Forecasting for Load with High DER

Current Initiatives and R&D Needs

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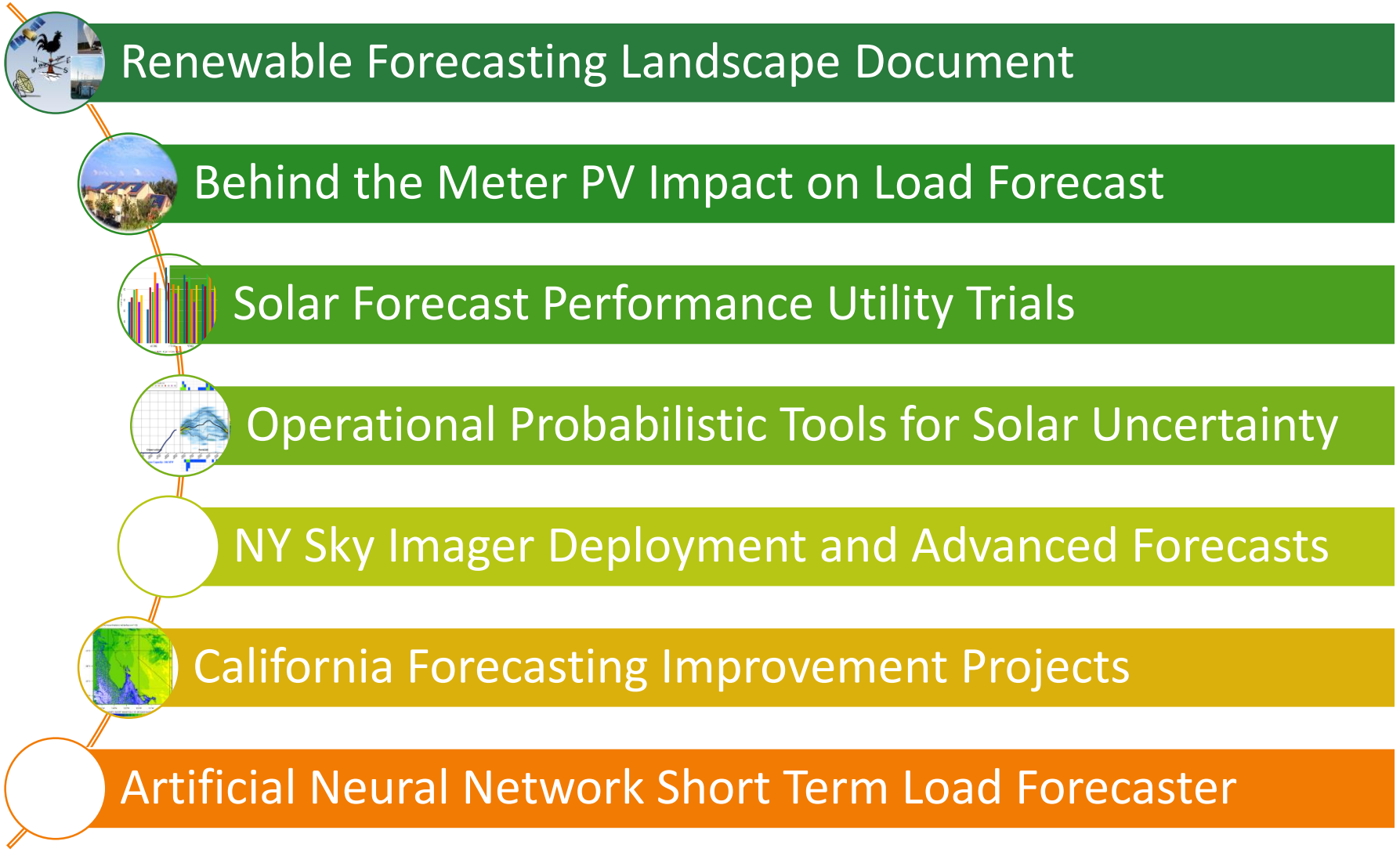
EPRI Grid Operations and Planning

DOE SETO Challenges for Distribution Planning, Operational and Real-time Planning Analytics Workshop

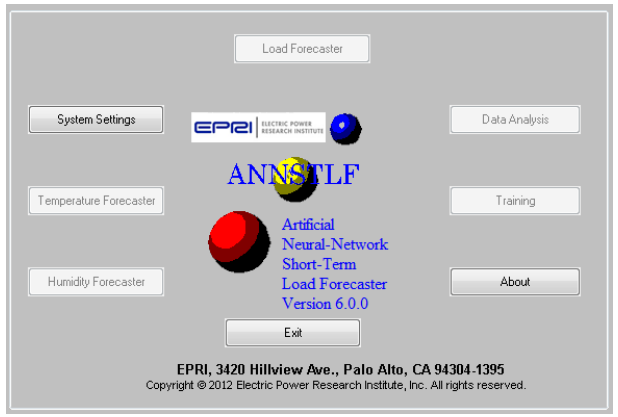
May 16, 2019

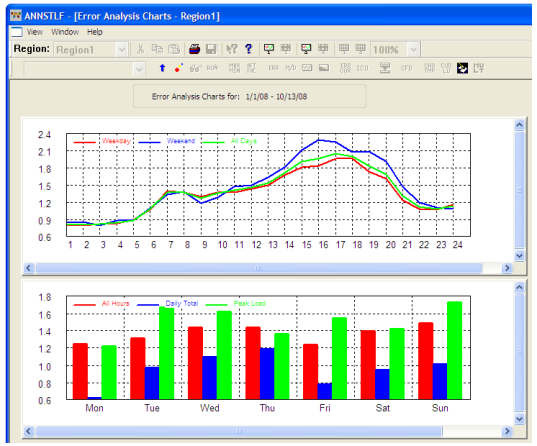
EPRI Variable Generation Forecast Integration Efforts



