Distribution system state and topology monitoring using a mixed set of measurements

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Challenges

- Lack of Observability
  - Spatial : Not enough PMUs, not enough SCADA measurements
  - Temporal : AMI measurements (low sampling rate)
- Fast and scalable estimation method to handle large scale systems
- Detect and identify switched lines (unreported)

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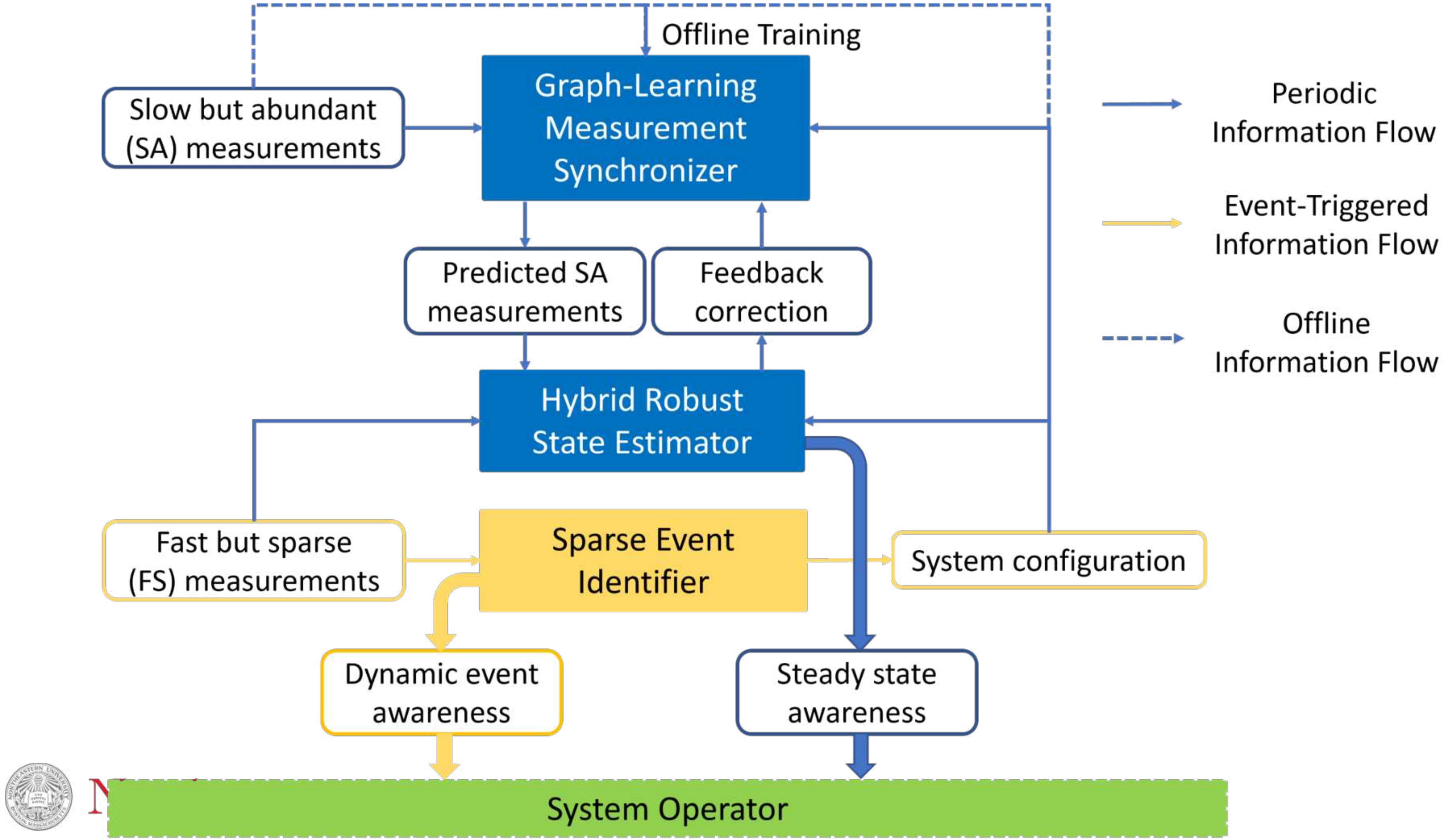
Objectives

- Utilize *Slow but Abundant* (SA) measurements received every 30-minutes to predict *Fast and Sparse* (FS) measurements every few minutes
- Execute a fast and scalable state estimator using the predicted measurements
- Detect and identify changes in topology due to switched but unreported lines as a result of fault clearing.

