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Optimization of Hybrid Parks

Techno-Economic Analysis of Co-Location of Wind,
Solar, and Battery Storage

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Abstract

This thesis explores how integrating solar power and battery storage into an existing wind farm can increase profitability and operational flexibility, effectively transforming it into a hybrid park. An optimization-based model was developed to evaluate the techno-economic performance of various hybrid configurations over the years 2023 and 2024. The model consists of three components: a power prediction module using Quantile Regression Forests (QRF) trained on historical weather forecasts and production data, a market participation optimization that places bids on the day-ahead electricity market and the mFRR down ancillary service market, and finally a financial evaluation module that calculates key investment metrics, including internal rate of return (IRR).

Over 8,000 hybrid park configurations were simulated, varying in solar capacity, battery size, grid capacity, and market participation. The results show that solar power can lead to an IRR of around 7%, small batteries are generally favored, and larger batteries can be viable when combined with high solar capacity. Participation in the mFRR down market consistently improves profitability. Grid expansion beyond the existing connection is rarely economically justified due to high costs and limited gains from reduced curtailment.

The study concludes that hybrid parks are a promising solution for enhancing the value of renewable energy assets. Investment outcomes are most sensitive to capital expenditure (CAPEX) and day-ahead electricity prices. While the cannibalization effect poses a challenge to renewable investments, hybrid parks offer resilience by combining complementary technologies. Future research should investigate additional ancillary service markets and how varying levels of installed wind capacity affect the overall profitability of hybrid parks.

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Sammanfattning

Denna studie undersöker hur integration av solkraft och batterilagring i en befintlig vindkraftpark kan öka både lönsamhet och operationell flexibilitet. En optimeringsbaserad simuleringsmodell har utvecklats för att utvärdera olika hybridparker ur ett tekniskt och ekonomiskt perspektiv för 2023 och 2024. Modellen består av tre huvudkomponenter: 1) Effektprognoiser där historiska väderprognoser och produktionsdata använts för att träna ett antal Quantile Regression Forests (QRF) 2) Optimering av marknadsdeltagande genom bud på dagen före-marknaden samt mFRR ned och 3) Finansiell utvärdering med beräkning av bland annat internränta (IRR).

Över 8 000 olika hybridparker har simulerats, med variationer i solkraftskapacitet, batteristorlek, nätanslutning och deltagande på olika marknader. Resultaten visar att solkraft generellt är lönsamt över ett brett kapacitetsintervall, att små batterier ofta är att föredra, samt att större batterier kan vara ekonomiskt motiverade när de kombineras med hög solkraftskapacitet. Deltagande i mFRR ned-marknaden förbättrar konsekvent lönsamheten medan utbyggnad av nätkapaciteten utöver den befintliga anslutningen är sällan motiverad ur ett ekonomiskt perspektiv, på grund av höga kostnader och begränsad lönsamhet från minskad nedreglering.

Långtidsprognoser tyder på för sjunkande kapitalkostnader (CAPEX) och stigande dagen före-priser, vilket är fördelaktigt då känslighetsanalysen visar att investeringar i hybridparker är särskilt känsliga för just CAPEX och dagen före-marknaden. Kannibaliseringseffekten å andra sidan, att priset under timmar med mycket sol- och vindenergi tenderar minska med ökad andel förnybar kraft i systemet, utgör en utmaning för investeringarnas lönsamhet. Där erbjuder hybridparker en ökad motståndskraft genom att kombinera kompletterande teknologier. För framtida forskning rekommenderas vidare studier av andra stödtjänstmarknader samt analyser av hur olika nivåer av installerad vindkraft påverkar hybridparkers övergripande lönsamhet.

Acknowledgement To all the friendly people at Holmen who have welcomed us with open arms, quick response to all our questions, and fun coffee breaks. Special thank you to Sara for teaching us how the energy market works, Alexis for providing data, Oscar and Martin for sharing your technical know-how and Urban for encouragement and support.

Contents

1	Introduction	1
1.1	Purpose and goals	2
1.2	Delimitations	2
1.3	Thesis outline	3
2	Background	4
2.1	Hybrid parks	4
2.2	Nordic electricity market	5
2.2.1	Actors on the market	6
2.2.2	Electricity markets	7
2.2.3	The cannibalization effect	11
3	Model	11
3.1	Power prediction	12
3.1.1	Weather data	12
3.1.2	Photovoltaic system modeling	13
3.1.3	Random forest	13
3.1.4	Quantile random forest	14
3.1.5	Performance	15
3.2	Market optimization	17
3.2.1	Day-ahead model	17
3.2.2	mFRR model	20
3.2.3	Battery model	23
3.3	Financial evaluation	29
3.3.1	Long term market development	30
3.3.2	Base case comparison	31
3.4	Model parameters	32
3.5	Model validation	33
4	Results and Discussion	34
4.1	Simulation results	34
4.2	Sensitivity analysis	37
5	Conclusions	39
5.1	Further research	41
A	Appendix	45
A.1	Random forest	45
A.2	Additional figures	47

List of abbreviations

**Terminology used in this thesis might differ slightly from other sources.*

Term	Description
MW	Megawatt. Unit of instantaneous power.
MWh	Megawatt-hour. Unit of energy. Equal to one MW sustained for one hour.
Day-ahead market	Electricity market where participants place buy and sell energy production or consumption for each hour of the upcoming day.
Day-ahead bid*	Sold or bought energy volume (MWh) on the day-ahead market. In this thesis positive values represent sold energy.
mFRR CM	Manual Frequency Restoration Reserve Capacity Market. Market where producers bid to reserve capacity available for frequency regulation. Only downward direction is included in this thesis.
mFRR EAM	Manual Frequency Restoration Reserve Energy Activation Market. A market where reserved capacity is activated to correct frequency imbalances in real-time. Only downward direction is included in this thesis.
mFRR*	Used in this thesis to refer to both mFRR CM and mFRR EAM in only downward direction.
Imbalance volume	Difference between day-ahead bid and delivered energy. Adjusted by mFRR EAM.
Imbalance price	Price for imbalance volume. Generally equals to mFRR EAM down price for hours with mFRR down activation and vice versa for hours with up regulation. The same as day-ahead price for hours without mFRR activation.
Imbalance income*	Income from energy deviations from day-ahead plan. Positive (income) or negative (cost) based on imbalance volume direction and imbalance price.
Imbalance fee*	Fixed cost for not producing as bid, in proportion to imbalance volume.
mFRR penalty*	Penalty incurred if reserved mFRR capacity is not available.

Term	Description
C-rate	Measure of battery charge/discharge rate. Defined as the rate at which a battery is charged or discharged relative to its capacity (MWh). C-rate 1.0 means full discharge in one hour, C-rate 0.5 full discharge in two hours etc.
SoC	State of charge. How much charge the battery has left, from 0 to 1 representing 0% to 100% charge.
Grid capacity	Maximum power that can be transmitted through the grid connection at any given moment.
Curtailment	Reduction of energy generation below available levels due to grid constraints.
Energy arbitrage*	Practice of taking advantage of price differences, such as charging batteries when electricity prices are low and discharging when prices are high.

1 Introduction

The demand for electricity in the near future is expected to rise significantly. According to Svenska Kraftnät's long-term market analysis [1], Sweden will require an annual expansion of electricity production between 2025 and 2045 in the range of 2 to 7.5 TWh to meet this growing demand. A substantial share of this increase is projected to come from wind and solar power. However, the integration of a higher share of renewable energy sources will lead to greater variability in electricity production, thereby increasing the need for flexibility and energy reserves in the power system.

The energy production of wind farms is highly dependent on wind conditions, making it largely uncontrollable. Similarly, solar power generation relies on the level of solar irradiance at any given time. Interestingly, these two technologies tend to complement each other in terms of production timing—solar energy is typically generated during the day, while wind energy is often more abundant during evenings or nights and in different seasonal patterns. Combining both wind and solar power behind a shared grid connection can therefore increase the stability and consistency of energy output. Furthermore, the integration of a battery storage system can enhance this setup by smoothing out fluctuations in production, reducing curtailment losses, and maximizing the utilization of the available grid capacity [2]. When multiple technologies are installed behind a shared grid connection, the system is referred to as a hybrid park.

By integrating multiple technologies within the same site, producers can extract more value from their existing assets. Co-location enables the shared use of infrastructure, such as substations, access roads, and grid connections, resulting in cost savings by avoiding redundant construction. Additionally, the inclusion of battery storage systems opens up opportunities for energy arbitrage, where the battery is charged during hours with low price and discharged at price peaks. Also, participation in the ancillary service markets can provide further revenue streams and operational flexibility [2].

This thesis is conducted in collaboration with Holmen Energi, a company that operates several wind farms across Sweden. The aim of the study is to investigate how Holmen's wind farm Varsvik can be further developed into a hybrid park, and how such a transformation could generate additional value. Varsvik is the largest wind farm in the Uppland region which is located in the south of Sweden. The park contains of 17 wind turbines with a total installed capacity of 52 MW and an estimated annual electricity production of 150 GWh [3].

Determining how a potential development of Varsvik into a hybrid park should be designed is not a straightforward task. Numerous factors must be considered, including different sizes and combinations of technologies, grid capacity constraints, bidding

strategies, participation in ancillary service markets, and potential future developments in technology costs and energy prices. This thesis presents a combined simulation and optimization model that incorporates and evaluates these factors, with the aim of supporting informed decision-making in the planning and design of hybrid parks.

1.1 Purpose and goals

The purpose of this thesis is to evaluate the technical and financial value of adding solar power and battery storage to existing wind power infrastructure with a specific focus on the wind farm Varsvik in Uppland.

Research questions:

- Which combinations of wind, solar, and battery storage are the most value-creating, and why?
- What is an appropriate size for batteries and solar panels in a hybrid park based on profitability and technical constraints?

1.2 Delimitations

This thesis focuses solely on identifying the optimal combination of technologies based on economic profitability. Other important considerations, such as environmental impacts, are not addressed. Legal aspects, such as compliance with network codes and permitting requirements, can vary depending on the technologies selected for the hybrid park. However, these regulatory factors are also outside the scope of this thesis.

For ancillary services, mFRR¹ was selected, as it represented the service in Sweden with the highest amount of prequalified capacity for wind power in Q4 2024 [4]. While it would be advantageous to consider a broader range of services, especially since batteries enable participation in various other services, the scope of this thesis did not allow for such an expansion.

The hybrid park is modeled solely as a generator on the electricity market, meaning it only delivers energy to the grid and does not consume energy, for example through

¹Both the mFRR capacity and energy activation in downward direction is included. This is further explained in section 2.2.2

charging operations as is possible with battery systems. The battery in this study only charges from the parks production.

This study does not account for battery degradation, which may affect long-term performance and profitability in real-world applications.

During the simulations, the parks were simulated over the years 2023 and 2024. As the study was conducted in 2025, these were the two most recent years for which historical data was available for simulation and evaluation purposes. All prices in this thesis are calculated on an hourly basis, in line with how the energy market operated during 2023 and 2024. The transition to a 15-minute market structure, which was introduced in early 2025, is not considered in this study.

1.3 Thesis outline

In **Chapter 2**, a background is provided to hybrid parks and the Nordic energy market. **Chapter 3** present the model with its three major components: power prediction, market optimization, and financial evaluation. The model chapter is concluded with a table of parameters. The main results from the simulations are presented and discussed in **Chapter 4**, together with a sensitivity analysis. Finally, the main conclusions are drawn in **Chapter 5**, along with suggestions for further research.

Some figures which do not directly add to the conclusions but might still be of interest are therefore provided in the appendix. The appendix also includes a mathematical description of the power forecast model.

2 Background

2.1 Hybrid parks

Hybrid parks with wind, solar and/or battery storage are a relative new concept in Sweden, with only three parks being in operation as of 2025², as shown in Table 1. The C-rate in existing and planned hybrid parks is often around 1, and the battery capacity over 20 MWh, and for some parks close to the installed wind power.

Table 1: Operational hybrid parks in Sweden, along with those currently under construction or planned for development as of 2025. The list does not include all parks that are under the development or planning phase. N/A means that it is applicable for that site and the technology is not present.

Name	Status	Installed wind (MW)	Installed solar (MW)	Battery capacity (MWh)	Battery C-rate	Source
Hjuleberg	Operational	36	N/A	30	0.86	[5]
Höge väg	Operational	37	N/A	29	0.86	[6]
Eken	Operational	N/A	12	2	1	[7]
Fröskog	Under construction	36	19	N/A	N/A	[8]
Skåramåla	Under construction	50	39	N/A	N/A	[9]
Årjäng	Battery planned	40	N/A	20	1	[10]
Femstenaberg	Battery and solar planned	46	30	20	1	[11]

The power production from wind and solar power is negatively correlated, meaning their generation patterns complement each other. This results in a smoothing effect on the overall power output, leading to a more stable and consistent energy supply [12]. Such complementary behavior not only improves grid utilization but also enhances the predictability of the combined power production. Lindberg [12] notes that this co-location of wind and solar generation can contribute to more accurate power forecasts, as the overall production becomes more balanced and less variable.

²Other types of hybrid parks with a combination of hydropower and batteries have been in operation for a longer time, but is not part of this study

2.2 Nordic electricity market

The Nordic electricity market is deregulated, meaning it operates under free competition where prices are determined by supply and demand. One important aspect of the electricity market is the requirement for continuous real-time balance between electricity production and consumption. Since large-scale electricity storage is currently limited, the amount of electricity generated must always match the amount consumed. Consequently, the structure and functioning of the electricity market are shaped by the physical constraints of the power grid [13].

