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Outstanding Doctoral Dissertations in Power and Energy Systems

Distribution System Situational Awareness: From Model-Based to Data-Driven and Beyond

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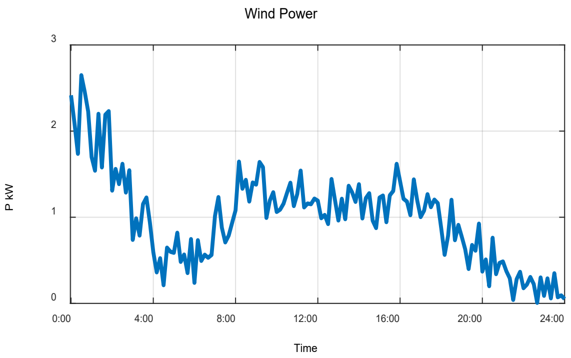
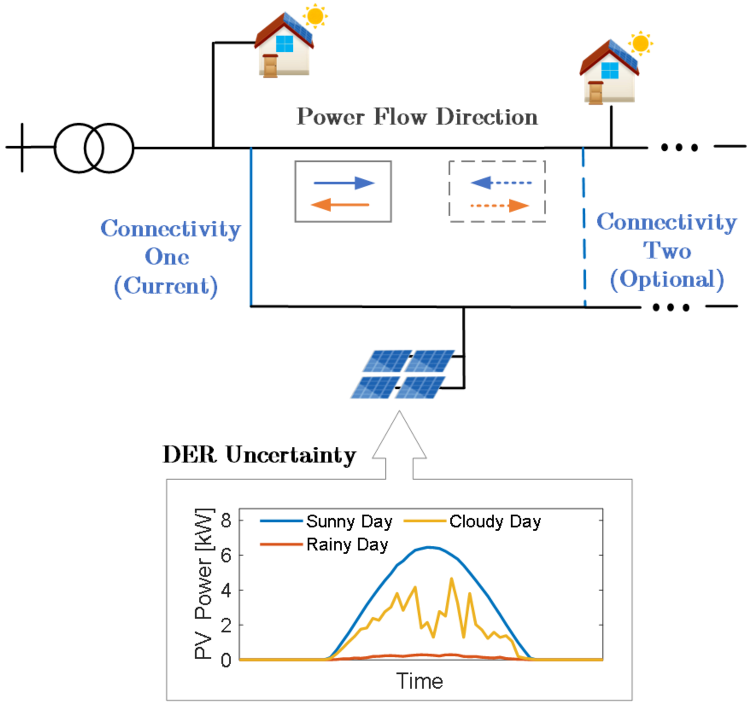
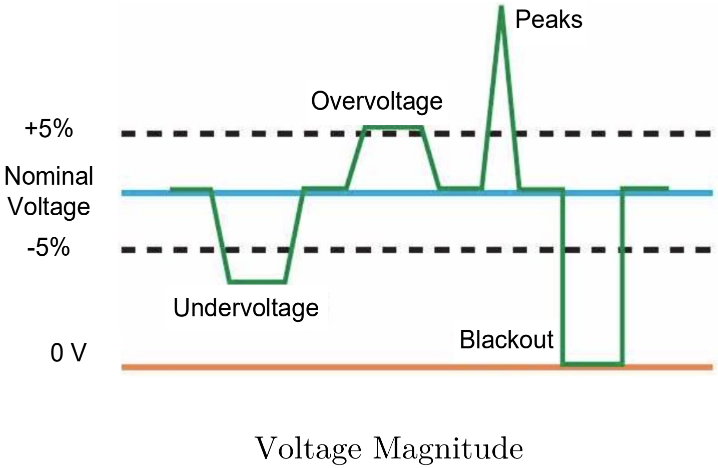
Renewable & DER Integration Bring Challenges