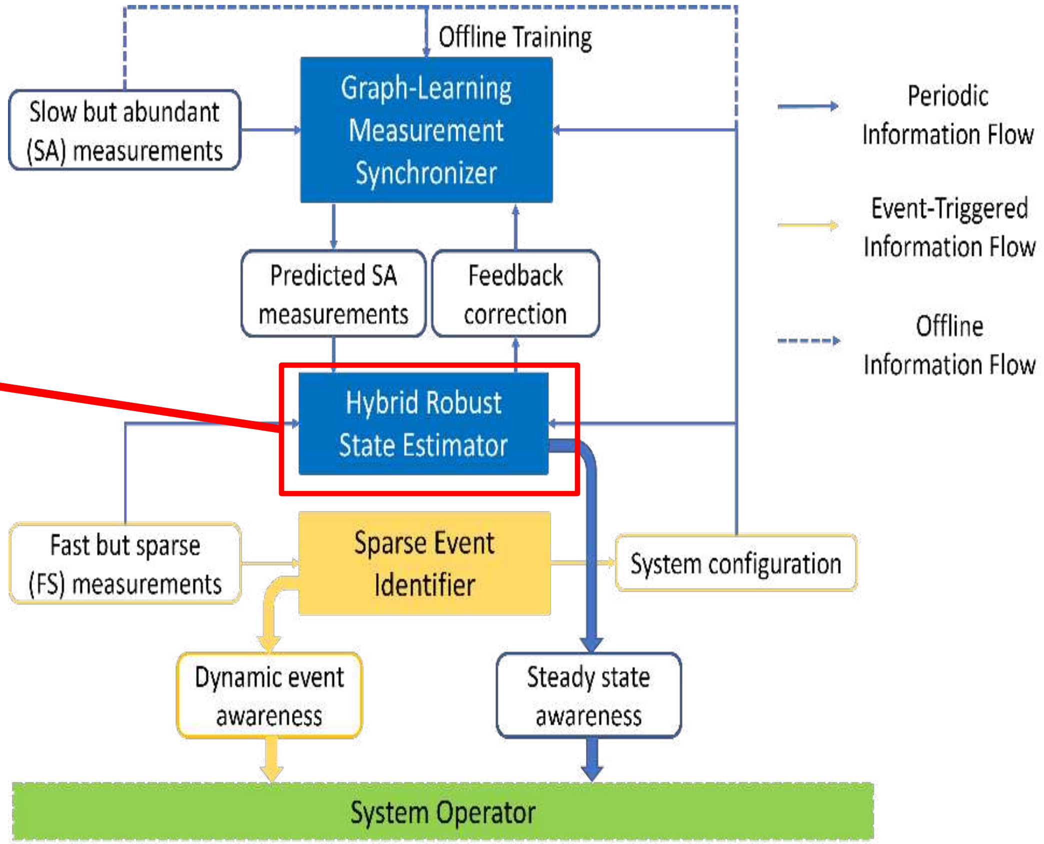
PROPOSED FRAMEWORK FOR MONITORING THE POWER GRID



Robust Scalable State Estimator

Robustness of WLAV Estimator:

- **Automatically rejects gross errors provided that there are sufficient measurements locally at the bus of interest.**
- **Measurement redundancy is reduced at the boundary of neighboring areas since boundary injections cannot be used !**
- **Hence, states associated with boundary buses cannot be reliably estimated due to low redundancy around them.**



Proposed solution:

Make copies of the overall system

Partition each copy in a different way such that every bus appears as an "internal bus " in at least one copy.

Solve partitions of all copies in parallel and consolidate the solutions.

