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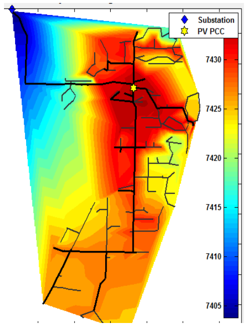

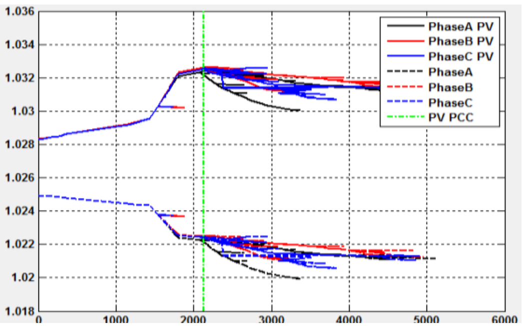

Sandia National Laboratories

Exceptional service in the national interest

Vermont Regional Partnership: Facilitating the Effective Expansion of Distributed Energy Resources (The VT FEEDER Project)

Task 3: DER Forecast Assessment

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Sandia National Laboratories
October 17, 2017

U.S. DEPARTMENT OF ENERGY
NNSA National Nuclear Security Administration

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Task 3 Project Objectives

- **Task 3 – Validation and Improvement of Forecasting Engine** The analysis and validation of high-resolution solar, wind, and load forecasting will enable predictive generation to reduce the uncertainty associated with controlling for intermittent resources.

- Evaluation of forecast performance.
- Development of event-specific forecast metrics.
- Identification of opportunities for forecast improvement.

Data Received

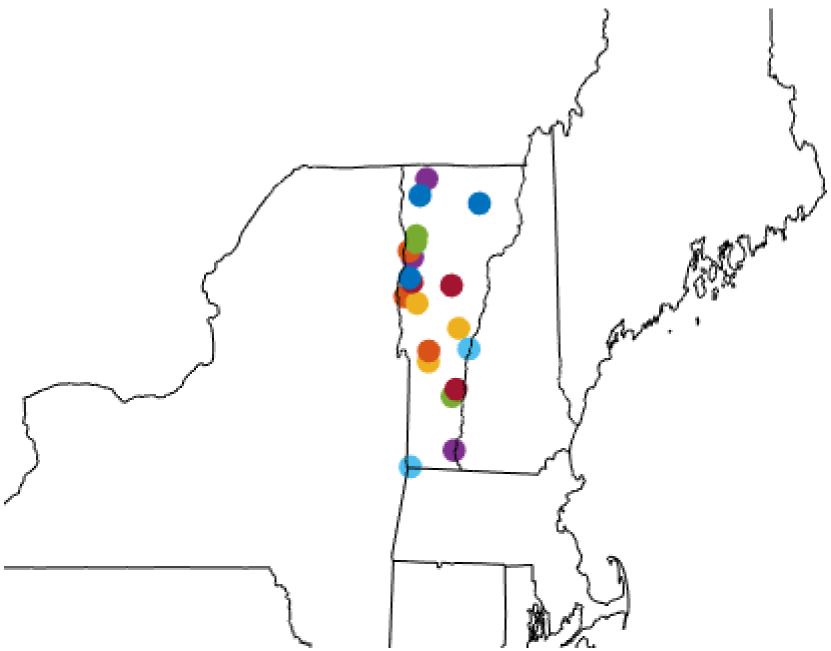
- PV farms:
  - 4-months of measured and forecasted PV power output for 21 PV farms spread across Vermont at 1-hour resolution
  - 1-year of measured and forecasted PV power output for one PV farm
  - Forecasted irradiance data for all PV farms, overlapping with available forecasts for ~2 moths

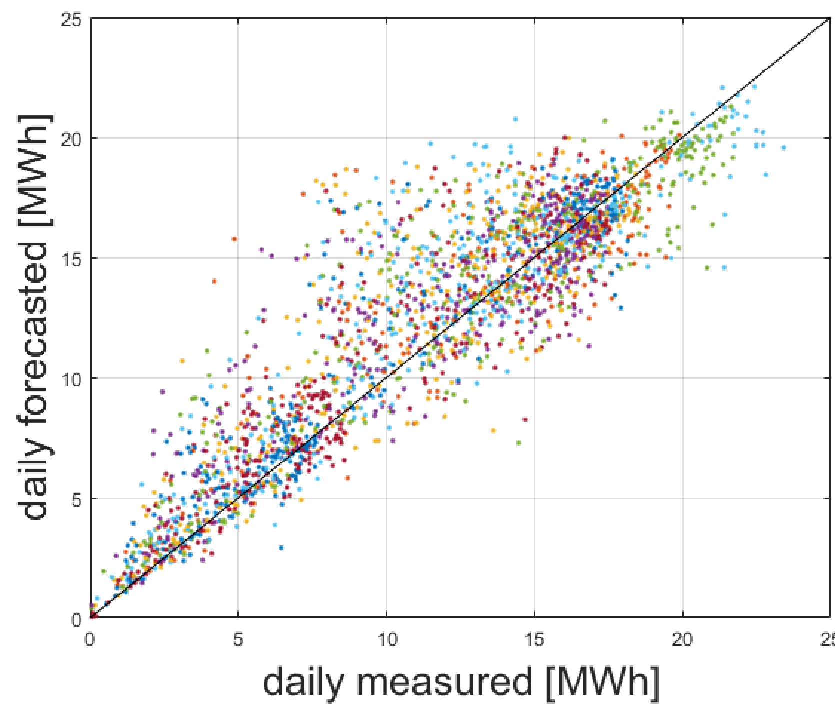
  Forecasts are at 1-hour intervals and typically 1-24 hours ahead. One sample with different time horizons: 1-24, 25-48, 49-72 hours ahead
- Distributed PV:
  - 1-year of measured and forecasted distributed PV, distributed load, and distributed net load for
    - 4 substations with high PV penetration
    - the aggregate of nearly 200 substations

  All forecasts are 1-24 hours ahead and at 1-hour resolution.

Forecast Performance: PV Farms

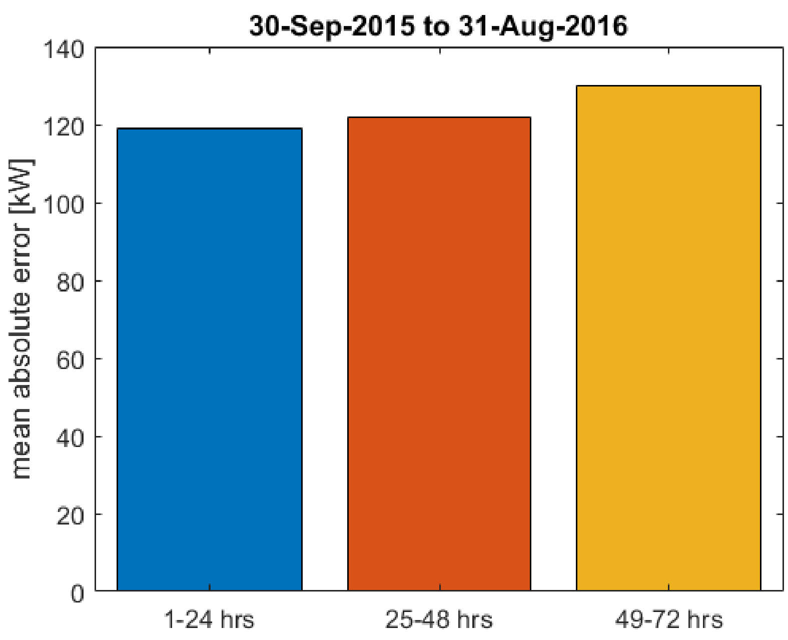
- 21 PV farms spread across state of Vermont
  - Most 2-3MW
- Forecast well-correlated with measured

