Profitability of stationary battery storage in day-ahead trading considering uncertainty, degradation, and the changing market environment

Leo Semmelmann, Sarah Henni, Christof Weinhardt

Karlsruher Institut für Technologie (KIT), Kaiserstraße 12, 76131 Karlsruhe
leo.semmelmann@kit.edu, sarah.henni@kit.edu, weinhardt@kit.edu

Kurzfassung:

In this study, we investigate the profitability of a battery energy storage system that is solely used for day-ahead trading for the Germany/Luxembourg electricity market from January 2020 to August 2022 by comparing amortization periods with battery lifetime. We are regarding price uncertainty by implementing an XGBoost day-ahead forecast and battery degradation through the SimSES framework. The simulation is conducted with a Sony/muRata 1MWh battery with Lithium-Ion cells and Lithium-Ferrophosphate Cathodes. The study shows that profitable operation of a BESS, without any additional revenue streams such as participation on reserve markets, is possible with electricity spot market prices from 2022.

Keywords: Battery storage systems, Day-ahead market, Day-ahead trading, Price forecasting, XGBoost

1 Motivation

Increasing shares of renewable generation require additional flexibility options in power systems. Battery energy storage systems (BESSs) can provide this flexibility and recover investment costs by participating in day-ahead spot market trading. However, existing works as [1] state that historically, trading alone could not cover the BESS's costs. In [2A], profitable battery operation is achieved by serving multiple applications, including peak shaving, frequency regulation, self-consumption and spot market trading. As spot market prices have been subject to significant volatility in the past year, this study investigates the profitability of day-ahead BESS trading in the current German market environment. To regard degradation and uncertainty, which have been often neglected in previous studies, we incorporate an XGBoost forecast and the SimSES battery degradation modeling framework. The remainder of this work is structured as follows. First, an introduction into day-ahead trading with BESSs, as well as price forecasting and battery degradation simulation is given. Second, our methodology is described. Third, our case study is outlined, and the underlying dataset is described. Fourth, our results are depicted, focusing on amortization periods of BESSs solely used for day-ahead spot market trading. Finally, a conclusion and an outlook on further research topics are given.

2 Background

This section aims to give an overview of current research in the field of BESS profitability simulations and day-ahead price forecasting.

In several studies, possible operation strategies for BESSs trading on day-ahead markets are explored. For instance, in [3], a bidding strategy is created with the means of problem decomposition. The study is conducted with market data from the Californian ISO energy market and considers battery size, efficiency and charging rates. With an optimized operation schedule, the BESS is able to generate profits. However, the study does not correspond to a realistic market scenario, since perfect foresight is assumed. In contrast, the authors of [4] analyze the profitability of a grid-scale lithium-ion BESS after the splitting of the German-Austrian electricity bidding zone. In this study, a seasonal autoregressive integrated moving average model (ARIMA) is implemented to forecast day-ahead prices. The authors find that without perfect forecasting, only in one specific scenario a slightly positive NPV is reached. It is concluded that either improvements in forecasting accuracy must be reached, or the participation in additional markets, such as the reserve market, is required for the BESS to achieve a profitable operation.

The improvement of electricity price forecasting algorithms is covered in various studies. In [5], day-ahead electricity prices are forecasted with the means of a wavelet transform and an ARIMA model. The wavelet transformation is used to decompose the price time series. The approach is then evaluated in a case study with electricity prices from Spain in 2002. More recent works like [6] have combined the wavelet transformation with a Long-Short Term Memory (LSTM) neural network. After the wavelet transformation, the data shows a more stable variance. The approach is then evaluated on two datasets from Australia and France. Another suitable method for electricity price forecasting is the XGBoost algorithm, which is based on weak learners composed of classification and regression trees. Through an ensembling technique, these weak learners are combined to a strong combined model [7]. In [8], an adapted XGBoost is used to forecast short-term electricity prices in Singapore. The authors show that even a simple XGBoost model outperforms a simple neural network and least-squares support vector machines and is only slightly worse than an LSTM-based approach or a Gated Recurrent Units neural network. We have therefore chosen an XGBoost model for the forecasting of electricity prices in this study due to its easily reproducible results and stable performance.

Many studies that are investigating the profitability of battery trading on electricity markets, as [9,10], are using a simplified battery degradation model in their cost analysis, which might not reflect realistic costs of BESS trading operations. Hence, this study utilizes the SimSES battery simulation and degradation framework [11].