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Scalable Implementation

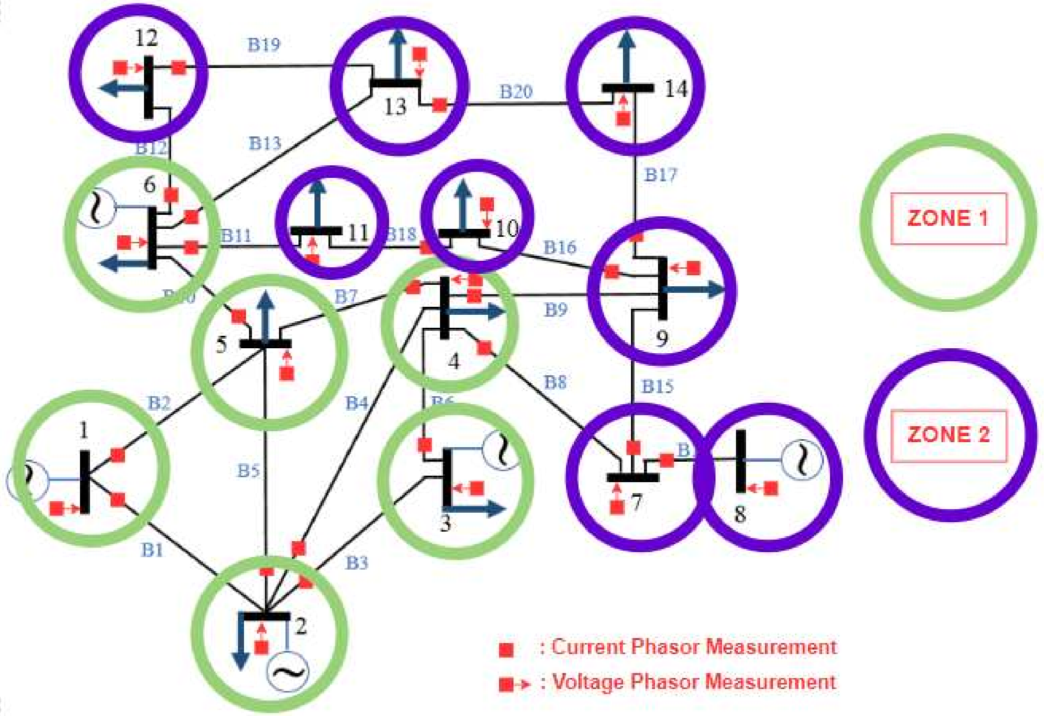
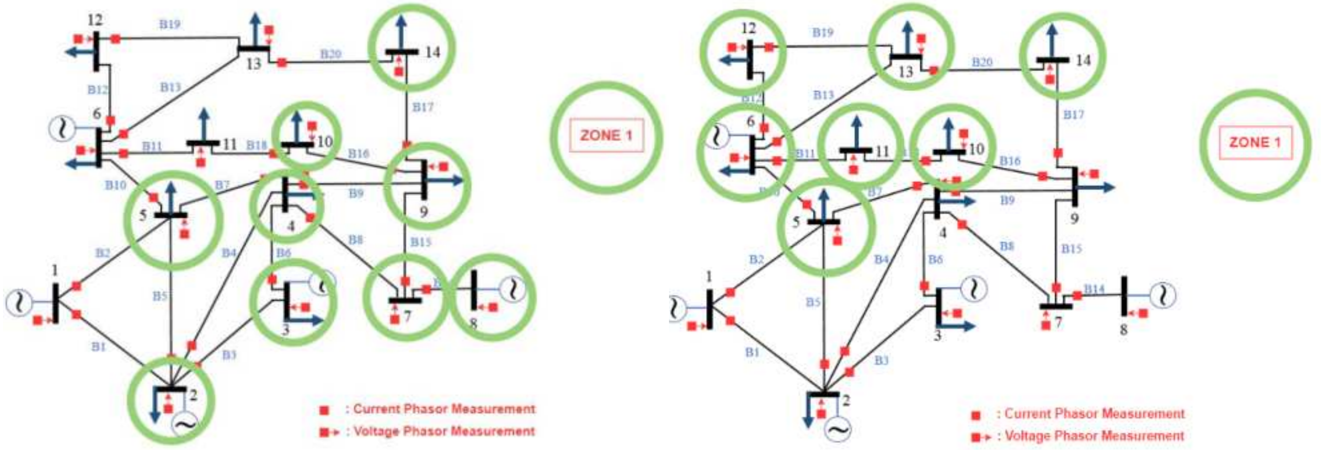


Fig A1 : IEEE 14 bus system partitioned into 2 zones



(a) (b)

Fig A2: Additional zones generated in IEEE 14 bus system (a) in Copy 2, (b) in Copy 3.

