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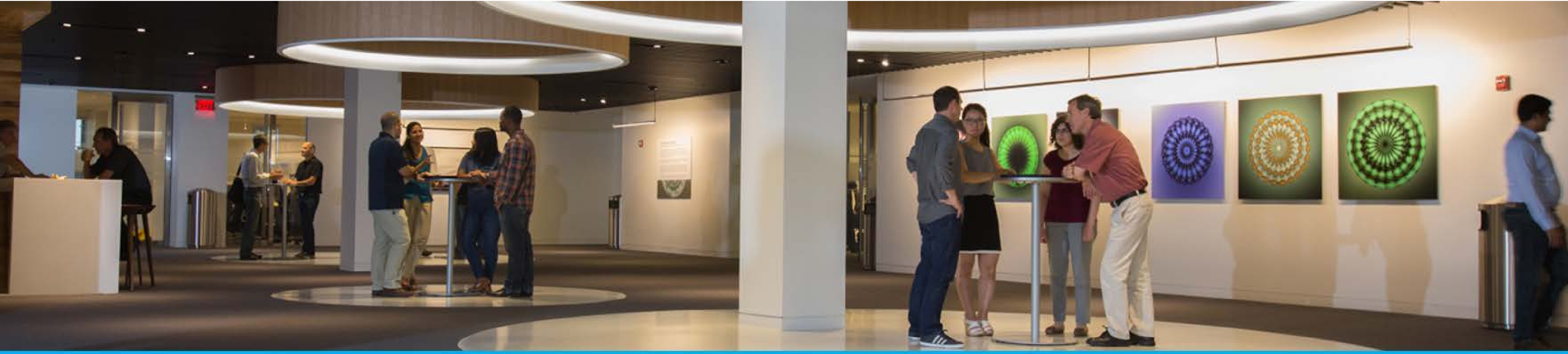

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Shishir Shekhar, MSEE, MBM, SMIEEE
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Sr. Application Engineer – Power & Utilities

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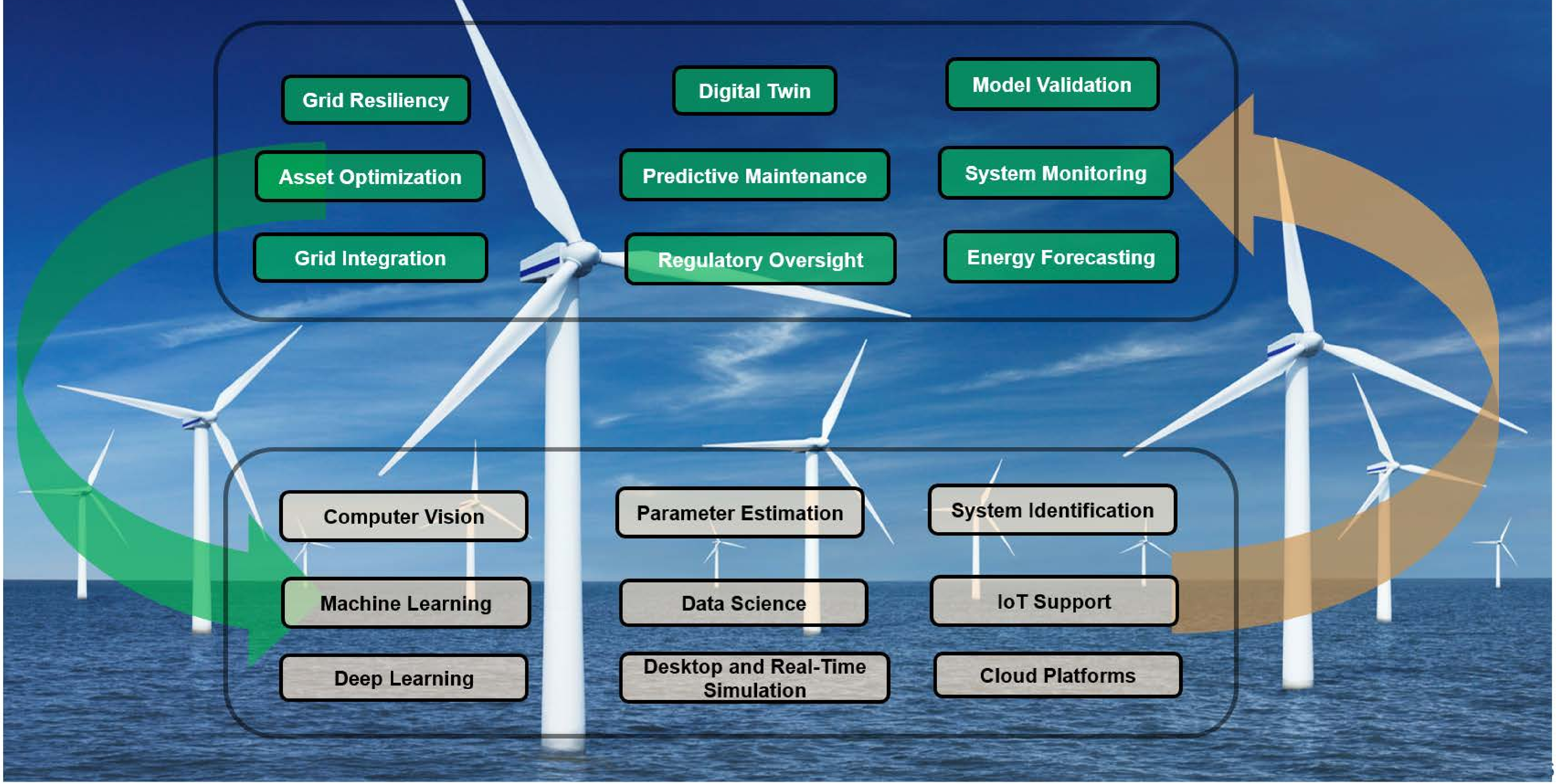
Sr. Account Manager – Power & Utilities

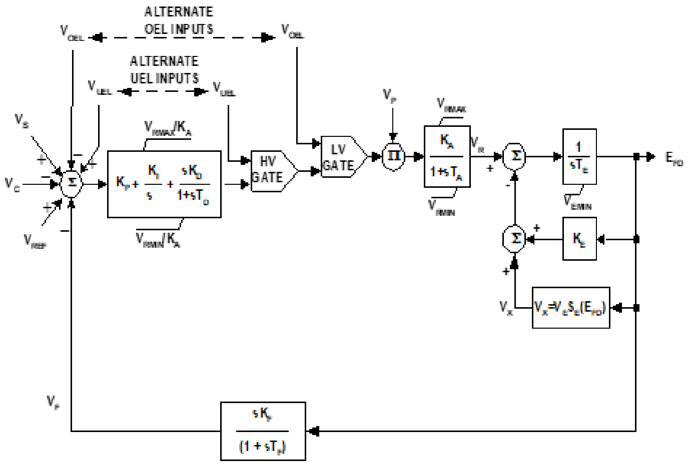
Grid Modernization Drives the Need for Innovative Computation Tools & Techniques



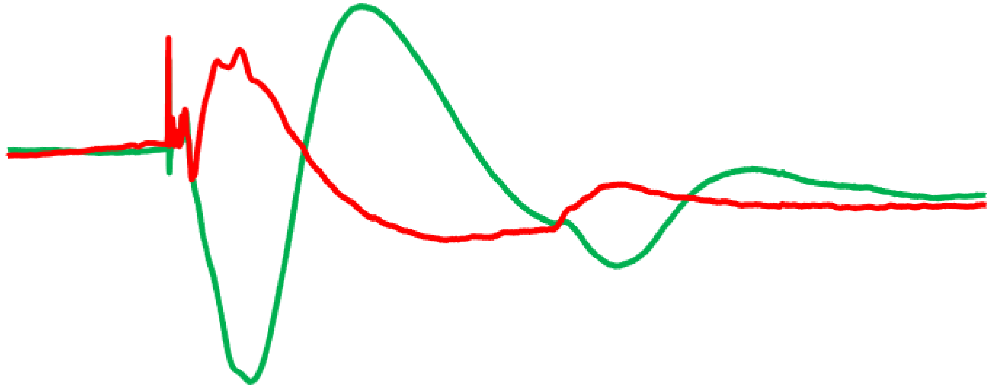
Power Plant Model Validation for Regulatory Compliance

Power Generation Equipment

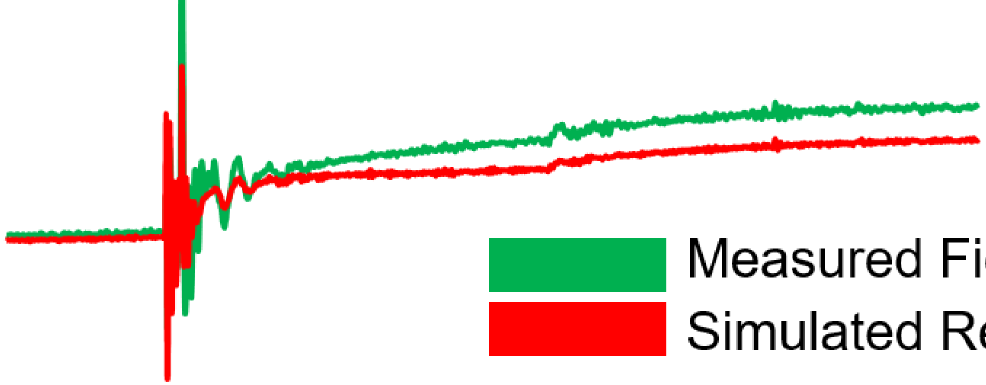
Standardized Models of Equipment



Active Power Response



Reactive Power Response



Measured Field Data

Simulated Response

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is a **Leader** in the Gartner Magic Quadrant for 2020 Data Science and Machine Learning Platforms

Figure 1. Magic Quadrant for Data Science and Machine Learning Platforms

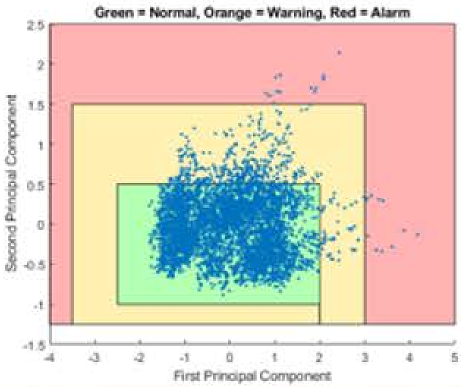
Source: Gartner (February 2020)

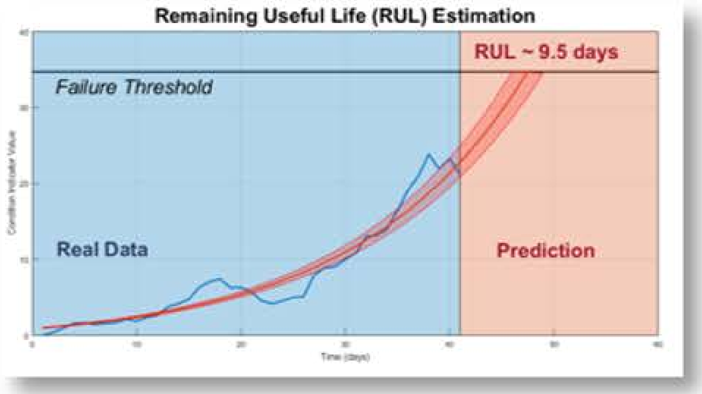
*Gartner Magic Quadrant for Data Science and Machine Learning Platforms, Peter Krensky, Erick Brethenoux, Jim Hare, Carlie Idoine, Alexander Linden, Svetlana Sicular, 11 February 2020 .

