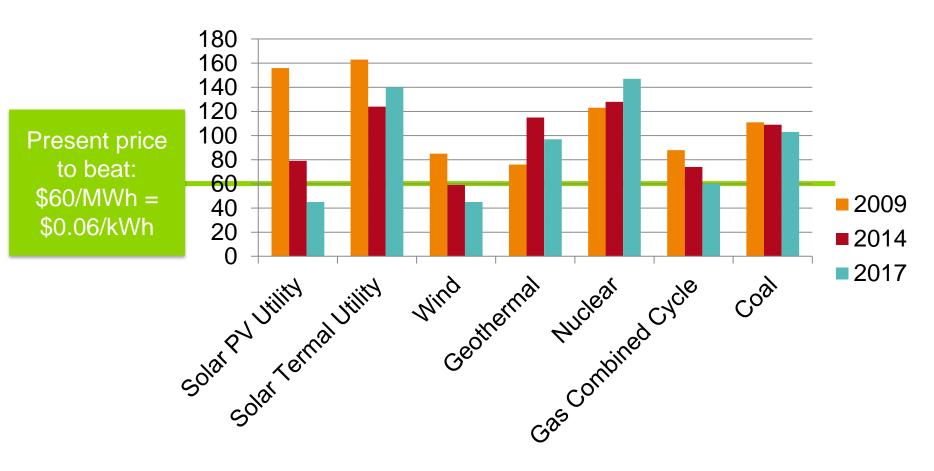
## Renewables



## TOWARDS A CONSISTENT MACHINE LEARNING-BASED PREDICTION SYSTEM FOR RENEWABLE GENERATION AND LOAD

Dr. Daniel Kirk-Davidoff, Lead Research Scientist Ken Pennock, Global Director, Grid Solutions April 10, 2019

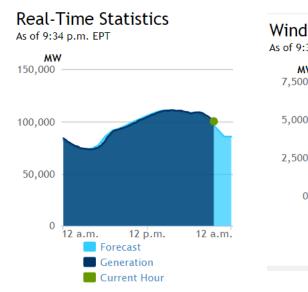
### AN ELECTRICAL GRID IN TRANSITION

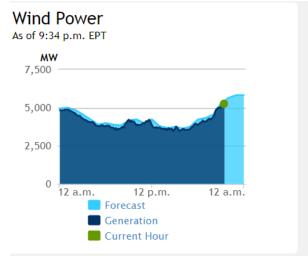


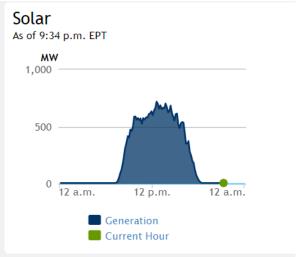
Sources: <a href="https://www.lazard.com/perspective/levelized-cost-of-energy-2017/">https://www.lazard.com/perspective/levelized-cost-of-energy-2017/</a><a href="https://blog.cleanenergy.org/files/2009/04/lazard2009\_levelizedcostofenergy.pdf">https://blog.cleanenergy.org/files/2009/04/lazard2009\_levelizedcostofenergy.pdf</a><a href="https://www.lazard.com/media/1777/levelized\_cost\_of\_energy">https://www.lazard.com/media/1777/levelized\_cost\_of\_energy\_-version\_80.pdf</a>

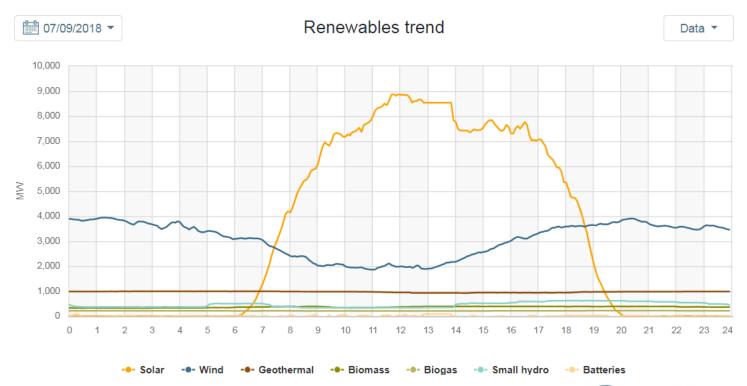


In the past, the forecast of electrical load was the main basis for decision making about tomorrows electrical supply...

