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Economic Impact of Forecast Errors on BESS Participation in Day-Ahead Electricity and Reserve Markets

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Abstract:

This paper quantifies the effect of price-forecast uncertainty on the profitability of a battery energy storage system (BESS) that participates simultaneously in the Nordic day-ahead (DA) market and the three frequency containment reserves: FCR-N, FCR-D up, and FCR-D down. A mixed-integer linear programming model has been developed, which co-optimizes DA arbitrage and multi-market reserve provision, subject to battery power and energy limits, ENTSO-E reserve technical requirements, and cycle- and calendar-aging costs. Price uncertainty is represented through forecast scenarios with a systematic bias and a zero-mean dispersion term. The forecast-based schedule is embedded in a forecast–decision–realization scheme, settled at realized prices, and compared against a perfect-information benchmark to determine the cost of uncertainty. Using 2025 DA and FCR markets and activation data from Nord Pool SE3 and Svenska kraftnät, respectively, for fictitious 1 MW/1 MWh BESS, three results emerge. First, the revenue is earned almost entirely from the reserve capacity: FCR-N alone contributes to about 78% of the total revenue, while DA arbitrage contributes to only about 3%. Second, the mean cost of uncertainty stays below 1.5% of the total annual revenue even at a 50% forecast bias, but the loss is concentrated on a small number of high-cost days. Third, the loss depends substantially more on the coherence of forecast errors across markets than on their magnitude. Incoherent errors across the DA and reserve markets are an order of magnitude costlier than coherent errors of the same size.

1 Introduction

The rapid expansion of renewable energy generation and the electrification of industry are reshaping power systems. These developments increase variability in electricity supply and demand, thereby intensifying the need for flexible resources. BESS has emerged as a key solution, offering fast response, modular deployment, and the capability to provide multiple services across different market timeframes. In liberalized electricity markets, such as the Nordic system, BESS operators can simultaneously participate in the DA energy market and ancillary service markets, including frequency containment reserves (FCR), enabling the stacking of multiple revenue streams.

From the perspective of battery owners and operators, participation in electricity markets is primarily driven by the opportunity to generate revenue streams that justify the high upfront investment costs of BESS. Rather than operating solely for a single application, such as energy arbitrage, owners increasingly seek to maximize asset utilization by accessing multiple markets. However, deciding how and where to participate is a complex task, as different markets offer distinct revenue mechanisms, time resolutions, and technical requirements. The DA market allows participants to buy and sell electricity for each hour of the following day based on price forecasts, making it suitable for energy arbitrage strategies. FCR markets procure reserve capacity to maintain the system frequency in real time, requiring fast and reliable response from assets. While FCR markets typically provide more stable and capacity-based revenues, they impose strict operational constraints on the market participants, such as availability

commitments and state-of-charge limitations, which may restrict their participation in other markets.

A growing body of research has investigated the participation of BESSs in electricity markets as a means of generating revenue and enhancing system flexibility. Early studies primarily focused on energy arbitrage in DA markets [1]. More recent work has expanded this perspective to include ancillary service markets, such as frequency regulation and reserve markets, where BESS provide fast-response services to maintain grid stability [2]. Several studies highlight the importance of multi-market participation (revenue stacking). For instance, the results of [3] show that combining services such as DA trading and reserve provision significantly increases profitability compared to single-market operation [3]. Similarly, broader techno-economic analyses confirm that determining the optimal combination of services is a key challenge for maximizing BESS revenues, particularly under varying market conditions. In addition, recent work has explored multi-service and hybrid optimization frameworks, where a BESS is co-optimized across multiple markets. The study of [4] develops a MILP-based multi-market optimization model for a PV-integrated hybrid energy storage system participating in the DA, fast frequency reserve (FFR), and frequency containment reserve for normal operation (FCR-N) markets, and shows that joint market participation can increase the annual revenue by 544.8% compared with single-market strategies. In [5] a stochastic co-optimization framework for Nordic DA market, FCR-N, and FCR-D markets is proposed and shows that forecast-informed coordinated bidding improves expected returns. In [6] it is shown that simultaneous DA and FCR participation can better exploit both arbitrage and reserve revenues, provided SoC and reserve-delivery

constraints are modeled carefully. The work [7] develops a MILP based optimization model for a simulation DA, FCR-N, and FCR-D participation of a BESS considering battery degradation and Swedish market constraints, and reports higher profitability than single-market FCR participation. These studies demonstrate that coordinated participation in energy and FCR markets can capture both capacity-based and energy-based revenue streams, improving overall system value.

