SOURCING STATEMENT OF WORK

Contractor Name: Arizona State University

EPRI Contract ID: ???

Contract Title: “Data-Driven Real-Time State Estimator Using Machine Learning for Transmission Systems”

EPRI Task ID: 1-113850-01-01

Introduction, Background and Objectives

State Estimation (SE) is used in transmission control centers for monitoring the operating condition of the grid by computing a statistical estimate of the system state represented by the voltage magnitude and phase angle of system buses. Conventional SE fits SCADA measurements provided by Remote Terminal Units (RTUs) into a single phase, positive sequence model of the transmission system using an iterative non-linear estimation solver (typically weighted least-squares). This approach is referred to as static SE, assumes quasi steady-state operation of the system, and the computational time is typically in the order of several seconds to a few minutes.

Recent advancements in Synchrophasor Technology and the continuously increasing deployment of Phasor Measurement Units (PMUs) have enabled the development of enhanced SE. PMU measurement-only based Linear SE (LSE) have also been developed since with the use of PMU measurements (voltage and current synchrophasors) the SE can have a linear mathematical formulation. LSE has enhanced convergence properties compared to conventional SE and can be executed at high rates. However, the accuracy of its output still depends on the accuracy of the underlying grid model. Also, a Gaussian distribution for the measurements errors is still assumed.

The objective of this project is to develop a novel Bayesian state estimator that uses Machine Learning (ML) techniques and PMU measurements to provide enhanced situational awareness. The salient aspects of the proposed ML-based SE are the following:

* Capable of estimating states in the presence of measurements from topologically unobserved systems: Complete system observability by PMUs is not required
* Independent of measurement error distribution: No presumptions regarding the characteristics of the measurement noise
* Capable of estimating states at the rate of 30 samples per second utilizing time-synchronized measurements as real-time inputs: Retains the high-speed advantage of a PMU-only linear state estimator
* Overcomes SCADA/PMUs synchronization issues: Decouples usage of SCADA and PMU data to prevent problems related to improper synchronization

Third Party Intellectual Property

Tasks

*Task 5: Machine Learning Based State Estimation Output Post-Processing*

A ML-based state estimation methodology was developed in Tasks 1-4 in the first year of this project. This state estimator performed high-speed, time-synchronized estimation of the states of a transmission system that was PMU-unobservable. The ability of this state estimator to handle non-Gaussian noise in the measurements as well as topology changes was also demonstrated. In this task, the following aspects of the proposed ML-based state estimation methodology will be investigated:

*Mechanism to replace bad data and/or missing data:* In Task 3, once bad data and/or missing data was identified for a particular PMU measurement, it was simply replaced by the average value for that measurement obtained from the training database, without taking into account the other PMU measurements that were available. Although this approach will work when all the PMU measurements are bad/missing, such an occurrence rarely happens in reality. That is, in practice, only some measurements are bad enough that they need replacement by suitable pseudo-measurements. In this task, such pseudo-measurements will be obtained in real-time using the other available measurements and the training database. The output of this replacement mechanism will be tested against scenarios in which the bad/missing data is not replaced at all, or the data are replaced by the mean value obtained from the training database.

*Ability to distinguish between bad data and extreme scenarios:* In Task 2, the impact of extreme scenarios on the performance of the ML-based state estimator was investigated. In Task 3, the Wald test was proposed as a methodology to detect bad data in real-time. Now, it may so happen that the Wald Test flags valid data that corresponds to an extreme operating condition of a system as bad data, if the data violates the specified thresholds of the Wald Test. To avoid such an occurrence, in this task, appropriate filters will be designed that will suppress the decision of the Wald Test when extreme scenarios manifest.

*Identifying events:* It is possible that due to its slower speed, a SCADA-based state estimator may fail to “observe” an event that has occurred in the grid. Under such circumstances, the operators often have to rely on training and prior experience to make the correct decision. With a data-driven state estimator working in parallel with the conventional estimator, the operators could be able to identify anomalies that may have been missed by the SCADA-based estimator.

*Dynamic line parameter estimation:* The ML-based state estimation methodology can estimate the voltages without using knowledge of the line parameters in real-time. Therefore, an accurate and realistic estimate of the state obtained using the proposed methodology may also assist in getting a more realistic and accurate estimate of the time varying line parameters. This can also help in understanding the effects that load and temperature variations have on the line parameters.

*Task 6: Machine Learning Based State Estimation Software Development*

Under this task, a research grade software tool will be developed that will implement the features of the proposed ML-based state estimator developed in the previous tasks. This task will involve running power flow cases in MATLAB, PSLF, and/or PSS/E, and generating requisite data for validating the created deep neural network (DNN). The DNN will be built using Python. A GUI will also be prepared to facilitate usage. Appropriate example files including Read-Me files will be created to ensure that individuals not familiar with ML can still execute the software tool and get desired results.

*Task 7: Machine Learning Based State Estimation Case Studies*

Under this task, the proposed ML-based state estimator and the corresponding software tool will be applied using field data provided by project participants. We would prefer having (1) Snapshots of solved SE cases (PSLF or PSS/E .sav files) containing information about load and generation as well as system topology. The snapshots are expected to be at least 5 minutes apart and should be for at least 3 months; 6 months, possibly spread across different seasons, will be preferred. (2) Locations where the PMUs are already placed in the system. (3) PMU measurements for a couple of hours during those periods. From the obtained snapshots, loads and generation, and complex voltages and currents from the power flow solution will be extracted, processed, and fed to the DNN during training and testing. The performance of the DNN on testing data will be demonstrated, and the resulting case-studies shared with the project partners.

Deliverables

1. Final Report
2. Software Tool

Schedule

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| **Task/Milestone/Deliverable Description** | **Due Date** |
| Task 5 | April 30, 2022 |
| Task 6 | September 30, 2022 |
| Task 7 | December 31, 2022 |
| Final Report and Software Tool | December 31, 2022 |
| Monthly status report by teleconference | Once a month. Dates to be defined by project team depending on availability |
| Final Report | December 31, 2022 |

EPRI Material/Other Documents