

Emerging Applications of Waveform and Synchro-Waveform Data Analytics in Electric Utilities

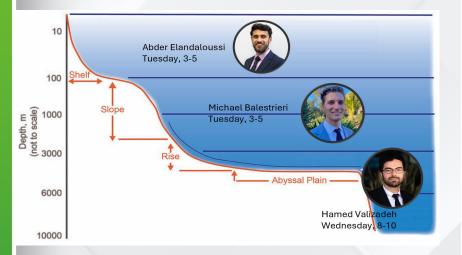
Panel Session: Synchro-Waveforms Data Analytics and Data-Driven Applications

Hamed Valizadeh, Southern California Edison (SCE)



- Distribution Waveform Analytics (DWA) project introduction
- Challenges of detecting and locating grid anomalies
- Waveform analytics and feature engineering for anomaly detection and classification
- Real experiences and application





Distribution Waveform Analytics (DWA)



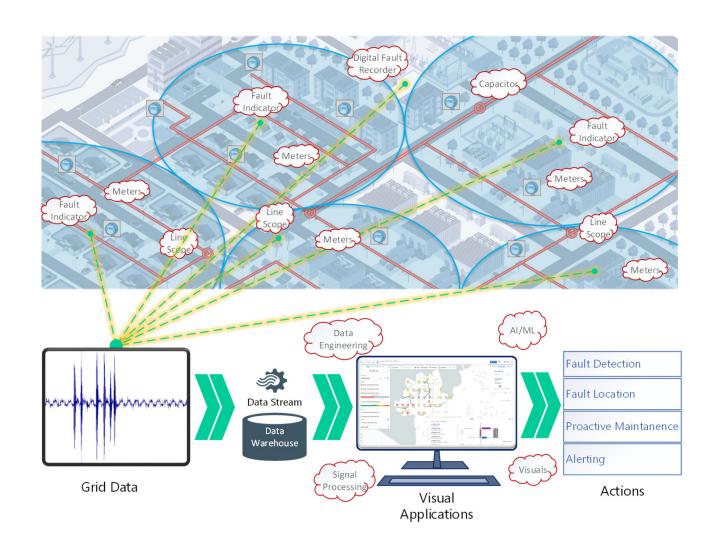


Business Objective: Provide situational awareness to incipient events that could potentially spark a wildfire.

Technical Objective: Integrate disparate grid data sources from existing equipment into a single analytics platform and run analytics.

Devices in Scope:

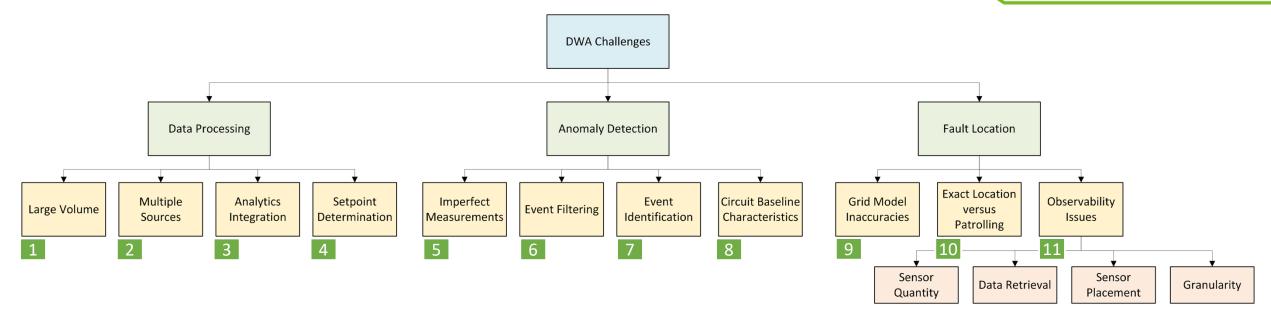
- <u>Digital Fault Recorder (DFR):</u> Records highresolution data at the feeder head that can record up transient events
- <u>SCADA Devices:</u> Switches, interrupters, capacitors, and fault indicators that record status events and system conditions
- Smart Meters (AMI): Customer meters provide real-time events at the endpoint level



