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*Review*

# IMPROVING THE STRATEGIES OF THE MARKET PLAYERS USING AN AI-POWERED PRICE FORECAST FOR ELECTRICITY MARKET

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**Abstract.** This paper analyses the recent evolution of the electricity price of one of the East-European countries' Balancing Markets (BM) – Romania, aiming to understand the prices trend and predict them in the current economic and geopolitical context. This is especially important as the electricity producers have to allocate their output between wholesale electricity market, ancillary services markets and BM targeting to maximize value and achieve a sustainable economic development. Therefore, in this paper, we propose an AI-powered electricity price forecast using several types of standout Machine Learning (ML) algorithms such as classifiers and regressors to predict the electricity price on BM. This approach, consisting of two steps, identifies the imbalance sign and significantly enhances the performance of the price forecast. The proposed method offers valuable insights into the market participants' trading opportunities using two prediction solutions. The first prediction solution consists of averaging the results of five ensemble ML algorithms. The second one consists in weighting the results of the five forecasting ML algorithms using either a linear regression or a decision tree algorithm. Thus, we propose to combine supervised and unsupervised ML algorithms and find the fundamentals for creating optimal bidding strategies for electricity market players.

**Keywords:** electricity price forecast, balancing market, machine learning, classification, bidding strategy, trading probabilities.

**JEL Classification:** Q47, C53, F14.

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## Introduction and literature review

### *General context of the electricity markets timeline*

On one hand, electricity is a special commodity that is used in almost every activity of modern society, including the manufacture of goods and services. Therefore, electricity prices are sensitive to the geopolitical movements and the intensity of the social activities, and they influence the prices of other commodities. On the other hand, Artificial Intelligence (AI) is widely used in the process of creating systems that possess the mental abilities that distinguish humans from other animals, such as the capacity to reason, find meaning, generalize, or learn from previous mistakes. In order to facilitate problem-solving, like price prediction, the discipline of AI integrates computer science with substantial multiple data sets from various sources, including social media. Additionally, it includes the branches of AI known as Deep Learning and Machine Learning, which are commonly addressed together. These fields use AI algorithms to build expert systems that make predictions or categorize information based on the available data. Today, AI is a crucial component of all significant e-commerce businesses that have begun to investigate ways to automate numerous processes using cutting-edge Machine Learning (ML) algorithms and Deep Neural Networks (DNN) as a result of the expansion of the information industry and substantial study in the field of AI over the past 20 years. With dedicated staff and funds for research and development of cutting-edge AI applications, several IT giants and start-ups have already made significant strides in this area. Today's online retail platforms are heavily powered by algorithms and applications that use AI. ML is used in a variety of ways, from inventory control and quality assurance in the warehouses to product recommendations, forecast and sales analytics on the internet.

Bidding the energy and capacity of a generator or group of generators is a complex task that has to rely on forecasting techniques. The transition from consumerism to prosumerism is advancing due to the growth of local electricity markets and energy communities. Reaching new targets for energy conservation, energy generation and distribution efficiency is made achievable by the combination of electric cars and smart grids (Lazaroiu & Roscia, 2022). The causality between energy consumption and economic growth in the V4 countries was investigated (Krkošková, 2021) analyzing the long-term relationship between energy consumption and Gross Domestic Product (GDP) from 2005 to 2019. The results indicated that the long-term the energy consumption positively influences the GDP in Hungary, Slovakia and the Czech Republic. Only in Poland, there is no significant relationship between energy consumption and the GDP. Additionally, the topological structural analysis of new energy stock market in China was studied (Yin et al., 2020) considering a multi-dimensional data network perspective. The authors examined daily prices of 60 stocks of China stock index from 2012 to 2019. They applied the RV coefficient that can better show the similarity between stocks. The result indicates that the energy storage facilities are promoters of RES generation. The dependence between the clean energy stock prices and the oil and carbon prices was investigated (Yilanci et al., 2022) considering a nonlinear perspective. Moreover, Soava et al. (2018) suggested that there is a positive impact of RES on economic growth. The effects of positive and negative shocks in energy security on economic growth in Turkey was further analyzed in Kartal (2022) using an asymmetric causality analysis.

First, on a timeline, the bilateral contracts have to be considered in the market strategy, then the Day-Ahead Market (DAM) and Intraday Market (IDM), followed by the Ancillary Service Market (ASM) and finally the Balancing Market (BM) (Martini et al., 2001; Oprea et al., 2020). In Martini et al. (2001), DESPOT (decision-support simulator for power trading) is introduced. It is a program for simulating the short-term wholesale electricity market that provides information on unit commitment, system hourly pricing, profit, and estimated bid. The market simulator model considers both the bilateral long- or medium-term agreements and short-term offers on day-ahead, auxiliary services, and BM, which provides the whole trading solution, related cash-flow and hazards. Its importance consists in supporting the producer in resource planning and income projection by running numerous trading scenarios and choosing the best one.

Bilateral contracts are the most stable long and mid-term solution to trade, but the standard contracts with fixed intervals, week and weekend days do not comply with all types of generators (especially Renewable Energy Sources (RES)-based generators), and the prices are lower in comparison with other markets (Adefarati & Bansal, 2016). It takes a variety of forecasting and decision-making methods to integrate RES in the power markets. To come at the best options, the conventional method entails estimating power output and market volumes, followed by including the findings into an optimization problem (Stratigakos et al., 2021).

Even for the most predictable generators, deviations from schedule may appear requiring a short-term trading solution that can be on DAM and IDM closer to the real time operation. However, deviations are still possible due to unexpected events that appear between the schedule and real time operation. Therefore, the system operator handles these deviations by organizing markets to reserve capacities. Additionally, for generators, the difference between the previous allocated capacities and the maximum power has to be offered on the BM for ramping up as well as the difference between the allocated capacity and the minimum power (that can be zero) for decreasing. The unbalancing prices are therefore set for increasing (+) as well as for decreasing (–) the output. Several pairs of prices and quantities (maximum 10) are offered for increasing and decreasing the output considering the technical capacity of the generators. In case of imbalance, the cheapest bids will be activated first. The market participant that deviates from notification has to pay the imbalance at the specific imbalance price depending on his deviation (sign and volume). The decision makers usually search for a trade-off between stability and benefits that various electricity markets can provide (Boomsma et al., 2014; Aasgård et al., 2019; Fleten & Pettersen, 2005). Placing the bids on DAM is thoroughly researched by generation companies or producers with controlled units (Klæboe et al., 2019). It is crucial to examine the possibility of coordinated bidding for energy market participants trading in consecutive markets with different price levels and risk exposure (Boomsma et al., 2014). DAM is also an option for electricity suppliers. In Fleten and Pettersen (2005), the situation of a price-taker who provides electricity to end users with high price sensitivity is investigated. The goal is to reduce the anticipated cost of acquiring power from the short-term BM and DAM.

### *Previous studies related to the electricity price forecast on BM and market strategies*

Several studies analyzed the BM prices and focused on predicting them using different methods. Most of them are performed using data sets from West European countries, Nordic countries (Boomsma et al., 2014), Australia, Canada or U.S.A. (Dimoulkas et al., 2016; Dumas et al., 2019; Lucas et al., 2020), probably because the ready-to-use data sets were available. It is believed that rather than being founded on speculation, electricity markets generally follow quasi-deterministic principles, which is why it is desirable to predict the price using factors that can characterize the outcome of the market. Numerous studies have attempted to solve this issue statistically or through the use of multiple-variable regressions, but they frequently only handle the time series analysis (Lucas et al., 2020). Furthermore, a benchmarking of the forecasting models for electricity price on the BM was performed in Klæboe et al. (2015). It appeared that information accessible before the DAM closes is effectively represented in the

DAM rate rather than the BM price because none of the benchmarked models offered useful day-ahead point forecasts. Models without balance state information overestimate variance, making them inappropriate for scenario development, according to analysis of the interval forecasts (Klæboe et al., 2015).

The increased volume of RES in the power system creates volatility in total generation leading to the difficulty of maintaining an equilibrium between supply and demand. Better prediction models are required to prevent balancing concerns and resulting stability issues, as old methodologies are not completely ready to cope with any of these new problems. As a result, forecasting systems based on AI are acquiring considerable attention in the field of power markets (Hameed et al., 2021). The multi-market bidding issue for electricity producers was given as a stochastic program in Aasgård (2022). It was also demonstrated how input to the stochastic program may be created by combining a forecast-based scenario generating approach with time-series models that anticipate future market values and turnovers. Nasrolahpour et al. (2018) described a decision-making tool for a merchant price-maker energy storage system based on a bilevel complementarity model for determining the most profitable trading activities in pool-based markets, including day-ahead (as combined energy and reserve markets) and balancing settlements. The unpredictability of net load variation in real-time was integrated into the model using a set of scenarios built from the available day-ahead projection. Wind generators' day-ahead projections are insufficiently precise, exposing them to an imbalance cost owing to wrong offers. Although the market operator regularly publicizes comprehensive and precise market data, past market data are rarely used efficiently to lower this cost. Dinler (2021) modeled the imbalance cost reduction challenge as a binary classification problem and then builds a framework comprised of a long short-term memory auto-encoder and a combination of advanced classifiers.

