Expressing Solar Power Forecast Uncertainty

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radiant SOLUTIONS

Overview

radiant SOLUTIONS is the new brand name for ***MDA Information Systems LLC***. We have been issuing solar generation and irradiance forecasts for five years. We are now seeing more interest in **probabilistic forecasts or other expressions of forecast uncertainty**. This poster illustrates different ways of presenting this information and shows examples of how this information could be used.

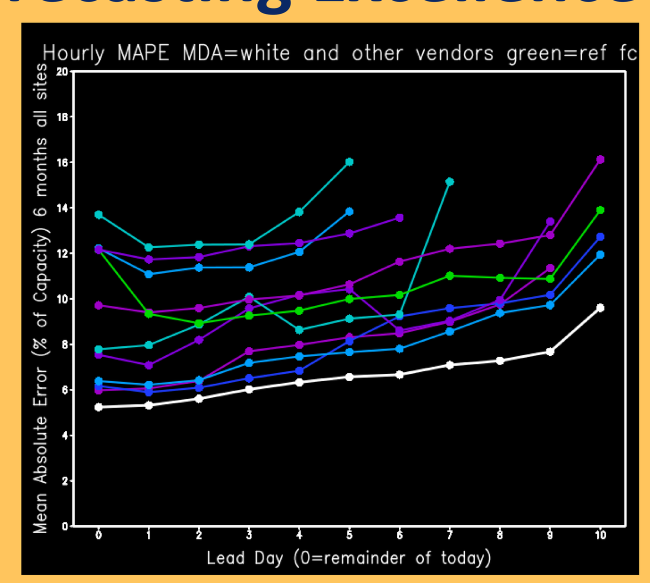
Radiant Solutions was created as a result of the acquisition of DigitalGlobe, Inc. by MAXAR Technologies Ltd (formerly McDonald Detweiller & Associates) on 5 October 2017. Radiant Solutions is a business unit of **MAXAR Technologies**. The combination of DigitalGlobe imagery and analytical tools combined with our solar forecasting system can lead to revolutionary behind-the-meter solar generation forecasts, utilizing always up-to-date detection of behind-the-meter installations even in the absence of a reliable site registry. If you are interested in this, please let us know. For more information about the transition from MDA Information Systems, LLC Weather Services to Radiant Solutions, see https://www.linkedin.com/pulse/mda-weather-services-now-within-radiant-up-our-next-travis-hartman

In previous years at the AMS Conference on Weather, Climate, and the New Energy Economy, we presented about

- Our state-of-the-science ***irradiance*** forecasting system utilizing the REST2 clear sky model, AERONET aerosol observations, and a variety of other public sources and proprietary site data
- Our solar ***power*** forecasting system, highlighting challenges we met ***predicting electric power generation*** for a single-axis PV farm in a challenging location beset by synoptic and local storms as well as sunny-day cumulus.
- Prediction of ***subhourly variability*** for ***irradiance and power*** at individual sites and real-time calculation of aggregate ***distributed generation***
- Challenges the solar power forecasting system overcomes from model forecasts that are too sunny to observations requiring extensive quality control and bias correction
- Forecast skill as a function of season, cloud cover, climate, array tracking, sun angle, etc. and compared to clear sky and various persistence/recent climatology forecasts

