Artificial Intelligence for Robust Integration of AMI and PMU Data for Distribution Grid Monitoring

Priyabrata Sundaray and Yang Weng
Arizona State University

Introduction

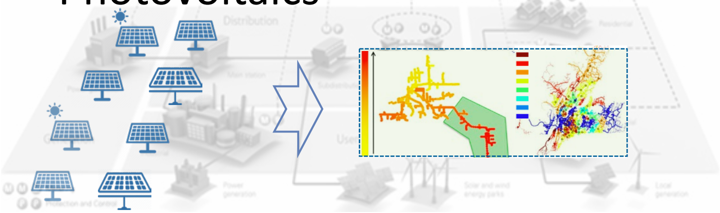
Motivation and Challenges
Big Picture of Proposed Solutions
Traditional Approaches

Motivation

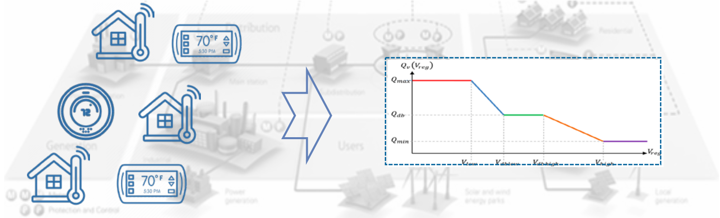
Chargers

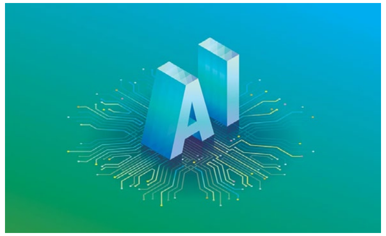
Electric Vehicles

Photovoltaics



Smart Thermostat



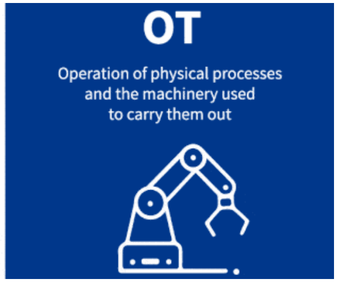


Technology

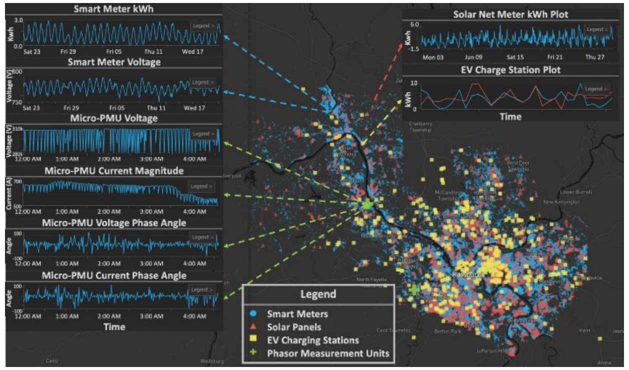
Data Management System

Solve

Data

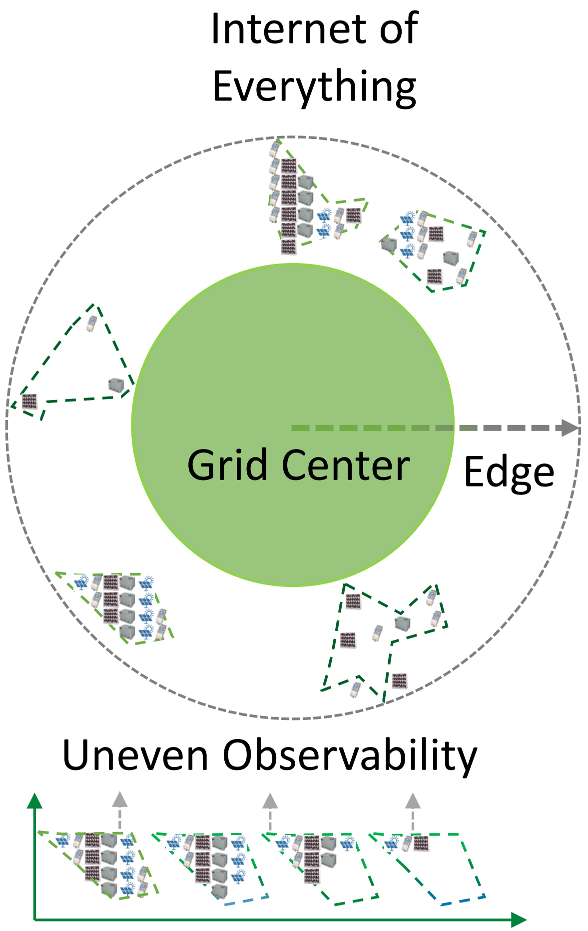


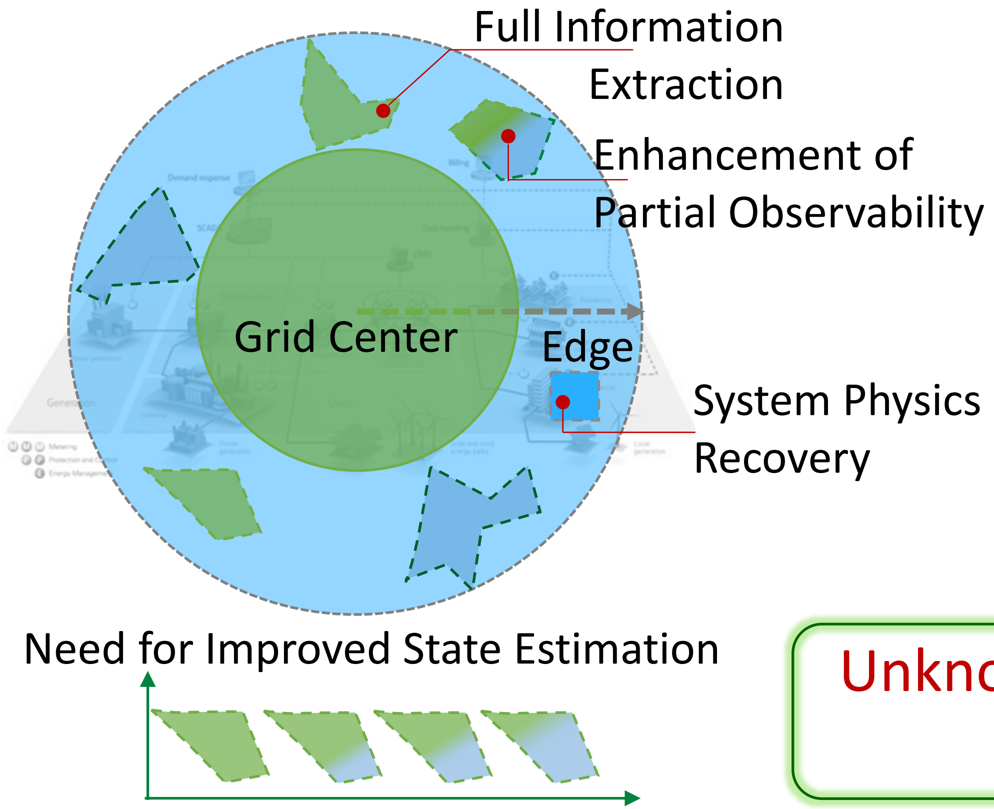
Planning, Monitoring, Protection, and Control.

