Optimization of bidding strategies for a battery storage system in the energy market

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Abstract

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The integration of renewable energies into the energy market has led to variability and intermittency in power generation, making effective energy storage solutions necessary. This thesis works on the optimization of bidding strategies for battery storage systems. The research begins with a comprehensive examination of the market and battery operational parameters. Building upon this foundation, the thesis presents an optimization model that incorporates these parameters to develop an optimal bidding strategy for battery storage actors. The model is then extended to include charge and discharge cycles, recognizing the degradation effects on battery performance over time. Furthermore, a second extension integrates risk-averse self-scheduling into the bidding strategy using Conditional Value-at-Risk (CVaR) to reflect the uncertainty in energy markets. By introducing a comprehensive optimization framework and extending it, this research contributes to the further development of effective bidding strategies for battery storage systems in energy markets.

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1. Introduction

The global energy storage market is developing rapidly as a consequence of the progress in renewable energy technologies and climate regulations. The UN Climate Change Conference in Paris back in 2015 marked a turning point for renewable energy. It not only strengthened the urgent call for a fast and global transition to renewable energies, but it also highlighted it as a realistic way to reach a sustainable development and prevent further disastrous climate change impacts (Ralon et al., 2017). This event created a momentum that emphasizes the need for collective action, as advocates around the world have long argued, for a more environmentally conscious and resilient future.
However, as the energy generated from renewables depends on the weather conditions, its supply is highly variable. At windy or sunny days, the energy production will be high and vice versa (Meier, 2014). Moreover, the electricity demand is on the rise due to the electrification of many applications, such as electric vehicles and heat pumps. During the past years, there have been efforts to reduce the conflict between the growing demand and limited generation. In order to overcome this gap to match supply and demand, energy must be stored (Chacra et al., 2005). Therefore, electricity storage will play a key role for the following stages of the energy transition. It will contribute to integrate higher proportions of variable renewable electricity (VRE), ensuring a smooth and reliable energy supply (Ralon et al., 2017).
According to Meng (2021), by 2022, the energy storage market's annual sales would reach over US$26 billion, with a compound annual growth rate of 46.5. This positive outlook not only calls attention to the need of storage solutions, but also shows an increasing acceptance of these technologies. The growth of the energy storage market holds the promise of a reliable energy grid, and because of this, storage optimization and bidding strategies are essential in order to keep the costs on the same level or lower than conventional fossil fuels. Bidding strategies must be investigated in order for market participants to benefit from the energy market. These strategies are also influenced by different factors like regulatory policies, market structures, resource characteristics, operational conditions, market power and competition, between others (Harris, 2006). By considering these factors, market participants can develop robust bidding strategies to maximize their profits.

1.1 Batteries

Energy storage is key in the energy transition as it depends more on renewables and less on fossil fuels. Among different energy storage technologies, battery storage is a promising alternative because of the fast response, adaptability, controllability, environmental friendliness, and geographical independence (Hannan et al., 2021). The geographical independence allows the storage facilities to be placed with the customer, generator, or even at the distribution grid level (Chattopadhyay et al., 2019), which allows more flexibility. Furthermore, in recent years, there have been significant advancements in battery technologies, extending life cycle and reducing costs, as well as promising higher storage capacities and improved safety profiles (Armand and Tarascon, 2008). The battery energy storage system is a supporting system with a quick response time due to the electrochemical reactions that take place (Chen et al., 2009). Electricity goes in and out of batteries because of those chemical reactions, giving them a near-instantaneous response time (Lund et al., 2015), providing grid stability by quickly adjusting the supply, great

for emergency backup of energy as well as good energy management, ensuring a balanced energy distribution. These ongoing innovations emphasise the dynamic nature of energy storage and the significant role to enable the transition to a more sustainable energy infrastructure. After the installation of high-performance and large-scale energy storage technology, electricity will become a commodity, and then it can be stored (Zhang et al., 2018).
However, the economic feasibility and the required regulatory environment must be considered, given the significant investment that takes place for the system deployment (Gallo et al., 2016). Consequently, the market penetration of the battery energy storage system needs an appropriate capital cost and life-cycle cost. The storage technologies can be globally used when it's cost is equal or lower than the cost of electricity generation with fossil fuel (Zhang et al., 2018). On the regulatory side, governments are starting to recognize the importance of energy storage in order to achieve energy security and reducing emissions. As a result, many countries are implementing policies and incentives, such as investment tax credits, grants and subsidies, in order to accelerate the development of energy storage systems, reducing the upfront costs of these projects and stimulating investment (Sheng et al., 2020).
The evolving energy market dynamics are reshaping the value of energy storage, with the introduction of renewable energy sources, the market needs flexible energy storage solutions to deal with the energy production fluctuations and provide grid stability (Eyer and Corey, 2010). As a consequence, optimal bidding strategies play an important role in minimizing the overall costs for market participants engaged in the buying and selling of electricity.

1.2 Problem analysis

Energy storage is a crucial aspect on the shift towards a sustainable and low-carbon economy. One of the many challenges is the balancing of supply and demand of energy, and energy storage is one of the means to resolve this challenge. This presents opportunities and challenges for market participants. In the context of energy markets, considering the supply and demand balancing in order to provide grid stability and reliability, the formulation of optimal bidding strategies becomes crucial for market participants. Therefore, an optimization problem is defined and studied in order to analyze the strategy that minimizes cost to market participants.
This research builds upon the papers by Herding et al. (2023) and Yurdakul and Billimoria (2023), which focus on developing models on bidding strategies for energy storage systems. While both papers build upon the same core model, they consider different additional constraints. The focus of this research is specifically in battery energy storage systems.
On the paper by Herding et al. (2023), they consider a microgrid comprised of a battery, power generator, photovoltaic system and an electricity load, however, as mentioned before, this thesis focuses only on a battery energy storage system. Consequently, only the battery parameters and constraints are considered in order to be consistent with the base model and the subsequent extensions. Here, the overall objective is to minimize the expected operational cost of the microgrid with a stochastic programming approach. The first stage decisions are the day-ahead market bidding curves, considering uncertainty in the electricity price. In this thesis, however, prices are known and from this paper only the constraints concerning charge and discharge cycles will be used.
On the other hand, in the paper by Yurdakul and Billimoria (2023) they consider risk-aversion in the optimization problem. The risk measure is done with Conditional Value-at-Risk (CVaR) and the goal is to minimize the cost while not surpassing a certain level of risk. CVaR is introduced as a linear program that is then merged with the base model and the first extension of the model based on the paper by Herding et al. (2023).
The takeaway from both of these papers is the recognition that an optimal bidding strategy is required by market participants in order to protect themselves from market volatilities,

particularly because of the ongoing transition towards renewable energy sources. As the energy landscape will keep evolving, building optimal bidding strategies becomes crucial. These strategies help to lower the costs and handle risk better, which makes it an important research area. This research seeks to develop a robust optimization problem based on the insights from stochastic programming and risk analysis, capturing the complexities of the energy market.

1.3 Research question

Bidding strategies play a crucial role for energy storage. As renewable energy sources continue to penetrate the market, the development of optimal bidding strategies becomes of great importance for market participants due to the production intermittency. After analyzing the problem, a research question can be formulated:

How should the optimization problem be defined such that it results in a bidding strategy that leads to the most profit for a market participant with battery energy storage system?

Through a combination of modeling and quantitative analysis, this research aims to contribute to the knowledge surrounding energy bidding strategies optimization.

2. Background

This section provides a literature review from previous research, for a more in-depth analysis. The goal is to provide a clear context, which will make the analysis more meaningful and thorough.

2.1 Market bidding strategies

The operation of the traditional power grid is always in a dynamic balance status between electricity generation and electricity consumption. The electricity that is produced is immediately used by consumers. Therefore, the planning, operation and control of the power grid is based on the balance between supply and demand, this means that there must be a real-time balance between demand and supply.
The installation of renewable energy systems represents a challenge and highlights the limitations of the current power grid. The rising of renewable energy is an important step in promoting energy saving and CO_2 emission reduction (Wang et al., 2013).
Because of the introduction of renewables, the power market is being restructured, with the intention to reduce the costs of energy to consumers. This can be achieved by introducing competition among producers, elimination of the most expensive and inefficient technologies and implementation of more efficient technologies.
In a competitive electricity market, there are two main entities participating: customers and suppliers. Every participant in the energy market is required to submit bids for buying and selling energy. Aggregated hourly supply and demand bid curves are then constructed to determine the market clearing price as well as the corresponding supply and demand schedules (Prabavathi and Gnanadass, 2015). An energy bid is made up of two components: energy quantity and a price. Additionally, in the energy sector there exists the real-time and day-ahead markets, each with its own function to ensure an efficient operation. The day-ahead market allows market participants to submit bids for buying or selling electricity that will be delivered the next day. These bids are based on previous supply and demand conditions, as well as generation costs, constraints, and forecasts (Hogan, 2002). On the other hand, the real-time market operates closer to the actual delivery time. Market participants are able adjust their generation or consumption in real-time by submitting bids based on updated information. The real-time market is crucial for maintaining grid stability, since it ensures that supply and demand match instantaneously (Barbieri and Coulondre, 2012).

2.1.1 Merit order

Once the supply and demand bids have been submitted by the customers and suppliers, the market operator elaborates, for every hour of the day-ahead market, a merit order dispatch by ordering the supply bids in ascending price order and demand bids in descending order (Roldan-Fernandez et al., 2016). This is shown in Figure 2.1, where renewable and clean energies are prioritized over conventional forms of energy, meaning that all the energy generated by renewables will be used first and when demand cannot be met anymore by it, demand will be satisfied with the following types of energy.

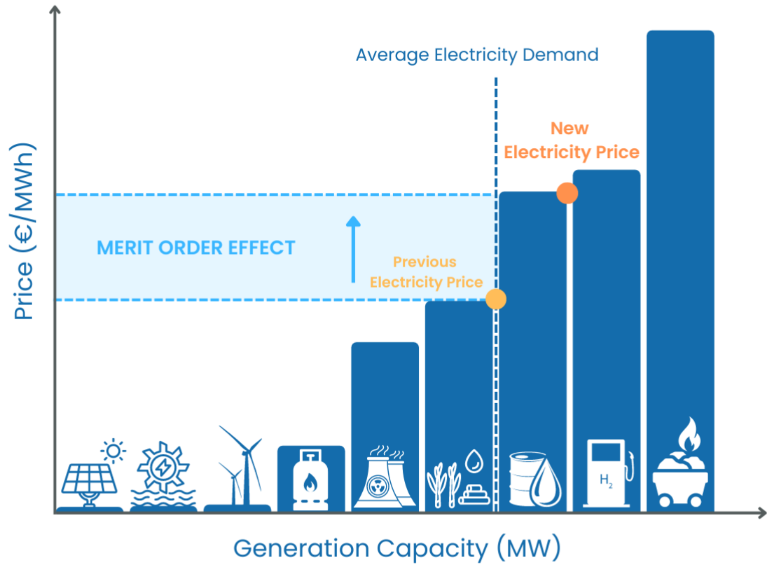

Figure 2.1: Merit order

2.1.2 Market clearing price

The point of intersection between the supply and demand curve determines the market clearing price. This point is called equilibrium point and it is where the market is cleared (Shahidehpour and Alomoush, 2017). In Figure 2.2, MCP is the market clearing price and MCV is the market clearing volume. The equilibrium price is such that the quantity that the suppliers are willing to offer is equal to the quantity that the customer desires to attain.