Challenges





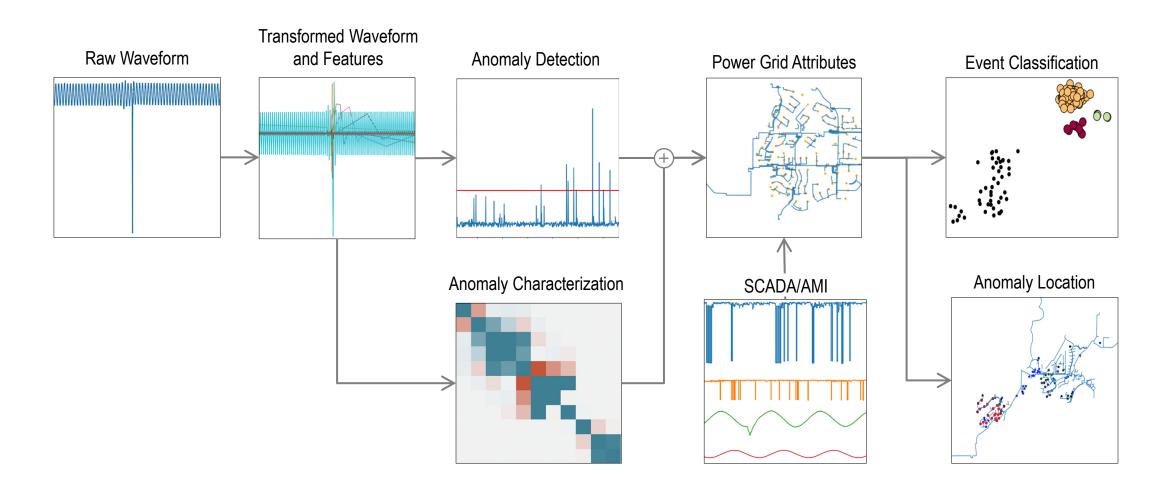


- 1) A waveform recorder produces roughly 1 GB of continuous point-onwave data per day per circuit with event data ranging 0-1 GB per day
- 2) Inconsistencies between various measurements and sensors
- 3) Data silos between systems (DFR, SCADA, AMI), and operational data in separate databases with no singular analytics platform
- 4) Determination of settings for selective sensor communications
- 5) Currently available grid edge measurements are imperfect
- 6) Prioritization of actionable issues
- 7) Profile of a fault voltage and current can vary across different fault types and grid layouts
- 8) Circuit characteristics influence anomaly detection and setpoints

- 9) The performance of the methods that rely only on the accuracy of the grid impedance parameters are not consistent due to the high sensitivities and imperfect data management
- 10) Inconsistencies between various measurements and sensors
- 11) Measurements lack in quantity, placement, and granularity, and data retrieval is sub-optimal at best with the aging wireless networks in place



