Assessing the impact of net-load forecast quality improvement on balancing mechanism

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***Abstract*—The increasing integration of renewable energy sources, storage technologies, and European electricity networks has made the real-time balance of supply and demand increasingly complex for transmission system operators (TSOs). This study explores the impact of improving net-load forecast quality on adjustment costs and grid security, focusing on the optimality of adjustment volumes and timing rather than individual offers. We simulated operator decisions using modeling and gradient boosting methods to predict the need for and magnitude of adjustments. After simulating operations for the year 2023 with baseline data, we applied the same model to synthetic data with reduced forecast errors. Results indicate that a 20% improvement in forecast quality might reduce adjustment costs by 22% for margin adjustments and 2% (€7 million) for last-minute balancing. Additionally, forecasted critical situations decrease by 26%, significantly enhancing grid security assessments. These findings highlight the value of advanced forecasting models in reducing costs and increasing power system reliability forecasts.**

***Index Terms*—Balancing mechanism, Forecasts quality, Security criteria, System imbalance**

I. Introduction

As the French Transmission System Operator (TSO), RTE's primary mission is to ensure the continuous real-time balance between electricity supply and demand (SDB). To achieve this, RTE relies on balancing mechanisms (BM), which primarily involve increasing or decreasing electricity production to match consumption. These adjustments are based on national production and consumption forecasts, enabling RTE to anticipate risks and imbalances. Poor forecasts, however, can have severe consequences for maintaining SDB, potentially jeopardizing system security and incurring higher costs.

The increasing penetration of renewable energy sources, such as photovoltaic and wind power, has significantly complicated the task of production forecasting. These energy sources are inherently variable and subject to uncertainties arising from weather conditions, making accurate predictions more challenging. As a result, the need for adjustments and system flexibility has grown substantially in recent years [1]. Moreover, national balancing mechanisms will face significant disruptions in the coming years. Two main factors drive these challenges: the development of battery storage, which introduces a new layer of complexity to balancing algorithms [2], and the harmonization of balancing processes at the European level [3]. The latter obliges TSOs to adapt to standardized methods and practices, requiring significant operational adjustments.

However, advances in forecasting techniques and artificial intelligence suggest that substantial improvements in forecasting models are achievable [4], [5]. These innovations could address challenges posed by the growing share of renewable energy and the evolving European energy landscape. Improved forecasts promise to enhance the accuracy of predictions for production and consumption, thereby reducing uncertainties and enabling more effective management of imbalances.

As balancing mechanisms face new challenges and opportunities, improving the quality of forecasting models has become increasingly central to their effectiveness. Enhanced forecasts have the potential to better align operational practices with real-time system needs, thereby reducing adjustment costs and bolstering grid security.

In this context, we aim to evaluate the impact of improved forecast quality on adjustment costs and system security.

We focus on two types of adjustments. First, *margin adjustments* ensure RTE has sufficient reserves to cover 99% of the risks and uncertainties that may arise on the grid. Margins are calculated using a convolution-based risk model named MAUI which process is described in Fig. 1. MAUI leverages the outputs of forecasting models to provide RTE with *required margins* at various time horizons, indicating the capacity RTE must maintain for upward or downward adjustments. For example, suppose the *required margin* for upward adjustments at a 15-minute horizon is 1780 MW. In that case, this means that RTE must have sufficient reserves (available margin) to increase national production by 1780 MW, if necessary.

Additionally, RTE calculates *available margins*, representing its effective adjustment capacity within a specified timeframe. When available margins fall short of the required margins, margin adjustments are triggered.