The optimization of the balancing electricity bidding strategies as a mixed-integer nonlinear program was shown in Schäfer et al. (2019), considering both price estimates for the ASM and hourly spot market prices. This two-stage strategy was solved by decomposing it into two problems: a nonlinear bidding problem and a mixed-integer linear scheduling problem. In Bringedal et al. (2023), it was considered that the profit from coordinating transactions is based on the accuracy of the BM projections. To evaluate the influence of the forecasting model on the gain, they provided a benchmarking framework for two additional prediction models: a naïve forecast that predicts zero imbalance in expectation and a perfect information forecast. Load flexibility features and BM price projection scenarios were utilized in a price-taker technique to determine optimal load-shifting offers under uncertainties. The problem was expressed as a stochastic mixed-integer linear program that can be solved in an acceptable amount of time (Bobo et al., 2018). Paper written by van der Veen and Hakvoort (2016) provided policymakers with a methodology for identifying significant design elements and performance criteria that play a role in the creation and development of European BM. Policymakers can solve the BM design dilemma by using a systematic approach that considers design factors, performance criteria, market circumstances, system advancements, and resulting market incentives. It is anticipated that the growth and regional development of BM would lower the price of frequency regulation services. As the use of variable RES for power generation increases balancing costs, this is becoming more and more crucial Krstevski et al. (2021). According to Bunn et al. (2021), system imbalance pricing demonstrated a regime-switching behavior, driven by inaccurate weather and demand forecasts as well as other system influences, according to the results of a non-linear modeling technique. Unexpectedly, balancing prices can be predicted outside of samples, and a particularly different specification is more reliable than a linear model.

Among commodity markets, electricity markets are thought to be the most volatile. Extremely short-lived swings in energy pricing are frequently a result of the non-storability of power and the requirement for instantaneous demand and supply balancing. Paper written by Stathakis et al. (2021) presented a multiclass Support Vector Machine model to predict prices when price spikes may occur in the German IDM. The authors (Brijs et al., 2015) showed positive relationships with scheduled RES generation and rigid base load, as well as negative relationships with scheduled system load. Additionally, there is a correlation between the frequency of negative pricing and the positive and negative prediction errors of RES output and demand.

Another approach presented in Olsson and Söder (2008) uses a Seasonally Auto-Regressive Integrated Moving Average (SARIMA) and discrete Markov process combination to estimate real-time BM prices. The goal is to simulate prices in order to build scenario trees that depict potential realizations of the stochastic prices. Controllable production units normally engage in the BM as "active" players. RES are treated as "passive" participants who cause imbalances and thus are susceptible to less competitive prices. In light of this, they suggest a novel market structure in which a balanced market member is permitted to serve as an active agent during some trading periods and a passive agent during others (Mazzi et al., 2019). A model where agents that use naive, rule-based, and reinforcement learning tactics that are compared against the impact of a standalone energy market for balancing on economic efficiency was described in Poplavskaya et al. (2020). According to their findings, even in a competitive market with strategic bidders, the creation of a stand-alone BM lowers the cost of balancing.

### *Research questions, contribution and organization of the current analysis*

Considering the importance of the electricity price forecast and the powerful ML algorithms, we propose to find answers to the following research questions:

**RQ1.** *How to improve the electricity price forecast on BM?*

**RQ2.** *How to make trading strategies using the AI-powered price forecast?*

In this paper, we propose an improvement of the economic strategies of the market players using an AI-powered electricity price forecast based on several types of standout ML algorithms to predict the electricity price and imbalance sign on the BM. This approach, consisting of two steps, identifies the imbalance sign by classification and significantly enhances the performance of the price forecast using regressors. The results are incorporated to identify the optimal trading solution. Thus, we propose a method to combine supervised and unsupervised machine learning algorithms and find the fundamentals for creating optimal bidding strategies for electricity market players.

The contribution of this paper consists of the following aspects:

- We focus on the recent electricity price of one of the East-European countries' Balancing Markets (BM) – Romania, aiming to understand the evolution of prices and predict them in the current economic and geopolitical context. Previous studies focused on West-European countries' BM, such as: Germany, Austria, France or Nordic countries. From this point of view, our current study is innovative as little concern has been given to the East-European region.
- A combo-method is proposed that includes prediction of the imbalance sign and then using it as a new variable in the input data set to predict the electricity prices on BM. Thus, we combine supervised and unsupervised ML algorithms to obtain significant improvements.
- A trading strategy is proposed using the predicted prices and the risks of trading failure on DAM and BM. By varying the available quantities between DAM and BM and multiplying these quantities with the predicted prices, the market participants can estimate the income from trading on both markets.

The paper is structured into several sections, including introduction and literature review, input data analysis, method, results, discussions and conclusion. In the second section, the data set created based on various open data sources, for the two years (2021 and 2022), is presented. The third section presents the method of using classifiers and regressors to predict the imbalance sign and the electricity prices. The results of the simulations, including a recommendation for bidding on DAM and BM considering the predicted prices, are provided in section four. The paper ends with a discussion and conclusion section.

## 1. Input data analysis

In this study, we propose to collect, create and analyze a data set from various open data sources, such as: ENTSO-E transparency platform[1], Romanian Market Operator – OPCOM[2] and Transelectrica – the Romanian Transmission System Operator[3] (TSO). The imbalances between notifications and real generation/consumption that market participants are responsible for are paid at the imbalance price for deficit or surplus. Using the created data set, we aim to predict the price of imbalance for deficit or surplus. To ensure the balance between generation and consumption, the TSO organizes a BM where generators bid to reduce their output up to zero or to minimum technical power or increase the generation up to the maximum power. However, in the last two years, the BM has been influenced by higher inflation after COVID-19 pandemic and the geopolitical conflict in the Black Sea region. During the pandemic years, the request for commodities decreased, but after the lockdowns were removed, the request rapidly increased due to the intensified business and traveling around the world. This high request led to higher inflation that increased the electricity price that further influenced inflation and interest rate like a snowball effect. The request for commodities has been additionally increased by the conflict in Ukraine.

[1] https://transparency.entsoe.eu/balancing/r2/imbalance/show

[2] https://www.opcom.ro/grafice-ip-raportPIP-si-volumTranzactionat/ro

[3] https://www.transelectrica.ro/ro/web/tel/home

The prices on the DAM and BM have started to increase since October 2021 and they influenced the electricity prices on the BM as well. This trend has been noticed at the European DAM level. The prices went 4–5 times higher. They started to decrease again after a year – in October 2022. The price and imbalance fluctuations are presented in Figures 1–4. In Figure 1, the imbalance price for deficit in 2021 is shown. It shows a funnel shape indicating the increase of the price at the end of 2021. Figure 2 shows that the same trend is maintained in 2022 until October–November 2022 when the prices have started to decrease.

The number of surplus and deficit cases and the total surplus and deficit in 2021 and 2022 are presented in Table 1. The number of deficit cases and total amount in 2022 were smaller than in 2021. Market participants tended to avoid deficit cases as the prices for deficit are higher. Therefore, they preferred to be on the surplus side.

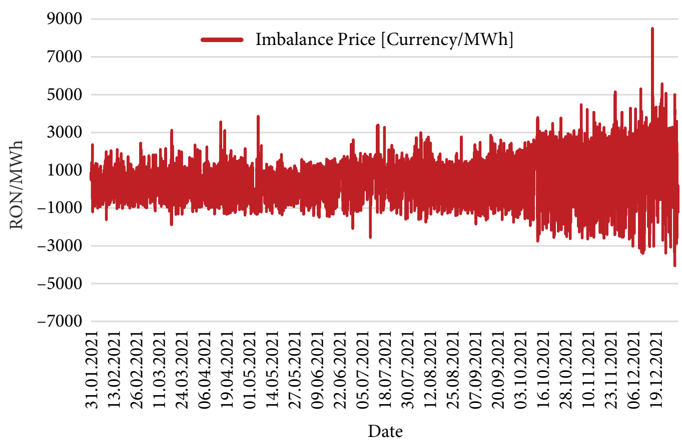


**Figure 1.** Imbalance price for deficit in 2021

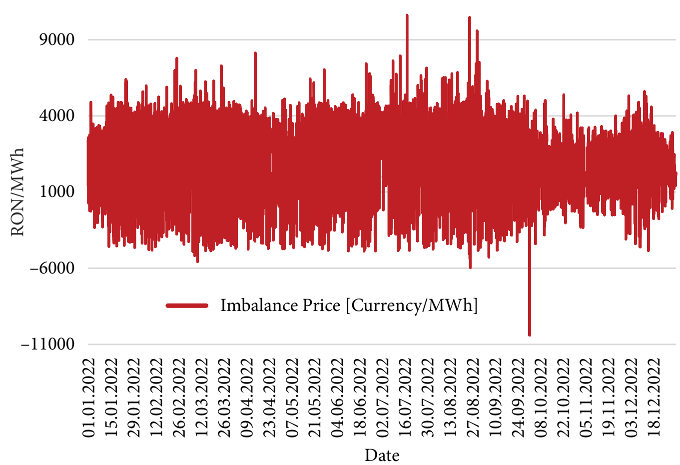


**Figure 2.** Imbalance price for deficit in 2022

**Table 1.** Surplus and deficit cases and totals

| Year | 2021 | 2022 |
|---|---|---|
| No. of Surplus cases | 16,644 | 21,469 |
| No. of Deficit cases | 15,428 | 13,571 |
| Total Surplus [MWh] | 952,231 | 1,243,989 |
| Total Deficit [MWh] | 859,076 | 629,431 |

Figure 3 and Figure 4 show the imbalance volume in 2021 and in 2022 when it was higher with 62,113 MWh.