Multi-market BESS operation can be affected by several sources of uncertainties, including those from electricity price, reserve activation, bid acceptance, and market price forecast. These uncertainties influence the final bidding and scheduling decision by altering the relative “attractiveness” of different markets, the amount of capacity allocated to each service, and the ability of the battery to satisfy state-of-charge and delivery constraints in real-time operation. Consequently, deterministic optimization may overestimate achievable profits, whereas stochastic, robust, or risk-constrained approaches can produce more reliable market participation strategies under uncertain conditions.

Some recent studies have incorporated uncertainty into the multi-market participation of BESS, particularly in coordinated DA energy and FCR markets. Stochastic and scenario-based optimization approaches have been used to capture uncertainties in electricity prices and reserve activation. For example, stochastic scheduling models for Nordic markets consider uncertainty in FCR activation by representing frequency deviations through scenario sets, enabling co-optimization of energy and reserve provision [8]. Similarly, two-stage stochastic bidding models account for uncertainties in market prices and revenues, showing that forecast errors can influence profitability and bid acceptance in DA and FCR markets [5]. Other works further incorporate uncertainty in FCR utilization factors and market prices, demonstrating that deviations between expected and realized values may lead to infeasible battery operation or reduced profits [9]. In these studies, even where price uncertainty is considered, few studies isolate its monetary cost of forecast errors by comparing forecast-based schedules against a perfect-information benchmark, or examine how the direction and coherence of forecast errors across the DA and FCR markets shape that cost.

This paper addresses this gap by isolating and quantifying the monetary cost of day-ahead and FCR price-forecast uncertainty of a BESS that stacks its revenue across the DA and three FCR markets. The contribution of the paper is threefold. First, a MILP-based multi-market bidding model, incorporating ENTSO-E reserve technical requirements and cycle/calendar battery degradation, is combined with a forecast–decision–realization scheme that benchmarks forecast-based schedules against a perfect-information solution, providing a direct monetary measure of the cost of price-forecast uncertainty rather than only expected-revenue estimates under uncertainty. Second, the model evaluates this cost of uncertainty not only in expectation but also through its upper-tail behavior (percentiles and conditional value-at-risk), allowing the economic risk of forecast error to be characterized beyond the average case. Third, the framework varies the sign of the forecast bias independently across the DA and FCR markets, enabling an assessment of how the direction and coherence of forecast errors across markets, rather than only their magnitude, affects realized profitability.

The remainder of this paper is organized as follows. Section 2 describes the modelling framework and the forecast–decision–realization scheme used to quantify the cost of forecast uncertainty. Section 3 formulates the day-ahead and FCR multi-market bidding problem. Section 4 presents the results. Section 5 concludes the paper and discusses implications for forecasting and bidding strategy.

2. Methodology

2.1 System and market setup

The system under study is a grid-connected BESS that participates simultaneously in four markets. The DA energy market and the three frequency containment reserves, FCR-N, FCR-D up, and FCR-D down. In the DA market the battery earns an energy margin by arbitraging the price spread. The FCR products are instead paid mainly for capacity that is reserved and held available. FCR-N is symmetric and additionally settles the energy that is activated, whereas FCR-D up and FCR-D down are one-directional capacity products. Since reserved capacity can be offered in almost every hour without necessarily moving energy, these streams can be stacked, provided every accepted reserve bid remains deliverable under full activation, as required by the ENTSO-E endurance rules. These markets do not clear at the same instant. The FCR auctions and the DA market have separate day-ahead (D-1) gate closures, the first FCR auction closing before the DA market and the second after it clears. Because a submitted bid is binding, we co-optimize the bids for all four markets as a single decision, taken before the earliest gate closure (the first FCR auction). Scheduling the asset is therefore a trade-off between energy-driven arbitrage and capacity-driven reserve provision, under the battery's shared power, energy (state-of-charge), and degradation limits.

