BI

WISEflow
Europe/Oslo(CEST)
30 Jun 2022

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	16-01-2022 09:00	**Termin:**	202210
Sluttdato:	01-07-2022 12:00	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202210||10936||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

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Informasjon fra deltaker

Tittel *:	Risk modelling and optimization of hedging strategy for a Norwegian hydropower producer
Navn på veileder *:	Geir Høidal Bjønnes

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	256
Andre medlemmer i gruppen:	Deltakeren har innlevert i en enkeltmannsgruppe

Master Thesis

- Risk modelling and optimization of hedging strategy for a Norwegian hydropower producer

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Acknowledgements

This master's thesis was written during the spring of 2022 at BI Norwegian Business school, Department of Data Science and Analytics, within the field of Business Analytics.

I would like to acknowledge and express my gratitude to the people who made this master's thesis possible. First and foremost, I would like to thank Karl Hartwig from Haflsund Eco for providing me with this opportunity as well as his enthusiasm and guidance throughout the process. Further, I would like to thank Hafslund Eco's financial trading team as well as many others from the firm who assisted me and provided me with data. Next, I wish to thank my supervisor, Professor Geir Høidal Bjønnes, for his assistance. At last, I would like to thank my family and friends for their continuous support.

Oslo, 1 July, 2022

Eline Johansen Nielsen

Abstract

Presented in collaboration with Hafslund Eco, this thesis examines the process of decision making for a Norwegian hydropower producer over the medium term. As part of this process, risk modelling and optimization of the hedging strategy are undertaken in order to establish an effective frontier between the expected income and downside risk. The effective frontier reveals the relationship between expected income and downside risk, more specifically how minimizing downside risk influences expected income. Having such a model available is a valuable decision support tool for anyone involved in managing the hedging portfolio of a hydropower company. Therefore, the author of this thesis considers it to be an important element of risk management. The main contributions made by this thesis include a stochastic optimization model for optimizing the hedging portfolio of a Norwegian hydropower producer and a general analysis of this model. Additionally, this thesis examines the cost of eliminating the lower-tail outcomes. By eliminating lower-tail outcomes from the revenue distribution, higher-tail outcomes are to some extent eliminated as well. However, this depends on the distribution of the price scenarios and how volatile these are. The model can be used for speculative trading as well as for hedging. As a result, the thesis compares the two scenarios in terms of expected income, low income scenarios and high income scenarios. The thesis concludes with a discussion of tax effects on downside risk and hedging.

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Chapter 1

Introduction

The purpose of this thesis is to provide an analysis of medium-term decision making for a Norwegian hydropower producer. In particular, medium-term decision making refers to how a hydropower producer can secure their income on an intermediate horizon against large fluctuations in the electricity price.

In comparison with other commodities, electricity is a rather volatile product since long-term storage is both costly and impractical. In the Nordic electricity market, short-term oscillations have historically been less intense than those experienced in the continent due to the existence of large hydropower reservoirs that limit the differences in the daily power balance. Despite this, electricity prices can still fluctuate widely between years due to weather conditions and the inflow to hydropower reservoirs. Large fluctuations in the price of electricity, combined with the uncertainty surrounding precipitation and inflow, result in highly uncertain income scenarios for Norwegian hydropower producers. Furthermore, the Nordic electricity market has become more connected to mainland Europe and Britain via sub sea power cables. Consequently, the foundation for Nordic electricity prices is changing and including more uncertain factors connected to electricity supply in other countries.

In light of this, risk management has become even more critical to Norwegian hydropower producers in order for them to ensure a steady dividend payment to their shareholders. Risk management for a Norwegian hydropower producer is complex as both volume uncertainty in available energy and price uncertainty from a volatile market must be considered. The income risks faced by producers can be reduced by hydropower disposal or financial hedging in the futures markets. The focus in this thesis is on the latter. More precisely, an optimization model using stochastic linear programming is presented to identify how risk-reducing hedging may reduce expected income and possible income in high price scenarios.

The model objective function depends on a chosen risk-aversion level which functions as a weighing parameter between maximizing expected income and maximizing the income in the lowest revenue scenarios. By varying the weight between downside risk and expected income and re-running the model, an effective frontier is created between expected income and downside risk. Based on this frontier the decision maker can choose between higher expected income or lower downside risk. The methodology presented is influenced by previous work on the subject made by Morente (2011). This work was chosen based on the quality of the work and the transferability to this case. The methodology presented in this thesis differs from Morente in that the income function is fitted to a Norwegian producer and the model includes possible restrictions on hedging volume.

The model presented is a good decision support tool for anyone handling the hedging portfolio at a hydropower company because it includes a trade-off between expected income and downside risk. The model presented provides value by suggesting which financial products to hedge, by how much and how this hedging activity influences the income distribution. Based on available price and production scenarios, as well as a financial forward curve, the model reduces the probability of the worst income scenarios by hedging available monthly, quarterly, and yearly futures contracts. By reducing the probability of the worst income scenarios and securing production towards one price level, the income distribution converges towards the expected income and the probability of high-income scenarios are reduced as well. The analysis of the model clearly shows that the model chooses to over-hedge in certain situations where the forward price is beneficial. Moreover, the analysis shows that the model effectively reduces the probability of low income scenarios while at the same time increasing expected income compared to a situation with no financial hedging. As taxes are included in the income function for a Norwegian hydropower producer, the analysis includes a discussion on tax effects that concludes that both hedging volume and income are influenced by the resource rent tax level.

The second chapter provides a detailed description of the Nordic electricity markets, hedging techniques, and how the model presented contributes to hedging. Previous work on the subject is reviewed in the third chapter, along with a discussion on how this thesis adds to the existing literature. The fourth chapter summarizes the methodology of this thesis, including assumptions, restrictions, chosen risk measure, and an overview of the solution method. Following this, the data is presented in the fifth chapter with data exploration and statistics. The analysis of the model results and an overview of a few scenarios is covered in chapter six. Finally, chapter seven offers a conclusion and a proposal for future work.

Chapter 2

Electricity markets

The purpose of this section is to provide information about electricity markets, particularly the Nordic electricity markets. Additionally, a small discussion will be given on hedging, why it is important, and how this thesis will contribute to it.

2.1 Physical market in the Nordic region

Power producers generate electricity from hydropower plants and sell the electricity they produce to consumers. Electricity can be sold through the physical energy market or through bilateral agreements with consumers. In the Nordic region, the energy system is composed of different price areas corresponding to different geographical areas, as well as an additional price called the system price (see figure 2.1). The system price functions as a market clearing reference price for the entire Nordic region and is the price that would be attained if there was no physical limitations on power transfer between the different price areas.

The primary trading venue for Nordic power producers is the Nord Pool day-ahead market, which is also known as the spot market. It consists of different bidding areas that reflect the different price areas, where the price for the hour of the following day is determined according to the equilibrium of supply and demand in each area, as well as the transmission capacity constraints between the areas. Several factors affect the hourly price, including consumption patterns, the weather, and the level of water in hydropower reservoirs. Changes in any of these variables can result in dramatic fluctuations in the price and, ultimately, in the income for energy producers and their owners. As a result, power producers need some way of limiting these fluctuations to avoid low income scenarios.

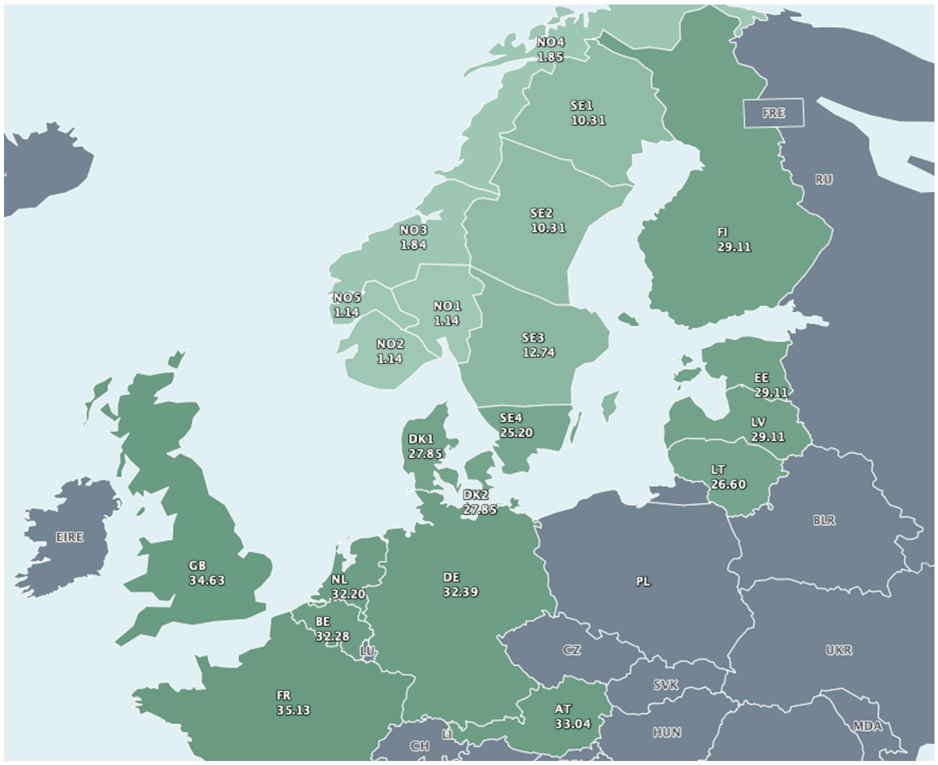

Figure 2.1: Price areas in the Nordic, Baltic and CWE (Prices for 01.07.2020, image from Nord Pool)

2.2 Hedging

The large fluctuations in income make it necessary for power producers to have a degree of risk management to stabilize profits. In order to reduce this income risk, the electricity production can be hedged in the financial markets. By definition, hedging is a method of managing investment risks by taking an opposite position in a related asset. Although it cannot eliminate all losses, the practice of hedging can significantly reduce the impact of negative events.

Hedging usually involves the use of financial instruments known as derivatives. Derivates are contracts between two or more parties whose value is determined by the value of an underlying asset. Among the most popular derivatives are options and futures. An option is a contract which grants the holder the right to buy or sell the underlying asset at a specific price on or before the contract expiration date. In contrast, futures are contracts to buy or sell a commodity or security at a predetermined price and date in the future. In the case of electricity production, it is most common to use futures as a financial hedging instrument since the available option contracts have very low turnover/liquidity. This can be attributed to the general lack of liquidity on the Nordic electricity markets as well as the fact that speculative trading has taken place on other, more profitable markets.

Hydropower producers can offset their potential losses from selling power on the physical market by selling the same volume of futures contracts in the financial market. By selling a futures contract with a specific price, the energy producer ensures that the production will be able to be sold at that price in the future. If the market price moves downward, the energy producer has made a good hedge. In other words, they can sell their production at a higher price than what the market price is at the time. If, however, the price rises, the energy producer has made a poor hedge. Consequently, they will need to sell their production at a lower price than what the market price is at the time. In this way, hedging can be a form of insurance against large fluctuations in the electricity price, but it does come with a price. For electricity traders to make a successful hedge, they must form an opinion regarding the future direction of market prices.

As there are many factors affecting electricity prices, predicting how they will evolve is a difficult task. When faced with these types of situations, the availability of prediction models can aid traders in making informed decisions. This means not only forecasting where the market price will move, but also predicting how hedging will affect the expected income and possible income in high price scenarios. In other words, a model can not only predict what should be hedged and when, but can also provide insights into how both the potential upside as well as downside risks are reduced through hedging. This thesis presents a model that addresses this very issue, finding the optimal contracts to hedge and examining how this action impacts expected income and high income scenarios.

2.3 Financial market in the Nordic region

NASDAQ OMX Commodities (hereinafter Nasdaq) currently serves as the Nordic market's primary financial market. The market is purely financial, which means that no physical energy is exchanged. The Nordic system price can be hedged on Nasdaq by trading futures and options. Their maturity ranges from a day up to a year.

Nasdaq offers futures, deferred settlement (DS) futures, monthly DS futures, options, and electricity price area differentials (EPADs). Power futures are either base load (for all 24 hours) or peak load (for only peak hours of the day), and they can be traded in the spot reference period or delivery period with full contract size. Contract settlements are mark-to-market[1] throughout the entire trading period, including the spot reference period. However, in DS future contracts, the mark-to-market value is accumulated during the trading period and settled at delivery. The option contracts offered are of the European style in which you acquire the right to buy or sell the underlying contract (future) at a predetermined price at a predetermined date in the future. Finally, the EPAD's are contracts that hedge the difference between an area price and an index price (e.g. the Nordic system price) (n.d.).

The purpose of these contracts is to hedge producers' basis risk, which is incurred when they sell their production at an area spot price and trade their power futures at the system spot price. Nevertheless, the EPAD contracts traded on Nasdaq

[1] Mark-to-market means that the trading account is updated daily with the current market price. This is done to ensure that margin requirements are being met.

suffer from low liquidity. There has been a high correlation between the NO5 area price and the system price until recently. Therefore, it has not been necessary to hedge the area price difference as well. The difference between the system spot price and NO5 area spot price has increased since the end of 2021, leading to a higher basis risk for power producers (See figure 2.2). Therefore, the EPAD's may become more popular in the future if the correlation between the area prices and the system price continues to decrease. However, this also depends on what hedging instrument the power producers choose in the future.

Having a market that is increasingly connected with mainland Europe and Britain, it is likely that there will be new hedging instruments which can be more effective for the Nordic power producers in the form of future contracts representing the electricity prices of these connected markets. It should be noted, that this dissertation focuses on the Nordic system price as a hedging instrument, rather than discussing this topic in greater detail. Nonetheless, the methodology presented in this thesis could be extended to include contracts related to connected markets when the available data increases.

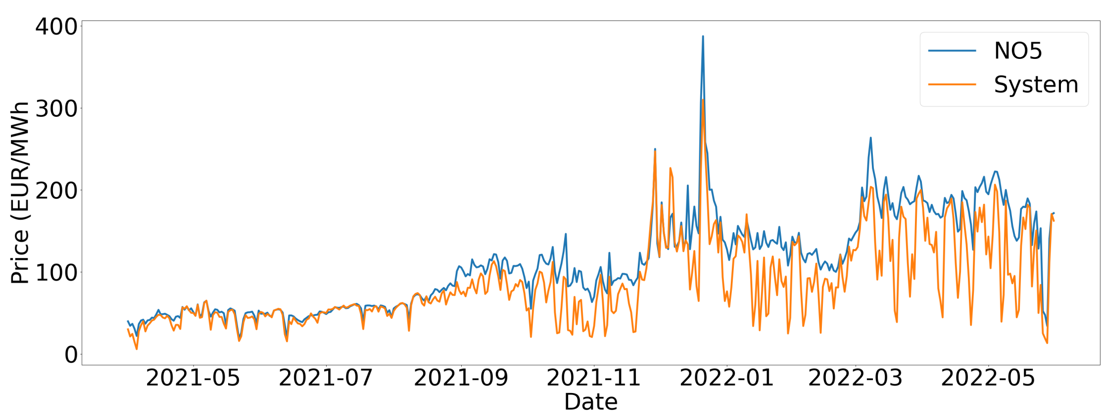

Figure 2.2: Historical NO5 price compared to historical Nordic system price with price on the y-axis and month on the x-axis.

Chapter 3

Literature review

A summary of relevant literature is presented in this section, which discusses similar or related research questions.

According to Gemill (1985) futures markets offer commodity exporting nations an attractive means of reducing the fluctuations in export revenues between years. In addition, in the article by Benninga, Eldor and Zilcha (1985), the authors also argue that for an exporting firm it is even more important to hedge their production since they are faced with both commodity price uncertainty and exchange rate uncertainty. Hedging refers to a method of reducing a company's market risk, and in the literature, several methods exist for measuring market risk. While hedging has often been used to minimize the variance in income, Stulz (1996) suggests a new method of focusing on eliminating the possibility of costly lower-tail outcomes. Rather than minimizing the variance in income, companies should seek to eliminate any possibility of the lowest income scenarios, as reducing variance also eliminates high outcome scenarios.

Conlon, Cotter and Gencay (2013) examines the impact of investor preferences on the optimal hedging strategy and the associated performance of hedging. The article concludes that for high risk-aversion levels the most effective risk reducing performance is obtained over long horizons, as there is larger uncertainty and therefore risk further into the future. Securing this uncertainty by hedging is therefore very effective to reduce risk. For low risk-aversion levels, the amount of residual risk is found to increase at long horizons, due to the speculative component associated with the hedge ratio. High uncertainty in future outcomes can have potentially high returns, as a result, a low risk-aversion level leads to over-hedging and higher risk. The article uses a mean-variance hedging approach.

