SAND2021-11229C

Sandia National Laboratories

Machine Learning Based Fault Detection And Location In Electric Power Distribution Systems

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2021 INFORMS Annual Meeting

Panel Session “Data-Driven Analyses of Field Failures and Faults for Critical Infrastructure Systems”

October 25, 2021

U.S. DEPARTMENT OF ENERGY NNSA

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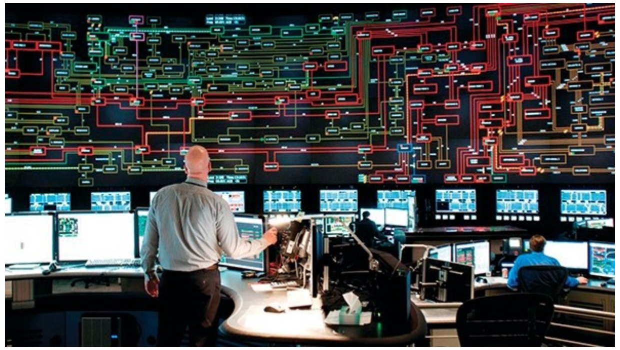
Introduction

The electric power grid provides roughly 4000 TWh of power per year, delivering power to critical aspects of America's economy, transportation, water, emergency services, telecommunications, manufacturing, defense facilities, and residences.

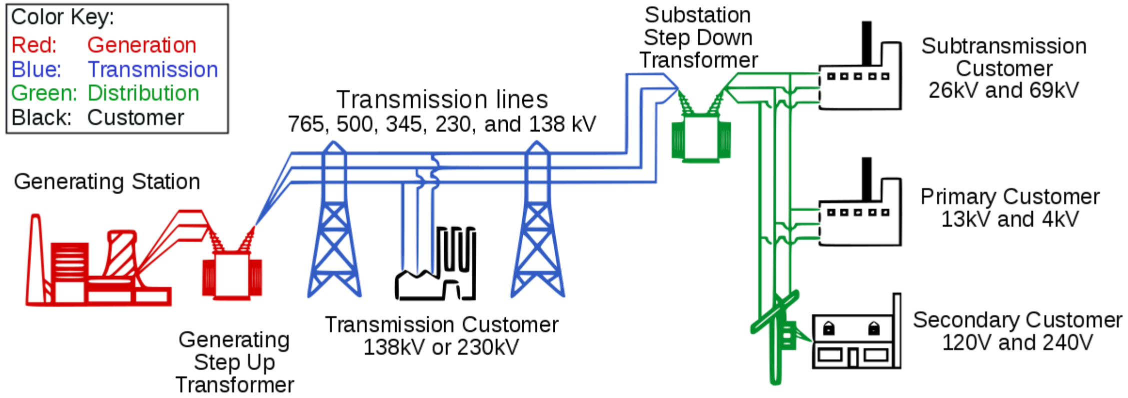
Transmission System (up to 500kV) transfers power throughout the U.S.

- Real-time measurements (PMU, 1-3 second SCADA, etc.)
- State Estimation, Optimization, and Control



Distribution System (4kV – 35kV) connects to the customers

- Much less monitoring or control due to the size
  - ~300,000 miles of transmission lines vs. ~6,000,000 miles of distribution lines
  - ~20,000 substation transformers vs. ~200,000,000 service transformers
- Visibility into distribution system operations is limited, and models are prone to errors



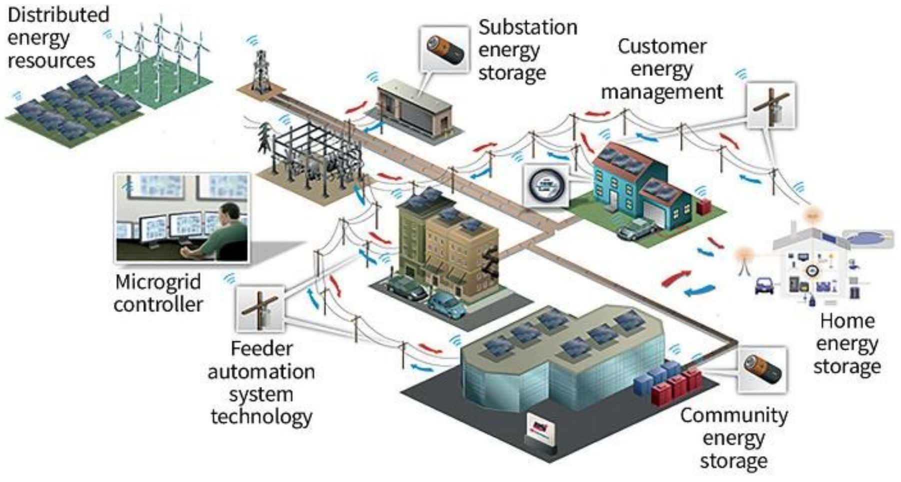
http://www.ferc.gov/industries/electric/indus-act/reliability/blackout/ch1-3.pdf

