Predictive Analytics for Energy Systems State Estimation

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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 these data?
Motivation

- Power Systems Situational Awareness
- Predictive System Operations
State-of-the-Art

Resource Forecasting
Load Forecasting

Future
Future
Future
Future

Distribu'tion
Transmission

Future
Future
Future
Future

Nodal Voltage
Load
DER
DER
DER

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

Integrated Resource and Load Forecaster (IRLF)

Wind Speed
Solar Irradiance
Temperature
Precipitation

DER
Load

Grid Data
- Grid Topology
- SCADA, AMI, Inverter, DMU

Grid Measurements

Online Learning Algorithm

Interrelation of State Variables
State Estimation
Time Progression

Statistical Methods
Confidence Interval

Current System States
\[ P_t, Q_t, V_t, \theta_t \]

Future System States
\[ P_{t+n}, Q_{t+n}, V_{t+n}, \theta_{t+n} \]

Grid Estimator and Forecaster (GEF)

Resource Dispatch
Real-time Market
Applications
Overview of Sky Imager Forecast

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

Sky Imager

source: Google Earth

source: Bryan Urquhart
Sky Imager (SI) forecast

SI with Radiative Transfer Model (RTM)
Cloud transmittance and reflectance of irradiance

All-sky broadband irradiances

AOD, θ, g, ω, PWV, P, ozone, ...

REST2

Clear-sky transmittance and reflectance

Surface albedo

Xie et al., Solar Energy (2016)
min GHI Forecast for a Cloudy Day

\[ \text{rMAE}_{\text{SI}} = 19.2\% \]
\[ \text{rMAE}_{\text{SI RTM}} = 8.7\% \]
\[ \text{rRMSE}_{\text{SI}} = 28.9\% \]
\[ \text{rRMSE}_{\text{SI RTM}} = 12.2\% \]
Error Metrics

• Relative Mean Absolute Error (rMAE):

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

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

\[ rRMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (GHI_n^f - GHI_n^{obs})^2} \times \frac{100\%}{GHI^{obs}} \]
Model-Based Load Forecasting

- User Preference
- Weather Forecast

- System Identification
- Model-Predictive Control Target Function
- Statistical Learning

- Battery Storage
- PV Inverter
- HVAC
- Water Heater
- Mechanical Loads
- Data Center

Load Forecast
weights
patterns
data
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
    \[ \rho_{i\ell} = \sum_{j=1}^{N} \sum_{k=1}^{3} \left( r_{i\ell},(jk)p_{jk}^Y + b_{i\ell},(jk)q_{jk}^Y \right) + w_{i\ell} \]
  – Similarity metric
    \[ \alpha_{p,Y}^{i\ell,(jk)} := \frac{\partial \rho_{i\ell} / \partial p_{jk}^Y}{\partial \rho_{jk} / \partial p_{jk}^Y} = \frac{r_{i\ell},(jk)}{r_{(jk),(jk)}} \]
    \[ \alpha_{q,Y}^{i\ell,(jk)} := \frac{\partial \rho_{i\ell} / \partial q_{jk}^Y}{\partial \rho_{jk} / \partial q_{jk}^Y} = \frac{b_{i\ell},(jk)}{b_{(jk),(jk)}} \]
  – 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 \( f : \mathcal{X} \rightarrow \mathcal{Z} \)
  \[
  \mathcal{H}_K := \left\{ f(x) = \sum_{p=1}^{\infty} K(x_p, x) a_p, \; x_p \in \mathcal{X}, \; a_p \in \mathbb{R}^D \right\}
  \]
  – Regularized least-squares problem
  \[
  \hat{f} := \arg\min_{f \in \mathcal{H}_K} \sum_{c=1}^{D} \frac{1}{L} \sum_{n=1}^{L} (f_c(x_n) - (z_n)_c)^2 + \lambda \|f\|_K^2
  \]
  – Solution
  \[
  \hat{f}(x) = \sum_{n=1}^{L} K(x_n, x) a^*_n
  \]
  \[
  a^* = (K(X, X) + \lambda L I)^{-1} z
  \]
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
Thank you!

Q & A