FORECAST VALUE CONSIDERING ENERGY PRICING IN CALIFORNIA

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1. INTRODUCTION

Forecasting of weather conditions such as solar irradiance and wind speed and direction is essential for efficient integration of solar and wind power into the energy portfolio. Several metrics can be used to evaluate forecast effectiveness: consistency, quality, and value [1]. Consistency refers to the correspondence between the forecast and the judgments made by forecasters to determine the forecast (i.e. do the same inputs that are used to determine a forecast produce the same forecast). Quality refers to the difference between forecasts and observations. Finally, value refers to the incremental monetary benefits of forecasts to users. There are two prominent groups that use solar forecasts: solar power generators and system operators. In an open market, solar power generators would primarily rely on the value criterion because forecast quality does not necessarily translate to forecast value. For example, a forecast that has a higher quality during peak net load times of the day, when energy prices are high and errors would be more costly, may be more valuable than a forecast that has an overall higher quality, but not necessarily at the critical time of day. System operators, however, are primarily concerned with the quality of a forecast, as reliability and accurate planning of the power grid is their primary concern. Secondary is forecast value to operate the energy market optimally reducing energy generation, transmission, and reserve costs on the grid. For example, an underforecast would result in over-procurement of energy at a higher marginal cost and possibly transmission congestion near the solar power plant; an overforecast would result in under-procurement of energy, purchase of energy from reserves or regulation, and potential operation of transmission lines below capacity.

The mismatch between what constitutes a good forecast for system operators and power generators has been a recent topic of discussion. It is possible for a power generator to benefit economically from using biased (rather than neutral) forecasts, which is detrimental to the systems operator's goal of reliability of the power grid [2]. As such, system operators cannot rely solely on the information obtained through energy market commitments or generation schedules and have contracted with third party forecasting providers to correctly forecast delivered energy from renewable energy systems.

The California Independent Service Operator (CAISO) allows solar power producers participating in the market process to participate in the Participating Intermittent Resource Program (PIRP). PIRP requires current estimates and historical observations of production and meteorological data (global horizontal irradiance (GHI), direct normal irradiance (DNI), temperature, wind) [3]. Although plant operators submit day-ahead and hour-ahead hourly forecast schedules under PIRP, deviations are netted over the month and 'uninstructed imbalance energy' charges are assessed on the net which can be positive or negative (reimbursement), i.e. no penalties for forecast errors are applied. Under PIRP there is no incentive for generators to provide accurate forecasts. However, utility-scale solar power plants will eventually participate in the energy market following the same bidding and settlement rules as conventional power sources (as is already the case for Red Electrica in Spain), including wind power (in most energy markets). Recent studies investigated integration of renewable energies, predominately wind power, into energy markets. From a power generator's perspective, several studies focused on optimal bidding strategies. Botterud et al. (2011) found that, using price data from Midwest ISO (MISO), in a market structure with a day ahead commitment process, real time settlement, and no deviation penalty, optimal wind energy bids in the day ahead market are mostly driven by price expectations (rather than expected energy output); however, adding a deviation penalty diminished the difference between the optimal wind energy bid and the wind energy forecast [4]. Fabbri et al. (2005) estimated the costs associated with errors in wind power forecasts for the Spanish energy market by assuming errors are balanced by reserve energy and found that error prediction costs can be as much as 10% of the total income annually from the energy generation [5].

Studies evaluating the value of a forecast from a system operator's perspective examined how forecasts affect the overall cost of operations. Milligan et al. (1995) found that the most accurate forecast yields the highest benefit from the wind power resource, however they found that improving a forecast to 100% accuracy has declining marginal benefits [6]. Using price data from New York ISO (NYISO) Ruiz et al. (2009) showed that the cost of operations, optimized based on the constraints of the power system, is reduced by up to 2% when using a stochastic based forecast when determining unit commitment needs versus a deterministic based forecast [7]. The Western Wind and Solar Integration Study (WWSIS, Lew et al., 2010) found that – for a 2020 25% wind and 5% solar (by energy) scenario – using state-of-the-art day-ahead wind and solar forecasts in the unit commitment process would reduce Western Electricity Coordinating Council (WECC) operating costs by up to $5 billion/yr, with additional cost savings of $500 million/yr for using a perfect forecast [8].