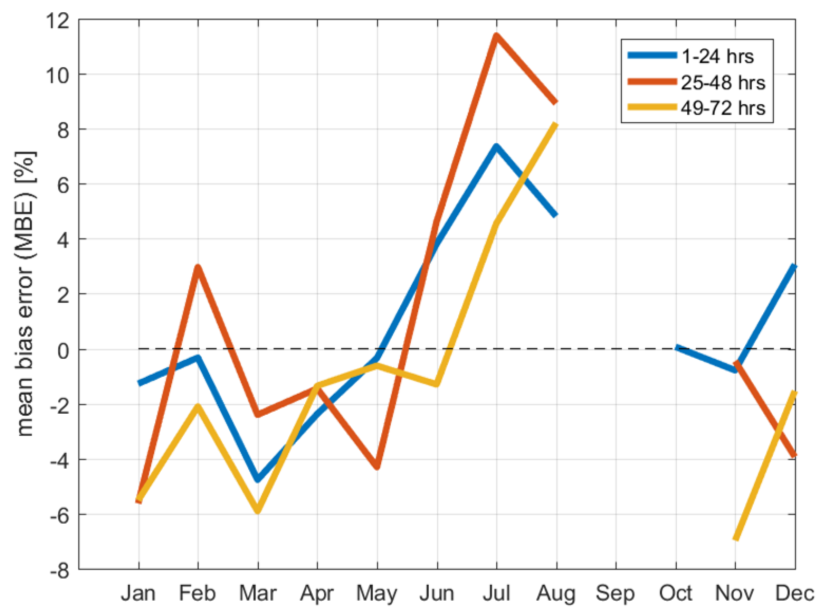




Forecast Performance: PV Farms

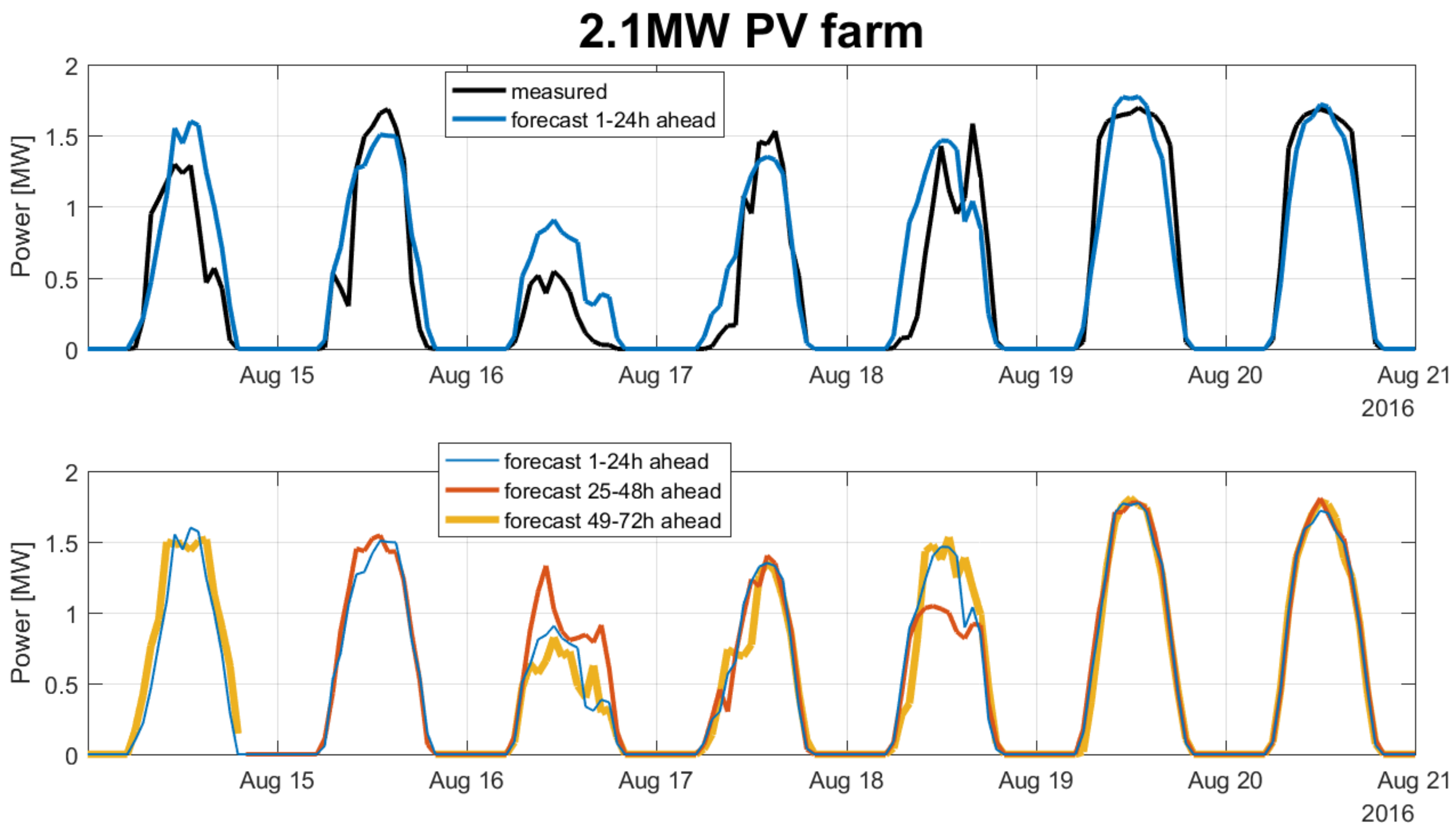
- From 1-year of data (PV Farm 3)
  - Day ahead, 2 day ahead, 3 day ahead have similar performance
  - Seasonal trends in forecast performance





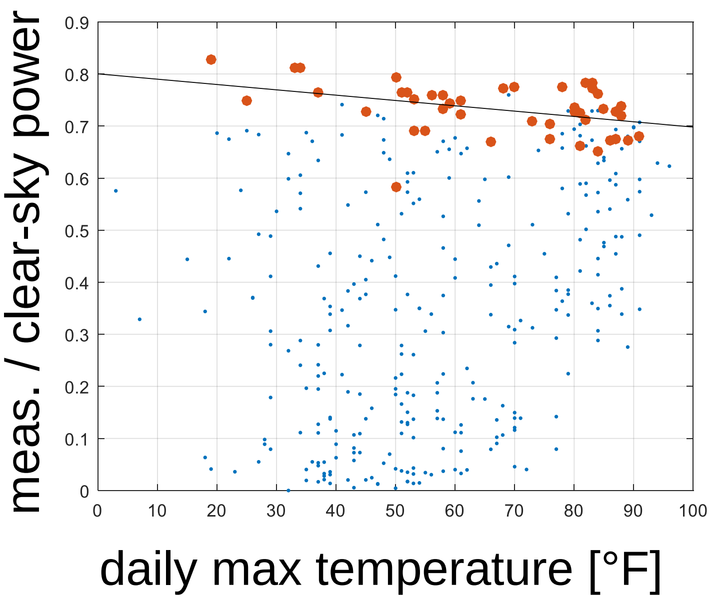
Forecast Performance: PV Farms

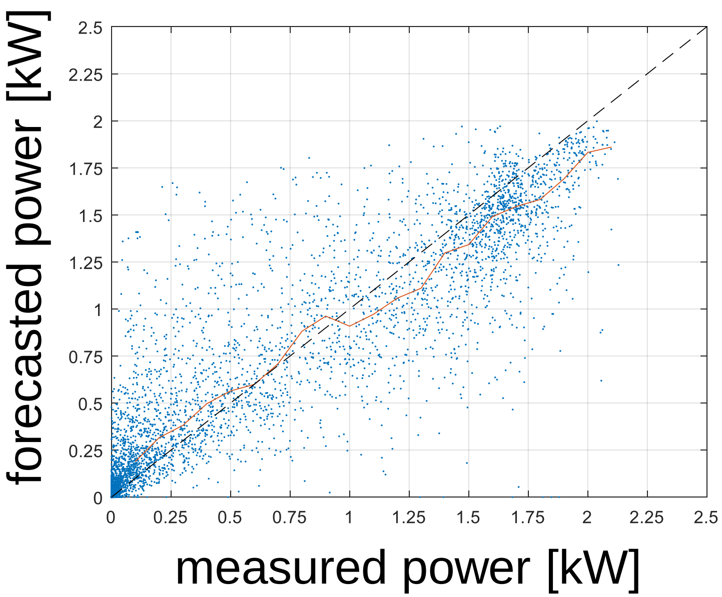
- Example week (PV Farm 3):
  - Forecast evolves from 3-day ahead to 1-day ahead



Forecast Performance: PV Farms

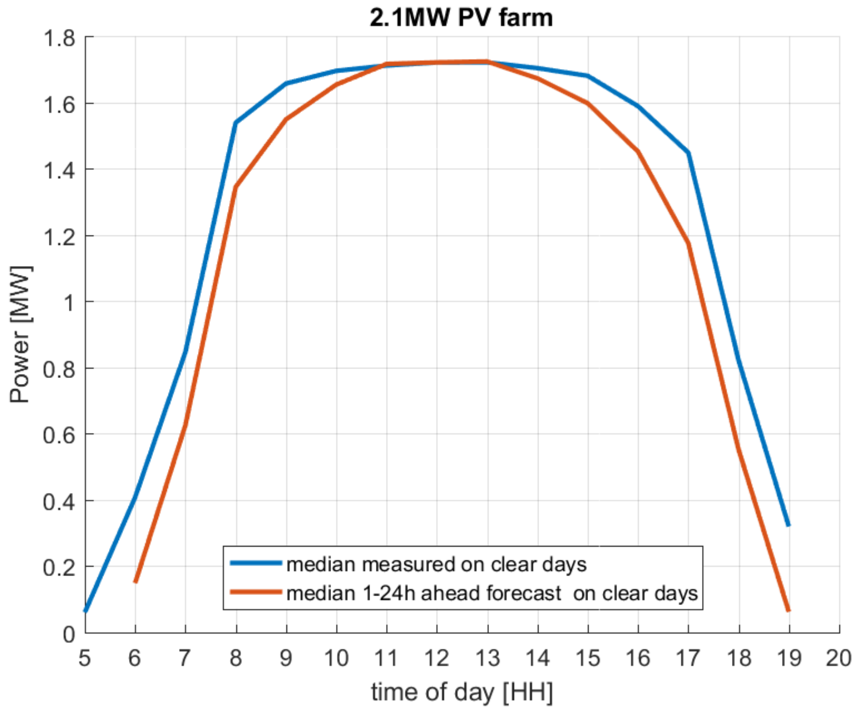
- Benefits/drawbacks to machine learning
  - Benefit: accurately captures less than 100% power output due to temperature, soiling, etc.
  - Drawback: optimized for mean values
    - Over prediction during cloudy periods
    - Under prediction during clear periods





