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Targeted Evaluation of Utility-Scale and Distributed Solar Forecasting

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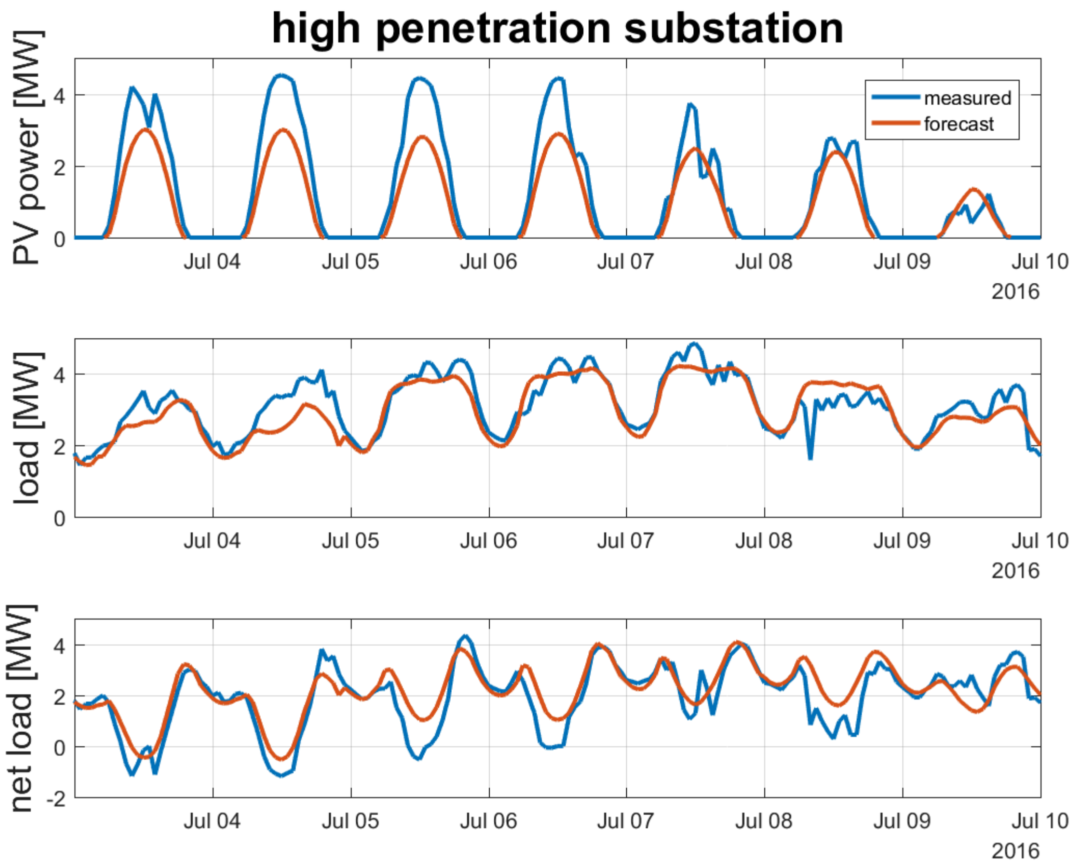
Forecast Data Evaluated

- Commercial forecast – same forecast provided to system operators
- Forecast uses historical training based on machine learning
  - algorithms retrained on a regular basis as the historical database expands
- Three scenarios:
  - Single substation with high PV penetration
  - Aggregate of several substations, representative of a utility's full PV portfolio
  - Utility-scale PV farm
- 1-year of forecasted and measured PV generation, at 1-hour intervals; forecasts published at midnight UTC
- For substations, also forecasted and measured load

High Penetration Substation

- Maximum PV generation 4.7MW; maximum load of 5.7MW
  - Reverse power flow (PV generation > load) occurs > 10% of the time