The value of a forecast should be evaluated from both a power generator's and system operator's perspective, as both are users of forecasts, and such information would be helpful in determining the level of investment into solar energy forecasts. However, modeling the value of a forecast to a system operator is very complex, requiring knowledge of available resources, start-up and running costs of these resources, and the unit commitment rules used by the system operator. These factors vary among system operators and consequently such a study would be specific to each ISO. Large-scale studies such as WWSIS have already generalized these factors to investigate cost savings due to wind and solar forecasts. Rather, the purpose of this paper is to investigate the spread between the day-ahead market (DAM) and real-time market (RTM) prices and its correlation to DAM solar forecast error to assign a more general value of solar forecasts to market participants such as solar power generators (after discontinuation of PIRP). The study is applied to the CAISO market which at the end of 2010 contained 47% of the installed solar power nationwide [9]. Methods are discussed in Section 2, results and discussions are presented in Section 3, and conclusions are outlined in Section 4.

2. METHODS

2.1 Energy Price Data and Market Structure

Energy price data was obtained from the CAISO Open Access Same-time Information System (OASIS). OASIS has over 4,500 nodes at which a Locational Marginal Price (LMP) is reported. These nodes represent locations in the CAISO power grid where energy can be sold into the market. The LMP is the sum of three components: energy, loss, and congestion. The energy component represents the average price of generating a MWh 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 values the transmission constraints in delivering electricity to a price node. All LMP components 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 DA forecast horizon is 18.5 to 42.5 hours. 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. HA prices are not used in this study.

DAM LMP (the market price at which a DA forecast is committed) and RT market (RTM) LMP (the price at which settlements are made) from June 1, 2010 to May 31, 2011 for the 63 nodes collocated with solar resource measurement stations was used for this study. DAM LMP are reported on the hour for the following hour (i.e the 08:00 DAM LMP is used for 08:00-09:00) and were averaged to correspond to instantaneous on the hour GHI data (i.e. for 08:00, the mean of the 07:00 and 08:00 DAM LMP is used). RTM LMP are reported every five minutes for the following 5 minutes (i.e the 08:00 RTM LMP is used for 08:00-08:05). To determine hourly RTM LMP, the prices for the half hour before and after the hour were averaged (i.e. for 08:00, the mean of values from 07:30 – 8:25 RTM LMP were taken).

In calculating revenue from energy sales, we assume that PIRP is discontinued and that – like most other generating resources –PV plants participate in the wholesale energy market. We further assume that the 2010/2011 LMP are valid, i.e. the LMP does not change due to participation of the additional PV plants in the market. In reality, DAM prices would be reduced with increasing solar generation and the RTM price could increase or decrease if solar forecast trend to either over- or under-predict [10].

Since forecast are submitted in the DAM and errors have to be made up in the RTM, the value of the forecast depends on the spread between the DAM and RTM pricing (Table 1). For example, if the RTM is much greater than the DAM price and there is an overforecast (the amount of energy forecasted exceeds actual delivered energy), there will be a large loss in revenue because additional units of energy will need to be purchased at the higher RTM price. Conversely, if there is an underforecast (the amount of energy forecasted is less than that which was delivered), there could be a large gain in revenue by selling excess energy in the RTM at the higher RTM price. However, energy is not always guaranteed to sell in the RTM, and for this reason, excess energy sold in the RTM will be considered only as a potential gain in revenue. The case when the RTM price is less than the DAM price can also be considered. If there is an underforecast (overforecast) there could be loss (gain) of revenues because greater revenue could have been achieved in the DAM (energy to make up for the overforecast can be purchased at a lower price in the RTM). Table 1 summarizes the possible outcomes considering forecast error and the price difference between the RTM and DAM.

TABLE 1: SUMMARY OF MARKET/FORECAST OUTCOMES

DAM price – RTM price	**Forecast Bias**	**Outcome**	**Restrictions Imposed**
< 0	Over-forecast	Have to buy additional energy at higher RTM price: *loss of revenue*	None
> 0	Over-forecast	Still have to buy additional energy to cover under delivery of energy, but the price will be at the lower RTM price and thus total revenue will be greater than if no forecast error occurred: *gain of revenue*	If RTM LMP < 0, then RTM LMP = 0
< 0	Under-forecast	Potential to sell additional energy at higher RTM price: *potential gain of revenue* *(only monetized when implementing a deviation penalty)*	If RTM LMP > 0, then RTM LMP = 0
> 0	Under-forecast	Could have sold additional energy at higher DAM price: *loss of revenue*	none