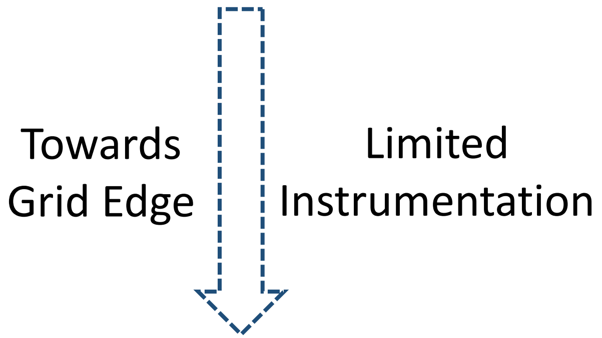


AI: Artificial Intelligence.
IT: Information Technology.
OT: Operational Technology.

Challenges: Limited Instrumentation and Partial Observability







Unknown system topology and line parameter.

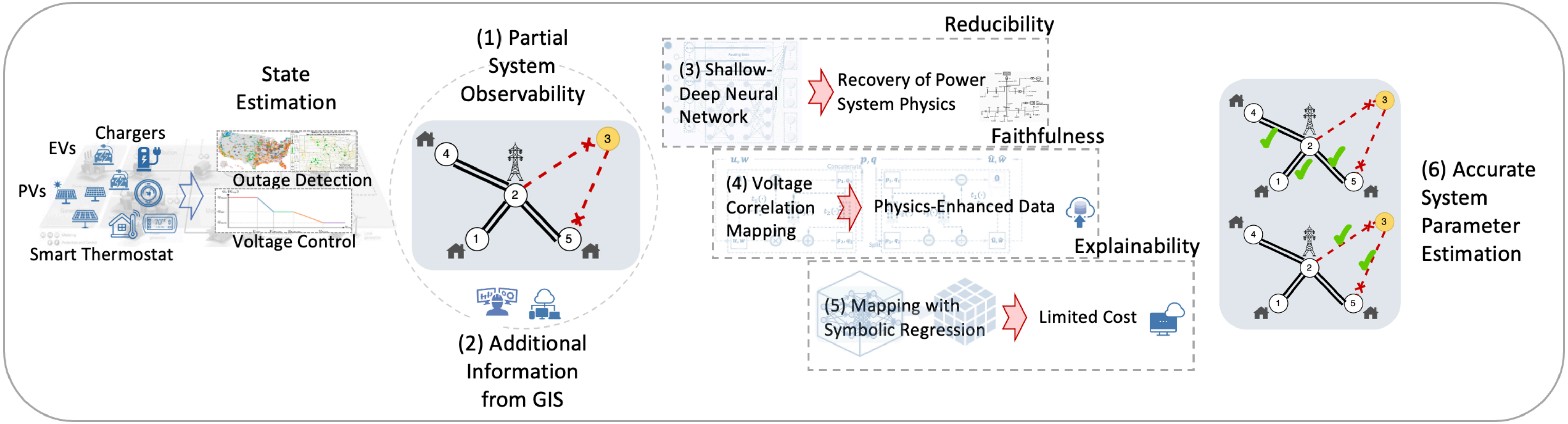
Distribution System State Estimation

System physics
Measurement errors

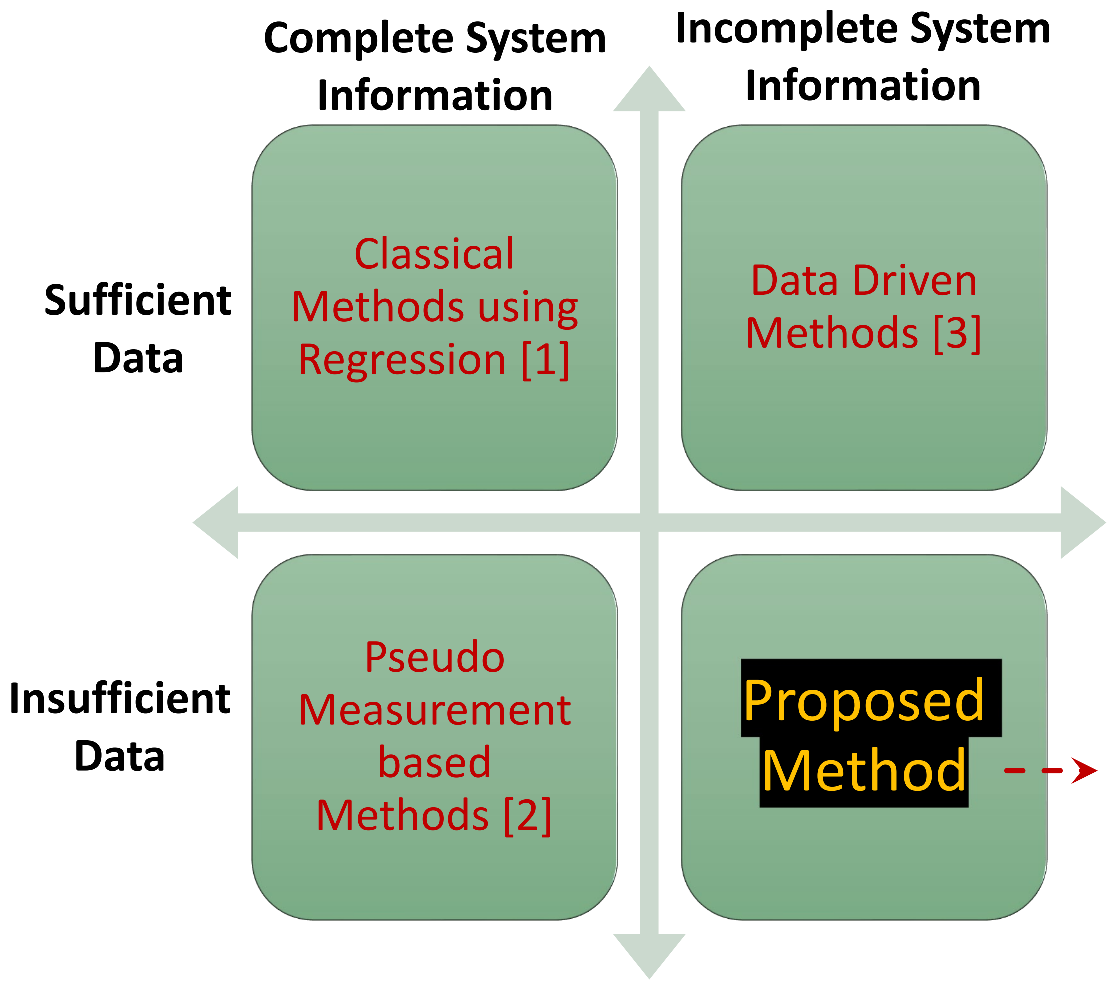
Given: Observations, $y = f(x) + \in$

Objective: To estimate the object of interest, $\hat{x}$ or $\hat{f}$

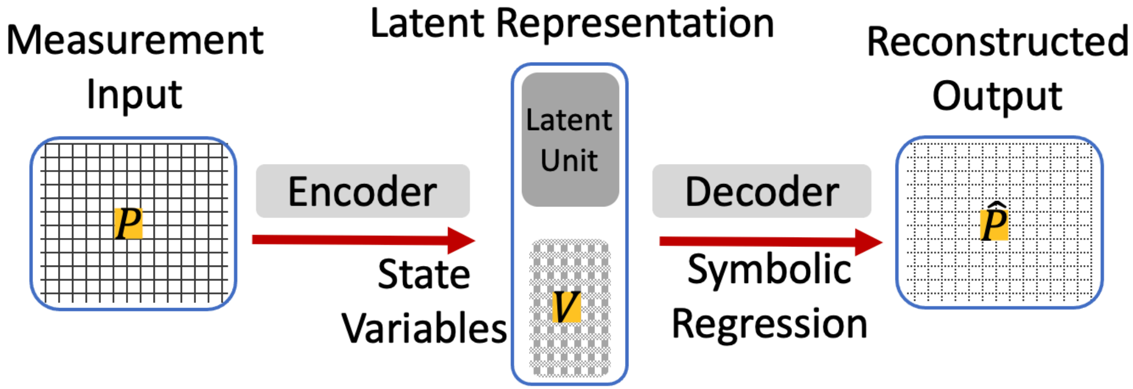
Big Picture of the Proposed Method



Traditional Approaches



Legend	Two-way Information Flow	Explainability
Traditional Methods	No	No
Proposed Method	Yes	Yes



[1] Shweppe JW, Rom D. Power system static state estimation: Part I, II, and III. Power Industry Computer Conference. 1969.
[2] Clements KA. The impact of pseudo-measurements on state estimator accuracy. IEEE Power and Energy Society General Meeting. 2011.
[3] Luan W, Peng J, Maras M, Lo J, Harapnuk B. Smart meter data analytics for distribution network connectivity verification. IEEE Transactions on Smart Grid. 2015.

Traditional Approaches

Classical Methods Using Regression

Are the classical methods reliable for sustainable operation of the grid with incomplete knowledge about the distribution network?

Challenge of making decisions under partial information.

[1] Shweppe JW, Rom D. Power system static state estimation: Part I, II, and III. Power Industry Computer Conference. 1969.
[2] Clements KA. The impact of pseudo-measurements on state estimator accuracy. IEEE Power and Energy Society General Meeting. 2011.
[4] Monticelli A. State Estimation in Electric Power Systems: A Generalized Approach. Springer Science & Business Media. 1999.
[5] Baran ME. Challenges in state estimation on distribution systems. IEEE Power Engineering Society Summer Meeting. 2001.

Traditional Approaches

Pseudo Measurement Based Methods

Is it practically feasible to have a rich statistical description of loads and generators?

Challenge of accuracy with incomplete knowledge of the system.

[2] Clements KA. The impact of pseudo-measurements on state estimator accuracy. IEEE Power and Energy Society General Meeting. 2011.
[6] Baran ME, Kelley AW. State estimation for real-time monitoring of distribution systems. IEEE Transactions on Power systems. 1994.

Traditional Approaches

Data Driven Methods

Are the measurement variables of the system reproducible?

Challenge of information lost without an accurate system model assumption.

Auto-Encoder based Methods

Lack of physical constraint in the latent representation layer → Lack of explainability.