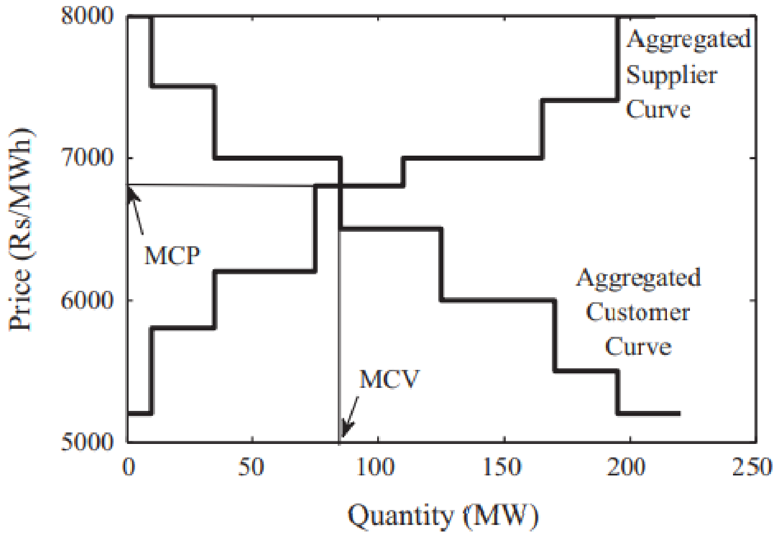

Figure 2.2: Market clearing process

After the market clears, generators are dispatched based on their bids. Those who bid below the clearing price are dispatched, and they receive the clearing price for their electricity. Consumers who bid above the clearing price pay the clearing price for their purchase.
There are several clearing mechanisms to match supply with demand. The mechanism used

depends on each market and its regulations (Herding et al., 2023). The following are some of the clearing mechanisms that exist:

- **Pay-As-Bid:** each accepted bid is cleared at the price that was specified on the bid. This can result as an incentive for participants to make more accurate bids (Von Meier, 2006).
- **Single clearing price:** all accepted bids are cleared at the same price. The price is based on the intersection of the aggregate supply and demand curves, which is the case in 2.2 (Bushnell et al., 2008).
- **Locational marginal pricing:** this clearing mechanism reflects the marginal cost of supplying electricity at different locations (Gómez-Expósito et al., 2018).

2.1.3 Economic bid

In economic bidding, market participants submit bids specifying the quantity of electricity they are willing to supply and the price at which they are willing to sell it. These bids are typically based on the generators' operating costs, fuel prices, market conditions, and other factors (Mohsenian-Rad, 2015).
Then, as mentioned in subsection 2.1.2, the bids of the supplier are ordered from lowest to highest price, and dispatch starts with the lowest bids, until there is enough supply to meet demand. In the case of consumers, the bids are ordered from highest to lower price.
Economic bidding allows competition between suppliers, as well as ensuring that the most cost-effective resources are used to meet demand.

2.1.4 Self-scheduling

In self-scheduling bidding, a supplier submits a bid specifying only the quantity of electricity they intend to supply, without including a price (Mohsenian-Rad, 2015), meaning that the supplier is a price taker and will schedule its generation based only on its operational constraints. This type of bid states that the supplier will generate a certain amount of electricity regardless of the market price. After submitting the bids, the market operator accepts them based on the market rules, clearing mechanisms, system constraints, demand, between other factors. The market operator also determines the price at which all cleared bids will be compensated.

2.2 Charge and discharge cycles

Charge and discharge cycles are the amount of times that the battery is allowed to charge and discharge per time period. This cycle is essential for the safety of the battery and to prevent performance degradation (Jeon and Baek, 2011), maintaining the efficiency of the battery at an acceptable level. With its high specific energy density and strict application requirements, the battery has to be restricted and protected by continuously checking the single battery cell voltage and current in the process of charge and discharge (Rahimi-Eichi et al., 2013). Maintaining the safety and performance of a battery involves carefully managing its charge and discharge cycles. To ensure the long-term operation and improve the utilization efficiency of the battery pack, balancing the electric quantity of each single battery cell is essential. This not only contributes to the prolonged operation of the battery but also plays a vital role in sustaining a stable power supply. (Kaiser, 2007). Moreover, since the life cycle of rechargeable batteries is commonly expressed in number of discharge cycles, by limiting the amount of these cycles, the lifetime of the battery can be extended (Mohsenian-Rad, 2015).

2.3 Mixed integer linear programming (MILP)

Mixed integer linear programming (MILP) is an optimization technique to solve problems where decision variables can be a mix of integer and continuous values. MILP problems can be

found in many fields, such as logistics, finance and engineering, where decisions need to be made on discrete choices, for example, production scheduling, while considering linear relationships and constraints (Wolsey, 2020).
According to Vielma (2015) MILPs are comprised of the following:

- Objective function - linear function to be minimized or maximized.
- Decision variables - these variables can be integers, continuous, or a mix of both.
- Constraints - linear equations or inequalities that the decision variables must satisfy.

MILP has become one of the most widely explored methods for scheduling problems because of its flexibility and extensive modeling capability (Floudas and Lin, 2005).

2.4 Stochastic optimization

Stochastic optimization encloses a variety of communities, with some overlapping notational systems and algorithmic strategies tailores to specific problem domains (Powell, 2019). More specifically, it is a collection of methods for minimizing or maximizing objective functions when uncertainties are present, either through the cost function or the set of constraints. In addition, stochastic optimization deals with single stage problems as well as multistage problems (Hannah, 2015).

2.5 Value-at-Risk (VaR)

Value at Risk (VaR) is a statistical measure used to quantify the potential loss on an investment over a specific time period with a certain confidence level (Linsmeier and Pearson, 2000). The basic idea behind VaR is to assess the risk of an investment by analyzing the potential range of outcomes and it is expressed as a specific amount of money or a percentage of the initial investment. The confidence level represents the probability that the actual loss will not exceed the VaR.
There are different methods for calculating VaR, including historical simulation, parametric methods, and Monte Carlo simulation. Each method has its own assumptions and limitations (Stambaugh, 1996). It's important to note that while VaR provides a useful measure of risk, it does not capture the full distribution of potential outcomes and may not account for extreme events or tail risks (Yurdakul and Billimoria, 2023). Therefore, it is often used next to other risk measures to provide a more comprehensive and reliable risk assessment.

2.6 Conditional Value-at-Risk (CVaR)

Conditional Value at Risk (CVaR) is an extension of Value at Risk (VaR). While VaR provides a single, specific measure of the maximum potential loss at a certain confidence level, CVaR goes further by providing an average of the losses beyond the VaR threshold. This makes CVaR particularly useful in capturing the tail risk or the severity of losses beyond the VaR level (Rockafellar and Uryasev, 2002) as shown in Figure 2.3.

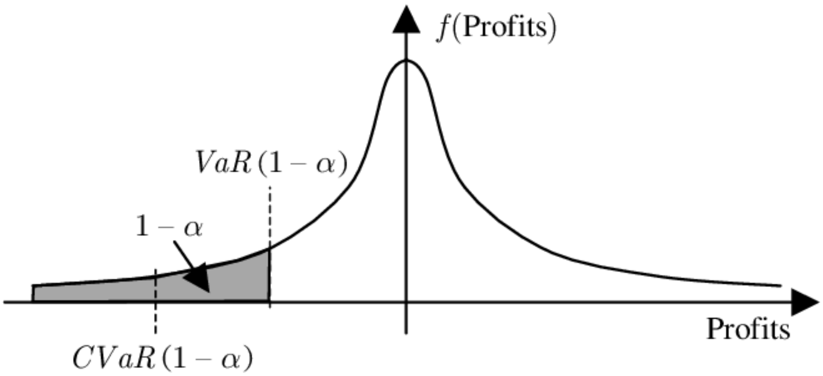

Figure 2.3: VaR vs CVaR

Mathematically, if VaR is denoted by VaR_α, where α is the chosen confidence level, CVaR is the expected value of losses exceeding VaR_α. It is expressed as:

$$CVaR_\alpha = \frac{1}{1-\alpha} \int_{-\infty}^{VaR_\alpha} x \cdot f(x)\, dx \tag{2.1}$$

Here, f(x) is the probability density function of the distribution of returns. CVaR provides a more comprehensive view of the risk compared to VaR alone, as it takes into account not only the likelihood of extreme events but also their potential severity (Sarykalin et al., 2008).

2.7 Auxuliary variable

In optimization problems, auxiliary variables are introduced in order to transform the original problem into a more manageable one. It is a common technique in various methodologies, such as linear programming, nonlinear programming and constrained optimization (Hillier, 1967). The primary purposes of introducing auxiliary variables include:

- Objective function transformation
- Constraint simplification
- Introduction of slack variables
- Dual variables
- Optimality analysis
- Variable substitution

3. Model

In this section, the optimization problem for an actor with a battery is modelled and the extensions studied in this research are introduced. The model aims to determine the most cost-effective strategy for buying and selling electricity in the real-time energy market, over different time periods.
The model includes constants related to the battery specifications and characteristics, such as the minimum and maximum charging powers, minimum and maximum battery levels, and charging and discharging efficiencies, as well as the length of the time steps (Δt) and the real-time electricity prices ($\lambda(t)$).
The goal of the optimization problem is to minimize the cost of buying/selling electricity in the energy market, determined in the objective function by the product of the real-time electricity price and the difference between the charging and discharging powers. The constraints of the model ensure that the state of charge of the battery is updated in each time period, based on charge/discharge actions, while respecting the battery's operational limits, which are also enforced by different constraints.
In addition to the before mentioned constraints, the binary variable u(t) introduces the exclusivity of charging (u(t) = 0) and discharging (u(t) = 1) modes, meaning that the battery can only do either action at the time and not simultaneously.

Here, a list of the model's constants and variables is laid out:

Model constants

Δt: market time resolution
$\lambda(t)^{\omega}$: predicted electricity price
$\overline{p_c}$: maximum charging power of battery
$\overline{p_d}$: maximum discharging power of battery
$\underline{e}$: minimum battery level
$\overline{e}$: maximum battery level
η_c: charging efficiency
η_d: discharging efficiency
L^B: integer multiplicator to limit battery utilisation

Model variables

$p_c(t)$: charging power
$p_d(t)$: discharging power
$e(t)$: state of charge of battery
$u(t)$: binary variable to ensure mutual exclusivity of charging and discharging modes. Note that u(t) = 0 and u(t) = 1 model charging and discharging, respectively.
z^{ω}: auxiliary variable
ζ : α-CVaR of the loss associated with a decision

3.1 Optimization problem

The optimization problem studied in this research is of the form of (3.1), where there is an objective function, equality constraints, inequality constraints, and lower and upper bounds defined.

$$\begin{aligned} \text{minimize} \quad & f^T x \\ \text{subject to} \quad & Ax \leq b \\ & Ex = d \\ & \underline{x} \geq x \geq \overline{x} \end{aligned} \tag{3.1}$$

The optimization problem studied in this research, which models an actor with a battery, is based in model (3.2), where the objective function intends to minimize the cost. In this section, scenarios are not yet introduced, therefore, the variables introduced are only dependent on t and not ω. An analysis of the constraints is done further in this section.

$$\begin{aligned} \underset{p_c, p_d, e, u}{\text{minimize}} \quad & \Delta t \sum_{t=1}^{T} \lambda(t)(p_c(t) - p_d(t)) \\ \text{subject to} \quad & e(t) = e(t-1) + \eta_c p_c(t)\Delta t - \frac{1}{\eta_d} p_d(t)\Delta t, \ \forall t, \\ & \underline{e} \leq e(t) \leq \overline{e}, \ \forall t, \\ & p_d(t), p_c(t) \geq 0, \ \forall t, \\ & u(t) \in \{0, 1\}, \ \forall t, \\ & p_d(t) - \overline{p_d} u(t) \leq 0, \ \forall t, \\ & p_c(t) - \overline{p_c}(1 - u(t)) \leq 0, \ \forall t \end{aligned} \tag{3.2}$$

The equality constraint $Ex = d$ shown in (3.1) is represented by $e(t) = e(t-1) + \eta_c p_c(t)\Delta t - \frac{1}{\eta_d} p_d(t)\Delta t$ in (3.2). This constraint introduces the dynamics of the battery and updates the state of charge over time. The term $\eta_c p_c(t)\Delta t$ is the amount of energy added to the battery during charging at time period t. Here, η_c represents the charging efficiency, and when multiplied by $p_c(t)\Delta t$, it accounts for the fact that when charging, not all energy drawn from the grid gets stored, due to the losses during the charging process. Similarly, the term $\frac{1}{\eta_d} p_d(t)\Delta t$ is the amount of energy removed during discharging at time period t. Here, $\frac{1}{\eta_d}$ represents the inverse of the discharging efficiency, and when multiplied by $p_d(t)\Delta t$, it accounts for the fact that more energy is withdrawn from the battery than actually delivered to the grid, due to the losses during the discharging process. In the case that $\eta_c, \eta_d = 1$, no energy would be lost during the charging and discharging processes, however, that would not be realistic.