2.2 Solar Energy Forecasts and Actual Generation

An hourly DA solar forecast for June 1, 2010 through May 31, 2011 was calculated at 63 CIMIS station locations, assuming for illustrative purposes a 1 MW PV plant located at the CIMIS station location. Actual hourly delivered energy was calculated to be proportional to the CIMIS GHI (Eq. 1). This will overestimate (underestimate) solar energy production in higher (lower) panel temperatures such as in the afternoon or at inland sites, but is reasonably accurate and chosen here for generality and simplicity. The automated network of over 120 CIMIS weather stations is managed by the California Department of Water Resources (DWR). Data quality control yielded 63 CIMIS stations with complete and accurate records for the time period under investigation. CIMIS GHI is measured every minute using a LI200S Li-Cor pyranometer and reported as an hourly average with an hour-ending time stamp. Data were interpolated to instantaneous on the hour values in order to match the forecasted GHI data.

In practice, day-ahead solar forecasts are generated using numerical weather prediction. Forecasted GHI from the North American Mesoscale Model (NAM) was used to calculated hourly forecasted energy output for the DAM (Eq. 2). Hourly NAM GHI data is published by the National Oceanic and Atmospheric Administration’s (NOAA) NCEP on a 12.5 km x 12.5 km grid and is available up to 36 h ahead at four times daily, 00, 06, 12, and 18 UTC. DAM bids were set equal to the NAM forecasts issued at 12 UTC (0400 local standard time, before the closing of the DAM) on the previous day for the NAM gridpoint closest to the CIMIS stations.

$$E_{CIMIS,h} = \frac{GHI_{CIMIS,h}}{1000\ \mathrm{W\ m^{-2}}} * 1\ \mathrm{MW} * 1\mathrm{h} \qquad (1)$$

$$E_{NAM,h} = \frac{GHI_{NAM,h}}{1000\ \mathrm{W\ m^{-2}}} * 1\ \mathrm{MW} * 1\mathrm{h} \qquad (2)$$

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. found that long-term averaged NAM forecasts are positively biased by up to 150 W m^{-2} [11]. Costal sites exhibited the largest positive bias, especially in summer months, which was attributed to issues in modeling the prevalent summer marine layer clouds in these regions. Inland sites generally had a much lower bias than coastal sites. Model-output-statistics (MOS) was employed to remove bias error as a function of forecast clear sky index and solar zenith angle. This correction was applied independently for each CIMIS station using a dynamic training set of 8 weeks of (rolling) up-to-date data. Overall, for our dataset, bias-corrected NAM forecasts reduced the MBE in GHI from 57.5 W m^{-2} to 7.0 W m^{-2}. The root mean square error (RMSE) was reduced from 134.2 W m^{-2} to 114.1 W m^{-2}. We will examine whether this increase in accuracy also yields larger revenue.

2.3 Revenue and Forecast Value

The total yearly revenue for solar energy sales, R, is calculated using the DAM LMP and RTM LMP (Eq. 3). We impose (Table 1) that if an overforecast occurs, negative RTM LMP are set equal to zero (this insures that power sellers do not get paid for under delivering in the DAM; however, they can procure energy to make-up the forecast error at zero cost in the RTM). 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 cannot profit from selling excess energy in the RTM as energy is not guaranteed to be traded in the RTM). To determine the forecast value of "best accuracy" forecasts, we also assume that a non-revenue-biased forecast is used when bidding into the market.

$$R_{NAM} = \sum_{h=1}^{h=8760} E_{NAM,h} * \left(LMP_{DAM,h} - LMP_{RTM,h}\right) + E_{CIMIS,h} * LMP_{RTM,h} \qquad (3)$$

To investigate the impact of an alternative market structure on forecast value, a deviation penalty, P_{dev}, is defined as:

$$P_{dev,h} = DPF * \max\left(LMP_{DAM,h}, LMP_{RTM,h}\right) * \left|E_{NAM,h} - E_{CIMIS,h}\right|, \quad (4)$$

where DPF is the deviation penalty factor. There is no precedent for the magnitude of the DPF, but a factor of 1.5 is used as it ensures that the deviation penalty is always at least 50% larger than the possible gain of a biased forecast. In other words, the generator is charged 1.5 times the largest possible value of the forecast error. A proper DPF causes the highest quality forecast also to be the most valuable forecast while still not excessively diminishing total revenue for the solar energy generator (i.e. if the DPF is too high solar energy generators will be penalized too harshly for providing even near perfect forecasts). An optimal DPF was not investigated. When implementing a deviation penalty, we allow all excess energy to be sold in the RTM. The total yearly revenue considering a deviation penalty becomes:

$$R_{NAM} = \sum_{h=1}^{h=8760} E_{NAM,h} * \left(LMP_{DAM,h} - LMP_{RTM,h}\right) + E_{CIMIS,h} * LMP_{RTM,h} - P_{dev,h} \qquad (5)$$

