A Study of Fault Detection Thresholds under Stochastic Conditions Intrinsic to Power Distribution Systems

Dr. Karen N. Miu & Nicholas S. Coleman

Drexel University
power.ece.drexel.edu

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Outline

- Introduction & Motivation
- Fault Record Database
- Detector Design
  - Discrete Wavelet Transformation
    - Quarter-cycle Feature Generation
  - Support Vector Machines
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Introduction & Motivation

- Intrinsic Distribution System Characteristics
  - Unbalanced phase voltages
  - Uncertain net nodal power injections (loads & sources)
  - Uncontrolled phase angles at fault inception
- Investigate:
  - the sensitivity of wavelet-based fault detection thresholds with respect to injection level & intrinsic phase differences
  - online quarter-cycle detection
- How: Hardware Laboratory Environment
  - Unbalanced utility source voltage
  - Range of configurable, power injections

Fault Record Database: RDAC

- **R**econfigurable **D**istribution **A**utomation & **C**ontrol (RDAC) Laboratory @ Drexel [1,2]

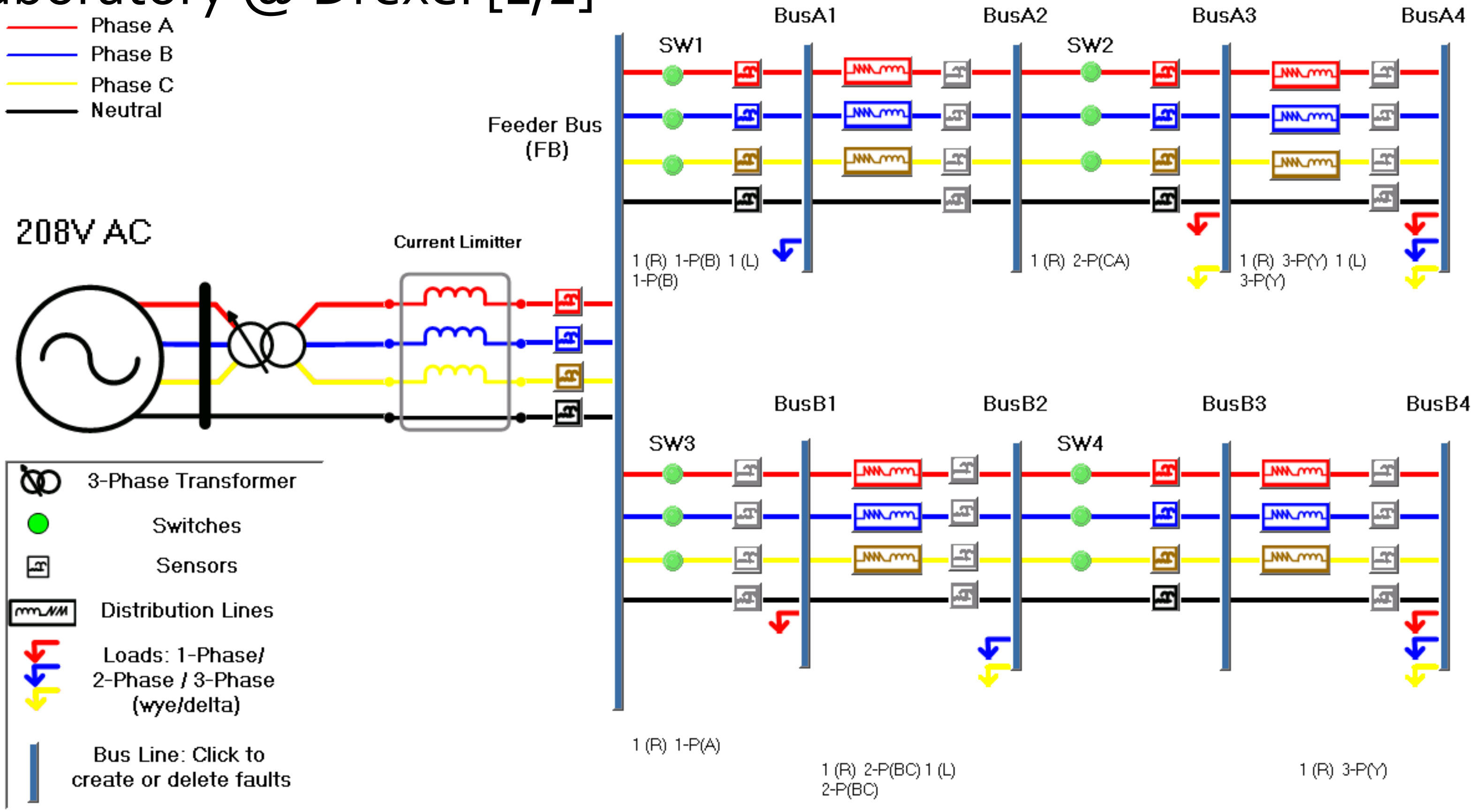

Fig. 1. Unbalanced multi-phase power flow experiment in RDAC.

Fault Record Database

- 551 short-circuit fault events sensed in RDAC laboratory

Table I. Number of available event records of each type.

Fault Type	Injection Level			Total	
	Light	**Medium**	**Heavy**		
AG	20	17	20	**57**	**181 LG**
BG	21	22	21	**64**	
CG	20	21	20	**61**	
AB	20	21	20	**61**	**181 LL**
BC	19	20	20	**59**	
CA	22	21	19	**62**	
ABG	21	21	21	**63**	**187 LLG**
BCG	21	21	20	**62**	
CAG	21	21	20	**62**	
Total	**185**	**185**	**181**	**551**	

- Sampled phase voltage waveforms captured for each event
- 60 samples / cycle (15 samples / quarter-cycle)

Detector Design

- Discrete Wavelet Transform
  - Capture time-localized disturbances in signals
- Power system applications
  - Tap changing, capacitor energization [3]
  - Voltage sag / swell / flicker [4]
  - Fault detection / classification [5]-[8]
- Daubechies-4 (db-4) Wavelet
  - 2nd level detail coefficients

~¼-Cycle Feature Generation

- 16 samples / quarter-cycle
- Filter and down-sample at each level
- (4) 2nd-level detail coeff. / **feature**
- Feature: four-coefficient signal energy
  - Sum-of-squares of prev. (4) 2nd-level coefficients