Furthermore, the inequality constraint $Ax \leq b$ shown in (3.1) is represented by two constraints in (3.2), which are $p_d(t) - \overline{p_d} u(t) \leq 0$ and $p_c(t) - \overline{p_c}(1 - u(t)) \leq 0$. These constraints ensure that the charging and discharging powers do not exceed their highest possible values, $\overline{p_c}$ and $\overline{p_d}$, respectively. When u(t) = 1, the battery is in discharge mode and the charging power should be zero. The constraint ensures that the discharge power does not exceed the maximum allowed discharging power $\overline{p_d}$. However, when u(t) = 0, the same (but opposite way) happens. The battery is in charging mode and the discharging power should be zero. The constraint ensures that the charging power does not exceed the maximum allowed charging power $\overline{p_c}$. These constraints are essential to define the exclusivity of the charging and discharging modes since the battery is not able to do so simultaneously, as well as limiting the charging and discharging powers so that they do not exceed their operational limits.

The lower and upper bounds in the optimization problem guarantee that the battery operates within safe limits regarding its storage capacity and also ensures the charging and discharging power non-negativity, as well as the charging and discharging exclusivity. These bounds are represented by $\underline{e} \leq e(t) \leq \overline{e}$, $p_d(t), p_c(t) \geq 0$ and $u(t) \in \{0, 1\}$, respectively. These constraints are essential for the safety of the battery operation within the defined bounds, and also ensure that the charging and discharging levels remain within the specified capacity of the battery.

3.2 Model extension

In this research, two extensions of the base optimization problem are introduced. These extensions are based on the papers by Herding et al. (2023) and Yurdakul and Billimoria (2023), where other constraints and variables are considered. A first extension is in order to include charge and discharge cycles, therefore protecting the lifetime of the battery and its efficiency. Furthermore, a second extension incorporates risk-averse self-scheduling, where the effect of risk taking from decision makers is considered in the optimization problem.

3.2.1 Charge and discharge cycles

The first extension of the optimization problem is based on the paper by Herding et al. (2023). Here, they consider a microgrid comprised of a battery, power generator, photovoltaic system and an electricity load. Since this research focuses only on battery storage, only the constraints related to batteries are considered. The constraints gained from this paper are the charging and discharging cycles, and they are presented in (3.3) and (3.4).

$$\Delta t \sum_{t=1}^{T} p_c(t) \leq L^B \overline{e}, \ \forall t, \tag{3.3}$$

$$\Delta t \sum_{t=1}^{T} p_d(t) \leq L^B \overline{e}, \ \forall t \tag{3.4}$$

The objective function introduced in section 3.1 in (3.2) remains the same and constraints (3.3) and (3.4) are added to the optimization problem. Charging and discharging cycles limit the amount of times that the battery energy storage system is fully charged and discharged over the time horizon. Here, L^B is an integer multiplicator of the battery capacity to limit daily battery utilisation. The constraints state that the cumulative dis/charging power over the time horizon should not exceed a certain fraction L^B of the maximum allowable stored energy $\overline{e}$. Excessive cycling can increase the risk of an unsafe situation as well as the degradation of the battery performance. Introducing these constraints allows the battery lifetime to be protected and ensuring the safe operation of it.

3.2.2 Risk-averse self-scheduling (RASS)

The second extension of the optimization problem introduces risk-averse self-scheduling, based on the paper by Yurdakul and Billimoria (2023). In the paper, they claim that risk-averse storage resources tend to have a myopic operational perspective, meaning that the participants focus on short-term opportunities, and not capitalize from price peaks and dips. As a result, risk-averse

participants remain inactive when there are periods of high and low prices, while risk takers are reactive to this changes. This can lead storage resources to fail to respond to strong price signals during times of scarcity.
Risk is introduced with the linear program in (3.5), which evaluates the α-CVaR, denoted by ζ , with an associated confidence level α, of the uncertain charging cost over the problem horizon. The constraint ensures that the losses do not go beyond the threshold, with the introduction of the auxiliary variable z^{ω}. It can be observed that in this paper, scenarios are introduced by ω and these are defined by $\lambda(t)^{\omega}$, denoting the energy price in time period t of scenario ω. The auxiliary variable z^{ω} is introduced for each $\omega \in \Omega$ and π^{ω} denotes the probability of each scenario. Here, z^{w} and ζ are introduced as decision variables of the optimization problem in addition to $p_c(t)$, $p_d(t)$, $e(t)$ and $u(t)$.

$$
\begin{aligned}
\underset{z^{\omega},\zeta}{\text{minimize}} \quad & R_{\alpha}(x) := \zeta + \frac{1}{1-\alpha}\sum_{\omega=1}^{\Omega} \pi^{\omega} z^{\omega} \\
\text{subject to} \quad & z^{\omega} \geq \sum_{t=1}^{T} \lambda^{\omega}(t) p_c(t) - \zeta, \ \forall t, \\
& z^{\omega} \geq 0
\end{aligned}
\tag{3.5}
$$

In addition to the minimization of the risk of incurring high charging costs, the paper considers the maximization of profits over the time period with (3.6).

$$
P(x) := \Delta t \sum_{\omega=1}^{\Omega} \pi^{\omega} \left[\sum_{t=1}^{T} \lambda^{\omega}(t)(p_d(t) - p_c(t)) \right]
\tag{3.6}
$$

We can notice that this is the opposite of the objective function on the base model that was previously introduced in section 3.1, however, a maximization of profits is modelled here instead of a minimization of cost. This becomes a minimization again with the objective function expressed in (3.7).

$$
\underset{p_c,p_d,u,e,z^{\omega},\zeta}{\text{minimize}} \quad - P(x) + \beta R(x)
\tag{3.7}
$$

The weight parameter $\beta \in [0, \infty)$, multiplying the objective function of the CVaR linear program (3.5), regulates the degree of risk-aversion. Setting the value of β close to zero represents a more risk-neutral decision maker (Yurdakul and Billimoria, 2023). Setting $\beta = 0$ implies the desire to maximize profits, independent of the risk it might entail and taking chance in the price drops and peaks. On the other hand, when β is not close to zero, it represents a risk-averse decision maker who will remain inactive during these uncertainty periods.

3.2.3 Complete optimization problem

The trade-off between the objective functions and constraints presented in section 3.1, subsection 3.2.1 and subsection 3.2.2 leads to the complete optimization problem for this research and is then expressed as in (3.8). This is the model which will be studied under real-life data in chapter 4.

$$
\begin{aligned}
\text{minimize} \quad & -P(x) + \beta R(x) \\
\text{subject to} \quad & e(t) = e(t-1) + \eta_c p_c(t)\Delta(t) - \frac{1}{\eta_d} p_d(t)\Delta(t), \ \forall t, \\
& \underline{e} \leq e(t) \leq \overline{e}, \ \forall t, \\
& p_d(t), p_c(t) \geq 0, \ \forall t, \\
& u(t) \in \{0, 1\}, \ \forall t, \\
& p_d(t) - \overline{p_d} u(t) \leq 0, \ \forall t, \\
& p_c(t) - \overline{p_c}(1 - u(t)) \leq 0, \ \forall t, \\
& \Delta t \sum_{t=1}^{T} p_c(t) \leq L^B \overline{e}, \ \forall t, \\
& \Delta t \sum_{t=1}^{T} p_d(t) \leq L^B \overline{e}, \ \forall t, \\
& z^\omega \geq \sum_{t=1}^{T} \lambda^\omega(t) p_c(t) - \zeta, \ \forall t, \\
& z^\omega \geq 0
\end{aligned}
\tag{3.8}
$$

In Appendix A, the model is transformed to matrix notation. This notation allows a compact representation of the optimization problem and further enables an efficient computational modelling when solving it in an optimization software. These are the matrices that are later introduced in the optimization codes in Appendix B for the computational modelling, evaluated with real-life data.

4. Experiments and results

In this chapter, the optimization problem introduced in chapter 3 is studied under real-world data collected from the Australian National Electricity Market, as it was done in the paper by Yurdakul and Billimoria (2023). Pre-dispatch prices ($\lambda^{\omega}(t)$) are considered from two representative days. For Case I, June 12, 2022, which marks the last day before the cumulative price threshold in Victoria was surpassed, leading to a market intervention and for Case II, January 16, 2019, which was a day in which prices were highly volatile. Scenarios were constructed upon the historical differences between the pre-dispatch and real-time market prices from 2019. From the observations obtained, they randomly selected 100 observations to form the scenarios of the cases they studied. This data can be accessed in [1] on the paper by Yurdakul and Billimoria (2023). The goal in this section is to analyze the behavior of market participants and the battery energy storage system under different conditions. This involves modifying certain parameters related to risk-adversity and the battery characteristics and constraints in order to observe the different outcomes.

In the optimization problem, there are certain parameters which are set as constant because of the characteristics of the battery that is being studied, in this case, the Victorian Big Battery. Therefore, in Table 4.1 these parameters are defined.

Constant	Value
T	48
Δt	0.5
$\lambda^{\omega}(t)$	retrieved from ANEM
$\overline{e}$	450 MWh
$\underline{e}$	0 MWh
$e(0)$	0 MWh
η_c	0.85
η_d	0.85
$\overline{p_c}$	300 MW
$\overline{p_d}$	300 MW

Table 4.1: Values for the constants in the optimization problem

It is important to mention that there is a reasoning behind the values that these parameters take. For instance, in practice, the efficiency of batteries is 85 to 90% (Alamgir and Sastry, 2008); on that account, an efficiency of $\eta = 0.85$ will be considered for both charging and discharging of the battery. In addition, the maximum battery level $\overline{e}$ is set to 450 MWh, and the maximum charging ans discharging powers, $\overline{p_c}$ and $\overline{p_d}$, are set equal to 300 MW, since that is the built capacity and charging/discharging powers of the Victorian Big Battery.

It can be observed that the maximum battery level ($\overline{e}$) is greater than the charging and discharging powers p_c and p_d, respectively. This can be due to several reasons, like operating flexibility, safety, efficiency and system design (Salman et al., 2020). Finally, the time horizon considered is a whole day divided in segments of 30 minutes, therefore, $T = 48$ and $\Delta t = 0.5$. Combined, these values reflect the operational characteristics of the battery energy storage system. For the experiments, a value of $\alpha = 0.95$ is used unless stated otherwise.

4.1 Case I

The first study case on this research is done with price data from June 12, 2022. This day marks the last day before the cumulative price threshold in the Victorian market was surpassed, meaning that the prices had been increasing and reached a critical point. As a consequence, a market intervention took place.

4.1.1 Case I.A

Dispatch decisions with $L^B = 2$ and different values of β

In this first part of Case I, the integer multiplicator to limit battery utilisation L^B, introduced in subsection 3.2.1, is set equal to 2. Next to this, different values of β, ranging from $\beta = 0.0$ to $\beta = 1.0$, are considered to observe the behaviour of risk-neutral and risk-averse market participants with a limited amount of charge and discharge cycles, taking into consideration that the same set of prices λ^ω are used in the studies. This will provide a better understanding of how a battery energy storage system adjusts its schedule based on varying price signals (price peaks and dips) with self-scheduling.
As mentioned in subsection 3.2.2, setting β closer to zero represents a risk-neutral participant, meaning that the participant would take advantage of price drops and peaks. This behaviour can be observed in Figure 4.1, where β was set equal to zero in the optimization problem. The net discharging power, calculated by subtracting the charging power from the discharging power, follows the behaviour of the prices, effectively exploiting the price drops and peaks over the time period.