Revenue from a perfectly accurate forecast was calculated assuming that the delivered energy calculated using CIMIS data (Eq. 1) was bid perfectly into the DAM and no RTM settlement took place.

$$R_{Perfect\ Forecast} = \sum_{h=1}^{h=8760} E_{CIMIS,h} * LMP_{DAM,h} \qquad (6)$$

3. RESULTS AND DISCUSSION

3.1 Day-Ahead and Real-Time Market Price Trends

Figure 1 shows the average DAM LMP and RTM LMP for each of the price nodes collocated with a CIMIS station. Mean hourly DAM LMP range from \$25 to \$41 with fairly consistent trends over the course of the day and year. The highest DAM LMP occur in the late afternoon during July through September. RTM LMP are more volatile, but mean hourly RTM LMP are similar to that of the DAM (\$21 to \$34). The highest RTM LMP also occur during July through September. RTM LMP are sometimes negative, indicating that there is an oversupply of electricity and a power supplier would be paid to reduce delivery of energy. Both DAM and RTM prices vary by location, but yearly averaged prices show no strong spatial trends (not shown). 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 that \$7/MWh). For the RTM, the highest yearly averaged prices are spread throughout the state. In addition to daily and monthly trends, yearly trends in energy prices exist, which are ignored in our analysis. Since on a year-to-year basis absolute revenues of different forecasts vary more than ratios, we report only ratios of yearly total revenue to compare forecasts.

As presented in Table 1, the difference between the DAM and RTM LMP is important to forecast value. Over a majority of the year, the DAM and RTM prices are equal or differ by less than 5 \$/MWh, and hourly averages of DAM-RTM over the entire year and for all sites yield mean values greater than zero (Fig 1c,f). This means that on average, the DAM prices are higher than the RTM prices, which is an incentive for overforecasting in the DAM since additional energy can likely be procured at a lower price in the RTM. Additionally, seasonal trends in the DAM-RTM show that overforecasting in the mornings in May through September will be particularly profitable as the DAM prices tend to be much higher than the RTM prices for those time periods. While evenings in June, July, August, and September could yield high profits for an underforecast because the excess energy would be sold at the higher RTM price, we do not allow such profits (Table 1).

3.2 Comparison of Forecast Value

Revenue was calculated for a 1 MW power plant at each CIMIS station for real forecasts (NAM, bias-corrected NAM, Eq. 3) and a perfectly accurate forecast (Eq. 6). Figure 2a depicts the ratio of yearly revenue using the NAM forecast to yearly revenue assuming a perfect forecast for each site. The perfect forecast always yields a higher yearly revenue than the NAM forecast, with the mean ratio of yearly revenue of 0.96 (Fig 2b). In some locations (mainly inland), the NAM forecast revenue is as large as 98% of the perfect forecast revenue. The likely reason for this is that forecasts are generally more accurate at inland sites due to lower cloud occurrence. Figure 2b shows the distribution of site revenue considering the ratio of yearly revenue using a real forecast to a perfect forecast. Four real forecast scenarios are analyzed: the NAM forecast and the corrected NAM forecast (Eq. 3), and the NAM forecast with deviation penalties and the corrected NAM forecast with deviation penalties (Eq. 5). The mean ratios, considering all sites, were 0.96, 0.93, 0.59, and 0.76, respectively. The box plot indicates that without deviation penalties, the NAM forecast has more value than the corrected NAM forecast for almost all sites; on the other hand with a deviation penalty (as expected) the corrected NAM forecast has more value than the NAM forecast for all sites (Fig 2b).

