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A New Artificial Intelligence-Based System for Optimal Electricity Arbitrage of a Second-Life Battery Station in Day-Ahead Markets

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Abstract: Electric vehicles (EVs) are widely regarded as a crucial tool for carbon reduction due to the gradual increase in their numbers. However, these vehicles are equipped with batteries that have a limited lifespan. It is commonly stated that when the battery capacity falls below 70%, it needs to be replaced, and these discarded batteries are typically sent for recycling. Nevertheless, there is an opportunity to repurpose these worn-out batteries for a second life in electric power systems. This study focuses on the arbitrage situation of a second-life battery (SLB) facility in day-ahead electricity markets. This approach not only contributes to balancing supply and demand in the electric power system but also allows the battery facility to achieve significant gains. We propose an artificial intelligence system that integrates optimized deep learning algorithms for market price predictions with a mixed-integer linear programming (MILP) model for market participation and arbitrage decisions. Our system predicts prices for the next 24 h using Neural Hierarchical Interpolation for Time Series (N-HiTS) and decides when to enter the market using the MILP model and incorporating the predicted data and the statuses of the batteries. We compare the accuracy of our trained deep learning model with other deep learning models such as recurrent neural networks (RNNs), Long Short-Term Memory (LSTM), and Neural Basis Expansion Analysis for Interpretable Time-Series Forecasting (N-BEATS). We test the efficiency of the proposed system using real-world Turkish day-ahead market data. According to the results obtained, this study concludes that substantial gains can be achieved with the predicted prices and the optimal operating model. A facility with a total battery energy capacity of 5.133 MWh can generate a profit of USD 539 in one day, showcasing the potential of our study. Our new system's approach provides proof of concept of new research opportunities for the participation of SLB facilities in day-ahead markets.

Keywords: day-ahead market; energy arbitrage; electric vehicle second-life batteries; price prediction with deep learning; time-series prediction; neural hierarchical interpolation for time series

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1. Introduction

1.1. Motivation

The number of electric vehicles (EVs) is seen to be increasing globally in line with carbon neutrality targets, and it is estimated to reach 145 million by 2030 [1]. Many EVs contain lithium-ion batteries, which are generally retired after 8–10 years as their capacity is reduced to around 70–80% of the initial value [2]. It can be said that retired batteries still hold significant energy capacity. Additionally, lithium-ion production can have significant negative environmental impacts, requiring approximately 250 tons of ore or 750 tons of mineral-rich brine to produce 1 ton of lithium ions [3]. Producing 1 kWh of battery requires 1900 tons of water and consumes 50–65 kWh of energy. From this perspective, the use of retired batteries in a second life and leveraging them whenever possible becomes important.

Second-life batteries (SLBs) are preferred in various applications in power systems. For example, they are beneficial for peak load reduction, facilitating the integration of renewable energy, supporting carbon neutrality goals, and engaging in arbitrage in electricity markets. Furthermore, SLBs can be beneficial for both sellers and buyers. EV owners can reduce upfront costs by selling their retired batteries, while facilities purchasing these batteries can save significant costs compared to purchasing fresh batteries.

When considering the participation of SLBs in electricity markets to profit from price differentials between different rates, it is inevitable to address the process of price prediction. In other words, electricity is bought at relatively cheap rates and then sold at higher prices, generating profit. According to market clearing procedures, bids for buying and selling energy over the next 24 h are typically collected until noon the day before. Then, the market clearing price is announced, and physical deliveries are made at the relevant rates. However, accurate price prediction is key for profiting in electricity markets.

In the literature, prediction methods can be categorized into three main types: statistical time-series analysis, traditional machine learning models, and deep learning (DL) models. Statistical time-series analysis methods are often limited due to theoretical premises. Additionally, traditional machine learning models may be inadequate for predicting high-frequency data with long memory. In contrast, deep learning models can overcome these limitations and offer high-precision advantages for intelligent price predictions. Moreover, it is noted that deep learning models demonstrate superiority under suitable data conditions [4].

In light of the above information, it should be emphasized that a facility with many SLBs can profitably participate in electricity markets after predicting prices using deep learning methods. This approach also offers various benefits for the grid, including alleviating grid constraints during peak hours and ensuring uninterrupted fulfillment of regional energy demand. Therefore, in this study, after predicting Türkiye's day-ahead electricity market prices using deep learning models, the subject of participation in electricity markets is addressed through an optimal energy trading model.

1.2. Literature Review

In recent years, researchers have shown significant interest in the integration of second-life batteries into power systems for various purposes, the participation of battery energy storage systems in electricity markets to balance supply and demand, and the prediction of electricity market prices for arbitrage situations.

There are some studies on SLBs in the literature. Deng et al. [5] investigated the use of second-life batteries to meet the energy demand of residential communities. The authors proposed a bi-level framework for short-term operational objectives. At the upper level, a many-objective energy management model is explained, while at the lower level, community load is regulated, and additionally, energy costs at the upper level are allocated to houses.

Sindha et al. [6] conducted a techno-economic analysis of a battery swap station, taking into account energy trading with the power grid using aged batteries, namely SLBs. Additionally, a model was presented that minimizes the total charging cost by considering the predicted battery demand and time-of-use prices. The use of SLBs was stated to result in a 19% cost reduction. White et al. [7] examined significant performance differences among EV battery designs. In their paper, the aim was to provide important information for the design of SLB energy arbitrage projects. Moreover, it was stated that Volt and EnerDel batteries can provide the highest capacity among batteries in terms of performance. Al-Wreikat et al. [8] presented a model for calculating the payback period when SLBs obtained from EVs are used as residential energy storage systems. In their study, daily electricity consumption data of a house in the UK were used and the model was tested with MATLAB software.

It should be underlined that there are limited studies in the literature on the participation of second-life batteries in electricity markets. Tang and Wang [9] suggested

a comparative life cycle economic analysis for a building, taking into account new and second-life batteries. Their study stated that second-life EV batteries are a good alternative for buildings instead of buying new batteries. Thakur et al. [10] presented a two-stage operation structure for EV batteries. In the first stage, the most appropriate charging strategy for an EV battery is explained, and in the second stage, the EV battery is evaluated as an SLB in a house. Then, the authors carried out a test study consisting of six scenarios. According to the results obtained from the study, with the use of SLBs, battery life can be extended by 3–5 years and savings of over 23% can be achieved. Zhang et al. [11] described a framework for implementing auction-based peer-to-peer energy trading in a residential energy market. While the economic layer and the physical layer were optimized in the model, each home energy management system tried to maximize its profit. In the study, both fresh batteries and SLB situations were taken into account. The feasibility of SLBs was confirmed in test studies. Xu et al. [12] investigated the participation of EV SLBs in Danish electricity markets. The authors determined the aim of the study as maximizing the profits obtained from the markets. They also conducted test studies taking into account various situations, and it was announced that the structure has environmental–economic benefits. However, historical Denmark electricity market price data were used in this study. It should be underlined that no predictions were made for future electricity prices when trading in electricity markets. Fallah and Fitzpatrick [13] conducted a techno-economic analysis of the electricity trade of EV SLBs in the Irish electricity market. In the results, it was stated that SLBs are economically suitable as their cost decreases compared to a new battery.

