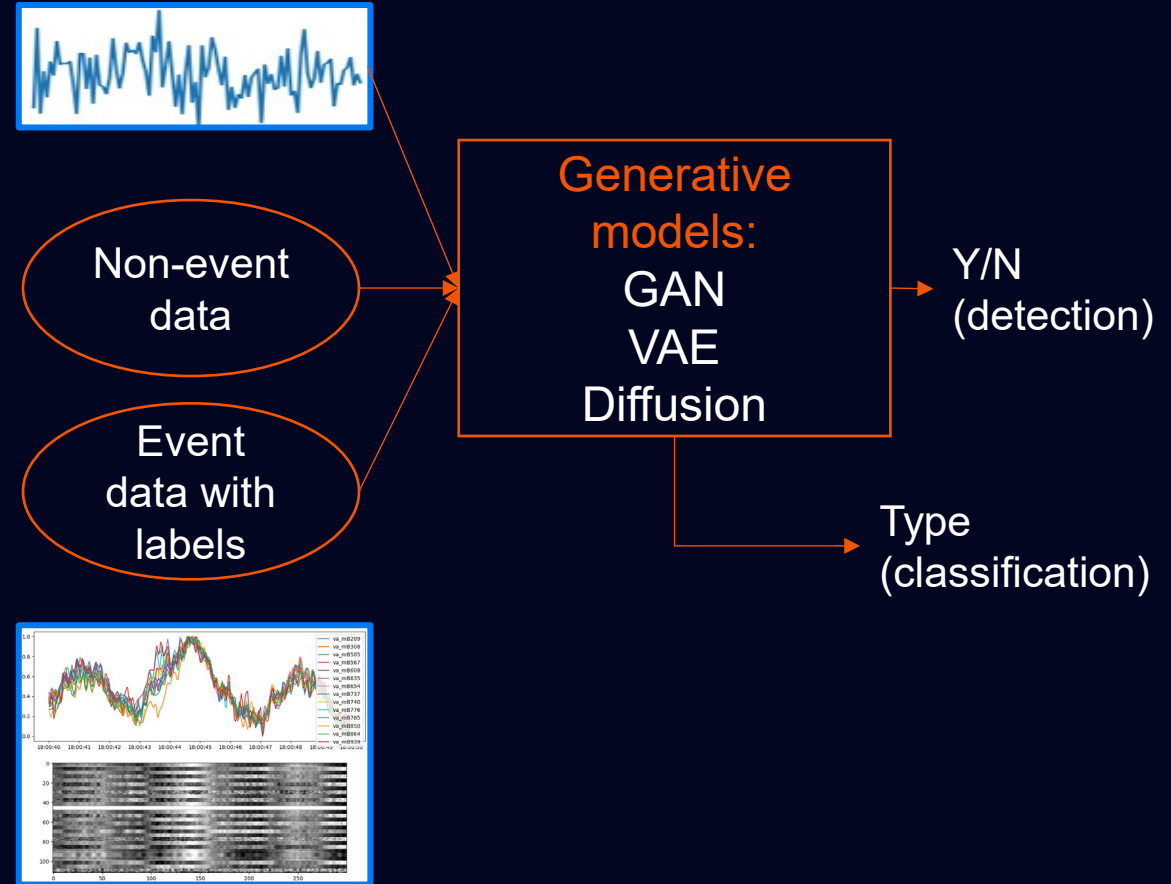
Basic Idea (Generative Models)

Generative models:

Most data is collected under non-event conditions. Learn the distribution of non-event patterns in the training set; deviations are flagged as events.

Objectives:

High-accuracy PMU event detection and classification; ability to detect unknown events (not shown in training set).



Data Pre-Processing

Only use non-event data.

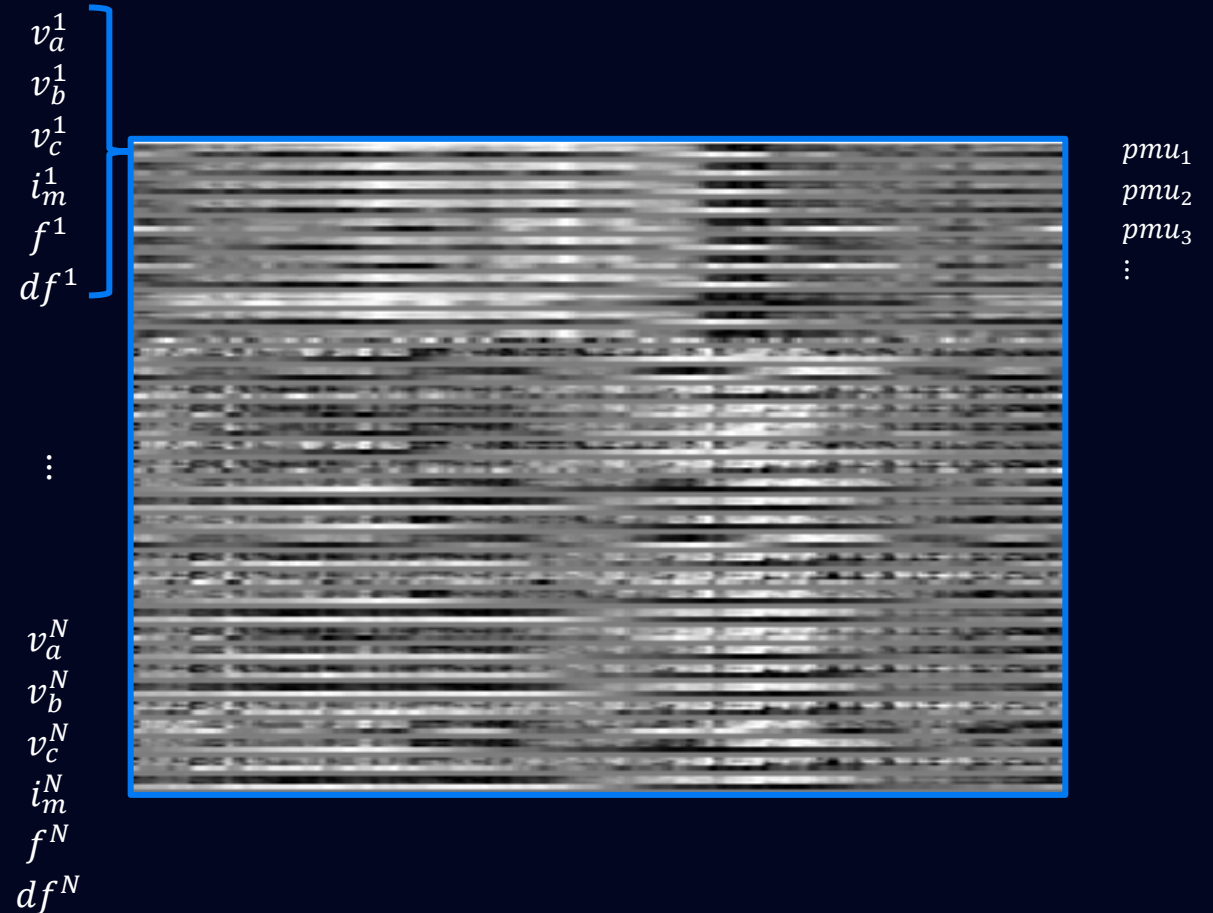
For n^{th} PMU:

$$v_{pu}^n = \frac{v_a^n}{v_{rate}^n}$$

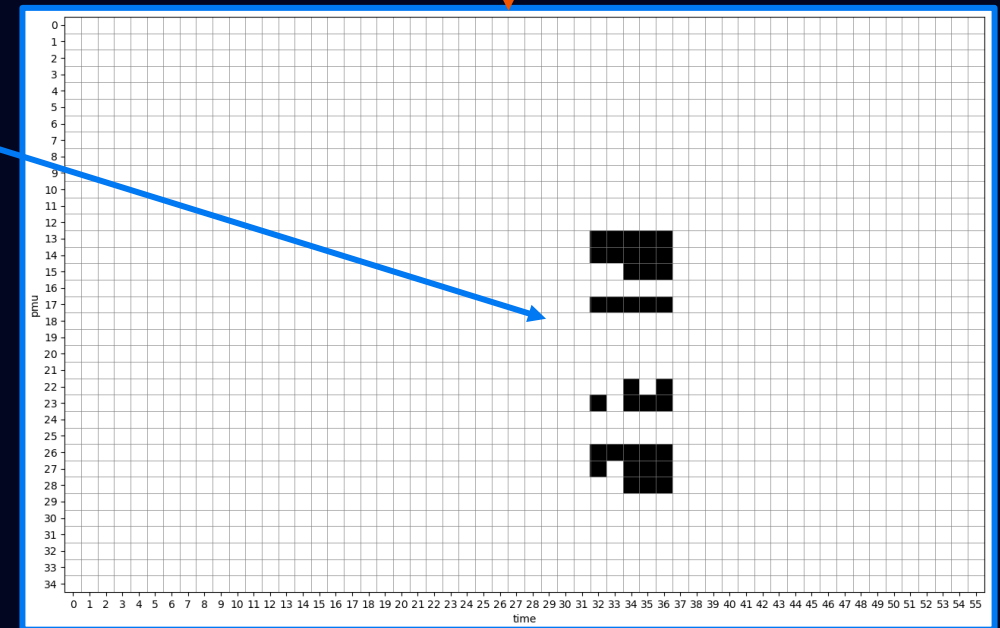
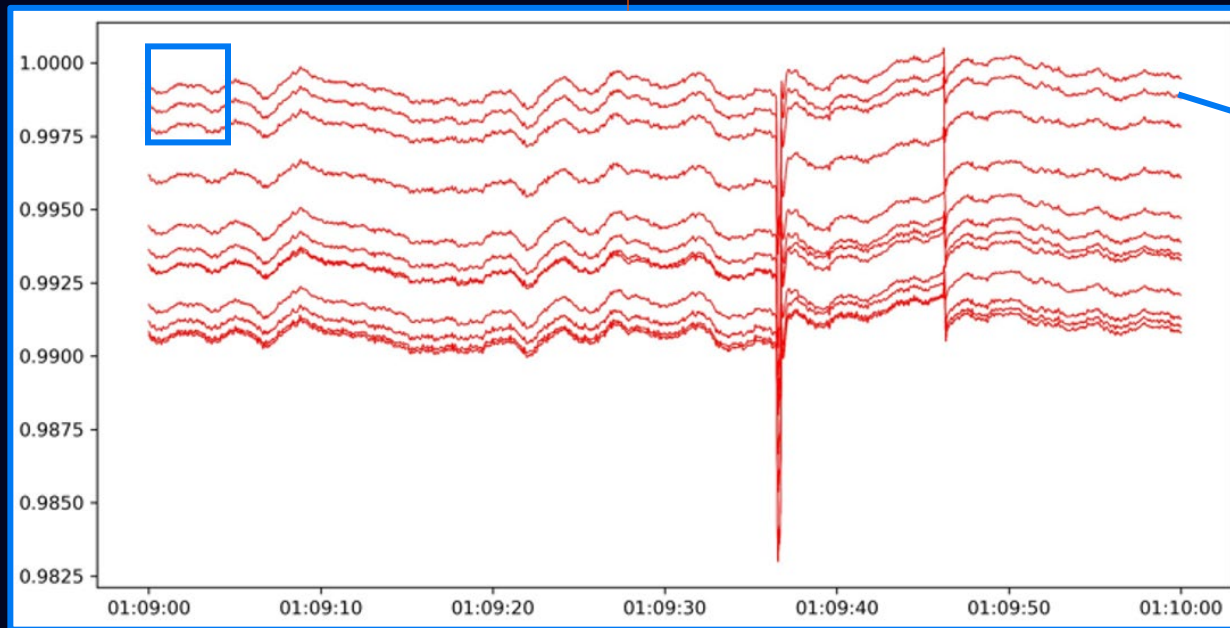
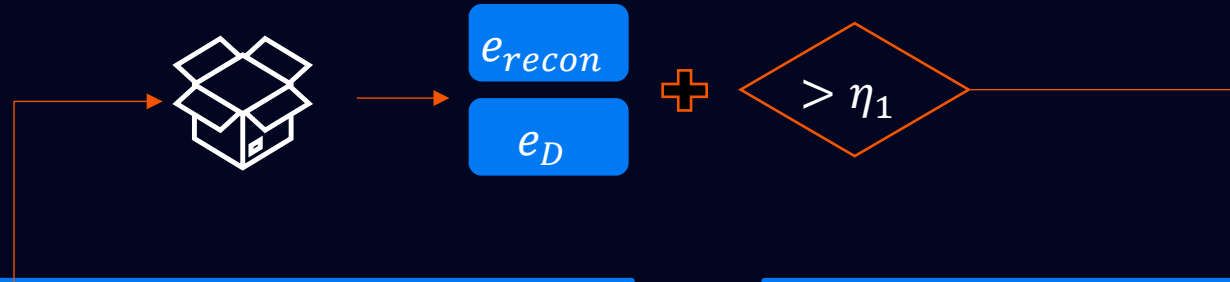
$$v_{norm}^n = v_{pu}^n - \text{mean}(v_{pu}^n)$$