Where we are now: Example load forecasting tool at EPRI

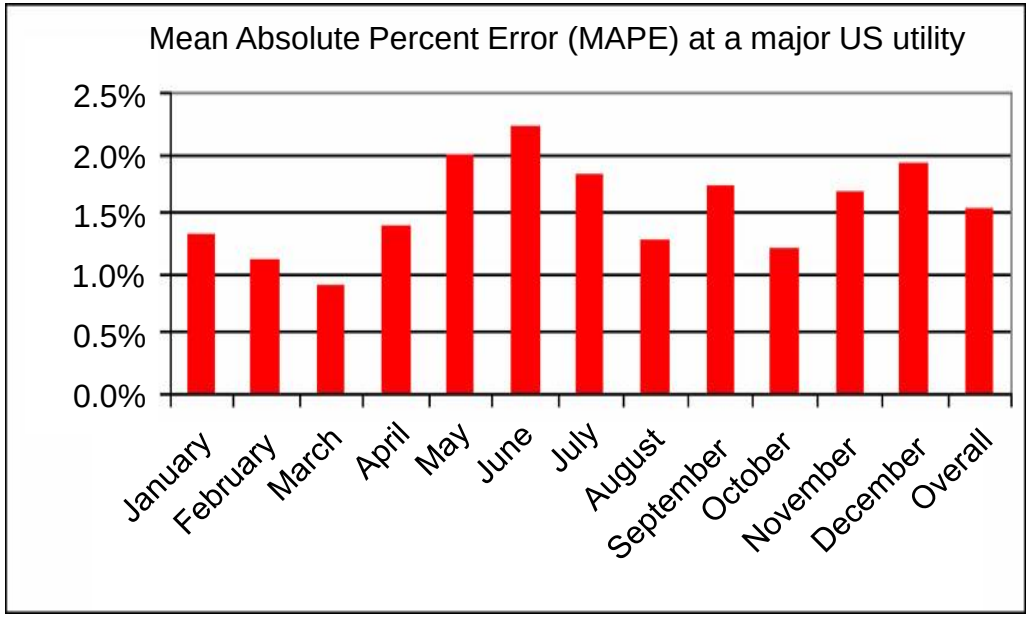
- **Artificial Neural Network Short Term Load Forecaster (ANNSTLF) - Commercial Grade Desktop Application**
- **STLF Users:** vital for utilities, system operators, and power marketers
- **Benefit**: efficient gen dispatch and power transactions





Used for 20+ Years

- Hourly load forecasts for gen dispatch efficiency & reliability
- Hour(s)-ahead, Day-Ahead to Week Ahead hourly forecast
- Accuracy is guaranteed within 3%, but typical 1-2.5% range
- **BUT: DER (PV, EV, etc.) challenge accurate load forecasting**



Understanding Impacts of Distributed PV on Load Forecasting

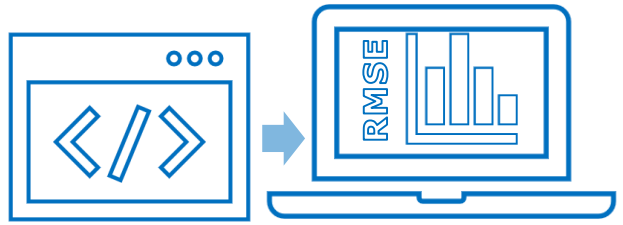
Individual Utility/ISO Study

- Data Requirements & Collection
- Clean and Explore Data
- Define Study Scenarios
- Analyze Data and Process Impacts on PV Forecasts
- Analyze PV Data and Process Impacts on Load Forecasts
- **DELIVERABLE** Recommendations & Report Per Company

Comparison Across Partner Utilities/ISOs

DELIVERABLE
Comparative Recommendations & Report

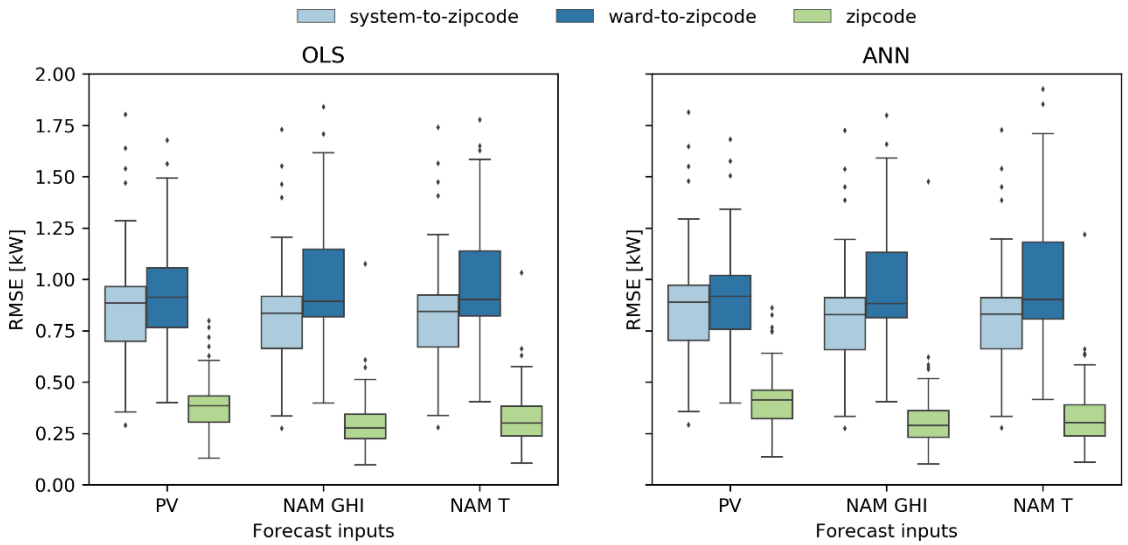
DELIVERABLE
Python Scripts to Repeat Some Analyses