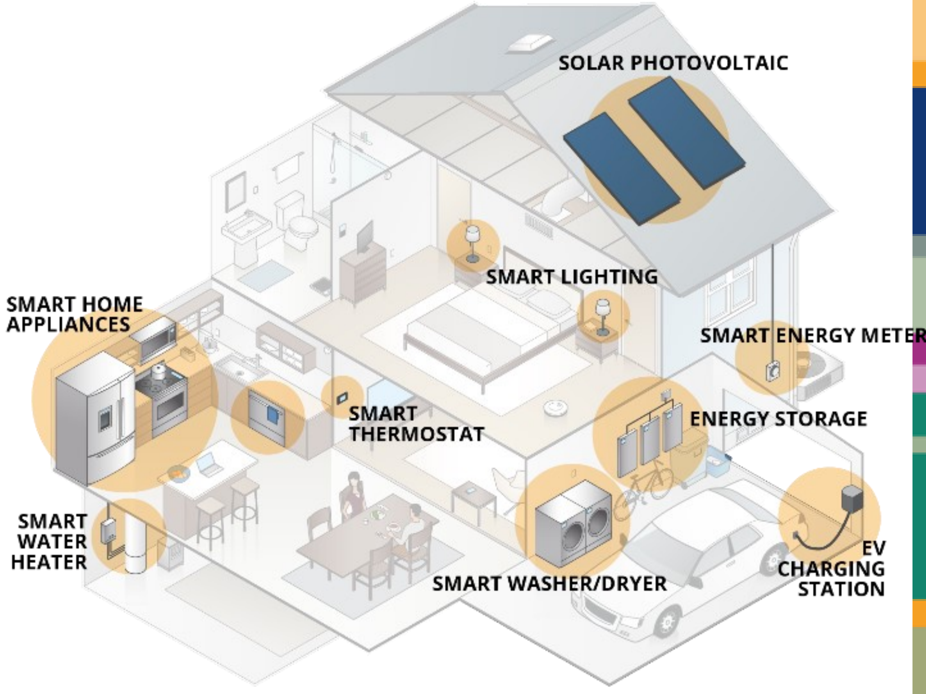
Electric Power Systems

Power Systems is a perfect application for Machine Learning due to the complex systems and large amounts of data. This is made possible recently due to:

- Advances in computing power for real-time learning and decision making
- Additions of new sensing equipment such as smart meters and PMU
- New Artificial Intelligence algorithms to handle large datasets, transferable learning, and physics-based algorithms

Distributed machine learning (ML) algorithms sense the grid using local sensors and make real-time decisions to improve power system reliability and resilience





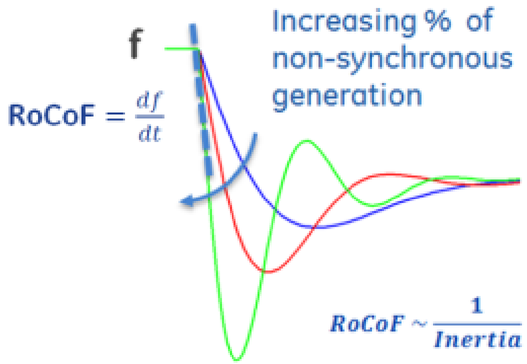
Power System Protection

The protection system is designed to maintain safe operation and reliable service

- Rapidly remove the fault and minimize the disconnection of customers
- Relays measure voltage and current flowing through the line. Conventional protection uses logic pre-determined by a protection engineer to flag anomalous events (current is too high) for detecting faults and opening a breaker to isolate the part of the system with the fault
- Relays are coordinated and provide backup using time delays depending on the location of the fault.

