Machine Learning Based State Estimation for PMU-Unobservable Transmission Systems – TVA Case Study

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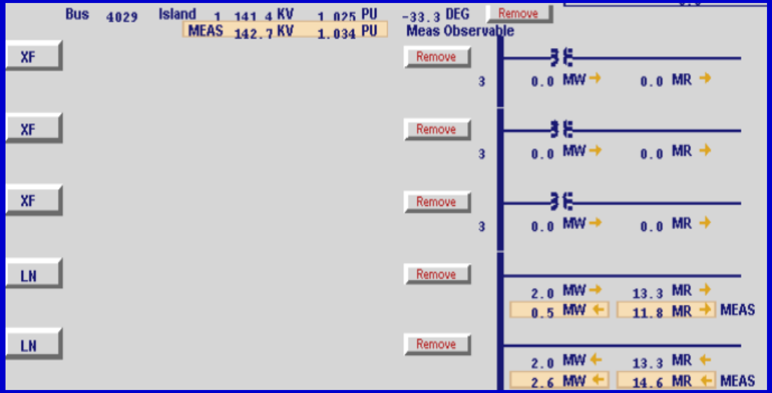
NASPI Work Group Meeting
April 16-17, 2024
Salt Lake City, UT

State Estimation

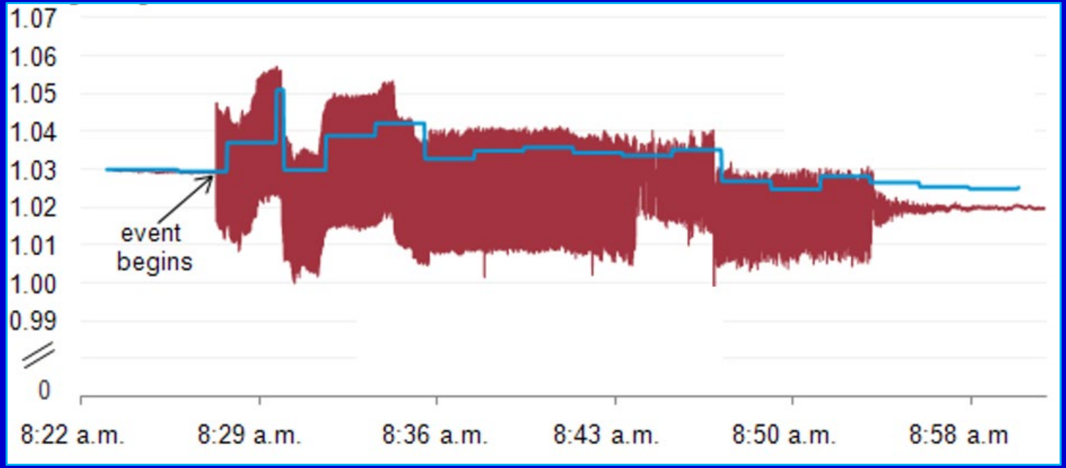
Backbone EMS Function for Situational Awareness

SCADA/EMS State Estimation



- **State Definition [x]**: Positive sequence voltage phasors (bus voltage magnitudes and angles) of system’s buses
- **Measurement Set [z]**: SCADA data
  - Voltage magnitude, current magnitude, real & reactive power flows and injections
  - Measurement model: Nonlinear
  - Gaussian distribution of measurement error
- **Solution Algorithm:** Weighted Least Squares
  - Iterative Solution