Second, RTE performs *P=C adjustments*, which are last-resort measures to ensure SDB within minutes. These adjustments are activated when the projected imbalance between injections and withdrawals is non-zero, enabling

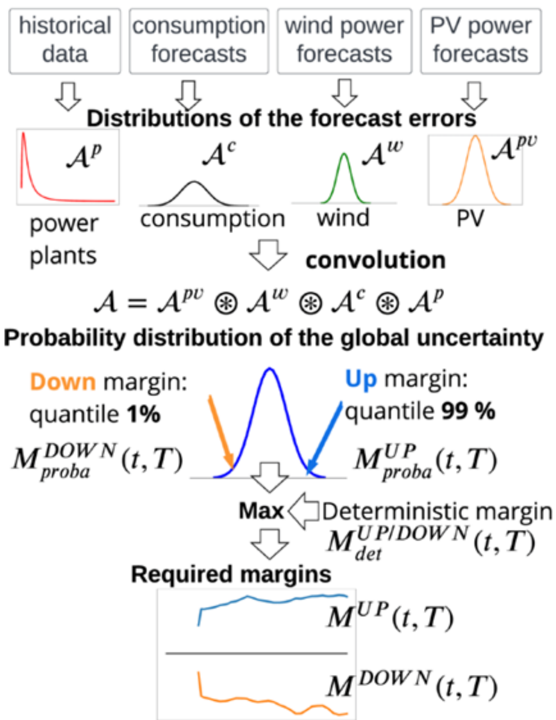

Fig. 1. MAUI process [6]

RTE to restore equilibrium rapidly.

This article contributes to the ongoing discussion on the role of advanced forecasting techniques in supporting grid reliability and cost-effectiveness. By simulating the effects of enhanced forecast quality on RTE's operational decisions, we provide insights into how improved predictions can reduce adjustment costs and forecasted critical situations, ultimately enhancing grid security.

Section II presents the methods used to improve forecast quality and the results of these improvements on margin adjustments. Section III focuses on the P=C adjustments, analyzing how enhanced forecasts impact their magnitude and associated costs. Finally, we conclude with a discussion of the implications of these findings and propose directions for future research.

II. Margin Adjustment

A. Methodology

We first focused on RTE margins: both required and available. Situations in which available margins are, in absolute terms, lower than required margins represent critical risks are referred to as *margin deficit situations*. These deficits occur when RTE can no longer cover 99% of potential uncertainties, as dictated by its safety policy. Minimizing these situations is crucial for grid reliability. It is crucial to understand that following the MAUI process, the value of the margins is directly influenced by the forecast errors of the production and consumption forecast models.

In this section, we artificially improve the forecasts for 2023, simulate the processes for calculating margins and adjustments for margin deficits, and compare the results against historical data. This comparison evaluates how forecast improvements impact adjustments made due to margin deficits.

Our approach to artificially improving forecast quality relies on two techniques. Since we have retrospectively access to actual values, we first bring the forecasts closer to their actual values by a defined percentage (e.g., 20%):

$$\text{forecast}_{\text{new}} = \text{forecast} + \lambda \times \text{error} \tag{1}$$

with

$$\text{error} = \text{observation} - \text{forecast}. \tag{2}$$

Additionally, we reduce the standard deviation of probabilistic forecasts, tightening their distribution and decreasing uncertainty. To reduce the standard deviation, we apply a coefficient:

$$\sigma_{\text{new}} = \sigma \times 0.8 \tag{3}$$

Convoluting these enhanced forecasts gives improved available margins. This process mechanically reduces the number of margin deficit situations since required margins are negatively correlated with the magnitude of forecast model errors, reducing their error can only have this effect. For example, Fig. 2 illustrates this effect: there are three deficit situations under baseline conditions. The dotted blue curve representing the historically available margin crosses the dotted orange curve 3 times: the orange required margin. Conversely, the solid curves representing the situation after improved forecasts no longer cross each other, which shows that, in this example, improved forecast quality makes it possible to avoid certain margin deficits.

