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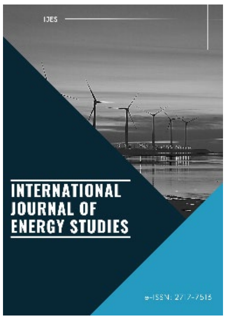

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Beyond forecast accuracy: A statistical and financial evaluation of machine learning models for small hydropower forecasting

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Highlights

- Upstream generation data were used as an operational proxy in the absence of detailed meteorological inputs.
- Random Forest and MLP outperformed operator-based heuristic forecasts in statistical terms.
- Statistical superiority did not always translate into the lowest market-related forecasting cost.

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ABSTRACT

This study develops and evaluates a machine learning-based forecasting framework for improving the day-ahead production estimates of a run-of-river hydropower plant operating under Turkish electricity market conditions. The analysis is based on hourly operational data and compares operator-based heuristic forecasts with four alternative modeling approaches: Multilayer Perceptron (MLP), Random Forest (RF), standard XGBoost, and a cost-aware XGBoost (CA-XGBoost) formulation. To reflect real-world operational constraints, the framework relies on a parsimonious feature structure composed of the operator's original forecast and a proxy variable derived from the upstream plant's generation data with a 16-hour hydraulic lag. In this way, the study aims to provide a practical forecasting approach for data-constrained hydropower settings where detailed meteorological inputs may not be readily available. The models are evaluated through both statistical and financial criteria. Statistical performance is assessed using MAE, RMSE, and (R^2), while financial performance is examined through imbalance-related market costs calculated using hourly Market Clearing Price and System Marginal Price data under the asymmetric settlement structure of the Turkish electricity market. The results show that Random Forest achieved the best overall economic performance, yielding the lowest total imbalance cost and the lowest MAE, whereas MLP produced the best RMSE and (R^2) values. By contrast, the CA-XGBoost approach model did not outperform the benchmark machine learning models, although it did alter the directional structure of forecast errors. The findings reveal that improvements in statistical accuracy do not necessarily imply superior financial performance. Accordingly, the study demonstrates the importance of evaluating hydropower forecasting models not only in terms of conventional error metrics but also with respect to their economic consequences under market-based imbalance pricing. From a practical perspective, the CA- XGBoost proxy-based framework offers a lightweight and potentially scalable decision-support approach for small hydropower plants operating under limited data availability.

Keywords: Hydropower generation, Machine learning, Imbalance cost, Turkish electricity market

1. INTRODUCTION

The integration of small-scale hydropower (SHP) into renewable energy portfolios plays an important role in supporting environmental sustainability and diversifying electricity generation mixes. In addition to requiring lower initial investment and shorter development periods than large-scale hydropower projects [1], SHP can also improve energy access in remote or underserved regions [2]. Beyond these advantages, SHP offers operational value as a decentralized, relatively reliable renewable energy source that can complement more intermittent technologies such as solar and wind. Nevertheless, the practical effectiveness of SHP depends heavily on operators' ability to manage production variability. In competitive electricity markets, this makes generation forecasting not merely a technical task but an operational and economic necessity, since inaccurate forecasts may reduce both system reliability and project viability.

The increasing penetration of variable renewable energy (VRE) has further amplified the operational and financial consequences of forecast errors. Inaccurate generation forecasts may increase total system costs by requiring additional balancing actions and greater reliance on backup thermal generation [3]. In liberalized electricity markets, such deviations may also contribute to price volatility during scarcity periods, thereby affecting both consumers and producers. For hydroelectric generators, the problem is particularly important because differences between scheduled and realized output may lead to revenue losses and imbalance-related penalties, especially for storage and run-of-river facilities [4]. Recent studies have therefore emphasized the need for forecasting frameworks that move beyond symmetric error minimization and account for market-specific risk structures [5, 6].

This issue is highly relevant in the Turkish electricity market, which has evolved from a state-controlled monopoly into a liberalized market structure following the enactment of Law No. 4628 in 2001. Today, licensed market participants trade electricity through several mechanisms operated by Energy Exchange Istanbul (EXIST or EPİAŞ) and Turkish Electricity Transmission Cooperation (TETC or TEİAŞ), including bilateral contracts, the day-ahead market (DAM), and the intraday market (IDM) [7]. In this market environment, generation companies face financial consequences when their realized generation deviates from previously submitted schedules [8]. The efficiency of this structure has been supported by improved market-clearing procedures and algorithmic developments [9]. At the same time, the interaction between day-ahead prices and imbalance behavior has also attracted increasing scholarly attention [10, 11]. Beyond its institutional structure, Türkiye's electricity market has also been shaped by its renewable energy support framework. Under the Renewable Energy Resources Support Mechanism (YEKDEM), fixed feed-in tariffs have incentivized substantial investment in hydropower and other renewable sources, contributing to a significant expansion of installed renewable capacity [12]. However, the rapid growth of variable renewable generation has introduced new market pressures, including pronounced price reductions during peak generation periods and an increasing burden of system-wide imbalance costs [13, 14]. In this context, small hydropower plants face particular challenges in optimizing their day-ahead market participation, as their generation schedules must be submitted under conditions of hydrological and operational uncertainty [15].

A substantial body of research has addressed short-term hydropower forecasting, and model performance has typically been evaluated using conventional statistical indicators such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Recent studies have shown that advanced machine learning algorithms, including XGBoost and Random Forest, often outperform traditional Multi-Layer Perceptron (MLP) models in terms of statistical prediction accuracy [16,17]. In the Turkish context specifically, machine learning methods have also been applied to short-term forecasting problems in the electricity sector. Arifoğlu and Kandemir [18] demonstrated that deep learning models including MLP, LSTM, and GRU can achieve highly accurate day-ahead price forecasts in the EPİAŞ market, further confirming the applicability of neural network-based approaches in the Turkish electricity sector. Yılan and Beykent [19] demonstrated that XGBoost outperforms alternative models in day-ahead price forecasting within the Turkish market, while Atalay and Zor [20] and Bulut [21] showed that tree-based and LSTM-based approaches can achieve strong predictive accuracy for hydroelectric generation forecasting. Atalan et al. [22] further demonstrated that ensemble methods such as Random Forest and Adaptive Boosting can achieve notably low error rates in renewable energy production estimation. At the same time, a growing stream of literature has begun to question whether statistically superior models are also economically preferable in electricity-market applications. To address this issue, several studies have incorporated asymmetric loss structures, particularly in LSTM- and attention-based architectures, to penalize certain forecasting errors more heavily and thereby reduce operational risk [23, 24]. Such approaches have produced measurable financial gains, including contract-capacity optimization and cost savings under market-specific pricing uncertainty [25, 26].

In the Turkish context, this issue becomes even more important because renewable energy producers operate under an imbalance pricing structure that encourages risk-averse forecasting and bidding behavior [27, 28] Under the imbalance settlement practice applied in Türkiye, positive imbalance prices are commonly calculated as ($min(MCP_t, SMP_t) \times 0.97$), whereas negative imbalance prices are calculated as ($max(MCP_t, SMP_t) \times 1.03$) [8,27], where MCP denotes the Market Clearing Price and SMP denotes the System Marginal Price. Furthermore, Polat et al. [27] and Ozozen et al. [15] highlighted that forecasting quality directly influences financial outcomes for renewable generators operating under this settlement structure, underscoring the need for market-aware evaluation frameworks. Despite this clear asymmetry, the literature remains limited in directly embedding Türkiye's imbalance pricing structure into the learning phase of gradient-based forecasting models for hydropower generation. More broadly, an important tension remains between statistical accuracy and financial usefulness: a model that minimizes conventional regression errors does not necessarily minimize market-related imbalance costs.

Against this background, the present study develops a comparative forecasting framework for a run-of-river hydropower setting and evaluates both the statistical and financial implications of alternative prediction strategies. Using anonymized hourly data from two hydropower plants, the study compares operator-based heuristic forecasts with several machine learning approaches, namely MLP, Random Forest, standard XGBoost, and a CA-XGBoost formulation incorporating an asymmetric loss function. Rather than assuming that a statistically better model is automatically economically superior, the study explicitly examines whether improvements in forecast accuracy translate into lower imbalance-related costs under Turkish market conditions. In this sense, the main contribution of the study is twofold: first, it introduces and tests a market-informed, asymmetric loss formulation within the XGBoost framework as an exploratory variant; second, it evaluates forecasting performance using both conventional statistical indicators and an ex post financial assessment based on hourly market prices. This dual perspective aims to provide a more operationally meaningful basis for decision support in small-scale hydropower forecasting.

2. METHODS

The overall methodological framework of this study is presented in Figure 1. The analysis begins with data preparation and proxy-based feature generation, continues with the development of benchmark and CA-XGBoost forecasting models, and concludes with a two-layer evaluation based on both statistical accuracy and financial performance. In addition, a sensitivity analysis is conducted to examine whether the economic ranking of the models remains stable under alternative market conditions. This structure enables the study to move beyond purely statistical forecasting and to assess the practical implications of forecast errors under the imbalance settlement logic of the Turkish electricity market.