$$i_{norm}^n = i_m^n - \text{mean}(i_m^n)$$

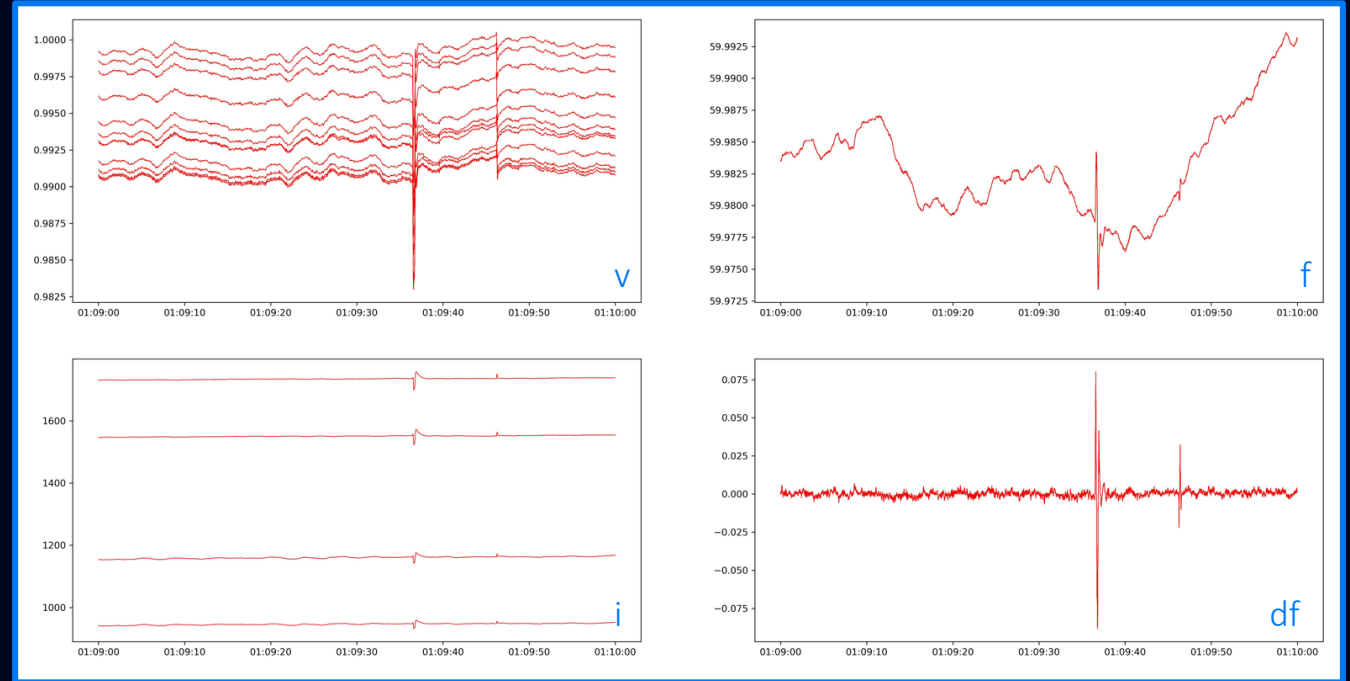
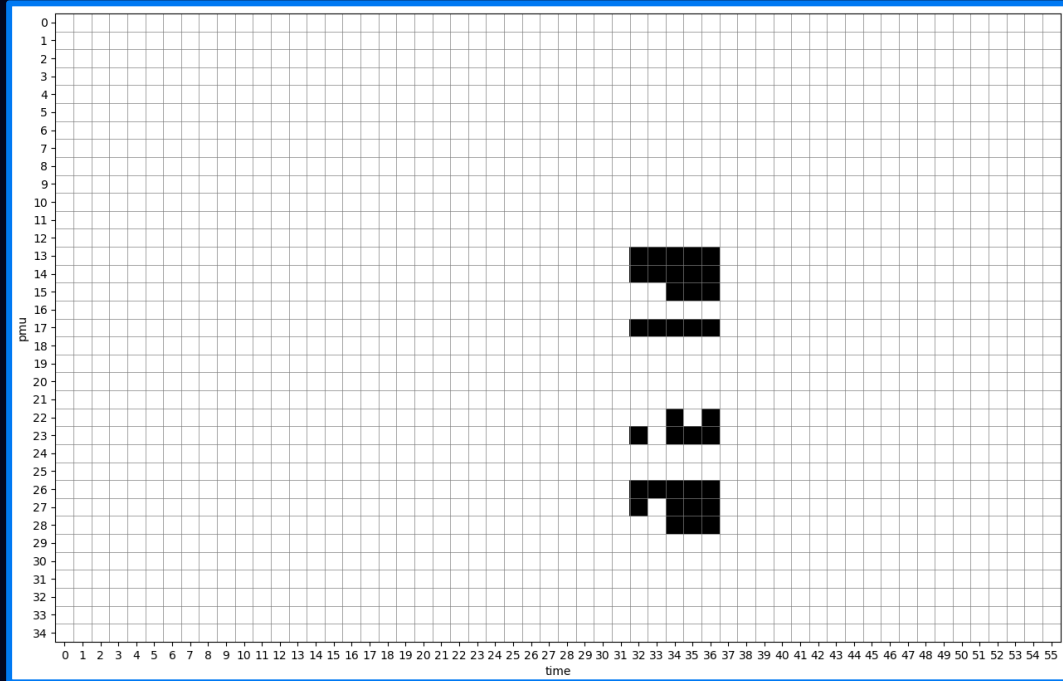
$$f_{norm}^n = f^n - \text{mean}(f^n)$$



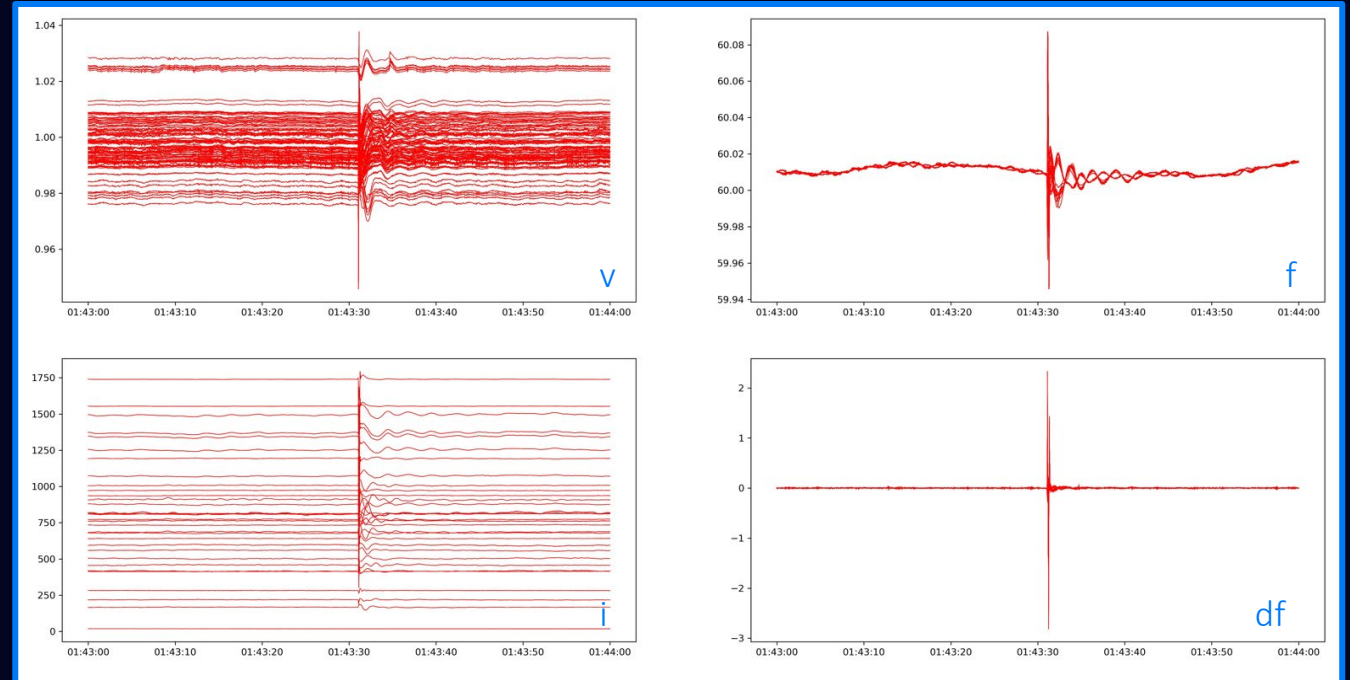
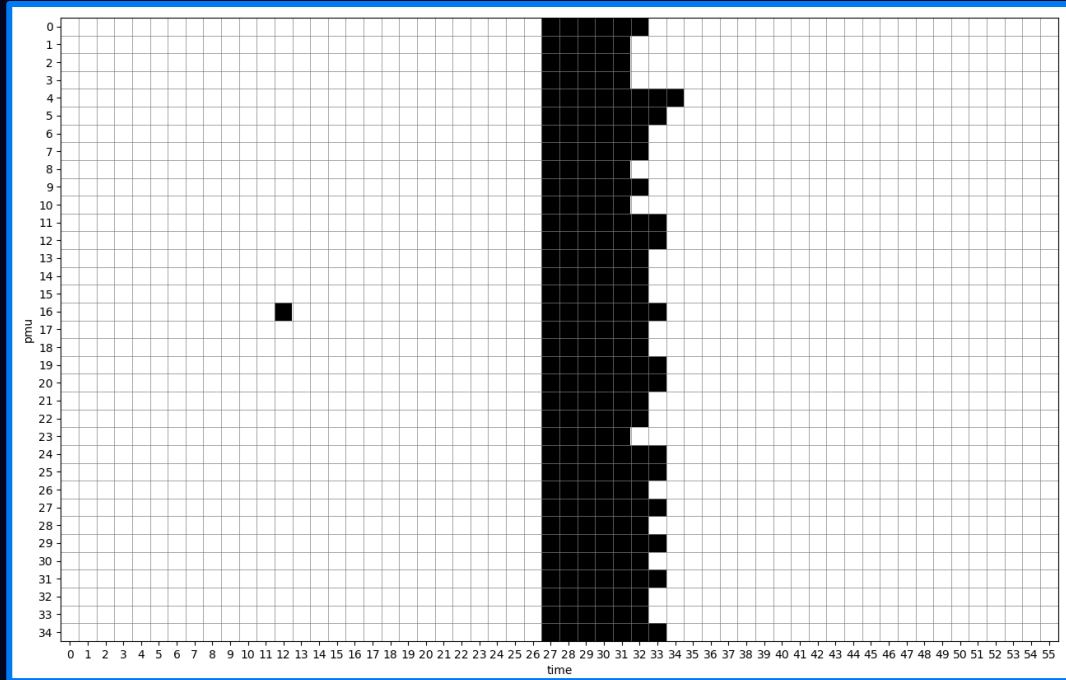
Sliding Window for PMUs