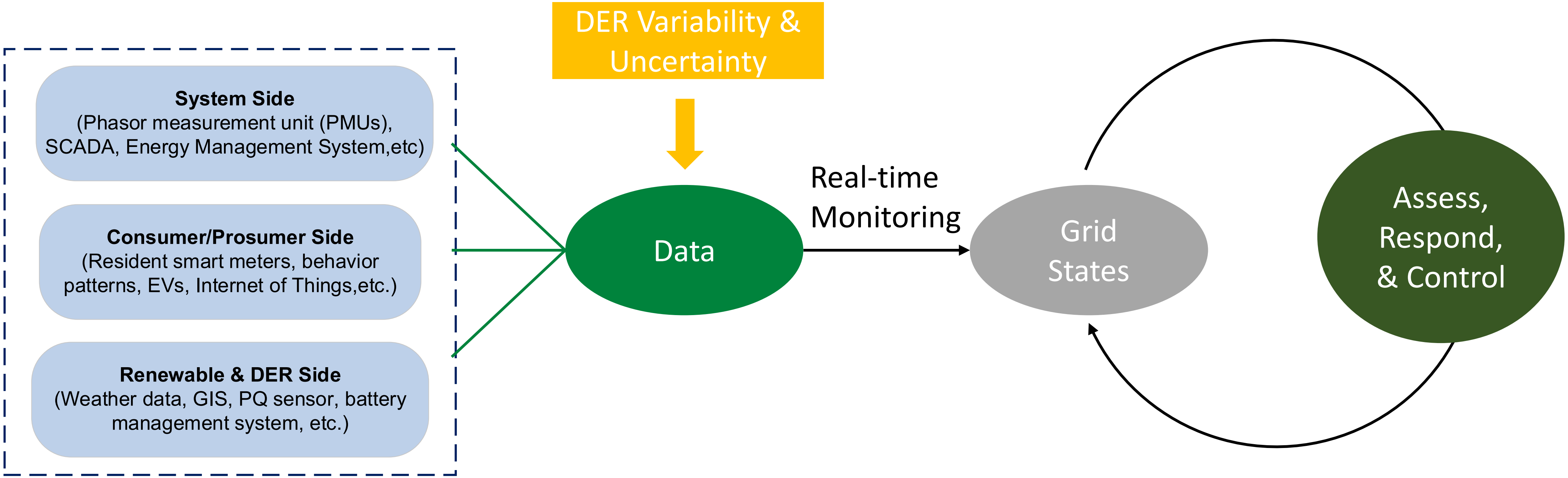




Y. Zhang, J. Wang, Uncertainty modeling of distributed energy resources: techniques and challenges, **Current Sustainable/Renewable Energy Report**, 2019.

DSSA: From Model-Based to Data-Driven and Beyond

Distribution System Situational Awareness (DSSA)

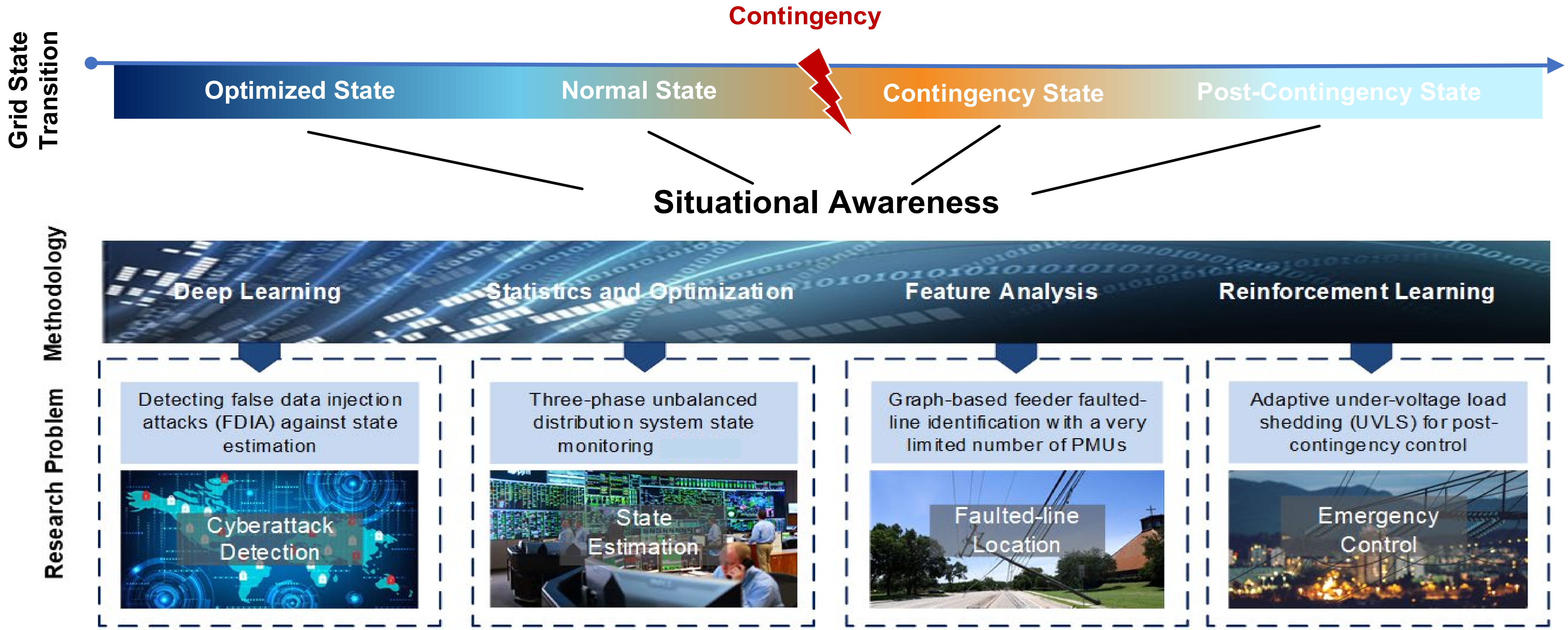


Methodology:
Model-based, Data-driven, Physics-informed (Data-driven-aided)

Y. Zhang, Model-based and Data-driven Situational Awareness for Distribution System Monitoring and Control, **Ph.D. Dissertation, 2020**.
This work received the 2023 IEEE Power and Energy Society Outstanding Doctoral Dissertation Award.