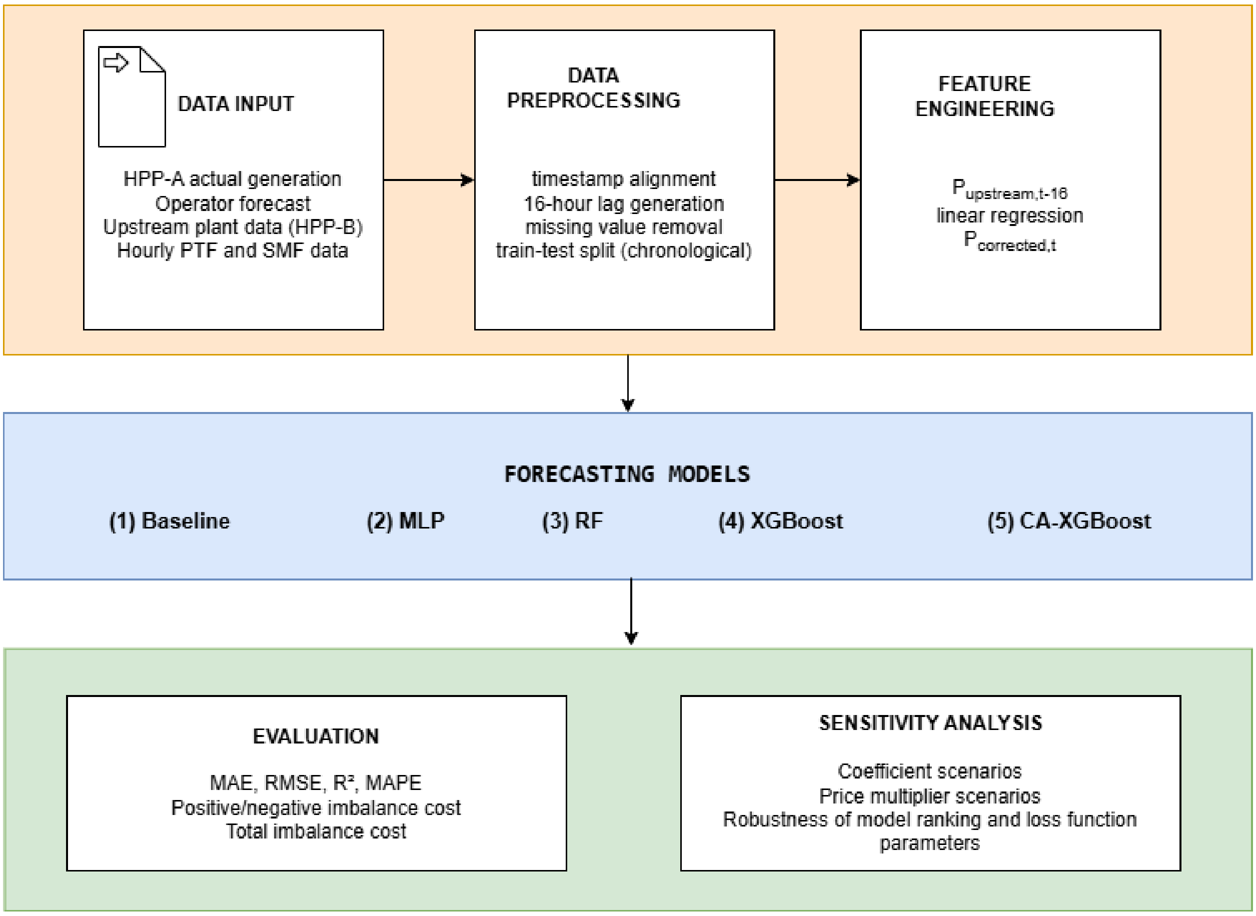

Figure 1. Methodological flow of the study

2.1 Forecasting Models

This study compares the forecasting performance of three benchmark machine learning techniques -Multi-layer Perceptron (MLP), Random Forest (RF), and standard XGBoost -against the operator's heuristic forecasts. In addition, a CA-XGBoost model is introduced in order to examine whether integrating market-oriented asymmetry into the learning objective can improve financial performance under imbalance settlement conditions.

2.1.1 Model Descriptions

- **The MLP model** is a feed-forward artificial neural network capable of capturing nonlinear relationships between inputs and outputs through hidden-layer transformations [30, 31] Owing to its flexibility and ability to approximate complex functional forms, MLP has been widely used in short-term forecasting problems, including applications in electricity and renewable energy [32, 33].
- **The Random Forest model** is a tree-based ensemble learning method that combines the outputs of multiple decision trees in order to improve predictive accuracy and reduce overfitting. By repeatedly sampling both observations and predictor subsets, Random Forest can capture nonlinear and interaction effects in a stable, robust manner [34, 35]. For this reason, it has frequently been employed in electricity-related forecasting tasks [36, 37].
- **The standard XGBoost model** is a gradient-boosting framework in which trees are built sequentially, with each new tree attempting to correct the residual errors of the previous stage. Owing to its strong predictive power, regularization capability, and flexibility, XGBoost has become one of the most widely used machine learning methods in short-term energy forecasting studies [38].
- **Cost-aware XGBoost** The CA-XGBoost approach was implemented within the XGBoost framework because this algorithm allows the direct incorporation of customized objective functions through user-defined gradient and Hessian terms. In contrast, applying an equivalent cost-sensitive learning structure to Random Forest is less straightforward, since its tree-building mechanism does not naturally support explicit modification of the loss function. Similarly, although cost-aware learning can, in principle, be incorporated into neural network models, doing so would generally require a lower-level implementation environment and a fully customized training procedure beyond the standard configuration adopted in this study [39].

2.1.2 Cost-Aware Objective Function

In its standard form, XGBoost minimizes the conventional squared-error loss as given in Eq. 1:

$$L = \frac{1}{2}.(\hat{y} - y)^2 \tag{1}$$

where $\hat{y}$ denotes the predicted production and y denotes the realized production. This loss function treats overestimation and underestimation symmetrically. However, in electricity-market applications, forecast deviations do not necessarily have symmetric financial consequences.

To reflect this asymmetry, a modified cost-aware objective was introduced. Let $r = \hat{y} - y$ denote the forecast residual. The piecewise loss function is expressed as in Eq. 2:

$$L(r) = \begin{cases} c_{over} . r^2, & if\ r > 0 \\ c_{under} . r^2, & if\ r \leq 0 \end{cases} \tag{2}$$

In this study, the penalty parameters were set as $c_{over} = 1.0$ and $c_{under} = 3.0$, thereby assigning a higher penalty to underestimation than to overestimation. $c_{under} = 3.0$ was selected as an initial approximation of the imbalance cost asymmetry observed in the Turkish market, where underestimation penalties generally exceed overestimation costs. The robustness of this choice is examined in Section 4.4. This formulation was intended to alter the directional error structure of the model in accordance with market-related imbalance risk. Accordingly, the CA- XGBoost model should be interpreted as an exploratory cost-aware learning formulation designed to test whether an asymmetric training objective can improve financial outcomes.

2.2 Performance Evaluation and Financial Metrics

The forecasting framework was evaluated from two complementary perspectives: statistical performance and financial performance. This dual evaluation structure was adopted in order to determine not only whether the machine learning models improve predictive accuracy, but also whether these improvements translate into lower imbalance-related market costs.

2.2.1 Statistical metrics

Traditional regression-based performance indicators were used to quantify the discrepancy between actual generation y_t and forecasted generation $\widehat{y_t}$.

The Mean Absolute Error (MAE) measures the average absolute deviation between predicted and realized values, shown in Eq. 3:

$$\mathrm{MAE} = \frac{1}{n} . \sum_{t=1}^{n} |\widehat{y_t} - y_t| \tag{3}$$

The Root Mean Square Error (RMSE) gives greater weight to larger deviations and is defined as given in Eq. 4:

$$RMSE = \sqrt{[\frac{1}{n}.\sum_{t=1}^{n}(\widehat{\mathrm{y_t}} - \mathrm{y_t})^2]} \tag{4}$$

The coefficient of determination (R^2) indicates the proportion of variance in the realized generation explained by the forecasting model:

$$R^2 = 1 - \frac{\sum_i (y_i - \widehat{y_i})^2}{\sum_i (y_i - \bar{y})^2} \tag{5}$$

where $\bar{y}$ denotes the mean of the realized generation values in Eq. 5.

2.2.2 Financial evaluation metrics

In addition to statistical performance, this study evaluates the financial consequences of forecast errors under actual market conditions. For this purpose, hourly market data obtained from EPIAS's Transparency Platform were used to translate forecast deviations into imbalance-related costs [40,41].

For each observation, the forecasted production value was compared with the realized production. When forecasted generation exceeded realized generation, the deviation was treated as a positive imbalance; when realized generation exceeded forecasted generation, the deviation was treated as a negative imbalance. Since imbalance pricing is asymmetric, the financial impact depends not only on the magnitude of the deviation but also on its direction and the hourly market price conditions.