Table A1 : Internal and boundary buses after partitioning

Copy \ Bus	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	I	I	I	B	I	B	B	I	B	I	B	B	B	I
2	NA	NA	NA	NA	B	I	NA	NA	NA	B	I	I	I	B
3	NA	B	I	I	B	NA	I	I	I	B	NA	NA	NA	B

$$\hat{x}_i = \left(\frac{1}{n^*_{zones}}\right) \cdot \sum_{c=1}^{n^*_{zones}} x^c_{i,internal}$$

where $x^c_{i,internal}$ is the estimation of the state of an internal bus in copy c, and n^*_{zones} is the number of zones that $\hat{x}_i$ is the state of an internal bus.

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Computational Performance

TEST SYSTEMS:

- **MESHED** VLSN has **12589 buses and7529 branches,**
- **RADIAL** VLSN has **12589 buses and 12588 branches**.

LAV Based state estimation tests are conducted in MATLAB environment using the Massachusetts Green High Performance Computing Center facilities which houses;

- 128 Core, 2.4 GHz Intel CPUs, 8 GB RAM.

Table A2: The performance of MPD SE in Meshed VLSN

Number of Zones in the Original Copy	1	4	8	16	32	48
Computational Time (seconds)	194.92	31.20	12.11	2.59	1.26	0.70
Number of Required Cores	1	8	20	36	75	104

Table A3: The performance of MPD SE in Radial VLSN

Number of Zones in the Original Copy	1	4	8	16	32
Computational Time (seconds)	17.70	4.45	2.27	1.08	0.61
Number of Required Cores	1	5	11	21	42

