Unsupervised Anomaly Detection for Identifying Arcing Hazards on Power Distribution Systems

IEEE PES Big Data Webinar

Jhi-Young Joo, Ph.D.
Engineer – Distribution Automation Lead
joo3@llnl.gov

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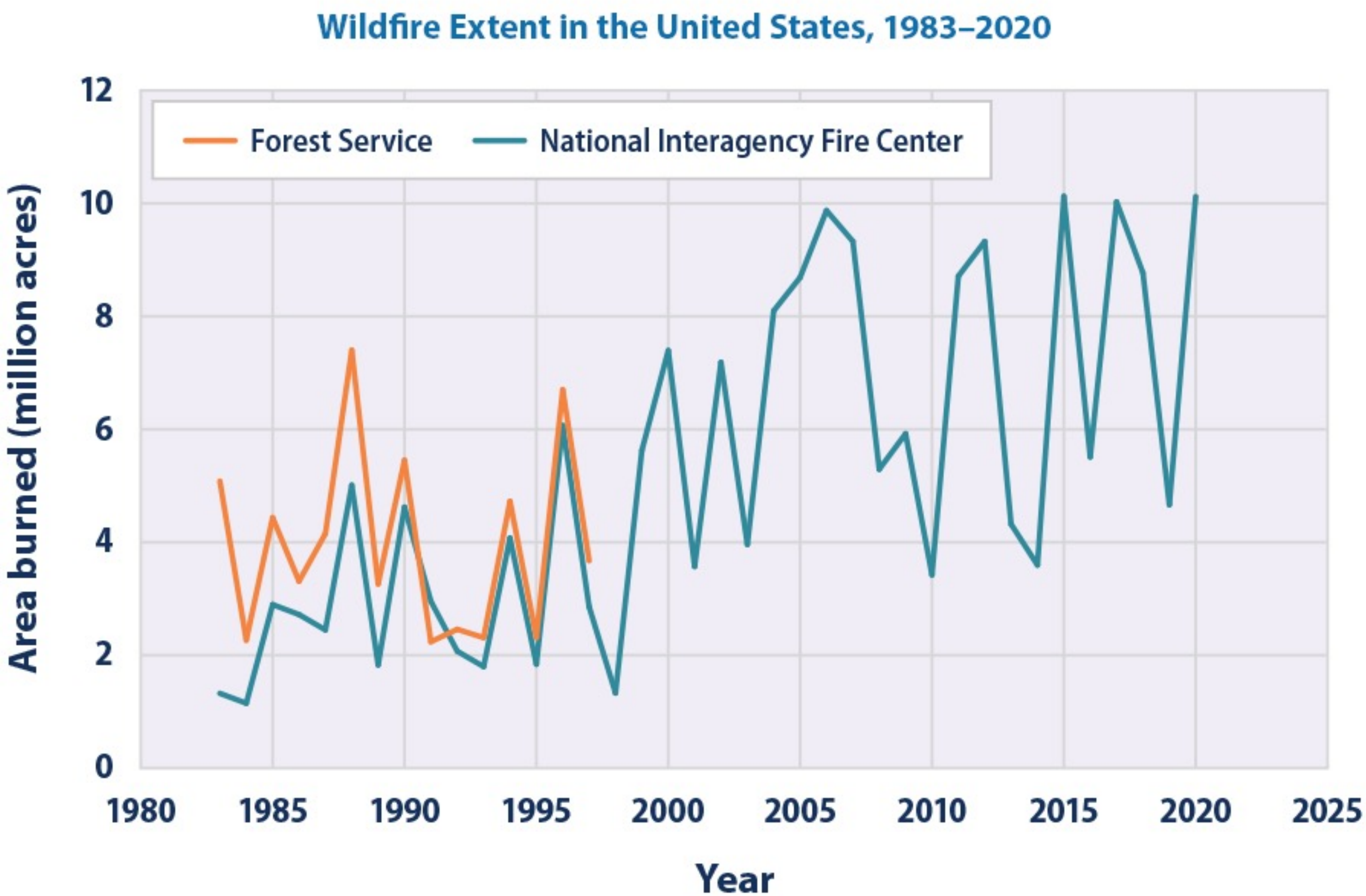
- Oak Ridge National Laboratory
- Pacific Gas & Electric

Outline

- Background
  - Wildfires and utilities
  - Arcing faults
  - Sensing and measurements on distribution systems
- Analytics of high-resolution grid data
  - Overall approach
  - Unsupervised learning for event detection and clustering
  - Supervised learning for labeling events
  - Data management and visualization
- Conclusion and future work