The imbalance pricing structure was modeled using hourly Market Clearing Price (MCP) and System Marginal Price (SMP) values. Accordingly, the positive imbalance price and negative imbalance price were defined as below and given respectively in Eq. 6 and Eq. 7:

$$P_t^+ = min(MCP_t, SMP_t) \times 0.97 \tag{6}$$

$$P_t^- = max(MCP_t, SMP_t) \times 1.03 \tag{7}$$

Using this structure, the hourly imbalance cost was calculated as given in Eq. 8:

$$Total\ Cost = \sum_{t=1}^{n} Cost_t \tag{8}$$

To facilitate comparison across models, Eq. 9 is defined as the relative cost reduction with respect to the operator-based baseline:

$$Cost\ reduction = \frac{C_{baseline} - C_{model}}{C_{baseline}} \times 100 \tag{9}$$

This metric constitutes the primary economic decision criterion in the study, since it directly reflects the financial burden created by forecasting errors under the imbalance settlement structure of the market. The financial evaluation is conducted using hourly MCP and SMP data obtained from EPİAŞ's Transparency Platform for a recent market period, rather than the historical period from which the production forecasting data were drawn. This methodological choice was deliberate. The primary objective of the financial analysis is not to reconstruct the original settlement costs incurred during the data collection period, but rather to assess the financial consequences of each model's error structure under current market rules and price conditions. The imbalance settlement coefficients (0.97 and 1.03) are defined by regulation and remain structurally unchanged. While the absolute cost figures are naturally sensitive to the prevailing price level, the relative ranking of models is primarily driven by the directional and magnitude characteristics of their forecast errors. Current market prices were therefore selected to ensure that the absolute financial magnitudes reported reflect a realistic and policy-relevant benchmark. This approach is consistent with scenario-based financial evaluation frameworks employed in related literature [5,6,25,26], and its implications are further examined through the sensitivity analysis presented in Section 3.2.3.

3. APPLICATION

3.1 Data Description and Preprocessing

In the Turkish day-ahead market, participants must submit their bids for the following day before actual generation conditions are realized. As a result, accurate production forecasting is essential, since deviations between scheduled and realized generation may lead to imbalance exposure and associated financial consequences.

The empirical basis of this study consists of operational data obtained from two interrelated run-of-river hydropower plants located in the same river basin in Türkiye. To preserve commercial confidentiality, these plants are anonymized as HPP-A and HPP-B. HPP-A serves as the primary forecasting target of the study, whereas HPP-B serves as the upstream reference plant. HPP-A operates three identical generation units, each with an installed capacity of 3.2 MW, for a total of 9.6 MW. As a run-of-river plant with negligible storage capability, its production depends directly on the instantaneous river discharge.

The raw dataset consists of approximately one year of consecutive hourly observations. Three main variables are used in the forecasting framework and are summarized in Table 1.

Table 1. Primary variables used in the study

Variable	Definition
Actual Generation (P_{actual})	The realized hourly electricity production of HPP-A.
Operator's Forecast (F_{base})	The day-ahead production schedule submitted by the plant operator; used as the baseline forecast.
Upstream Reference ($P_{upstream}$)	The realized generation of HPP-B, which is located upstream of HPP-A.

A key characteristic of the study area is the hydraulic travel time between the two plants. Historical flow and production patterns indicate that the water discharged from HPP-B reaches HPP-A with an average delay of approximately 16 hours. Therefore, the generation of HPP-B lagged by 16 hours is used as a hydrological proxy for the downstream plant. This transformation is expressed as in Eq. 10:

$$X_{lagged,t} = P_{upstream,t-16} \tag{10}$$

This proxy-based structure was intentionally adopted to reflect a realistic operational setting in which detailed meteorological, hydrological, or flow-rate measurements may not be readily available. In such conditions, upstream generation data can serve as a practical surrogate variable, implicitly capturing temporal and spatial patterns of river flow behavior [29]. Accordingly, the forecasting framework was designed as a parsimonious and operationally transferable approach, particularly suitable for data-constrained small hydropower plants.

Since the plant operator's submitted forecast may contain systematic bias due to human judgment and heuristic estimation, a correction stage was introduced. A linear regression model was fitted between lagged upstream generation and HPP-A's realized production. The resulting coefficients, α and β, were then used to transform the upstream reference series into a corrected predictor in Eq. 11:

$$P_{corrected,t} = \alpha . P_{upstream,t-16} + \beta \tag{11}$$

This corrected series serves as a normalized estimate of HPP-A's potential production and constitutes the second core predictor used in the machine learning models.

After feature generation, rows containing null values were removed to preserve a contiguous, reliable dataset. These missing values were associated not only with the 16-hour lag structure but also with operational interruptions such as maintenance periods and outage-related gaps. After preprocessing, the final dataset contained 8,706 hourly observations, corresponding to approximately 363 days of usable data.

To preserve the temporal structure of the time series, the processed dataset was partitioned chronologically rather than randomly. The first 80% of the observations were used for training, model calibration, and hyperparameter tuning, whereas the remaining 20% were reserved for out-of-sample testing. The final feature matrix used in the forecasting models consisted of two variables: the operator-based forecast (F_{base}) and the corrected upstream proxy($P_{corrected}$). To improve transparency regarding the data structure, Table 2 presents a representative sample of six consecutive observations from the processed dataset, illustrating the input and output variables used in the forecasting framework. Exact timestamps are withheld to preserve commercial confidentiality. (P_{actual}: realized hourly generation of HPP-A; F_{base}: operator's day-ahead forecast; $P_{upstream}$: realized generation of HPP-B; $X_{lagged,t}$: upstream generation lagged by 16 hours (Eq. 10); $P_{corrected}$: regression-corrected upstream proxy (Eq. 11).

3.2 Model Implementation

3.2.1 Hyperparameter Optimization

All benchmark models were optimized using an exhaustive grid search strategy (GridSearchCV) combined with time-series-aware cross-validation. Specifically, TimeSeriesSplit with five folds (k=5) was employed in order to preserve the temporal ordering of observations and prevent data leakage between training and validation periods. Hyperparameter tuning was performed only on the training set, and Mean Absolute Error (MAE) was used as the optimization criterion, consistent with the primary statistical evaluation framework adopted in this study.

Table 2. Sample observations from the processed dataset (first six rows after preprocessing)

Timestamp (t)	P_{actual} (MW)	F_{base} (MW)	$P_{upstream}$ (MW)	$X_{lagged,t}$ (MW)	$P_{corrected}$ (MW)
16:00	2.452	2.400	3.381	2.001	3.603
17:00	2.336	2.200	3.053	1.949	3.341
18:00	2.342	2.200	2.812	2.208	3.166
19:00	2.308	2.200	2.622	2.398	2.904
20:00	2.320	2.200	2.622	2.449	2.555
21:00	2.710	2.200	2.415	2.363	2.555

The explored hyperparameter search spaces are summarized in Table 3. For the MLP model, the search included hidden-layer configurations, activation functions, regularization strength, and initial learning rate. For Random Forest, the number of estimators, maximum tree depth, and minimum sample constraints were varied. For standard XGBoost, the grid included the number of estimators, tree depth, learning rate, subsampling ratio, and column sampling ratio. The cost-aware XGBoost model was not subjected to an independent hyperparameter search; instead, it inherited the optimal configuration identified for the standard XGBoost model, while replacing the conventional squared-error objective with the asymmetric piecewise loss function defined in Eq. (2). This design ensured that any observed difference between the two XGBoost variants could be attributed to the learning objective itself rather than to differences in model structure or regularization settings.

Table 3. Hyperparameter search spaces and optimization settings

Model	Search Strategy	CV Scheme	Metric	Hyperparameter Space
MLP	Grid Search	TSS (k=5)	MAE	hidden_layer_sizes ={(20,), (30,30), (50,30)}; activation = {relu, tanh}; α ={0.0001, 0.001}; learning_rate_init = {0.001, 0.01}
Random Forest	Grid Search	TSS (k=5)	MAE	n_estimators ={200, 300}; max_depth = {5, 8, None}; min_samples_split ={2, 5, 10}; min_samples_leaf = {1, 2, 4}
XGBoost	Grid Search	TSS (k=5)	MAE	n_estimators ={200, 300}; max_depth = {3, 4, 6}; learning_rate = {0.03, 0.05, 0.1}; subsample = {0.8, 0.9, 1.0}; colsample_bytree = {0.8, 0.9, 1.0}
CA-XGBoost	--	--	--	Inherited from XGBoost; objective replaced by Eq. (2); $c_{over} = 1.0$, $c_{under} = 3.0$

3.2.2 Optimized Parameters

In this study, the benchmark machine learning models and the CA-XGBoost model were implemented in Python using the Scikit-learn and XGBoost libraries. To ensure reproducibility and transparent benchmarking, the optimized model configurations are summarized in Table 4.