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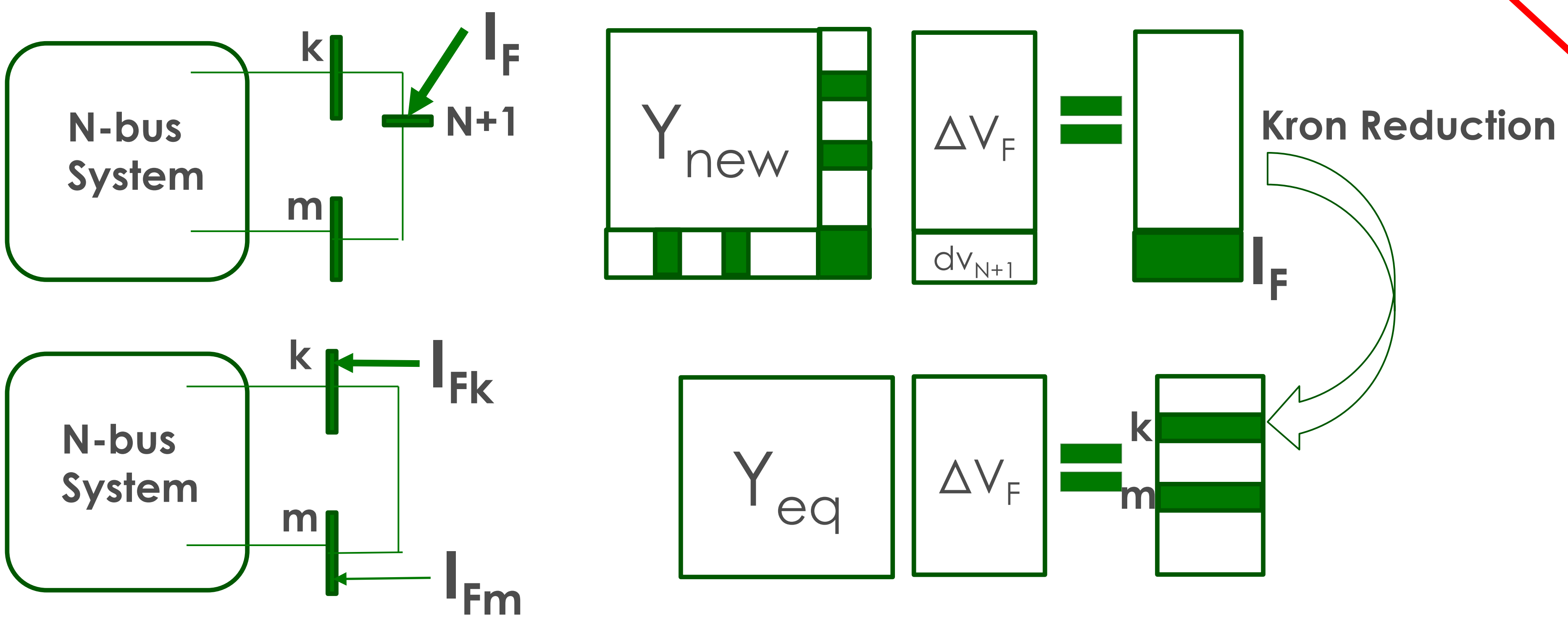
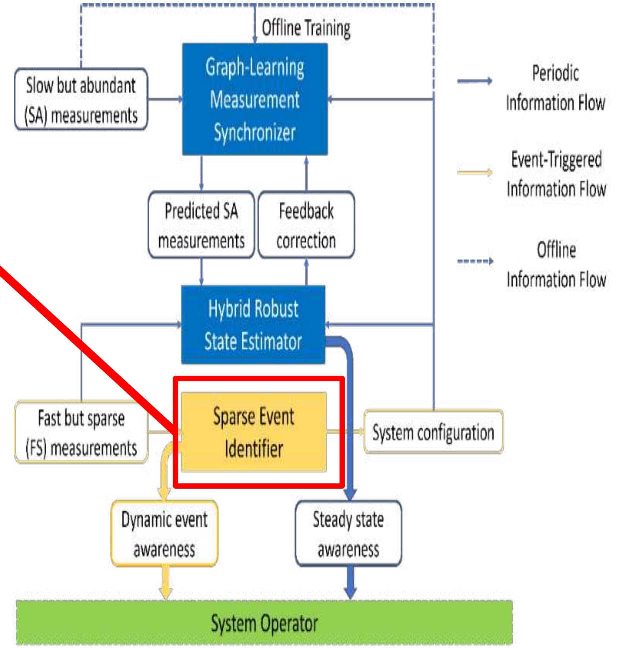
Improved Performance via Closed-loop SE Feedback

TABLE IV: FS measurement prediction results with different data over the first group of bus voltage control and distribution system topology information in terms of MAE.

Data	Active Power	Reactive Power
Clean	11.9233	5.7904
Corrupted	29.1641	9.7516
Residual-Corrected	13.9248	6.2632

Fault Detection and Identification





It can be shown that $Y_{eq} = Y_0$!

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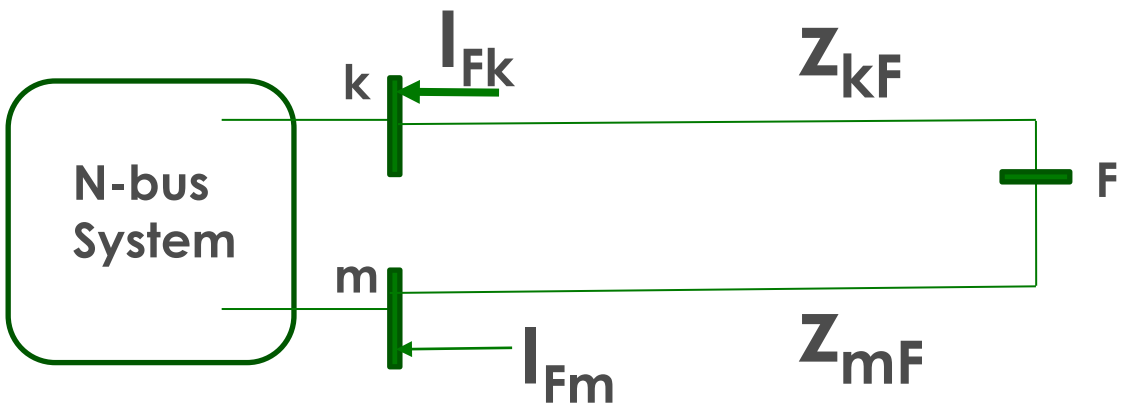
Virtual Injections and Fault Location