Within the scene of electricity markets, Boroumand et al. (2015) investigates the hedging problem for electricity retailers. The hedging problem is evaluated utilizing both the conditional value-at-risk and value-at-risk as risk measures where the joint price and quantity risk faced by a retailer is managed on an hourly basis using intra-day hedging strategies[1]. The article concludes that intra-day hedging strategies have superior efficiency compared to daily, weekly or monthly strategies because the loss with intra-day hedging is nine times smaller than with daily hedging. However, there is a challenge related to liquidity within intra-day financial contracts.

Kettunen, Salo and Bunn (2010) also addresses the problem of hedging for electricity retailers. In this article, a stochastic optimization model based on load and price correlation is presented. Additionally, risk premiums are also implemented for forward contracts, as well as temporal risk preferences[2] during intermediate periods of the contracting horizon. Conditional value-at-risk is used as the main measure of risk due to its coherent properties. The authors conclude that stochastic optimization is more efficient for risk management than either periodic optimization[3] or fixed allocation[4].

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[1]Intra-day hedging strategies are strategies where the optimization period is within one day hedging hourly prices. They often involve intra-day options

[2]Temporal risk preferences refer to the risk associated with a change in price or volume over time.

[3]Periodic optimization is referred to as a method where one optimal portfolio is determined for each predefined period.

[4]Fixed allocation is referred to as a strategy where a fixed percentage of futures are purchased.

While the hedging problem for electricity retailers can be related to the hedging problem for an electricity producer, there are also some literature focusing specifically on the latter. In the article by Fleten, Bråthen and Nissen-Meyer (2010), an optimization model for deriving static hedging strategies for an electricity producer is presented. In this example, the hedge positions are derived by maximizing the expected revenue subject to constraints on the portfolio variance and value-at-risk (VaR). The static strategies[5] are compared to the case with no hedging also called the natural hedging strategy. The results show that hedging with use of forward contracts significantly reduces the risk in terms of VaR, CVaR and standard deviation. However, it has been shown that a static position is hard to derive for a longer period of time because of the rapid shift in characteristics of the forward contracts. This suggests that a model that incorporates possible future shifts in the weights during optimization may yield better results.

There is support for this statement in another article by Fleten, Wallace and Ziemba (2002). This article considers the perspective of a price-taking electricity producer operating in the wholesale market. A basic stochastic linear optimization model for portfolio management is presented. The study concludes that using dynamic stochastic models for production schedules and static models for financial contracts and running them sequentially is not the most effective method to minimize risk. The stochastic programming implementation of the integrated dynamic model on an example portfolio indicates a risk reduction of about 32 percent (for the same level of expected profit) compared to industry practices.

Aside from the articles mentioned above, there are also some dissertations on decision making for power producers. In the doctoral thesis by Morente (2011), the main objective was to create a mathematical programming model for a power producer's decision making over the medium-term horizon. The thesis proposes a stochastic programming model for modeling the uncertainty in the electricity pool

[5]Static hedging strategies are strategies where the positions are not changed as new market information becomes available.

price as well as the possibility of generator failure. Since stochastic programming may result in a large number of scenarios, the thesis also includes a few scenario reduction techniques to reduce complexity and speed up calculations. The conditional value-at-risk was selected as a risk measure due to its strong mathematical properties. The risk aversion level of the producer is also considered. In summary, the thesis contributed to the literature through its analysis of a two-stage stochastic programming problem with recourse that included risk from volatility in the pool price and risk of failure in the generating units.

In the master thesis of Nersten and Dimoski (2018), the authors examine how to manage the market risk of a Norwegian hydropower producer. This thesis presents a long-term dynamic hedge model for a price-taking hydropower producer with a single plant that participates in the Nordic electricity markets. The nested conditional value-at-risk (CVaR) was employed to model risk preferences. The time frame was two years and the granularity was semi-monthly. Taxes and transaction costs were also included, but the tax effects were dismissed as being minimal. The analysis concludes that a sequential approach in which optimal production is determined first, and then cash flows are hedged through the use of electricity futures, is more beneficial than a simultaneous approach. This is mainly because the simultaneous model does not treat production as a risk-neutral maximization problem, as it considers risk-aversion. This conclusion is in contrast to Fleten, Wallace and Ziemba (2002). Finally, based on the modeling results, they conclude that over-hedging expected production is optimal.

An additional master thesis by Galvez (2011) points out the fact that the medium term risk generated by stochastic fluctuations of locational electricity prices is extremely relevant for power producers with electricity generators available in more than one location on the same market. To address this risk, the thesis developed a methodology for recommending contractual positions that maximize expected profits while balancing the risk exposure. Moreover, the thesis stated that the correlation between different locational electricity prices is of interest since it may impact the relationship between expected profit and risk. A major contribution by this thesis is to consider a power producer with generating units located at several different locations, each setting up its own electricity pricing scheme. Changes in the correlation parameter of the model presented for locational electricity prices also had a significant impact on the efficient frontier between expected profit and risk.

3.1 Summary

All of the literature discussed in this section is relevant to what this thesis examines. There is already considerable literature surrounding medium-term risk management in the hydropower sector. The literature presented suggests that hedging is an effective method of reducing fluctuations in revenues between years. Additionally, it has been demonstrated that eliminating the possibility of lower-tail outcomes can be more effective than minimizing income variance because the effect on higher-outcome scenarios is minimal. It is shown that linear stochastic optimization with the use of the conditional value-at-risk as a risk measure is a sound methodology that is backed by multiple sources. It is also demonstrated that such a model would add value to the risk management strategies of hydropower companies.

A debate exists in the literature over whether a sequential or an integrated model is preferable. Production schedules and hedging of this production can be determined within the same model, although this model requires a large amount of computing power. Hence, a sequential model in which the production schedule is planned first, and then the hedging portfolio is chosen through stochastic optimization, can be an excellent alternative. This is because it is easier to run and still takes into account potential future shifts in weights.

Morente (2011) and Nersten and Dimoski (2018) had a bigger impact on the methodology proposed in this thesis because they addressed some of the same issues as is presented here. Comparatively to the thesis by Morente (2011), this thesis focuses on the Nordic energy market and a Norwegian hydropower producer, and it can be assumed that these changes influences the model. In addition, this thesis does not take into account the failure of generating units, as this is taken into account by entities other than the hedging portfolio. In contrast to the thesis by Nersten and Dimoski (2018), which is also concerned with a Norwegian hydropower producer, this dissertation aims to analyze why over-hedging occurs and what the model results are without over-hedging. Finally, this thesis also considers tax effects more carefully and discuss how these effects affect the model and the hedging strategy.

In summary, his thesis differs from previous literature in the way that it looks at a hedging horizon of 2,5 years including monthly, quarterly, and annual contracts. Furthermore, this thesis examines how the income gained in low income scenarios and the income lost in high income scenarios change when the model objective changes. In addition, this thesis examines the Nordic market, specifically Norway, which impacts the model as, for example, Norway has a high resource rent tax level. Finally, this thesis discusses how the resource rent tax influences the model results and the optimal hedge strategies. The next chapter presents the methodology chosen for the model in this thesis, as well as some limitations to the model.

Chapter 4

Methodology

This chapter provides a description of the methodology. Among the items presented is a list of all the assumptions made in the model, an overview of the chosen risk measure and a description of the solution method.

4.1 Assumptions

This thesis examines the hedging problem faced by a price-taking hydropower producer operating in a deregulated market. The above is a simplified assumption, and it is reasonable to assume that not all hydropower producers are price takers in such a market, especially if there are only a few large producers with large water reservoirs. However, in order to simplify the problem, a price-taking producer is considered.

The producer may choose to create a power portfolio that includes long positions in physical production and short positions in financial futures contracts. Hafslund Eco already has advanced stochastic optimization models for optimizing their hydropower disposition. These models are based on sample spaces from weather scenarios and price scenarios. In consequence, the model presented in this thesis does not optimize the production policy of a hydropower producer. Rather, this thesis examines how a producer can optimize their portfolio of derivatives in order to meet their risk preferences when faced with different production scenarios. In other words, the paper examines the trade-off between securing income against volatility in power prices and maximizing expected income.

The producer featured in this thesis owns several hydropower plants in the NO1, NO3 and NO5 price areas in Norway. Their sizes and production capacities vary. Additionally, some of the plants have a low regulating ability since they are run-of-river plants. At the time of the data collection (June 2020), the portfolio of hydropower plants had a total production volume of 14 TWh. In this model, NO5 represents the area price of all areas. This is a simplification mainly due to the fact that NO1 and NO5 are highly correlated in price (see figure 4.1) and the volume produced in NO3 is very small.

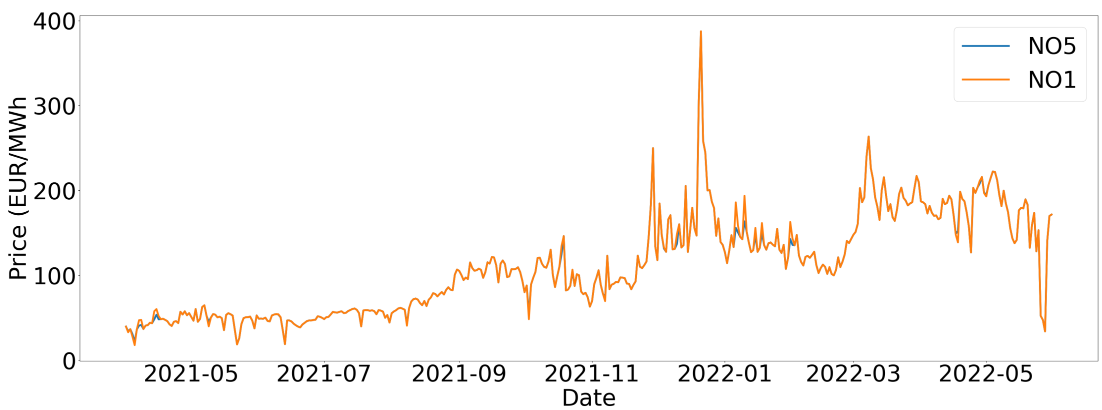

Figure 4.1: Historical NO5 price compared to historical NO1 price with price on the y-axis and month on the x-axis.

Furthermore, all financial trading is carried out with the Nordic system price as the trading instrument. The uncertainty in the production volumes per month, as well as in the prices of NO5 and the system price are modeled by Hafslund Eco. Although the financial trading is conducted with the Nordic system price and the physical trading is conducted with the NO5 area price, the model in this thesis does not account for trading of EPAD contracts. The reason for this choice is that there has been a low level of liquidity on the EPAD market for many years. In addition, there has been a low difference in price between the NO5 area price and the system price. Moreover, the model assumes that exchange rate hedging of the difference between EUR and NOK is handled outside the model. The model proposed in this thesis has a timeframe of 2,5 years.

The model proposes trading volumes where positive numbers represent volumes sold and negative numbers represent volumes bought. Moreover, the model assumes infinite liquidity. This means that the model assumes that the producer is able to trade the entire volume at that exact time and at that exact price. Additionally, the model assumes no transaction costs. These are simplifying assumptions, as the producer would have difficulty selling that volume at that price in the market. The producer may be required to split the volume and trade it at different prices. However, this depends on how frequently the model runs and how often the prices are updated. Once the model is operational, it could be run every minute or less to obtain the latest prices and thus would be more accurate.

The model also accounts for corporate tax and resource rent tax. The corporate tax affects all earnings, whereas the resource rent tax only affects the volume traded on the physical market. In the baseline model, the corporate tax rate is 22 percent and the resource rent tax is 37 percent. As a profit maximising producer Hafslund Eco cannot tolerate a negative income over the course of one financial year in any scenario. Accordingly, the model includes a constraint that the annual revenue from each scenario must be positive. This constraint includes the year 2020 even though there only exists data for half of the year. Negative income scenarios are thus excluded. Finally, as trading volume is not restricted, speculative trades are allowed in the model if it is optimal. The next section provides a description of the chosen risk measure to the model.

4.2 Risk measure

The conditional value-at-risk is used as the risk metric in the model presented in this thesis. This is due to the fact that, as explained in the article by Stulz (1996), eliminating lower tail income scenarios is more advantageous than minimizing the portfolio's variance as a whole. By eliminating the lower tail income scenarios, the worst case scenarios are excluded from the distribution. This is more beneficial than reducing the overall variance of the distribution, which may also result in an elimination of the high income scenarios.

The conditional value-at-risk for a confidence level α of a profit distribution is defined as the conditional expectation of the values of the probability distribution lower than the α-quantile. It is closely related to the value-at-risk which is the income at the α-quantile. The conditional value-at-risk is favored in this scenario because it considers long and short tails in the income distribution, while value-at-risk only considers the threshold values at a specific point in the distribution. Moreover, the conditional value-at-risk is convex and can therefore be modeled effectively using linear programming (2011). Since the conditional value-at-risk is convex, there should exist a global optimum for a given solution space. In addition, the use of conditional value-at-risk as a risk metric is well documented in the literature (by (2011), (2018), (2015), and (2010)).

In figure 4.2, the conditional value-at-risk is demonstrated on a profit probability density function.

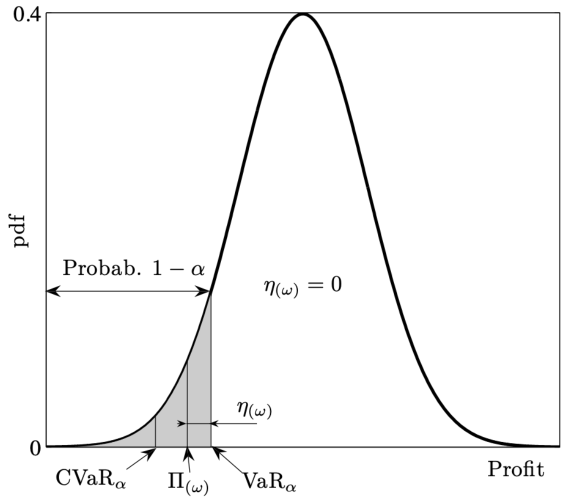

Figure 4.2: Illustration of the conditional value-at-risk for a probability density function (Copied from Morente (2011)). The value-at-risk is included, as well as an example of a profit scenario (Π_w) below VaR where η_w is the difference between that profit scenario and the VaR at otimal solution of CVaR. α is referred to as the confidence level used to calculate the CVaR or VaR.

4.3 Solution method

Stochastic programming provides an appropriate modeling framework for problems involving uncertainty. This framework is based on the knowledge of the distribution functions of the uncertain parameters. Based on these distributions, it is possible to generate a set of plausible outcomes for the uncertain factors, with associated weights or probabilities of occurrence. Having generated outcomes, or scenarios, it is possible to formulate a mathematical programming problem that determines optimal decisions in accordance with a given objective function.

The stochastic optimization problem considered in this dissertation is stochastic linear programming, which is multi-period linear programming that accounts for uncertainty during the planning process. The uncertain parameters in this thesis is the NO5 area price, the Nordic system price and the production level per month. As mentioned, these uncertain parameters are represented by different scenarios with associated probabilities of occurrence. The probabilities or weights associated with the scenarios in this thesis is equal, meaning that all scenarios are equally possible.

The objective is to determine the optimal course of action in the futures market given a certain level of risk-aversion, current prices in the futures market, and underlying price-volume simulations. Based on a chosen level of risk aversion, the program visualizes an effective frontier where the end-user can discover the optimal trading volume per futures contract by varying the weight between downside risk and expected income.

To evaluate whether the model is able to reduce the worst income scenarios, a scenario with no hedging is compared to a scenario with optimal hedging. In view of this, the first optimization problem is to maximize the conditional value at risk in the absence of hedging. In a no-hedging situation, the hydropower producer would only sell their production on the spot market. Therefore, the income function would look as follows,

$$\Pi_w = \sum_{m=1}^{M} \lambda_{m,w}^{NO5} P_{m,w} L_m^M (1 - \tau^r - \tau^c) \quad \forall_w \in \Omega \tag{4.1}$$

where $\lambda_{m,w}^{NO5}$ is the spot price of the NO5 area price for month m in scenario w, $P_{m,w}$ is the production volume for month m in scenario w, L_m^M is the length of month m in hours, τ^r is the resource rent tax and τ^c is the company tax.