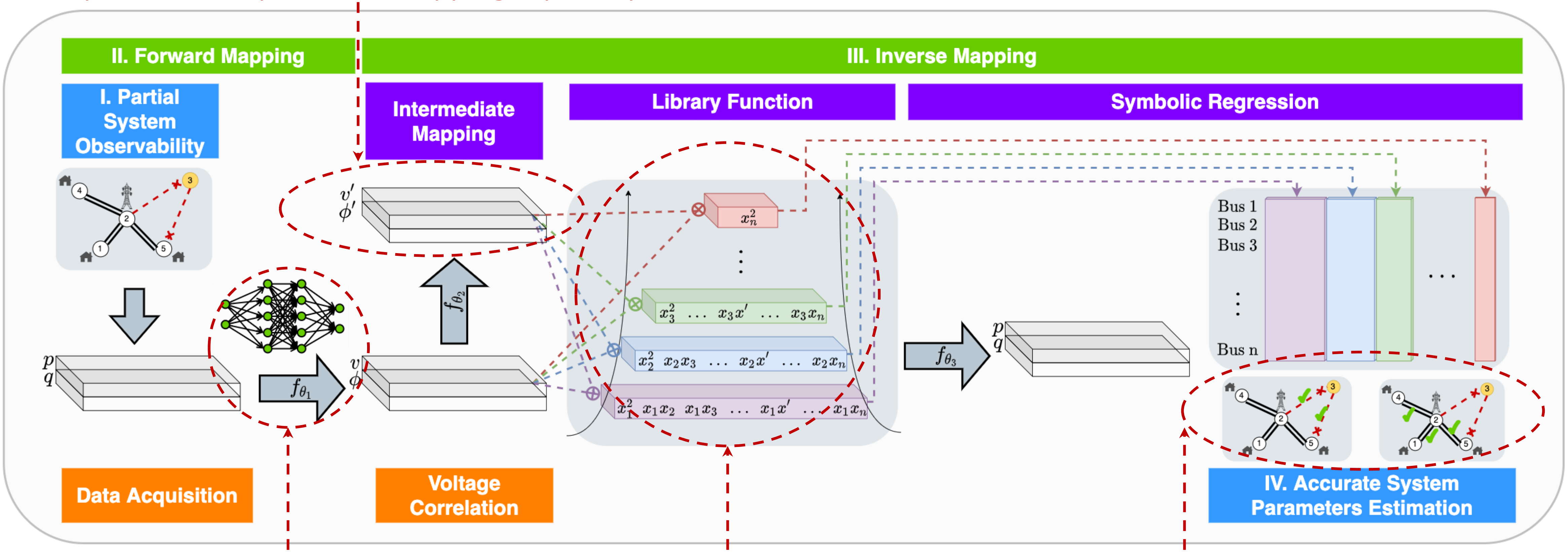
[3] Luan W, Peng J, Maras M, Lo J, Harapnuk B. Smart meter data analytics for distribution network connectivity verification. IEEE Transactions on Smart Grid. 2015.
[7] Muller HH, Rider MJ, Castro CA, Paucar VL. Power flow model based on artificial neural networks. IEEE Russia Power Tech. 2005.
[8] Singh R, Manitsas E, Pal BC, Strbac G. A recursive Bayesian approach for identification of network configuration changes in distribution system state estimation. IEEE Transactions on Power Systems. 2010.
[9] Hayes B, Escalera A, Prodanovic M. Event-triggered topology identification for state estimation in active distribution networks. IEEE PES Innovative Smart Grid Technologies Conference Europe. 2016.
[10] G. Cavraro, V. Kekatos, and S. Veeramachaneni, "Voltage analytics for power distribution network topology verification," IEEE Transactions on Smart Grid, 2019.

Proposed Method and Result

Two-way Information Flow
Computational Complexity Improvement
Performance Guarantee for Quantifying Uncertainty

Proposed Method: Model-X

Latent nodes capture the unobservability of the system and improve the mapping capability.



Captures physics of the observable subsystem

Library function terms create explainability

Accurate system parameter estimation for all nodes

Combined Optimization: Model X

$$\arg\min_{\psi}\{\| f_{\theta_1}(y_{\mathcal{O}}) - x_{\mathcal{O}} \|_2^2 + \| x_{\bar{\mathcal{O}}} - f_{\theta_2}(x_{\mathcal{O}}) \|_2^2 + \| y_{\mathcal{O}} - w^T \Theta \|_2^2 + \beta \| w \|_1\}$$

Forward mapping using deep learning

Intermediate mapping for voltage correlation

Inverse Mapping using library function creation

Hyperparameter for ℓ_1-regularization

System Parameters

Observable state variables

Unobservable state variables

Observable measurements

Weights of basis function terms

Two-way Information Flow

Forward Mapping Model

Learns:

(i) Learns physics of observable subsystem,

(ii) Infers algebraic coupling between observable measurements.