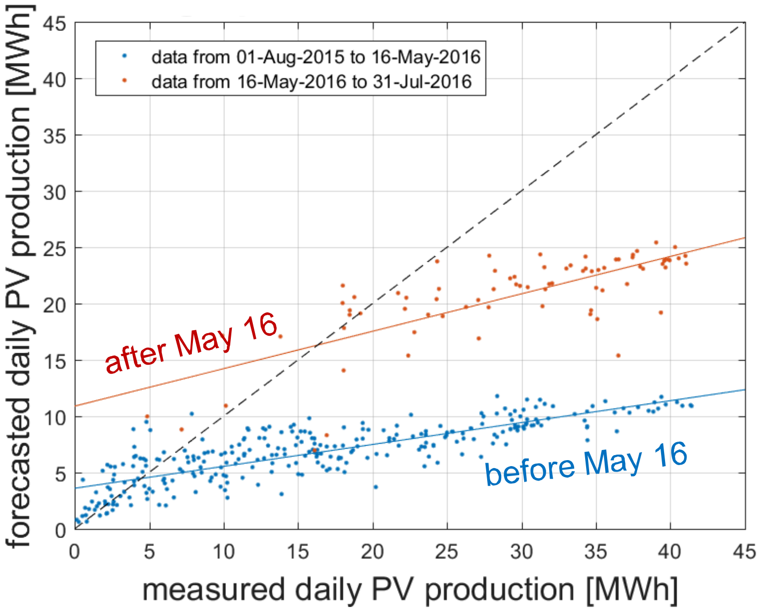
- Negative (under-prediction) errors in PV forecast.
- Load forecast under-predicts midday.
- There partially cancel in net load: midday forecasts mostly match measured



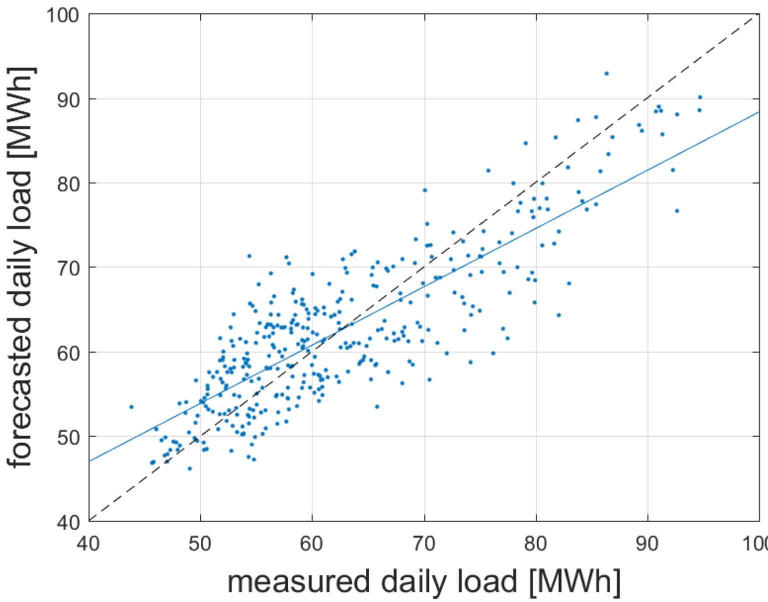
High Penetration Substation

- PV forecast follows linear trends, but not correct magnitude
  - Change in magnitude on May 16th, but forecast still low
- Load forecast matches measured much better