Table 4. Model parameters and configurations

Model	Parameters
MLP	Hidden layer size = 20; activation = ReLU; learning rate = 0.001; alpha = 0.001
Random Forest	(n_estimators=300); (max_depth=5); (min_samples_split=2); (min_samples_leaf=1)
XGBoost	(n_estimators=300); (max_depth=4); (learning_rate=0.1); (subsample=1.0); (colsample_bytree=0.8)
CA-XGBoost	(n_estimators=300); (max_depth=4); (learning_rate=0.1); (subsample=1.0); (colsample_bytree=0.8); (c_{over}=1.0); (c_{under}=3.0)

3.2.3 Sensitivity analysis

To further examine the robustness of the financial evaluation, a sensitivity analysis was conducted under alternative market conditions. This analysis was designed to test whether the relative economic performance of the forecasting models remained stable across varying imbalance settlement structures and market price levels.

Two market-level sensitivity dimensions were considered. First, the imbalance settlement coefficients were varied across multiple scenarios to represent alternative degrees of asymmetry in the pricing of positive and negative imbalances. Second, hourly market prices were proportionally scaled using different multipliers to simulate lower and higher price regimes. For each scenario, total imbalance costs were recalculated for all forecasting models while keeping the underlying forecast values unchanged. This procedure enabled an assessment of whether the economic ranking of the models remained robust across different regulatory and market conditions.

In addition, a model-specific sensitivity analysis was performed for the cost-aware XGBoost formulation. Since the proposed asymmetric objective depends on the penalty parameters c_{over} and c_{under}, the robustness of the selected baseline configuration was further examined by varying c_{under} across a predefined range while holding cover constant. This additional analysis was designed to determine whether the observed performance of the cost-aware formulation was driven by a specific parameter choice or reflected a broader behavioral pattern of the asymmetric loss structure.

Finally, an auxiliary asymmetry analysis was conducted using the hourly MCP and SMP values in the dataset. For each time step, positive and negative imbalance unit costs were computed in order to examine the degree of directional market asymmetry at the unit-cost level. This analysis was not used for model training, but served to provide an empirical reference point for interpreting the asymmetric weighting adopted in the cost-aware objective.

4. RESULTS

4.1 Statistical Performance and the Accuracy Paradox

To enhance the predictive information available for the downstream plant, an upstream forecast correction step was first implemented. Based on the relationship between the lagged upstream series and realized production, the corrected upstream predictor was obtained as defined in Equation (11), with the estimated coefficients $\alpha = 1.0037$ and $\beta = 0.1073$. ($P_{corrected,t} = 1.0037 \times P_{upstream,t-16} + 0.1073$). This result indicates that the upstream series was already closely aligned with downstream production dynamics, while still benefiting from a modest linear calibration before being incorporated into the comparative forecasting framework. The coefficient $\alpha = 1.0037$ suggests a near-unity scaling relationship between the upstream and downstream plants, while the small intercept $\beta = 0.1073$ reflects a minor systematic offset, confirming that the hydraulic proxy captures downstream generation dynamics with high fidelity.

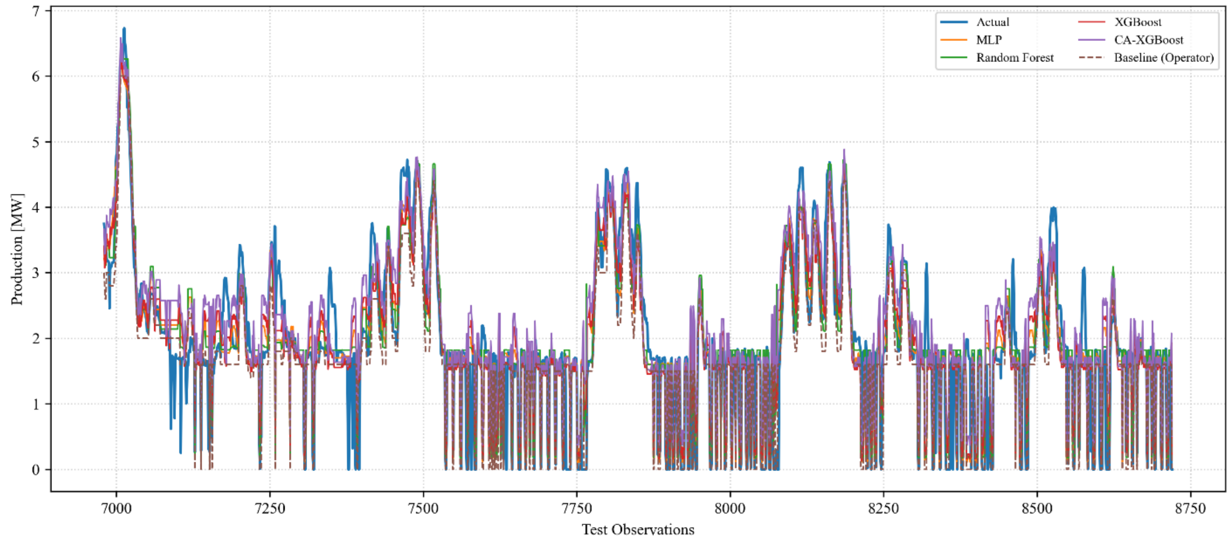

Figure 2. Actual vs. Predicted graph for the implemented models

Figure 2 compares the actual generation series with the predicted values produced by the operator-based baseline and the implemented machine learning models over the test period. The statistical performance of the implemented models is summarized in Table 5 using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) and training time (t). Training times are approximate and reflect the mean of several independent runs on the same hardware; variations across runs are expected due to parallel processing.

Table 5. Statistical performance of the forecasting models

Model	MAE	RMSE	R^2	Time (s)
Random Forest	0.3594	0.5871	0.766	51.6
MLP	0.3701	0.5827	0.770	23.7
Baseline	0.4024	0.6318	0.729	0.0
XGBoost	0.4356	0.6154	0.743	34.8
CA-XGBoost	0.4932	0.6702	0.700	0.6

From a purely statistical perspective, the results reveal a notable divergence among conventional accuracy indicators. The MLP model achieved the lowest RMSE (0.5827) and the highest R^2 (0.7695), indicating the strongest overall fit to the observed generation series. However, the Random Forest model yielded the lowest MAE (0.3594), suggesting that it was more effective in minimizing the average absolute forecasting deviation. By contrast, the operator-based baseline performed worse than both MLP and Random Forest across the principal statistical metrics, with an MAE of 0.4024, an RMSE of 0.6318, and an R^2 of 0.7291. The standard XGBoost model remained slightly superior to the baseline in terms of (R^2), yet it did not match the performance of MLP or Random Forest. The CA-XGBoost model produced the weakest statistical results overall, yielding the highest MAE and RMSE and the lowest (R^2) among all tested approaches.

These findings illustrate what may be described as an accuracy paradox in forecasting evaluation. Although the MLP model achieved the best RMSE and (R^2), it did not produce the best MAE. Conversely, Random Forest yielded the lowest MAE but did not dominate all statistical indicators simultaneously. This divergence suggests that no single metric is sufficient to fully characterize forecasting quality, particularly in operational settings where the distribution, direction, and consequences of forecast errors may matter as much as their average magnitude. In other words, a model that appears statistically superior according to one metric may not necessarily be the most advantageous when evaluated from a broader operational or economic perspective.

In terms of computational efficiency, the baseline operator forecast requires negligible processing time as it involves no model training. Among the machine learning models, MLP completed the hyperparameter optimization in approximately 23.7 seconds, while Random Forest and standard XGBoost required 51.6 and 34.8 seconds respectively, due to their larger search spaces. The CA-XGBoost model, by contrast, required only 0.6 seconds, as it does not undergo an independent hyperparameter search but instead inherits the optimal configuration identified for the standard XGBoost and replaces only the objective function. These differences should be interpreted in the context of an offline training setting, where computational cost is a secondary concern relative to forecast quality.

Overall, the statistical analysis shows that Random Forest and MLP consistently outperform the operator's heuristic forecasts, thereby confirming the value of data-driven forecasting for hydropower scheduling. At the same time, the results demonstrate that improvements in statistical accuracy do not automatically imply superiority under all evaluation criteria. This observation forms the basis for the next stage of the analysis, in which the models are further examined from a financial perspective under the imbalance settlement structure of the electricity market.

4.2 Financial Performance and Economic Efficiency

The financial evaluation provides a more application-oriented perspective by examining how forecast errors translate into imbalance-related market costs under hourly settlement conditions. In contrast to the statistical assessment, which focuses on predictive accuracy through indicators such as MAE, RMSE, and (R^2), this stage evaluates the practical market consequences of forecast deviations by distinguishing between positive and negative imbalance amounts and their corresponding financial impacts. The cost comparison of the alternative forecasting approaches is presented in Figure 3 and Table 6.

