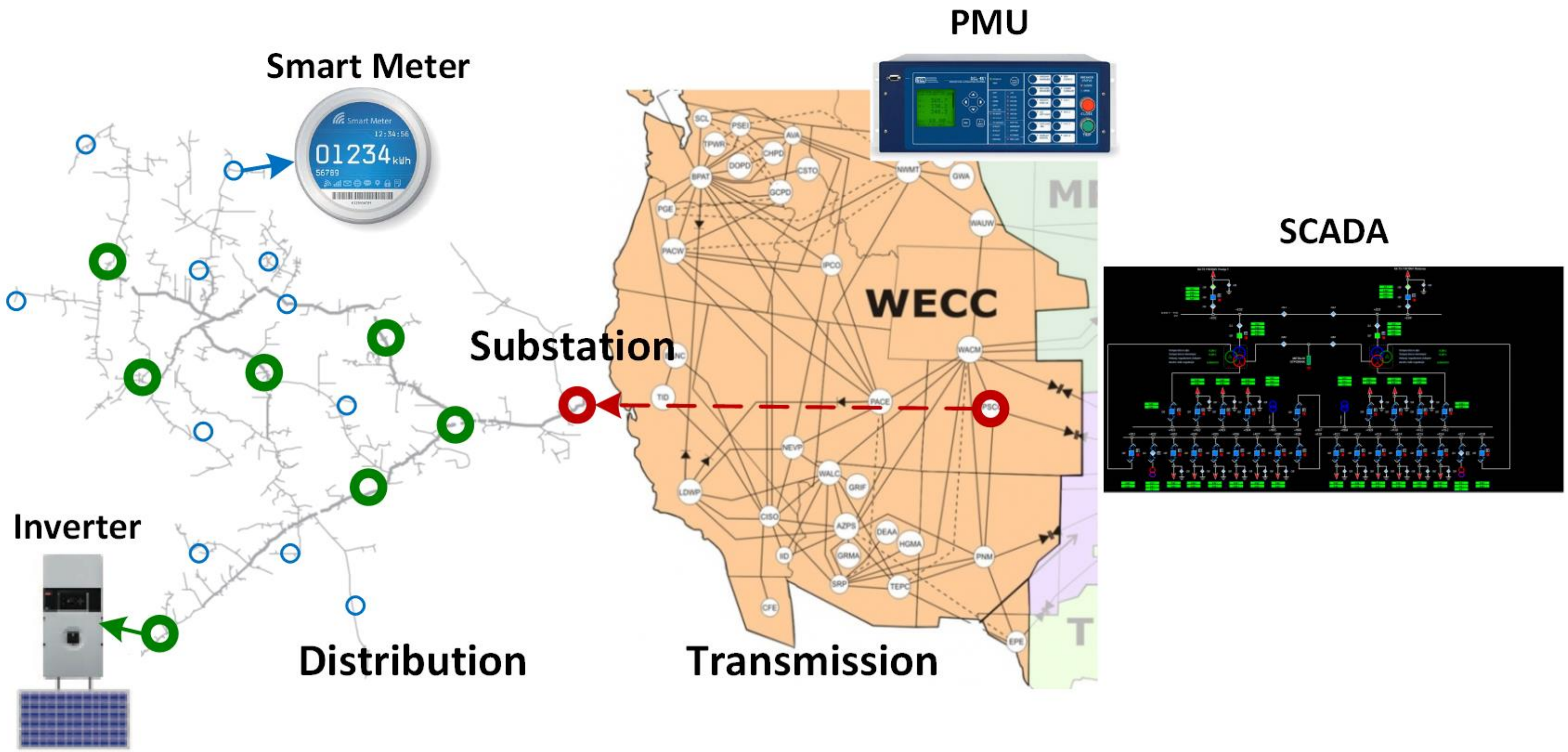
Predictive Analytics for Energy Systems State Estimation

Presenter: Yingchen (YC) Zhang
National Renewable Energy Laboratory (NREL)

Team: Andrey Bernstein, Rui Yang, Yu Xie, Anthony Florita, Changfu Li, Scott Carmichael