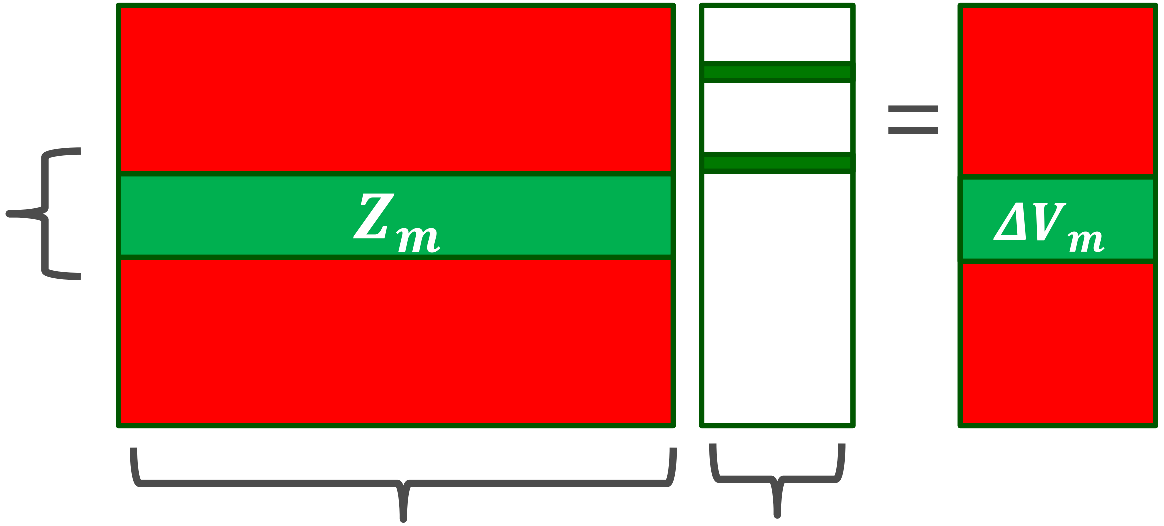


It can be shown that:

$$I_{Fk} + I_{Fm} = I_F \qquad \frac{I_{Fk}}{I_{Fm}} = \frac{z_{mF}}{z_{kF}}$$

Fault Location Problem ⟷ Sparse Regression

Buses with PMU measurements



$[Y_0]^{-1} = Z_{bus}$ $\quad I_f$

$$[Z_m][I_f] = [\Delta V_m]$$

Very Sparse

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Fault Detection via Sparse Estimation (LASSO)

Undetermined Set of Equations

$$[\boldsymbol{X}][\boldsymbol{\beta}] = [\boldsymbol{y}] \xrightarrow{\text{Fault Equivalent}} \underbrace{\boldsymbol{Z_r}}_{n \times p} \; \underbrace{\boldsymbol{I_f}}_{p \times 1} = \underbrace{\boldsymbol{\Delta V_r}}_{n \times 1}$$

where,

- k out of p entries are known to be significantly larger than the remaining $(p-k)$ entries.
- Z is the bus impedance matrix.
- ΔV represents the post – pre fault voltage phasors.
- I_f is the virtual current injection vector.

Least Absolute Shrinkage and Selection Operator (LASSO)

$$\Delta \mathrm{I}_{\boldsymbol{f}} := \min_{\Delta I_{\boldsymbol{f}}} \left\| \Delta \boldsymbol{V} - \boldsymbol{Z_r} \Delta I_{\boldsymbol{f}} \right\|_2^2 - \lambda \left\| \Delta I_{\boldsymbol{f}} \right\|_2$$

R. Tibshirani, “Regression shrinkage and selection via the lasso,” Journal of the Royal Statistical Society. Series B (Methodological), pp. 267–288, 1996.