Radiant Solutions Solar Power and Irradiance Forecasting Excellence

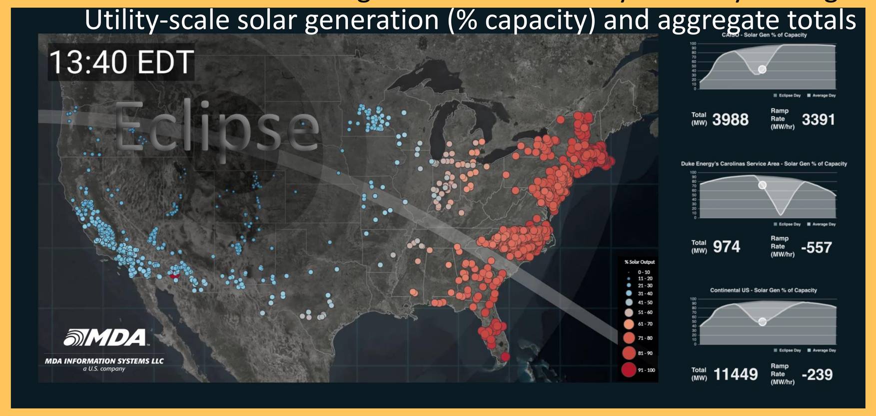
Results shown to the right are from a recent six-month trial administered by an independent third party. Forecast locations included arid and humid climates and fixed tilt and tracking arrays. Our solar generation forecast average mean absolute error (white) at all forecast lead times from same day to 10 days and averaged over all forecast locations were lower than all other submitted forecasts (blue and purple) and a smart reference forecast (green).



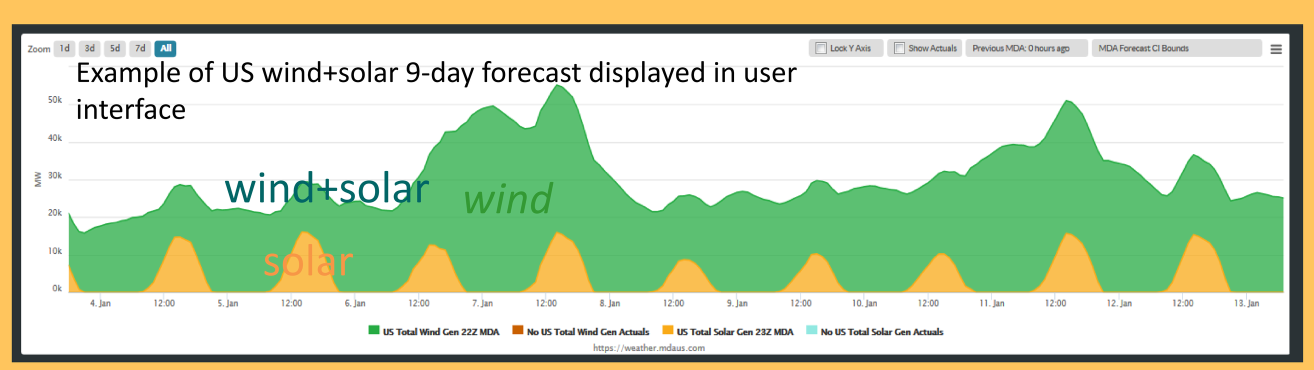
The forecast system has wide-ranging capabilities adaptable to any forecast need:

- Individual sites, utilizing real-time and history data and outage information when available
- Panels of any tilt or sun-tracking
- Any forecast lead time
- All irradiance types including Global Horizontal Irradiance, Direct Normal Irradiance, Plane of Array Irradiance
- Uncertainty, probabilistic forecasts, and sub-hourly variability
- Distributed generation
- Forecast generation at ~ 2000 utility-scale solar farms >= 1 MW AC capacity, aggregated to regional, RTO, national totals
- Combined with the wind generation forecast system to yield regional, RTO, national totals of wind + solar

Utility-scale solar generation (% capacity) and aggregate totals



Example of US wind+solar 9-day forecast displayed in user interface



Our solar forecasting system derives skill through

- Leveraging the REST2 (Gueymard, 2008) clear sky model as a foundation for time interpolation, bias correction, and direct beam calculation
- Employing a variety of public data sets to obtain aerosol-related and other parameters needed for REST2 and for considering cloudy atmospheres
- NWP bias correction as a function of key variable combinations
- Skill-based blending of NWP models and time-lag ensembles
- Accounting for short-term fluctuations in irradiance based on conditional statistics we generated based on data from high-quality irradiance monitoring sites
- Converting irradiance to power using multivariate relationships derived from site data passed through our quality control

