

Knowledge-Based Fault Diagnosis for a Distribution System with High PV Penetration

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Highlights

- Fast and accurate fault location is critical for distribution system protection and recovery
- Development of a robust database of fault signal traces for a distribution system with high solar PV penetration.
- Development of a machine learning (ML) and Deep Learning (DL)-based fast fault detection, localization and classification method.

Problem Description

- Five measurement devices are deployed in the system to record the measurements needed to train the ML and DL models.
- Three types of faults are considered: Single-Line-to-Ground (SLG), Line-to-Line (LL), and Three-Phase (3P). The sampling frequency used for measurement devices is 10 MHz.
- Next, Isolation Forest (IF) detects the anomalies in the recorded signals. The signal is cropped ± 0.5 ms the fault is detected to occur.

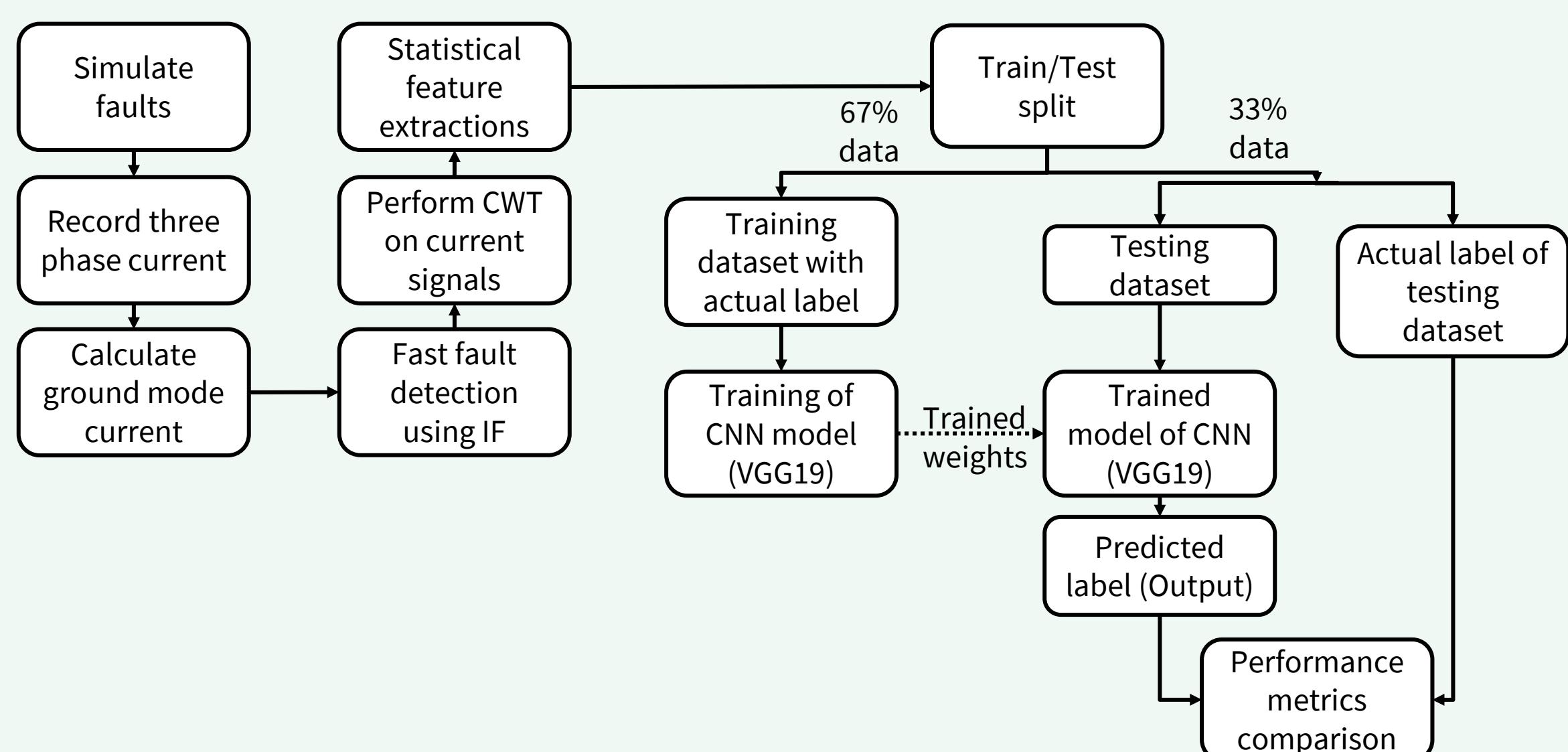


Figure: Overall workflow for the fault detection and location/classification.

