Real-time Faults Location in Power Grid through Deep Learning

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Abstract

Faults location in power grid is crucial to improve power system stability, but existing methods have limitations including high sampling rate, offline, or require the complete system observability. This paper proposes to locate multiple types of faults through a convolutional neural network (CNN) in real-time when the system is fully or partially measured by phasor measurements units (PMU). Moreover, a greedy PMU placement algorithm is designed to maximize the location accuracy when limited buses are measured.

Background and Motivations

- More than 2000 PMUs are installed in the North America, and algorithms based on PMU are promising to automatically detect, locate and identify abnormal conditions in power grid;
- Locating faults in real time is crucial to improve the power system stability and reliability [1];
- Impedance-based methods often assume loads are static and are sensitive to topology change;
- Traveling-wave-based method require high sampling rate and accuracy of measurements;
- Artificial intelligent methods have some limitations: High sampling rate like 2400 Hz [1], DC model based [2], only for single fault and complete observability required [2-3].

Feature Extraction

Given voltage PMU data of the power system with n buses before and during fault $U^0, U' \in \mathbb{C}^n$ and admittance matrix $Y^0 \in \mathbb{C}^{n\times n}$ before the fault, and $\Delta U = U^0 - U'$, we first define the feature vector $\psi \in \mathbb{C}^n$ in (1):

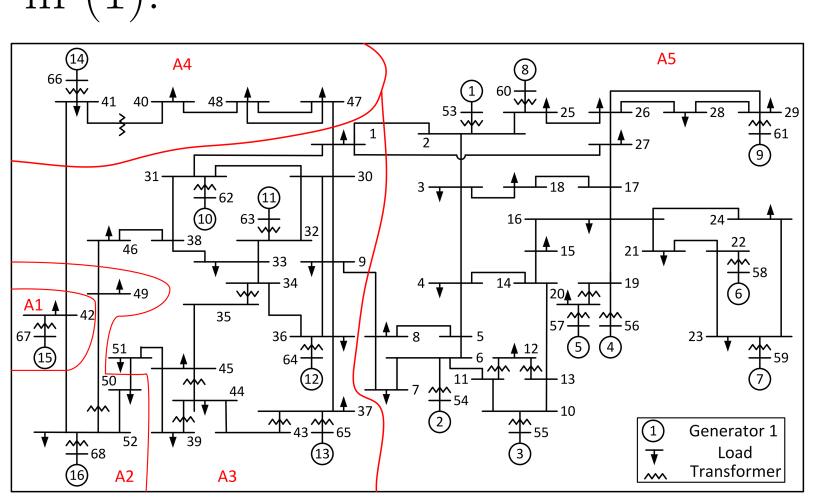

Figure 1: The IEEE-68 bus system

$$\psi = Y^0 \Delta U \tag{1}$$

Interpretation of Feature ψ

Based on the substitution theory:

$$\psi = \Delta I^u + \Delta I \tag{2}$$

- where ΔI^u is a sparse vector with nonzero values at the terminal buses of the faulted line; ΔI denotes current variations;
- Thus ψ is closely related to fault locations.

Example of Feature ψ

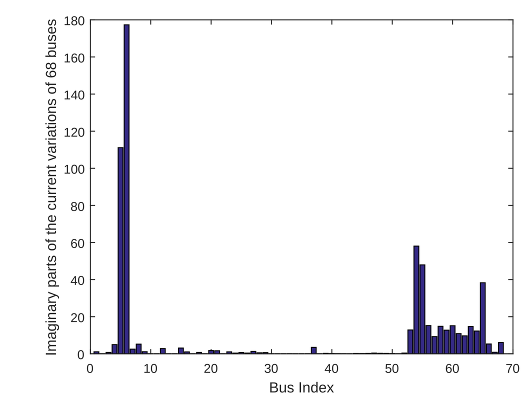

Figure 2: The imaginary parts of ψ

- When the line 5-6 in Figure 1 is faulted, the values corresponding to the bus 5 and 6 of ψ are relatively larger than others.

