NREL
NATIONAL RENEWABLE ENERGY LABORATORY

2018 PV Systems Symposium
Albuquerque, NM





Predictive Data Analytics for Enhanced Observability at Grid Edge

Yingchen Zhang, Ph.D.

Group Manager

Power Systems Engineering Center

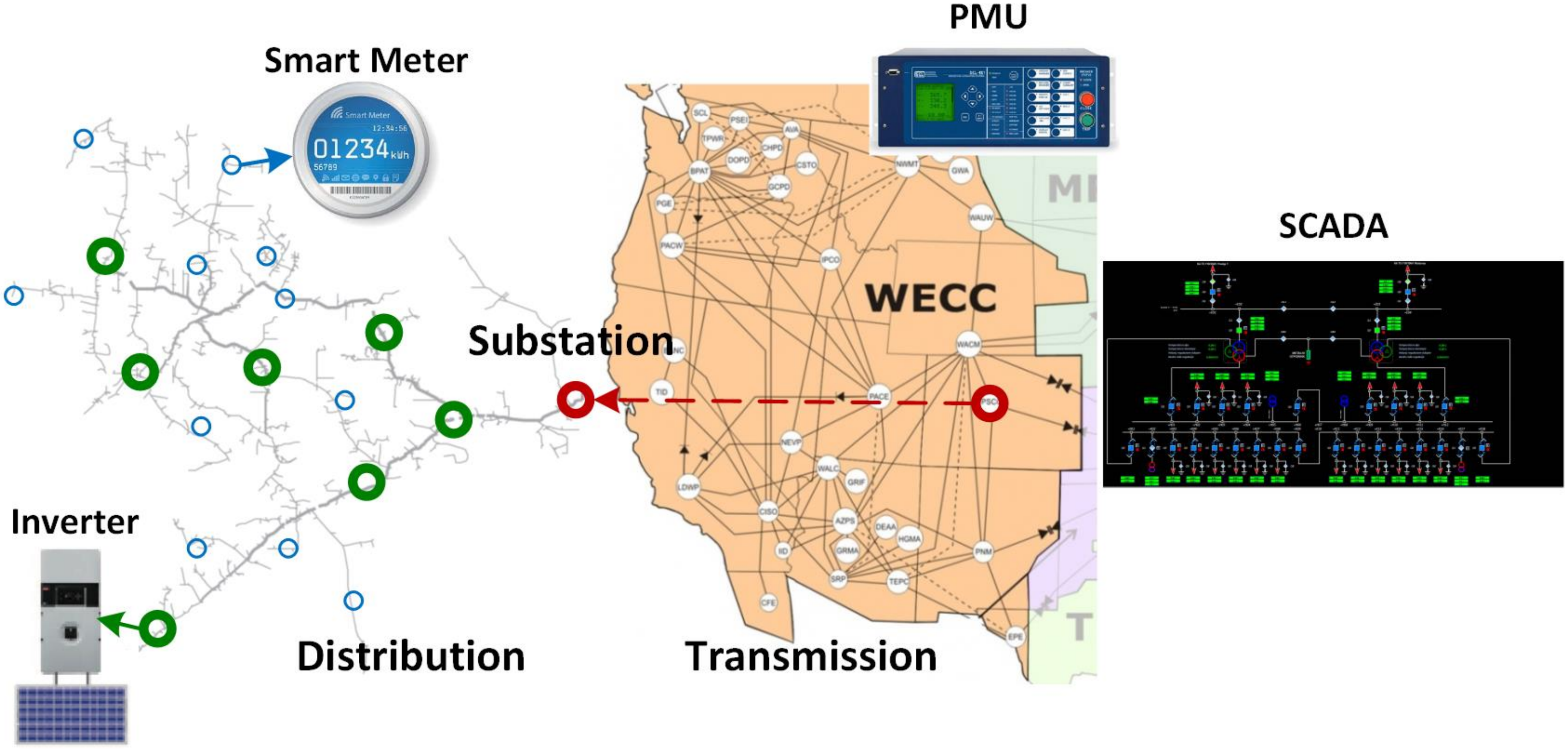
National Renewable Energy Laboratory

August 28, 2017

NREL/PR-5D00-70018

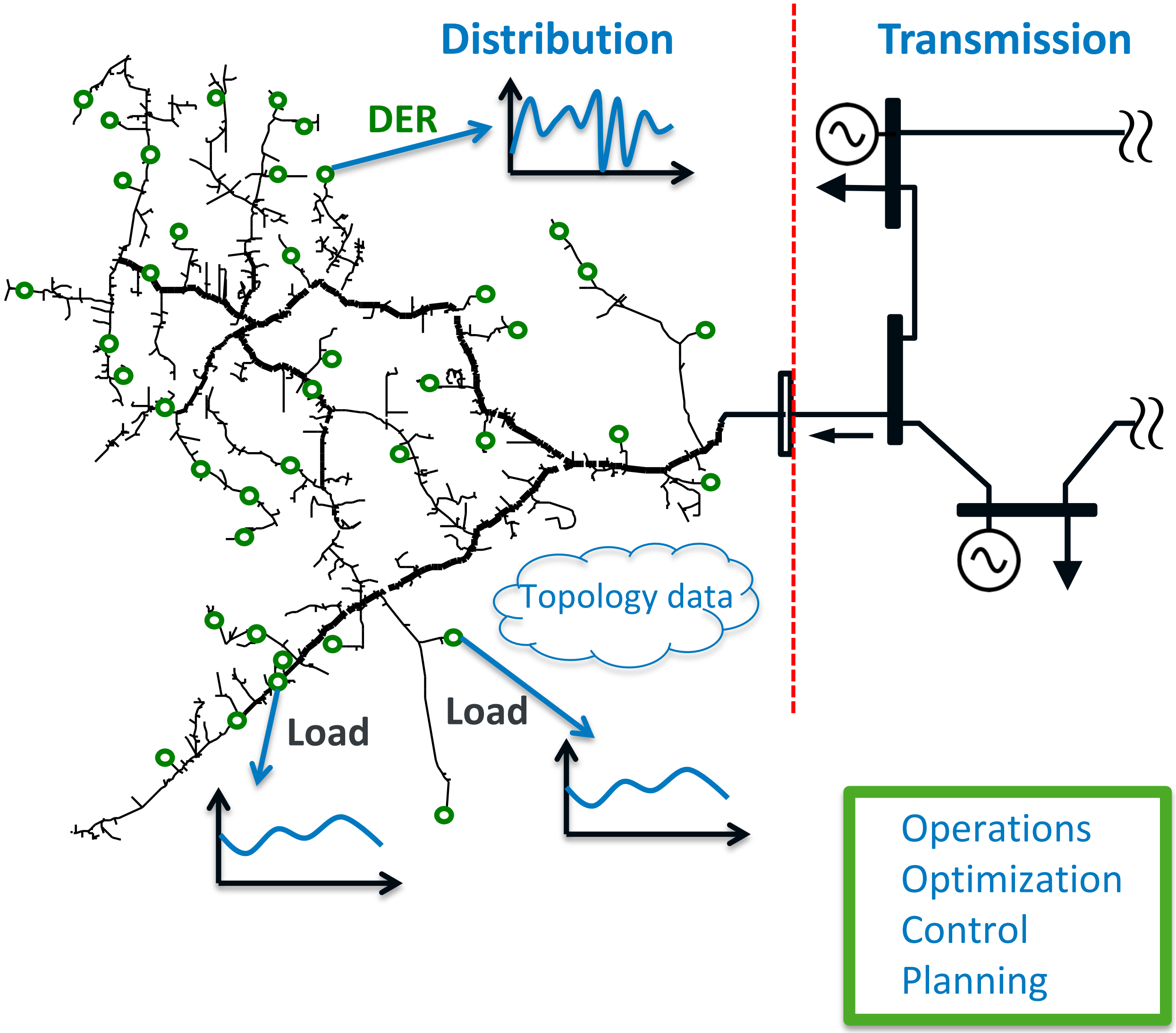
Motivation

- Increased Amount of Data in Power Systems



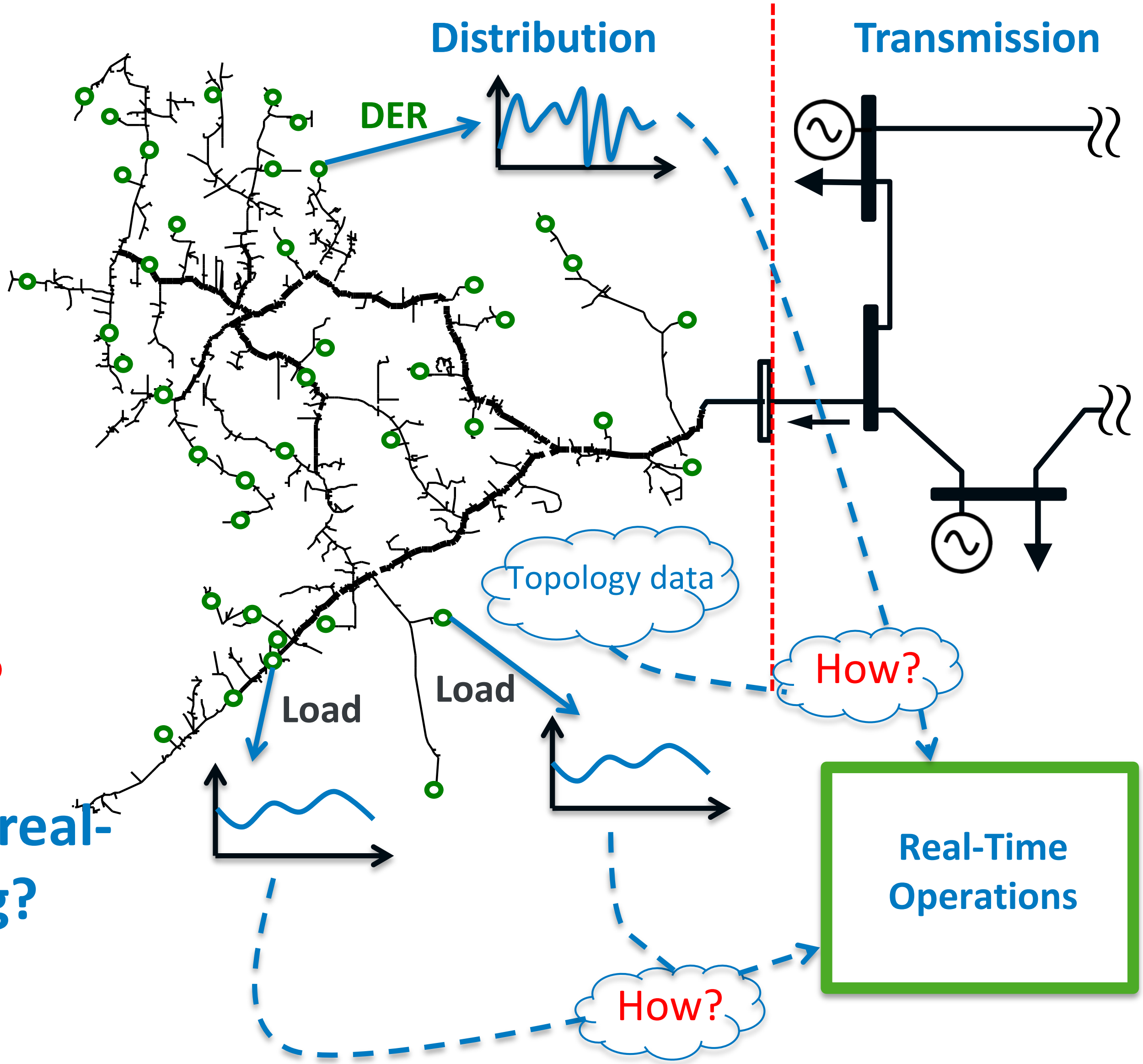
Motivation

- Data
  - Nonpervasive
  - Heterogeneous
  - Highly variable
  - Different resolution



