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ECONOMIC VALUE OF SOLAR FORECASTS FOR DIRECT MARKETING OF PV PRODUCTION

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Summary

Energy market operation strongly depends on the accuracy of PV power forecasting. Forecasting errors affect the smooth integration of solar energy into the grid because they influence market balance and, therefore, the revenues of energy producers. This paper investigates the impact of different levels of forecasting errors on the producers' income in the Californian market settlements. To this end, a PV system was simulated in this region along with forecasts generated using persistence models and a numerical weather prediction (NWP) model. Also, the benefits of participating in the intraday market compared to relying exclusively on the day-ahead market are assessed for this market structure. Forecast performance is evaluated using standard error metrics, revealing correlations between forecast mean bias and the imbalance penalties. Advanced forecasting approaches such as NWP models reduce forecasting errors and increase market revenues compared with persistence models, while systematic overestimation of production can be economically advantageous depending on market structure.

PV power forecasting, Market structure, Intraday market, Forecasting errors

Field of application for the findings: Electricity grid operation, Solar production management

Addressed audience: Solar power producers, Solar forecasters, Grid operators

1. Introduction

The rapid deployment of photovoltaic (PV) power systems is transforming electricity systems worldwide. However, the increasing penetration of PV power generation also introduces new operational challenges because its production is strongly dependent on variable meteorological conditions. Forecast errors therefore create deviations between scheduled and actual production, which are subsequently settled through balancing mechanisms and can directly affect producer revenues (Antonanzas et al., 2016; Sobri et al., 2018).

Many forecasting methods has been developed, including persistence models, numerical weather prediction (NWP), statistical approaches, machine learning, and hybrid methods (Antonanzas et al., 2016; Chu et al., 2021). Forecast performance is generally evaluated using statistical metrics such as the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Bias Error (MBE). These metrics provide complementary information on forecast quality, but improved statistical performance does not necessarily result in a proportional economic benefit. The financial impact of forecast errors also depends on electricity prices and imbalance settlement mechanisms.

Several studies have investigated the economic consequences of PV forecast errors. Luoma et al. (2014) demonstrated that forecast errors can significantly affect the revenues of utility-scale PV plants in North American electricity markets, while Wang et al. (2022) analysed forecast error costs across several U.S. Independent System Operators and showed their dependence on market and PV penetration conditions. More recently, Klyve et al. (2023) proposed an economic model combining Day-Ahead, Intraday, and balancing-market participation and demonstrated the potential value of intraday forecast updates in reducing imbalance costs.

Despite these contributions, the relationship between conventional forecast verification metrics and economic performance remains insufficiently investigated. In particular, it is unclear whether MAE, RMSE, or MBE provides the most meaningful indication of producer revenue under a specific market design. This question is especially relevant for the California Independent System Operator (CAISO), where the high penetration of PV power generation and the characteristics of the imbalance settlement mechanism can significantly influence the economic consequences of forecast errors.

This study therefore investigates the relationship between PV forecast quality and economic value under CAISO market conditions. The analysis considers both Day-Ahead and Intraday market participation. This distinction makes it possible to assess whether the economic value of intraday participation is related to the magnitude of the forecast correction or to other characteristics of the market process.

The main contributions of this study are:

1. Develop a framework linking conventional PV forecast quality metrics with producer revenue under CAISO market conditions;
2. Quantify the relationship between forecast quality and economic value for forecasting approaches with different error characteristics; and
3. Evaluate the relative economic relevance of MAE, RMSE, and MBE in the Day-Ahead market and the statistical characteristics of forecast updates in the Intraday market.

2. Methodology

The objective of this study is to quantify the relationship between PV forecast quality and the corresponding economic value under the CAISO electricity market. The proposed methodology consists of five sequential stages. First, a reference PV production profile is generated from historical meteorological observations using a physics-based simulation model. Second, deterministic forecasting methods are used to produce forecasts exhibiting different error characteristics. Third, forecast quality is evaluated using the most used error metrics (Yang et al., 2020). Fourth, the forecasts are introduced into the economic model presented in Section 5 to calculate producer revenues under historical CAISO market conditions. Therefore, we do not take into account price forecasts in this work and we only study the effect of the generation forecast error. Finally, statistical analyses are performed to quantify the relationship between forecast quality and economic value.