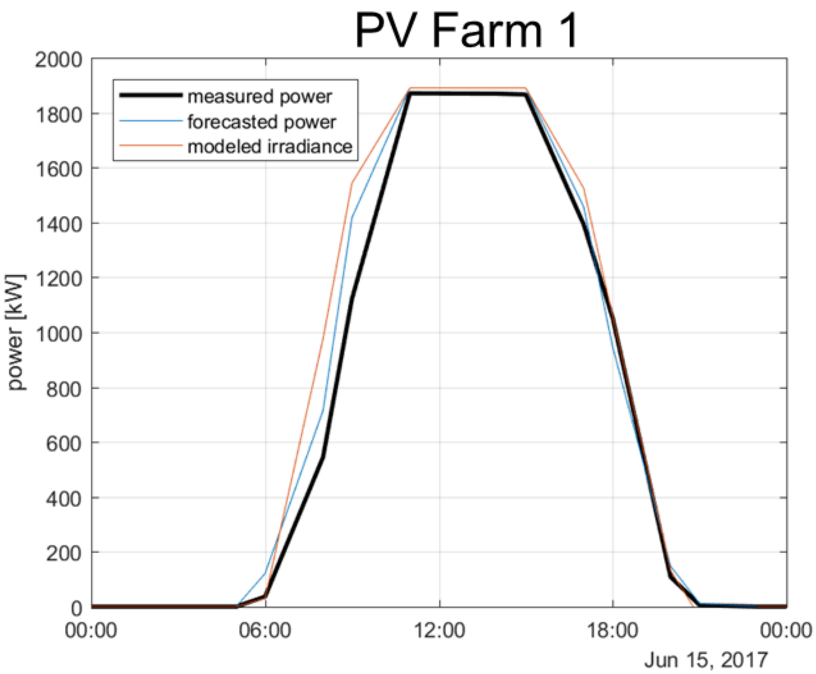
Forecast Performance: PV Farms

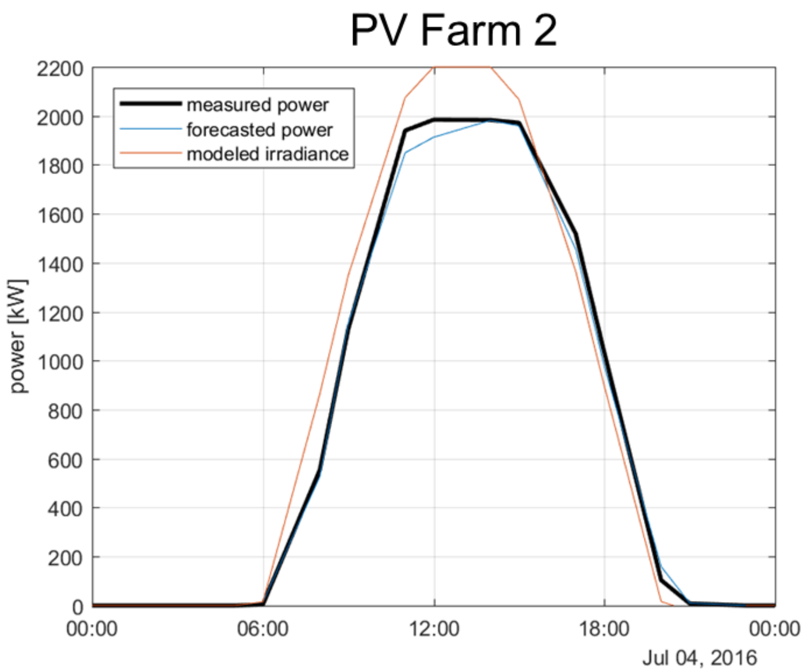
- Drawback: only accounts for tilt, not azimuth
  - Errors for tracking or non-south facing systems



Forecast Performance: PV Farms

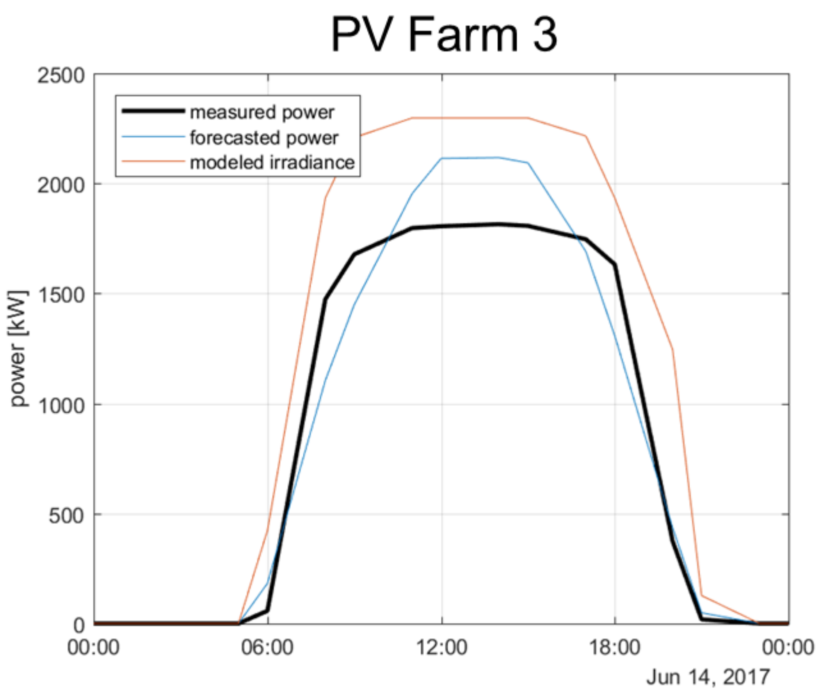
- Irradiance forecast compared to power forecast
  - PV Farm 1 ~as expected
  - PV Farm 2 forecast beats irradiance (may be due to soiling, shading, failed strings, etc.)