DSSA: From Model-Based to Data-Driven and Beyond

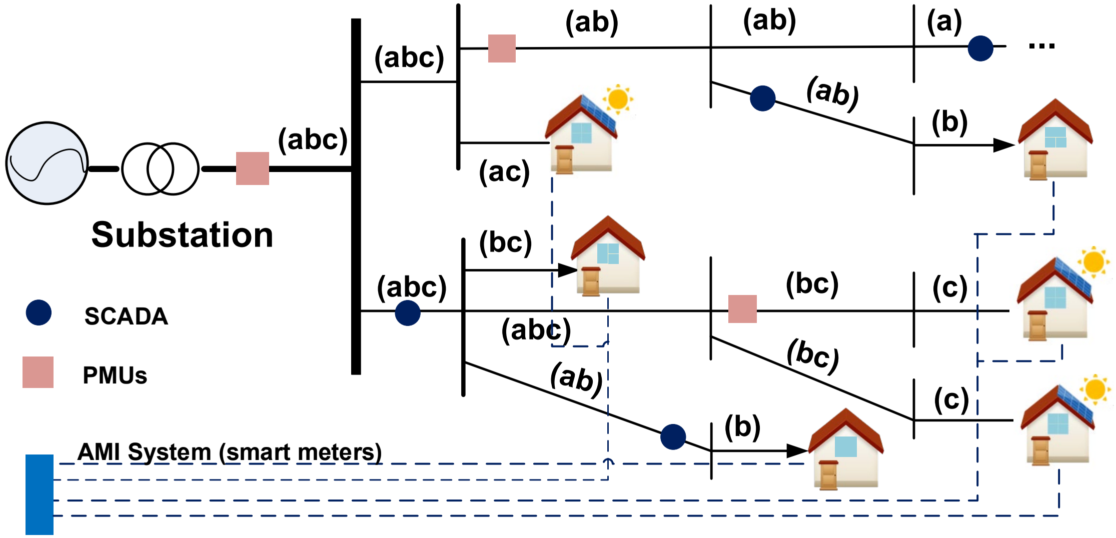
Research Outline



Y. Zhang, Model-based and Data-driven Situational Awareness for Distribution System Monitoring and Control, **Ph.D. Dissertation, 2020**.

DSSA: From Model-Based to Data-Driven and Beyond

Distribution System State Estimation (DSSE)



Characteristics of system operation

- Three-phase unbalanced operation
- Uncertainty introduced by high DER penetration
- Poor observability & Heterogeneous measurements

State Estimation

$$z = h(x) + e$$

Weighted Least Square (WLS):

$$\hat{x} = \arg\min J = \arg\min \, [z - h(x)]^T W [z - h(x)]$$

Gauss-Newton Method runs until each component of the vector Δx at iteration t is sufficiently small.

$$\partial J / \partial x^{(t)} = \mathbf{0}$$

$$H(x^{(t)})^T W H(x^{(t)}) \Delta x = H(x^{(t)})^T W [z - h(x^{(t)})]$$

$$x^{(t+1)} = x^{(t)} + \Delta x$$

Multiple Uncertainty Sources Degrade Existing DSSE

Limitations of WLS-based DSSE

- Fail when the statistical information or measurements regarding DER outputs are not available
- Cannot handle imprecise line parameters

Measurement Noises

Stochastic DER Outputs

Imprecise Line Parameters

Y. Zhang and J. Wang, Towards highly efficient state estimation with nonlinear measurements in distribution systems, ***IEEE Transactions on Power Systems***, vol. 35, no. 3, pp. 2471-2474, May 2020.

Update WLS to Interval State Estimation (ISE)

- Modeling: Regression, Gaussian distributions' 3σ criteria,
- Approach: Statistical Optimization, Interval Arithmetic (Improved Krawczyk-Moore operator method)
- Convergence of Solution: Fixed-Point Theory

- Directly solve Interval variable, i.e., upper and lower bounds of all voltage variables, a tight solution hull under combined uncertainty impacts.