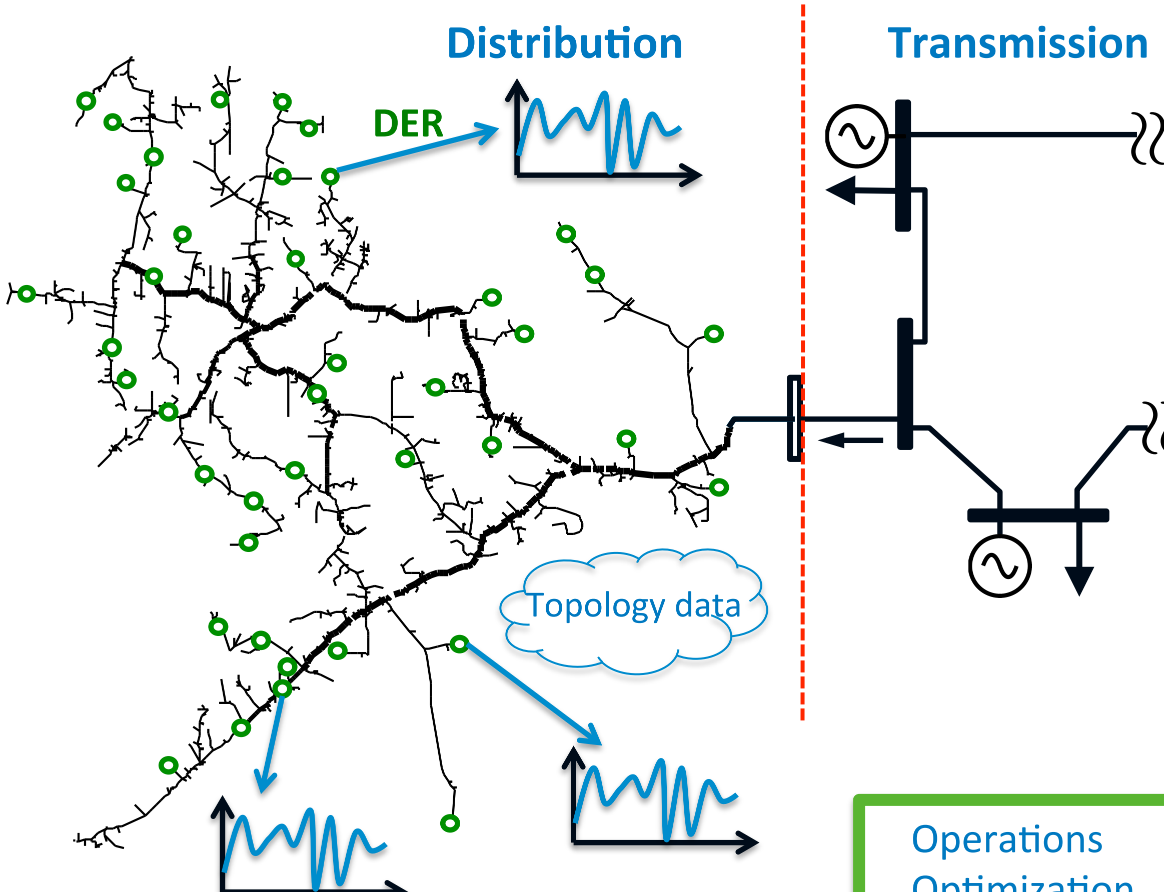
Motivation

- Increased Amount of Data in Power Systems



Motivation

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

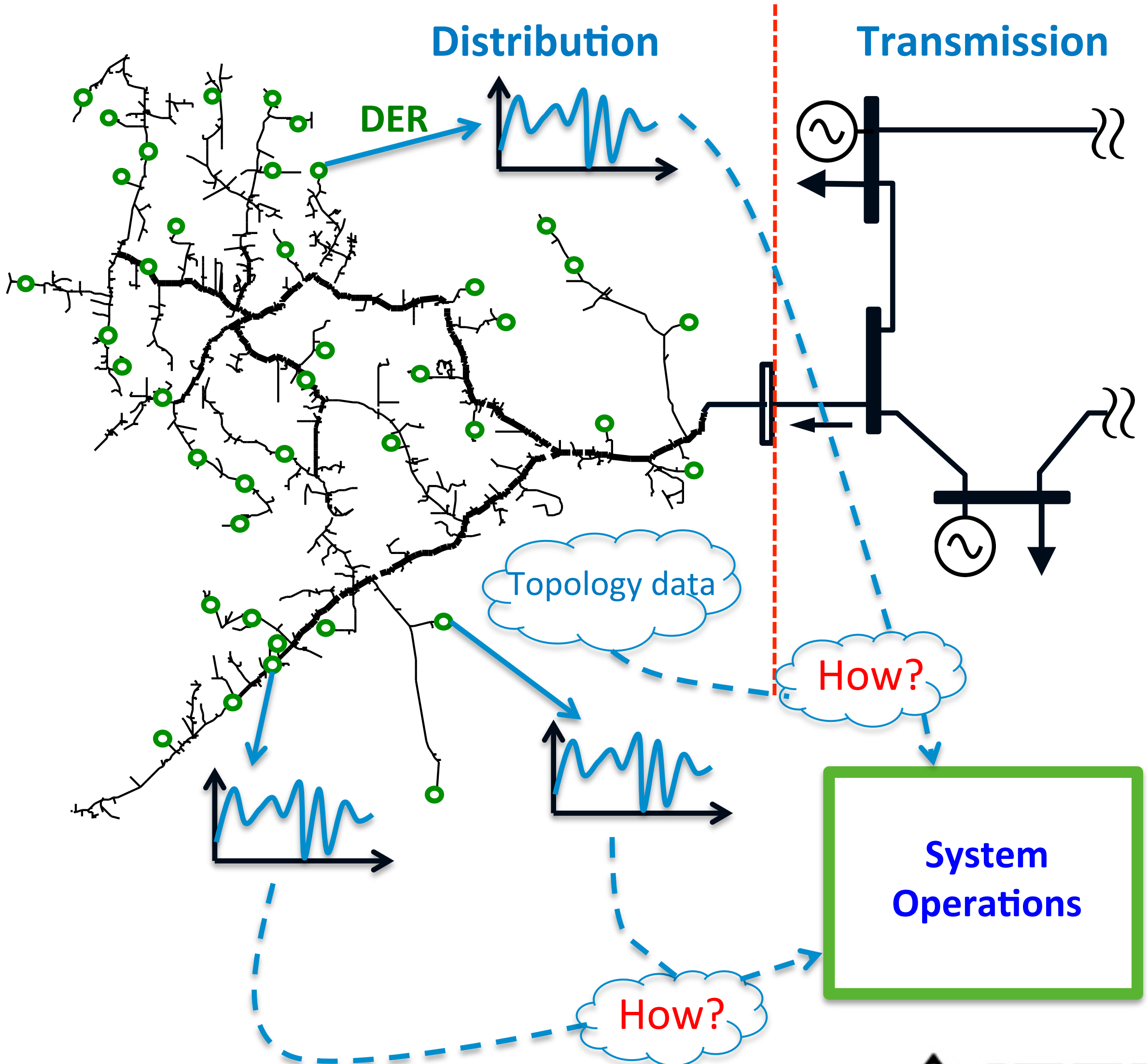


Operations
Optimization
Control
Planning

Motivation