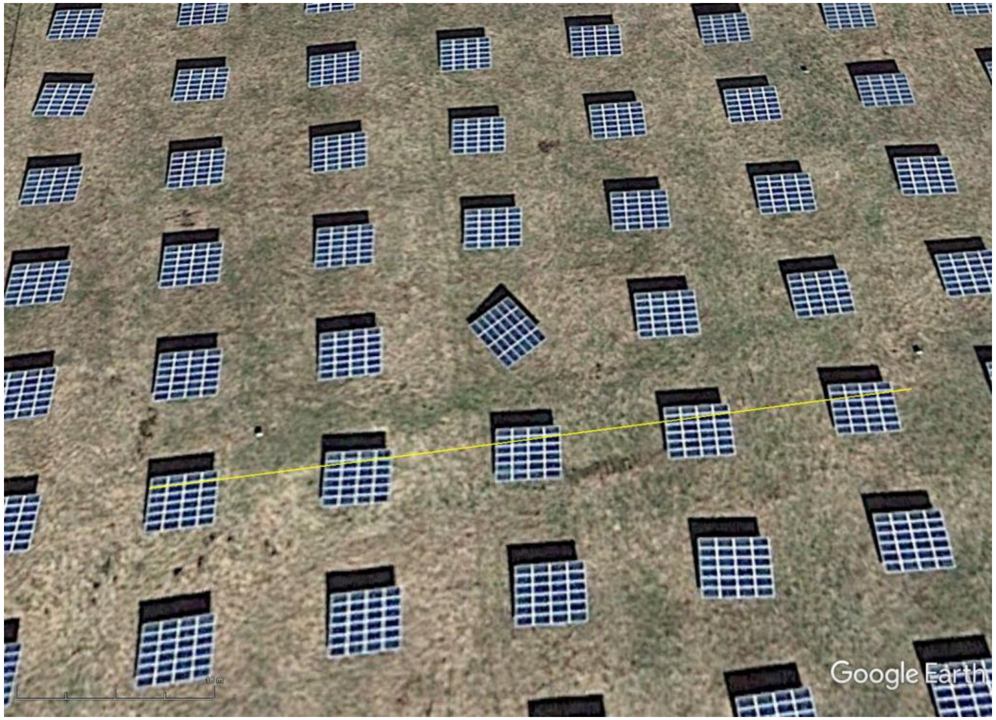




Forecast Performance: PV Farms

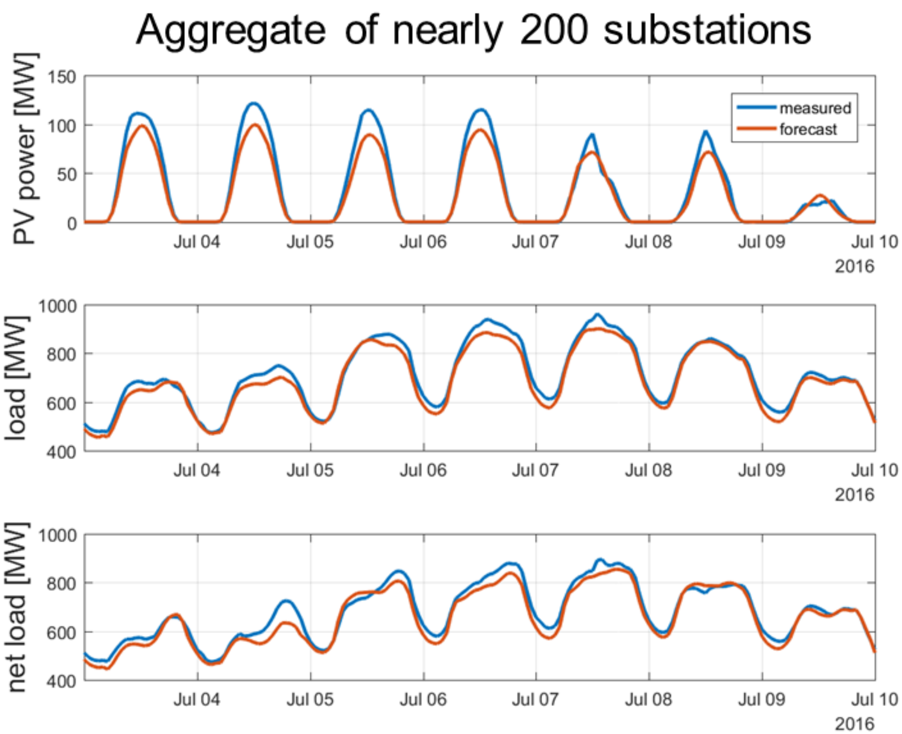
- Irradiance forecast compared to power forecast
  - Power forecast does not account for 2-axis tracking (noted previously)
  - Measured power lower than expected, likely because not all modules are correctly tracking





Forecast Performance: Distributed

- Evaluated high penetration substations and the aggregate of nearly 200 substations (representing a full utility service area)
  - Over substation aggregate, net load (residual load) errors are small
    - Good load forecast, relatively small PV penetration

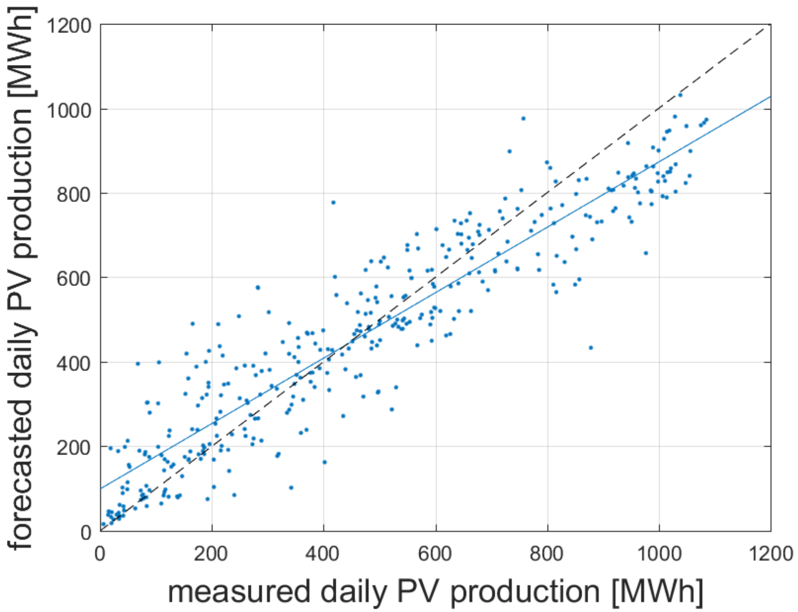


Forecast Performance: Distributed

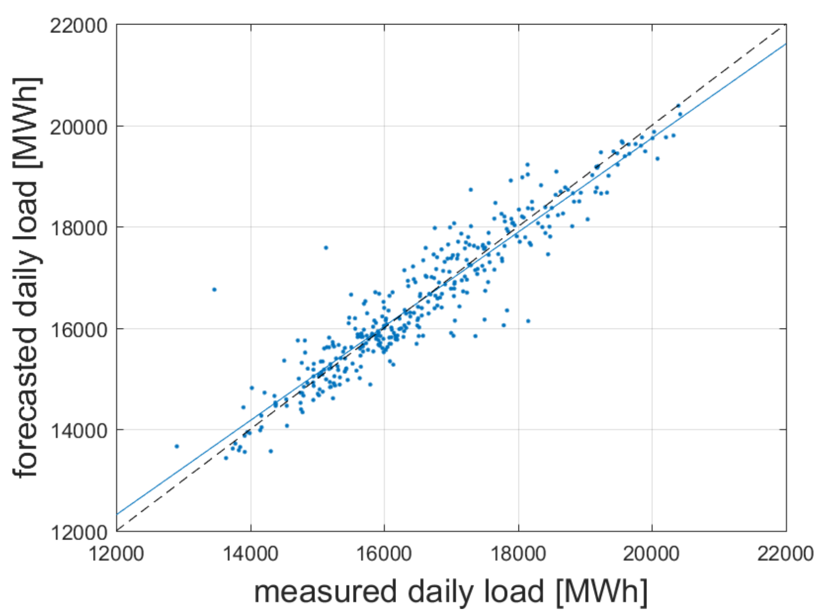
Aggregate of nearly 200 substations:

- PV forecast has slight over-prediction at low PV production; slight under-prediction at high PV production.
- Load forecast matches measured very well

PV



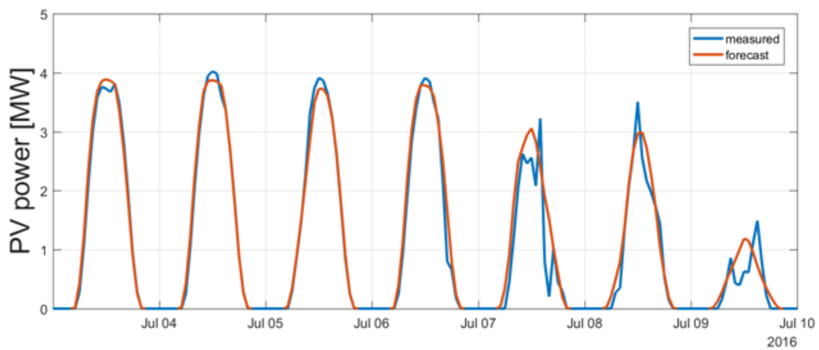
load



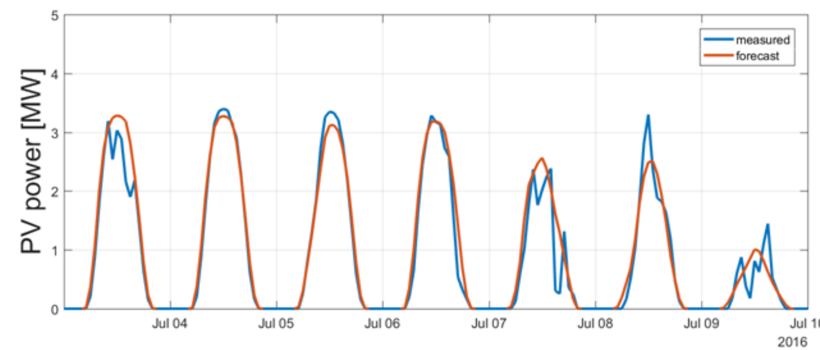
Forecast Performance: Distributed

- PV forecast varies by substation
  - Often low, likely due to additional PV added since forecast calibrated