In the physical electricity grid, bottlenecks can occur in areas where there is a mismatch between electricity production and consumption. One example is the north and south of Sweden, where there is a surplus of production in the north and higher consumption in the south. The transmission capacity between these regions is limited and cannot fully balance the flow, which can prevent uniform electricity prices across the country. To manage this, Sweden is divided into four bidding zones, as shown in Figure 1. Electricity prices are determined separately for each zone, based on the local balance between production and consumption and the limited transfer of energy between bidding zones [13]. This study focuses on the wind park Varsvik, which is located in bidding zone SE3. Therefore, electricity prices from SE3 are used in the simulations and evaluations.



Figure 1: *The four bidding zones in Sweden [14].*

2.2.1 Actors on the market

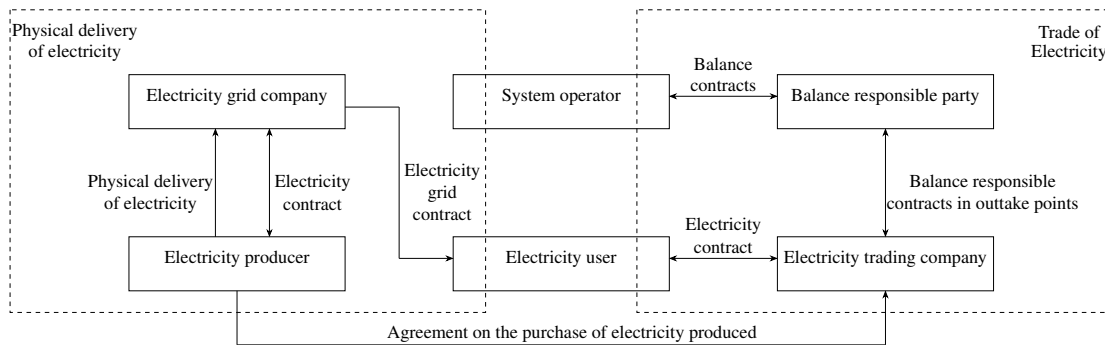


Figure 2: *Overview of actors, contracts, and physical flows in the electricity market. Simplified version from Svensk energi [15].*

This chapter provides a brief overview of six key actors in the energy market. While the actual market structure is more complex, these actors are the most relevant for the scope of this thesis. Figure 2 shows the relationship between these actors.

Electric grid company

The electrical grid companies are responsible for transporting electricity from producers to end users. This transmission occurs through a hierarchical structure: electricity is first transmitted via the high-voltage transmission grid, then distributed through the regional grid, and finally delivered to consumers through the local grid [15].

Electricity producers

An electricity producer generates electrical power and delivers it to an intake point on the grid. Typically, the produced electricity is sold to an electricity trading company, which is responsible for marketing and selling the electricity to end users or on the open market [15].

Electricity user

An electricity user is defined as anyone that consumes electricity from the grid, including both households and companies. Electricity users purchase their electricity through an electricity trading company [15].

Balance responsible party

Each intake and outtake point in the electricity grid must be assigned a balance responsible party. Their role is to ensure that electricity consumption is balanced with production and market trades. If this balance is not maintained, the system operator calculates imbalance costs, which are then charged to the responsible party [15].

Electricity trading company

Electricity trading companies purchase electricity either directly from producers or through other trading platforms, such as Nord Pool which is the nordic power market. The purchased electricity is sold in competition with other trading companies, and the price is determined through agreements between buyers and sellers. Electricity trading companies can also function as balance responsible parties [15].

System operator

Svenska kraftnät (Svk) is Sweden's system operator and a government agency responsible for managing the national transmission grid. They ensure the grid frequency stays at 50 Hz by balancing electricity supply and demand in real time. When imbalances occur, they buy or sell electricity and allocate the costs to those responsible. Balance-responsible companies must settle these imbalances financially [15].

2.2.2 Electricity markets

Due to the complex nature of the electrical grid, the electricity market is divided into several segments. These are explained in the following section, with particular emphasis

mFRR down and imbalance settlement. Figure 3 show how the different markets relate to the physical delivery of electricity.

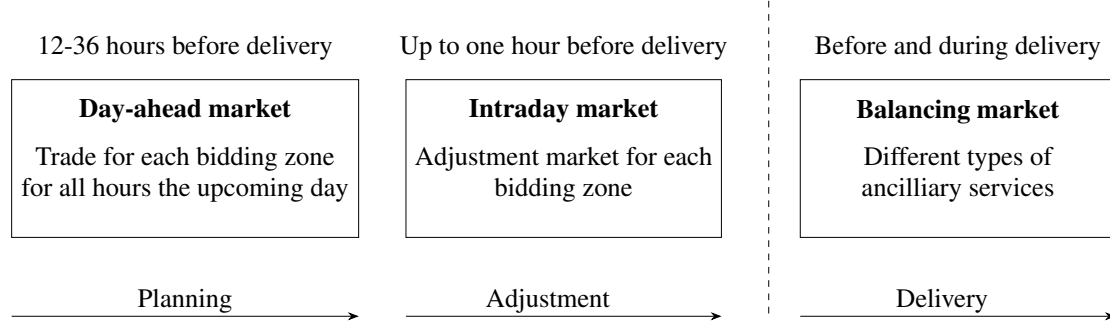


Figure 3: Order of energy markets before delivery [13]

Day-ahead market

The majority of electricity is traded on the day-ahead market, which closes at 12:00 CET on the day prior to delivery. This market operates on a common European platform with several exchanges, the largest and most widely used being Nord Pool. Although multiple exchanges exist, their prices are interconnected, so it does not matter on which exchange the bid is placed on as the price is the same. Bidding is organized by geographical bidding zones; in Sweden, there are four such zones, SE1, SE2, SE3, and SE4, numbered from north to south. Market prices are determined by supply and demand and can fluctuate significantly between individual hours [13].

Intraday market

Factors such as weather conditions and unexpected maintenance can result in energy producers being unable to match their bids on the day-ahead market. To adjust for these changes, producers can revise their bids up until the delivery hour by trading on the intraday market. This market handles smaller volumes compared to the day-ahead market and is mainly used by balance responsible parties to decrease their imbalance volume [13].

Balancing market

Svenska kraftnät, the system operator in Sweden, is responsible for ensuring the stability of the electricity grid. To manage imbalances that may occur at the time of delivery and to maintain a stable electricity grid, Svenska kraftnät buys and activates ancillary services. These services vary in terms of response time, capacity, and duration [13].

Figure 4 shows the different ancillary markets in Sweden. Ancillary services are used to restore the grid frequency to 50 Hz in case of deviations. This thesis will focus on the mFRR down market, for further information about the other services, see Svenska

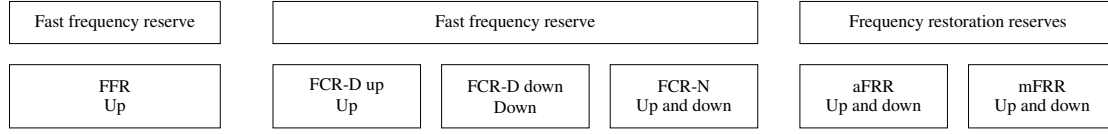


Figure 4: Overview of the ancillary services in Sweden

kraftnät [13].

mFRR stands for manual Frequency Restoration Reserve and is a slower ancillary service used to adjust larger volumes of electricity in the power system. There are separate markets depending on the direction of the mFRR services: mFRR up and mFRR down. mFRR up requires increased energy supply to the grid, while mFRR down involves reducing supply. In theory, a hybrid park can participate in both mFRR up and mFRR down. However, in this thesis, participation is limited to mFRR down. Since the park modeled in this study functions solely as a generator, participating in mFRR down involves reducing its power output to help balance the electricity grid.

To participate in the mFRR market, an actor must apply to Svenska kraftnät and meet their technical and organizational requirements. Once qualified, they can take part in two separate markets: the mFRR Capacity Market (CM) and the mFRR Energy Activation Market (EAM) [16].

Bids for mFRR CM must be submitted by 07:30 on the day before delivery. In this market, actors offer a certain capacity they are prepared to provide. If the bid are accepted, they receive payment for this commitment regardless of whether the capacity is actually activated. The mFRR EAM market closes 45 minutes before the activation hour. Bids submitted here must be at least equal to the corresponding CM bid, as they represent the actual energy the actor is ready to deliver if called upon. On the EAM market, only bids that are activated receive payment.

In this thesis mFRR EAM down and mFRR CM down is included. When referring to mFRR EAM down or mFRR CM down, the downward direction will be assumed and thus referred to as only mFRR EAM or mFRR CM. When both mFRR EAM down and mFRR CM down is referred to it will be simply be called mFRR.

Imbalances

The calculation of imbalance volume is shown in figure 5.

$$\text{Production} - \text{Consumption} \pm \text{Trade}^* \pm \frac{\text{Imbalance adjustment}}{\text{Imbalance}} \pm \frac{\text{MGA imbalance}}{\text{Imbalance}} = \frac{\text{Imbalance volume}}{\text{Imbalance}}$$

Figure 5: Equation for calculating imbalances [17]. *Trade refers to the combined trading on both the day-ahead and intraday markets.

This is calculated for each hour (and every 15 minutes starting in 2025) for each balance responsible party. The imbalance adjustment reflects the total volume of all activations on the balancing market, while the MGA (Market Grid Area) imbalance accounts for discrepancies due to metering errors or data issues in the grid [17]. In a well-functioning system, the MGA imbalance is typically zero.

If the imbalance volume is positive, meaning that the physical delivery of electricity to the grid exceeds the sold volume, the surplus energy is sold at the current imbalance price. If the imbalance volume is negative, meaning the delivery is less than the sold, the balance responsible party must buy the missing energy at the current imbalance price. For hours where mFRR EAM down is activated, the imbalance price is generally lower than the day-ahead price. A positive imbalance will then generate less income than if a day-ahead bid which matched the actual production had been made. A negative imbalance will lead to a smaller cost than the income already earned from the day-ahead market, and is thus economically profitable.

For hours with mFRR EAM up activation, the imbalance price is generally higher than the day-ahead price. A positive imbalance will then generate a larger income than a correctly placed day-ahead bid while a negative imbalance will cause a greater cost since the missing energy must be bought for a higher price than the already sold day-ahead bid. In summary, from an economical perspective it is optimal for the imbalance to be in the same direction as the dominating imbalance price direction. In addition to this, a fixed fee in EUR/MWh is charged based on the absolute value of the imbalance volume [17].

This implies that a balance responsible party does not necessarily incur a loss in the event of an imbalance. The financial outcome depends on the current imbalance prices and the imbalance fee. It is important to note that a strategy where a balance responsible party intentionally chooses imbalance in order to profit will not be viable. The system relies on maintaining balance in the grid, and Svenska kraftnät does not permit participation from actors who are frequently imbalanced without valid reasons.

2.2.3 The cannibalization effect

Both wind and solar power exhibit significant variability in their production due to changing weather conditions. As the number of wind and solar parks increases, these production patterns begin to influence electricity prices on the market. When there is abundant wind and/or sunlight, the resulting surge in renewable energy production increases the overall energy supply, which in turn leads to lower electricity prices. This price suppressing effect increases as the share of renewable energy in the energy market grows and has been termed the "cannibalization effect".

The increased share of solar power has led to a general decrease in day-ahead electricity prices during midday, with higher prices typically occurring in the morning and especially in the evening. This phenomenon results in a price pattern often referred to as the duck curve, where the "belly" represents the midday price dip caused by high solar output, the "tail" reflects the morning peak, and the "head" corresponds to the steep evening peak as solar generation declines and demand rises.

Traditional capital budgeting literature, which is used to assess the financial viability of investment projects, has largely overlooked this effect. Reichenberg [18] demonstrated, through numerical examples, that projected profits relative to investment costs can drop from an expected 33% to between 13% and -40%, depending on the assumed rate of future expansion in renewable energy capacity .

3 Model

In order to evaluate different combinations of wind, solar and battery storage, an approach which combines simulation and optimization was chosen. Each feasible hybrid park was simulated using a Python-model. Within each simulation, machine learning was used to create a power forecast. Numeric optimization was then used to find the optimal bids on the energy market and a battery strategy for each hour during one year. Based on the economical and technical result from one year a financial model was used to evaluate the long term investment. Figure 1 illustrates these three major components of the model, with the primary inputs and outputs. In the following sections the three components are explain in further detail, with a concluding table of technical and economic parameters.