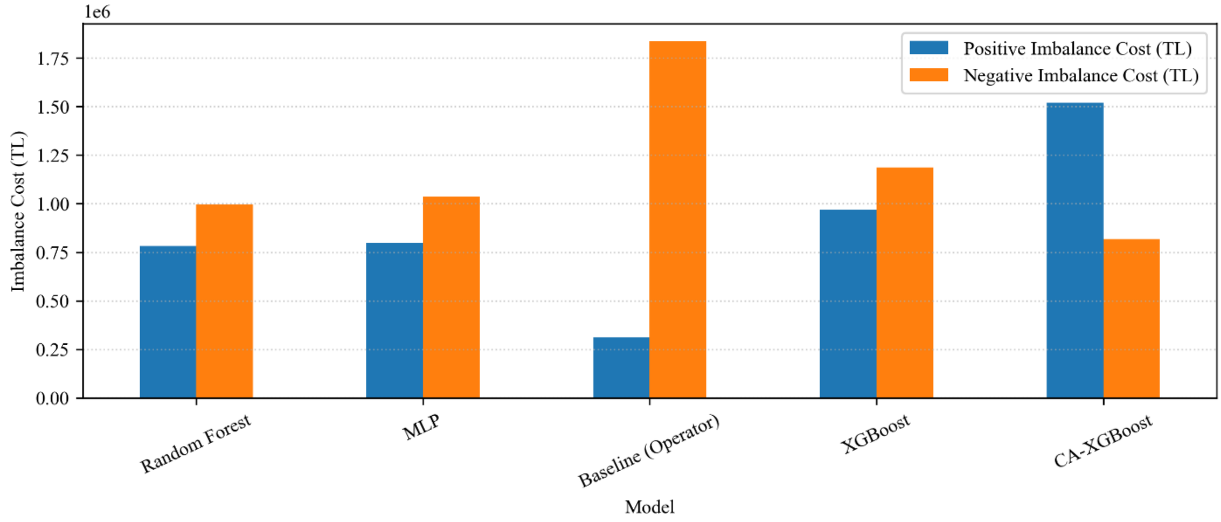

Figure 3. Positive and negative imbalance costs for the implemented models

Table 6. Financial performance of the forecasting models

Model	Positive Imbalance Cost (TL)	Negative Imbalance Cost (TL)	Total Imbalance Cost (TL)	Cost Reduction vs. Baseline (%)
Random Forest	781475.78	997195.28	1778671.07	17.15
MLP	797905.90	1035677.04	1833582.94	14.60
Baseline	312880.96	1834090.38	2146971.34	0.00
XGBoost	970541.69	1186720.37	2157262.06	-0.48
CA-XGBoost	1517465.09	817384.51	2334849.60	-8.76

The results indicate that the Random Forest model achieved the best overall economic performance. It produced the lowest total imbalance cost, amounting to 1,778,671 TL, corresponding to a 17.15% reduction relative to the operator-based baseline, as calculated using

Eq.(9). This improvement was primarily driven by a substantial reduction in negative imbalance volume, which decreased from 575.69 MWh in the baseline case to 314.16 MWh. Since negative imbalances are settled under less favorable conditions, this reduction had a pronounced effect on total market cost.

The MLP model also delivered strong financial results, generating a total imbalance cost of 1,833,583 TL and achieving a 14.60% cost reduction compared with the baseline forecasts. Although the MLP model showed the best statistical fit in terms of RMSE and (R^2), it remained slightly less efficient than Random Forest from a financial standpoint. This again indicates that superior statistical performance does not necessarily translate into the lowest economic burden under imbalance settlement rules.

The standard XGBoost model did not provide a meaningful financial advantage. Its total imbalance cost reached 2,157,262 TL, which is marginally higher than the baseline cost of 2,146,971 TL, corresponding to a 0.48% increase rather than a reduction. Although this model remained competitive from a statistical perspective, its error structure appears to have been less favorable in economic terms, particularly with respect to the balance between positive and negative deviations. The CA-XGBoost model yielded the weakest financial outcome among all tested approaches. Despite being specifically designed to internalize asymmetric market penalties, it resulted in a total imbalance cost of 2,334,850 TL, which is 8.75% higher than the operator baseline. Interestingly, this model reduced the negative imbalance amount to 259.45 MWh, the lowest value among all alternatives, but at the same time produced a very large positive imbalance amount of 599.18 MWh. As a result, the increase in positive imbalance cost outweighed the savings associated with the lower negative imbalance exposure. This finding suggests that the asymmetric learning mechanism, in its current configuration, overcompensated in one error direction and therefore did not achieve the intended economic improvement.

A more detailed comparison between the baseline forecasts and the machine learning models further highlights the asymmetric structure of market costs. In the baseline case, the total positive imbalance cost was limited to 312,881 TL, whereas the negative imbalance cost reached 1,834,090 TL. This imbalance confirms that the operator's heuristic forecasts were particularly vulnerable to costly negative deviations. By contrast, Random Forest and MLP achieved a more balanced error structure, substantially lowering negative imbalance costs while maintaining positive imbalance costs at manageable levels. Accordingly, their economic superiority arises not merely from lower forecast errors in a statistical sense, but from generating deviations that are financially less harmful under actual market settlement conditions.

Overall, the financial analysis shows that Random Forest is the most effective approach when economic efficiency is used as the primary decision criterion. MLP represents a strong alternative, while both standard and CA-XGBoost configurations remain less attractive in terms of total cost. These findings reinforce the main argument of the study: forecasting methods in electricity-market applications should be evaluated not only according to statistical accuracy, but also according to the financial implications of their error structure under real market pricing mechanisms.

4.3 Error Distribution and Risk Profile Analysis

Figure 4 illustrates the residual density distributions of the benchmark and cost aware models, where residuals are defined as $(Actual - Predicted)$. Under this definition, positive residuals indicate underestimation, whereas negative residuals indicate overestimation. Unlike summary error metrics, this figure reveals the directional behavior and dispersion of forecast errors, thereby providing additional insight into the operational risk profile of each model.

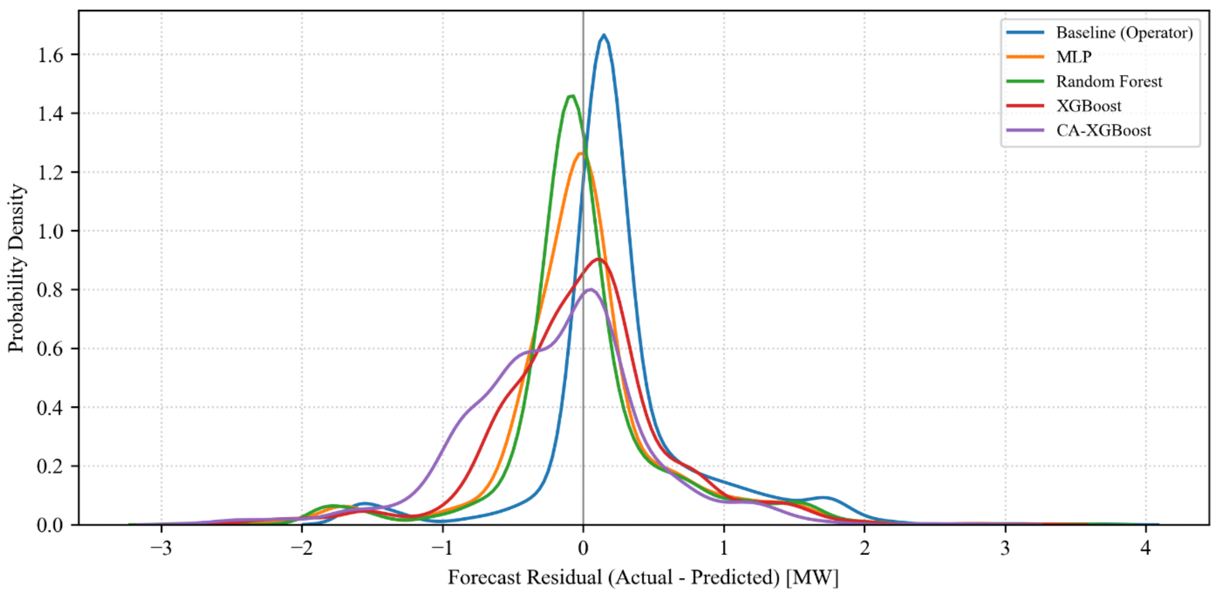

Figure 4. Residual for each forecasting methods

The baseline forecasts exhibit a more noticeable rightward shift, indicating a stronger tendency toward underestimation. In contrast, Random Forest and MLP produce residual distributions that are more concentrated around zero, suggesting a more balanced and stable forecasting structure. Among them, Random Forest appears to yield the most compact distribution, which is consistent with its superior MAE performance. The standard XGBoost model shows a broader spread, indicating weaker control over forecast deviations. The proposed cost-aware XGBoost model displays the most pronounced asymmetry, implying that the asymmetric learning mechanism altered the directional error structure, even though it did not improve the overall financial outcome. Overall, the figure confirms that model evaluation should not rely solely on aggregate performance metrics. In electricity-market forecasting, the distribution and direction of forecast errors are also critical, since they directly shape the financial risk associated with imbalance settlement.