Asset Health Monitoring by IMCorp using AI

EUEC 2020, San Diego, CA – Energy, Utility & Environment Conference

Machine Learning and Deep Learning provide risk categorization to Underground Utility Distribution Cable Systems





Presented by:

Steffen Ziegler - *IMCORP Director – Signal Analysis and Artificial Intelligence*
steffen.ziegler@imcorp.com

Shishir Shekhar - *Worldwide Manager – Energy, Power and Utilities Industry*
sshekhar@mathworks.com

IMCORP Power Cable Reliability

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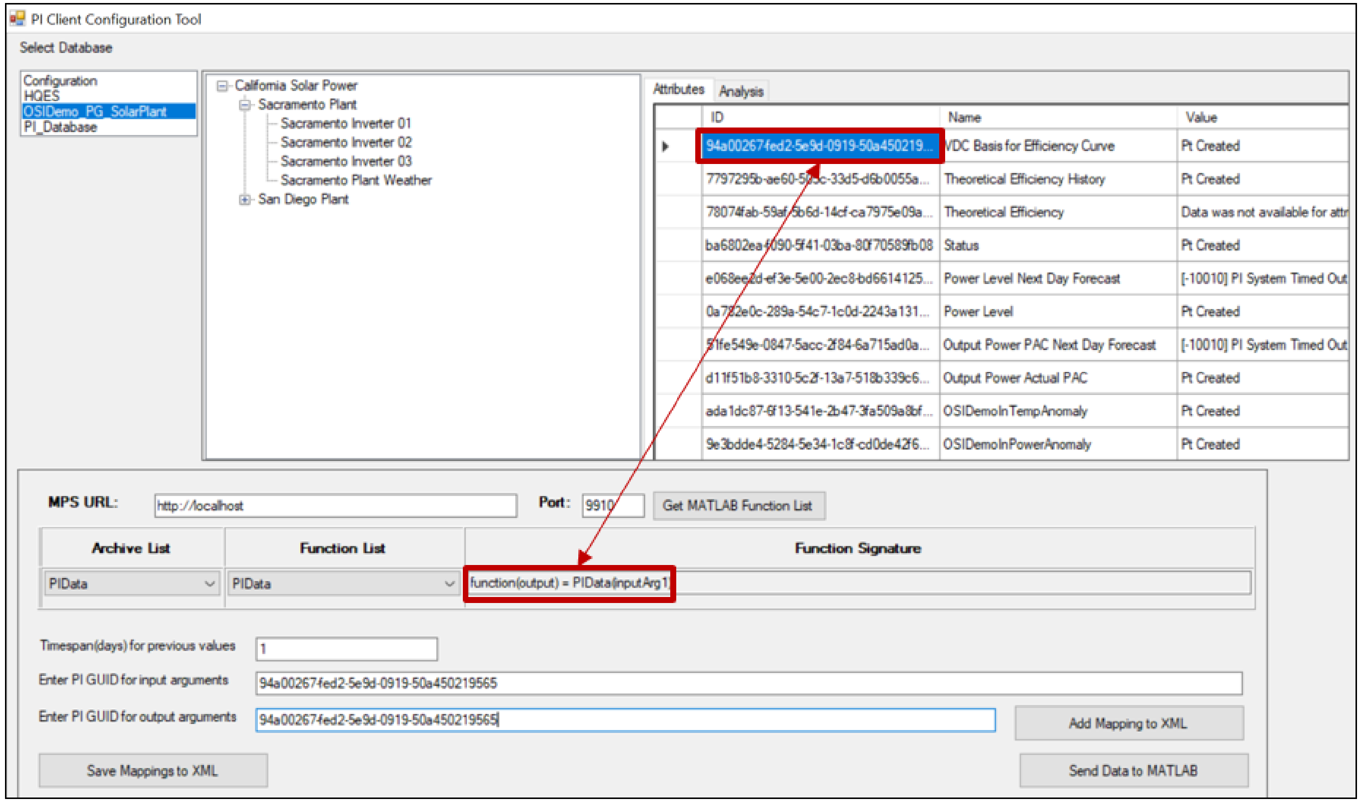
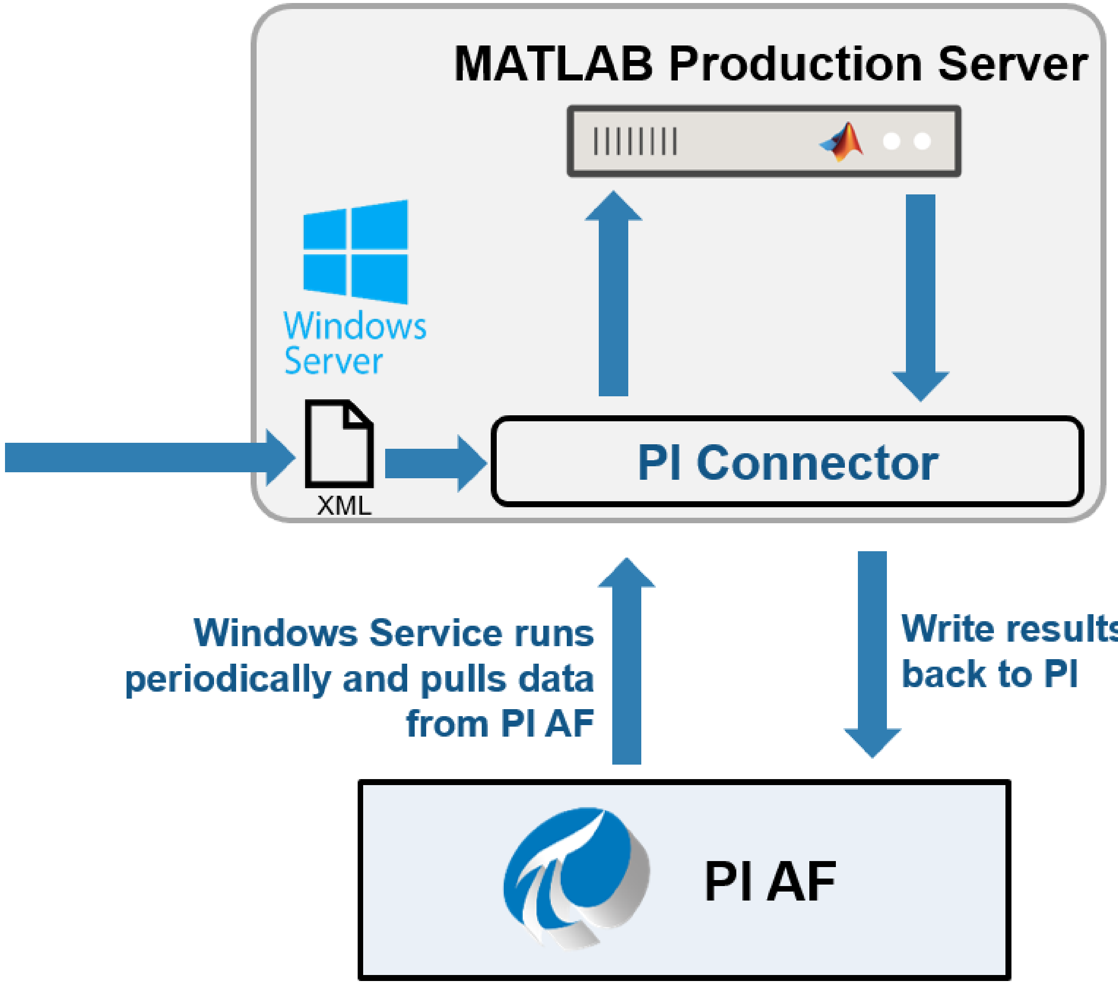
MATLAB Production Server Interface for OSIsoft PI System

Deploy Advanced Analytics into PI Asset Framework





Worked Example: Determining Fault Location Using Voltage Sag Measurements and Machine Learning

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We acknowledge the support of Patrice Brunelle, Principal Scientist at Hydro-Quebec

Background

24th International Conference & Exhibition on Electricity Distribution (CIRED)

12-15 June 2017

Session 2: Power quality and electromagnetic compatibility

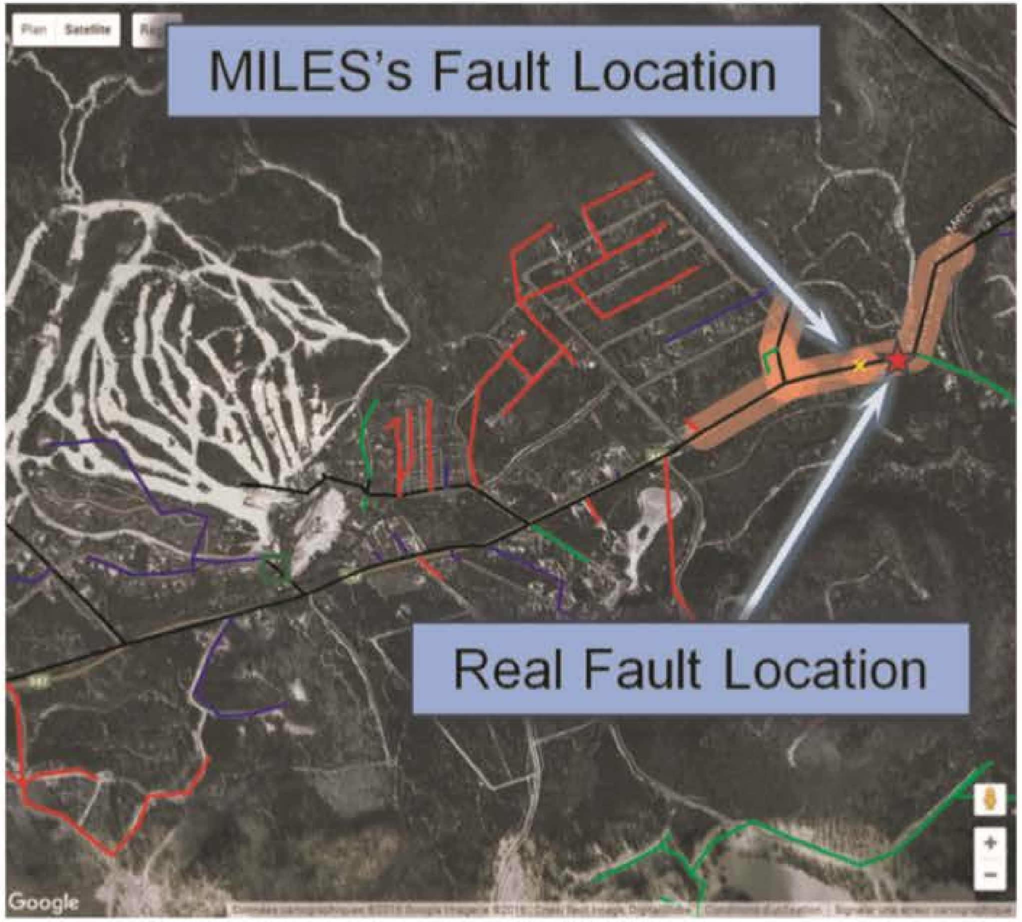
Using voltage sag measurements for advanced fault location and condition-based maintenance

ISSN 2515-0855
doi: 10.1049/oap-cired.2017.0066
www.ietdl.org

Mario Tremblay ✉, Bruno Fazio, Denis Valiquette

Researcher – Electrical Equipment, Hydro-Quebec Research Institute - IREQ, Varennes (Canada)
✉ E-mail: tremblay.mario@ireq.ca