Furthermore, when there is no hedging, the objective function is limited to maximising the conditional value at risk (CVaR) of the income distribution. This is because in the absence of hedging there is only one distribution of income, and the CVaR from this situation should be compared with the CVaR of a scenario with hedging. As the worst-case scenarios in the income distribution is examined, CVaR is a function of income. Consequently, the $CVaR_\alpha$ of an income distribution can be calculated solving the following optimization problem,

$$Maximize \quad CVaR_{\alpha}[\Pi] = \xi - \frac{1}{1-\alpha}\sum_{w=1}^{\Omega}\pi_w \eta_w \tag{4.2}$$

$$subject \quad to \quad \xi - \Pi_w - \eta_w \leq 0 \quad \forall_w \in \Omega \tag{4.3}$$

$$0 \leq \eta_w \quad \forall_w \in \Omega \tag{4.4}$$

where Π_w is the income in scenario w with an associated probability of π_w and ξ is an auxiliary variable whose optimal value is the VaR_{α}. At the optimal solution, the value of η_w represents the difference between the VaR_{α} and the value of the income in scenario w, for all scenarios having a profit lower than the VaR_{α}. In the other scenarios, η_w is equal to zero.

Henceforth, the conditional value-at-risk is expressed as $CVaR_{\alpha}[\Pi]$ and it always refers to equation 4.2. Throughout this model α is equal to 0.95, which signifies that CVaR is calculated for the 5% worst income scenarios. This is done in order to capture the income in the outer points of the lower income distribution.

Following the first optimization and saving the resulting CVaR, the model proceeds to the second optimization. With this optimization, hydropower producers can hedge their production in the financial markets. As a result, the income function has been altered,

$$\begin{aligned}\Pi_w = &\sum_{m=1}^{M}\lambda_{m,w}^{NO5}P_{m,w}L_m^M(1-\tau^r-\tau^c) \quad + \\ &\sum_{m=1}^{M}(\lambda_m^{MC}-\lambda_{m,w}^{sys})H_m^M L_m^M(1-\tau^c) \quad + \\ &\sum_{q=1}^{Q}(\lambda_q^{QC}-\lambda_{q,w}^{sys})H_q^Q L_q^Q(1-\tau^c) \quad + \\ &\sum_{y=1}^{Y}(\lambda_y^{YC}-\lambda_{y,w}^{sys})H_y^Y L_y^Y(1-\tau^c) \quad \forall_w \in \Omega\end{aligned} \tag{4.5}$$

where the first part is evident as the income from the spot market as explained in equation 4.1. In the new parts, λ_m^{MC} represents the last close price of the financial contract for month m, λ_q^{QC} represents the last close price of the financial contract for quarter q, λ_y^{YC} represents the last close price of the financial contract for year y and $\lambda_{m,w}^{sys}$ represents the spot price of the system price for month m in scenario w (Same for $\lambda_{q,w}$ and $\lambda_{y,w}$, only for quarters and years). H_m^M, H_q^Q and H_y^Y represent the hedging volumes sold in the futures market for the month m, quarter q and year y respectively. Each contract is measured in hours, to account for differences in lengths of each contract, and represented by L_m^M, L_q^Q and L_y^Y. As in the equation 4.1, τ^c represents the company tax and τ^r represents the resource rent tax on hydropower.

To make quality decisions regarding their investments, the hydropower producer must determine whether they are seeking to maximize their expected income, maximize their conditional value at risk, or something in between. In that regard, the objective function of the second optimization problem consists of a consideration between the expected income and the CVaR. To represent the consideration between these two measures, a weighting parameter $\beta \in \{0..1\}$ is introduced. In the case where β is zero, the objective function is to maximize expected income and it reflects a situation where the producer has no risk aversion. When β is one, the objective function is to maximize the CVaR of the income distribution, and the producer is considered to be highly risk averse. Values between zero and one represent a situation where the hydropower producer weighs both options into the model. As the goal is to provide an overview of the results for different levels of risk aversion, the optimization runs from $\beta = 0$ to $\beta = 1$, with an increment of 0.5 for each run.

$$Maximize \quad (1-\beta)E[\Pi] + \beta CVaR_{\alpha}[\Pi] \tag{4.6}$$

$$subject \quad to \quad \xi - \Pi_w - \eta_w \quad \forall_w \in \Omega \tag{4.7}$$

$$0 \leq \eta_w \quad \forall_w \in \Omega \tag{4.8}$$

$$0 \leq \Pi_{w,y} \quad \forall_{w,y} \in \theta \tag{4.9}$$

where β represents the weight on $CVaR_{\alpha}[\Pi]$, $E[\Pi]$ represents the expected income and $\Pi_{w,y}$ represents the income in year y for scenario w. Equation 4.7 and 4.8 are as described above. As a profit maximizing producer, the constraint represented by equation 4.9 indicates that negative income over a year in any scenario is unacceptable. The optimal hedging volume resulting from each increase in β is extracted to perform the last optimization, in which the optimal $CVaR_{\alpha}$ for each beta is calculated. As a last optimization, the optimal hedging volume from the second optimization is used as input into the income function (4.5) and optimization 4.2 is repeated with the extended income function as input. The last optimization aims to find the optimal $CVaR_{\alpha}$ for each β so the model is able to establish an effective frontier between expected income and CVaR. As a result of this frontier, the hydropower producer is able to see the impact that different levels of β has on expected income and the resulting CVaR, and the trade-off between them. The next chapter will provide a description of the data used in the model and how it is generated.

The model has been programmed using Python PULP which is a python package with a linear programming modeler. The optimizer used is COIN-OR CLP, which is the COIN-OR Linear Programming solver. The code related to each optimization problem and the income function can be found in Appendix 3.

Chapter 5

Data

This chapter provides a closer look at the data used in the analysis of the model. The presentation includes a description of where the data originates, how it is structured, and an exploration of the data. The table 5.1 gives a brief overview of the data that is used in this thesis. Hafslund Eco has provided all of the data and has either produced it from internal models or acquired it from their internal database. The data was collected on the 14^{th} of June 2020 and reflect the market conditions at that time.

Datatype	Time-frame	Granularity	Rows
NO5 area price scenarios	15.06.2020-31.12.2022	Monthly	990
System price scenarios	15.06.2020-31.12.2022	Monthly	990
Production scenarios	15.06.2020-31.12.2022	Monthly	990
Financial forward curve	15.06.2020-31.12.2022	Daily	930

Table 5.1: Table of short data overview

5.1 Scenario generation

Price scenarios produced by Hafslund Eco are presented for the Nordic system price and the NO5 area price. They have a monthly granularity. The production scenarios represent the total production of the hydropower portfolio, with a monthly granularity as well.

Hafslund Eco, as many other Norwegian hydropower producers, have a close collaboration with Sintef, an independent research organization. As a result, some of the models that Hafslund Eco use in their prognoses are from Sintef. One of these models is EMPS or EFI's Multi-area Power-market Simulator. This model is a tool for forecasting and planning in electricity markets, accounting for transmission constraints and hydrological differences between major areas or regional subsystems (C. B. M. Sintef n.d.) (See more information in appendix 4). At Hafslund Eco they use EMPS to simulate power prices. EMPS simulate power prices based on historical weather data from 1981 to 2015 and the result is 35 price scenarios. ProdRisk is another modelling tool made by Sintef, based on stochastic dual dynamic programming. ProdRisk enables stochastic optimization with a large number of reservoirs. The solution approach combines system simulation and strategy computation to find an optimal hydro release strategy (C. H. O. H. Sintef n.d.) (See more information in appendix 5). In Haflsund Eco they use ProdRisk to make production volume scenarios based on historical weather data from 1981 to 2015.

In addition to EMPS and ProdRisk, Hafslund Eco use an energy and trading risk management system called Elviz for price simulations. Elviz is an Energy trading and risk management (ETRM) system used to manage the core business area of Hafslund Eco. The system is used from managing contracts to monitoring hedging and trading activities, calculating profit and loss , measuring risk , simulating price scenarios, and reporting. In Elviz, a Monte Carlo simulation of price paths is performed for the same period as EMPS. The reference period 1981 to 2015 is used as a baseline for weather scenarios. The price scenarios in Elviz are based on a stochastic model that simulates forward prices for power and other commodity markets. The volatility used in the simulation is spot price volatility. The time resolution of the prices from Elviz is also monthly and 990 prices are simulated per month for the Nordic system price and NO5 area price. To customize the 35 production scenarios and 990 price scenarios, a connection is made between Elviz and the 35 production scenarios generated from ProdRisk. The idea is to connect one or more price scenarios from Elviz to a production scenario from ProdRisk with corresponding price scenario in EMPS, which is somehow the closest price scenario from Elviz.

Hafslund Eco uses a minimization of mean root squared errors to evaluate which production scenarios the price scenarios should be connected with. In practise, for each price in the 990 scenarios from Elviz, the model calculates a square deviance for each price from EMPS. This results in a matrix which is used to connect price scenarios from Elviz with production scenarios from ProdRisk. This method was developed with the help of Norsk Regnesentral. The result is a sample space for both price scenarios and production scenarios, where there are 990 price scenarios combined from two different models and 35 production scenarios that are duplicated up to 990 scenarios.

5.2 Financial prices

As input to the model, financial prices are based on an internally produced forward curve derived from the Nordic financial prices provided by Nasdaq. The forward curve is compiled from an internal Hafslund Eco database. In order to produce the forward curve, Hafslund Eco has gathered data from all the yearly contracts traded on Nasdaq. All monthly prices are equal to the corresponding yearly price. Afterwards, all quarterly contracts are gathered, and the monthly prices are adjusted to match those of the corresponding quarter. The weighted average of all quarterly prices within a year should be equal to the annual price so that there are no arbitrage opportunities. When there are only available quarterly contracts for half of the year, one has to adjust the remaining months so that the weighted average for the entire year is equal to the yearly price. The same procedure applies for monthly and weekly contracts. To account for the fact that some weeks might fall within multiple months, the forward curve is adjusted to daily prices. Using hours as weights, the curve is also adjusted for summertime and wintertime.

In order to incorporate monthly, quarterly, and yearly contract prices into the model, some data manipulation was performed. The daily prices were multiplied by the number of hours during the day, summed, and divided by the number of hours in a month to obtain monthly prices. The same procedure was used for months to calculate quarterly prices, and for quarterly prices to calculate yearly prices. By taking the weighted average, the difference in hours during a period is reflected in the price, including differences related to summertime and wintertime. It is also ensured that there are no arbitrage opportunities. The resulting data were monthly, quarterly, and yearly prices from the financial forward curve, which are incorporated into the model as hedging contracts.

5.3 Data exploration

The purpose of this section is to examine the data used in the model. The data is analyzed and displayed to obtain further insight into how the data that enters into the model behaves. The price and production scenarios are discussed first, with a focus on how they develop over time. Finally, the financial forward curve is analyzed and compared with the price scenarios.

5.3.1 Price and production scenarios

The scenarios are divided into three separate CSV-files, one for the NO5 area price scenarios, one for the system price scenarios and one for the production scenarios. The scenario generation model ran on the 14^{th} of June 2020, so these price scenarios are based on what the model predicted at that time. As a result, all of the CSV-files cover the same period from mid-June 2020 to the end of December 2022. As the files contain only half of June, the contract is no longer available for trading at Nasdaq and therefore June is not included in the data. Each column represents a month, and each row represents one scenario. In total, there are 990 rows in the CSV files, corresponding to 990 scenarios. In appendix 1 there is a snippet of the data from each CSV file, divided into columns for better reading (See Appendix 1). Additionally, in appendix 2 there are graphs of the different datasets (See Appendix 2).

The NO5 area price data set contains prices ranging from 3,08 EUR/MWh a month to 64,70 EUR/MWh a month. Based on figure 5.1, the NO5 area price is affected by seasonality, where the price is higher during the winter months and lower during the summer. Norway experiences extremely cold weather during the winter, which coupled with a high degree of electrical heating results in a large demand for electricity. Additionally, the country experiences relatively mild weather during summer, which results in a modest air conditioning load. However, the figure indicates that the difference between summer and winter prices in this data set is relatively low. Furthermore, the difference between the mean price and the max price is larger than the difference to the min price. This may indicate that the majority of the scenarios are lower in price than the max price. Last but not least, the difference between the lowest and highest price scenario is greatest during the winter months.

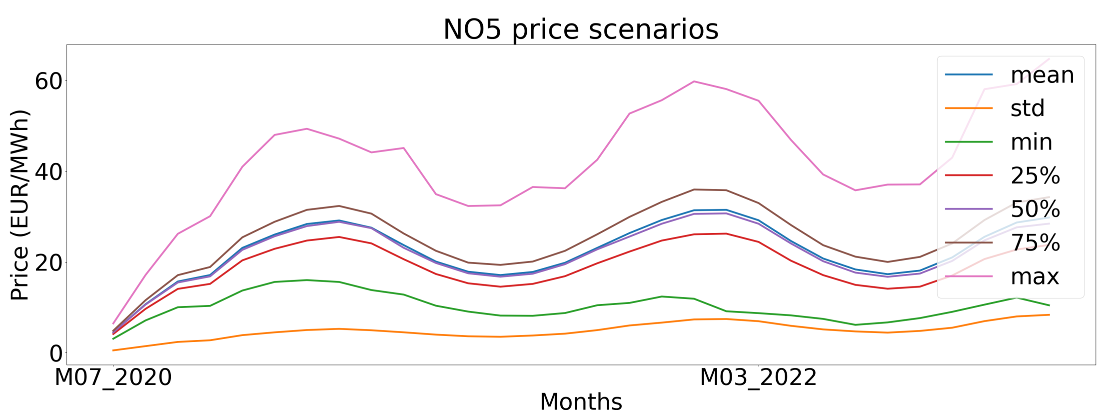

Figure 5.1: Plot of NO5 price scenario statistics with price on the y-axis and months on the x-axis from 07.07.2020 to 31.12.2022. Lines represent different statistics of the underlying data.

The system price data set includes prices ranging from 4,37 EUR/MWh per month to 67,81 EUR/MWh per month. The system price exhibits the same seasonality as the NO5 price, as shown in figure 5.2. Considering that the two prices have been highly correlated for many years and represent a similar geographical area, this is not surprising. However, it appears that the system price has higher peaks than the NO5 area price dataset during the winter months. It is difficult to determine why this is so without having full knowledge of how the scenarios were generated, although it may have something to do with the fact that the system price is a composite of all price areas.

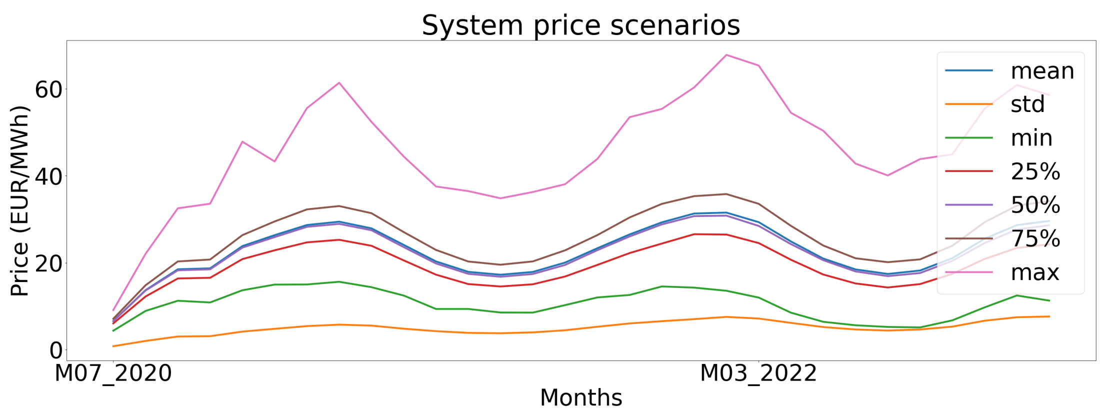

Figure 5.2: Plot of system price scenario statistics with price on the y-axis and months on the x-axis from 07.07.2020 to 31.12.2022. Lines represent different statistics of the underlying data.

By looking at the average price scenario for each month, it is clear that the NO5 area mean price and the mean system price are highly correlated throughout the period, almost identical (Figure 5.3). This may be an indication that the Nordic system price is a good hedging instrument for the NO5 area price for the investigated time period.

