Aalto University
School of Science

Master’s Programme in Mathematics and Operations Research

Scenario analysis of uncertainties impacting investment headroom of an electricity producer

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Master’s Thesis
2026

Aalto University
School of Science

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Title Scenario analysis of uncertainties impacting investment headroom of an electricity producer

Degree programme Mathematics and Operations Research

Major Systems and Operations Research

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Collaborative partner Fortum Oyj

Date 25 May 2026 **Number of pages** 53 **Language** English

Abstract

Electricity markets are volatile due to increased share of renewable energy production and recent global crises. To reach their business targets in such conditions, energy producers need to actively manage risks and conduct careful financial planning. Financial simulation models can be used to estimate electricity producer's future financial status and to support investment decisions. However, uncertainties in model inputs may affect the model output, and thus cause the decision maker to either invest too much with respect to their risk attitude or miss opportunities by investing too cautiously.

This thesis examines how uncertainty in key model inputs, spot price scenarios and counterparties' probability of defaults (PDs), affect investment headroom. Scenarios are created that reflect the input uncertainty through spot price and counterparty PD perturbations. The impact of these perturbed input scenarios on investment headroom, defined as the maximum CapEx investment that can be made while respecting financial constraints, is evaluated for decision makers with different risk attitudes.

The results indicate that input uncertainty does not significantly affect investment headroom for risk-averse decision makers. However, for risk-neutral and risk-seeking decision makers, accounting for input uncertainty allows higher CapEx investments. From the model inputs, uncertainty in spot price scenarios has the largest impact on investment headroom. In addition, the spot price scenarios used in the financial simulation model are found to have historically underestimated spot prices, which may lead to systematically overly conservative investment recommendations.

Overall, the results suggest that electricity producers should account for input uncertainty in financial planning, and that its impact depends on the decision maker's risk attitude. Furthermore, it is recommended to address the bias in the spot price scenarios to improve the reliability of the financial simulation model results.

Keywords Electricity markets, scenario analysis, decision support, price risk, counterparty credit risk, risk management

Aalto-yliopisto
Perustieteiden
korkeakoulu

Tekijä Ilmari Saarinen

Työn nimi Sähköntuottajan investointipäätöksiin vaikuttavien epävarmuuksien skenaarioanalyysi

Koulutusohjelma Mathematics and Operations Research

Pääaine Systems and Operations Research

Työn valvoja Prof. Ahti Salo

Työn ohjaaja DI Mikko Huotari

Yhteistyötaho Fortum Oyj

Päivämäärä 25.5.2026 **Sivumäärä** 53 **Kieli** englanti

Tiivistelmä

Sähkömarkkinat ovat epävakaat uusiutuvan energiantuotannon osuuden kasvun ja viimeaikaisten maailmanlaajuisten kriisien takia. Saavuttaakseen liiketoimintatavoitteensa epävakaassa ympäristössä sähköntuottajien on pystyttävä hallitsemaan riskejä aktiivisesti ja harjoittamaan taloudellista suunnittelua huolellisesti. Taloudellisia simulointimalleja voidaan käyttää arvioimaan sähköntuottajan tulevaa taloudellista tilaa ja tukemaan investointipäätöksiä. Mallin syötteisiin liittyvä epävarmuus saattaa kuitenkin vaikuttaa mallin tuloksiin, mikä saattaa johtaa päätöksentekijän tekemään liian suuria investointeja suhteessa riskiasenteeseensa tai menettämään mahdollisuuksia liian varovaisen investoinnin johdosta.

Tässä työssä tarkastellaan, miten epävarmuus mallin keskeisissä syötteissä, eli spot-hintaskenaarioissa ja vastapuolten maksukyvyttömyystodennäköisyyksissä, vaikuttaa investointipäätöksiin. Epävarmuutta kuvataan muodostamalla skenaarioita, joissa käytetään erilaisia oletuksia spot-hinnoille ja maksukyvyttömyystodennäköisyyksille. Näiden skenaarioiden vaikutusta taloudelliseen suunnitteluun arvioidaan eri riskiasenteen omaaville päätöksentekijöille. Vaikutusta taloudelliseen suunnitteluun mitataan vertailemalla suurinta sallittua investointimenoa (CapEx), joka voidaan tehdä eri skenaarioissa taloudelliset rajoitteet huomioiden.

Tulosten valossa syötteiden epävarmuus ei vaikuta merkittävästi riskiä karttavan päätöksentekijän suurimpaan sallittuun investointimenoon. Sen sijaan riskineutraalille ja riskihakuiselle päätöksentekijälle epävarmuuden huomioiminen mahdollistaa suuremmat investointimenot. Mallin syötteistä spot-hintaskenaarioihin liittyvä epävarmuus vaikuttaa eniten taloudelliseen suunnitteluun. Lisäksi havaitaan, että mallin syötteenä käytetyt spot-hintaskenaariot ovat olleet vastaavia toteutuneita spot-hintoja matalammat, mikä johtaa systemaattisesti liian varovaisiin investointisuosituksiin.

Tulosten perusteella syötteiden epävarmuus tulee huomioida taloudellisessa suunnittelussa. Syötteiden epävarmuuden vaikutuksen suuruus riippuu päätöksentekijän riskiasenteesta. Lisäksi spot-hintaskenaarioiden systemaattinen virhe on syytä korjata simulointimallin tulosten luotettavuuden parantamiseksi.

Avainsanat Sähkömarkkinat, skenaarioanalyysi, päätöksenteon tukeminen, hintariski, vastapuoliluottoriski, riskienhallinta

Use of artificial intelligence

Microsoft Copilot has been used to assist in the creation of figures, proofreading and improving the structure of the text.

Preface

I would like to thank Professor Ahti Salo for his support throughout this project. He consistently provided valuable perspectives beyond my own. During the final stages of the thesis, he challenged me to push my work further and to strive for the best possible outcome. I also wish to thank my advisor, Mikko Huotari, for his continuous guidance, particularly during demanding and evolving phases of the project, as both the project focus and external conditions changed.

I am also deeply grateful to my family and friends for the unforgettable moments shared during my studies and beyond. Dipoli Reima restaurant also deserves special thanks for its generous take-away lunches during the most challenging pandemic years.

Finally, I would like to thank my partner, Johanna. Her support, exemplified by always providing delicious meals even during the busiest times when I could hardly think about cooking myself, meant more than words can express.

Espoo, 25 May 2026

Ilmari Saarinen

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List of abbreviations

CapEx	Capital Expenditure
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortisation
FIR	Fortum Internal Rating
MC	Monte Carlo
MtM	Mark-to-Market
OTC	Over-the-Counter
PD	Probability of Default
VaR	Value-at-Risk
WACC	Weighted Average Cost of Capital

1 Introduction

Electricity markets are growing. Cutting carbon emissions and transitioning to clean energy production are one of the main reasons for the rapid growth of electricity demand [1]. The global electricity consumption in 2023 was 26 000 TWh, and is expected to increase to 50 000 TWh by 2050 [1]. The pursuit of carbon neutrality has increased the share of electric solutions in sectors such as transport and heating. This implies that individuals and companies have become even more dependent on the electricity sector.

The electricity market is also vulnerable and unstable. Following Russia's attack in 2022, the price of European gas futures rose to all time highs, also shaking the electricity market due to the dependence between natural gas and electricity markets [2]. The increase in renewable energy production increases the overall volatility of electricity supply due to the volatile nature of renewables, especially wind and solar power. Electricity is not an easily storable commodity. However, for example, hydropower can provide flexibility and storage capabilities that wind and solar power lack [3].

In addition, electricity demand can change rapidly and may be difficult to predict accurately due to varying weather conditions, for example. Fluctuations in demand and supply cause the electricity price to be unstable. In the wholesale market, prices are available only one day before trading. This makes financial planning difficult for both customers and suppliers.

From the viewpoint of customers, it is important that electricity producers can reliably provide electricity despite possible disturbances in the energy markets. Many electricity producers also share the target of providing more sustainable energy, which can be reached by investing in new renewable energy. To provide sustainable energy reliably, electricity producers must endure the prevailing volatile circumstances and manage disruptions, including unforeseen maintenance or counterparty defaults.

In general, companies face different financial risks, such as market risk, credit risk, and liquidity risk [4]. Market risks include price risk and production risk [5]. Electricity prices may drop to levels that are lower than the cost of generation, or electricity production may be lower than expected, so that the electricity supplier cannot match all demand. Credit risk includes, for example, counterparty credit risk and concentration risk. Counterparty credit risk is the risk that the counterparty defaults before completing all agreed payments [6]. This risk is significant for electricity producers because many electricity derivatives are traded bilaterally rather than through exchanges. Concentration risk refers to the risk that arises from relying only on a few counterparties in bilateral trading. The liquidity risk refers to the failure to meet short-term obligations due to insufficient cash availability.

Electricity producers mitigate risks by conducting risk management actions. Market risk can be reduced by hedging [7]. By hedging, the electricity producer can secure future revenues from electricity sales by locking the selling price in advance. The process of hedging involves trading electricity derivatives, like forwards and futures. Credit risk can be controlled by diversifying the portfolio and assessing the credit quality of counterparties. The price of the forward contract should reflect the estimated credit quality of the bilateral counterparty and thus compensate for the credit risk. Mathematical modelling can be used to manage and estimate financial risks.

This thesis is written for Fortum Oyj, one of the biggest electricity producers in the Nordics. Internally, Fortum uses a probabilistic financial model to simulate Fortum's future financial status. The model creates multiple scenarios with different spot prices, production estimates, and other market conditions, as well as with different counterparty default events within the bilateral portfolio. Scenarios are useful in risk management as they aim to "describe images of the future that challenge current assumptions and broaden perspectives" rather than just trying to forecast the future as precisely as possible [8]. The model assigns each scenario a probability and produces a probability distribution of the quantity of interest, usually a financial indicator such as EBITDA (earnings before interest, taxes, depreciation, and amortisation), at a given time point. The output distribution can be seen as a measure of aleatory uncertainty of the quantity of interest. Aleatory uncertainty is the form of uncertainty that the modeller considers irreducible [9].

The model can simulate Fortum's financial status for different time horizons. The simulation results can be further utilised in the decision-making process. The model can also simulate financial leverage, which reflects the relative amount of debt used in a company's financing compared to equity, according to Rayan [10]. Financial leverage can be measured with different financial leverage ratios, such as net debt over EBITDA. Too high a net debt/EBITDA ratio has a negative effect on company profitability [11], while profitable companies can benefit from increasing the leverage ratio [10].