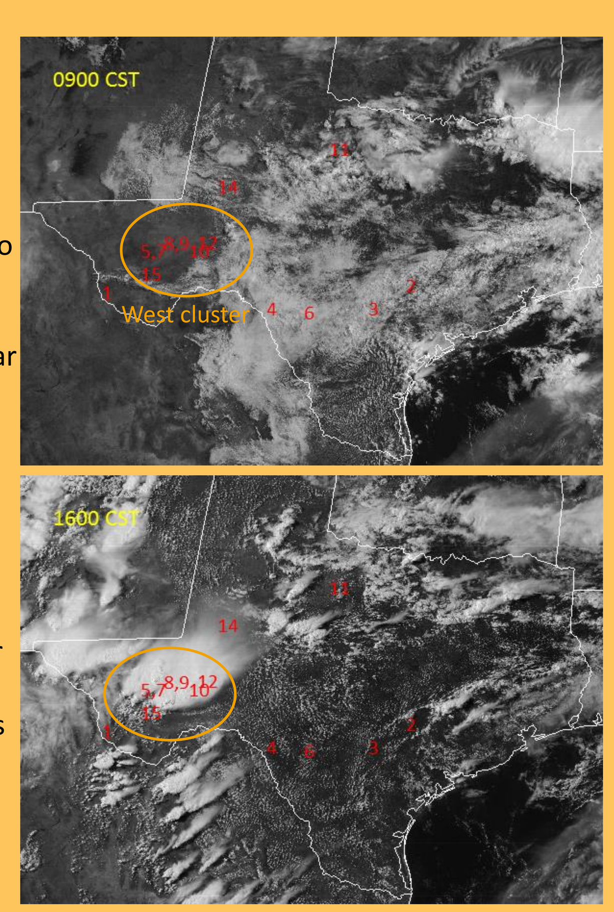
Reference: Gueymard, C. A., 2008: REST2: High-performance solar radiation model for cloudless-sky irradiance, illuminance, and photosynthetically active radiation – Validation with a benchmark dataset. *Solar Energy*, **82**, 272-285

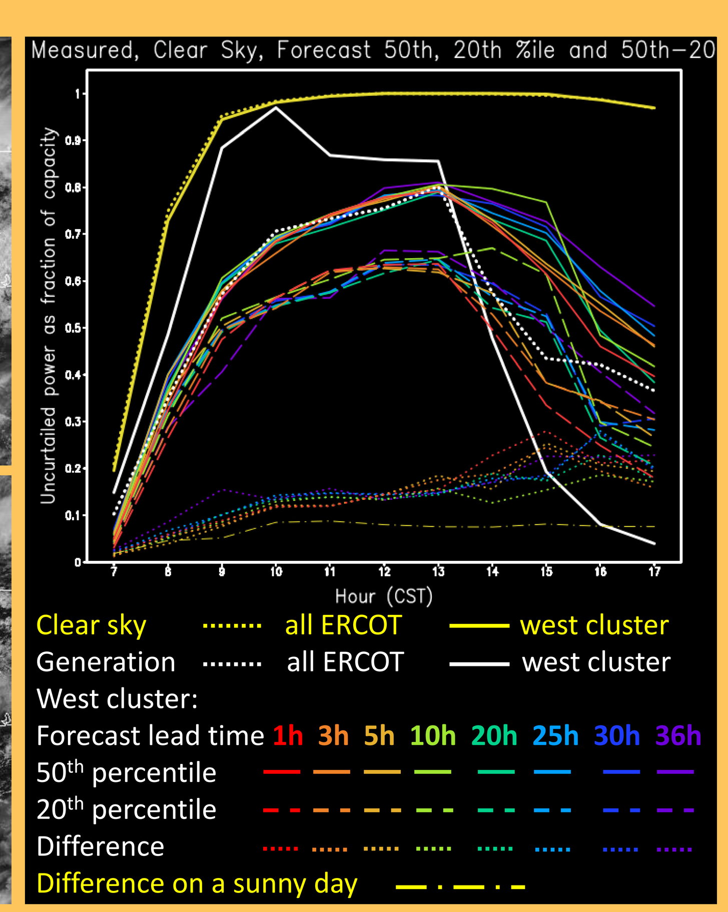
Example of Uncertainty Information in Difficult Forecast