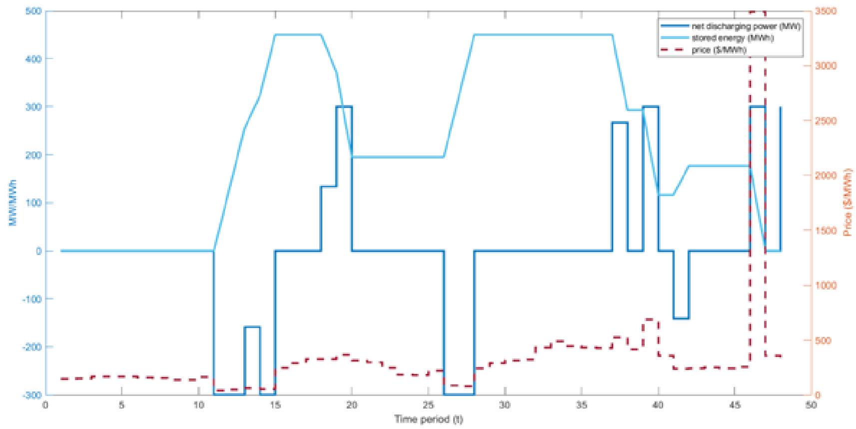

Figure 4.1: Optimal storage dispatch decisions for $\beta = 0.0$

It is initially observed between $t = 11$ and $t = 19$. When the prices drop at $t = 11$, the battery charges (or buys energy), and when the prices start to go up again around $t = 17$, the battery discharges (or sells energy). This behaviour can be observed again between $t = 23$ and $t = 39$, where the battery goes through a charging and discharging process again. Finally, at $t = 41$ the prices drop a little bit and the battery starts a charging process, however, at $t = 46$ there is a dramatic increase of the price and the battery quickly switches to discharging. This represents clearly the behaviour of a risk-neutral market participant, since in every slight change of prices, the participant reacts immediately and capitalizes over those fluctuations.

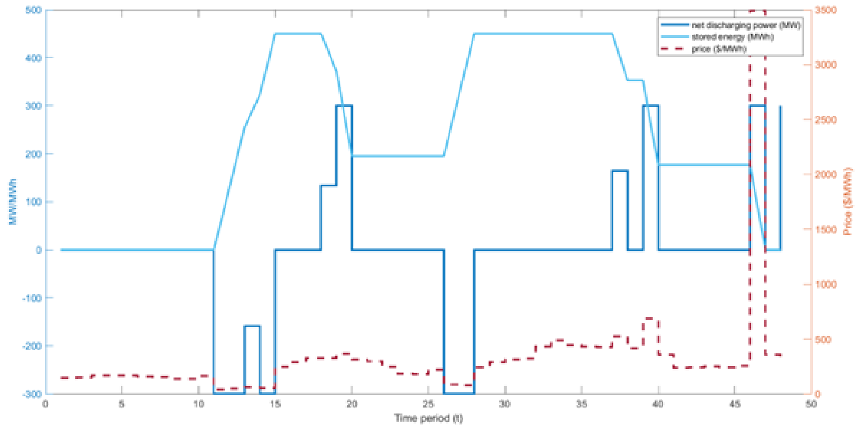

Figure 4.2: Optimal storage dispatch decisions for $\beta = 0.5$

Then, the case of $\beta = 0.5$ is plotted in Figure 4.2. A similar behaviour as in the case of $\beta = 0$ in Figure 4.1 can be observed, however, there are some differences that can be already noticed. First of all, there is no charging taking place around $t = 41$ and most importantly, the battery is charging and discharging less MW compared to the case of $\beta = 0$. For example, around $t = 37$, the battery discharges 165 MW compared to the 300 MW it discharges in the case of $\beta = 0$. Another difference can be noted between $t = 41$ and $t = 42$, where there is no discharge in the case of $\beta = 0.5$ while there was in the case of $\beta = 0$, meaning that the risk-averse participant missed an opportunity to make profit.

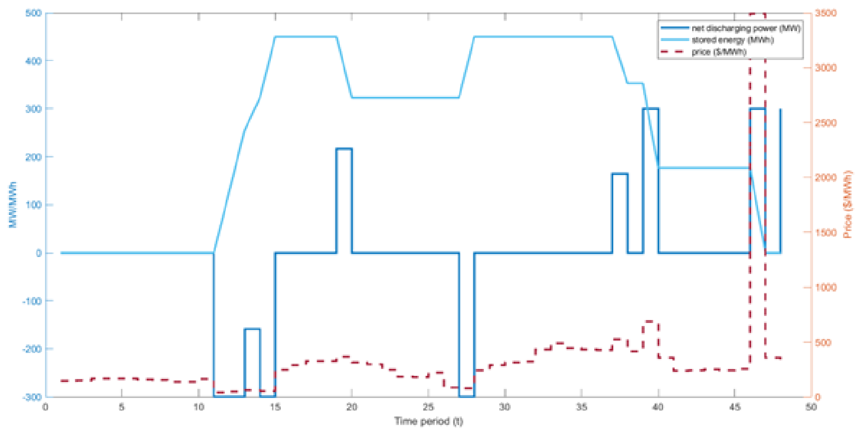

Figure 4.3: Optimal storage dispatch decisions for $\beta = 1.0$

The differences are even more clear to identify in the case where $\beta = 1$, this case is plotted in Figure 4.3. It can be observed that there are not as much cycles compared to the previous cases and additionally, the amount of energy (MW) being charged and dispatched is more conservative, meaning that market participants focus on short-term opportunities, missing out on the possibility to make profit on the price peaks and dips.

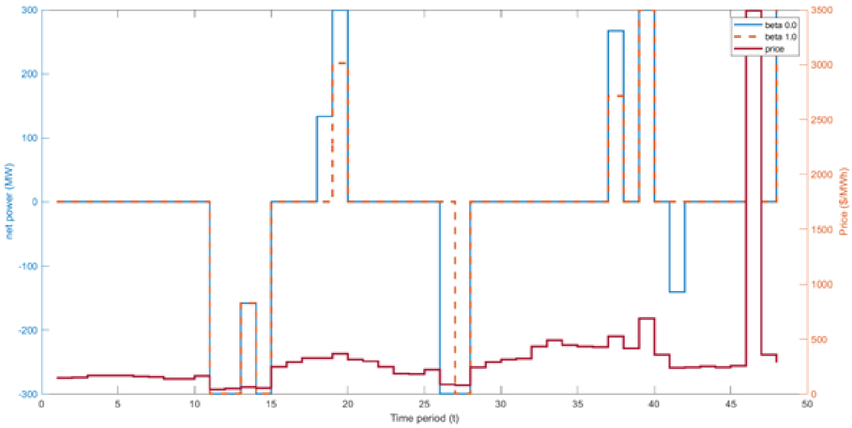

Figure 4.4: Optimal storage dispatch decisions under different values of β

In Figure 4.4, the dispatch decisions for $\beta = 0$ and $\beta = 1$ with $L^B = 2$ are plotted together to have a more clear comparison. The first charging cycle of the battery between $t = 11$ and $t = 14$ is the same in both cases, however, in the first discharging cycle, between $t = 17$ and $t = 19$ a difference can be noticed. It is observed that the more risk-neutral participant is more sensitive to the price changes and responds to this before the more risk-averse participant. In addition, we can observe that the risk-averse participant discharges less energy. This behaviour is later observed between $t = 26$ and $t = 28$, as well as during $t = 37$, where the risk-neutral market participant reacts earlier and capitalizes more. The last difference that can be observed is during $t = 41$, where the risk-neutral market participant benefits from the price drop while the risk.averse abstains from charging.

4.1.2 Case I.B

Dispatch decisions with $L^B = 5$ and different values of β

After analysing the behaviour of the market participants with the integer multiplicator to limit battery utilisation $L^B = 2$ and different values of β, now we analyze the behaviour allowing more charging and discharging cycles by setting $L^B = 5$. Here, it is interesting to observe if the more risk-averse market participant will allow more charging and discharging cycles due to the increase on the parameter L^B.

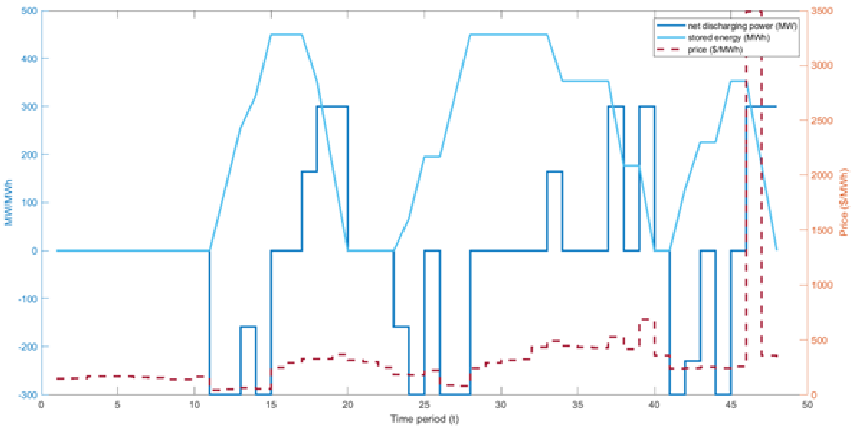

Figure 4.5: Optimal storage dispatch decisions for $\beta = 0.0$

In Figure 4.5, we can observe that, as expected, the risk-neutral market participant follows the flow of the price set. In this case, we can perceive that in addition to following the price curve, the participant also benefits from the increase to $L^B = 5$, presenting more charge and discharge cycles compared to the case when $L^B = 2$. It is first noticed at the end of $t = 20$, when the battery is fully discharged, while in the previous case it did not fully discharge up until the end. Furthermore, we observe an additional charging cycle between $t = 23$ and $t = 25$, which did not occur previously. Then, the charging cycles around $t = 34$ and $t = 40$, which leave the battery fully discharged for a second time, making it necessary to charge a higher load between $t = 41$ and $t = 45$, all compared to the case for $L^B = 2$. Apart from having more charge and discharge cycles, we perceive that these also happen with higher loads. This comparison can be seen in Figure 4.6, where both cases with $\beta = 0$ are plotted under the different values of L^B.

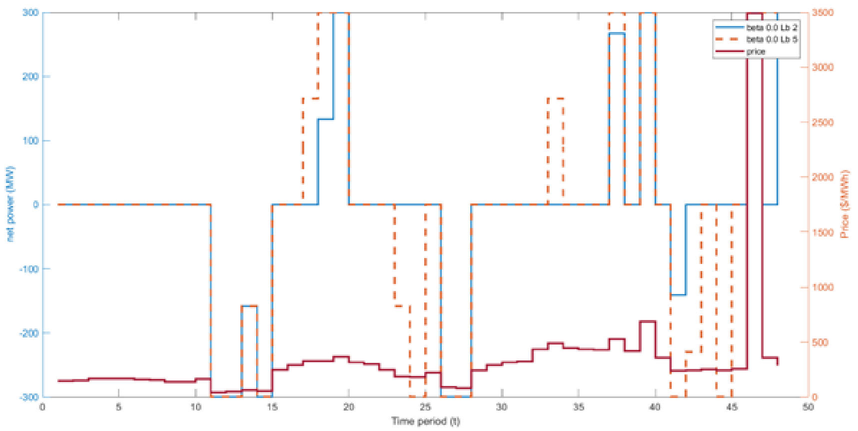

Figure 4.6: Optimal net discharging levels with $\beta = 0.0$ under different values of L^B

Then, we analyze the cases where $\beta = 0.5$ and $\beta = 1$ presented in Figure 4.7 and Figure 4.8. The first thing that we immediately notice is that there is a decrease in the participant's activity compared to the case when $\beta = 0$, as was the case in subsection 4.1.1. In addition, the quantity of energy being charged and discharged into and out of the storage system is also less quantity, due to the introduction of risk adversity. In these cases, the battery storage level $\bar{e}$ only equals 0 MWH at the beginning and end of the time horizon of the optimization problem, showing a more conservative behaviour, characteristic of the risk-averse decision maker. We can also notice that the plots for $\beta = 0.5$ and $\beta = 1$ remain exactly the same as in the previous case with $Ł^B = 2$, meaning that providing more charge and discharge cycles (L^B) does not influence the behaviour of risk-averse decision makers.