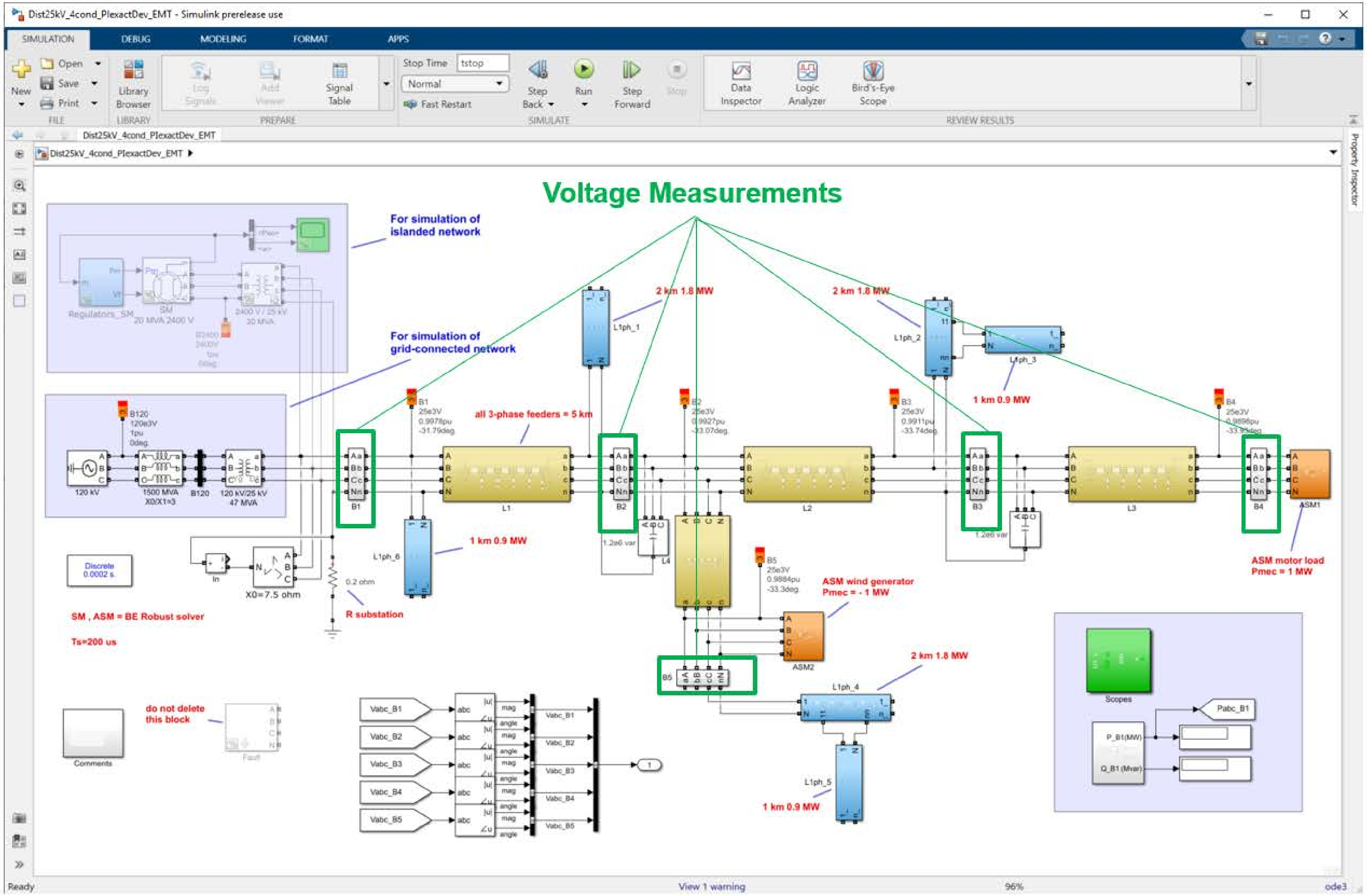
Abstract: The results of a condition-based maintenance system using a new fault location technique based on voltage dip measurements is discussed here. Hydro-Quebec (HQ) named this system MILES for maintenance and investigation of LIneS. The technique used was presented in previous CIRED publications in 2007 and 2011 as the voltage drop-based fault location technique. So far, the MILES system has shown a very good potential for permanent and temporary-fault location on overhead radial distribution system and has been deployed on 40 feeders located mainly at HQ and also at two other Canadian utilities.



Overview

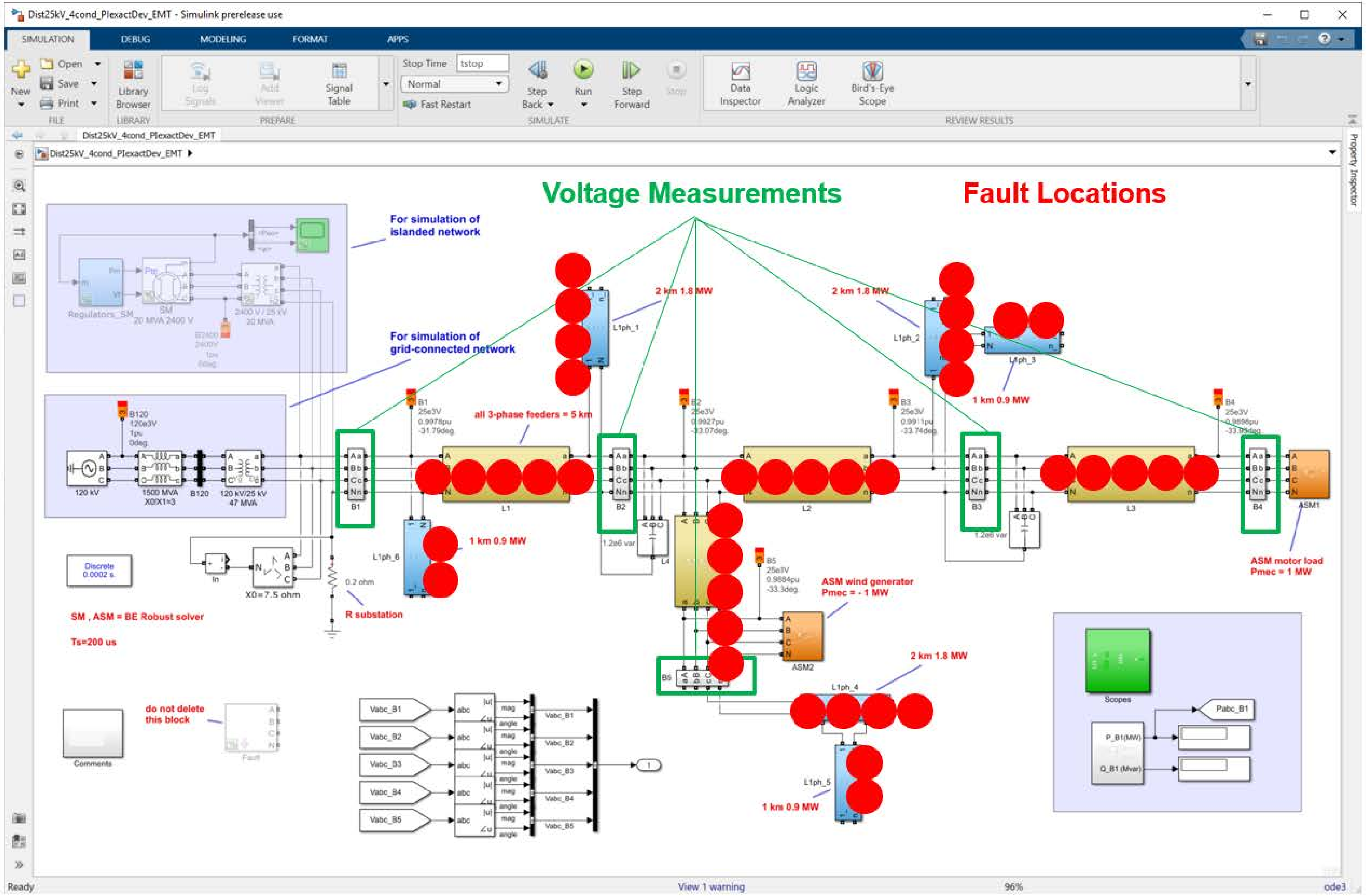
- In this presentation, we explore the use of machine-learning techniques to classify fault locations on an electric grid.
- A simulation model is used to generate synthesized data, which is then labeled and used as the input to classification algorithms.

The System



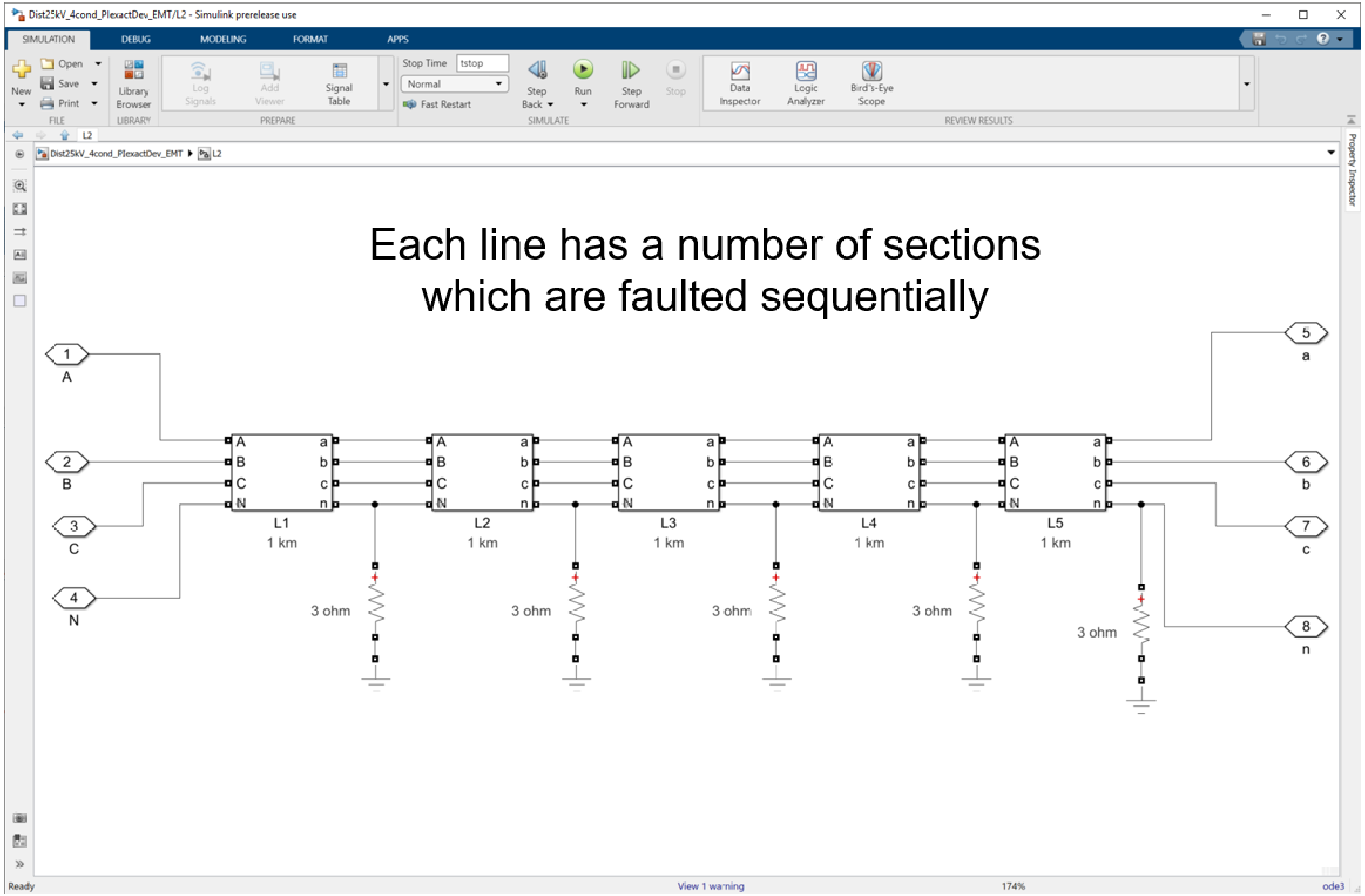
Dist25kV_4cond_PlexactDev_EMT - Simulink prerelease use
SIMULATION
DEBUG
MODELING
FORMAT
APPS
Voltage Measurements
For simulation of islanded network
For simulation of grid-connected network
2 km 1.8 MW
2 km 1.8 MW
1 km 0.9 MW
all 3-phase feeders = 5 km
1 km 0.9 MW
ASM motor load Pmec = 1 MW
ASM wind generator Pmec = - 1 MW
R substation
SM , ASM = BE Robust solver
Ts=200 us
do not delete this block
2 km 1.8 MW
1 km 0.9 MW
Scopes
Ready
View 1 warning
96%
ode3