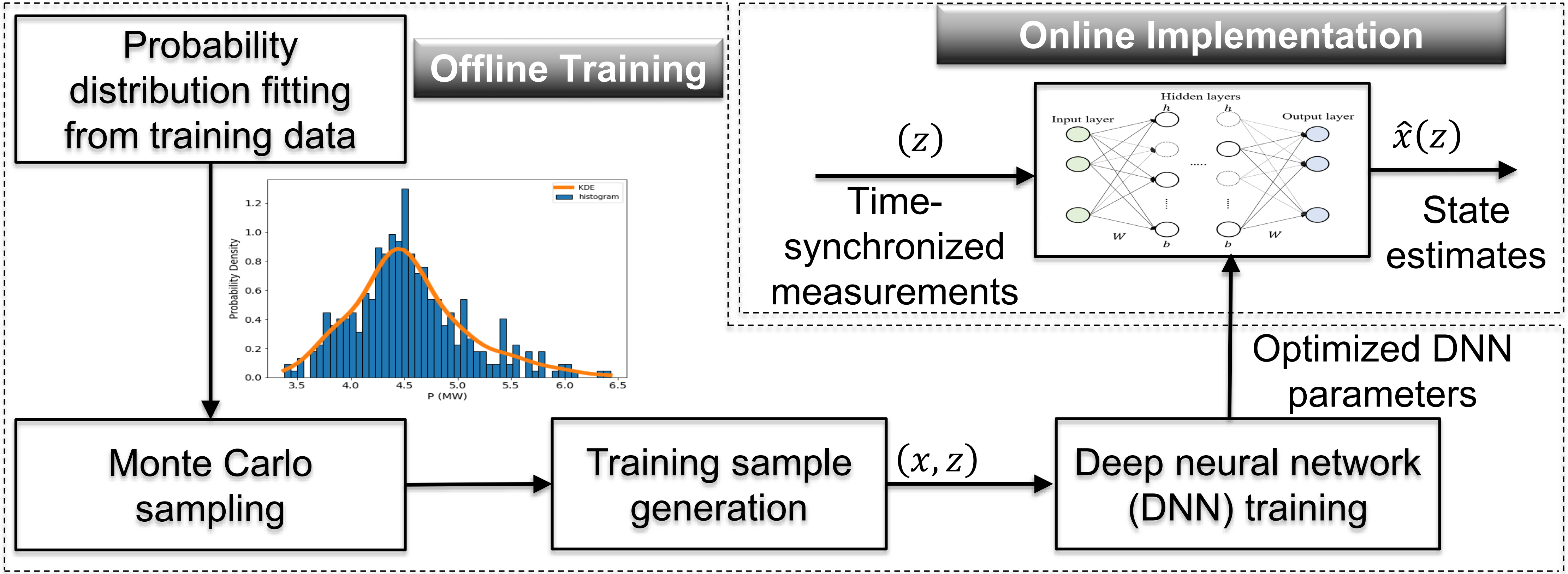
PMU Based State Estimation



- a.k.a Linear State Estimation
- **Measurement Set [z]**: Phasor Measurement Unit (PMU)
  - Voltage and current phasors
  - Measurement model: Linear
  - Gaussian distribution of measurement error
- **Solution Algorithm**: Weighted Least Squares
  - Direct Solution

Objective

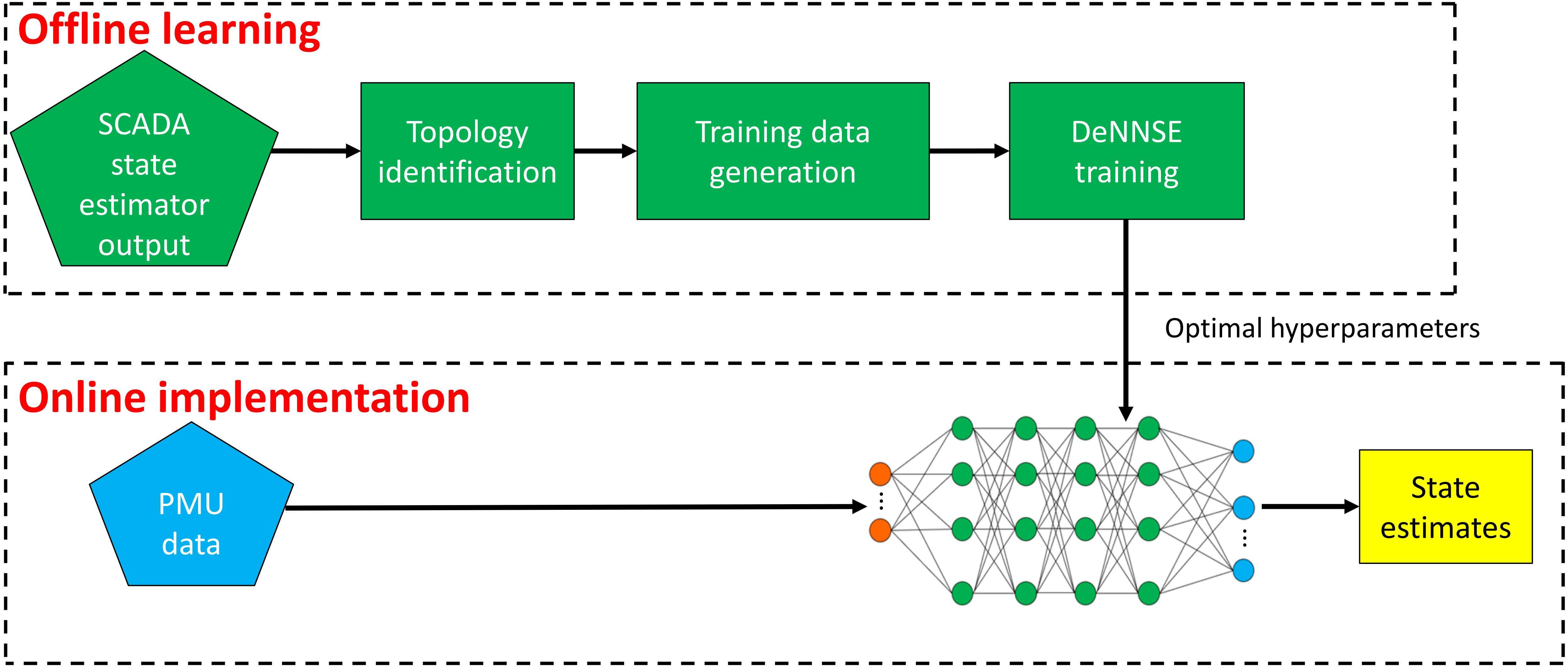
Development of a Machine-Learning Based State Estimator