In some studies, the participation of new batteries in the electricity markets was taken into account. It should be underlined that SLBs could not be used in these studies. Mustafa et al. [14] evaluated battery energy storage systems as a flexibility tool for the healthcare sector. In their study, they proposed a model for a UK hospital with a PV system for arbitrage in the electricity market and providing ancillary services. Ellis et al. [15] investigated the degradation status of lithium-ion batteries performing arbitrage and providing frequency regulation services. It was determined that the degradation rate is rapid in the initial 1000 cycles during arbitrage and then it stabilizes. Biggins et al. [16] proposed an operation framework for a battery energy storage system in Great Britain providing Great Britain's Firm Frequency Response (FFR) and realizing arbitrage. In their study, machine learning classifiers such as Random Forest, Naive Bayes, Decision Tree, and neural network algorithms to predict market outcomes are utilized. The results indicated that engaging in arbitrage could yield a significant amount of revenue. Rangarajan et al. [17] empirically evaluated the service of battery energy storage systems providing frequency control ancillary services in the Australian electricity markets. The results indicated that batteries significantly reduce ancillary service market prices. Mercier et al. [18] examined the historical value of electricity storage in the day-ahead electricity market of the EU-28 countries, Norway, Switzerland, and Türkiye. The model was solved considering that storage durations ranged from 1 h to 10 h and round-trip efficiency ranged from 50% to 100%. Campana et al. [19] presented an operation model for commercial buildings including lithium-ion batteries for peak shaving and price arbitrage and a PV system for self-consumption. The results stated that if the battery price is below 250 USD/kWh, the net present value is positive. Pusceddu et al. [20] discussed energy arbitrage and the fast frequency response situations for battery energy storage systems. The authors examined this situation with a techno-economic model. In the results, they stated that the proposed structure provides profit and that a battery that can be discharged for 1.5–2 h at full power is suitable for the system. Legrand et al. [21] proposed a framework for a 100 MWp PV system with liquid air energy storage, located in southern Spain, to engage in arbitrage in the Iberian energy market. Núñez et al. [22] examined the arbitrage situation in the day-ahead electricity market for batteries in European countries for 2019. However, herein, it should be stated that a 1-year long-term evaluation was made based on historical electricity prices. Komorowska and Olczak [23] discussed the suitability of lithium-ion batteries for the arbitrage situation in European electricity markets. The results showed that Romania

and the United Kingdom could achieve operating profits of 10,000–13,000 EUR/1 MWh of capacity. Gaspar et al. [24] explained a structure for renewable energy sources with battery energy storage to perform arbitrage in the Iberian electricity market. Additionally, Long Short-Term Memory (LSTM) was used for price prediction. In the results of their study, it was stated that the profit can be increased by 21% to 36% with the prediction model and also that the most suitable storage system is a lithium-ion battery. Zhang et al. [25] presented a method for the arbitrage of different energy storage technologies in California markets. It was stated that an income of 270 USD/MW was obtained with California electricity market prices. Hurta et al. [26] conducted a long-term economic analysis of battery energy storage systems in the German and Austrian day-ahead power markets. They also realized a scenario by predicting electricity prices with the seasonal autoregressive integrated moving average (SARIMA) model.

There are several works that propose methods for predicting electricity demand and/or prices. Manowska [27] used an LSTM network to predict the demand for electricity in Poland. Mazen et al. [28] forecasted solar power using the GRU–Temporal Fusion Transformer Model and the DILATE loss function. They also compared their results with different deep learning-based and traditional machine learning algorithms such as XGBoost, N-BEATS, and N-HiTS. Yang et al. [29] used graph convolutional networks for forecasting locational marginal prices to make bidding strategies. Mohamed et al. [30] proposed a forecasting model of four successive stages based on neural networks and an optimization framework for battery energy storage systems. Their focus was the Single Electricity Market in the island of Ireland. Kaya et al. [31] conducted an empirical study on Turkish markets for electricity price estimation, focusing on normal and COVID-19 pandemic periods. They used the Transformer Encoder–Decoder with Self-Attention (TEDSE) model. Gunduz et al. [32] discussed transfer learning opportunities for artificial neural networks to predict the next 24 steps of hourly data. Tschora et al. [33] compared various machine learning approaches including deep neural networks (DNNs) and convolutional neural networks (CNNs) on day-ahead electricity markets. Le et al. [34] proposed a model using a combination of bi-directional LSTM and CNNs to improve predictions. They used data from Canada, France, Italy, Japan, Brazil, Mexico, and Türkiye. Brusaferri et al. [35] suggested a novel methodology for probabilistic energy price prediction in day-ahead markets based on Bayesian deep learning techniques. Meng et al. [36] presented the usage of attention-based LSTM networks trained by crisscross optimization for electricity price prediction. Li et al. [37] proposed a hybrid approach integrating LSTM-based deep learning with feature selection algorithms to forecast day-ahead electricity prices considering market coupling effects. Their study underscored the significance of accurate prediction in the context of European market harmonization and demonstrated the effectiveness of their approach, particularly highlighting the impact of features from integrated markets, with the German market playing a prominent role in Nord Pool price generation. Grothe et al. [38] put forward a straightforward method, leveraging copula techniques, to generate multivariate probabilistic forecasts for day-ahead electricity prices based on univariate point forecasts. Their approach accounted for the dependence structure across hours and demonstrated applicability across five benchmark datasets, showcasing its potential for constructing realistic prediction intervals for various energy market scenarios. Tan et al. [39] proposed a novel hybrid deep learning-based model, combining convolutional neural networks and stacked sparse denoising auto-encoders, along with an improved decomposition method called complete ensemble empirical mode decomposition with adaptive noise, to enhance day-ahead electricity price forecasting accuracy. Their experimental results on the Australian national electricity market demonstrated superior prediction performance, particularly in forecasting price spikes, while also offering faster convergence speed compared to traditional neural network models, thus providing valuable insights for electricity market participants.

1.3. Contribution

This study presents a system for predicting electricity prices in the Turkish day-ahead market and facilitating the participation of a facility composed of multiple second-life batteries in the electricity market. The contributions of this study to the literature are listed below:

- The optimum trading model is presented for the participation of a facility established by purchasing old EV batteries as SLBs, and instead of recycling them, using them in the day-ahead electricity market.
- The next 24 h electricity prices in the day-ahead electricity market are predicted using the N-HiTS deep learning model. Additionally, price predictions are compared with five other common or trending methods in the literature (Naïve Seasonal Prediction, RNNs, LSTM, GRU, N-BEATS).
- Various case studies are conducted using real prices from the day-ahead electricity market in Türkiye. This study can serve as a pathfinder for researchers and system developers exploring the arbitrage opportunities of SLBs in Türkiye and other countries.

It should be underlined that, to the best of the authors' knowledge, this is the first proposed system in the literature where SLBs are directly taken into account for arbitrage in the day-ahead market and where electricity prices are predicted via deep learning methods using real prices from Türkiye.

1.4. Paper Organization

The rest of this paper is organized as follows. The overall system structure is explained in Section 2. Section 3 describes the models for the prediction of day-ahead electricity market prices and reveals the obtained prediction values and comparisons. Section 4 explains the mathematical model related to the participation of SLB energy storage systems in the electricity market. Section 5 is dedicated to presenting the test studies and detailed comparisons. Finally, the significant findings are emphasized in Section 6.

2. Explanation of the Overall System Structure

A general example of the proposed framework is presented in Figure 1. In this illustration, the plant consists of numerous second-life batteries, each assumed to have different energy capacities. EV batteries are usually replaced with new ones when the battery energy status falls below 70%, and old batteries are sent for recycling. However, with the method presented here, these batteries are used in SLB facilities. As a result of their use in EVs, their capacity values have decreased. The Battery Storage System Manager predicts the 24 h electricity prices for the next day in the day-ahead electricity market. Based on these predictions, it manages energy buying and selling transactions for the next day. The system enables EV owners to earn revenue from their old batteries, and the battery facility can acquire them at a reduced price. Moreover, prolonging the lifespan of these batteries will have a beneficial impact on the environment. In this study, it is assumed that by being in a price-taking position and having a relatively small capacity, the storage plant does not influence the market price.

This system can be adapted to different electricity markets, but it would require adjustments to local regulations, pricing mechanisms, and market participation rules. Variability in electricity prices, market dynamics, and infrastructure differences, such as grid reliability and storage technologies, may also introduce challenges that need to be addressed.

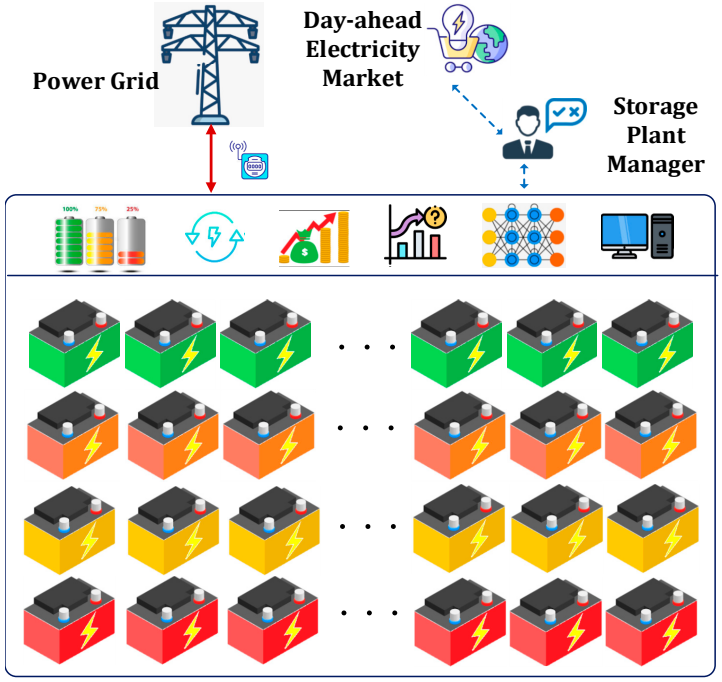


Figure 1. A general schematic illustration that depicts the proposed structure.