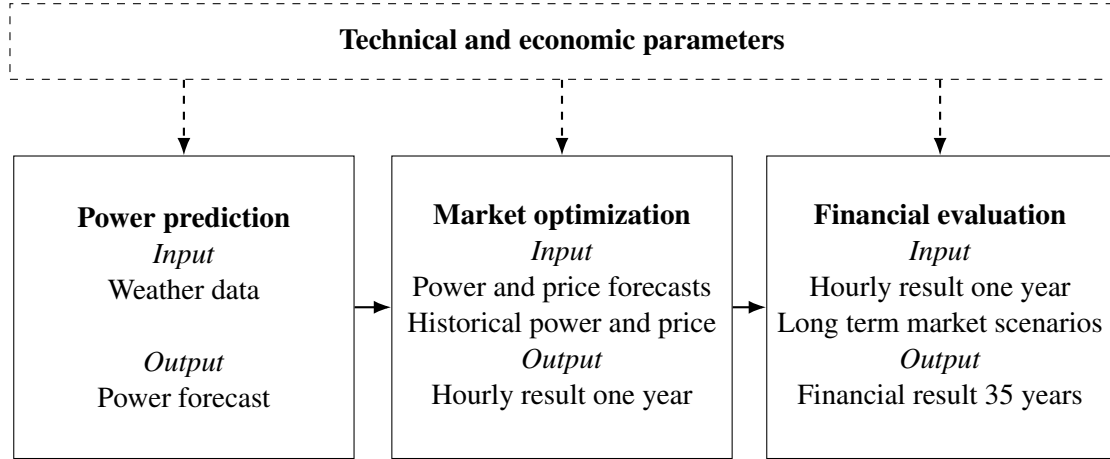


Figure 6: High level overview of the three major model components.

3.1 Power prediction

Power prediction for wind and solar power was found using historical wind power and modeled PV power together with historical weather forecasts and machine learning. For the machine learning model, Quantile Random Forest (QRF) was chosen due to its frequent use in previous studies in the same field [12]. It provided good predictive performance and included prediction intervals, allowing uncertainty to be quantified alongside the forecasts.

3.1.1 Weather data

Numerical Weather Predictions (NWP) are the most common form of weather predictions. NWPs uses mathematical computer models to predict future weather forecasts based on current weather observations [19].

The data for weather predictions are taken from The Norwegian Meteorological Institute [20]. The data includes a reference time from when the forecast was issued as well as a valid time for what hour the forecast applies to. The timestamps are followed with different values for different parameters. For this thesis, the parameters "wind speed, global horizontal irradiance, air temperature, relative humidity, precipitation amount, and air pressure at sea level" were chosen. See Table 2 for an example.

In this dataset, wind speed predictions are provided at a height of 10 meters. For more accurate modeling of wind power production, wind speed data at hub height would be

preferable [12]. However, due to the scope and limitations of this thesis, such data was not available and therefore not included in the analysis.

Table 2: Example of NWP forecast values with the parameters wind speed (WS), global horizontal irradiance (GHI), air temperature (AT), relative humidity (RH), precipitation amount (PA), and air pressure at sea level (APSL).

Reference time	Valid time	WS	GHI	AT	RH	PA	APSL
2020-01-01 12:00:00	2020-01-01 12:00:00	5.6	62.9	277.1	0.73	0.0	101156.6
2020-01-01 12:00:00	2020-01-01 13:00:00	5.5	41.1	276.9	0.7	0.0	101128.0
...	...	...	...	...	...	...	...
2024-12-30 12:00:00	2024-12-31 23:00:00	5.8	0.0	272.5	0.9	1.5	99827.9

Forecasts were collected for each day at 12:00, with a horizon of 12-60 hours.

3.1.2 Photovoltaic system modeling

Since only historical wind data was available, solar modeling was necessary to simulate the performance of a hybrid park. Through modeling, power production from PV systems with different installed power was simulated. The expected solar power production was based on historical weather conditions, using physical and empirical relationships between irradiance, temperature, and system design parameters to simulate power production.

To estimate solar power production from a PV system, a Python-based modeling pipeline was implemented using the PVlib library [21]. The model used data from STRÅNG using SMHIs API [22]. The PV system simulation assumes monocrystalline silicon modules rated at 440 W.

3.1.3 Random forest

Random forests is a machine learning model based on an ensemble of decision trees. From a set of independent observations, training data is collected and split into feature data and target data. The target is the variable the model aims to predict, and the feature data consists of the input variables used to make that prediction, for example, weather conditions such as wind speed, temperature, or solar irradiance when predicting power production. The model generates a large amount of decision tree by using a technique

known as bootstrapping, where a random subset of the observations are selected with replacement to train each of the individual decision trees. Additionally, each tree is only trained on a randomly selected subset of the features, which introduces further variability and reduces the risk of overfitting [23].

When new feature data is presented, each of the decision tree in the ensemble produces a prediction for the given observation. These individual predictions are then aggregated to produce the final output. For classification tasks, the output is typically determined by majority voting, while for regression problems, the mean of all tree predictions is used [23]. For an explanation of random forest with mathematical notations, see appendix.

3.1.4 Quantile random forest

Building on the foundation of the Random Forest model, Ridgeway [24] proposed that tree-based predictions could be used not only to estimate the mean but also to approximate the full conditional distribution of the target variable. The core idea behind Quantile Regression Forests (QRF) is to use the set of values within each leaf node to construct a distribution, rather than simply computing the mean. From this distribution, prediction quantiles (or confidence intervals) can be derived. In this thesis, these intervals were used not only to obtain point predictions of power output but also to estimate a range within which the actual output is likely to fall, providing a measure of forecast uncertainty. For a more detailed explanation of QRF, see appendix and [24].

Eight QRF models were used in this thesis, as presented in 3

Table 3: *QRF models. * wind speed, air temperature, relative humidity, precipitation, and air pressure **global horizontal irradiance and air temperature.*

QRF	Feature	Target	Horizon	Training
Wind power	*	Historical wind power 2023	12-36	2020-2022
Wind power	*	Historical wind power 2023	36-60	2020-2022
Wind power	*	Historical wind power 2024	12-36	2020-2023
Wind power	*	Historical wind power 2024	36-60	2020-2023
Solar power	**	Simulated solar power 2023	12-36	2020-2022
Solar power	**	Simulated solar power 2023	36-60	2020-2022
Solar power	**	Simulated solar power 2024	12-36	2020-2023
Solar power	**	Simulated solar power 2024	36-60	2020-2023

3.1.5 Performance

The results of wind models are presented in Table 4. The evaluation metrics include the 95% coverage, which represents the proportion of true values falling within the 95% prediction interval, and the mean absolute error (MAE). For the solar power prediction, each installed capacity level (ranging from 1 to 100 MW) had its own simulated production forecast. Accordingly, a variation of the solar power machine learning model was applied to each capacity level. In general, the prediction accuracy for the solar models was comparable to that of the wind models when evaluated relative to the installed capacity. Although lower-capacity installations resulted in lower absolute prediction errors, the relative accuracy, measured as error in proportion to production, remained consistent across sizes.

Table 4: Coverage and Mean Absolute Error (MAE) for one-day and two-day forecasts for wind power in 2023 and 2024.

Metric	2023	2024
Coverage 95% One Day (%)	89.6	91.1
Coverage 95% Two Day (%)	90.3	91.2
Mean Absolute Error One Day (MW)	8.31	7.89
Mean Absolute Error Two Day (MW)	8.77	8.62

As expected, the prediction error increases slightly for the two-day forecasts compared to the one-day forecasts. However, the coverage of the 95% interval remains relatively stable. This is due to the prediction intervals becoming wider to account for the increased uncertainty in longer-term forecasts, thereby maintaining a similar level of confidence. Figure 7 show an example from five days predictions.

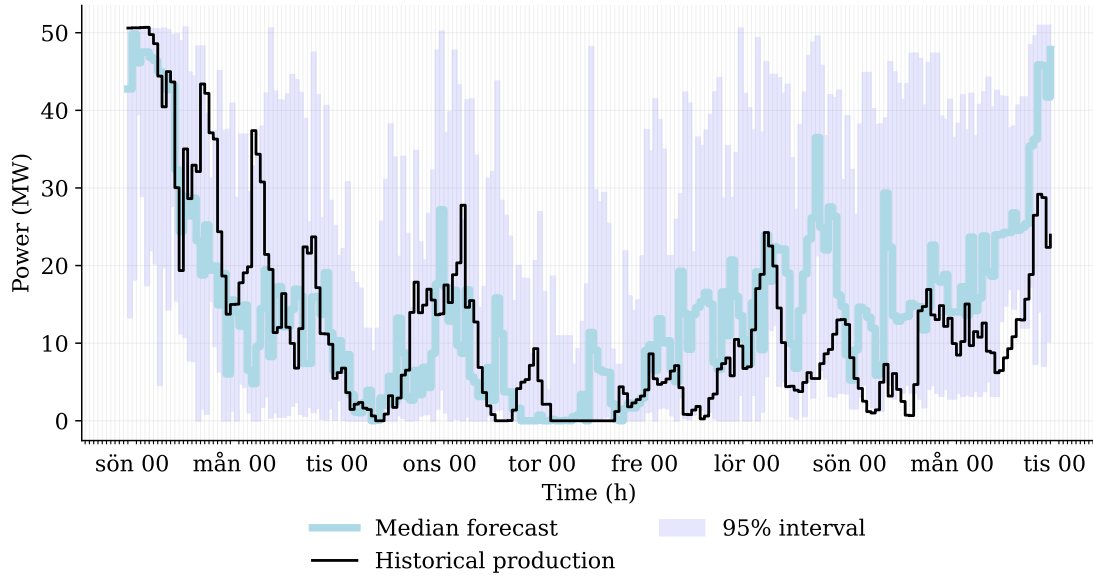


Figure 7: Median and 95% power prediction and historical wind power production.

Previous research has introduced additional modifications to the QRF forecasts to enhance the accuracy of power predictions for hybrid parks. One known limitation of using QRF for power prediction is its tendency to produce overly narrow prediction intervals. Specifically, it often fails to predict values close to zero in the lower quantiles and values near the maximum installed capacity in the upper quantiles. This issue can be addressed by training a separate quantile regression model for each quantile, thereby improving the representation of extreme values.

Furthermore, the model developed in this thesis generates independent predictions for each hour. In reality, weather conditions, and thus renewable power production, are correlated between hours. Capturing these dependencies can further enhance the accuracy of the power forecasts. One approach to modeling such temporal correlation is through the use of a Gaussian copula, a mathematical tool that enables modeling the dependency structure between random variables. For a more detailed description of these improvements, read Lindberg's work [12].

For the purposes of this thesis and due to the limited scope, the results obtained without these improvements were considered adequate.

3.2 Market optimization

The market optimization is presented in three stages for pedagogical purposes, which also reflects the development of the model. First, a simplified model is introduced in which the hybrid park participates only in the day-ahead market. Next, the model is extended to include mFRR³. In the third step, a battery which maximize income through energy arbitrage is added. The data used is presented in table 5.

Table 5: Data used for market model.

Data	Source
Power forecast	From QRF
Historical wind power production	Holmen
Historical solar power production	Authors PV-model
Day-ahead price forecast	Holmen
Historical day-ahead prices	Nordpool [25]
Historical imbalance prices	Nordpool [25]
Historical mFRR EAM activation	Nordpool [26]
Historical mFRR CM capacity	Nordpool [26]

3.2.1 Day-ahead model

In the simple day-ahead model, the optimal bids bid_t^{da} for each hour of the upcoming day are found by solving (1) where π_t^{da} is the forecast day-ahead price, π_t^{imb} is the forecast imbalance price, P_t^{out} is the forecast power to grid, π_t^{fee} is a fixed imbalance fee which penalize imbalance regardless of positive or negative imbalance. $P_t^{curtail}$ and P_t^{renew} was added so that the optimization might handle cases where the forecast renewable production was larger than the grid capacity.

$$\max_{bid^{da}} \sum_{t=1}^{24} \pi_t^{da} bid_t^{da} + \pi_t^{imb} (P_t^{out} - bid_t^{da}) - \pi_{fee} |P_t^{out} - bid_t^{da}| - K P_t^{curtail} \quad (1)$$

$$s.t. \quad P_t^{renew} - P_t^{curtail} = P_t^{out} \quad (2)$$

$$P_t^{renew} - P_t^{curtail} \leq P^{grid\ cap} \quad (3)$$

³As mentioned in section 2.2.2, mFRR refers to mFRR EAM down and mFRR CM down.

A well known feature of the nordic energy market is that if 1) the imbalance prices were known in advanced, 2) the production is unaffected by the bids and, 3) the imbalance fee is neglected, the optimal bid would always be zero when the imbalance price is higher than the day-ahead price, which is the case when the grid requires more energy. Vice versa the optimal bid would be maximal bid (grid capacity) whenever the imbalance price is lower than the day-ahead price, such as when there is too much energy in the grid.

Even though this is a optimal strategy, it is unrealistic due to the requirements from Svenska Kraftnät (Svk) and since the imbalance prices are settled after the delivery hour. Therefore π_t^{imb} was assumed to equal π_t^{da} . Also assuming that $P_t^{\text{renew}} < P^{\text{grid}}$, (1) can then be simplified to

$$\max_{bid^{\text{da}}} \sum_{t=1}^{24} \pi_t^{\text{da}} P_t^{\text{out}} - \pi^{\text{fee}} |P_t^{\text{out}} - bid_t^{\text{da}}| \quad (4)$$

where the trivial and realistic solution is that bid_t^{da} equal P_t^{out} .

In the Python model, the optimization problem was solved using Gurobi⁴[27]. After the bids where placed, historical power and price was used to evaluate outcome according to the flowchart in Figure 8.