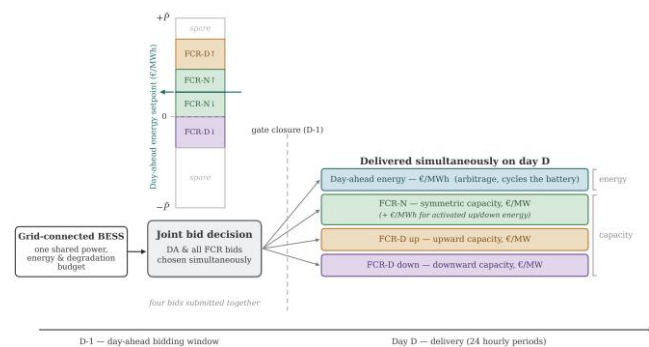


Fig. 1 Participation of the BESS in the DA, FCR-N, FCR-D up, and FCR-D down markets

2.2 Forecast–decision–realization framework

Bids must be submitted before the corresponding prices are known, so the bidding decision is taken under forecast uncertainty while the resulting profit is settled at the prices that actually occur. To isolate the monetary cost of this uncertainty, the optimization is embedded in the three-stage forecast

decision–realization scheme shown in Fig. 2, applied independently to each day of the study horizon.

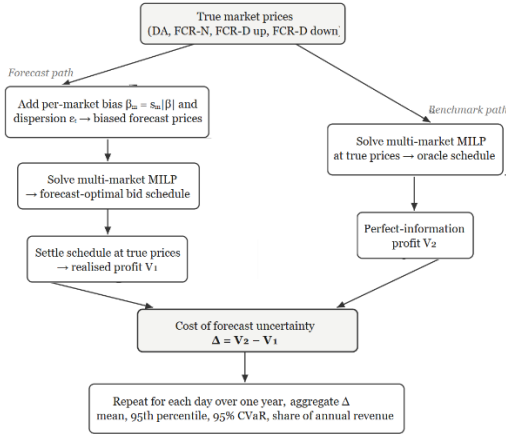


Fig. 2 The forecast–decision–realization scheme used to quantify the cost of forecast uncertainty.

In the forecast stage, a price forecast is built for every market by perturbing the true price series with a systematic, per-market bias and a zero-mean dispersion term, producing a finite set of price scenarios. The bias represents a consistent over- or under-estimation of a market, and the dispersion term captures non-systematic forecast noise. In the decision stage, the multi-market MILP is solved on these scenarios to obtain the bid schedule that is optimal under the forecast. In the realization stage, that schedule is settled at the true prices, giving the realised profit V_1 . Then, it is compared with a perfect-information benchmark V_2 , as the profit that would have been earned if the true prices had been known at bidding time. The cost of forecast uncertainty on a given day is the gap between the two, as $\Delta = V_2 - V_1$. The precise definitions of the forecast-error model and of V_1 , V_2 , and Δ are given in Section 3. The scheme is repeated as successive daily optimizations over a full year.

3. Mathematical Formulation

This section formulates the scheduling and bidding model of a BESS that participates in the DA electricity market and in the FCR-N, FCR-D up and FCR-D down, simultaneously. The formulation is a MILP and is solved once per day over a set of hourly time steps $t \in T$. Since the bids are submitted before the realized prices are known, the decisions must be made under uncertain price forecasts.

3.1 Objective function

The objective maximizes the expected daily profit, given by the expected DA and FCR revenues net of the DA energy cost, minus the battery degradation cost.

$$F = \max \sum_{\omega \in \Omega} \pi_{\omega} (R_{\omega}^{DA} + R_{\omega}^{FCR} - C_{\omega}^{DA}) - C^{DEG} \quad (1)$$

ω indicates the scenario. The DA revenue (R_{ω}^{DA}) and cost (C_{ω}^{DA}) are obtained from the discharge and charge powers p_t^{ds} and

p_t^{ch} , the spot price $\lambda_{\omega,t}^{spot}$, the grid-usage charge λ^g and the energy tax λ^{tax} .

$$R_{\omega}^{DA} = \sum_t (\lambda_{\omega,t}^{spot} + \lambda^{tax}) p_t^{ds} \quad (2)$$

$$C_{\omega}^{DA} = \sum_t (\lambda_{\omega,t}^{spot} + \lambda^{tax} + \lambda^g) p_t^{ch} \quad (3)$$

And the FCR revenue (R_{ω}^{FCR}) is the sum of the revenues from the three products:

$$R_{\omega}^{FCR} = \sum_t R_{\omega,t}^N + R_{\omega,t}^{D-up} + R_{\omega,t}^{D-down} \quad (4)$$