Our CNN Classifier and the Main Ideas

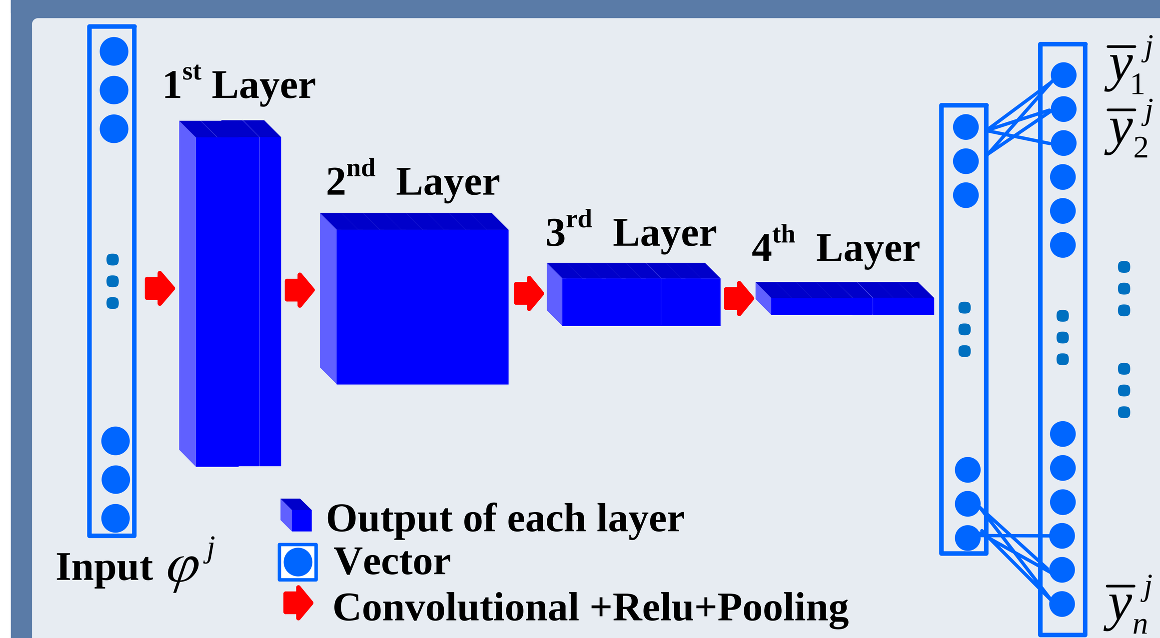

Figure 3: CNN Structure

The Main Ideas of Our Method

- Extract feature vector ψ^j of the jth historical PMU data with n lines and label them by the faults locations;
- Train the CNN by inputting the extracted N features $\psi^j, j = 1, \cdots, N$;
- CNN outputs the probabilities $\bar{y}_i^j$, $i = 1, \cdots, n$ of jth data for the ith line;
- The line with the highest probability indicates the fault location.

PMU Placement Algorithm

Given the number of measured buses m, the proposed algorithm selects the ith bus having a large degree d_i and largely reducing loss function (3).

Greedy PMU Placement

1: Input parameters: $m, \beta = 1$
2: Initialize : $\mathcal{S}_0 = \emptyset$ and the loss value $l = \infty$
3: **for** $k = 0, \cdots, m$ **do**
4:   **for** bus $i = 1, \cdots, n$ **do**
5:     Compute $l_i = \min_\Theta l(\Theta, \{\mathcal{S}_k \cup i\})$ of (3)
6:   **end for**
7:   $i^* = \arg\min_i(\frac{\beta}{d_i} + l_i)$, where d_i is the degree of bus i, β is a weight parameter.
8:   **if** $l_{i^*} < l$ **then**
9:     $\mathcal{S}_{k+1} = \{\mathcal{S}_k \cup i^*\}, l = l_{i^*}$
10:   **else**
11:     $\mathcal{S}_{k+1} = \mathcal{S}_k$
12:   **end if**
13: **end for**
14: Return: $\mathcal{S}_m$

Algorithms Comparison

$$l'(\Theta, \mathcal{S}) = \min_\Theta \frac{1}{N} \Sigma_{j=1}^N \Sigma_{i=1}^n y_i^j \log \bar{y}_i^j(\Theta, \mathcal{S}) + \lambda \|\Theta\|_F^2 \tag{3}$$

$$\text{s.t. } |\mathcal{S}| \leq m \tag{4}$$

where $\Theta, \mathcal{S}, \lambda, N$ denote the set of learned parameters, the set of measured buses, regulation coefficient and the total number of datasets, $y_i^j, \bar{y}_i^j$ are the label and estimated probability of the jth dataset.