3. Price Predictions Using Deep Learning Models

3.1. Dataset, Preprocessing, and Training Environment

Publicly available data were obtained from EPİAŞ [40] for this study. EPİAŞ is a Turkish Energy Exchange that publishes data for the transparent and fair functioning of the energy markets by the directives of the Energy Market Regulatory Board.

Each prediction utilized the last 365 days of data with hourly prices for each day, with USD prices converted from TRY using the official exchange rate provided by the Central Bank of Türkiye. While additional data were accessible, we opted for a limited training dataset due to several factors.

- Rolling Model Adaptation: Our proposed system employs a rolling approach, necessitating its adaptation to real-world fluctuations. A smaller training dataset facilitates faster adaptation and mitigates overfitting concerns.
- Data Volatility: The COVID-19 pandemic and significant fluctuations in the USD/TRY exchange rate introduced substantial volatility into certain data periods. Using a smaller training set helps to limit the influence of these volatile outliers on model performance.
- Regulatory Changes: Legal regulations governing day-ahead market trading have undergone changes in recent years. A smaller training set allows for easier incorporation of these changes and their potential impact on the market dynamics.

3.2. Time-Series Forecasting Models

3.2.1. Naïve Seasonal Prediction

Naïve Seasonal Prediction is a simple statistical forecasting method that assumes that the forecast will be the same as the most recent observed value from the corresponding season or period in the past. For instance, in the daily periodic context in our study, the forecast for a given day would be based on the observed value from the same day in the previous season or cycle. We use this method as the baseline in predictive modeling to compare the performance of more sophisticated forecasting methods and to evaluate whether other models offer statistically significant improvements over a straightforward approach.

3.2.2. Simple Recurrent Neural Networks (Simple RNNs)

Simple recurrent neural networks (RNNs) have emerged as powerful tools for time-series forecasting due to their ability to process sequential data and capture inherent temporal dependencies. Unlike traditional feedforward neural networks, RNNs incorporate recurrent connections that enable information to persist across processing steps. This internal "memory" allows RNNs to learn evolving patterns and long-term dependencies within the data, making them well suited for tasks like predicting future values in a time series.

However, simple RNNs suffer from significant limitations when applied to large and complex time-series datasets. The major challenge lies in the vanishing and exploding gradient problems. Vanishing gradients occur when information from earlier data points gradually fades during backpropagation, making it difficult for the network to learn long-term dependencies. Conversely, exploding gradients can amplify information, leading to unstable training and unreliable predictions.

3.2.3. LSTM (Long Short-Term Memory) Networks

LSTM networks augment the standard RNN architecture with specialized memory cells, alongside the traditional hidden state units. These memory cells possess the intriguing ability to selectively remember or forget information over extended periods. This selective control is achieved through three crucial gating mechanisms [41]:

- Forget gate: This gate, activated by the current input and the previous hidden state, determines which information from the previous cell state becomes irrelevant and should be discarded. It learns a multiplicative factor between 0 and 1 for each cell element, essentially forgetting information deemed unimportant for future predictions.
- Input gate: While the forget gate decides what to discard, the input gate controls the flow of new information from the current input vector into the cell state. It also utilizes the previous hidden state to modulate the importance of new information. This gated mechanism ensures that only relevant new information updates the cell state.
- Output gate: Finally, the output gate determines what information from the current cell state, should be exposed as the output. It applies a sigmoid activation function on both the current cell state and the previous hidden state, generating a vector with values between 0 and 1, effectively controlling the contribution of cell state information to the overall output.

3.2.4. Gated Recurrent Units (GRUs)

While drawing inspiration from the powerful Long Short-Term Memory (LSTM) networks, GRUs offer a streamlined approach by streamlining the internal gating mechanisms, resulting in a more parsimonious architecture with fewer parameters. This translates to significant advantages in terms of training speed and computational efficiency, making them particularly well suited for large-scale time-series forecasting tasks [42]. They consist of three key components: the update gate, the reset gate, and current memory.

- Update Gate: This controls the extent to which the candidate hidden state, incorporating new information, replaces the previous hidden state. It determines which information to retain from the past.
- Reset Gate: This decides how much of the past hidden state to forget before incorporating new information. It effectively resets the memory when necessary.
- Current Memory: This captures the current understanding of the sequence, reflecting the combined influence of previous inputs and the update gate's selection.

3.2.5. Neural Basis Expansion Analysis for Interpretable Time-Series Forecasting (N-BEATS)

N-BEATS is a deep learning architecture that is designed for time-series forecasting. N-BEATS is built upon a stack of fully connected layers, referred to as "blocks", which are responsible for capturing different patterns and trends within the time-series data. Each

block consists of a fully connected feedforward neural network. The architecture allows for flexibility in capturing various temporal patterns, such as trends, seasonality, and irregular fluctuations [43].

3.2.6. Neural Hierarchical Interpolation for Time-Series Forecasting (N-HiTS)

Neural Hierarchical Interpolation for Time-Series Forecasting (N-HiTS) stands as a significant advancement in the field, aiming to improve both the accuracy and computational efficiency of predictions. Building upon the foundational N-BEATS framework, N-HiTS introduces a novel hierarchical approach that integrates multirate sampling techniques with multiscale synthesis strategies. This innovative architecture addresses two key challenges in long-range time-series forecasting: computational complexity and prediction volatility [44].

The core of N-HiTS lies in its hierarchical construction. Each model comprises multiple stacks, each housing several blocks. These blocks leverage Multi-Layer Perceptrons (MLPs) to predict coefficients for both backcasting and forecasting tasks associated with their assigned basis functions. Backcasting serves to refine subsequent inputs, while the collective forecast outputs from all blocks are ultimately aggregated to generate the final prediction. Each stack within the architecture specializes in capturing distinct data attributes by utilizing unique sets of basis functions, offering increased flexibility and adaptability to varying data characteristics.

The hierarchical approach in N-HiTS manifests in two key aspects:

- Multirate sampling: Blocks closer to the input receive data at a higher sampling rate, enabling them to capture fine-grained details and higher frequency components. Deeper blocks receive downsampled data, focusing on larger trends and lower frequencies. This hierarchical sampling promotes computational efficiency by allocating resources where they are most beneficial.
- Multiscale synthesis: Predictions from each block are synthesized at different scales depending on their level within the hierarchy. High-frequency components are reconstructed first, followed by the gradual incorporation of lower frequency information. This progressive approach helps to mitigate volatility in long-range forecasts, offering more stable and reliable predictions.

By integrating these hierarchical strategies, N-HiTS achieves a balance between efficiency and accuracy. Compared to its predecessor N-BEATS, N-HiTS demonstrates improvements in both computational speed and long-range forecast quality, making it a valuable tool for real-world applications where both precision and efficiency are critical.

3.3. Training Prediction Models

To determine the most suitable forecasting model for the system, we evaluated Naïve Seasonal Prediction, GRU, LSTM, N-BEATS, and N-HiTS models in various configurations on randomly selected days throughout 2023. Given the inherent variability in the market data, it is unrealistic to expect a single model to consistently perform best every day. However, in the initial testing phase, N-HiTS demonstrated superior overall performance during both training and validation, making it the primary model chosen for the proposed system. We trained N-HiTS models on the target dataset using the hyperparameters and details indicated in Table 1.