Features

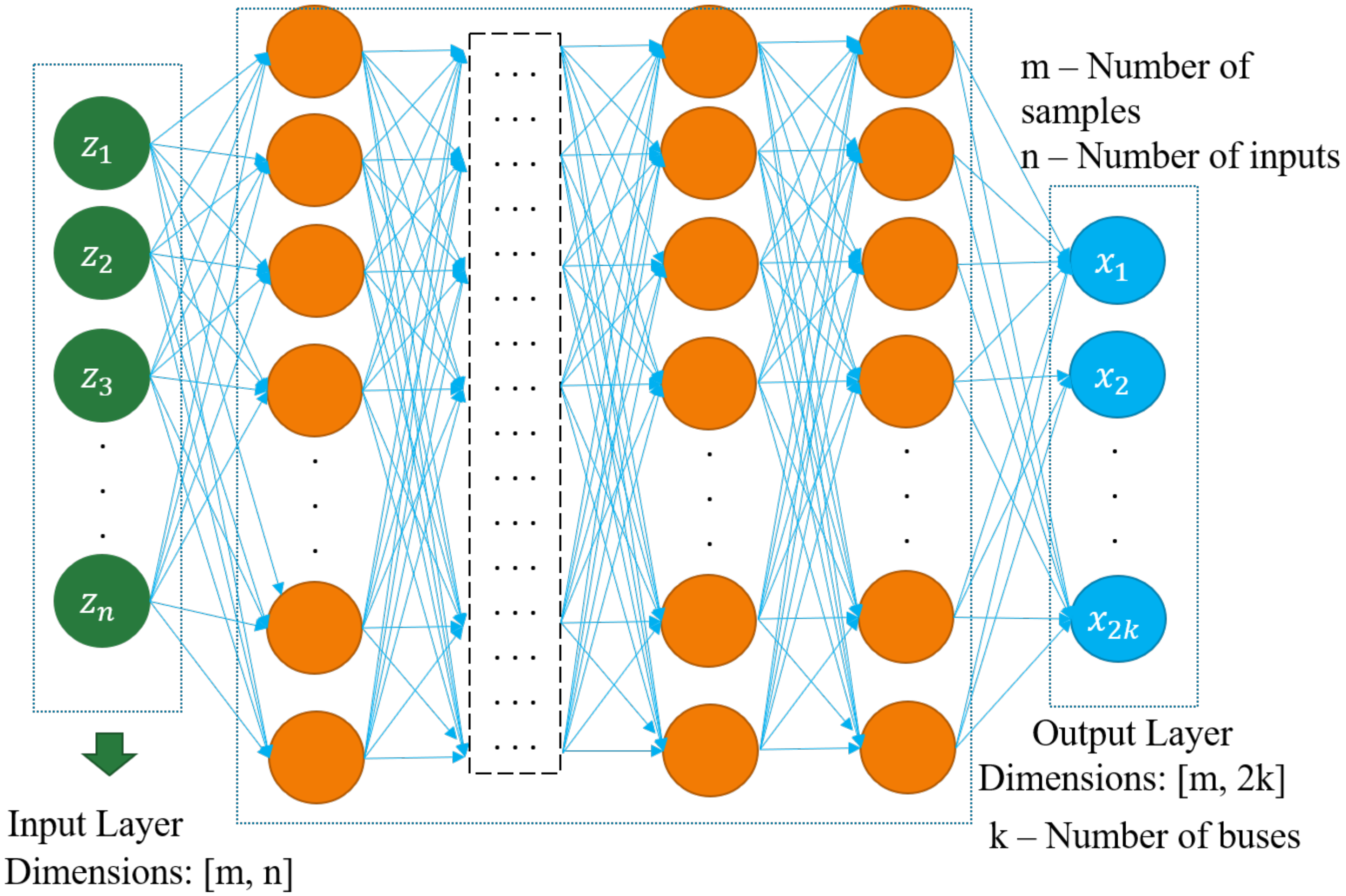
- Model Independent
- Independent of Measurement Error Distribution
- Overcomes SCADA/PMU Synchronization Issues
- Achieves Full System Observability with Limited Number of PMUs
- High Speed

Deep Neural Network-based State Estimator (DeNNSE)



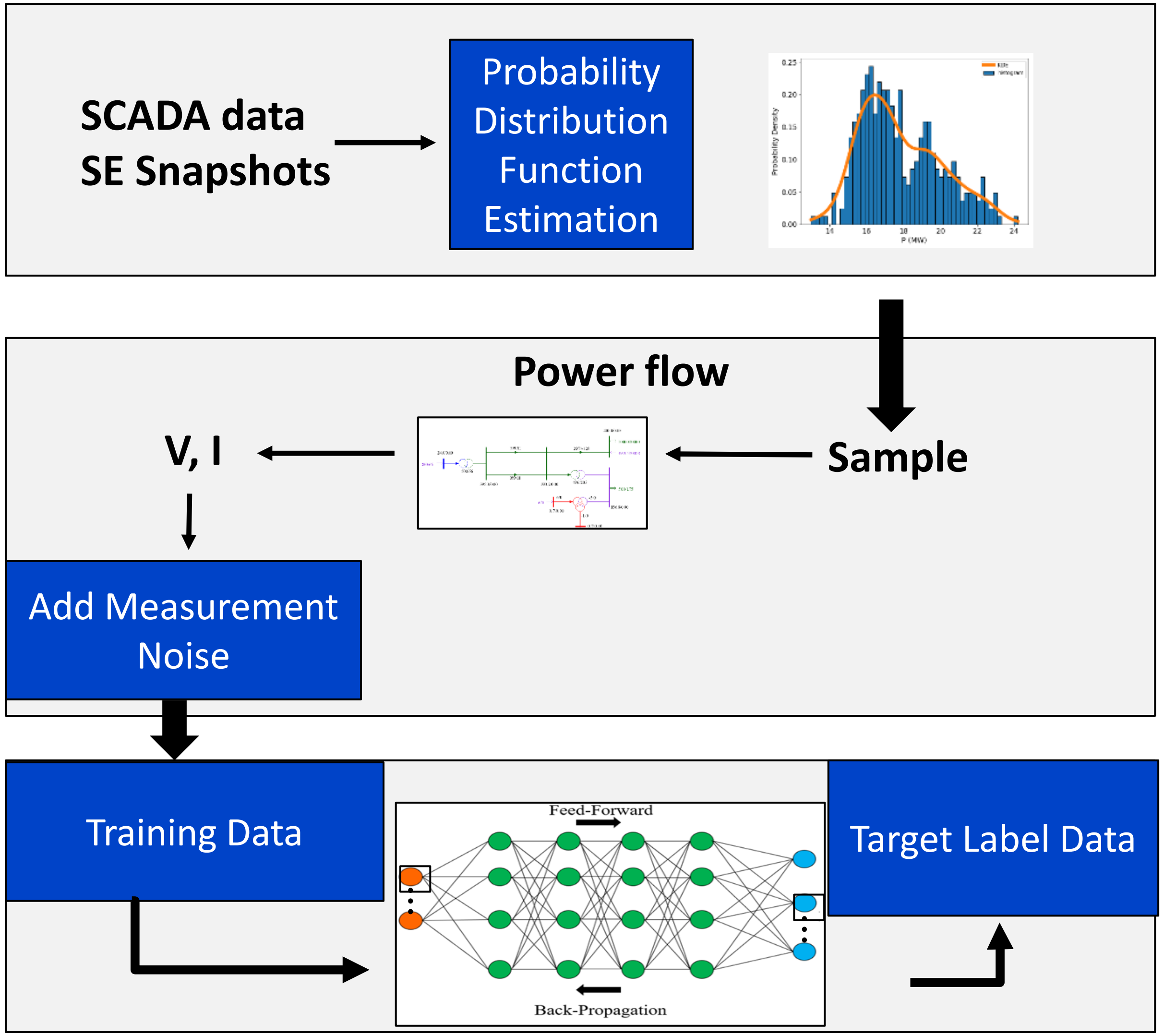
Deep Neural Network (DNN)

