DETERMINATION OF FORECAST VALUE CONSIDERING ENERGY PRICING IN CALIFORNIA

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ABSTRACT
Forecast value is investigated using day-ahead market (DAM) and real-time market (RTM) locational marginal prices (LMP) from the California Independent Service Operator (CAISO) Open Access Same-time Information System (OASIS) database. Assuming a 1 MW PV plant is collocated at California Irrigation Management Information System (CIMIS) stations throughout California, revenue is calculated using global horizontal irradiance (GHI) forecasts from the North American Mesoscale Model (NAM) and recorded GHI from the CIMIS stations. Comparison of the true forecast revenue to a perfect forecast revenue shows that the perfect forecast revenue is always greater, but the yearly true forecast revenue is within 5% of the perfect forecast revenue for some sites. Revenue from a bias-corrected NAM forecast is used to show that biased forecasts can have a higher forecast value than neutral forecasts, which causes a disconnect between what makes a valuable forecast for a power seller versus a system operator.

1. INTRODUCTION
Different metrics can be used to evaluate how good a forecast is. Three types of goodness are outlined by Murphy [1]: consistency, quality, and value. Consistency refers to the correspondence between the forecast and the judgments made by forecasters to determine the forecast. Quality refers to the correspondence between forecasts and observations. Finally, value refers to the incremental benefits of forecast to users. There are two prominent groups that use solar forecasts: solar power generators and system operators. For solar power generators, determining forecast goodness using value is the most crucial in terms of economic gains. The price of energy and the output of solar energy are not directly related, thus a forecast that has a higher quality at certain times of the day, when energy prices are high, may be more valuable than a forecast that has a higher quality over the whole day, but not necessarily at the critical time of day. System operators, however, are firstly concerned with the quality of a forecast, as maintaining operation of the power grid is their primary concern. Secondary is forecast value, evaluated in terms of cost to maintain the grid, as systems operators have to compensate for errors in power forecasts by purchasing additional units of energy in the form of reserves. This mismatch between what makes a forecast good for system operators versus power producers has been a recent topic of concern, specifically with respect to wind power. With asymmetric penalties for deviations in delivered power from the forecasted power, it is possible for a power producer to benefit economically from using biased forecasts rather than neutral, which is detrimental to the systems operators’ goal of reliability of the power grid [2]. System operators have begun to implement policies to insure they are able to correctly forecast delivered power from PV systems. The California Independent Service Operator (CAISO) requires any solar power producer participating in the market process to follow guidelines outlined by the Participating Intermittent Resource Program (PIRP). Most notably, PIRP requires the acquisition of production and meteorological data (GHI, DNI, temperature, wind) for a minimum of 60 days such that forecast models, such as artificial neural networks, can be trained [4]. Other studies investigating forecast value have shown that error prediction costs can account for up to 10% of the total power generator incomes [3], investigate optimal bidding strategies [5], and provide alternative approaches for unit commitment policies used to manage uncertainty caused by renewable energy [6].

Modeling the value of a forecast in terms of a system operator requires knowledge of available resources, start-up costs of these resources, and the unit commitment policies...
used by the system operator. All of these factors vary widely among system operators and such a study would be specific. Rather, the purpose of this paper is to investigate and summarize the behavior to the day-ahead market (DAM) and real-time market (RTM) prices as well as assign a more general value to solar forecasts from a solar power seller’s perspective. Additionally, we will show that a forecast with improved quality generally leads to an improved forecast value, but in some instances a biased forecast has the greatest value.

2. METHODS

The CAISO Open Access Same-time Information System (OASIS) has over 4,500 nodes at which a Locational Marginal Price (LMP) is reported. These nodes represent locations in the CAISO power network in which power can be sold into the energy market. LMP is the sum of three components: energy, loss, and congestion. The energy component represents the average price of generating a unit of electricity in the market and by convention is the same for all price nodes. The loss component represents the cost of transmission losses associated with the delivery of electricity to that price node. The congestion component represents the transmission constraints in delivering electricity to a price node. Congestion LMP are reported for the day-ahead (DA) market, hour ahead (HA) market, and real-time (RT) market. The DA forecast is submitted at 0530 prior to the operating day, which begins at midnight on the day of submission and covers (on an hourly basis) each of the 24 hours of that operating day. Therefore, the day ahead forecast is provided 18.5 to 42.5 hours prior to the forecasted operating day. The vast majority of conventional generation is scheduled in the DA market (DAM). The HA forecast is submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. Data for DAM LMP (the market price at which a DA forecast is committed at) and RTM (RTM LMP (the price at which settlements are made) from April 1, 2010 to March 31, 2011 for 54 nodes was used for this study. DAM LMP are reported on the hour for the proceeding hour (i.e. the 08:00 DAM LMP is used for 08:00-09:00) and were shifted such that data fell on the hour (i.e. for 08:00, the average of 07:00 and 8:00 were taken). RTM LMP are reported every five minutes for the proceeding 5 minutes (i.e the 08:00 RTM LMP is used for 08:00-08:05). To determine hourly RTM LMP, the prices for 30 minutes before the hour and 25 minutes after were averaged (i.e. for 08:00, the average of values from 07:30 – 8:25 were taken).

