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Feasibility study of implicit balancing in the Slovak power system using battery storage

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Abstract. Recently, a debate about proposed changes in rules governing the interaction between Slovak energy markets and the Slovak power transmission network reached a mainstream media, while opposing views on expected impacts of newly proposed imbalance settlement mechanism were presented. The proposed changes were justified by the expected reduction in implicit balancing that should lead to more favorable prices for industrial end consumers. Being motivated by this debate, we present a forecasting model for the imbalance settlement price, and we evaluate simple implicit balancing strategies while using battery storage. Our goal is to assess how difficult it is to derive some economic profit from implicit balancing while using publicly available data. The results show that implicit balancing can generate a positive gross profit, but it is not sufficient to fully cover storage-related costs, which plays a decisive role in the economic viability of BESS-based implicit balancing.

1 Introduction

The energy system in Slovakia has been operating in an environment of constant change in recent years – both due to the commissioning of new generation units (for example, the recent launch of a new nuclear block) and due to regular amendments to the Operational Rules of OKTE, a.s. (the Short-Term Electricity Market Operator) [1].These changes have sparked debates at both professional and public levels. For instance, a recently publicized debate revealed differing views: critics of the proposed changes claimed that the new rules could lead to increased implicit balancing activities and higher prices for consumers, while OKTE argued exactly the opposite – that the adjustments would deliver a more stable and predictable environment [2]. In response to this current situation, the aim of this article is to assess how demanding it is to profit from implicit balancing today and to demonstrate to what extent it is possible to use the mechanism – whose primary objective is to achieve a balance between the traded quantity of energy and the actually consumed quantity of energy – for generating economic profit. System imbalance is defined as the difference between the agreed produced/consumed quantity of electricity of all subjects constituting a balancing group and actual quantity of electricity in MWh supplied or extracted from the power grid. Each balancing group is represented by a Balance Responsible Party (BRP), which bears financial responsibility for the imbalance of its portfolio. In the Slovak electricity market, the BRP corresponds to the Subject of Settlement, i.e., an entity that has concluded an Imbalance Settlement Agreement with the Imbalance Biller (OKTE, a.s.). The Imbalance Biller is responsible for the evaluation and financial settlement of imbalances of BRPs based on registered daily schedules and measured electricity production and consumption [3].

2 Literature review

Recent research on imbalance management has increasingly focused on the use of data-driven predictive models trained on empirical data. These approaches enable the direct estimation of future imbalance values and their integration into operational decision-making processes, complementing earlier modelling strategies [4]. Within the broader European context, several studies analyze how Battery Energy Storage Systems (BESS) can actively participate in implicit balancing. Smets et al. [5] demonstrate that batteries can strategically take out-of-balance positions in single-pricing markets. Using a realistic Belgian case study, they develop a stochastic Model Predictive Control framework supported by neural-network forecasts of system imbalance, showing that such strategies improve both system efficiency and balancing-responsible party (BRP) profitability. Extending this direction, Karimi Madahi et al. [6] use a distributional reinforcement learning (RL) framework that jointly optimizes expected profit and risk exposure while considering battery degradation constraints. Testing on 2022 Belgian imbalance data, their risk-averse controller only engages in balancing actions under high-confidence predictions, resulting in more stable profits than risk-neutral RL