To demonstrate both the efficacy of the N-HiTS architecture and the proposed system as a whole, we adopted a seasonal cross-validation approach. Four representative months were randomly chosen for each season in the year 2023, resulting in the selection of February (winter), April (spring), July (summer), and October (autumn). Predictions were generated for the 15th day of each chosen month, utilizing the preceding 365 days' worth of hourly data for model training. Subsequently, the trained model was leveraged to predict the next 24 h, relying on the past week's data as input. A performance comparison of the predictions was conducted using established metrics, with the predicted data additionally employed in

an SLB storage system as a proof-of-concept demonstration. Our results demonstrate that N-HiTS is superior in most scenarios, but it is still profitable when it is not the best model.

Table 1. The hyperparameters and training details of the trained N-HiTS model.

Model Architecture	3 stacks with 1 block each that has 2 fully connected layers with 512 neurons each
Dropout	0.1
Loss Function	MSE
Activation Function	ReLU
Batch Size	32
Epochs	50
Training Environment	NVIDIA RTX 3090 GPU, Python 3.11, PyTorch 2.1.1 and CUDA 11.8

To evaluate the findings, we used some common metrics such as the Mean Absolute Error (MAE) (1), Mean Squared Error (MSE) (2), Root Mean Squared Error (RMSE) (3), Coefficient of Variation (COEV) (4), Mean Absolute Percentage Error (MAPE) (5), and Mean Directional Accuracy (MDA) (6). The MAE quantifies the average magnitude of errors between predicted values and actual observations, providing a straightforward indication of forecasting accuracy. It is calculated by averaging the absolute differences between predicted and observed values. However, the MAE does not account for the direction of errors, treating both underestimations and overestimations equally. In contrast, the MSE squares the errors before averaging them, offering a more sensitive measure by penalizing larger discrepancies. This property makes the MSE particularly useful for identifying outliers and amplifying the impact of large errors on the overall assessment of model performance. The RMSE, a derivative of the MSE, shares its benefits while addressing the issue of scale inherent in the MSE. By taking the square root of the MSE, the RMSE yields a metric that is interpretable in the same units as the original data, facilitating a more intuitive understanding of prediction accuracy. The COEV offers a normalized assessment of forecasting accuracy by considering the variability relative to the mean of the observed data. The MAPE provides a percentage-based evaluation of forecasting performance, making it highly interpretable and widely favored in practical applications. The MAPE computes the average of the absolute percentage errors between predicted and observed values, offering insights into the relative accuracy of predictions across different scales of the time-series data. The MDA compares the forecast direction (increments or decrements in value) to the actual realized direction. It should be noted that the MDA does not directly reflect the accuracy of the forecast but demonstrates how accurately a model can predict changes in the directions that might affect the system's decision-making process.

Metrics are calculated using the Equations (1)–(5), where N denotes the number of data points in the test data. y_t denotes the actual value and $\hat{y}$ denotes the predicted value. $\overline{y_t}$ is the average of y_t. A comparison of model predictions vs. the actual data is given in Table 2.

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{t}=1}^{\mathrm{N}}|\mathrm{y_t} - \hat{\mathrm{y}}_\mathrm{t}| \tag{1}$$

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{t}=1}^{\mathrm{N}}(\mathrm{y_t} - \hat{\mathrm{y}}_\mathrm{t})^2 \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{t}=1}^{\mathrm{N}}\frac{(\mathrm{y_t} - \hat{\mathrm{y}}_\mathrm{t})^2}{\mathrm{N}}} \tag{3}$$

$$\mathrm{COEV} = 100.RMSE(y_t, \hat{y}_t)/\ \overline{y_t} \tag{4}$$

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (5)$$

Predictions of the selected model (N-HiTS) vs. the other top two performing models according to the MSE (GRU and LSTM) and the actual values are compared in Figure 2.

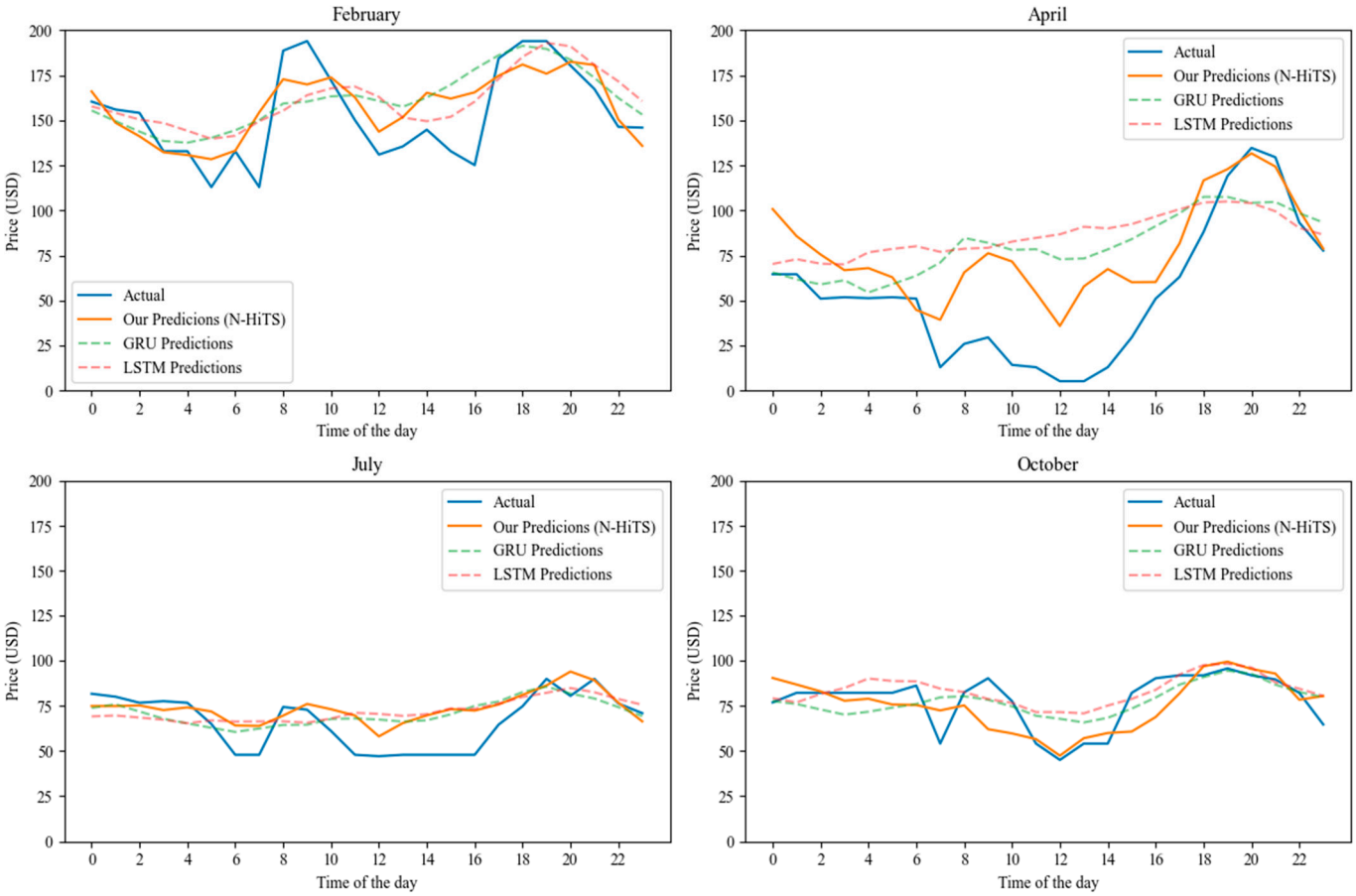


Figure 2. Comparison of our predictions vs. actual values.

Table 2. Comparison of prediction accuracy using common metrics.