3 Methodology

We evaluate the profitability development of BESS day-ahead trading from January 2020 to August 2022. To this end, we are simulating a straightforward trading model, based on a day-ahead price forecast and the SimSES battery simulation framework. The whole process is illustrated in Figure 1.

To regard price uncertainty in our analysis, we conduct day-ahead forecasting with an XGBoost model that is trained on past price data and a feature engineered dataset. First, the hourly day-ahead electricity price dataset is enriched with weather. The weather data encompasses temperature, precipitation, wind speed and solar radiation data points. Furthermore, features for holiday dates are engineered, as well as variables for the weekday, hour and month. For every analyzed month, a dedicated XGBoost model is trained with data from the previous 365 days. Then, based on the engineered features, hourly electricity prices are forecasted. Based on the day-ahead forecast for each day, the BESS is charged in the hour with the lowest price and discharged in the subsequent hour with the highest day-ahead price, if a profit margin, i.e., a difference between the lowest and highest price, of at least 25% is reached. Each month's resulting battery operation pattern is then used as input for the SimSES battery simulation framework with a Sony/muRata 1MWh battery with lithium-ion cells and lithium-ferrophosphate cathodes [11]. The SimSES framework uses data from underlying real-world degradation experiments. To evaluate if the spot market prices of a month would allow a profitable BESS operation, a five-year simulation is run, repeating the monthly operation pattern. The resulting degradation after five years is interpolated until reaching a pre-defined End-of-Life criterion (EOL) due to limited computing resources. Finally, based on a 0.65 EOL [4] and battery costs of 350€/kWh [13] the BESS's resulting lifetime and amortization time are calculated. The maximum State-of-Charge (SOC) of the battery is limited at 0.95 and the maximum Depth-of-Discharge is set at 0.05 to prevent excessive battery degradation [11]. Additionally, SimSES is used to evaluate every charging and discharging operation. Due to the technical representation of the battery within the SimSES simulation, it can happen, that the battery is not charged fully. We then fully charge the battery in the subsequent timestep. Additionally, the SimSES system implements efficiency losses into the trading simulation.

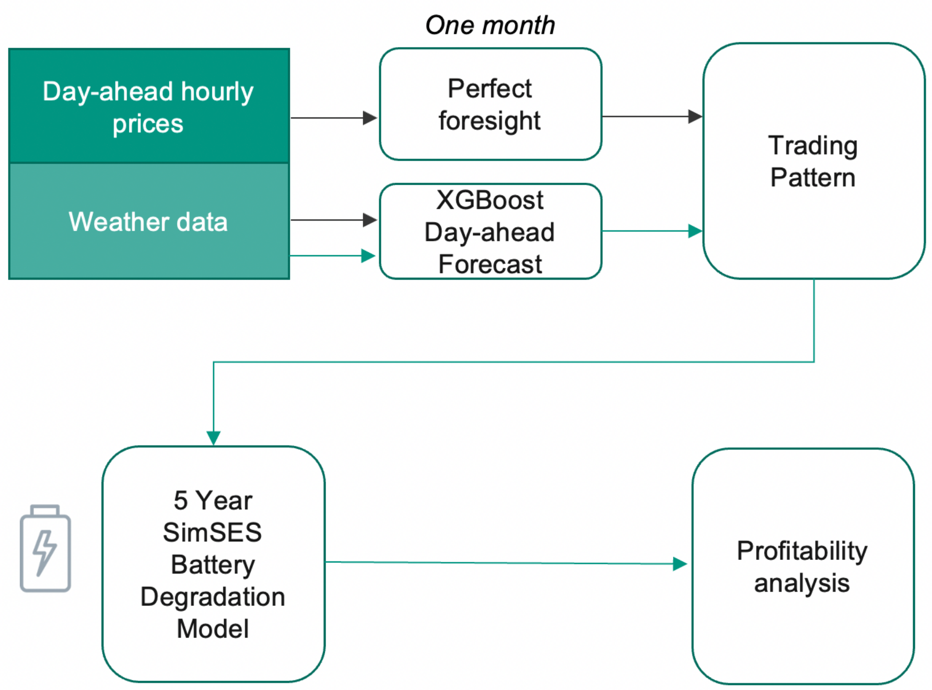

Figure 1: Overview of general simulation framework which is applied to each month in the considered period.