PV

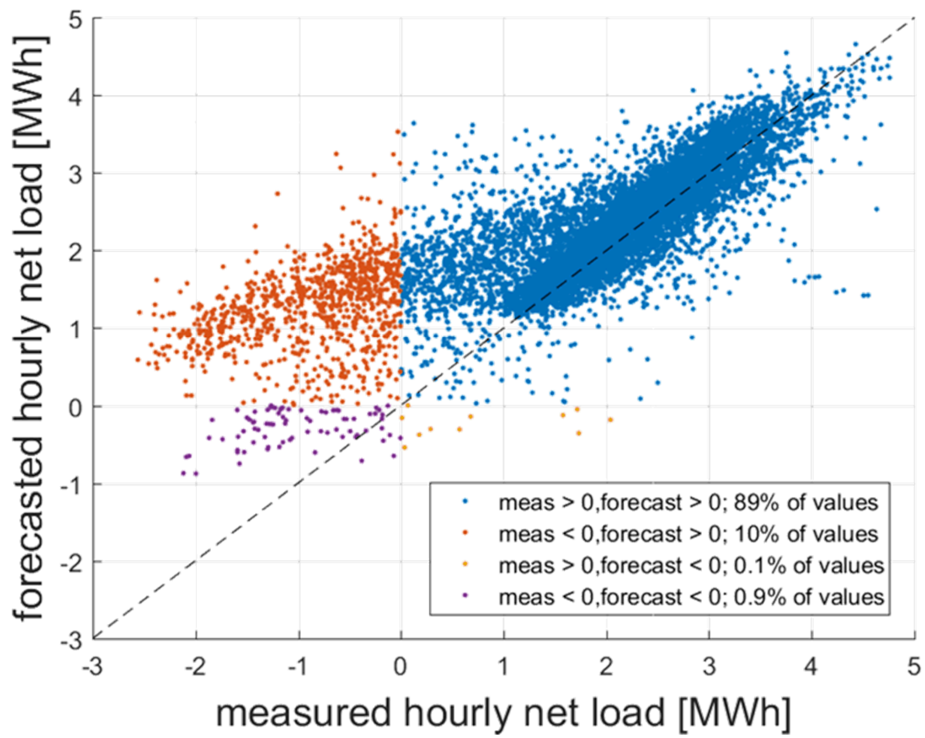


load



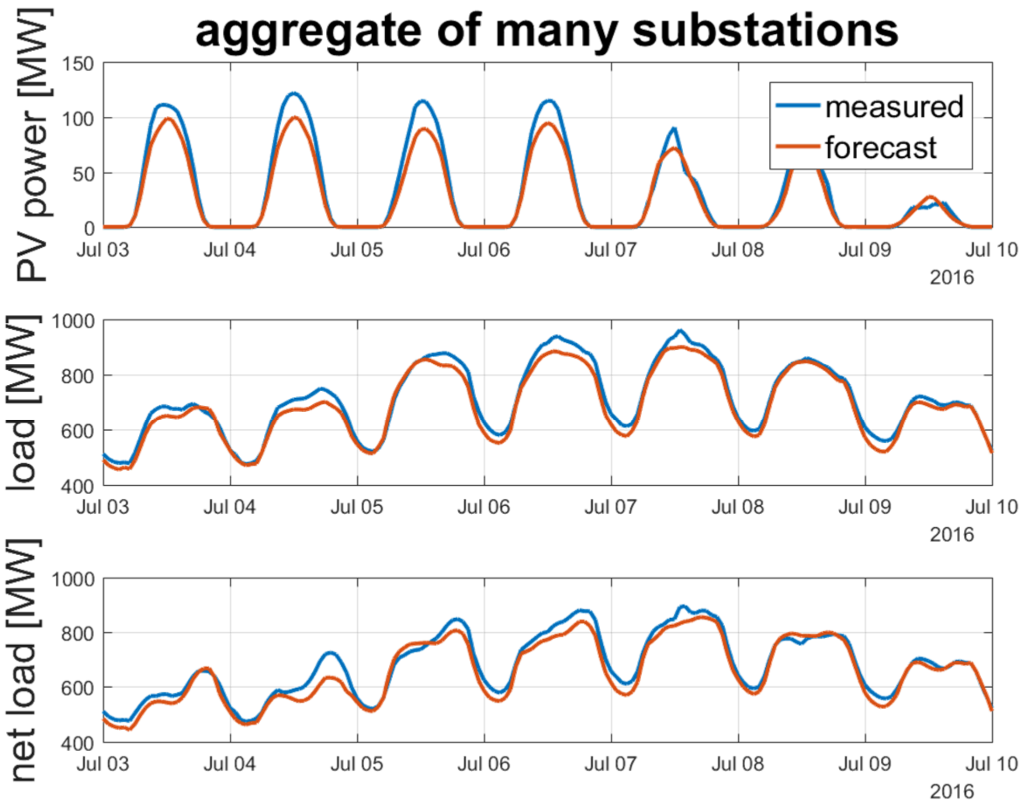
High Penetration Substation

- Net load shows reverse power flow
- For 10% of the values, measured showed reverse power flow but forecast predicted positive flow
  - Mostly caused by under-prediction of PV power



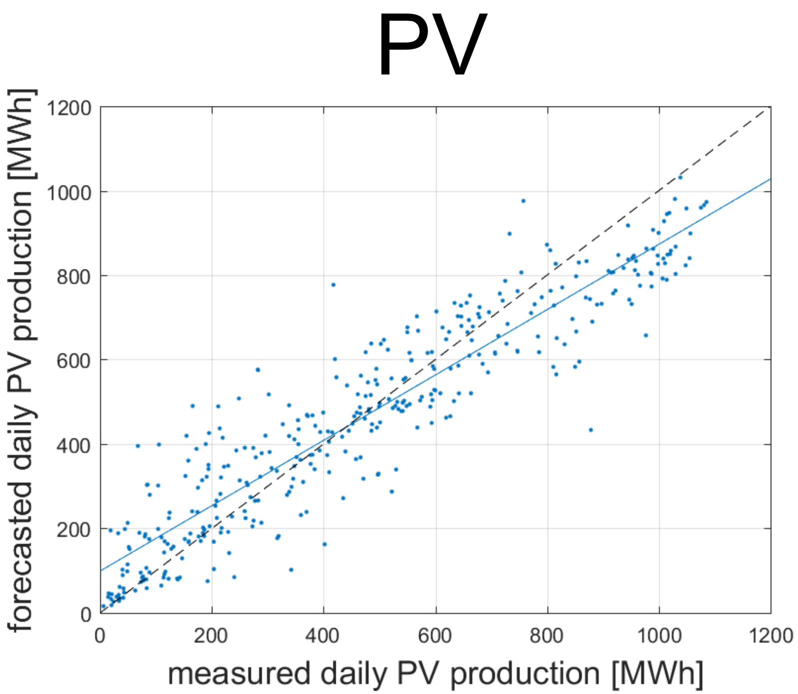
Aggregate of Many Substations