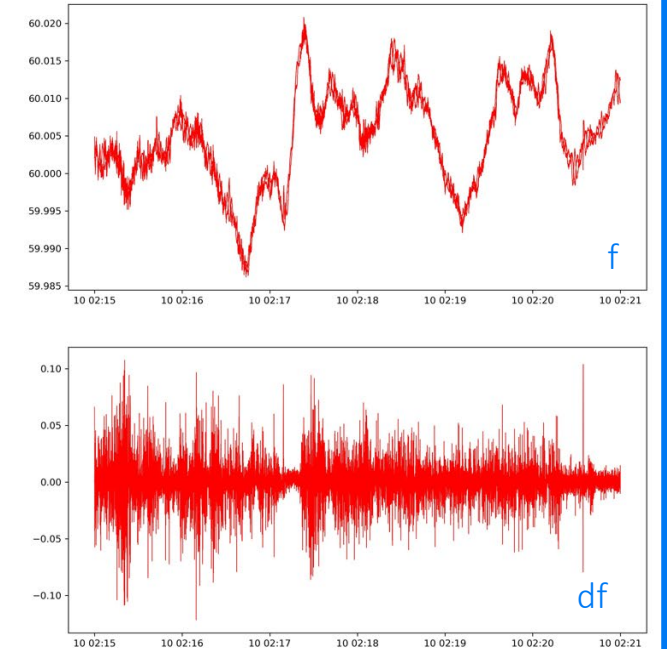
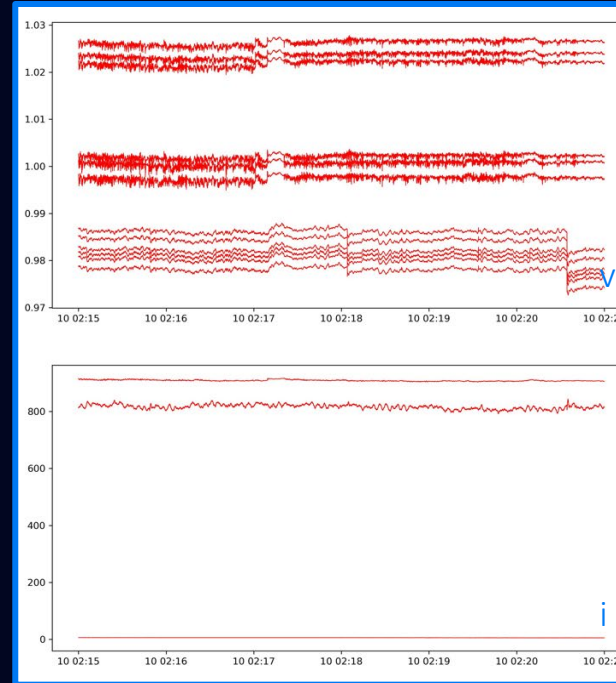
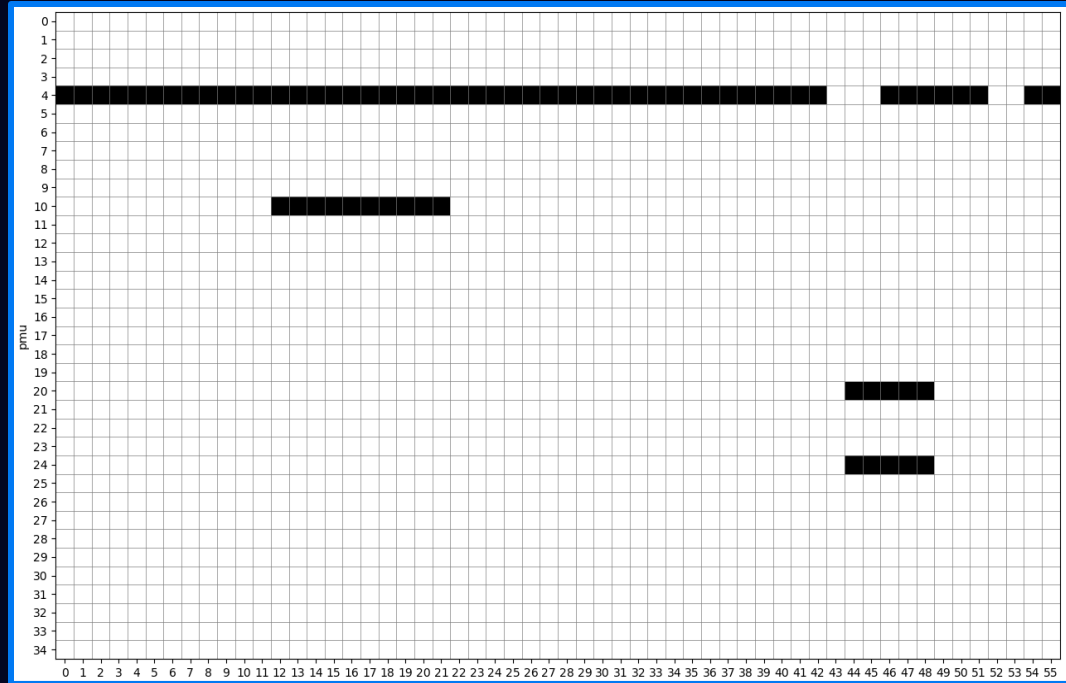
Detected Event Example