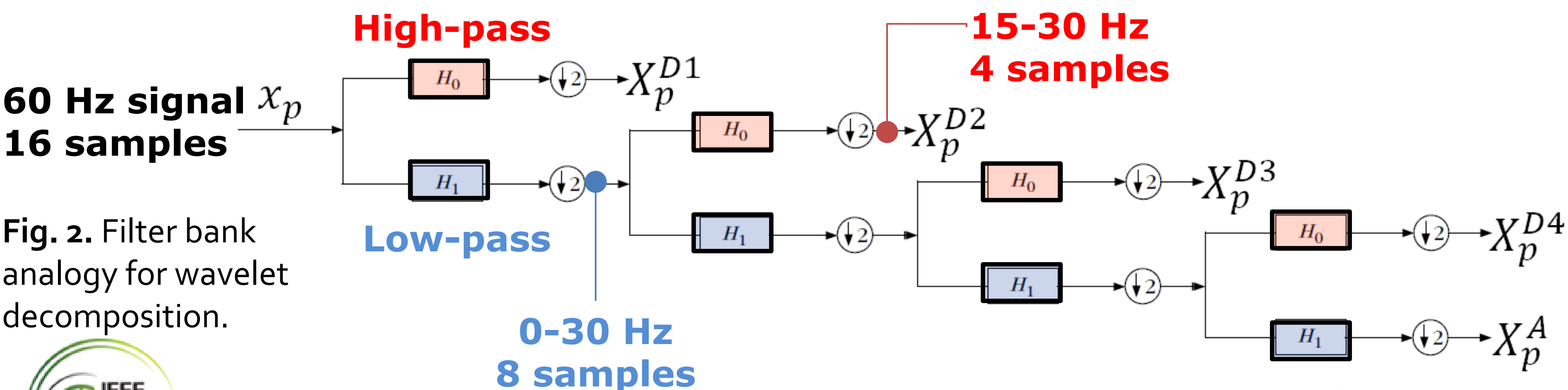

Fig. 2. Filter bank analogy for wavelet decomposition.