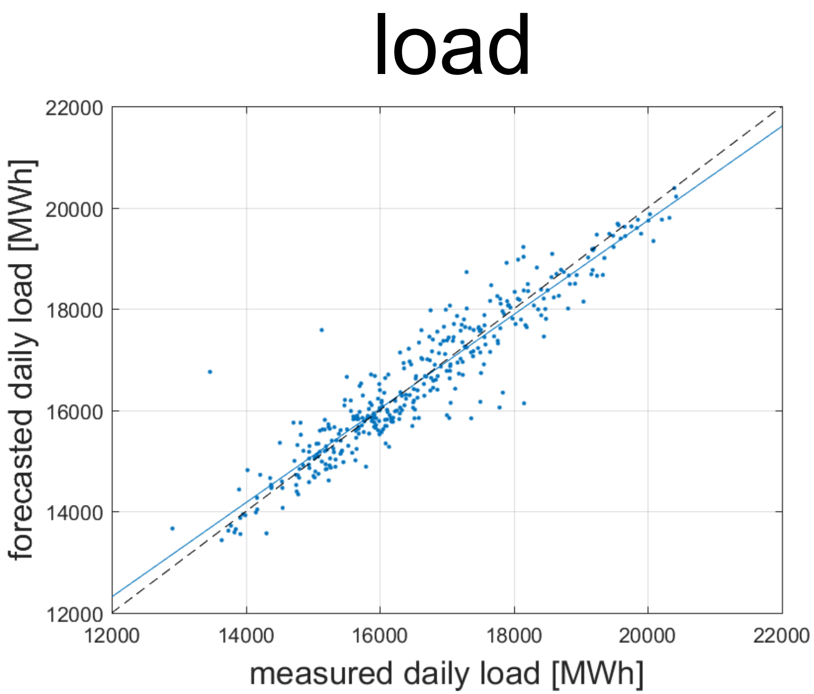
- Maximum PV generation only 12.6% of maximum load
  - Reverse power flow never occurs, load forecasts have more impact on net load than PV forecasts
- PV forecasts match better, but still low.
- Load forecasts match well.
- Net load forecasts depend mostly on load forecasts; reverse power flow never occurs.