The prediction of the electricity price on BM is a challenge because the results of a baseline model are not accurate and reliable to create bids. To improve the electricity price forecast, the imbalance sign is predicted first using ten ML classification algorithms and inserted into the data set to predict the electricity price for deficit or surplus. This method is explained in the following section. Moreover, a method to estimate the income for generators and create optimal bids is proposed knowing the predicted prices on the electricity markets.

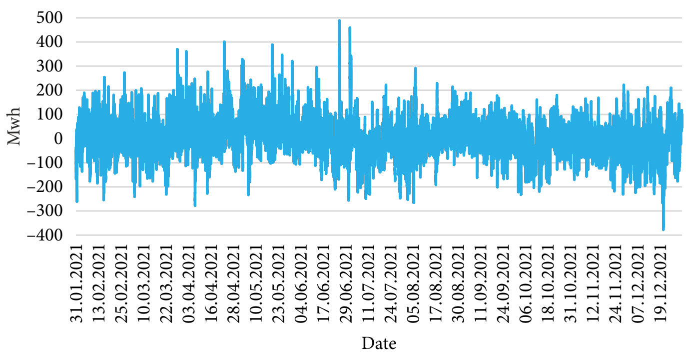


**Figure 3.** Imbalance volume for deficit in 2021

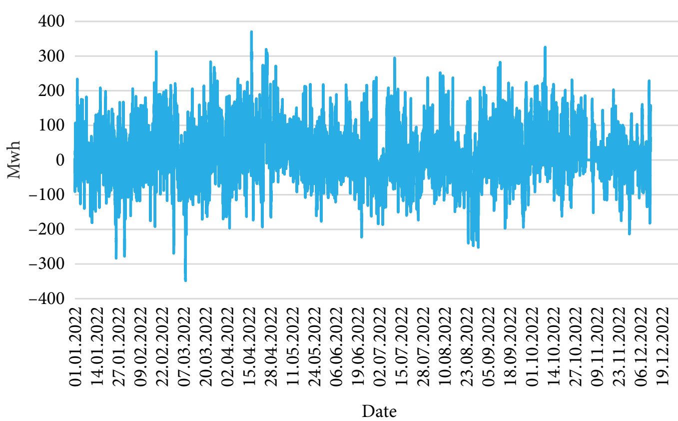


**Figure 4.** Imbalance volume for deficit in 2022

## 2. Methodology

In this section, the electricity price for deficit will be predicted and a trading solution will be provided considering predicted prices, the remaining quantity after other transactions and associated risks of trading failure.

Considering the two RQ exposed in the first section, the proposed method consists of 3 steps: Step 1 – Data collection and Step 2 – BM electricity price forecast, that also includes the prediction of the imbalance sign. They are designed to answer the first question:

**RQ1.** *How to improve the electricity price forecast on BM?*

Whereas, in Step 3, the trading income is estimated taking into account the risks and trading probabilities of both markets (DAM and BM) in order to answer the second research question:

**RQ2.** *How to make trading strategies using the AI-powered price forecast?*

For implementing the proposed methodology, the following variables and abbreviations are considered:

### Nomenclature

#### *Variables*

| | |
|---|---|
| $\widehat{IS_{BM}^{h+24}} \in \{0,1\}$ | Predicted sign of the system |
| $\widehat{P_{BM^-}^{h+24}}, \widehat{P_{BM^+}^{h+24}}$ | Predicted prices on BM for the next day |
| $C^h$ | Hourly consumption |
| $Ex^h$ | Sold or exchange with other systems |
| $FW_{DAM}^{h+24}$, $FPV_{DAM}^{h+24}$ | Day-ahead forecast of PV and W generation for DAM |
| $FW_{IDM}^{h+24}$, $FPV_{IDM}^{h+24}$ | Day-ahead forecast of PV and W generation for IDM |
| $Fin_{BM}^h$ | Financial neutrality on BM |
| $G^h$ | Hourly total generation |
| $G_k^h$ | Generation breakdown by type of generator<br>(coal, oil and gas, hydro, wind, photovoltaic, biomass, nuclear) |
| $IS_{BM}^h \in \{0,1\}$ | Sign of the system (that can be deficit 0 or surplus 1) |
| $P_{BM-/+}^{h-24}$, $P_{BM-/+}^{h-48}$, $\overline{P_{BM-/+}^{h-}}$ | BM prices of the last 2 days and their average |
| $P_{BM^+}^h$, $P_{BM^-}^h$ | Hourly prices on BM for current day for surplus and deficit |
| $P_{DAM}^{h+24}$, $Q_{DAM}^{h+24}$ | Prices and traded quantities on DAM |
| $Q_{BCM}^{i,h}$ | Total capacity traded on BCM |
| $Q_{BM}^h$ | Imbalance volume |
| $Q_{BM}^{i,h}$, $Q_{DAM}^{i,h}$ | Capacities to be traded on BM and DAM |

| | |
|---|---|
| $Q_T^{i,h}$ | Total capacity |
| $Q_r^{i,h}$ | Remaining quantity to be traded |
| $XIS^{h+24}$ | Input data set for sign prediction |
| $XP^{h+24}$ | Input data set for price prediction |

### *Abbreviation*

| | |
|---|---|
| AI | Artificial Intelligence |
| ASM | Ancillary Service Market |
| AUC | Area Under the Curve |
| BCM | Bilateral Contract Market |
| BM | Balancing Market |
| D | Number of days |
| DAM | Day-Ahead Market |
| FPR | False Positive Rate |
| $H$ | Hour |
| HGBR | Histogram Gradient Boosting Regressor |
| $i$ | Day |
| I | Income |
| IDM | Intra-Day Market |
| LGBR | Light Gradient Boosting Regressor |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| ML | Machine Learning |
| PV | Photovoltaic |
| $R$ | Risk of trading failure |
| $R^2$ | coefficient of determination |
| RES | Renewable Energy Sources |
| RFR | Random Forest Regressor |
| RMSE | Root Mean Squared Error |
| ROC-AUC | Receiver Operating Characteristic – Area Under the Curve |
| SARIMA | Seasonally Auto-Regressive Integrated Moving Average |
| T | Time interval |
| TPR | True Positive Rate |
| TSO | Transmission System Operator |
| VR | Voting Regressor |
| XGBR | eXtreme Gradient Boosting Regressor |
| W | Wind |

## Step 1 – Data collection

To analyze and predict the electricity prices for deficit and surplus on the BM, four public data sets recorded between 1st of January 2021 and 31st of December 2022 were collected and merged:

- Prices $P_{DAM}^{h+24}$ and traded quantities $Q_{DAM}^{h+24}$ on DAM from the Romanian market operator – OPCOM;
- Hourly prices on BM for current day for surplus and deficit ($P_{BM^+}^h$, $P_{BM^-}^h$), imbalance volume $Q_{BM}^h$, financial neutrality $Fin_{BM}^h$ and the sign of the system $IS_{BM}^h \in \{0,1\}$ extracted from ENTSO-E transparency platform;
- Day-ahead forecast of Photovoltaic (PV) and Wind (W) generation for IDM, $FW_{IDM}^{h+24}$, $FPV_{IDM}^{h+24}$ and for DAM, $FW_{DAM}^{h+24}$, $FPV_{DAM}^{h+24}$ extracted from ENTSO-E transparency platform;
- Power system hourly data regarding total consumption $C^h$, total generation $G^h$, its breakdown (coal, oil and gas, hydro, wind, solar – PV, biomass, nuclear) and sold or exchange with other systems $Ex^h$ from the Romanian Transmission System Operator – Transelectrica (TSO).

The data sets are merged using the Date and Hour features. Additionally, the BM prices of the last 2 days ($P_{BM^{-/+}}^{h-24}$ and $P_{BM^{-/+}}^{h-48}$) and their average $\overline{P_{BM^{-/+}}^{h-}}$ are considered as input features in the data set to predict the electricity price for deficit/surplus.