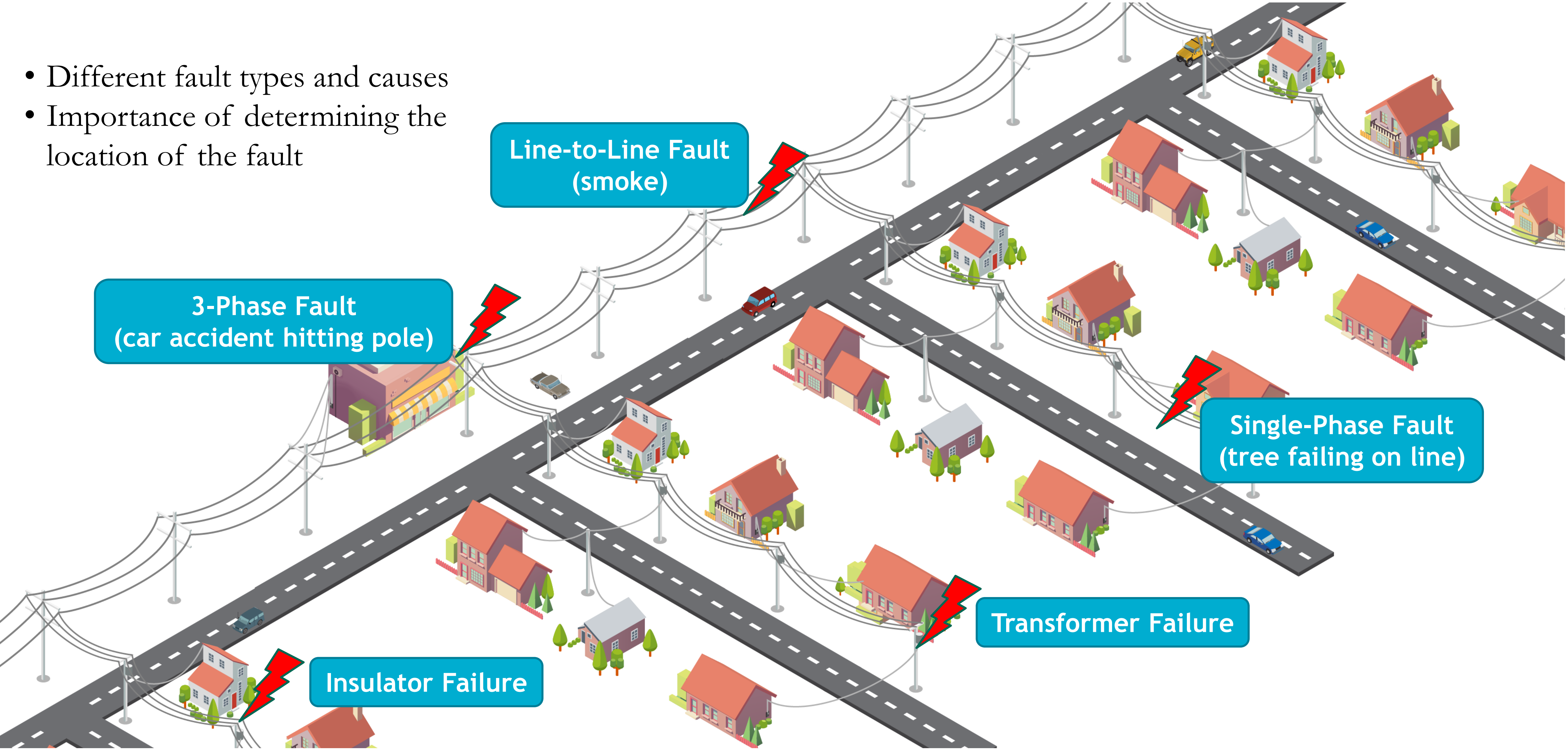
Power System Protection is getting more significant and more complicated:

- Inverter-based generation does not have the same fault characteristics
- Protection challenges in downtown networked system
- Electric faults causing wildfires in California
- Fast-tripping protection schemes limited by communication networks
- Cyberattacks (e.g., 2016 Ukraine) on relays could cause damage or cascading outages