- DNN Input: PMU measurements
- DNN Output: States of the system
- Target accuracy:
  - <0.1% error in magnitude
  - <0.5° error in angle



DNN Training

- Collect historical SE data (Load, generation, system model)
- Probability distribution function fitting
- Monte Carlo sampling and PF/OPF solution
- Embed noise functions to mimic instrumentation errors: “Synthetic Measurements”
- Identify dominant topologies
- Train DNN hyperparameters for base topologies and specific PMU placement

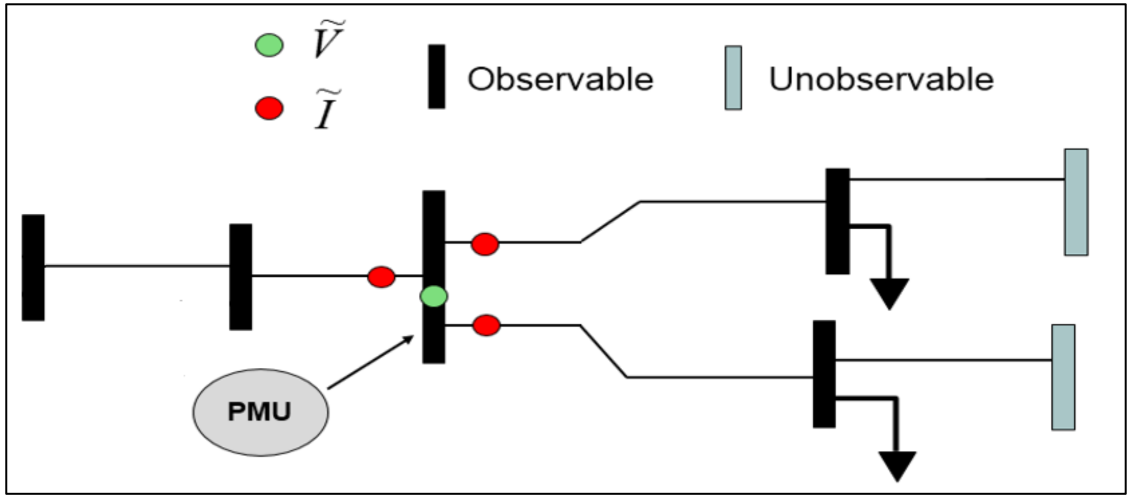


LSE vs ML-SE - Topological Observability

Full Grid Observability with Limited Number of PMUs

- Linear State Estimation (LSE): number of estimated states depends on topological observability from PMUs
- ML based SE: entire system state estimation without need for topological observability

PMU Observability

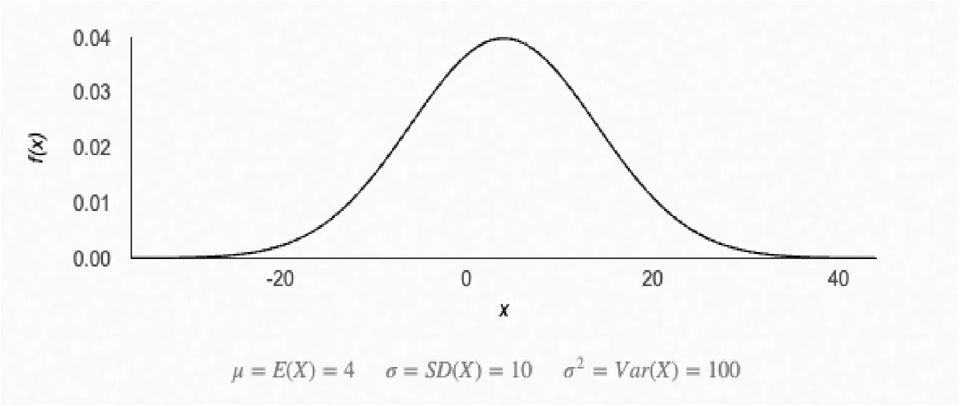


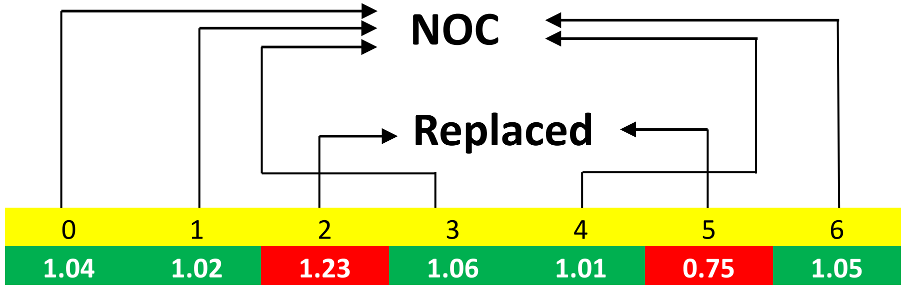
IEEE 118 Bus System – Estimation Error		
Scenario / Metric	LSE 32 PMUs	ML-SE 13 PMUs
Voltage Magnitude	0.00100 p.u.	0.0010 p.u.
Voltage Angle	0.00199 rad	0.0020 rad