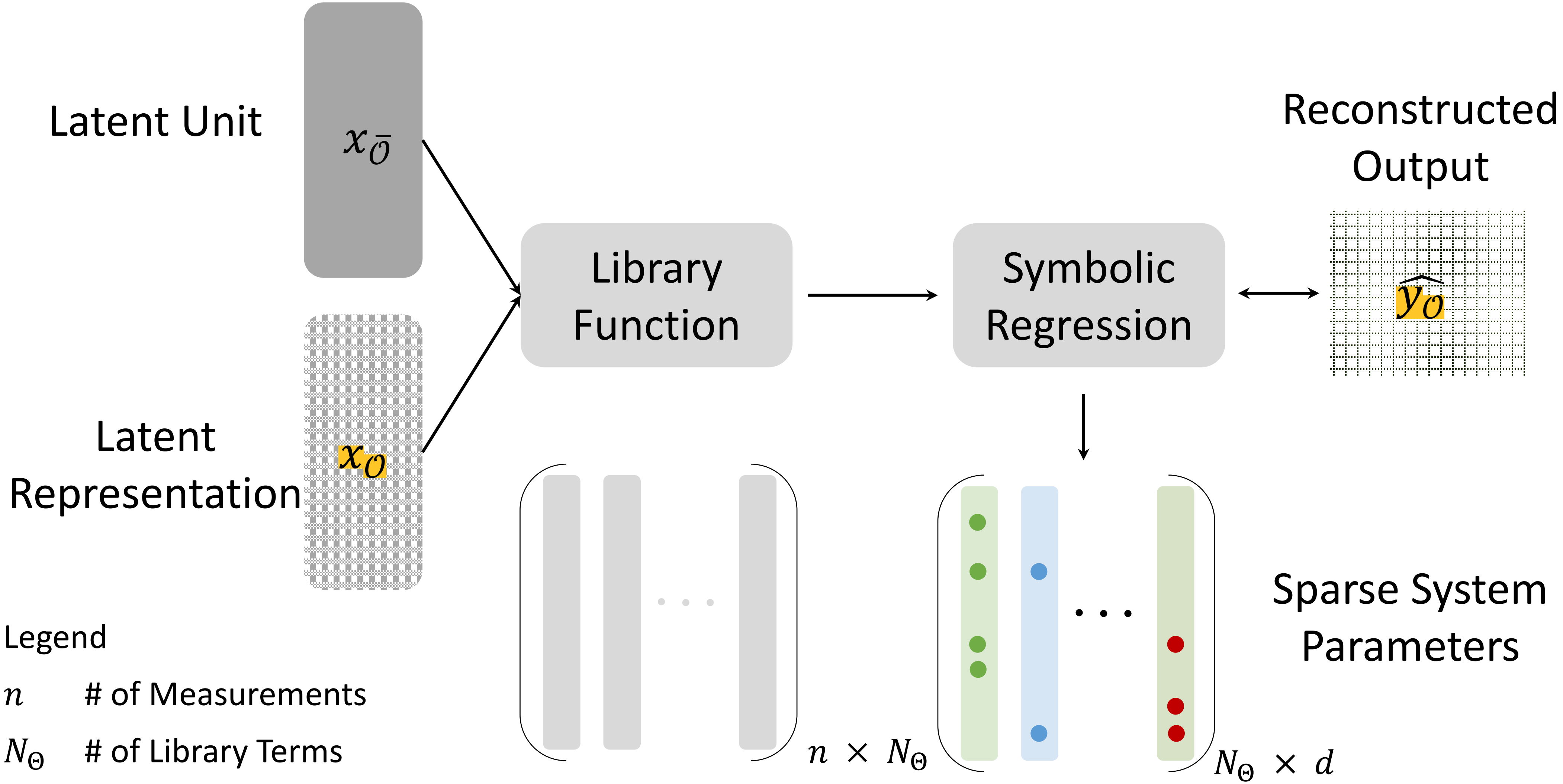
Inverse Mapping Model

Learns:

(i) Learns unobservable subsystem as a latent unit using voltage correlation,

(ii) Estimates system parameter using sparse symbolic mapping function.