Detected Event Example



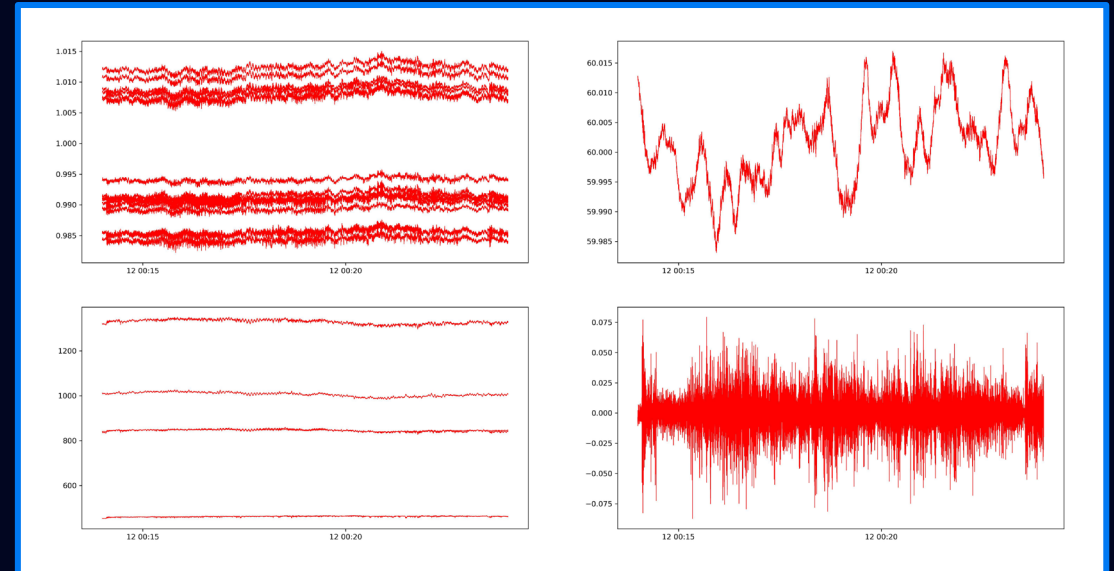
Detected Event Example



Group Adjacent Events

Adjacent detections within Δt are merged into a single event.

| StartTime | EndTime | N_PMU |
|---------------------|---------------------|-------|
| 2016-07-12 00:00:00 | 2016-07-12 00:01:00 | 0 |
| 2016-07-12 00:01:00 | 2016-07-12 00:02:00 | 0 |
| 2016-07-12 00:02:00 | 2016-07-12 00:03:00 | 0 |
| 2016-07-12 00:03:00 | 2016-07-12 00:04:00 | 0 |
| 2016-07-12 00:04:00 | 2016-07-12 00:05:00 | 0 |
| 2016-07-12 00:05:00 | 2016-07-12 00:06:00 | 0 |
| 2016-07-12 00:06:00 | 2016-07-12 00:07:00 | 0 |
| 2016-07-12 00:07:00 | 2016-07-12 00:08:00 | 0 |
| 2016-07-12 00:08:00 | 2016-07-12 00:09:00 | 0 |
| 2016-07-12 00:09:00 | 2016-07-12 00:10:00 | 0 |
| 2016-07-12 00:10:00 | 2016-07-12 00:11:00 | 0 |
| 2016-07-12 00:11:00 | 2016-07-12 00:12:00 | 0 |
| 2016-07-12 00:12:00 | 2016-07-12 00:13:00 | 0 |
| 2016-07-12 00:13:00 | 2016-07-12 00:14:00 | 0 |
| 2016-07-12 00:14:00 | 2016-07-12 00:15:00 | 4 |
| 2016-07-12 00:15:00 | 2016-07-12 00:16:00 | 5 |
| 2016-07-12 00:16:00 | 2016-07-12 00:17:00 | 5 |
| 2016-07-12 00:17:00 | 2016-07-12 00:18:00 | 2 |
| 2016-07-12 00:18:00 | 2016-07-12 00:19:00 | 5 |
| 2016-07-12 00:19:00 | 2016-07-12 00:20:00 | 2 |
| 2016-07-12 00:20:00 | 2016-07-12 00:21:00 | 4 |
| 2016-07-12 00:21:00 | 2016-07-12 00:22:00 | 2 |
| 2016-07-12 00:22:00 | 2016-07-12 00:23:00 | 2 |
| 2016-07-12 00:23:00 | 2016-07-12 00:24:00 | 2 |
| 2016-07-12 00:24:00 | 2016-07-12 00:25:00 | 0 |
| 2016-07-12 00:25:00 | 2016-07-12 00:26:00 | 0 |



| StartTime | EndTime | N_PMU |
|---------------------|---------------------|-------|
| 2016-07-12 00:14:00 | 2016-07-12 00:24:00 | 6 |
| 2016-07-12 00:33:00 | 2016-07-12 00:36:00 | 5 |
| 2016-07-12 00:37:00 | 2016-07-12 00:40:00 | 6 |
| 2016-07-12 01:14:00 | 2016-07-12 01:21:00 | 8 |
| 2016-07-12 02:11:00 | 2016-07-12 02:15:00 | 5 |
| 2016-07-12 02:24:00 | 2016-07-12 02:31:00 | 10 |
| 2016-07-12 02:58:00 | 2016-07-12 02:59:00 | 5 |

Data Processing and Modeling Overview

| Component | Details |
|-----------------------------|--|
| Dataset | Total labeled events: 210 Train/test split: training: 146 events (70%)/test: 62 events (30%) Unlabeled test data: 210 data |
| Cross-validation | 5-fold cross-validation (20% of the training set) |
| Classes | Faults Frequency disturbances Oscillations Transients Voltage disturbances |
| Models evaluated | Random Forest, XGBoost, and MLP |
| Hyperparameter optimization | Optuna |
| Evaluation and analysis | Accuracy, precision, recall, F1 score Learning curve Misclassified event details and probabilities Multi-label events (more than one class) |