3.3 Example for Coastal Sites

Figure 3a shows that the ratio between yearly revenue (without deviation penalties) using the corrected NAM forecast to the NAM forecast is lowest at coastal sites. To illustrate why the NAM forecast is more valuable, particularly at coastal sites, Figure 3b plots the Revenue Improvement Factor (RIF, defined as $RIF = \frac{R_{NAMcorr} - R_{NAM}}{R_{PF}}$) by hour of day and month of year for all sites within 20 miles of the coast. The corrected NAM yields smaller revenue during the evening year-round and throughout the entire day from July through November, but especially in the mornings during July, August, and September. This trend is a product of the NAM over-predicting irradiance in coastal areas in the summer mornings due to the prevalent marine layer clouds that are forecast to burn off too quickly by the NAM. The bias-corrected forecast is more accurate than the uncorrected forecast during the summer mornings, but this is when the spread between the DAM LMP – RTM LMP is between 0-5 \$/MWh (Fig 1c). Thus, an overforecast during summer mornings (which was the case before the correction), actually causes a gain in revenue in the settlement process (over a perfect forecast) because the price at which additional energy is procured in the RTM is less than the commitment price in the DAM (see Table 1). In other words, if the DAM price is higher than the RTM, the most profitable bid (for a market structure without deviation penalties) would be to forecast energy output at maximum capacity. The bias-corrected forecast trends away from forecasting at maximum capacity, thus leading to an overall loss of revenue as compared to the uncorrected forecast. Adding in a deviation penalty disincentivizes forecast errors, which is why the bias-corrected forecast always produces more value than the uncorrected forecast when deviations penalties are considered.

3.4. Forecast Value Versus Error Metrics

Figure 4a shows the the RIF as a function of $\Delta MBE = MBE_{NAM} - MBE_{NAMcorr}$ and $\Delta RMSE = RMSE_{NAM} - RMSE_{NAMcorr}$) for each site. The negatively-sloped trend line (linear fit) illustrates that without a deviation penalty, as MBE and RMSE improve, forecast value decreases, as measured by the RIF. However, Figure 4b shows that by adding a deviation penalty and allowing for excess energy to be sold in the RTM, forecast value increases as MBE and RMSE improve (as indicated by the positively-sloped trend line). Without the deviation penalty the magnitude of the slope of the linear regression line is much larger for the MBE versus the RMSE. This indicates that a RMSE improvement (especially if it was bias-neutral) is more likely to increase revenue, while a reduction in bias is strongly correlated to a decrease in revenue.