Aggregate of Many Substations

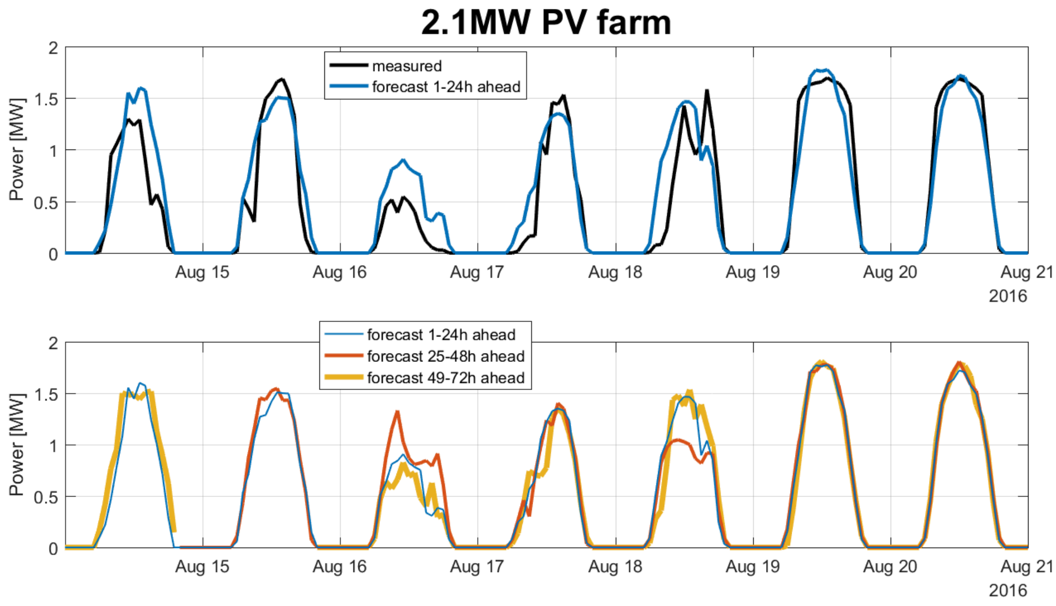
- PV forecast better matches measured
  - Slight over-prediction at low PV production; slight under-prediction at high PV production.
- Load forecast matches measured very well