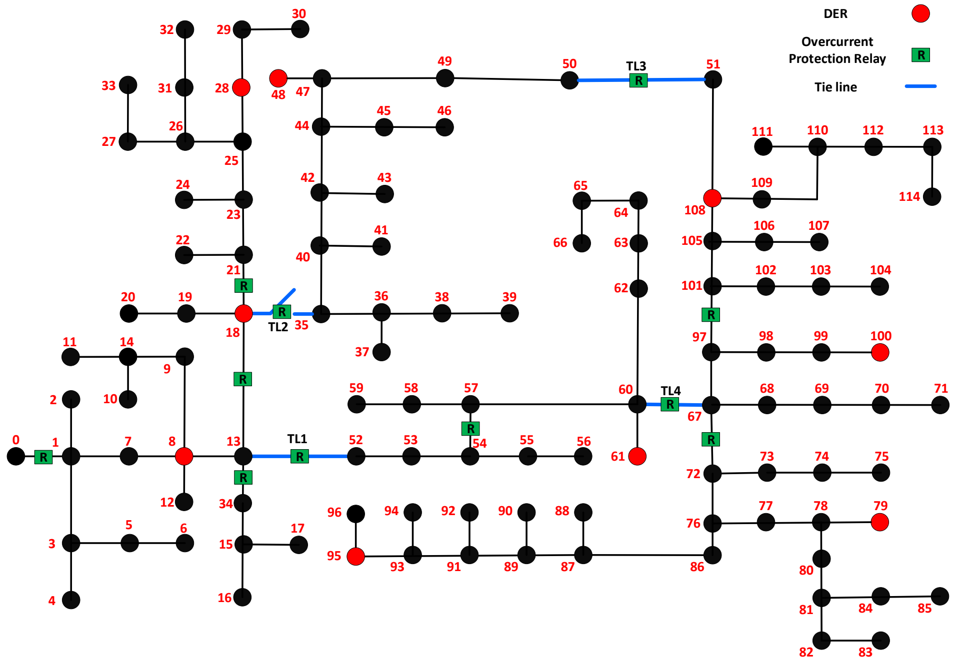


Distribution System Faults

- Different fault types and causes
- Importance of determining the location of the fault

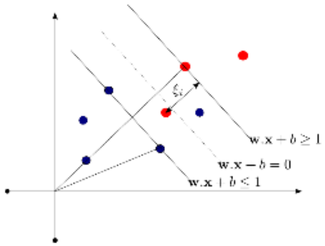


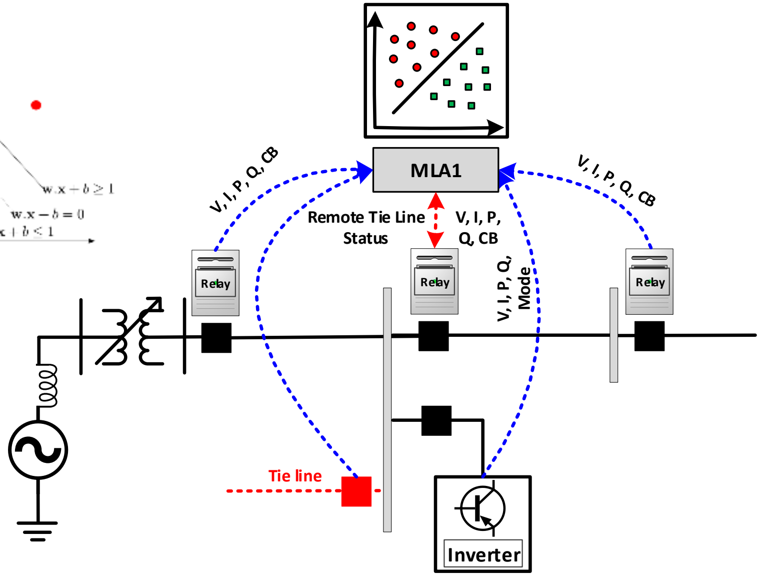
Machine Learning for Power System Operations

