Real-time power grid fault detection

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Motivation: Faults in power systems cause excessive currents and pose safety threats to people and property, and even cause major fires. Traditional statistical/machine learning fault detection methods use high fault current magnitude and current flow direction. Integration of inverter based (solar, wind) distributed energy resources reduced the effectiveness of the traditional methods.

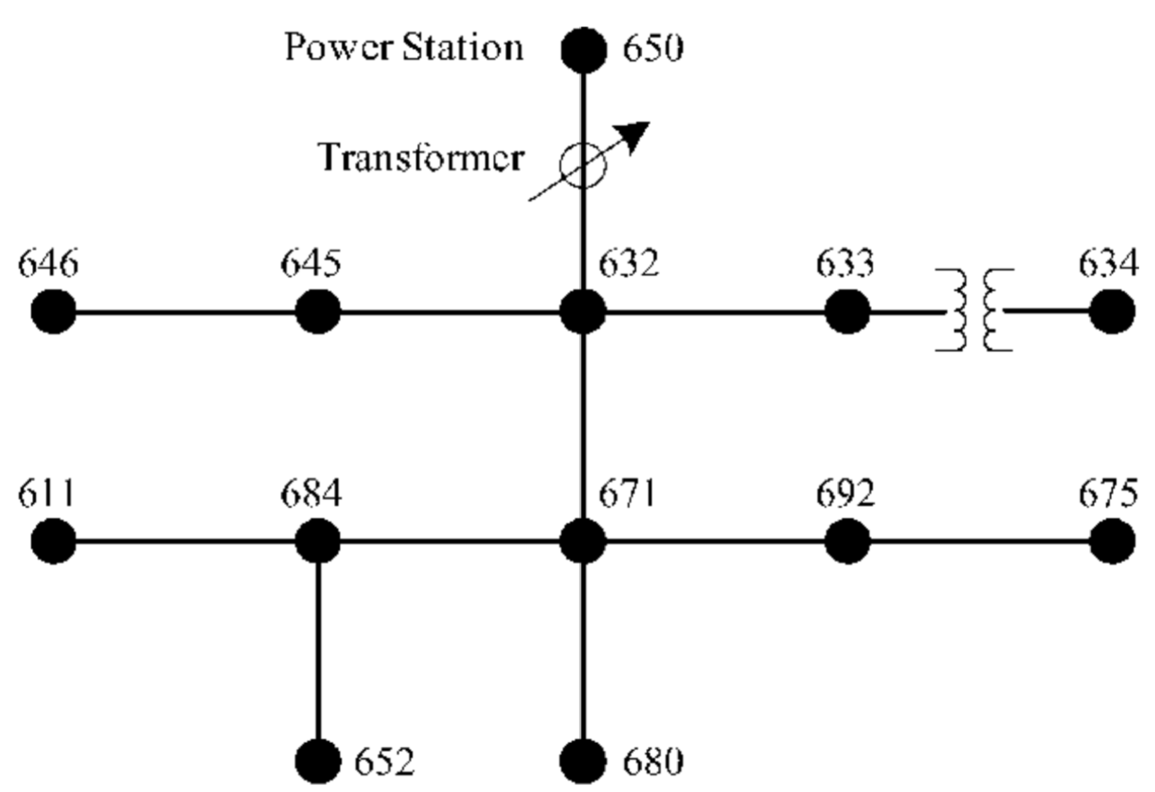
Objectives:

- Propose statistical fault detection methodology applicable to high-frequency data streams that are becoming available in modern power grids;
- Develop fast, fully data-driven and scalable algorithms that are adjustable for different phases combinations of voltage, current, and frequency measurements.

Data (IEEE 13 bus feeder)

The data is provided by National Renewable Energy Laboratory (NREL) using hardware and software to generate faults of any type at specified times and locations within a grid.