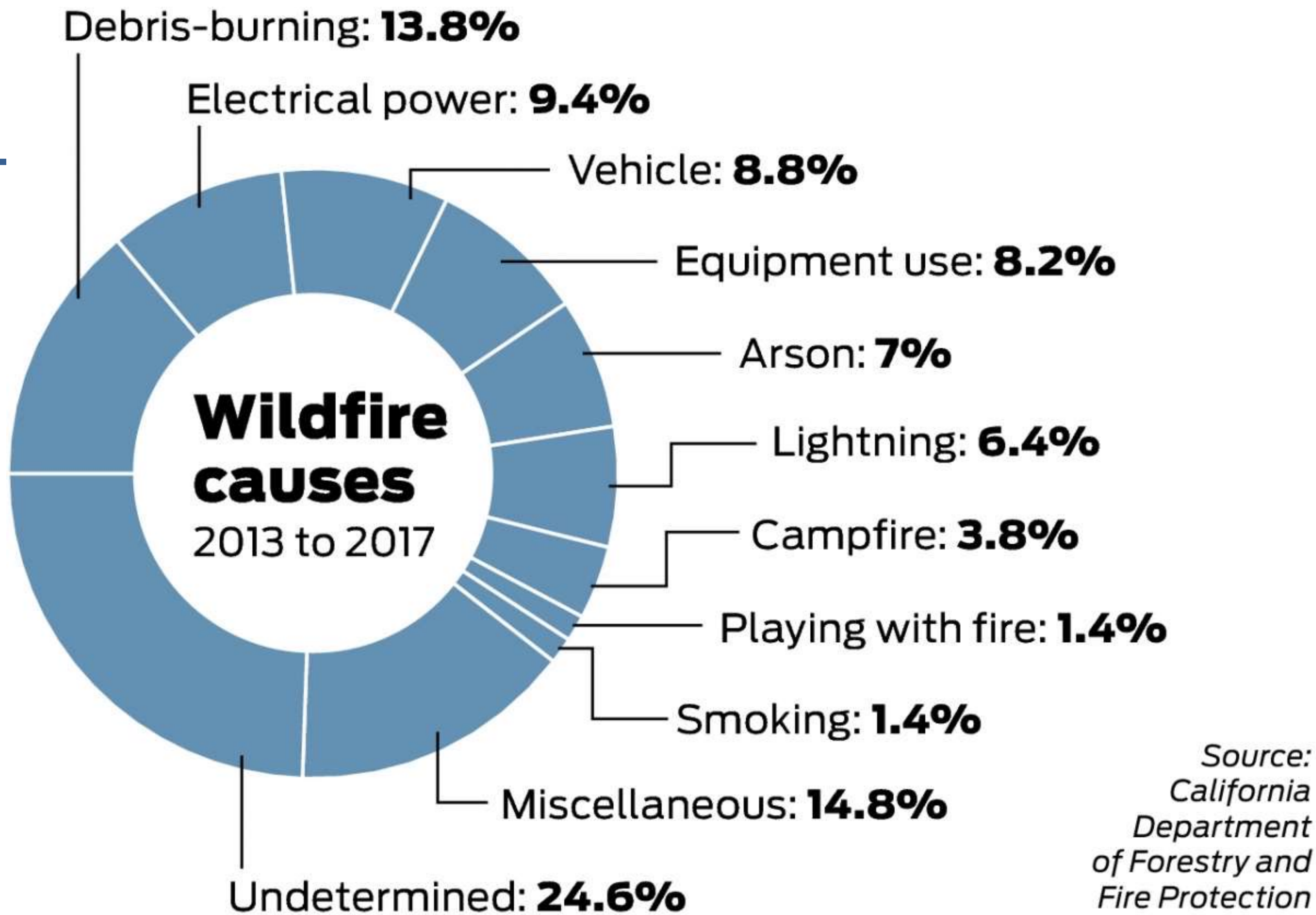


Data sources:

- NIFC (National Interagency Fire Center). 2021. Total wildland fires and acres (1983–2020). Accessed March 2021. www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html.
- Short, K.C. 2015. Sources and implications of bias and uncertainty in a century of U.S. wildfire activity data. Int. J. Wildland Fire 24(7):883–891.

For more information, visit U.S. EPA's "Climate Change Indicators in the United States" at www.epa.gov/climate-indicators.

U.S. Environmental Protection Agency. Climate Change Indicators in the United States. Ecosystems, Wildfires. Accessed May 2021. https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires.



https://www.sfchronicle.com/bayarea/article/How-California-s-biggest-wildfires-ignited-13907244.php Todd Trumbull / The Chronicle

The PG&E transmission tower that sparked the Camp Fire, in Pulga, Calif., Feb. 28, 2019.
| Max Whittaker / The New York Times

Arcing faults

- Definition of arc faults
  - Arc flash, arc burst, arc fault…
  - Fault current: a current that flows from one conductor to ground or to another conductor owing to an abnormal connection (including an arc) between the two
  - For this work, faults induced by vegetation or insulation breakdown
- Examples

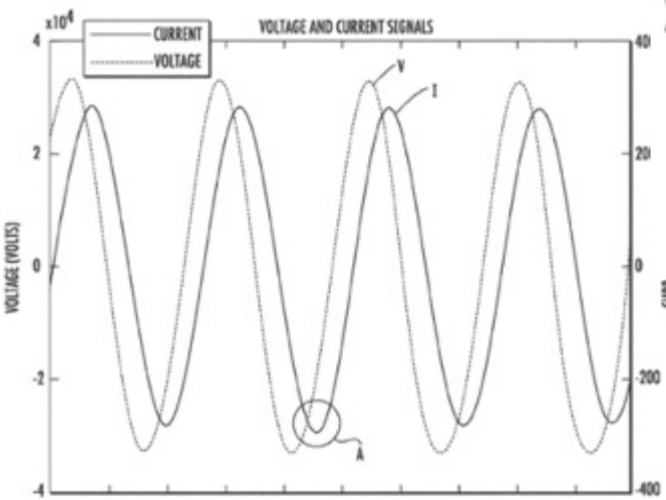
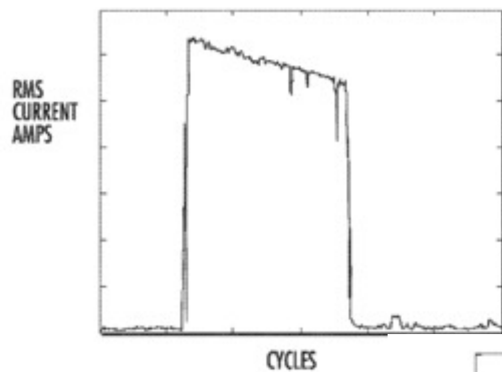
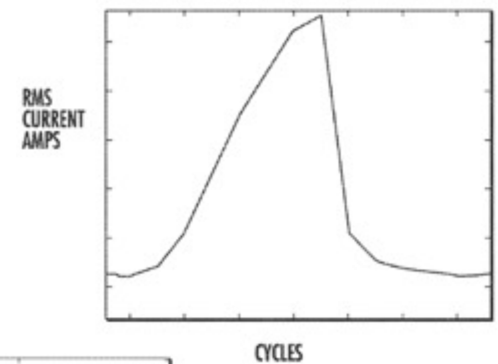
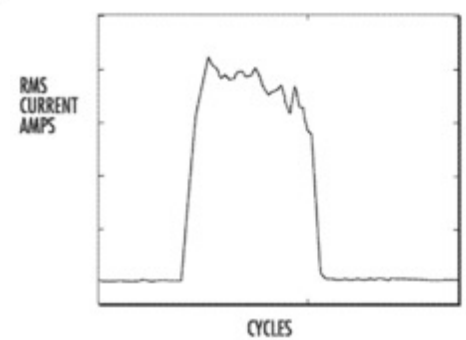


FIG. 2







Pictures from U.S. Patent US9046563B2
Arcing event detection

Detecting faults and measuring devices/systems

- Protection devices
  - Relays
  - Digital fault recorders
- Continuous measurements
  - SCADA
  - AMI (advanced metering infrastructure)
  - PMU (phasor measurement unit)
  - Point-on-wave (POW)
- Event records
  - Outage and maintenance records
  - Device activation records

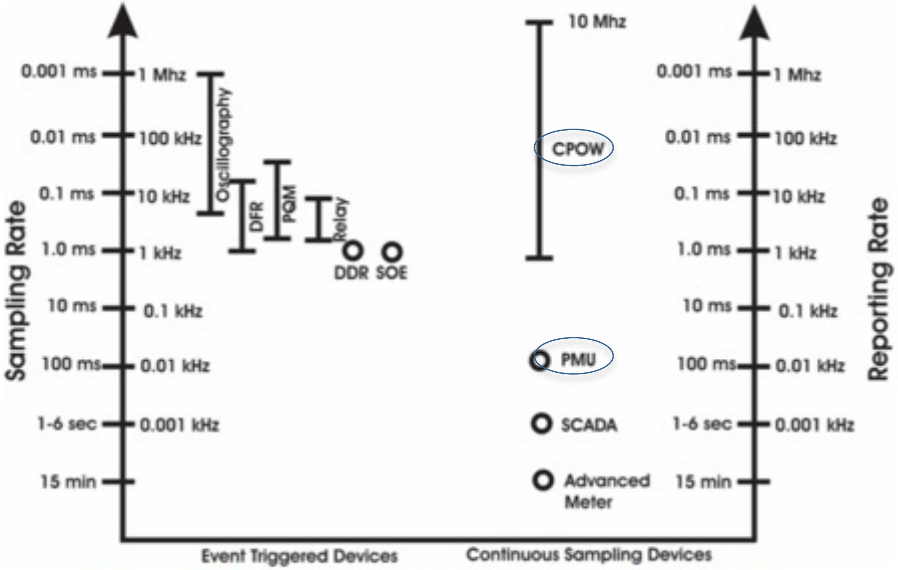


Figure 18: Grid monitoring devices by resolution and data continuity[1].