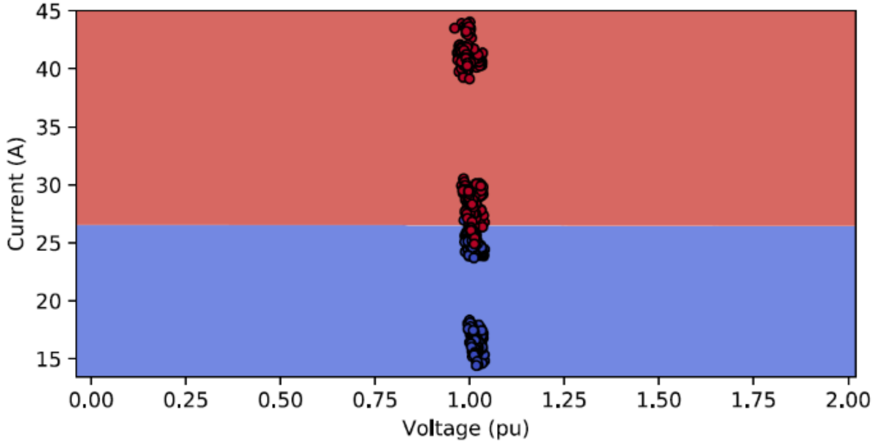


- During resilience events, there can be uncertainty in the status of the grid (breaker open/closed, microgrid connected or islanded) with possible loss of communication and many events happening at the same time
- Machine learning algorithms can learn correlations between local measurements and the configuration of the grid. This ensures reliable communication-free operations during resilience events
- Using Support Vector Machine (SVM) to learn and classify each switch in the network as open or closed

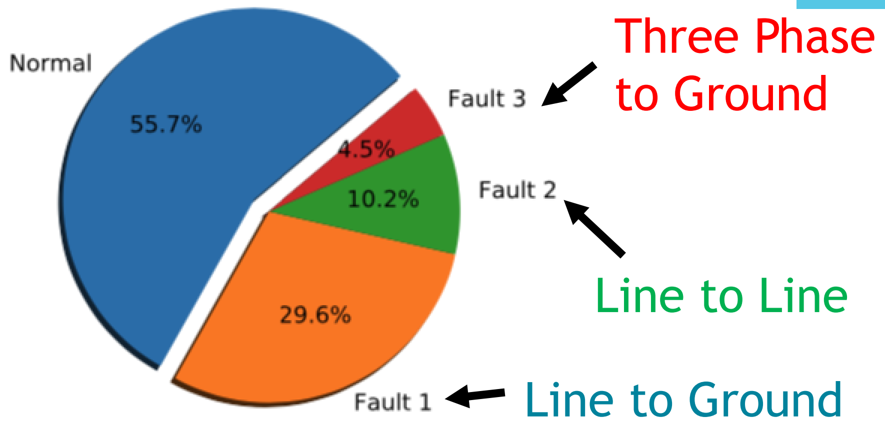
Tie Line / Breaker	Accuracy
TL1	98.2%
TL2	98.0%
CB2	99.5%
CB3	96.9%