Interval line parameters

$m_1 \times 1$ interval measurement vector

$$\begin{bmatrix}[\boldsymbol{H}_1]\\ \boldsymbol{H}_2\end{bmatrix}^T \begin{bmatrix}\boldsymbol{W}_1 & 0\\ 0 & \boldsymbol{I}\end{bmatrix}\begin{bmatrix}[\boldsymbol{H}_1]\\ \boldsymbol{H}_2\end{bmatrix}[\boldsymbol{x}] = \begin{bmatrix}[\boldsymbol{H}_1]\\ \boldsymbol{H}_2\end{bmatrix}^T\begin{bmatrix}\boldsymbol{W}_1 & 0\\ 0 & \boldsymbol{I}\end{bmatrix}\begin{bmatrix}[\boldsymbol{z}_1]\\ [\boldsymbol{z}_2]\end{bmatrix}$$

$n \times 1$ interval state vector

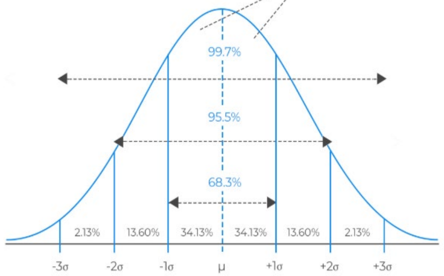
$m_2 \times 1$ interval DG outputs

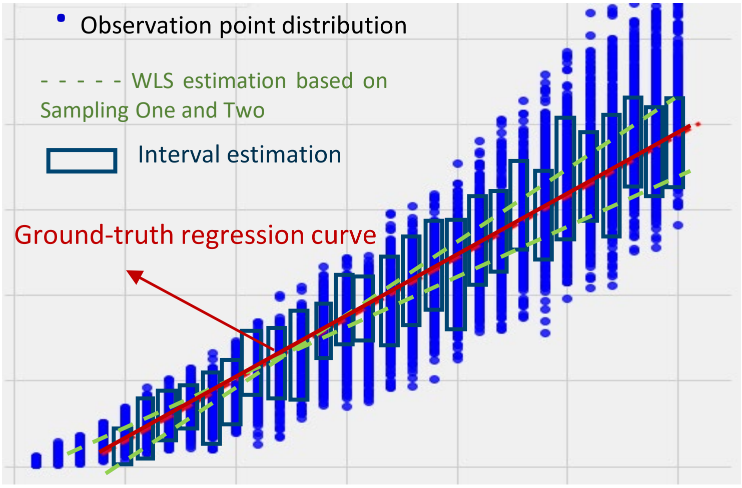
$$[\boldsymbol{H}]^T\boldsymbol{W}[\boldsymbol{H}][\boldsymbol{x}] = [\boldsymbol{H}]^T\boldsymbol{W}[\boldsymbol{z}]$$

$$[\boldsymbol{A}][\boldsymbol{X}] = [\boldsymbol{B}]$$

$e \sim N(0, \sigma^2)$

$Z_m \in [Z_0 - 3\sigma, Z_0 + 3\sigma]$

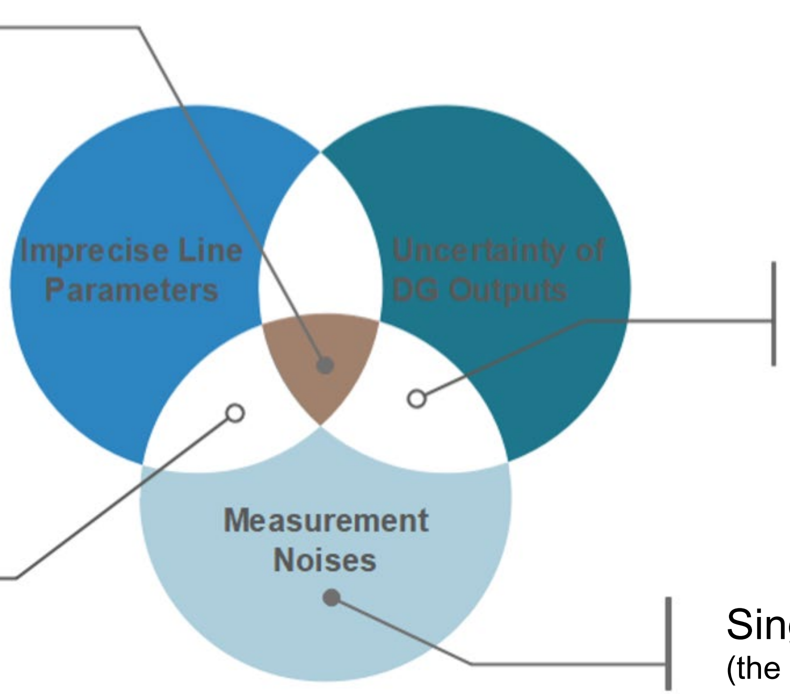




Y. Zhang, Z. Li, J. Wang. Interval state estimation with uncertainty of distributed generation and line parameters in unbalanced distribution systems, ***IEEE Trans. Power Systems***, 2020.