- The 1 ms gives enough time to collect necessary information regarding the fault dynamics to support accurate fault diagnosis.
- CWT metrics are calculated from this 1 ms signal

Fault Simulation

- Three types of faults are simulated in the IEEE 34-bus distribution feeder.
- The faults simulated in PSCAD for different combinations of parameters involves two stages: Transient to steady-state and fault transient.
- In the first stage, the simulation is conducted for 2 seconds without the fault.
- A snapshot is taken and saved after 2 s of simulation. In the second stage, 2 ms of fault cases are simulated.
- The snapshot is considered as the starting point, and the fault occurs as 1 ms and 2 ms.
- The first half of the measurement data records the regular operation, and the last half records the incipient fault current transients.

Statistical, ML and DL Techniques

Continuous Wavelet Transform

- The convolution of the product between a signal $f(t)$ and the daughter wavelet is known as the Continuous Wavelet Transform (CWT) of the signal.

$$CWT_x(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt$$

Isolation Forest (IF) for Fault Detection

- IF works in two stages. In the first stage, the IF model is trained, and it constructs the forest of random itrees.
- In the second stage (scoring phase), the IF assigns an anomaly score to all the observations in the dataset.
- The anomaly score is computed as: $s(x, n) = \frac{E(h(x))}{c(n)}$
- Where,

$$E(h(x)) = \frac{\sum_{i=1}^t h_i(x)}{t}$$

- Here, x , $h(x)$, and $E(h(x))$ represent the observation, path lengths, and average path length of x over t itrees, respectively. $C(n)$ stands for the average path length of the unsuccessful search in the BST.
- IF determines whether an observation x is an anomaly or not based on the following condition:

$$x = \begin{cases} \text{Anomaly,} & \text{if } s(x, n) \sim 1 \\ \text{Not anomaly,} & \text{if } s(x, n) < 0.5 \end{cases}$$

CNN for Fault Diagnosis

- The CWT matrices are treated as images. The CWT matrices of the 1 ms recorded measurements (0.5 ms before and after the ground mode arrival time) are saved for the training process of CNN (VGG19).
- The VGG19 model is trained with the measurements from each measurement devices for fault location/classification.

Numerical Results and Discussion

Case Description

- The IEEE 34-bus case is adopted for fault simulations in PSCAD using the python Automation Library.