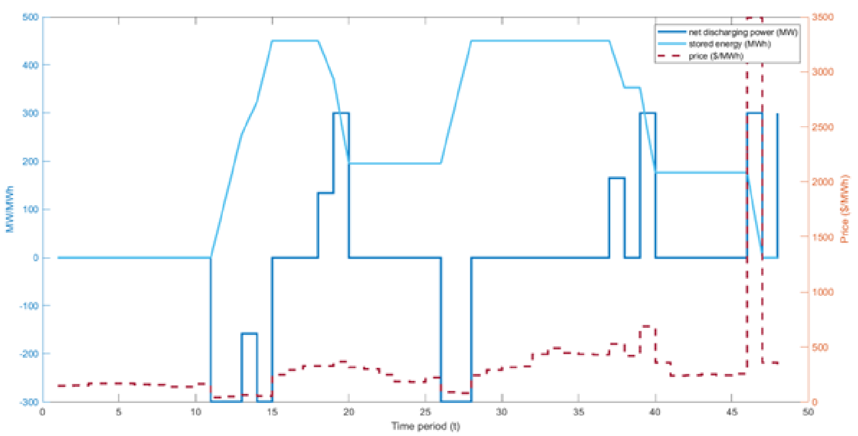

Figure 4.7: Optimal storage dispatch decisions for $\beta = 0.5$

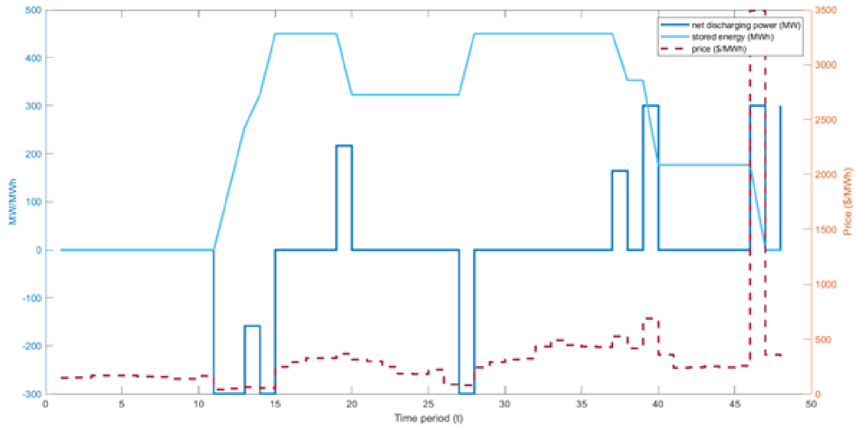

Figure 4.8: Optimal storage dispatch decisions for $\beta = 1.0$

Finally, we have the comparison of the risk-neutral ($\beta = 0$) and more risk-averse ($\beta = 1$) market participants plotted in Figure 4.9, showing the dispatch decisions in the case of $L^B = 5$. The first thing, is that there are noticeably more charge and discharge cycles for $\beta = 0$. Between $t = 23$ and $t = 25$, the risk-neutral participant charges while the risk-averse participant remains idle. After that, the same situation happens around $t = 34$ and between $t = 41$ and $t = 45$. The risk-neutral market participant senses the price signals and acts upon them while the risk-averse participant abstains from taking advantage of these fluctuations. The results on both cases, from subsection 4.1.1 and subsection 4.1.2, reflect the same behaviour of the market participants regarding their degree of risk adversity.

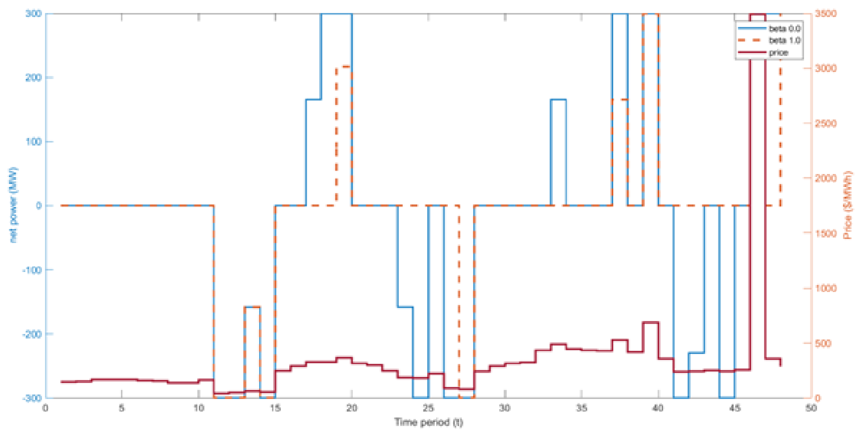

Figure 4.9: Optimal net discharging levels under different values of β

4.1.3 Profits Case I

Since the purpose of the optimization problem is to minimize costs, therefore maximizing profits, these are analyzed in this section. First of all, a comparison of the profits of Case I.A with $L^B = 2$ and Case I.B with $L^B = 5$ under different values of β are studied. From Figure 4.10 it is very clear that when the market participants are risk-averse, the profit will remain the same even if more discharge and charge cycles are allowed. This is because, as observed in the figures from subsection 4.1.1 and subsection 4.1.2, the participants do not take advantage on the increase of charge and discharge cycles, remaining with the same amount of cycles no matter the maximum allowed. This is a characteristic of risk-averse decision makers, who focus only on short-term opportunities and might result in the storage resources to fail to respond to price signals during times of scarcity. The profit gap from $L^B = 2$ to $L^B = 5$ of the risk-neutral participants, represented by $\beta = 0$, is of 4%. Therefore, the influence on the increase of charge

and discharge cycles would need to be analyzed in order to identify the effects on the battery performance and safety, and assess if it is worthy for a 4% increase in profit.
On the other hand, the profit difference between a risk-averse participant and a risk-neutral participant with $L^B = 2$ is of 15%, while with $L^B = 5$ is of 18%. This shows that risk-neutral participants benefit considerably more from the price peaks and dips, and most importantly, they are more likely to respond to price signals in times of scarcity.

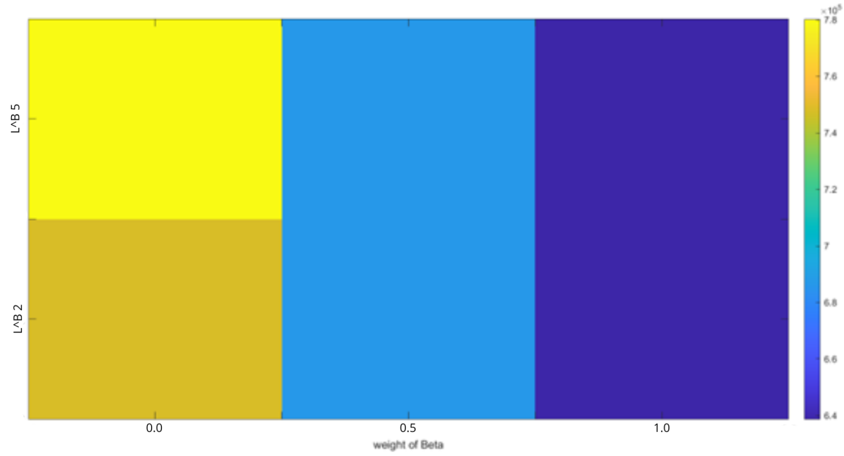

Figure 4.10: Expected profits under different values of β and L^B

Additionally, a study comparing variations in the battery's maximum energy capacity ($\overline{e}$) and different values of β was conducted with the purpose of exploring how an increased and decreased capacity of the system would affect the profits. Therefore, we repeat the experiments by varying $\overline{e}$ from 350 MWh to 550 MWh with 50 MWh increments. The results can be seen in Figure 4.11 and Figure 4.12.

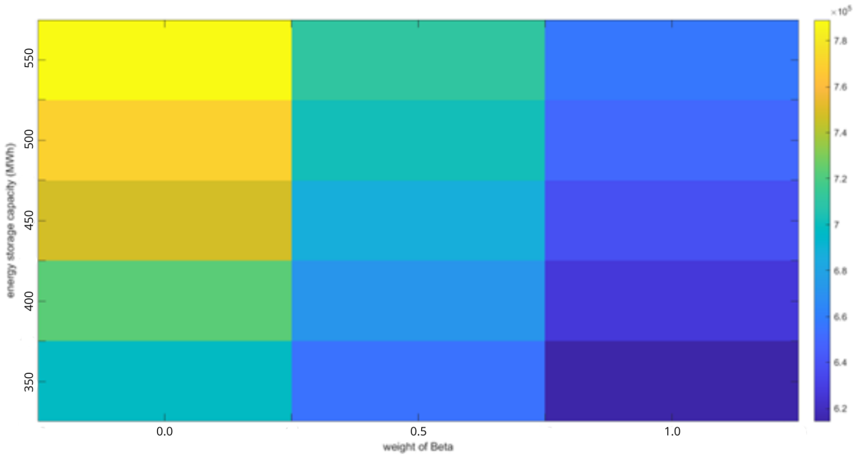

Figure 4.11: Expected profits under different values of β and $\overline{e}$ with $L^B = 2$

Initially, the case was done with the charge and discharge cycle multiplicator $L^B = 2$ and can be observed in Figure 4.11. We can first notice that across the different values of β, the total expected profits increase with higher values of $\overline{e}$, which can be due to a better capability to take advantage over price differences under larger storage capacities. We can also observe that an increased capacity influences the profits of risk-neutral participants a bit more than the more risk-averse participants. From the highest storage level (550 MWh) to the lowest (350 MWh), there is a difference of 7% in the case of $\beta = 1$ and for $\beta = 0$ the difference is of 11%. This shows that risk attitudes can create a barrier to noticing the possibility of greater profits, which is not diminished by an increased storage capacity.

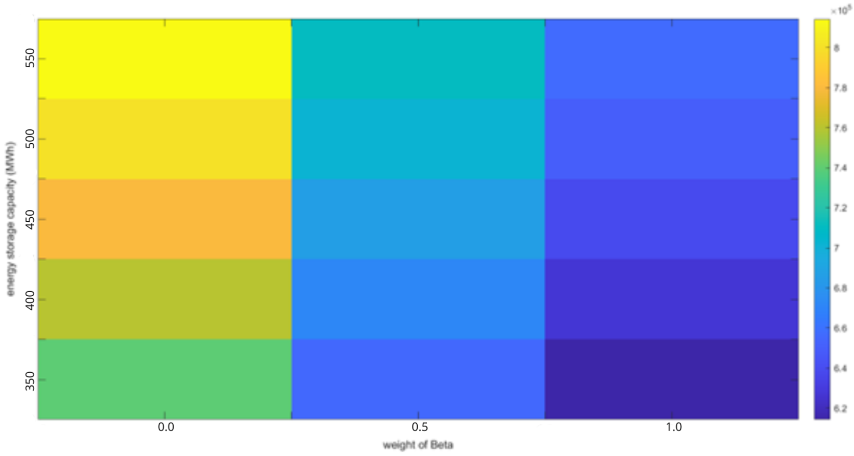

Figure 4.12: Expected profits under different values of β and $\overline{e}$ with $L^B = 5$

Finally, we replicate the experiment for the case where $L^B = 5$ to regulate the charge and discharge cycles. The results from the experiment are plotted in Figure 4.12. What we first perceive, is that the profits from $\beta \neq 0$ remain the same as the previous case, where $L^B = 2$, despite the increase on the charge and discharge cycles allowed as well as larger storage capacities, showing again the risk attitude, which does not allow participants to identify more opportunities to capitalize. However, for the risk-taker profits increase with an average climb of 5% compared to the case of $L^B = 2$. As mentioned before, the effects on the battery efficiency over time would need to be analyzed in order to determine the feasibility of increasing the limit of battery utilisation L^B. These results confirm the relationship between risk and profit. By making less conservative decisions, characterized by values of β approaching zero, expected profits escalate.

4.2 Case II

For this second study, the price data from January 16, 2019, a highly volatile day were considered in order to investigate the battery dispatch decisions. Price volatility in the real-time market is caused by a variety of factors, specially changes in supply and demand (Karakatsani and Bunn, 2010).

4.2.1 Case II.A

Dispatch decisions with $L^B = 2$ and different values of β

As it was done for Case I, this first part of Case II sets the integer multiplicator to limit battery utilisation $L^B = 2$, and with different values of β ranging from $\beta = 0.0$ to $\beta = 1.0$. In Figure 4.13 the behaviour from a risk-neutral participant is portrayed, represented by $\beta = 0$. We can first observe that, compared to Case I.A, the market participant does not closely follow the behaviour of the prices. However, this is reasonable since there are more notable peaks and dips of the prices and the limitation of $L^B = 2$ exists. What can be noticed is that decisions to charge and discharge are done where the drops are the lowest and peaks are the highest, respectively. For example, around $t = 5$ and $t = 8$ there is a significant drop and the participant decides to charge, as well as during $t = 29$ and $t = 43$. On the other hand, the biggest discharging occurs between $t = 35$ and $t = 37$, where the prices are the highest and the participant looks to benefit from that climb. There are other price peaks around $t = 13$ and $t = 20$ as well as between $t = 25$ and $t = 28$ that the participant ignores. Therefore, the behaviour might seem a bit risk-averse, however, the limitation in this case is most likely the parameter L^B.