## Step 2 – BM electricity price forecast

The baseline or the initial forecast consists of training Machine Learning (ML) algorithms to obtain the day-ahead electricity price on BM. To improve the results, we propose a two-stage approach (as shown in Figure 5): 1) determine the imbalance sign for day-ahead ($\widehat{IS_{BM}^{h+24}} \in \{0,1\}$); 2) use $\widehat{IS_{BM}^{h+24}}$ as a new feature to predict the BM price ($\widehat{P_{BM^-}^{h+24}}$, $\widehat{P_{BM^+}^{h+24}}$) for the next day.

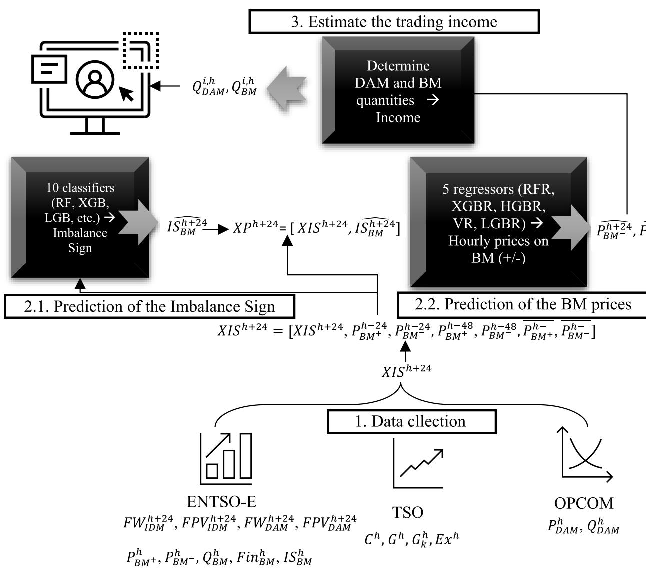


**Figure 5.** Steps of the proposed method

***Step 2.1 – Determine the imbalance sign for day-ahead*** ($\widehat{IS_{BM}^{h+24}} \in \{0,1\}$)

The imbalance sign is determined using ML classification algorithms, trained on the input data set (*XIS*) composed by the following variables from the initial data set:

$$XIS^{h+24} = [P_{DAM}^{h+24},\ Q_{DAM}^{h+24},\ P_{BM^+}^{h},\ P_{BM^-}^{h},\ Fin_{BM}^{h},\ FW_{IDM}^{h+24},\ FPV_{IDM}^{h+24},$$
$$FW_{DAM}^{h+24},\ FPV_{DAM}^{h+24},\ C^h,\ G^h,\ G_k^h, Ex^h]. \tag{1}$$

where $G_k^h$ represent the type of generator (coal, oil and gas, hydro, wind, photovoltaic, biomass, nuclear).

Then $XIS^{h+24}$ is appended with the previous day prices on BM for deficit and surplus and their average values:

$$XIS^{h+24} = [XIS^{h+24},\ P_{BM^+}^{h-24},\ P_{BM^-}^{h-24},\ P_{BM^+}^{h-48},\ P_{BM^-}^{h-48}, \overline{P_{BM^+}^{h-}},\ \overline{P_{BM^-}^{h-}}]. \tag{2}$$

Ten ML classifiers are trained and tested to determine the imbalance sign: Logistic Regression (LR), Stochastic Gradient Descent (SGD), eXtreme Gradient Boosting (XGB), Decision Tree (DT), Random Forest (RF), Multi-Layer Perceptron (MLP), Light Gradient Boosting (LGB), Quadratic Determinant Analysis (QDA), K-Neighbour (KN), Ada Booster (AB). To evaluate the results of the classification, the confusion matrix, the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) and F1-score are used as metrics. As analyzed in section 4, RF provides the best results, therefore it is used to provide the imbalance sign for the next day:

$$\widehat{IS^{h+24}} = RF.predict\left(XIS^{h+24}\right). \tag{3}$$

***Step 2.2 – Determine the BM electricity price*** ($\widehat{P_{BM^-}^{h+24}}, \widehat{P_{BM^+}^{h+24}}$)

The output of the classification ($\widehat{IS_{BM}^{h+24}}$) is inserted into the input data set (*XP*) to predict the day-ahead electricity prices on BM ($\widehat{P_{BM^-}^{h+24}}, \widehat{P_{BM^+}^{h+24}}$).

$$XP^{h+24} = [XIS^{h+24},\ \widehat{IS_{BM}^{h+24}}]. \tag{4}$$

The input $XP^{h+24}$ is splitted into a training interval that spans from 1st of January 2021 until 2nd of March 2022 and a testing and evaluation interval between 3rd of March and 31st of December 2022.

The proposed method consists of using the following five standout ML regressors: Random Forest Regressor (RFR), Voting Regressor (VR), Light Gradient Boosting Regressor (LGBR), Histogram Gradient Boosting Regressor (HGBR) and eXtreme Gradient Boosting Regressor (XGBR).

The final prediction can be obtained by averaging the results provided by the ML regressors ($fR_m$) as in Equation (5):

$$\widehat{P_{BM^-}^{h+24}}, \widehat{P_{BM^+}^{h+24}} = \frac{\sum_m fR_m.predict\left(XP^{h+24}\right)}{5}. \tag{5}$$

Another method for obtaining the prediction of the BM prices is to weigh each individual forecast with a coefficient determined by a simple regressor, such as linear regression or decision tree.

The following performance metrics are calculated to assess the electricity price prediction: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), coefficient of determination ($R^2$). These metrics are calculated for both estimated values (deficit and surplus) for the entire test set ($h \in T$) using Equations (6)–(9):

$$RMSE = \frac{1}{T}\sum_{h=1}^{T}\left(P_{BM^{+/-}}^{h} - \widehat{P_{BM^{+/-}}^{h}}\right)^2; \tag{6}$$

$$MAE = \frac{1}{T}\sum_{h=1}^{T}\left|P_{BM^{+/-}}^{h} - \widehat{P_{BM^{+/-}}^{h}}\right|; \tag{7}$$

$$MAPE = \frac{1}{T}\sum_{h=1}^{T}\frac{\left|P_{BM^{+/-}}^{h} - \widehat{P_{BM^{+/-}}^{h}}\right|}{\left|P_{BM^{+/-}}^{h}\right|}\times 100\%; \tag{8}$$

$$R^2 = 1 - \frac{\sum_{h=1}^{T}\left(P_{BM^{+/-}}^{h} - \widehat{P_{BM^{+/-}}^{h}}\right)^2}{\sum_{h=1}^{T}\left(P_{BM^{+/-}}^{h} - \overline{P_{BM^{+/-}}^{h}}\right)^2}., \tag{9}$$

where $P_{BM^{+/-}}^{h}$ represents the actual hourly target and $\widehat{P_{BM^{+/-}}^{h}}$ represents the prediction for the hourly prices for surplus/deficit on BM.

## Step 3 – Estimate the trading income

The revenue from trading on DAM and BM can be estimated using the proposed price prediction method and the probabilities of trading or the risks associated with trading failure. The risks associated with trading on DAM ($r_{DAM}$) are usually smaller (20–25%) than the risks associated with trading on BM ($r_{BM}$) (65–70%). The objective target or function ($f$) for a producer is to maximize the income I on both markets (DAM and BM) that can be obtained by trading the remaining capacity (after trading on BCM).

$$\max I = f\left(P_{DAM}^{h},\ Q_{DAM}^{h}, \widehat{P_{BM^-}^{h}}, \widehat{P_{BM^+}^{h}}, Q_{BM}^{h}\right). \tag{10}$$

The income on DAM ($I_{DAM}$) for an interval (D) is the price ($P_{DAM}^{i,h}$) multiplied by the traded quantity ($Q_{DAM}^{i,h}$) and the probability of trading on DAM ($1-\frac{r_{DAM}}{100}$), where $r_{DAM}$ is the risk of trading failure on DAM.

$$I_{DAM} = \sum_{i=1}^{D}\sum_{h=1}^{24}P_{DAM}^{i,h}\times Q_{DAM}^{i,h}\times\left(1-\frac{r_{DAM}}{100}\right). \tag{11}$$

Usually, the estimated income on BM ($I_{BM}$) is calculated as the predicted price for deficit/surplus multiplied by the traded quantity and the probability of trading on BM ($1-\frac{r_{BM}}{100}$), where $r_{BM}$ is the risk of trading failure on BM.

$$I_{BM} = \left(1-\frac{r_{BM}}{100}\right)\times\left(0.5\times\sum_{i=1}^{D}\sum_{h=1}^{24}\widehat{P_{BM^-}^{i,h}}\times Q_{BM}^{i,h} + 0.5\times\sum_{i=1}^{D}\sum_{h=1}^{24}\widehat{P_{BM^+}^{i,h}}\times Q_{BM}^{i,h}\right). \tag{12}$$