⁴Gurobi is a commercial solver for mathematical optimization

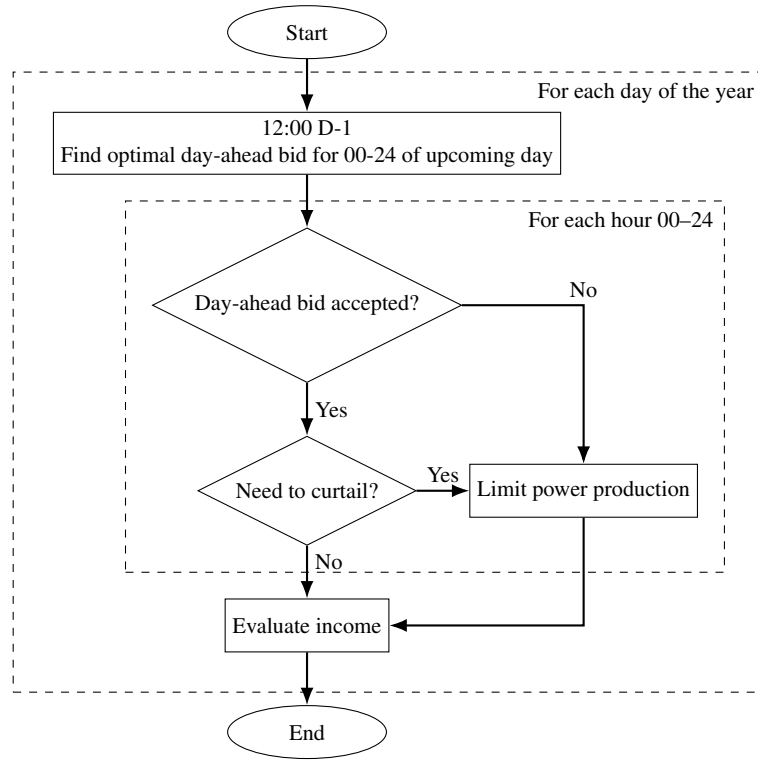


Figure 8: Flowchart of the simple day-ahead model.

Figure 9 shows how day-ahead bids are placed during two days. As expected, the day-ahead bids are equal to the power forecast and all of the produced power is delivered to the grid. Also, power to grid is equal to the renewable power production, as there is no battery involved and the grid capacity is not exceeded. As the model operates with a hourly resolution, the power is assumed to be constant during each hour.

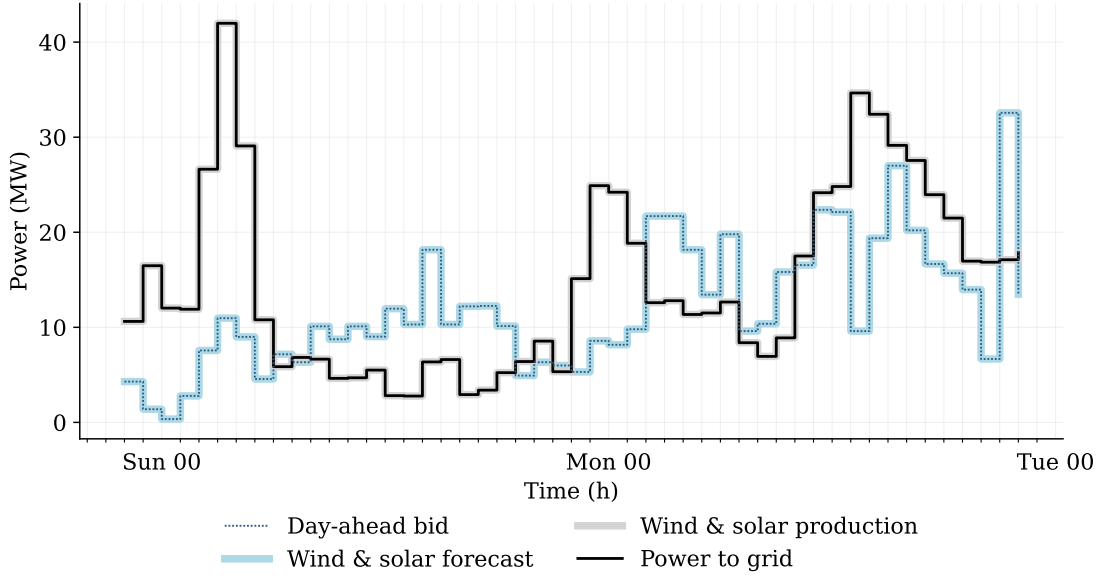


Figure 9: Day-ahead bids and power production according to the simple day-ahead model.

3.2.2 mFRR model

In order to include mFRR⁵ CM, both the power forecasts and day-ahead optimization had to be modified. Contrary to the real mFRR CM market where bids for 00-24 the upcoming day are placed 07:30, the model place mFRR CM bids based on forecasts 12:00 two days before. The main reason for this design was model simplicity and computational efficiency. A crucial point for model realism is that the mFRR CM bids for the upcoming day are placed before the day-ahead bids, and based on a previous power forecast. The mFRR CM bids were placed on the 25% quantile of the power prediction.

In order to avoid cases with negative power production (consumption), an additional constraint was included in the day-ahead-optimization:

$$bid_t^{da} \geq bid_t^{mFRR,CM} \quad (5)$$

An example might illustrate why this is necessary: Assume the 25% quantile of the power forecast issued on Sunday 12:00 is 10 MW for Tuesday 16:00, and the model therefore bid 10 MW to mFRR CM. Further assume the median quantile of the forecast issued Monday 12:00 for Tuesday 16:00 is 5 MW and the model therefore bid 5 MW on the day-ahead market. If mFRR EAM is activated Tuesday 16:00, the desired power

⁵As mentioned in section 2.2.2, only the downward direction of mFRR CM and mFRR EAM is included in this thesis

output will be -5 MW (5 - 10), which is not possible to deliver from at hybrid park which only operates in generator mode, as the model assumes.

In the mFRR EAM market, bids can be placed up to 45 minutes before each delivery hour. This is simplified in the model, where the mFRR EAM bids for all hours of the upcoming day are placed at 12:00, directly after the day-ahead bids have been placed.

Like the mFRR CM bids, mFRR EAM bids are based on the 25% quantile of the power prediction, but as the mFRR CM bids are based the forecast from the previous day, they are not necessarily equal. The model accurately captures the limitation of mFRR EAM bids from already placed CM bids, such that if a CM bid has been accepted, the EAM bids must be at least of equal size. The minimum bid for both CM and EAM bids was set to 1 MW⁶ and mFRR EAM activations are assumed to last one hour.

After mFRR CM, day-ahead and mFRR EAM bids have been placed, the historical power, price and mFRR data is used together with the bids to evaluate the parks operation and income. Figure 10 illustrates the model operation.

⁶During 2024, the minimum bid size was generally 5 MW, but at the time of writing this thesis, 1 MW was the minimum bid size

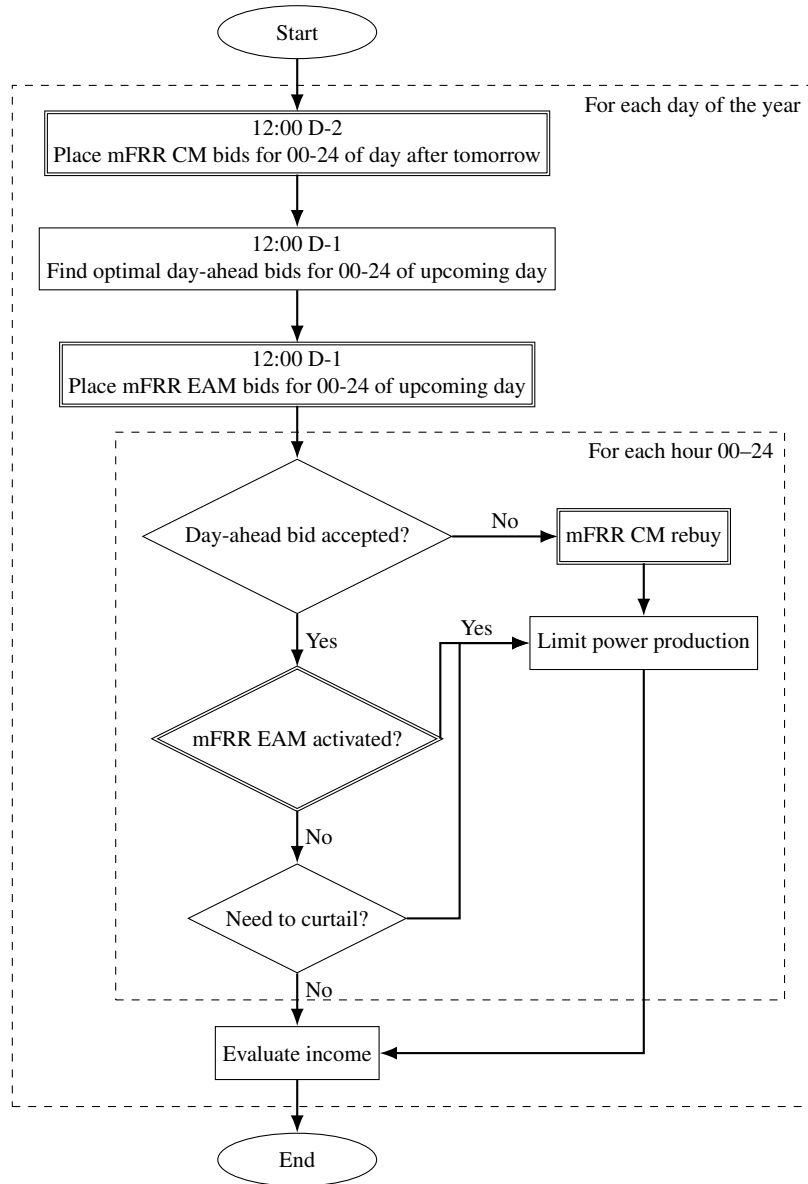


Figure 10: Flowchart of the day-ahead model with mFRR, boxes with double borders are mFRR additions.

Figure 11 illustrates the mFRR bids and operation during two days. mFRR⁷ bid size is shown as filled area under the day-ahead bid and the red area represent hours where mFRR EAM is activated. Optimal power⁸ to grid during hour without mFRR EAM

⁷mFRR EAM and mFRR CM bids happened to be same during these hours and therefore combined

⁸Optimal in the sense that no imbalance is introduced

activation is thus the same as the day-ahead bid. For hours with mFRR EAM activation, optimal power to grid is the bottom of the filled mFRR area. Notice that for hours with mFRR activation but no mFRR bids, such as the first hours of both Monday and Sunday, the power to grid can exceed the day-ahead bid. The lack of mFRR bids can be caused by mFRR prices not exceeding the minimum mFRR price limit or because the 25% production quantile was zero. The purple line indicate power forecast error, where positive values mean more than expected power is produced.

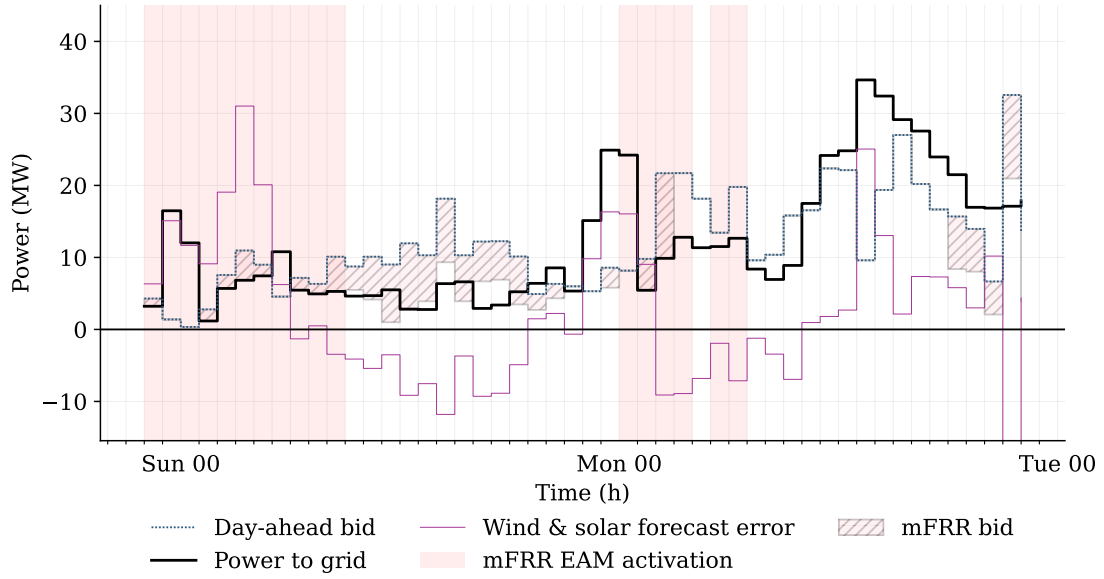


Figure 11: Model with mFRR active during two days.

3.2.3 Battery model

When adding a battery storage to the model, two new decision variables were added to the target function: P_t^{ch} for battery charge and P_t^{dis} for battery discharge.

The initial battery strategy was to maximize the day-ahead income through energy arbitrage, where the battery is charged during hours with low day-ahead price and discharge during hours with high day-ahead price. A penalty C_{cost} for charge and discharge was added to the target function to reflect the fact the battery lifetime limited by the number of charge cycles. This penalty can be thought of as how large the income difference must be in order to utilize the battery. The value for C_{cost} was calculated based on the cost per MWh for the battery. To match the expected battery lifetime of 25 years, the variable was scaled using a constant determined iteratively by comparing the estimated

lifetime based on energy throughput with the assumed 25-year lifetime until the two aligned.