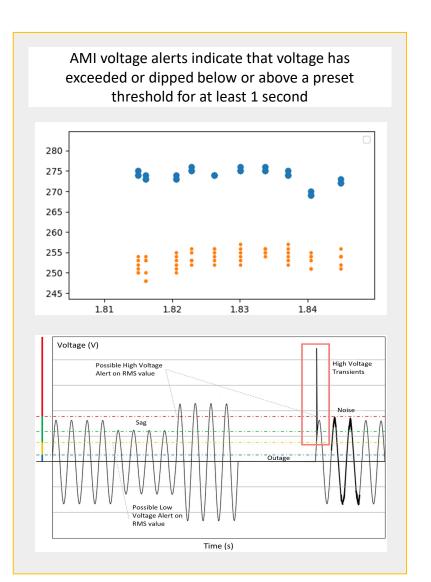


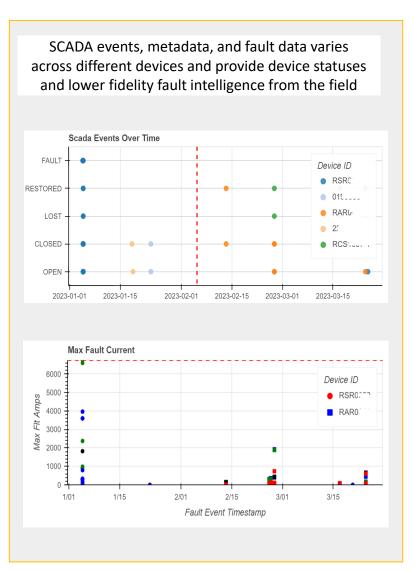


Example Data Types



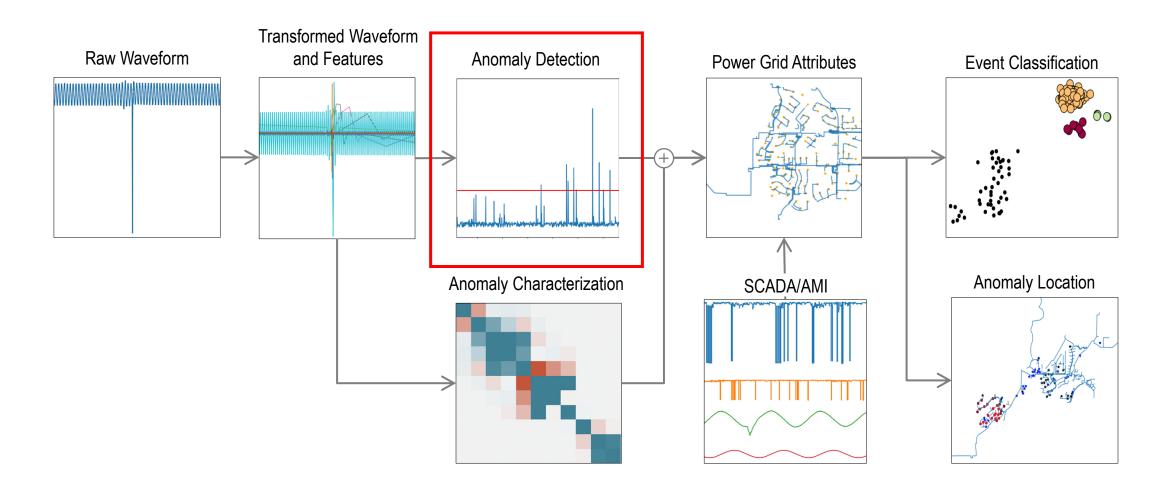










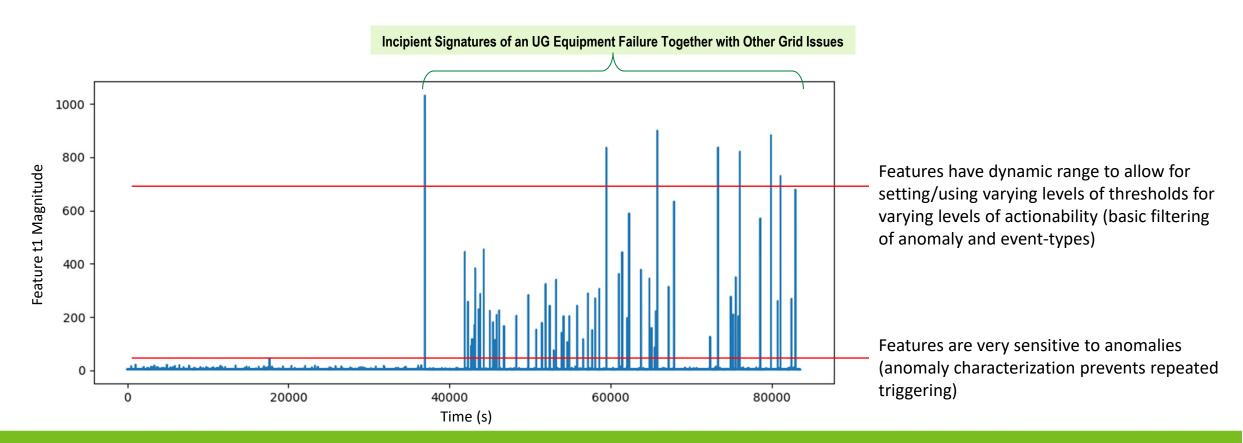


Waveform Features for Anomaly Detection



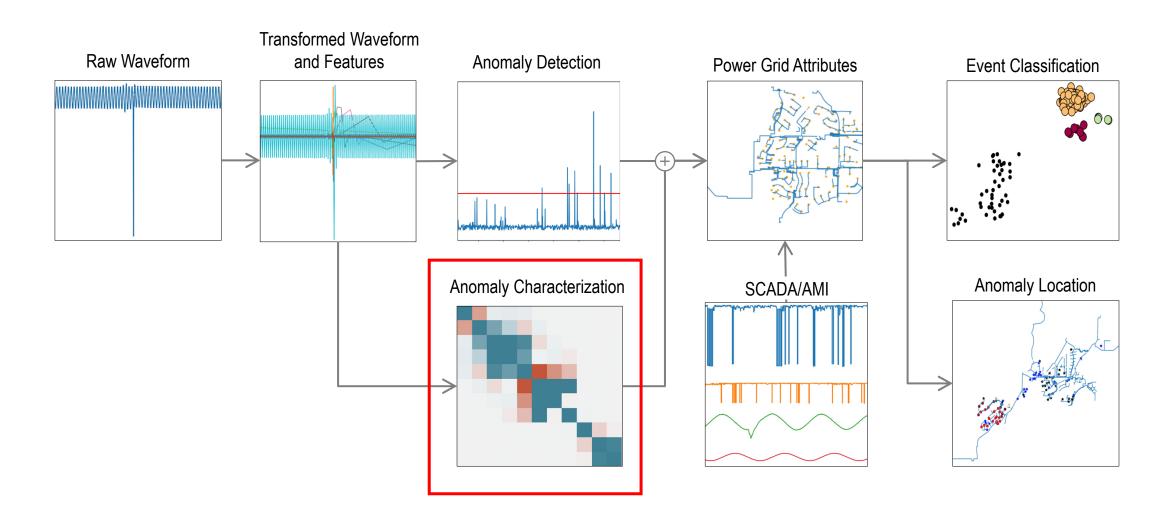


- A threshold is intended to detect when something is abnormal. Abnormalities aren't always problems.
- Any alert you set on a metric exceeding what you think is a normal threshold is going to fire a lot.
- A monitoring system needs to know the difference between an unusual state and a real problem, and this
 isn't possible with <u>only</u> a threshold.