Unlike traditional forecast verification studies, which evaluate forecasting methods solely through statistical indicators, the proposed framework links forecast quality directly to market revenues, providing an economic interpretation of forecast performance.

3. Case study

The considered case study is a 30 MW utility-scale PV plant located within the area covered by the CAISO balancing authority. Northern California was selected because of the high penetration of PV generation and the availability of publicly accessible meteorological observations and electricity market data. The hypothetical plant is assumed to be located at the same geographic coordinates as an existing solar farm, namely 37.125°N, 120.325°W. This location enables the use of the corresponding CAISO pricing node and associated electricity market prices for the economic assessment.

Hourly meteorological data for the period from 1 January to 31 December 2022, including global horizontal irradiance, ambient temperature, and wind speed, were obtained from the National Solar Radiation Database (NSRDB) (Sengupta et al., 2018). The reference PV production profile was simulated using the open-source pvlib Python library (Holmgren et al., 2018).

Since the CAISO Real-Time market operates with a 15-minute settlement interval, the hourly simulated production was linearly interpolated to obtain the corresponding 15-minute time series required for the Intraday analysis.

Historical Day-Ahead, Real-Time, and Fifteen minute market prices were obtained from the CAISO Open Access Same-Time Information System (OASIS), using the pricing node geographically closest to the simulated PV plant.

4. Forecast generation and quality assessment

To generate forecasts with different error characteristics, two persistence approaches were considered. For the Day-Ahead market, 24-hour and 48-hour persistence forecasts were used as deterministic benchmark models. For the Intraday market, a 15-minute persistence forecast was adopted, where the PV production forecast at each settlement interval is assumed to be equal to the most recent observation available 15 minutes earlier. This choice is consistent with the 15-minute resolution of the CAISO Real-Time settlement process and provides a realistic benchmark for short-term forecast updates. ECMWF deterministic forecasts were also evaluated for both market stages (Persson and Grazzini, 2007). ECMWF forecasts were extracted from several neighbouring grid points surrounding the PV plant, providing naturally different forecast accuracy levels without introducing artificial errors. In addition, ECMWF ensemble prediction system (EPS) members were treated independently as deterministic forecasts. The ensemble prediction system represents atmospheric uncertainty through perturbations of initial conditions and model physics, allowing each member to provide a distinct but physically consistent PV forecast (Molteni et al., 1996; Leutbecher and Palmer, 2008).

The resulting forecasts were evaluated using standard statistical metrics and introduced into the economic model described in Section 5 to calculate producer revenues under historical CAISO market conditions.

Finally, statistical analyses were performed to quantify the relationship between forecast characteristics and economic performance. This framework therefore links conventional forecast verification metrics directly to market revenue, providing an economic assessment of PV forecasting performance rather than relying solely on quality.

Forecast performance was evaluated using three deterministic statistical metrics that characterize complementary aspects of forecast quality (Antonanzas et al., 2016; Yang et al., 2020).

The Mean Absolute Error (MAE) measures the average magnitude of forecast errors,

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |F_i - O_i|.$$

The Root Mean Square Error (RMSE) gives greater weight to large forecasting errors,

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)^2}.$$

Finally, the Mean Bias Error (MBE) quantifies systematic forecast overestimation or underestimation,

$$MBE = \frac{1}{N} \sum_{i=1}^{N} (F_i - O_i).$$

5. Economic Value Framework

5.1 Market settlement

The increasing participation of PV generation in competitive electricity markets makes accurate production forecasting essential for both system operation and producer profitability. Utility-scale PV producers must submit generation schedules before delivery, while actual production remains dependent on variable meteorological conditions. Deviations between scheduled and actual generation therefore result in energy imbalances that are settled through balancing mechanisms and can affect producer revenues (Antonanzas et al., 2016; Sobri et al., 2018).