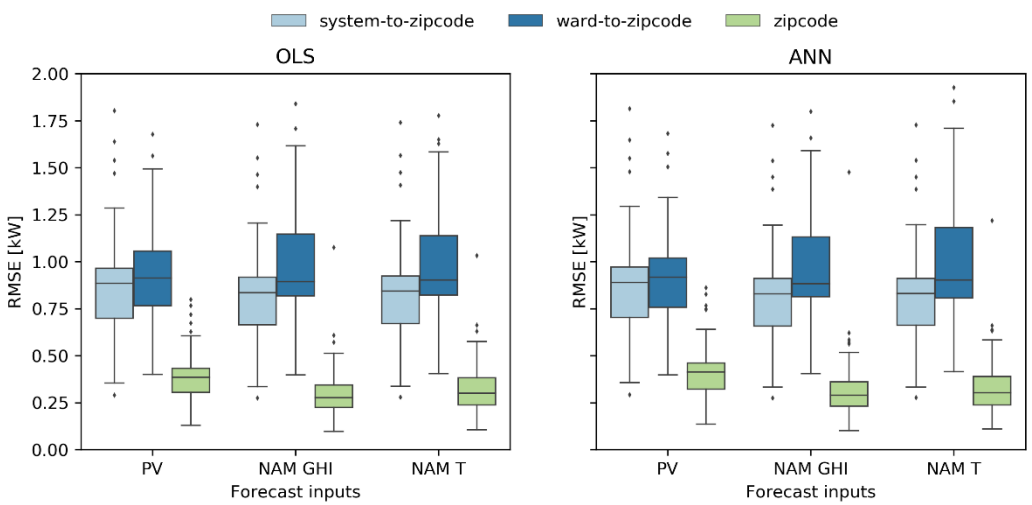
Goal is not to produce the very best forecast but to determine data and process that consistently improve load forecasts

Preliminary Results Top-down Day-Ahead DPV & Load Forecasts

DPV Forecasts



Load Forecasts

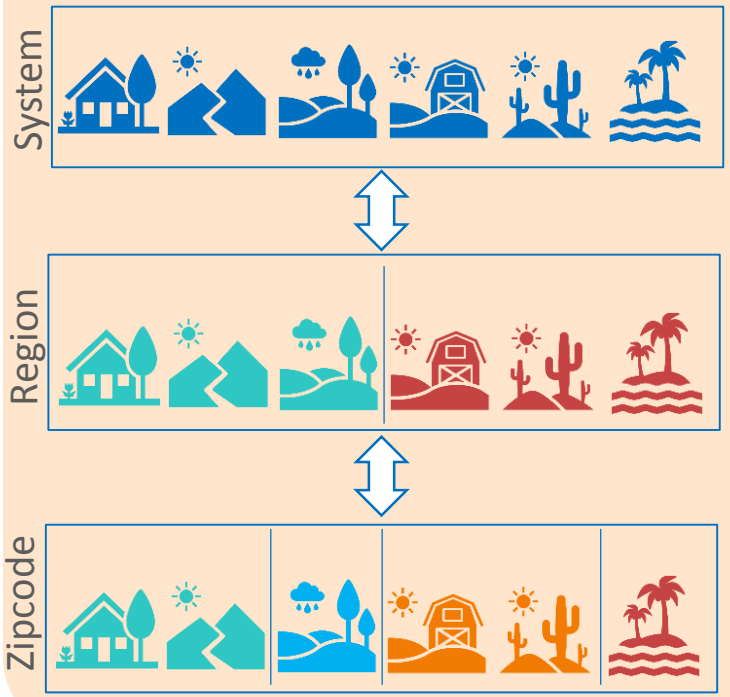


NAM GHI & Temp Improves Both DPV and Load – *collect data*

Significant improvement to forecast at zipcode rather than use distribution factors

Sensitivities Being Studied – Day-Ahead to Hours-Ahead

Geographical Resolution



PV Forecast Inputs

- Geographical resolutions
- Weather forecasts (NWP)
  - NAM, HRRR
  - Grid points, update resolution
  - Irradiance, temp.
- Local weather stations
  - Availability
  - Desirable locations
  - Irradiance, temp.
- *Satellite (GOES) Image Channels*