The System



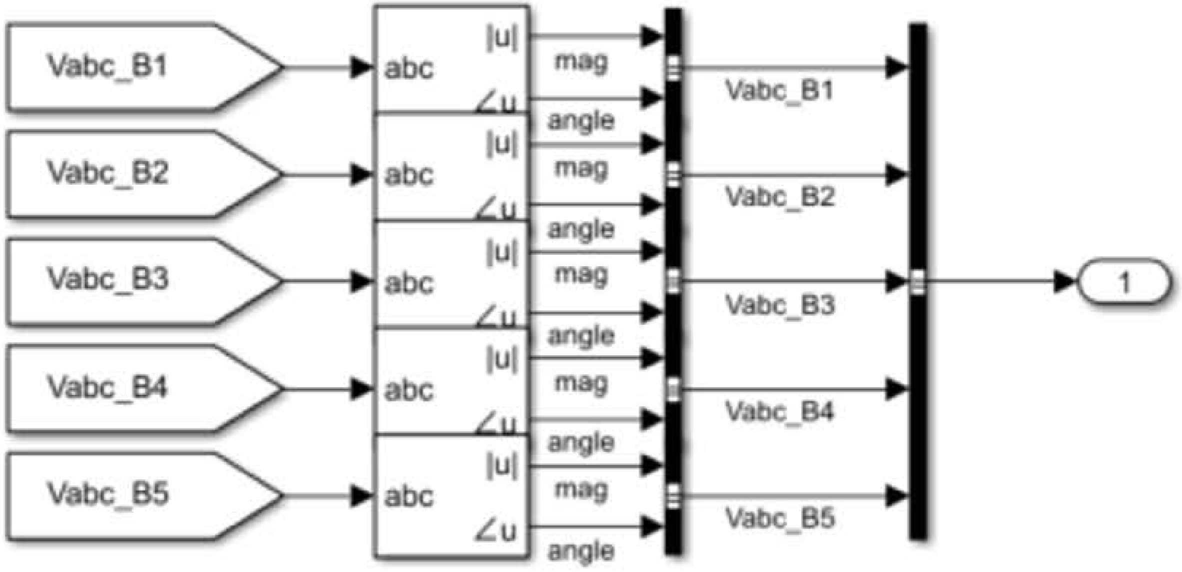
Dist25kV_4cond_PlexactDev_EMT - Simulink prerelease use
Voltage Measurements
Fault Locations
For simulation of islanded network
For simulation of grid-connected network
2 km 1.8 MW
1 km 0.9 MW
all 3-phase feeders = 5 km
ASM motor load Pmec = 1 MW
ASM wind generator Pmec = - 1 MW
SM , ASM = BE Robust solver
Ts=200 us
R substation
do not delete this block
X0=7.5 ohm
Scopes

The System


Dist25kV_4cond_PlexactDev_EMT/L2 - Simulink prerelease use
SIMULATION
DEBUG
MODELING
FORMAT
APPS
Open
Save
Print
New
Library Browser
Log Signals
Add Viewer
Signal Table
Stop Time
tstop
Normal
Fast Restart
Step Back
Run
Step Forward
Stop
Data Inspector
Logic Analyzer
Bird's-Eye Scope
FILE
LIBRARY
PREPARE
SIMULATE
REVIEW RESULTS
Dist25kV_4cond_PlexactDev_EMT
L2
Each line has a number of sections which are faulted sequentially
1
A
2
B
3
C
4
N
5
a
6
b
7
c
8
n
L1
1 km
L2
1 km
L3
1 km
L4
1 km
L5
1 km
3 ohm
Ready
View 1 warning
174%
ode3

The System

The Positive, Negative and Zero-Sequences are extracted from the voltage measurements



Synthesized Data

The fault data is organized in a table, which includes sequence information on each bus voltage measurement, and also the fault location. The example below shows only a few data points for Bus 1 magnitude and angle for positive, negative and zero sequences.

B1_M_PNZ			B1_A_PNZ			Fault
0.50181	0.35942	0.34116	-36.718	-153.64	90.58	{'L1_Section_1'}
0.56625	0.31577	0.28432	-37.635	-153.43	98.954	{'L1_Section_2'}
0.61069	0.27646	0.26031	-37.253	-151.76	93.851	{'L1_Section_3'}
0.68313	0.28238	0.053955	-36.931	-151.44	161.2	{'L1_Section_4'}
0.67987	0.22307	0.20944	-37.028	-150.74	95.411	{'L1_Section_5'}

For this example, there are 38 fault locations and 288 simulations were run for each location with varying phase and neutral fault resistances, making a total of 10,982 simulation runs.

Synthesized Data

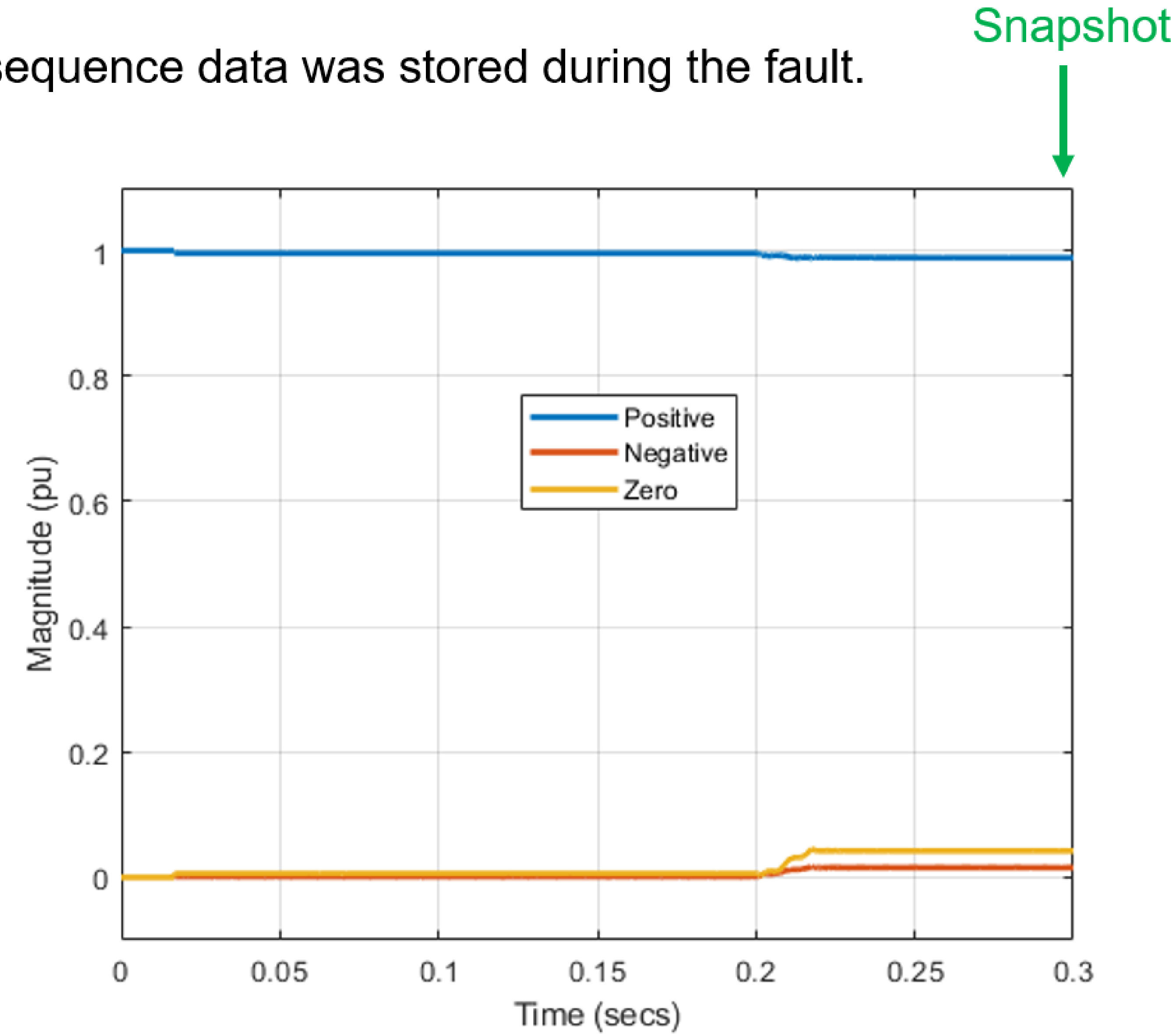
For each fault location, 288 combinations of phase and neutral resistance were used.

```
Rphase = logspace(log10(1e-4),log10(20),17); % go from 1e-4 to 20 on a logarithmic scale
Rneutral = logspace(log10(1e-4),log10(20),17); % go from 1e-4 to 20 on a logarithmic scale

for il1 = 1:numel(Rphase)

    set(hfb,'Rphase',num2str(Rphase(il1)));

    for il2 = 1:numel(Rneutral)

        set(hfb,'Rneutral',num2str(Rneutral(il2)));

        out = sim(sys,0.3);

    end

end
```

A snapshot of Voltage sequence data was stored during the fault.

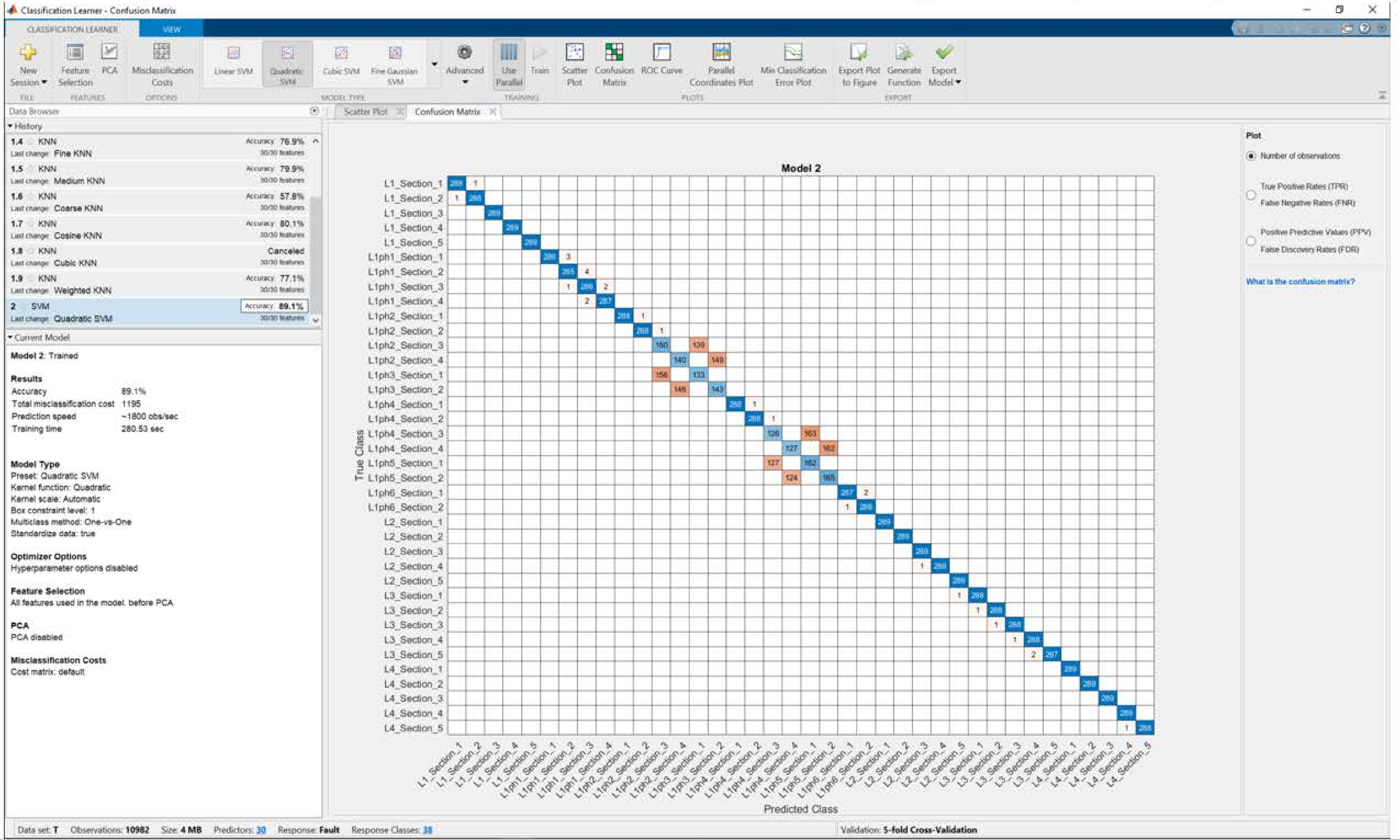
Synthesized Data

A snapshot of Voltage sequence data was stored during the fault.