Motivation

- Data
  - Nonpervasive
  - Heterogeneous
  - Highly variable
  - Different resolution

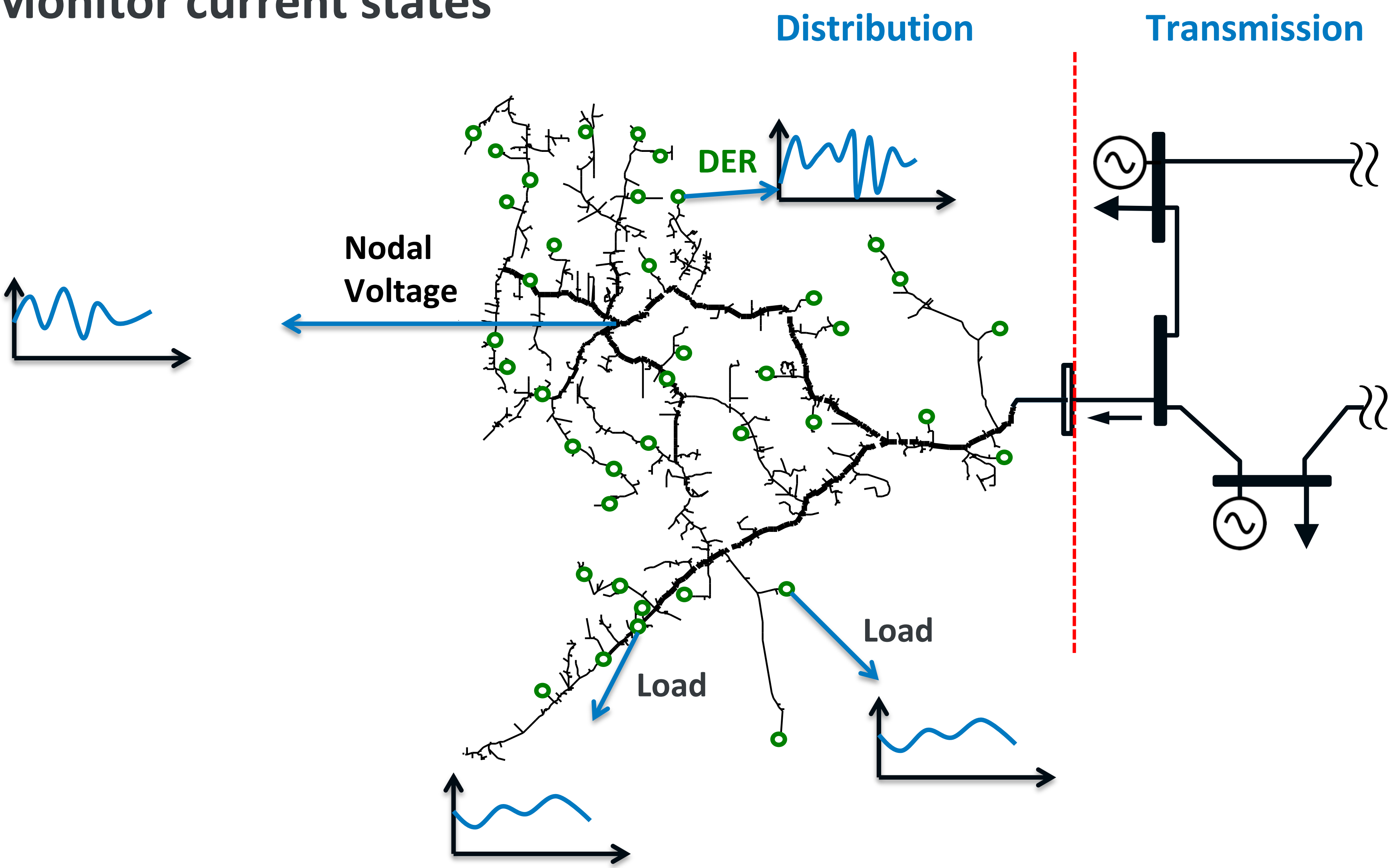


How to use the data?

How to facilitate the real-time decision-making?

Power System Situational Awareness

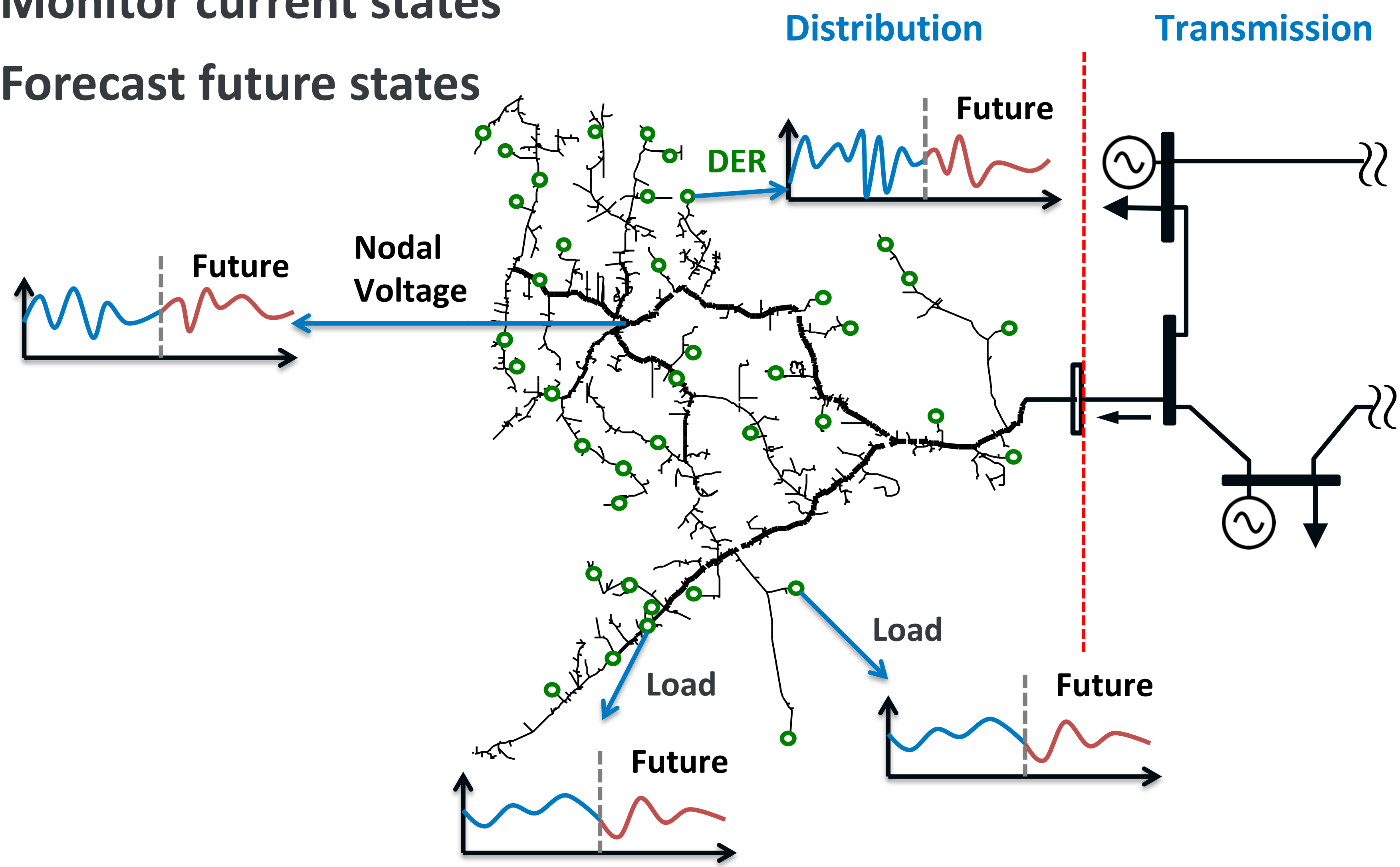
Monitor current states



Power System Situational Awareness

Monitor current states

Forecast future states

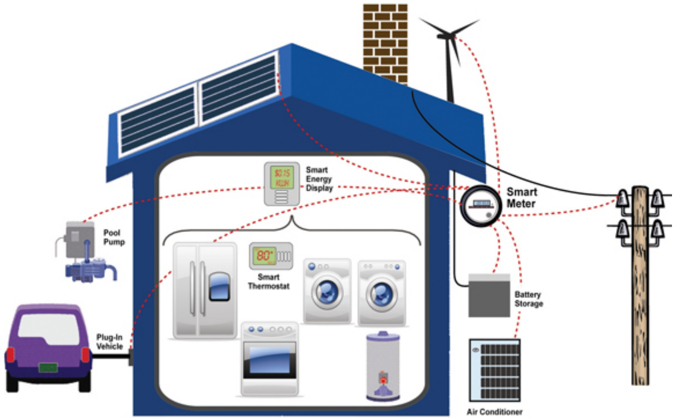


Flexible Resources

- Renewable with Smart Inverters
  - Able to adjust power generation
  - Providing grid services