Proposed Generalized Solution Against Uncertainties

- Combined optimization techniques with distribution system power flow formulation, we decouple the impact of multiple uncertainties
- ONE generalized model to handle ALL the combinations of different uncertainties.



Generalized Model

Most works address one or two types of uncertainties!

Two types
(when line parameters are accurate)

Two types
(when sensors installed on DER side)

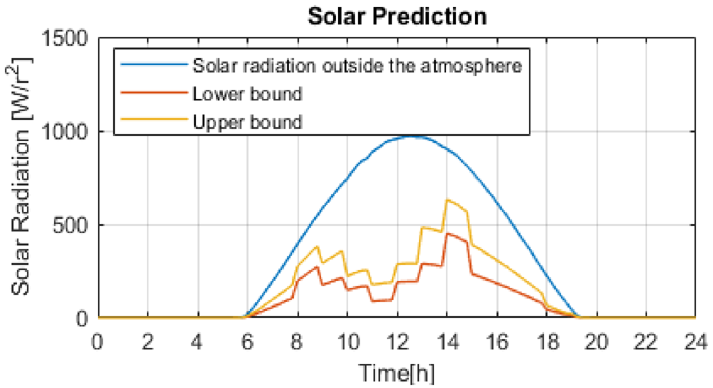
Single type
(the simplest situation)

Y. Zhang, Z. Li, J. Wang. Interval state estimation with uncertainty of distributed generation and line parameters in unbalanced distribution systems, ***IEEE Trans. Power Systems***, 2020.

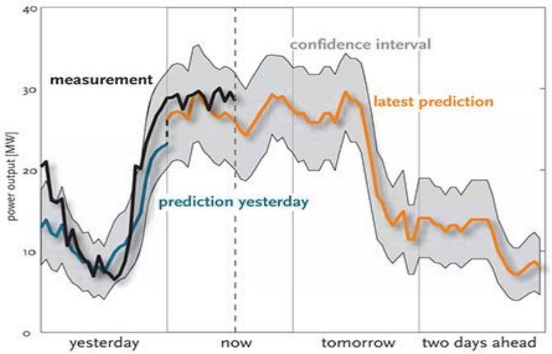
DSSA: From Model-Based to Data-Driven and Beyond

ISE is Feasible and Flexible in Practice

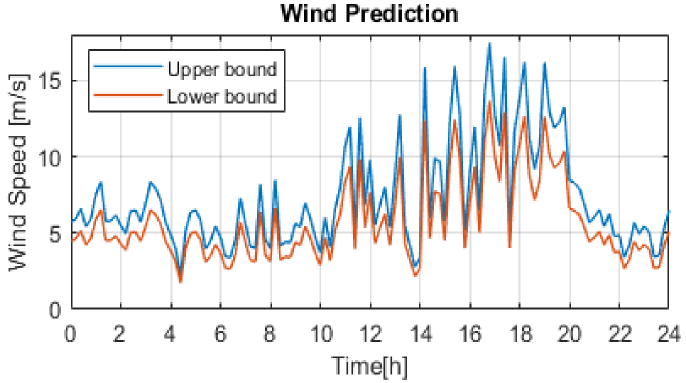
- Capable of accommodating no sensor installation or measurement missing.
- No need for the known statistical distribution of DER generation
- Flexibly interface with the existing interval prediction techniques for renewable (with confidence interval).



Wind Power Prediction



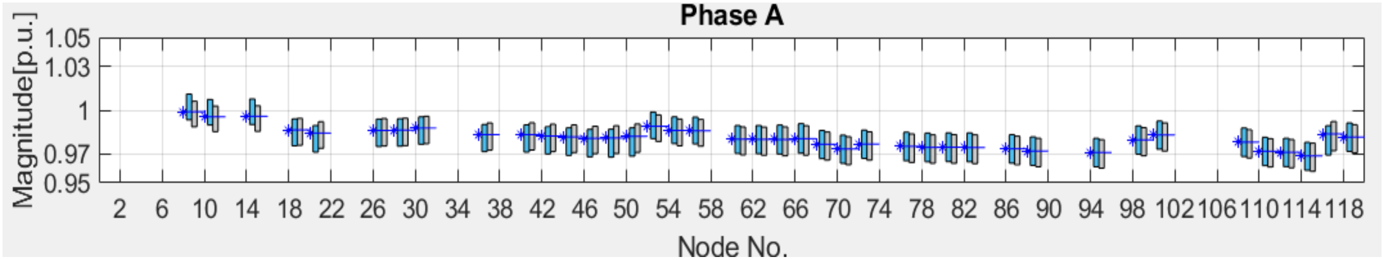
Predicting accurate statistical distribution is hard! Errors always exist



*Data source: NREL weather stations for prediction of DER power output.