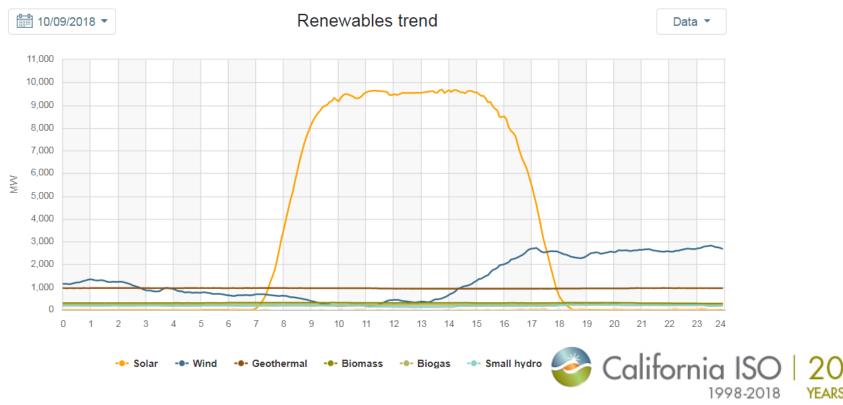




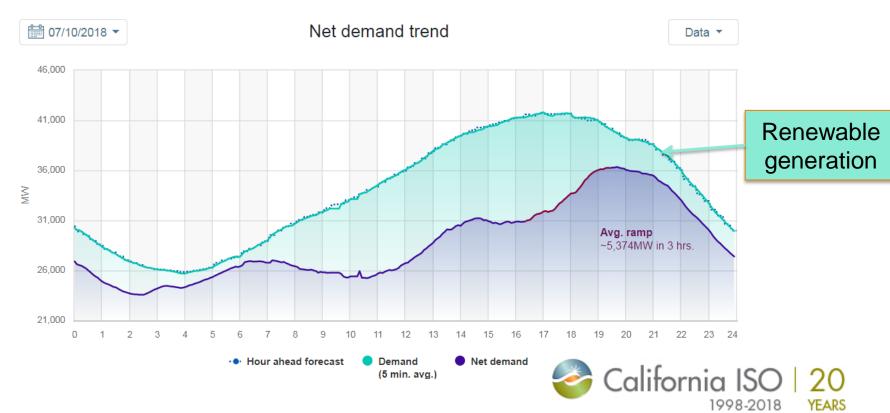




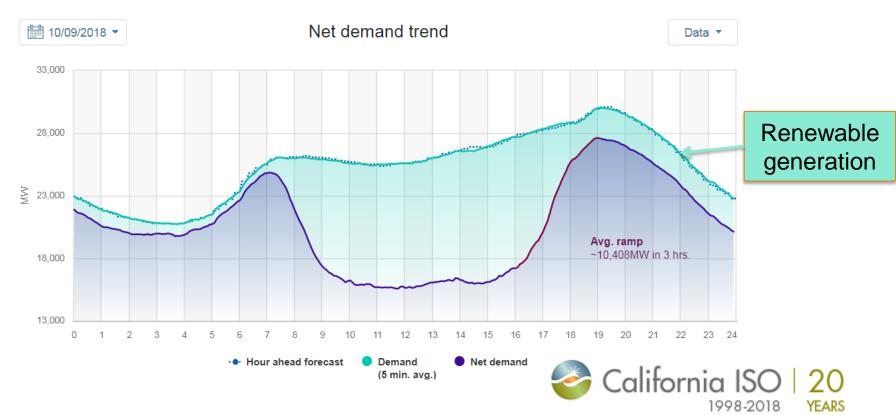






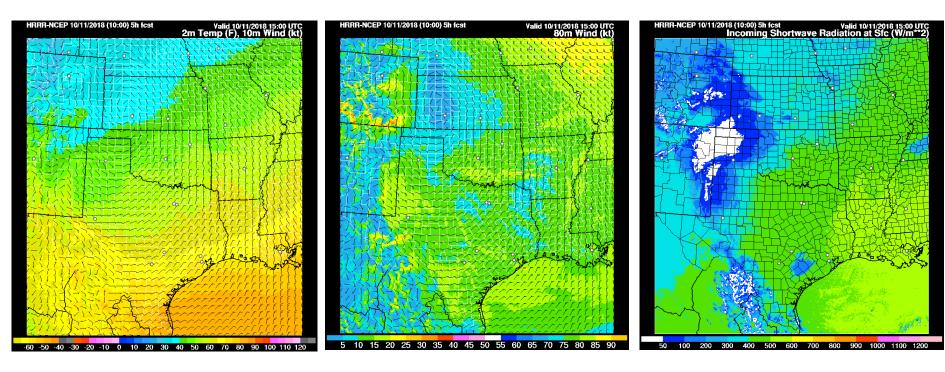






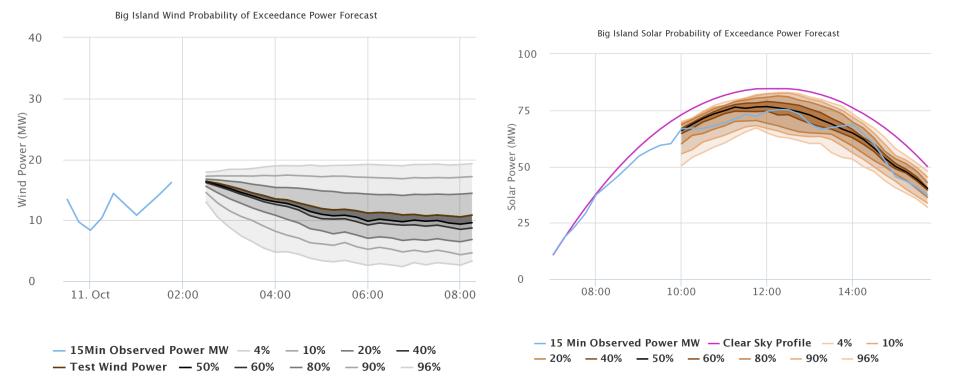


# WEATHER'S MULIT-FACETED INFLUENCE ON THE GRID

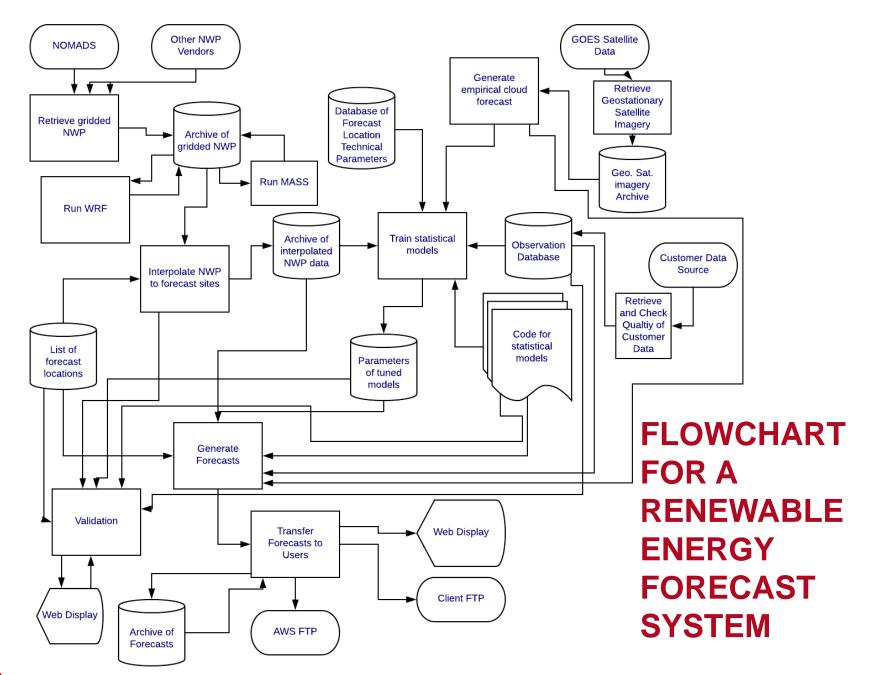




## WEATHER'S MULIT-FACETED INFLUENCE ON THE GRID









#### PATHWAYS TO FORECAST IMPROVEMENT

- Improving NWP
  - Additional models
  - Additional ensemble members
  - Improving existing models
    - Data assimilation
    - Parameterizations
    - Resolution
- Improved post-processing
  - Progress in Al/machine-learning algorithms
  - Better treatment of probabilistic forecasting
- Longer timeseries for training