¼-Cycle Feature Example

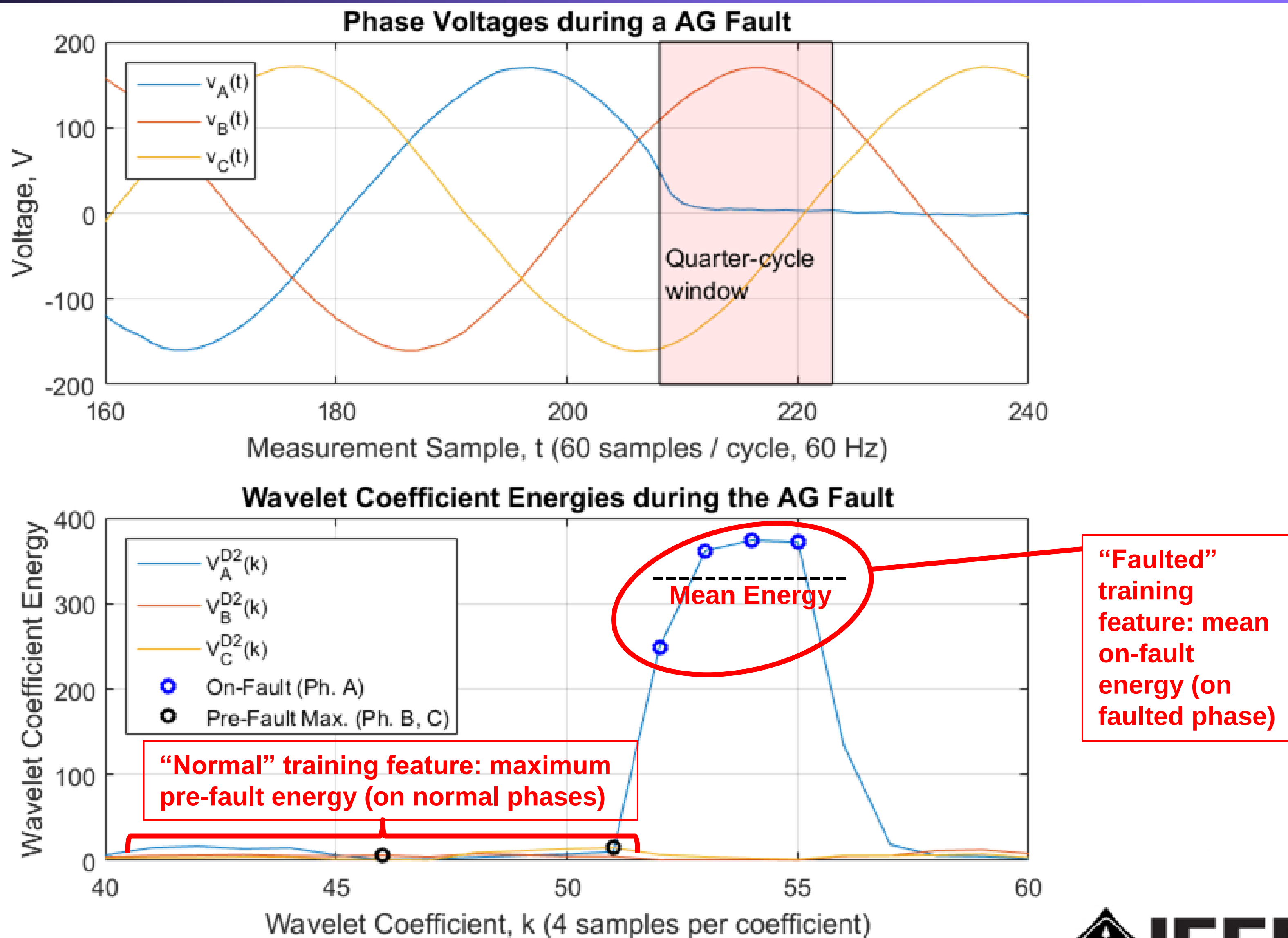

Fig. 3. ¼-cycle feature generation example.

Decision Boundary Training

- Generate **(1) feature per phase** for each training set event
- Use **support vector machines to find optimal boundaries** between "faulted" and "normal" features in e_p-space
- Training set: ~70% of fault events from each load level

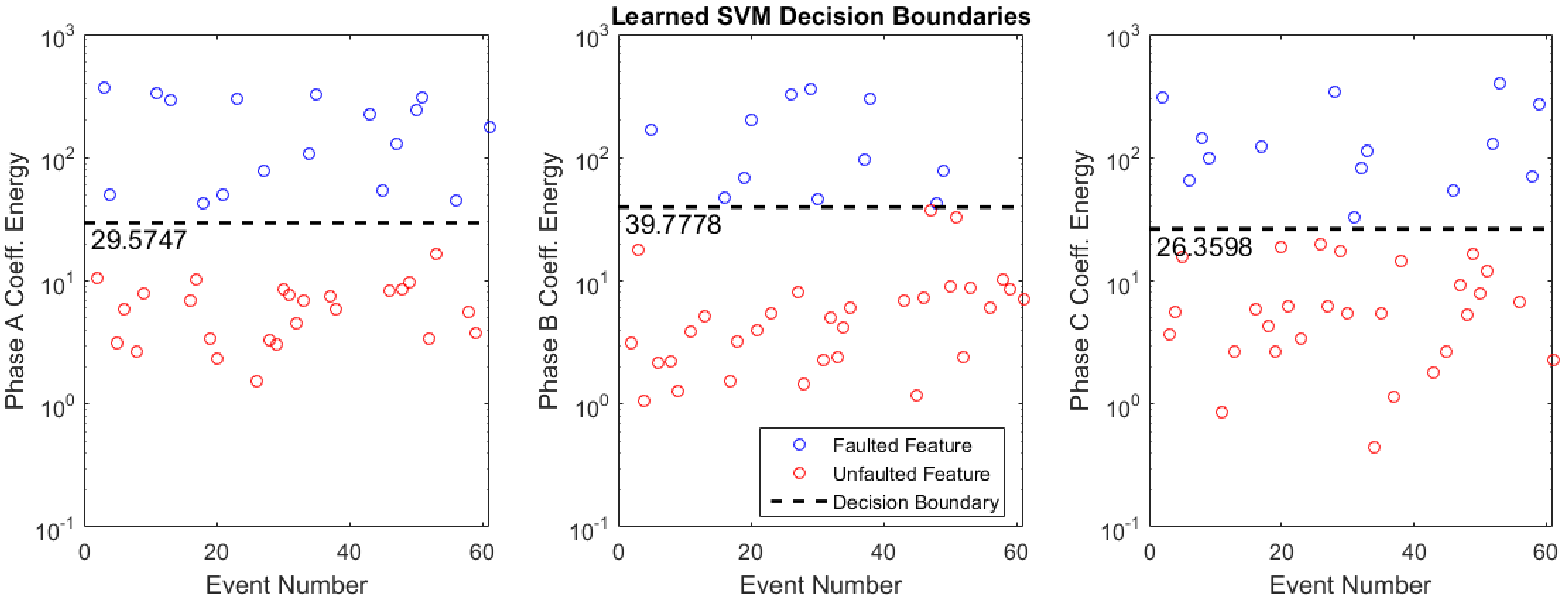

Fig. 4. Decision boundary training example: LG faults, light injection level, phases considered separately.