Model/Metric	MAE				MSE				RMSE			
	February	April	June	October	February	April	June	October	February	April	June	October
Naïve Seasonal Prediction *	24.74	50.31	11.56	12.75	926.2	3143.63	236.72	305.37	30.43	56.07	15.39	17.47
Simple RNN	15.97	40.94	12.62	7.85	403.18	2427.15	256.52	149.23	20.08	49.29	16.02	12.22
LSTM	16.07	38.88	12.41	8.1	381.88	2166.13	210.99	136.86	19.54	46.54	14.53	11.7
GRU	16.46	32.57	10.81	8.72	458.87	1667.21	167.29	120.56	21.42	40.83	12.93	10.98
N-BEATS	20.1	30.22	12.52	12.87	746.58	1206.96	252.78	283.46	27.32	34.74	15.9	16.84
N-HITS	13.73	24.46	10.06	9.01	309.61	893.18	159.26	136.4	17.6	29.89	12.62	11.68

Table 2. *Cont.*

Model/Metric	COEV				MAPE				MDA			
	February	April	June	October	February	April	June	October	February	April	June	October
Naïve Seasonal Prediction *	19.84	104.25	23.18	22.51	16.26	283.83	20.8	18.49	0.52	0.52	0.52	0.52
Simple RNN	13.09	91.6	24.13	15.73	11.57	279.18	23.44	13.35	0.65	0.48	0.57	0.65
LSTM	12.74	86.54	21.88	15.07	11.28	268.0	22.14	13.27	0.61	0.57	0.48	0.48
GRU	13.97	75.92	19.48	14.14	11.76	226.62	19.31	13.36	0.61	0.61	0.52	0.57
N-BEATS	17.81	64.6	23.95	21.68	14.11	167.46	22.68	17.19	0.61	0.74	0.70	0.57
N-HITS	11.47	55.57	19.01	15.04	9.57	154.15	18.45	11.78	0.7	0.74	0.57	0.57

*: given as a baseline for comparison.

4. Mathematical Formulation of Market Participation

In this subsection, a mathematical formulation is provided for the optimal participation of the second-life battery plant in the day-ahead market. The day-ahead electricity market is an organized market used for energy trading, operated by the Market Operator, one day before the delivery day. Electricity buying and selling transactions are conducted at 1 h time intervals. For example, in the day-ahead electricity market in Türkiye [27], participants submit their bids until 11:30 every day. The hourly day-ahead electricity prices for the next day are announced at 14:00.

The proposed structure is addressed with a mixed-integer linear modeling approach, which is a common optimization technique used to identify the most effective solution from a range of feasible options. The primary objective is to maximize the profit obtained by the SLB energy facility in the electricity market, which is presented by Equation (6). This maximization is crucial for ensuring the financial sustainability of the energy facility. The relevant equation comprises the revenue generated from electricity sales and the costs incurred from electricity purchases, emphasizing the need to balance these two components for profitability. Equation (7) describes the energy state of each *sl* SLB in the energy storage facility. Here, the energy state is obtained by adding the energy charged if the battery is being charged or subtracting the energy discharged if the battery is being discharged, based on the energy in the previous hour. This dynamic calculation allows the model to continuously monitor battery performance over time, which is essential for effective energy flow management. Additionally, the charge and discharge efficiencies of each battery, reflecting real-world battery performance and ensuring that energy losses are accurately accounted for in the model, are taken into account. In (8), it is ensured that each second-life battery can be charged up to its maximum energy capacity. This is a logical condition imposed for the maximum energy capacity due to the technical specifications of the battery. In the first hour of the day, the energy state of each second-life battery is defined in (9), establishing a baseline for energy management. When calculating the total energy purchased from the market to charge the SLBs each hour, (10) is used, while (11) determines the total energy sold to the electricity market by discharging the batteries each hour. These expressions represent the bid values for the amounts of energy bought and sold for energy trading at the relevant hour in the current market. The maximum charge and discharge amounts for each SLB are presented in (12) and (13), respectively, ensuring that the model adheres to the physical constraints of battery operation. (14) and (15) utilize binary decision variables to ensure that selling and buying transactions do not occur within the same hour. This constraint is essential for maintaining clear operational boundaries within the model, thus preventing conflicting trading actions. Similarly, preventing the charging and discharging processes for each battery each hour is explained in (16) and (17),

respectively. Here, $u1_t^{bin-dec}$ and $u2_t^{bin-dec}$ are auxiliary binary decision variables used to prevent two situations from occurring at the same time.

$$\text{Maximum}(Income) = \left(\sum_t \left(E_t^{selling} \cdot \chi_t^{pred-price}\right) - \sum_t \left(E_t^{buying} \cdot \chi_t^{pred-price}\right)\right) \quad (6)$$

$$SOE_{sl,t}^{bat} = SOE_{sl,(t-1)}^{bat} + E_{sl,t}^{charging} \cdot \delta_{sl}^{charging} - \frac{E_{sl,t}^{discharging}}{\delta_{sl}^{discharging}}, \ \forall sl, \ t > 1 \quad (7)$$

$$SOE_{sl,t}^{bat} \leq SOE_{sl}^{bat-max}, \ \forall sl \quad (8)$$

$$SOE_{sl,t}^{bat} = SOE_{sl}^{bat-init}, \ \forall sl, \ t = 1 \quad (9)$$

$$E_t^{selling} = \sum_{sl} E_{sl,t}^{discharging}, \ \forall t \quad (10)$$

$$E_t^{buying} = \sum_{sl} E_{sl,t}^{charging}, \ \forall t \quad (11)$$

$$E_{sl,t}^{charging} \leq E_{sl}^{ch-max}, \ \forall sl, t \quad (12)$$

$$E_{sl,t}^{discharging} \leq E_{sl}^{disch-max}, \ \forall sl, \ t \quad (13)$$

$$E_t^{selling} \leq u1_t^{bin-dec} \cdot N, \ \forall t \quad (14)$$

$$E_t^{buying} \leq \left(1 - u1_t^{bin-dec}\right) \cdot N, \ \forall t \quad (15)$$

$$E_{sl,t}^{charging} \leq u2_t^{bin-dec} \cdot N, \ \forall t \quad (16)$$

$$E_{sl,t}^{discharging} \leq \left(1 - u2_t^{bin-dec}\right) \cdot N, \ \forall t \quad (17)$$

5. Test and Results Regarding Market Participation

This section includes test studies regarding the optimal participation of the SLB facility in electricity markets. The proposed structure is tested using GAMS v.24.1.3 software and CPLEX v12 solver. The subsections cover input data and case studies with comparisons.

5.1. Input Data

In this study, it is assumed that the SLB facility is located in Türkiye. It is hypothesized that the facility conducts arbitrage in the day-ahead electricity market through second-life EV batteries. The facility consists of 102 SLBs, with a total energy value of 5133 MWh. The batteries comprise 10 different types of aged EV batteries. These batteries are composed of those belonging to the best-selling EVs in Türkiye in 2023, namely Togg T10X, Tesla Model Y, Renault Megane E-Tech, MG4, Skywell ET5, Opel Corsa-e, Renault Zoe, Opel Mokka-e, Dacia Spring, and Mercedes-Benz EQB. All of these vehicles have lithium-ion batteries. Information on the batteries from each EV is presented in Table 3. Additionally, the table includes the number of batteries.

It is assumed that the batteries in the facility have energy capacities in the range from 55% to 80%. Figure 3 presents the current capacity value of each battery. For example, while the fresh battery capacity of battery 10 is 88.5 kWh, the capacity value in the SLB facility is 55.76 kWh. Additionally, the charging and discharging efficiency of each battery is set at 95%. It is assumed that the batteries can be fully charged and discharged within one hour, while the minimum energy limit is set at 5%. There are 102 batteries in the SLB facility. The total energy capacity of these is 5133 kWh. However, due to the minimum battery capacity, only 4877 kWh of energy can be actively traded.

To demonstrate the effectiveness of the presented model, four different case studies are conducted by predicting the next 24 h of electricity market prices for the 15th day of

February (Case-1), April (Case-2), June (Case-3), and October (Case-4). Real data of the Türkiye day-ahead electricity market and the predicted data are shown in Figure 4.

Table 3. Data related to the battery of the EV models used in this study.