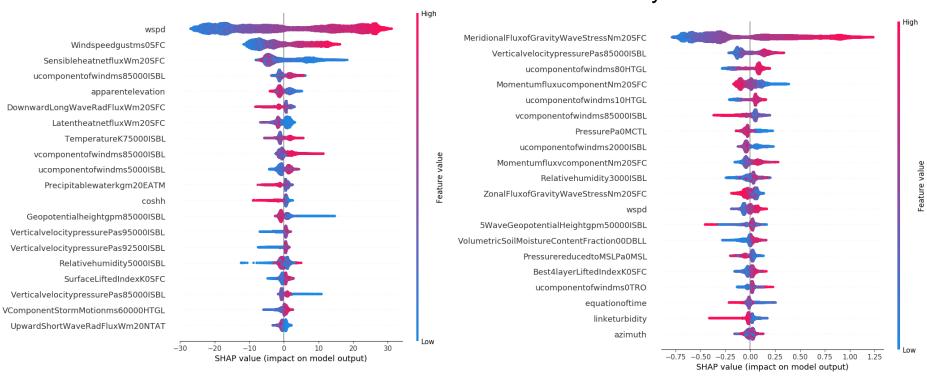


### **MAKING AI METHODS MORE TRANSPARENT**

New methods of displaying feature importance

#### Plains wind farm

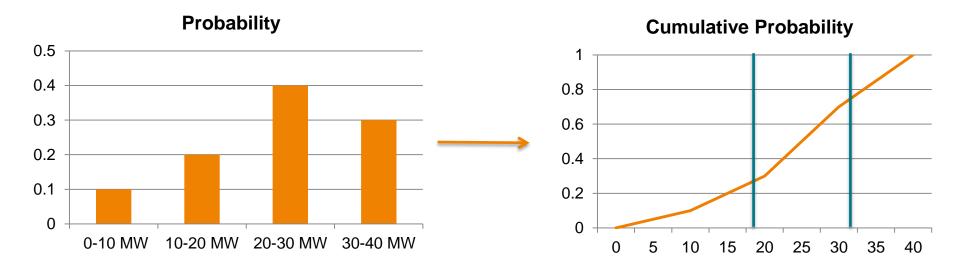
#### Valley wind farm





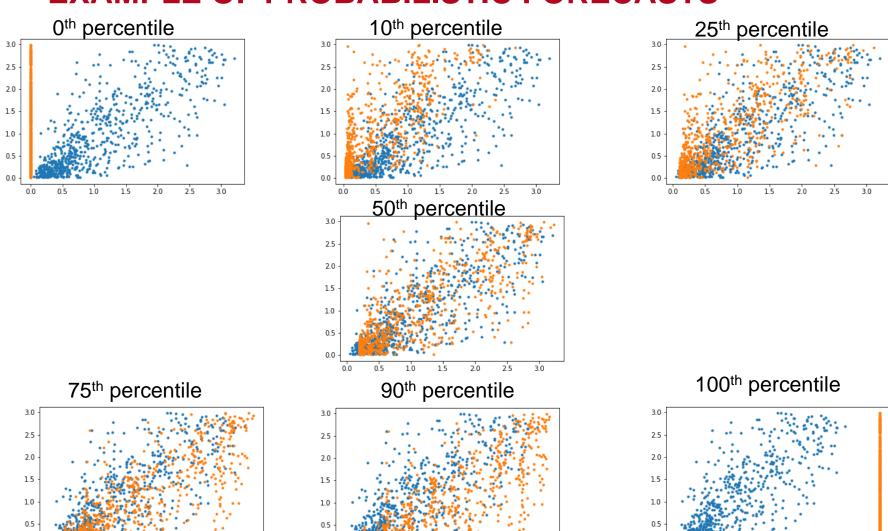
# UNCERTAINTY FORECASTING USING MACHINE LEARNING (DOE SOLAR FORECAST IMPROVEMENT)

A lot of the heritage of machine learning techniques involves categorical prediction (is the image more likely of a cat or a dog)? This