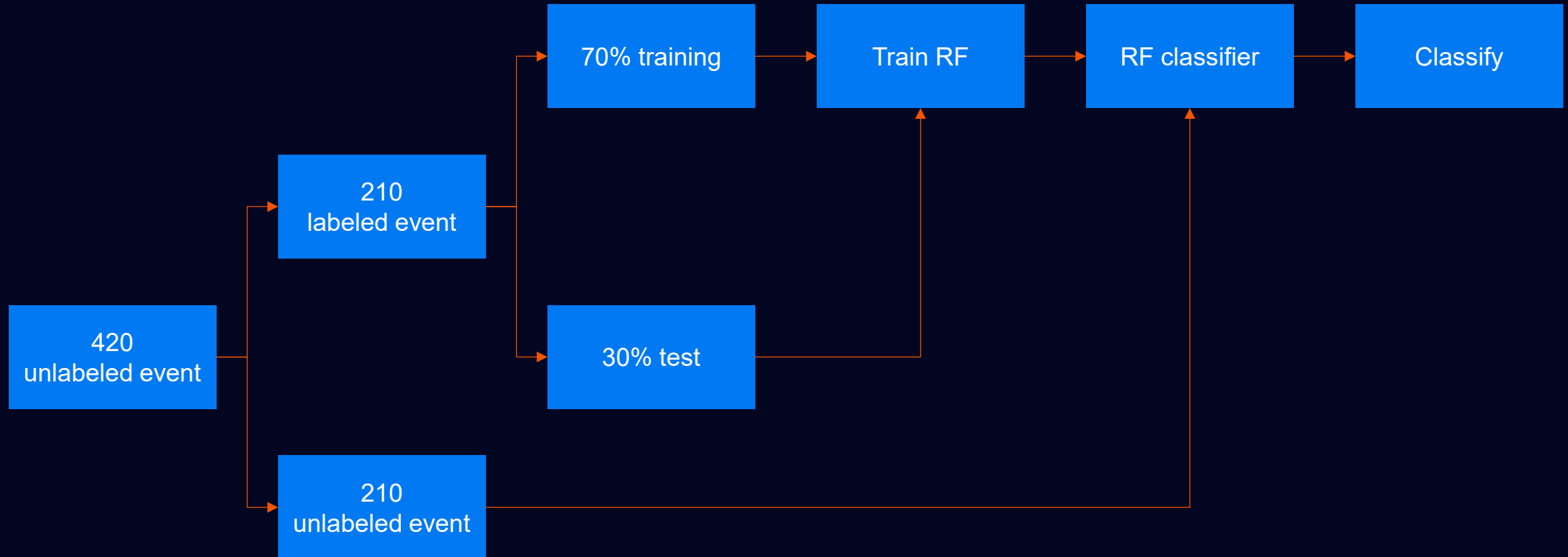
Extracted Features

| Feature category | Features extracted |
|---------------------------|--|
| Basic statistics | Minimum, maximum, mean, variance, standard deviation (StdDev), range, peak-to-peak |
| Derivatives | First, second of voltages and frequency |
| Envelope area | Maximum, minimum, mean |
| Shape descriptors | Skewness, shape factor, impulse factor |
| Frequency-domain features | Spectral centroid, spectral flatness, spectral entropy |
| Other indicators | Number of PMUs |

Selected Feature Importance

| Feature 1 | Feature 2 | Feature 3 | Feature 4 | Feature 5 |
|---|------------------------------|-------------------------------|--------------------------------|------------------------|
| Spectral centroid of frequency derivative | Second derivative of voltage | First derivative of voltage | Second derivative of frequency | Peak-to-peak amplitude |
| Feature 6 | Feature 7 | Feature 8 | Feature 9 | Feature 10 |
| Median ROCOF envelope area | Time-domain shape factor | Maximum voltage envelope area | Spectral entropy of frequency | Number of PMUs |

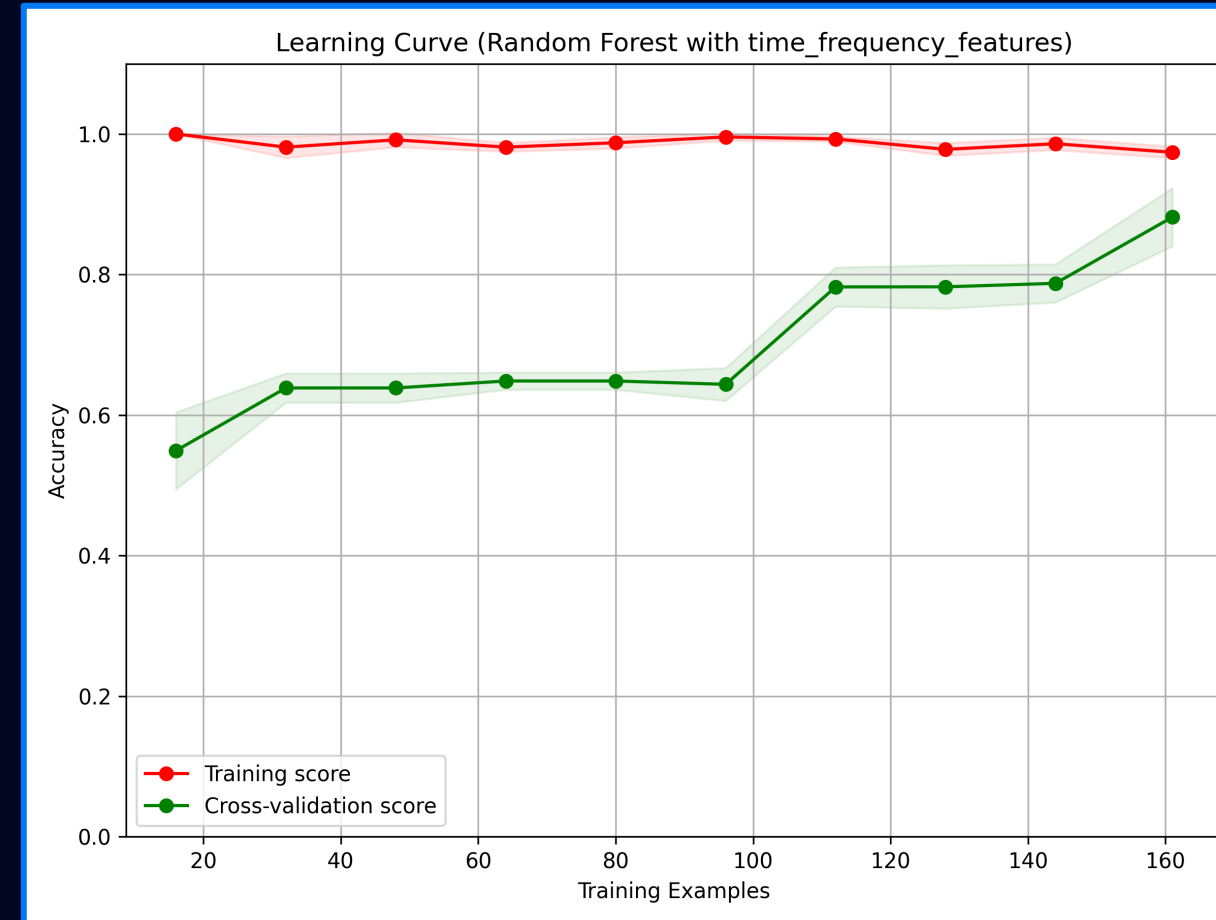
Unlabeled Event Classification – Overview



Random Forest Run 2

Accuracy: 95%
Test size: 62

| Class | Precision | Recall | F1 score |
|------------------------|-----------|--------|----------|
| Faults | 0.8300 | 1.0000 | 1.0000 |
| Frequency disturbances | 1.0000 | 1.0000 | 1.0000 |
| Oscillations | 0.9500 | 1.0000 | 0.9744 |
| Transients | 0.9333 | 0.9333 | 0.9333 |
| Voltage disturbances | 1.0000 | 1.0000 | 1.0000 |