PV forecast quality is commonly evaluated using statistical metrics such as the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Bias Error (MBE) (Yang et al., 2020). Although these metrics are useful for comparing forecasting methods, they do not directly quantify their financial consequences. Forecasts with a similar error indicator may generate different revenues depending on electricity prices, market conditions, and imbalance settlement rules (Luoma et al., 2014; Wang et al., 2022).

Most modern wholesale electricity markets operate through a sequential trading process in which electricity producers progressively refine their generation bids before energy delivery.

Initially, producers submit their expected energy production to the Day-Ahead market. As updated meteorological information becomes available, these schedules can be modified through the Intraday market using updated forecasts, reducing forecast uncertainty and expected imbalance costs (Klyve et al., 2023).

After delivery, actual photovoltaic generation is compared with the final committed schedule. Any remaining deviation constitutes an energy imbalance that is settled through the balancing market. Depending on the direction of the imbalance and the corresponding balancing prices, producers are charged for production differences (Morales et al., 2014).

The complete market sequence considered in this work is illustrated in the following diagram 1.

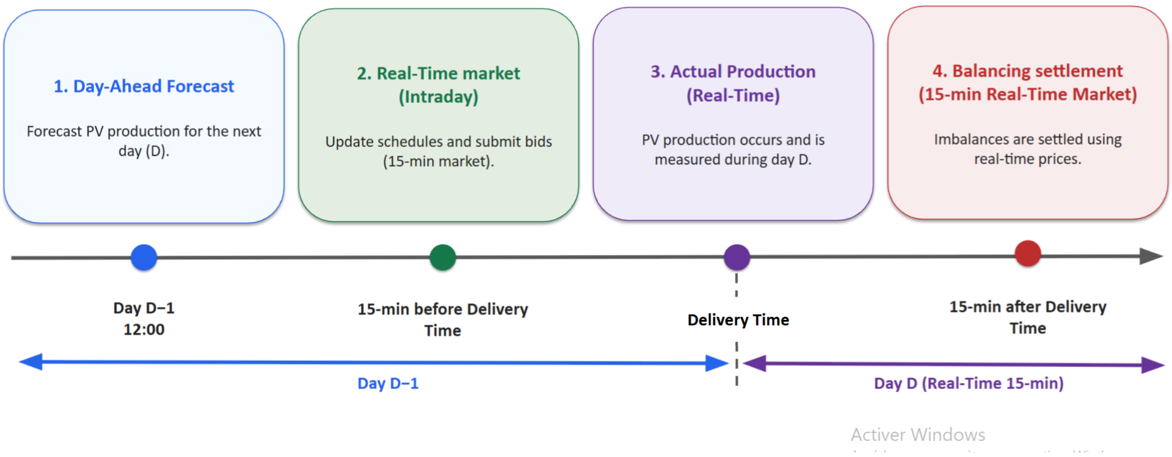

Fig. 1: Overview of CAISO Market Settlement Process

This sequential framework illustrates that producer revenue depends not only on forecast accuracy but also on the timing of forecast updates and the imbalance settlement rules adopted by the electricity market.

5.2 Economic revenue model

The economic value of photovoltaic forecasts is evaluated using the market revenue formulation proposed by Klyve et al. (2023) and adapted to the CAISO market. The model represents sequential participation in the Day-Ahead, Intraday, and Real-Time markets. The total producer revenue is given by

$$\Pi = \sum_{t=1}^{T} \left[E_t^{DA} p_t^{DA} + \delta_t (E_t^{ID} - E_t^{DA}) p_t^{ID} + E_t^{reg} p_t^{reg} \right], \tag{1}$$

where E_t^{DA} and E_t^{ID} are the Day-Ahead and Intraday scheduled energies, p_t^{DA} and p_t^{ID} are their corresponding prices, p_t^{reg} is the Real Time dispatch price, and δ_t indicates whether an Intraday transaction occurs.