Performance Comparison with WLS-based DSSE

- Realize comparable solution accuracy of the existing method, the WLS-based method, through 3000 times of Monte Carlo simulation.



- Only need to run once to get the upper and lower bounds and more computationally efficient than the iterative WLS-based DSSE process.

CPU Time [s]	IEEE 123-node distribution systems		
	Ours	WLS (3000 Monte Carlo trials)	Nonlinear programming
Case 1	**0.847**	5655.5	164.68
Case 2	**0.965**	6209.7	-*

Realize 1000x acceleration!

*NLP CANNOT deal with the uncertainty in line parameters.

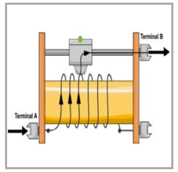
Volt-VAR Optimization (VVO)

- About 40% of total energy losses occur at the distribution side. (the U.S. Energy Information Administration)

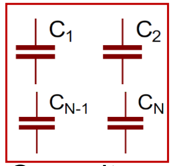
- The primary goal of VVO is to maintain voltages at all buses within normal operation ranges, *e.g.*, 0.95~1.05 of nominal values. (ANSI C84.1 standard)

- The secondary goal is to reduce power losses.

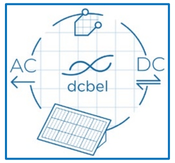
5,000,000 combinations of all discrete control actions!



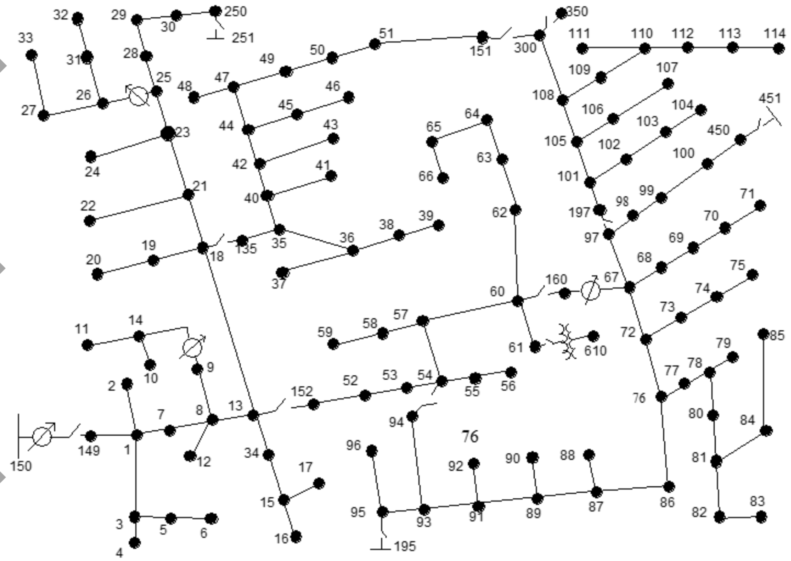
Regulator



Capacitor



Smart PV Inverter



IEEE 123-bus unbalanced distribution network

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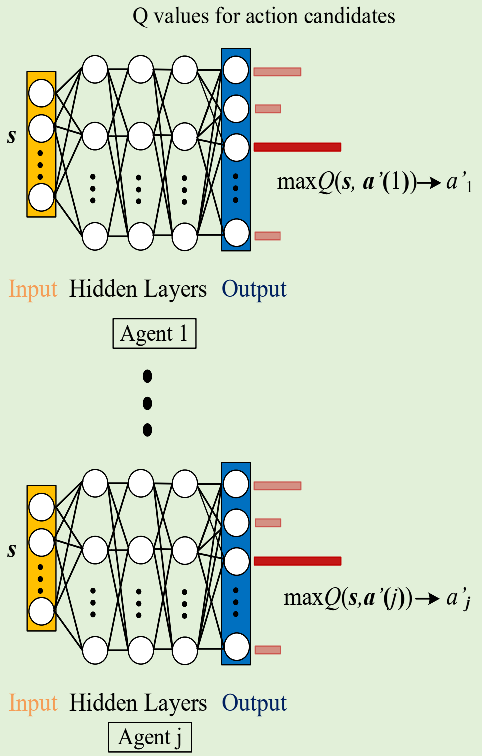
Deep Reinforcement Learning (DRL)-based VVO Scheme



Agent

Voltage regulator

Action choice:
0.9-1.1 with each step of 0.00625

Capacitor bank

Action choice:
The status (on/off)