The combined day-ahead, mFRR, and battery optimization is given by (6)

$$\max_{bid_t^{da}, P_t^{ch}, P_t^{dis}} \sum_{t=1}^{48} [\pi_t^{da} bid_t^{da} + \pi_t^{imb} (P_t^{out} - bid_t^{da}) - \pi_t^{fee} |P_t^{out} - bid_t^{da}| - C_{cost} (P_t^{ch} + P_t^{dis}) - K P_t^{curtail}] \quad (6)$$

$$s.t. \quad P_t^{renew} + P_t^{dis} - P_t^{ch} - P_t^{curtail} = P_t^{out} \quad (7)$$

$$P_t^{out} \leq P_{grid}^{cap} \quad (8)$$

$$P_t^{ch} \leq P_t^{renew} \quad (9)$$

$$P_t^{ch} \leq P^{bat, max} \quad (10)$$

$$P_t^{dis} \leq P^{bat, max} \quad (11)$$

$$SoC_t \geq SoC^{min} \quad (12)$$

$$SoC_t \leq SoC^{max} \quad (13)$$

$$SoC_{t-1} + \frac{\eta_{ch} P_t^{ch}}{E^{cap}} - \frac{P_t^{dis}}{E^{cap} \eta_{dis}} = SoC_t \quad (14)$$

$$bid_t^{da} \geq bid_t^{CM} \quad (15)$$

$P^{bat, max}$ is the maximum battery power (MW), and E^{cap} is the battery capacity (MWh). The output of the optimization now includes preferred charge and discharge schedule. SoC_t is the state of charge for that time and SoC^{min} is the minimal charge set to 0.2 and the SoC^{max} is the maximum charge set to 1. η_{ch} is the charging efficiency, representing the proportion of energy retained during charging, set to 0.97, while η_{dis} is the discharging efficiency, set to 0.98.

Since the optimization is done per day, the income for one day is generally maximized by leaving the battery in a discharged state at the end of each day. To avoid this unrealistic short term behavior and better capture price differences between days, the optimization at 12:00 was performed for both the upcoming and the next day. Hence the target function includes 48 hours instead of 24. After optimizing, historical power, price and mFRR data is used to evaluate the park operation and income during the upcoming day. The battery SoC is then fed into the optimization for the next day. An example might clarify this: at 12:00 Monday the optimization is done for 00-24 both Tuesday and Wednesday. The historical outcome of Tuesday is then used to evaluate the SoC at

the end of Tuesday. This is fed into the optimization which is done at Tuesday 12:00 for Wednesday and Thursday. Hence the actual SoC at the end of each day is known at 12:00, 12 hours in advance.

At delivery hour evaluation, where the historical power and mFRR data is used, the model first evaluate mFRR operation. If there is no mFRR EAM activation, the park will attempt to charge or discharge as scheduled from the optimization. Figure 12 illustrates the combined day-ahead, mFRR and battery model.

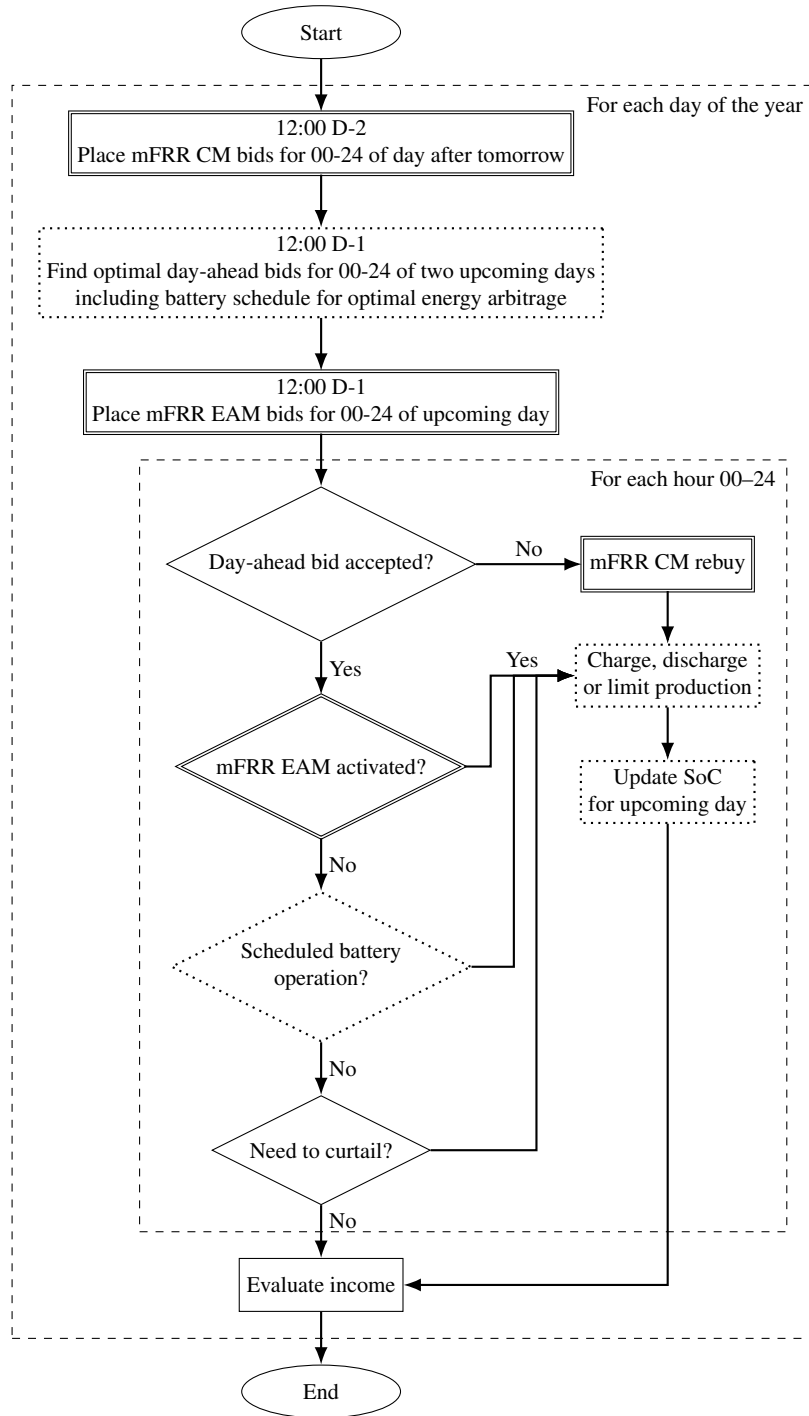


Figure 12: Flowchart of the day-ahead model with mFRR and battery. Boxes with double borders relate to mFRR and dotted boxes to the battery.

Figure 11 show the day-ahead bids and forecast battery operation based on forecast day-ahead price and power production. The filled green area represent the forecast SoC which is limited between 20% and 100%. Notice how the day-ahead bid is larger than the power forecast when the day-ahead price is high and the SoC is dropping, hence the battery is discharging. This can be seen at Sunday morning. The opposite situation can be seen around Monday midnight, where the power forecast is larger than the day-ahead bid because the battery is scheduled to charge.

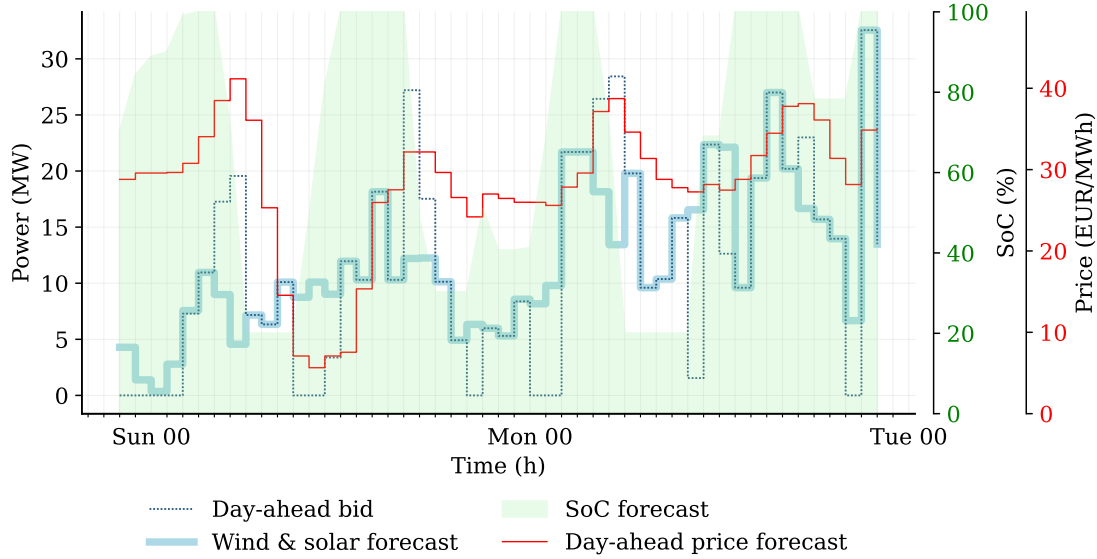


Figure 13: Day-ahead bids and scheduled battery operation based on power and day-ahead price forecast.

After the optimization is done, the operation is evaluated based on historical data. The battery will try to charge and discharge according to the optimization, but as shown in Figure 14, that is not always possible. At times where the power forecast error is negative, meaning less power is produced than expected, it is not always possible to charge as scheduled. The dark green area is the historical ⁹ SoC, which is lower than the light green around Sunday midday because there was not enough power produced to charge the battery. Also notice how the battery discharge during Sunday morning, even though more power is produced than expect, causing an even larger imbalance.

⁹Historical here means corrected by historical production values

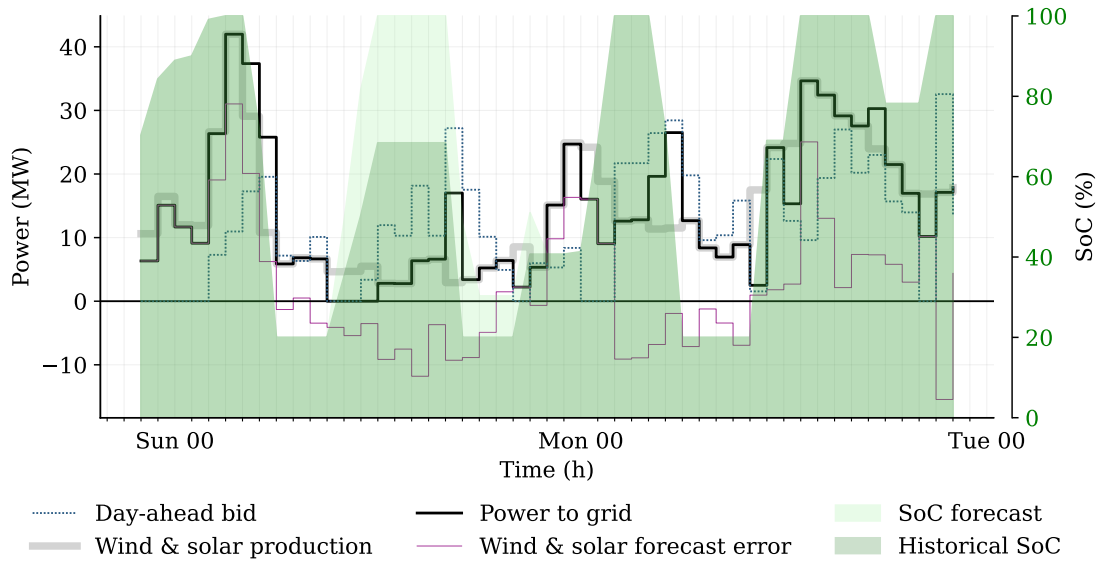


Figure 14: Battery operation corrected by historical power production without mFRR participation.

The final model combines mFRR participation with a battery. The operation during two days can be seen in Figure 15. Notice that for hours where the power to grid is limited by mFRR EAM activation, the battery will be charged if there is available production, even if no charging was scheduled. This is to charge the battery instead of down regulating production. An example of this can be seen at Sunday morning in Figure 15.

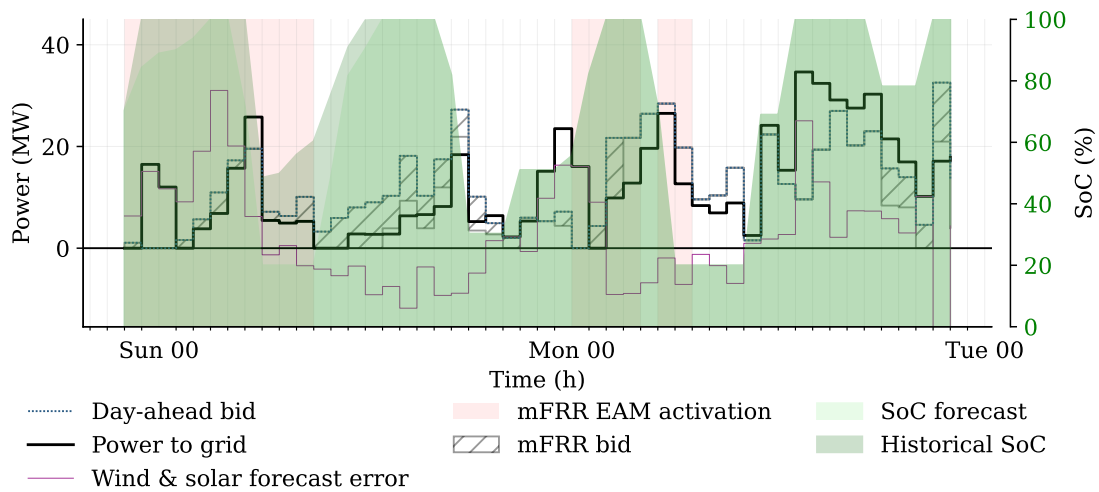


Figure 15: Final model behavior for two days with battery and mFRR participation.