Source: PV Magazine

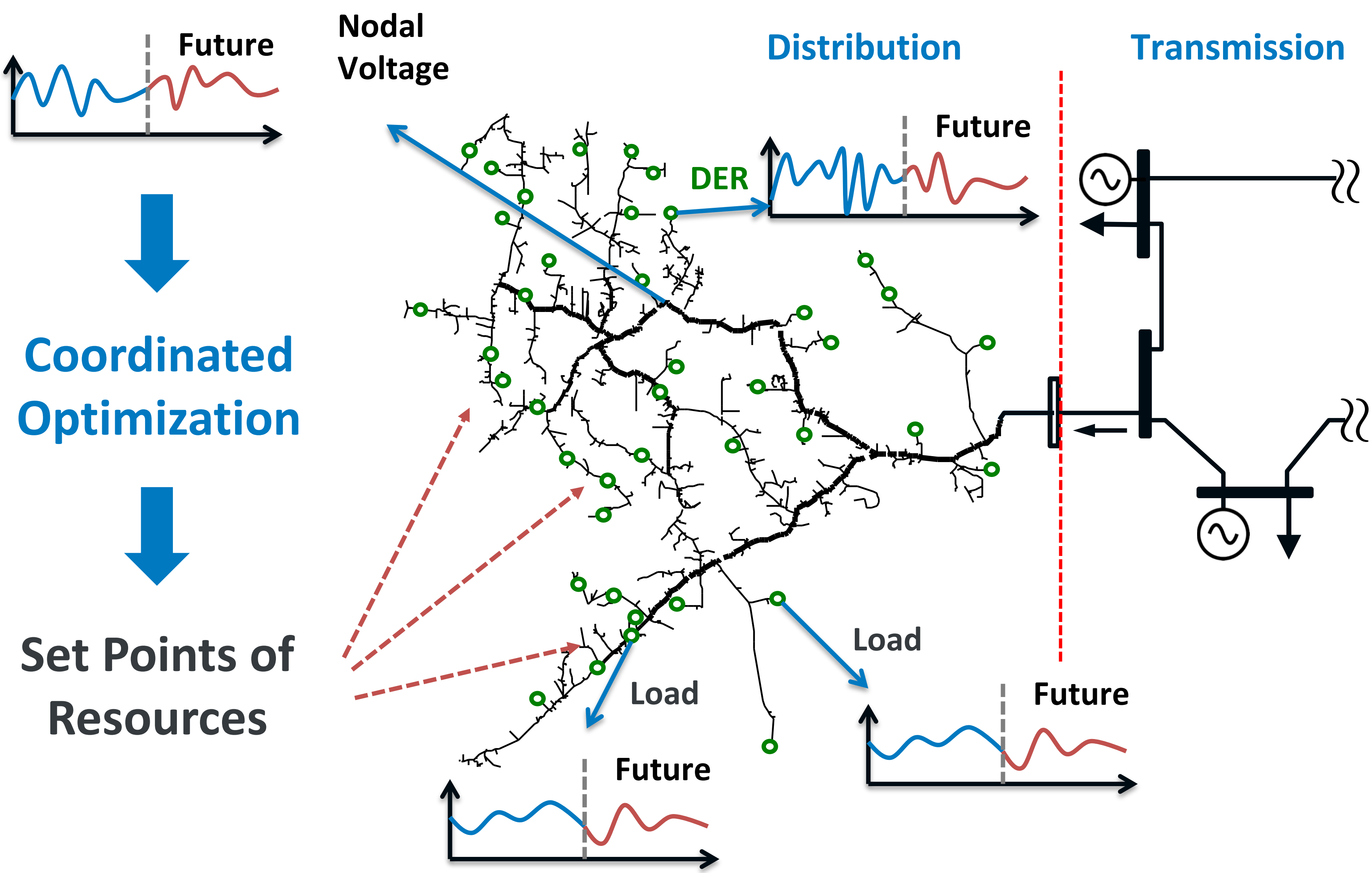
- Smart Loads
  - Smart appliances
  - Flexible power consumption



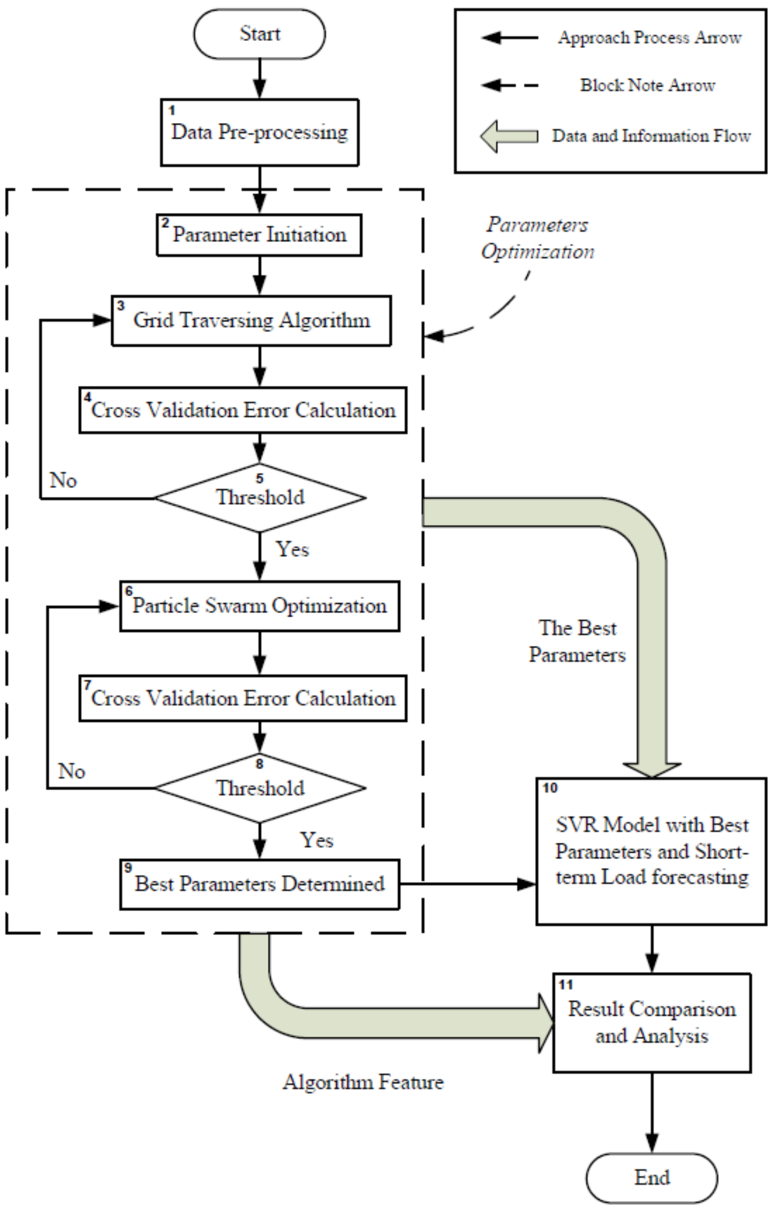
Source: Microchip Technology Inc.

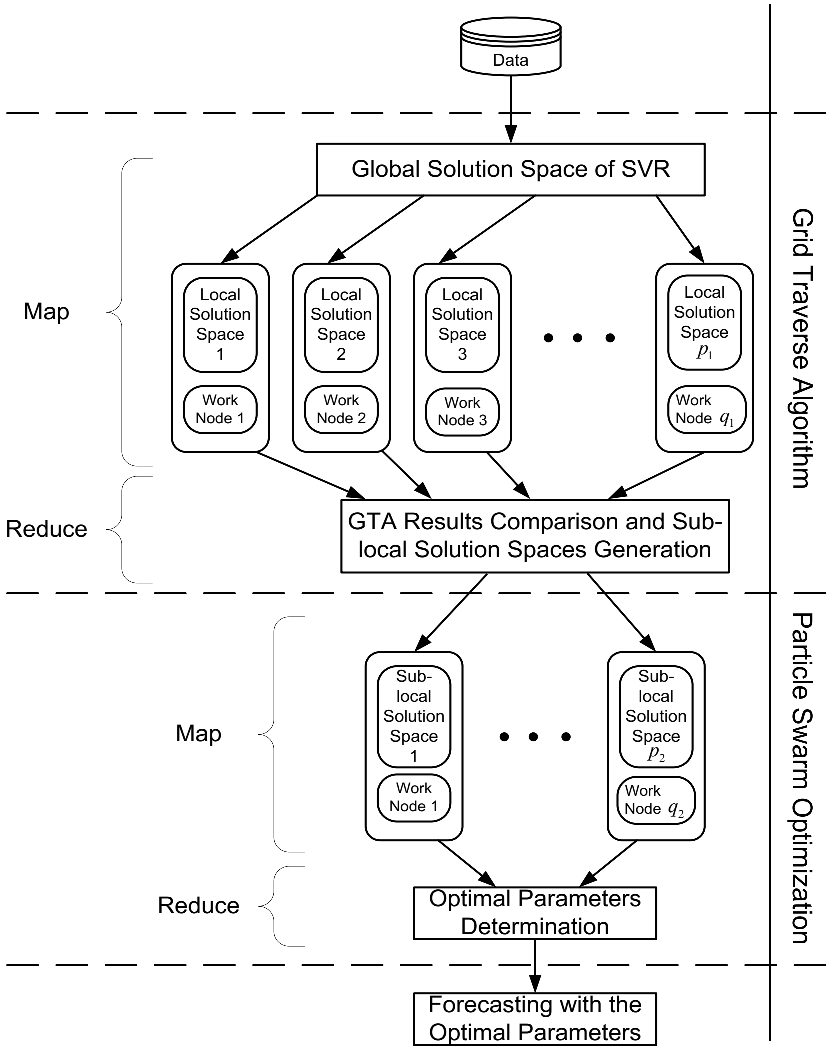
- Challenge – Lack of Coordination
  - Not necessary to benefit the overall system operations
  - Not fully utilizing the flexibility brought by these resources

Predictive System Operations



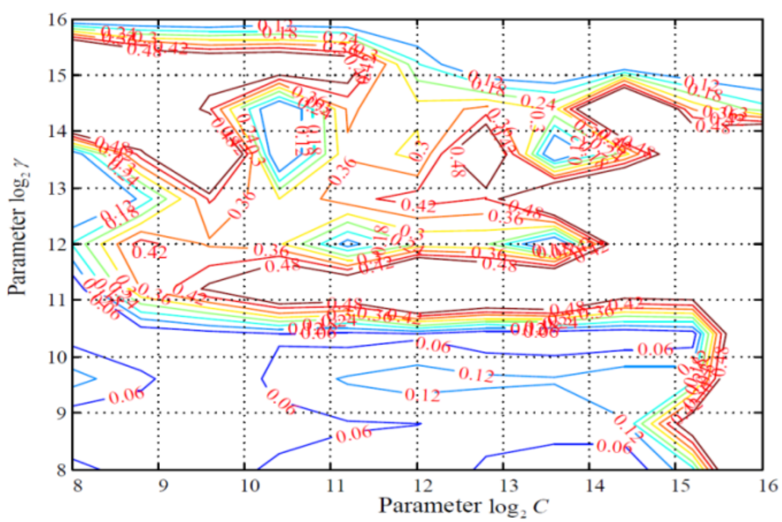
Flowchart of the load forecasting approach

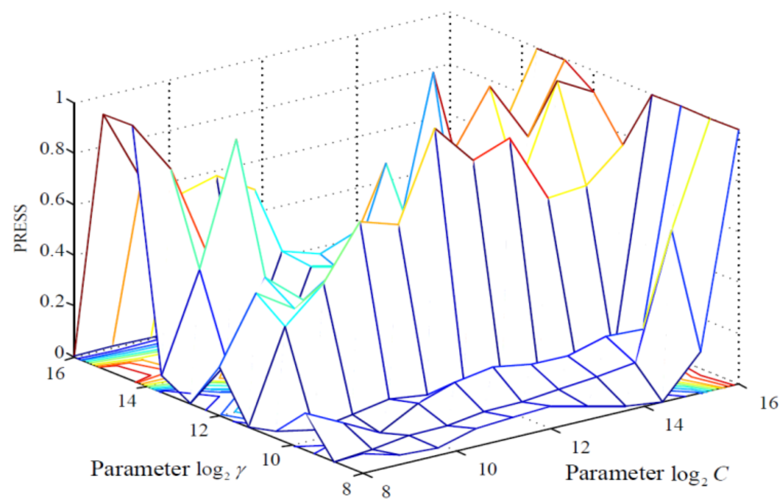




GTA for Parameter Optimization

- **Objective**: Transfer the global optimization problem to one or several local optimization problems.
- **Initialization**: Initialize γ, C, and ε; then compute Λj, and build the traverse vector **H**.
- **Grid Traverse Searching**: For the element factor $Hj2$,
- $Hj2 \in \mathbf{H}$, $j2 \in \{1, 2, \ldots, m1 \times m2 \times m3\}$, the *RCV can be computed.*
- **Determine Local Solution Space**: With the generated contour map, the local solution space with minimum *RCV* is selected for next step of optimization.