Detection Process

- Testing set events (~30% of database) scanned sample-by-sample
- Faulted phase(s) 'detected' where a threshold is crossed
- Example: BCG fault
  - Voltage distortion causes false alarm on Ph. C prior to actual BCG fault

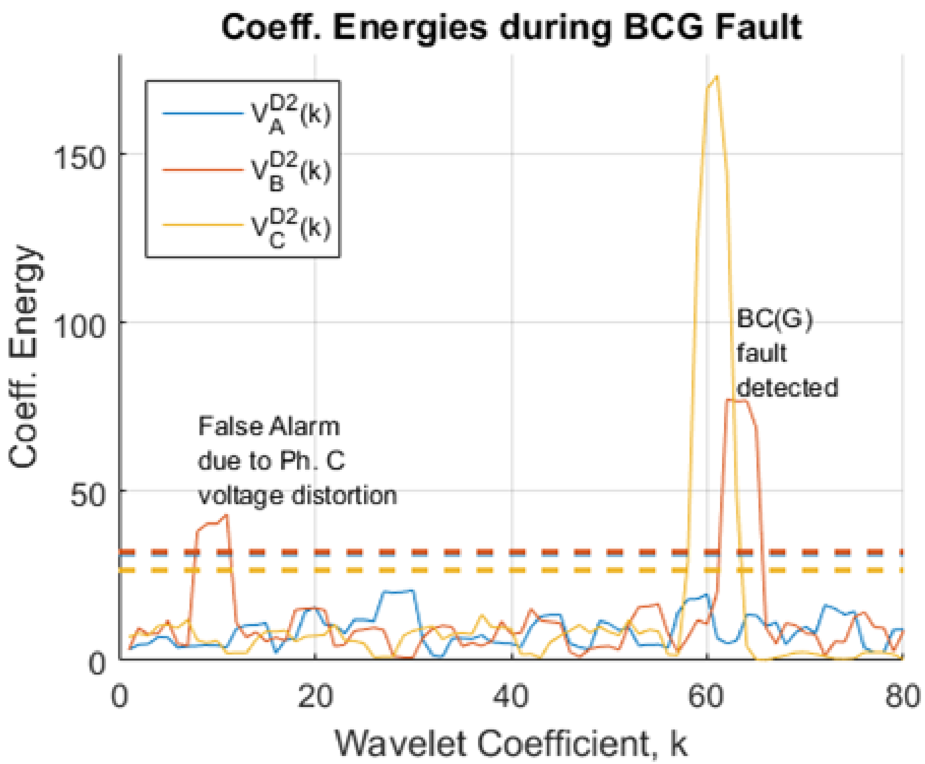

Fig. 5. Detection example: false alarm at coefficient k=8.

Results

Obtained to investigate the impacts of:

- Injection level
  - How does injection level impact the thresholds?
  - Is there a “best” training set to use?
- Intrinsic phase differences
  - How do thresholds vary across the phases?
  - Is it necessary to train phase thresholds separately?