3.3 Financial evaluation

The market optimization model provides annual income, but does not take capital expenditure¹⁰ (CAPEX), operational expenditure¹¹ (OPEX) or other expenses into consideration. In order to evaluate the economical feasibility of the hybrid parks, a model for financial evaluation was built in Python. The model is illustrated in Figure 16.

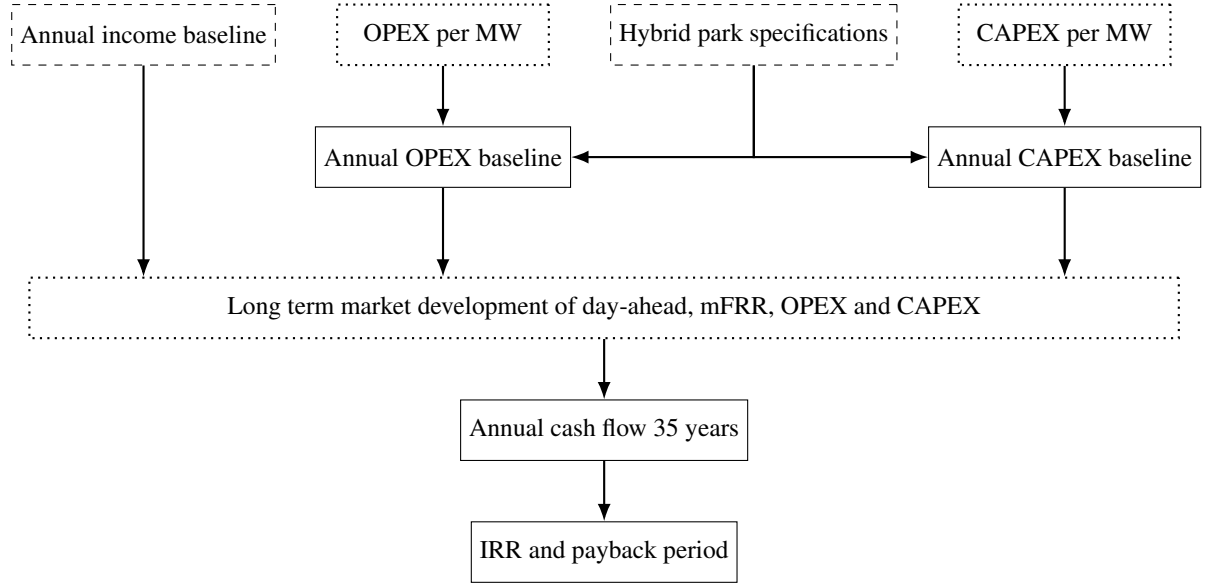


Figure 16: Financial model overview. Dotted boxed represent common inputs across all scenarios and dashed boxes are inputs from the market optimization model.

The cash flow for one year is given by

$$\text{cash flow} = \text{income} - \text{OPEX} - \text{tax} - \text{CAPEX} \quad (16)$$

where tax is given by

$$\text{tax} = (\text{income} - \text{OPEX} - \text{depreciation}) \cdot 0.206 \quad (17)$$

for positive values, otherwise 0. Depreciation is a financial metric for an investments loss of value, in this project. After discussions with Holmen, the depreciation period is set to five years, which means the tax will be lower the first five years. 20.6% is the corporate income tax level in Sweden [28].

¹⁰Such as investment cost

¹¹Such as maintenance cost

In financial analysis internal rate of return (IRR) is a standard metric for evaluating the profitability of an investment [29]. It can be understood as the expected annual value growth from an investment. A simplified example helps illustrate the concept: imagine investing 1,000 MEUR in a solar park with a lifetime of 35 years, or instead placing the same amount in a bank offering a guaranteed 4% annual interest over the same period. For the investment in the park to be financially worthwhile, its total income over 35 years must exceed the amount that would have been earned from the bank. If both options result in the same final amount after 35 years, the internal rate of return (IRR) of the solar power investment is 4%. The IRR was calculated using Equation (18).

$$\sum_{y=0}^{35} \frac{\text{cash flow}_y}{(1 + IRR)^y} = 0 \quad (18)$$

Where cash flow_y is cash flow for a given year. The calculation period was set to 35 years to match the expected life time of the solar park.

The payback period of an investment is another common financial metric which is provided from the model. It is calculated by finding the number of years before the cumulative cash flow becomes positive.

3.3.1 Long term market development

In order to conduct a financial evaluation of the different hybrid parks, CAPEX and OPEX per MW as well as long term development of day-ahead, imbalance, and mFRR prices needed to be assumed. The development is presented Figure 17, based on sources in Table 6.

Table 6: Sources for cost and price data.

Cost	Source	CAPEX	OPEX ($\frac{kEUR}{MW}$)
Wind power	IRENA [30]	Figure 17	24
Solar power	IRENA [31]; Agora [32]	Figure 17	10
Batteries	Energistyrelsen Denmark [33]	Figure 17	0.57
Grid	Thunder Said Energy [34]	Figure 17	3.6
Income	Source	Mean price ($\frac{EUR}{MWh}$)	
Day-ahead	Svenska Kraftnät [1]	Figure 17	
mFRR CM down	Svenska Kraftnät [1]	18.5	
mFRR EAM down	Svenska Kraftnät [1]	17.7	

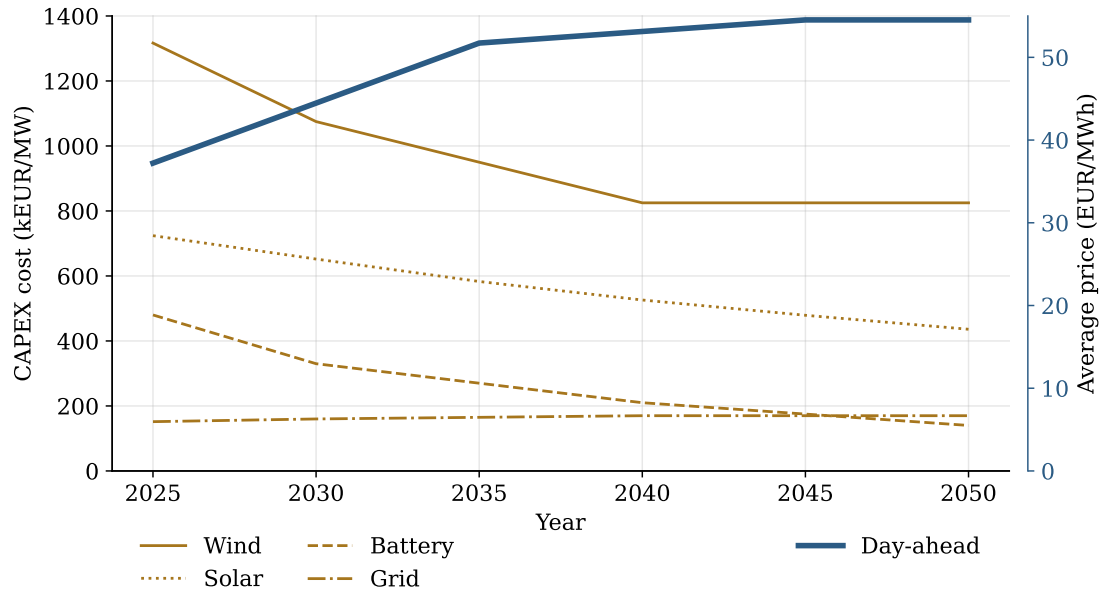


Figure 17: CAPEX cost (left axis) and average day-ahead price (right axis) forecasts from 2025 to 2050 (Source: Author's calculations based on data from various sources presented in Table 6)

The day-ahead price is believed to increase mostly due to increased demand for electrical energy [1] and the drop in CAPEX is expected because of increased large scale production and technological development [31].

3.3.2 Base case comparison

Since this project is focused around evaluating the economic impact of installing solar and batteries in an already existing wind park, it was necessary to isolate the effect from solar and batteries from the existing wind park, while including synergies between the technologies. This was done on an hourly basis by subtracting the output from the existing wind park.

Introducing mFRR participation added complexity, as hybrid parks with solar and batteries yield different outputs due to both new components and market participation. To isolate the effect of mFRR, additional base cases were created where the original wind park was simulated with mFRR. Thus, hybrid parks with mFRR in 2024 were compared to a 2024 base case that also included mFRR.

Figure 18 shows annual income across base cases, with the leftmost bar as a reference.

To evaluate the impact of using forecasts, the model was also run with historical power and price data as forecast, thus removing forecast error. These simulations, shown as semi-transparent bars labeled "Perfect", reveal that for 2023, forecasts slightly reduced income, while increasing it for 2024. This is due to imbalance volume happened to correlate with the imbalance price such that the income was greater than the fee. The figure also highlights the substantial income boost from mFRR participation that year, and that the day-ahead prices during production hours in 2024 were substantially lower.

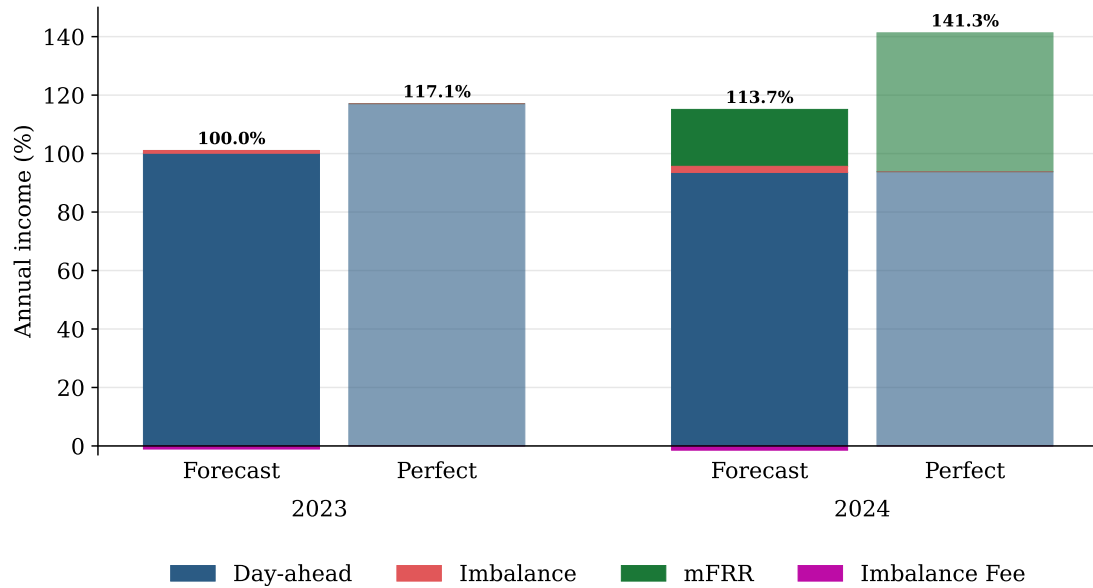


Figure 18: Breakdown of income, fee, and penalty for the different base cases.

3.4 Model parameters

The model parameters were determined in collaboration with Holmen and are presented in Table 7. Square brackets indicate evaluated ranges. Upper limits of solar and battery capacity was based on internal studies conducted by Holmen. The upper and lower limits of the grid capacity was set such that a slight decrease and significant increase, compared to the current 51 MW, was included in the range.

Table 7: *Model parameters.*

Parameter	Value
Installed solar (MW)	[0, 40]
Grid capacity (MW)	[45, 100]
Battery capacity (MWh)	[0, 40]
Battery C-rate (/h)	[0.5, 1.5]
Evaluated years	2023 and 2024
Calculation period for investment (yr)	35
Lifetime solar (yr)	35
Lifetime batteries (yr)	25
Tax rate (%)	20.6
Minimum day-ahead price (EUR/MWh)	-5.5
Minimum mFRR CM price (EUR/MWh)	7
mFRR bid quantile (%)	25
inflation rate (%)	2

3.5 Model validation

As the model consists of three main parts, validation was conducted for each model component: power prediction, market optimization and financial evaluation.

For the power prediction, the performance showed in section 3.1.5 was compared to internal power forecasts from Holmen¹². The internal forecast outperformed the QRF model. However, when comparing the model's annual income to historical income¹³, the difference was sufficiently small to consider the power prediction acceptable.

The market optimization was primarily validated through automated checks of edge cases and manual inspection of model behavior for selected days during winter and summer. Some of the automated checks are presented in Table 8

¹²Not revealed in this thesis

¹³Not revealed in this thesis

Table 8: Some of the automated check done after each model change. For the two first cases, the forecasts were manually set to zero which in turn should lead to the day-ahead bids being set to zero as well.