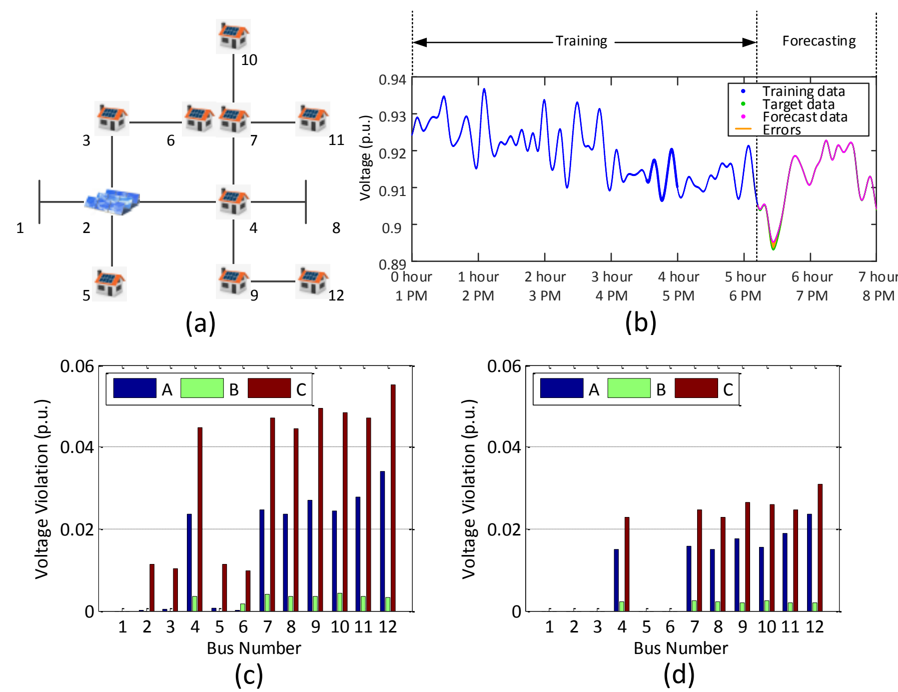
- Data
  - Nonpervasive
  - Heterogeneous
  - Highly variable
  - Different resolution

How to use these data?



Motivation

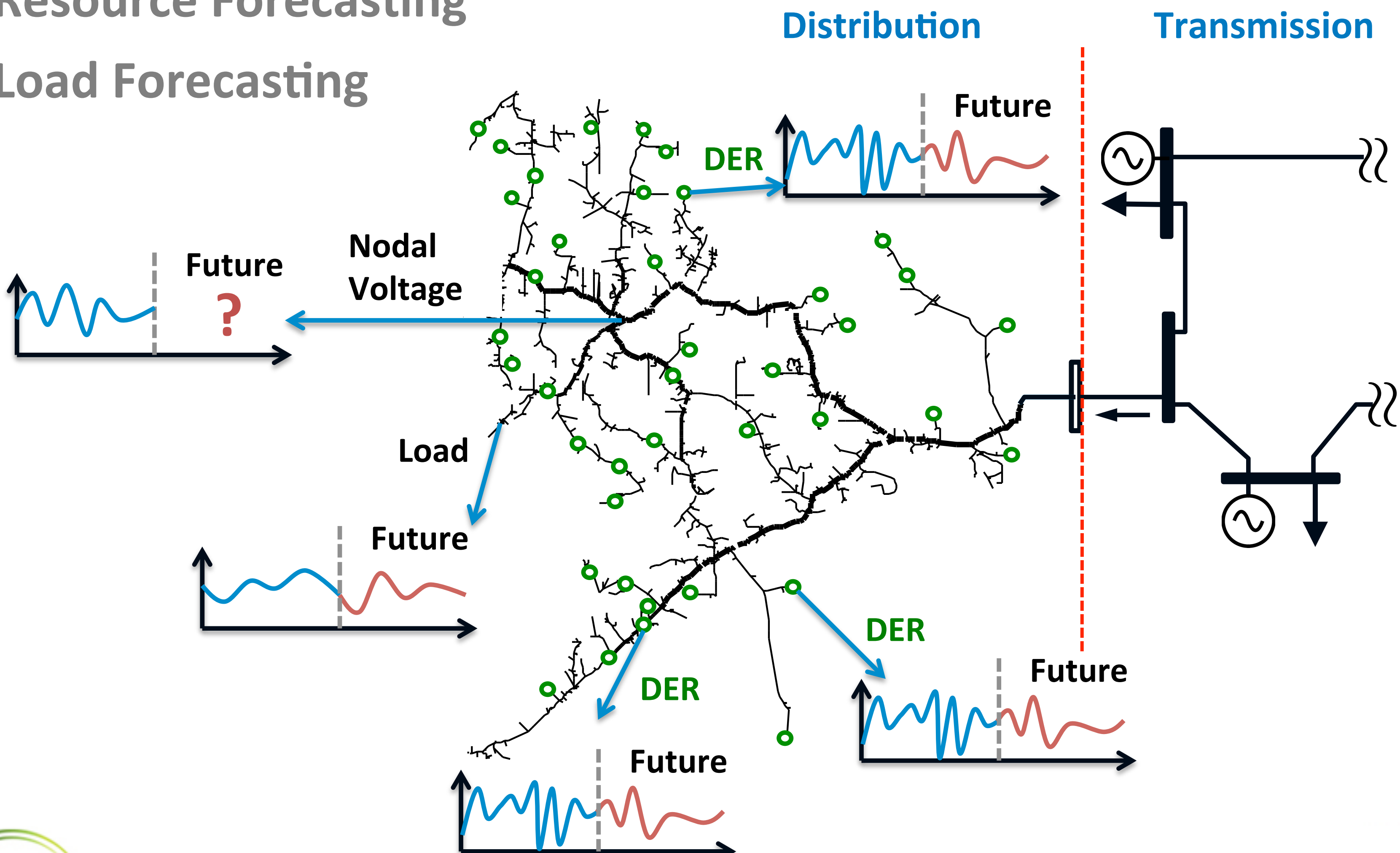
- Power Systems Situational Awareness
- Predictive System Operations