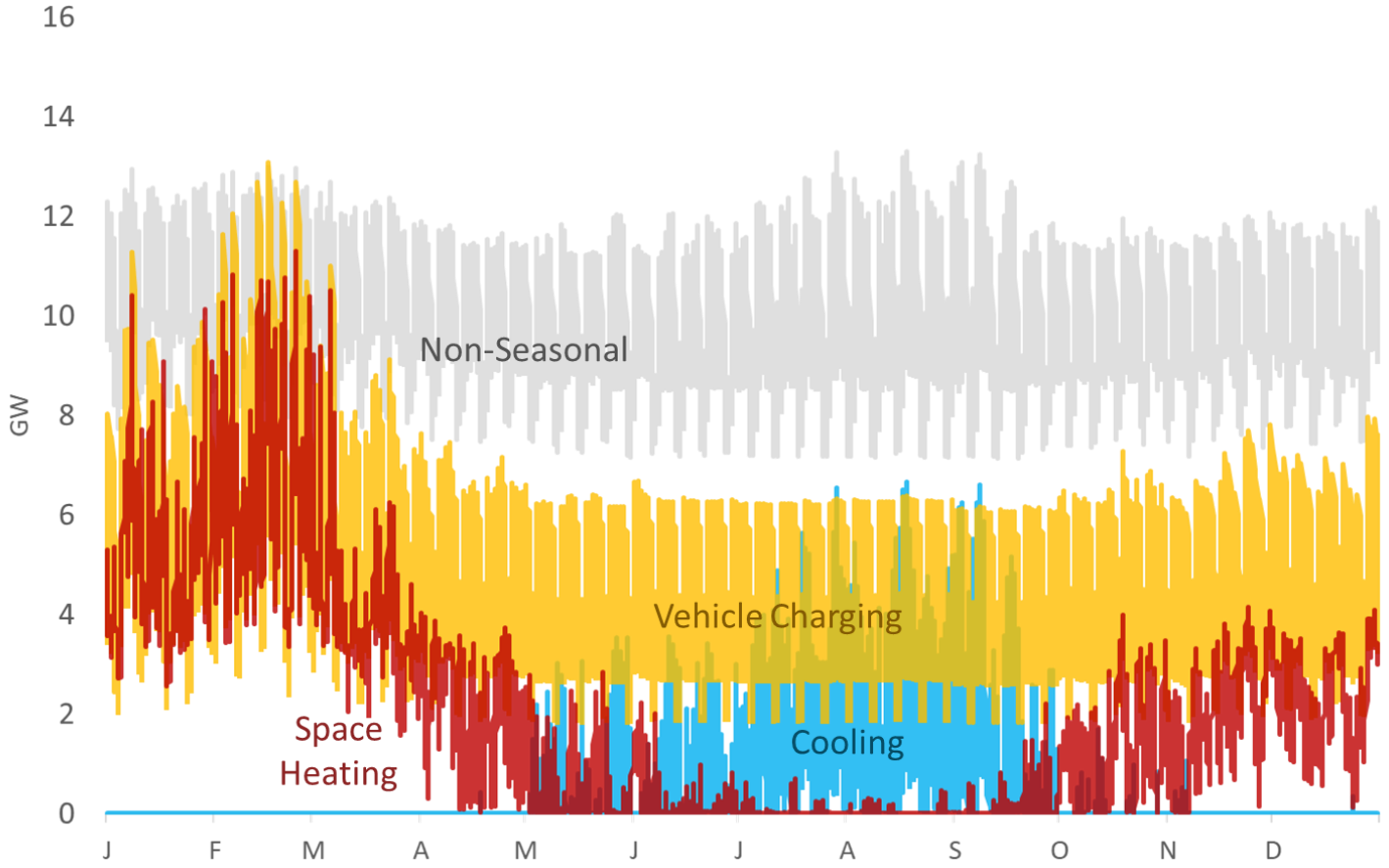
Load Forecast Inputs

- Geographical resolutions
- PV Forecasts
  - of geographical resolutions
  - of update resolutions
- Weather forecasts NAM, HRRR
  - Grid points, update resolution
  - Irradiance, temp.
- Local weather stations
- Gross and Net load

FORECAST MODELS: ➲Persistence, ➲ Least-Squares Linear Regression, ➲ Artificial Neural Network

What other resources will need to be forecasted? Example of EVs in future resource mix

- Potential load profile in ISO-NE region in 2050 under reference case
- Vehicle charging could be a significant load much earlier than this in many regions
- How can we forecast EV, space heating, etc. in such a future?
- Data gathering and analytics will continue to grow in importance as new resources come into the system



EPRI US National Electrification Assessment
https://www.epri.com/#/pages/product/3002013582

Can we use on-site and off-site data to improve forecasting systems? CEC solar forecasting project

Sonoma Technology, Inc.