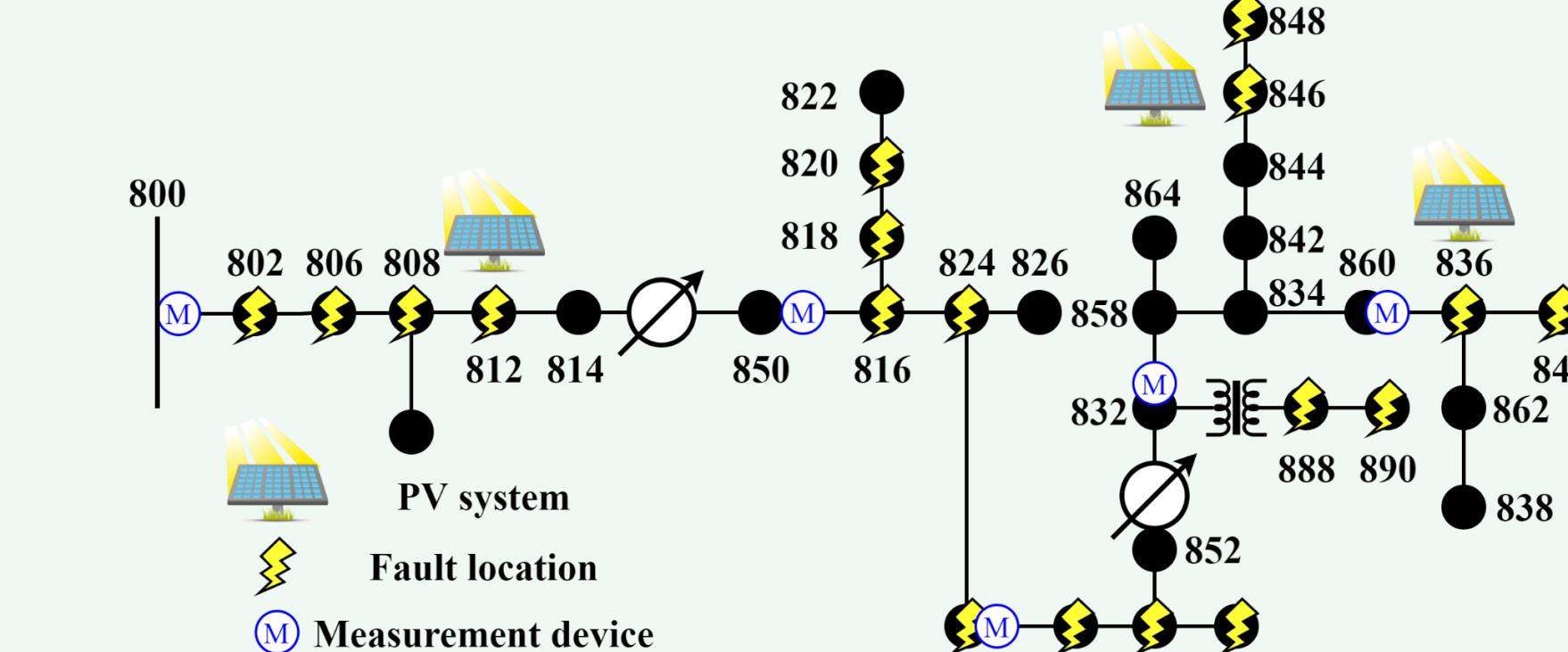
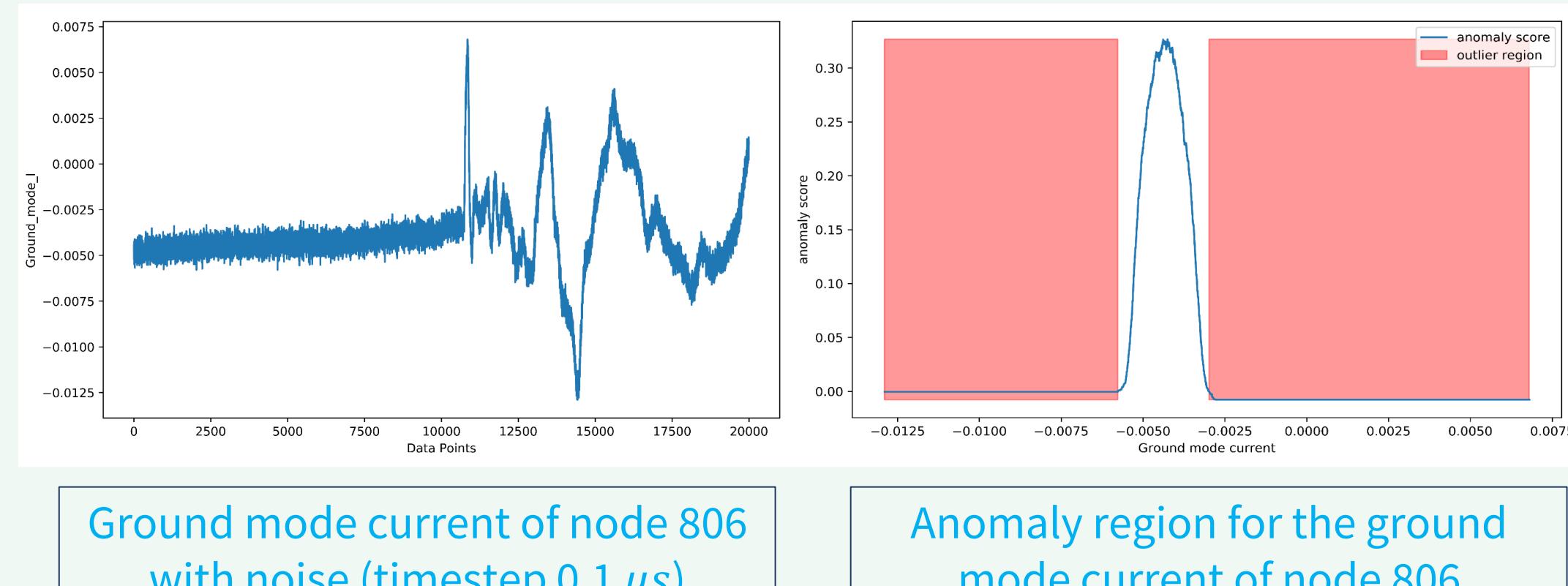


Figure: IEEE 34-bus test case in consideration.

- A total of 13,440 fault cases (measurements recorded by the 5 measurement devices) were simulated.
- For each case, the CWT matrices were obtained.

Fault Detection



	s	1	2	3	4
Precision	76%	89%	90%	89%	91%
Recall	75%	88%	89%	89%	91%
F-score	75%	88%	89%	89%	91%
Accuracy	75%	88%	89%	89%	91%

Fault location metrics for all the measurement devices using the VGG-19 model

Fault Classification

	s	1	2	3	4
Precision	76%	89%	90%	89%	91%
Recall	75%	88%	89%	89%	91%
F-score	75%	88%	89%	89%	91%
Accuracy	75%	88%	89%	89%	91%

Fault type classification

Conclusions

	s	1	2	3	4
Proposed method	96%	99%	99%	99%	99%
Baseline [1]	93.97%	94.83%	93.10%	93.10%	93.11%

Results comparison for type classification

- In both fault location and classification, we improved the accuracy considering many fault scenarios (compared to [1]).

References

[1] M. J. Aparicio, M. J. Reno, P. Barba, and A. Bidram, "Multi-resolution analysis algorithm for fast fault classification and location in distribution systems," IEEE International Conference on Smart Energy Grid Engineering (SEG), 2021.