Estimating the sign, the income on BM is calculated either using the forecasted price for increasing or decreasing capacity ($\widehat{P_{BM^{-/+}}^{i,h}}$) as follows:

$$I_{BM} = \left(1 - \frac{r_{BM}}{100}\right) \times \left(\sum_{i=1}^{D}\sum_{h=1}^{24} \widehat{P_{BM^{-/+}}^{i,h}} \times Q_{BM}^{i,h}\right). \tag{13}$$

Therefore, the total income $I$ is the sum between the estimated income on DAM ($I_{DAM}$) and estimated income on BM ($I_{BM}$):

$$I = \sum_{i=1}^{D}\sum_{h=1}^{24} P_{DAM}^{i,h} \times Q_{DAM}^{i,h} \times \left(1 - \frac{r_{DAM}}{100}\right) + \left(\sum_{i=1}^{D}\sum_{h=1}^{24} \widehat{P_{BM^{-/+}}^{i,h}} \times Q_{BM}^{i,h}\right) \times \left(1 - \frac{r_{BM}}{100}\right). \tag{14}$$

The prices are predicted using ML algorithms as described in step 2, whereas the quantities $Q_{DAM}^{i,h}$, $Q_{BM}^{i,h}$ are unknown and they should be determined to create optimal bids on DAM and BM. The total capacity of the producer or the total quantity that can be traded can be divided into three. The total capacity ($Q_T^{i,h}$) and the capacity already traded on BCM ($Q_{BCM}^{i,h}$) are known in advance. The problem is to adequately split the remaining capacity ($Q_r^{i,h}$) after trading on the BCM to DAM or/and BM.

$$Q_T^{i,h} = Q_{BCM}^{i,h} + Q_{DAM}^{i,h} + Q_{BM}^{i,h}; \tag{15}$$

$$Q_r^{i,h} = Q_T^{i,h} - Q_{BCM}^{i,h}. \tag{16}$$

To avoid working with two unknown variables, the traded capacity on BM ($Q_{BM}^{i,h}$) is the difference between the remaining capacity ($Q_r^{i,h}$) and traded capacity on DAM $Q_{DAM}^{i,h}$.

$$Q_{BM}^{i,h} = Q_r^{i,h} - Q_{DAM}^{i,h}. \tag{17}$$

Replacing $Q_{BM}^{i,h}$ in the objective function, we obtain:

$$I = \max\left(f\left(P_{DAM}^{i,h},\ Q_{DAM}^{i,h}, \widehat{P_{BM^-}^{i,h}}, \widehat{P_{BM^+}^{i,h}}, Q_r^{i,h}\right)\right). \tag{18}$$

Therefore, the problem is to calculate the $Q_{DAM}^{i,h}$ that maximizes the income. The solution is further presented in the next section. Furthermore, the results of the proposed prediction method that embeds both classification and prediction algorithms are presented in the following section.

## 3. Results

For prediction the electricity prices on BM, training interval spans from 1st of January 2021 until 2nd of March 2022 and a testing and evaluation interval between 3rd of March and 31st of December 2022. The forecasting horizon can be chosen from 1 to 6 days as the short and mid-term forecasts are usually required. The sample of the prediction results of the baseline model (without classification) for the four next days (3rd – 6th of March) are shown in Figure 6. Obviously, the prediction (orange and blue lines) does not follow the actual price curve (green line) and it is quite far from it.

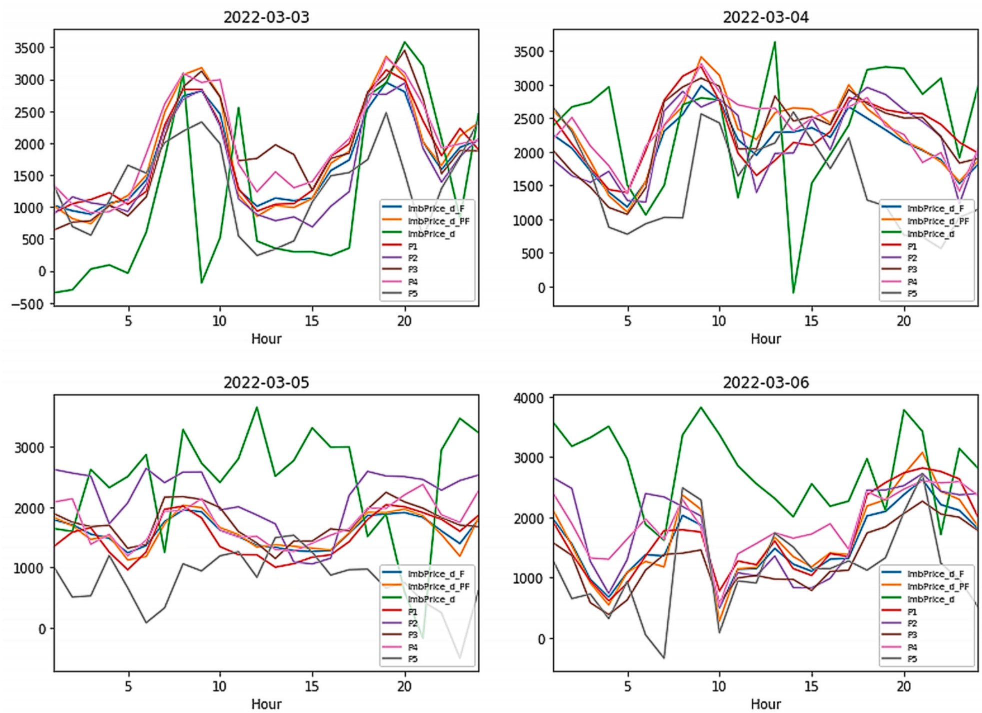


**Figure 6.** Electricity price forecast for 3rd – 6th of March 2022 (baseline model)

P1-P5 are the predictions obtained with the ML regressors algorithms mentioned in step 2.2. *ImbPrice_d* is the target or the real imbalance price for deficit ($P^h_{BM^-}$), *ImbPrice_d_F* is the average prediction ($\widehat{P^h_{BM^-}}$) using P1–P5 (the blue line) and *ImbPrice_d_PF* is the weighted prediction using the linear regression algorithm ($\widehat{Pr^h_{BM^-}}$) with the results of the 5 ML algorithms (the orange line). Instead of linear regression, a decision tree algorithm can be also applied.

To improve the prediction results, the imbalance sign is predicted using binary classification, considering the deficit or surplus state in which the system can be. The prediction is then added as an input to the data set. For classifying the imbalance sign, ten algorithms are trained as discussed in step 2.2 and the best results were obtained with RF classifier closely followed by LGB and XGB. The ROC-AUC score is 0.822 showing the capacity of the method to classify the two values: 0 for deficit, 1 for surplus. The confusion matrices for the three most performant classifiers are presented in Figure 7. One can notice that out of the 2,043 deficit cases, RF succeeds to correctly predict 1,506 deficit cases, LGBM 1,414 and XGB 1,408.

The feature correlation coefficients for the baseline model and proposed method are presented in Table 2. The predicted imbalance sign ($\widehat{IS^{h+24}_{BM}}$) inserted in the input data set (*XP*) is highly correlated with the target (–0.87). Furthermore, the other three new features ($P^{h-24}_{BM^-}$, $P^{h-48}_{BM^-}$, $\overline{P^{h-}_{BM^-}}$) improve the correlation with the target and the results are expected to improve.

The ROC-AUC curves for the 10 classifiers are shown in Figure 8.

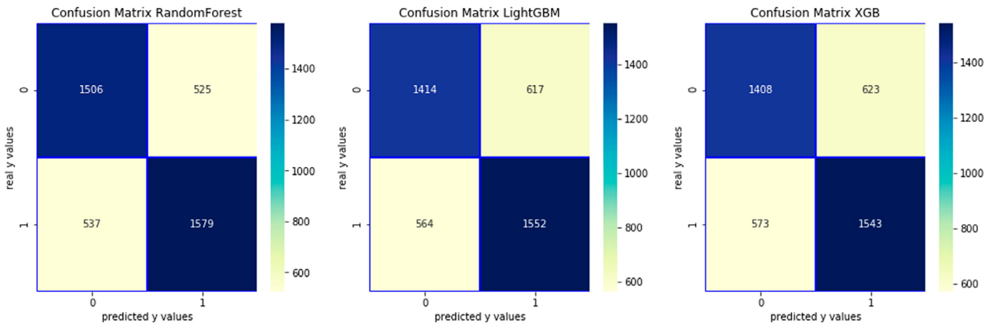


**Figure 7.** Confusion matrices for RF, LGB and XGB

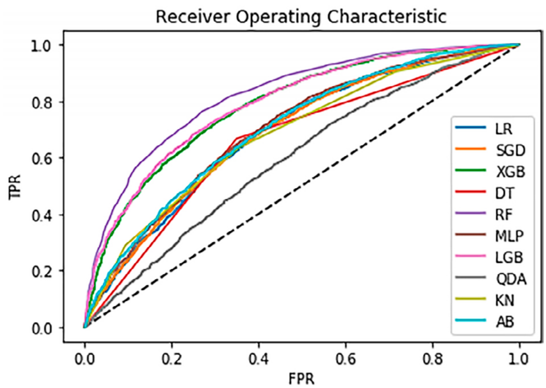


**Figure 8.** ROC-AUC curves for 10 classifiers

TPR and FPR are the True Positive Rate (known as sensitivity, recall, hit rate) and False Positive Rate (also known as fall-out). They are the axis of the ROC-AUC curves. Figure 8 shows that Random Forest outperforms the other classifiers, and it is closely followed by XGB and LGB.