FCR-N is remunerated both for reserved capacity and for the energy activated during up- and down-regulation. Let p_t^N be the FCR-N capacity bid, a_t^{N-up} and a_t^{N-down} the realised up/down activation signals. By having $\lambda_{\omega,t}^N$, λ_t^{N-up} , and λ_t^{N-down} as the capacity and up/down regulation-energy prices, respectively:

$$R_{\omega,t}^N = \lambda_{\omega,t}^N p_t^N + \lambda_{\omega,t}^{N-up} a_t^{N-up} p_t^N + \lambda_{\omega,t}^{N-down} a_t^{N-down} p_t^N \quad (5)$$

FCR-D up and down are remunerated for capacity only, with bids p_t^{D-up} and p_t^{D-down} :

$$R_{\omega,t}^{D-up} = \lambda_{\omega,t}^{D-up} p_t^{D-up}; R_{\omega,t}^{D-down} = \lambda_{\omega,t}^{D-down} p_t^{D-down} \quad (6)$$

3.2 Battery operation constraints

The state of energy (SoE) S_t evolves with the baseline charge/discharge and with the net FCR-N and FCR-D activation energy, where η is the round-trip efficiency, E the usable capacity and Δt the time-step length:

$$S_t = S_{t-1} + [(\eta p_t^{ch} - p_t^{ds}/\eta) + (a_t^{N-down} - a_t^{N-up}) p_t^N + a_t^{D-down} p_t^{D-down} - a_t^{D-up} p_t^{D-up}] \Delta t / E \quad (7)$$

As the problem is being solved on daily basis and to connect the S_{24} of a day to S_1 of the next day:

$$S_1 = S_{24} \quad (8)$$

$$S_{\min} \leq S_t \leq S_{\max} \quad (9)$$

The charge and discharge powers are bounded by the converter rating, and simultaneous charging and discharging is prevented by a binary variable $u_t \in \{0,1\}$. $\bar{P}$ is the converter power rating.

$$0 \leq p_t^{ch} \leq \bar{P} u_t; 0 \leq p_t^{ds} \leq \bar{P} (1 - u_t) \quad (10)$$

3.3 FCR market and technical requirements

Following the ENTSO-E technical requirements for limited-energy reservoirs, the accepted power bids must be deliverable within the physical power limits of the battery. The headroom constraints for the up- and down-regulation directions, respectively are stated in (11) and (12).

$$1.34 p_t^N + p_t^{D-up} + 0.2 p_t^{D-down} \leq \bar{P} + p_t^{ch} - p_t^{ds} \quad (11)$$

$$1.34 p_t^N + 0.2 p_t^{D-up} + p_t^{D-down} \leq \bar{P} - p_t^{ch} + p_t^{ds} \quad (12)$$

$$(p_t^{D-up}/3 + p_t^N) \Delta t / \eta \leq (S_t - S_{\min}) E \quad (13)$$

$$(p_t^{D-down}/3 + p_t^N)\eta\Delta t \leq (S_{max} - S_t)E \quad (14)$$

constraints (11)–(12) guarantee that the converter can supply the reserve power on top of the day-ahead setpoint. Every accepted reserve bid must also be deliverable in energy over its mandated full-activation duration. This is enforced by (13) and (14). Nordic technical requirements for LER units [10] states that the endurance requirement for FCR-N is 1 hour of full activation in the upward and downward directions, and for FCR-D up and down, the endurance requirement is 20 minutes. These constraints have been indicated in (13) and (14).

3.4 Battery degradation

The battery degradation cost C^{DEG} sums a cycle-aging and a calendar-aging term. The cycle-aging percentage per step is the linearised form of the empirical model, with temperature τ (°C) and power throughput as μ_t :

$$\mu_t = p_t^{ds}/\eta + p_t^{ch}/\eta \quad (15)$$

$$U_t^{cyc} = (q_1 \tau^2 + q_2 \tau + q_3)(v_1 \mu_t) \Delta t \quad (16)$$

Where U_t^{cyc} is the per-step cycle-aging capacity loss (%). q_1, q_2, q_3 are the temperature-polynomial coefficients and v_1 is the linear throughput coefficient of the empirical cycle-aging model [7]; and Δt is the time-step length. The calendar-aging percentage follows an Arrhenius form in absolute temperature, where $G(S_t)$ is a piecewise-linear function of the SoE, with E_a being the activation energy, R the gas constant and Q the battery age in days:

$$U_t^{cal} = G(S_t) e^{-\frac{E_a}{R(\tau + 273.15)}} Q^{0.5} \quad (17)$$

Both aging percentages are converted to monetary values through the net present value of the battery B^{BAT} and the end-of-life capacity threshold EOL (%).