4.4 Sensitivity Analysis under Variable Market Conditions

To further evaluate the robustness of the forecasting framework, a sensitivity analysis was conducted under alternative market conditions. First, the imbalance settlement coefficients were varied between 1% and 10% in order to test whether changes in the penalty structure would alter the relative performance of the competing models (Figure 5). Second, hourly market prices were proportionally scaled by multipliers of 0.8, 1.0, and 1.2 to represent lower, baseline, and higher price environments, respectively (Figure 6).

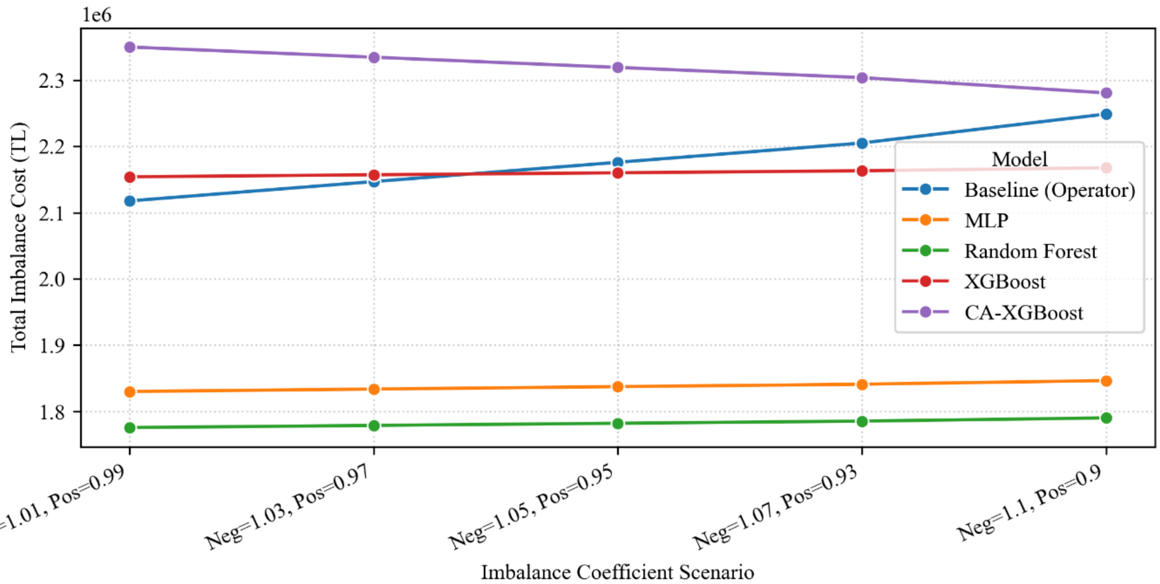

Figure 5. Sensitivity analysis to imbalance coefficients

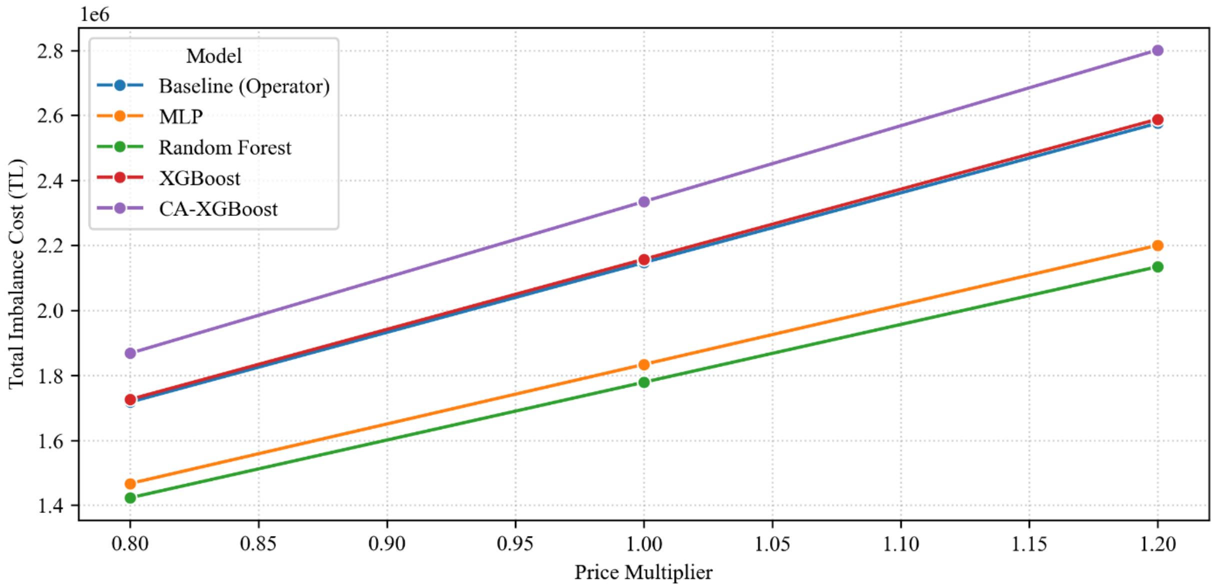

Figure 6. Sensitivity analysis to price multipliers

The results show that the relative ranking of the models remained unchanged across all coefficient scenarios. In every case, the Random Forest model yielded the lowest total imbalance cost, followed by MLP, while the operator-based baseline and the two XGBoost variants remained less efficient. This indicates that the economic advantage of Random Forest is not limited to the current imbalance settlement parameters but persists even when the regulatory penalty structure becomes either milder or more severe.

A similar pattern was observed in the price-level sensitivity analysis. Although total imbalance costs increased proportionally as the market price multiplier rose from 0.8 to 1.2, the ranking of the models remained fully stable. The Random Forest model consistently produced the lowest total cost, while the proposed cost-aware XGBoost remained the weakest performer in all price environments. This finding suggests that the financial superiority of Random Forest is robust not only to changes in imbalance coefficients but also to fluctuations in the general price level of the market.

Another notable result concerns the proposed cost-aware XGBoost model. As the negative imbalance coefficient increased and the positive imbalance coefficient decreased, its total cost gradually declined relative to its own base-case scenario. This pattern indicates that the asymmetric learning mechanism did indeed alter the directional error profile of the model. However, this adjustment was still insufficient to outperform the benchmark machine learning models or even the operator baseline. Therefore, while the proposed approach appears sensitive to regulatory asymmetry, its current formulation does not translate this sensitivity into economic superiority.

Overall, the sensitivity analysis confirms that the main conclusions of the study are stable under a wide range of alternative market assumptions. In particular, the Random Forest model preserves its leading position across all tested penalty and price regimes, thereby demonstrating the strongest robustness from an economic perspective.

As described in Section 2.1.2, the baseline configuration was set to $c_{under} = 3.0$ based on the asymmetric penalty structure of the market. To evaluate whether this specific value drives the observed underperformance, or whether it reflects a broader behavioral pattern of the asymmetric loss function, c_{under} was varied across a wider range {1.0, 1.5, 2.0, 2.5, 3.0, 4.0, 5.0} while keeping c_{over} fixed at 1.0. The results are presented in Figures 7 and 8. In Figure 7, the left panel shows total imbalance cost (TL) and the right panel shows MAE (MW) across $c_{under} \in \{1.0, 1.5, 2.0, 2.5, 3.0, 4.0, 5.0\}$, with c_{over} fixed at 1.0. The dashed red line indicates the baseline configuration used in the main analysis ($c_{under} = 3.0$) both in Figure 7 and 8.

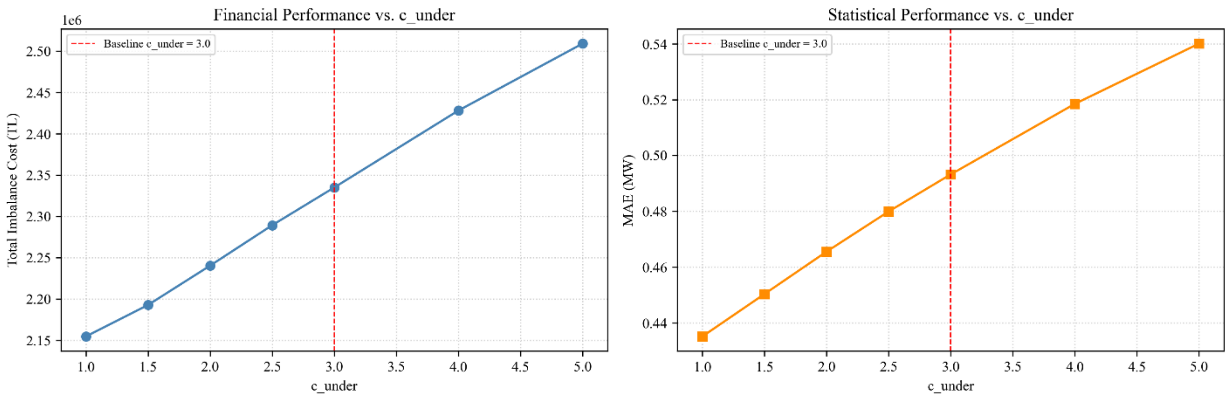

Figure 7. Sensitivity of CA-XGBoost performance to the c_{under} penalty parameter.