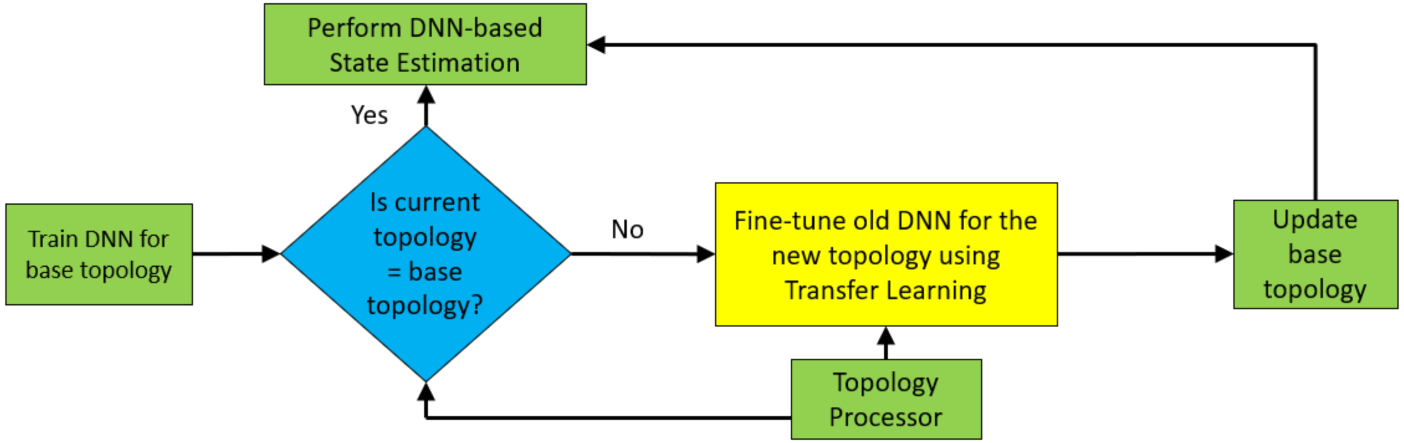
Bad/Missing Data & Topology Changes

- Bad/Missing data detection based on Wald Test
- Bad/Missing data replacement with Nearest Operating Condition (NOC) from training dataset
- Transfer Learning used for DNN update when topology changes

Bad Data







TVA Case Study

Data Received from TVA

State Estimator Cases

- PSS/E .raw files from July 1 to December 31 (6 months)
- 2 files for each day (at 2:00 PM and 2:30 PM) → 366 files
- The TVA area was chosen for this study

PMU Measurements

- PMU data for 5 days of 5 months (2:00 PM – 3:00 PM in every file)

Aug. 15 | Sep. 15 | Oct. 15 | Nov. 15 | Dec. 15

- PMU measurement data

V_{mag} | V_{ang} | ~~Freq.~~ | I_{mag} | I_{ang}

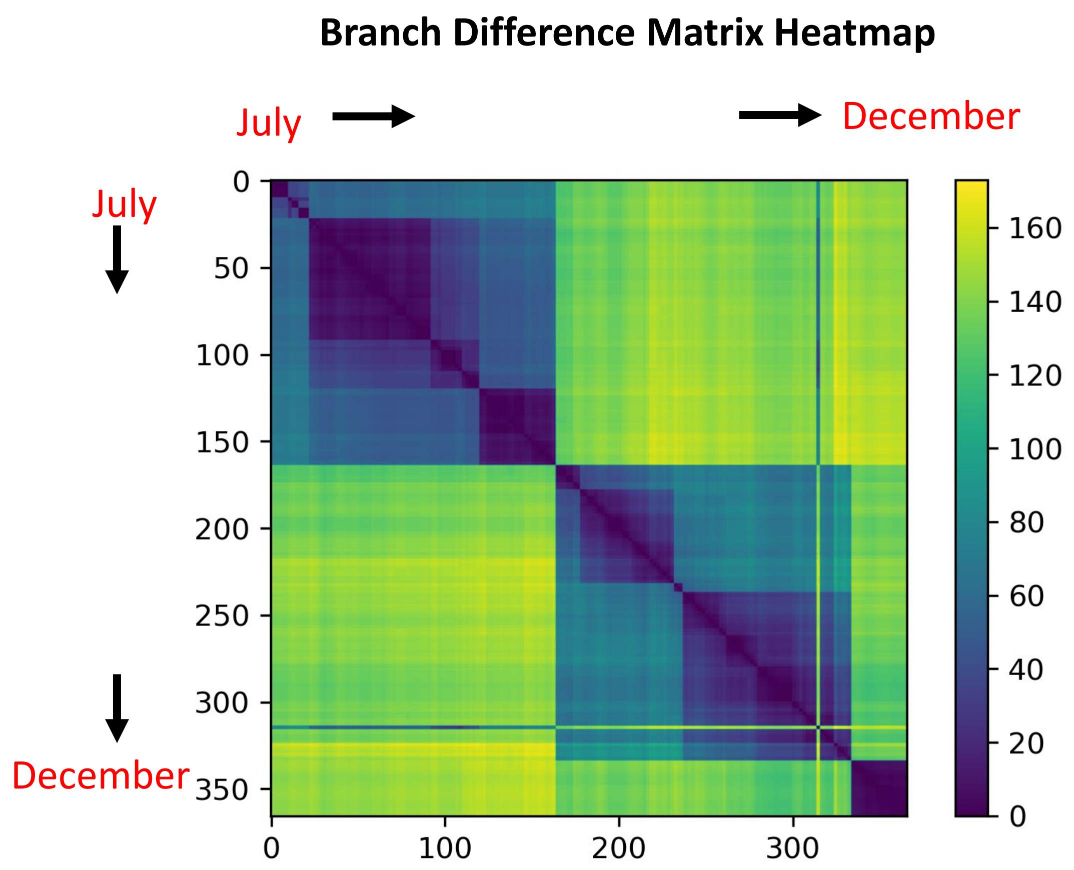
- PMU data resolution: 1 sample/second
- 709 voltage and current measurement channels each

kV Level	#PMUs	#Substations
500	130	29
345	3	1
230	15	5
161	517	92
<=138	44	19

PMU Observability: 20-25%

Topology Identification

- Topology clustering
  - Branch difference matrix for consecutive cases
  - Applied K-means clustering to the matrix