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approaches. In the Central European region, related work has addressed imbalance optimization with conventional generation. A PhD thesis of Kratochvil [7] studied the possibility of adjusting a power plant's output to create a balance group imbalance in the opposite direction to the system imbalance, supported by a forecasting model using multiple exogenous variables. Although this work does not involve battery storage, it is one of the few contributions directly concerning the Czech Republic with implicit balancing behaviour. Forecast-driven trading has also been explored more broadly. Sedláček [8] investigates strategy that exploits price discrepancies for the same asset or security in different geographic locations which is called spatial arbitrage in European electricity markets using econometric and machine-learning methods (ARIMAX, PCA, Lasso, Ridge, Random Forest). Although the focus is on electricity futures rather than imbalance settlement, his results illustrate that even moderately accurate forecasts can yield profitable trading strategies. This reinforces a key insight relevant to imbalance-based optimization: profitability is highly sensitive to forecast quality and model updating frequency. Research on implicit balancing with batteries in the context of Slovakia remains limited. Some works examine system adequacy and long-term flexibility needs. Zabojník & Hricovský [9] find that Slovakia's renewable and hydrogen potential will not fully satisfy future demand under EU "Fit for 55" targets, implying an increasing need for flexible resources such as storage. Similarly, Joklová et al. [10] highlight batteries, pumped storage, demand response, and emerging virtual flexibility (e.g., energy communities) as essential tools for maintaining grid stability as renewable penetration increases. While these studies do not model imbalance strategies explicitly, they underscore the structural need for fast-acting flexibility in Slovakia, creating a strong motivation for research on BESS-enabled implicit and counter-imbalance strategies. A notable example in the Slovak context is the work of Tomašov et. al. [11], who built optimization model of the prosumer energy system and applied it to maximize the economic profit considering system imbalance penalties/rewards, photovoltaic production, electric vehicle charging demand, and battery storage utilization. Their study explicitly evaluates whether a flexible asset can profit from system imbalance—intentionally acting opposite to the system imbalance to capture imbalance settlement revenues—under actual Slovak market rules. Their results show that counter-imbalance may be economically feasible, but only under high forecast accuracy and in selected windows, highlighting both the potential and the operational risks associated with predictive imbalance-based strategies.

3 Contribution and structure of the paper

The paper starts by describing the structure and sources of the dataset, followed by an analysis of correlations and preprocessing steps used to prepare the data for sequential modeling. The methodology section introduces an LSTM-based prediction model with a thresholding mechanism and a sign-aware loss formulation designed to prioritize correct sign prediction. We then propose and simulate an implicit balancing strategy driven by the model's predicted values and confidence scores. Finally, the results section evaluates forecasting performance and the economic impact of the balancing strategy, and the conclusions summarize the key findings and practical implications.

4 Materials and methods

4.1 Dataset and feature engineering

We compiled a dataset with multiple features. Values of features are released at different times, and the availability of data was carefully considered. This dataset is a combination of features from different sources such as OKTE [3], SEPS [12] and meteorological data from SHMU [13]. Each observation corresponds to a 15-minute interval. TABLE I presents the features and their descriptions, along with the categories into which they are divided. Every feature corresponds to a 15-minute interval. Some of the data was extracted from Data Management and Accounting System (DAMAS)

Table 1. Dataset – input features

Category	Feature	Description
Day-Ahead Market (DAM), Intraday Market (IDM15/IDM 60)	Price (DAM/ IDM)	Price of electricity
	pSVol (DAM/IDM15/IDM60) Successful purchases volume	Successful purchases volume
	pTVol (DAM/IDM15/IDM60) Total purchases volume	Total purchases volume
	sSVol (DAM/IDM15/IDM60) Successful sales volume	Successful sales volume
	sTVol (DAM/IDM15/IDM60) Total sales volume	Total sales volume
Calendar variables	weekend	Binary value 1 if weekend, 0 if working day
	holiday	Binary value 1 if holiday, 0 if not holiday
Meteorologica l variables	ghi	Global horizontal irradiance
	Precipitation_rate	The amount of precipitation (rain, snow, etc.)

	wind_speed_10m	Wind speed 10 meters above ground
	air_temp	Air temperature [°C]
Time	period_end	End of time interval
	period	The sequence number of the time interval in the day (96per day)
Market	ISP	Imbalance Settlement Price
	si	System imbalance
	si_damas	System Imbalance according to DAMAS
Electricity	Re_with_gcc	Regulation Energy with grid control correction
	Re_lag_2– Re_lag_15	Historical regulation Energy with grid control correction (lag= delay)

4.2 Data analysis

Since one of the objectives of this study is to forecast the Imbalance Settlement Price (ISP), the tables below present the Pearson correlation coefficients between selected input features and the ISP value. Table 2 highlights variables with the strongest positive correlation, suggesting that as these feature values increase, the ISP tends to increase as well. On the coefficient gradually decreases from 0.32 to 0.19 in roughly even steps. This indicates that past values have a limited influence on the ISP.