$$B_t^{cyc} = \frac{B^{Bat} U_t^{cyc}}{100 - EOL}, B_t^{cal} = \frac{B^{Bat} U_t^{cal}}{100 - EOL} \quad (18)$$

$$B^{Bat} = \frac{(1 - r_{sv})C^{REP}}{(1+i)^L} + \frac{C^{OM}[(1+i)^L - 1]}{i(1+i)^L} \quad (19)$$

where B_t^{cyc} and B_t^{cal} , as the two elements forming C^{DEG} , are the monetary cycle- and calendar-aging costs; r_{sv} is the salvage-to-replacement cost ratio; C^{REP} and C^{OM} are the replacement and annual operation-and-maintenance costs; i is the interest rate; and L is the reference battery lifetime (years).

3.5 Cost of forecast uncertainty

Price forecasts are generated from the true price series by applying a systematic bias β_m per market $m \in \{DA, FCR-N, FCRD-U, FCRD-D\}$ and a zero-mean dispersion term $\varepsilon_{\omega,t}$:

$$\hat{p}_{\omega,t}^m = \rho_{mt}(1 + \beta_m)(1 + \varepsilon_{\omega,t}) \quad (20)$$

$\hat{p}_{\omega,t}^m$ is the forecast price of market in scenario ω at time t , and ρ_{mt} is the actual price at t . A positive β_m represents a consistent over-forecast of that market and a negative β_m an under-forecast, while $\varepsilon_{\omega,t}$ captures non-systematic forecast noise. $x^*(\rho)$ denotes the optimal bid schedule obtained by solving (1)–(19) with a given price input (ρ) , and $F(x, \rho)$ is the resulting profit evaluated at prices ρ . For each day and each forecast setting, two quantities are computed:

$$V_1 = F(x^*(\hat{\rho}), \rho) \quad (21)$$

$$V_2 = F(x^*(\rho), \rho) \quad (22)$$

Here, V_1 is the profit realised when the forecast-based schedule is settled at the true prices; and V_2 is the perfect-information (oracle) profit obtained if the true prices were known before bidding. The cost of uncertainty caused by imperfect forecasting is:

$$\Delta = V_2 - V_1 \quad (23)$$

Finally, to study how the direction of forecast errors across markets affects the outcome, the per-market bias is written as $\beta_m = s_m |\beta|$, with sign pattern $s_m \in \{+1, -1\}$ for each market. The metrics (21)–(23) are evaluated over a full year of successive daily optimizations. Aggregated results are reported as the mean, the upper percentiles and the conditional value-at-risk of the daily cost of uncertainty, as well as its share of the total annual revenue.

4 Results

The model is solved as successive daily optimizations over the year 2025 for a 1 MW/1 MWh BESS in bidding zone SE3, using historical DA and FCR capacity prices, up/down regulation-energy prices, and measured FCR activation signals extracted from ENTSO-E and Svenska kraftnät mimer database. The forecast bias for the prices is swept from 0 % to 50 % while the direction of the per-market error in forecast is varied in different experiments. All monetary results are reported in Swedish Krona (SEK) (1 € $\approx$ 11 SEK).

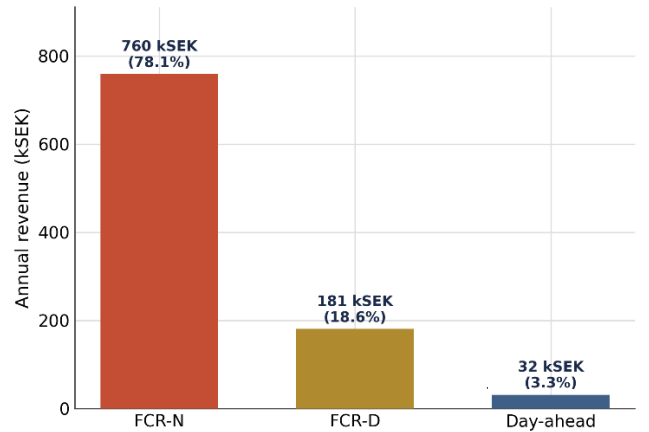


Fig. 3 distribution of the total revenue among capacity and energy markets

4.1 Annual profitability and revenue composition

Under perfect information the BESS earns 843 kSEK/year, with a median of 1.9 kSEK/day. The revenue is almost entirely from the reserve markets as depicted in Fig. 3. FCR-N contributes 78.1 %, FCR-D up and down 18.6 %, and DA arbitrage only 3.3 % of the revenue. The reason for this distribution of the revenue is both structural and price specific. FCR payment is done for both for battery's reserved capacity and the energy activation. However, as physically cycling the battery between a low- and a high-price hour is required for