4 Case Study

We apply our methodology to the hourly day-ahead prices from the German-Luxembourg market zone [13] from January 2019 to August 2022. The first year of data is solely used for training the XGBoost model. We enrich our dataset with temperature, precipitation, wind speed and solar radiation weather features from measurement stations in Frankfurt, Kiel, Konstanz, Cologne and Munich [13]. In Figure 2, the mean monthly prices during the considered period are depicted. Prices are on average lowest in April 2020, with a value of 17.09€/MWh. The highest mean monthly price is reached in August 2022 at €465.18€/MWh.

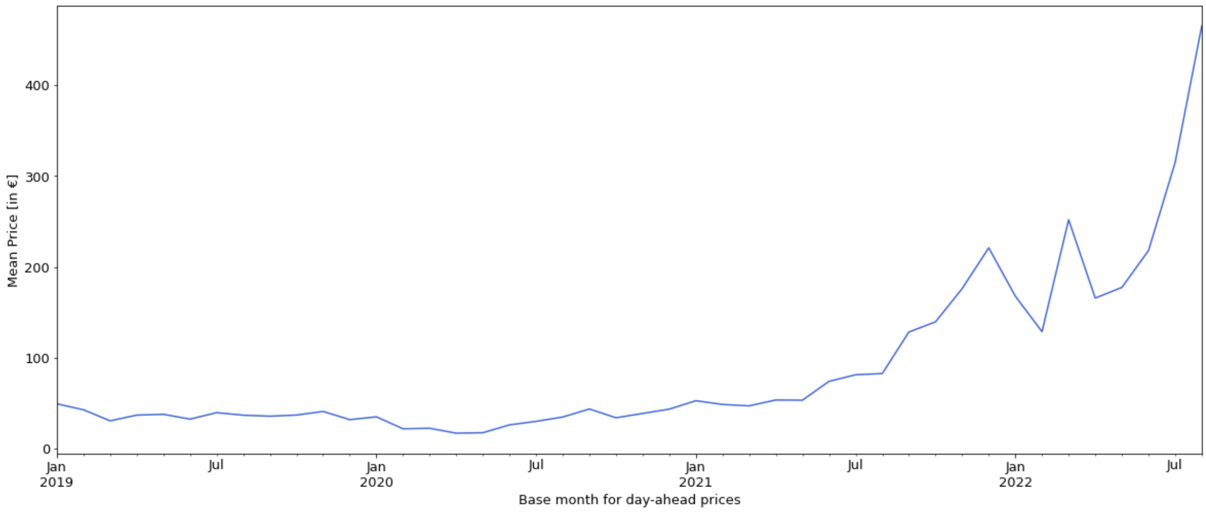

Figure 2: Mean monthly day-ahead prices for German/Luxembourg market zone.

5 Results

We structure our results in three parts. First, we focus on the forecasting accuracy of the XGBoost day-ahead electricity price forecast. Second, we evaluate the profitability of BESS-based day-ahead spot market trading, based on perfect foresight and the XGBoost forecast. Finally, we analyze the effects of the spot-market market trading on the battery degradation.

To evaluate the accuracy of our forecast, we calculate distinct error metrics for the forecasting period between January 2020 and August 2022. The Symmetric Mean Absolute Percentage Error (SMAPE) amounts to 37.2%, the Root Mean Squared Error (RMSE) amounts to 52.9%. For comparison, a naïve week-before forecast that takes the prices of the same previous weekday reaches a 42% SMAPE and 61.2 RMSE. The forecast correctly predicts the time of the highest price in 34.5% of the evaluated time steps. Here, the naïve week-before forecast reaches an accuracy of 37.37%. However, the Mean Absolute Error (MAE) of the XGBoost price peak time prediction lies at 3.43, whereas the naive forecast results in an MAE of 4.55. This means that the price peak time forecast deviates on average about 3.4 hours in the case of the XGBoost forecast and 4.6 hours in the case of the naïve benchmark.

In the following, the XGBoost forecast is utilized for daily day-ahead trading decisions and benchmarked with a perfect foresight scenario. The trading pattern for one exemplary day is depicted in Figure 3. At 16:00, the XGBoost model forecasts the lowest price, leading to a charging decision. The scheduled loading operation is evaluated by SimSES.. At 19:00, the highest electricity price after the charging event is forecasted, leading to a complete discharge of the battery. With perfect foresight, the optimal discharging would have occurred one hour later at 20:00.