Confidence Categorization Events

For each event prediction, extract the **two highest predicted class probabilities**:

- P1 = probability of the most likely class.
- P2 = probability of the second most likely class.
- $P_i > 0.3$.

| Delta Range | Interpretation |
|-------------------------------------|---------------------------------------|
| $(P1 - P2) < 0.1$, P1 and P2 > 0.3 | Very uncertain (very similar) |
| $0.05 \leq (P1 - P2) < 0.1$ | Moderately uncertain (mildly similar) |
| $0.1 \leq (P1 - P2) < 0.3$ | Mildly uncertain (moderately similar) |
| $(P1 - P2) \geq 0.3$ | Confident (not similar) |

| Event | True label | Predicted label | Faults | Frequency disturbances | Oscillations | Transients | Voltage disturbances | P1 - P2 | Confidence category |
|----------|--------------|-----------------|----------|------------------------|--------------|------------|----------------------|---------|----------------------|
| event_44 | Oscillations | Oscillations | 0 | 0 | 1 | 0 | 0 | 1.0 | Confident |
| event_55 | Transients | Transients | 0.008333 | 0.02781 | 0.3687015 | 0.553794 | 0.041333 | 0.1850 | Mildly uncertain |
| event_28 | Transients | Oscillations | 0.025901 | 0.022523 | 0.521396 | 0.426802 | 0.003378 | 0.0945 | Moderately uncertain |
| event_14 | Oscillations | Transients | 0.0015 | 0.006418 | 0.439932 | 0.438968 | 0.004731 | 0.0009 | Very uncertain |

Estimating System Inertia Constant

- Availability of PMU data can be used to interpret the inertial response of a system.
- Frequency (f), Rate of Change of Frequency (ROCOF), and Voltage (V) measurements can be represented as a function of H for a given system.
- A Deep Neural Network (DNN) algorithm can capture their relationships from the training data and can predict H for unseen samples from those measurements.
- This concept can be utilized to predict the individual H of each synchronous machines as well.
- A lower number of training samples and irregular data resolutions might result in erroneous predictions.

Take historical f , ROCOF, V as input and H as output to train the DNN and validate it

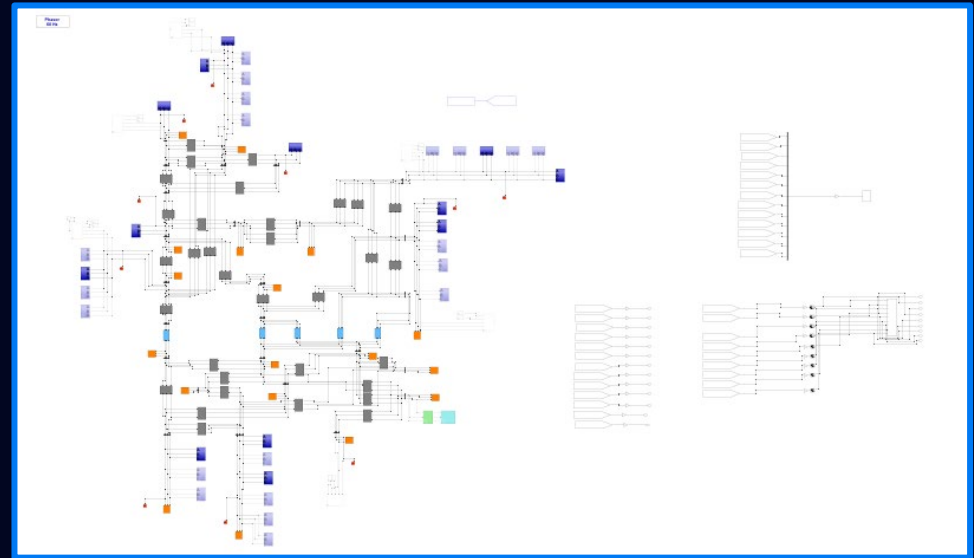
Use the DNN to predict H for different sets of measurements

Estimating system inertia constant

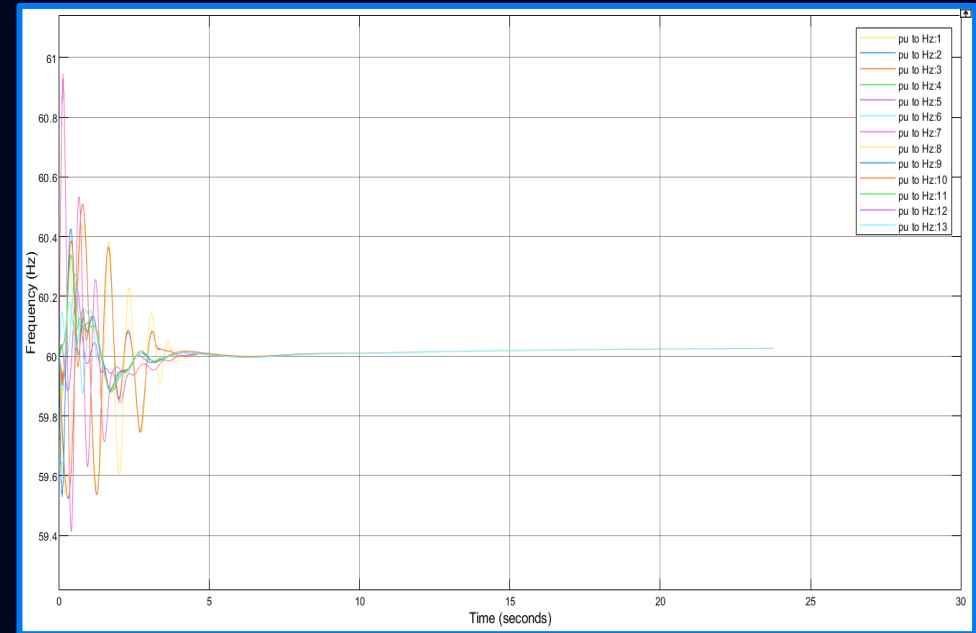
Generating Simulated Data Samples

1. IEEE 24-bus system is used to generate data for training and validating the DNN model.
2. The system H is known, and only ambient measurements are taken for training and testing the model.
3. Collecting the data below for the DNN model:
 - Input: Frequency, ROCOF, voltage at generator buses
 - Output: System inertia constant.