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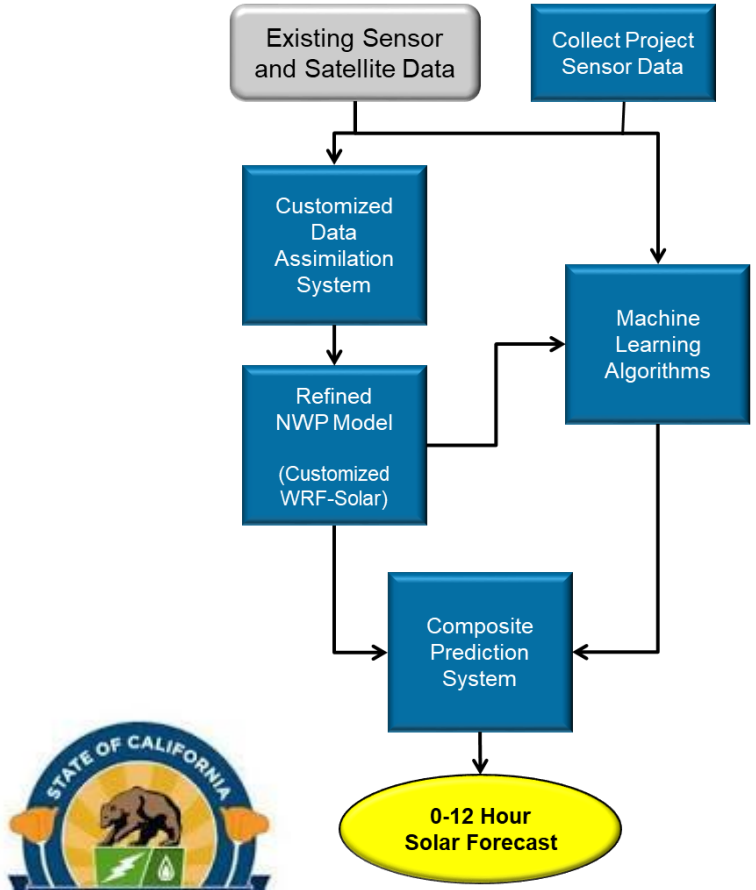
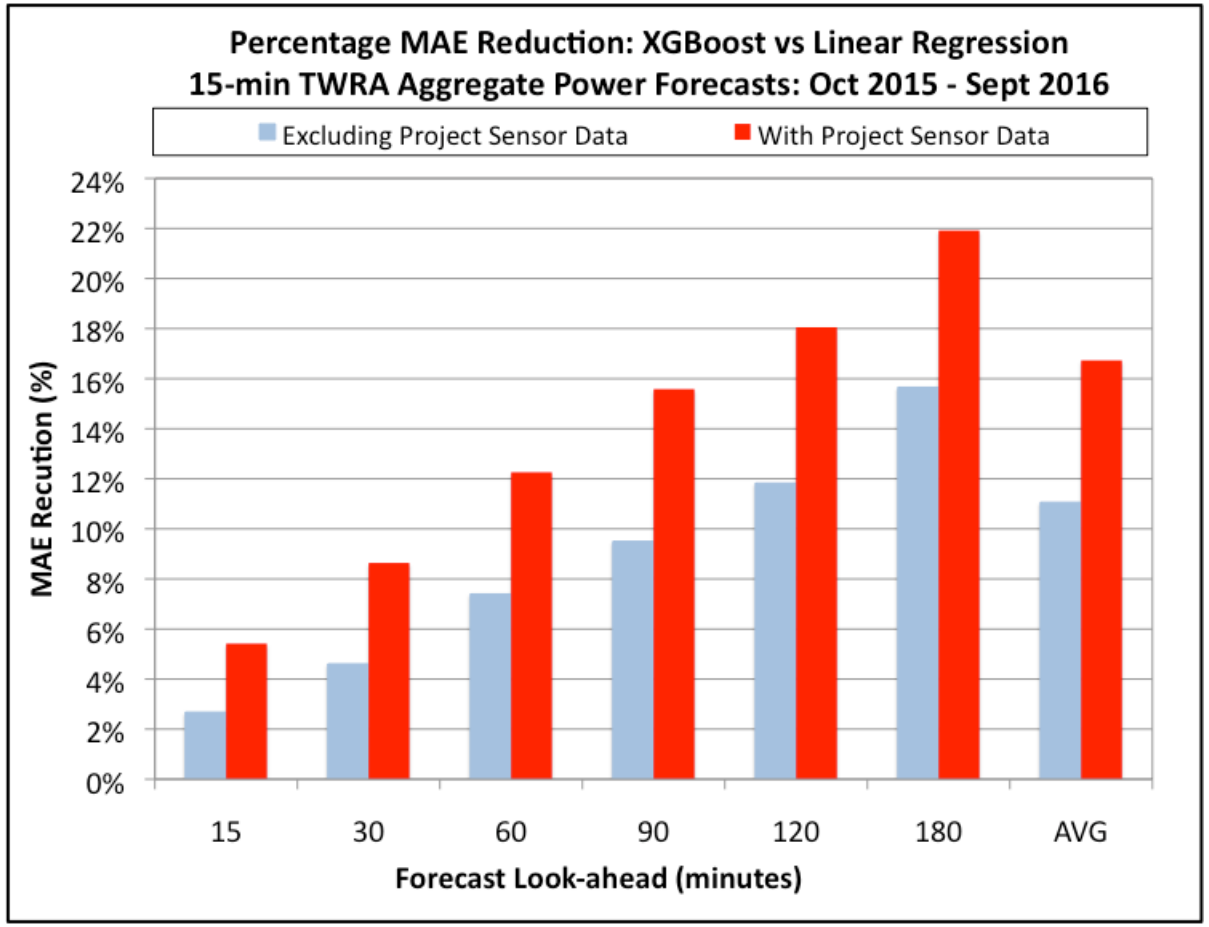
- Apply customized data assimilation methods into rapid update (1-hour cycle) Numerical Weather Prediction (NWP) model
- Perform targeted refinements of physical processes related to fog and stratus formation/dissipation in the NWP model
- Apply machine learning (ML) methods for very-rapid-update (15-minute cycle) fog and stratus prediction based on real-time sensor data
- Optimally integrate physics-based (NWP) and statistical (ML) components into a composite forecast system
- Evaluate performance of integrated system and each component relative to a pre-existing baseline forecast



Potential improvements – example from wind



- Advanced machine learning algorithm (XGBoost) yields better results!
  - With project data the overall 0-3 hr MAE is 16.7% lower than linear regression
  - Peak benefit is at 180 minutes
  - Minimum benefit is at 15 minutes
- **Improvement over linear regression is greater with project data (0-3 hr AVG of 16.7% versus 11.1%)**

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Key Findings & Results from Data Collection for solar

Successes

- Successful deployment of new project sensors and integration of existing sensor networks.
- Unique data collected during numerous summer and winter stratus episodes during 2018 and early 2019.
- Website to support real-time monitoring and retrospective analysis.