The monthly pattern of trading decisions is repeated for five years and evaluated through the battery degradation framework SimSES. The degradation after 5 years is then interpolated to 20 years, thereby enabling the calculation of the amortization period and the battery lifetime. The results are illustrated in Figure 4. Assuming the price structure of January 2020, the BESS would reach its EOL after 17.5 years but would need to be operated 106.1 years to be profitable. In October 2021, the expected battery life (18.65 years) exceeds the amortization period (18.61 years) for the first time (when considering uncertainty). Since March 2022, the lifetime exceeds the expected battery life in almost every month. Conditions were best in August 2022, where the amortization period amounts to 7.57 years and the lifetime lies at 17.63 years. Assuming perfect foresight significantly overestimates BESS profitability. For instance, in August 2022, the amortization period lies at 5.49 years, which is 26.6% lower than the XGBoost-based equivalent.

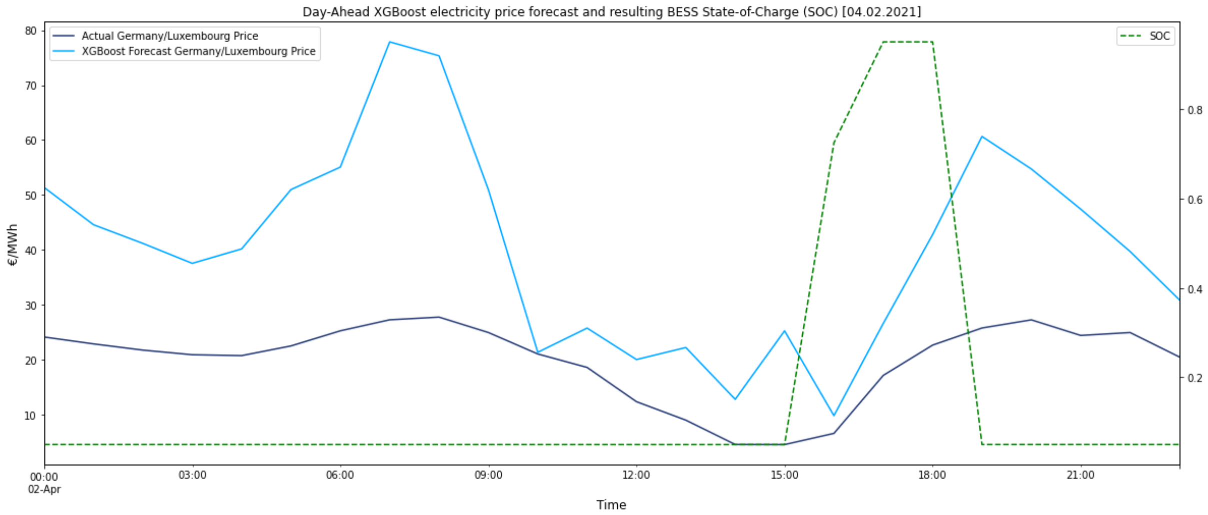

Figure 3: Exemplary daily electricity price forecast compared w. real prices and resulting battery State-of-Charge (SOC).

The battery lifetime consistently reaches around 20 years. Taking a deeper look at the SimSES battery simulations for the XGB case in August 2022, we can observe that 88.8% of the BESS degradation are induced by calendric aging, while only 11.1% are induced by cyclic aging, indicating that the BESS could well be used for additional use cases or more trading cycles per day. The overall round-trip efficiency is 93.99%, on average the charging direction is changed 1.93 times per day. The average length of resting times lies at 1365 minutes per day, also indicating high idle times that could be potentially used to participate in additional revenue streams.