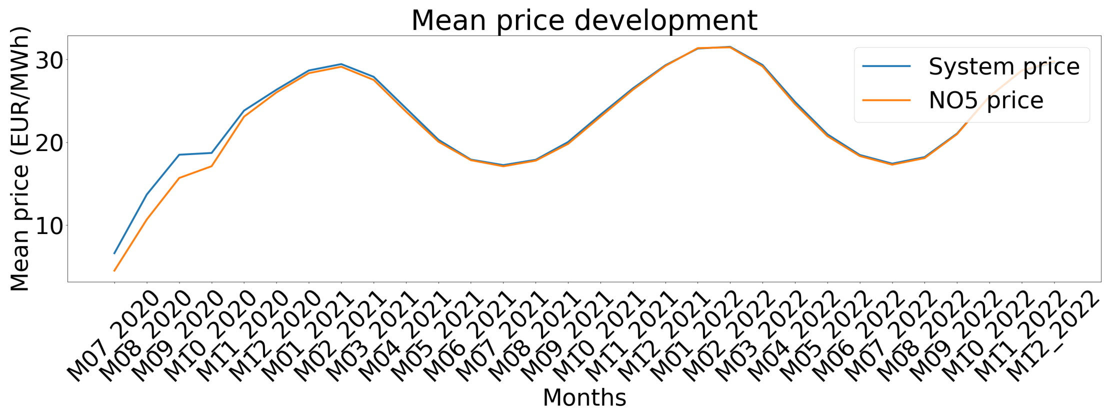

Figure 5.3: Plot of mean price of NO5 and system price scenarios with price on the y-axis and months on the x-axis. Lines represent the mean price scenario of the system price and the NO5 area price.

There are also quarterly and yearly price scenarios for the Nordic system price, which are derived to match the granularity of the financial hedging contracts. The quarterly price scenarios range from 5,69 EUR/MWh to 64,10 EUR/MWh, with the first quarter of 2022 having the highest mean price. The quarterly price scenarios are shown in figure 5.4, which exhibit the same seasonality as the monthly price scenarios. Prices are typically highest in the first quarter, including January, February, and March of each year. In the meantime, prices are at their lowest in the third quarter, which includes July, August, and September. With respect to the yearly price scenarios, they range from 12,46 EUR/MWh to 65.25 EUR/MWh, where 2022 has the highest mean price scenario. According to figure 5.5, it appears that the mean prices of both years are almost identical. The data confirm this, as the difference in the mean price scenario is 2,25 EUR/MWh. The figure also indicates that the year 2022 has a higher volatility of price scenarios than the year 2021.

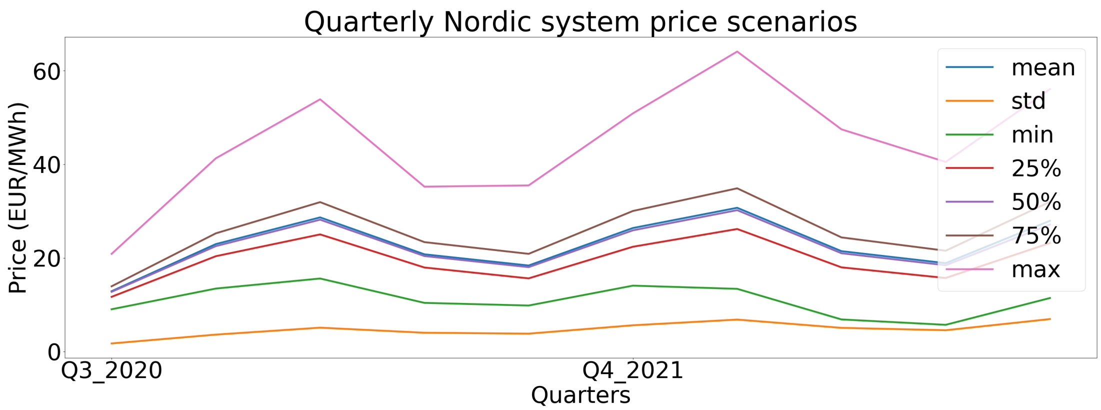

Figure 5.4: Quarterly system price scenario statistics with price on the y-axis and quarters on the x-axis from Q3-2020 to Q4-2022. Lines represent different statistics of the underlying data.

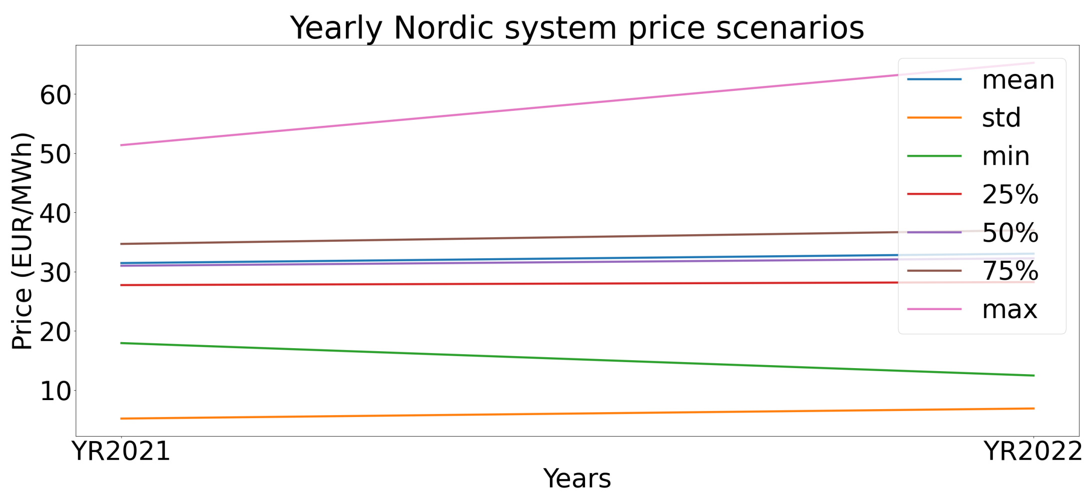

Figure 5.5: Yearly system price scenario statistics with price on the y-axis and years on the x-axis (YR2021 and YR2022). Lines represent different statistics of the underlying data.

The production scenarios range from 437,3 MWh per month to 1871,7 MWh per month. According to the figure 5.6, the production volume also exhibits some seasonality, with the production expected to be lowest in April each year. The reason for this is that Norway usually experiences spring flooding in April after the snow melts in the mountains. The spring flood leads to an increase in unregulated run-of-river power plants which have no, or very small reservoirs, and hence produce the majority of its power from local inflows and precipitation.

A producer who mostly owns this type of power stations would anticipate a surge in production during this month. However, since this uncontrolled increase in electricity usually coincides with decreased demand for electricity due to warmer weather, electricity prices are low, leading to owners of more controllable power plants holding back their power in preparation for periods of increased demand. Due to this, the low production level during April in this dataset indicates that Hafslund Eco has more controllable power stations with large reservoirs than run of river power stations. The result is a decrease in production in April. Lastly, production is at its highest during the winter, which is due to a higher demand and a higher price.

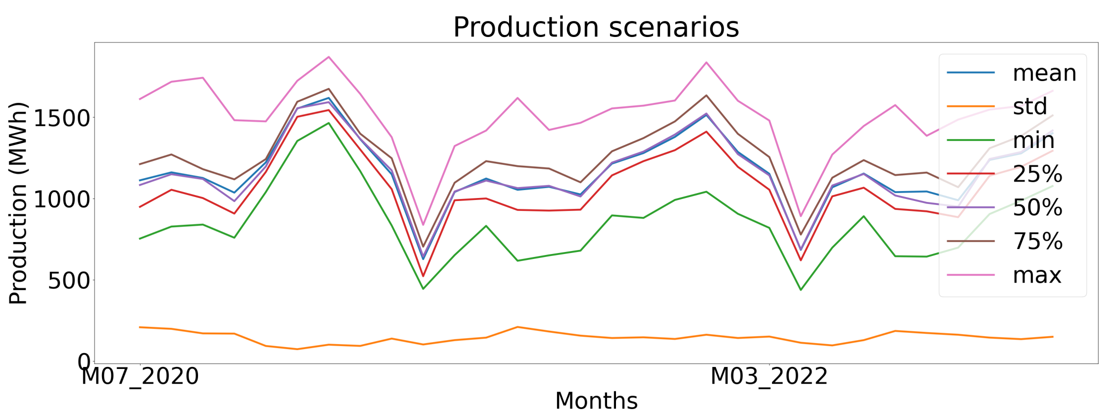

Figure 5.6: Plot of production scenario statistics with production on the y-axis and months on the x-axis from 07.07.2020 to 31.12.2022. Lines represent different statistics of the underlying data.

In figure 5.7, the mean production scenario is compared to the average price scenario for NO5. The figure indicates that when the mean price scenario for NO5 is high, the mean production scenario is also high. This seems reasonable since the producers will want to produce at high prices. The biggest deviation from this trend occurs in April of each year, when production is at its lowest.

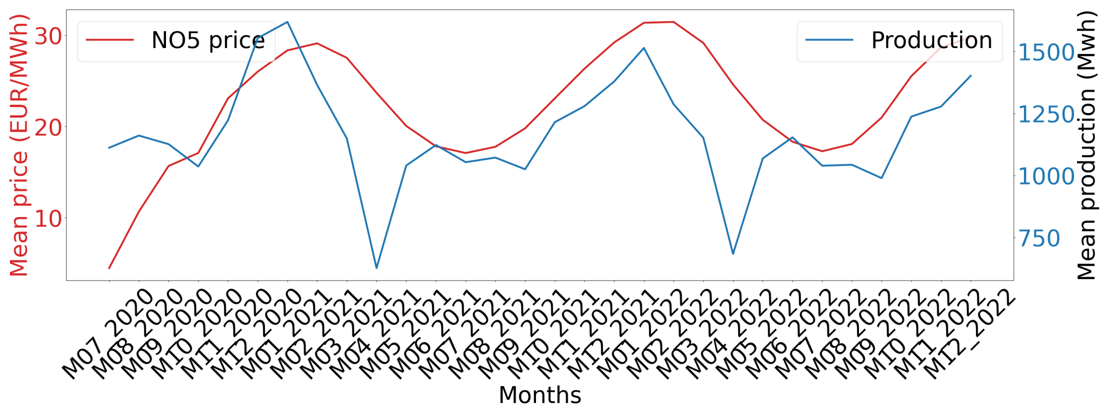

Figure 5.7: Plot of mean production compared to NO5 mean area price with production and price on the y-axis and months on the x-axis. Lines represent mean NO5 price scenario and mean production scenario

5.3.2 Financial prices

The financial forward curve is stored in a CSV file. The forward curve was generated on the 14^{th} of June 2020, so the prices reflect the market outlook on that date. As a result, the CSV-file contains data from June 2020 to December 2022. The CSV-file contains one column for dates and one for price, each row representing one day. The total number of rows is 930. The forward curve has a daily granularity, with prices ranging from 2,86 EUR/MWh to 31,7 EUR/MWh.

The monthly forward price is displayed in figure 5.8. As with the price scenarios, the forward curve also reflects seasonality with lower prices during the summer months. This is also evident from figure 5.9, which shows the quarterly prices. In figure 5.10, the yearly prices are displayed. They show that the forward price for 2022 is higher than that for 2021.

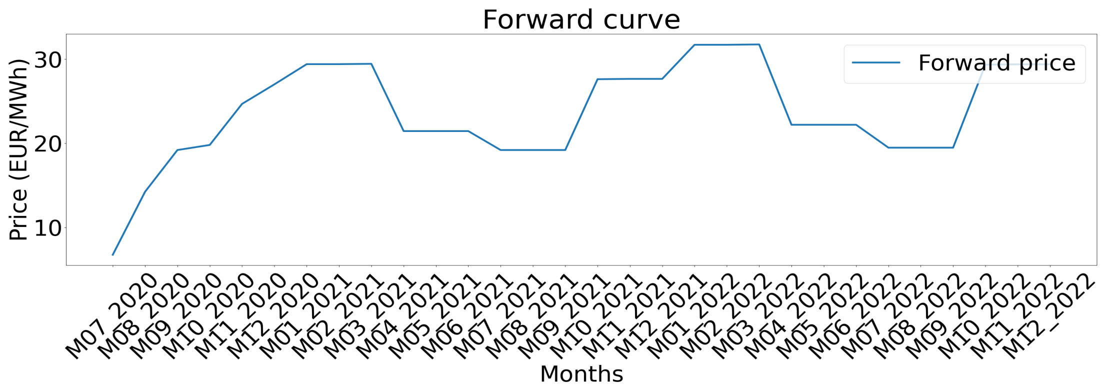

Figure 5.8: Forward curve (monthly granularity) with price on the y-axis and months on the x-axis.

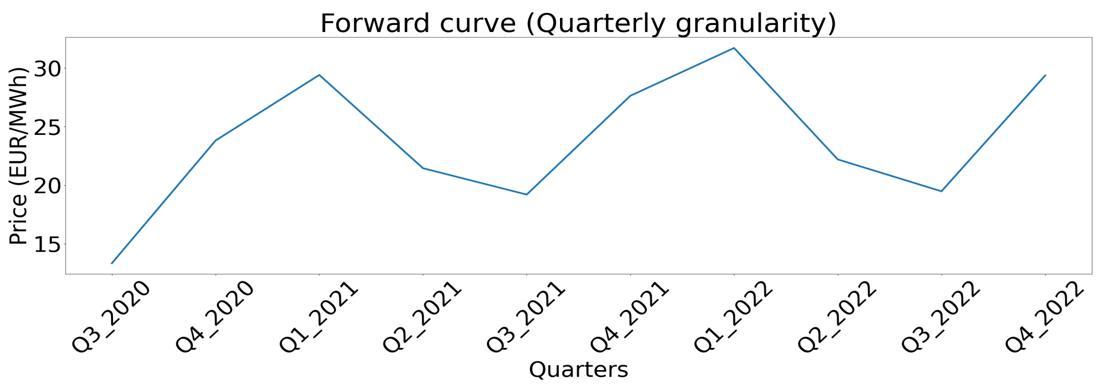

Figure 5.9: Forward curve (Quarterly) with price on the y-axis and quarters on the x-axis.

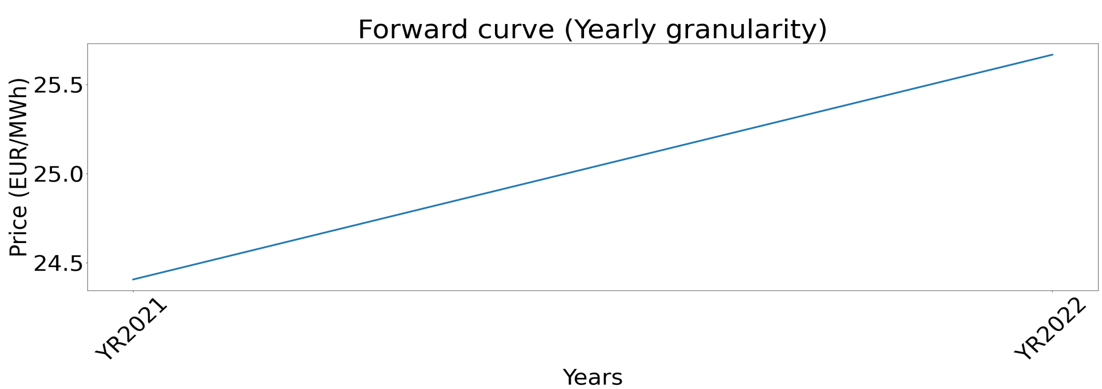

Figure 5.10: Forward curve (Yearly) with price on the y-axis and years on the x-axis.

Figure 5.11 compares the forward price to the NO5 mean area price and the mean system price. From the figure, it can be seen that the prices are highly correlated, although the forward price is a bit higher during the summer months.

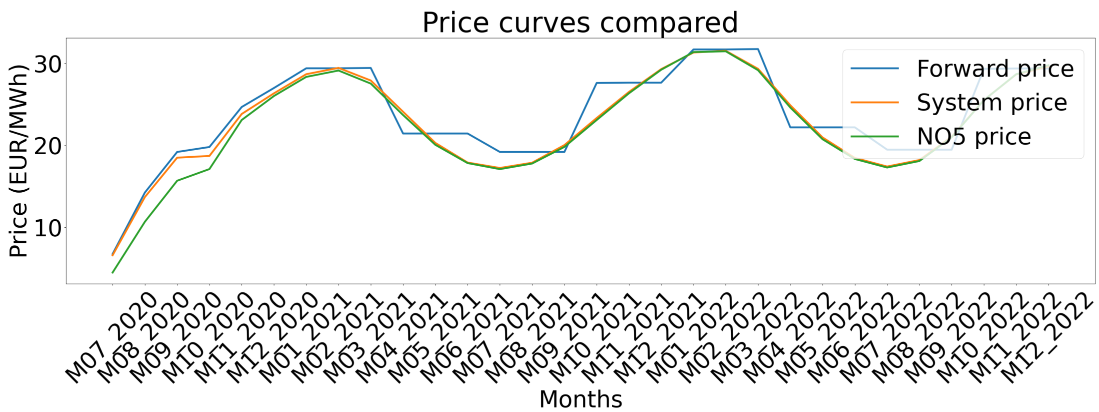

Figure 5.11: Forward curve, system price and NO5 area price compared with price on the y-axis and months on the x-axis.