Challenges

- Difficult to site certain instruments where they may be most needed (e.g., Sodar or RASS in urban areas).
- Limited number of winter radiation fog cases compared to summer advection stratus cases.
- Untimely breakdowns of the Microwave Radiometer instrument.

Next Steps for Improving Solar Forecasting

- Assess the impact of project sensor data on NWP solar forecasting through data assimilation.
- Use time series data from project sensors to inform and improve statistical and machine-learning approaches.
- Assess the impact of project sensor data on statistical and machine-learning forecasts.

System Operations - High Dependence on Data from Many Sources

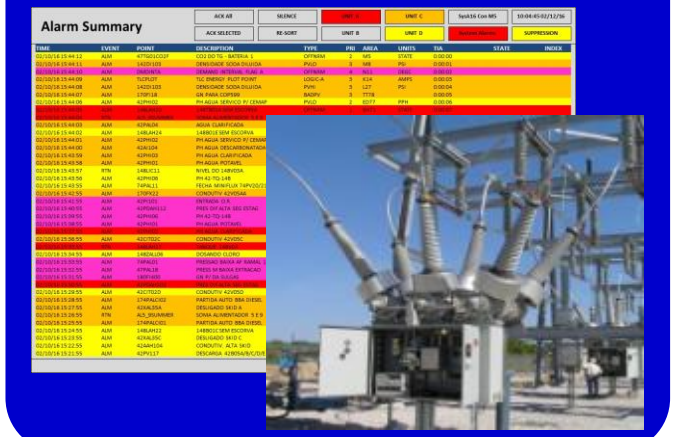
System Measurements

- SCADA
- Synchrophasors
- Fault Recorders
- SoE Recorders
- Trend Recorder
- PQ Meters
- Meters & AMI

- State Estimation
- Contingency
- Model data
- Outage Request
- Markets
- Planning Sims
- Operator Action

Analysis Results

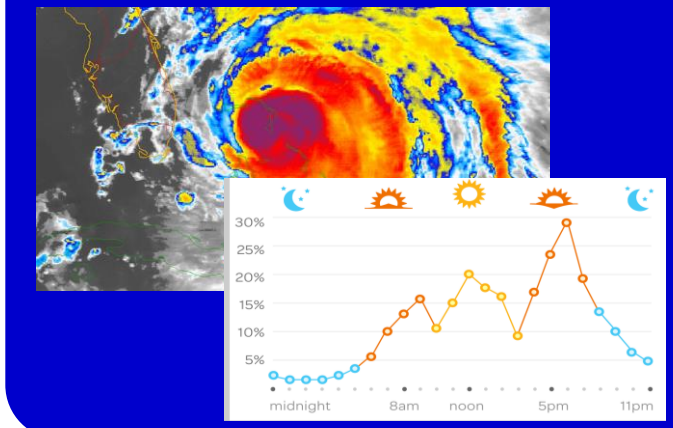
Equipment & Alarms



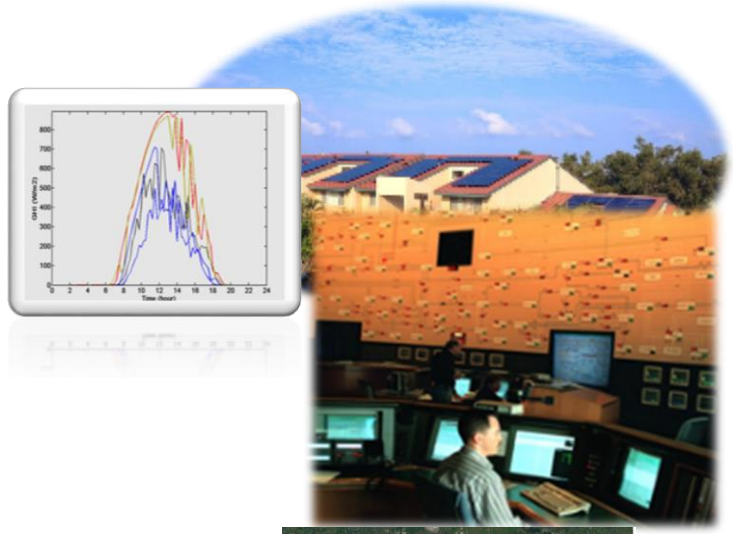
- Alarms
- Generators
- Transformers
- Breakers
- Relays
- Shunts
- DER, BESS, etc.