EV Model	Battery Capacity [kWh]	Number of Batteries
Togg T10X	88.5	41
Tesla Model Y	75	25
Renault Megane E-Tech	60	6
MG4	64	6
Skywell ET5	71.7	6
Opel Corsa-e	50	4
Renault Zoe	52	4
Opel Mokka-e	54	4
Dacia Spring	26.8	3
Mercedes-Benz EQB	70.5	3

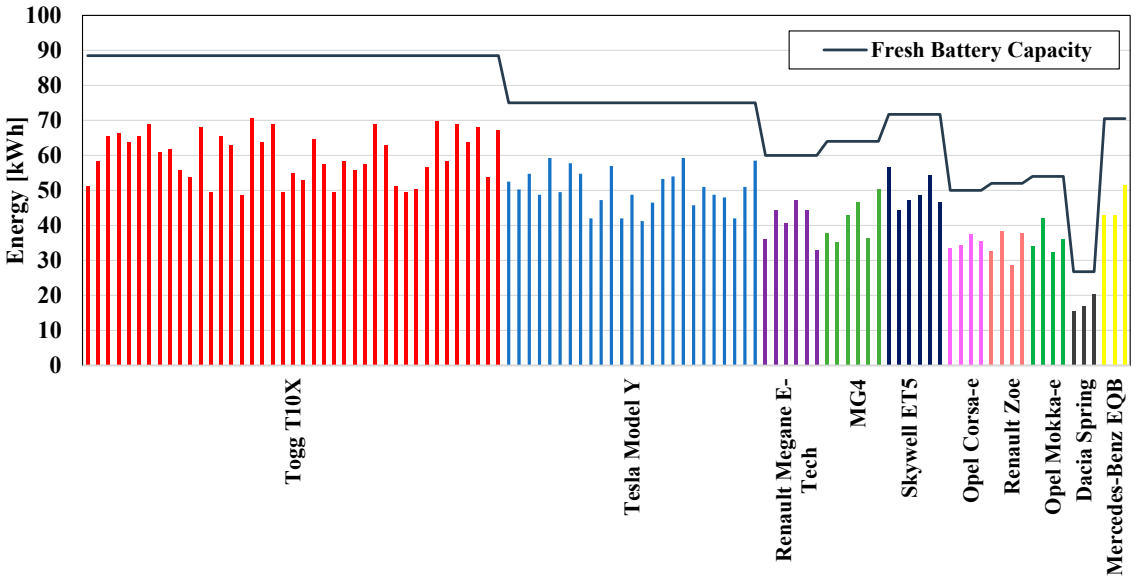


Figure 3. Energy capacity data of SLBs.

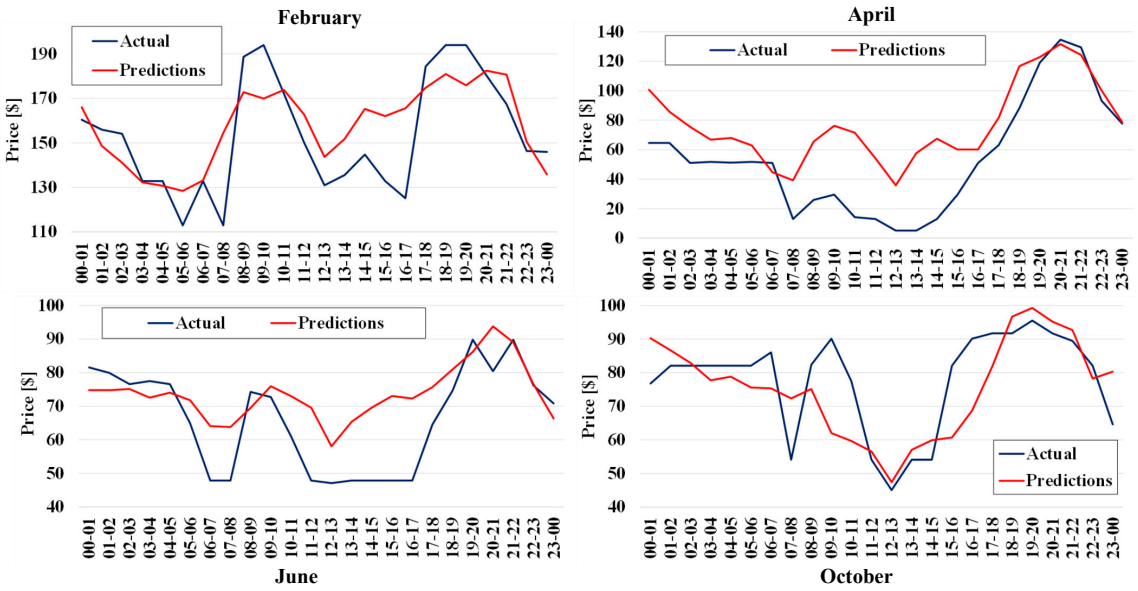


Figure 4. Actual and predicted electricity price data for test studies.

5.2. Test Results and Comparisons

The results obtained from the case studies are presented in Table 4. Here, the expected earnings for the months of February, April, June, and October are realized as USD 250.90, USD 578.38, USD 163.57, and USD 216.39, respectively. Expected income should be stated as the expected earnings from the previous day according to predictions. However, after the market clearing procedure, different prices can emerge for each hour. If the energy offer provided by the SLB facility is accepted, it is traded based on the market clearing price. It should also be recalled that the SLB facility is in the price-taking position in this study, so it does not influence the market price, and it is assumed that the offered amounts are accepted. Maximum gainable prices define the income that could be obtained if all actual prices were known one day before, which is impossible. The earned profits, on the other hand, were realized as USD 371.39, USD 539.01, USD 218.72, and USD 195.99, respectively, in the case studies. Profit above the expected income for February and June has been achieved because the market prices were relatively high. However, in April and October, the realized prices were slightly below the expected because the market prices were relatively lower than expected. When compared to the results obtained when the future price is known, this study can yield a profit of 85.48% in terms of ratio. Even in the worst-case scenario, a profit of 52.10% is obtained without mentioning any losses, which should be noted as a significant gain.

Table 4. Results obtained from case studies.

Cases	Month	Expected Profit [USD]	Obtained Profit According to Predicted Prices [USD]	Gainable Maximum Profit According to Actual Prices [USD]	Rate of Obtained and Gainable Maximum Profit [%]
Case-1	February	250.90	371.39	601.09	61.79
Case-2	April	578.38	539.01	630.552	85.48
Case-3	June	163.57	218.72	278.21	78.72
Case-4	October	216.39	195.99	376.20	52.10

Table 5 presents the income, cost, purchased energy, and sold energy quantities for each month. The highest income is earned in February with USD 1902.17, while in April, although the income is lower, the profit obtained is the maximum. Additionally, the amount of sold energy is lower than the amount of purchased energy because of the efficiencies of charging and discharging the batteries. Charge and discharge efficiencies cause some amount of energy loss.

Table 5. The energy costs and incomes achieved as a result of the transactions.

Cases	Month	Income [USD]	Cost [USD]	Energy Selling [kWh]	Energy Buying [kWh]
Case-1	February	1902.17	1530.78	10,990.45	12,177.78
Case-2	April	932.07	393.06	15,623.42	17,311.26
Case-3	June	841.54	622.82	10,990.45	12,177.78
Case-4	October	584.07	388.08	6357.48	7044.30

Optimum energy trading information for February is presented in Figure 5 based on the prediction and actual prices. According to the prediction prices, energy from batteries is sold to the electricity market between 00:00 and 01:00, followed by recharging the batteries between 05:00 and 06:00. Then, this energy is sold to the market between 10:00 and 11:00. However, based on the actual prices, selling occurs between 06:00 and 07:00, purchases between 07:00 and 08:00, and selling again between 10:00 and 11:00. According to the

prediction prices, batteries are recharged between 12:00 and 13:00, and energy sales take place between 20:00 and 21:00. In actual trading, energy purchases shift to 16:00–17:00, and purchased energy is sold between 18:00 and 20:00. Finally, between 23:00 and 00:00, batteries are brought to the desired energy level.