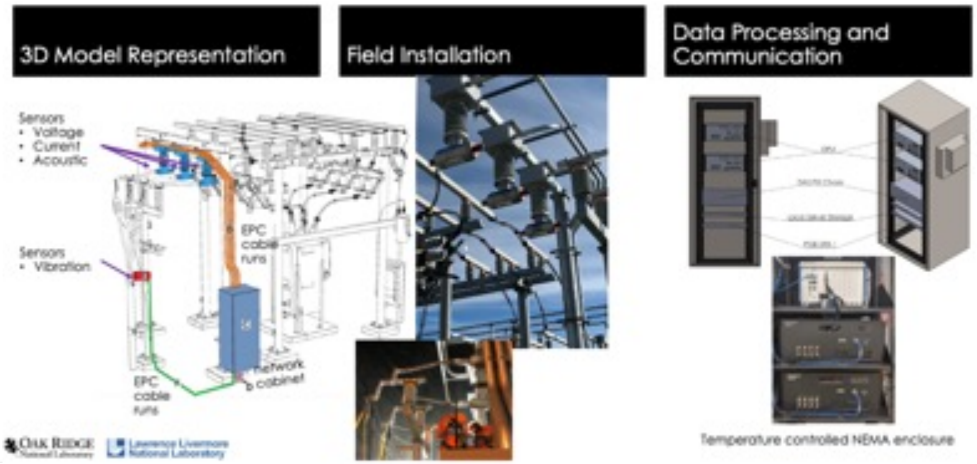
Silverstein, Alison, and Jim Follum. 2020. "High-Resolution, Time-Synchronized Grid Monitoring Devices." NASPI

Sensors deployed

- microPMU
  - Sampling rate: 512 samples per cycle
  - Reporting rate: 120 samples per second
  - Internal storage
  - Measurements (calculated)
    - Voltage and current magnitudes
    - Phase angles
    - Frequency
    - Active and reactive power
    - Power factor

- Electric Phenomena Cluster (EPC)
  - Sampling and reporting rate: 20,000 samples per second
  - Optical sensor processing unit, data acquisition system (processing 14 channels analog outputs), local data storage
  - Measurements: voltage, current, acoustics, vibrations