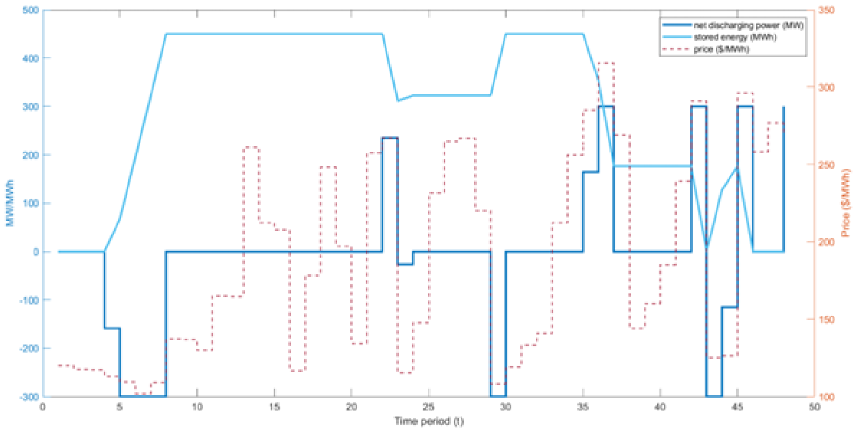

Figure 4.13: Optimal storage dispatch decisions for $\beta = 0.0$

Afterwards, the behaviour under $\beta = 0.5$ is plotted in Figure 4.14, where we can immediately notice that the charge and discharge are less compared to $\beta = 0$. In addition, the quantity (MW) being charged and discharged also decreases, revealing the behaviour of a participant who is in-between being risk-neutral and risk-averse participants. This participant takes more risks than a risk-averse participant but is more cautious than a risk-neutral one. However, we can also observe that the charging and discharging happen at the lowest and highest points of the set of prices, specifically during $t = 6$ and $t = 29$ for charging, and $t = 36$ for discharging.

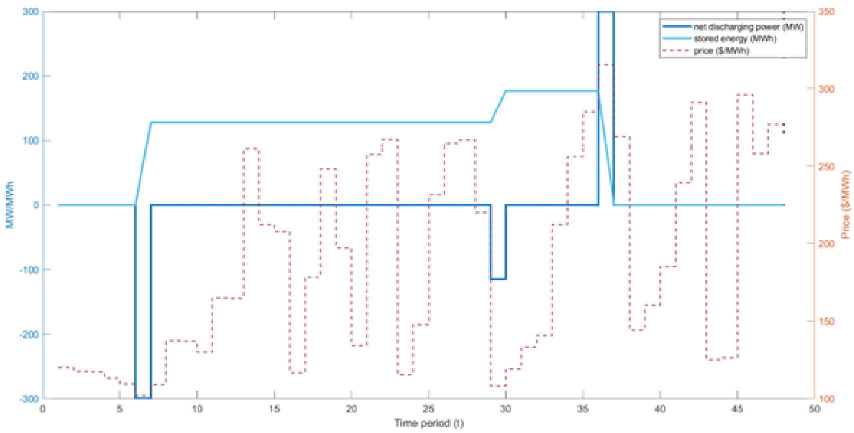

Figure 4.14: Optimal storage dispatch decisions for $\beta = 0.5$

Lastly, we have the case of $\beta = 1$ in Figure 4.15, where the participant remained inactive during the whole period. This perfectly reflects the behaviour of a risk-averse participant facing volatility in prices. The participant does not capitalize at all due to the uncertainty of the price fluctuation and prefers to stand idle rather than taking even the smallest of risks. From $t = 0$ to $t = 48$ there is absolutely no participation in the market.

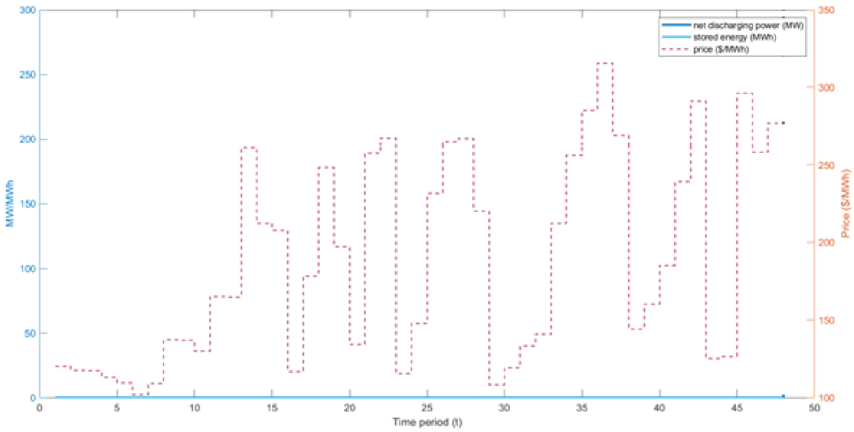

Figure 4.15: Optimal storage dispatch decisions for $\beta = 1.0$

4.2.2 Case II.B

Dispatch decisions with $L^B = 5$ and different values of β

After analysing the behaviour of the market participants with the integer multiplicator to limit battery utilisation $L^B = 2$ under different values of β, now we analyze the behaviour allowing more charging and discharging cycles by setting $L^B = 5$.
In this second part of Case II, we will be able to confirm if the behaviour from the risk neutral participant ($\beta = 0$) in Case II.A is due to the limitation on the integer multiplicator to limit battery utilisation $L^B = 2$ by setting $L^B = 5$ therefore allowing more charge and discharge cycles. As we can already perceive from Figure 4.16, the dispatch decisions perfectly follow the behaviour of the price set. The risk-neutral participant takes every opportunity presented and because of the price volatility, it results in a chaotic and continuous charging and discharging of the battery. In some cases, the battery even goes directly from charging to discharging and vice versa as seen in time period $t = 20$ and afterwards during $t = 23$. This behaviour might lead to damaging the battery and possibly reducing its lifetime. These impacts would need to be further analyzed.

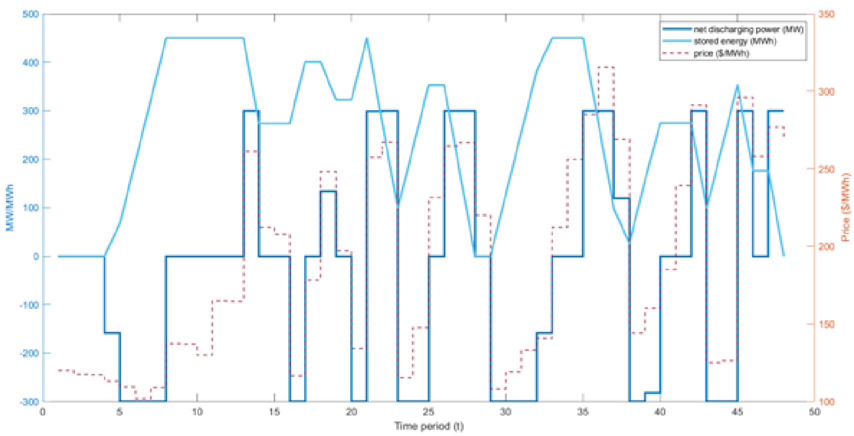

Figure 4.16: Optimal storage dispatch decisions for $\beta = 0.0$

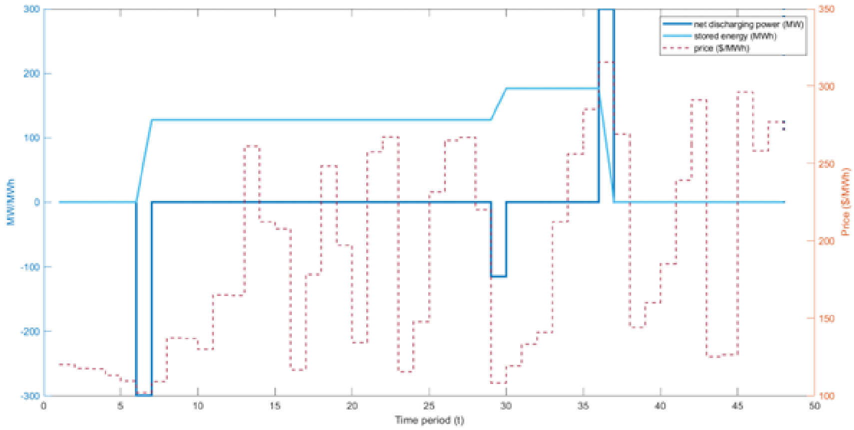

Figure 4.17: Optimal storage dispatch decisions for $\beta = 0.5$

After observing the difference of behaviour for the case of $\beta = 0$ with $L^B = 5$ compared to $L^B = 2$, we study the case where $\beta = 0.5$. It is expected that activity in the market will also increase, however, the results can be observed in Figure 4.17, where the behaviour is exactly the same as in Case II.A under the same conditions, meaning that providing an increase on the allowed charge and discharge cycles (L^B) does not influence the behaviour of the participant. The same can be concluded for the more risk-averse participant ($\beta = 1$) shown in Figure 4.18, where there is no activity throughout the whole period. This situation is present in Case I and now repeated in Case II.

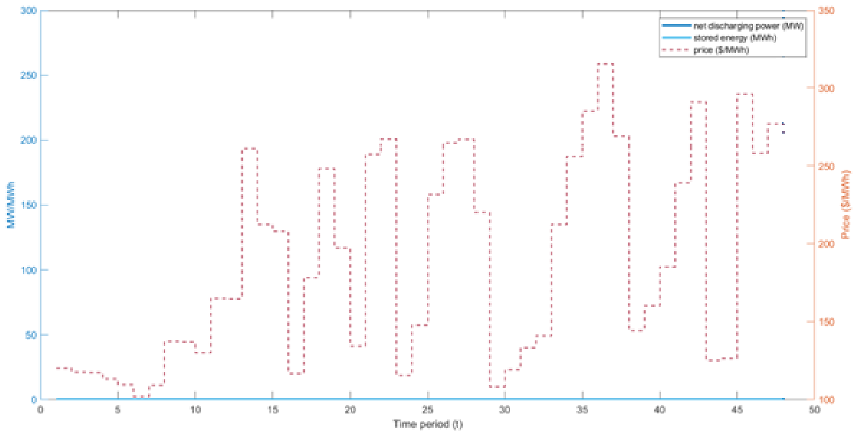

Figure 4.18: Optimal storage dispatch decisions for $\beta = 1.0$

4.2.3 Profits Case II

Finally, since the goal of the optimization problem is to minimize costs, the same profit analysis that was run in Case I is conducted for Case II. First, in Figure 4.19 a comparison of the profits with different values of the integer multiplicator to limit battery utilisation L^B under different values of β is studied. The behaviour of the risk-averse participants is directly reflected in the profits, with values close to zero and no difference between the profits they made with $L^B = 2$ and $L^B = 5$. However, for the case of risk neutral participants ($\beta = 0$), we can perceive a larger difference in profits with a 38% increase from $L^B = 2$ to $L^B = 5$. In this case, it might be beneficial to allow more charge and discharge cycles for the sake of increasing profits at expense of the battery's degradation, however, further analysis would be required to study the level of degradation and performance at later stages. Furthermore, the difference between the most risk-averse ($\beta = 1$) and risk-neutral ($\beta = 0$) on profits is of 69% in the case of $L^B = 2$ and 81% in the case of $L^B = 5$. This shows that risk-neutral participants benefit substantially more on a high price volatility day and are gonna react to price signals, which is specially important in times of scarcity.