the DA arbitrage, it is bounded by the single daily price spread and consumes cycle life. Additionally, one MW of standing capacity can be sold in every hour of the year while a few arbitrage cycles can be completed per day. Therefore, the capacity-based products yield far more value per unit of installed power.

4.2 Operating strategy

Fig 4 shows that the SoC is tightly concentrated around 0.53 and seldom leaves the (0.45, 0.60) band. This is imposed by the FCR-N service. Because FCR-N is symmetric, the battery must be able to both absorb and inject energy for one hour of full activation at any time. Satisfying endurance requirements in both directions simultaneously forces the SoC toward the middle of its range, where the up- and down-headrooms are balanced.

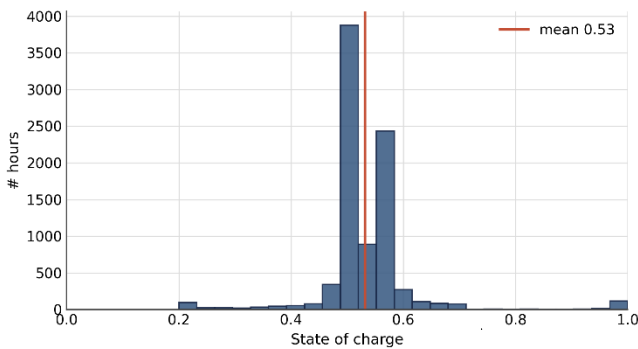


Fig. 4 Battery SOC distribution over the year

4.3 Cost of price forecast uncertainty

The cost of price forecast uncertainty (Δ) is defined as the revenue lost at the realized prices, when the battery follows the schedule that was chosen under the biased forecast, instead of the schedule that would have been chosen with perfect knowledge. As shown in Fig. 5, the cost of uncertainty increases super-linearly with the forecast bias, and at the forecast bias of 50 %, it corresponds to only 1.46 % of the total annual revenue. The objective function is linear with respect to the market prices. A systematic bias scales forecast prices up or down, but it does not change the order in which the market products are preferred. As long as every product remains profitable and this preference order is preserved, the optimal bid volumes remain the same as under perfect information.

The biased forecast merely assigns incorrect monetary order to a schedule that the battery would have selected regardless. Thus, a realized loss occurs only when the bias becomes large enough to alter a decision. On most days in the simulation period, the bias does not alter any decision. Therefore, the loss is zero and the median of Δ is low. On the minority of days, the realized prices lie close to a decision boundary, and a single altered decision produces a disproportionately large loss. The distribution of Δ is consequently heavy tailed. At a 50 % bias its 95th percentile reaches 236 SEK/day, its 95 % conditional value-at-risk 520 SEK/day, and its worst-case value 1190 SEK/day, which is more than thirty times the mean. Thus, the

economic susceptibility to forecast error is concentrated in a small number of high-cost days.

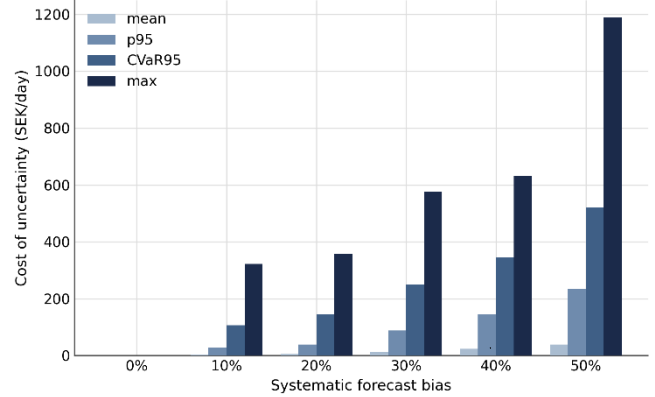


Fig. 5 Cost of uncertainty for different forecast bias levels

However, a small loss does not imply that the forecast has little effect on the battery's operation schedule. A "change in the schedule" here means that, each hour, the battery divides its available power differently among the four products compared to the one chosen under perfect information.