Case	Check
Zero forecast	No day-ahead bids
Zero forecast and historical production	Imbalance volume = historical production
Parks With battery	State of charge (SoC) within 20-100%
All parks	$0 \leq \text{Day-ahead bid} \leq \text{Grid capacity}$
All parks	$0 \leq \text{Power to grid} \leq \text{Grid capacity}$

The manual inspection of model behavior was done by plotting representative, as shown in Figure 15. The relationship between forecasts, day-ahead bids, mFRR bids, mFRR activation, and battery operation were visually examined to detect unexpected behavior.

The financial model, based on relatively simple equations, was validated through manual inspection of the annual cash flow for selected scenarios.

4 Results and Discussion

The results are presented and discussed in this chapter, along with a sensitivity analysis.

4.1 Simulation results

The results in this chapter is based on 8367 simulations using the parameters from Table 7. The parameters that varied are the installed solar, battery capacity, grid capacity and battery C-rate. For 2024, all cases were simulated with and without participation in the mFRR market.

The main result is presented in Figure 19 as a parallel coordinate plot, where each colored line represents one simulated hybrid park configuration. The five left vertical axes show the input parameters used in the simulations, such as the amount of installed solar capacity and battery size. The rightmost vertical axis represents the IRR. The color of each line corresponds to its IRR value, with warmer colors indicate higher IRR and cooler colors indicates lower IRR.

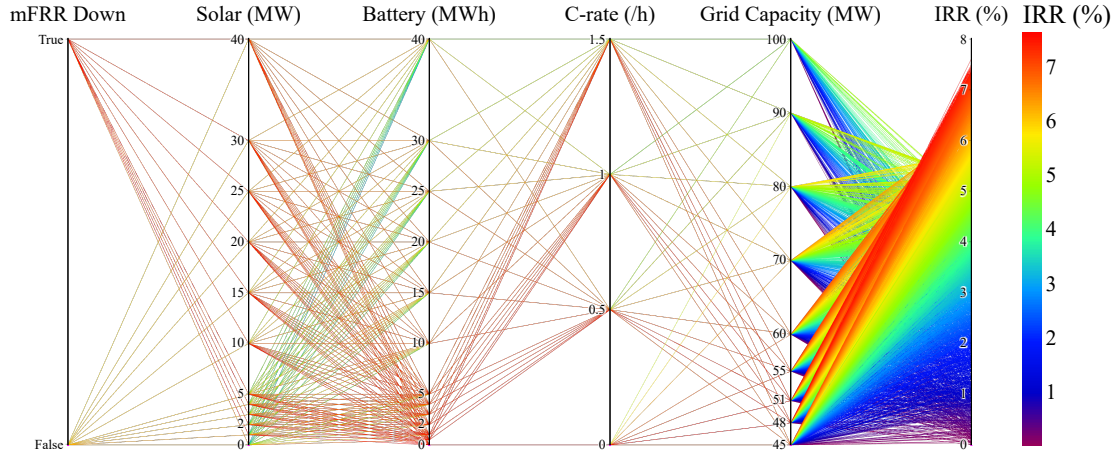


Figure 19: Parallel coordinates plot for 5062 of 5578 simulations with positive IRR for 2024.

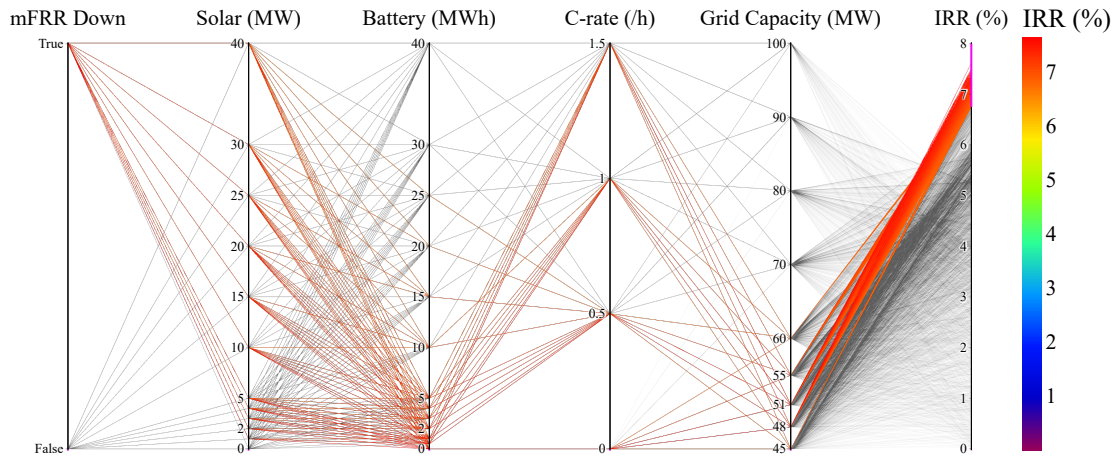


Figure 20: Same as Figure 19 with 6.5% IRR filtered.

Figure 19 presents the simulation results for 2024, and figure 20 shows the same results but with a filter for the cases with the highest IRR. The simulations for 2023 showed similar patterns but with overall higher profitability. This increase is primarily attributed to the higher average day-ahead electricity prices in 2023. The corresponding graphs for 2023 with additional output variables are included can be found in the appendix, see Figures 23. In all scenarios, the existing wind park, with an installed capacity of 52 MW, is included.

Among the highest IRR cases, it is clear that a wide range of installed solar capaci-

ties, from 1 MW up to 40 MW, can yield profitable investments. This suggests that the additional investment cost of installing more solar panels is justified by the corresponding increase in returns, making both small and large scale solar installations financially viable. However, there are other factors that may limit the size of solar capacity. One notable constraint is land availability, as solar panels require significant space, commonly estimated at approximately 1.5 hectares per megawatt of installed capacity.

For battery storage, the simulations generally favor smaller battery sizes, and while lower C-rates tend to be slightly more favorable, the C-rate overall appears to have a limited impact on IRR. This outcome is primarily due to the high CAPEX associated with batteries, combined with the relatively modest revenue potential from energy arbitrage alone. The profits generated by shifting energy volumes between low and high price hours are often insufficient to justify the cost of larger battery systems. However, larger batteries are not entirely unprofitable, for example one scenario involving a 40 MWh, 0.5 C-rate battery, 40 MW solar, and 51 MW grid capacity achieved an IRR of 6.38%. A common trend among the most favorable configurations that include a large battery is the presence of a high installed solar capacity. This is reasonable, as a larger battery can perform energy arbitrage more effectively when there is greater energy production available to shift between low and high price periods. Among the currently operational hybrid parks in Sweden (see Table 1), the two parks combining wind power with battery storage have battery capacities slightly below their installed wind power capacities. These are relatively large batteries, indicating that there is existing interest and potential in deploying larger-scale battery systems alongside wind power.

It is reasonable to assume that participation in additional ancillary service markets could enhance the profitability of larger batteries. Only mFRR services do not fully capture the operational potential of battery systems. Furthermore, if energy price volatility increases in the future, as might be expected due to the cannibalization effect for example, larger batteries could benefit from moving greater energy volumes between price peaks, thereby improving their economic performance.

In the most profitable simulation cases, the optimal grid connection capacity was typically around the current level of 51 MW, with slightly lower and higher values ranging from approximately 48 MW to 60 MW. This suggests that expanding the grid capacity beyond this range does not provide a sufficient return to justify the additional investment. The limited benefit from reduced curtailment losses, when total installed capacity is increased, appears to be outweighed by the high cost of grid expansion. See Figure 24 in the appendix for visual representation of the curtailment loss for different cases. Several factors may explain this result. Expanded grid connections are expensive, while solar installations are relatively inexpensive. Additionally, curtailment tends to occur during periods of simultaneous high solar and wind production, conditions that often coincide with low electricity prices. In such cases, the economic loss from curtailed en-

ergy is minimal. It is reasonable to assume that this relationship will remain valid in the future, particularly if electricity prices continue to fall during periods of high renewable generation and the cost of solar technology continues to decline.

Another noteworthy observation is that participation in the mFRR market consistently resulted in higher profitability compared to cases without such participation. This holds true even when these cases were evaluated relative to a base case that already included mFRR participation and exhibited significantly higher income, as shown in Figure 18. The reason behind this is relatively straightforward: increased energy production enables higher bids on the mFRR market, which in turn leads to greater revenue from ancillary services.

As previously mentioned, hybrid parks benefit from improved power forecast accuracy due to the complementary and smoother generation profile of wind and solar. This advantage also strengthens their position in the mFRR market. With more reliable forecasts, operators can confidently place larger mFRR bids without significantly increasing the risk of failing to deliver the committed volumes.

4.2 Sensitivity analysis

Figure 21 displays a sensitivity analysis for the 25 simulated hybrid parks with highest IRR for 2024, where there is at least 5 MW solar and 5 MWh battery. Four parameters were varied: CAPEX, OPEX, mean day-ahead price and mean mFRR-price¹⁴. The slope of the lines is a measure of how sensitive the IRR is to changes in that parameter. The faintly shaded 100% interval encompasses all 25 cases, and the slightly darker area includes the 90% quantile. The colored lines represent the mean value. As shown in Figure 21, the values among the top-performing cases are very similar. This is likely due to the fact that both capital and operational expenditures (CAPEX and OPEX) are scaled linearly with capacity, measured in EUR/MW. The dashed 7.5% IRR line was added as a reference as it is sometimes used as a lower limit for company investments.

¹⁴This includes the price for both mFRR EAM down and mFRR CM down

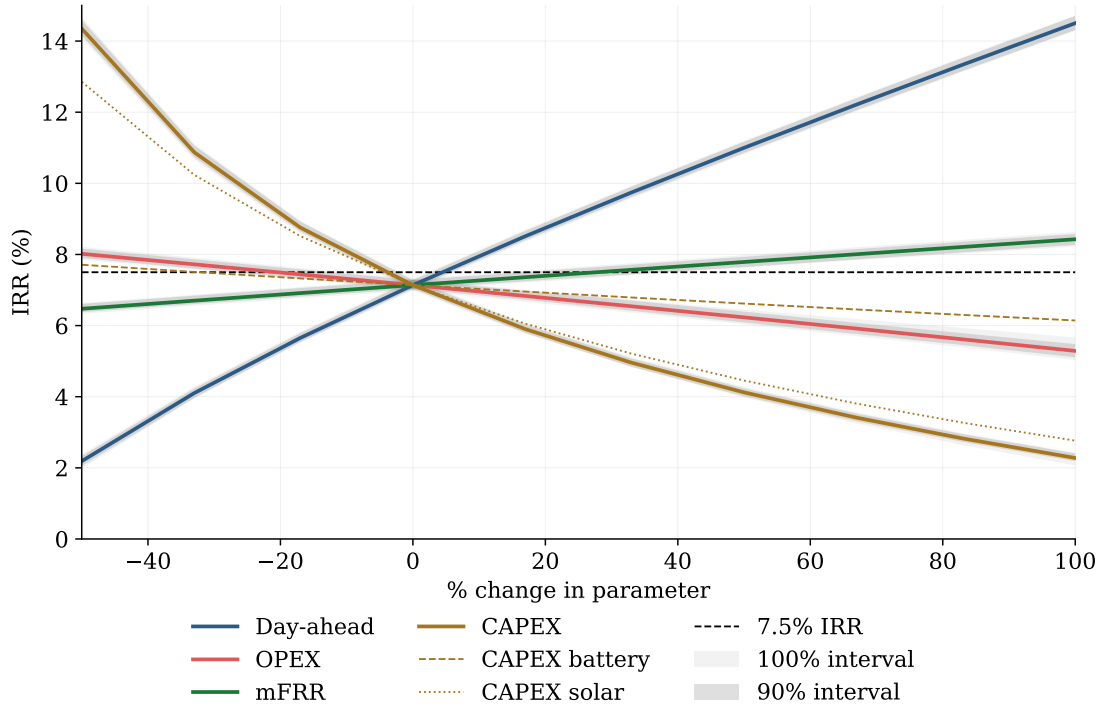


Figure 21: Top 25 IRR 2024 with CAPEX and OPEX cost, and the mean day-ahead and mFRR prices. Only parks with at least 5 MW solar and 5 MWh battery are included.

It is evident that CAPEX and the mean day-ahead price are the two most influential factors affecting IRR, which is expected since they represent the largest cost and revenue drivers. Interestingly, the mFRR price has a relatively limited impact on IRR, despite contributing significantly to income in the base case (see Figure 18). This suggests that the investment is not highly sensitive to potential reductions in mFRR prices compared to 2024 levels, even though mFRR can generate notable income.

Given that the costs of wind, solar, and battery technologies are projected to decrease, and the mean day-ahead electricity price is expected to rise (see Figure 17), future investments in hybrid parks may result in higher IRRs, as suggested by this sensitivity analysis. On the other hand, the cannibalization effect, discussed in **Chapter 2**, could significantly influence the IRR for hybrid parks. Its impact is closely tied to the future development of the Nordic energy market and the pace of renewable energy expansion. However, increased price volatility resulting from the cannibalization effect may, in turn, enhance the profitability of energy arbitrage strategies in battery operation since greater fluctuations in electricity prices provide more opportunities for charging at low prices and discharging at high price. As the sensitivity analysis in Figure 21 only vary the mean day-ahead price, this sensitivity analysis does not capture how larger battery

capacity can increase profit if the day-ahead market is highly volatile.