State-of-the-Art

Resource Forecasting

Load Forecasting

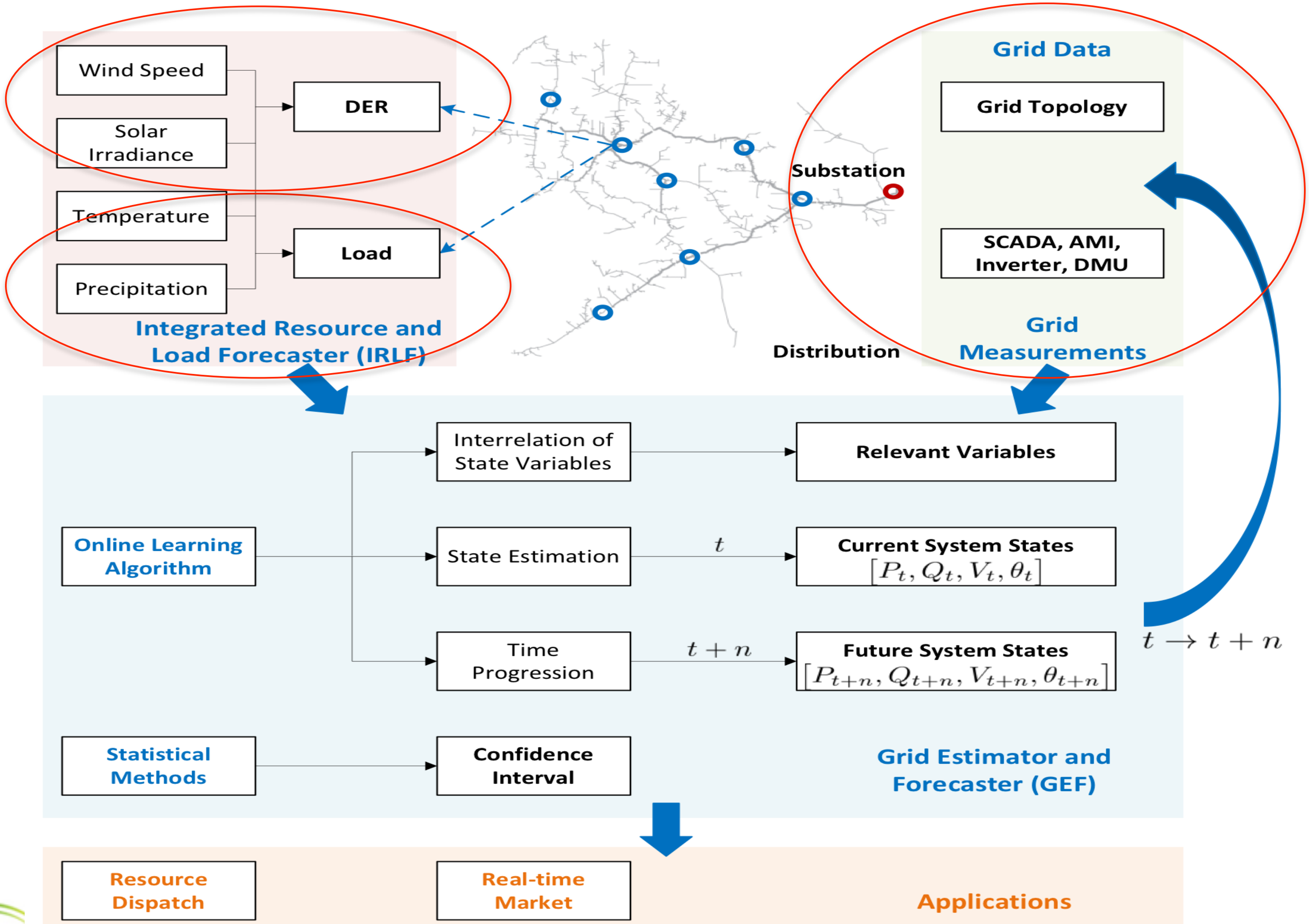


Objectives

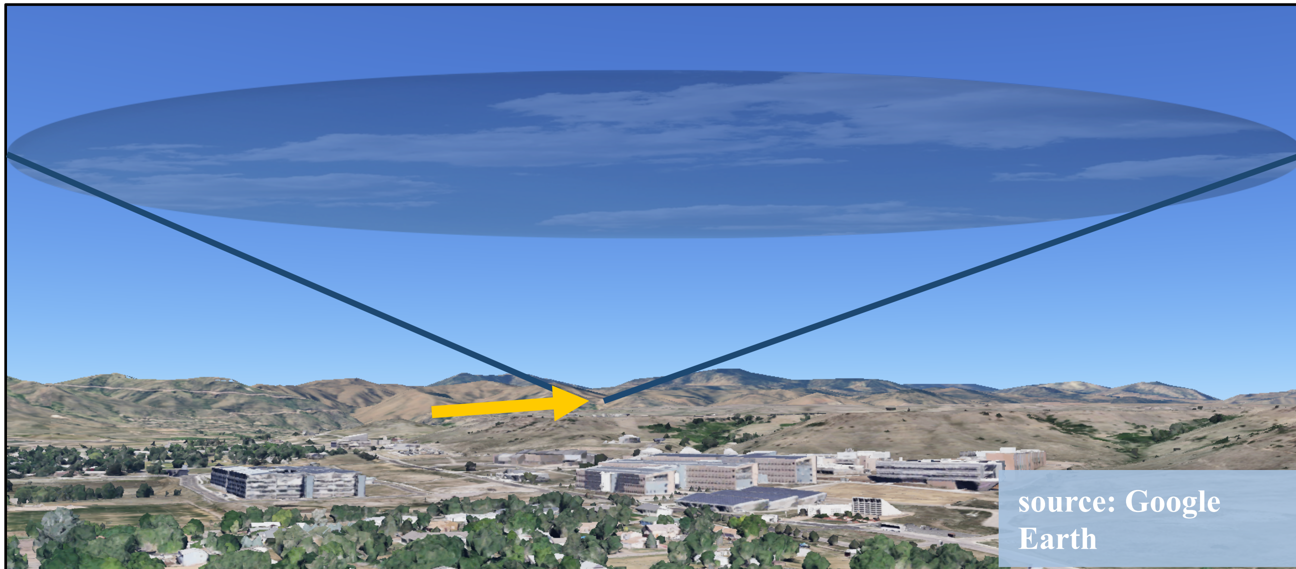
- Integrate the look-ahead state estimation method with short-term resource and load forecasting
- Develop a robust grid estimation and forecasting platform
- Develop a novel comprehensive deep learning method for multimodal knowledge discovery
- Reliably forecast grid conditions in 5-minute resolution with 30-minute look-ahead window