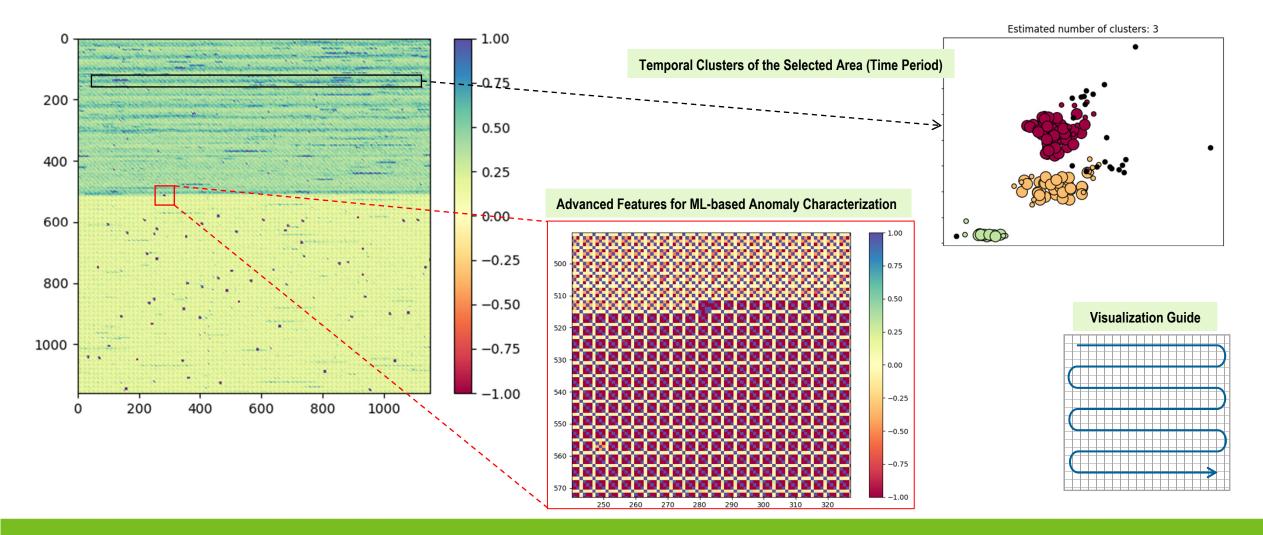


Waveform Features for Anomaly Characterization



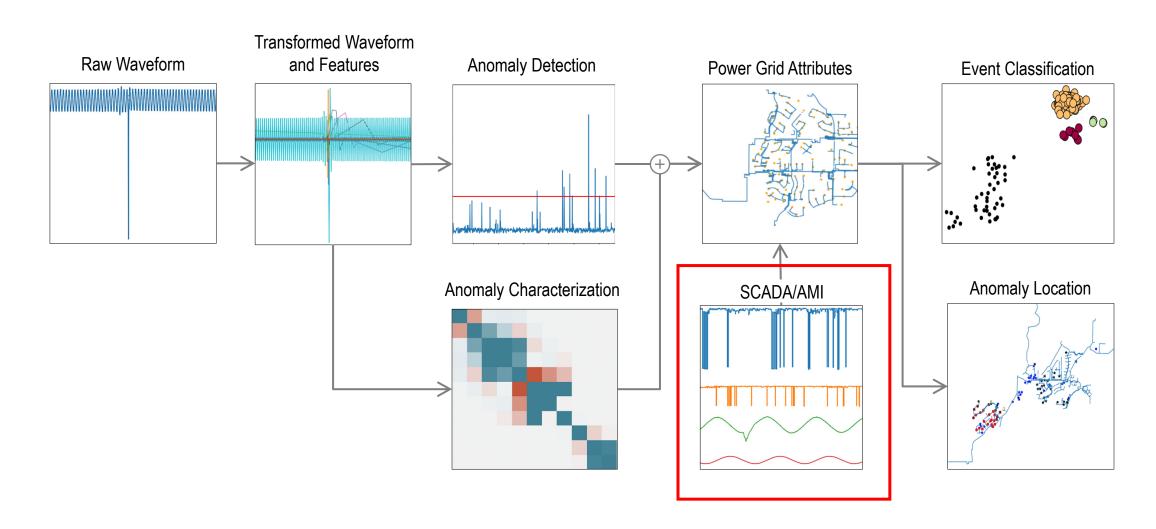


Anomaly characterization (by temporal clustering) is developed together with the anomaly detection.