Machine Learning for Fault Detection and Location

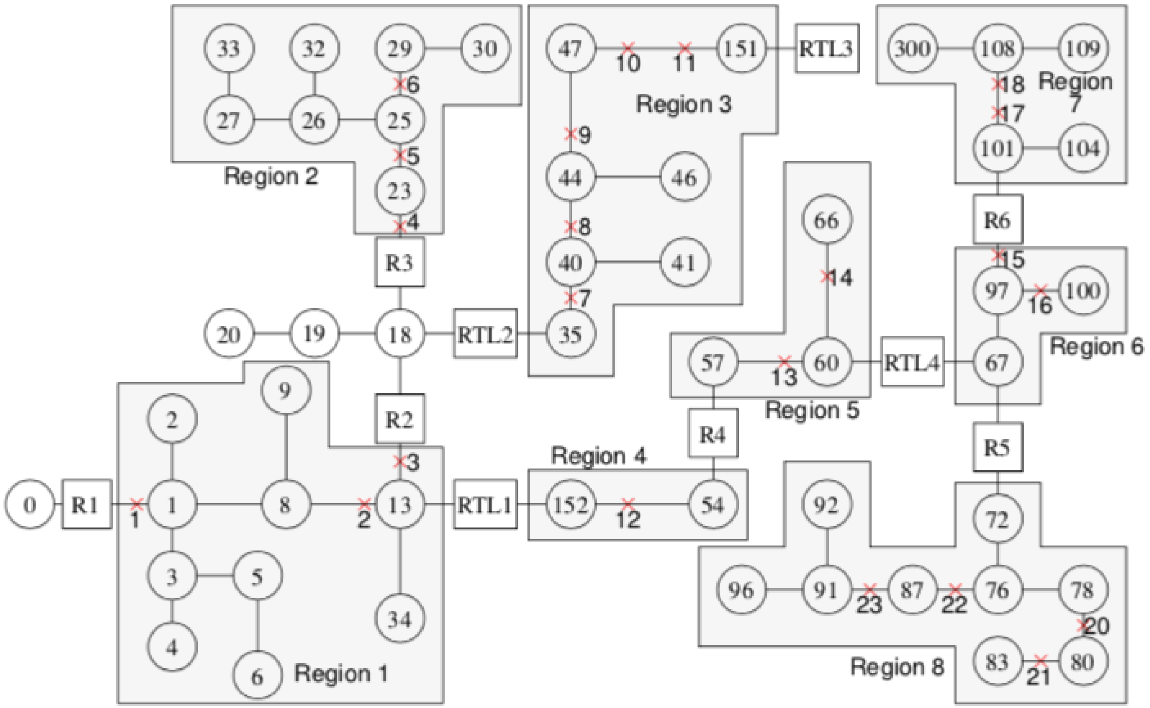


Machine Learning (ML) Fault Analysis

- Using ML for power system protection instead of relays
- Test approach on IEEE 123 Model (Matlab Simulink)
- Simulate 3 fault types at 19 locations with varying resistances at different times of year

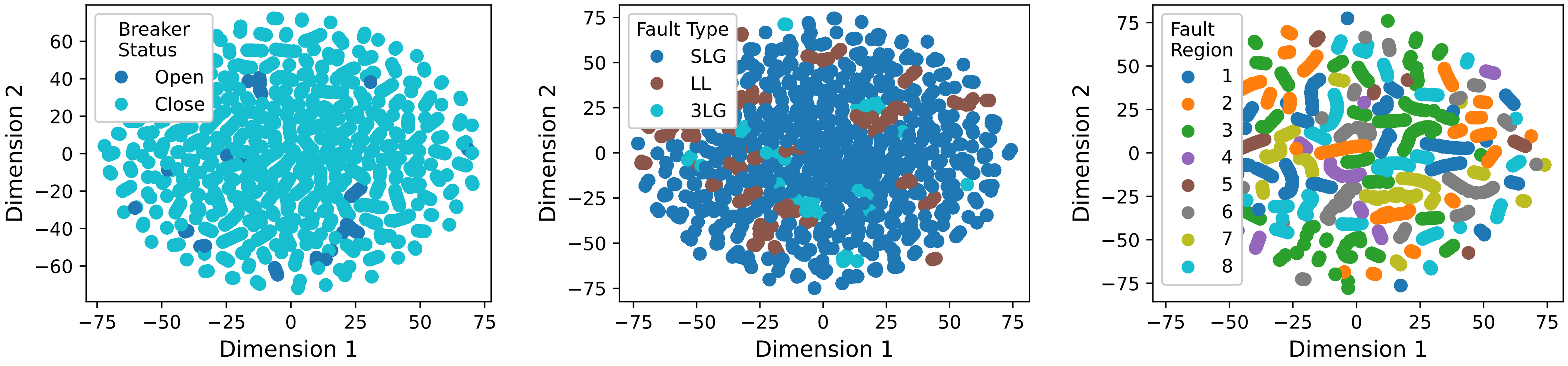
Intelligent Decision Making with Support Vector Machines

- Uses Sequence Current (I_0,I_1,I_2) and Voltages (V_0,V_1,V_2) as input features to SVM
- System specific learning that adapts
- ML at each breaker can distinguish faults inside its protective zone/region



Machine Learning Embedded in Relays

- SVM classified if there is a fault, fault type, and fault location. Tested on IEEE 123-node with 9 relays.
- No false trips in yearlong testing with varying and dynamic loads
- Correctly detects all fault events at different buses, resistances, etc.
- 100% accuracy for classifying the type of fault (SLG, LL, 3LG)
- Correct coordination (which relay trips first) for 99.6% of faults