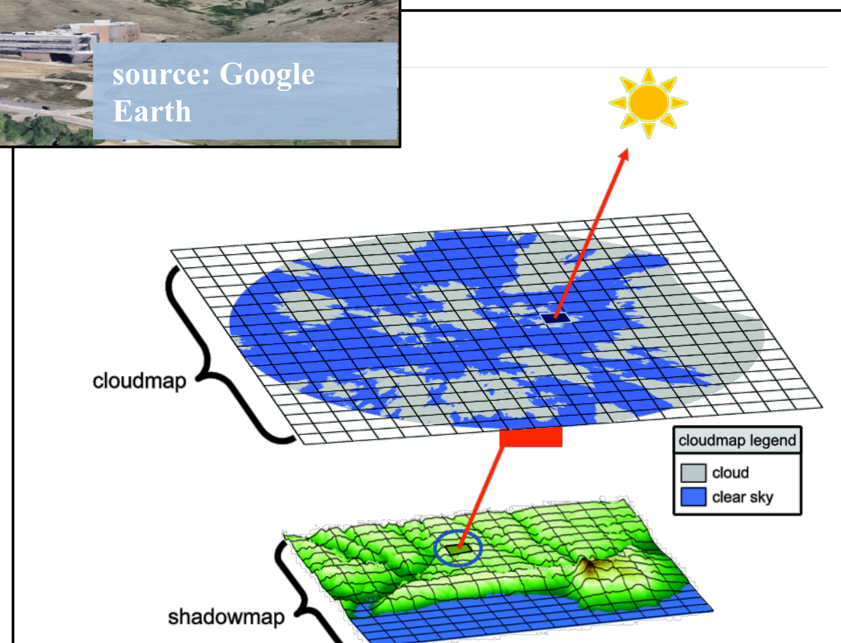
Predictive Analytics for Grid Estimation (PAGE)

PAGE Platform



Overview of Sky Imager Forecast





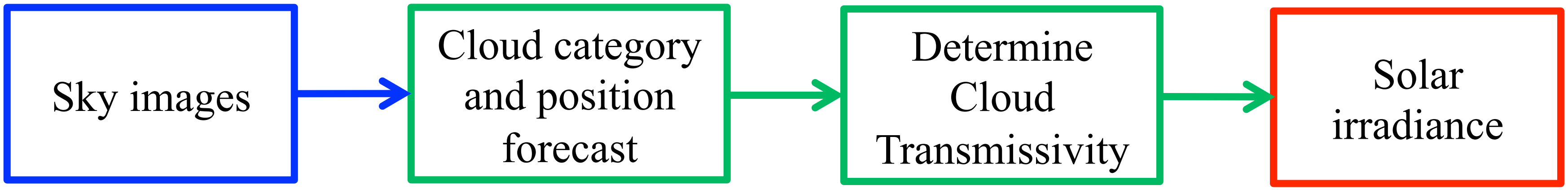
source: Bryan Urquhart

Sky Imager

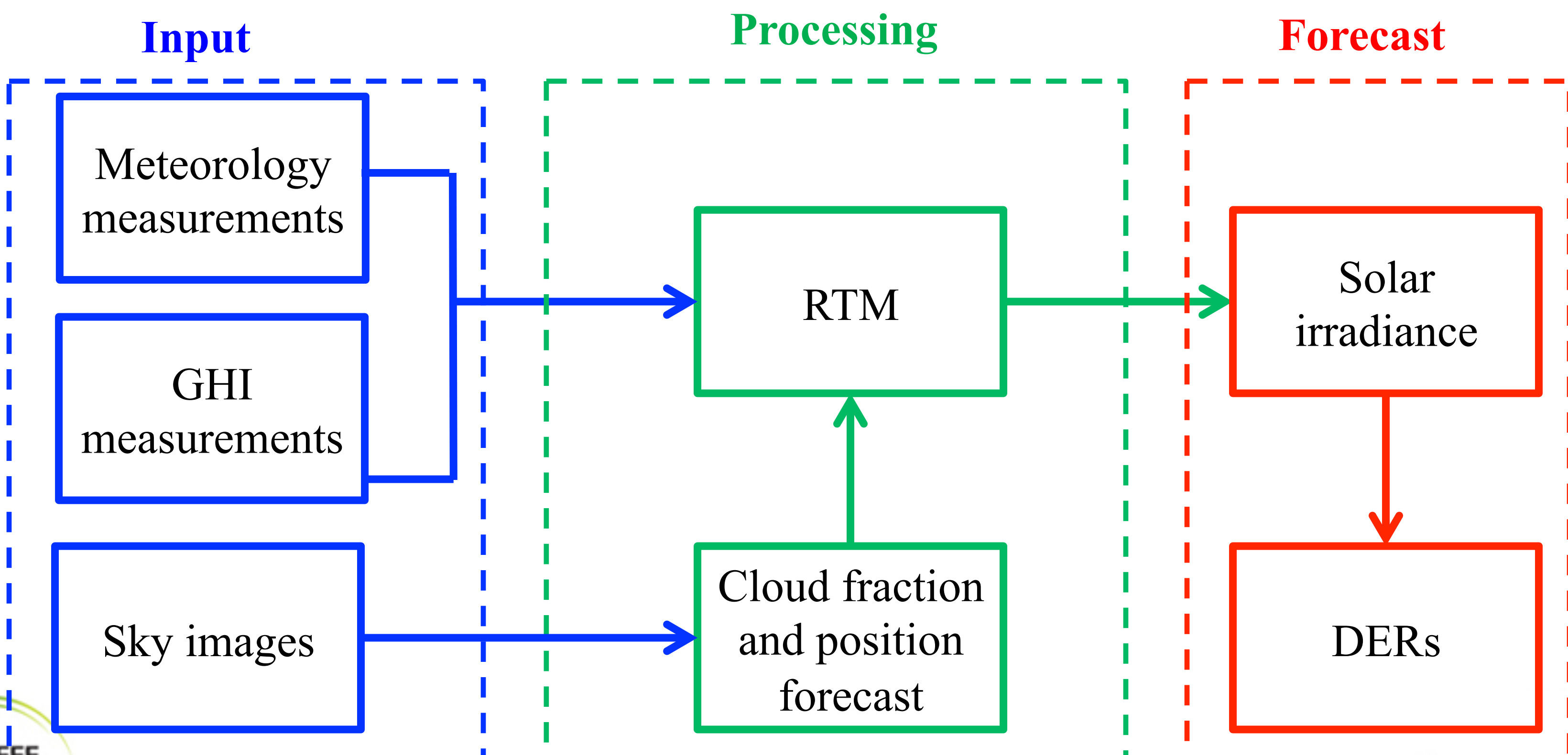
Forecast Procedures:

1. Identify clouds;
2. Position clouds;
3. Track cloud movement;
4. Predict GHI;

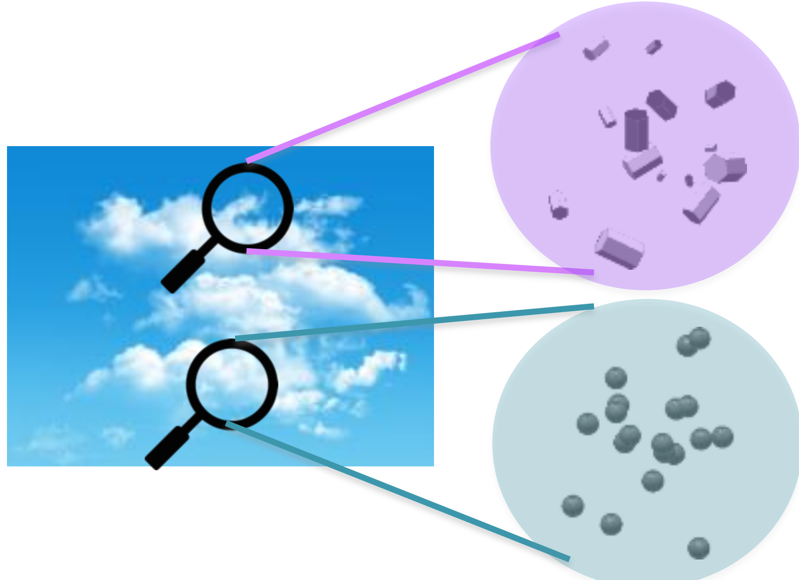
Sky Imager (SI) forecast



SI with Radiative Transfer Model (RTM)



Fast All-sky Radiation Model for Solar applications (FARMS)