The remaining imbalance is defined as

$$E_t^{reg} = E_t - E_t^{DA} - \delta_t (E_t^{ID} - E_t^{DA}), \tag{2}$$

where E_t is the observed PV production. Thus, when $\delta_t = 0$, the imbalance is calculated relative to the Day-Ahead schedule, whereas for $\delta_t = 1$, it is calculated relative to the updated Intraday schedule.

In a single-price imbalance settlement scheme, positive and negative deviations are settled using the same imbalance price for a given settlement interval. The applicable price is determined by the prevailing system balancing conditions rather than by the direction of the individual producer's forecast error. Consequently, the economic impact of a PV forecast error depends on both the magnitude and sign of the deviation and the system-wide imbalance price at the time of settlement. This approach differs from dual-price schemes, where separate prices are applied to upward and downward deviations.

5.3 Revenue calculation

The economic value of each forecast was calculated using the revenue model introduced in the previous section 5.2 .

For every forecast, the Day-Ahead scheduled energy was first determined from the predicted PV production. A 15-minute persistence forecast was used as the Intraday benchmark, with the PV production forecast at each 15-minute settlement interval based on the most recent available observation. The updated Intraday schedule was then compared with the observed PV production, and the remaining imbalance was finally settled according to the CAISO Real-Time prices. This procedure was repeated for every forecasting approach over the entire study period, producing a corresponding annual revenue for each forecast.

To evaluate the financial benefit of forecast updates, two market participation strategies were analysed:

- *Day-Ahead participation only*, in which the initial forecast remains unchanged until delivery;
- *Day-Ahead plus Intraday participation*, where the Day-Ahead commitment is updated before Real-Time operation using improved forecasts.

The difference between these two strategies quantifies the economic benefit associated with intraday forecast updates.

6. Results and discussion

6.1 Day-Ahead market performance

The economic performance of the different forecasting approaches was first evaluated considering participation in the Day-Ahead (DA) market only. For each forecasting method, the annual producer revenue was calculated using the revenue model presented in Section 5.2 and compared with the corresponding forecast quality metrics. Annual producer revenues are expressed per installed megawatt (USD.MW^{-1}) to normalize the results by PV plant capacity and facilitate comparison between forecasting approaches. The perfect forecast, represented by the observed photovoltaic production, defines the producer revenue when no forecast errors occur and, consequently, no imbalance settlements are required. The remaining forecasting approaches introduce different levels of forecast uncertainty, allowing the relationship between statistical forecast quality and economic performance to be investigated.

Figure 2 presents the relationships between annual producer revenue and the three forecast quality metrics considered in this study: MAE, MBE and RMSE. Together, these figures show that improvements in forecast quality generally lead to higher producer revenues through a reduction in imbalance costs. However, the strength of this relationship varies significantly depending on the metric considered.

The persistence forecasts exhibit the lowest economic performance, with annual revenues close to 1.2×10^5 USD.MW^{-1}. Their relatively large MAE and RMSE values result in substantial deviations between scheduled and actual production, increasing the amount of energy settled in the balancing market. In contrast, the deterministic ECMWF forecasts consistently provide the highest revenues among the non naive forecasting approaches, while the ECMWF ensemble members form a compact cluster with similar revenues despite the variability between individual ensemble realizations.

Different regression formulations were initially tested to characterize the relationship between the forecast quality metrics and annual producer revenue. Linear and second-degree polynomial regressions were considered, and the resulting coefficients of determination (R^2) were compared to identify the formulation that best represented the observed relationship. A clear relationship is observed between MAE and annual producer revenue. Forecasts with lower average absolute errors generally achieve higher revenues because lower forecast