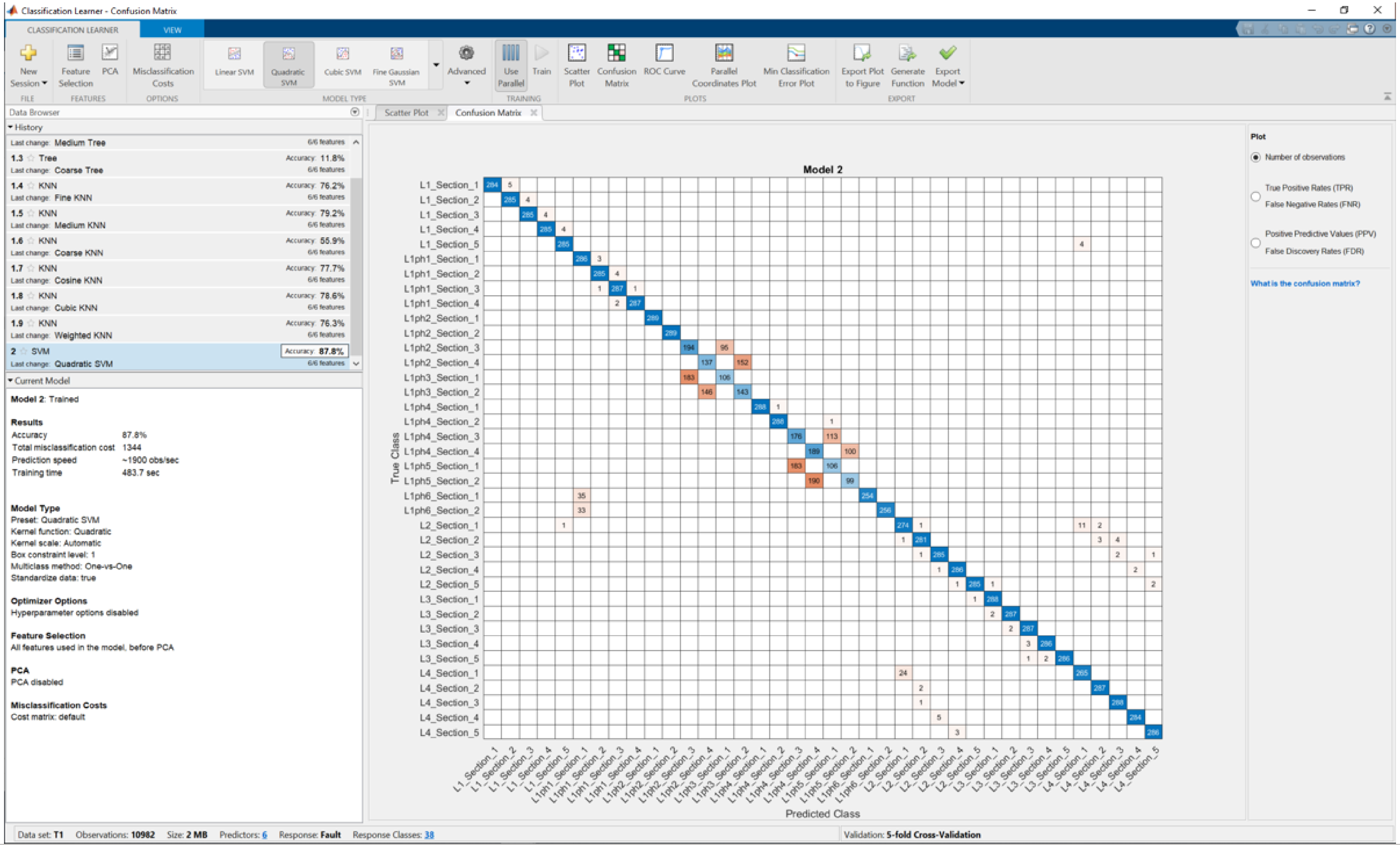
Classification using Five Voltage Measurements

Using the classificationLearner, we can quickly train a number of classification models for the data. A quadratic support-vector machine gave the best result with an accuracy of 89.1%. Note from the matrix below, that the classifier struggles with L1ph2 and L1ph3, and Lines L1ph4 and L1ph5.



Classification using One Voltage Measurement

Now we consider using only Bus 1 voltage. A quadratic support-vector machine gave the best result with an accuracy of 87.8%. Note from the matrix below, that the errors are now ‘crossing the boundaries’ of other lines, and so while the overall accuracy is comparable to when we use 5 voltage measurements, the probability of classifying incorrect lines is increased. This result is still surprisingly good however.



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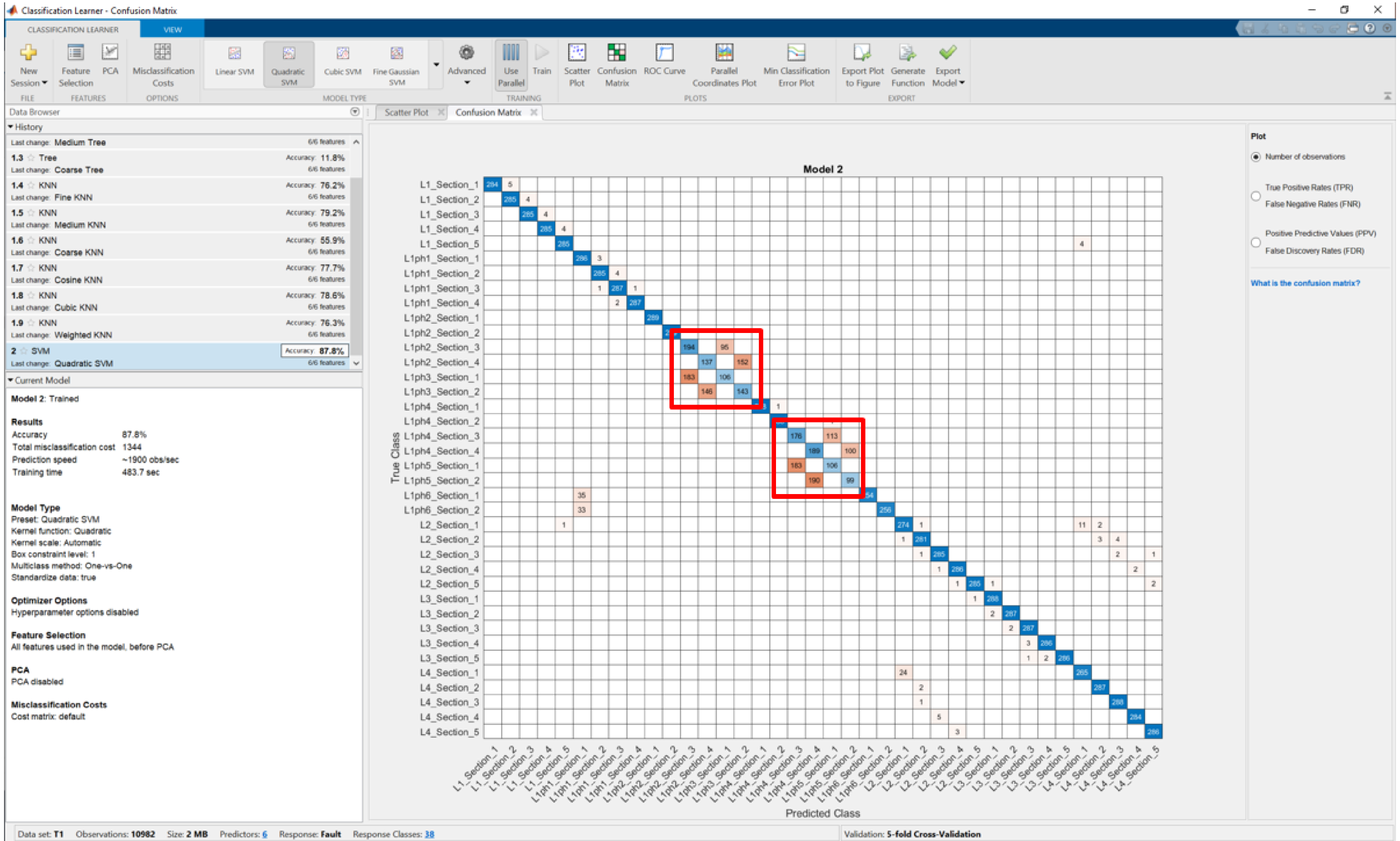
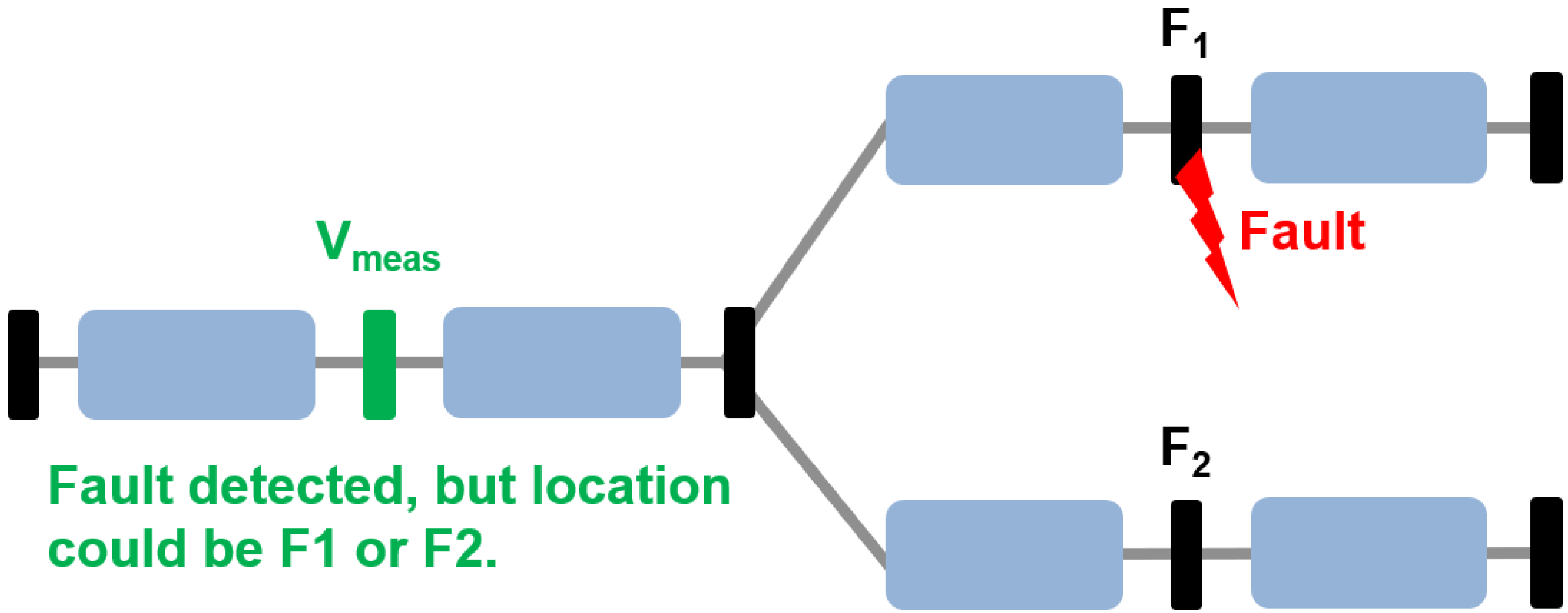