PSO for Parameters Optimization

- Initialization

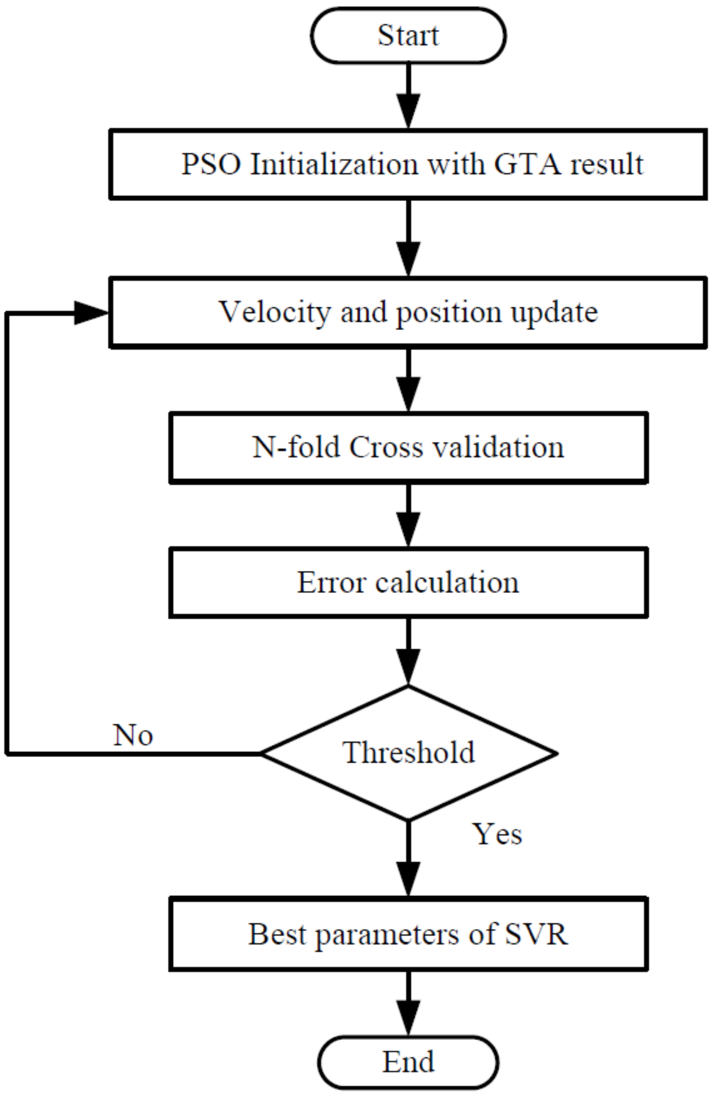
$$\boldsymbol{\alpha}_{i_4}^{\Omega} = [\alpha_{i_4,1}^{\Omega}\alpha_{i_4,2}^{\Omega}\cdots\alpha_{i_4,n_{OBJPSO}}^{\Omega}]$$
$$\boldsymbol{\nu}_{i_4}^{\Omega} = [\nu_{i_4,1}^{\Omega}\nu_{i_4,2}^{\Omega}\cdots\nu_{i_4,n_{OBJPSO}}^{\Omega}]$$
$$\boldsymbol{\eta}_{i_4}^{\Omega} = [\eta_{i_4,1}^{\Omega}\eta_{i_4,2}^{\Omega}\cdots\eta_{i_4,n_{OBJPSO}}^{\Omega}]$$

- Velocity Updates

$$\boldsymbol{\nu}_{i_4}^{\Omega}(t) = \boldsymbol{\nu}_{i_4}^{\Omega}(t-1) + \varphi_1\theta_1(\boldsymbol{\eta}_{i_4}^{\Omega} - \boldsymbol{\alpha}_{i_4}^{\Omega}(t-1)) + \varphi_2\theta_2(\boldsymbol{\eta}_{g}^{\Omega} - \boldsymbol{\alpha}_{i_4}^{\Omega}(t-1))$$

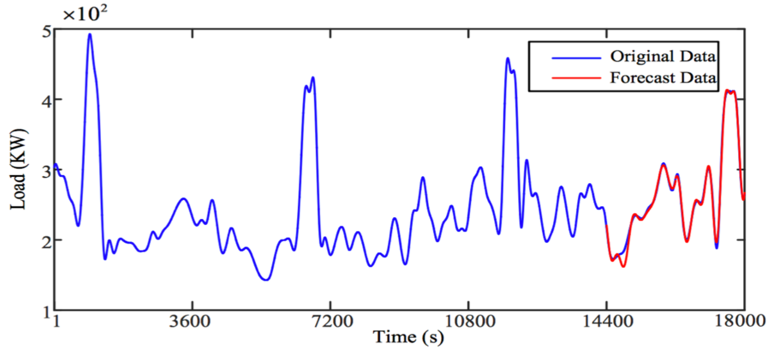
- Position Updates

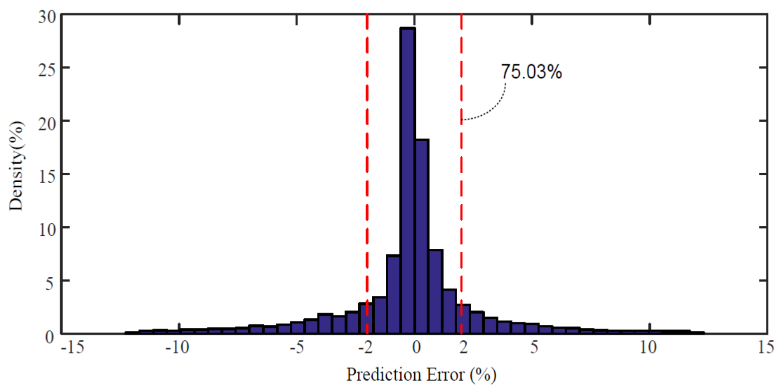
$$\boldsymbol{\alpha}_{i_4}^{\Omega}(t) = \boldsymbol{\alpha}_{i_4}^{\Omega}(t-1) + \boldsymbol{\nu}_{i_4}^{\Omega}(t)$$



Numerical Results

- The tested data set composes 80 days of load captured from a partner utility's distribution feeder. It includes data from winter (Dec.-Feb.), spring (Mar.-May.), summer (Jun.-Aug.), and autumn (Sep.-Nov.) for 20-days each season. With the sampling rate of 1 Hz, the total data length is 6,912,000.





Minutes-ahead forecasting

Methods	Max. Error (%)	MAPE (%)
ARIMA	31.25	11.21
GA based SVM	21.16	5.27
ANN	25.97	6.62
Proposed	14.11	2.53

Performance Comparison

Methods	20 minutes (S)	4 hours (S)
ARIMA	11.25	77.21
GA based SVM	45.16	1412.7
ANN	40.9	683.62
Proposed	12.89	83.53

Time Consumption Comparison

H. Jiang, Y. Zhang, J.J. Zhang, and E. Muljadi, *"A Short-term Load Forecasting Approach Using Support Vector Regression with Hybrid Parameter Optimization in Distribution System,"* IEEE Transactions on Smart Grid, 2016.

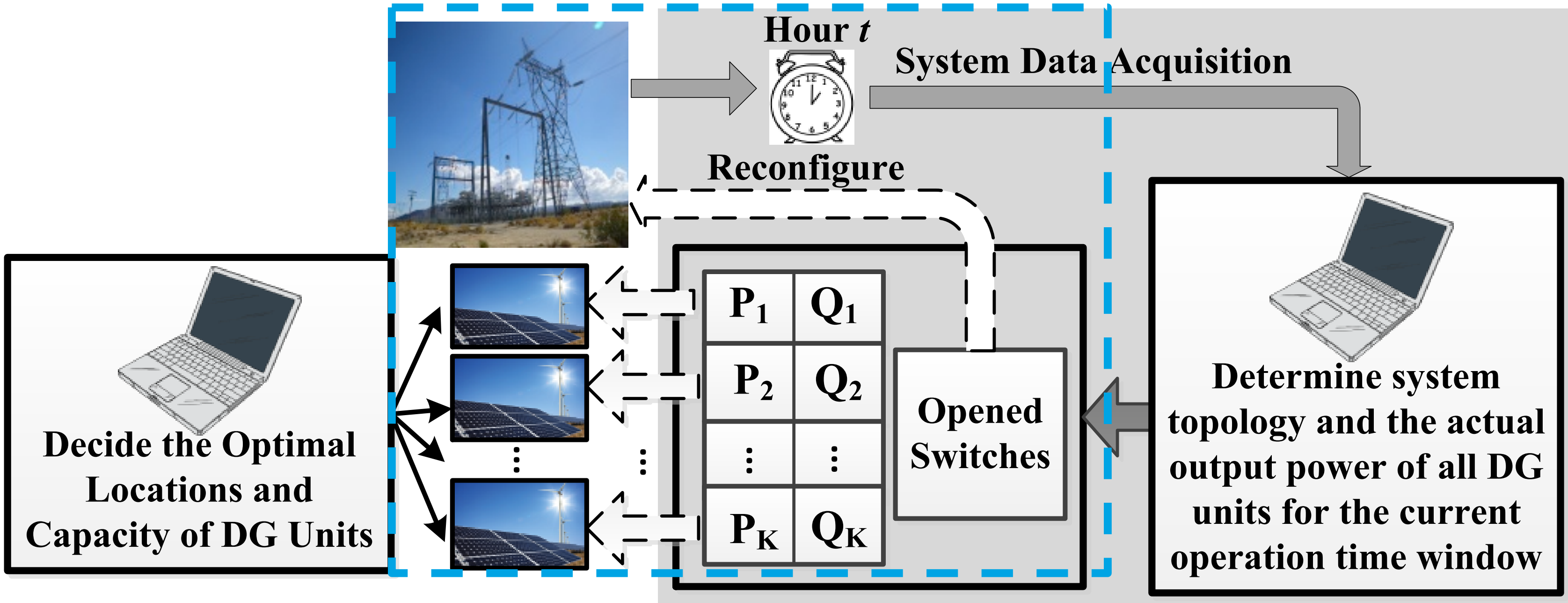
Application in Network Reconfiguration

- Distribution system loads become more fluctuant and unpredictable.
  - Large impacts from end users to distribution system
  - More stochastic abrupt deviations than transmission systems.

- Traditional distribution reconfiguration cannot meet the requirements of modern distribution systems.
  - Traditional distribution reconfiguration is static.
  - Dynamic end user profiles require a dynamic control strategy for distribution system reconfiguration.

- An automatic distribution network reconfiguration approach is designed based on short-term load forecasting.