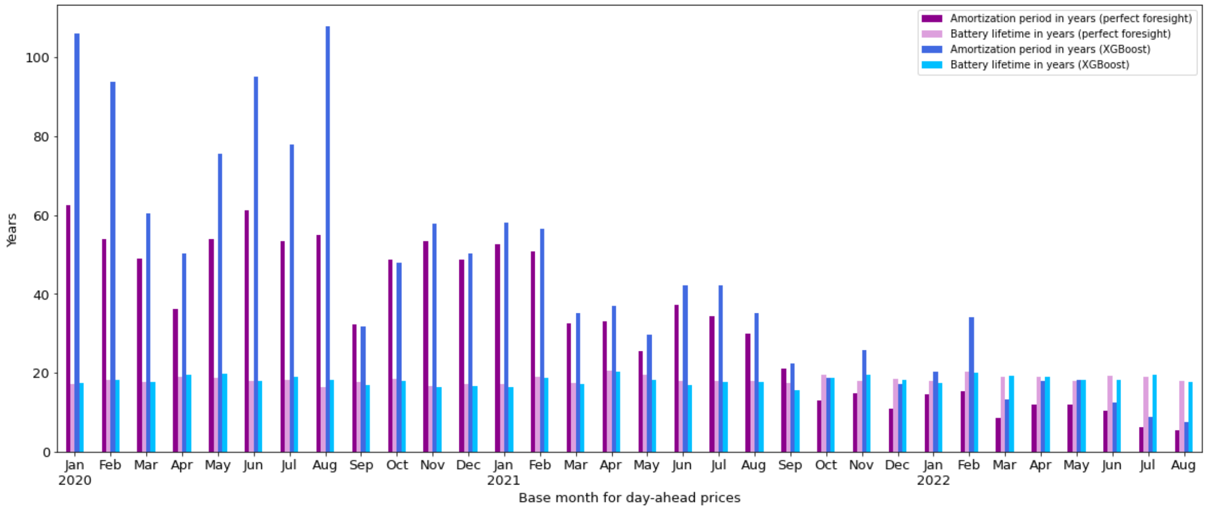

Figure 4: Comparison of the BESS's amortization period and battery life time in the respective monthly day-ahead prices (perfect foresight vs. XGBoost forecast)

In Table 1, the results of a sensitivity analysis for the simulation parameters with August 2022 prices are depicted. Sensitivities are analyzed for the BESS cost, the minimum profit margin, as well as the EOL. For the BESS cost, we can see a linear relationship between cost and amortization periods. With 25% higher BESS cost, the amortization time increases to 9.47 years. In contrast, the minimum profit margin that must be achieved to pursue a buying and selling decision, has no impact on the amortization period. This is caused by high relative differences between lowest and highest (forecasted) prices every day. Only minimum profit margins larger than 150% lead to a decrease in profitability and an increase in amortization period. The assumed EOL has the strongest impact on the profitability of the BESS. By increasing the EOL by 25% to 0.8125, the battery lifetime drops to 9.44 years, while a 25% decrease of the EOL to 0.4875 leads to an increased battery lifetime of 25.81 years.

Value	-25%	-10%	Base case	+10%	+25%
BESS Cost [350€/kWh]	5.68	6.82	7.58	8.33	9.47
Minimum Profit Margin [25%]	7.58	7.58	7.58	7.58	7.58
End-of-Life Criterion [0.65]	25.81	20.91	17.63	14.35	9.44

Table 1: Sensitivity analysis for amortization period and battery lifetime (in years) with August 2022 prices, based on XGBoost day-ahead forecast

6 Discussion

This study considers price uncertainty and battery degradation for the simulation of a BESS that trades on the day-ahead electricity spot market. Our study shows that for the first time, due to recent high price levels and volatility, it is possible to profitably operate a day-ahead trading BESS without any additional revenue streams. These current market conditions are a strong signal for utilities and energy trading firms on the German electricity market, indicating the high value of flexibility and therefore possibly incentivizing BESS projects in the future.

These private BESS installations are highly necessary to reach a carbon-free energy system, as shown in current studies like [15]. However, the profitability of the BESS is subject to changing electricity price levels.

A key point of this study is the comparison between amortization periods reached with perfect foresight-based trading and XGBoost forecast-based trading. By improving the day-ahead forecast, the amortization period could be lowered by 26.6% in August 2022, for instance. The forecast in this work can be seen as baseline reference case with room for improvement. Future works in this context can improve the forecast by engineering addition features, by optimizing hyperparameters and by comparing different models, such as neural networks.

The results of the SimSES battery degradation model show that the main driver of the BESS's degradation is calendric instead of cyclic aging, indicating that the battery could be also used for additional revenue streams, such as reserve market trading or intraday-trading, which would further increase the profitability of the BESS.

7 Conclusion

In summary, the study shows that with current market prices, day-ahead trading with BESSs can be profitable in a real-world scenario with uncertain prices, day-ahead forecasting and a realistic battery degradation model. The BESS's profits could be even increased further when additional revenue streams are added, such as participation on reserve markets. Furthermore, the study shows that current XGBoost electricity price forecasting models are sufficient for profitable BESS market operation. However, by improving forecasting models, amortization periods could be lowered further.

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