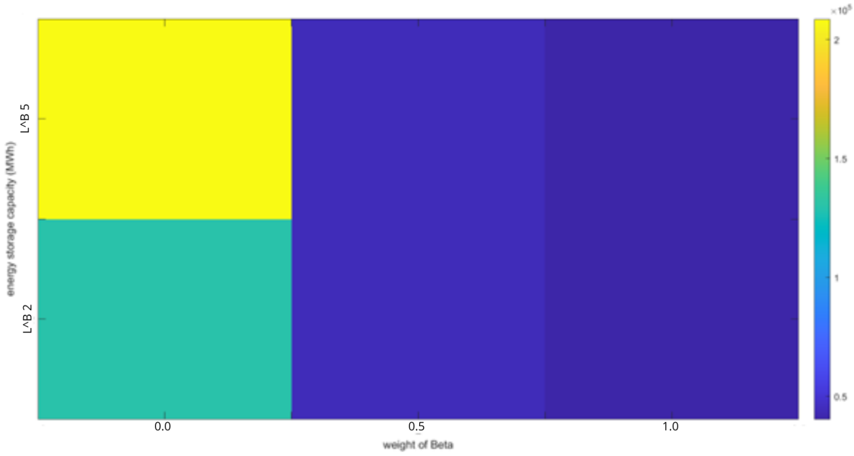

Figure 4.19: Expected profits under different values of β and L^B

In addition, a study with different maximum storage capacities ($\overline{e}$) was carried out in order to detect if it would influence the behaviour on participants with $\beta = 0.5$ and $\beta = 1$ as well as seeing the reaction from risk neutral participants ($\beta = 0$). Therefore, the experiments are repeated, varying $\overline{e}$ from 350 MWh to 550 MWh with 50 MWh increments, alternating between $L^B = 2$ and $L^B = 5$. The results are reflected in Figure 4.20 and Figure 4.21.

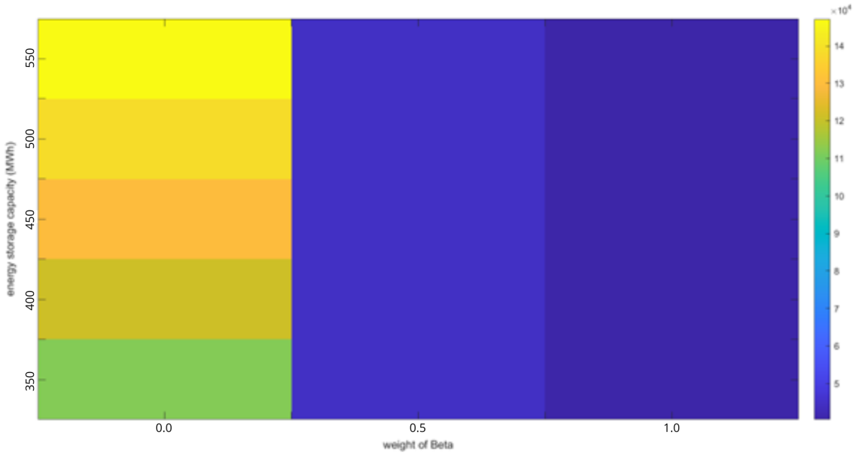

Figure 4.20: Expected profits under different values of β and $\overline{e}$ with $L^B = 2$

To start with, since we already know from the previous sections, the behaviour of risk-averse participants leads to no modifications on their profits in the case of $\overline{e} = 450MWh$. However, increasing and decreasing the battery's maximum storage capacity has no influence either. This can be observed in Figure 4.20 and Figure 4.21, where the profits remain exactly the same. Furthermore, the differences on profits from the risk-neutral participants are analyzed. In the case where $L^B = 2$, the difference from lowest (350 MWh) to highest (550 MWh) maximum storage capacity ($\overline{e}$) is of 24%, showing a benefit from increasing the battery's capacity, however, the investment costs would need to be considered. Additionally, from the current state of the battery's maximum storage capacity (450 MWh) to increasing it to 550 MWh there is only and increase in profits of 12%. Finally, in the case where $L^B = 5$, the difference from lowest to highest storage capacities is of 18% while the difference from the current storage capacity of 450 MWh and a capacity of 550 MWh, the difference is only of 6%, therefore, it might not be worth the investment. As a final remark, these results highlight the relationship between risk and profit. More risky decisions lead to higher expected profits.

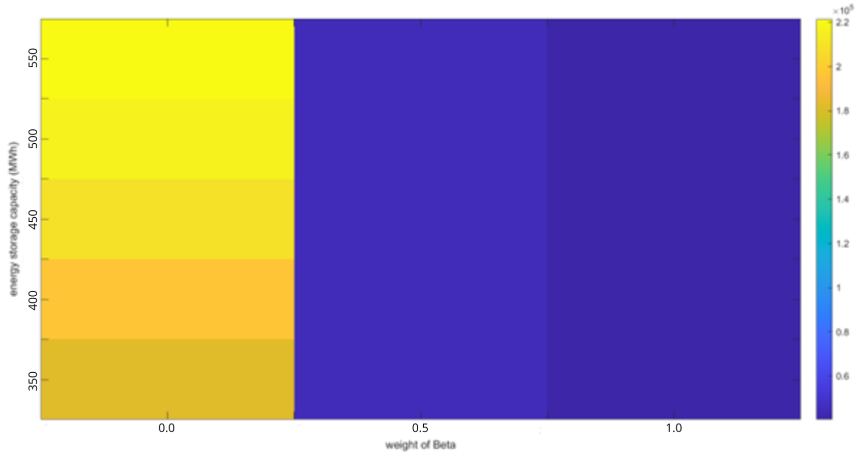

Figure 4.21: Expected profits under different values of β and $\overline{e}$ with $L^B = 5$

5. Conclusion and Discussion

An optimization problem modelling an actor with a battery as energy storage system was developed and studied, considering parameters and constraints which ensure the battery's operational safety as well as the battery's performance protection. In addition, the model also integrates risk into the problem by using a linear program which uses CVaR with a weight parameter (β) to denote the level of risk a market participant is willing to take. Four key results were obtained from the analysis and are further discussed in this section.

Discussion

First, is that risk-aversion leads to market participants to miss out on opportunities where they could have capitalized, taking short-term opportunities rather than bidding further ahead with the expectation of risky but more profitable decisions. **Second** is that risk-aversion leads to reduced profits because of the conservative attitude that the participant takes. This conservatism migh lead to failing in the response to price signals in times of scarcity, missing opportunities to dispatch (sell) energy when the prices are highest because of the scarcity. **Third**, we learned that increasing the parameter which limits the charge and discharge cycles (L^B) benefits only the risk-neutral participants, who take advantage in the price conditions during the simulation, while risk-averse participants act more cautiously and do not change their behaviour. However, the degradation of the battery with increasing the charge and discharge cycles would need to be studied and find a solution to optimize the parameter L^B in order to depreciate the battery at a low rate. **Finally**, increasing the storage capacity showed no impact on the profits of risk-averse participants. In the case of risk-neutral decision makers, the profits did increase, however, the large investment that needs to be done to increase the storage capacity of the system would need to be taken into consideration and analyze if it represents a significant advantage. There are some implications that arise from the study. The market operator would need to be aware of the risk-aversion in the system and because this quality is not visible to the human eye, the market operator might face making unreliable forecasts in the short and medium-term, risking the decision on market intervention. This could be controlled with system transparency, helping the market operator to have a clear view specially on the available stored energy. As a conclusion and in order to answer the research question, a bidding strategy which integrates risk into the model formulation alongside constraints that protect the battery leads to distinct results, proving that the risk-neutral strategies yield a higher profit in both case studies.
Advances in materials science, nanotechnology, and electrochemical engineering are moving forward the evolution of innovative energy storage solutions, alongside developments in battery technologies. An relevant is the progress seen in supercapacitors and hybrid energy storage systems, which offer the promise of enhancing conventional batteries, which enhance the response times of the system with high-power capabilities, making them suitable for applications that demand frequent charge and discharge cycles (Miller and Simon, 2008). The optimization of bidding strategies would still play a big role despite the advancements in technology and would probably need to incorporate additional constraints and parameters to the problem formulation. That being said, some improvements are considered for the optimization problem studied in this research and which are mentioned in the following section.

5.1 Future work

Although the results obtained from this study already provide an insight on the behaviour of market participants under different circumstances, there is still space to extend the optimization problem and make it more robust such that the battery is more protected operationally and responds more efficiently to the market signals.

Some of the extensions that could be considered for the model are the following:

- **Battery degradation** - Since the model included charge and discharge cycles in subsection 3.2.1, it would be interesting to explore the effects of the battery degradation and how it would influence on the performance of the system. This would provide an insight on the battery lifetime and would determine if the increase on profits by allowing more charge and discharge cycles is beneficial compared to the duration of the operational life as well as the safety of the battery.
- **Discharge risk** - In the risk-averse self-scheduling extension of the model in subsection 3.2.2, the constraint implemented considers only the charging cycle. It would be irresponsible not to mention that there also exists a risk associated with discharging the resource, which involves the possibility of generating less revenues if the RTM prices are considerably low compared to pre-dispatch prices.
- **Monotonicity constraint** - This term is introduced in the paper by Herding et al. (2023) and it states that bidding curves have to be monotonically decreasing or decreasing, for buying and selling electricity, respectively.
- **Nonanticipativity constraints** - This term is introduced in the paper by Herding et al. (2023). It imposes the condition that scenarios that share the same information history should make the same decisions. This ensures that the solutions obtained are implementable. (Higle, 2005)

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A. Matrix forms

A.1 Base model matrices

$$f = \begin{bmatrix} \lambda(t) \\ -\lambda(t) \\ 0_{T\times 1} \\ 0_{T+1\times 1} \end{bmatrix} \Delta t \tag{A.1}$$

$$x = \begin{bmatrix} p_c(t) \\ p_d(t) \\ u(t) \\ e_0 \\ e(t) \end{bmatrix} \tag{A.2}$$

$$A = \begin{bmatrix} I_T & 0_{T\times T} & \overline{p_c} I_T & 0_{T\times T+1} \\ 0_{T\times T} & I_T & -\overline{p_d} I_T & 0_{T\times T+1} \end{bmatrix} \tag{A.3}$$

$$b = \begin{bmatrix} \overline{p_c} \cdot 1_{T\times 1} \\ 0_{T\times 1} \end{bmatrix} \tag{A.4}$$

$$E = \begin{bmatrix} \eta_c I_T \Delta t & -\frac{1}{\eta_d} I_T \Delta t & 0_{T\times T} & N \end{bmatrix} \tag{A.5}$$

$$d = 0_{T\times 1} \tag{A.6}$$

$$\underline{x} = \begin{bmatrix} 0_{T\times 1} \\ 0_{T\times 1} \\ 0_{T\times 1} \\ e_0 \\ \underline{e} \cdot 1_{T\times 1} \end{bmatrix} \tag{A.7}$$

$$\overline{x} = \begin{bmatrix} inf \cdot 1_{T\times 1} \\ inf \cdot 1_{T\times 1} \\ 1_{T\times 1} \\ e_0 \\ \overline{e} \cdot 1_{T\times 1} \end{bmatrix} \tag{A.8}$$

A.2 Charge and discharge cycle matrices

$$f = \begin{bmatrix} \lambda(t) \\ -\lambda(t) \\ 0_{T\times 1} \\ 0_{T+1\times 1} \end{bmatrix} \Delta t \tag{A.9}$$

$$x = \begin{bmatrix} p_c(t) \\ p_d(t) \\ u(t) \\ e_0 \\ e(t) \end{bmatrix} \tag{A.10}$$

$$A = \begin{bmatrix} I_T & 0_{T\times T} & \overline{p_c} I_T & 0_{T\times T+1} \\ 0_{T\times T} & I_T & -\overline{p_d} I_T & 0_{T\times T+1} \\ \Delta t \cdot 1_{1\times T} & 0_{1\times T} & 0_{1\times T} & 0_{1\times T+1} \\ 0_{1\times T} & \Delta t \cdot 1_{1\times T} & 0_{1\times T} & 0_{1\times T+1} \end{bmatrix} \tag{A.11}$$

$$b = \begin{bmatrix} \overline{p_c} \cdot 1_{T\times 1} \\ 0_{T\times 1} \\ L^B \overline{e} \\ L^B \overline{e} \end{bmatrix} \tag{A.12}$$

$$E = \begin{bmatrix} \eta_c I_T \Delta t & -\frac{1}{\eta_d} I_T \Delta t & 0_{T\times T} & N \end{bmatrix} \tag{A.13}$$

$$d = 0_{T\times 1} \tag{A.14}$$

$$\underline{x} = \begin{bmatrix} 0_{T\times 1} \\ 0_{T\times 1} \\ 0_{T\times 1} \\ e_0 \\ \underline{e} \cdot 1_{T\times 1} \end{bmatrix} \tag{A.15}$$

$$\overline{x} = \begin{bmatrix} inf \cdot 1_{T\times 1} \\ inf \cdot 1_{T\times 1} \\ 1_{T\times 1} \\ e_0 \\ \overline{e} \cdot 1_{T\times 1} \end{bmatrix} \tag{A.16}$$