Basic Framework of Network Reconfiguration



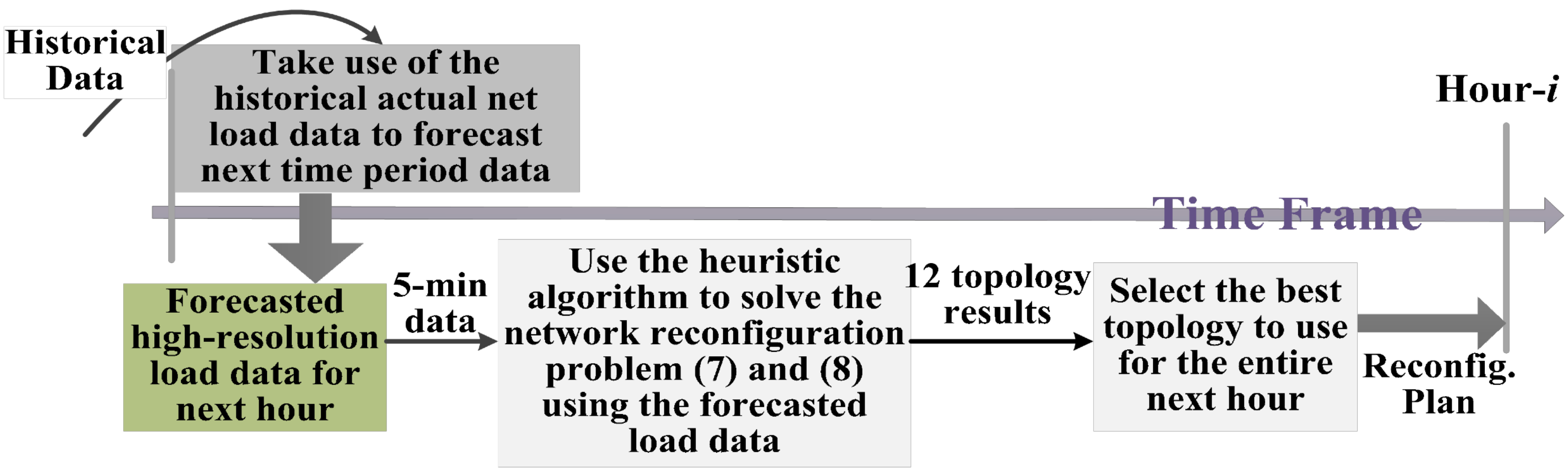
$$P_{loss} = \gamma(e, f)$$
$$s.t.\ h(e, f, P_{inject}, Q_{inject}) = 0$$

$$\Delta P_{loss} = \mathbf{M_S} \cdot \begin{bmatrix} \Delta \mathbf{P_{inject}} \\ \Delta \mathbf{Q_{inject}} \end{bmatrix}$$

Objective: minimize total energy losses in the unbalanced distribution system with the initial topology

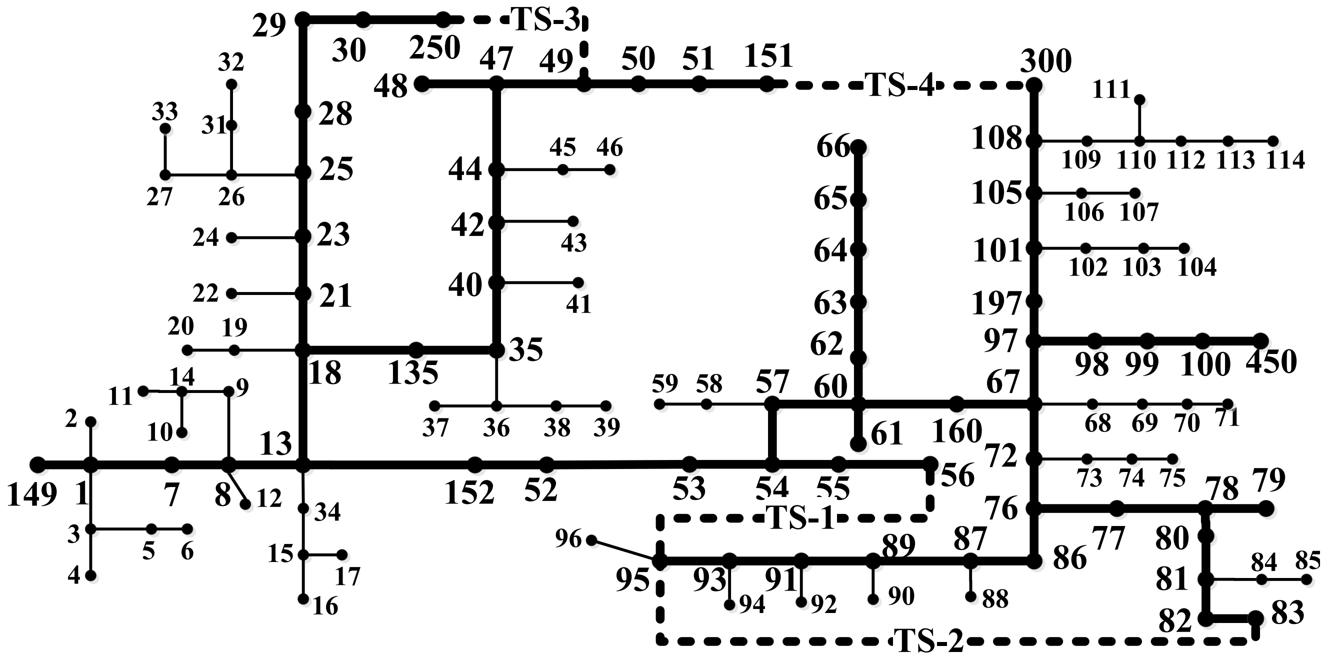
How to use load forecast?

- The short-term load forecasting is executed using the historic actual high-resolution data.
- The reconfiguration problem is solved for every 5 min in this paper, finally leading to 12 results of the system topology for the next hour and each result for a 5-min time slot.
- Among all 12 system topologies for the 5-min time slots, the topology that achieves the most loss reduction will be selected and used for the entire next hour.



Test Bench IEEE 123-bus System

Four initially opened tie switches (TS-1, TS-2, TS-3 and TS-4) are added to make the system topology changeable, and all voltage regulators are removed to fully address the impact of network reconfiguration on reducing losses.



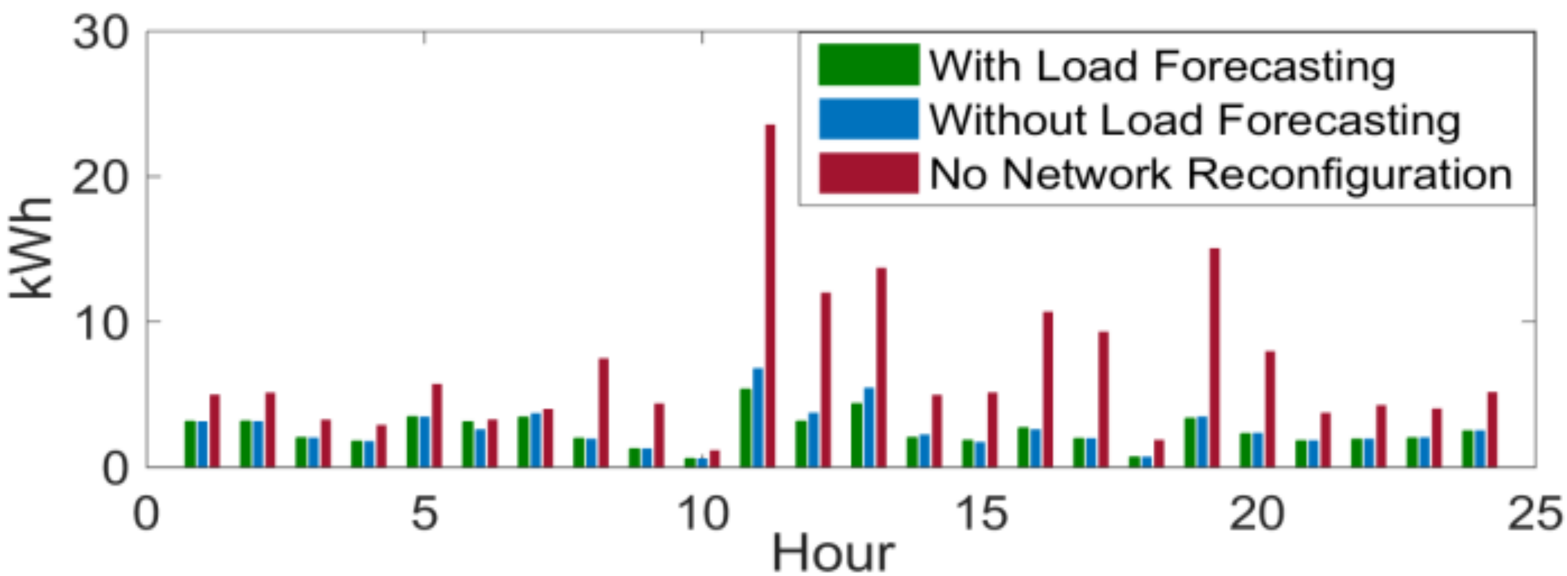
Numerical Results (1): One day (24 hours) Simulation

Hour	Opened Switches	Loss Reduction
1	93-95, TS-2, 29-30, 101-105	36.71%
2, 3, 4, 5	93-95, TS-2, 29-30, 101-105	--
6	TS-1, TS-2, 29-30, 101-105 (for 0–15 mins)	0.089%
	TS-1, TS-2, 29-30, 105-108 (for 15–30 mins)	2.686%
	87-89, TS-2, 29-30, 108-300 (for 30–60 mins)	2.55%
7	87-89, TS-2, 29-30, 108-300	--
8	87-89, TS-2, 29-30, 105-108 (for 0–10 mins)	3.356%
	87-89, TS-2, 29-30, 57-60 (for 10–60 mins)	53.02%
9	91-93, TS-2, 29-30, 57-60 (for 0–20 mins)	0.484%
	67-72, TS-2, 29-30, 57-60 (for 20–60 mins)	5.513%
10	67-72, TS-2, 29-30, 57-60 (for 0–5 mins)	--
	67-72, TS-2, TS-3, 57-60 for (5–10 mins)	2.336%
	67-72, TS-2, 29-30, 57-60 for (10–15 mins)	1.685%
	67-72, TS-2, TS-3, 57-60 for (15–45 mins)	0.575%
	67-72, TS-2, 18-21, 57-60 for (45–60 mins)	23.32%
11, 12, 13	67-72, TS-2, 18-21, 57-60	--

Hour	Opened Swithes	Loss Reduction
14	67-72, TS-2, 18-21, 57-60 (for 0–15 mins)	--
	67-72, TS-2, 21-23, 57-60 (for 15–20 mins)	0.721%
	67-72, TS-2, 18-21, 57-60 (for 20–30 mins)	3.212%
	67-72, TS-2, 21-23, 57-60 (for 30–35 mins)	3.805%
	67-72, TS-2, 18-21, 57-60 (for 35–45 mins)	1.080%
	67-72, TS-2, 21-23, 57-60 (for 45–55 mins)	2.547%
	67-72, TS-2, 18-21, 57-60 (for 55–60 mins)	0.975%
15	67-72, TS-2, 18-21, 57-60 (for 0–10 mins)	--
	67-72, TS-2, 21-23, 57-60 (for 10–30 mins)	2.435%
	67-72, TS-2, 18-21, 57-60 (for 30–60 mins)	0.862%
16	67-72, TS-2, 18-21, 57-60 (for 0–25 mins)	--
	67-72, TS-2, 21-23, 57-60 (for 25–30 mins)	3.060%
	67-72, TS-2, 18-21, 57-60 (for 30–35 mins)	1.783%
	67-72, TS-2, 21-23, 57-60 (for 35–45 mins)	1.745%
	67-72, TS-2, 18-21, 57-60 (for 45–50 mins)	4.084%
	67-72, TS-2, 21-23, 57-60 (for 50–60 mins)	2.053%
17	67-72, TS-2, 21-23, 57-60 (for 0–10 mins)	--
	67-72, TS-2, 18-21, 57-60 (for 10–15 mins)	2.420%
	67-72, TS-2, 21-23, 57-60 (for 15–25 mins)	7.240%
	67-72, TS-2, 18-21, 57-60 (for 25–60 mins)	3.520%
18, 19, 20, 21, 22, 23	67-72, TS-2, 18-21, 57-60	--
24	67-72, TS-2, 18-21, 57-60 (for first 15 mins)	0.354%
	67-72, TS-2, 21-23, 57-60 (for last 45 mins)	0.501%