The sample of the prediction results of the proposed method are depicted in Figure 9. The forecast curve follows more accurately the actual electricity price curve in all four cases: 3$^{rd}$ – 6$^{th}$ of March. On 4$^{th}$, 5$^{th}$ and 6$^{th}$ of March – that are the second, third and fourth prediction days, the accuracy is lower than on the first prediction day. More samples of the prediction results for six consecutive, randomly chosen days in April 2022 are provided in Appendix (Figures A1 and A2). The correlation coefficients calculated with the new features included in the proposed method are also depicted in Figure 10.

The following performance metrics are calculated: MAE, MAPE, RMSE, $R^2$ as in Table 3. The first three metrics should be small, whereas $R^2$ varies between 0 and 1 and it should be closer to 1. The results show that the accuracy of the prediction with the proposed method almost doubled from the MAE point of view. The testing interval spans from March to December 2022. In the nine-month testing interval, the prediction performance was not significantly influenced by the seasonality of the input data. On average, MAE improved by 45.91% and RMSE by 48.88%. $R^2$ for the proposed method also indicates that it is reliable for predicting electricity prices on BM. Similarly, the traded volume can be predicted.

**Table 2.** Feature correlation

| Feature | Correlation coefficient baseline | Correlation coefficient proposed method |
|---|---|---|
| Imbalance price for deficit (ImbPrice_d) $P^{h}_{BM^-}$ | 1.000000 | 1.000000 |
| Electricity price on DAM (Price_DAM) $P^{h+24}_{DAM}$ | 0.467342 | 0.467342 |
| Consumption $C^h$ | 0.306382 | 0.306382 |
| Oil and gas generation (Oil&Gas_gen) $OG^h$ | 0.210341 | 0.210341 |
| Hydro generation (Hydro_gen) $Hy^h$ | 0.209528 | 0.209528 |
| Imbalance price for surplus (ImbPrice_s) $P^{h}_{BM^+}$ | 0.203067 | 0.203067 |
| Generation $G^h$ | 0.178520 | 0.178520 |
| Exchange (Sold) $Ex^h$ | 0.144710 | 0.144710 |
| Traded quantity on DAM (Q_DAM) $Q^{h+24}_{DAM}$ | 0.138148 | 0.138148 |
| Hour $h$ | 0.077618 | 0.077618 |
| Financial neutrality for deficit (FinNeutrality_d) $Fin^{h}_{BM}$ | 0.069480 | 0.069480 |
| Coal generation (Coal_gen) $Co^h$ | 0.046672 | 0.046672 |
| Biomass generation (Biomass_gen) $Bi^h$ | 0.045826 | 0.045826 |
| Wind generation (Wind_gen) $Wi^h$ | 0.026996 | 0.026996 |
| Nuclear generation (Nuclear_gen) $Nu^h$ | –0.002436 | –0.002436 |
| PV generation (PV_gen) $Pv^h$ | –0.022895 | –0.022895 |
| Forecast of wind generation for DAM (GenWindDAM) $FW^{h+24}_{DAM}$ | –0.031966 | –0.031966 |
| Forecast of wind generation for IDM (GenWindIDM) $FW^{h+24}_{IDM}$ | –0.040526 | –0.040526 |
| Forecast of PV generation for DAM (GenSolarDAM) $FPV^{h+24}_{DAM}$ | –0.102805 | –0.102805 |
| Forecast of PV generation for IDM (GenSolarIDM) $FPV^{h+24}_{IDM}$ | –0.108241 | –0.108241 |
| Total imbalance (Total_Imb) $Q^{h}_{BM}$ | –0.256840 | –0.256840 |
| Mean previous prices (Prev_price_mean) $\overline{P^{h-}_{BM^-}}$ | – | 0.263368 |
| 24-h previous price (Prev_price24) $P^{h-24}_{BM^-}$ | – | 0.236953 |
| 48-h previous price (Prev_price48) $P^{h-48}_{BM^-}$ | – | 0.175650 |
| Imbalance Sign prediction (ImbSign) $\widehat{IS^{h+24}_{BM}} \in \{0,1\}$ | – | –0.870947 |

**Table 3.** Metrics

| Indicator | Baseline model | Proposed method |
|---|---|---|
| MAE | 752.637 | 345.573 |
| MAPE | 4.969 | 1.212 |
| RMSE | 997.066 | 487.383 |
| $R^2$ | 0.189 | 0.88 |