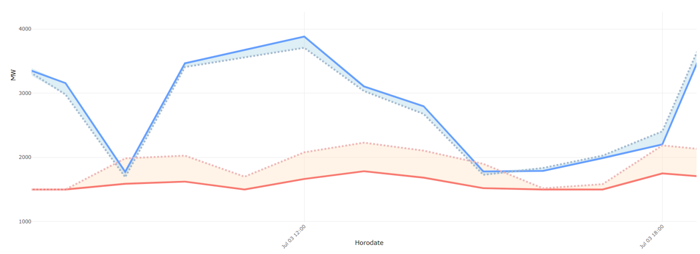

Fig. 2. Original versus improved margin comparison.

B. Results

We obtained the following results by generalizing this procedure across all time steps and horizons for 2023.

The Figure 3 demonstrates the expected negative relationship between reduced margin deficit situations and the level of forecast improvement. The more we drastically improve forecast quality, the more we reduce the number of days margin deficits are recorded. Here, the relationship between the two variables is almost linear. Notably, for upward adjustments, a 20% improvement in forecast quality results in a 26% reduction in margin deficit situations. This finding is significant, as such situations are critical and pose substantial risks to grid stability.

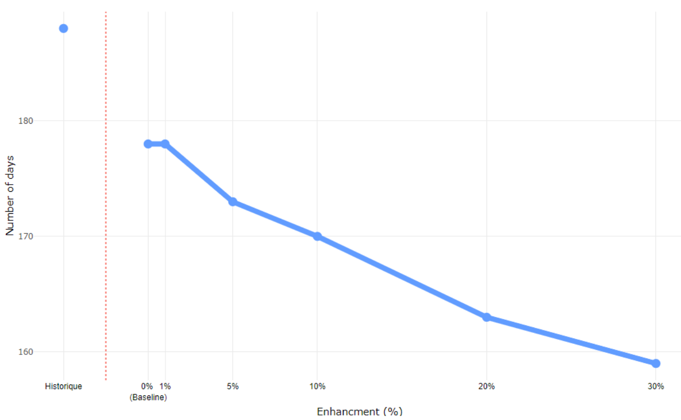

Fig. 3. Number of days with forecasted margin deficit situation given the forecast improvement rate

The reduction in margin deficit situations should theoretically lead to fewer activations of adjustments for margin deficits. However, this relationship is less straightforward in practice, as the link between these two variables is not always clear. The results in table I are less robust due to the limited volume of training data, as margin adjustments for upward deficits are rare and virtually non-existent for downward deficits (e.g., only 3 days across 2023). Despite this, our estimation suggests that a 20% forecast improvement could reduce the cost of upward adjustments by approximately 22%, whereas no significant reduction is observed for downward adjustments.

TABLE I
UPWARDS MARGIN ADJUSTMENT COST ESTIMATION

Scenario	Prices (€)		
	Total Price	Daily Mean Price	Savings
Historical	2,424,000	202,000	-
Estimation	1,886,000	314,000	22%

In conclusion, we demonstrated that a 20% improvement in forecast quality significantly reduces margin deficit situations by 26%, enhancing system security. Furthermore, this reduction in deficit situations is estimated to lower the number of upward margin adjustments and associated costs by approximately 22%.

III. P=C ADJUSTMENTS

A. Context

Most adjustment volumes and costs stem from P=C adjustments, constituting 92% of total adjustments occurences. This section focuses on these decisive adjustments, as their prevalence makes them a key factor in overall system balancing costs. Unlike margin adjustments, which are directly and entirely dependent on the quality of RTE's forecasts, P=C adjustments rely on the ability to accurately predict the system imbalance but not exclusively. While the precision of imbalance forecasts can significantly impact adjustment actions, even perfect forecasts cannot eliminate the reality of imbalances caused by market participants. Therefore, adjustments will always be necessary. The goal is to investigate whether improved forecasts lead to more optimal actions, reducing costs and risks while enhancing system security.

