Study Committee C2

Power System Operation & Control

Paper ID-10224_2022

Automated System-wide Event Detection and Classification Using Machine Learning on Synchrophasor Data

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Motivation

- System operators in control rooms are unable to process large amount of synchrophasor data efficiently and rapidly.
- There is need for automated ways to analyze the big synchrophasor data to extract actionable information quickly and cost effectively.

Methodology

We developed a machine learning-based prototype tool for the Control Room use that automatically analyses data properties from synchrophasor system measurements taken across the USA. The data collected from several hundreds of PMUs located across the three US Interconnections over a period of two years have been made available for our extensive study. As a result, we were able to identify several big data properties that influence how Machine Learning (ML) methodology is applied to select, develop, train and test the data models that can eventually be used for the tool implementation. The resulting set of candidate algorithms spans unsupervised, supervised, semi-supervised and transfer-learning approaches.

Investigation Objective

Many ML techniques, such as decision trees, multinomial logistic regression, feed-forward neural networks, K-nearest neighbor, multiclass support vector machine, and single and multi-channel convolutional neural networks, are implemented, and their performance is examined.

Experimental Setup

We utilize historical field measurements collected over two years, 2016-2017 from 38 anonymized PMUs placed in the Western interconnect and from 178 anonymized PMUs placed in the Eastern interconnect in the U.S. electric power system. Grid topology was also removed. This 25 TB data is organized it two disjoint subsets:

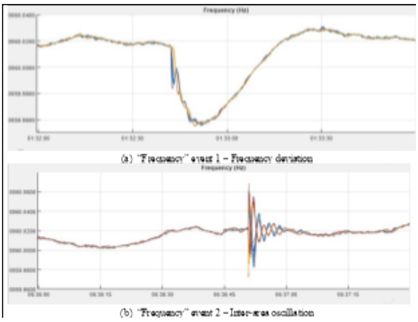
(a) Training dataset covering approximately ¾ of the recordings from two years of data.

(b) Test dataset obtained by cutting out sections of the overall dataset used for models' evaluation.

Provided event log was based on the SCADA event logs and contained temporally imprecise labels. In addition, event logs did not necessarily occur in the vicinity of the PMUs, due to the sparsity of PMU locations in a large network.

System-Wide Events of Interest

- **Fundamental Frequency Deviations** – Fundamental frequency deviations from the nominal value may exceed the controlled range for certain frequency events, such as low frequency oscillations and large frequency excursions. Frequency events generally can be "seen" by all PMUs within an interconnection as shown here for two types of events:



(a) "Frequency" event 1 – Frequency deviation

(b) "Frequency" event 2 – Inter-area oscillation

- **Low Frequency Oscillations** – Various types of low frequency oscillations occur in an interconnected power system all the time. Most of the oscillations are short-lived natural oscillations that have little impact on power system normal operation and reliability. However, certain types of low frequency oscillations, namely an inter-area oscillation (i.e., two groups of generators in two different areas oscillate with each other) or a forced oscillation driven by a source of oscillation such as a connection of a group of renewable generators, could impact a wide area of an interconnected system and may lead to system instability or severely limit the power transfer capacity of transmission lines if not timely mitigated.
- **Generator or Transmission Line Tripping** – Generator tripping causes sudden large supply shortage in the area where generator(s) was(were) connected, which could lead to large frequency drop in the area beyond the controlled range. Major tie-line(s) tripping could create two areas: one with excessive supply and one with large supply shortage leading to frequency jump in the excessive supply area and frequency drop in the other.

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continued

ML Pipeline for Event Detection and Classification

Aim: Predict event type $y \in \{0, \ldots, C\}$ that occurred at time $[t-\Delta, t+\Delta]$ by learning from scarce observations and low precision labels of multiple anonymized PMUs (removed grid topology)

- **Step 1: Automated Feature Engineering**

Objective: Simplify the problem by reducing data dimensionality through a construction of a lower featured vector corresponding to a univariate signal segmented to $\mathbf{s}(t-\Delta, t+\Delta)$

Knowledge-based Approach: For each time segment s(t-Δ,t+Δ) of each PMU compute $(f_{max} - f_{min}) * (V_{max} - V_{min})$, where

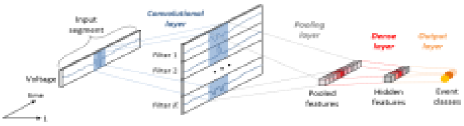
- f_{max} and f_{min} are the max and min frequency values,
- V_{max} and V_{min} are the max and min positive sequence voltage magnitude recorded

Machine learning approach: Aggregate all PMUs to a single sequence, where each PMU view is reduced to a lower resolution signal by binning time segments to buckets and summarizing each; importance weight for specific PMUs are updated dynamically by Soft Dynamic Time Warping.