- Weather
- Space weather
- Satellite Images
- Geospatial
- Customer
- Gas system
- Transportation

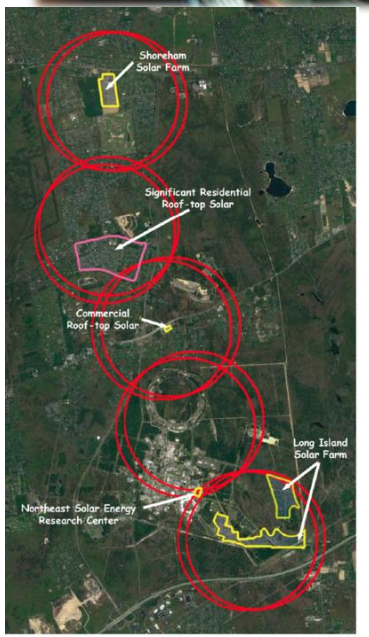
Non-Electrical



NY Solar Forecasting Deployment & Demonstration Incorporating HD Sky Imaging



- **NYPA Initiated concept and support**
  - Partner with relevant stakeholders – NYPA, Brookhaven, NCAR, U Albany, NYISO
  - Multiple phases employed to progress aims
  - Recently awarded funding for phase 3 of the project
- **Project Goals**
  - Deploy networked HD Sky Imagers at multiple locations across NY state to improve short term solar, system load and building load forecasting
  - Incorporate into NCAR numerical weather based forecasting systems, and deploy these across the state, with focus on selected regions
  - Evaluate benefits to system and utility operations for solar integration, load forecasting and building load control
- **Expected Results**
  - Online forecasts & data available to utilities
  - Data/models available to commercial forecast vendors (w/license)
  - Roadmap for future NYS forecast development



Partners

NEW YORK STATE OF OPPORTUNITY. | NY Power Authority

BROOKHAVEN NATIONAL LABORATORY

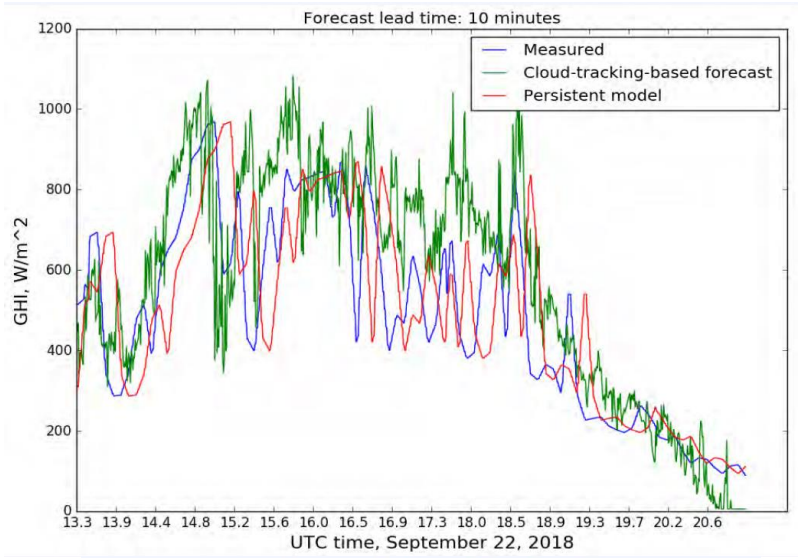
NCAR NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

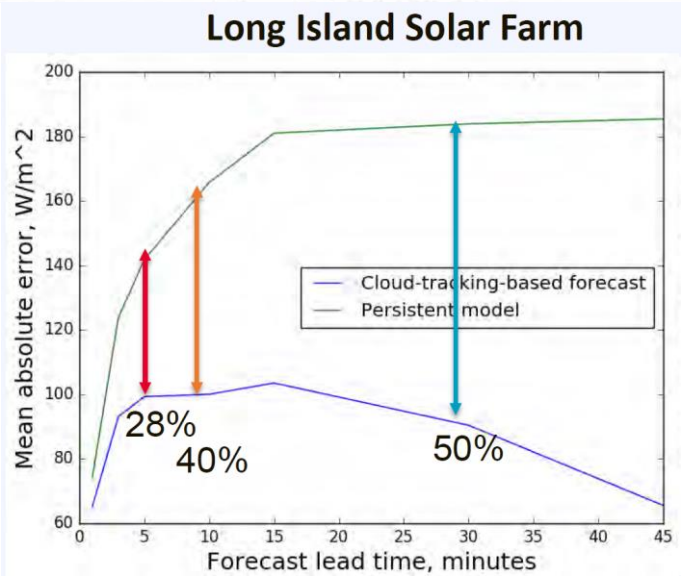
Funders:

NEW YORK STATE OF OPPORTUNITY. | NYSERDA

SOLAR ENERGY TECHNOLOGIES OFFICE
U.S. Department Of Energy

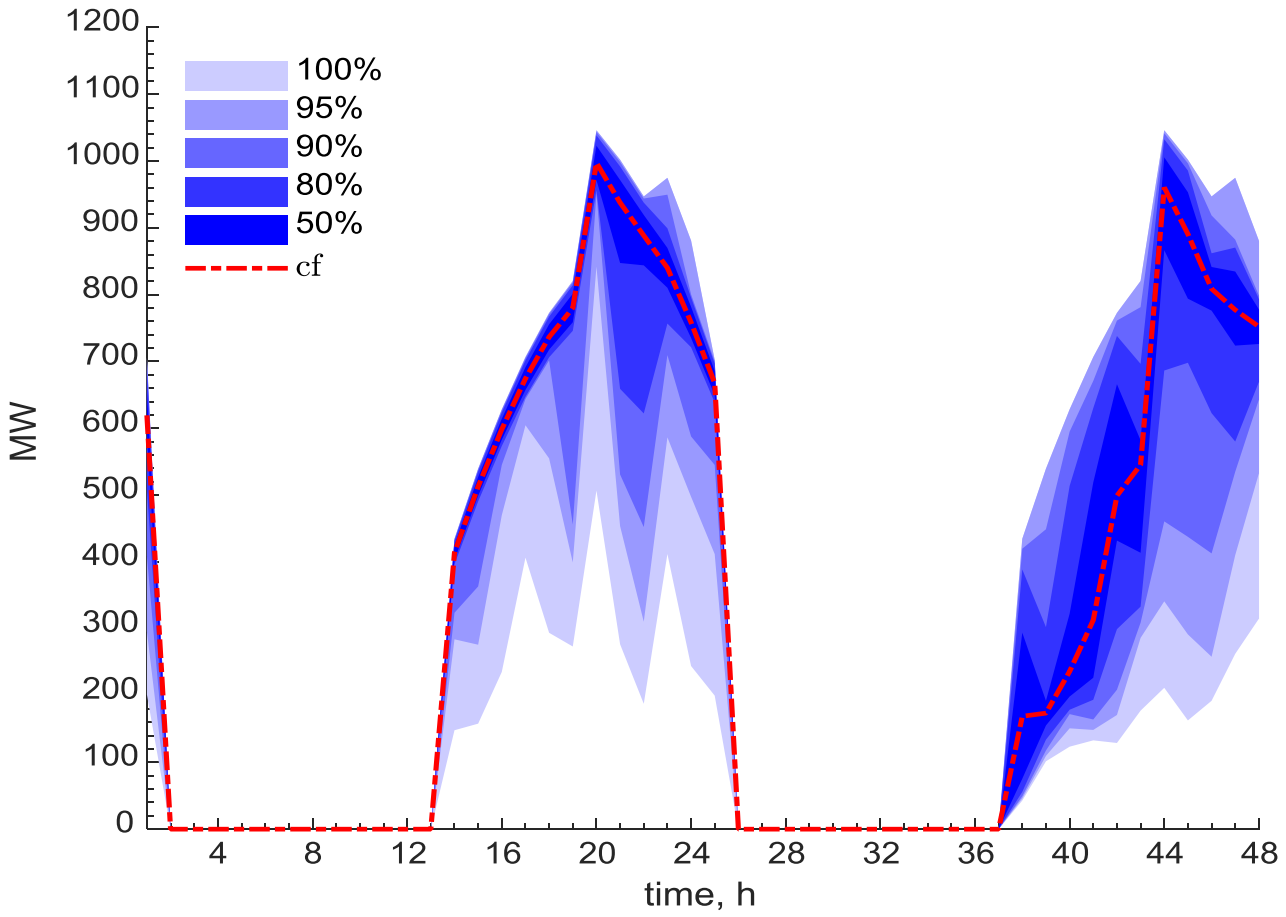
Initial results and observations





- Sky imager based forecasts for local PV based short term forecasting
- Improves upon current persistence methods significantly using cloud based tracking to forecast solar
- Showed promise from initial study, continuing work in NYSERDA/DOE/NYPA funded project that will also apply machine learning and physical modeling to go from 0-15 mins out to DA
- Will cover system wide forecasts and, for certain regions, distributed PV and building level forecasts

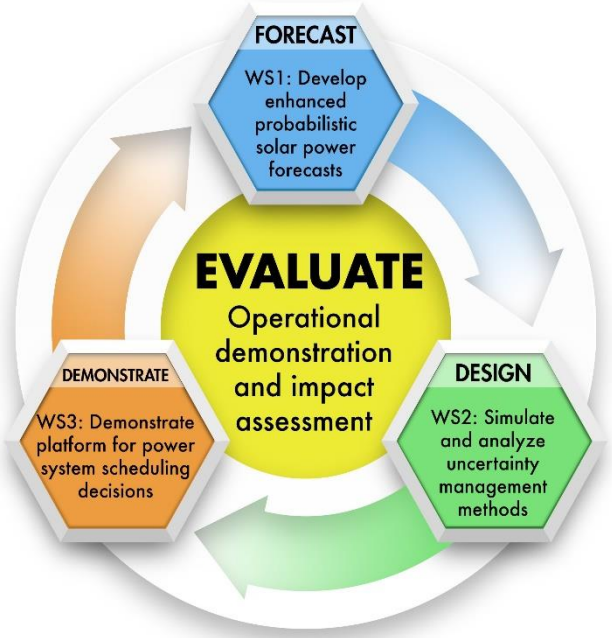
Next – Use Probabilistic Forecasts



Probabilistic data, in useful form, can be used for more than awareness

EPRI DOE Solar Forecasting Project– Three Workstreams

- 3 Year Project, anticipated $1,8M DOE funding, $760k EPRI/utility cost share ($110k from 173.05 over 3 years)
- A Forecasting Work Stream to develop and deliver probabilistic forecasts with targeted improvements for utility scale and behind-the-meter (BTM) solar
- A Design Work Stream to identify advanced methods for managing uncertainty based on results from advanced scheduling tools
- A Demonstration Work Stream to develop and demonstrate a scheduling management platform (SMP) to integrate probabilistic forecasts and scheduling decisions in a modular and customizable manner



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DUKE ENERGY.

SOUTHERN COMPANY

POLARIS
SYSTEMS OPTIMIZATION

Hawaiian Electric

R&D needs related to forecasting and integration

- What data do we need for forecasting
  - Different temporal and spatial scales, and end uses
  - Cost/benefit of enhanced data and new data streams

- What is the value of improved forecasting?
  - Metrics and tools to assess value of improved forecasts
  - Move to probabilistic or risk based operational methods

- How do we characterize new resources and loads?
  - Ensure forecasting models can be trained
  - Understand customer behavior, e.g. with EV

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