means that many of the popular techniques are well-suited to probabilistic forecasts.



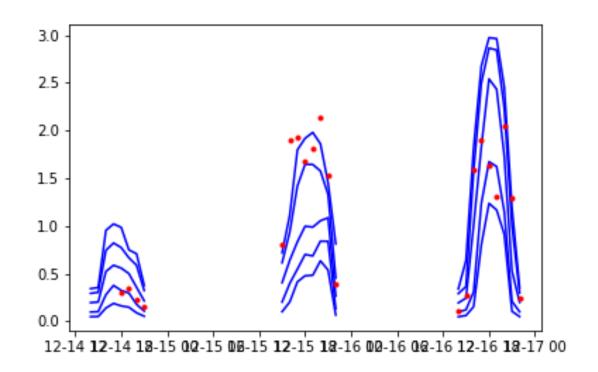


## **EXAMPLE OF PROBABILISTIC FORECASTS**





## **EXAMPLE OF PROBABILISTIC FORECASTS**





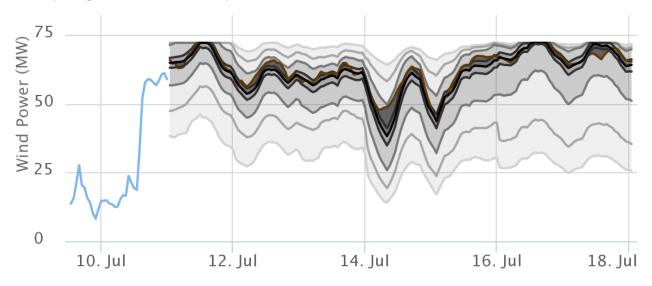
## **EXAMPLE OF PROBABILISTIC FORECASTS**

UKM **ICON** 2.5 2.5 2.0 2.0 1.5 1.5 1.0 1.0 0.5 0.5 0.0 0.0 1.0 1.5 2.0 2.5 3.0 0.5 2.5 0.0 0.5 1.0 1.5 2.0 GFS 2.5 2.0 1.5 1.0 0.5 0.0 2.5 3.0 1.5 1.0 2.0 0.0 0.5