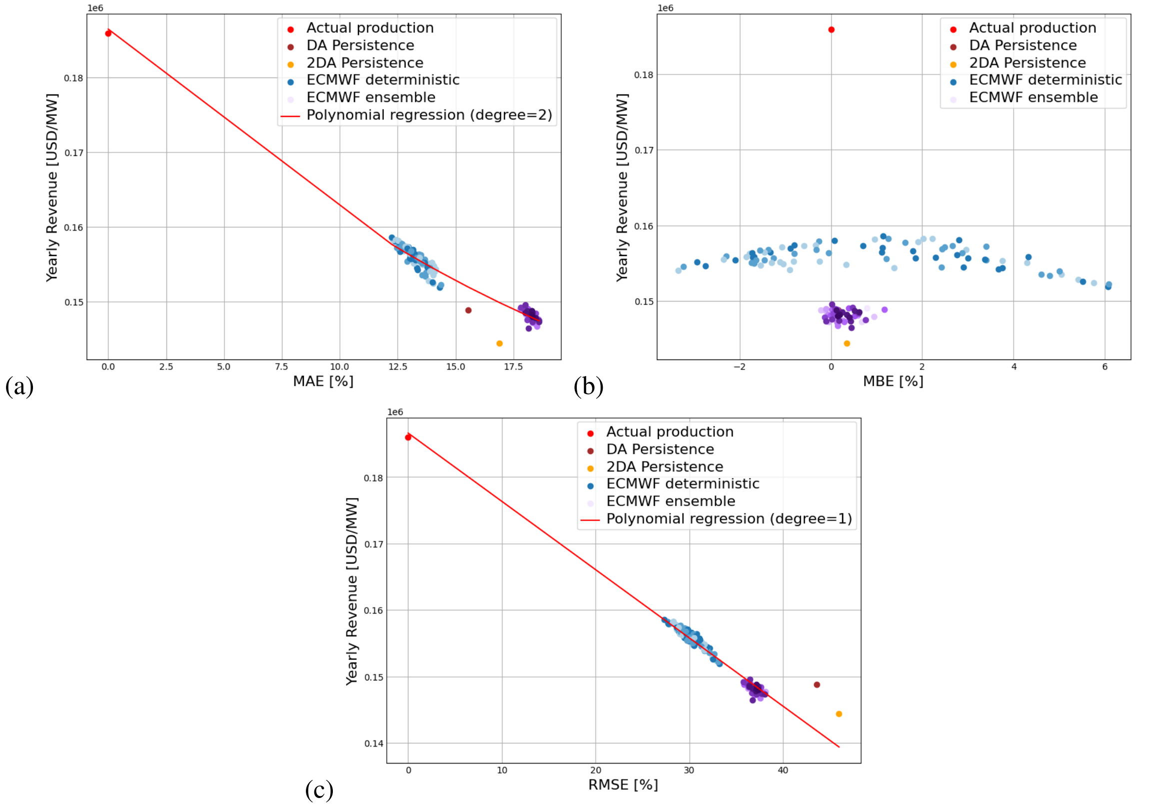

Fig. 2: Relationship between annual producer revenue and the three forecast quality metrics considered in this study: (a) Mean Absolute Error (MAE), (b) Mean Bias Error (MBE), and (c) Root Mean Square Error (RMSE).

deviations reduce the amount of energy exposed to balancing settlement. This relationship is strongly supported by the regression analysis presented in Table 1, which gives an R^2 of 0.967 for MAE. This result identifies MAE as a highly informative indicator of economic performance in the Day-Ahead market.

Tab. 1: Polynomial regression statistics between forecast quality metrics and annual producer revenue.

Metric	R^2	Regression model
MAE	0.967	$40.2X^2 - 2846.35X + 186467.8$
MBE	Fail	Fail
RMSE	0.959	$-1027.1X + 186606$

The polynomial regression for MBE was not considered representative because the ECMWF ensemble forecasts form a highly clustered group of points with similar MBE values and revenues. This limited the effective range of the regression and prevented the quadratic model from reliably capturing the overall relationship between MBE and revenue. The results indicate that the magnitude and distribution of forecast errors are more important determinants of Day-Ahead economic performance than the average systematic bias alone.

RMSE exhibits also a strong relationship with annual producer revenue in the polynomial regression, with an R^2 of 0.959. This result differs from the previous regression analysis and indicates that the relationship between RMSE and economic performance is better represented using a non-linear formulation.