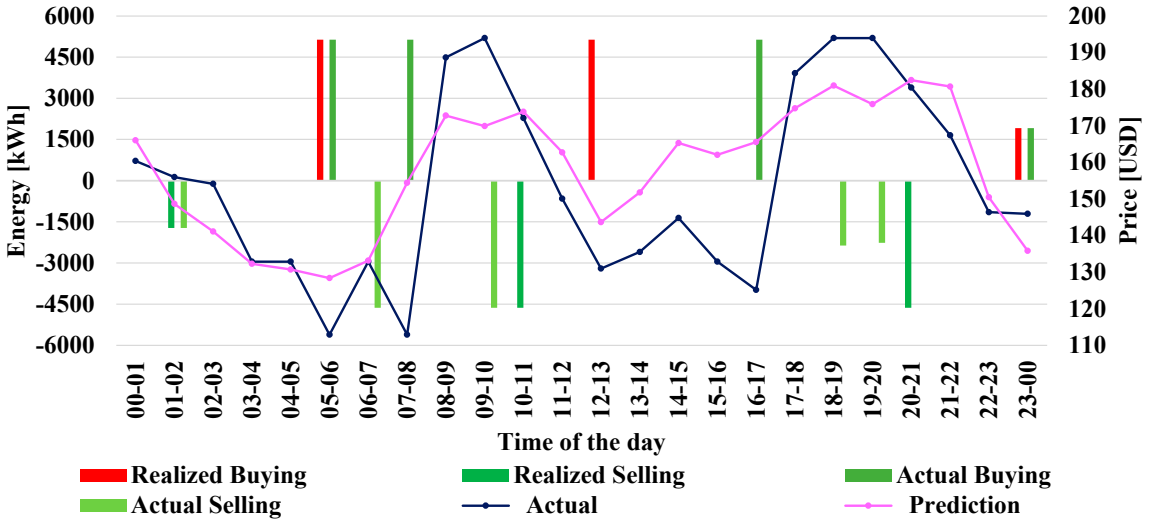


Figure 5. Energy transactions for February.

The energy transactions for April are shown in Figure 6. Energy purchases and sales based on prediction and actual prices are identical until 10:00. Similarly, energy trading is exactly the same after 20:00. According to the prediction, batteries are charged and discharged twice between 12:00 and 21:00, while based on the actual prices, there is one buy–sell transaction within this interval. It should be emphasized that sales are made at peak prices in the 20:00–21:00 interval.

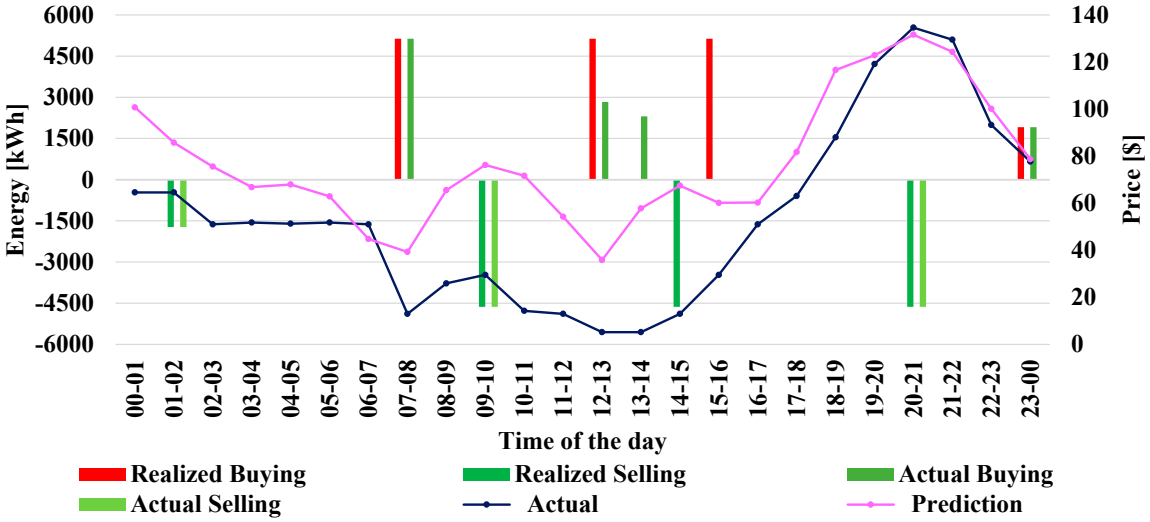


Figure 6. Energy transactions for April.

The information regarding energy trading for June is provided in Figure 7. It should be noted that trades closely matched the predictions, with minor deviations until 19:00, based on the actual data. Additionally, buying transactions occur during the cheapest price intervals between 06:00 and 08:00 and between 12:00 and 13:00, where it should be emphasized that the actual prices are closely followed. Energy was purchased at actual prices between 20:00 and 21:00 and sold between 21:00 and 22:00, resulting in profit. It

should be highlighted that this situation significantly contributed to the increase in revenue. However, it should be noted that energy trading only occurs in the day-ahead electricity market and predicting the next 24 h prices from 24 h in advance may make capturing such subtle arbitrages challenging.

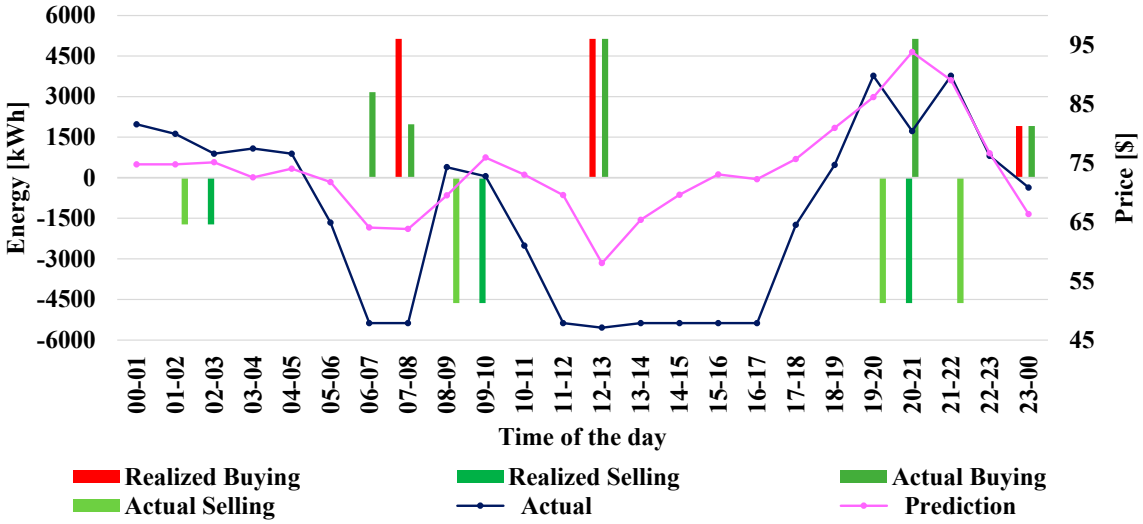


Figure 7. Energy transactions for June.

For October, energy trading is presented in Figure 8. While the realized selling occurred between 01:00 and 02:00, if the actual prices were known, the sale would have taken place between 06:00 and 07:00. Additionally, it should be noted that a significant difference in the actual prices occurs due to the energy buying and selling differences between 07:00–08:00 and 09:00–10:00. A profitable situation is achieved here with the actual prices. However, it should be emphasized that the predictions accurately realize energy purchases at 12:00–13:00 and energy sales at 19:00–20:00. The predictions successfully capture the lowest and highest prices quite accurately. At the end of the day, some energy is purchased to ensure the desired energy level in the SLB.

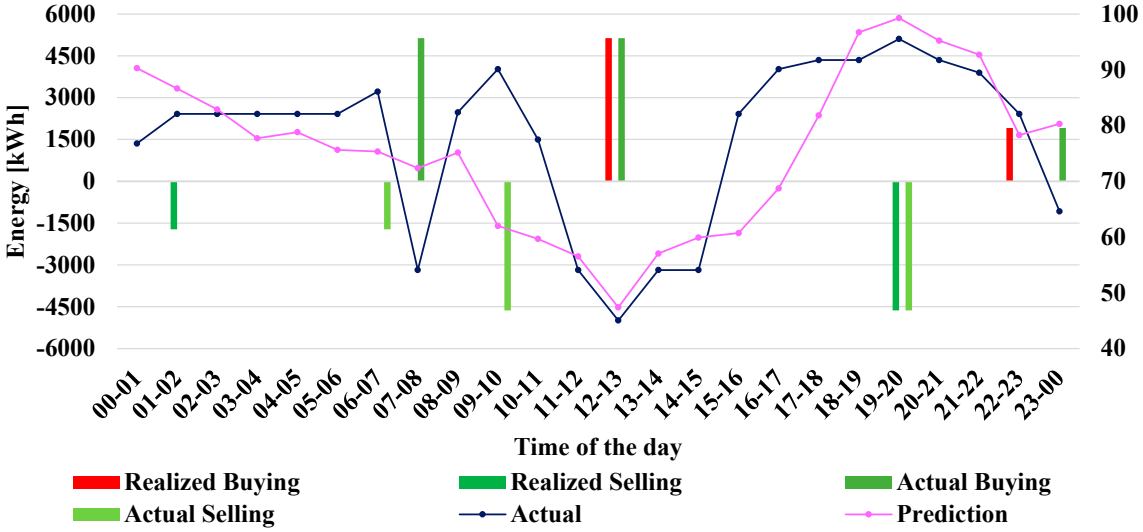


Figure 8. Energy transactions for October.