Inverse Mapping: Symbolic Regression



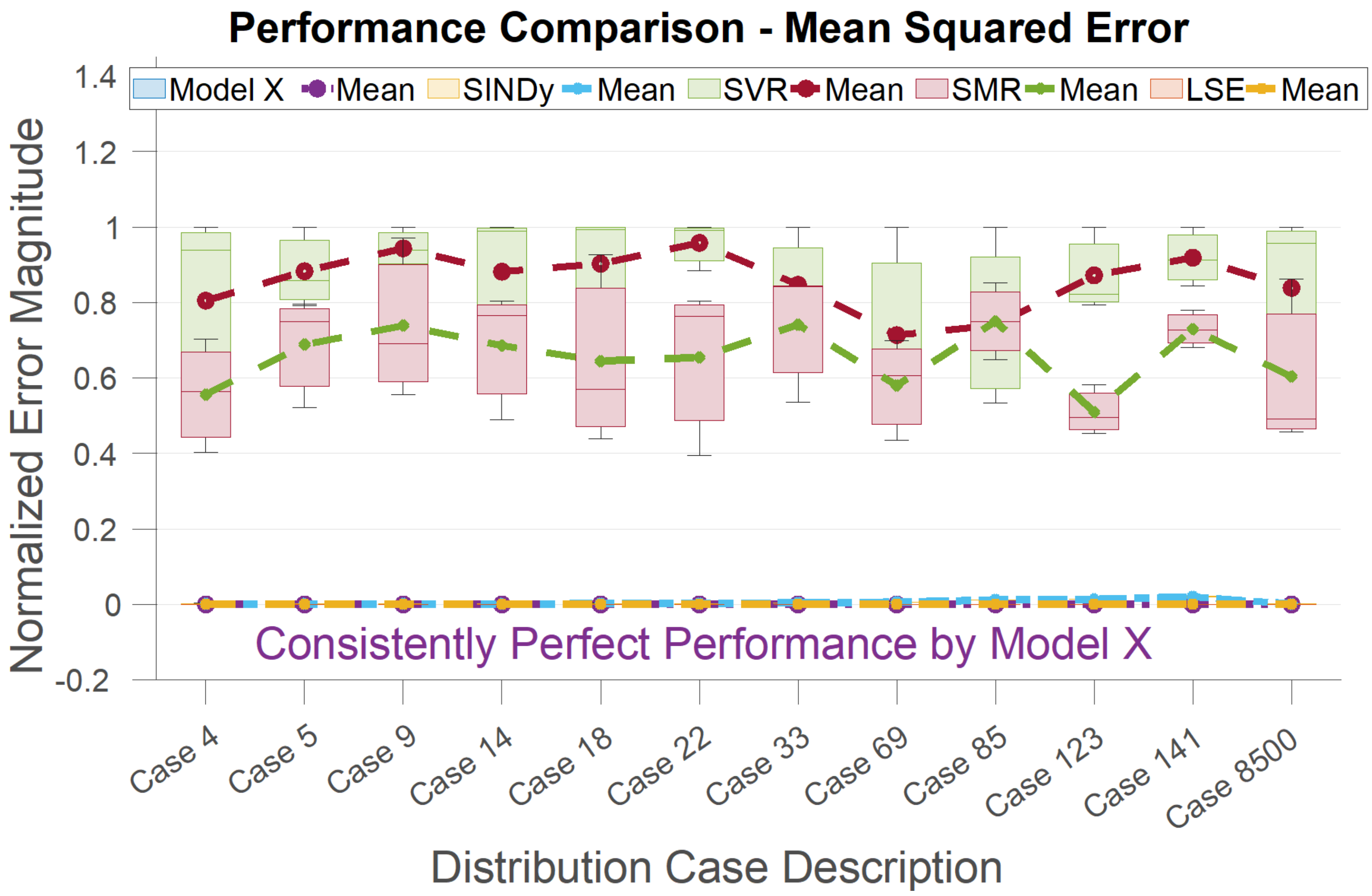
Legend

n # of Measurements

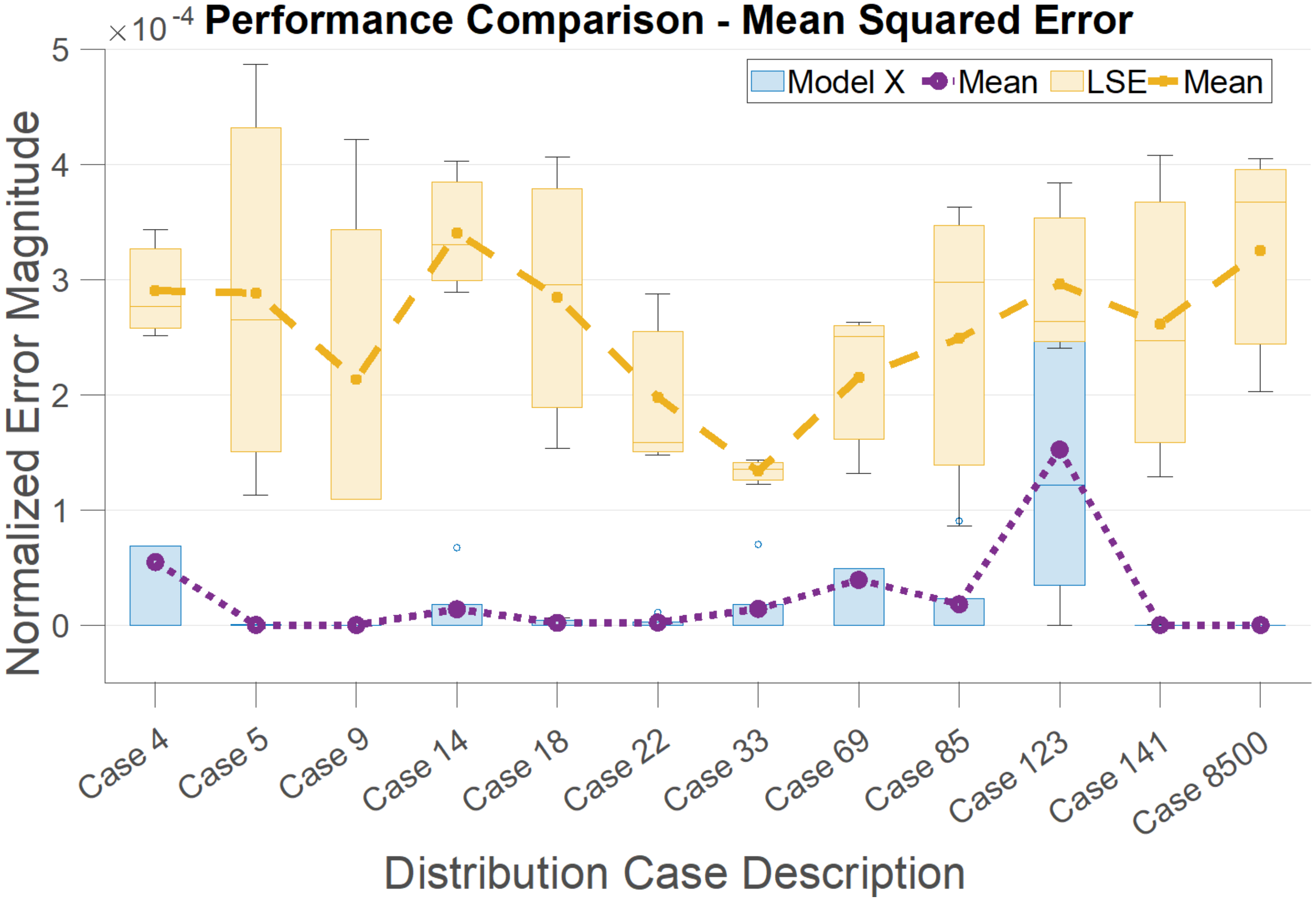
N_{Θ} # of Library Terms

d # of Dimensions