In the following section, some of the main expectations from the data are highlighted.

5.4 Expectations from the data

This section explains the main expectations from the data. According to intuition, the model should choose to hedge in months where production is expected to be high. In the context of hedging, these periods would be beneficial, as they are when the volume of production is at its peak. Therefore, a decrease in price would significantly affect income during these periods. Thus, from figure 5.6, it is evident that the model would hedge the months within quarter one, three, and four.

Figure 5.11 illustrates that the forward curve is significantly higher than the mean modelled prices for certain months, such as June, July and October. Given that the financial market income is calculated by subtracting the modelled price from the financial price, it can be expected that the model will hedge these months. This is in contrast to the previous statement as June is a part of the second quarter.

Since the financial income function and therefore the volume of financial hedging depends on the difference between forward prices and the modelled price scenarios, it is reasonable to assume that the price effect of a high financial price in the model is greater than the production volume effect. As a result, it should be expected from the data that the model will hedge June, July, and October.

Based on the data presented in this chapter, the next chapter provides an analysis of the model results.

Chapter 6

Analysis

This section of the thesis evaluates whether the model is able to perform as expected, I.E. whether the CVaR increase as the weight on risk increases. Additionally, the analysis looks at how this affects the expected income and the highest income scenarios. The analysis also includes a study of tax effects, as well as what happens when hedging volume is restricted to avoid over-hedging.

The optimization problem has 1033 decision variables and 4950 constraints in the base case scenario. Running the optimization problem on an Intel Core i7-10510U CPU with 16GB RAM took approximately five minutes.

6.1 General analysis of the model results

After running the model as described in the solution method, the results contain trading volumes proposed by the model for the different β values. Moreover, the results contain an income distribution for each hedging strategy. In figure 6.1, the trading volumes are displayed in a stackplot where the x-axis shows the different values of β. The plot demonstrates that the trading volume is higher for a low β than a high β. This may seem counter-intuitive at first, however if there is a sufficient amount of low price scenarios in the model input, over-hedging provides risky opportunities for high incomes. Over-hedging is risky because it leads to speculative investments if the underlying deliverable is non-existent when the contract gets to delivery. In that case, the producer would have to get the corresponding volume on the open market. This would result in a profit or a loss depending on how the price develops over the time period.

As there is no limitation on trading volume in the model, when β is low, the model trades more financial contracts as long as it results in higher expected income. Since the financial prices are based on the market price and the price scenarios are based on a modelled price, there may be larger differences in prices in the model than in reality. If the market price is higher than the modelled price the optimization model chooses to trade more contracts. The trading volume goes down as β increases because more trading volume, and trading volume above hedging levels, equals over-hedging and speculative trades. The upside can be significant, but the downside increases as well. Hence, when β is low and the weight on minimizing the risk exposure is low, the model over-hedges to maximize the expected income. When β is high and the weight on minimizing the risk exposure is high, the trading volume goes down as the speculative positions contribute with excessive downside.

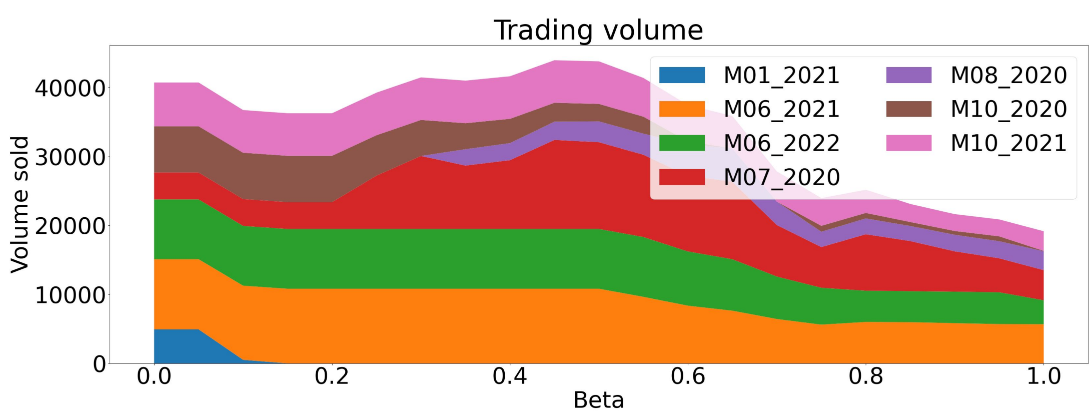

Figure 6.1: Stackplot of total hedging volume proposed by the model per β. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The x-axis represents the level of β, while the y-axis represents volumes sold. The different colors represent different futures contracts and the widths of the lines represent volumes within each contract.

In table 6.1, the volume proposed for each futures contract, as well as the volume produced in each month and the percentage of futures volume compared to production is displayed. The table exemplifies that the model performs over-hedging because the contract for June 2021 is over-hedged nine times. It is clear from this result that in order to maximize expected income, the model proposes over-hedging. This is because the upside can be extremely high and the risk exposure is not taken into account when $\beta = 0$.

Contract	Volume sold	Est. production	% secured
Jan-2021	4932.25	1619.37	304%
Jun-2021	10171.63	1123.03	905%
Jun-2022	8667.53	1153.87	751%
Jul-2020	3887.07	1112.08	349%
Oct-2020	6714.92	1036.32	647%
Oct-2021	6338.71	1215.04	521%

Table 6.1: Traded volume table ($\beta = 0$, which means that the model maximizes expected income)

When β increases, trading volume should decrease to only risk-reducing positions. However, when β is increased to 1 and the model only maximizes CVaR, the model still proposes to enter speculative positions (Table 6.2). For most contracts the positions are reduced in table 6.2 compared to table 6.1, but they are still over-hedged. The reason behind this would be the data that is used in the model. The price scenarios produced for these months are much lower than the market price from the forward curve. Resulting in the model selling more than what is necessary for hedging purposes because the trades don't add any risk exposure.

Contract	Volume sold	Est. production	% secured
Jun-2021	5678.62	1123.03	505%
Jun-2022	3474.52	1153.87	301%
Jul-2020	4355.11	1112.08	391%
Aug-2020	2740.45	1161.15	236%
Oct-2020	53.88	1036.32	5%
Oct-2021	2849.52	1215.04	234%

Table 6.2: Traded volume table ($\beta = 1$, which means that the model maximizes CVaR)

In figure 6.2, a histogram over income for each β is shown with a corresponding probability-density function. From the figure it is clear that the income distribution changes as β increases. In the upper left diagram the lowest income scenarios are well below 100 MEUR, while in the lower right diagram the lowest income scenarios are above 150 MEUR. As the lowest income scenarios increase, the higher income scenarios decrease from around 490 MEUR to around 400 MEUR.

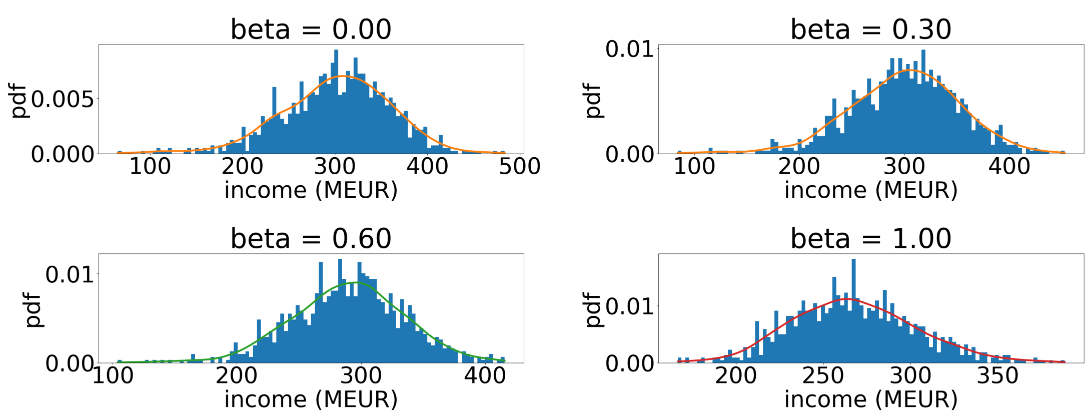

Figure 6.2: The plot consists of four different income distributions at β=0.0, β=0.3, β=0.6 and β=1. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The x-axis represents income scenarios and the y-axis represents the density of probability. As β converges towards 1, the income distribution become more narrow.

Figure 6.3 illustrates the different probability density curves superimposed on the same graph. In this figure, it is apparent how the income distribution changes as β varies. As β increases, the income distribution converges to one income level and becomes narrower. As a result, fewer low income scenarios exist, as well as fewer high income scenarios. In addition, there is a greater likelihood that the income is equal to one income level. In other words, the variability of income is reduced. When $\beta = 0$, the model is only maximizing the expected income, resulting in the highest expected income of the lines in the graph. However, the probability of each income scenario decreases, resulting in a more uncertain and volatile distribution of income. Furthermore, the tails of the distribution are longer. When β increases, the expected income decreases and the CVaR increases as a result of the shifting priorities of the model. In addition, the tails of the distribution are shorter and the sample space of the income distribution is smaller. The results are in line with expectations and it appears that the model is performing as intended.

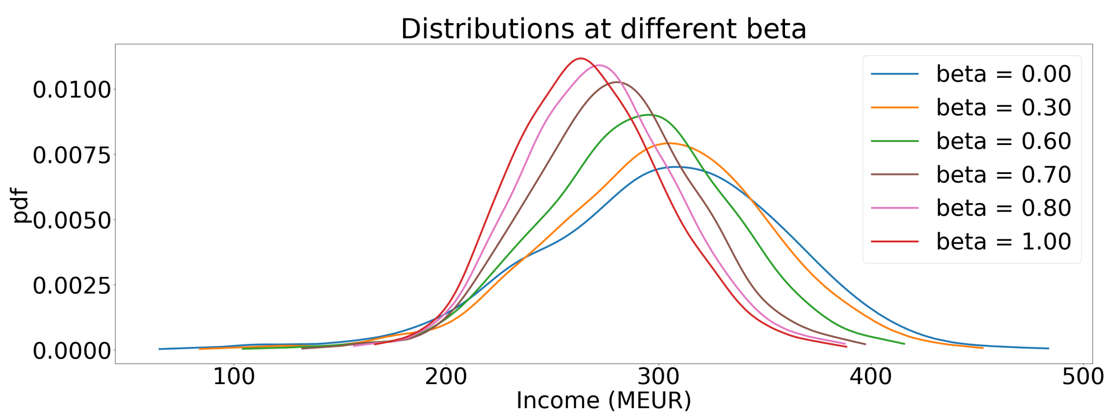

Figure 6.3: The plot contains income distributions for different levels of β. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The x-axis represents income in MEUR and the y-axis represents the density of probability.

Comparing the income distribution for $\beta = 1$ with that of a scenario excluding hedging, it is shown that the volumes proposed by the model reduce the lowest income scenarios while also increasing expected income (Figure 6.4).

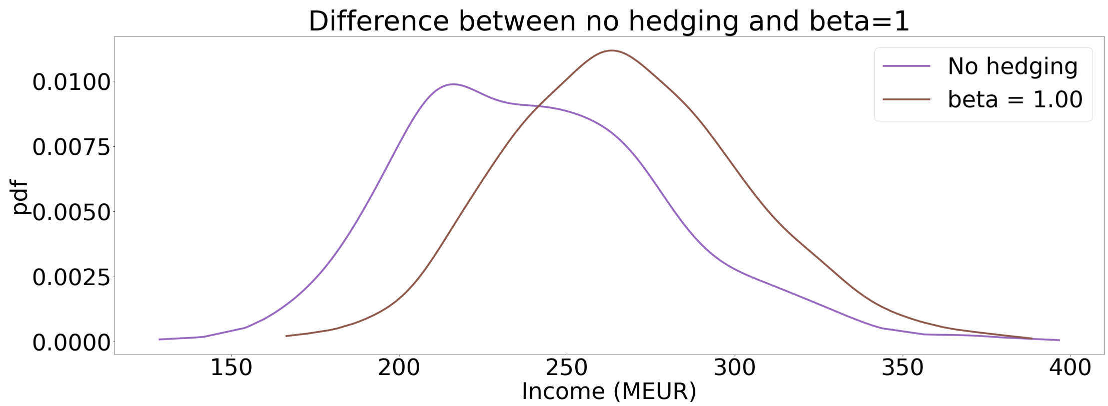

Figure 6.4: The plot demonstrates the income distributions for a situation with no hedging and a situation where $\beta = 1$. Where $\beta = 1$ means that the model maximizes CVaR. The x-axis represents income in MEUR and the y-axis represents the density of probability. The situation where hedging is allowed eliminates the probability of the lowest income scenarios while increasing expected income.

Figure 6.5 shows the cumulative distribution of income per β. The figure confirms what has been shown in the previous charts, which is that when β increases, the likelihood of obtaining income between 200 MEUR and 350 MEUR increases. Consequently, as β increases, the model secures a greater number of income scenarios.

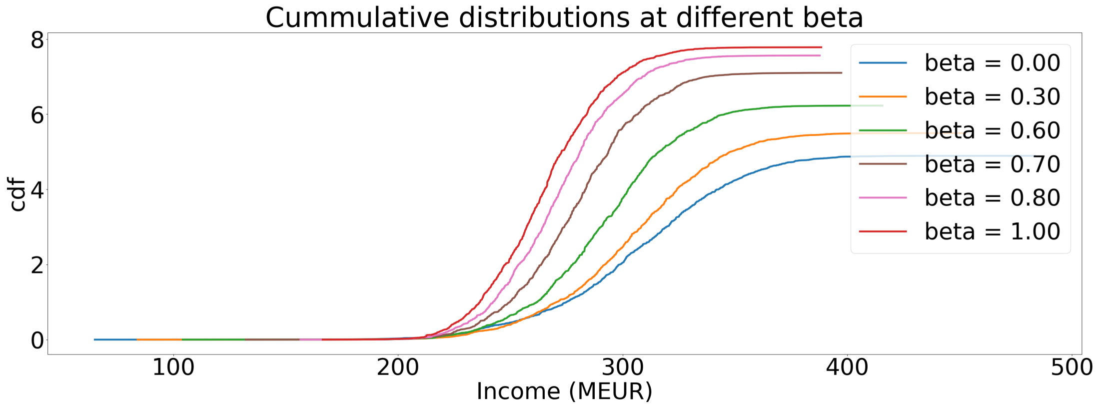

Figure 6.5: The plot show the cumulative income distributions for different levels of β. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The x-axis represents the income in MEUR and the y-axis represents the probability of any event less than the x-axis value. As β increases, the model secures a greater number of income scenarios.

Table 6.3 shows the different income levels per β. The scenario that omits financial hedging has the lowest expected income and the lowest income at the 5-, 25-, 50- and 75-quantile levels. This indicates that the model is capable of improving the distribution of income at all levels of β. However, the lowest income scenario is lower for $\beta = 0$ and $\beta = 0.5$ than the situation with no hedging. This is due to the increased risk when the model over-hedges the production. In the case of a low β, the expected income and the income at the higher tail quantiles are the highest. If β is higher, the lowest income scenarios will be greater. It reflects the intuition that for a low β, the model maximizes expected income while for a higher β, the model minimizes risk. The difference in income for the 75-quantile for $\beta = 0$ and $\beta = 1$ is approximately 52 MEUR, whereas the difference in the lowest income scenario is approximately 101 MEUR. As a consequence, the income lost at the 75-quantile is less than the income gained in the lowest income scenarios.

β	Expected	Lowest	5-quantile	25-quantile	50-quantile	75-quantile
No trading	240.59	128.68	184.50	211.67	237.31	265.52
0	301.36	65.00	202.33	264.49	303.57	341.18
0.5	299.30	84.35	215.15	265.82	301.67	333.30
1	267.54	166.45	212.61	242.36	266.33	289.94

Table 6.3: Table of income at different β (in MEUR). Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR.

Figure 6.6 shows the difference in CVaR at different levels of beta, compared to the base case with no hedging. The figure demonstrates that when $\beta = 0$ and the model maximizes expected income, the CVaR is lower than in a situation without hedging. When β increases, the difference between the CVaR with hedging and without increases. As a result, when the model maximizes CVaR through hedging in the financial market, the worst income scenarios are eliminated and trading has a risk-reducing effect as expected.