The value of the forecast depends on the spread between the DAM and RTM pricing. If the RTM is much greater than the DAM price, there is potential for a large gain or loss in revenue during settlement in the RTM, depending on whether or not the amount of power was over- or under-forecasted. For example, if there is an overforecast (the amount of power forecasted exceeds that which was delivered), there will be a large loss in revenue because additional units of power will need to be purchased at the higher RTM price. Conversely, if there is an underforecast (the amount of power forecasted is less than that which was delivered), there could be a large gain in revenue by selling excess power in the RTM at the higher RTM price. However, power is not always guaranteed to sell in the RTM (the market is a complex system in which CAISO will select the most economically viable sources of power depending on what the market dictates). For this reason, excess power sold in the RTM will be thought of as only a potential gain in revenue. However, if the RTM price is negative and excess power is produced, power sellers will be charged for injecting too much power onto the grid and there is a loss of revenue. The case when the RTM price is less than the DAM price can also be considered, however these instances are less likely to occur. Table 1 summarizes the possible outcomes considering forecast error and the price difference between the RTM and DAM.

To calculate forecast value, an hourly day ahead power output forecast for May 31, 2010 through January 1, 2011 was calculated at 54 California Irrigation Management Information System (CIMIS) station locations, assuming a 1 MW PV plant was installed at the CIMIS station location and using the North American Mesoscale Model (NAM) GHI nearest to the CIMIS station location (Eq. 1). Actual hourly delivered power was calculated using the CIMIS GHI (Eq. 2).

$$P_{NAM, h} = \frac{GHI_{NAM, h}}{1000} \times CEC \text{ PTC Rating}$$

$$P_{CIMIS, h} = \frac{GHI_{CIMIS, h}}{1000} \times CEC \text{ PTC Rating}$$

The total yearly revenue, \( R \), is calculated using the DAM LMP and RTM LMP (Eq. 3). We impose that if an overforecast occurs, RTM LMP that are less than zero are equal to zero (this insures that power sellers do not get paid for under delivering due to favorable market conditions; however, they are not penalized for under delivering in these conditions). We also impose that if there is an underforecast, RTM LMP that are greater than zero are set to zero (this insures that power generators are charged for over delivering if the RTM LMP is less than zero but they do not profit from selling excess power in the RTM as power is not guaranteed to be purchased in the RTM). In calculating revenue, we assume that PV plants use time-of-use pricing (currently PV plants are considered price-takers in the energy market) and that the LMP does not change due to participation of PV plants in the market. In reality, the RTM price could be driven up or down if solar forecast trend to either over- or under-predict. Because asymmetric
penalties for forecast deviations occur, we also assume that 
an honest, non-revenue-biased forecast is used when 
bidding into the market.

\[ R_{NAM} = \sum_{h=1}^{8760} P_{NAM,h} \times LMP_{DAM,h} + (F_{CIMIS,h} - F_{NAM,h}) \times LMP_{RTM,h} \]  

(3)

Revenue from a perfect forecast was calculated assuming 
that the delivered power calculated using CIMIS data (Eq. 
2) was bid perfectly into the DAM and no settlement 
process took place.

\[ R_{PerfectForecast} = \sum_{h=1}^{8760} P_{CIMIS,h} \times LMP_{DAM,h} \]  

(4)

To investigate the effects of a higher quality forecast on 
forecast value, the value of a bias-corrected NAM forecast 
was compared to the value of the NAM forecast. Mathiesen 
et al [7] found that for some conditions, the NAM forecast 
was positively biased by as much as 150 W m\(^{-2}\). To correct 
this, model-output-statistics (MOS) was employed to 
remove bias error as a function of forecast irradiance and 
solar zenith angle. This correction was applied 
independently for each CIMIS station using a dynamic 
training set of 8 weeks of up-to-date data. Overall, bias-
corrected NAM forecasts had MBE of 7.0 W m\(^{-2}\), 50.5 W m\(^{-2}\) 
less than raw NAM forecasts.