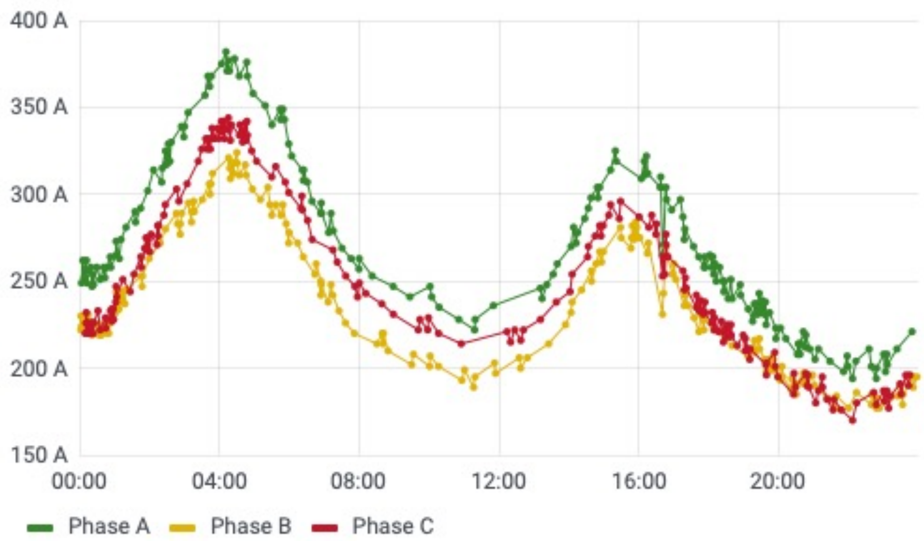
EPC Sensor Installation 12kV/1200 amp

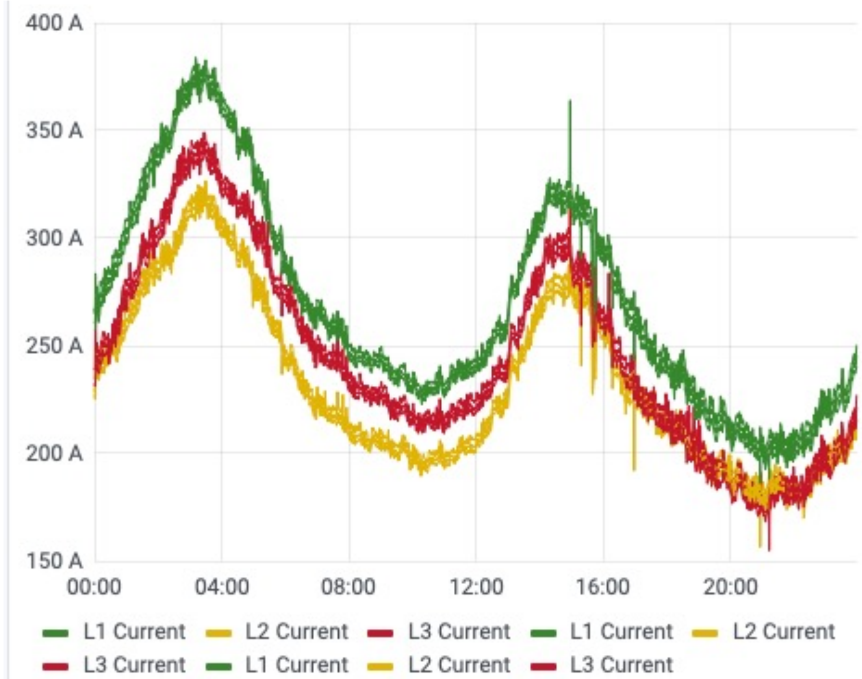


Data management and visualization

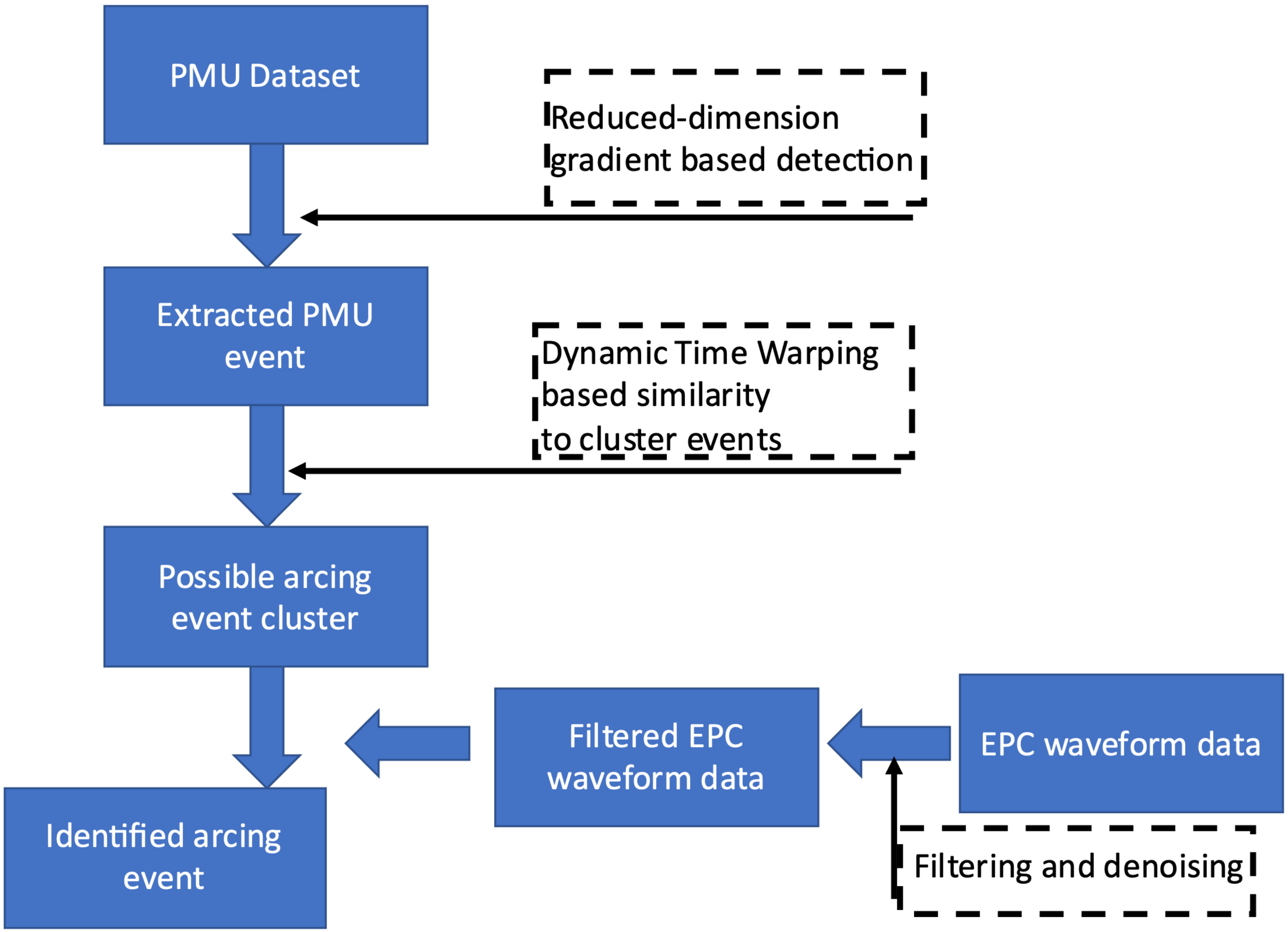
- Data storage needs per month
  - microPMU: ~25 GB per device
  - EPC ~750 GB
  - Cellular connection from device storage
- Database setup and data visualization
  - Data formats and conversion (.dat, COMTRADE)
  - PostgreSQL-based TimescaleDB
  - Grafana for visualization
- Measurement verification and calibration
  - PT/CT ratios
  - Verification with existing measurement data (e.g., SCADA)

SCADA vs. microPMU





Overview of analytics



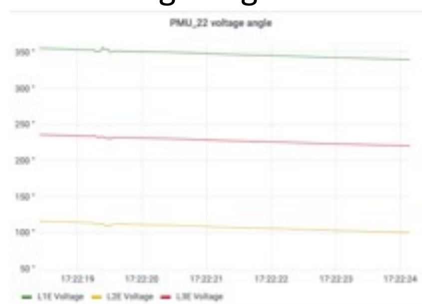
Gradient-based detection

- Filter events based on a set threshold
  - Three-phase voltage magnitudes and phase angles, current magnitudes and phase angles
  - Three-phase active and reactive power

rms voltage

rms current

voltage angle



current angle

Active power

Reactive power

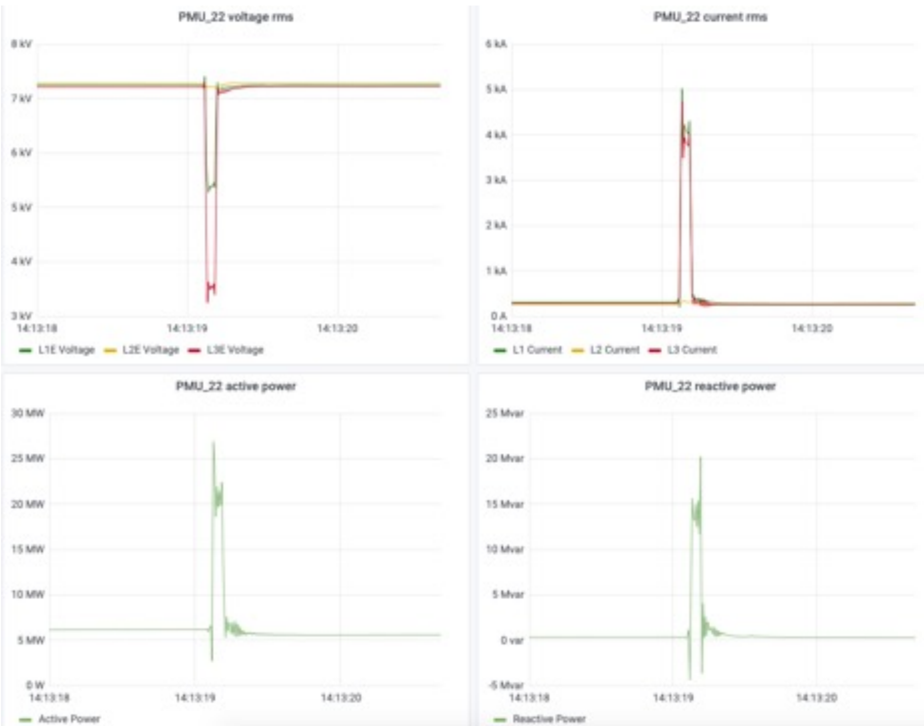
Gradient-based detection

- Reduced-order dataset
  - Principal component analysis
    → reduced data space to 2
  - Filtering w separate variables either missed a lot of events or captured too many events when threshold set low
  - Normal bounds of the reduced order set by a “normal” day + epsilon