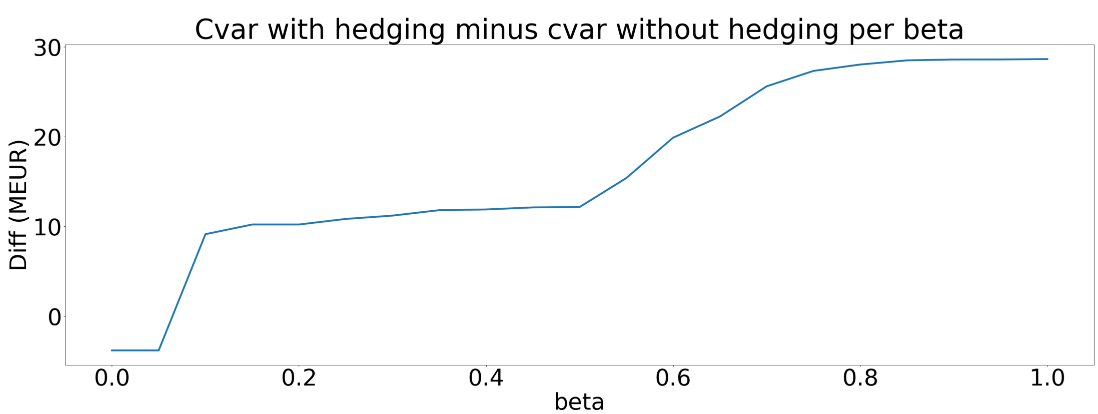

Figure 6.6: The plot demonstrates the difference between CVaR for no hedging and CVaR for different levels of β. The x-axis represents the level of β and the y-axis represents the difference in MEUR. For $\beta = 0$ the difference is negative indicating that the hedging had a risk increasing effect compared to a situation with no hedging. As β increases the difference increases as well, indicating that the hedging has a risk reducing effect.

In figure 6.7 an effective frontier is shown between expected income and CVaR for different levels of β. The figure indicates that as the value of CVaR increases, the expected income decreases. An increase in CVaR indicates that in the worst-case scenarios, a greater income is likely. The figure also demonstrates that the economic trade-off to increase CVaR is smallest for a low CVaR. Consequently, the reduction in expected income caused by an increase in CVaR is beneficial for a CVaR below 185MEUR. By using the effective frontier, one can depict the trade-off between expected income and CVaR. Hydropower producers could use this figure to determine how much expected income they are willing to sacrifice to obtain a higher income in the worst case scenario.

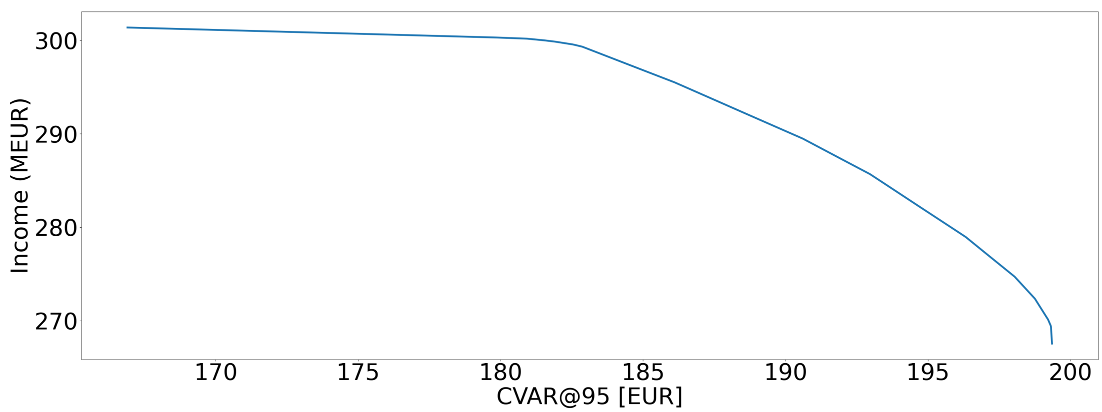

Figure 6.7: The plot shows an effective frontier between expected income and CVaR for different levels of β. The x-axis represents the CVaR at $\alpha = 0.95$ (in MEUR) and the y-axis represents the income in MEUR. The graph has a downward slope indicating that a lower expected income equals a higher CVaR.

6.2 Scenarios

In addition to the analysis of the main model results, this thesis looks at two alternative scenarios. In the main model, it was shown that the model could over-hedge in scenarios where this would be beneficial. Yet, it would be interesting to see how the model performs in a situation where the hedge volume has to be smaller or equal to the expected production. Lastly, there is a discussion on the consequences of changing the resource rent tax.

6.2.1 Hedging volume cannot exceed expected production

A constraint was added to the model to simulate that for each contract, the total volume hedged for that contract could not exceed the expected production. As an example, the total volume hedged for the contract January 2021 would include the volume traded in January plus one-third of the volume traded in the first quarter contract for 2021 and one-twelfth of the volume traded for the yearly contract for 2021. The hedged volume resulting from this process is shown in figure 6.8. As can be seen from the figure, there are more contracts included than previously. When β is low, the model trades more volume than when β is high. This might be because some of the contracts have high upsides but also high downsides, as explained in the previous section.

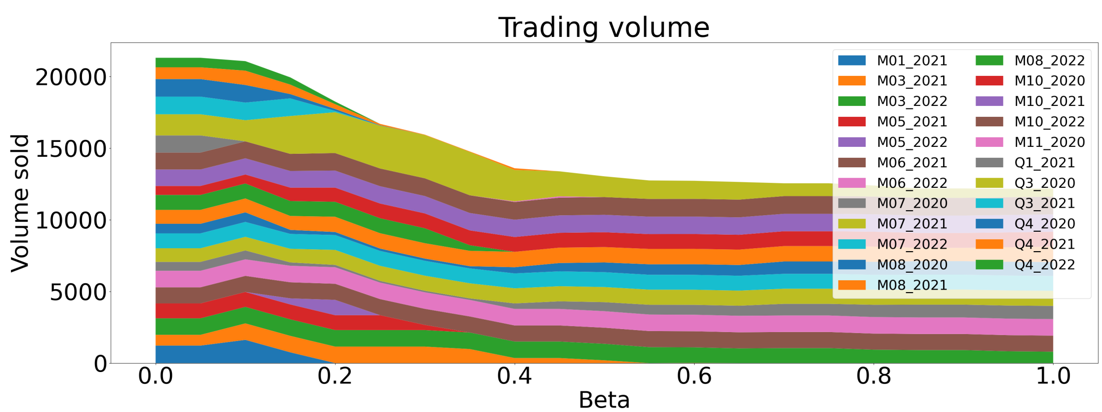

Figure 6.8: The plot demonstrates hedged volume when the volume cannot exceed expected production. The x-axis represents the different levels of β and the y-axis represents hedged volume. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The different colors represent different contracts. They are stacked on top of each other to also demonstrate total volume hedged.

The resulting hedging volume for $\beta = 0$ is displayed in table 6.4. $\beta = 0$ is a situation where the model objective is to maximize expected income. From the table we can see that with some additional contracts, this model also trades the same contracts as the main model. According to the model, this may indicate that these contracts are necessary for the hedging portfolio during this period. If we compare this table to figure 5.11, we can see that the contracts sold by the model match with the points on the curve where the financial forward curve is above the mean price of NO5 and the system price. Hence, the model trades the contracts that would make sense to trade based on the data.

In reality, one would think that the model hedged Q1 and Q4 primarily due to higher sample spaces in price and high production volumes during these quarters. As you can see from the table, Q1 is secured at approximately 76%, however Q4 is at or below 50%. The quarter with the highest percentage secured in the table is Q3. In addition, the table indicates that the model hedges the period closest to delivery. This is contrary to the claim from the article by Conlon, Cotter and Gencay (2013), that effective hedging was achieved over longer time horizons. This may indicate that the price and production scenarios are not a true reflection of reality at longer horizons.

Contract	Hedged volume	Est. production	% secured
Jan-2021	1220.42	1619.37	99.99%
Mar-2021	750.46	1149.41	99.99%
Mar-2022	1152.25	1152.25	100%
May-2021	1040.32	1040.32	100%
Jun-2021	1123.03	1123.03	100%
Jun-2022	1153.87	1153.87	100%
Jul-2020	620.02	1112.08	100%
Jul-2021	951.20	1053.73	100%
Jul-2022	1039.51	1039.51	99.99%

Aug-2020	669.68	1161.15	100%
Aug-2021	969.68	1072.21	100%
Aug-2022	1043.43	1043.43	99.99%
Oct-2020	627.23	1036.32	99.99%
Oct-2021	1146.64	1215.04	99.99%
Oct-2022	1182.18	1237.50	99.99%
Q1-2021	1196.84	4134.14	76.62%
Q3-2020	1476.15	3399.69	81.33%
Q3-2021	1230.28	3151.17	99.99%
Q4-2020	1227.27	3812.85	48.63%
Q4-2021	820.76	3874.13	50.78%
Q4-2022	663.81	3917.63	47.12%

Table 6.4: Hedging volume table ($\beta = 0$)

The resulting hedging volume when $\beta = 1$ can be seen in the table 6.5. In comparison with the table above, some contracts have been excluded which resulted in high expected income but also a high level of downside risk. The table 6.5 illustrates the hedging portfolio that minimizes the downside risk when you allow the model to only hedge equal to the expected production volume. To put it another way, this table contains the risk reducing financial contracts.

Contract	Hedged volume	Est. production	% secured
Mar-2022	790.73	1152.25	68.62%
Jun-2021	1123.03	1123.03	100%
Jun-2022	1153.87	1153.87	100%
Jul-2020	922.23	1112.08	100%
Jul-2021	1053.73	1053.73	100%
Jul-2022	1039.51	1039.51	99.99%

Aug-2020	971.30	1161.15	100%
Aug-2021	1072.21	1072.21	99.99%
Oct-2020	1036.32	1036.32	99.99%
Oct-2021	1215.04	1215.04	100%
Oct-2022	1237.50	1237.50	99.99%
Q3-2020	569.54	3399.69	72.45%

Table 6.5: Hedging volume table ($\beta = 1$)

Figure 6.9 illustrates the different income probability-density distributions. This figure is very different from the figure 6.3, which includes speculative trades. This figure shows a larger difference in income distributions for lower values of β, and for β above 0.5, the distributions appear almost identical. This is interesting since it seems that no matter which level of β you choose above 0.5, they all produce the same outcome.

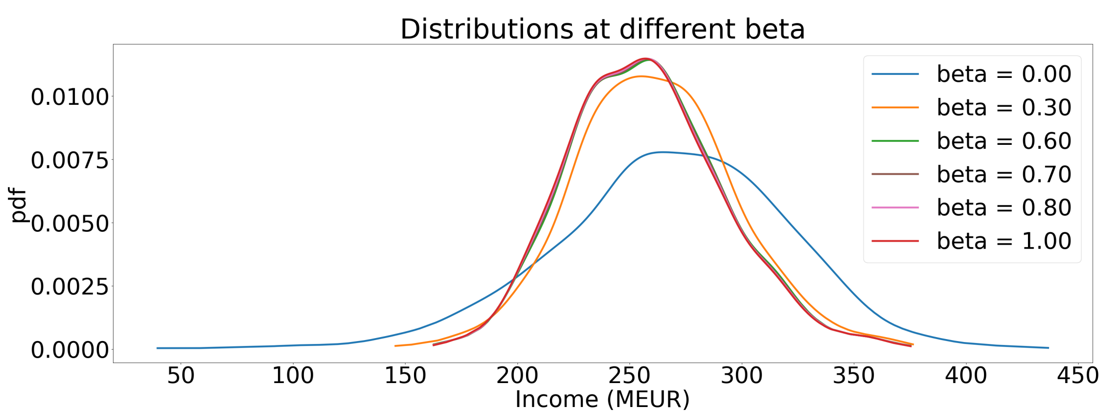

Figure 6.9: The plot demonstrates the income distributions at different β values when the model only hedge volumes equal to the expected production. The x-axis represents the income in MEUR and the y-axis represents the density of probability. Each line represent the income distribution for a level of β. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR.

To determine if the model works as intended, we must also compare a situation without hedging with one in which $\beta = 1$. In figure 6.10, the income probability density function for a scenario involving no hedging is compared to a scenario where $\beta = 1$ and the model maximizes CVaR. By hedging the volume in the financial market, the model is able to reduce the downside risk introduced by the price scenarios. On the other hand, it is also apparent that the highest income scenarios have been eliminated as the curve where $\beta = 1$ ends ahead of the curve without hedging. However, some of the high income scenarios have a greater chance of occurring in the case of hedging. As a result, it seems like the hedging proposed by the model is very effective without reducing too much of the possible high income scenarios.

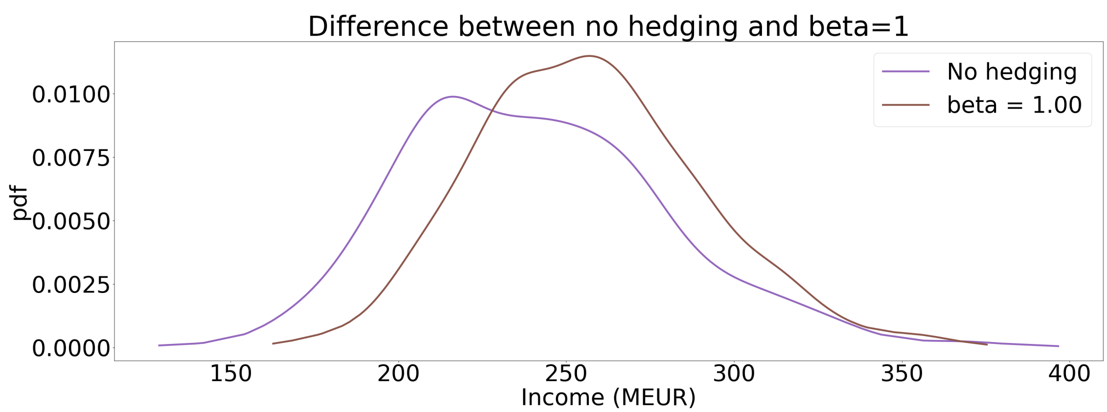

Figure 6.10: The plot demonstrates the income distributions for no financial trading vs $\beta = 1$ when the model only hedge volumes equal to the expected income. The x-axis represents the income in MEUR and the y-axis represents the density of probability. One line represents the income distribution for a scenario with no hedging and the other one represents the income distribution for a scenario where CVaR is maximized.

The comment that it seems that the income scenarios are more or less identical at a β level above 0.5 is confirmed by table 6.6. In general, the difference between $\beta = 0.5$ and $\beta = 1$ in income is minimal for all income levels, with the greatest difference occurring for high-income scenarios. In addition, for any β greater than 0.5, the hedging volume proposed by the model leads to higher income in all income scenarios compared to a situation with no hedging. This strengthens the claim that the model is performing well in regards to minimizing risk exposure and maximizing expected income.

β	Expected	Lowest	5-quantile	25-quantile	50-quantile	75-quantile
No trading	240.59	128.68	184.50	211.67	237.31	265.52
0	268.38	39.59	179.55	238.78	270.64	303.91
0.5	258.12	161.52	204.84	234.40	356.99	280.33
1	256.86	162.65	204.85	232.82	254.55	278.39

Table 6.6: Table of income at different β (in MEUR and with limitations on hedging volume)

6.2.2 Changing the resource rent tax

Resource rent tax has been a topic of discussion in the Norwegian energy environment for many years. The resource rent tax is a tax levied on hydropower plants with generators of more than ten megawatts. It was introduced because hydropower production often results in profits exceeding normal returns to capital. Furthermore, as hydropower is a common good and natural resource, hydropower producers should return some of the money they earn from that good to society in general (Norway n.d.). The rationale behind the resource rent tax is sound. However, the resource rent tax has been increased several times and is now at an all-time high of 37%, which is higher than the company tax of 22%. For some time, hydropower producers have been arguing that the resource rent tax prevents them from investing in new projects. Therefore, it would be interesting to examine the effects of the resource rent tax on the trading model. This is to determine whether the tax also influences hedging strategies. The following scenario examines how the model performs when the resource rent tax is decreased by 20% and increased by 20%.

Tax rate down by 20%

There is a stackplot of the total volume traded in figure 6.11. The figure appears to be the same as figure 6.1. It is because the traded contracts are the same and the difference in traded volume as β changes is the same. The only difference between this figure and 6.1 is that the total volume traded has increased by approximately 20 000 MWh. This is a result of the reduced risk of paying high taxes in cases where the delivered price is higher than the financial price at which the power was sold on the futures market.