Transformer

Action choice:
0.9-1.1 in ratio with each step of 0.01

Action

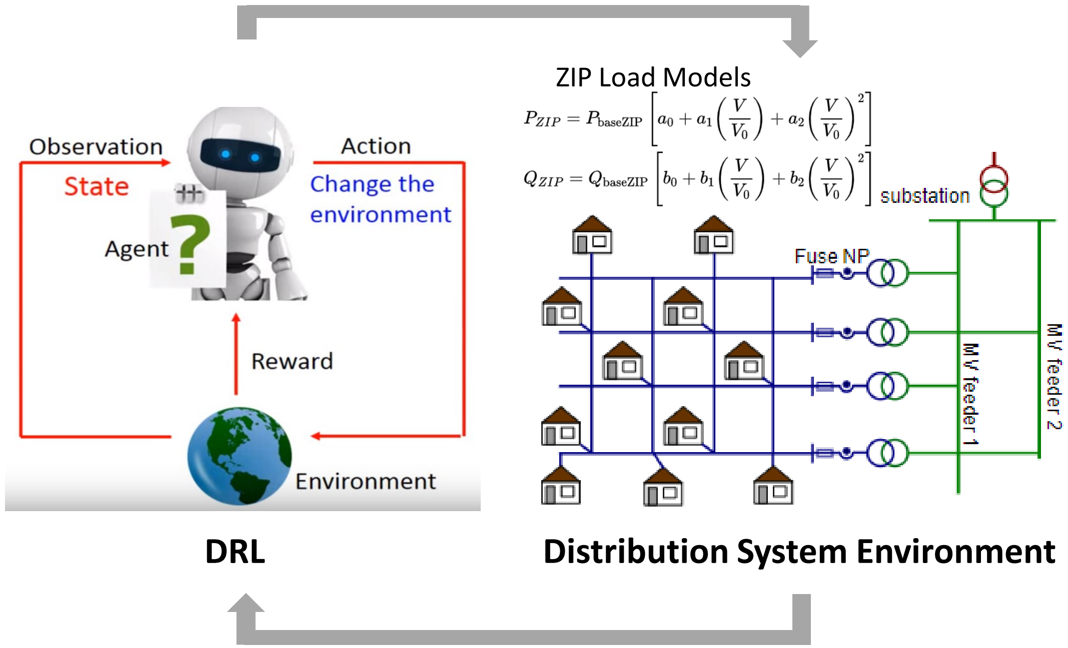
Action-reward Q function (Bellman Equation):

$$Q_j^{t+1}(\boldsymbol{s}, \boldsymbol{a}) = Q_j^t(\boldsymbol{s}, \boldsymbol{a}) + \underbrace{\alpha}_{\text{Learning rate}} \boxed{(r^t + \underbrace{\gamma}_{\text{Discount rate}} \underbrace{\max Q_j^t(\boldsymbol{s}', \boldsymbol{a}')}_{\text{New actions}} - \underbrace{Q_j^t(\boldsymbol{s}, \boldsymbol{a})}_{\text{Old actions}})}$$

NN loss function:

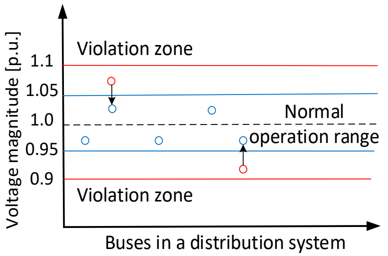
$$\min \quad \mathcal{L}_j(\boldsymbol{\theta}_j) = \mathbb{E}\left[\left(r^t + \gamma \cdot \max Q_j^t(\boldsymbol{s}', \boldsymbol{a}') - Q_j^t(\boldsymbol{s}, \boldsymbol{a})\right)^2\right]$$

Case Study: Multi-agent DRL-based VVO



Voltage Regulation

System Scale	Number of Test Scenarios	Success Rate
13-bus System	1000	99.80%
123-bus System	4000	99.975%



Power Loss Reduction

System Scale	Average Power Loss Saving[kW]	Maximum Power Loss Saving[kW]
13-bus System	45.38	67.79
123-bus System	75.23	86.36

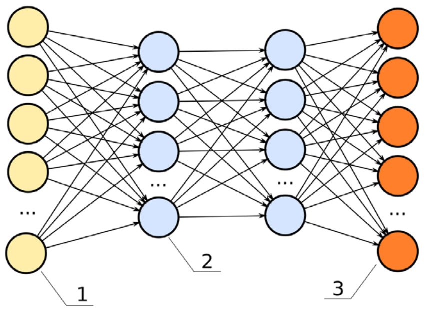
Average Executive Time: 46.2 ms in the 123-bus system.