The comparison between the three metrics identifies MAE and RMSE as the two most informative indicators of Day-Ahead economic performance, with R^2 values of 0.967 and 0.959, respectively. These results indicate that the economic consequences of PV forecasting errors are primarily related to the overall magnitude and distribution of forecast deviations rather than to the average systematic bias alone.

The results also highlight the importance of considering non-linear relationships when assessing the economic value of an improvement in forecasting quality. The high R^2 value obtained for MAE indicates that the relationship between forecast quality and producer revenue is not necessarily adequately represented by a simple linear trend. Polynomial regression can therefore provide a more appropriate representation of the observed economic response over the range of forecast errors considered.

6.2 Influence of the intraday market

Unlike the Day-Ahead analysis presented in Section 6.1, where forecast quality was evaluated with respect to the observed PV production, the intraday market analysis focuses on the value of forecast updates. Indeed, the economic benefit of intraday trading originates from the correction applied to the initial Day-Ahead schedule before electricity delivery. Consequently, the statistical indicators are no longer calculated using the observed production but instead quantify the difference between the updated Intraday forecast and the initial Day-Ahead forecast.

Three deterministic metrics are therefore introduced to characterize the magnitude of the forecast update. The Mean Absolute Error of the update ($\mathrm{MAE_{ID}}$) is defined as

$$\mathrm{MAE_{ID}} = \frac{1}{N}\sum_{i=1}^{N} \left| F_i^{\mathrm{ID}} - F_i^{\mathrm{DA}} \right|, \tag{3}$$

where F_i^{DA} and F_i^{ID} denote the Day-Ahead and Intraday photovoltaic forecasts, respectively.

Similarly, the Root Mean Square Error of the forecast update is expressed as

$$\mathrm{RMSE_{ID}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \left(F_i^{\mathrm{ID}} - F_i^{\mathrm{DA}} \right)^2}, \tag{4}$$

while the Mean Bias Error of the update is given by

$$\mathrm{MBE_{ID}} = \frac{1}{N}\sum_{i=1}^{N} \left(F_i^{\mathrm{ID}} - F_i^{\mathrm{DA}} \right). \tag{5}$$

These indicators quantify the average magnitude, dispersion and systematic direction of the forecast corrections introduced during the intraday trading stage. Unlike the conventional forecast verification metrics used in Section 6.1, they do not measure the quality of the forecast with respect to the observed production. Instead, they evaluate the extent to which the Day-Ahead production schedule is modified before real-time operation, thereby providing an estimate of the potential economic value associated with intraday forecast updates.

Figure 3 presents the relationship between the annual producer revenue and the three intraday update metrics. Compared with the Day-Ahead analysis, the economic behavior is markedly different. The deterministic ECMWF forecasts exhibit $\mathrm{MAE_{ID}}$ magnitudes ranging from approximately 13% to 15%, whereas the ensemble forecasts are concentrated around 16%. Despite these differences in update magnitude, the corresponding annual revenues are distributed approximately between 0.8×10^6 and 0.9×10^6 USD.MW^{-1}. Persistence forecasts require the largest forecast corrections but remain the least profitable forecasting approaches.

This behavior indicates that the economic benefit of intraday participation is not determined solely by the magnitude of the forecast correction. Instead, producer revenue depends on how effectively the updated production schedule reduces the remaining imbalance energy before the final balancing settlement. The Real-Time prices at which Intraday forecast corrections are settled can take either positive or negative values, meaning that a given forecast correction may have either a positive or negative impact on the producer's revenue. Consequently, forecasts with similar error magnitudes can generate different annual revenues, since the economic impact of a given correction depends on its timing and the electricity prices prevailing at the time of settlement. A given forecast error magnitude can consequently correspond to different economic values in the Intraday market.