The decision maker may have a reference threshold that the leverage ratio should be kept below to control financial risks, such as being unable to pay the debt back or the risk of getting a credit rating downgrade. Depending on the decision maker's risk attitude, they can select a fixed metric of the simulated results to represent their estimate of the leverage ratio at the future time point. By comparing the estimate obtained for the leverage ratio with the reference threshold, the decision maker can decide how much can be invested over the next year, for example, in CapEx (capital expenditure). The maximum amount that can be invested in CapEx without violating financial restrictions is called CapEx headroom. When deciding investments, the allowed maximum CapEx investment can be used as a constraint.

Usually, a mathematical model's output distribution does not match exactly the true distribution of the quantity of interest. This can be due to inaccurate or insufficient input data, or that the model is based on erroneous or too simplistic assumptions. This type of uncertainty is called epistemic uncertainty, which can be reduced by collecting more data, improving the accuracy of the data, or refining the scientific principles used in the model [9]. In this thesis, the model is asssumed to be accurate, and thus any inaccuracy in the output distribution is due to inaccuracies and shortcomings in the input data.

This thesis examines the impact of input uncertainty during a one-year time period on investment headroom, defined as the size and number of investments allowed to be made. The thesis includes a case study with Fortum's financial simulation model. The model's main inputs are electricity spot price scenarios and counterparties' probability of defaults, which are used in the market risk and credit risk estimation, respectively. Electricity spot price scenarios aim to represent the aleatory uncertainty in electricity prices that is caused by varying factors such as weather conditions. Each counterparty in the bilateral portfolio is assigned a probability of default that reflects the probability that the given counterparty defaults in a year's time.

The effect of input uncertainty is studied by creating scenarios in which the inputs of the model are perturbed. The main purpose of these what-if scenarios is not to find the most plausible future outcomes but, rather, to discover outcomes that differ from the initial model output [12]. In risk management, the aim has usually been to prevent negative consequences. In this thesis, the inputs are perturbed such as both the upside and the downside are considered. If the true leverage ratio was higher than the simulated leverage ratio, the decision maker would make too large investments. On the other hand, if the true leverage ratio was better than the simulated one, the decision maker, by being overly cautious, would lose the opportunity to invest more. If the uncertainty in the input of the model is low, the decision maker can trust that the output distribution matches the true distribution well, assuming that the model otherwise accurately represents reality.

It is not trivial to determine how much the inputs should be varied. The aim is that the realisation of the what-if scenarios would be unlikely, but not impossible. The size of the perturbation in electricity spot price scenarios can be determined based on historical electricity spot prices. There may also be new factors that will affect electricity prices in the future or some long-term trends that are not yet visible in the price history. These trends may be related, for example, to technological developments, international policies, and climate change [13].

However, these long-term trends are not likely to have a significant impact on electricity prices in the one-year time horizon. An alternative non-public electricity spot price forecast model is used, along with the electricity spot price history, as a reference to estimate the size of possible inaccuracies in the electricity spot price scenarios. The alternative forecast model might use assumptions and methodologies different from those in the forecasting model used to construct price scenarios used in the financial simulation model. Historical spot price forecasts are compared to historical realised spot prices and corresponding forecasts produced with the alternative model. The spot price perturbations are created based on these comparisons.

It is useful to model credit risk with internal models by using internal default data as the main data source for PD (probability of default) estimation [14]. However, Fortum does not have sufficient internal data, which is why external credit rating agencies' ratings and PD estimates are utilised in PD modelling. Due to the lack of internal data from Fortum's own portfolio, it is not possible to validate PD estimates with historical data. Thus, PDs are perturbed using a more pragmatic approach. It is not possible to rigorously derive probabilities for these perturbed spot price and default scenarios. However, approximate probabilities are given to illustrate the overall effect of the input uncertainty.

The financial simulation model output can also be expressed as maximum CapEx investment distribution, where the maximum CapEx investment denotes the amount company's net debt can be increased without violating leverage ratio constraint. The difference between the maximum CapEx investment distribution produced with the perturbed inputs and with the original non-perturbed inputs is used as an estimate of the input uncertainty.

In general, decision makers with different risk attitudes are interested in different metrics of the output distribution. For example, a risk-neutral decision maker might make decisions based on the expected value of the maximum CapEx investment, while a risk-averse decision maker focuses on the lower quantiles of the output distribution, such as the 0.05 quantile. The 0.05 quantile denotes the same values as the 5th percentile; 5% of realisations can be expected to be below this value. The risk-averse decision maker prepares for the most unfavourable scenarios, and the true value will likely be higher than the allowed CapEx investment size indicated by the 0.05 quantile. Thus, it is likely that the risk-averse decision maker could have invested more in CapEx, but they want to be certain that the leverage ratio constraint is not violated.

The main goal of this thesis is to help the decision maker assess the possible impacts of input uncertainty in financial planning. The focus is on whether the presence of this uncertainty would change the maximum amount allowed to invest in CapEx. The hypothesis is that the input uncertainty is not significant and is already taken into account in the scenarios that are used as inputs in the model. However, if the hypothesis is rejected, that would indicate a need to refine the financial simulation model, to improve the input quality, or adjust the leverage ratio threshold, or otherwise take the uncertainty into account in the decision-making process. The secondary objective is to validate the hypothesis that out of all model inputs, the electricity spot price scenarios have the largest impact on financial planning. This is evaluated by comparing the maximum CapEx investment distribution produced with changed PDs to the distribution produced with changed electricity spot price scenarios.

In summary, this thesis will answer this research question: *How do uncertainties over a one-year horizon in electricity spot price forecasts and counterparties' probability of default estimates impact the size of an investment an electricity producer can make without violating financial constraints?*

2 Background

2.1 Financial risk modelling for a Nordic electricity producer

The Nordic electricity market has several key characteristics. Price volatility is large due to the high share of renewable production, and demand has a large seasonal variance. Different contracts are agreed for a long-term horizon, and a large part of trades are conducted bilaterally rather than through exchanges. The popularity of long-term contracts arises from the high volatility of the spot price. Electricity producers need to secure stable earnings to make financial planning easier and customers want stable and predictable expenses. Furthermore, long-term contracts reduce future cash flow volatility compared to selling most of the electricity on the spot market or through short-term contracts. However, long-term contracts also introduce risks, such as credit risk related to defaulting counterparties and liquidity risk arising from low market depth, which can make trading difficult [15].

Thus, there are many aspects that expose the electricity producer to financial losses. To manage the losses, the companies conduct risk management, of which financial risk modelling is an essential part. In the risk management process, the relevant risks are first identified. Then, a mathematical model is created that can be used to illustrate how uncertainties propagate through the system of interest. Finally, based on the significance of the risks indicated by modelling, decisions may be made to mitigate the risks. Alternatively, risk modelling can be used to assist in the decision-making process by helping quantify the effect and likelihood of different risks.

Modelling can provide support for decisions affecting complex systems. Without modelling, it would be impossible to estimate uncertainties or consequences of decisions. As stated by Eck [16], mathematical modelling requires many assumptions and simplifications to be made due to the complexity of real-word problems. Also, the application in which the model is used defines how the model should be created. It is also important to note that even the best and most accurate model is useless if the model inputs are too inaccurate or the model does not use all relevant inputs. In this thesis, the model is assumed to be perfectly accurate but the inputs are inaccurate, which causes uncertainty in the model output.

Statistical analysis is a powerful tool in risk modelling, as it can be used to identify processes and relations that follow statistical principles [17]. However, often the interest is not only in statistically predictable events, but also in possible undesired events that cannot be predicted based on previous events. To perform decision analysis on systems with level 3 or 4 uncertainties, where knowledge of future outcomes is very limited, modelling techniques beyond standard statistical analysis are needed. Different levels of uncertainties are further discussed in Section 2.3.1.

Lewis [17] mentions several financial risks that electricity producers face such as liquidity risk, basis risk, price risk, and credit risk. Liquidity risk can relate to OTC (Over-the-Counter) contracts that are customisable contracts between two counterparties. These bilateral contracts lack liquidity in the sense that they cannot be easily converted into cash unlike the regulated financial instruments that are traded through exchanges, like Nasdaq in the Nordics.

On the other hand, when buying or selling electricity derivatives on exchanges, the MtM (Mark-to-Market) value of a contract is recalculated daily to reflect the current market price. If the MtM value decreases, the losses are subtracted from the initial margin held in the account. If the margin of the account drops below a certain threshold, a margin call is triggered, requiring the market participant to add funds to the account to restore the initial margin level. During the 2022 energy crisis, electricity futures prices rose quickly to extremely high levels. This exposed some of the electricity producers to high margin calls as they had agreed earlier to sell electricity at a significantly lower price, which led to severe liquidity problems [18].

Due to this liquidity problem related to exchange-traded contracts, the share of bilateral contracts increased after the energy crisis [19]. However, bilateral contracts expose companies to increased counterparty credit risk, as they are only settled at contract delivery, and in case the counterparty defaults, it can be costly to replace the lost contract. Furthermore, the increase of bilateral trading decreases the robustness of futures contract prices since the OTC contract prices are not publicly observable. This can further increase the transaction costs in both OTC and exchange trading [19].

Price risk is the producer's exposure to volatile income from electricity sales. Basis risk relates to the ability of a hedge to protect the electricity producer from the price risk. The value of the financial contract used in hedging may not exactly correspond to the value of the physical contract. Thus, for example, a fully hedged position might not be fully hedged in reality.

Price risk and counterparty credit risk, and their modelling, are addressed later in this section as they are the main risk components included in the financial simulation model. It is important to note that risks are often correlated [17]. Thus, a comprehensive risk modelling framework that incorporates all the most relevant risks is valuable to the decision maker who wants to make informed decisions.

2.1.1 Price risk modelling

After the liberalisation of many electricity markets in the late 20th century and the increasing share of renewable energy production, the electricity price risk has been among the key financial risks for both electricity production and distribution companies [20] [21]. After the liberalisation, the electricity prices were no longer stable and predictable due to the allowed non-regulated competition. This exposes production and distribution companies to price risk, meaning they face uncertain revenues or costs when selling or buying electricity.