A thunderstorm complex erupted in the afternoon over a cluster of large solar farms comprising slightly more than half of the ERCOT total of large utility-scale solar capacity on this day. This dropped solar generation in that region by more than 60% of capacity over two hours while it would have been steady near capacity on a clear day, dropping system-wide ERCOT generation by around 35% of capacity in those two hours.

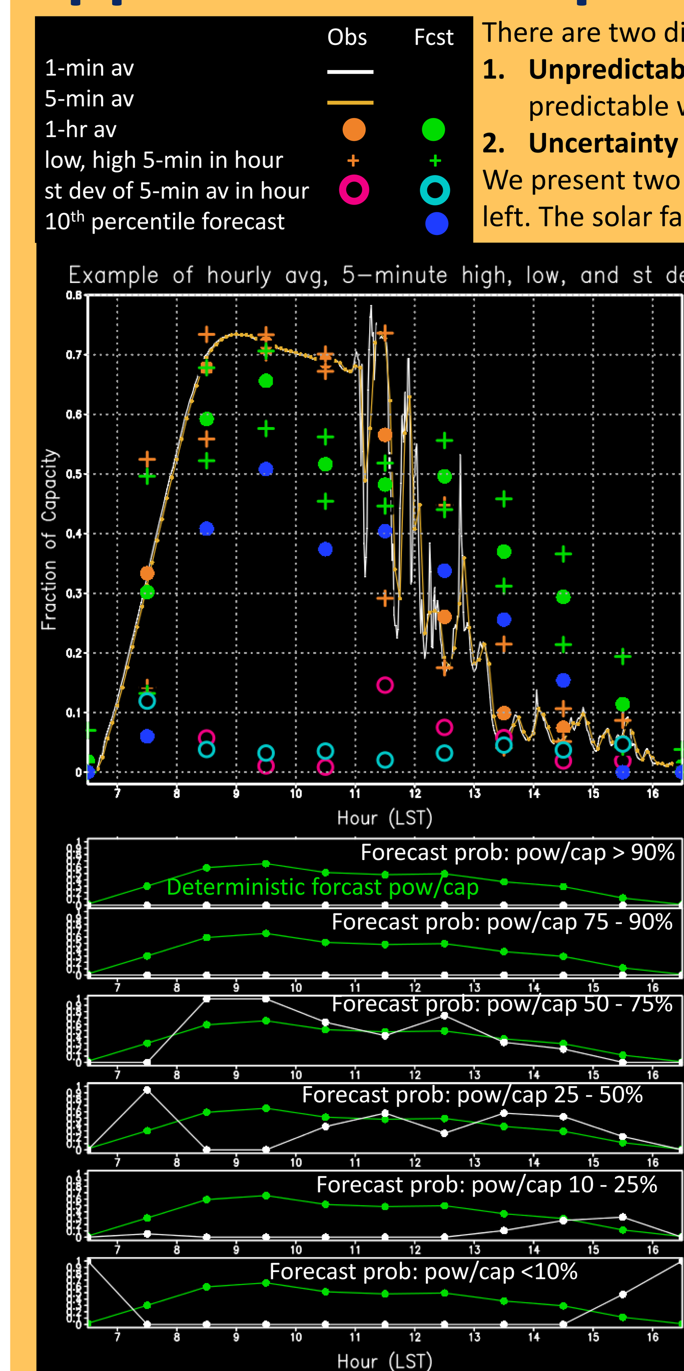
The satellite images are labeled with locations of large utility-scale solar farms. The 9AM CST image shows a sunny morning over the cluster of solar farms in west Texas while extensive cloud cover blankets most of the other ERCOT solar farms. It also shows a boundary which moved north and later triggered convection, which is seen coinciding with the solar farm locations in the 4PM CST image while the rest of the state is mostly sunny.