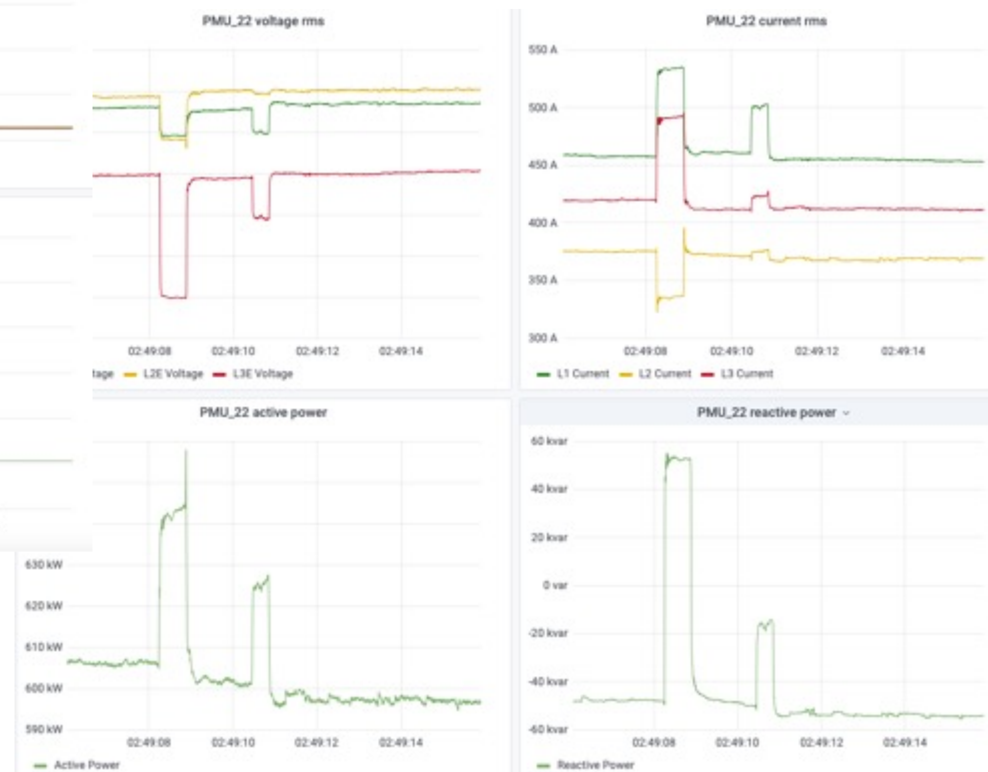
Eliminate non-arcing events

- Voltage regulation (cap bank switch, tap changes)
- Fuse and reclosers
- Motor start inrush

Sample fault signatures



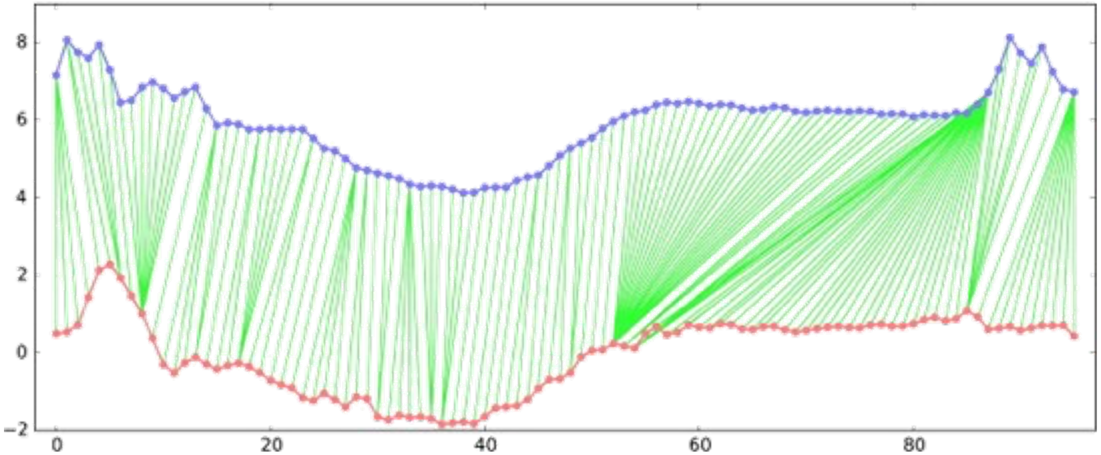
Recloser open



Vegetation. Fuse. Tree came down and took out wire and pole

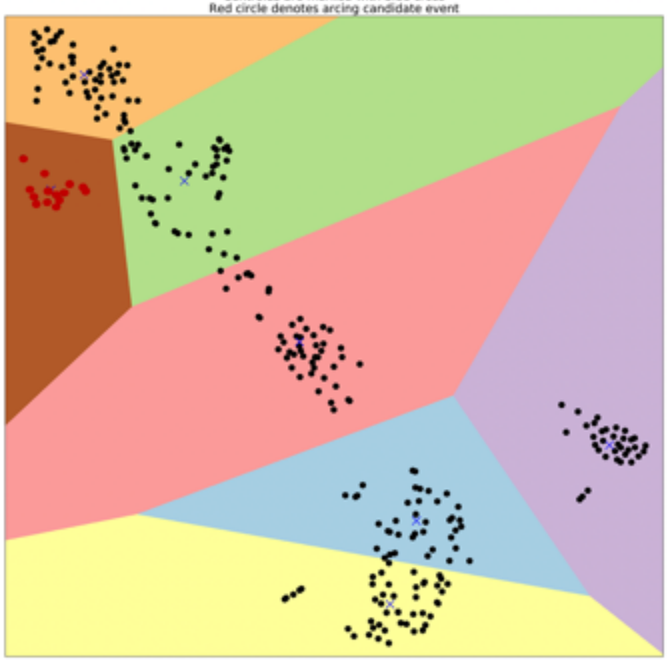
Clustering of events

- Dynamic time warping
  - Calculate similarity between the captured events
- K-means clustering
  - Find optimal number of clusters with elbow method