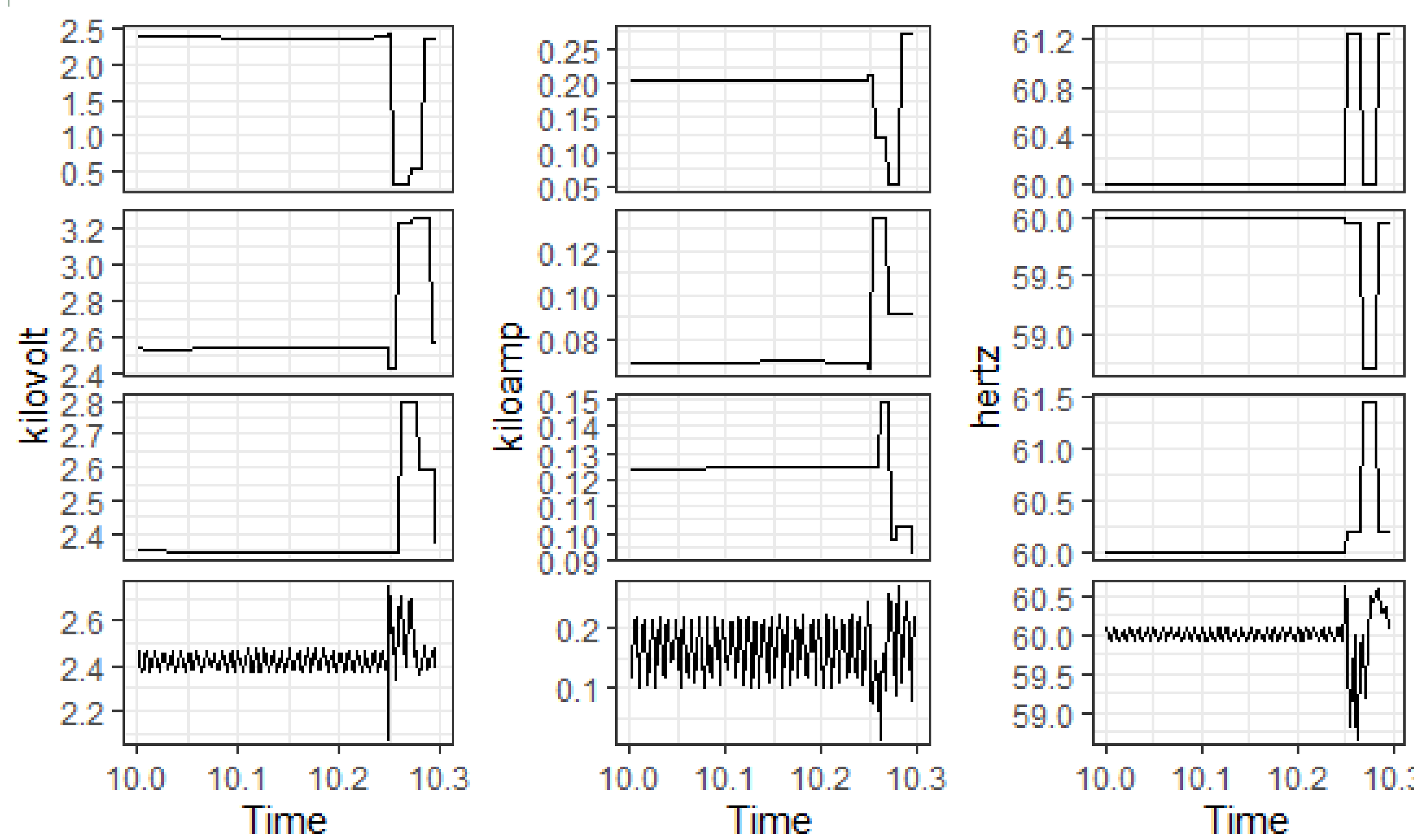
The general structure of the IEEE 13 bus feeder:



Due to feeder connections, we use 6 buses data: 650, 632, 634, 671, 675, 680. At each bus, we have measurements of 12 variables: voltage (in kilovolts), current (in kiloamperes) and frequency (in hertz) for phases A, B, C, and three-phase.

For this study, 55 different simulations of faults were conducted. In each simulation, different types of faults were applied to 9 different locations. The fault was applied at the beginning of second 10 and the simulation was running for another 5 seconds. Additionally, one 35 seconds simulation was generated without the fault.

Typical measurements of data (measurements at Bus 637 with phase A fault applied at Bus 632, the first 0.3 seconds after the fault):



Challenges

- Data is measured irregularly around every 0.002 seconds;
- Different variables are measured on different basis;
- Multiple streams of data (12x6=72);
- Some faults causes minor/almost none effect to some variables;
- The proposed methodology should be derived using non-fault data as generating faults in real life is expensive/nearly impossible.