The plot to the right shows our forecast 50th percentile and 20th percentile (80% probability of exceedance) at various lead times for the west cluster of solar farms. Once the event starts, the 20th percentile is a much better forecast. Even at lead times of 24+ hours, the forecast uncertainty 50th-20th percentile was much larger than on a sunny day.





Approaches to Expressing Solar Power Forecast Uncertainty



There are two distinct types of uncertainty in the irradiance forecast and consequent solar generation forecast:

1. **Unpredictability associated with short-term fluctuations** such as shadows of passing cumulus clouds. The presence and to some degree the amplitude of fluctuations may be predictable while individual fluctuations are not predictable
2. **Uncertainty in the forecast scenario** – cloudy, partly cloudy, sunny, or optically thick vs. thin clouds

We present two methods of expressing each of these two types of uncertainty, fluctuations and scenario. These are illustrated with one day of solar farm and forecast data plotted to the left. The solar farm generation 1-minute and 5-minute averages are shown by the continuous-looking curves while various hourly measures are shown by marks in the middle of the hour represented. Below that are probability forecasts for power in different bins as a fraction of capacity and juxtaposed against the single best estimate forecast.

Fluctuations:

1. **Highest and lowest 5-minutes** in each hour.
2. **Standard deviation of the twelve 5-minute averages** in the hour.

To the extent that these can be predicted, they have the advantage of allowing the predictable aspect on an hourly time scale to be conveyed. They have the disadvantage that morning and evening ramps also show as times of sub-hourly power variation without conveying any information about their nature or difference from a clear day. Scaling by clear sky fraction would alleviate that problem but may be less useful for users who primarily care about the power delivered to the grid.

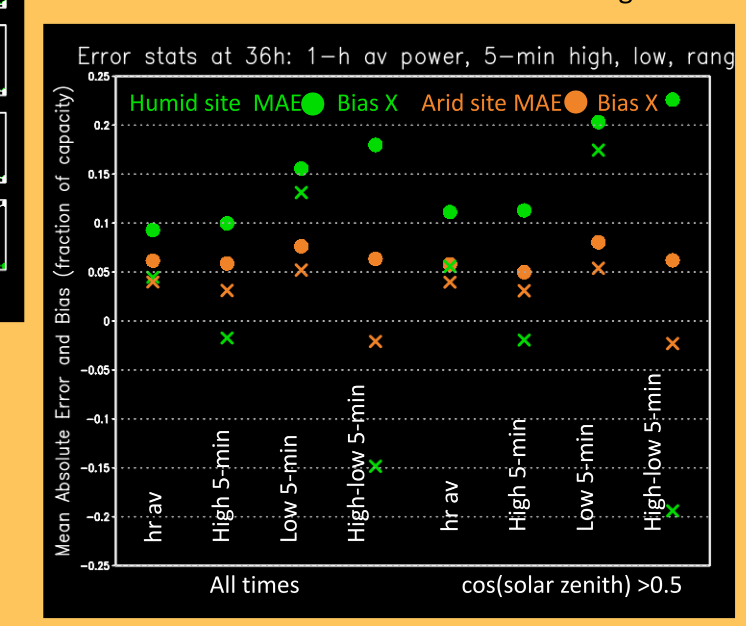
Scenario:

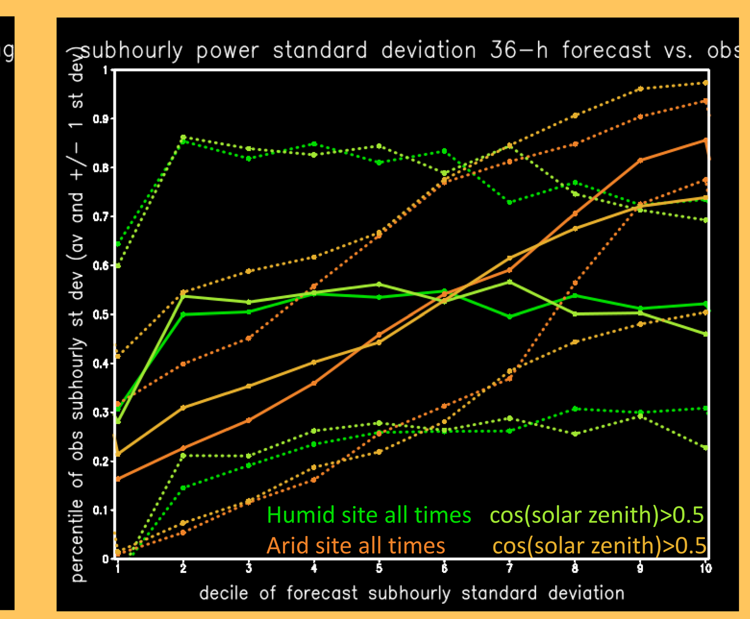
1. **Probabilities of exceedance or percentiles**, such as the 10th percentile shown in blue to the left, or even full forecast distributions
2. **Probability that the power will be within prespecified ranges**, as shown to the left for 6 bins of power as a fraction of capacity

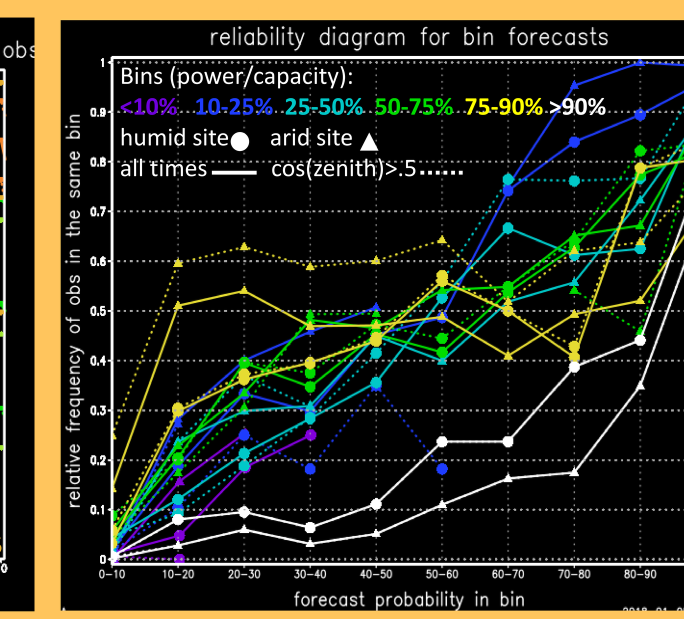
We validated uncertainty measures from operational forecasts we issued over a 7-month time period. The validation data from a solar farm in a moist climate and from several in an arid climate are shown separately for comparison. We quality controlled the data to remove times of stuck loggers and various artifacts. Also, evaluation was performed for both all available times and restricting times to when the sun was at least 30 degrees above the horizon to avoid influence of the morning and evening ramp periods. The results shown are for hourly forecasts issued with a 36-hour lead time. The general picture is the same for other lead times.