## CURRENT PRACTICE IN PROBABILISTIC FORECASTING

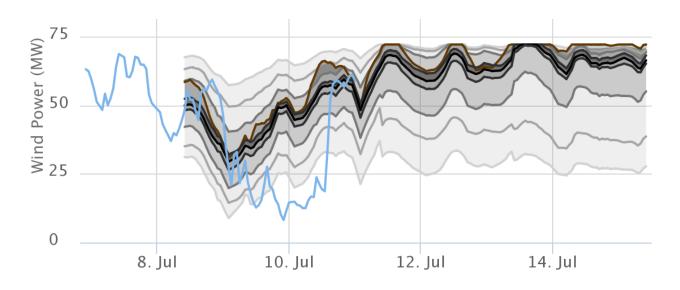
We forecast wind and solar generation for utilities and grid operators, providing various percentiles of the cumulative probability distribution. Operators tend to pay by far the most attention to the 50<sup>th</sup> percentile. To convince them to pay attention to the full distribution we need to do a better job clarifying the reliability and usefulness of the full distribution.





## CURRENT PRACTICE IN PROBABILISTIC FORECASTING

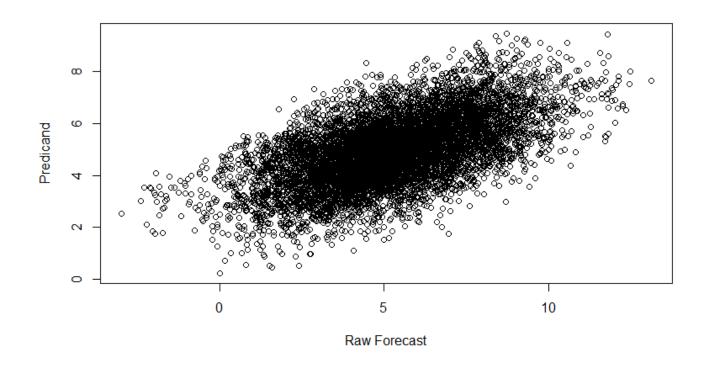
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## IMPROVING THE PDF CAN BE ASSOCIATED WITH A BETTER FORECAST

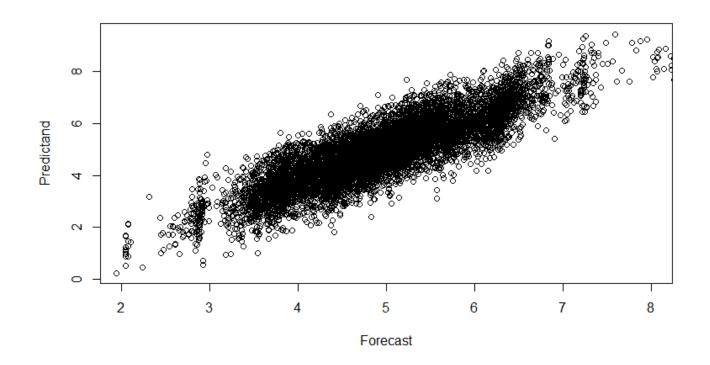
Original Forecast (50th percentile)





## IMPROVING THE PDF CAN BE ASSOCIATED WITH A BETTER FORECAST

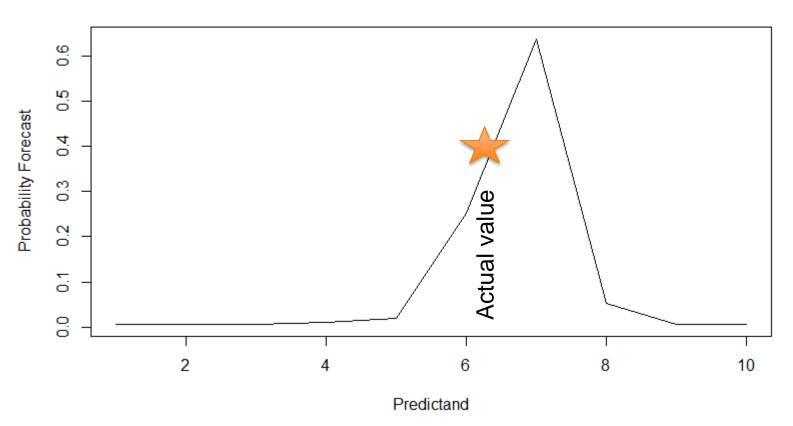
Machine-learning improved forecast (50th percentile)