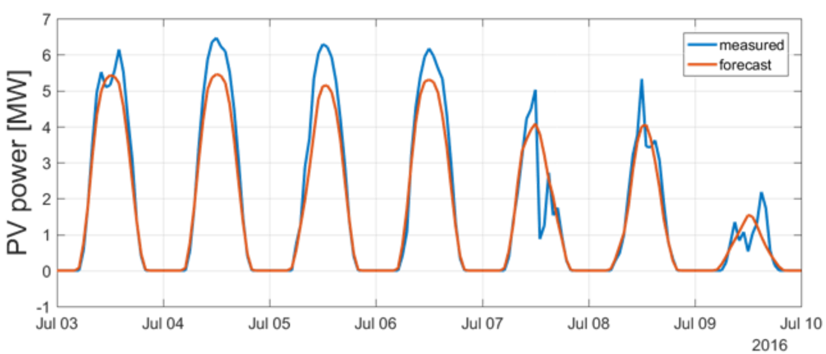
Substation 1



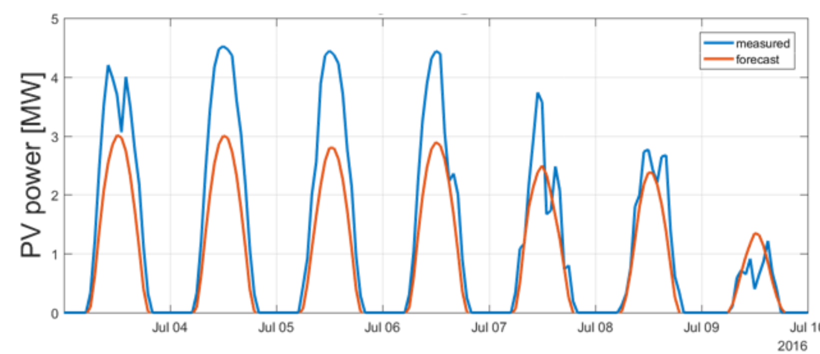
Substation 2



Substation 3

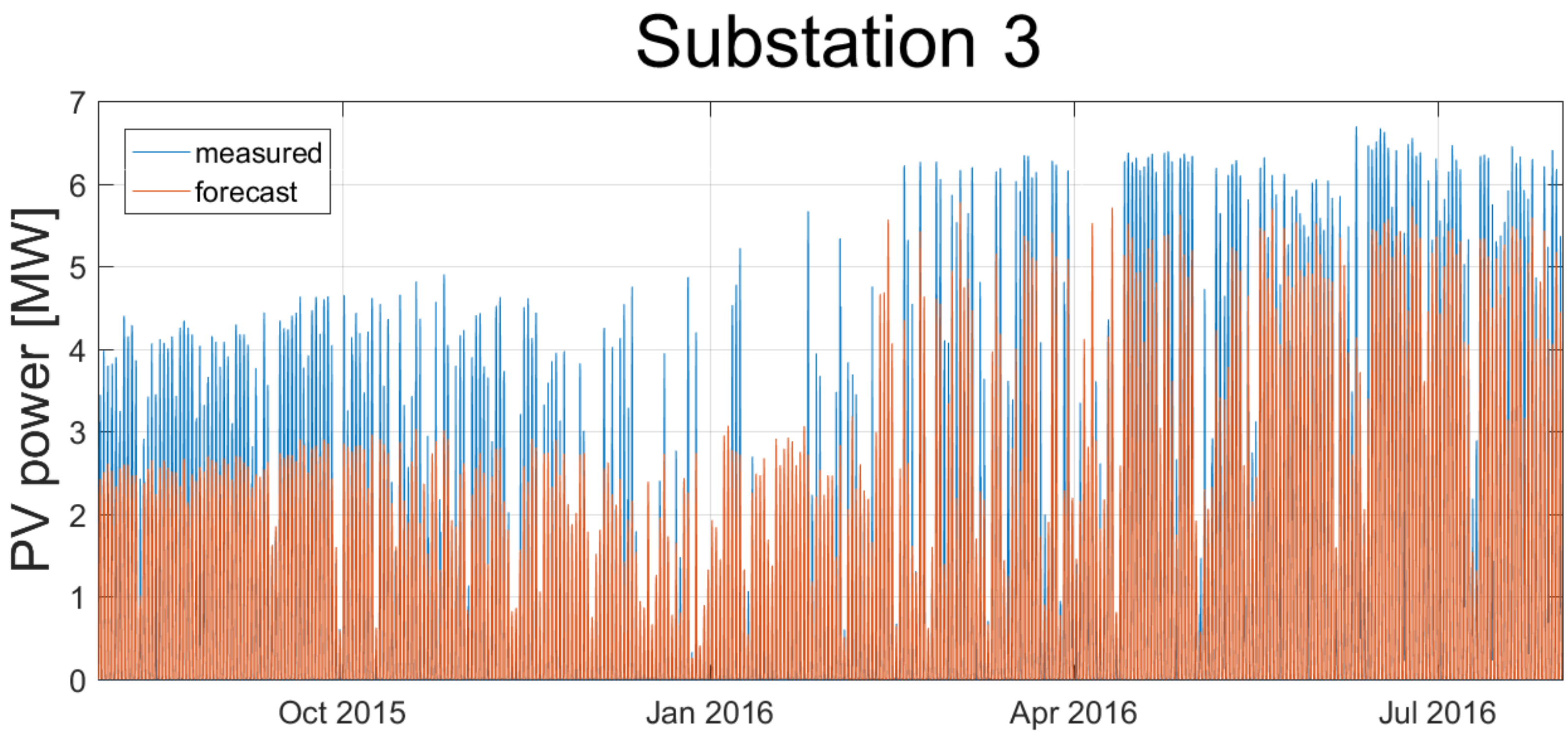


Substation 4



Forecast Performance: Distributed

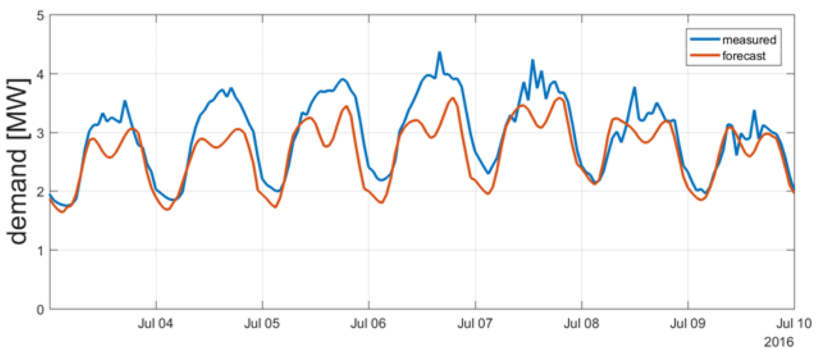
- Occasional adjustments to amount of PV
  - About once per 6-months