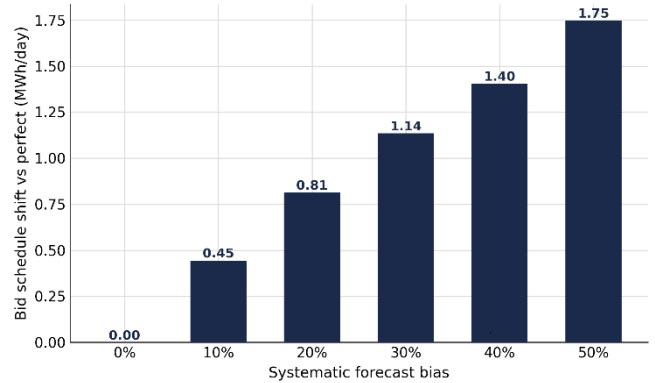


Fig. 6 Bid schedule change against the perfect knowledge scenario

This re-allocation barely affects profit. At a 30 % bias the schedule is rearranged within the reserve family rather than between reserves and DA arbitrage, and over the year the FCR-D up bids increase by 93 MWh while the FCR-D down bids decrease by 91 MWh. The hourly change in the FCR-N bid is strongly negatively correlated with the change in the FCR-D bids, with the correlation -0.73 . In other words, capacity withdrawn from one reserve product is redirected almost one-for-one into another, leaving the total reserve commitment and the physical operation of the battery largely unchanged.

4.4 Effect of the error magnitude and direction in forecasting different prices

Error in forecasting the DA or FCR-N price is the most expensive, in comparison with other markets. The FCR-D products are capacity offers and their contribution is a smooth linear term in the objective function. Accordingly, a price error changes their value but rarely their optimal volume. On the other hand, FCR-N and DA drive the energy that flows through the battery and interact with the endurance and SoC

constraints. Therefore, the error in forecasting them is more likely to move a binding constraint and change the dispatch.

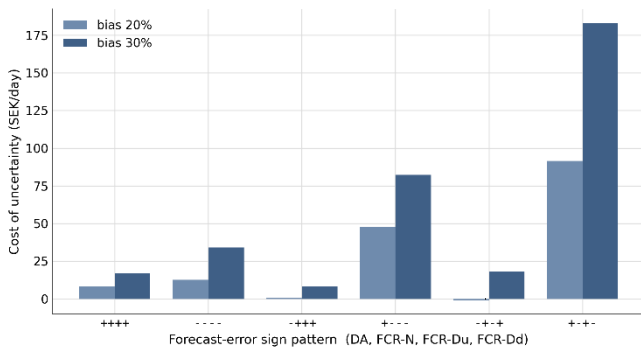


Fig. 7 Cost of uncertainty for different bias directions

From Fig. 7 it can be stated that the direction of the errors matters more than their size. When all prices are biased the same way (first and second columns in Fig. 7), the relative value of the markets is preserved. Therefore, no thresholds are crossed and the loss is small. In contrast, when the DA price is over-estimated while the reserve prices are under-estimated (pattern $+-+$ in Fig. 7), the perceived merit order is inverted. In this case, the model shifts capacity toward DA arbitrage that is not in fact profitable and withdraws from reserves that are. The same 30 % magnitude then costs 183 SEK/day on average and more than 1500 SEK/day on the worst day.

5 Conclusion

This paper quantified the profit a BESS might lose by the imperfect price forecasting when it stacks revenue across the day-ahead and FCR markets, using a MILP bidding model with reserve technical requirements and battery degradation. Three main results emerged. First, the battery earns almost all its revenue from reserve capacity, which is paid on availability rather than on energy delivered. Second, a biased forecast changes the realized profit only when it is large enough to flip a binding decision. Therefore, the average cost of uncertainty is small and under 1.5 % of revenue even at 50 % bias. It is worth mentioning that the risk lives in a few high-cost days and must be measured with tail statistics. Third, the loss is driven by the coherence of the errors across markets far more than by their magnitude. In fact, errors that invert the merit order between DA and the reserves are about an order of magnitude more expensive than aligned errors of the same size. These mechanisms indicate the forecasting and bidding effort should go toward the reserve prices rather than the DA price, as the forecasting accuracy of FCR prices is the main driving factor of revenue loss.

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