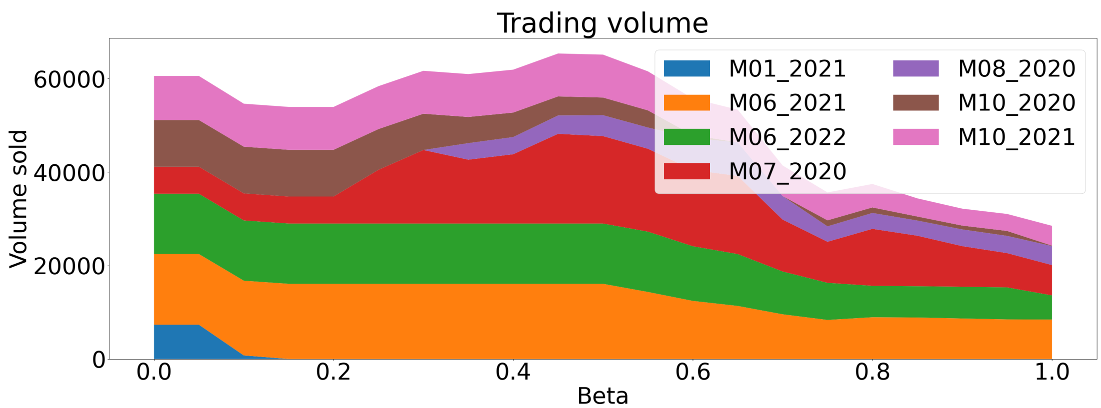

Figure 6.11: The stackplot shows the total traded volume proposed by the model per β for a lower tax level. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The x-axis represents the levels of β and the y-axis represents the volume traded. The different colors represent different futures contracts.

There are no differences in the shapes of the income distributions in figure 6.12 and figure 6.3, other than the fact that all scenarios have proportionally larger incomes.

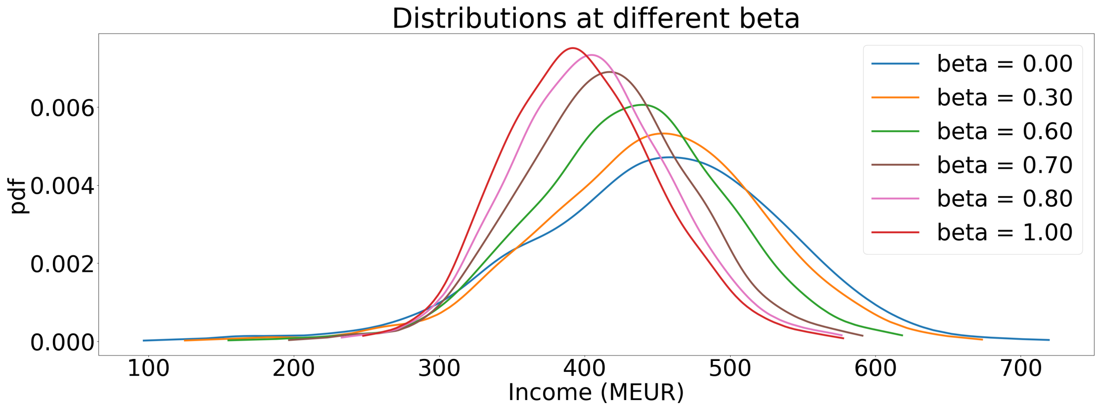

Figure 6.12: The plot demonstrates the income probability density curves after a reduction in the resource rent tax. The x-axis represents income in MEUR and the y-axis represents the density of probability. The different lines represent the income distributions for different levels of β.

The same is true for figure 6.13. It is identical to the graph in 6.4 except for the proportional increase in income in all scenarios.

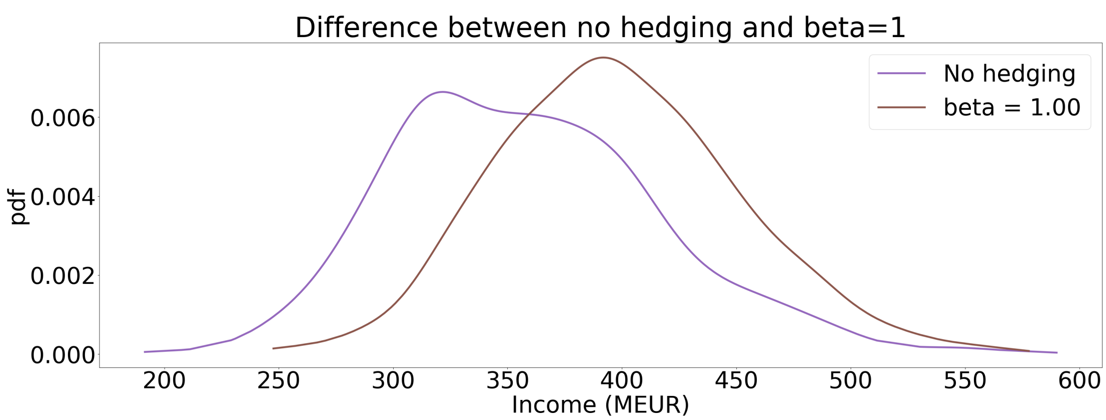

Figure 6.13: The plot demonstrates the income probability density curves for $\beta = 1$ and for no hedging, after a reduction in the resource rent tax. The x-axis represents income in MEUR and the y-axis represents the density of probability.

These graphs indicate that changes in the resource rent tax do not influence the selection of contracts for this data set. However, in all scenarios, a reduction in the resource rent tax will result in an increase in trade volume and income.

Tax rate up by 20%

A stackplot of the total volume traded can be found in Figure 6.14. Upon examining the figure, it appears exactly the same as that shown above. This figure differs only in that the total volume traded has decreased by approximately 20 000 MWh compared to the other two. This is a result of the increased risk of paying high taxes in cases where the delivered price is higher than the financial price at which the power was sold on the futures market.

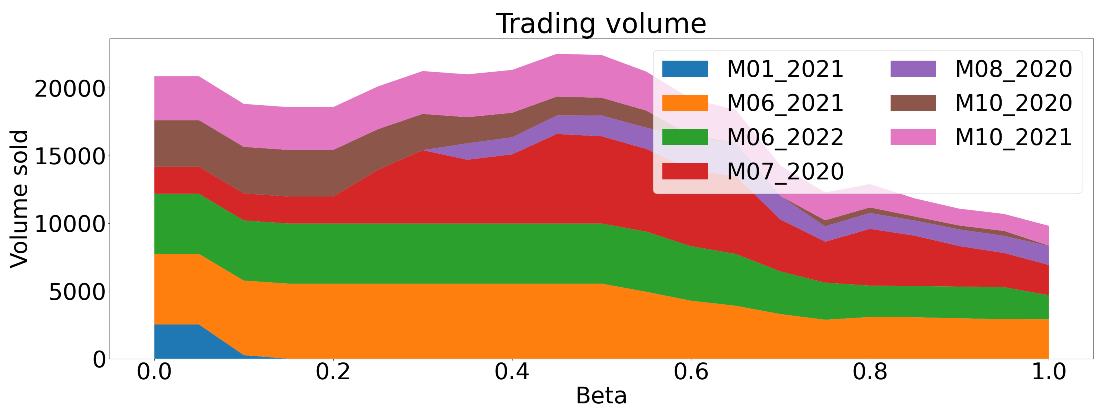

Figure 6.14: The stackplot shows the total traded volume proposed by the model per β for a higher tax level. Where $\beta = 0$ means that the model maximizes expected income and $\beta = 1$ means that the model maximizes CVaR. The x-axis represents the levels of β and the y-axis represents the volume traded. The different colors represent different futures contracts.

The income distributions in figure 6.12 follow exactly the same pattern as the distributions in the other two figures. The only difference is that all scenarios have a proportionally lower income.

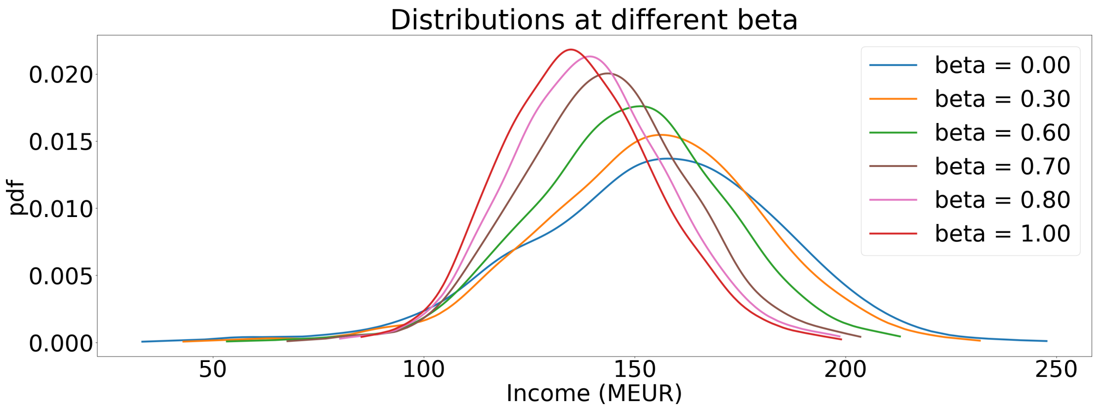

Figure 6.15: The plot demonstrates the income probability density curves after an increase in the resource rent tax. The x-axis represents income in MEUR and the y-axis represents the density of probability. The different lines represent the income distributions for different levels of β.

Likewise, figure 6.13 appears identical to the other two figures, except for the proportional decrease in income for each scenario.

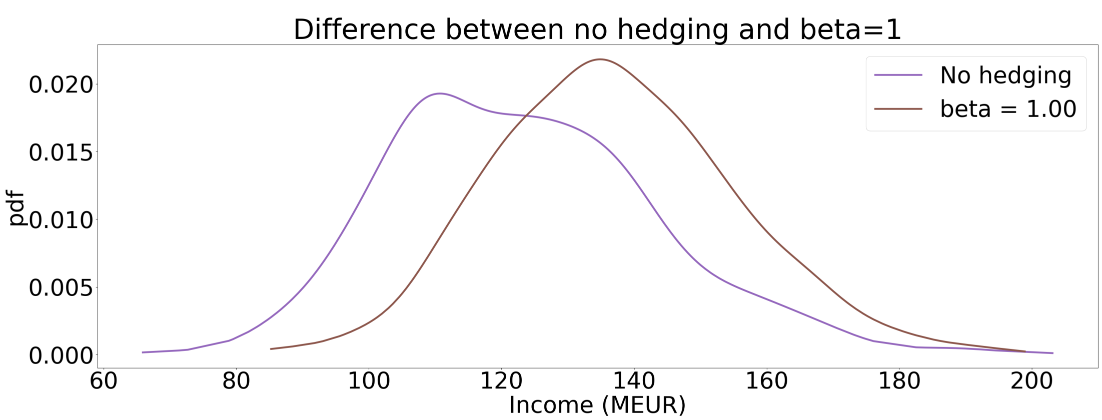

Figure 6.16: The plot demonstrates the income probability density curves for $\beta = 1$ and for no hedging, after an increase in the resource rent tax. The x-axis represents income in MEUR and the y-axis represents the density of probability.

Based on these graphs, the resource rent tax has no effect on the choice of contracts traded. However, it does affect the total volume traded and income.

Chapter 7

Conclusion and further work

As part of this thesis, a methodology and a prototype model have been developed for the problem of financial trading and hedging faced by a Norwegian hydropower producer. Tax rates, price scenarios, production scenarios and financial trading in monthly, quarterly, and yearly contracts were included in the model. By adjusting the value of a weighting parameter β, the model considers the trade-off between maximizing expected income and maximizing conditional value-at-risk. In the end, the model produces an effective frontier between expected income and conditional value-at-risk. This effective frontier can be helpful to hydropower producers when hedging their risk exposure on the financial market, as it shows how much income needs to be sacrificed in order to increase the income in the worst case scenarios.

Due to the fact that the model has no restrictions on volume, when the financial market price exceeds the modelled price scenarios, the model chooses to over-hedge production. If the model is run at a time when market prices are less favorable, it is likely to show a different outcome. As demonstrated in the sub-section "Hedging volume cannot exceed expected production", this can be avoided by imposing a new constraint. Both in the case of over-hedging and in the case of only hedging, it is immediately apparent that the expected income and the highest income scenarios decrease as the model prioritizes to minimize the risk exposure. However, this effect is minimal and the model is able to reduce downside risk quite effectively without sacrificing too much upside.

As β increases, the income probability density curve becomes more narrow and as a result the hydropower producer will have a higher probability of reaching a given level of income. In other words, optimizing CVaR in the model does indeed reduce the risk associated with the lower tail and secures the income of the hydropower producer. Based on the price scenarios used as input into the model and the market price from the financial forward curve, the model chooses to trade the contracts where the market price is above the price scenarios. Thus the model performs as expected based on the data.

Lastly, the thesis also discussed how the resource rent tax affects the model. The results reveal that the resource rent tax influences the total volume traded by the model. However, it does not influence the specific contracts that are favored by the model. As the tax rate decreases, the total volume increases. Furthermore, and not surprisingly, low resource rent tax leads to higher income in all scenarios.

In order to improve the model even further, a closer examination of how price and volume scenarios are generated would be beneficial. As a model is only as good as the data it is fed, as the scenarios improve, so will the model. In addition, it may be worthwhile to examine the hedge instrument chosen. In this thesis, the Nordic system price was used as the hedging instrument due to its historical correlation with the NO5 area price. However, this situation is changing as the power market is becoming more connected to mainland Europe and Britain. The difference between the Nordic system price and the NO5 area price has never been larger than it is at present. In light of this, it might be useful to investigate whether some other contracts would be better hedging instruments in the future, for example German prices or CO2 prices.

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Appendix

1. Price and production scenarios - a snippet of the data

	A	B	C	D	E
1	Simulation	15.06.2020 - 30.06.2020	01.07.2020 - 31.07.2020	01.08.2020 - 31.08.2020	01.09.2020 - 30.09.2020
2	1	1.245455513	5.229449381	10.67482768	15.5052312
3	2	1.082458533	3.96775414	9.614918596	16.95521501
4	3	0.955454822	3.644058322	9.635954185	16.94655068
5	4	1.08094609	4.429021876	11.71225283	15.43740202
6	5	1.047341401	3.824900208	9.299674675	14.49771677
7	6	1.285581873	5.104083643	11.52791745	16.86118499
8	7	1.207520724	4.430416079	8.309648067	14.46691069
9	8	1.096027396	4.262726705	11.00248495	16.8172758
10	9	1.347888423	5.193900594	13.83927263	21.14945481
11	10	1.204292185	4.831923002	10.59731495	13.83838253
12	11	1.168612502	3.809637331	7.113265773	13.10115421
13	12	1.163939602	4.108803201	9.528458907	16.748579
14	13	1.194656196	4.096683147	9.033638429	13.95388829
15	14	1.27376011	4.480648774	10.25087647	16.5668301
16	15	1.21434043	4.641326186	10.22545131	15.52082666
17	16	1.376477958	4.782706944	10.42805441	15.37249313

Figure 7.1: NO5 area price scenarios (a snippet)

	A	B	C	D	E
1	Simulation	15.06.2020 - 30.06.2020	01.07.2020 - 31.07.2020	01.08.2020 - 31.08.2020	01.09.2020 - 30.09.2020
2	1	4.428112132	8.092262093	14.60994185	19.33844678
3	2	3.66551615	5.894083218	11.46258207	17.61122344
4	3	3.385624952	4.939417002	9.419555297	13.3233234
5	4	4.442213269	7.374362132	17.06040666	21.53213429
6	5	4.029911428	6.11348796	10.83036981	17.89557668
7	6	4.349139713	7.411113387	13.94465704	15.41894623
8	7	3.829728199	7.284547737	14.14423598	21.73787874
9	8	3.572072292	7.102334639	12.94234331	18.23021572
10	9	3.369598675	6.183359183	15.62818502	20.73316384
11	10	4.294951658	8.095766901	14.37571808	17.90703324
12	11	3.755744511	6.415693987	11.47017833	14.50687878
13	12	3.326702213	5.769396686	13.59810878	19.77884793
14	13	3.707545352	6.268937698	11.01795608	15.39916976
15	14	4.376783542	6.229578887	13.22102979	20.4057247
16	15	4.143268569	6.27518483	12.13165305	16.73184275
17	16	3.865481563	6.791923638	13.03814822	17.57597105

Figure 7.2: System price scenarios (a snippet)

	A	B	C	D	E	F	G
1	r	2020	2020	2020	2020	2020	2020
2	ProdMatch	6	7	8	9	10	11
3	1	395	1066	1262	959	1076	1239
4	2	489	1475	1468	1411	1130	1209
5	3	499	949	1121	1003	1067	1164
6	4	472	1212	1074	1152	1275	1295
7	5	522	1196	1294	1120	884	1226
8	6	472	1212	1074	1152	1275	1295
9	7	480	753	1155	1154	898	1145
10	8	559	1584	1719	1743	1080	1238
11	9	474	999	1150	1081	785	1165
12	10	537	1083	870	984	923	1190
13	11	522	1196	1294	1120	884	1226
14	12	426	900	1060	1160	1049	1184
15	13	486	1199	1114	986	823	1105
16	14	522	995	867	840	1158	1160
17	15	522	1012	1061	1092	1386	1243