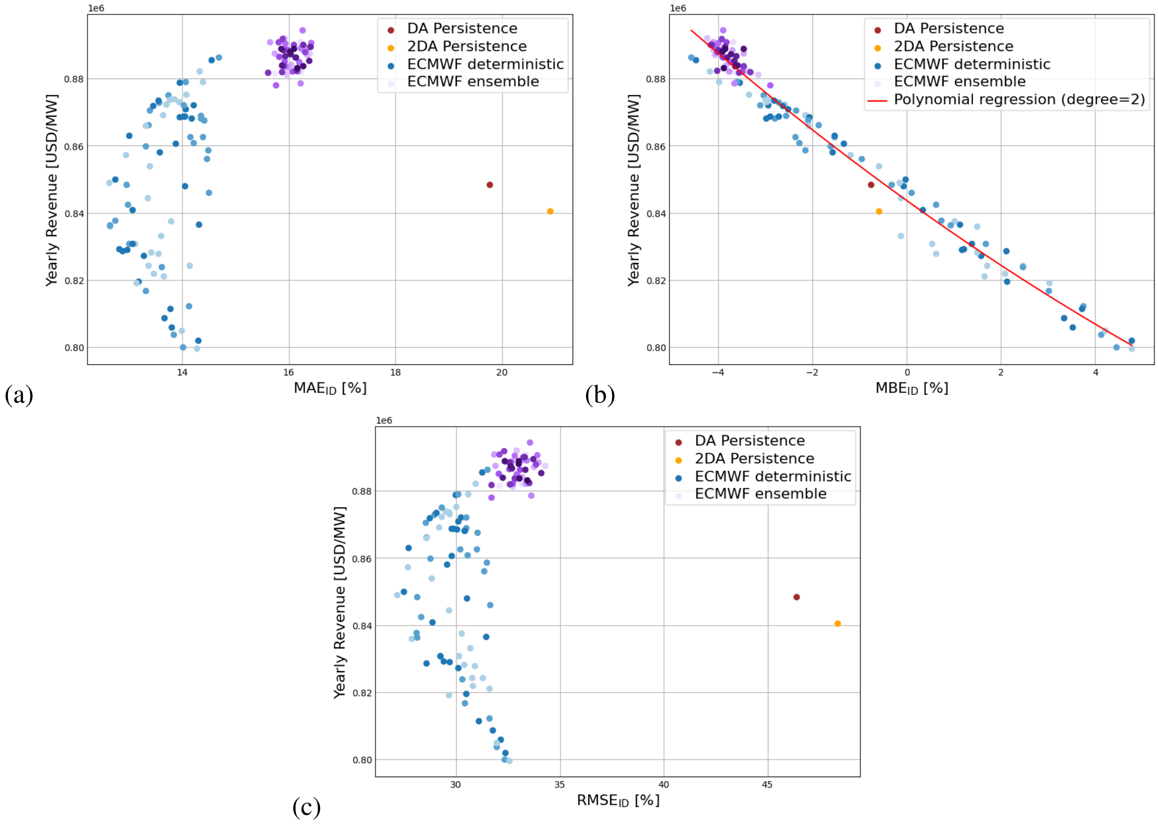

Fig. 3: Relationship between annual producer revenue and the forecast update metrics : (a) MAE_{ID}, (b) MBE_{ID}, and (c) RMSE_{ID}.

The higher revenues observed for negative MBE_{ID} values indicate that downward Intraday corrections generally improved the economic outcome by reducing the remaining imbalance between the committed and actual PV production. The economic benefit is further influenced by the Real-Time prices associated with these corrections.

To quantify these relationships, a polynomial regression analysis was performed between the annual producer revenue and each intraday update metric. The polynomial fits for MAE_{ID} and RMSE_{ID} were not considered representative because the corresponding data show substantial dispersion and no stable quadratic relationship with annual revenue.

Tab. 2: Polynomial regression statistics between intraday update metrics and annual producer revenue.

Metric	R^2	Regression model
MAE_{ID}	Fail	Fail
MBE_{ID}	0.978	$220.4X^2 - 10092.8X + 843668$
RMSE_{ID}	Fail	Fail

The strongest relationship is obtained for MBE_{ID}. The polynomial regression gives an R^2 of 0.978. It suggests that the direction of the forecast correction between the Day-Ahead and Intraday stages is highly relevant to the economic outcome.