Modelling electricity prices is an important part of price risk modelling. In price modelling, the aim is to forecast future electricity prices. Then, in price risk modelling, forecasted prices can be used in financial planning, hedging optimisation, or various decision-making processes. For example, if it is estimated that in the long-term future the price trend is down, it is likely not profitable to invest extensively in new production facilities.

An example of price risk modelling from the literature is the use of extreme value theory to predict the VaR (Value-at-Risk) of daily electricity price changes [22]. Janczura & Wójcik [21] create price scenarios based on day-ahead price forecasts and use these scenarios to optimise the trading strategy with different objectives such as maximising profits or minimising variance. Azevedo et al. [23] use long-term price forecasts to optimise the use of physical and financial contracts to protect the producer from price risk.

Electricity price forecasting is not trivial due to the special characteristics of electricity prices. The central challenge is the accurate estimation of the size and frequency of the extreme prices. Electricity prices are volatile compared to other commodities, and the volatility varies over time. Electricity prices are positively skewed, meaning that high prices occur more likely than low prices that are as far from the mean [24]. Given the challenges in forecasting electricity prices, it is useful to question the accuracy of these predictions and consider scenarios where actual prices differ from the forecasts.

Point forecasting, interval forecasting, and creating multiple price scenarios are the three approaches that have been used to model uncertainty in electricity prices [25]. Point forecasts are not very useful in risk modelling because they do not indicate the underlying distribution. Confidence intervals are better in risk modelling, although they do not illustrate the shape of the distribution. Scenario approaches are popular in risk modelling due to their ability to demonstrate uncertain events, but the possibility of not emphasising them too much through the use of scenario probabilities.

Due to its importance, electricity price forecasting is a widely studied topic. Most methods aim to create as accurate point forecasts as possible. Price scenarios can be made, for example, by creating point forecasts with different fuel prices or weather assumptions [26]. Zhao et al. [27] estimate the price and its variance using a nonlinear conditional heteroscedastic forecasting model and then create the confidence intervals for the electricity price based on the estimates.

Numerous reviews, such as [26] and [28], present the current techniques used for electricity price point forecasting. O'Connor et al. [28] divide predictive models into statistical models, machine learning models, and hybrid models. Statistical models include foundational techniques such as the ARIMA model widely used in time-series forecasting and the GARCH model that is able to model time-series with time dependent variance. ARIMA models can be extended to incorporate external factors, such as demand forecasts. Machine learning models include deep learning models, such as deep neural networks and convolutional neural networks, and traditional machine learning algorithms such as random forest and gradient boost.

The aforementioned econometric models use statistical analysis to predict electricity prices. In contrast, fundamental models try to model the underlying factors affecting electricity prices, namely electricity demand and supply. In general, fundamental models are either equilibrium or simulation models. Econometric models are more suitable for short-term forecasting, while fundamental models are more accurate for medium- and long-term forecasting. Hybrid methods combine these approaches. [29]

2.1.2 Counterparty credit risk modelling

Counterparty credit risk is a type of credit risk. Credit risk generally means the exposure when lending money. Only the party granting the loan is exposed to credit risk. However, parties involved in contracts such as electricity forwards are both exposed to counterparty credit risk. This arises from the potential of the MtM value to be either negative or positive for both parties involved.

For example, consider a forward contract where a producer agrees to deliver electricity for 40 €/MWh during a given period. If the buyer defaults before delivery and the current forward price for the same period has decreased to 30 €/MWh, the MtM value of the contract is 10 €/MWh for the producer. To replace the lost contract, a new contract would be needed to agree at a price close to 30 €/MWh, resulting in a loss of approximately 10 €/MWh. Counterparty credit risk has two components: the risk of not receiving the agreed payments and the fluctuations in market prices that affect the value of the contracts that might be lost.

Trading on exchanges reduces the exposure of companies to counterparty credit risk. However, as mentioned earlier, bilateral OTC contracts have become more common, mainly because of the liquidity risk associated with exchange trading. Modelling counterparty credit risk is important because bilateral trading can lead to large losses in the case of counterparties defaulting. Modelling helps to understand the size of the total exposure as well as the expected credit loss, which is derived from the exposure by multiplying by probability of default and loss given default, which indicates the percentage of exposure that is lost when a default occurs.

As an example, consider a framework for modelling the counterparty credit risk created by Pykhtin and Zhu [6]. Their framework helps to estimate portfolio-level exposure and consists of three steps: scenario generation, instrument valuation, and portfolio aggregation. First, market scenarios are created to simulate possible future states of price factors. Price factors such as electricity demand and fuel prices influence the value of the portfolio mainly through their effect on the forward price. Then, the MtM value for every trade within the portfolio is assessed in relation to each market scenario that represents different realisations of price factors. Finally, trades are aggregated inside the portfolio. In the presence of a netting agreement with a specific counterparty, trades are aggregated with that counterparty. A lost contract having a positive MtM value can be compensated by a contract with the same counterparty, that has a negative MtM value. Thus, a counterparty-level exposure is determined for each market scenario, and a portfolio-level exposure is obtained by summing the individual exposures.

Assessing potential credit exposure is useful in riks management, and counterparty credit risk can be managed for example by setting a maximum limit for exposure towards a single counterparty. However, credit exposure does not yet indicate the likelihood of credit losses. Probabilities of default can be estimated using internal default data [14]. However, not all companies have sufficient default data, and they need to rely on external credit rating agencies that provide credit ratings associated with probability of default estimates.

For instance, S&P rates companies on a scale from AAA to D to evaluate their relative creditworthiness [30]. Credit rating agencies also assign yearly PDs to the ratings, which indicate the probability of default during that specific year, given that the company has not defaulted previously. With the help of external PDs, the framework of Pykhtin and Zhu [6] can be extended to estimate credit losses instead of exposure by simulating defaults inside the portfolio. Due to the usual large number of counterparties and low PDs, it is not feasible to simulate all possible combinations of defaulting counterparties. Thus, it is useful to create scenarios with different default events.

It is challenging to separate adjacent credit ratings and their PDs. For example, there is no guarantee that a company with a rating of A should not actually have a rating of A+, A- or even AA [31]. Investment grade ratings (AAA-BBB) have also been shown to be more difficult to distinguish, while speculative grade ratings (BB-D) are more likely to accurately represent the actual probability of default [31]. If uncertainty in PDs or their correlation between different counterparties is ignored, it can lead to severe inaccuracies when estimating credit risk [32].

Methods to estimate confidence intervals for probabilities of defaults have been developed. Using bootstrapping and historical credit ratings data, it is possible to estimate the confidence intervals for PDs [33][31]. Both studies emphasise the difficulty of separating low-risk ratings from each other, especially for short time horizons such as one year. In addition, some speculative grade PDs are non-monotonic, in the sense that for some rating pairs the PD of the worse rating is not greater than or equal to that of a better rating. For example, Hanson et al. [31] found that, on a 95% confidence interval, the one-year PD of the BB+ rating is not lower than that of the BB rating.

It is also possible that the probability of default of a company may differ for different counterparties. For example, a company can fail to make some payments to other counterparties while still paying their electricity bill. Electricity producers such as Fortum also trade with many small companies that do not have an official credit rating from a large credit rating agency such as S&P. In that case, an internal rating system or some smaller rating provider is needed. In that case, the accuracy of the PDs can be even worse. Also, the number of rating levels can be lower, leading to larger distortions if a wrong rating is assigned.

In addition, the frequency with which the PDs are updated might vary. It is possible that a one-year-old PD is used right before the PDs are updated. Due to these PD uncertainties and the significance of counterparty credit risk, it is important to consider scenarios with different credit rating assumptions and observe how they affect financial planning.

2.2 Description of the financial simulation model

In this section, a general description of the financial simulation model used in Fortum is given. The main inputs of the model and the uncertainties related to the inputs are ilustrated. The main objective of the financial simulation model is to produce reliable estimates of the future financial status that can be used in decision making, such as deciding investments. The model creates scenarios with different assumptions about price risk and counterparty credit risk. For every scenario, the metric of interest, such as EBITDA or the leverage ratio, is calculated, and the overall output distribution is then derived using the probabilities assigned to each scenario.

The model uses 135 distinct spot price scenarios. The spot price scenarios consider different weather conditions and commodity prices that significantly affect spot prices. Weather factors include wind and solar conditions, temperature, and water inflow to hydro reservoirs. The prices of different commodities such as EU emission allowances, coal, and natural gas affect the spot prices as well. The methodology for creating the spot price scenarios is outside the scope of this thesis. Thus, the spot price scenarios as such are considered as input for the model. The set of spot price scenarios is denoted as

$$S = \{s_i \mid i = 1, \dots, 135\}, \tag{1}$$

where s_i is a vector of monthly spot prices for the next 12 months. The forecast horizon of the scenarios can be extended beyond one year, but in this thesis, the interest is in the financial status one year ahead. Thus, having spot price scenarios for the next 12 months is sufficient.

Each spot price scenario s_i contains price forecast for seven nordic electricity price areas. The set of price areas is denoted as A and contains the price areas FI, SE1-SE4, NO1, and NO4. Those areas are used because Fortum's electricity production and retail are mainly located on those areas. The spot price forecast of scenario s_i for the price area $a \in A$ is denoted as $s_{i,a}$. All spot price scenarios are assumed to be equally likely. The probability of each price scenario s_i is $p_{s_i} = \frac{1}{135}$. Since spot price scenarios also depend on the forecast date, an additional subscript f is presented, which denotes the month when the spot price forecast is made. The notation $s_{i,a,f}$ represents the vector of monthly spot prices, similar to s_i, but now $a \in A$ denotes the area and $f \in F$ denotes the forecast month. This more precise notation is used later in Section 3.1.1, where the spot price forecast is compared to realised prices over multiple forecast months. F denotes the set of all forecast months that have historical spot price forecasts available.