Numerical Results (2): Results comparison

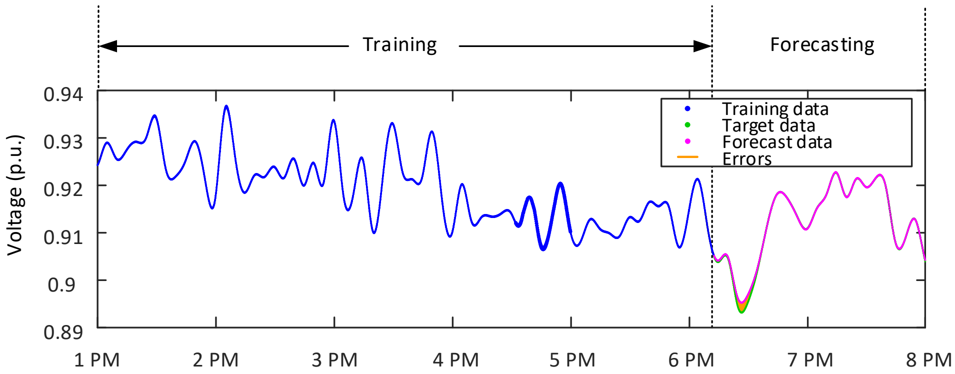
- The total energy losses in a day for these three scenarios are **60.49 kWh** (with load forecasting), 71.81 kWh (without load forecasting), and 164.23 kWh (no network reconfiguration), respectively.
- In addition, compared to the traditional network reconfiguration approach, the proposed approach **reduces** system energy loss by approximately **15%** and network reconfiguration operations by **50%**.

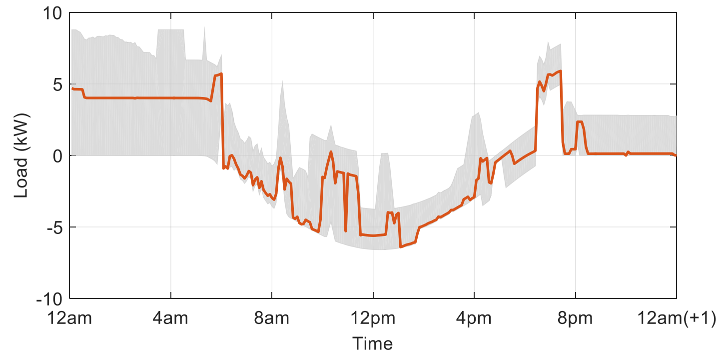


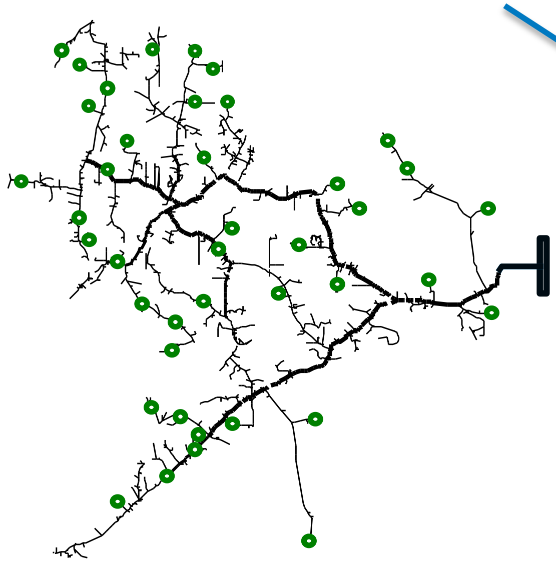
H. Jiang, F. Ding, Y. Zhang, "Short-Term Load Forecasting Based Automatic Distribution Network Reconfiguration", *2017 IEEE Power & Energy Society General Meeting (PESGM)*, pp. 1-5, 2017.

Applications

- State Forecasting-Based Voltage Regulation [1, 2]
- Consumer Behavior-Aided Dispatch [3-5]





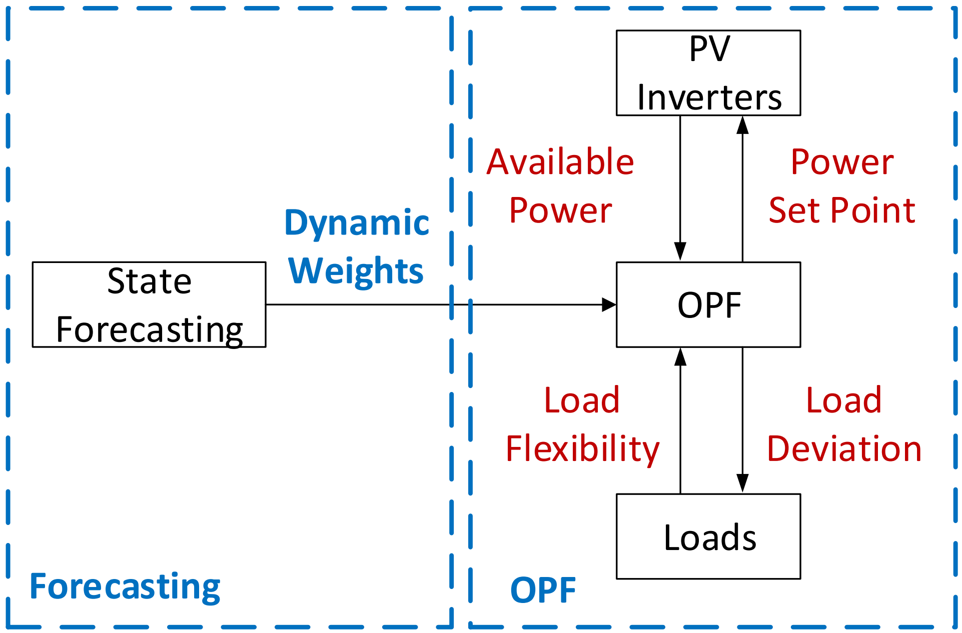


$$
\begin{aligned}
\min_{x,u} \quad & f(x,u) \\
\text{s.t.} \quad & g(x,u) = 0 \\
& h(x,u) \leq 0
\end{aligned}
$$

Coordinated Optimization

State Forecasting-Based Voltage Regulation

- Goals
  - Accurately forecasting system states in the near future
  - Prioritizing the control needs
- Approach



Dynamically Weighted OPF

$$
\begin{aligned}
\min_{P_{S,m}^{\phi}, Q_{S,m}^{\phi}, P_{L,k}^{\phi}} \quad & \sum_{i \in \mathcal{N}} \sum_{\phi \in \mathcal{P}_i} \omega_i^{\phi} \cdot s_i^{\phi} \\
& + \omega_L \cdot \sum_{k \in \mathcal{N}_L} \sum_{\phi \in \mathcal{P}_{L,k}} \left(\frac{P_{L,k}^{\phi} - \widetilde{P}_{L,k}^{\phi}}{\widetilde{P}_{L,k}^{\phi}} \right)^2 \\
\text{s.t.} \quad & P_{G,i}^{\phi} + P_{S,i}^{\phi} - P_{L,i}^{\phi} = \Re\{V_i^{\phi} \cdot (I_i^{\phi})^*\} \\
& Q_{G,i}^{\phi} + Q_{S,i}^{\phi} - Q_{L,i}^{\phi} = \Im\{V_i^{\phi} \cdot (I_i^{\phi})^*\} \\
& \underline{V}_i^{\phi} - s_i^{\phi} \leq |V_i^{\phi}| \leq \overline{V}_i^{\phi} + s_i^{\phi}, \; s_i^{\phi} \geq 0 \\
& 0 \leq P_{S,m}^{\phi} \leq \overline{P}_{S,m}^{\phi} \\
& P_{S,m}^{\phi^2} + Q_{S,m}^{\phi^2} \leq S_m^{\phi^2} \\
& \underline{P}_{L,k}^{\phi} \leq P_{L,k}^{\phi} \leq \overline{P}_{L,k}^{\phi} \\
& Q_{L,k}^{\phi} = \sqrt{\frac{1}{\eta_{L,k}^{\phi^2}} - 1} \cdot P_{L,k}^{\phi}
\end{aligned}
$$