Cluster	Cases in each Cluster	Days in each Cluster
T_1	Case 1 to Case 22	July 1 to July 11
T_2	Case 23 to Case 92	July 12 to August 15
T_3	Case 93 to Case 120, Case 314, Case 315	August 16 to August 30, Dec. 10
T_4	Case 121 to Case 164	August 29 to Sep. 21
T_5	Case 165 to Case 178	Sep. 22 to Sep 28
T_6	Case 179 to Case 236	Sep 29 to Oct 27
T_7	Case 238 to Case 278	Oct 28 to Nov 17
T_8	Case 279 to Case 334 (excluding 314, 315)	Nov 18 to Dec 20, excluding Dec. 10
T_9	Case 335 to Case 366	Dec 21 to Dec 31

DeNNSE Training Input

- DNN requires a large amount of data (big data) to learn the mapping relations between the input features and the output variables

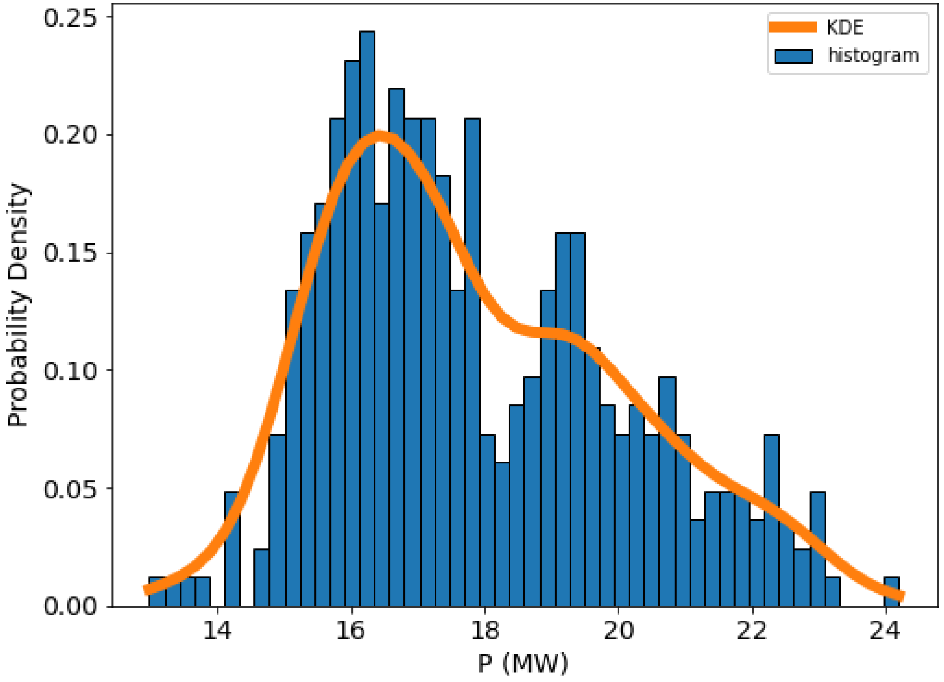
P_{load}, Q_{load} (from SCADA SE)

↓

Kernel density estimation (KDE)

↓

$P_{load\text{-}training}$ $Q_{load\text{-}training}$ → Power flow → $V_{training}$ $I_{training}$