- High and low 5-minute periods: Mean absolute error and bias for the highest 5-minute period are similar to those of hourly averaged power but forecasts of the lowest 5-minute period tended to be not nearly low enough, resulting in underestimation of the high-low spread.
- Standard deviations: Forecast standard deviations were often too low. To better gauge their usefulness, forecast and observed standard deviations were ranked and the percentiles in the observed distribution were compared to each decile in the distribution of forecasts. The observed subhourly standard deviations indeed correspond nicely to those forecast at the arid location but not as well at the moist location.
- Probabilities within pre-specified bins: The reliability diagram shows good agreement between the probability predicted for a bin and the frequency the bin verified for lower and middle bins, while the 75-90% of capacity bin was a bit too flat and the >90% bin was used much too often.

Some of these error characteristics can be mitigated through tuning the postprocessed products while some are related to excessively sunny underlying NWP forecasts.







Application of Forecast Uncertainty Information: Energy Markets

The percentile and bin forecasts were utilized in a simple illustrative market to see how they compare as a function of the penalty for forecast errors. The market rules were as follows:

- "Bid" for hourly generation made at forecast lead time using 16 different bid types based on the various forecasts
- Market pays $1 per percent of capacity bid which was generated
- Market pays nothing for overgeneration but no penalty
- Penalty applies for undergenerating, at the real-time cost. 14 costs were tested ranging from negative pricing to steep pricing. Penalties tested were real-time=bid time rate * (-10, -5, -1, 0, .5, .75, .9, 1, 1.1, 1.25, 1.5, 2, 5, 10)

The plots show the average number of dollars per hour for each bid type when the sun was up over the 7-month period for the humid (circles) and arid (triangles) locations at four forecast lead times. The arid site always does better because it is more productive. Shorter lead times yield better results due to better forecast accuracy. However, negative prices flip everything, poorer forecasts are better because more "buying" is needed under these rules. Comparing the various bid types, the deterministic "best" forecast outperforms the others under moderate conditions while high penalties favor more conservative forecasts, as would be expected. Correctly anticipating the nature of the market while having access to the full variety of probabilistic forecasts would allow an adaptive strategy, choosing different types of bids to fit the different anticipated market conditions.

16 bids:

1. 10th percentile
2. "best" forecast

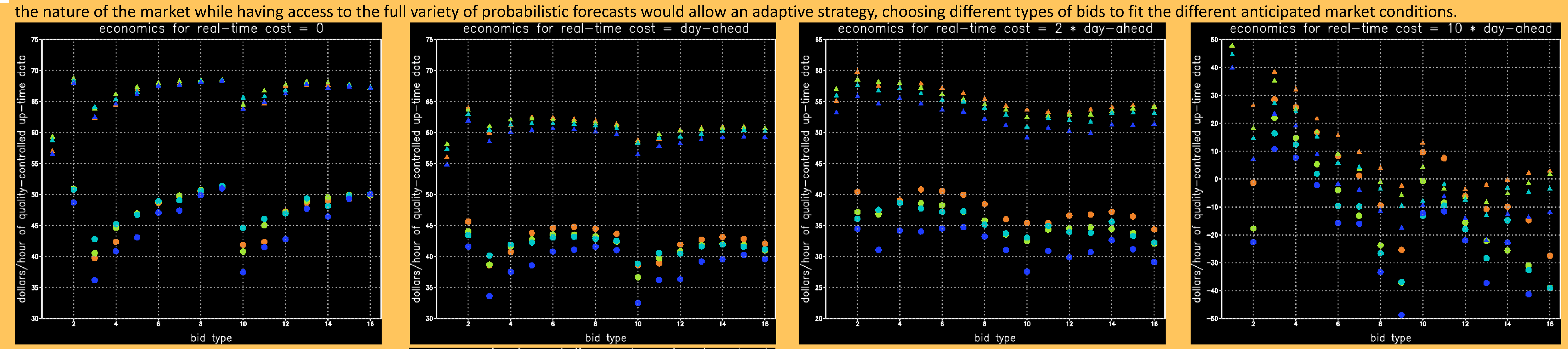
midpoint of bin containing:

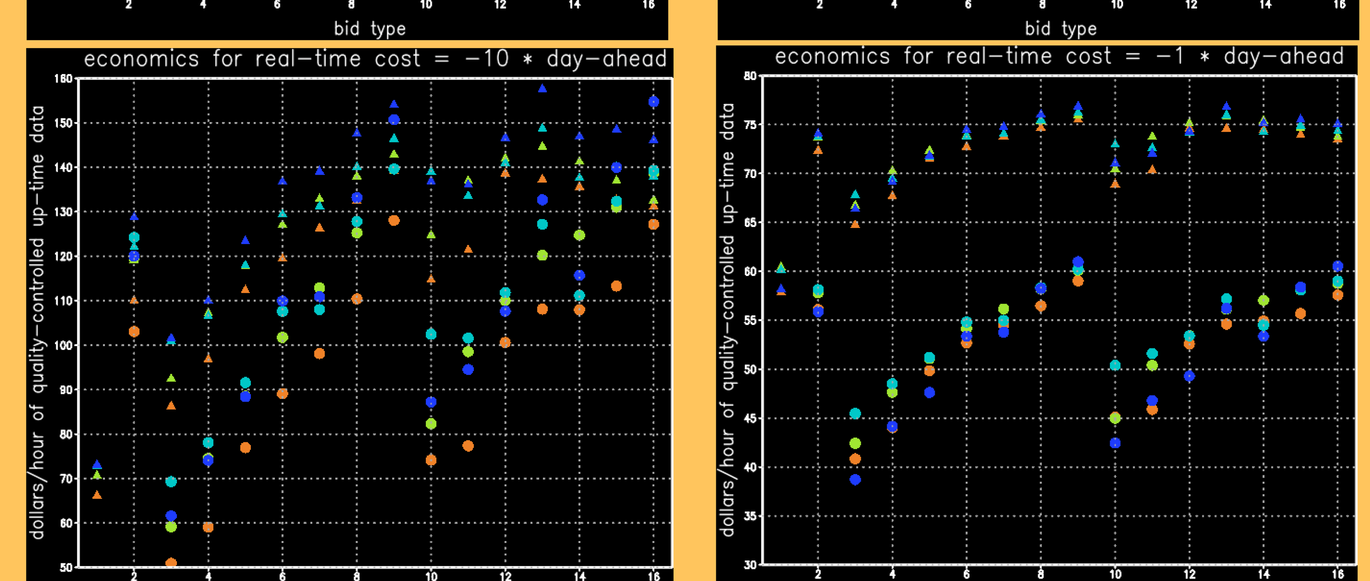
3. 10th %ile
4. 20th %ile
5. 30th %ile
6. 40th %ile
7. 50th %ile
8. 60th %ile
9. 70th %ile

interpolated within bin:

10. 10th %ile
11. 20th %ile
12. 30th %ile
13. 40th %ile
14. 50th %ile
15. 60th %ile
16. 70th %ile

lead	arid	humid
3 hr	▲	●
36 hr	▲	●
72 hr	▲	●
168 hr	▲	●





The Way Forward: SUMMER-GO

A goal of the electric power industry, forecast providers, and the Department of Energy is to more effectively and efficiently manage the power system through utilizing information on forecast uncertainty. So far, this information is not widely utilized in power system operations. We aspire to change this through participating in the Solar Uncertainty Management and Mitigation for Exceptional Reliability in Grid Operations (SUMMER-GO) project selected for award under the Solar Forecasting II announcement. The overarching goal is to integrate advanced probabilistic solar power forecasts into power system operations at multiple timescales to allow greater solar power penetrations while lowering system operating costs and increasing reliability. Our contribution will be to refine the accuracy, sharpness, and calibration of our multi-model ensemble-based probabilistic solar power forecasts. The National Renewable Energy Laboratory is leading this project and wll be developing a variety of tools including risk parity dispatch to integrate this information into operations, and the Electric Reliability Council of Texas will test it in a real-time operational environment.