To capture the counterparty credit risk arising from potential counterparty defaults, the model creates 11 default scenarios d_j. Default scenario d_1 does not include any counterparty defaults. Scenarios d_2 to d_{11} contain counterparty defaults such that the defaults in scenario d_i are more severe than in scenario d_j if $i > j$. The severity of the defaults is defined as the total value of the open contracts with the defaulting counterparties. In every scenario d_j, the specific month in which each of the defaulting counterparties defaults during the one-year period is specified. Thus, the exact value of the remaining contract at the time of default can be determined. The set of default scenarios is denoted as

$$D = \{d_j \mid j = 1, \dots, 11\}. \tag{2}$$

The probability of the default scenario d_j is denoted as p_{d_j}. To create the default scenarios, the model needs several input variables. The PDs of the counterparties in the bilateral portfolio are considered as input variables because the interest is in their effect on the output. Each counterparty is mapped to one of the five credit rating levels in FIR (Fortum's internal rating) system based on the counterparty's external credit rating. Each level of the internal credit rating system is assigned a PD, which is determined based on the PDs of the ratings that are mapped to that internal rating. The PDs for each internal rating grade differ between the countries the counterparties are located in. Fortum's counterparties are mainly located in the Nordics.

Other factors needed in the creation of default scenarios are kept constant in this thesis and hence are considered as parameters. These parameters consist of the number of default scenarios and the bilateral portfolio, which is defined by the counterparties, their credit ratings, and the nominal values and maturities of the contracts. By nominal value, we denote the contract price per MWh multiplied by the contract's remaining volume in MWh that has not been delivered yet. The nominal value of the contracts is used instead of the MtM value to avoid the need to use price scenarios to estimate the MtM value of the contracts in the future. Thus, in the financial simulation model, the correlations between default and spot price scenarios are presumed to be zero.

It is impossible to directly derive the exact probability distribution of the total nominal value of contracts that are lost due to defaulting counterparties. This is due to the significant number of possible combinations of default events. Any number of counterparties from the bilateral portfolio can default during a period of one year. Thus, the number of different combinations of defaulting counterparties is $\sum_{k=0}^{n_c} \frac{n_c!}{k!(n_c-k)!}$. If the number of counterparties, n_c, in the bilateral portfolio is, for example, 200, the number of different default combinations is astronomically large. The problem becomes even more complex when considering the nominal value of lost contracts, which also depends on the timing of the defaults during the period. Thus, the space of lost nominal value is divided into ten intervals to reduce computational burden. Each nominal value interval corresponds to a default scenario $d_j, j = 2, \ldots, 11$. The probabilities of the intervals, p_{d_j}, associated with the corresponding default scenarios d_j, are estimated using MC (Monte Carlo) sampling.

An individual MC sample involves some of the counterparties defaulting, resulting in a loss equal to the sum of the nominal values of the individual remaining contracts with the defaulting couterparties. The higher the counterparty's PD, the more likely it is to default in a single MC sample. Each default scenario $d_j, j = 2, \ldots, 11$ is characterised by a nominal value interval $(N_{j-1}, N_j]$. The lower limit of d_2 is $N_1 = 0$ and the upper limit N_{11} of d_{11} is the sum of the outstanding nominal values of contracts with all counterparties inside the bilateral portfolio at the time of evaluation. d_1 is the scenario without defaults. Thus, each MC sample falls within one default scenario based on the lost nominal value. The probability p_{d_j} is derived by dividing the number of MC samples inside the corresponding nominal value interval by the total number of MC samples. The total number of MC samples is large enough that the probabilities of the default scenarios are stable between model runs.

The model creates a representative realisation for each default scenario d_j. Realisations are chosen such that the number of defaulting counterparties is not limited, but the sum of the lost nominal value must be within the nominal value interval of the corresponding default scenario. For example, if $N_2 = 100$M€ and $N_3 = 200$M€, the d_3 scenario could consist of counterparties A, B, and C defaulting within a one-year time period, such that the sum of the nominal values of the contracts with these counterparties at the time of default is between 100M€ and 200M€. The representative realisations of the default scenarios are not dependent on the MC sampling. Thus, changing counterparty PDs affects the propabilities p_{d_j} of the default scenarios, not the representative realisations.

The spot price scenarios and default scenarios are finally combined using the

Cartesian product. These combined scenarios are denoted as

$$\Omega = S \times D = \{\omega_{i,j} = (s_i, d_j) \mid s_i \in S, d_j \in D\}, \tag{3}$$

where $\omega_{i,j}$ denotes the individual combined scenario, for which the probability is given by

$$p_{\omega_{i,j}} = p_{s_i} \cdot p_{d_j} = \frac{1}{135} \cdot p_{d_j}. \tag{4}$$

The price scenarios and default scenarios are assumed to be independent. In practice, high electricity spot prices may cause more defaults. However, since bilateral counterparties buy at least part of their total electricity need at a fixed price, price fluctuations should not affect default rates much, at least in the short one-year time horizon. Thus, it is safe to assume that spot prices and defaults are independent.

The combined scenarios $\omega_{i,j}$ are used to estimate the joint effect of spot prices and default events. The model creates deterministic forward curves for each spot price scenario. The electricity forward curves predict the development of the forward price in different price areas until a certain delivery period. In the presence of default events, the forward price indicated by the forward curve determines the size of the termination payment that must be paid to the defaulting counterparty if the MtM value of the contract is negative from the seller's perspective. In addition, the forward curves determine the price at which a new similar contract can be made when the previous contract is lost. However, in this thesis, no replacement contracts are made.

Now that scenarios are defined, the financial simulation model can be denoted as

$$M(S, D(x)) \to Y, \tag{5}$$

where the inputs of the model M are the spot price scenarios S and the counterparty PDs denoted by x, which affect the default scenarios. Y denotes the output distribution of the model, for example, the EBITDA distribution in one year. Y depends on the spot price and default scenarios, and it can be written as

$$Y = \{(y_{i,j}, p_{\omega_{i,j}}) \mid i = 1, \dots, 135, j = 1, \dots, 11\}, \tag{6}$$

where the output distribution is characterised as the set of pairs $(y_{i,j}, p_{\omega_{i,j}})$, where $y_{i,j}$ is the model output, such as EBITDA or leverage ratio, related to the scenario $\omega_{i,j}$ paired with its probability. Finally, the cumulative probability distribution of the output can be formulated as

$$F_Y(t) = P(Y \leq t) = \sum_{i=1}^{135} \sum_{j=1}^{11} \mathbf{1}_{\{y_{i,j} \leq t\}} \cdot p_{\omega_{i,j}}, \tag{7}$$

where Y is the random variable of the output quantity y and $\mathbf{1}_{\{y_{i,j} \leq t\}}$ is the indicator function that obtains the value 1 when $y_{i,j} \leq t$ and zero otherwise.

Rather than summarising the model result with a single number such as the expected value, the output distribution is used because it is more informative and allows the decision maker to incorporate their own risk attitude into the decision-making process using, e.g., VaR approach. For example, a risk-averse decision maker might use the 0.05 quantile of the cumulative EBITDA distribution as an estimate one year ahead. Thus, it is likely that the true EBITDA one year ahead will be higher than the estimate. This approach is useful if severe problems arise if EBITDA is overestimated. On the other hand, a more neutral decision maker might choose the median or the expected value as the estimate. In addition, the context of the decision problem affects the choice; if the purpose is to make as accurate estimates as possible, the expected value is chosen. The topic of risk attitude is more thoroughly addressed in Section 2.3.3.

The output distribution Y quantifies the overall uncertainty in predicting financial outcomes arising from the real-world uncertainties, such as weather conditions that affect spot prices. However, the model itself is likely imperfect, and the parameters may be uncertain due to insufficient data or limitations in the sub-models used to estimate them. Thus, it is important to acknowledge that the output distribution does not fully capture all of the uncertainty present in the true underlying quantity. In reality, the distribution of the true quantity can be wider, more narrow, or differently located due to these uncertainties.

In this thesis, the model output y, some financial metric of Fortum, is considered at a single time point, one year from the modeling date with an accuracy of one month. The model can estimate different financial metrics, such as EBITDA, cash flow, or CapEx. However, here the leverage ratio is used as the model output y. The leverage ratio has different formulations, but here it is defined as net-debt-to-EBITDA, presented in [34], as

$$\text{Leverage Ratio} = \frac{\text{Net debt}}{\text{EBITDA}}. \tag{8}$$

The net-debt-to-EBITDA ratio illustrates how many years it would take for a company to pay its debt off using its EBITDA. It is often useful to take debt instead of, for example, issuing new equity. For example, debt related expenses such as interest payments have tax benefits. However, highly leveraged companies have more expenses than benefits from the high amount of debt. Thus, an optimal capital structure can be defined for companies that indicates the optimal relation between debt and equity. It is also shown that high net debt/EBITDA ratio has a negative effect on firm's profitability. [11]

The high net debt/EBITDA ratio also has practical disadvantages. The leverage ratio is a key metric used by credit rating agencies such as S&P to assess the credit quality of companies [30]. S&P has defined a practical threshold for Fortum that the leverage ratio should be kept below to maintain the investment grade credit rating. Thus, instead of defining a theoretical optimal leverage ratio for Fortum, a certain threshold that should not be exceeded when making debt financed investments is used.

2.3 Decision analysis

Decision analysis combined with financial risk modelling tools can assist decision making processes such as financial planning. Decision analysis helps to understand the preferences of the decision maker, take into account the limitations, and discover the optimal decision for the decision maker.

Decision analysis is a field of research and practice that emerged in the 1960s. It combines the concepts of subjective probability and preferences under uncertainty through the concept of expected utility [35]. Howard Raiffa is one of the founding creators of decision analysis, being the author of *Decision Analysis* in 1968 [35][36].

The purpose of decision analysis is to illustrate real-world problems with mathematical models to obtain insight into the complex systems being analysed. These insights are intended to help the decision maker make better decisions. The principle of decision analysis is captured by the idea that a "good" decision does not necessarily imply a good outcome, while a "bad" decision can result in a lucky outcome. [37]

The following fundamental aspects are common to decision problems:

1. A need to achieve some objectives.
2. Many alternatives to be chosen, from which one should be selected.
3. Choosing different alternative leads to different outcome.
4. Consequences of each alternative might be uncertain.
5. Some consequences are more preferred than others. [38]

The objective to be achieved can be, e.g., maximising cash flow, or there can be multiple objectives such as minimising environmental damage while minimising costs. The possible decision alternatives might include deciding whether to invest in a new wind farm or to refrain from investing. Investing might lead to bigger profits, while not investing might keep the cash flow stable. Investing in the wind farm might be highly profitable in the future, but if electricity consumption decreases, the investment becomes unprofitable. Some decision makers prefer the alternative with the highest expected net present value. However, some decision makers could prefer the option that involves less risk, which is likely to not invest in the new wind farm. These decision makers want the result to be fairly satisfactory, even in the face of misfortune.