A.3 Complete model matrices

$$f = \begin{bmatrix} \sum_{\omega=1}^{\Omega} \pi^\omega \sum_{t=1}^{T} \lambda^\omega(t) \Delta t \\ -\sum_{\omega=1}^{\Omega} \pi^\omega \sum_{t=1}^{T} \lambda^\omega(t) \Delta t \\ 0_{T\times 1} \\ 0_{T+1\times 1} \\ \beta \frac{1}{1-\alpha} \pi^\omega \\ \beta \end{bmatrix} \tag{A.17}$$

$$x = \begin{bmatrix} p_c(t) \\ p_d(t) \\ u(t) \\ e_0 \\ e(t) \\ z^\omega \\ \zeta \end{bmatrix} \tag{A.18}$$

$$A = \begin{bmatrix} I_T & 0_{T\times T} & \overline{p_c} I_T & 0_{T\times T+1} & 0_{T\times\omega} & 0_{T\times 1} \\ 0_{T\times T} & I_T & -\overline{p_d} I_T & 0_{T\times T+1} & 0_{T\times\omega} & 0_{T\times 1} \\ \Delta t \cdot 1_{1\times T} & 0_{1\times T} & 0_{1\times T} & 0_{1\times T+1} & 0_{1\times\omega} & 0 \\ 0_{1\times T} & \Delta t \cdot 1_{1\times T} & 0_{1\times T} & 0_{1\times T+1} & 0_{1\times\omega} & 0 \\ \lambda^T & 0_{\omega\times T} & 0_{\omega\times T} & 0_{\omega\times T+1} & -I_\omega & -1_{\omega\times 1} \end{bmatrix} \tag{A.19}$$

$$b = \begin{bmatrix} \overline{p_c} \cdot 1_{T\times 1} \\ 0_{T\times 1} \\ L^B \overline{e} \\ L^B \overline{e} \\ 0_{\omega\times 1} \end{bmatrix} \tag{A.20}$$

$$E = \begin{bmatrix} \eta_c I_T \Delta t & -\frac{1}{\eta_d} I_T \Delta t & 0_{T\times T} & N & 0_{T\times\omega} & 0_{T\times 1} \end{bmatrix} \tag{A.21}$$

$$d = 0_{T\times 1} \tag{A.22}$$

$$\underline{x} = \begin{bmatrix} 0_{T\times 1} \\ 0_{T\times 1} \\ 0_{T\times 1} \\ e_0 \\ \underline{e} \cdot 1_{T\times 1} \\ 0_{\omega\times 1} \\ -inf \end{bmatrix} \tag{A.23}$$

$$\overline{x} = \begin{bmatrix} inf \cdot 1_{T\times 1} \\ inf \cdot 1_{T\times 1} \\ 1_{T\times 1} \\ e_0 \\ \overline{e} \cdot 1_{T\times 1} \\ inf \cdot 1_{\omega\times 1} \\ inf \end{bmatrix} \tag{A.24}$$

The term N in matrices (A.5), (A.13) and (A.21) is obtained by computing the transpose of a triangular matrix of dimension T+1 by T+1 and then computing the inverse of the resulting matrix. Finally, it takes rows 1 to T and columns 1 to T+1 as shown in (A.25) in the case of T = 4. It is computed with T+1 since the optimization problem considers e(0) in the constraints.

$$N = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix} \tag{A.25}$$

B. Matlab Codes

B.1 Core model code

```
% Constants
T = 48;
ubar_e = 0;
bar_e = 450;
Δ_t = 0.5;
eta_c = 0.85;
eta_d = 0.85;
pbar_d = 300;
pbar_c = 300;
e0 = 0;
lambda = rand(T, 1);

H = zeros(T,1);
G = zeros(T+1,1);
K = zeros(T,T);
R = zeros(T,T+1);
L = ones(T,1);
I = eye(T);
M = tril(ones(T+1,T+1));
MT = transpose(M);
MTI = inv(MT);
N = MTI(1:T,:);

A = [I K pbar_c*I R; K I -pbar_d*I R];
b = [pbar_c*L; H];
E = [eta_c*I*Δ_t -(1/eta_d)*I*Δ_t K N];
d = H;

model.A = sparse([A; E]);
model.obj = [lambda; -lambda; H; G]*Δ_t;
model.rhs = [b; d];
model.lb = [H; H; H; e0; ubar_e*L];
model.ub = [inf*L; inf*L; L; e0; bar_e*L];
model.sense = [repmat('<',1,2*T) repmat('=',1,1*T)];
model.vtype = [repmat('C',1,2*T) repmat('B',1,T) repmat('C',1,T+1)];
model.modelsense = 'min';

params.outputflag = 0;

result = gurobi(model, params);

disp(result);

fprintf('Obj: %e\n', result.objval);

p_c = result.x(1:T);
p_d = result.x(T+1:2*T);
u = result.x(2*T+1:3*T);
e = result.x(3*T+1:end);
```

B.2 Charge and discharge cycle code

```
% Constants
T = 48;
ubar_e = 0;
bar_e = 300;
Δ_t = 0.5;
eta_c = 0.85;
eta_d = 0.85;
pbar_d = 300;
pbar_c = 300;
e0 = 0;
lambda = readmatrix('discharge.xlsx');
Lb = 5;

H = zeros(T,1);
G = zeros(T+1,1);
K = zeros(T,T);
R = zeros(T,T+1);
L = ones(T,1);
I = eye(T);
M = tril(ones(T+1,T+1));
MT = transpose(M);
MTI = inv(MT);
N = MTI(1:T,:);

A = [I K pbar_c*I R; K I -pbar_d*I R; Δ_t*L' H' H' G'; H' Δ_t*L' H' G'];
b = [pbar_c*L; H; Lb*bar_e; Lb*bar_e];
E = [eta_c*I*Δ_t -(1/eta_d)*I*Δ_t K N];
d = H;

model.A = sparse([A; E]);
model.obj = [lambda; -lambda; H; G]*Δ_t;
model.rhs = [b; d];
model.lb = [H; H; H; e0; ubar_e*L];
model.ub = [inf*L; inf*L; L; e0; bar_e*L];
model.sense = [repmat('<',1,2*T+2) repmat('=',1,1*T)];
model.vtype = [repmat('C',1,2*T) repmat('B',1,T) repmat('C',1,T+1)];
model.modelsense = 'min';

params.outputflag = 0;

result = gurobi(model, params);

disp(result);

fprintf('Obj: %e\n', result.objval);

p_c = result.x(1:T);
p_d = result.x(T+1:2*T);
u = result.x(2*T+1:3*T);
e = result.x(3*T+1:end);
```

B.3 Risk-averse self-scheduling code

```
T = 48;
ubar_e = 0;
bar_e = 450;
Δ_t = 0.5;
eta_c = 0.85;
eta_d = 0.85;
pbar_d = 300;
pbar_c = 300;
e0 = 0;
omega = 100;
lambda = readmatrix('datos.xlsx');
lambda_plot = mean(lambda,2);
Lb = 2;
alpha = 0.95;
p = 0.01*ones(1,omega);

H = zeros(T,1);
G = zeros(T+1,1);
K = zeros(T,T);
R = zeros(T,T+1);
L = ones(T,1);
I = eye(T);
M = tril(ones(T+1,T+1));
MT = transpose(M);
MTI = inv(MT);
N = MTI(1:T,:);
W = zeros(T,omega);
X = zeros(omega,1);
Y = zeros(omega,T+1);
C = eye(omega);
D = ones(omega,1);

beta = 0.4;

A = [I K pbar_c*I R W H; K I -pbar_d*I R W H; Δ_t*L' H' H' G' X' 0; H' Δ_t*L' ...
    H' G' X' 0; lambda' W' W' Y -C -D];
b = [pbar_c*L; H; Lb*bar_e; Lb*bar_e; X];
E = [eta_c*I*Δ_t -(1/eta_d)*I*Δ_t K N W H];
d = H;

model.A = sparse([A; E]);
model.obj = [Δ_t*lambda*p'; -Δ_t*lambda*p'; H; G; p'*beta*(1/(1-alpha)); beta];
model.rhs = [b; d];
model.lb = [H; H; H; e0; ubar_e*L; X; -inf];
model.ub = [inf*L; inf*L; L; e0; bar_e*L; inf*D; inf];
model.sense = [repmat('<',1,2*T+2) repmat('=',1,1*T) repmat('<',1,1*omega)];
model.vtype = [repmat('C',1,2*T) repmat('B',1,T) repmat('C',1,T+1) ...
    repmat('C',1,1*omega) 'C'];
model.modelsense = 'min';

params.outputflag = 0;

result = gurobi(model, params);

disp(result);

fprintf('Obj: %e\n', result.objval);
```

```
p_c = result.x(1:T);
p_d = result.x(T+1:2*T);
u = result.x(2*T+1:3*T);
e = result.x(3*T+1:4*T);
z = result.x(4*T+1:5*T);
zeta = result.x(5*T+1:end);
```

C. Expected profits

As the battery energy storage system being studied and the price data utilized is from the Victorian Big Battery, the expected profits are expressed in Australian dollars (AUD). The exact expected profits from subsection 4.1.3 and subsection 4.2.3 can be observed in this appendix.

	$\beta = 0.0$	$\beta = 0.5$	$\beta = 1.0$
$L^B = 0.5$	780221.30 AUD	686830.00 AUD	638610.60 AUD
$L^B = 0.2$	747936.40 AUD	686830.00 AUD	638610.60 AUD

Table C.1: Case I - Expected profits for market participants under different values of L^B and β

	$\beta = 0.0$	$\beta = 0.5$	$\beta = 1.0$
$\overline{e} = 550$MWh	788950.40 AUD	711106.30 AUD	657267.40 AUD
$\overline{e} = 500$MWh	770382.10 AUD	701979.40 AUD	650127.80 AUD
$\overline{e} = 450$MWh	747936.40 AUD	686830.00 AUD	638610.60 AUD
$\overline{e} = 400$MWh	723253.40 AUD	671680.50 AUD	627093.40 AUD
$\overline{e} = 350$MWh	698221.90 AUD	654881.90 AUD	614353.60 AUD

Table C.2: Case I - Expected profits for market participants under different values of $\overline{e}$ and β with $L^B = 2$

	$\beta = 0.0$	$\beta = 0.5$	$\beta = 1.0$
$\overline{e} = 550$MWh	814211.30 AUD	711106.30 AUD	657267.40 AUD
$\overline{e} = 500$MWh	800363.40 AUD	701979.40 AUD	650127.80 AUD
$\overline{e} = 450$MWh	780221.30 AUD	686830.00 AUD	638610.60 AUD
$\overline{e} = 400$MWh	760079.20 AUD	671680.50 AUD	627093.40 AUD
$\overline{e} = 350$MWh	739340.60 AUD	655653.50 AUD	614353.60 AUD

Table C.3: Case I - Expected profits for market participants under different values of $\overline{e}$ and β with $L^B = 5$

	$\beta = 0.0$	$\beta = 0.5$	$\beta = 1.0$
$L^B = 0.5$	208699.60 AUD	44698.36 AUD	40443.99 AUD
$L^B = 0.2$	129980.60 AUD	44698.36 AUD	40443.99 AUD

Table C.4: Case II - Expected profits for market participants under different values of L^B and β

	$\beta = 0.0$	$\beta = 0.5$	$\beta = 1.0$
$\overline{e} = 550$MWh	147101.30 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 500$MWh	138641.50 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 450$MWh	129980.60 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 400$MWh	121263.40 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 350$MWh	112081.20 AUD	44698.36 AUD	40443.99 AUD

Table C.5: Case II - Expected profits for market participants under different values of $\overline{e}$ and β with $L^B = 2$

	$\beta = 0.0$	$\beta = 0.5$	$\beta = 1.0$
$\overline{e} = 550$MWh	221347.20 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 500$MWh	216411.20 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 450$MWh	208699.60 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 400$MWh	196301.00 AUD	44698.36 AUD	40443.99 AUD
$\overline{e} = 350$MWh	182399.90 AUD	44698.36 AUD	40443.99 AUD

Table C.6: Case II - Expected profits for market participants under different values of $\overline{e}$ and β with $L^B = 5$