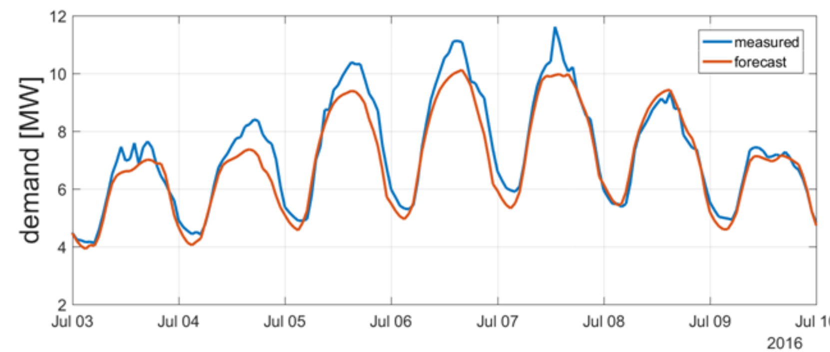
Forecast Performance: Distributed

- Demand forecast generally matches measured well

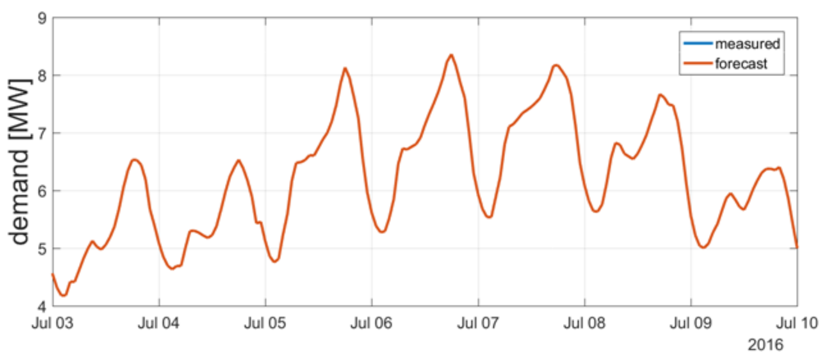
Substation 1



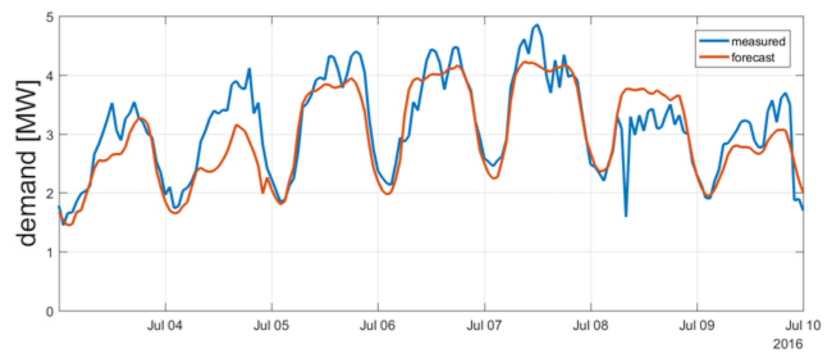
Substation 2



Substation 3

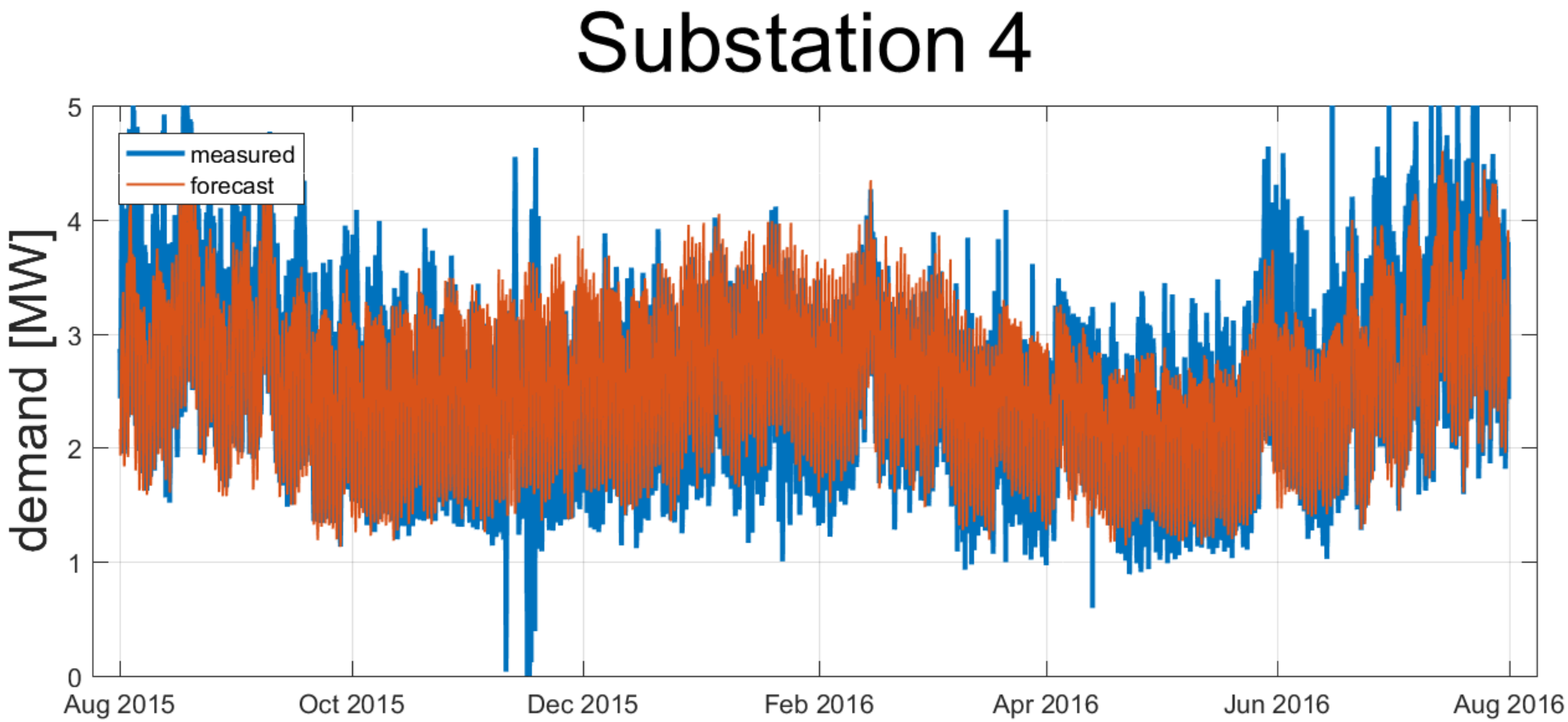


Substation 4



Forecast Performance: Distributed

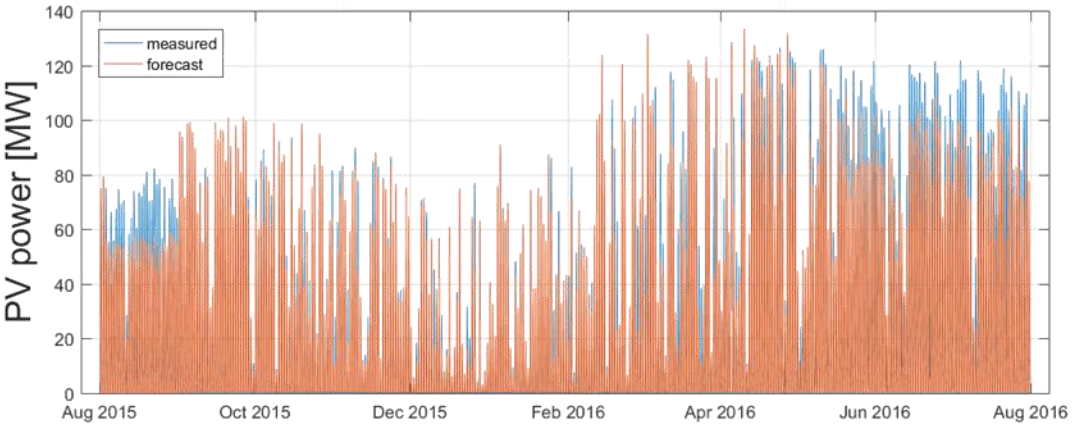
- Good match of load seasonal trends
  - Slight seasonal pattern to forecast error (high in summer, low in winter)



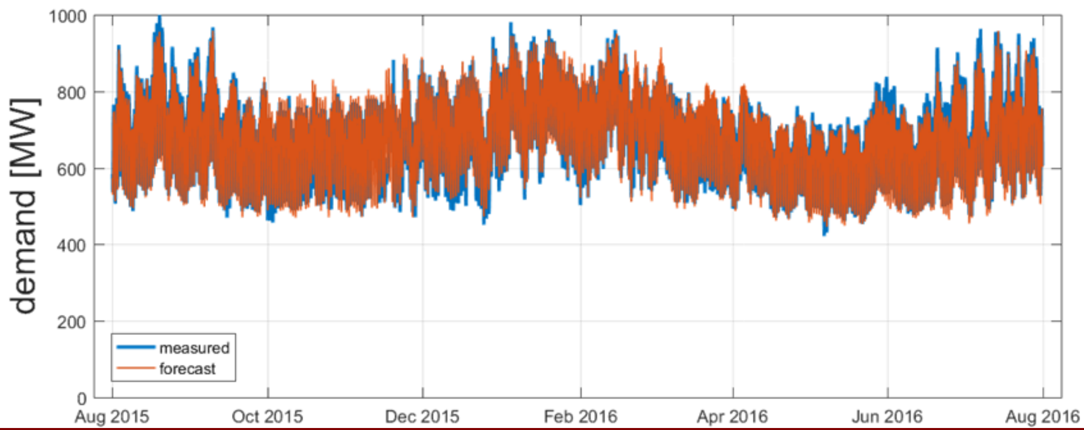
Forecast Performance: Distributed

- Over aggregate of many substations, forecast performance is better than individual substations