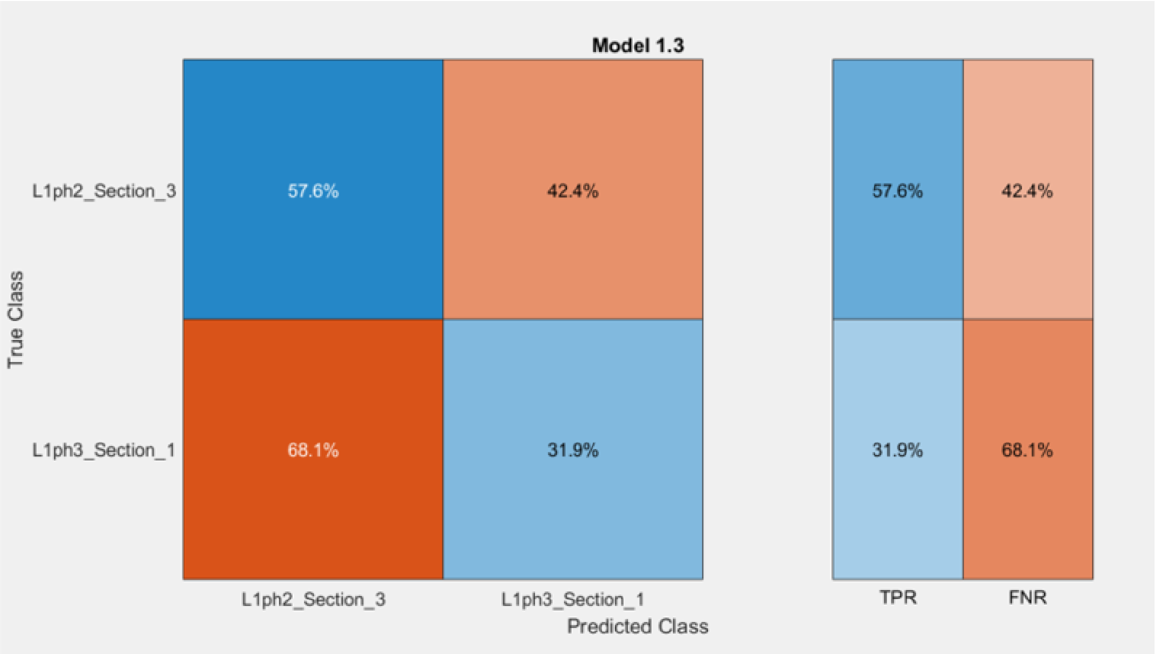
Forked Lines

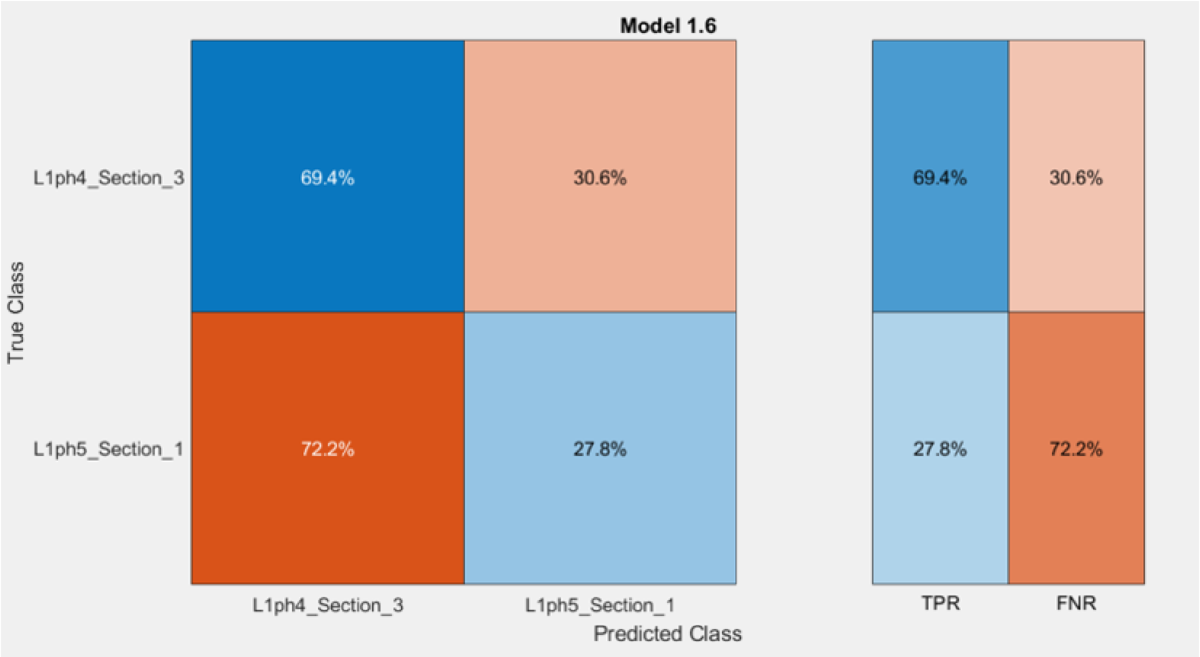
- If we make a measurement upstream from a forked line, then we cannot differentiate which fork has the fault



Forked Lines

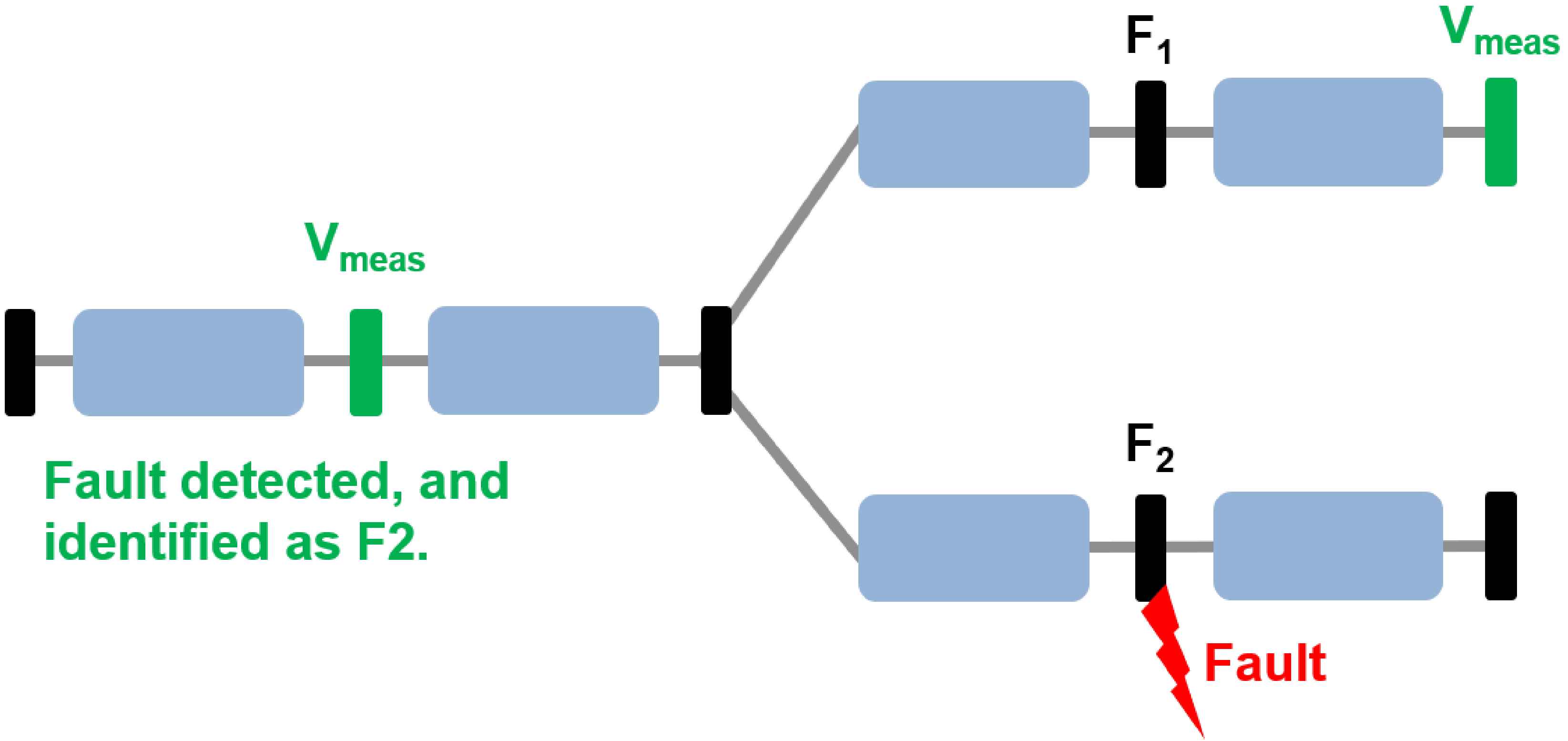
- We see this issue clearly with classification models attempting to differentiate faults on L1ph3 – L1ph2 and L1ph4-L1ph5



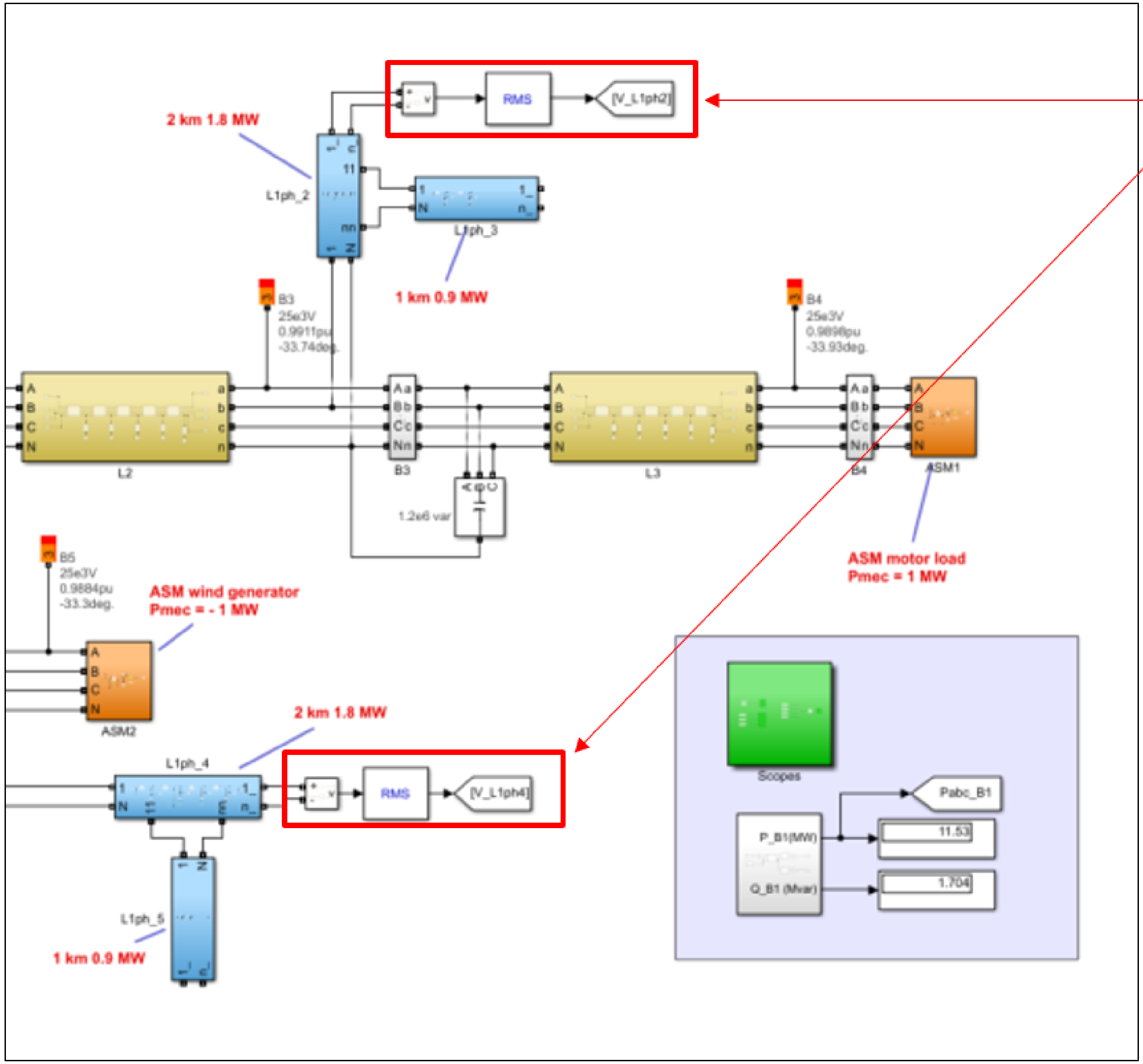


Forked Lines

- We therefore make an additional voltage measurements at the end of a fork – note we need Y-1 additional measurements, where Y is the number of forks.