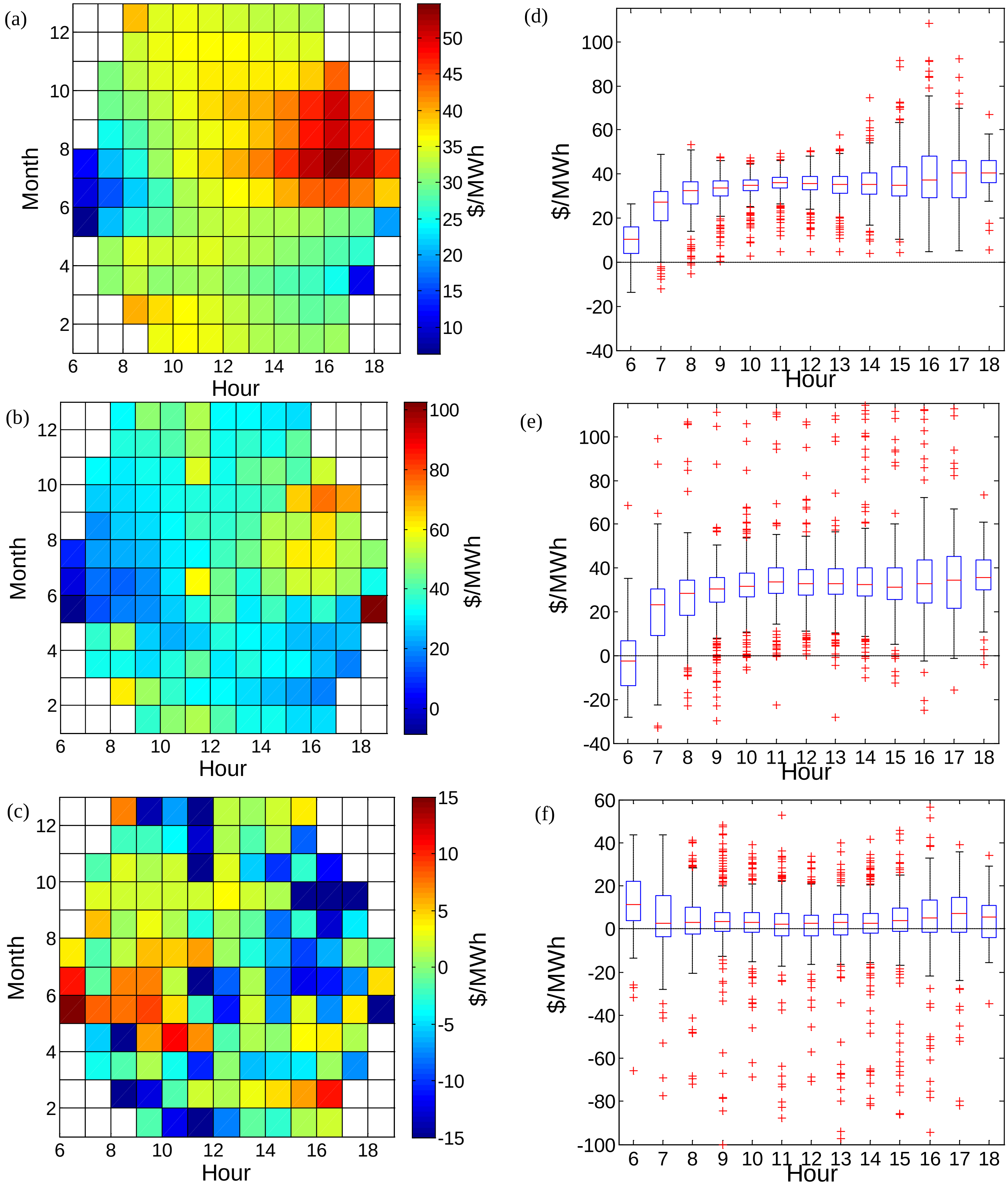

Figure 1: Average DAM LMP (a), RTM LMP (b), and DAM LMP-RTM LMP (c) for June 1, 2010 – May 31, 2011 for all 63 price nodes by time of day (for hours with a non-zero solar forecast) versus month. Box plots for DAM LMP (d), RTM LMP

(e), DAM LMP-RTM LMP (f) indicating mean, 25th and 75th percenticles, ends, and outliers (red crosses). For RTM LMP, outliers greater than 115 \$/MWh (83) are not shown. For DAM LMP –RTM LMP, outliers less than -100 \$/MWh (66) are not shown.

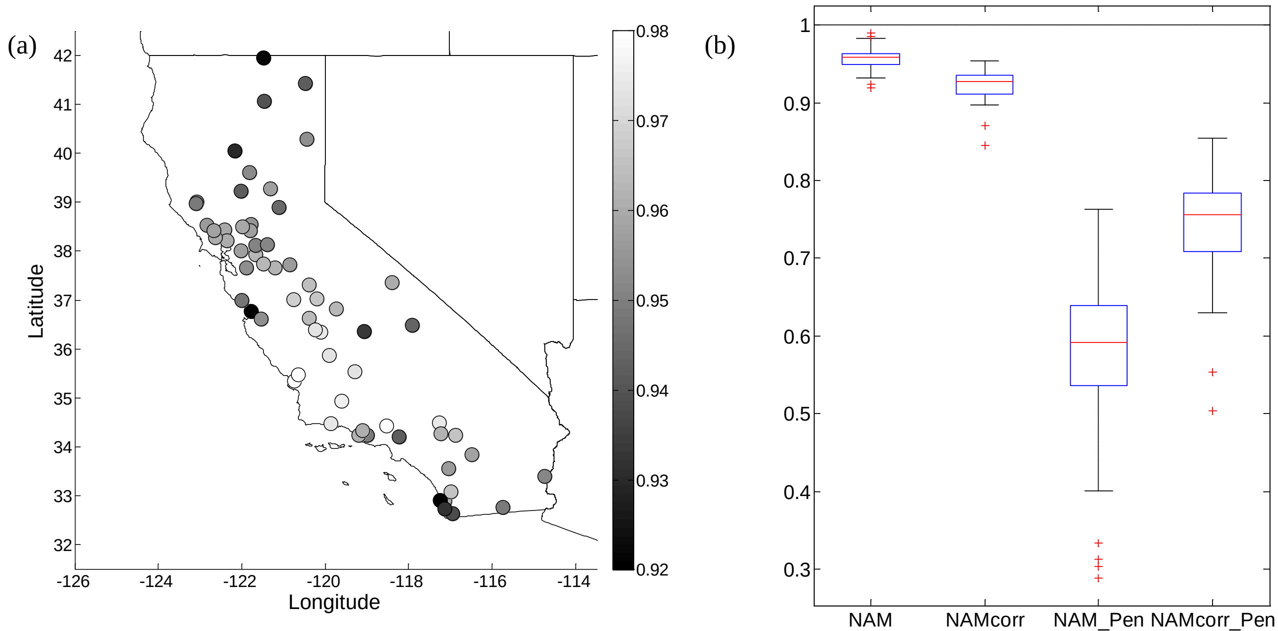

Figure 2: (a) Ratio of yearly revenue using NAM forecast (Eq. 3) over using a perfect forecast (Eq. 6). (b) Box plot showing distribution of site revenue performance based on yearly revenue ratio using a real forecast to a perfect forecast (Eq. 6); real forecasts consist of (from left to right) NAM ('NAM', mean 0.96), corrected NAM ('NAMcorr', mean 0.93) (Eq. 3), NAM with deviation penalty ('NAM_Pen', mean 0.59) and corrected NAM with deviation penalty ('NAMcorr_Pen', mean 0.76)(Eq. 5). Box plots indicate mean, 25th and 75th percenticles, ends, and outliers (red crosses).