The imbalance forecast is calculated by RTE based on its various consumption and production forecasts. The goal is to anticipate how many MW the system will be imbalanced by and in which direction. Ideally, this forecast would equal zero. In practice, however, for example, the imbalance forecast for one hour ahead could indicate an upward imbalance of 250 MW. In this case, RTE would need to perform a P=C adjustment to address the forecasted imbalance for the following hour. To achieve this, RTE might request a producer to increase their production.

B. Methodology

P=C adjustments are operational actions taken by RTE operators to maintain equilibrium between electricity supply and demand in real-time. These decisions, executed within minutes, are primarily informed by forecasts of system imbalance. To replicate this process, we developed a machine learning model designed to predict whether an adjustment is required and, if so, determine its magnitude. This model, built using the *HistGradientBoosting* algorithm from the *scikit-learn* [7] Python library, was trained on 2023 historical data. To ensure optimal performance, the model's hyperparameters were fine-tuned using Bayesian optimization with *Optuna* [8].

The key aspect lies in the training variables used by the model: it only has access to the variables that operators consider during their decision-making process. Therefore, the model is trained on the following variables:

- Forecasted imbalances for various time horizons;
- Last adjustment values;
- Production and consumption forecasts;
- Adjustment offers prices;
- Time variables (day, hour).

Evaluation metrics demonstrate the model's predictive capacity, making it a satisfactory proxy for dispatcher decision-making. Table II reveals that the upward and

TABLE II
HISTGRADIENTBOOSTING EVALUATION METRICS.

Model	Metrics		
	MAE	RMSE	R^2
Upward (Train)	181.92	257.57	0.634
Upward (Test)	221.08	320.12	0.435
Downward (Train)	229.91	312.74	0.655
Downward (Test)	266.22	365.96	0.528

downward fit prediction models are imperfect, with non-negligible error metrics. Still, their ability is adequate for the task we seek to perform. To get an idea of the orders of magnitude, in our training data, 90% of non-zero upward adjustments are between 60 and 1600MW.

Furthermore, the model effectively captures the relationships we aim to predict. For instance, Fig. 4 presents the partial dependence plot of downward adjustments relative to the imbalance forecast, clearly illustrating the expected decreasing relationship: the less negative the imbalance forecast, the smaller the necessary downward adjustments.

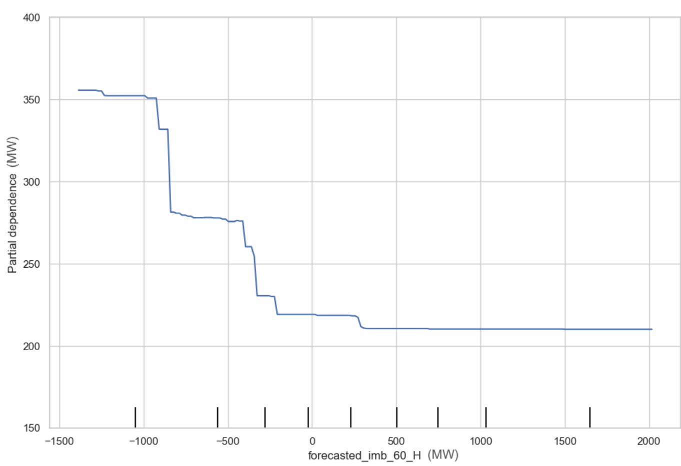

Fig. 4. Partial dependence plot of downward adjustments with forecasted imbalance at time horizon 60 minutes.

In addition to the baseline dataset, we created a synthetic dataset representing improved forecasts for 2023. This dataset incorporated enhancements in imbalance forecasts and other forecast variables. The forecast-enhancement techniques used here are the same as in the previous section. Using these datasets, we conducted a cross-validation process, applying the trained model monthly to predict P=C adjustments under improved and historical forecast scenarios.

We analyzed the differences between model predictions under the two scenarios to quantify the impact of forecast improvements. These differences reveal how enhanced forecasts influence the frequency, magnitude, and associated costs of P=C adjustments.