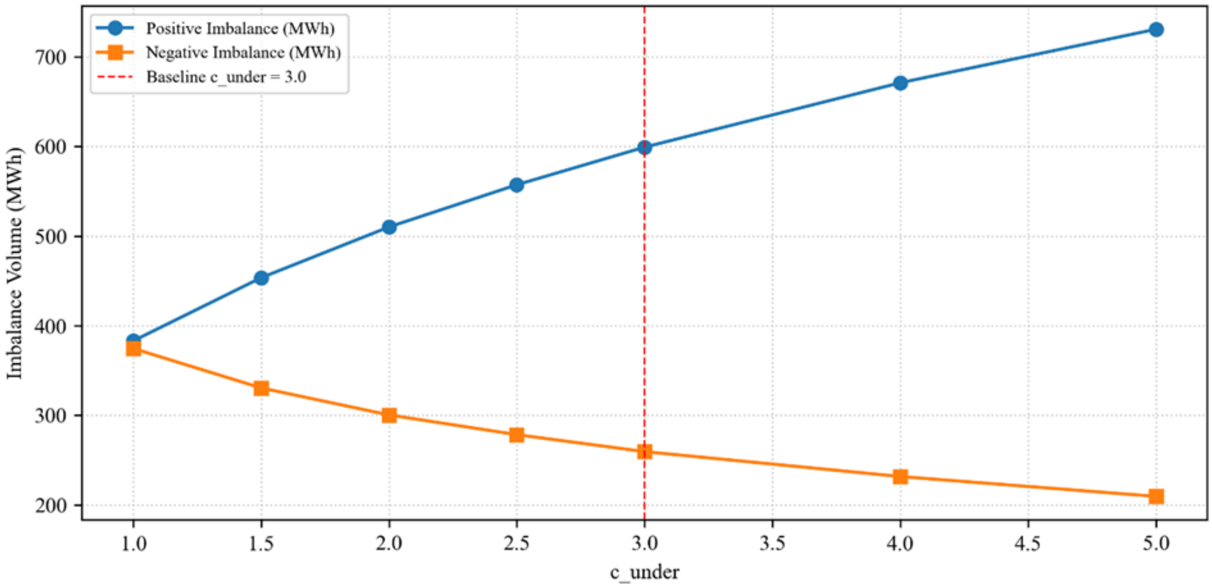

Figure 8. Effect of the c_{under} penalty parameter on positive and negative imbalance volumes (MWh) for the CA-XGBoost formulation.

As shown in Figure 7, both total imbalance cost and MAE increase monotonically as c_{under} rises. The lowest financial cost is observed at c_{under} = 1.0, which corresponds to a symmetric loss formulation equivalent to standard XGBoost, while performance deteriorates continuously at higher penalty levels. This pattern indicates that the underperformance of the CA-XGBoost formulation is not a consequence of a suboptimal parameter choice; rather, it reflects a systematic limitation of the asymmetric learning mechanism under the present data and market conditions. As illustrated in Figure 8, increasing c_{under} progressively shifts the model's error structure toward overestimation: positive imbalance volume rises from approximately 385 MWh at c_{under} = 1.0 to approximately 730 MWh at c_{under} = 5.0, while negative imbalance volume declines from approximately 380 MWh to approximately 210 MWh over the same range. Although the asymmetric objective successfully suppresses underestimation as intended, the resulting overestimation creates a compensating cost burden that more than offsets any reduction in negative imbalance penalties. This overcompensation effect explains why no value of c_{under} tested in this analysis produced a financial outcome superior to the symmetric benchmark. These findings reinforce the conclusion that the directional correction induced by asymmetric loss functions does not automatically translate into financial improvement, and suggest that more nuanced formulations -such as dynamic penalty adaptation or price-conditional weighting- may be required to achieve economically meaningful gains.

To further examine the degree of market asymmetry, an auxiliary analysis was performed using the hourly MCP and SMP values in the dataset. At each time step, positive and negative imbalance unit costs were computed respectively as $(min(MCP_t, SMP_t) \times 0.97)$ and $(max(MCP_t, SMP_t) \times 1.03)$. The resulting hourly cost series revealed that negative imbalance unit costs were consistently higher than positive imbalance unit costs. The mean negative-to-positive unit cost ratio was approximately 2.0, suggesting a clear but moderate asymmetry. Therefore, the 1:3 weighting used in the proposed cost-aware objective should be interpreted as an exploratory asymmetric amplification rather than a direct empirical representation of the realized market cost ratio.

5. CONCLUSION

This study examined whether machine learning-based forecasting approaches can improve production forecasts for a hydropower plant operating under Turkish electricity market conditions, compared with operator-based heuristic estimates. The findings show that data-driven models, particularly Random Forest and MLP, achieved stronger statistical performance than the operator-based baseline. The financial evaluation further demonstrated that these improvements in predictive accuracy can translate into meaningful reductions in imbalance-related market costs. Among the tested alternatives, Random Forest yielded the most favorable overall results from an economic perspective, while MLP also showed strong, consistent performance.

An important contribution of the study is the distinction it establishes between statistical accuracy and economic effectiveness. The results indicate that the model with the best statistical fit is not necessarily the one associated with the lowest financial cost. This observation is especially relevant for electricity-market applications, where the magnitude, direction, and distribution of forecast errors have direct market implications. In this respect, the study extends conventional forecasting evaluation beyond standard statistical metrics by incorporating an operationally meaningful financial assessment based on hourly market prices and asymmetric imbalance pricing.

The study also introduced a CA-XGBoost formulation designed to internalize the asymmetric penalty structure of the market. Although the cost aware approach did not outperform the benchmark models, it provided useful evidence on how asymmetric objective functions can reshape the directional structure of forecast errors. Its results suggest that embedding market-oriented asymmetry directly into the learning objective can alter the directional structure of forecast errors, even if this does not automatically produce superior economic performance. Therefore, the cost aware approach should be interpreted as an exploratory contribution that may guide future methodological refinement.

It should be noted that the piecewise quadratic loss function employed in this study assigns fixed, time-invariant penalty weights to overestimation and underestimation errors. However, the actual financial cost of forecast deviations varies on an hourly basis depending on the prevailing MCP - SMP spread. This static formulation may partly explain the observed overcompensation effect, as the model cannot distinguish between hours in which underestimation is highly costly and hours in which the cost differential is negligible. Alternative formulations -such as a loss function weighted by the hourly imbalance price differential, or quantile-based objectives targeting specific conditional error quantiles- could potentially address this limitation by introducing time-varying or distributional sensitivity into the learning objective. Exploring such formulations remains a direction for future research.

Overall, the findings demonstrate that machine learning-based forecasting can improve both the statistical and economic performance of hydropower production estimates in market-oriented electricity systems. More importantly, the study shows that forecasting models should not be assessed solely on accuracy metrics, but also on the financial consequences of their error structure. From this perspective, the cost aware framework offers a practical and financially informed decision-support approach for small hydropower plants operating under imbalance risk.

Several limitations should be acknowledged. First, the forecasting dataset is based on operational records from past years, whereas the financial evaluation was conducted under a more recent market price regime. Accordingly, the economic analysis should be interpreted as a scenario-based assessment of the financial consequences of forecast errors under current market conditions, rather than as a reconstruction of the original historical settlement costs. Second, the forecasting framework intentionally relies on a limited set of operationally accessible predictors. Instead of incorporating a broad range of meteorological or hydrological variables, the models use the upstream plant’s forecast and realized production information with a 16-hour lag as a proxy for downstream generation behavior. Although this parsimonious structure does not fully represent all physical drivers of hydropower production, it reflects the type of information that may be readily available to operators in real-world practice.

From a practical and sustainability-oriented perspective, this simplified structure may also be considered a strength. Many small hydropower plants operate with limited data availability and may lack access to advanced meteorological forecasting systems or detailed hydrological modeling infrastructure. In such settings, a forecasting framework based on simple, transferable, and operationally observable proxy variables may offer a more scalable, accessible, and implementable decision-support alternative. In this sense, the contribution of the present study lies not only in predictive improvement but also in demonstrating a lightweight and potentially replicable approach for similar small-scale hydropower facilities.

Future research may build on this study in several directions. First, the proposed framework may be tested across multiple hydropower plants and over longer time horizons to evaluate its robustness under broader operational conditions. Second, the feature space may be enriched by integrating meteorological, hydrological, and reservoir-related variables to provide a more comprehensive representation of the physical determinants of generation. Third, future studies may refine the proposed cost-aware learning mechanism or develop alternative cost-sensitive formulations in order to better align model training with market settlement rules. Finally, applying the framework across a broader group of small hydropower plants would help assess the generalizability of the proxy-based approach and its broader relevance for sustainable, data-efficient energy management.

DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declare that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Meryem N. Morgül Tumbaz: Conceptualization, methodology, investigation, software development, formal analysis, visualization, and writing the original draft of the manuscript.
Mümtaz İpek: Supervision, validation, and reviewing and editing the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Klein SJW, Fox ELB. A review of small hydropower performance and cost. Renewable and Sustainable Energy Reviews 2022; 169: 112898.

[2] Rospriandana N, Burke PJ, Suryani A, Mubarok MH, Pangestu MA. Over a century of small hydropower projects in Indonesia: a historical review. Energy, Sustainability and Society 2023; 30(1): 30.

[3] Zhang Y, Davis D, Brear MJ. Least-cost pathways to net-zero, coupled energy systems: A case study in Australia. Journal of Cleaner Production 2023; 392: 136266.

[4] Du Y, Guo Y, Wang P, Lyu X, Xu Z, Ouyang Y, et al. Pumped Hydro Storage Multi-Market Trading Strategy Considering Electricity Price Forecast Errors. 4th International Conference on Energy Engineering and Power Systems (EEPS); 2024.

[5] Wang J, Zhou Y, Zhang Y, Lin F, Wang J. Risk-averse optimal combining forecasts for renewable energy trading under CVaR assessment of forecast errors. IEEE Transactions on Power Systems 2023; 39(1): 2296-2309.

[6] Gandhi O, Zhang W, Kumar DS, Rodriguez-Gallegos CD, Yagli GM, Yang D, et al. The value of solar forecasts and the cost of their errors: A review. Renewable and Sustainable Energy Reviews 2024; 189: 113915.

[7] Ilseven E, Gol M. Hydro-optimization-based medium-term price forecasting considering demand and supply uncertainty. IEEE Transactions on Power Systems 2017; 33(4): 4074-4083.

[8] Aydogdu A, Tor OB, Guven AN. CVaR-based stochastic wind-thermal generation coordination for Turkish electricity market. Journal of Modern Power Systems and Clean Energy 2019; 7(5): 1307-1318.

[9] Buke B, Sayin M, Tanrisever F. A dynamic multi-level iterative algorithm for clearing European electricity day-ahead markets: An application to the Turkish market. Journal of the Operational Research Society 2024; 75(4): 784-798.

[10] Matsumoto T, Bunn D, Yamada Y. Mitigation of the inefficiency in imbalance settlement designs using day-ahead prices. IEEE Transactions on Power Systems 2021; 37(5): 3333-3345.

[11] Gunduz, S, Ugurlu U, Oksuz I. Data Imputation for Electricity Price Forecasting in the Intraday Market. Avrupa Bilim ve Teknoloji Dergisi 2021; (25): 334-340.

[12] Artantas C. Green Electricity Promotion in Turkey. In: Promotion of Green Electricity in Germany and Turkey: A Comparison with Reference to the WTO and EU Law. Cham: Springer Nature Switzerland; 2023. pp. 169-187.
[13] Emre T. Renewable Energy Transition in Turkiye: The Impact of Solar and Wind Based Capacity Growth on Market Prices and Cost Dynamics. Balkan Journal of Electrical and Computer Engineering 2025; 13(3): 338-345.
[14] Selcuk O, Acar B, Dastan SA. System integration costs of wind and hydropower generations in Turkey. Renewable and Sustainable Energy Reviews 2022; 156: 111982.
[15] Ozozen A, Kayalica MO, Kayakutlu G. Day-ahead power market behavior for a small supplier: case of Turkish market. Environmental Economics 2018; 9(2): 70-79.
[16] Singh U, Vadhera S. Random forest and xgboost technique for short-term load forecasting. 1st International Conference on Sustainable Technology for Power and Energy Systems (STPES); 2022.
[17] Maciejewski D, Mudryk K, Sporysz M. Forecasting Electricity Production in a Small Hydropower Plant (SHP) Using Artificial Intelligence (AI). Energies 2024; 17(24): 6401.
[18] Arifoglu A, Kandemir T. Electricity Price Forecasting in Turkish Day-Ahead Market via Deep Learning Techniques. Mehmet Akif Ersoy University Journal of Economics and Administrative Sciences Faculty 2022; 9(2): 1433-1458.
[19] Yilan Y, Beykent A. Day-Ahead Electricity Price Forecasting Using the XGBoost Algorithm: An Application to the Turkish Electricity Market. Computers, Materials & Continua 2026; 86(1): 1.
[20] Atalay BA, Zor K. An Innovative Approach for Forecasting Hydroelectricity Generation by Benchmarking Tree-Based Machine Learning Models. Applied Sciences 2025; 15(19): 10514.
[21] Bulut M. Improving deep learning forecasting model based on LSTM for Türkiye's hydro-electricity generation. Sakarya University Journal of Computer and Information Sciences 2024; 7(3): 325-337.
[22] Atalan YA, Sahin H, Keskin A, Atalan A. Strategic forecasting of renewable energy production for sustainable electricity supply: A machine learning approach considering environmental, economic, and oil factors in Turkiye. PLOS ONE 2025; 20(8): e0328290.
[23] Siridhipakul C, Vateekul P. Enhance Attentional LSTM Models for Power Consumption Forecasting Using Asymmetric Loss and Renewable Energy Factors. 8th International Conference on Computer and Communications Management; 2020.

[24] Ghanim J, Issa M, Awad M. An asymmetric loss with anomaly detection LSTM framework for power consumption prediction. 21st Mediterranean Electrotechnical Conference (MELECON); 2022.
[25] Lin JL, Zhang Y, Zhu K, Chen B, Zhang F. Asymmetric Loss Functions for Contract Capacity Optimization. Energies 2020; 13(12): 3123.
[26] Wang Z, Mae M, Yamane T, Ajisaka M, Nakata T, Matsuhashi R. Novel Custom Loss Functions and Metrics for Reinforced Forecasting of High and Low Day-Ahead Electricity Prices Using Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) and Ensemble Learning. Energies 2024; 17(19): 4885.
[27] Polat E, Guler MG, Ulukus MY. Renewable GenCo bidding strategy using newsvendor-based neural networks: An example from Turkish electricity market. Electric Power Systems Research 2024; 231: 110301.
[28] Song Y, Yoon Y, Jin Y. Impact Analysis of Price Cap on Bidding Strategies of VPP Considering Imbalance Penalty Structures. Energies 2025; 18(15): 3927.
[29] Shang Y, Xu Y, Shang L, Fan Q, Wang Y, Liu Z. A method of direct, real-time forecasting of downstream water levels via hydropower station reregulation: A case study from Gezhouba Hydropower Plant, China. Journal of Hydrology 2019; 573: 895-907.
[30] Lin R, Zhou Z, You S, Rao R, Kuo CCJ. Geometrical interpretation and design of multilayer perceptrons. IEEE Transactions on Neural Networks and Learning Systems 2022; 35(2): 2545-2559.
[31] Wang S, Hasan M, Lu M. Global sensitivity analysis methodology for construction simulation models: multiple linear regressions versus multilayer perceptions. Journal of Construction Engineering and Management 2024; 150(5): 04024035.
[32] Dralus G, Kusznier MDJ, Dralus J. Application of artificial intelligence algorithms in multilayer perceptron and Elman networks to predict photovoltaic power plant generation. Energies 2023; 16(18): 6697.
[33] Mei J, Wang C, Luo S, Xu W, Deng Z. Short-term wind power prediction based on encoder-decoder network and multi-point focused linear attention mechanism. Sensors 2024; 24(17): 5501.
[34] Gonzalez C, Mira-McWilliams J, Juarez I. Important variable assessment and electricity price forecasting based on regression tree models: Classification and regression trees, Bagging and Random Forests. IET Generation, Transmission & Distribution 2015; 9(11): 1120-1128.

[35] Wang P, Xu K, Ding Z, Du Y, Liu W, Sun B, et al. An online electricity market price forecasting method via random forest. IEEE Transactions on Industry Applications 2022; 58(6): 7013-7021.

[36] Dudek G. A comprehensive study of random forest for short-term load forecasting. Energies 2022; 15(20): 7547.

[37] Magalhaes B, Bento P, Pombo J, Calado MDR, Mariano S. Short-term load forecasting based on optimized random forest and optimal feature selection. Energies 2024; 17(8): 1926.

[38] Beloev HI, Saitov SR, Filimonova AA, Chichirova ND, Babikov OE, Iliev IK. Short-Term Electrical Load Forecasting Based on XGBoost Model. Energies 2025; 18(19): 5144.

[39] Algarvio, H, Couto A, Estanqueiro A. A double pricing and penalties separated imbalance settlement mechanism to incentive self balancing of market parties. 20th International Conference on the European Energy Market (EEM); 2024.

[40] EPIAS. MCP, SMP and Imbalance Price Listing. [Online] Available at: https://seffaflik.epias.com.tr/electricity/electricity-market-reports/mcp-smp-and-imbalance-price-listing (Last Access: 24/02/2026).

[41] EPIAS. 2024 Faaliyet Raporu. 2024. [Online] Available at: https://www.epias.com.tr/epias-kurumsal/faaliyet-raporlarimiz/ (Last Access: 24/02/2026).