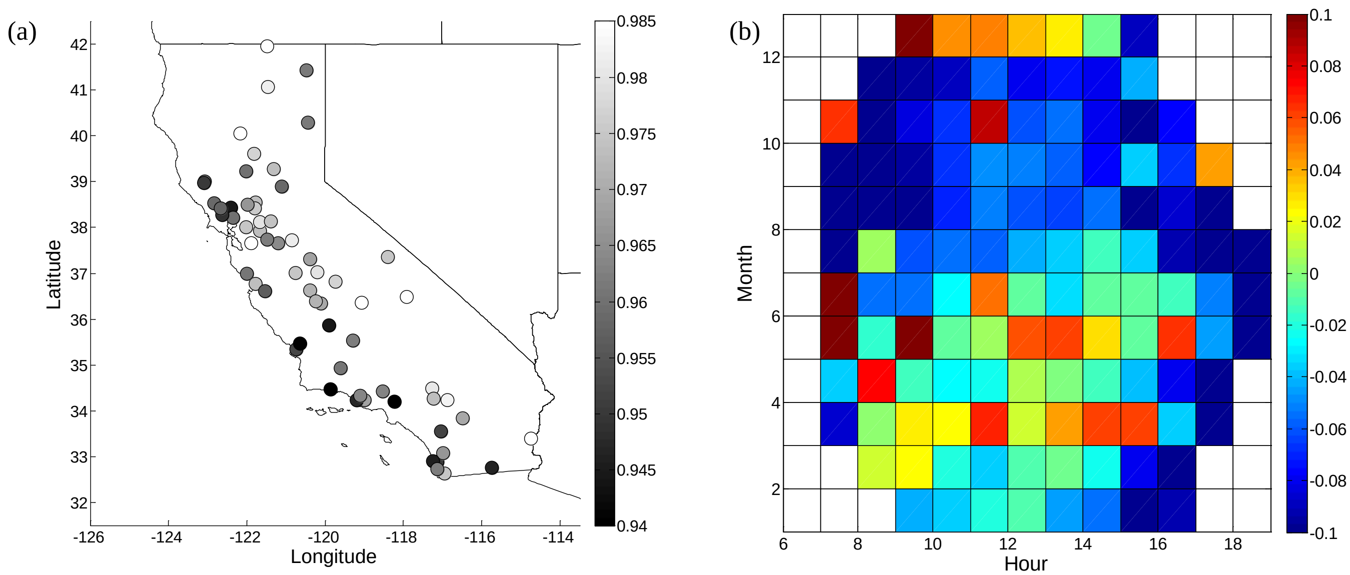

Figure 3: (a) Ratio of yearly revenue using corrected NAM forecasts to NAM forecasts (Eq. 3). (b) Revenue improvement factor [-] using corrected NAM to NAM plotted by time of day and month averaged for all sites within 20 miles of the coast.