Experiment/Database Characteristics

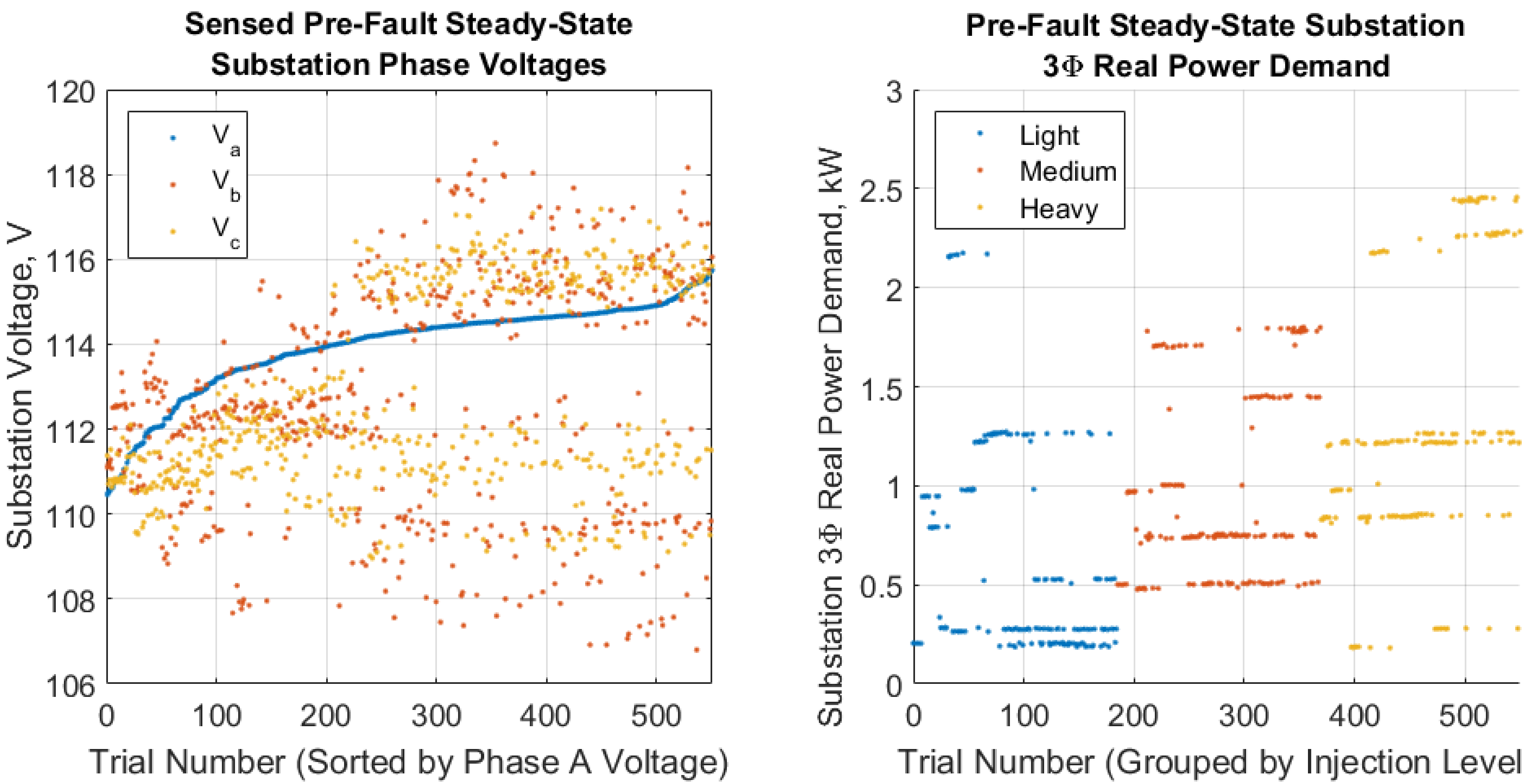

Fig. 6. Stochastic substation phase voltages (left) and total injection levels (in kW, right) in 551 RDAC studies.

Results: Injection Level

- How does injection level affect thresholds?

Table II. Sample threshold sets (rng seed = 22) when trained using events from each load level set and from a combination of the three load level sets.

Training Set Load Level	Learned Thresholds		
	Phase A	Phase B	Phase C
Light	30.47	37.64	27.90
Medium	30.65	35.14	29.30
Heavy	29.98	35.04	31.35
Combination	31.26	31.01	33.22

- In this case, different injection levels yield similar thresholds across the phases
- Variation across the phases is apparent

Results: Injection Level

- Is there a best training set?
  - Weaker detection performance observed when using thresholds trained at light injection level

Table III. Average performance across 100 training sets for each combination of trained threshold sets and testing data load levels.