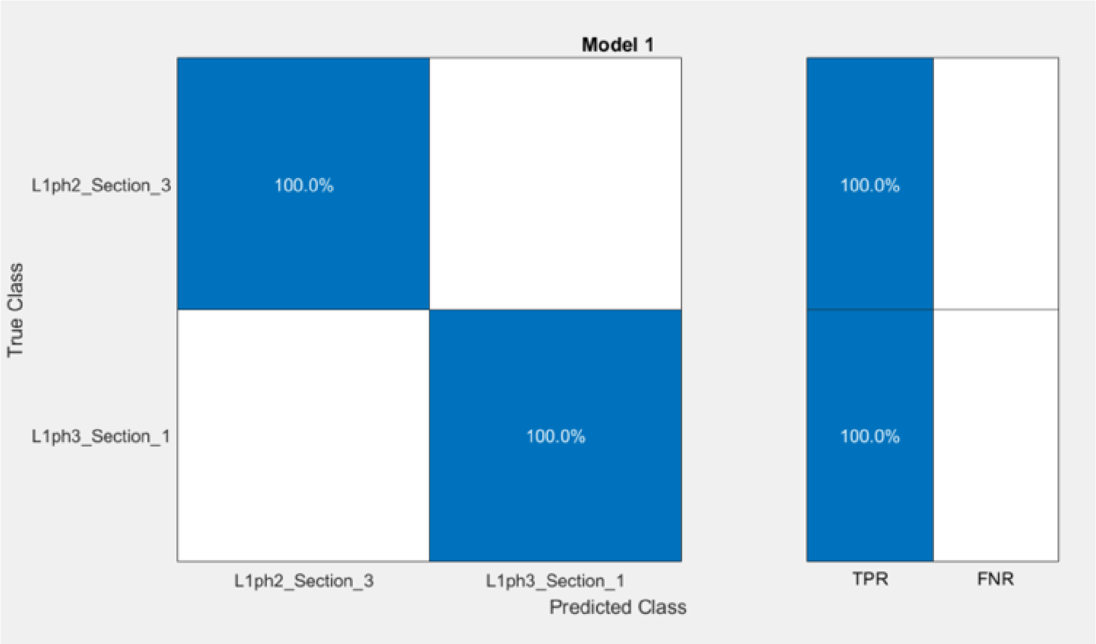
Forked Lines

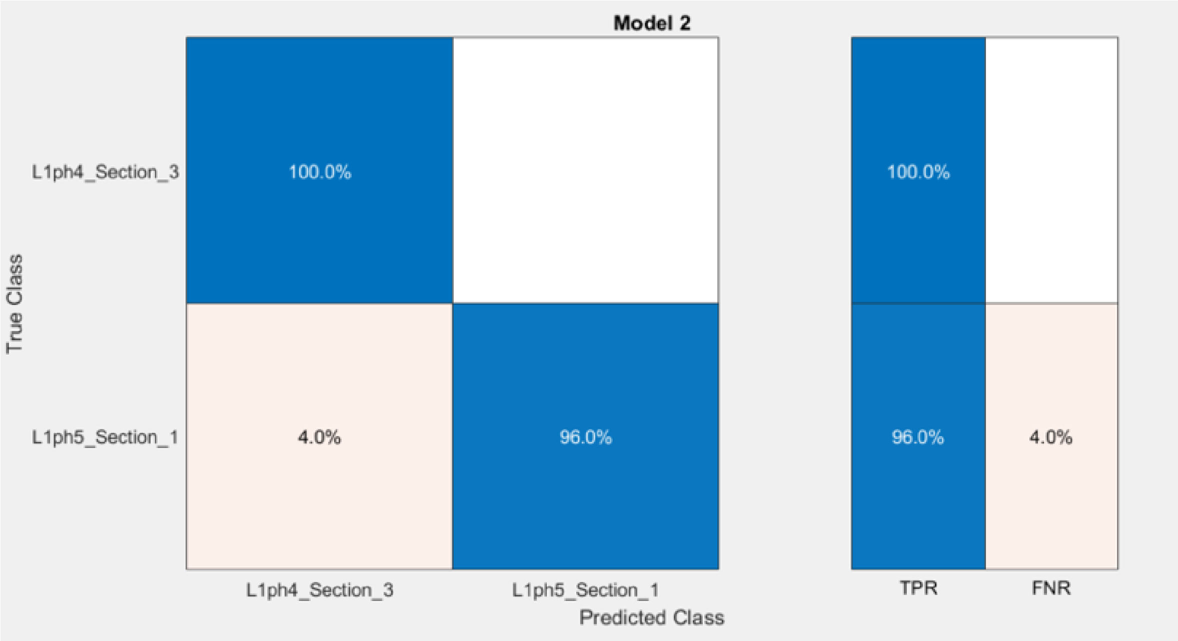


Additional Measurements

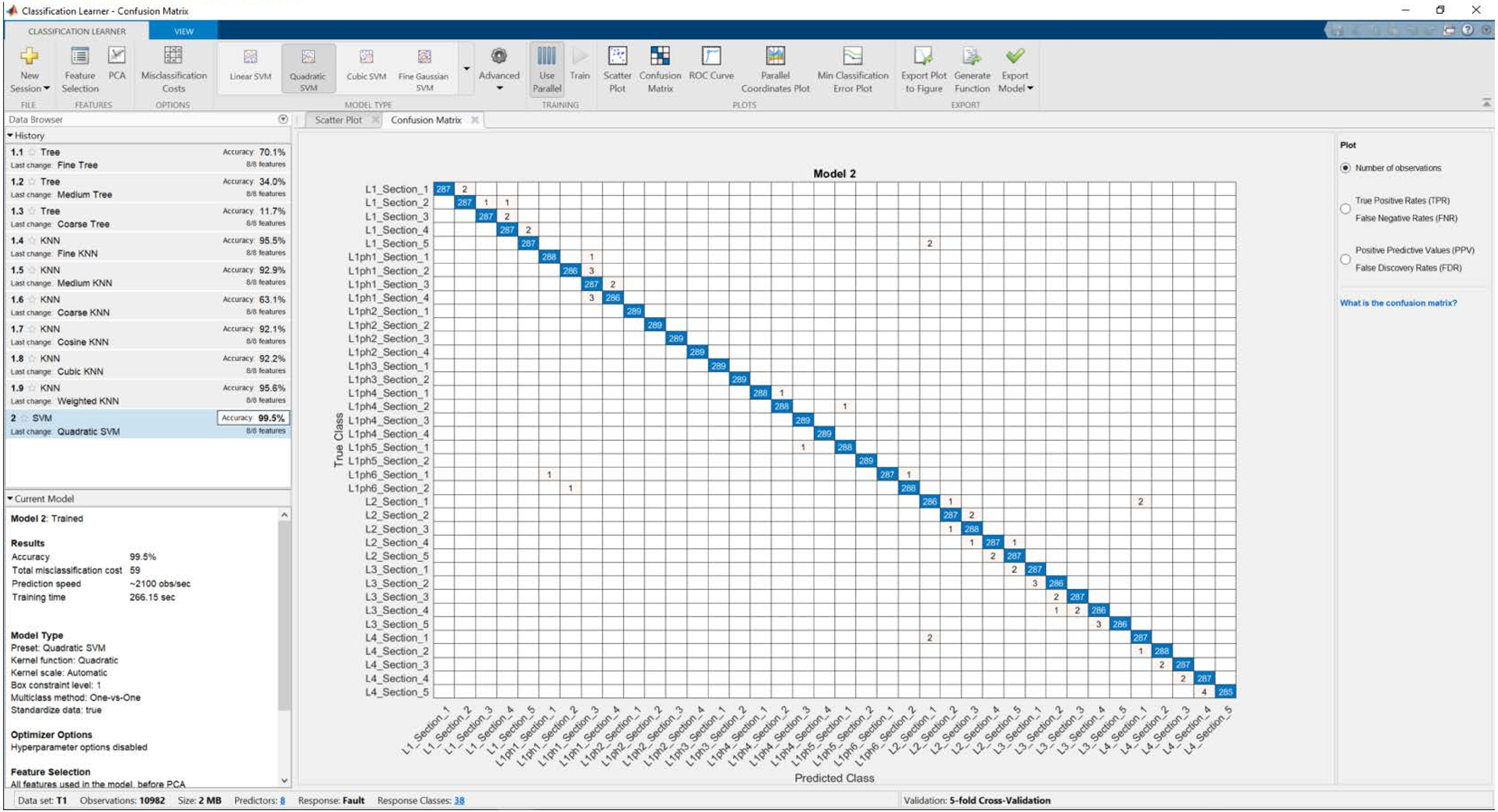
Forked Lines

- With additional measurement, the classification model is better able to differentiate fault location on L1ph3 – L1ph2 and L1ph4-L1ph5





Classification

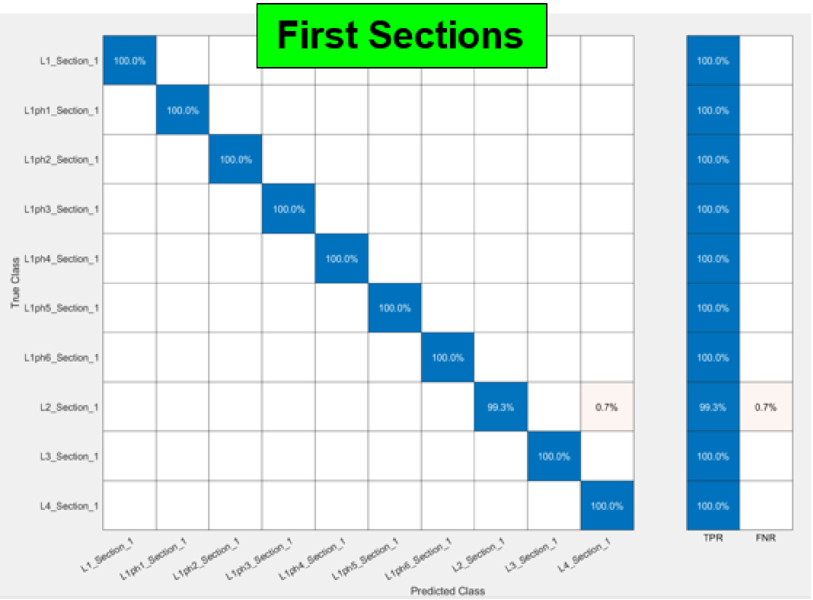


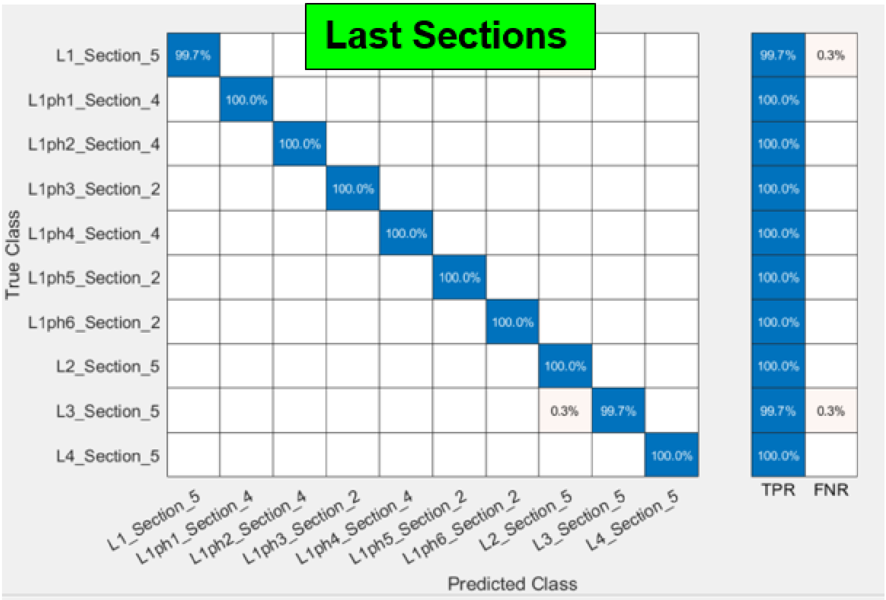
Training Only On Edge Cases

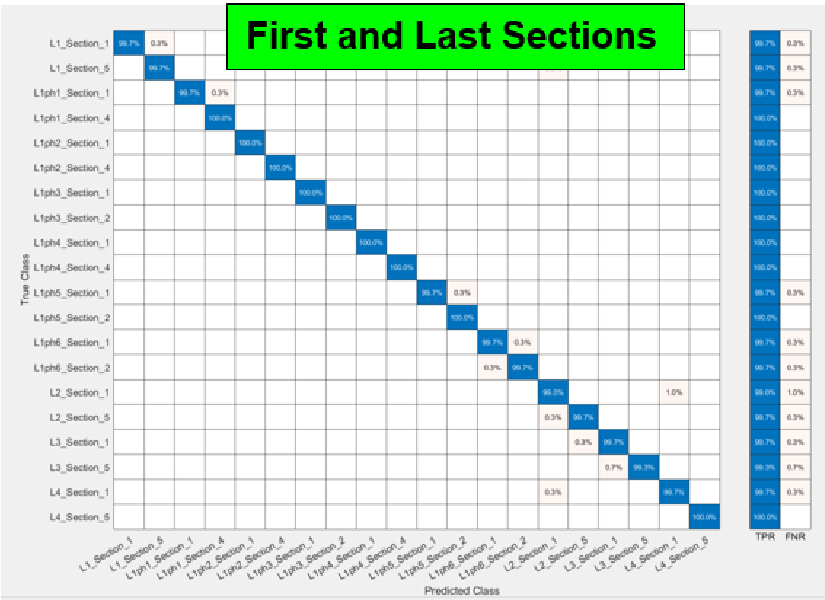
In this section, we assess the impact on classification if we train classifiers only on edge cases. The cases considered are,

- Train on faults only on first sections
- Train on faults only on last sections
- Train on faults on both first and last sections

From below, no surprise that the classifier is accurate for the data provided, but how will it respond when fault data from other sections is passed through it?