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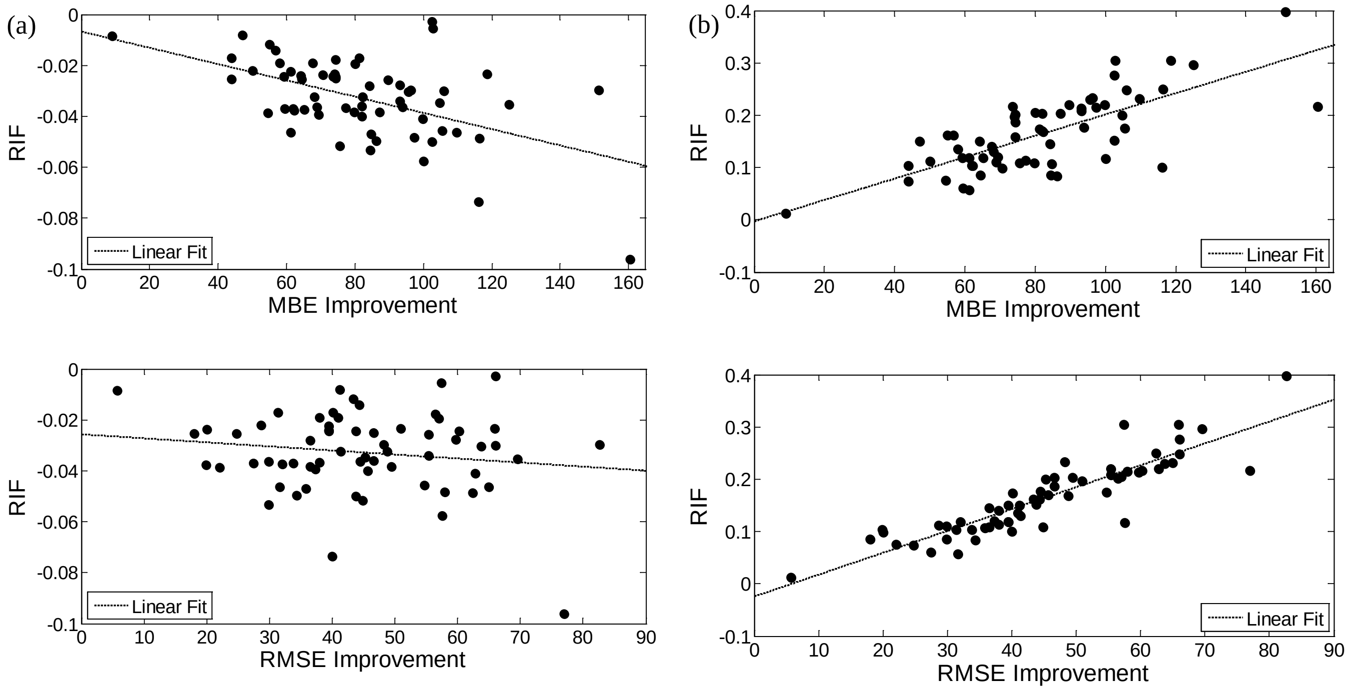

Figure 4: Revenue Improvement Factor (RIF, defined as $RIF = \frac{R_{NAMcorr-R_{NAM}}}{R_{PF}}$) as a function of change in MBE and RMSE due to the forecast bias correction for each site site without deviation penalties (a, Eq. 3) and with deviations penalties (b, Eq. 5).

4. CONCLUSION

For the California market and meteorological conditions, the yearly revenue of a real numerical weather prediction forecast by the NAM model is always less than that of a perfect forecast, but for some sites, the real forecast revenue is as much as 98% of the perfect forecast revenue. For this scenario the interests of a grid operator in accurate forecasts are aligned with the objective of an owner/operator to maximize revenue of energy sales. However, for real forecasts an improvement in forecast accuracy was found to decrease value for the CAISO energy market; the positively biased NAM forecast produces greater revenue than a less-biased forecast for all sites. This result is due to correlations in the difference between RTM LMP and DAM LMP and solar forecast errors. As illustrated for the coastal California sites the months with greatest excess DAM LMP (May through September) were also those with the largest positive forecast bias. The reduction in forecast bias in the improved forecast model reduces DAM energy sales and results in a negative revenue improvement factor during July – September.

Our simulations confirm findings [2] that biased forecasts can be more valuable to a solar power generator. If forecasts from generators are not representative of the energy that is expected to be received, market inefficiencies are created by forcing system operators to procure additional reserves or regulation to balance the additional uncertainty in the forecast. System operators can respond by producing internal forecasts or procuring forecast from independent 3rd parties. Market inefficiencies could also be mitigated through deviation penalties, which (by design) cause the value of an accurate forecast to increase. In this way, deviation penalties can internalize the external costs of inaccurate forecasts to the owner / operator, but the penalty factor must be chosen carefully to be reasonable to forecast providers.

We assume that solar power plants participate in the open market and that the LMP does not change due to participation of the additional solar power plants in the market. In reality, DAM prices would be reduced with increasing solar generation and the RTM price could be driven up or down if solar forecast trend to either over- or under-predict. Inclusion of the feedback of PV participation in the energy market is likely to promote accurate forecasts. Also the results are specific to California with unique forecast biases and DAM and RTM price spreads. Regardless, our approach to determining forecast value allows for the analysis of impact of different energy market structures on the value of accurate forecasts to market participants.

5. ACKNOWLEDGEMENTS

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