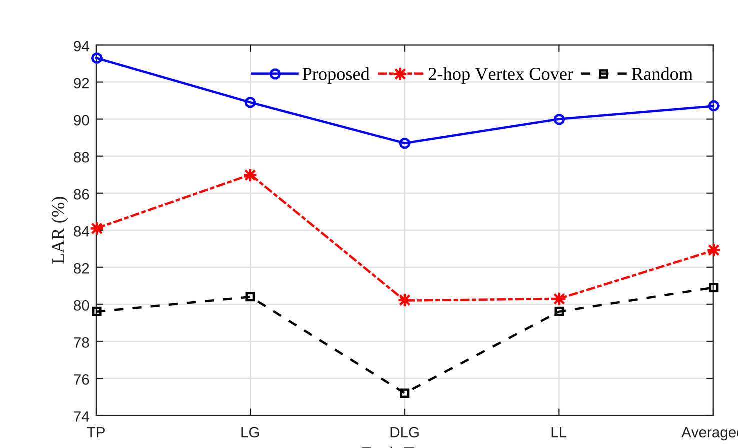

Figure 4: LAR of CNN based on different algorithms

- Three phase short circuit (TP), line to ground(LG), double line to ground (DLG) and line to line (LL) faults are tested in the IEEE 68-bus power system;
- The location accuracy rate (**LAR**) based on the 'Proposed' algorithm is higher than others.

Numerical Results

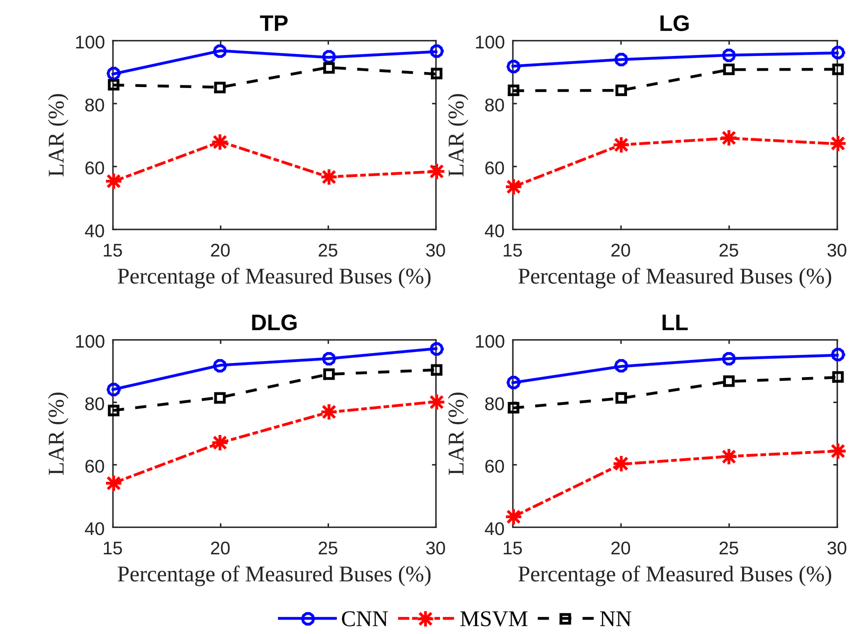

Figure 5: The LAR of CNN, MSVM, NN

- When the system is partially measured, the LAR of CNN is higher than that of multi-class support vector machine (MSVM) and NN.

Table 1: The ARC of CNN when $\leq 15\%$ buses are measured

Measured Ratio	TP	LG	DLG	LL
7 %	1.32	1.48	1.92	1.56
10 %	1.38	1.28	1.66	1.54
15 %	1.38	1.23	1.57	1.54

- The lines are sorted according to their probabilities from CNN and thus the Averaged Rank of Correct (ARC) line is defined;
- The ARC, less than 2, indicates that the correct is mostly within the lines of top-3 probability.

Conclusions

The proposed method is able to locate faults with a high accuracy when system is fully or partial measured, and the proposed algorithm is effective to improve LAR with limited buses measured.

Reference

[1] Mehrdad Majidi, Mehdi Etezadi-Amoli, and Mohammed Sami Fadali. A sparse-data-driven approach for fault location in transmission networks. *IEEE Transactions on Smart Grid*, 8(2):548–556, 2017.

[2] Manuel Garcia, Thomas Catanach, Scott Vander Wiel, Russell Bent, and Earl Lawrence. Line outage localization using phasor measurement data in transient state. *IEEE Transactions on Power Systems*, 31(4):3019–3027, 2016.

[3] Guangyu Feng and Ali Abur. Fault location using wide-area measurements and sparse estimation. *IEEE Transactions on Power Systems*, 31(4):2938–2945, 2016.

Acknowledge

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