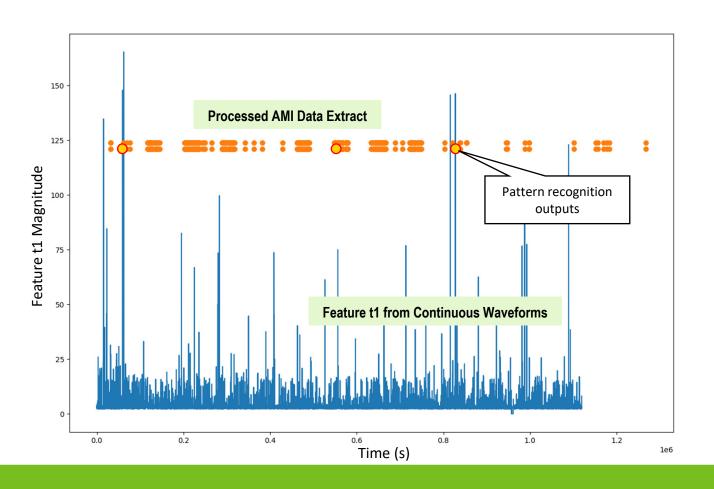


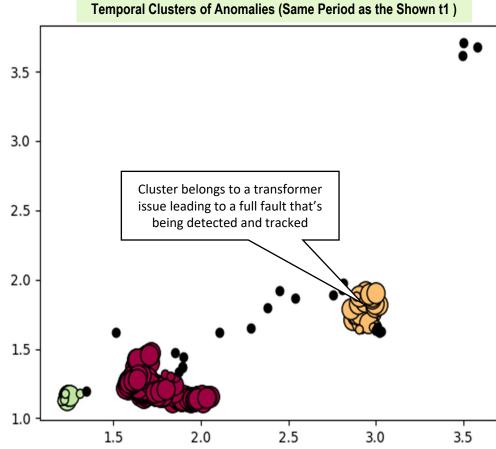
Waveform Features for Anomaly Detection





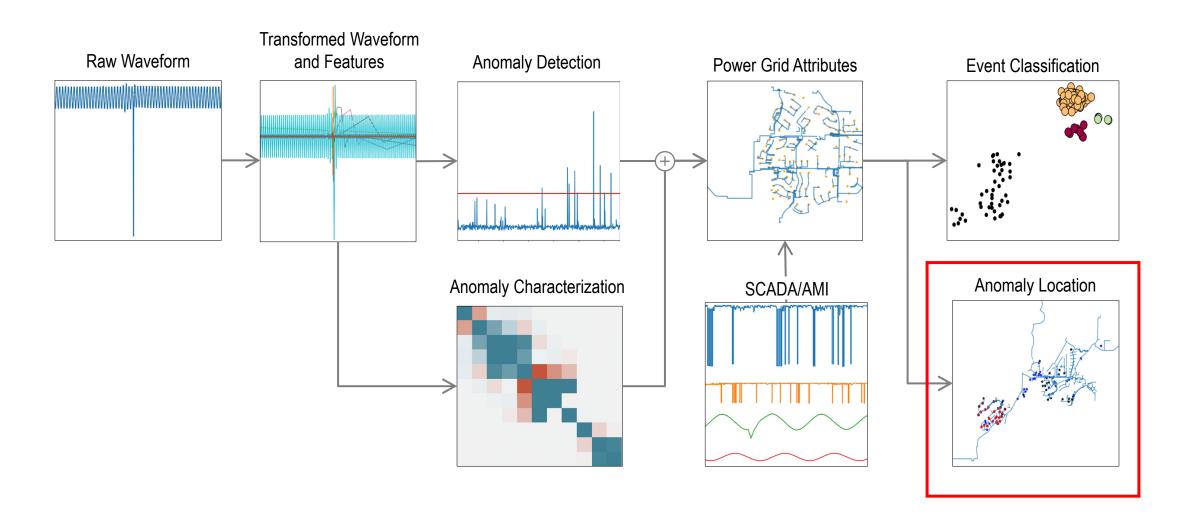
- AMI-based abnormal voltage recordings help pinpoint fault location via spatiotemporal modeling of imperfect and sporadic measurements
- Frequency of incipient signature occurrence increases over the course of the failure as time passes.









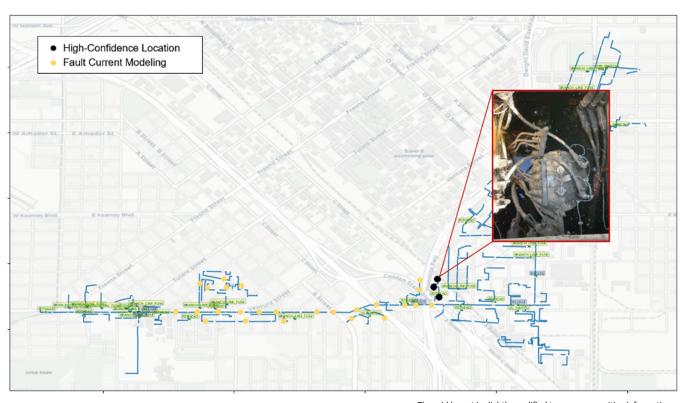


Real Example for Location Estimation





- Incipient underground fault
- Signatures started 92 days ahead of the final failure
- Several methods for fault location are implemented. Two methods shown:
 - Waveform-based estimation (yellow dots) relative to the known location
 - Multi-source high confidence estimation (black dots) include the location of final failure
- Multi-source estimation utilizes grid edge voltage alerts from AMI
 - GPS time synchronization is not required.
 Waveshape synchronization is sufficient
- Detection of event type and protection system awareness are key



The grid layout is slightly modified to remove sensitive information

Conclusions





- **Enhancing Model Performance**: By crafting features that capture the essence of the event, we enable our models to extract meaningful patterns and relationships from the data, leading to more accurate insights.
- Improving Model Interpretability: Engineering features that are interpretable, enables transparency and is essential for building trust in machine learning systems and making informed decisions based on model outputs.
- **Handling Complex Data**: Distribution grid data is rarely clean. It often contains missing values and outliers that can hinder model performance.
- Minimal Need for Labeled Data: Well-engineered features minimize the requirements for labeled signature libraries. .