C. Results

The results present a nuanced picture of the impact of improved forecasts. On average and median (cf. Fig. 5), the total volume of upward and downward adjustments remains unchanged, suggesting no global reduction in adjustment quantities. This finding indicates that, while improved forecasts may not reduce the need for adjustments outright, their effect lies in optimizing the timing and magnitude of these actions.

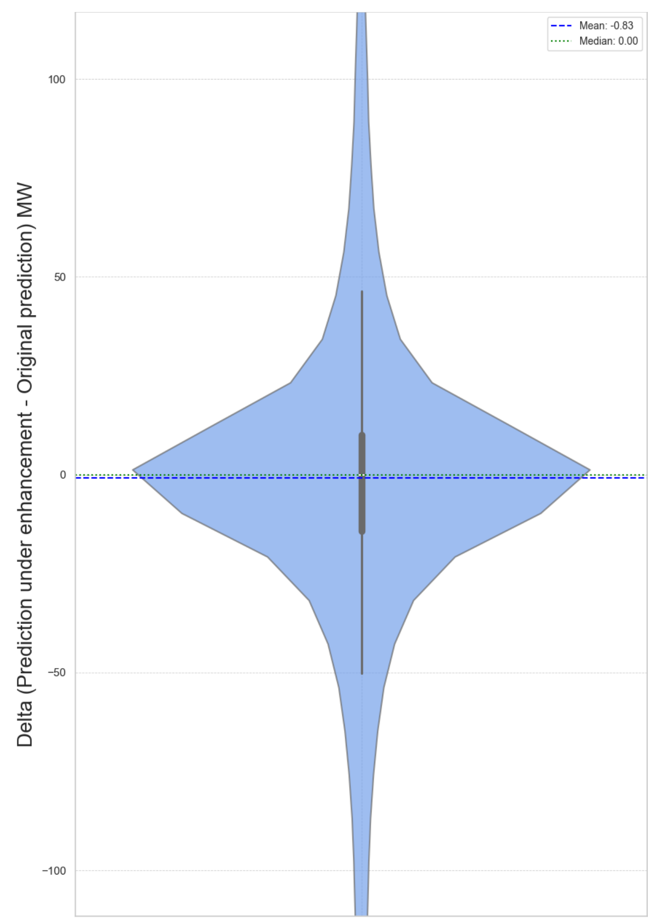

Fig. 5. Violin plot - Delta distribution for upward adjustments.

A closer analysis reveals a symmetric pattern: in some cases, adjustments increase, while in others, they decrease. This variability reflects the increased precision of decisions driven by improved forecasts. Enhanced forecast quality allows dispatchers—or, in this case, the model—to take more informed actions, ensuring adjustments are more closely aligned with real-time system needs. This greater precision mitigates the risk of suboptimal or erroneous adjustments, which can have costly or destabilizing consequences. In this way, improved forecasts contribute indirectly to system security by enabling more accurate and effective management of imbalances.

To validate these insights, we extended the analysis to include adjustment costs. Using detailed activation data for each adjustment, we implemented an algorithm that adapts the choice of offers based on model recommendations. For scenarios requiring fewer adjustments, the algorithm prioritizes deactivating offers in descending price (merit order). Conversely, for scenarios requiring increased adjustments, the algorithm saturates existing offers to their maximal power capacity price order. It supplements them, if necessary, with artificial offers based on historical price distributions.

TABLE III
EVOLUTION OF P=C ADJUSTMENT COSTS.