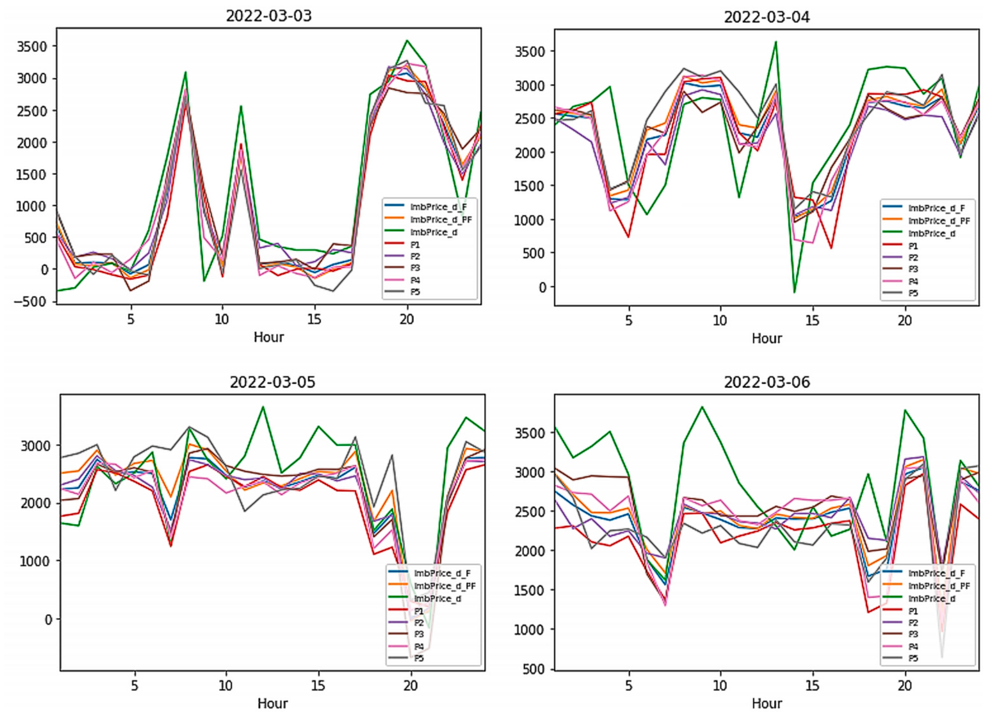


**Figure 9.** Electricity price forecast for 3rd - 6th of March 2022 (proposed method)

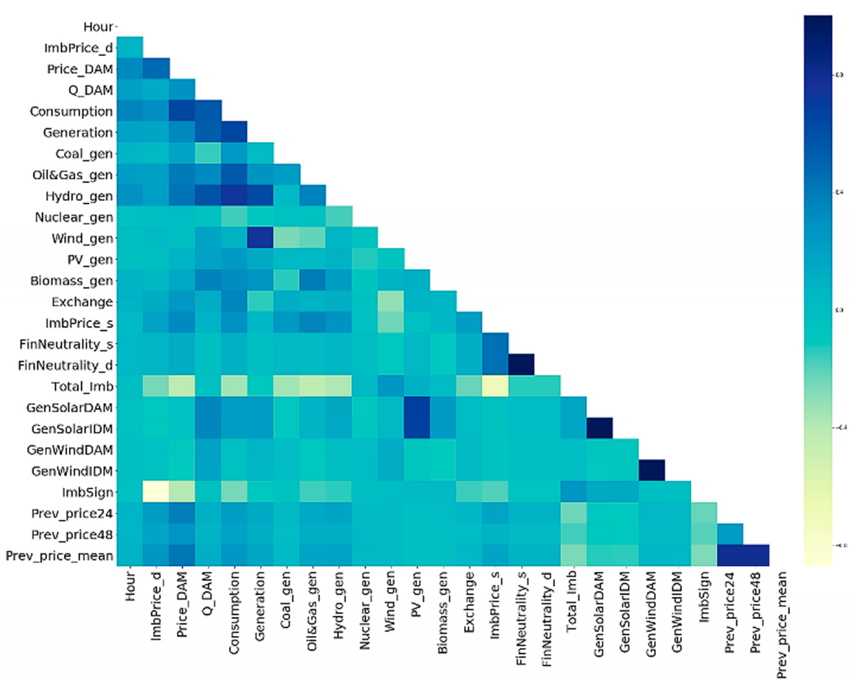


**Figure 10.** Correlation coefficients including the new features

With the price prediction, an electricity producer is able to create a better strategy for bidding. If the total capacity is 100 MW, for example, and 20 MW are already traded on the Bilateral Contract Market (BCM), the rest of 80 MW can be traded on DAM or BM depending on the prices. Most of the times, the prices on DAM ($P^h_{DAM}$) are lower than prices on BM ($P^h_{BM^{-/+}}$), but it is not always the case. For instance, on 3rd of March 2022, at h = 3, $P^3_{\mathrm{DAM}}$ = 346.27 RON/MWh, $P^3_{BM^+}$ = 26.805 RON/MWh and $P^3_{BM^-}$ = 26.805 RON/MWh, whereas at h = 19, $P^{19}_{\mathrm{DAM}}$ = 2028.97 RON/MWh, $P^{19}_{BM^+}$ = 2454.82 RON/MWh and $P^{19}_{BM^-}$ = 2940.275 RON/MWh. The total income and the income at market level at hour h = 3 are depicted in Figure 11a and at hour h = 19 in Figure 11b. These two cases indicate that the best solution is to bid on DAM the remaining quantity ($Q^h_r$).

Depending on the prices, the producer can choose between DAM and BM and estimate the income considering the risk associated with the transaction failure. Usually, there are significant risks associated with transaction failure on DAM (20–25%) and BM (65–70%) that have to be considered when estimating the revenue. For the above simulations, we considered $r_{DAM}$ = 0.25, whereas $r_{BM}$ = 0.7. Thus, the probability to trade on DAM is 0.75, whereas the probability to trade on BM is 0.3.

According to the simulations performed for one month (March 2022), using the predicted prices and a generating unit of 100 MW (with remaining available capacity of 80 for trading on DAM or BM), we obtain that it is more profitable to bid the remaining capacity

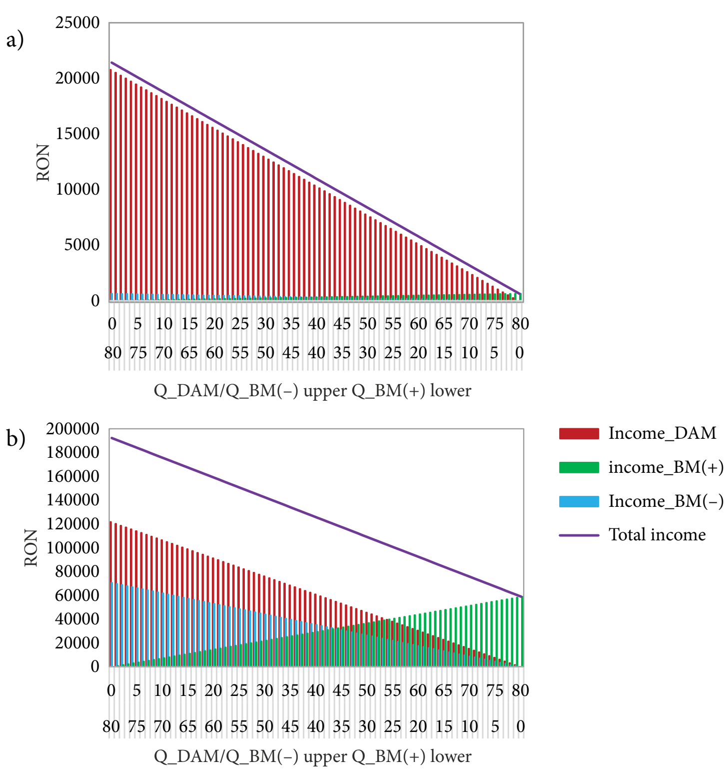


**Figure 11.** a) Income at h = 3; b) Income at h = 19

on DAM (as shown in Figure 11), but if the $P^{20}_{BM^+} = 3955.24\dfrac{RON}{MWh} \gg P^{20}_{DAM} = 690.11\dfrac{RON}{MWh}$ and $P^{20}_{BM^+} = 3955.24\dfrac{RON}{MWh} \gg P^{20}_{BM^-} = 1987.78\dfrac{RON}{MWh}$, then it is more profitable to bid the remaining capacity on BM (as in Figure 12). The predicted prices and optimal bidding quantities are provided in Table 4.

As the quantity traded on BM increases (as in the upper axis) from 0 to 80 MW, the total hourly income of the generating unit (of 100 MW) slightly increases from 89,113.32 to 94,925.760 RON. However, even if the producer chooses to bid on DAM, the income is considerable.

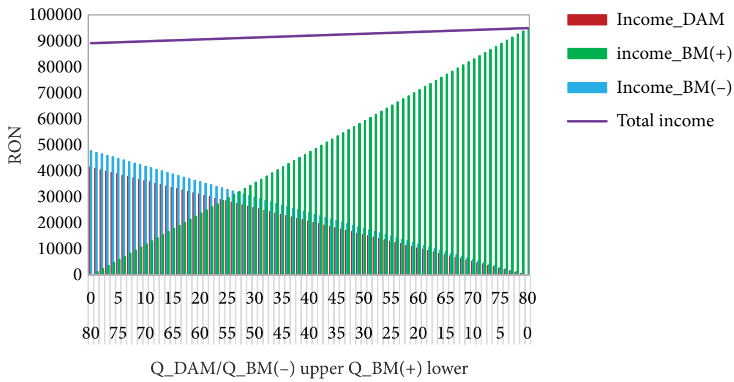


**Figure 12.** Income when $P^h_{BM^+} \gg P^h_{DAM}$, $P^h_{BM^+} \gg P^h_{BM^-}$

**Table 4.** Predicted prices and optimum bidding quantities

| Hour (h) | 3 | 19 | 20 |
|---|---|---|---|
| $P^h_{DAM}$ [RON/MWh] | 346.270 | 2,028.970 | 690.110 |
| $P^h_{BM^+}$ [RON/MWh] | 26.805 | 2,454.820 | 3,955.240 |
| $P^h_{BM^-}$ [RON/MWh] | 26.805 | 2,940.275 | 1,987.780 |
| Max I [RON] | 21,419.520 | 192,304.800 | 94,925.760 |
| $Q^h_{DAM}$ / $Q^h_{BM^-}$ [MW] | 80 | 80 | 0 |
| $Q^h_{BM^+}$ [MW] | 0 | 0 | 80 |

## Discussions and conclusions

The electricity price forecast is essential for market participants, especially for producers as they have to allocate their capacity to various markets and maximize value. The decision maker has to choose whether to bid more on DAM and less on BM or vice versa. The more predictable generators (such as gas-based generators) also have to choose between bidding more on DAM and less on BM for increasing, but more for decreasing or less on DAM and more on BM for increasing and less for decreasing.

Usually, the PV output is predicted in three scenarios: pessimistic, optimistic and moderate. Therefore, these predictions can be correlated with the electricity price forecast on DAM and BM. Even if the best prediction for a PV owner, for instance, is the moderate one, knowing the sign of the power system may determine the decision maker to choose between pessimistic and optimistic forecasts.

Thus, in this paper we proposed a method to forecast the electricity price for deficit as it is usually higher than for the surplus, and the market participants prefer to bid so as to avoid deficit. The proposed forecast method consists of two steps. First, the imbalance sign is predicted using 10 machine learning classifiers. The ROC-AUC score higher than 0.82 is obtained with Random Forest. Furthermore, Light Gradient Boosting and eXtreme Gradient Boosting perform well. Second, this new feature – imbalance sign is inserted into the input data set to predict the electricity price.

Using five ensemble machine learning algorithms – Random Forest Regressor, eXtreme Gradient Boosting Regressor, Histogram Gradient Boosting Regressor, Voting Regressor and Light Gradient Boosting Regressor, we trained these models using open data collected from ENTSO-E transparency platform for BM and forecast of RES (W and PV) for DAM and IDM, OPCOM for DAM and the Romanian TSO – Transelectrica for power system data from 2021 and 2022 to predict the electricity price for deficit.

To answer the two RQ exposed in the first section:

**RQ1.** *How to improve the electricity price forecast on BM?*

The proposed solution consists of combining the unsupervised ML algorithms (namely classification using several classifiers) and supervised ML algorithms for prediction. The prediction of the imbalance sign obtained with classifiers is inserted into the input data set for predicting the electricity price on BM.

**RQ1.** *How to make trading strategies using the AI-powered price forecast?*

To answer the second question, using the prediction of the electricity prices on BM, the market participants are assisted in making strategies to trade on DAM and BM. By varying the quantities traded on DAM or BM and multiplying these quantities with the predicted prices, the market participants estimate the income that can be obtained from trading in various scenarios. Also, the risks of trading failure for each market are included to estimate the income.