Training Set	Testing Set	Avg. Success Count	Avg. Missed Detections	Avg. Mis-classifications	Testing Set Count
Light	Light	41.64	2.46	11.90	56
	Medium	41.41	3.96	10.63	56
	Heavy	40.75	2.51	11.74	55
Medium	Light	48.18	1.38	6.44	56
	Medium	48.69	2.58	4.73	56
	Heavy	48.60	1.56	4.84	55
Heavy	Light	46.13	2.18	7.69	56
	Medium	45.93	3.05	7.02	56
	Heavy	46.41	2.29	6.30	55

Results: Phase Differences

- Table I showed nontrivial between-phase variations in ¼-cycle detection thresholds
  - Variations are small compared to the scale of faulted vs. normal features
- Little impact on performance with an "average" threshold
  - Combine training data, select median, etc.

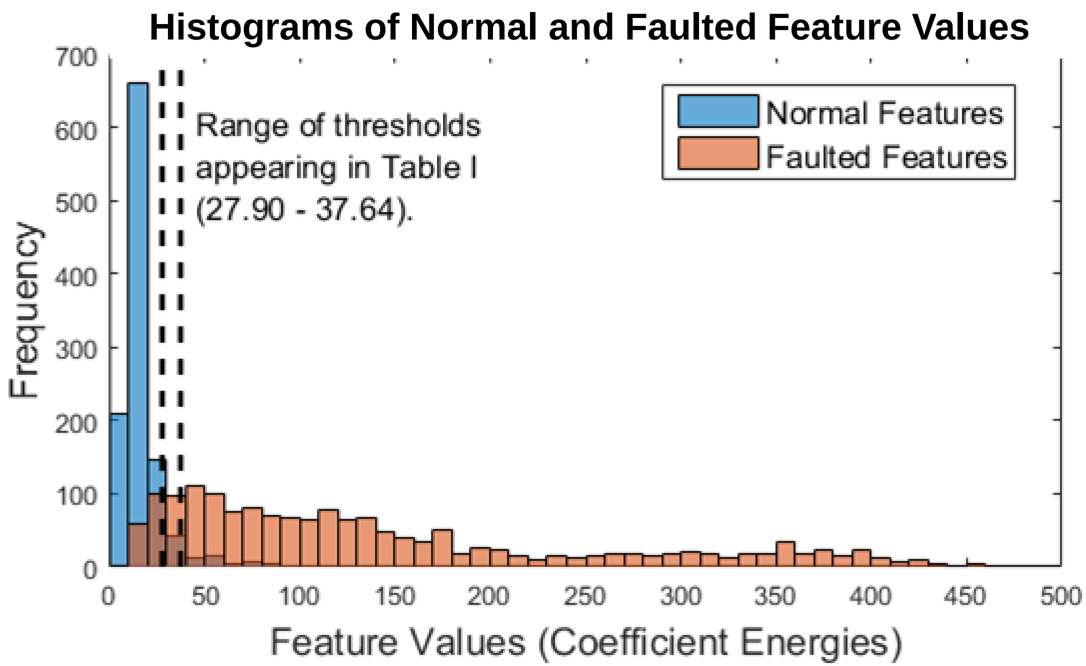

Fig. 7. Distributions of normal & faulted feature values vs. range of thresholds.

Remarks

- Despite intrinsic stochastic properties…
  – Distribution of phase voltages at the substation
  – Distribution of power demand and different injection levels
- … wavelet-based fault-detection thresholds can work under a variety of operating conditions.
- Optimal (SVM-placed) threshold range is small compared to the range of the feature space
- Observed performance bias **against** thresholds trained at light injection levels

Thank you for your attention!

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