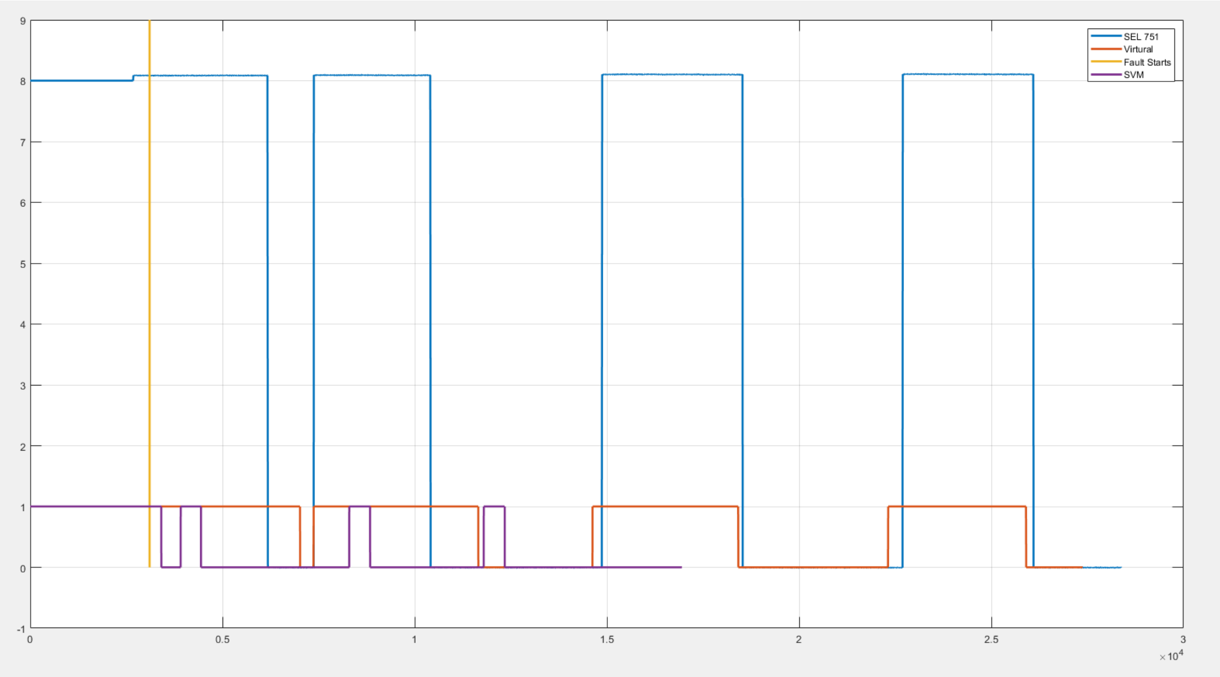
Hardware In the Loop Testing

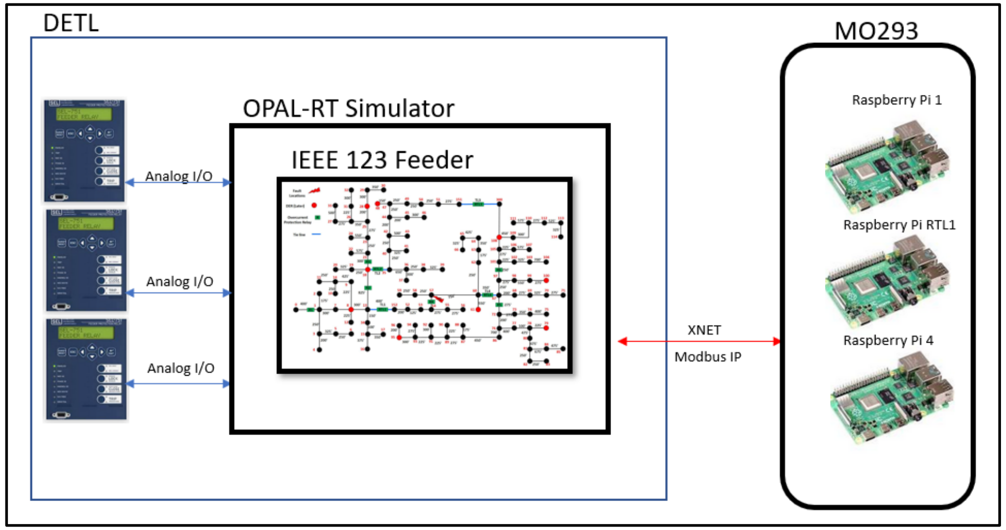
The trained machine learning algorithm is placed into a Raspberry Pi for testing