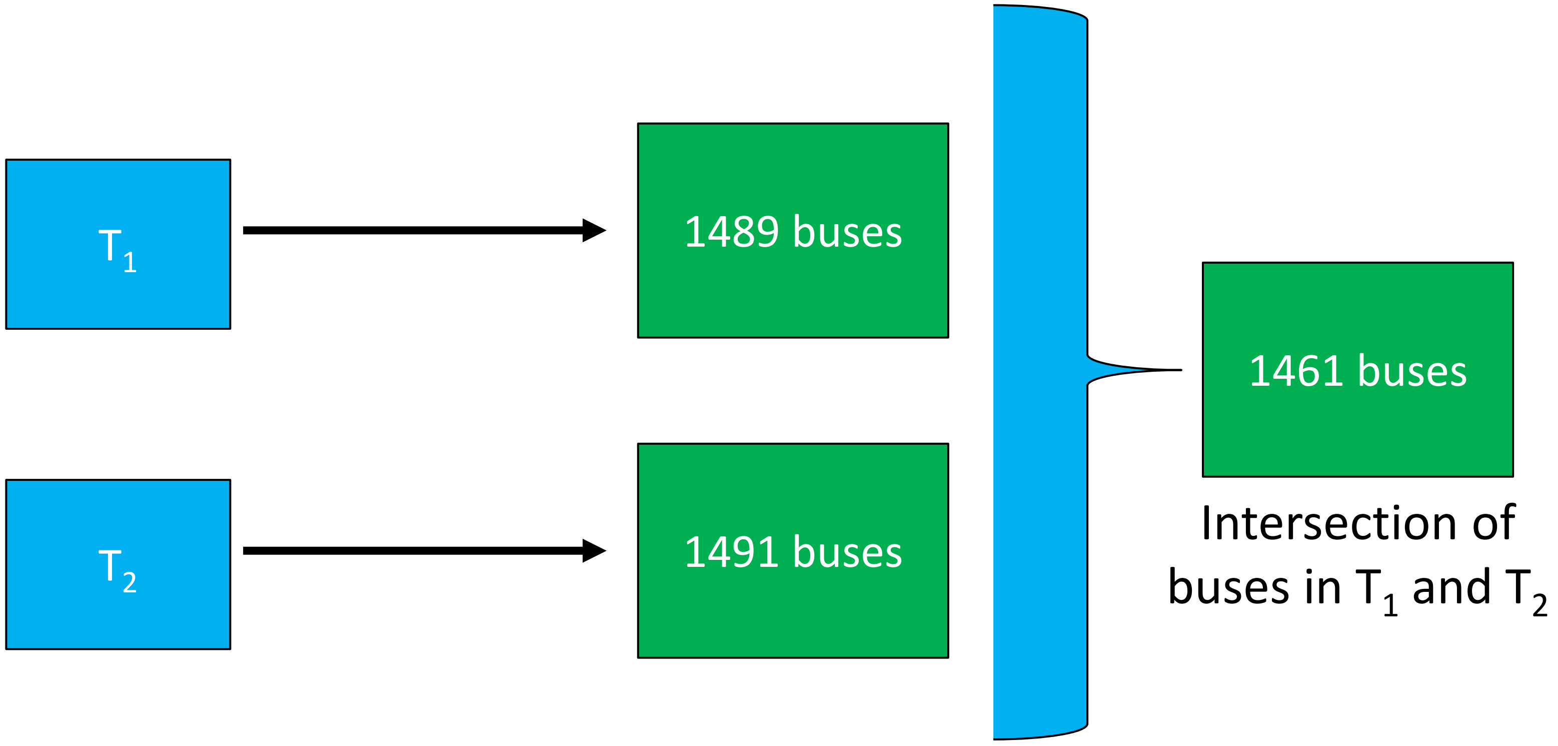
Input Features

- 687 Voltage phasors
- 447 Current phasors

- From the obtained probability density functions (PDFs), 8,000 samples were generated for each feature

DeNNSE Training Output

- DNN output: estimated states are voltages at 69 kV and higher, within the TVA area



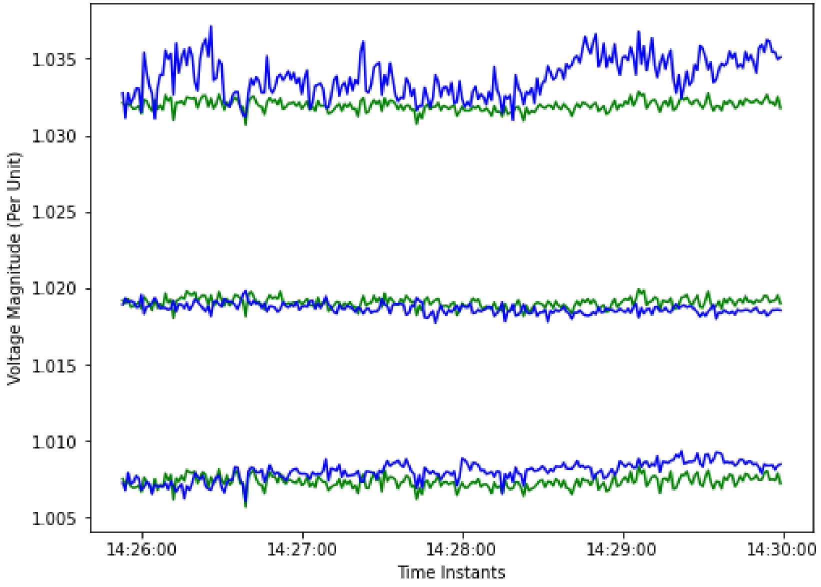
Voltage level (kV)	#States/Buses
500	52
345	1
230	17
161	1168
138	6
115	45
69	172

- The output dimension is determined considering the buses that are common to T_1 and T_2

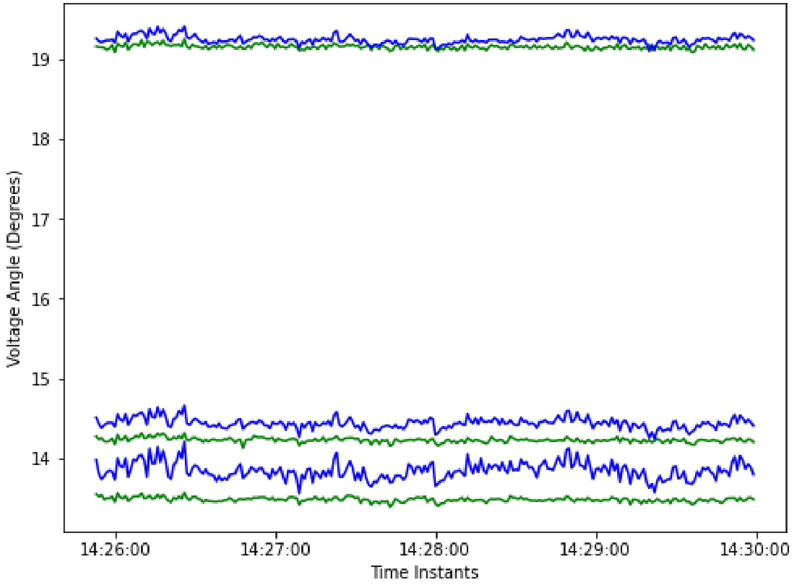
DeNNSE Results - Training for T_2

- DNN is trained and tested on T_2
- PMU data from Aug 15: 2:25 PM-2:30 PM is used for testing