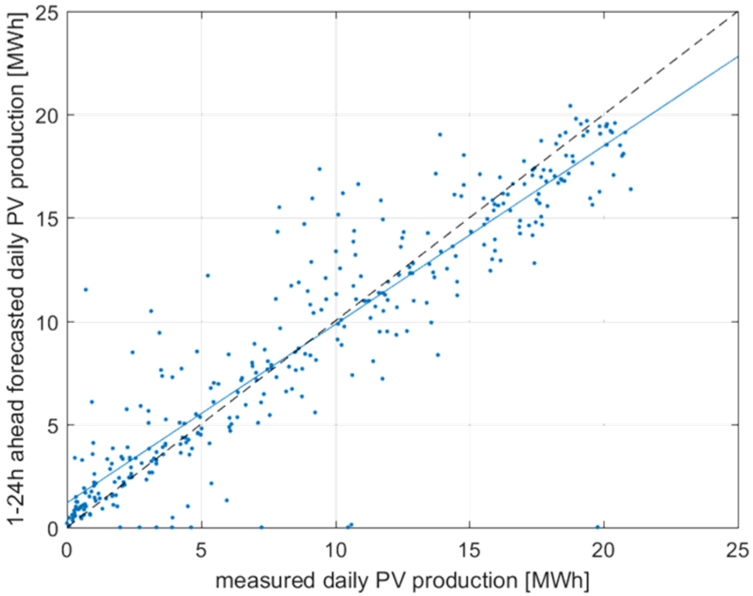
Utility-Scale PV Farm

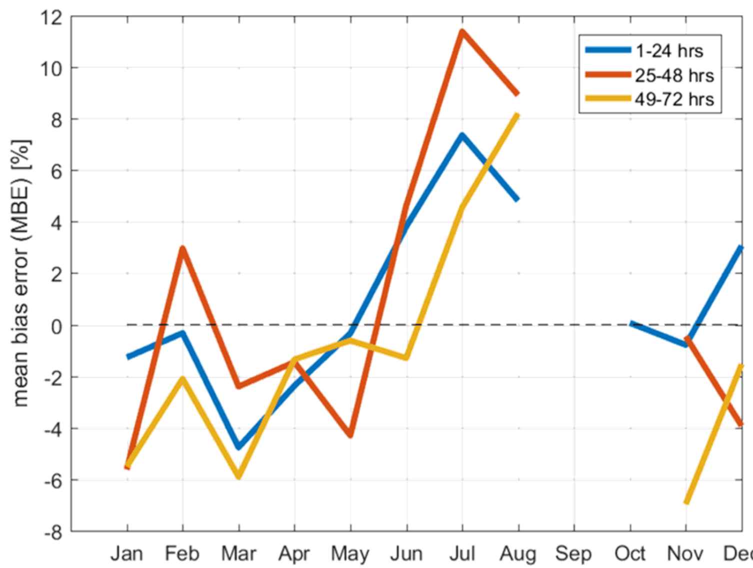
- 2.1MW PV farm
  - Included forecasts at 3 different time horizons: 1-24 hours ahead, 25-48 hours ahead, and 49-72 hours ahead.
- Clear days (Aug. 19, 20) predicted with reasonable accuracy.
- Cloudy days introduce more uncertainty (e.g., Aug. 16)
- More variability between time horizons on cloudy days
- No clear improvement at shorter forecast horizon.



Utility-Scale PV Farm

- Close agreement between measured and forecasted
  - Machine learning is more effective for PV farm than for substations – more consistent performance over time
- Slight over-prediction at low PV production; and vice-versa
  - This “centrist” behavior likely an artifact of machine learning
- Seasonal changes in bias: -6% in winter to +7-11% in July