The methodology of decision analysis can be divided into four parts [38]. First, the structure of the problem is defined. Decision alternatives and the objectives of the decision maker are defined. Second, the consequences of different alternatives are estimated. The consequence of a single alternative is rarely deterministic. Thus, the outcomes should be assigned probabilities based on historical data or expert elicitation. However, it is not always possible to associate probabilities with different outcomes. Third, the decision maker's preferences are elicited. This is equivalent to determining the utility function of the decision maker. The utility function describes the desirability of each outcome according to the decision maker. The risk attitude of the decision maker can be deduced from the utility function.

Finally, the alternatives are compared on the basis of the expected utility of each of them. The decisions resulting in the highest expected utility are recommended for the decision maker. It is also possible to assess the decision maker's risk attitude without determining the utility function by using the Value-at-Risk measure. It is also important to assess the sensitivity of the decision to different assumptions about event probabilities and utility function structure.

In this section, the following topics related to decision analysis are covered. First, different types of uncertainty and how they can be modelled are discussed. Second, scenario analysis, which can be used in decision analysis, is covered. It is especially beneficial in situations where precise probability estimates cannot be made, yet there is a need to examine how various decisions and events impact the outcome. Finally, the concept of risk attitude is covered as the interest is whether the changed model inputs have a different effect on decision makers with different risk attitudes.

2.3.1 Uncertainty

Uncertainty complicates decision making, as even the best choices with respect to the information available at the time of decision do not always result in the best outcomes due to uncertainty. Sometimes it is possible to estimate the probability of some uncertain event, but sometimes it is not even possible to predict what kind of uncertain event may happen. To help understand uncertainty and control its impact on the decision-making process, it is useful to categorise different uncertainties separately. This division can also help us identify uncertainties that can be reduced, such as by gathering more information.

In risk modelling and decision analysis, it is common to classify uncertainty into two types: aleatory and epistemic. Aleatoric uncertainty can be characterised as intrinsic randomness that cannot be reduced by gathering more information about the phenomenon. On the other hand, epistemic uncertainty is related to a lack of knowledge and can be reduced by acquiring relevant information or collecting more data. [9]

Uncertainty can originate from various sources, namely basic variable uncertainty, model uncertainty and parameter uncertainty [9]. Basic variables are fundamental input parameters used in modelling that can be drawn from a probability distribution. Weather variables such as temperature and wind speed are examples of basic variables. Uncertainty in basic variables can be either aleatoric or epistemic. Uncertainty associated with tomorrow's weather conditions is aleatoric if it is assumed to be infeasible to improve the accuracy of the prediction. However, if the prediction could be improved, for example, by collecting more data to improve the theoretical distribution, the uncertainty involved would be both aleatoric and epistemic.

Model uncertainty can arise from the fact that not all relevant variables on which the response variable is dependent are modelled. The exclusion of dependent variables can be due to a lack of knowledge of the dependence between the input variables and the response variable. The exact relation between the variables or the whole dependence might be unknown. Another reason for the model uncertainty is the inaccuracy of the model, which stems from a mismatch between the true relationship between the input and response variables and the mathematical approximation used in the model. Model uncertainty is usually interpreted at least partly as epistemic uncertainty because, by gathering more information, it should be possible to incorporate more relevant input variables and to reduce the gap between the mathematical approximation and the true variable relationship. It is also possible to define model uncertainty mainly as aleatoric if the missing input variables are aleatoric and existing scientific knowledge is limited in the sense that it does not allow further improvement of the model. [9]

Consider a probabilistic model that predicts the temperature for the next day. Based on historical weather data, it can be stated that, for example, the temperature is normally distributed with a mean of 20 °C. However, it is uncertain whether the estimated mean is correct. Parameter uncertainty can usually be reduced by improving the quality and quantity of the observational data; thus, it is epistemic by nature.

As discussed here, it is not always obvious when to define uncertainty as epistemic and when as aleatory. Indeed, it is the modeller's responsibility to subjectively define uncertainty types. The decision is based on the available data and the existing scientific knowledge related to the subject. However, the most important aspect is the context of modelling, i.e., the objective of the modelling and the appropriate level of complexity with respect to the decision-making process for which the model is used.

It is also possible to make a different division for different uncertainties. Marchau et al. [39] present four levels of uncertainty between two extreme levels, determinism, and total ignorance. Systems involving level 1 uncertainty are closest to deterministic systems. This level of uncertainty is typically associated with situations involving short-term decisions, where outcomes can be predicted based on past observations. For example, while it is almost certain that mail will be delivered, the exact timing is uncertain. Events involving level 2 uncertainty can be described probabilistically. Decisions related to systems involving level 2 uncertainty can be made based on the expected utility.

Systems involving level 3 uncertainty cannot be described probabilistically because of limited knowledge. There is a limited set of alternative futures or outcomes, but exact probabilities cannot be determined for them. Thus, decisions cannot be made based on the expected utility. However, scenarios can be created and optimal actions can be defined for these scenarios. Level 4 uncertainty is the deep uncertainty where the future or possible outcomes can be either bound around many different scenarios or it is not even known what the scenarios might be. It is not possible to predict events involving level 4 uncertainty based on previous events.

The financial simulation model is an example of a level 3 system, as exact probabilities cannot be assigned to input perturbations. On the other hand, it can be argued that level 4 uncertainty is also involved since the exact scenarios for, for example, spot price uncertainties cannot be determined but, rather, some bounds can be made for them. The uncertainty in the spot price and default scenarios is most likely both epistemic and aleatory because, in practice, it is challenging to make a distinction between them.

2.3.2 Scenario analysis

In scenario analysis, scenarios representing possible future events are created and used as input in modelling to analyse the outcomes of different events and decision consequences. Then, the whole modelling process or the modelling results are utilised as recommendations or references for the main problem. [40]

In this thesis, the results of the scenario analysis are used as a guide to making investment decisions. Scenario analysis can be used as a tool to characterise aleatory uncertainty in a system, and scenarios should be comprehensive, that is, they should cover exhaustively all possible states of the system [41]. However, in this thesis, the created scenarios are not exhaustive as they are only intended to point out the existence of uncertainty in input variables and the possible impact of uncertainty on decision making.

Maier et al. [42] present three alternative methods to deal with uncertainty when using models to improve decision making, namely uncertainty, sensitivity, and scenario analysis. Uncertainty analysis aims to determine the probability distribution of the model output by drawing samples from input variable distributions and propagating the uncertainty through the model to outputs. Sensitivity analysis measures the relative changes in output with respect to changes in inputs to determine the most significant input variables. Uncertainty or sensitivity analysis is not suitable because the precise distributions or bounds for the inputs are not known.

Scenario-based modelling approach is the most suitable choice for this thesis. Scenario analysis is useful when it is desired to avoid possible surprises in the future and also to broaden the thinking of the decision maker [43]. In this thesis, through perturbation of inputs, which effectively equals widening and changing the location of the original input distributions, it is possible to consider the impact of unexpected changes and improve decision making to account for these possibilities. The scenario generation process itself can also provide participants with valuable insights. For example, when creating scenarios with perturbed spot prices, it is possible to identify potential systematic bias in the spot price scenarios. It is important to define the exact aim of the scenario analysis before starting the analysis so that the scenarios to be created are adequate [12].

Börjeson et al. consider three main categories of scenarios: predictive, normative, and explorative scenarios. Predictive scenarios answer the question *What will happen?*. Predictive scenarios are further divided into forecasts and what-if scenarios. Forecasts predict what will happen most likely, while what-if scenarios can be used to predict outcomes conditional on external events or internal decisions. Predictive scenarios can highlight for the decision maker the potential challenges to avoid and opportunities to take advantage of. Normative scenarios describe what actions should be taken to reach a specific target. [44]

Explorative scenarios describe what can happen. Explorative scenarios are used to examine possible future evolutions. Usually, several scenarios are created to describe possible developments. Compared to what-if scenarios, explorative scenarios focus generally on long term developments, while what-if scenarios focus on short term developments starting from the present. Explorative scenarios are further divided into external and strategic scenarios. External scenarios cover scenarios that involve factors over which the decision maker has no control. Strategic scenarios aim to describe how the consequences of decisions change depending on the scenario. The focus is on the internal factors that the decision maker can control. [44]

The perturbed scenarios that are created in this thesis to assess the effect of input uncertainty can be characterised as what-if scenarios. The financial status is predicted, conditional on external events that represent deviations of electricity spot prices and the probability of defaults from the original forecasted values. New decision policies can be suggested for the decision maker if it appears that investments are either too large or too small. The perturbed scenarios also resemble external explorative scenarios because they are used to explore the possible future outcomes. However, the focus is on the one-year time horizon, while the explorative scenarios usually focus on long-term developments.

The main aim of scenario analysis is to support learning and enable better decision making. Learning can refer to, for example, raising awareness, considering the validity of current assumptions, considering a wider range of expert opinions, or improving collaboration across the topic [12]. The most relevant objectives in our context are raising awareness of possible but unlikely scenarios that can provide challenges or opportunities. As the decision maker becomes more aware, there may be changes in the way decisions are made.

However, it is not trivial to assess whether a decision was correct. A decision's successfulness can usually be evaluated only against a single past, which makes it difficult to separate the goodness of the decision and lucky outcomes related to the uncertainty in the system. The contribution of scenario analysis to decision making can be assessed by examining whether it supports making decisions that perform well despite uncertainties. [12]

2.3.3 Risk attitude

The risk attitude reflects the general orientation of the decision maker towards risk, that is, whether the decision maker appreciates the potential of positive outcomes or is averse to the possibility of negative outcomes [45]. Risk attitude and EU (Expected Utility) theory explain why different decision makers do not always choose the same decision alternative associated with the best expected outcome.

The EU theory was originally proposed by Bernoulli [46]. The basic idea is that each possible outcome is associated with utility. This relation between outcomes and utilities is called a utility function. Decision makers with different risk attitudes have utility functions with different shapes. Each decision alternative can be characterised by the expected utility of that alternative, which is the probability weighted sum of the utilities of possible outcomes. A decision maker following the EU theory chooses the alternative with the highest expected utility.