Another advantage of hybrid parks is that they help mitigate the risk associated with the cannibalization effect by combining multiple types of power production. For example, if the system wind power capacity were to increase significantly, day-ahead prices would begin to follow wind generation patterns, dropping during periods of high wind and rising during low wind conditions. However, since solar power production is negatively correlated with wind, solar energy can compensate by generating electricity when wind output is low and prices are higher. However, if both wind and solar power would increase in the Nordic and European area the cannibalization effect would impact a hybrid park negatively, potentially increasing the value of battery storage.

Given the expected CAPEX drop for batteries (see Figure 17) it is possible that the available battery capacity in the grid will increase the coming years. Since energy arbitrage is one likely strategy for those battery systems, that might decrease the cannibalization effect. Large scale increase in other types of flexibility, such as industries shifting their load to low price hours, could also dampen price volatility. This could have a positive effect on the profitability of wind and solar, but reduce value of batteries with energy arbitrage strategies.

It is also important to note that the higher day-ahead price forecast provided by Svenska kraftnät is based on the assumption that electricity consumption in Sweden will increase significantly in the coming years. If this increase in consumption does not occur as expected, the decreasing CAPEX for solar and wind power may still encourage more actors to invest in energy production. In such a case, where production grows faster than consumption, electricity prices may remain stable or even decrease, which leads to less income and a lower IRR as can be seen in Figure 21.

5 Conclusions

The research questions for this thesis are:

- Which combinations and sizes of wind, solar, and battery storage are the most value-creating and why?
- What is an appropriate size for batteries and solar panels in a hybrid park based on profitability and technical constraints?

These are addressed in the following chapter, along with suggestions for further research.

The simulations showed that all tested levels of installed solar capacity, ranging from 1 MW to 40 MW, can result in profitable investments. Therefore, factors such as land availability or spatial constraints may be more decisive in determining the actual installed capacity. For battery storage, when used solely for energy arbitrage and participation in the mFRR down market, smaller batteries in the range of 0.5 to 5 MWh are generally favored. However, larger batteries, up to 40 MWh, can also be financially viable when paired with higher levels of solar capacity, as they can more effectively utilize the increased energy production. Furthermore, participation in additional ancillary services is likely to enhance the overall profitability of battery storage systems.

Even in scenarios where the total installed generation capacity exceeds the grid connection capacity, large grid expansions are not economically favorable. The cost of increasing grid capacity outweighs the financial losses from curtailment. In this context, grid capacities near the current level of 51 MW, typically between 48 MW and 60 MW, were found to be optimal.

Participation in the mFRR market has shown strong potential for increasing profitability, even without the addition of new technologies, such as in the base case where the park operates solely as a wind power facility. The inclusion of solar power and battery storage also becomes more profitable when participating in the mFRR market. However, as demonstrated in the sensitivity analysis, the mFRR price does not have a major impact on whether the overall investment is profitable or not. It serves as a valuable additional revenue stream, but is not a critical factor in determining investment viability.

The most influential factors in determining investment viability are the CAPEX and the mean day-ahead price. The development of these factors is particularly important, as the current cost and prices gives the best hybrid parks an IRR around 7%, with 20% changes in CAPEX or day-ahead prices increasing or decreasing the IRR of roughly 2 percentage points each.

Long-term market analyses for capital expenditures on wind power, solar power, and battery storage, as well as projections for average day-ahead prices, generally indicate a trend toward decreasing technology costs and increasing electricity prices. However, these markets are inherently volatile and may not follow projected paths. In particular, long-term energy prices are difficult to predict, and a higher average price does not necessarily translate into greater profitability for wind and solar power, especially given the previously discussed cannibalization effect.

The cannibalization effect has several implications for hybrid parks. It can suppress electricity prices during periods of high wind and/or solar generation. However, the inclusion of both technologies within a hybrid configuration improves resilience. If one technology becomes dominant and drives prices down, the other may still benefit from

favorable conditions. Additionally, battery storage may play an increasingly important role in energy arbitrage if price volatility continues to grow.

5.1 Further research

This thesis does not fully capture the potential benefits of battery storage, as it focuses solely on participation in the mFRR down market. Further studies could explore participation in additional ancillary services to better understand how these markets might affect overall profitability. It would also be interesting to investigate scenarios in which the hybrid park operates not only as a generator but also as a consumer, with the ability to purchase and store energy for later resale during periods of higher prices.

As of 2025, the Swedish energy market has transitioned to a 15-minute market structure, which has influenced several aspects of market operation. Future research should incorporate this change to evaluate its impact on the profitability and operation of hybrid energy parks. One example is the potential effect of higher imbalance prices. If imbalance costs increase, a battery strategy focused solely on minimizing imbalance volumes could lead to higher profitability and help avoid significant losses during periods of sudden price spikes. However, this is an area that requires further investigation.

Since this thesis was based on a case study of the Varsvik site, the installed wind power capacity was not varied. However, when exploring optimal technology combinations for new hybrid parks, it would be valuable to include wind capacity as a variable.

Given the potential impact of the cannibalization effect on the profitability of hybrid parks, it may be beneficial to include this phenomenon in future financial evaluations.

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A Appendix

A.1 Random forest

To notate in mathematical expressions how a random forest predicts values in a regression problem, notations from Breiman [23] and equations from Ridgeway [24] is presented below.

Each tree is determined by randomness in the variables chosen (what features that are selected). Let θ represent these random choices. A single tree is then denoted as $T(\theta)$. Let Λ be the space in which the input data X lives, $X : \Omega \rightarrow \Lambda \subseteq \mathbb{R}^p$, where $p \in \mathbb{N}_+$ dimensionality of the features, i.e. the amount of features that the prediction is based on. For a given decision tree, each of its leafs corresponds to a rectangular subspace of Λ , denoted as $R_l \subseteq \Lambda$ for every leaf $l = 1, \dots, L$. For each observed variable x , there is only one leaf that fulfills $x \in R_l$. For the tree $T(\theta)$, this particular leaf is denoted as $l(x, \theta)$. When using a single decision tree for prediction, the value that the tree predicts for a new variable $X = x$ is the average of all the observed values in the corresponding leaf $l(x, \theta)$. When evaluating the value of the predictions, all of the values that are in the same corresponding leaf are contributing equally. This is represented by the weight vector $w_i(x, \theta)$ that is a positive constant if the new observation is in the same leaf, and zero if it is not. All of the weights sum up to one, see equation 19.

$$w_i(x, \theta) = \frac{\mathbf{1}_{\{X_i \in R_{l(x, \theta)}\}}}{\#\{j : X_j \in R_{l(x, \theta)}\}} \quad (19)$$

When the weights are calculated, a single tree predicts the value of variable $X = x$ is the weighted average over the observed values $Y_i, i = 1, \dots, n$. See equation 20

$$\hat{\mu}(x) = \sum_{i=1}^n w_i(x, \theta) Y_i \quad (20)$$

To construct the prediction of a random forest, instead of singular trees, the average prediction of the k individual trees are calculated. Each of the individual trees are constructed using different θ , lets call that vector $\theta_t, t = 1, \dots, k$. First a new weight vector is calculated, $w_i(x)$, which is the average of $w_i(\theta)$, see equation 21

$$w_i(x) = \frac{1}{k} \sum_{t=1}^k w_i(x, \theta_t) \quad (21)$$

The prediction of the random forest is then calculated in a similar way as the prediction for the singular tree, see equation 22

$$\hat{\mu}(x) = \sum_{i=1}^n w_i(x) Y_i \quad (22)$$

The result is the conditional mean of Y given $X = x$, which can be denoted as $E(Y|X = x)$

Quantile random forest

To calculate the full conditional distribution, the same weights that were calculated in 21 can be used. See equation 23 [24].

$$\hat{F}(y | X = x) = \sum_{i=1}^n w_i(x) \mathbf{1}_{\{Y_i \leq y\}} \quad (23)$$

This can then be used to generate quantiles for each prediction, see equation 24 [24].

$$Q_\alpha(x) = \inf \left\{ y : \hat{F}(y | X = x) \geq \alpha \right\} \quad (24)$$

A.2 Additional figures

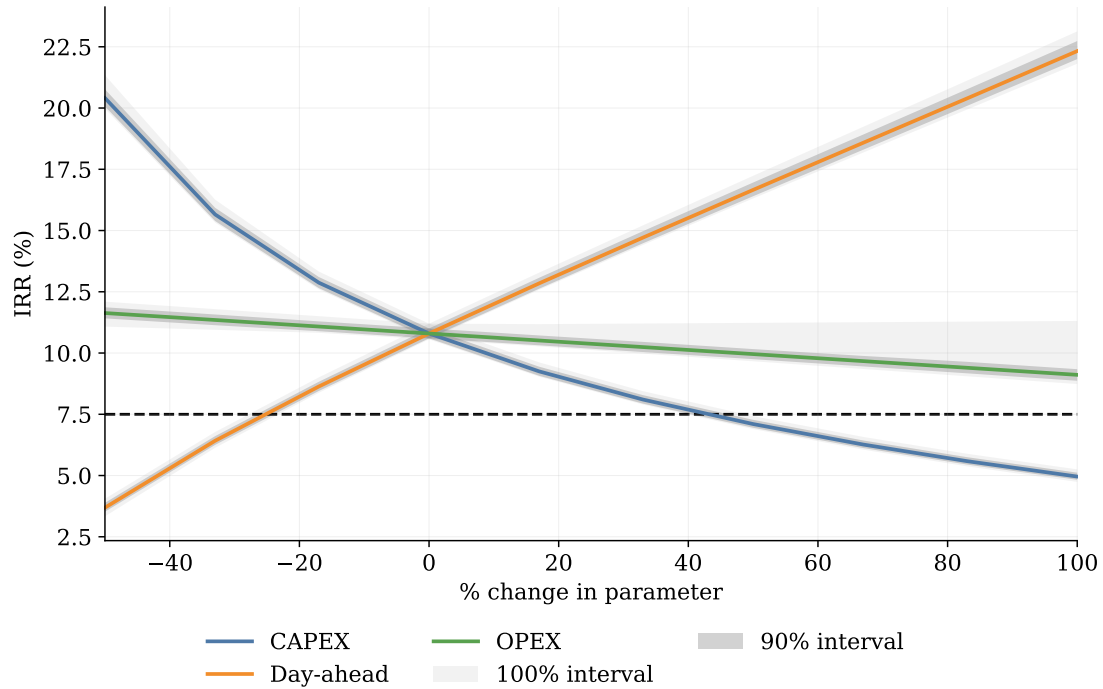


Figure 22: Sensitivity analysis of 200 hybrid parks with highest IRR for 2023. Battery capacity up to 5 MWh, C-rate 0.5, and solar 40 MW is included

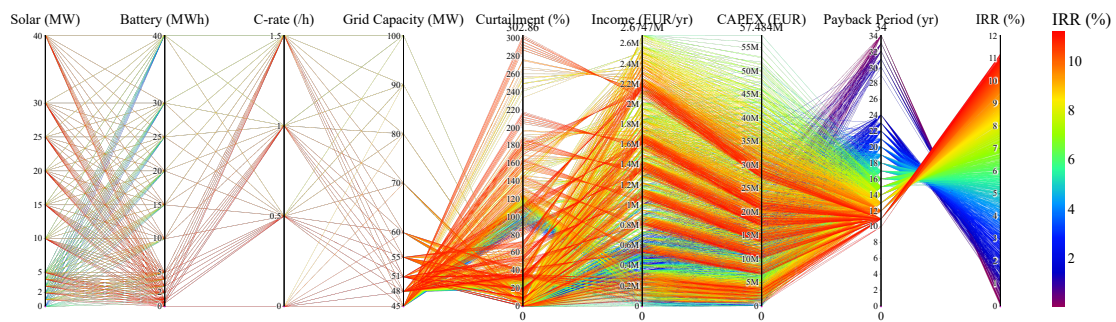


Figure 23: Results for 2023 with multiple output dimensions, curtailment is calculated as (downregulated power)/(power to grid). 100% curtailment thus means that 50% of available energy is lost

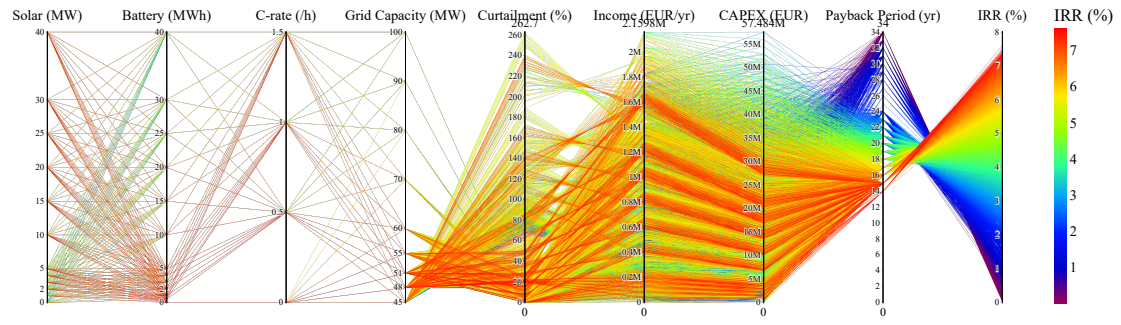


Figure 24: Results for 2024 with multiple output dimensions