Table 2. Input features with the highest correlation with isp

Variable	Correlation coefficient
wprice_IDM15	0.454
wprice_IDM60	0.365
re_lag_2	0.345

Table 3. presents input features with negative correlations, indicating that higher values of these features are generally associated with lower ISP values.

Variable	Correlation coefficient
si	-0.400
si_damas	-0.400
ghi	-0.110

Data was standardized and ISP was used as the prediction target. Time values were cyclically encoded.

4.3 Prediction model

The proposed prediction model is based on a recurrent neural network architecture employing a Long Short-Term Memory (LSTM) layer to process sequential input data. The network is initialized with an input shape corresponding to the temporal and feature dimensions of the dataset. The LSTM layer consists of 64 hidden units. A dropout rate of 0.2 is applied to the recurrent connections. The model is optimized using the Adam algorithm with an initial learning rate of 0.001. A key component of the model is the incorporation of a threshold-based post-processing mechanism parameterized by λ_{sign} which secures that low values are predicted as zero (corresponding to the situation when the implicit balancing is inactive) because of high risk of economic losses caused by unfavorable settlement price. Specifically, the output is transformed according to the following rule:

$$isp' = \begin{cases} 0, & |isp| - \lambda_{sign} = 0, \\ isp, & otherwise, \end{cases} \quad (1)$$

where λ_sign defines interval (-lambda, +lambda) in which the value of ISP is considered to be insufficient for implicit balancing.

In this article, we use a loss function that combines the Mean Squared Error (MSE) with an additional regularization term designed to discourage sign inconsistencies between yˆand y values. Since correctly predicting the sign of the output is more important for our application than predicting its exact magnitude, this additional term explicitly penalizes situations in which the model assigns an incorrect sign, even if the absolute value of the prediction is close to the target. To get an indicator of the prediction reliability we also include a separate sign-classification loss that trains the model to estimate the probability that the output should be positive or negative. Predicting the wrong sign could cause much higher economic losses than predicting the right sign with a slightly inaccurate value. For this reason, the combined loss formulation emphasizes sign correctness through both the penalization term and the auxiliary sign-classification loss, while still enforcing prediction accuracy

$$L = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 + \lambda \frac{1}{N}\sum_{i=1}^{N} p(\hat{y}_i, y_i) \quad (2)$$

Where λ denotes penalization coefficient, $\hat{y}_i$ is predicted ISP at the i-th period, y_i is real ISP at i-th period (ground truth value for predictions), N represents number of observations in one sequence used as input into LSTM and $p(\hat{y}_i, y_i)$ is penalty function used in the objective of the prediction model.

The prediction model returns, in addition to the sign and the value, also the confidence of the predicted sign.

4.4 Implicit balancing strategy

We apply a simple strategy to perform implicit balancing using a battery energy storage system (BESS).

The parameter values (percentage values appearing below in the strategy description) were set after experimenting with different values. Due to the majority of settlement prices being positive, we decided to charge battery whenever the predicted sign is positive. The following text describes the simulation and its operations at each step. At every step, decision-making actions are taken based on predictions, either to perform or not to perform a given action. The simulation proceeds as follows:

1. The battery is initially set to 100% of the capacity.
2. The simulation proceeds period by period.
3. In each period:
   - Data from the previous day is collected and passed to the model to predict the ISP.
   - Based on a prediction, a decision is made:
     - If the prediction confidence is below 70% and the price is negative, the situation is marked as low confidence. If the predicted value is zero, it is marked as predicted zero. The simulation then continues to the next period.
     - If the predicted sign is negative, the battery attempts to discharge.
     - If the predicted sign is positive, the battery attempts to charge.
   - The action may or may not proceed, depended on the battery SOC. A full battery cannot be charged further, and an empty battery cannot be discharged.
   - Whenever an energy exchange with the power grid occurs, the corresponding profit or loss is recorded.

5 Results

We performed predictions over 9,391 historical 15-minutes periods, what corresponds to approximately three months, during which the actual ISP values were already available. We evaluated the predictions using a confusion matrix (see Figure 1**Fig. 1.** Confusion matrix of predictions) The accuracy achieved the value of 86.93%.