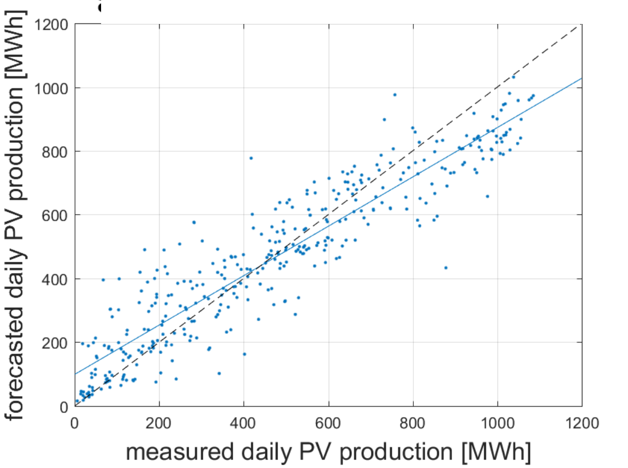
~200 substations



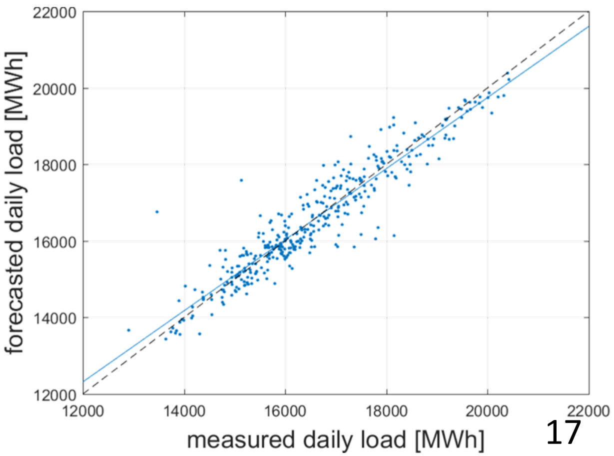
~200 substations



~200 substations PV



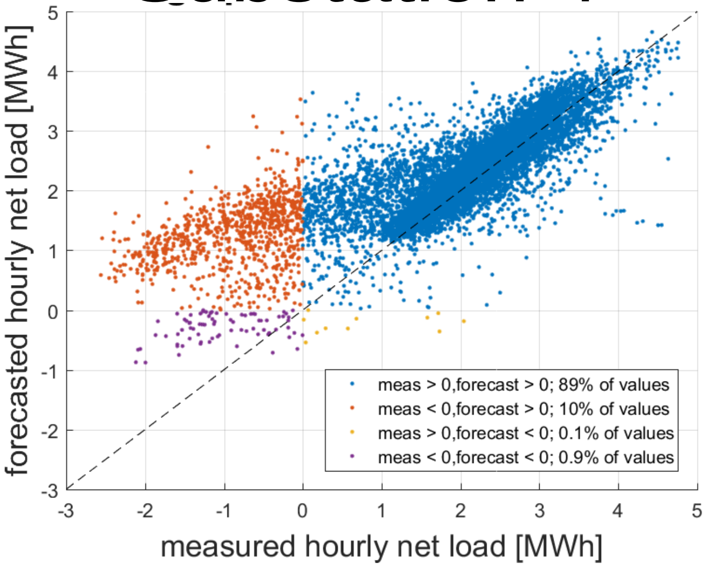
~200 substations load



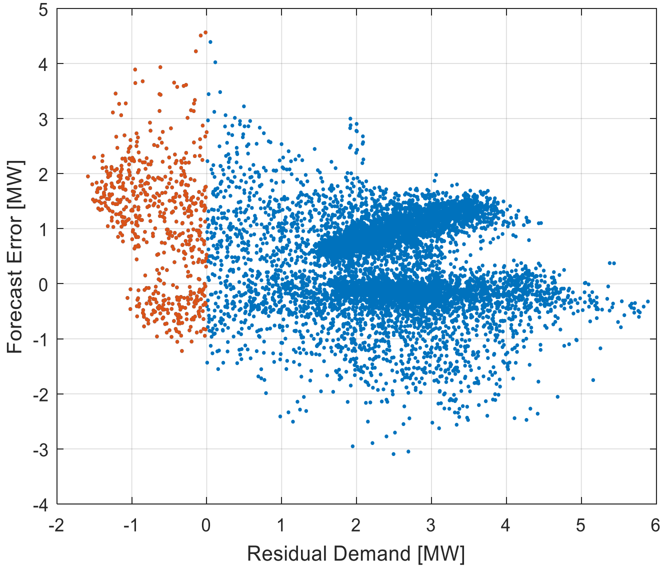
Event-Specific Metrics

- Looked at times of negative net load
  - Forecast often (~10% of time) misses reverse power flow

Substation 4



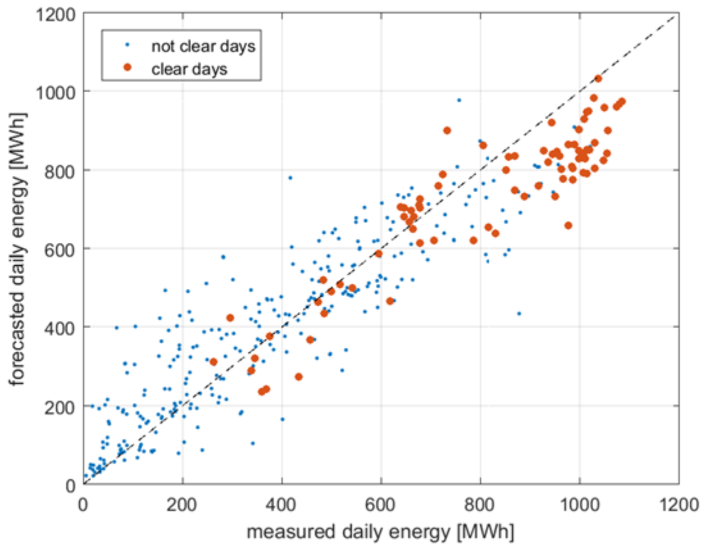
Substation 1

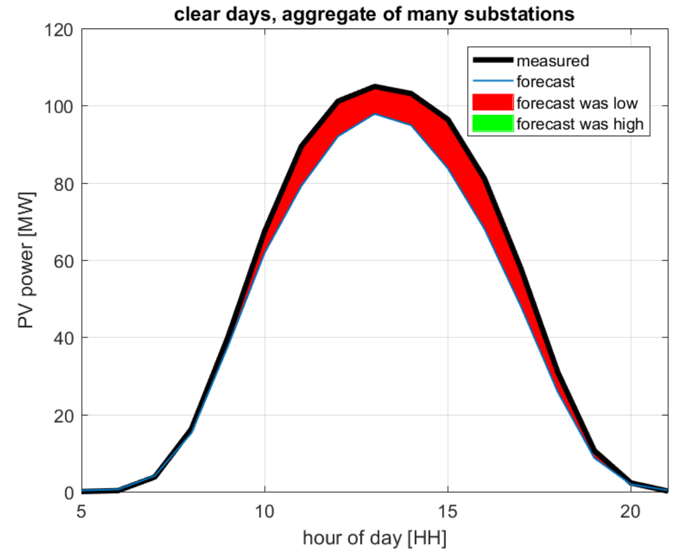


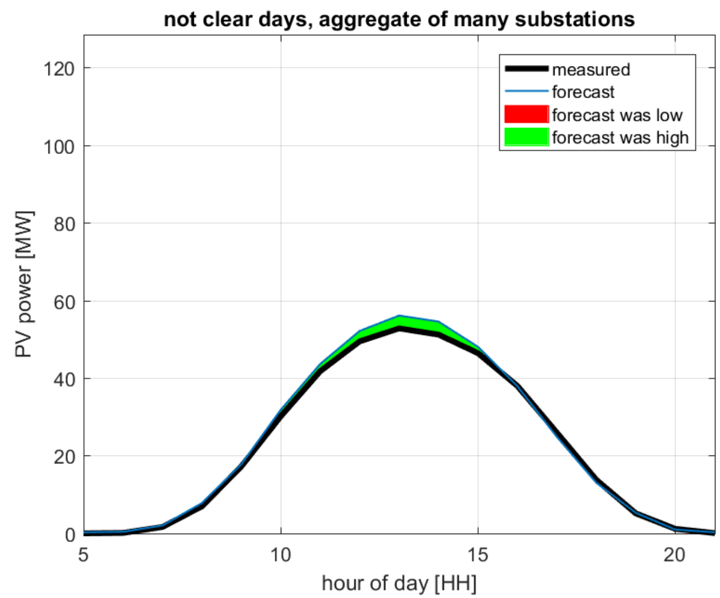
Event-Specific Metrics

- Clear vs. not clear days
- Forecast performance may be different
  - Under predict on clear days
  - Over predict on not clear days