# WE NEED A MEASURE OF FORECAST SKILL THAT COMBINES PDF ACCURACY AND PRECISION

#### Predicted PDF vs Observed Value





# WE NEED A MEASURE OF FORECAST SKILL THAT COMBINES PDF ACCURACY AND PRECISION

S: Score (calculated for each observation, can be averaged over a range of observations)

p(x): predicted probability that the predictand will have the value x

*X*: actual observed value of the predictand at the time in question

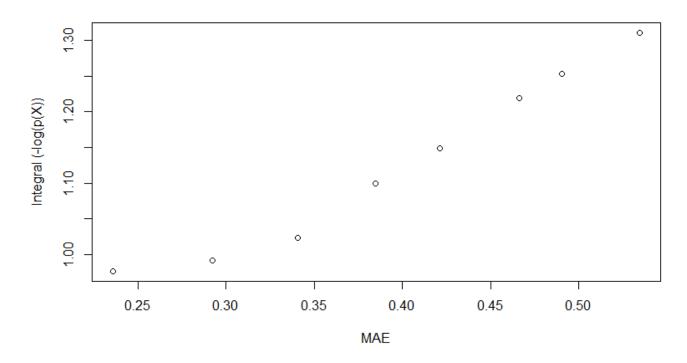
Ignorance:

$$S[p(x), X] = -\log p(X)$$

Proper linear score:

$$S[p(x), X] = \int p^2(z)dz - 2p(X)$$

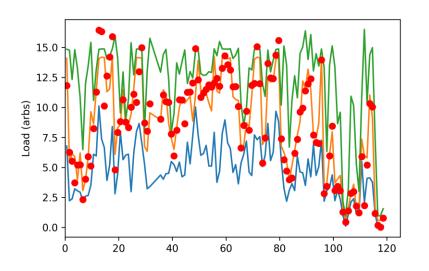
# IGNORANCE VS MEAN ABSOLUTE ERROR OF 50<sup>TH</sup> PERCENTILE FORECAST

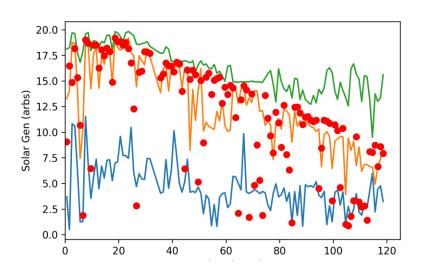


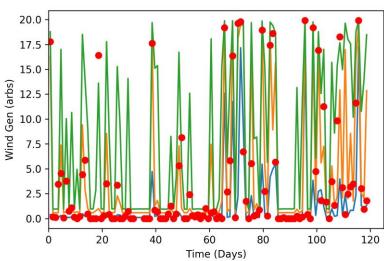
At low values of MAE, Ignorance is not falling off with continued improvements in MAE because the predicted probability distribution is getting very sharp, but biases are not decreasing: this is a forecast problem that can be addressed to improve performance.