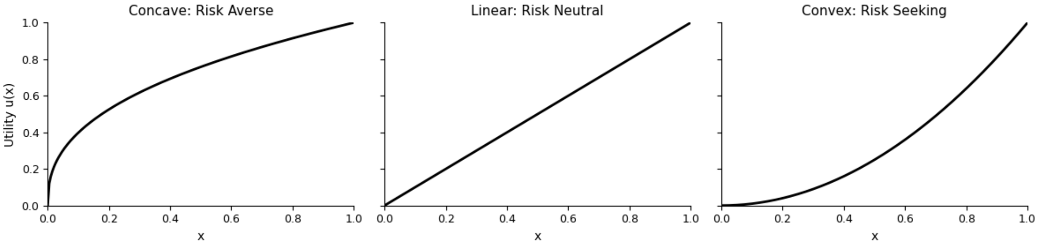

Figure 1: Relation between the shape of the utility function and risk attitude: concave for a risk-averse, linear for a risk-neutral, and convex for a risk-seeking decision maker.

Figure 1 illustrates the different shapes of utility functions and their relation to risk attitudes. For a risk-neutral decision maker, the relationship between the outcome and the utility is linear. Thus, the alternative with the highest expected value, such as in monetary terms, has the highest expected utility. The risk-averse decision maker has a concave utility function and is generally satisfied if the worst-case scenarios are avoided. The risk-seeking decision maker has a convex utility function. Only the best outcomes are associated with good utility. Thus, the risk-seeking decision maker is prepared to take more risk to possibly reach the best outcomes. A risk-averse decision maker may have various utility functions as long as it is concave. Similarly, the preferences of the risk-seeking decision maker can be presented by any convex utility function.

As an alternative to EU theory, the Value-at-Risk approach can be used in risk management. VaR is not directly based on utility functions- and risk attitudes, although the choice of quantile reflects the risk attitude of the decision maker. Traditionally, VaR has been defined as a specific quantile of the loss distribution [47]. For example, a restriction on the 0.05 quantile of the loss distribution could have been imposed so that only decisions for which at most 5% of the losses exceed the threshold are allowed. The choice of the confidence interval and the corresponding quantile depends on the risk attitude of the decision maker. The decision maker willing to withstand riskier decisions picks a larger quantile (smaller confidence level) and thus is willing to take larger losses as a tradeoff for the possibility of better upside outcome.

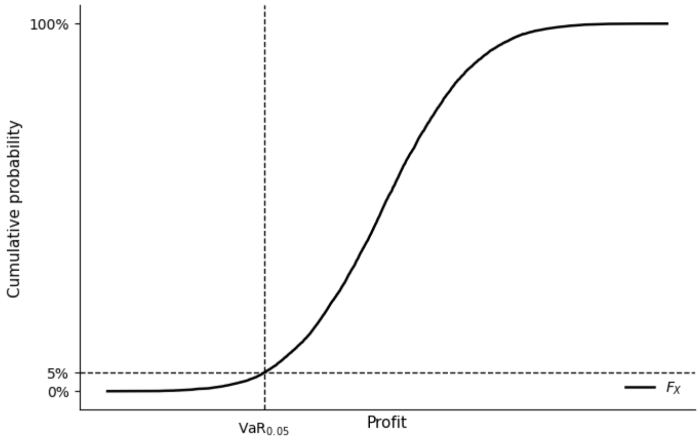

Figure 2: 5% Value-at-Risk of a profit distribution

Formally, VaR can be defined as

$$\mathrm{VaR}_\beta(X) = \inf\{x : F_X(x) > \beta\} = F_X^{-1}(\beta), \tag{9}$$

where X is a random variable representing, for example, profit, F_X is the corresponding cumulative probability distribution, and β is the chosen tail probability. The corresponding confidence level is $1 - \beta$. Figure 2 illustrates an example profit distribution, where the dashed lines indicate the 5% Value-at-Risk . In this case, the profit is at least $\mathrm{VaR}_{0.05} = F_X^{-1}(0.05)$ with a probability of 95%. VaR can also be applied to other quantities of interest, such as the distribution of the leverage ratio.

2.4 Investment decisions of an electricity producer

Investment decisions is part of the financial planning that electricity producers do. Carefully deciding investments is important for electricity producers as the complexity of power systems offers multiple investment possibilities. Existing capacity should be maintained and new power plant projects can be started from a portfolio of possible new projects [48]. Future production capacity can also be increased by extending the lifetime of existing power plants, such as nuclear power plants. There are many different technologies that can be invested in. To effectively plan investments, electricity producers use models that evaluate the profitability of different investment options.

Rohlfs and Madlener [49] describe a simple method that estimates the net present value of a project by discounting the estimated future cash flows. For example, the weighted average cost of capital (WACC) can be used as discount rate. WACC denotes the minimum required rate of return that the investment project needs to provide to meet the investors' demand and the cost of debt, depending on whether equity financing, debt financing or both are used. However, estimating future cash flows is not trivial due to the difficulty in estimating long-term electricity prices and demand development. Using scenarios helps quantify the risks related to investments. Rohlfs and Madlener present a model that accounts for the uncertainty in future cash flows in the presence of uncertainty related to different production technologies.

Koivunen and Hirvijoki [48] use GenX, a capacity expansion optimisation tool, to estimate, under different scenarios, the profitability of investing in wind, solar, small modular reactors, and natural gas turbine technologies. The GenX model minimises total costs, including investment, operation and maintenance, fuel, and other costs, subject to constraints such as investment decisions, demand balance, and flexibility constraints. Investment decision constraints can pose requirements for the profitability of investments. The demand constraints require the estimated electricity demand to be met. Flexibility constraints set requirements for the flexibility of energy generation and storage. [48]

The financial simulation model considered in this thesis is not used to evaluate the profitability of investment opportunities or to decide which generation technology to invest in but rather to assist in the investment process. The results of the financial simulation model can be used as an input to the actual model that is used to evaluate the investment opportunities. For example, if Fortum would use a model similar to GenX discussed in [48], the results of the financial simulation model could be used as constraints to that model.

Financial planning can include, for example, deciding funding strategies. However, in this thesis, financial planning focuses on simulating Fortum's financial status, including leverage ratio, over a one-year period, and defining investment headroom. Investment headroom represents the maximum investment size that keeps the leverage ratio below a predefined threshold with a propability dependent on the decision maker's risk attitude. If the number and size of defaults of the counterparties are low and spot prices are high during the one-year period, that lowers the leverage ratio, which further enables larger investments as the financial constraints are looser. Similarly, if spot prices are lower and there are more defaults, the possibilities for investments would be more constrained.

Possible investments that can be made include, for example, building new wind farms or maintaining existing production plants. All of these investments increase CapEx, which further raises the leverage ratio by increasing net debt, assuming that new investments are debt-financed rather than equity-financed. New investments can affect financial status over multiple years, but in this thesis only the effect on financial status after one year is considered. Also, this thesis does not directly assess how the uncertainties in spot prices and counterparty PDs affect which investments are made, but how the leverage ratio, which can be further used as a constraint when deciding investments, changes.

3 Methods

In this section, we discuss the methodology used to address the research question presented earlier: *How do uncertainties over a one-year horizon in electricity spot price forecasts and counterparties' probability of default estimates impact the size of an investment an electricity producer can make without violating financial constraints?* The methodology for the creation of the scenarios, including the perturbations of individual spot price and default scenarios is presented. Finally, the use of the output of the financial simulation model in decision making and the methodology to adjust these decisions based on the results of the scenario analysis is presented.

3.1 Scenario creation

A brief overview of the methodology for scenario generation is as follows. The perturbations are created for the spot price scenarios and default scenarios. Probabilities for these perturbations are derived. All the combinations of perturbed scenarios are generated that are used as model inputs and probabilities for them are determined based on the perturbation probabilities. Next, the methodologies for these steps are presented. In Section 3.2, it is described how these perturbed scenarios are used to demonstrate how potential uncertainties in the model inputs affect model output and further financial planning.

Three sets of spot price scenarios with different spot price perturbations are created. These sets of perturbed price scenarios are referred as $S^{(low)}$, $S^{(mean)}$, and $S^{(high)}$, while the set of the original, non-perturbed, spot price scenarios is denoted by S^0. These sets of perturbed spot price scenarios follow the notation in Eq. (1).

Similarly, two sets of perturbed default scenarios are created, denoted as $D^{(low)}$, and $D^{(high)}$. These two sets involve different counterparty PD assumptions, resulting in different default scenarios that are then used in the model. The set of original, non-perturbed, default scenarios is denoted by D^0. The sets of perturbed default scenarios and the set of original scenarios D^0 follow the notation in Equation (2).

Let the set of all sets of spot price scenarios be denoted as

$$\mathcal{S} = \{S^{(low)}, S^{(mean)}, S^{(high)}\}. \tag{10}$$

Thus, $\mathcal{S}$ contains the different spot price scenarios used as inputs in the model. Similarly, the set of all sets of default scenarios, that are used as model input, is denoted as

$$\mathcal{D} = \{D^0, D^{(low)}, D^{(high)}\}. \tag{11}$$

The set $\mathcal{S}$ contains the set of perturbed price scenarios $S^{(mean)}$ that, in the presence of minor input uncertainty, have spot prices close to those of the original scenarios S^0. For default scenarios, it is not easy to create corresponding perturbations close to the original scenarios, which is why D^0 is used in the set $\mathcal{D}$. Each set in $\mathcal{S}$ has 135 perturbed spot price scenarios. Similarly, each set in $\mathcal{D}$ has 11 perturbed default scenarios, excluding the set D^0, which has the original scenarios.

The number of perturbed default and spot price scenarios within each set in $\mathcal{S}$ and $\mathcal{D}$ remains the same as the number of original scenarios defined in Equations (1) and (2), respectively.

Next, the set of all input combinations is defined as the cross product of the sets $\mathcal{S}$ and $\mathcal{D}$:

$$C = \mathcal{S} \times \mathcal{D} = \{(S, D) \mid S \in \mathcal{S}, D \in \mathcal{D}\}, \tag{12}$$

where each element $(S, D) \in C$ represents one possible input combination for the model. The set C represents the different scenarios that correspond to different perturbations applied to the spot and default scenarios. The size of the set C, i.e., the number of combined perturbations is 9. The input for the model is the cross product of the combination (S, D) as defined in Eq. (3). Thus, the elements of C are inputs to the model, but with different perturbations to the spot price and default scenarios.