Result: Two-way Sparse Mapping

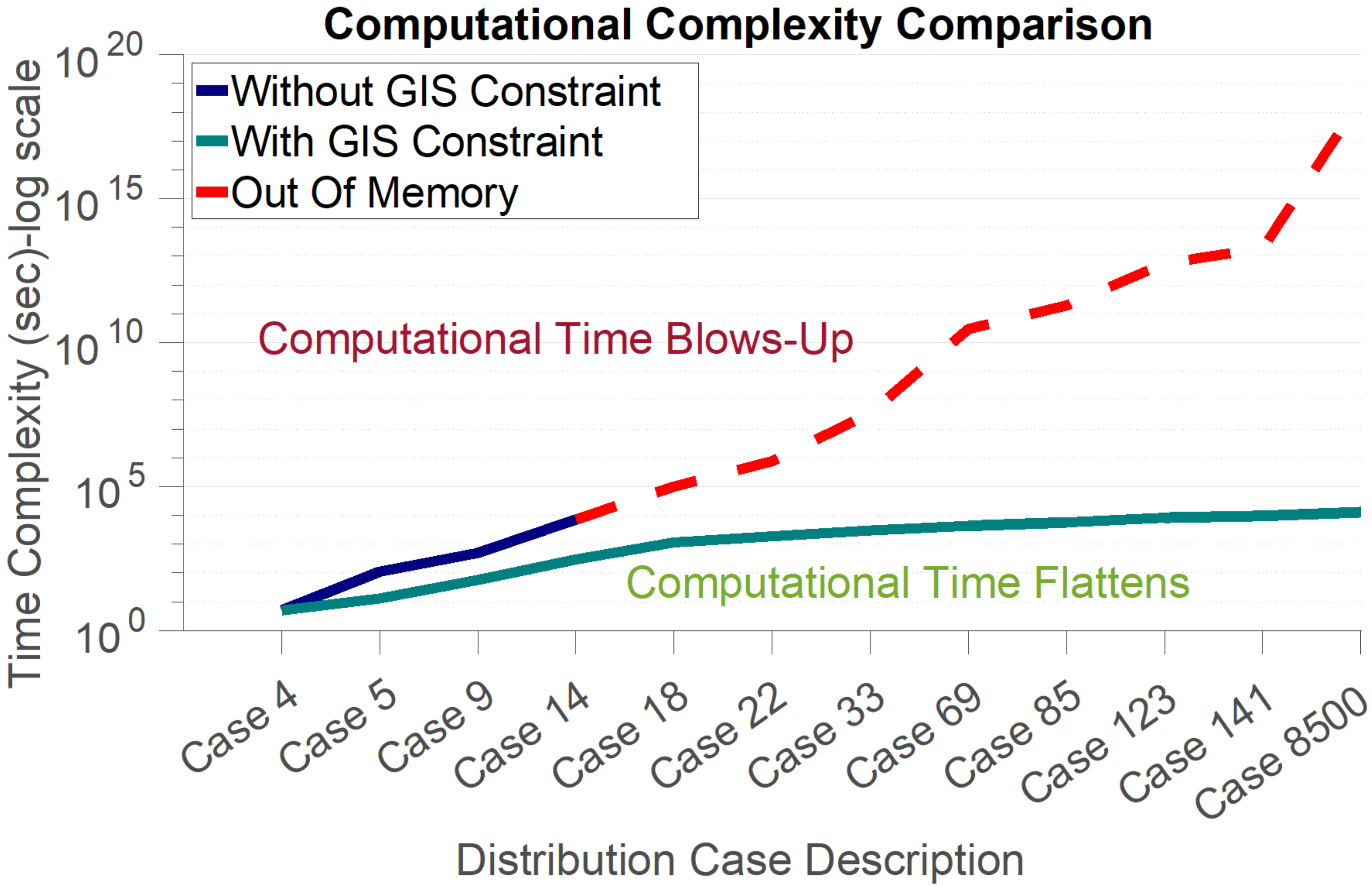


Result: Two-way Sparse Mapping



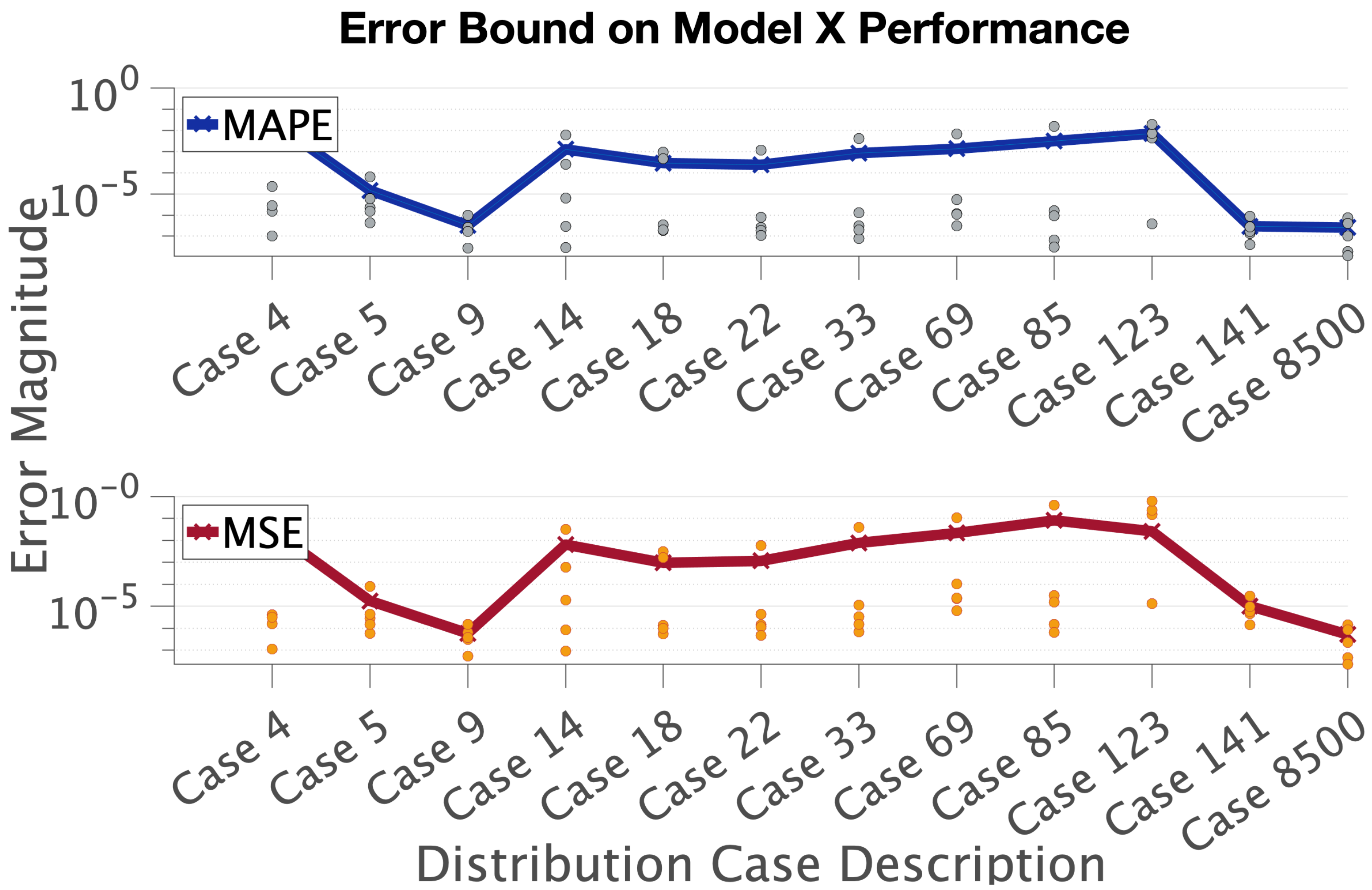
Accurate Estimation of System Parameters