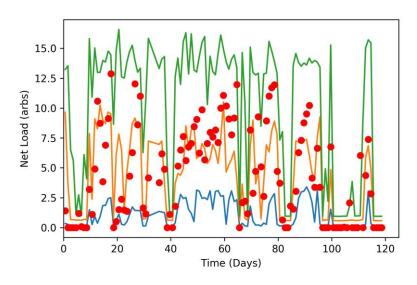


## **COMBINED RENEWABLES AND LOAD FORECAST**



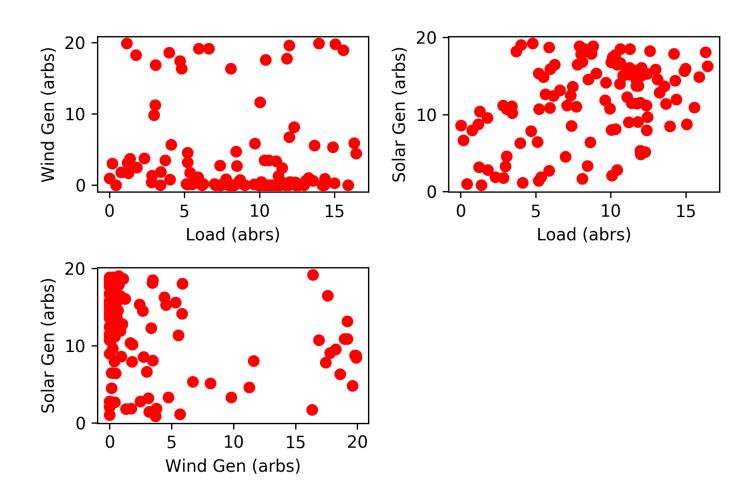






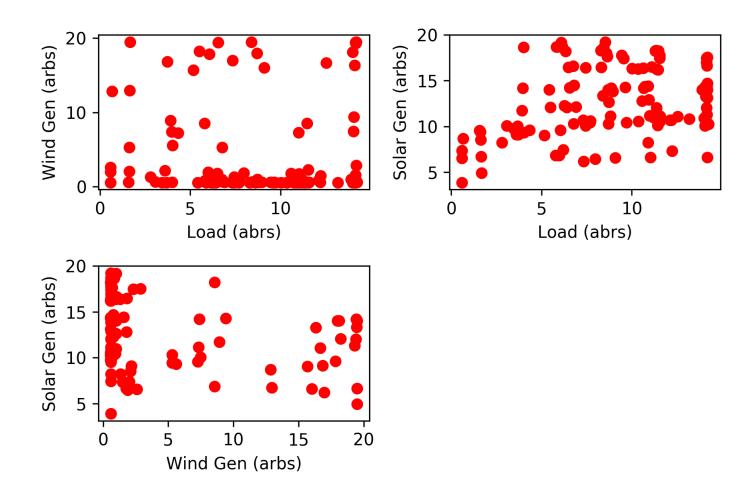


## **COVARIANCE OF LOAD AND GENERATION**



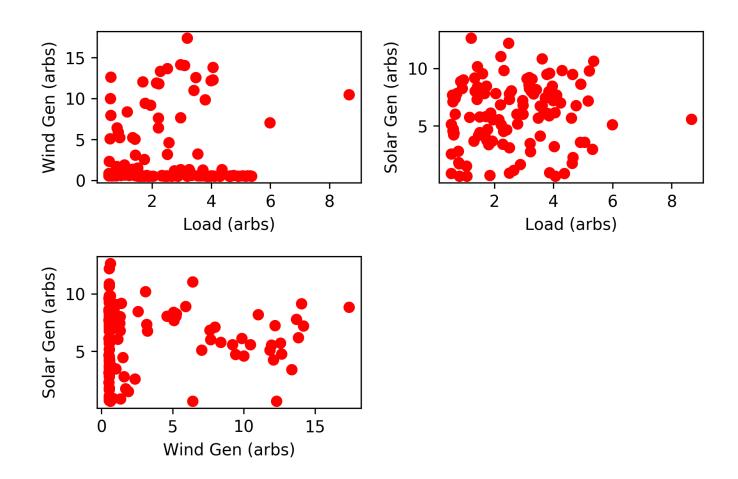


## COVARIANCE OF LOAD AND GENERATION FORECASTS





# COVARIANCE OF ERROR SPREAD (75<sup>TH</sup>-25<sup>TH</sup> PERCENTILES)





#### CONCLUSIONS

- Machine Learning Techniques allow unified treatment of load and renewable generation
- This allows forecast errors to be combined in a physically consistent way
- Improve error propagation should yield better results when probabilistic forecast are propagated through to decision support



### Questions?



## FIND US ON...