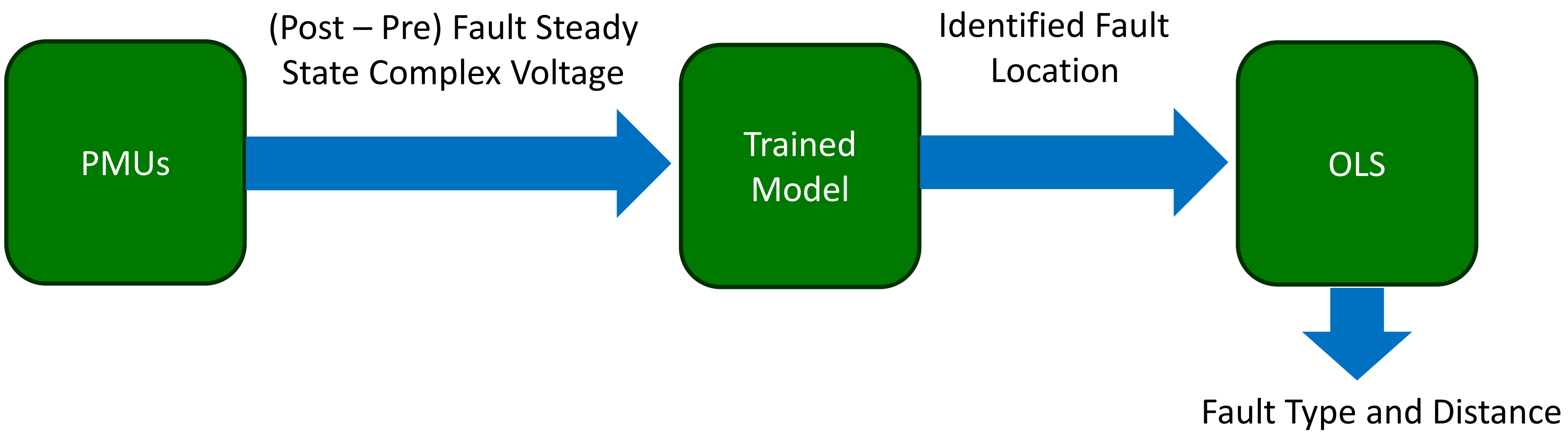
Data-Driven Methods

- Convolutional Neural Network (CNN):
  - Offers a distinct advantage in classification problems.
  - Can effectively learn and recognize spatial patterns in input features.
  - Is sensitive to variations in input data, making it ideal for detecting subtle changes in voltage phasors that carry information on faults.

- Multi-Layer Perceptron (MLP):
  - Captures complex relationships within the data.
  - Generally, involves simpler computations than CNN, offering faster training and prediction times.

Fault Detection and Localization

- Two-step process:
  - Step 1 – Identify: Collect voltage differences of post and pre fault event and apply data-driven methods to determine the location of the faulted branch.
  - Step 2 – Localize: Upon identification of the fault location, apply OLS Estimation to pinpoint the fault location on the identified faulted branch.



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Test Results: Fault Identification

Total Fault Cases	Utilized PMU Number	Used Method	Detected Faulted Branches	Performance
4116	50	**MLP**	3146	**76.43%**
4116	50	**LASSO**	3907	**94.92%**
4116	50	**CNN**	4092	**99.41%**

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Test Results: Fault Localization

Identification Method	Detected Locations	Utilized PMU Number	Localization Method	Detected Fault Type and Distance	Performance
MLP	3146	50	OLS	3092	**98.28%**
LASSO	3907	50	OLS	3860	**98.80%**
CNN	4092	50	OLS	4034	**98.58%**

Contributions

- ML assisted measurement prediction combined with robust state estimation Fast state estimation at scan rate estimation performance while retaining robustness against bad data.

- LASSO can effectively detect and identify faults for most branches. However, data driven methods such as CNN can aid fault detection and localization method for cases enabling ML assisted state estimation to remain robust against topology errors.

- Fast and robust state estimation is feasible while remaining scalable provided that there are sufficient cores running in parallel.