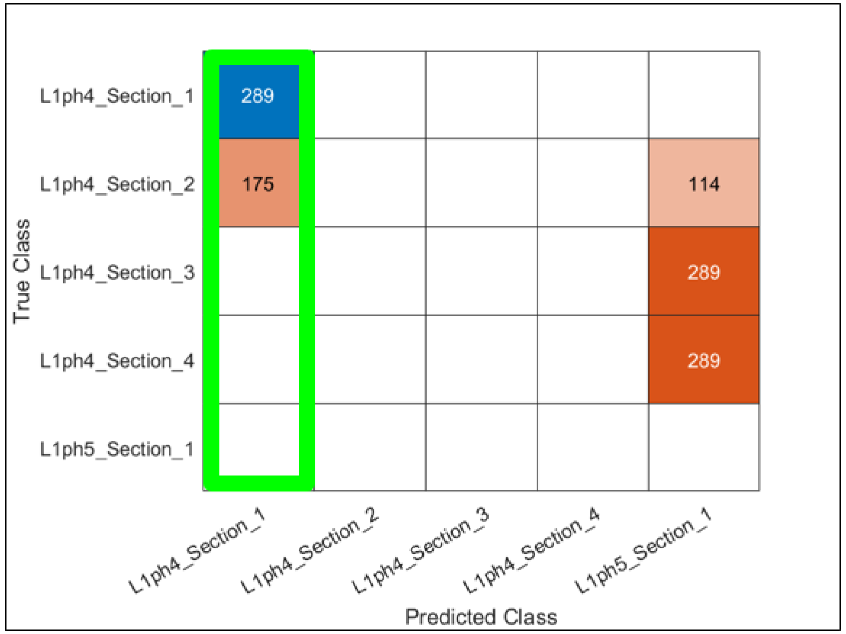




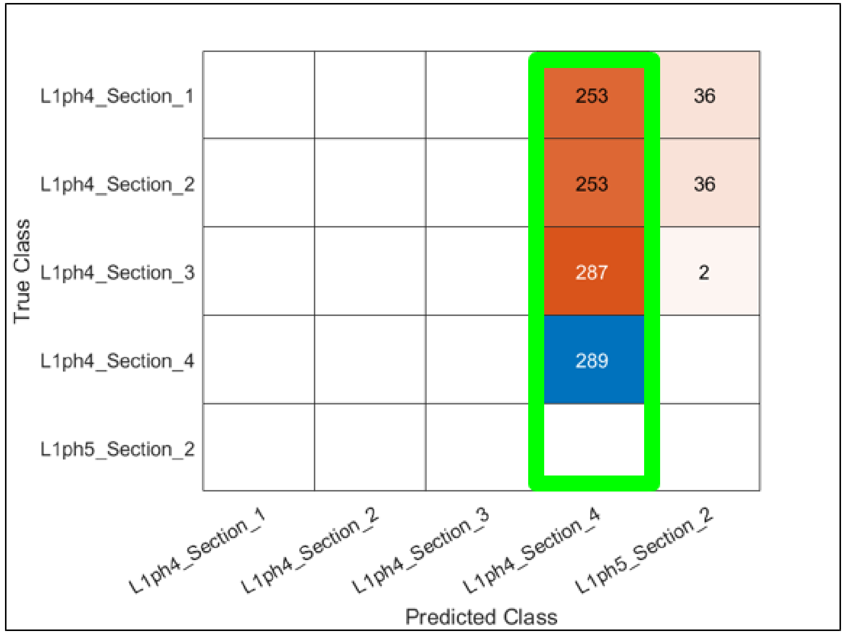
L1ph4

- On the diagonal is best. In the green box means we have identified the correct line. Anything outside the green box means we haven't identified the correct line.

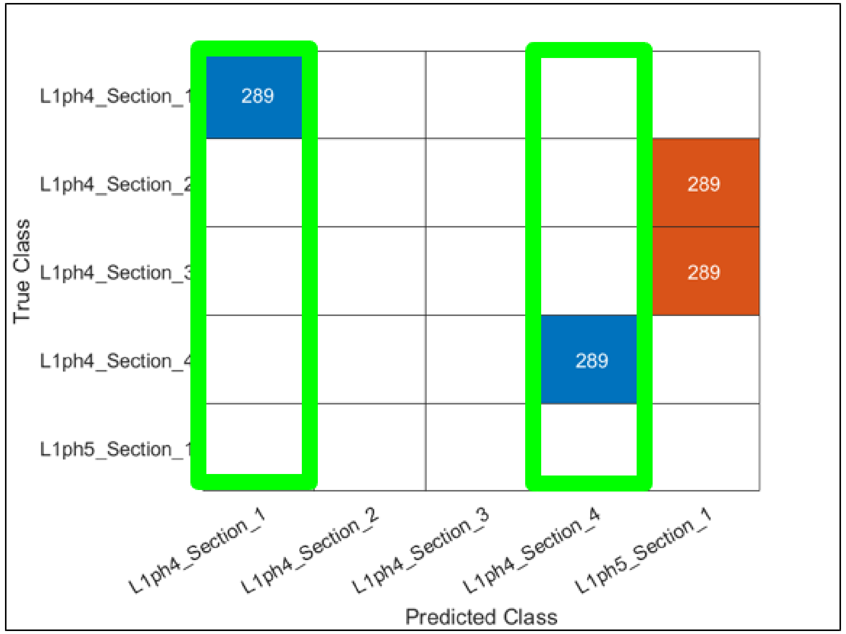
Trained on First Section



Trained on Last Section



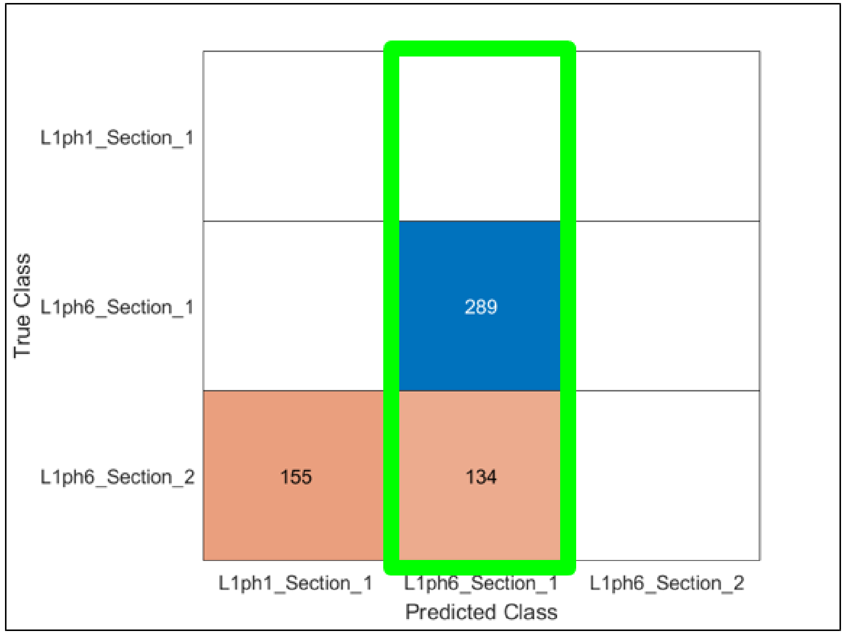
Trained on First and Last Section



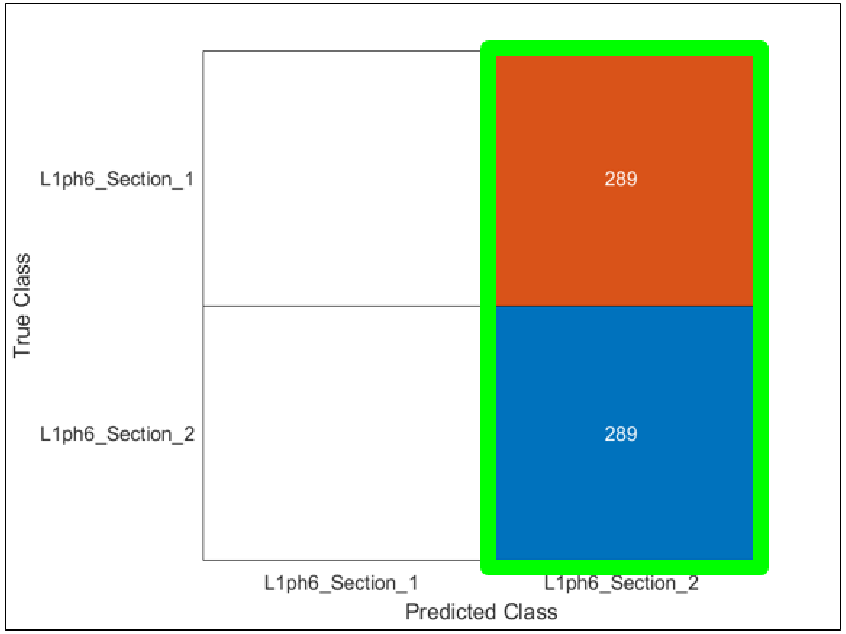
L1ph6

- On the diagonal is best. In the green box means we have identified the correct line. Anything outside the green box means we haven't identified the correct line.

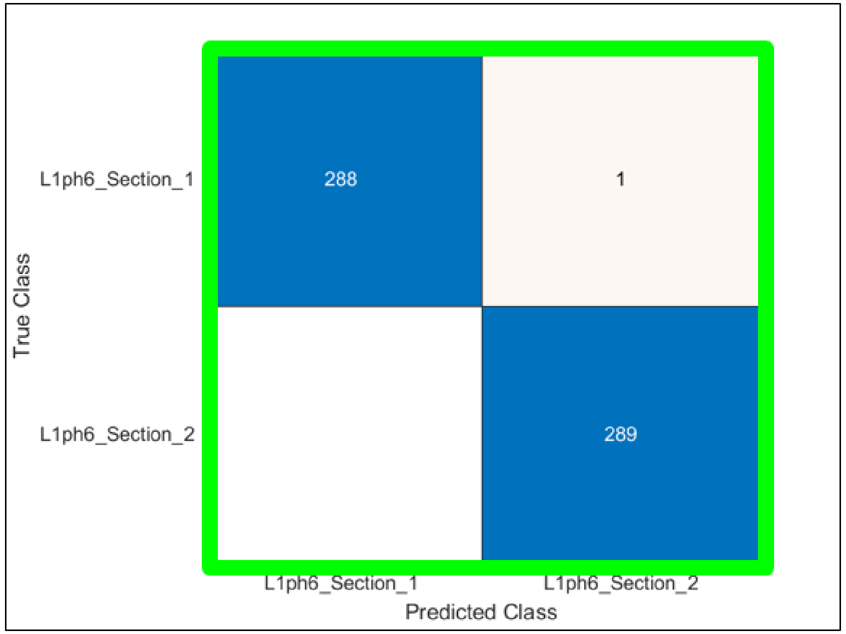
Trained on First Section



Trained on Last Section



Trained on First and Last Section



Summary

- The preliminary results are encouraging, showing that classification machine-learning algorithms can be used to classify fault locations with a relatively high degree of accuracy.

- Forked lines are problematic for upstream measurements, and so we recommend additional measurements at the end of a fork.

- Training only on first and last sections is insufficient to locate the correct line with an acceptable degree of accuracy.

Grid Modernization Drives the Need for Innovative Computation Tools & Techniques