3. RESULTS AND DISCUSSION

Figure 1 shows the average DAM LMP and RTM LMP for 
each of the 54 price nodes associated with a given CIMIS 
station. Average DAM LMP range in value from $23 to $47 
and their behavior is fairly predictable over the course of 
the day and year. The highest DAM LMP occur in the evening 
during July through September. RTM LMP are less 
predictable, and vary over a wider range of prices (-$5 to 
$100 , negative prices indicate that there is too much power 
being delivered to the grid and a power supplier would be 
paid to hold delivery of power). The highest RTM Prices 
also occur during July through September, but occur at any 
time throughout the day. Both DAM and RTM prices vary 
by location, but yearly averaged prices show no strong 
trends (Fig. 2). Usually, the highest yearly averaged prices 
for the DAM occur near the coast, but not all sites follow 
this trend and the difference from coastal to inland sites is 
small (less than $7/MWh). For the RTM, the highest yearly 
averaged prices are spread throughout the state.

Revenue was calculated for a 1 MW power plant at each 
CIMIS station for a true forecast (Eq. 3) and a perfect 
forecast (Eq. 4). Figure 3a depicts the ratio of yearly 
revenue using a true forecast to yearly revenue assuming a 
perfect forecast. The perfect forecast always yields a higher 
yearly revenue than the true forecast, however in some 
locations (mainly inland), the true forecast revenue is within 
5% of the perfect forecast revenue. This result is likely 
because inland sites generally have higher quality forecasts 
due to lower cloud occurrence. Figure 4b shows the monthly 
revenue for August using a true forecast versus a perfect 
forecast. The ratio is the smallest at coastal sites and 
increases inland. This trend is a product of the seasonal 

\begin{table}[h]
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\begin{tabular}{|c|c|c|}
\hline
\textbf{RTM price – DAM price} & \textbf{Forecast} & \textbf{Outcome} \\
\hline
> 0 & Overforecast & Have to buy additional power at higher RTM price: \textit{loss of revenue} \\
\hline
< 0 & Overforecast & Still have to buy additional power to cover under delivery of power, but the 
price will be at the lower RTM price and thus total revenue will be greater 
than if no forecast error occurred: \textit{gain of revenue} \\
\hline
> 0 & Underforecast & Potential to sell additional power at higher RTM price: \\
\hline
\end{tabular}
\end{table}
<table>
<thead>
<tr>
<th>&lt; 0</th>
<th>Underforecast</th>
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<tr>
<td></td>
<td>Could have sold additional power at higher DAM price:</td>
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<td>potential loss of revenue</td>
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**Figure 1**: Average DAM LMP (a) and RTM LMP (b) for May 1, 2010 – December 31, 2010 for all 54 price nodes associated with a given CIMIS station plotted for time of day (for hours in which a forecast was available) versus month. Yearly average DAM LMP (c) and RTM LMP (d) plotted with standard deviations for all price nodes.
Figure 2: The yearly averaged DAM LMP (a) and RTM LMP (b) are plotted for the 54 price nodes corresponding to a CIMIS station location.

Figure 3: Yearly (a) and monthly (for August) (b) plot of revenue using NAM forecast over revenue using a perfect forecast.
4. CONCLUSION

We have shown that the average yearly revenue using a true forecast is always less than that of a perfect forecast, but for some sites, the true forecast revenue is within 5% of the perfect forecast revenue. Spatial trends in forecast value are weak, but in general the ratio of yearly revenue using a true forecast to a perfect forecast will be lower for a coastal site than an inland site. Using a bias-corrected NAM forecast (which has an overall higher quality than the uncorrected NAM forecast) does not necessarily produce greater total yearly revenue, especially near coastal sites where the bias-correction improves morning forecasts (when DAM LMP are low) and the expense of the accuracy of afternoon forecasts (when DAM LMP prices are high). This confirms findings [2] that biased forecasts can be more valuable to a power seller than a neutral forecast. However, if a power seller uses a biased forecast, system operators will be negatively affected because they will not have accurate information about the amount of power they can expect to be delivered, and they will ultimately have to account for differences in the forecast from delivered power by purchasing additional units of power to maintain grid reliability. Policy development needs to occur in order to bridge the gap between what a valuable forecast is for power sellers and for system operators. Currently, adding deviation penalties to the CAISO settlement process is the easiest way to eliminate this gap.

5. ACKNOWLEDGEMENTS

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6. REFERENCES