Dynamically determined by the forecasted voltages

Power balance

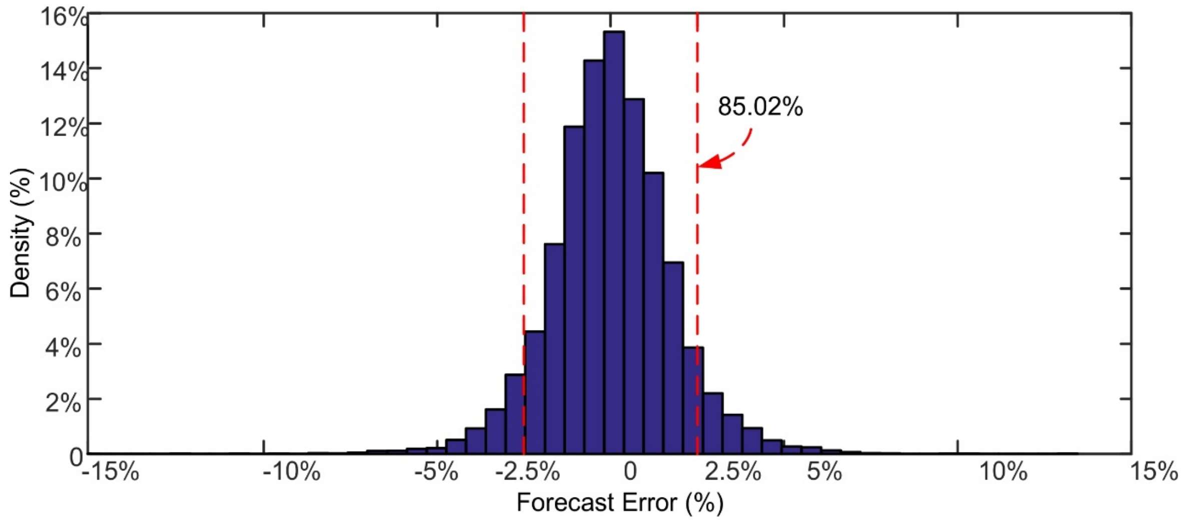
Voltage constraints

PV plant

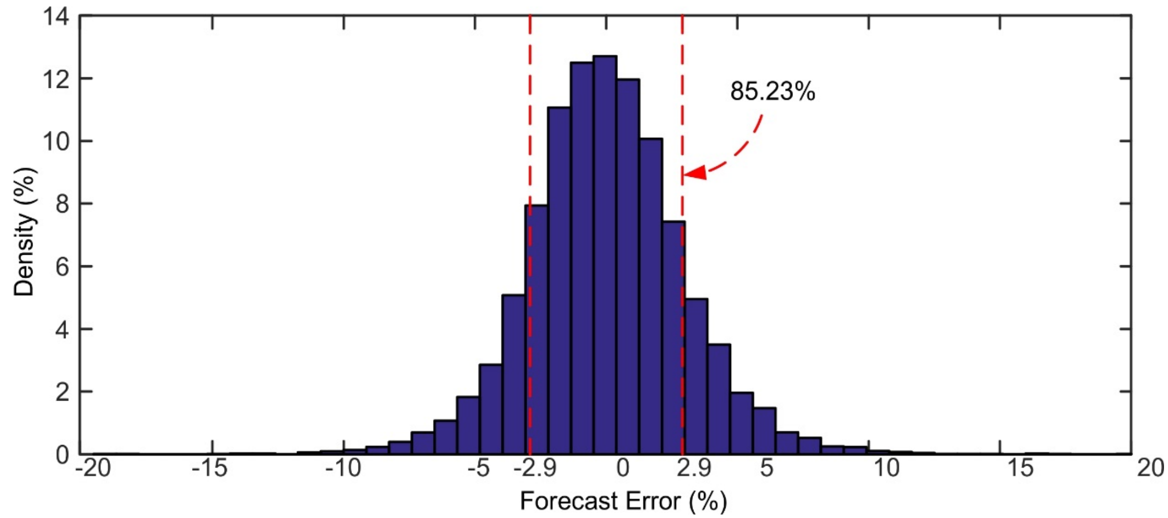
Smart load

Results – State Forecasting Error

Voltage Magnitude



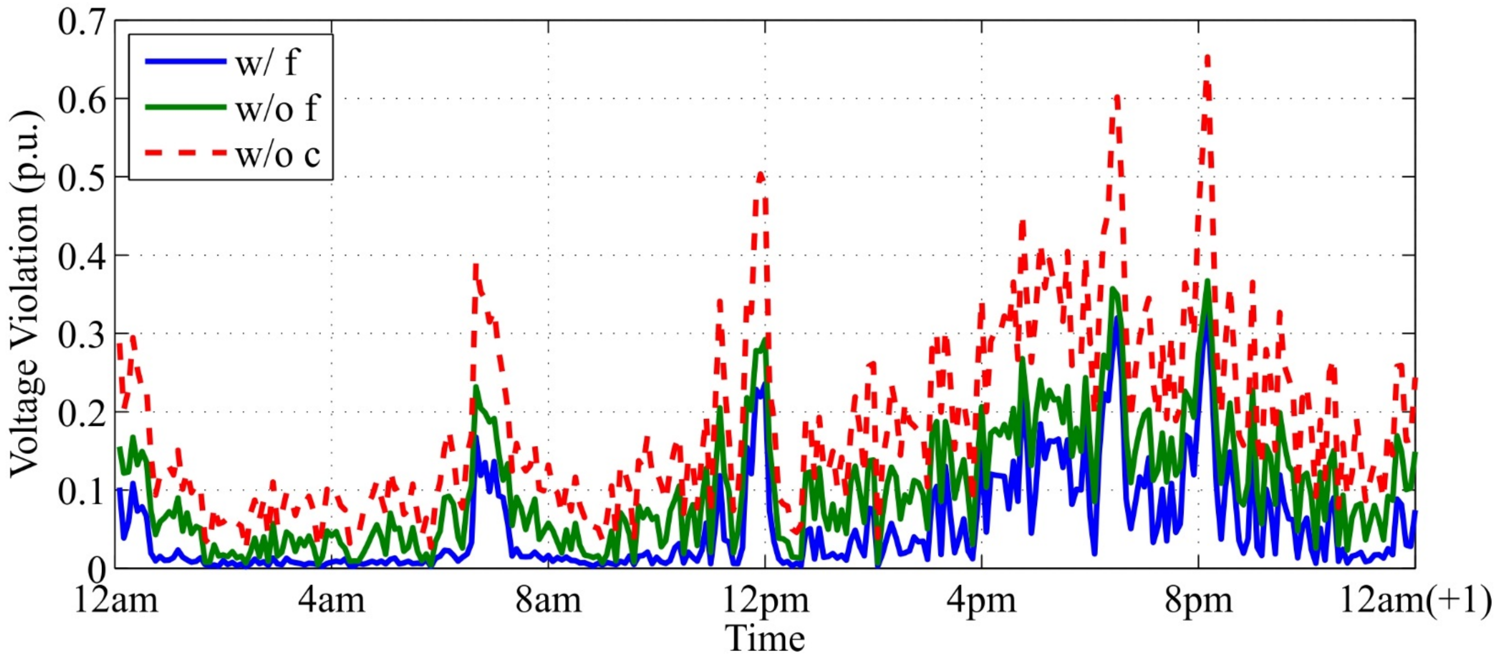
Voltage Angle



Accurate state forecast with machine learning methods

Results – Voltage Regulation

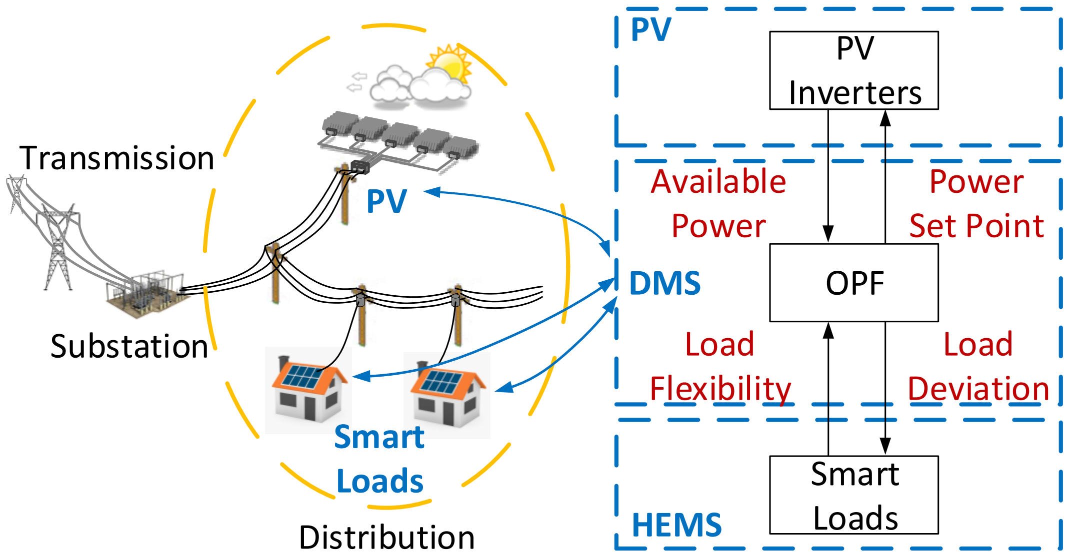
Voltage Violation



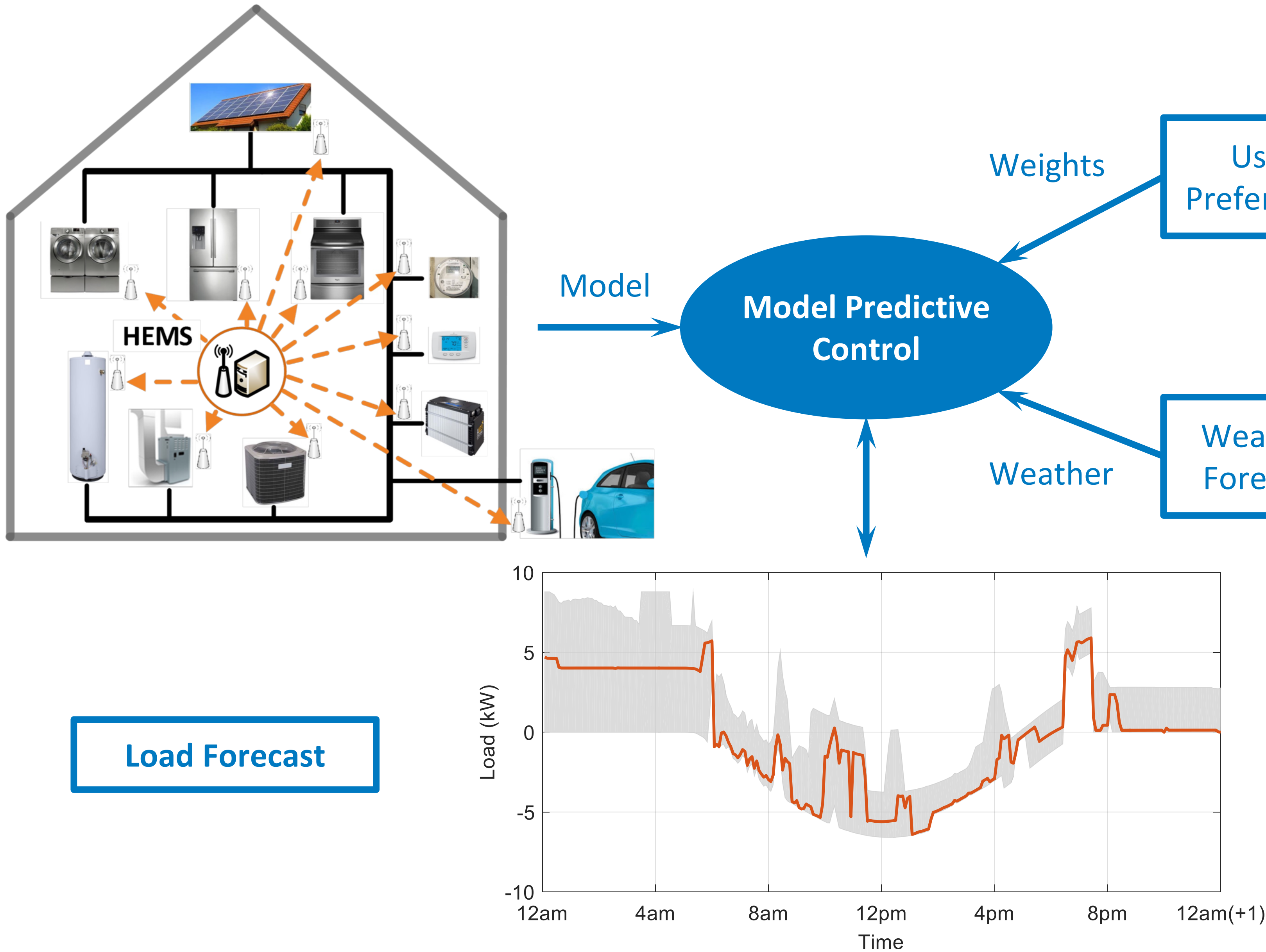
Voltage violations reduced significantly with state forecasting-based optimal scheduling