Using an Opal-RT real-time hardware-in-the-loop simulator, the real-time voltage and current signals from the system are fed into the analog inputs of the Raspberry Pi

SEL-751 hardware relays are also included with a standard time overcurrent curve for comparison

The SVM detects the faults in 0.17 seconds in comparison to the time overcurrrent of 1.94 seconds (11.4x faster)





Field Testing of Machine Learning for Fault Detection

Training must be done using simulations because there are only a few faults per year on a section of a distribution feeder, but there can be discrepancies between how the electric power system may operate in the real world vs. simulation training data

- Incorrect parameters/topology in the model, changes in the system
- Measurement noise, missing data, and differences in the fault

We trained an SVM classifier to identify faults and their type using simulation data

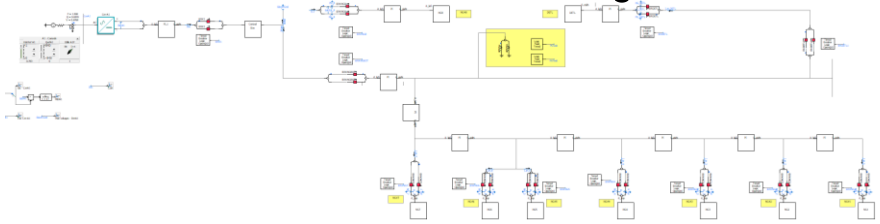
- The training data set (PSCAD simulation data) has a total of 160,000 points i.e. 40,000 points for each fault event

We then worked with Emera Technologies to install sensing and apply faults throughout their microgrid on Kirtland Air Force Base

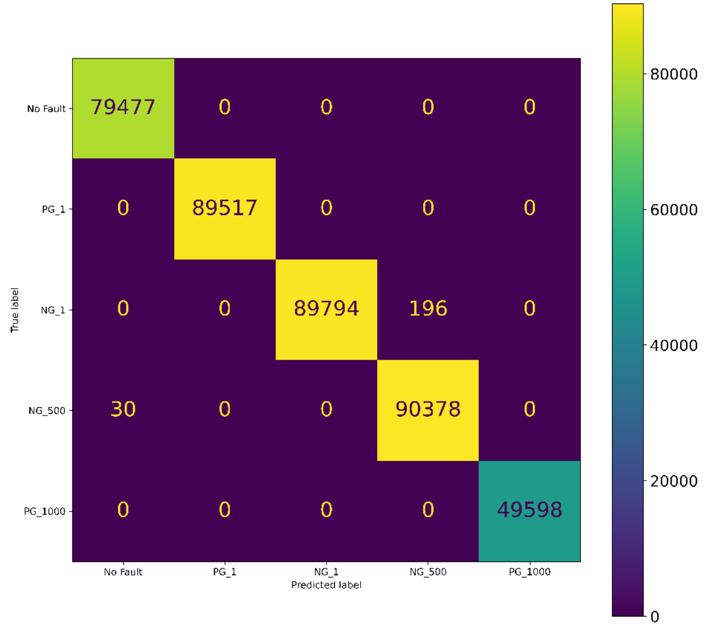
- The test data (captured from the actual system) has 400,000 data points, i.e. 100,000 data points for each fault event

The SVM multi-class algorithm embedded in the relay classified the faults with an accuracy of 99.943%.

PSCAD Model of the Microgrid



Actual Microgrid System



Conclusions

Electric distribution system protective relays equipped with machine learning (ML) algorithms can improve power system reliability and resilience by performing an automated and self-learning monitoring and decision making analysis.

ML algorithms can be trained offline using fault simulations of the system and location they are going to be installed. The trained algorithm is then embedded inside each relay to provide decision making support based on the grid measurements.

The results showed that the algorithm deployed inside each relay could accurately classify three fault conditions that occur anywhere on the feeder, estimate the fault's region, and define a specific action for the relay switch.

This assessment indicates that advanced, data-driven relay analysis could provide value in a typical feeder.

Questions?

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