Cost	**Direction**	
	Upward (€)	**Downward (€)**
Historical Total Cost	371,044,274	-77,320,444
Adjustment Decrease	-15,854,063 (-4.3%)	2,145,889 (2.8%)
Adjustment Increase	8,576,534 (2.3%)	-5,754,046 (-7.4%)
New Total Cost	363,766,746 (98.0%)	-80,928,621 (105%)
Global Difference	-7,277,529 (2.0%)	-3,608,157 (4.7%)

The cost analysis detailed in Tab. III yielded compelling findings. For upward adjustments, improved forecasts resulted in €9 million in additional costs from increased adjustments. However, these were offset by €16 million in savings from reduced adjustments, leading to a net reduction of €7 million in total upward adjustment costs (equivalent to 2% of 2023 costs). Notably, this cost reduction can be attributed to the greater optimality of adjustments driven by improved forecasts. By enabling the avoidance of high-cost crisis situations, enhanced forecasts allow for more economical system balancing.

IV. DISCUSSION

We believe the forecast quality improvements described in this study are realistic and achievable shortly. Wind and photovoltaic renewable energies are the primary sources of forecast errors and uncertainties for the French TSO. Due to the low observability of these energy sources—particularly distributed photovoltaic installations and wind farms connected to Distribution System Operators (DSOs)—current forecasting models exhibit significant bias. These biases are already being addressed, and we anticipate that the improvements projected in this study could materialize soon.

For photovoltaic production forecasting, RTE is developing an updated version of its model that incorporates satellite data for online PV power estimation. Additionally, a post-processing method to correct bias in wind power forecasting is also under development.

In conclusion, enhancing forecast quality offers a clear pathway to improving grid management and reducing operational costs. Beyond the immediate economic benefits, the gains in system security have far-reaching implications, contributing to a more resilient and reliable electricity network. As advances in forecasting technologies and data observability evolve, the potential for realizing these benefits becomes increasingly tangible. Our findings highlight the importance of sustained investment in improving forecast models to meet the growing challenges of grid management in an era of increasing renewable energy integration.

V. CONCLUSION AND PERSPECTIVES

This study provides several key insights into the impact of improved forecast quality on RTE's operational decisions and costs. Using our simulation approach for calculating required and available margins under the assumption of a 20% improvement in forecast quality, we demonstrated a significant reduction in margin deficit situations. For upward adjustments, 26% of these critical situations—where RTE faces risks exceeding its security policy thresholds—could potentially be avoided. The reduction in margin deficits theoretically leads to fewer margin-related adjustments. Despite the limited dataset available, we estimated a 22% reduction in costs associated with upward adjustments, indicating the economic benefit of improved forecasts.

In parallel, our use of machine learning models to simulate P=C adjustments yielded a central finding: while improved forecasts do not reduce the total magnitude of adjustments on average, they lead to cost reductions. This outcome is rooted in the inherent imbalances of the grid, which cannot be resolved solely through better forecasts. Instead, improved forecasts enable more judicious and optimal adjustment decisions. For instance, upward adjustment costs could be reduced by €7 million throughout 2023, primarily due to enhanced system security. Better imbalance anticipation allows for decisions that minimize costly crisis situations where RTE must deploy all available resources, regardless of expense, to maintain equilibrium.

These results underline the dual benefits of improved forecast quality: enhanced grid security and financial savings for the collective system.

However, it is important to acknowledge that our assessment of the economic impact of these security gains may be incomplete. If the described adjustment mechanism fails to resolve all imbalances, RTE activates alternative *exceptional measures*, which are highly costly. These measures range from interruptibility contracts to load shedding. While the societal cost of such interventions is challenging to quantify, it is reasonable to argue that improved system security reduces the frequency of these extraordinary measures. Consequently, the potential gains from forecast improvements are likely underestimated in this study.

Moreover, the proposed method could be improved in two main ways. First, we need a better understanding of the practical logic behind margin-related adjustments. Currently, we lack sufficient data to fully grasp the deep and precise mechanisms driving these adjustments. Similarly, our prediction model for P=C adjustments is not perfect and could benefit from closer alignment with the actual practices of operators. To address these two key challenges, we aim to collaborate with the operators responsible for adjustment decisions to refine our models based on their expertise and insights.

ACKNOWLEDGMENT

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