Consumer Behavior-Aided Dispatch

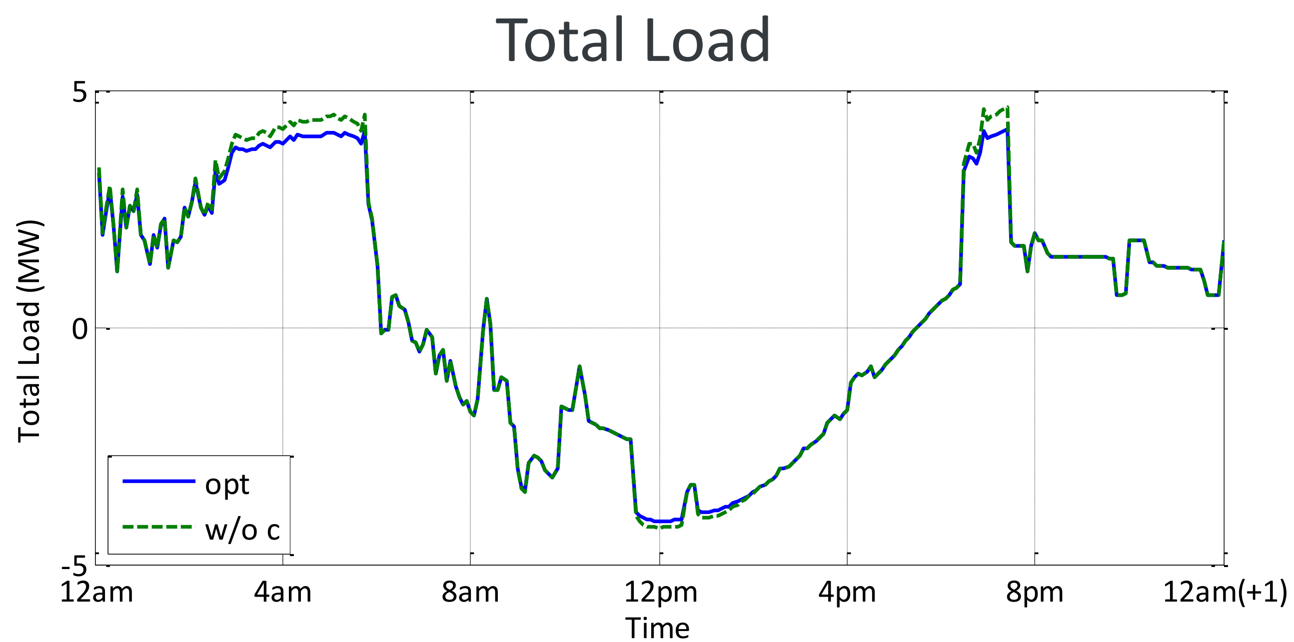
- Goals
  - Actively engaging electricity consumers
  - Achieving system-level control objectives without sacrificing consumers' needs
- Integrated Optimization Approach

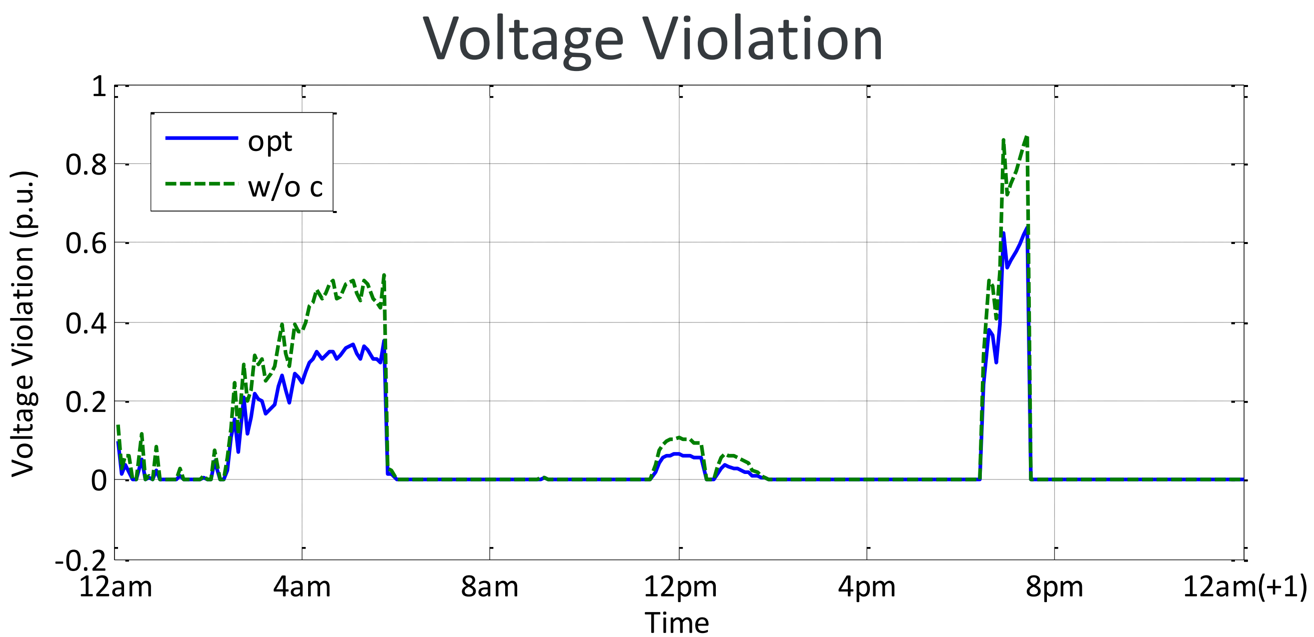


Model-Based Load Forecasting



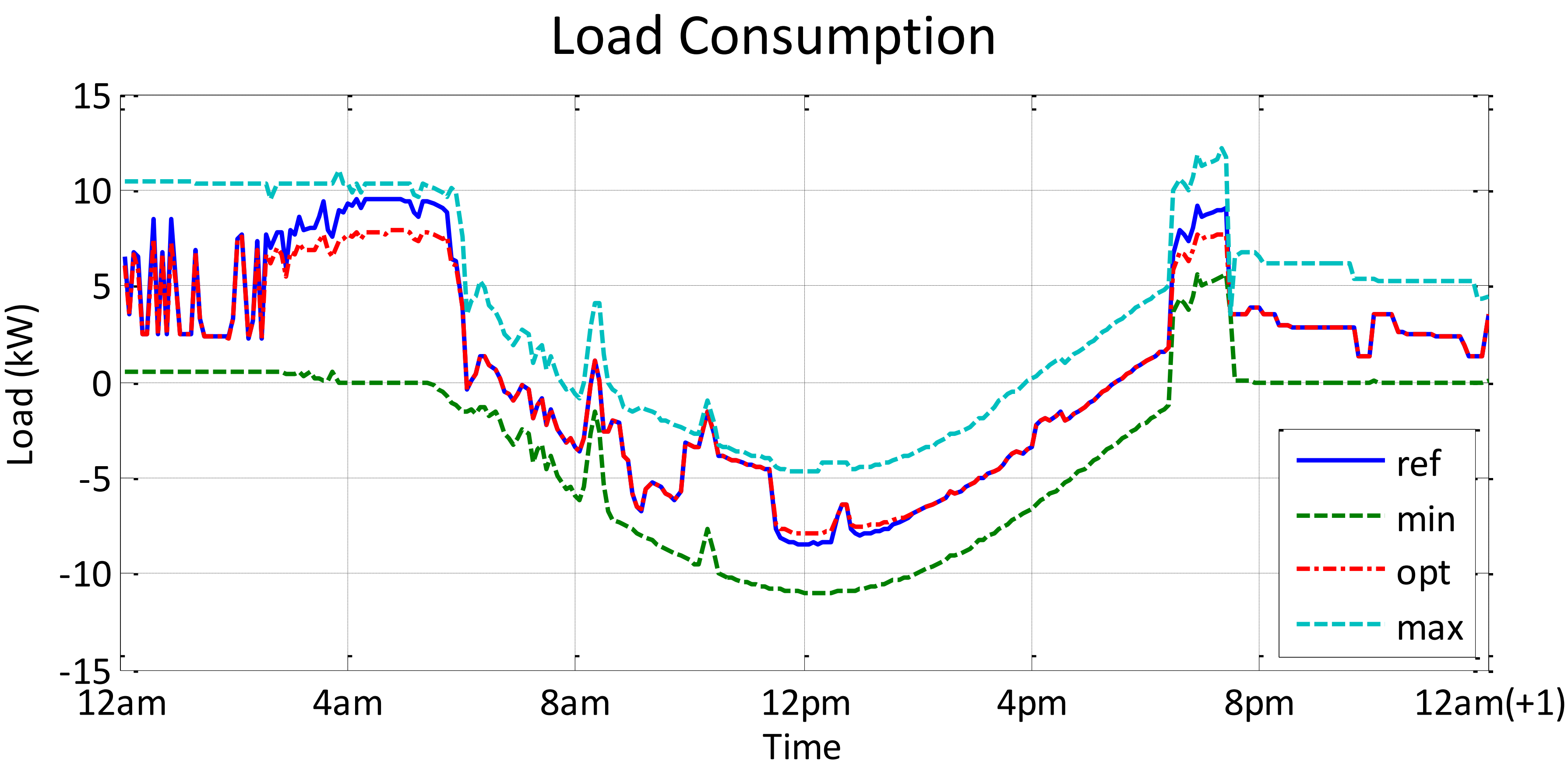
Results – Distribution System Level





Results – Home Level

- Example – One House



System performance improved without significant load deviation

Summary

- Predictive Analytics for Coordinated Optimization
  - Data analytics methods to facilitate the decision-making
  - Optimal coordination of various resources
- Ongoing Work
  - Data-driven, model-based, and hybrid methods for resource and load forecasts [6]
  - Integrated framework for system state estimation and forecasting [7]
  - Incentives to drive desirable behaviors of consumers [8]

References

[1] Huaiguang Jiang and Yingchen Zhang, “Short-term distribution system state forecast based on optimal synchrophasor sensor placement and extreme learning machine,” *IEEE PES General Meeting*, Boston, MA, July 2016.

[2] Rui Yang, Huaiguang Jiang, and Yingchen Zhang, “Short-term state forecasting-based optimal voltage regulation in distribution systems,” *IEEE Innovative Smart Grid Technologies*, Arlington, VA, April 2017.

[3] Rui Yang and Yingchen Zhang, “Coordinated Optimization of Distributed Energy Resources and Smart Loads in Distribution Systems,” *IEEE PES General Meeting*, Boston, MA, July 2016.

[4] Rui Yang, Yingchen Zhang, Hongyu Wu, and Annabelle Pratt, “Coupling energy management systems at distribution and home levels,” *IEEE Transactions on Smart Grid*, under review.

[5] Yingchen Zhang, Rui Yang, Kaiqing Zhang, Huaiguang Jiang, and Jun Jason Zhang, “Consumption behavior analytics-aided energy forecasting and dispatch,” *IEEE Intelligent Systems*, vol. 32, no. 4, pp. 59-63, 2017.

[6] Huaiguang Jiang, Yingchen Zhang, Eduard Muljadi, Jun Jason Zhang, and Wenzhong Gao, “A short-term and high-resolution distribution system load forecasting approach using support vector regression with hybrid parameters optimization,” *IEEE Transactions on Smart Grid*.

[7] Yingchen Zhang, “Predictive Analytics for Energy Systems State Estimation,” panel presentation, *IEEE PES General Meeting*, Chicago, IL, July 2017.

[8] Rui Yang and Yingchen Zhang, “Three-phase AC optimal power flow based distribution locational marginal price,” *IEEE Innovative Smart Grid Technologies*, Arlington, VA, April 2017.

Collaborators:

Rui Yang

Huaiguang Jiang

Andrey Bernstein

Contact:

Yingchen Zhang

Email: Yingchen. zhang@nrel.gov

Thank You!

www.nrel.gov

NREL
NATIONAL RENEWABLE ENERGY LABORATORY