~200 substations

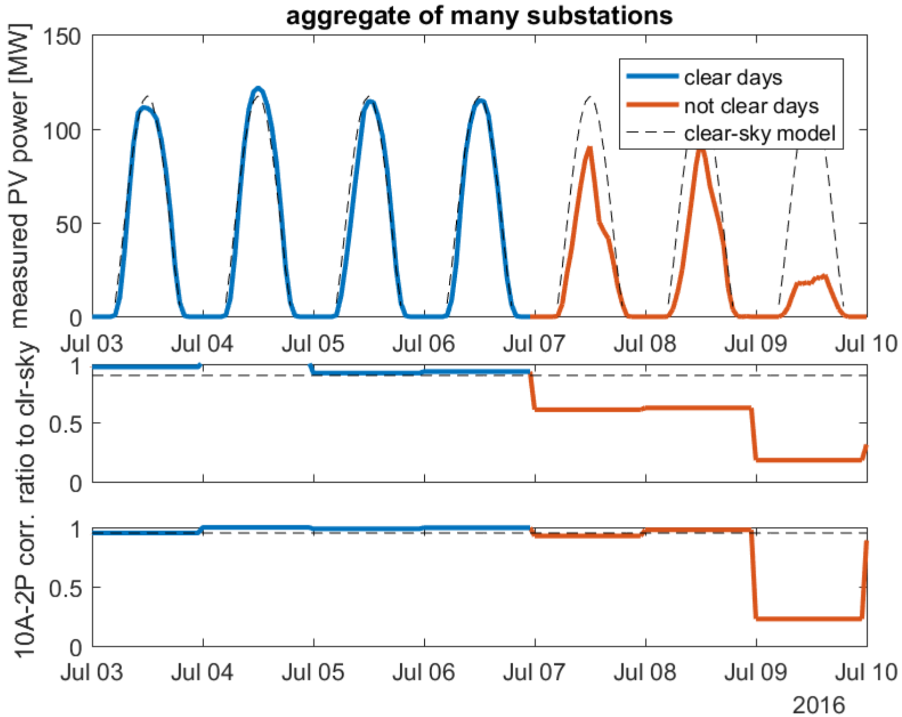






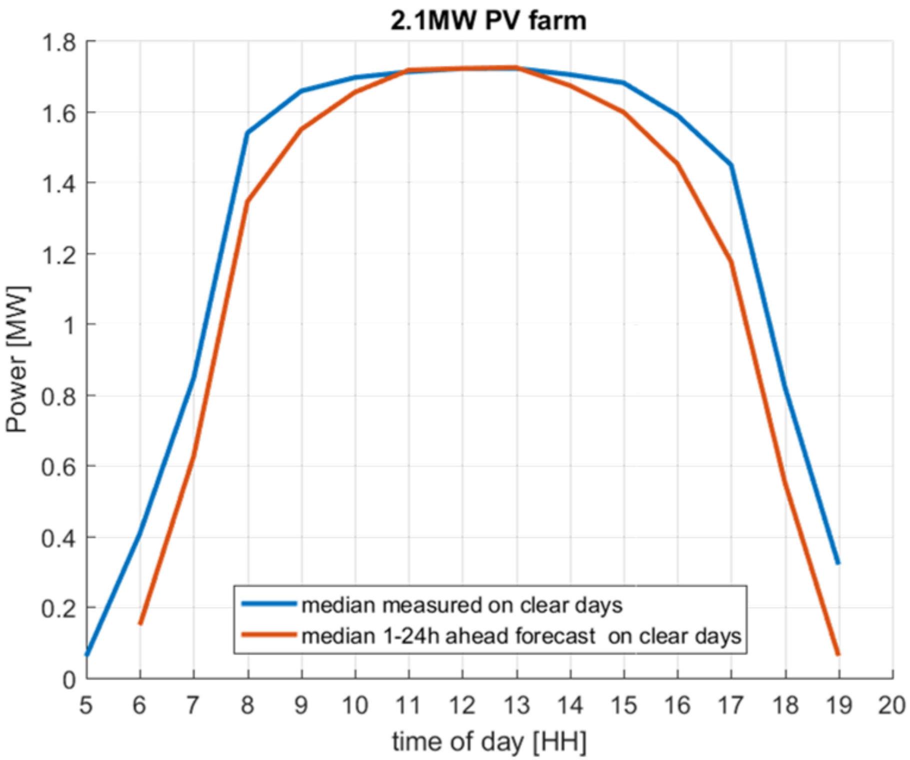
Event-Specific Metrics

- Simple clear-day definition:
  - Similar energy output as clear-sky model (>90%)
  - Highly correlated to clear-sky model at midday (10A-2P correlation >0.95)
  - Ineichen clear-sky model calculated from latitude/longitude



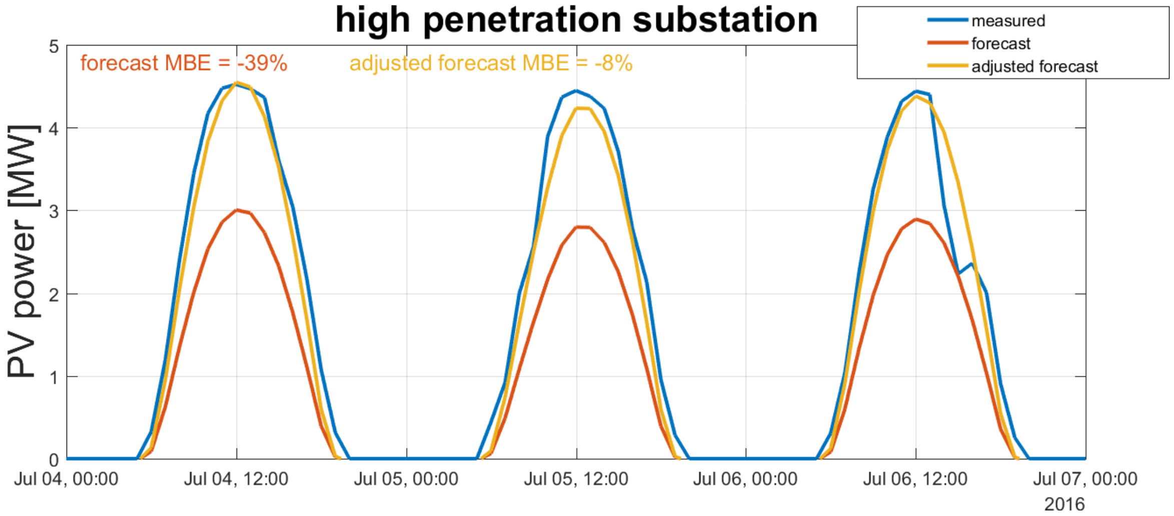
Suggested Improvements: PV Farms

- Directly account for tilt and azimuth angles
  - Current forecast only accounts for tilt (not azimuth)
  - Leads to inaccuracies, especially on clear days
  - Open question: way to post-process forecasts to correct for azimuth?



Suggested Improvements: Dist. PV

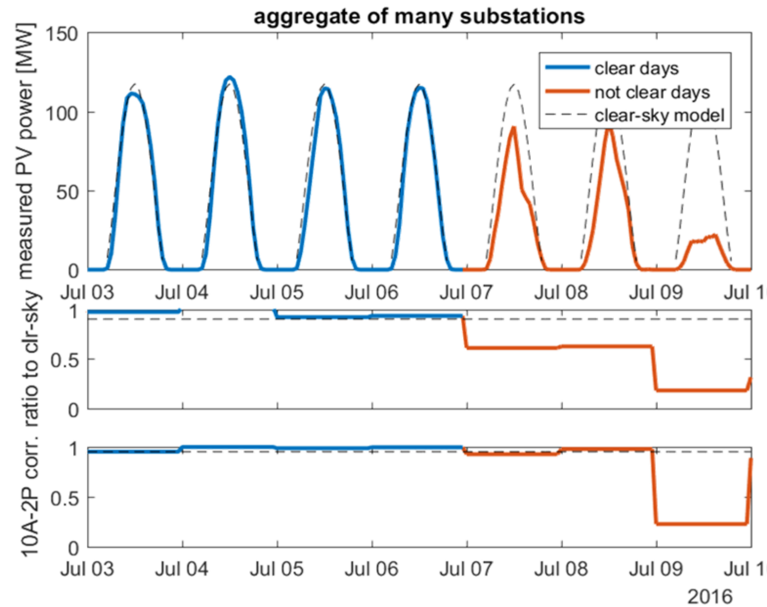
- Faster updates on PV capacity
  - We expect residential PV is installed all the time
  - Current forecast updates ~once per 6 months
  - Can lead to significant under prediction of PV production
- One simple solution: scale the forecast by the ratio of maximum measured to maximum forecasted power from the previous week

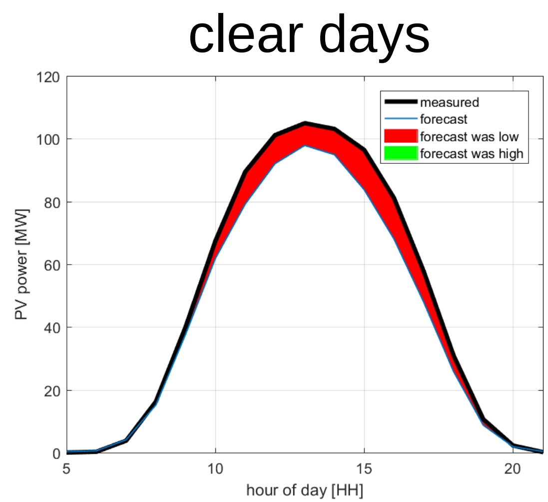


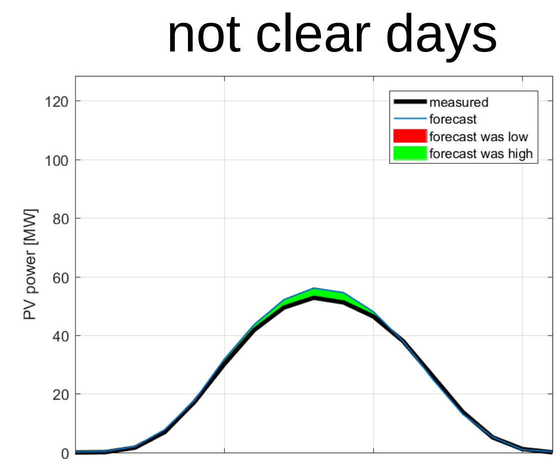
Suggested Improvements: Both

Separate Forecast Training for Clear vs. Other Days

- Machine learning trained on all days is “centrist” – over-predicts cloudy and under-predicts clear
- Can use simple clear-sky detection
  - Forecast on clear days can be based on a clear-sky model + historical clear data
  - Forecast on other days can be trained from the remaining historical data







Discussion

- How do/would you use a PV forecast?
  - Controlling storage or demand response to reduce peak
  - Distributed or PV farm
  - Load + PV
    - Distribution
    - Transmission-scale (e.g., compare PV production to ISO NE loads)
- What event-specific metrics are most relevant?
  - PV production during peak load / ISO-NE peak
  - Forecast accuracy for controls such as storage / hot water heaters
- What would be the next steps to make this most valuable
- How can we convey forecasts to users to make them valuable?
  - E.g., are forecast bounds useful?
  - Probabilities of specific events?