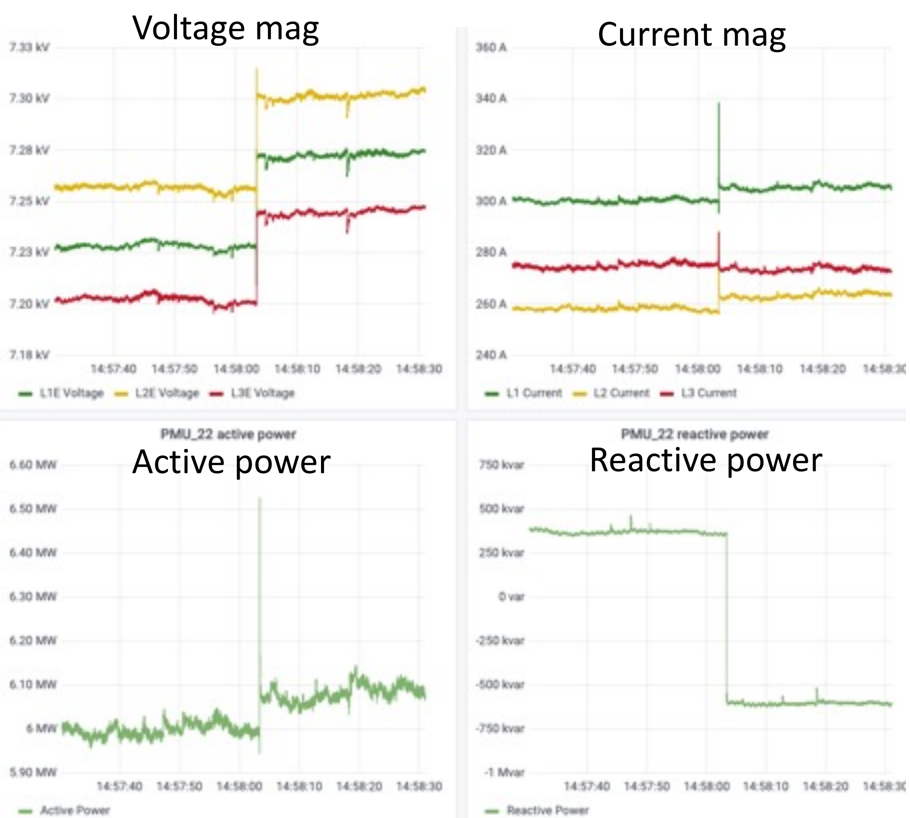
Picture source: Zheng Zhang, Ping Tang, Rubing Duan, Dynamic time warping under pointwise shape context, Information Sciences, Volume 315, 2015

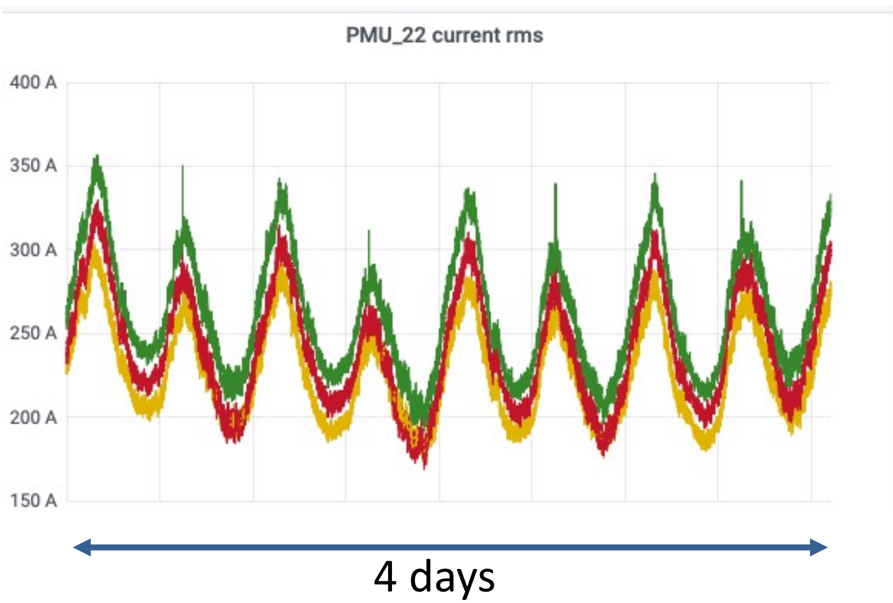
K-means clustering on the the similairty matrix of captured events
Centroids are marked with blue cross
Red circle denotes arcing candidate event