Compared with MBE_{ID}, MBE_{ID} and RMSE_{ID} therefore provides limited explanatory power for the economic value of Intraday forecast updates.

The comparison between the two market stages reveals an important difference. In the Day-Ahead market, MAE and RMSE provide the strongest relationships with revenue, whereas MBE has limited explanatory power. In the Intraday market, however, MBE_{ID} becomes the strongest indicator, with an R^2 of 0.978. This suggests that the economic relevance of a forecast metric depends on the market stage and on what the metric represents.

At the Day-Ahead stage, the forecast determines the initial production commitment, making the magnitude of the forecast error particularly important. During the Intraday stage, the relevant information is instead the correction applied to that initial commitment. The direction of this correction, represented by MBE_{ID}, appears to be strongly associated with intraday market prices in the present dataset.

Overall, the Intraday results indicate that the economic value of forecast updating cannot be characterized solely by the size of the correction. The direction of the correction and its ability to reduce the remaining imbalance before Real-Time settlement are also important. Therefore, the economic value of Intraday forecasting depends jointly on the direction of the forecast update, its ability to improve the market position, and the real-time prices prevailing during the corresponding settlement periods.

6.3 Conclusion

This study investigated the relationship between PV forecast quality and its economic value under the CAISO electricity market. An economic framework adapted from Klyve et al. (2023) was combined with persistence and ECMWF forecasting approaches to evaluate producer revenues under both Day-Ahead and Day-Ahead plus Intraday market participation.

The Day-Ahead results demonstrate that forecast quality has a strong influence on producer revenue. Persistence forecasts provide the lowest economic performance, whereas deterministic ECMWF forecasts generally achieve higher revenues. The polynomial regression analysis shows that MAE is the most informative Day-Ahead metric, with an R^2 of 0.968. RMSE also exhibits a very strong relationship with revenue, with an R^2 of 0.962. In contrast, the failed polynomial regression for MBE indicates that the average systematic bias provides limited information about annual producer revenue in the Day-Ahead market.

These results indicate that MAE and RMSE are complementary indicators of economic forecast value. MAE represents the average magnitude of forecast deviations, while RMSE gives greater weight to larger deviations. The high R^2 values obtained for both metrics indicate that the economic impact of forecast errors is strongly related to their magnitude and distribution. The results also demonstrate the usefulness of polynomial regression for representing the non-linear relationship between forecast quality and producer revenue.

The Intraday analysis reveals a different behaviour. The update metrics describe the correction between the Day-Ahead and Intraday forecasts rather than the error relative to observed production. The polynomial regression results show R^2 value of 0.978 for MBE_{ID}. Among the studied metrics, MBE_{ID} provides the strongest relationship with annual revenue, suggesting that the direction of the Intraday correction is particularly relevant to the economic outcome. MAE_{ID} provides a moderate relationship, whereas RMSE_{ID} has relatively limited explanatory power.

These results demonstrate that the economic relevance of forecast metrics depends strongly on the stage of the electricity market. In the Day-Ahead market, the magnitude of the forecast error is particularly important because it determines the initial imbalance exposure. In the Intraday market, the economic value instead depends strongly on how the updated forecast modifies the initial commitment and whether that correction effectively reduces the remaining imbalance before Real-Time settlement.

Overall, the study demonstrates that forecast quality should not be evaluated independently from the market decision that the forecast supports. Different metrics become relevant at different stages of the market process. For the CAISO case investigated here, MAE and RMSE provide strong indicators of Day-Ahead economic performance, while MBE_{ID} provides the strongest relationship with revenue during the Intraday stage.

The proposed framework provides a link between conventional PV forecast verification and economic performance and can therefore support both forecasting-system development and electricity-market decision-making. Future work should extend the analysis to probabilistic forecasts, allowing forecast uncertainty to be explicitly incorporated into market participation decisions.

7. Acknowledgment

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