



Detection, Characterization, and Mitigation of Disruptive Events (DECODE) by Combining Machine Learning/Artificial Intelligence on Synchrophasors and Physics-based Analysis

Final Project Report

S-100

Power Systems Engineering Research Center

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Detection, Characterization, and Mitigation of Disruptive Events (DECODE) by Combining Machine Learning/Artificial Intelligence on Synchrophasors and Physics-based Analysis

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Executive Summary

The advances in machine learning/artificial intelligence (ML/AI) over the last 10 years have enabled development and implementation of effective algorithms for the detection and classification of events using phasor measurement unit (PMU)/synchrophasor data. While many solutions have been proposed, there is a critical need for automated tools that are accurate, cost-effective, and computationally efficient when applied to large historical and streaming datasets captured by multiple PMUs. By leveraging over 20 years of research that used physics-based analysis to correlate synchrophasor data to disruptive events, this project has developed automated tools that combine various data-based and physics-based solutions in real-time to help system operators detect and classify three types of events, namely, faults, frequency, and oscillation events, that may lead to system emergencies.

The objectives of this project were attained by making progress on four fronts: 1) Development of data handling and sorting techniques for collecting large historical synchrophasor datasets to improve bad data detection, feature engineering, and event label assignment for automated ML/AI solutions; 2) Identification of the most effective ML/AI techniques for unsupervised, semi-supervised, and supervised learning associated with faults, frequency, and oscillation events, 3) Seamless integration of ML/AI-based and physics-based solutions for cost-effective and computationally efficient automated event characterization, and 4) Development and selection of appropriate transfer learning (TL) methodologies associated with detection and characterization of faults, frequency, and oscillation events that provided high accuracy when applied to datasets for which the ML/AI algorithm was not trained on.

The diversity of system topologies and changing PMU data distributions with each new dataset, which may even be from different grids, are challenging problems for traditional power system event detection and characterization techniques. To ensure validity of the detection and characterization methodologies developed in this project, they were applied to a wide range of datasets with diverse operating conditions. The proposed methodologies were found to significantly reduce the training effort while maintaining high accuracy of prediction. A unique challenge that was identified and subsequently addressed in this project was the analysis of new, small datasets that exhibited a scarcity or lack of event labels. These datasets were provided by industry partners but were often found to be insufficient for training robust ML/AI models. To overcome this challenge, the ML/AI models were developed for each event type and then TL techniques were utilized to transfer the models to the new datasets.

In the following paragraphs, a brief description of the research methodology starting with the datasets that were used in this analysis, is provided. This is followed by a summary of the main results as well as a discussion of their implications, including recommendations based on the project's findings.

Field-recorded synchrophasor measurements from various regions of the US and France were the primary sources of “real” data used in this study. However, the recorded measurements suffered from data-quality issues; these issues were tackled in the data preprocessing stage. The real-world measurements also lacked the occurrence of all three events that were the focus of this study. Training ML/AI models with an incomplete dataset could introduce bias and failure in accounting

for major, infrequent events that could significantly impact the system. Therefore, a wide range of “simulated” datasets were created for all three types of events to create a balanced training dataset for the ML/AI algorithms.

Feature engineering, which is an important step in the overall task of decoding power system events of interest using ML/AI models, was focused on next. It was observed that although synchrophasor data could be used directly or replaced by their simple statistical descriptors to be used as features, the extraction of relevant contrasting features for various events usually gave better results. As such, careful consideration was given in this study to select features that appropriately represent the underlying application (line fault events, frequency events, and oscillation events). To that end, features for fault, frequency, and oscillation events were extracted using principles of protection studies, modal decomposition, and image recognition, respectively.

The focus then shifted towards the development of the ML/AI models, particularly their training and testing. The developed ML/AI-based algorithms exploited the steps of data preprocessing and feature engineering to create useful training and testing datasets. These datasets were used as input to several supervised learning algorithms to form the base classifiers for each event type. TL methods were then explored to transfer the knowledge gained by models trained on simulated datasets or large, diverse field-recorded datasets to smaller, less diverse field-recorded datasets.

Next, the results obtained using the different ML/AI models were explored, and conclusions were drawn about suitability of the different models and approaches. The team found that correlation alignment (CORAL)-based TL with support vector machine (SVM) classifiers was particularly effective for line fault detection, while extreme gradient boosting (XGBoost) classifiers with fine-tuning based on Prony features demonstrated good performance for frequency event detection. Image-based ML/AI approaches showed promise for oscillation detection and classification as they were matched with neural network (NN)-based TL. The direct application of the base ML/AI classifiers trained using simulated datasets to field measurements during testing resulted in poor performance. However, exploring the TL capability of ML/AI models by utilizing simulated datasets along with limited field-recorded labeled events significantly improved the performance in classifying unlabeled field-recorded events.

Finally, the major study findings from this project along with reflections on some of the challenges that the team experienced with synchrophasor data quality in the datasets that were made available to them, was presented. The report concludes with some recommendations that stand out based on the team’s learning experience over the duration of this project and past experiences in a similar space and outlines the expected outcomes if these recommendations are considered.

Project Publications:

- [1] T. Mohamed et al., "Automated Detection and Classification of Critical Power System Events using ML on PMU Data," 2024 International Conference on Smart Grid Synchronized Measurements and Analytics (SGSMA), Washington, DC, USA, 2024, pp. 1-6, doi: 10.1109/SGSMA58694.2024.10571526.
- [2] T. Mohamed et al., “Transfer Learning on Synchrophasor Data for Automated Detection and Classification of Critical Power System Events,” Submitted to IEEE Transactions on Power Systems.

Student Theses:

- [1] Taif Mohamed, “Machine Learning Applications to the Detection and Classifications of Power System Faults,” PhD, August 2025.
- [2] Yadunandan Paudel, "Decoding Frequency Events in Power Systems using Machine Learning on Synchrophasor Data," PhD, May 2026.
- [3] Deepak Joshi, " Data-Driven Machine Learning Approaches for detecting and Classifying Oscillations in Power Systems," PhD, July 2025.