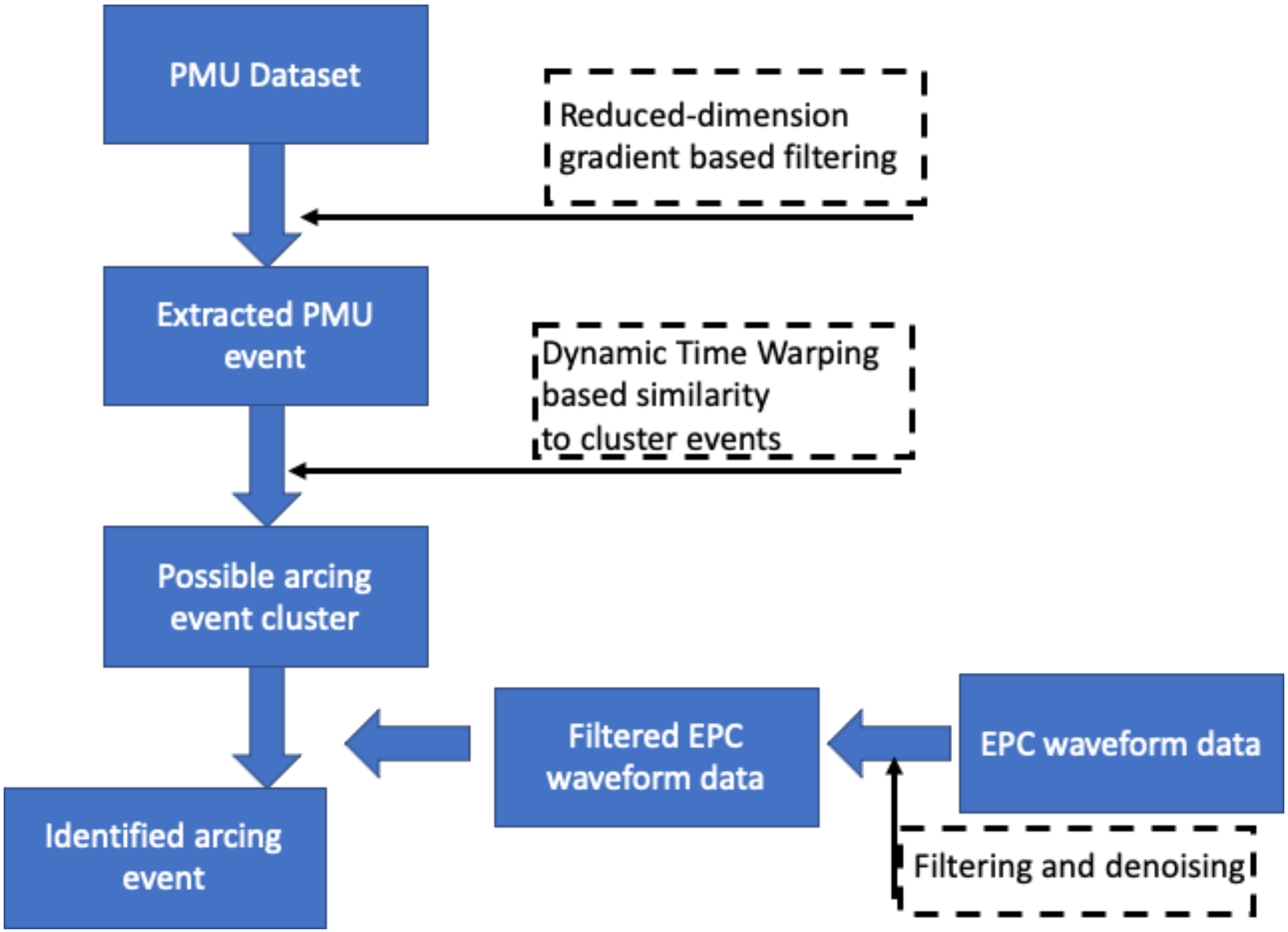
Analysis of captured events – example

- Voltage step change and current transients





Overview of analytics



Supervised learning of arcing events

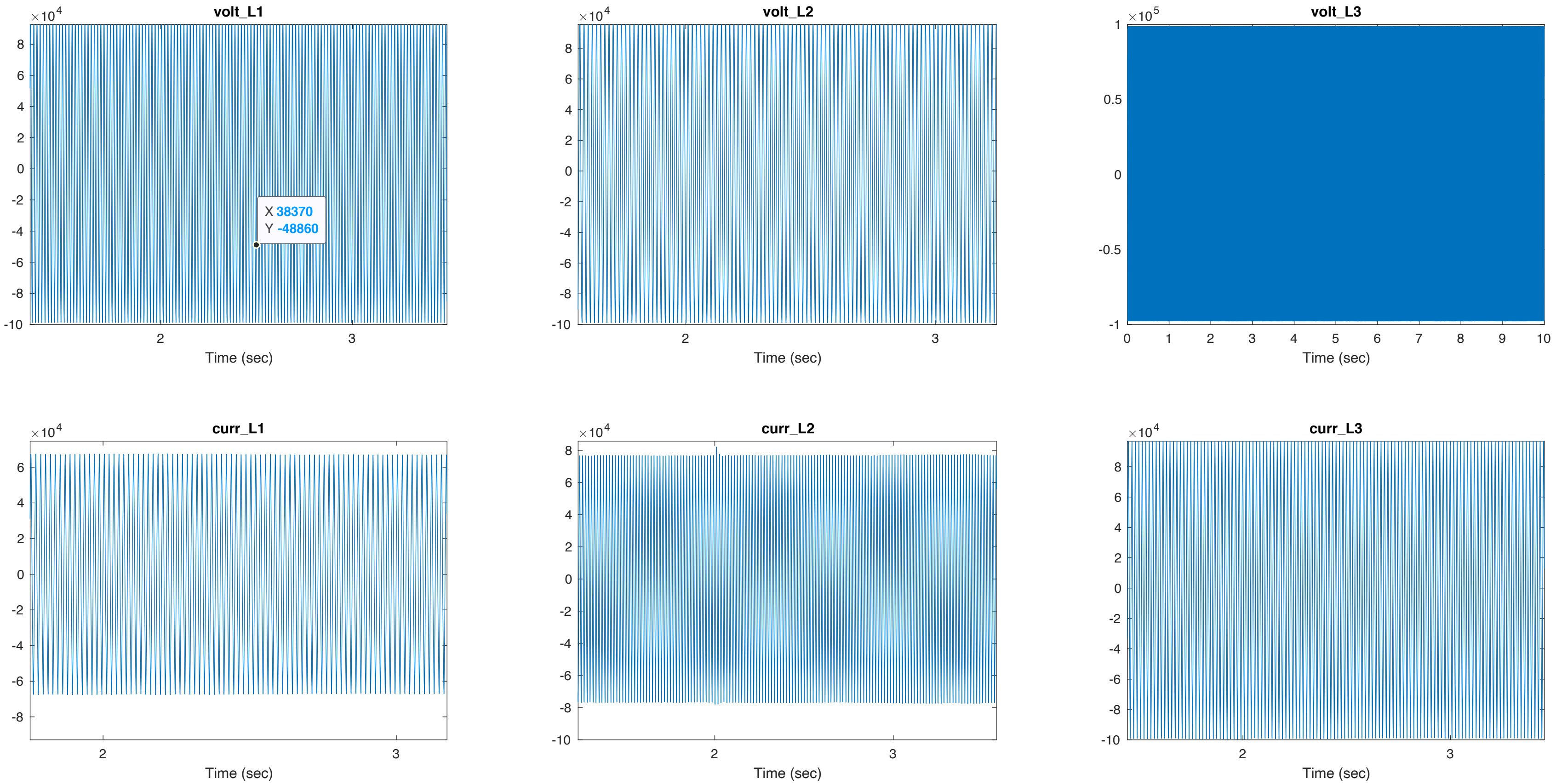
- Electric grid waveform signature library
  - Pool of labeled grid signatures including arcing faults
    - ORNL signature library https://darknet-01.ornl.gov/apps/siglib (this includes signature library from Texas A&M)
    - DOE/EPRI National Database Repository of Power System Events https://pqmon.epri.com

- Filtering waveform signatures for classifier training
  - Fast Fourier transformation (FFT)
    → filter out normal frequency
  - Inverse FFT of filtered event
    → transform back to time domain with normal signal filtered out
  - Noise attenuation
    → wavelet shrinkage denoising