Cloud transmittance and reflectance of irradiance

AOD, θ, g, ω, PWV, P, ozone, …

↓

REST2

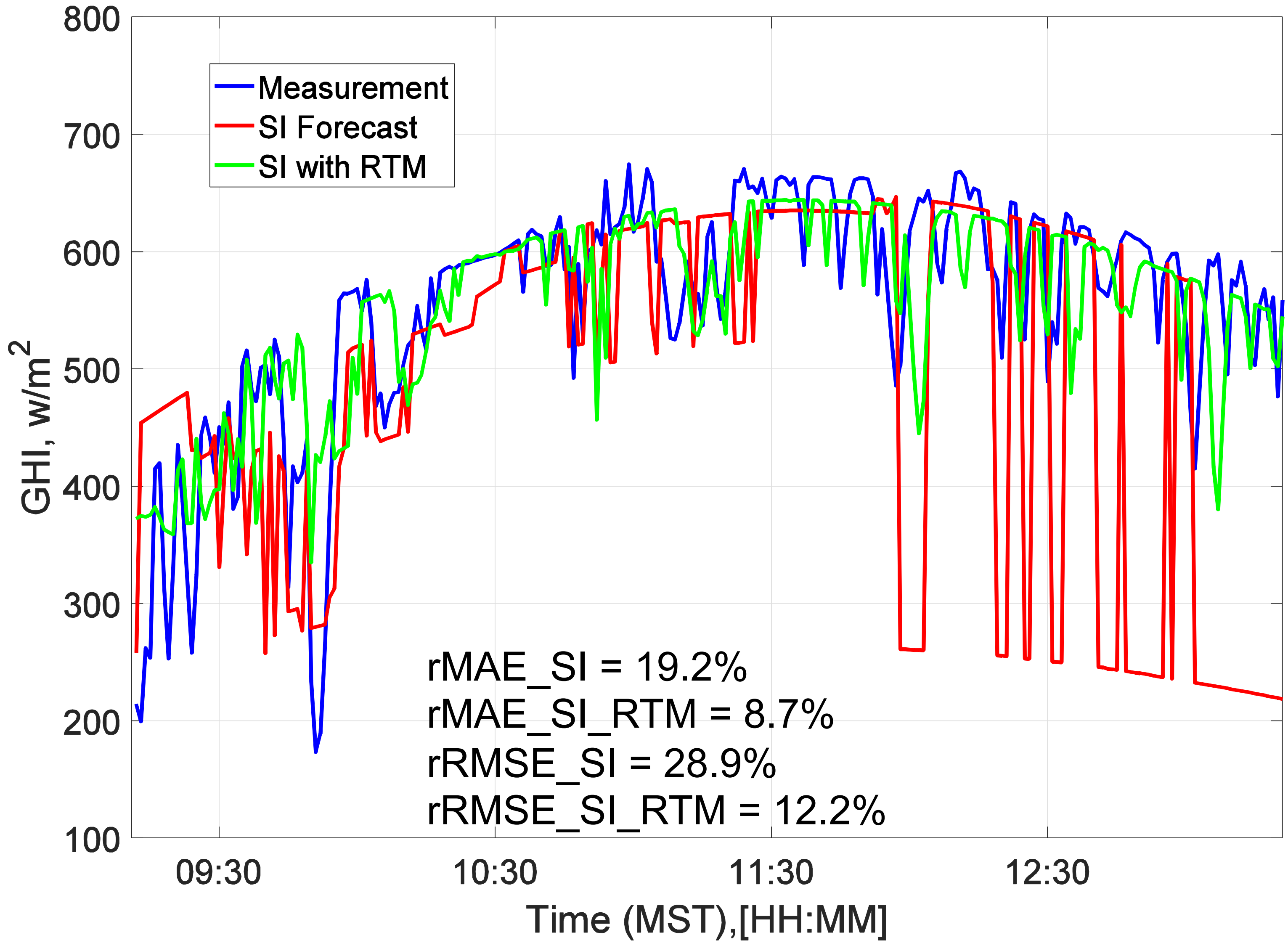
↓

Clear-sky transmittance and reflectance

Surface albedo

All-sky broadband irradiances

Xie et al., *Solar Energy (2016)*



min GHI Forecast for a Cloudy Day

Error Metrics

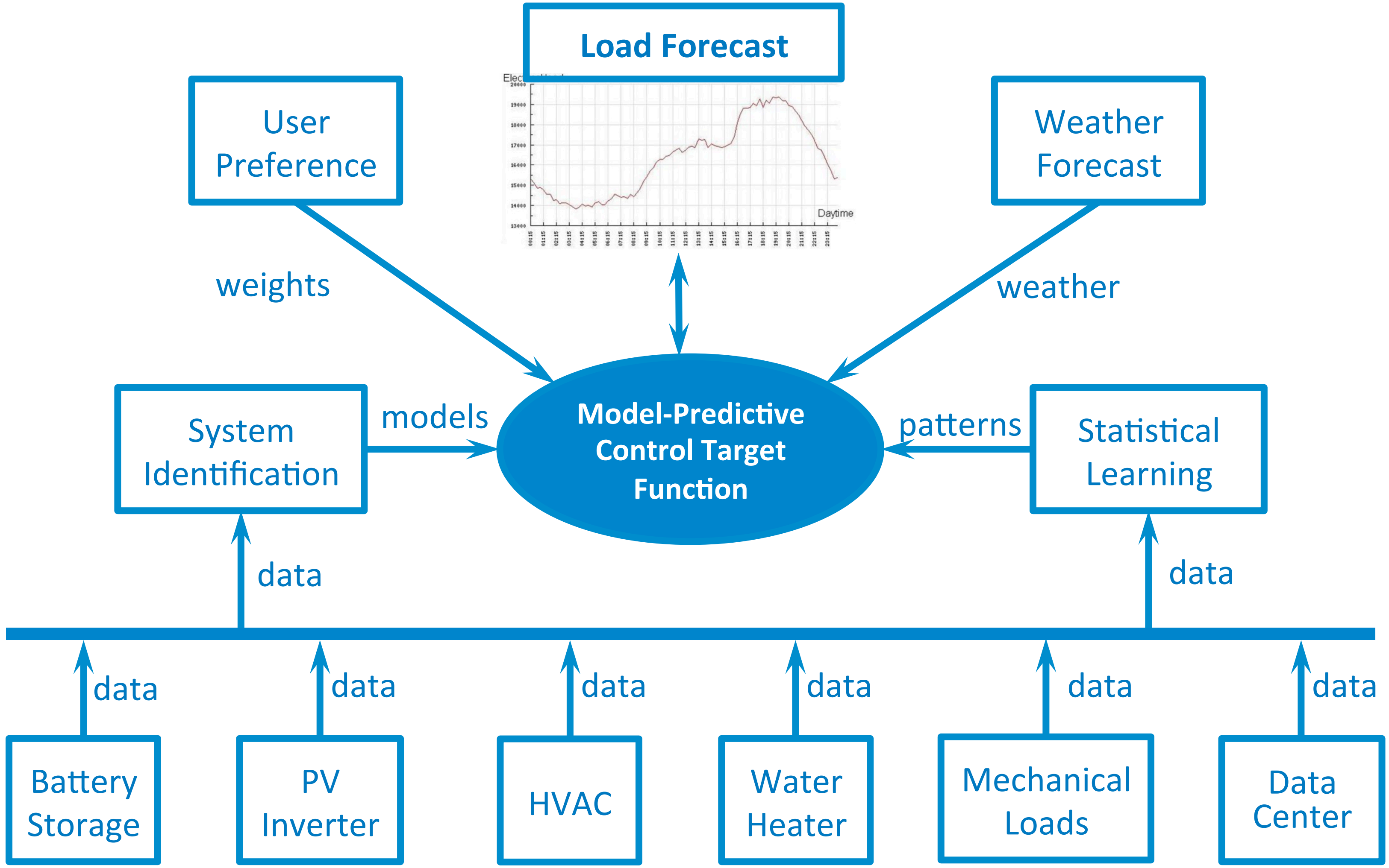
- Relative Mean Absolute Error (rMAE):

$$rMAE = \frac{1}{N}\sum_{n=1}^{N} |GHI_n^f - GHI_n^{obs}| \times \frac{100\%}{\overline{GHI}^{obs}}$$