Finally, the probabilities for the different spot price perturbations are denoted as p_S for each $S \in \mathcal{S}$ and for the different default perturbations as p_D for each $D \in \mathcal{D}$. The probabilities for the perturbations in C are defined as

$$p_{S,D} = p_S \cdot p_D \quad \forall\, S \in \mathcal{S},\ D \in \mathcal{D}, \tag{13}$$

and they satisfy

$$\sum_{S \in \mathcal{S}} \sum_{D \in \mathcal{D}} p_{S,D} = 1. \tag{14}$$

As evident from Equation (13), the correlations between the spot price scenarios and the default scenarios are presumed to be zero. This is due to the unability to estimate the size and direction of correlation between electricity price and defaults of Fortum's counterparties based on the available knowledge.

3.1.1 Construction of perturbed spot price scenarios

In this section, the methodology for constructing the sets of perturbed spot price scenarios $S^{(low)}$, $S^{(mean)}$, and $S^{(high)}$ is explained. A good approach would be to perturb the inputs, such as weather and consumption assumptions, used in the sub-model that generates the spot price scenarios, and then examine how these variations influence the resulting spot price scenarios. However, since we do not have access to that sub-model, the spot price scenarios need to be directly perturbed.

The magnitudes for the spot price scenario perturbations are determined by comparing the historical spot price forecasts, which are used to create the original default scenarios of S^0, with the historical spot prices and the historical alternative price forecasts created by an alternative price forecast model. Thus, historical spot prices and alternative forecasts are used as a reference to detect the uncertainty in the spot price forecast and quantify its size. The alternative price forecasting model made by an external party has different assumptions and methodology compared to the spot price forecast model used by Fortum. The spot price scenarios $s_{i,a,f} \in S$ used by the financial simulation model are derived from the spot price forecast such that the average of these price scenarios for each of the next 12 months after month f, for area a, equal the corresponding forecasted monthly values.

The forecast accuracy can be evaluated by examining the forecast errors, defined as the difference between the realised value and the forecasted value at a given time point. If the mean forecast error over multiple time points is significantly different from zero, it indicates that the forecast is biased and can be improved by simply adding the mean forecast error. If forecast errors are correlated, the errors carry information that could be used to improve the accuracy of the forecast. [50]

An option to create the *low* and *high* price scenarios would be to add and subtract a certain multiple of the standard deviation of the forecast error distribution from the price forecast and use the properties of the normal distribution to estimate the probability that the true value lies in the interval between these *low* and *high* scenarios [50]. However, electricity price distributions are typically strongly skewed [51], and forecast error distributions are also likely to be skewed. Thus, it is a better approach to use the quantiles of the forecast error distribution to estimate the size of the possible price scenario perturbations. The quantile approach takes into account the skewness of the error distribution.

It is assumed that monthly spot prices throughout the year have an approximately equal impact on the financial status in one year after the forecast month. In practice, a fixed change in spot prices has the biggest effect during the months when the electricity production volume is the highest. However, to simplify the creation of forecast error distributions, the average price of the entire year is used instead of monthly prices. Thus, the spot price vector $s_{i,a,f}$ for the area a forecasted at f for the next 12 months is summarised with $\mu_{s_{i,a,f}}$, which denotes the average price of scenario i, in the area a for the next 12 months after f.

Next, the average over the 135 spot price scenarios is denoted as

$$\mu_{a,f} = \frac{1}{135} \sum_{i=1}^{135} \mu_{s_{i,a,f}}, \tag{15}$$

which is the average of the scenario averages $\mu_{s_{i,a,f}}$. $\mu_{a,f}$ denotes the spot price forecast average for the year following the forecast month f in the area a. The corresponding realised average spot price in the area a for the year following f is denoted as $\mu^{obs}_{a,f}$. The corresponding yearly average of the alternative forecast is denoted as $\mu^{alt}_{a,f}$.

The set of months for which the historical price forecasts are available is denoted as F. Since each price forecast made during month $f \in F$ has prices for the next 12 months, the realised spot price associated with $f \in F$ also denotes spot price average for the next 12 months. For example, if the forecast month f^* is December 2024, μ^{alt}_{a,f^*} denotes the average of the alternative spot price forecast for the year 2025 in the area a forecasted in December 2024. Similarly, μ_{a,f^*} denotes the average of the original spot price forecast for the same year and area forecasted in December 2024. μ^{obs}_{a,f^*} denotes the mean realised spot price in the area a in 2025.

Given that for each month f, the forecasted average price or the realised average price of the following 12 months is considered, the adjacent months exhibit a significant correlation due to the overlapping time range. However, it is necessary to use adjacent months with overlapping prices because otherwise there would not be enough data points, given the limited availability of the historical price forecasts. The relative forecast error compared to the observed yearly average prices in area a at forecast time f is denoted as

$$E_{a,f}^{obs} = \frac{\mu_{a,f}^{obs} - \mu_{a,f}}{\mu_{a,f}}. \tag{16}$$

Relative error is used instead of absolute error because the absolute uncertainty in electricity prices is greater when the price level is higher. Similarly, the absolute uncertainty in the prices is lower then the price level is low. Thus, relative error is a more useful measure of uncertainty than the absolute error. Similarly, the relative error between the original forecast and the alternative forecast at time f is denoted as

$$E_{a,f}^{alt} = \frac{\mu_{a,f}^{alt} - \mu_{a,f}}{\mu_{a,f}}. \tag{17}$$

For all months $f \in F$, the relative error between the observed average price and the original forecasted average price is defined as $E_{a,f}^{obs}$. The set of all relative errors for months $f \in F$ is called the distribution of relative errors with respect to the observed prices. The α-quantile of the distribution of relative errors with respect to the observed prices in area a is denoted as

$$q_{\alpha,a}^{obs} = Q_\alpha(\{E_{a,f}^{obs}\}_{f\in F}), \tag{18}$$

where Q is the quantile function. The α-quantile of the distribution of relative errors with respect to the alternative forecast prices is written similarly but *obs* is replaced with *alt*. Similarly, the mean of the distribution of relative errors with respect to the observed prices in area a is denoted as

$$\bar{E}_a^{obs} = \frac{1}{|F|} \sum_{f\in F} E_{a,f}^{obs}, \tag{19}$$

where $|F|$ denotes the number of forecast months, which depends on the availability of historical price forecasts. The corresponding mean of the distribution of relative errors with respect to the alternative forecast prices is written similarly, but *obs* is replaced with *alt*. In that case, the number of forecast months is smaller because the historical prices forecasted using the alternative model are available over a shorter time span.

The perturbations to the original price scenarios are done based on the quantiles and the means of the distributions of relative errors:

$$k_a^{(low)} = \begin{cases} 1 + (\lambda \cdot q_{\alpha,a}^{obs} + (1-\lambda) \cdot q_{\alpha,a}^{alt}), & \text{if } a \in A' \subseteq A \\ 1, & \text{otherwise} \end{cases} \tag{20}$$

$$k_a^{(mean)} = \begin{cases} 1 + (\lambda \cdot \bar{E}_a^{obs} + (1-\lambda) \cdot \bar{E}_a^{alt}), & \text{if } a \in A' \subseteq A \\ 1, & \text{otherwise} \end{cases} \tag{21}$$

$$k_a^{(high)} = \begin{cases} 1 + (\lambda \cdot q_{(1-\alpha),a}^{obs} + (1-\lambda) \cdot q_{(1-\alpha),a}^{alt}), & \text{if } a \in A' \subseteq A \\ 1, & \text{otherwise,} \end{cases} \tag{22}$$

where A' denotes the subset of areas for which the spot prices are perturbed and λ is a weighting factor between the mean (quantile) of the distribution of relative errors with respect to the observed prices and the mean (corresponding quantile) of the distribution of relative errors with respect to the alternative forecast prices.

Now, k_a is the factor that is used to multiplied the spot prices to obtain the perturbed price scenarios. For example, perturbed prices in $S^{(low)}$ are obtained by multiplying the original price scenarios in S^0 by $k_a^{(low)}$. All areas are not perturbed because the significance of spot price for Fortum varies between areas. The choice of α in Equations (20) and (22) reflects the extremeness of the risk attitudes of risk-averse and risk-seeking decision makers. A low α means that the risk-averse decision maker is really careful and the risk-seeking decision maker takes large risks. A high α means that both behave more like a risk-neutral decision maker.

The *low* and *high* scenarios are created using the symmetric low and high quantiles of the error distributions. The *mean* scenario is created using the means of the error distributions. Choosing the value of the parameter λ is a design choice, it reflects whether the decision maker considers the forecast error with respect to the realised prices or with respect to the alternative forecast prices a more reliable predictor of future prices.

Finally, $S^{(low)}$, $S^{(mean)}$, and $S^{(high)}$ scenarios are created by multiplying the prices of the initial scenarios $s_{i,a,f}$ by the factors presented in Equations (20)-(22):

$$S^{(low)} = \{(k_a^{(low)} \cdot s_{i,a,f^*}) \mid a \in A, s_{i,a,f^*} \in S^0\} \tag{23}$$

$$S^{(mean)} = \{(k_a^{(mean)} \cdot s_{i,a,f^*}) \mid a \in A, s_{i,a,f^*} \in S^0\} \tag{24}$$

$$S^{(high)} = \{(k_a^{(high)} \cdot s_{i,a,f^*}) \mid a \in A, s_{i,a,f^*} \in S^0\}, \tag{25}$$

where f^* denotes the month when the financial simulation model is run and the CapEx investments for the following 12 months are decided. Ideally, $k_a^{(mean)}$ would be close to one, indicating that there would not be much systematic error present in the spot price forecast model. However, if it is significantly lower than one, the historical spot price forecasts have been systematically too high. Similarly, if it is higher than one, the historical forecasts have been systematically too low.

The α and $(1-\alpha)$ -quantiles of the error distributions represent more unlikely errors than the mean. They can also have different absolute values and, thus, take into account the skewness of the error distribution. It is not stated that $S^{(low)}$, $S^{(mean)}$, and $S^{(high)}$ would be more reliable estimates of future spot prices than S^0 but rather that the mean prices of those scenarios might be more likely than the mean price of S^0 based on historical prices and the alternative forecast model.