- Apply different classifiers to find the best fit

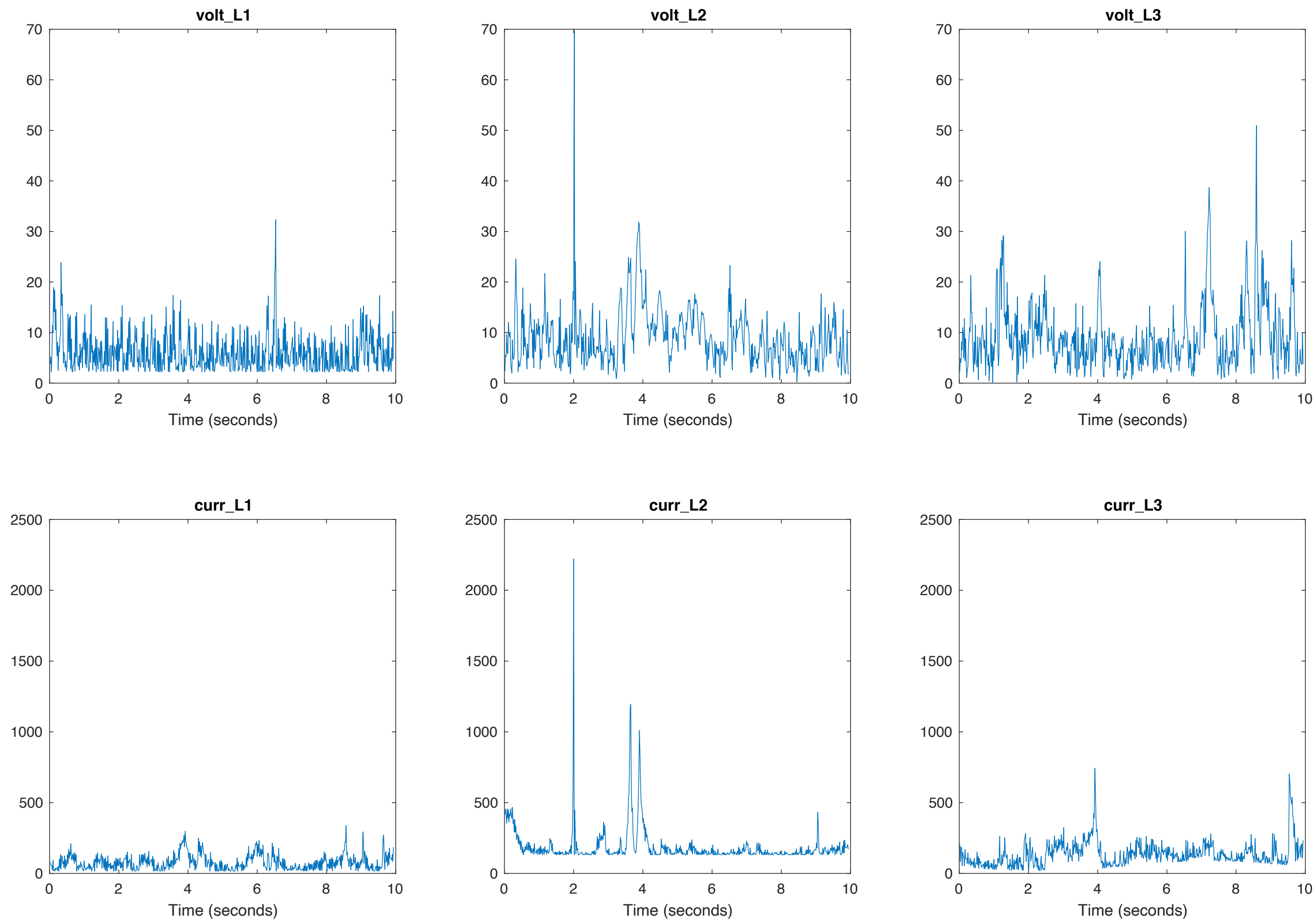
Filtering waveform signatures

- Waveform measurement of arcing event



Filtering waveform signatures

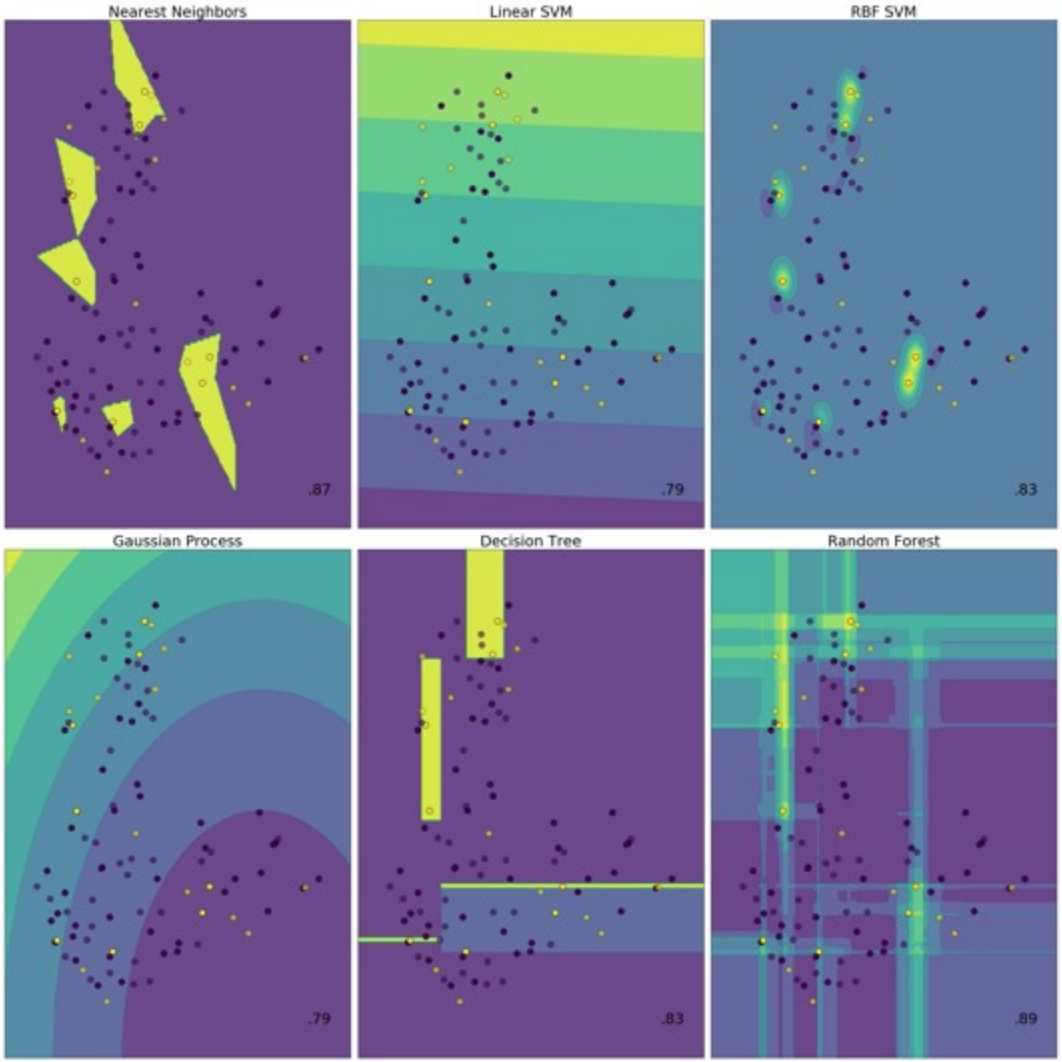
- Filtered waveform data of arcing event



Supervised learning of arcing events

- Application of classifiers on filtered data

Classifier	accuracy
Nearest neighbors	.87
Linear support vector machine (SVM)	.79
Radial-basis function SVM	.83
Gaussian process	.79
Decision tree	.83
Random forest	**.89**



Conclusion and future work

- Unsupervised anomaly detection and clustering
  - High-resolution measurements (synchrophasors, waveform)
  - Gradient-based detection in a reduced space
  - Needs user inspection and input for labeling
- Supervised classification with waveform data
  - Subcycle to few-cycle events difficult to identify with synchrophasor measurements
  - Threshold-based waveform data filtering can capture too many events including noisy measurements
  - Existing signature libraries (although not extensive) can help classify arcing events from phasor measurement events
- Future work
  - Filter events with waveform data trained classifier

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