Snapshot of
Simulink model

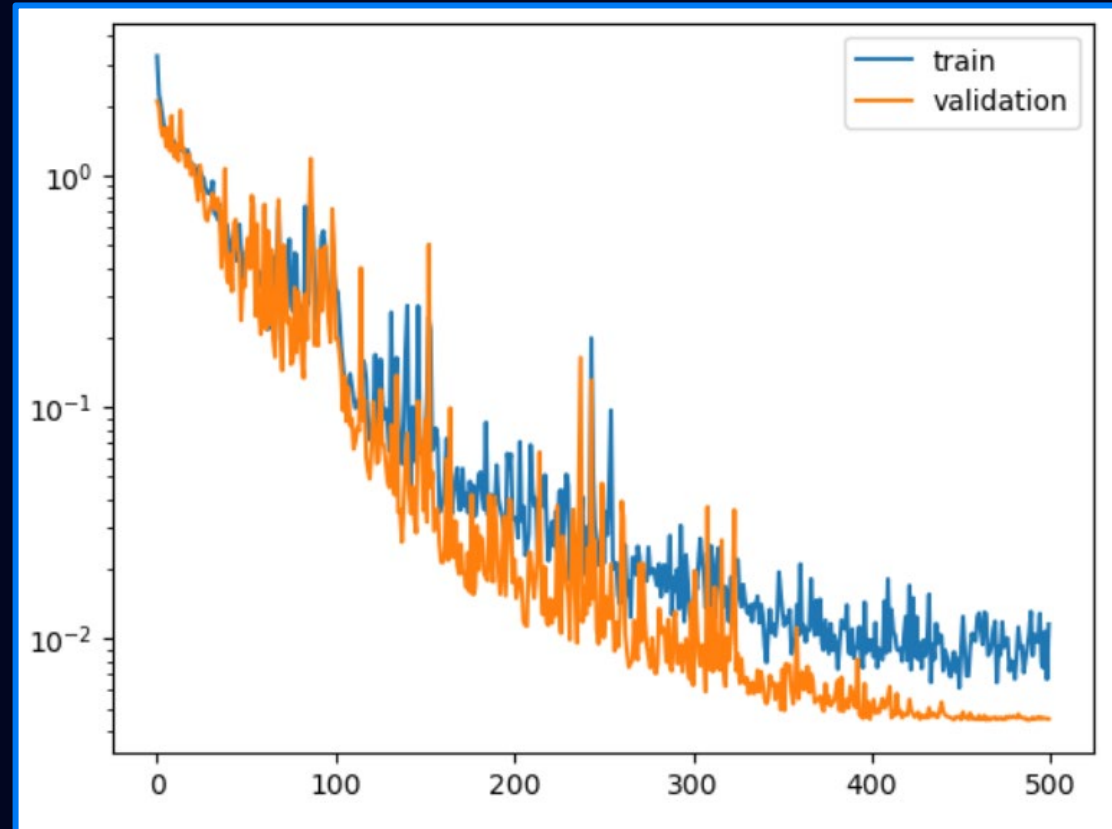


Frequency at each
generator bus



DNN Model Performance with Frequency and ROCOF Data

Loss

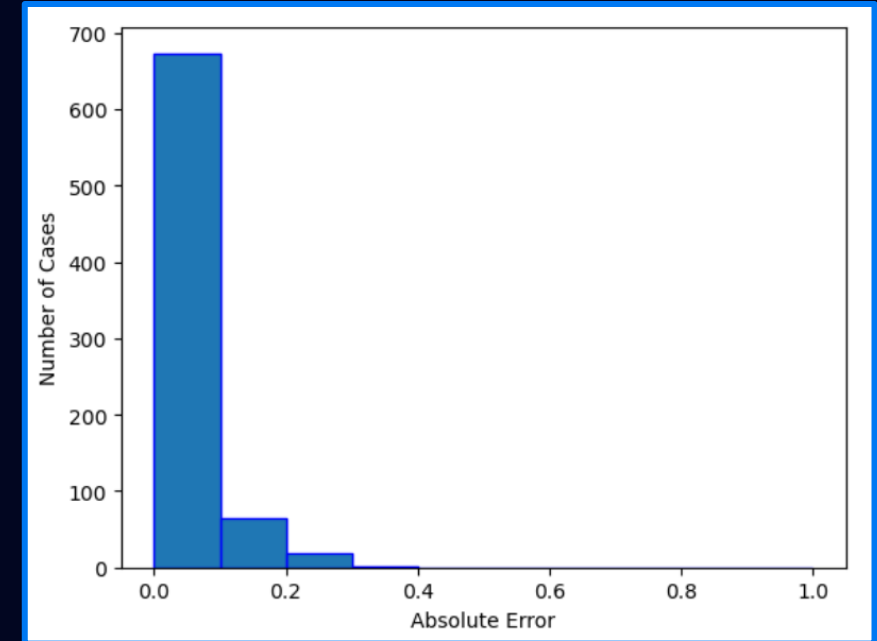
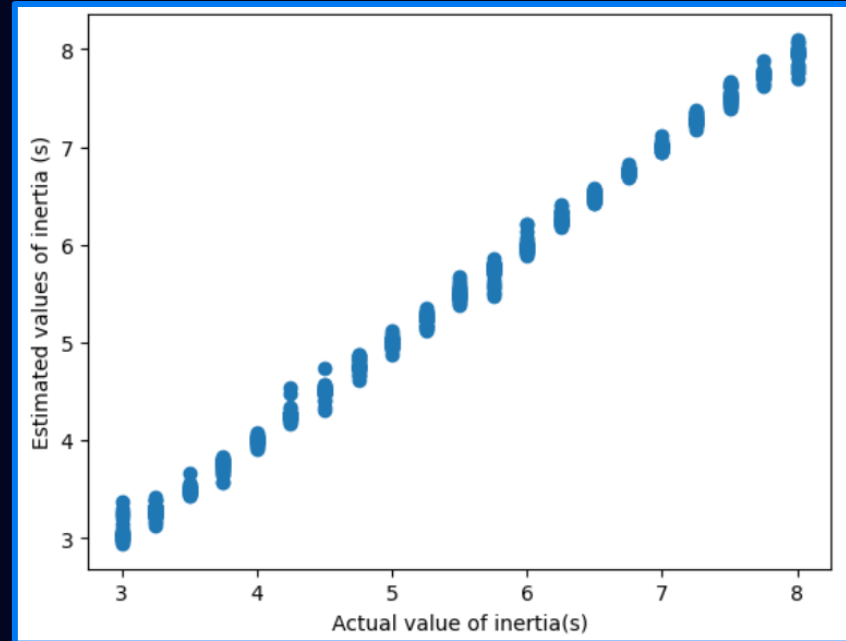


Number of epochs

Results with Frequency and ROCOF Data

MSE value after
training the model:
0.0045

Coefficient of
determination:
0.9979



| Accuracy (%) | Absolute error range |
|--------------|----------------------|
| 89.02 | 0.1 |
| 97.49 | 0.2 |
| 99.86 | 0.3 |

Metrics Comparison with Different Data Inputs

| Metrics | Data inputs | | | |
|--|-------------|--------|---------|-----------|
| | F | RoCoF | F+RoCoF | F+RoCoF+V |
| MSE | 0.0225 | 0.2362 | 0.0045 | 0.0074 |
| Coefficient of determination | 0.9933 | 0.8965 | 0.9979 | 0.9967 |
| Accuracy (%) (absolute error range is 0.3) | 96.69 | 72.61 | 99.86 | 98.54 |

Key Takeaways and Next Steps

- 1 Using ROCOF with frequency data improves the inertia estimation accuracy.
- 2 Current model with simulated data performs better than the state-of-the-art option with less data and measurements.
- 3 Model is tested for longer time windows and with data samples from different time windows, performed with similar accuracies when the absolute error threshold is >0.2 s.
- 4 Next steps:
 - Test with RTDS data and real-time PMU measurements
 - Incorporate IBRs and identify their contributions to system responses

Thank you!
Questions?

Farrokh Aminifar

Principal Advisor,
Monitoring, Protection, Automation, and Control
Quanta Technology
FAminifar@Quanta-Technology.com
(919) 451-0856