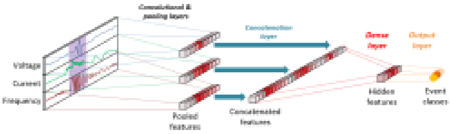
- **Step 2: Deep Learning for Event Detection and Classification Models from PMU Data**

Objective: Apply automated feature engineering techniques from Step 1 to measurements and use this knowledge representation to learn a Convolutional Neural Network (CNN) model

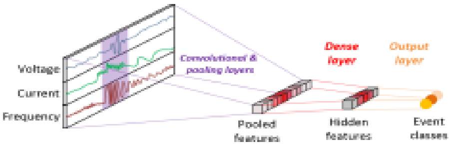
Single-Channel CNN Approach: Each convolution layer transforms an input segment by convolving it with a certain filter and the result is passed through another filter, where filters are automatically learned; the pooled features are further mapped to a hidden representation used to detect an event and estimate class probabilities.



Parallel Multi-Channel CNN Approach: Pooled features for voltage, current and frequency are produced separately, and the results are concatenated in a joint layer



Simultaneous Multi-Channel CNN Approach: All 3 channels are mapped to a joint pooled feature



Results:

(1) CNN was more accurate than traditional models in distinguishing frequency events from line faults and normal operation based on 2-years of PMU recordings at Western U.S. Interconnection;

(2) the best predictions were consistently obtained using multi-channel CNNs

- **Risk Mitigation Step: Transfer Learning Models for Event Detection from PMU Data**

Objective: Overcome limitations of supervised and unsupervised learning approaches when event logs are small and imprecise and PMUs are scarcely positioned in a large spatiotemporal system

Transfer learning approach: Leverage some of labeled event data available from a related event detection source task and a smaller number of cases from a target task where we would like to detect events; this is achieved by

(a) reducing dimensionality of the source and target domain (e.g., different interconnections) to the same latent space using an unsupervised Neural Network as an autoencoder

(b) localizing instance selection to address covariate shift and concept shift challenges

Results:

(1) transfer learning was significantly more accurate than unsupervised, semi-supervised, and supervised approaches when learning to detect events from limited labeled observations;

(2) transferring knowledge from only 20 representative labeled data instances measured at 38 PMU sites of the U.S. Western Interconnection grid was sufficient to significantly improve events detection in the U.S. Eastern Interconnection where recordings measurements were available from178 PMUs

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continued

Lessons Learned

- **Data Ingestion, Cleansing and Management** –Field PMU data could experience a variety of data quality issues for various reasons. A full scan of the historical data to identify these issues and to understand the overall data quality situation is a vital step before using the data for ML model training to recognize system-wide types of events. Data cleansing should only be performed for those data quality issues that have considerable impacts. An extremely important data management function is data labelling. To label an event, the best available sources of information should be used. We recommend that the end users deploy time stamping available from PMUs to identify the start/end of an event rather than using quite an inaccurate SCADA time reference.
- **Feature Engineering** – Knowledge-based feature engineering in big PMU data is typically easy to explain. While it might be too specific and possibly biased, it is computationally efficient. When data is large and heterogenous, our results provide evidence that event detection and classification could be significantly improved by automated feature learning.
- **Model Development** –When detecting and classifying events from many PMUs in big data, deep learning ML methods in general outperform traditional supervised learning models. In our experiments hierarchical deep-learning models consistently outperformed the standard multiclass variants. For event analysis voltage was more relevant than current and frequency, but the best results were achieved when signal from all 3 channels (phases) was analyzed jointly. When detecting events from limited even data, we found that transfer learning outperformed unsupervised, semi-supervised, and fully-supervised algorithms.

Discussion

- Poor data quality such as missing data, unreasonable measurement values, etc. directly affect the data analysis and should be mitigate if needed.
- Imprecise or missing event labling affects the training of supervised learning models resulting in low score in the test result. Cleaned lables lead to high test scores.
- The type of data analysis is limited when the system information, system model, and measurement locations are not provided.

Conclusion

In conclusion, several study findings are worth mentioning:

- If the models are going to be used for mission-critical applications, then the best possible data should be provided to the model developers;
- Assigning imprecise or inaccurate labels to the data may significantly impair ML model performance, so special care should be given to improving the labeling process;
- PMU and protective relay recordings with accurate timestamps are a better choice when determining and assigning event labels than SCADA information that has inherent limitations;
- The physics-based model simulations of the power system can significantly enhance the ability to achieve efficient and reliable ML model training;
- To make a business case for the use of ML for event analysis it is crucial to compare the automated ML benefits over the manual approach to the analysis
- The ML approaches have a constraint in the developing power systems that may experience events never seen before, so keeping the history of new events for training purposes is essential

Disclaimer