Voltage magnitude (Per unit)



Voltage angle (Degrees)



PMU Measurements   Estimated States

DeNNSE Results Summary with and without Transfer Learning

- To analyze the effectiveness of the transfer learning, two cases are studied
  - DeNNSE is trained and tested for T_2
  - DeNNSE is trained on T_1, adapted to T_2 using transfer learning, and then tested on T_2
- The PMU data from Aug 15: 2:25 PM-2:30 PM is used for testing in both cases

DeNNSE trained for T_2

Voltage Magnitude Error (%)	Voltage Angle Error (Degrees)
0.212	1.26

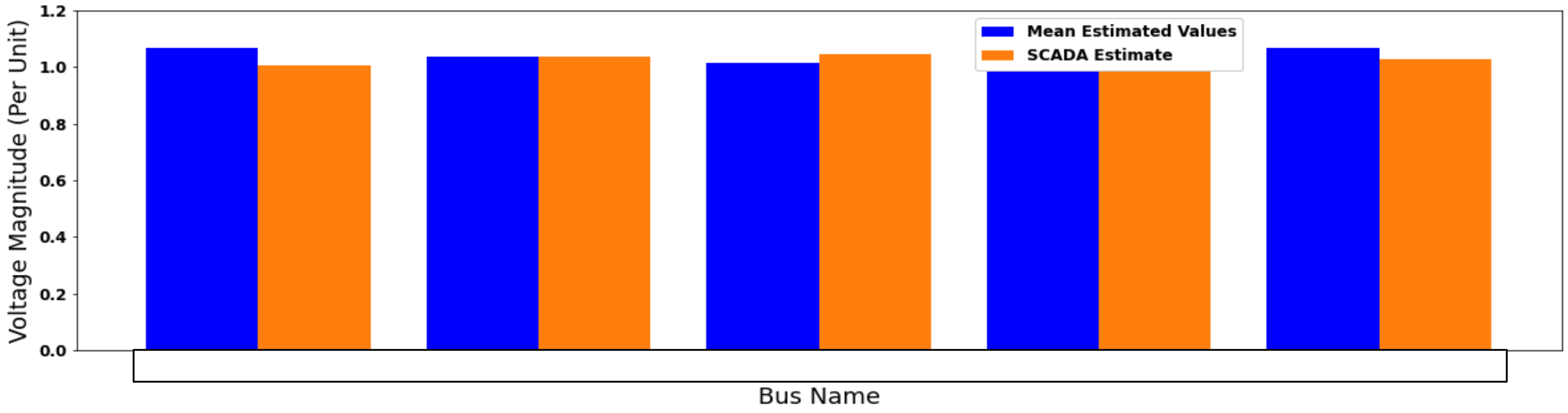
DeNNSE trained using T_1 and updated using Transfer Learning for T_2

Voltage Magnitude Error (%)	Voltage Angle Error (Degrees)
0.228	1.29

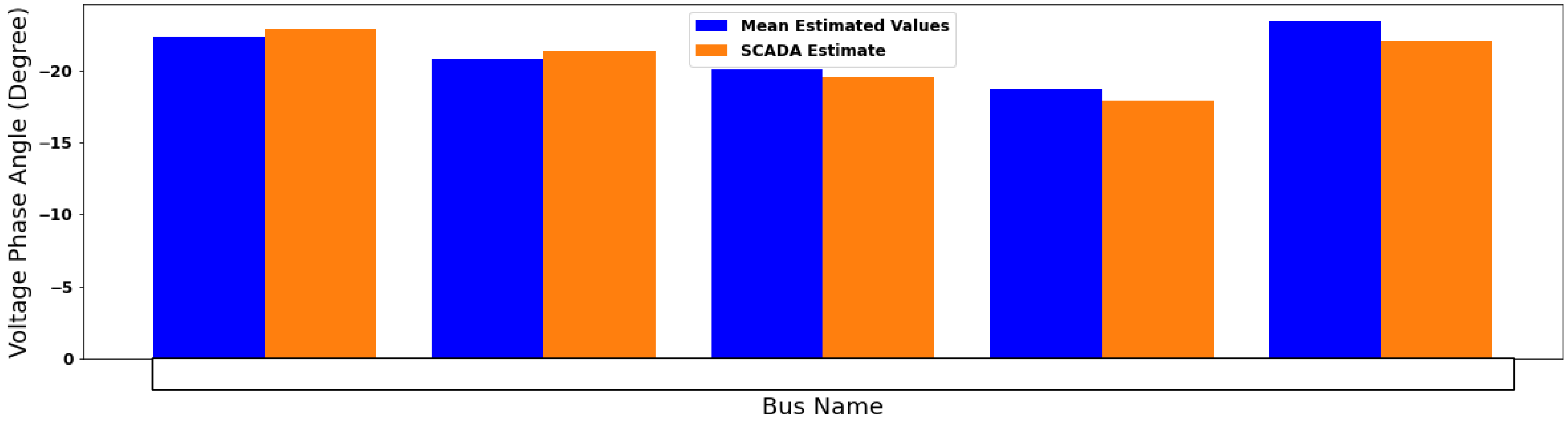
DeNNSE Results - Comparison with SCADA State Estimator - 500kV

- Comparison between SCADA-SE and DeNNSE for August 15th
- SCADA-based state estimator output at 2:30 PM is compared with the mean value of DeNNSE obtained using PMU data between 2:25 PM-2:30 PM

Voltage Magnitude



Voltage Phase Angle



Summary

DeNNSE: ML & PMU-based state estimation

1) Achieves full system observability with limited number of PMUs
2) High speed
3) Avoids synchronization challenges between PMU and SCADA data
4) Model used only for training

DeNNSE applied to the TVA system

Satisfactory DeNNSE results despite the limited PMU coverage

Project Participants

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