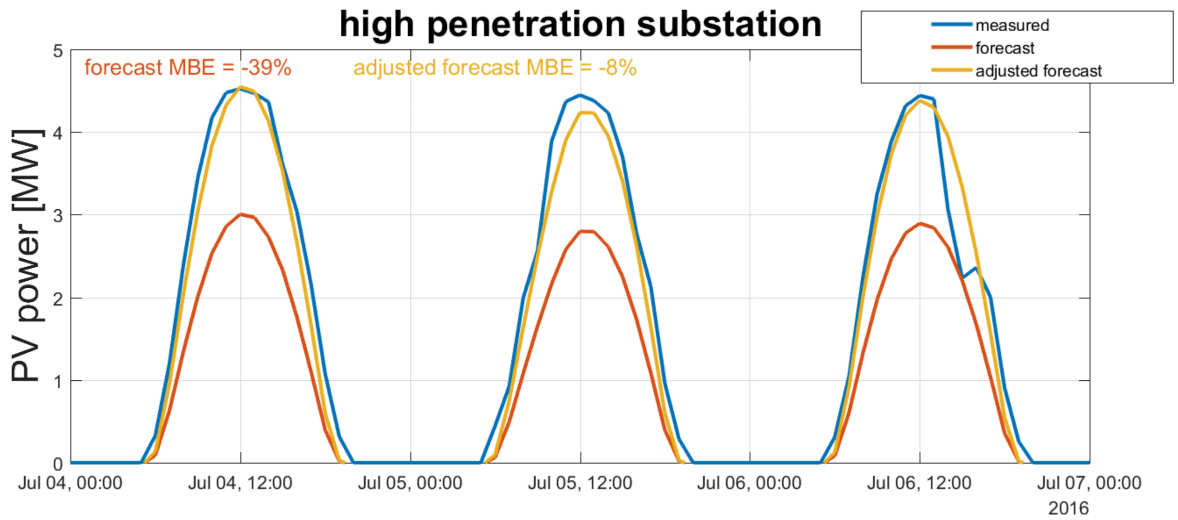




Suggested Forecast Improvements

Faster adjustment for changes in PV capacity

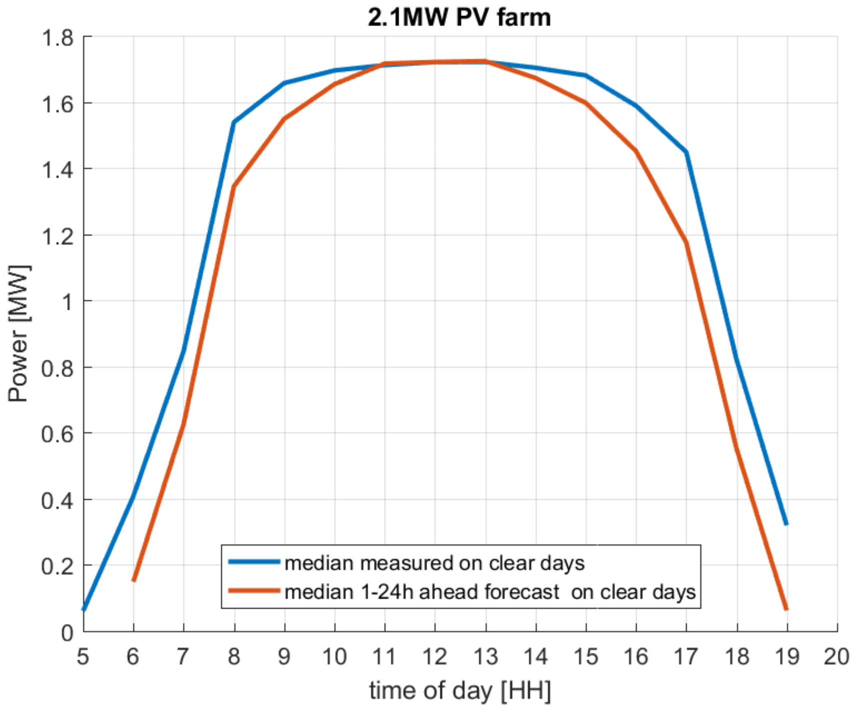
- Residential PV is installed all the time
  - Current forecast updates ~once per 6 months
  - Can lead to significant under prediction of PV production
- One simple solution: scale the forecast by the ratio of maximum measured to maximum forecasted power from the previous week