The difference between the baseline model and the proposed method is considerable (MAE improved by 45.91% and RMSE by 48.88%, $R^2$ = 0.88) and we intend to further enhance it by involving more AI in the prediction process. The proposed method provided two forecasting solutions: the first one is an average of the results of 5 ML algorithms, whereas the second one consists of weighting the results of the 5 ML algorithms using the linear regression or decision tree algorithms. The results for the first prediction day are slightly better than for the second, third and fourth prediction days, thus, the forecast has to be performed daily, but the results for the second, third and fourth days can be considered as indicative. Moreover, during the holidays, when the prediction is required for several days in advance, the prediction from 1 to 4-day even 6-day time horizon is useful.

Using the predicted prices, we proposed a method to create optimal bids, maximizing the income a generating unit can achieve by trading on DAM or/and BM. By implementing the proposed method, we found out that in most cases, it is more profitable to bid the remaining capacity on DAM as the risks of trading failure are lower and the income is higher, but if the price for increasing the capacity is much higher than the price on DAM and the price for decreasing the capacity on BM, then it becomes more profitable to bid on BM for increasing capacity. Even if DAM is chosen and $P^h_{BM^+}$ is double than $P^h_{BM^-}$, stacking the income from DAM and BM for decreasing the output almost equals the income from BM for increasing the output.

In this paper, we used numerous ML algorithms for classification (10 algorithms) and for prediction (5 algorithms). The hyperparameters were not extensively tuned; therefore, more room for improvement does exist. The multiple input data sets were extracted from open available sources; thus, the method can be easily replicated. We will continue to investigate the hyperparameters using Optuna or GridSearch as future work when we plan to use more data sets, including those extracted from social media and news channels and also study the market rules in other countries.

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# APPENDIX

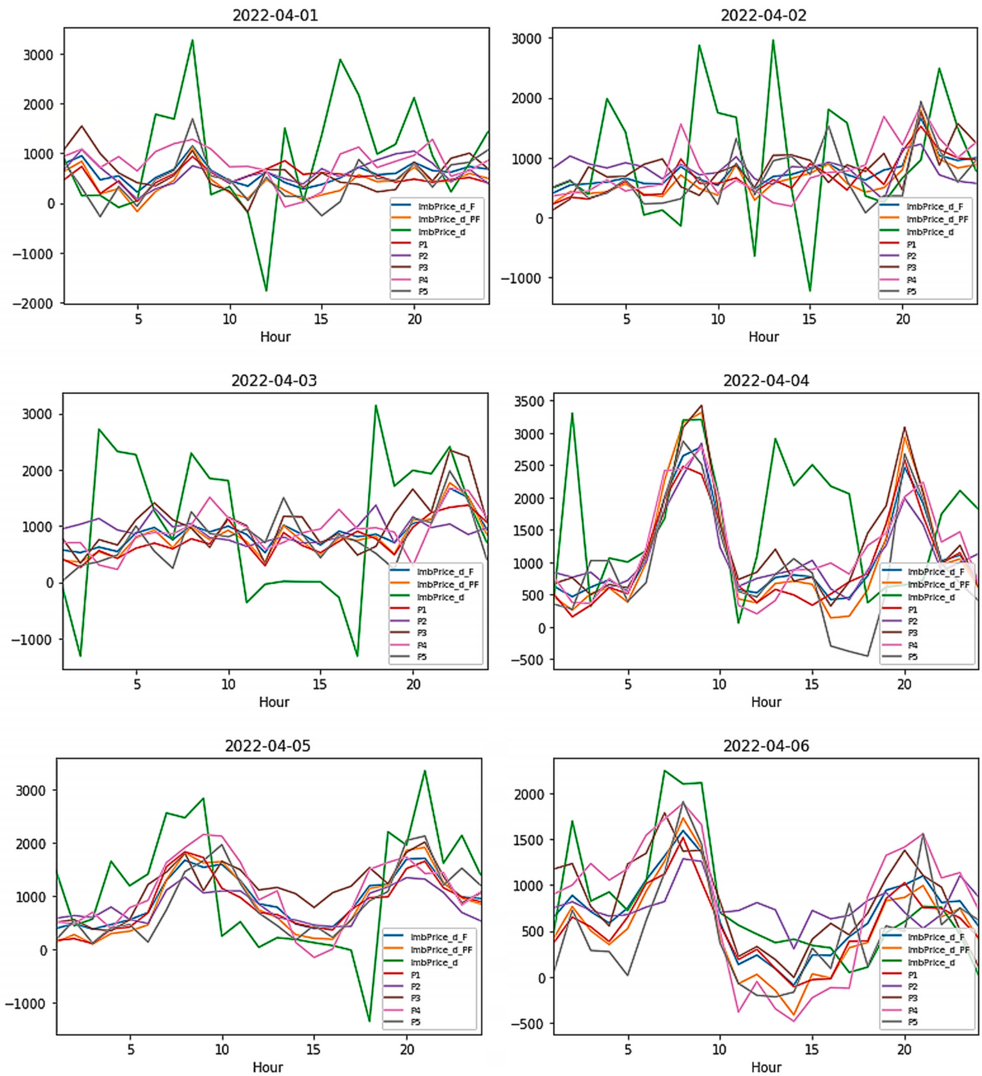


**Figure A1.** Results of the predicted prices – using the baseline model, during 1–6 of April 2022

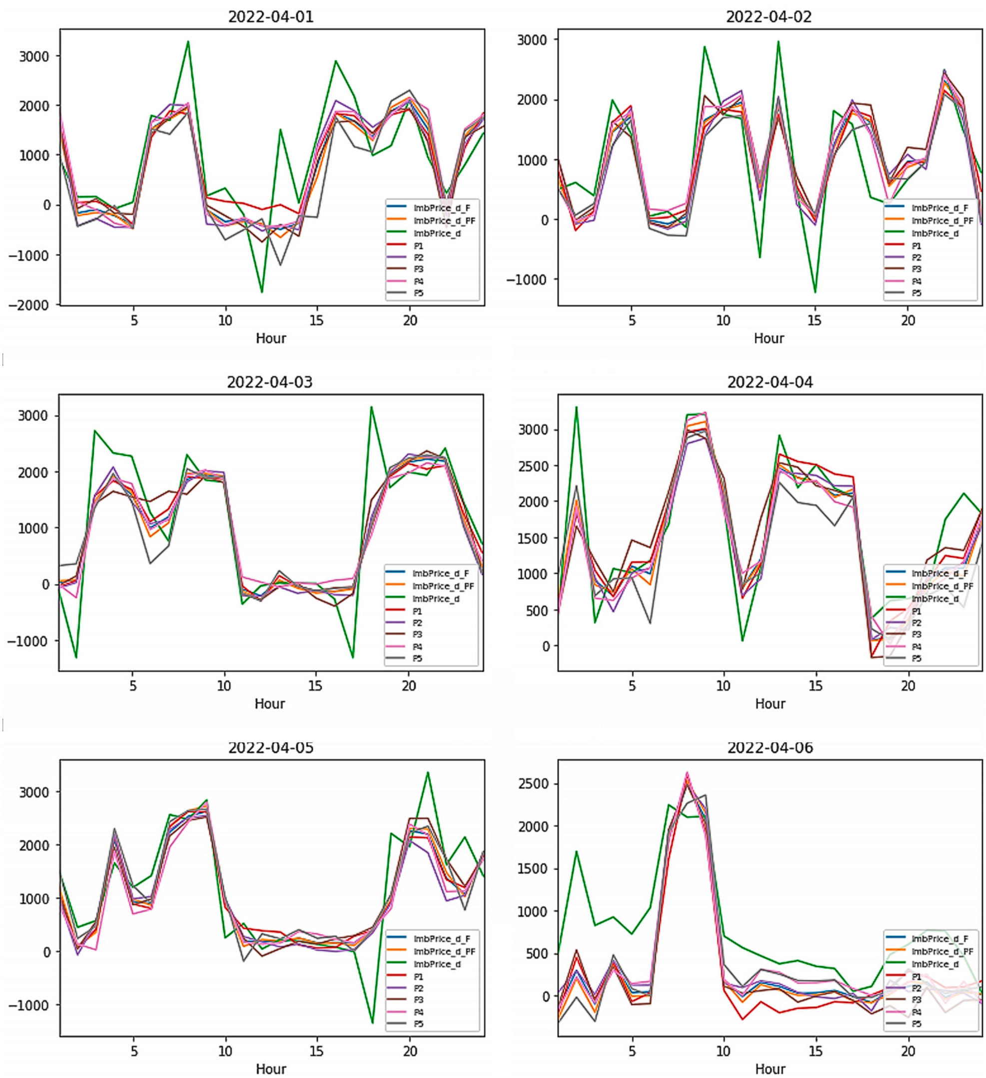


**Figure A2.** Results of the predicted prices – using the proposed model, during 1–6 of April 2022