Methodology

Regularization:

The regularized value of variable (b',k',f') is calculated as

$$X_{t_j} = \bar{X}_t, \text{ for } t_j - d < t \le t_j,$$

with $d = 0.002$.

Normalization:

We have regularized observations $X_{(b',k',f')}(t_i)$. Compute the sample mean and the sample standard deviation over the time period $t_i - l \le t_j < t_i - (1-p)l$. The normalized value is calculated as

$$Z_{(b',k',f')}(t_i) = \frac{X_{(b',k',f')}(t_i) - m(X_{(b',k',f')}(t_i))}{\mathrm{SD}(X_{(b',k',f')}(t_i))}.$$

Moving window detection algorithm:

Set difference statistics as

$$V_{(b',k',f')}(t_i) = \left[f(X_{(b',k',f')})(t_i) - \tilde{f}(X_{(b',k',f')})(t_i) \right],$$

where f is some function computed from the trajectory using the points t_j, such that $t_i - (1-p)l \le t_j \le t_i$ (the first interval) and $\tilde{f}$ is the same function on $t_i - l \le t_j < t_i - (1-p)l$ (the second interval).

The functions f considered in a study:

Name	$f(X_{(b',k',f')})(t_i)$	Definition
Mean	$\bar{X}_{(b',k',f')}$	The average of observations
SQMean	$\overline{X^2}_{(b',k',f')}$	The average of the squared observations
Range	$\max(X_{(b',k',f')}) - \min(X_{(b',k',f')})$	The range of observations
Median	$\mathrm{median}(X_{(b',k',f')})$	The median of observations

To combine the squared differences $\{V_{(b,k',f')}(t_i)\}^2$ into suitable real-valued statistics, we considered three methods, which result in $V_{\mathrm{mean}}(t_i)$, $V_{\mathrm{median}}(t_i)$, and $V_{\mathrm{trunc}}(t_i)$.

Define the time of the fault as

$$t_f = \min\{t_j : V_{\mathrm{stats}}(t_j) > \tau(t_j)\},$$

where $\tau(t_j)$ is a threshold that is adjusted in real time.

Threshold determination:

There are several tuning parameters like $l, p, V_{\mathrm{stats}}, f$. For threshold formulas, we considered

$$(1)\quad \tau_1(t_i) = 3\max_{t_j \in I_1(t_i)} V_{\mathrm{stats}}(t_j);$$
$$(2)\quad \tau_2(t_i) = \max_{t_j \in I_1(t_i)} V_{\mathrm{stats}}(t_j) + 3\mathrm{range}_{t_j \in I_1(t_i)} V_{\mathrm{stats}}(t_j);$$
$$(3)\quad \tau_3(t_i) = \max_{t_j \in I_1(t_i)} V_{\mathrm{stats}}(t_j) + 3\mathrm{SD}_{t_j \in I_1(t_i)} V_{\mathrm{stats}}(t_j).$$

where $I_1(t_i) = \{t_j : t_i - l \le t_j \le t_{i-1}\}$.

Results

First, we evaluated the methodology on the simulation without a fault. We recommend using

$$l = 0.25 \text{ s}, \quad p = 0.95, \quad \text{and } V_{\mathrm{stats}} = V_{\mathrm{trunc}} \text{ with } q = 0.1.$$

Results on simulation without a fault:

Table 1. Counts of false detections over the simulation with no fault using settings (8). The last column shows the count of false detections over the whole length of the interval (35s) which contains $35 \cdot 500 = 17,500$ regularized time points.

f	τ	Count	f	τ	Count
Mean	τ_1	0	Range	τ_1	0
Mean	τ_2	0	Range	τ_2	0
Mean	τ_3	4	Range	τ_3	5
Median	τ_1	3	SQMean	τ_1	3
Median	τ_2	3	SQMean	τ_2	2
Median	τ_3	21	SQMean	τ_3	21

Results on simulations with faults:

Table 2. Fault detection evaluation over 55 simulations with a fault using setting (8). Results are presented for the combinations of f and τ that showed the best results in Table 1.

f	τ	False detections	Correct detection
Mean	τ_1	0	1.00
Mean	τ_2	0	0.98
Range	τ_1	0	1.00
Range	τ_2	0	1.00

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