Result: Computational Complexity



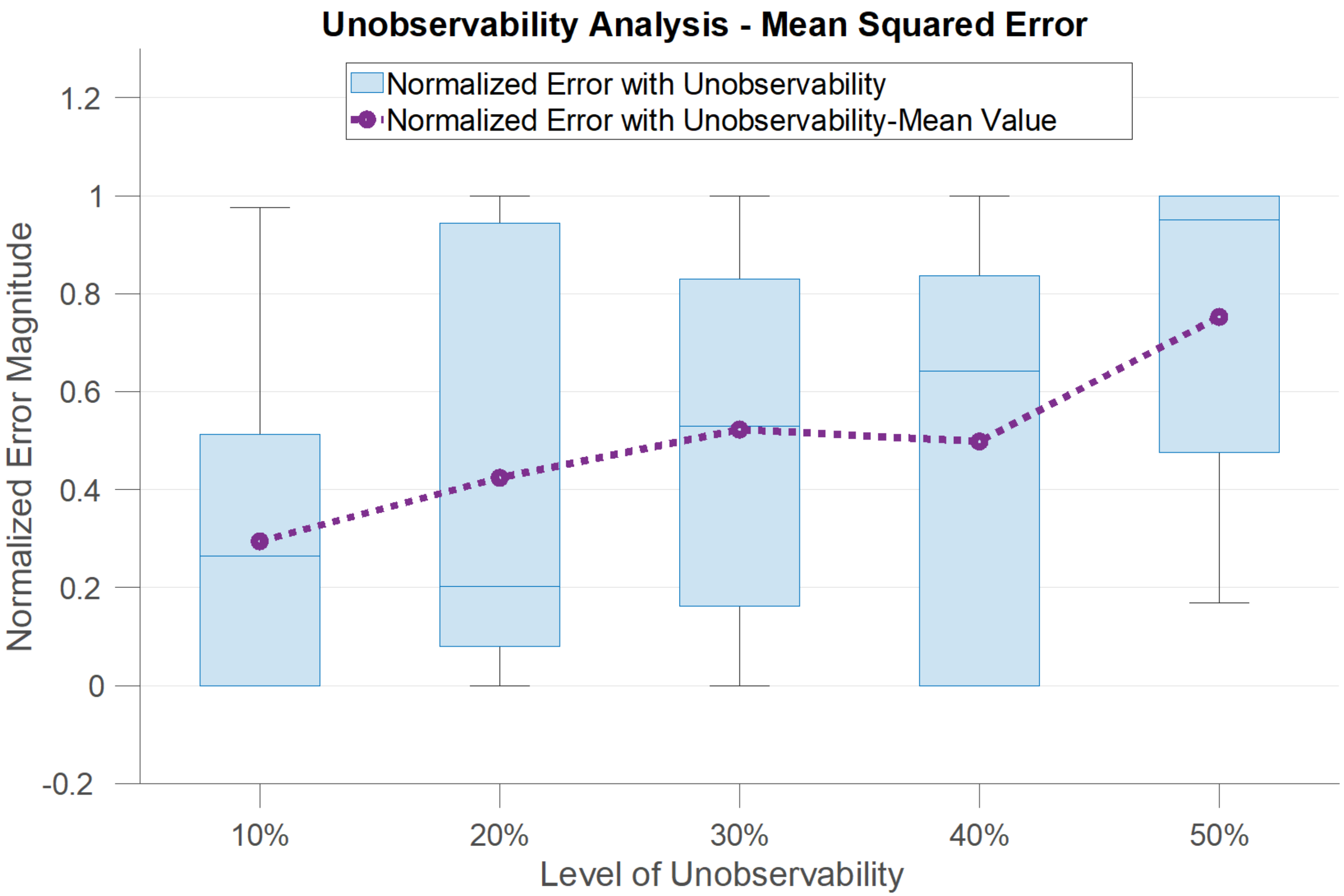
Power of GIS Information: Computational burden reduced significantly.

Result: Performance Guarantee for Quantifying Uncertainty



95% Confidence Interval – **Log Scale**

Robustness of Model-X



Conclusion

Conclusion

State Estimation in Systems with Unobservabilities

- Traditional Approaches
  - Two-way Mapping → **Impossible**
  - Explainability → **Limited**
  - Estimation Confidence → **Affected**
- Model-X
  - Two-way Mapping ✓ → Enhancement of System Physics Understanding
  - Explainability ✓ → Interpretable System Parameters
  - Estimation Confidence ✓ → Provide Bounds on Posterior Probability

Future Work: 1. Extension to Dynamic Scenario. 2. Explorations of Correlations.

Thank You

Questions?

References

[1] Shweppe JW, Rom D. Power system static state estimation: Part I, II, and III. Power Industry Computer Conference. 1969.
[2] Clements KA. The impact of pseudo-measurements on state estimator accuracy. IEEE Power and Energy Society General Meeting. 2011.
[3] Luan W, Peng J, Maras M, Lo J, Harapnuk B. Smart meter data analytics for distribution network connectivity verification. IEEE Transactions on Smart Grid. 2015.
[4] Monticelli A. State Estimation in Electric Power Systems: A Generalized Approach. Springer Science & Business Media. 1999.
[5] Baran ME. Challenges in state estimation on distribution systems. IEEE Power Engineering Society Summer Meeting. 2001.
[6] Baran ME, Kelley AW. State estimation for real-time monitoring of distribution systems. IEEE Transactions on Power systems. 1994.
[7] Muller HH, Rider MJ, Castro CA, Paucar VL. Power flow model based on artificial neural networks. IEEE Russia Power Tech. 2005.
[8] Singh R, Manitsas E, Pal BC, Strbac G. A recursive Bayesian approach for identification of network configuration changes in distribution system state estimation. IEEE Transactions on Power Systems. 2010.
[9] Hayes B, Escalera A, Prodanovic M. Event-triggered topology identification for state estimation in active distribution networks. IEEE PES Innovative Smart Grid Technologies Conference Europe. 2016.
[10] G. Cavraro, V. Kekatos, and S. Veeramachaneni, “Voltage analytics for power distribution network topology verification,”IEEE Transactions on Smart Grid, 2019.