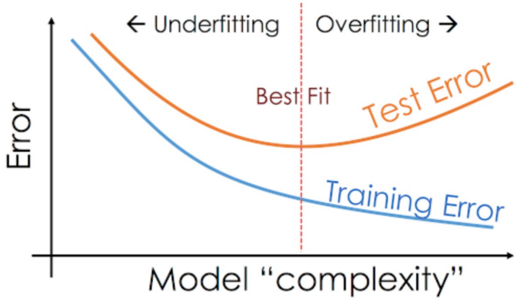
Y. Zhang, J. Wang, Deep reinforcement learning based volt-VAR optimization in smart distribution systems, ***IEEE Trans. Smart Grid***, vol.12, no.1, pp.361-371, Jan. 2021.

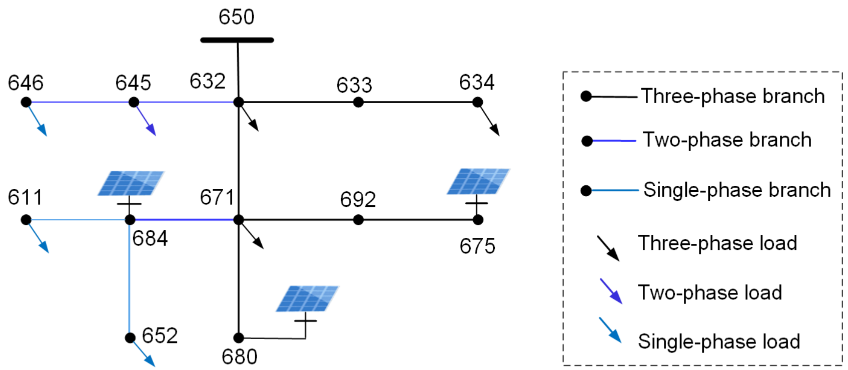
Physics-Informed NNs: Do More with Less

- Physics knowledge regarding power system operation can be integrated into NN design (structure and loss function, etc.).
- For example, **topology-pruned NN to inform the sparsity of the mapping between power injection and voltage.**

Fully-Connected NNs

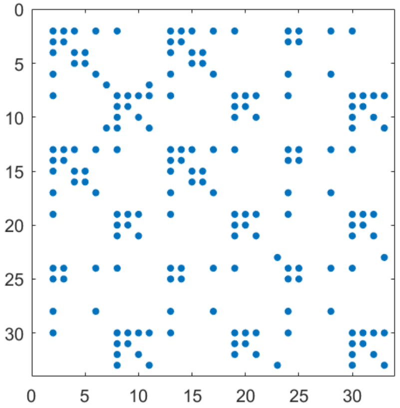






IEEE 13-bus Unbalanced Distribution Feeder

Sparsity of multi-phase nodal admittance matrix



Fully-connected NNs have redundant weight para. & not efficient!

Selected Publication

- **Y. Zhang**, M. Yue, J. Wang, and S. Yoo. Multi-agent graph-attention deep reinforcement learning for post-contingency grid emergency voltage control, *IEEE Transactions on Neural Networks and Learning Systems*, 2023.
- **Y. Zhang,** et al, Decentralized Coordinated State Estimation in Integrated Transmission and Distribution Systems, 2022 IEEE PES Innovative Smart Grid Technologies Conference (ISGT), New Orleans, LA, USA, 2022, pp. 1-5.
- **Y. Zhang**, X. Wang, J. Wang, and Y. Zhang, Deep reinforcement learning based volt-VAR optimization in smart distribution systems, *IEEE Transactions on Smart Grid*, vol.12, no.1, pp.361-371, Jan. 2021.
- **Y. Zhang**, J. Wang, and B. Chen, Detecting false data injection attacks in smart grids: a semi-supervised deep learning approach, *IEEE Transactions on Smart Grid*, vol.12, no.1, pp. 623-634, Jan. 2021.
- **Y. Zhang** and J. Wang, Towards highly efficient state estimation with nonlinear measurements in distribution systems, *IEEE Transactions on Power Systems*, vol. 35, no. 3, pp. 2471-2474, May 2020.
- **Y. Zhang**, J. Wang, and M. Khodayar, Graph-based fault location using micro-PMU data in distribution systems, *IEEE Transactions on Smart Grid*, vol. 11, no. 5, pp. 3982-3992, Sept. 2020.
- **Y. Zhang**, J. Wang, and Z. Li, Interval state estimation with uncertainty of distributed generation and line parameters in unbalanced distribution systems, *IEEE Transactions on Power Systems*, vol. 35, no. 1, pp. 762 -772, Jan. 2020.
- **Y. Zhang**, J. Wang, and J. Liu, Attack identification and correction for PMU GPS spoofing in unbalanced distribution systems, *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 762-773, Jan. 2020.
- **Y. Zhang**, J. Wang, and Z. Li, Uncertainty modeling of distributed energy resources: techniques and challenges**,** *Current Sustainable/Renewable Energy Report*, vol. 6, no. 2, pp. 42–51, Jun. 2019.