- Relative Root-Mean-Square Error (rRMSE):

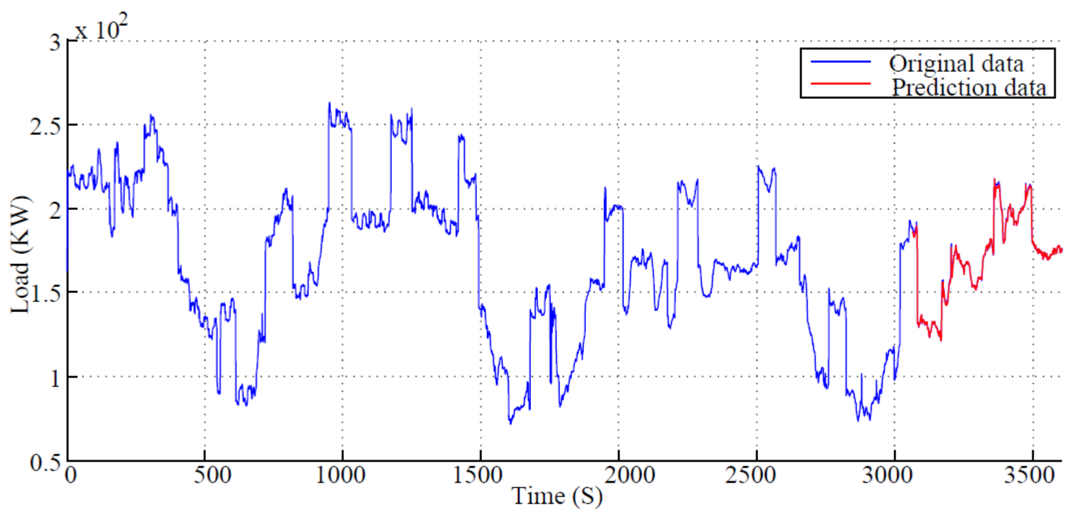
$$rRMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (GHI_n^f - GHI_n^{obs})^2} \times \frac{100\%}{\overline{GHI}^{obs}}$$

Model-Based Load Forecasting



Data-Driven Load Forecasting

- Machine Learning-Based Load Forecasting
  - Short-term
  - High-resolution
  - Using support vector regression
  - Hybrid parameter optimization



Load forecasting demonstration

Grid Forecasting

- Input
  - Individual power injections and withdraws
  - Individual forecasts given as multidimensional polytope
- Model
  - Linear approximation between state variables (voltage angle and magnitude) and withdrew/injected powers to compute a polytope that a forecast for grid-state
  - Multi-dimensional deep learning for system model and parameters

Grid Forecasting

- Clustering Method
  - Clustering buses according to the electric distance
  - Linear approximation of voltage magnitudes

$$\rho_{i\ell} = \sum_{j=1}^{N} \sum_{k=1}^{3} \left(r^{Y}_{(i\ell),(jk)} p^{Y}_{jk} + b^{Y}_{(i\ell),(jk)} q^{Y}_{jk} \right) + w_{i\ell}$$

  - Similarity metric

$$\alpha^{p,Y}_{(i\ell),(jk)} := \frac{\partial \rho_{i\ell} / \partial p^{Y}_{jk}}{\partial \rho_{jk} / \partial p^{Y}_{jk}} = \frac{r^{Y}_{(i\ell),(jk)}}{r^{Y}_{(jk),(jk)}}$$

$$\alpha^{q,Y}_{(i\ell),(jk)} := \frac{\partial \rho_{i\ell} / \partial q^{Y}_{jk}}{\partial \rho_{jk} / \partial q^{Y}_{jk}} = \frac{b^{Y}_{(i\ell),(jk)}}{b^{Y}_{(jk),(jk)}}$$

  - Distance

$$\alpha_{(i\ell),(jk)} := \left\| \left(\alpha^{p,Y}_{(i\ell),(jk)}, \alpha^{q,Y}_{(i\ell),(jk)} \right) \right\|_2$$

$$d_{(i\ell),(jk)} := \left\| \left(\alpha_{(i\ell),(jk)}, \alpha_{(jk),(i\ell)} \right) \right\|_2$$

Grid Forecasting

- Multi-Kernel Learning
  - Vector-valued function $\mathbf{f} : \mathcal{X} \to \mathcal{Z}$

$$\mathcal{H}_{\mathbf{K}} := \left\{ \mathbf{f}(x) = \sum_{p=1}^{\infty} \mathbf{K}(\mathbf{x}_p, \mathbf{x})\mathbf{a}_p,\ \mathbf{x}_p \in \mathcal{X}, \mathbf{a}_p \in \mathbb{R}^D \right\}$$

  - Regularized leas-squares problem

$$\widehat{\mathbf{f}} := \arg\min_{\mathbf{f} \in \mathcal{H}_{\mathbf{K}}} \sum_{c=1}^{D} \frac{1}{L} \sum_{n=1}^{L} \left(f_c(\mathbf{x}_n) - (\mathbf{z}_n)_c\right)^2 + \lambda \|\mathbf{f}\|_{\mathbf{K}}^2$$

  - Solution

$$\widehat{\mathbf{f}}(\mathbf{x}) = \sum_{n=1}^{L} \mathbf{K}(\mathbf{x}_n, \mathbf{x})\mathbf{a}_n^*$$

$$\mathbf{a}^* = \left(\mathbf{K}(\mathbf{X}, \mathbf{X}) + \lambda L \mathbf{I}\right)^{-1} \mathbf{z}$$

Conclusion

- **Integrated Resource and Load Forecaster (IRLF)**

  provide estimates on DER operation and customer loads for both current states and forecasts

- **Grid Estimator and Forecaster (GEF)**

  With the information produced by the IRLF and using the grid measurement data, the GEF will employ machine learning techniques to determine the interrelationship of state variables and will (1) estimate the current system states and (2) forecast the near-future system states

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Thank you!

Q & A