Figure 7.3: Production scenarios (a snippet)

2. Price and production scenarios - graphs (full dataset)

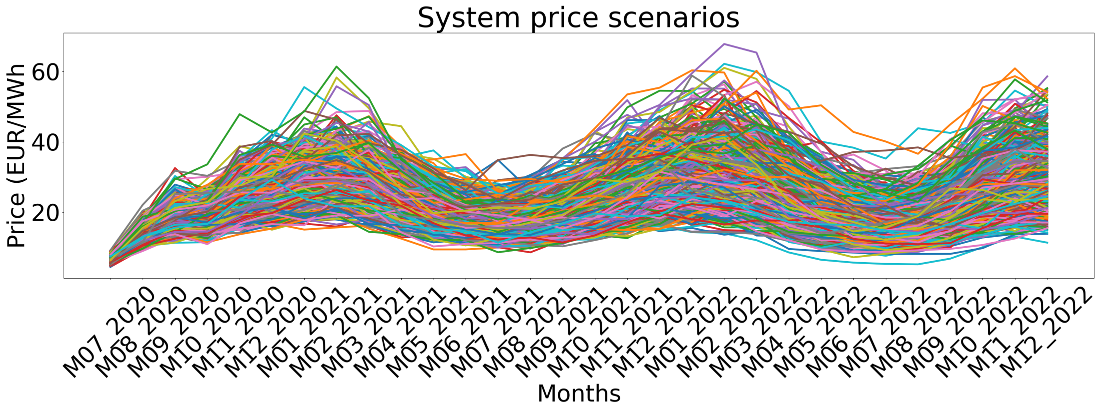

Figure 7.4: System price scenarios (Monthly)

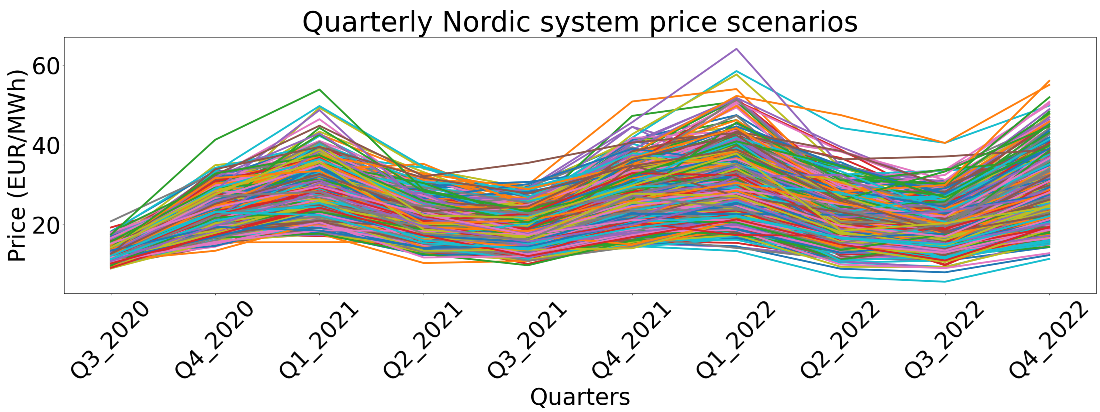

Figure 7.5: System price scenarios (Quarterly)

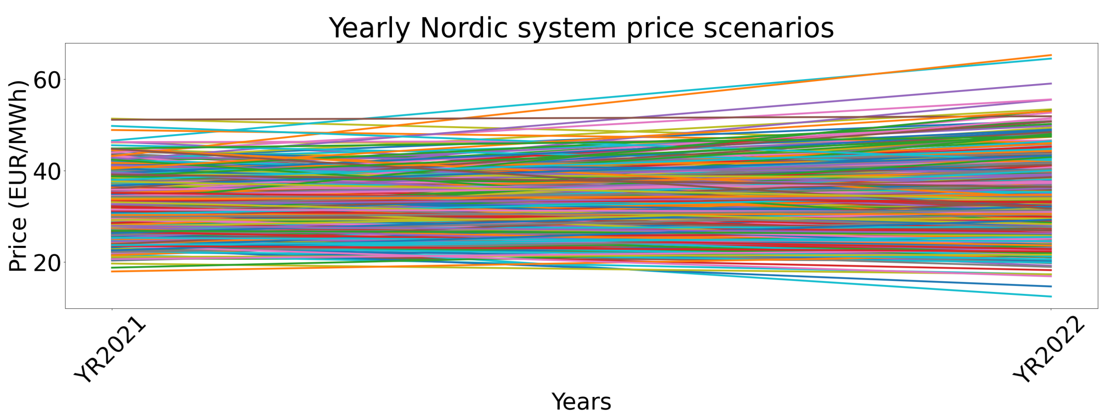

Figure 7.6: System price scenarios (Yearly)

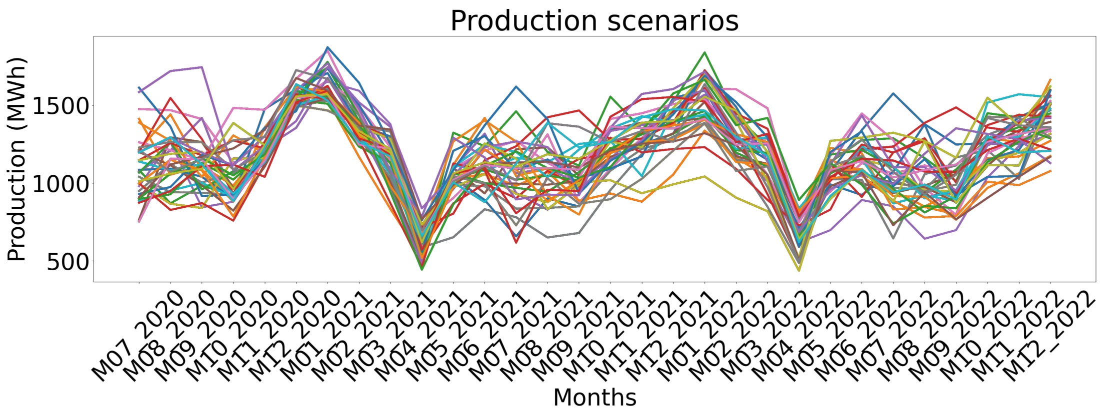

Figure 7.7: Production scenarios

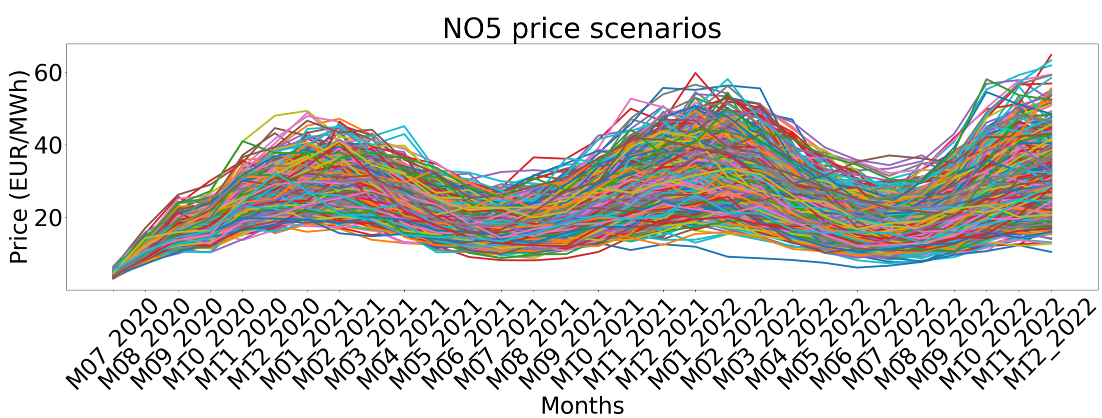

Figure 7.8: NO5 price scenarios

3. Images of the Python code

```python
# Determining income from spot market
income_spot = {}
for scenario in scenarios.keys():
    income_spot[scenario] = 0
    for key in list(months.keys()):
        income_spot[scenario] += production_level[(key, scenario)]*months[key]*prices_per_scenario_per_month_no5[(key, scenario)]*((1-tax_on_hydropower)-corporation_tax)

# Determining income from financial market
income_financial_month = {}
for scenario in scenarios.keys():
    income_financial_month[scenario] = 0
    for key in list(months.keys()):
        income_financial_month[scenario] += hedging_volume[key]*months[key]*(financial_prices_per_month[key]-prices_per_scenario_per_month_sys[(key, scenario)])*(1-corporation_tax)

income_financial_quarter = {}
for scenario in scenarios.keys():
    income_financial_quarter[scenario] = 0
    for key in list(hours_in_quarters.keys()):
        income_financial_quarter[scenario] += hedging_volume[key]*hours_in_quarters[key]*(financial_prices_per_quarter[key]-prices_per_scenario_per_quarter_sys[(key, scenario)])*(1-corporation_tax)

income_financial_year = {}
for scenario in scenarios.keys():
    income_financial_year[scenario] = 0
    for key in list(hours_in_years.keys()):
        income_financial_year[scenario] += hedging_volume[key]*hours_in_years[key]*(financial_prices_per_year[key]-prices_per_scenario_per_year_sys[(key, scenario)])*(1-corporation_tax)

# Adding spot and financial into total income
income = {}
for scenario in scenarios.keys():
    income[scenario] = income_spot[scenario] + income_financial_month[scenario] + income_financial_quarter[scenario] + income_financial_year[scenario]
```

Figure 7.9: Python code: Income function

```python
# Decision variables:
var = pulp.LpVariable("var", cat="Continuous")
diff_income_var = pulp.LpVariable.dicts("diff", indices=scenarios, lowBound=0, cat="Continuous")

# Creating the problem:
cvar_max = pulp.LpProblem(name="cvar_maximization", sense=pulp.LpMaximize)

cvar_max += (
    var - ((pulp.lpSum([(1/(1-0.95))*(list(scenarios.values())[scen]*diff_income_var[scen]) for scen in scenarios])))
)

# Adding constraints
for scenario in scenarios:
    cvar_max += (
        (var -
        pulp.lpSum([production_level[(key, scenario)]*months[key]*prices_per_scenario_per_month_no5[(key, scenario)]*((1-tax_on_hydropower)-corporation_tax) for key in list(months.keys())])
        - diff_income_var[scenario]) <= 0
    )

for scenario in scenarios:
    cvar_max += (diff_income_var[scenario] >= 0)

cvar_max.solve()
```

Figure 7.10: Python code: First optimization - spot trading

```python
# Decision variables:
var = pulp.LpVariable("var", cat="Continuous")
diff_income_var = pulp.LpVariable.dicts("diff", indices=scenarios, lowBound=0, cat="Continuous")
hedging_volume = pulp.LpVariable.dicts("hedge_volume", indices=indices_hedging_volume, lowBound=0, upBound=99999, cat="Continuous")

income = make_income_function(···

income_per_year = calculate_income_per_year(···

# Creating the problem:
cvar_max = pulp.LpProblem(name="cvar_maximization", sense=pulp.LpMaximize)

cvar_max += (
        (1-beta) * (pulp.lpSum([list(scenarios.values())[scenario]*income[scenario] for scenario in scenarios])) +
        beta * (var - ((pulp.lpSum([(1/(1-0.95))*(list(scenarios.values())[scen]*diff_income_var[scen]) for scen in scenarios]))))
    )

# Adding constraints
for scenario in scenarios:
    cvar_max += ((var - income[scenario] - diff_income_var[scenario]) <= 0)

for scenario in scenarios:
    cvar_max += (diff_income_var[scenario] >= 0)

for year in income_per_year.columns:
    for scenario in scenarios:
        cvar_max += income_per_year.loc[scenario, year] >= 0

cvar_max.solve()
```

Figure 7.11: Python code: Second optimization - Finding hedging portfolio

```python
# Decision variables:
var_2nd = pulp.LpVariable("var_2nd", cat="Continuous")
diff_income_var_2nd = pulp.LpVariable.dicts("diff_2nd", indices=scenarios, lowBound=0, cat="Continuous")

# Creating the problem:
cvar_max_95 = pulp.LpProblem(name="cvar_maximization_second", sense=pulp.LpMaximize)

cvar_max_95 += (
    var_2nd - ((pulp.lpSum([(1/(1-0.95))*(list(scenarios.values())[scen]*diff_income_var_2nd[scen]) for scen in scenarios])))
)

# Adding constraints
for scenario in scenarios:
    cvar_max_95 += ((var_2nd - income[scenario] - diff_income_var_2nd[scenario]) <= 0)

for scenario in scenarios:
    cvar_max_95 += (diff_income_var_2nd[scenario] >= 0)

cvar_max_95.solve()
```

Figure 7.12: Python code: Third optimization - Max CVaR of hedging portfolio

4. EMPS - more details

System optimization

The objective is to minimize the expected cost in the whole system subject to all constraints. In principle, this solution will coincide with the outcome in a well-functioning electricity market. The simulated system can e.g. be the Nordic system or Northern Europe. The basic time step in the EMPS model is one week, with a horizon of up to ten years. Within each week, the time-resolution is 1 hour or longer.

In the strategy evaluation, incremental water values (marginal costs for hydropower) are computed for each area using stochastic dynamic programming. A heuristic approach is used to treat the interaction between areas. In the simulation part of the model total system costs are minimized week by week for each climate scenario (e.g. 1931 – 2012) in a linear problem formulation.

Model elements

Hydropower: Each area in the model is an EOPS module. It is therefore possible to include a detailed representation of hydropower. In the simulation part, total hydro power production for each area is calculated. Thereafter, a rule-based reservoir drawdown model distributes production among all available plants within each area.

Other generation: Thermal power plants can be described individually by capacity, marginal cost (or fuel-type and efficiency), and start-up costs (optional). Plant outages may be modelled by an Expected Incremental Cost method. Windpower and solar-power have zero costs and stochastic generation.

Transmission: A capacity and availability is specified for each controllable transport channel. Detailed power flow can also be applied, cf. Samlast/Samnett.
Consumption: For each area demand can be specified by annual levels, within-year weekly profile, and within-week hourly profile. During simulation, the demand is affected by prices and temperatures.

Some tasks the EMPS-model may perform:
- Forecasting of electricity prices and reservoir operation
- Long term operational scheduling of hydro power
- Maintenance planning (transmission or production)
- Calculation of energy balances (supply, consumption and trade)
- Utilization of transmission lines and cables
- Analysis of overflow losses, and probability for curtailment
- Analyse interplay between intermittent generation, hydropower and thermal power
- Investment analysis; system development studies
- Calculation of CO2-emisssions from power generation

Information from Sintef (C. B. M. Sintef n.d.).

5. ProdRisk - more details

ProdRisk allows scheduling within a geographical area assuming no internal transmission grid bottlenecks, and can in principle be run in two modes; a market mode and an isolated mode. In the market mode, the system under consideration is connected to a market, and the market prices are exogenously given. In the isolated mode, all relevant parts of the power system are modelled, and ProdRisk performs the "market clearing" to obtain power prices.

ProdRisk is in operational use by many of the largest hydropower producers in the Nordic power market.

Solution approach

ProdRisk is based on SDDP which enables stochastic optimization with a large number of reservoirs. The solution approach combines system simulation and strategy computation to find an optimal hydro release strategy. In brief, this separation is achieved by dividing the overall problem in to smaller optimization problems, which are solved by using linear programming and coordinated by using on the principle of Benders decomposition. System constraints can be treated equally in both the system simulation and strategy computation. ProdRisk allows treating the power price as an exogenously given stochastic variable by integrating the principle of stochastic dynamic programming (SDP) in the SDDP scheme.

Modelling features

- solves the same scheduling problem as is solved by the EOPS model. That is, the market description and detailed hydro module description is similar for the two models;
- has a stochastic time-resolution of one week, but allows dividing the week in to load blocks with down to hourly time resolution;
- generates coupled water values (or cuts) which can serve as input to the short-term operational planning, providing a consistent coupling between the two;
- is designed for parallel processing;
- has functionality for risk management and dynamic hedging.

Transmission grid and wind power

In a research prototype named ProdNett, ProdRisk was extended to analyse transmission system bottlenecks by adding linearized power flow constraints, and model wind power as a stochastic variable.

Information from Sintef (C. H. O. H. Sintef n.d.)