For June, the energy statuses of the selected sample batteries for each EV type are provided in Figure 9. Here, initially, the energy from the battery is sold to the electricity market between 01:00 and 02:00. Then, energy is purchased at the predicted low-price

interval of 07:00–08:00 to recharge the batteries. Subsequently, it is predicted that the price will rise between 09:00 and 10:00, and the batteries will be discharged again. Additionally, it should be noted that another arbitrage is executed between 12:00–13:00 and 20:00–21:00. In the final hour of the day, energy is purchased to bring the energy level of the batteries to the desired level. In addition, the state of energy changes of the batteries according to the prediction and actual prices for February is discussed in Figure 10. In general, two arbitrages are carried out, namely during 05:00–11:00 and 12:00–21:00, according to the predicted prices, while in the case of actual prices, a total of three arbitrages are carried out and these transactions are carried out in a way to maximize the profit.

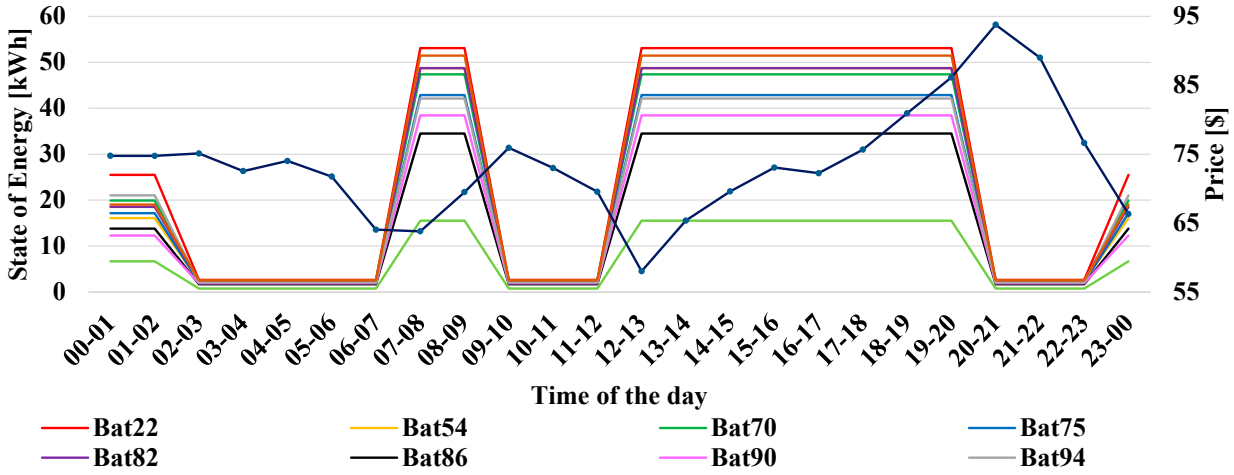


Figure 9. State of energy levels in SLBs for June.

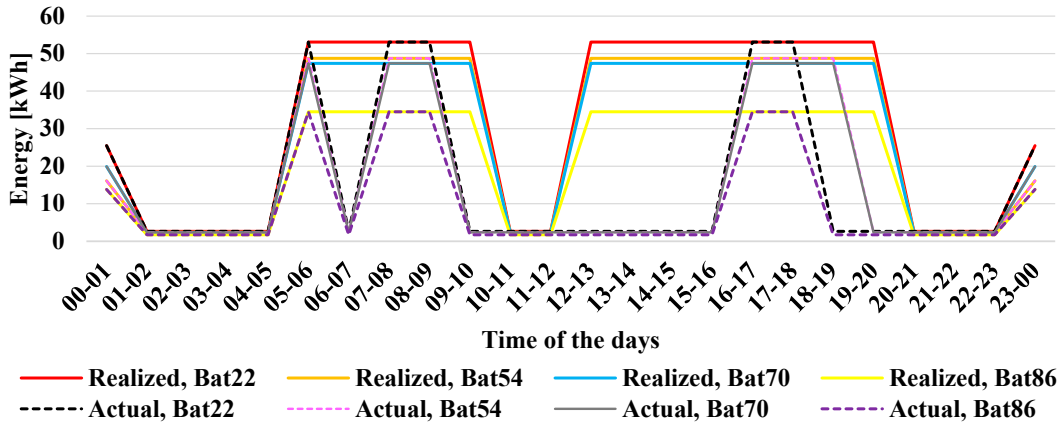


Figure 10. Predictions and actual prices for February.

6. Conclusions

In this study, we propose an artificial intelligence-based system that predicts day-ahead market prices using deep learning algorithms and the inclusion of SLBs in the market utilizing the MILP method. To predict the electricity market prices, an N-HiTS-based model is trained. Then, the trained model is compared to four deep learning architectures that are common in the literature (Simple RNN, LSTM, GRU, and N-BEATS). The SLB facility consists of 10 different battery types of the best-selling EVs in Türkiye in 2023. Various case studies are conducted to demonstrate the effectiveness of the system. It should be noted that the proposed system is tested on real market data from the Turkish day-ahead market. According to the test results, our system can generate gains of up to 85.48% of the maximum gainable profit without any loss. Our novel system approach serves as a proof of concept for exploring new research avenues regarding the involvement of SLB facilities in day-ahead markets.

The necessary regulations regarding incentives, implementation, and policies for the second-life usage of batteries, as well as the establishment and operation of SLB facilities, need to be established. It is worth mentioning that no policies have been implemented by governments on this matter so far. However, as the sector evolves, future policies may emerge to regulate it. In future studies, when long-term scenarios such as weekly, monthly, or yearly operations are considered, the impact of battery health and the effect of weather conditions on batteries can also be assessed and integrated into the analysis. Additionally, beyond the day-ahead market, other market structures such as intraday markets, balancing power markets, ancillary services markets, and futures markets can also be considered for further research.

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Informed Consent Statement: Informed consent was not required.

Data Availability Statement: Publicly available datasets were analyzed in this study. Access requires free registration. The data can be found here: https://seffaflik.epias.com.tr/electricity/electricity-markets/day-ahead-market-dam/market-clearing-price-mcp (accessed on 31 October 2024).

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Abbreviations	
EV	Electric vehicle.
SLB	Second-life battery.
Sets and Indices	
sl	The set of second-life batteries in the facility.
t	The set of day hours.
Parameters	
N	A sufficiently big positive number.
E_{sl}^{ch-max}	The maximum charging energy of the SLB sl [kW].
$E_{sl}^{disch-max}$	The maximum discharging energy of the SLB sl [kW].
$SOE_{sl}^{bat-init}$	The initial energy level of the SLB sl at the beginning of the day [kWh].
$SOE_{sl}^{bat-max}$	The maximum state of the energy level of the SLB sl [kWh].
$u1_t^{bin-dec}$	The binary decision variable used to prevent simultaneous selling and buying at the same hour. If it is 1, energy can be sold; if it is 0, energy can be purchased [0,1].
$u2_t^{bin-dec}$	The binary decision variable used to prevent simultaneous charging and discharging at the same hour. If it is 1, energy can be charged; if it is 0, energy can be discharged [0,1].
$\chi_t^{pred-price}$	The day-ahead electricity market price predicted with deep learning at time t [$].
$\delta_{sl}^{charging}$	The charging efficiency of the SLB sl [%].
$\delta_{sl}^{discharging}$	The discharging efficiency of the SLB sl [%].
Variables	
E_t^{buying}	The amount of energy purchased from the electricity market by the SLB facility during time t [kWh].
$E_{sl,t}^{charging}$	The charge energy of the SLB sl during time t [kWh].
$E_{sl,t}^{discharging}$	The discharge energy of the SLB sl during time t [kWh].
$E_t^{selling}$	The amount of energy sold from the SLB battery facility to the electricity market during time t [kWh].
$SOE_{sl,t}^{bat}$	The state of the energy level of the SLB during the time period t [kWh].

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