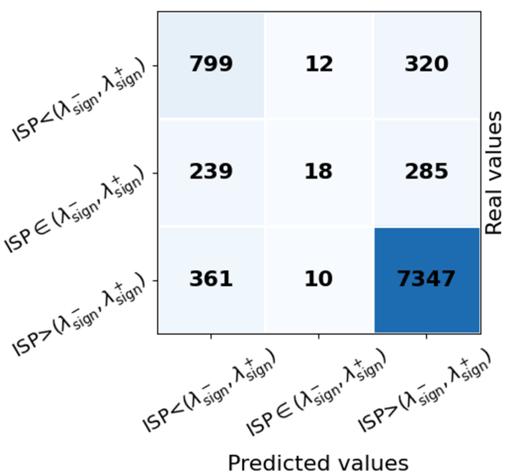

Fig. 1. Confusion matrix of predictions

5.1 Implicit balancing

The simulation consists of 9,391 15-minute periods, which represent the same number of simulation steps. We set the distribution fees to €50 per MWh for energy extracted from the grid. η_{char} (charging efficiency of BESS) and η_{dis} (discharging efficiency of BESS), were set to 95%. This means that if we extract 1 MWh from the battery, only 0.95 MWh is delivered to the grid. The battery capacity is 8 MWh. In each 15-minutes period we either charge or discharge 1 MWh. The simulation resulted in 690 discharge operations and 744 charge operations, while 2,925 periods were identified as either low confidence prediction or predicted as zero. The total traded energy without losses reached 1,434.0 MWh, and the total traded energy accounting for losses of 1,319.33 MWh, the battery was empty in 4,377 periods and fully charged in 655 periods. The Levelized Cost of Storage (LCOS) was set to 60€ per MWh. [14]

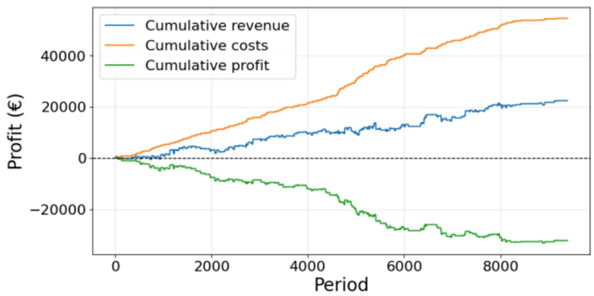

Fig. 2. Cumulative sum of profits for the simulation

In total, the proposed strategy achieved a gross profit of €21,277.02 when storage-related costs were not considered. During the simulation, there were periods in which the predicted sign was incorrect while the ISP reached higher magnitudes, leading to significant short-term losses. The cumulative LCOS-related cost associated with the energy discharged from the battery into the grid [15] is shown by the orange curve and increases steadily over time, reaching a total value of €54,528.90. The green curve represents the cumulative net profit after accounting for LCOS. Despite the positive gross profit, the inclusion of storage costs results in a negative final net profit of −€32,114.64, indicating that the revenues generated by the implicit balancing strategy are insufficient to cover the levelized cost of storage under the assumed LCOS value (see Figure 2).

6 Conclusion

In this paper, we developed a model that predicts the ISP price with an accuracy of nearly 87%. The predictions obtained from this model were then used in a simple trading strategy, where the results demonstrated that the strategy could operate profitably. However, this approach has several limitations. CAPEX and OPEX of the BESS are not considered, which increases the overall cost of the battery and extends its payback period. Also, degradation of battery is not considered. This method may still be useful for individuals who received subsidies for building a battery storage system and thus are not concerned with battery costs. Our strategy is simple and should be viewed primarily as a benchmark for the development of more advanced strategies. Many potential improvements are possible, for example future steps could focus on adjusting the amount of energy charged or discharged based on higher prediction confidence. Additional features could also be incorporated into the training process, for example, other sources carrying information about system regulation services, which may further enhance the accuracy of predictions.

During this research, artificial intelligence tools were used to assist with text editing and to support the development of the python code for statistical evaluation.

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