Suggested Forecast Improvements

Directly account for tilt and azimuth angles

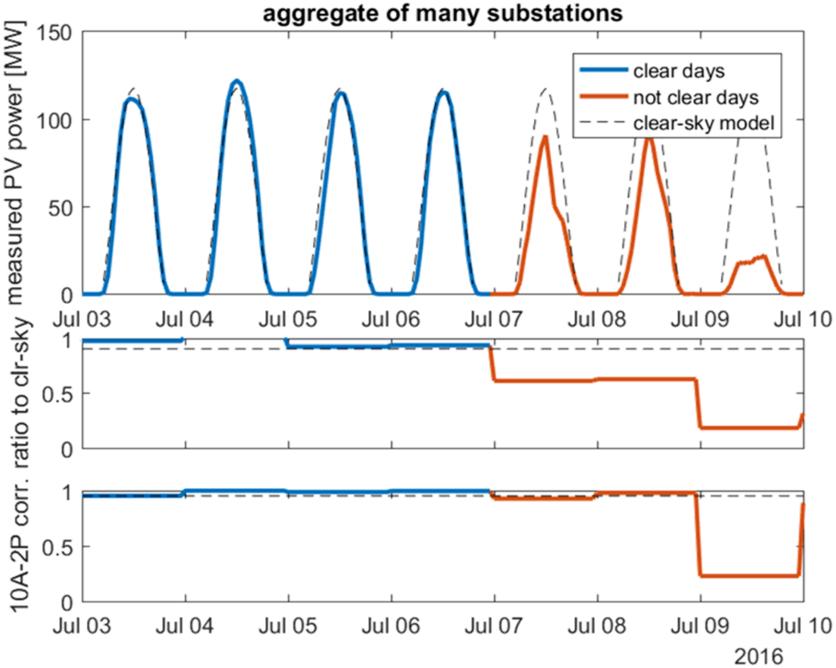
- Machine learning in the PV farm forecast only accounts for the tilt angle of the PV modules (not the azimuth)
- Systems deviating from due south result in time-of-day dependent forecast errors



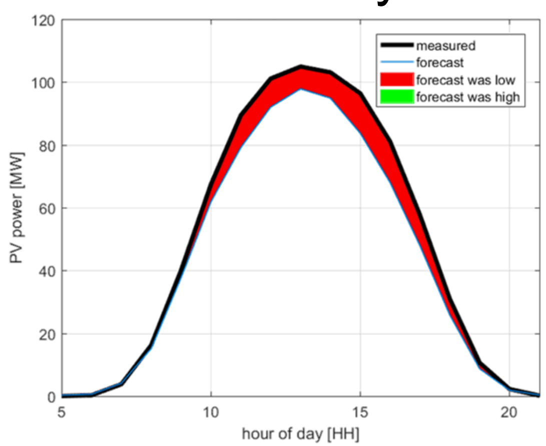
Suggested Forecast Improvements

Separate Forecast Training for Clear vs. Other Days

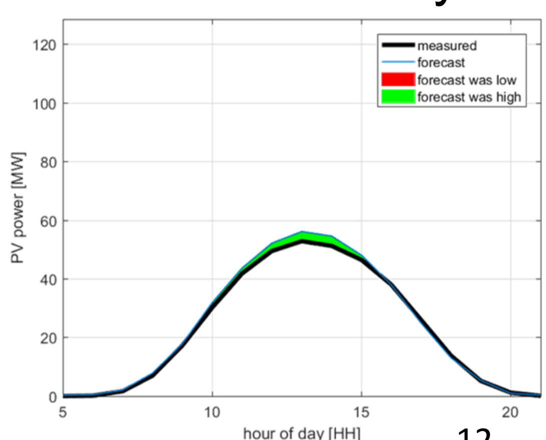
- Machine learning trained on all days is "centrist" – over-predicts cloudy and under-predicts clear
- Can use simple clear-sky detection
  - Forecast on clear days can be based on a clear-sky model + historical clear data
  - Forecast on other days can be trained from the remaining historical data



clear days



not clear days



Conclusions

- Load forecasts were generally accurate
- PV forecasts most accurate at PV farm; substation forecasts tended to be low, perhaps due to new PV installations

- Suggested three strategies for forecast improvement
  - accurately account for the total amount of distributed solar installed capacity, including fast updates to account for new installations
  - incorporate azimuth in addition to the tilt angle in forecast training
  - Segmenting clear from not-clear days for better training and more accurate forecasts, especially on clear days

- Forecast improvement suggestions have been well-received by the forecast provider and are already being implemented.