A simple approach to assign probabilities for scenarios $S \in \mathcal{S}$ is used. The probability of scenario $S^{(low)}$ is $p_{S^{(low)}} = \alpha$, where α is the quantile of the error distributions in Eq. (20) used to derive the factor $k_a^{(low)}$. Symmetrically, the probability of $S^{(high)}$ is $p_{S^{(high)}} = \alpha$. Thus, the probability of the scenario $S^{(mean)}$ is $p_{S^{(mean)}} = 1 - p_{S^{(high)}} - p_{S^{(low)}} = 1 - 2\alpha$.

This is not a fully accurate estimate of the probabilities. For example, the 0.05 quantile of the error distribution indicates that 5% of the errors have historically been even smaller. Thus, the probability that the forecast error in area a is exactly $q^{obs}_{0.05,a}$, defined in Eq. (18), is not 5%. Thus, this approach for determining probabilities for the price perturbations may assume lighter distribution tails. However, the use of this approach is based on the assumption that the errors are independent, which they are not. Thus, the real error distribution should be narrower when the previous errors are known. Also, some information is lost when most of the error distribution is summarised with the mean. However, this approach gives a reasonable estimate for the scenario probabilities and allows later aggregating the output distributions produced with different input perturbations. That allows assessing the overall effect of input uncertainty in the maximum CapEx investment instead of analysing the effect separately on single perturbation scenario level.

3.1.2 Construction of perturbed default scenarios

In this section, the methodology for constructing the sets of perturbed default scenarios $D^{(low)}$ and $D^{(high)}$ is explained. The financial simulation model creates the default scenarios based on the counterparties' probability of defaults used as input. As discussed in Section 2.1.2, there are multiple challenges in the accurate estimation of PDs. Thus, it is important to perturb the PDs and inspect the resulting change in model output.

There exists literature for determining confidence intervals for PDs associated with, for instance, S&P ratings, which can be further used to determine the likely deviations from the assigned ratings. However, the main obstacle to using external reference for creating *low* and *high* scenarios for PDs is that most of the counterparties in Fortum's bilateral portfolio do not have a credit rating from any of the largest credit rating agencies, S&P, Moody's or Fitch. Instead, the counterparties are rated by a smaller Nordic credit rating agency which has a credit rating system with only four or five country-specific ratings compared to the approximately 20 levels of the large credit rating agencies. Thus, in the FIR system, only five levels are used. However, if a counterparty is rated by, for exampe, S&P, that rating is mapped to the internal scale and some information is lost. Furthermore, the Nordic credit rating agency has country specific PDs for each rating class while S&P has universal PDs.

The approach used to create the spot price perturbations is that in the scenario $D^{(low)}$, the credit rating of each counterparty is increased by one level on the internal scale and the PD is changed correspondingly to the value associated with this better rating grade. If the counterparty already has the best internal rating (5), the credit rating and the PD are not changed. Thus, the credit risk involved in the scenario $D^{(low)}$ is lower than in the original scenario D^0. Similarly, in the scenario $D^{(high)}$, the credit rating of each couterparty is decreased by one level on the internal scale. If the counterparty already has the worst internal rating (1), the credit rating and the PD do not change. This scenario involves higher PDs and credit risk than in the original scenario.

Table 1 presents an example mapping between S&P ratings and the FIR system. In the example, FIR B presents better rating than FIR C. Usually, it holds that S&P A- has lower PD than FIR C. Similarly, BBB+ should have higher PD than FIR B.

Table 1: Example mapping of S&P ratings to FIR system

FIR	S&P Rating
⋮	⋮
FIR B	⋮ A-
FIR C	BBB+ BBB ⋮
⋮	⋮

However, for some countries and FIR levels, some S&P ratings should be, based on their PD, mapped to the adjacent FIR level instead of the level they are currently mapped in. This presented approach for creating the *low* and *high* scenarios takes into account the loss of information and inaccuracies in the mapping process.

If the S&P rating BBB+ is mapped to FIR C and the adjacent S&P rating A- to FIR B, it is possible that, for companies with those S&P ratings, the adjacent FIR rating would be more representative due to the difficulty in differentiating between S&P A- and BBB+. However, if BBB is also mapped to FIR C, it is less likely that a company rated BBB should belong to FIR B compared to a company rated BBB+. However, it is unlikely that the credit rating of all counterparties would be either under or overestimated.

It is challenging to determine the probabilities for scenarios $D^{(low)}$ and $D^{(high)}$ because there is no historical evidence of the accuracy of the FIR system. Also, the methodological basis of the external Nordic credit rating agency is not known, for example, whether or not the macroeconomic environment is factored in. According to [52], during the 1990s global recession and the 2008 financial crisis in the US, value weighted corporate default rates doubled or tripled from the preceding years. The magnitude of these changes corresponds approximately to the increase in PDs resulting from the reduction of the Fortum internal rating of each company by one level.

During the 150 year period ending to 2010, different financial crises leading to increased default rates occurred on average approximately every 20 years in the US [52], which translates to 5% annual probability if the crises are assumed independent. The default rates in the US are not directly comparable to those in the Nordics, but the $D^{(high)}$ scenario can be considered as an example of increased PDs in the presence of an unexpected crisis and assign it a probability of 5%. $D^{(high)}$ represents both possible crisis situations and a possible bias in the determination of credit ratings.

On the other hand, there are no similar events as financial crises but with a decreasing effect on the default probabilities of all companies that would justify using the $D^{(low)}$ scenario. Thus, the bias in the credit rating determination is seen as the main driver for this scenario. $D^{(low)}$ is assigned a probability of 2.5% which is less than the probability of the scenario $D^{(high)}$. Thus, the emphasis is put on the effect of underestimating credit risk rather than overestimating. If the initial hypothesis holds that the impact of the default scenario perturbations is small compared to the effect of price scenario perturbations, the lack of a robust methodology for determining probabilities for the default scenario perturbations does not induce major uncertainty in the results.

3.2 Output processing for decision support

As discussed previously, the model output is used to constrain the amount and size of investments the decision maker can make. Different decision makers have different confidence levels for keeping the leverage ratio below the threshold, meaning that some decision makers prioritise the possibility to make higher CapEx investment over the certainty that the leverage ratio will remain below the threshold. Instead of using explicit utility functions to model the decision maker's risk attitude, a Value-at-Risk approach is used, where the choice of confidence interval reflects the risk attitude.

Assume that the true distribution of the leverage ratio in one year matches the forecasted distribution. Then, for example, selecting the leverage ratio estimate indicated by 95% VaR and investing in CapEx such that the leverage ratio is at the threshold means that there is a 5% probability that the true leverage ratio will exceed the threshold. A more risk-seeking decision maker accepts a higher probability of exceeding the threshold.

Now that there are nine different scenarios for input perturbations as defined in Eq. (12), a perturbed output distribution that combines the outputs related to each of these perturbed inputs is presented. This perturbed output distribution is denoted as

$$Y_{com} = \bigcup_{(S,D)\in C} \{(y_{i,j},\ p_{\omega,i,j} \cdot p_{S,D}) \mid i = 1,\ldots,|S|,\ j = 1,\ldots,|D|\}. \tag{26}$$

where $p_{S,D}$ is the scenario probability for perturbation $(S, D) \in C$. Each output distribution $Y_{S,D}$ of the scenario (S, D) (defined in Eq. (6)) is scaled by the probability of the corresponding scenario $p_{S,D}$. The perturbed output distribution can be wider and shifted compared to the original output distribution.

The leverage ratio distribution is further transformed into the CapEx investment distribution so that the output distribution can be used to restrict the maximum size of investments. Consider an output distribution Y, which can be either the original output distribution Y_{S^0,D^0}, the perturbed output distribution Y_{com}, or an output distribution produced with any of the perturbed inputs in C. Each individual pair $(y, p) \in Y$ is associated with certain Net Debt and EBITDA figures that are used to derive the model output y, leverage ratio, as defined in Equation (8).

To obtain the CapEx investment distribution, the net debt of each scenario in Y is increased such that y is at the leverage ratio limit. The CapEx investment that can be made without breaching the leverage ratio limit is called CapEx headroom, and it can be determined by the following equation:

$$\frac{\text{Net debt} + \text{CapEx headroom}}{\text{EBITDA}} = 3.0. \tag{27}$$

If y is already at or above the limit, the net debt is not increased. Now each output in Y can be characterised by both the leverage ratio and the size of CapEx investment needed to reach the leverage ratio limit. Thus, the output distribution Y can be presented as either the leverage ratio or the maximum CapEx investment distribution. It is important to note that, for example, 0.05 quantile of the leverage ratio distribution corresponds to a favourable situation where a large CapEx investment can be made before the limit is reached, while 0.05 quantile of the maximum CapEx investment distribution corresponds to a weak financial situation as only a small CapEx investment can be made.

Now, the size of the investment needed to use all the available CapEx headroom in the presence of the perturbed scenarios can be compared to the CapEx investment in the presence of original price and default scenarios. Comparisons are made for decision makers with different risk attitudes using different quantiles of the CapEx investment distribution. A recommendation for the maximum size of the investment is given, and if it differs significantly from the original recommended maximum investment amount, it indicates that the model inputs should be refined. In addition, the effect of individual price and default scenario perturbations is investigated to obtain information about the effect of the different model inputs and their relative importance.

It may not always be advisable to use the entire headroom up to the absolute leverage ratio limit. In addition, a high CapEx investment can increase the counterparty credit risk if, for example, the investment creates an exposure to a large vendor, and thus lower the recommended size of the investment. However, for comparing the effect of different input assumptions, the use of the absolute leverage ratio limit as a limit for the maximum CapEx investment is convenient.

4 Case study

This section illustrates how uncertainties in electricity price scenarios and counterparty PDs over a one-year horizon impact Fortum's maximum CapEx investment through a case study using the methodology presented in Section 3. First, the perturbed spot price and default scenarios are created. The results of the scenario analysis are presented and the effect of input uncertainty is assessed for decision makers with different risk attitudes. Finally, the results are discussed, and suggestions for future development are proposed.

4.1 Scenario creation

First, the spot price scenario perturbations are created. Figure 3 shows the relative differences between the realised prices and the corresponding historical forecasts by the model used to provide price scenarios for the financial simulation model. Three electricity price areas that are most important from Fortum's perspective are chosen. Similarly, Figure 4 shows the relative differences between the historical alternative forecasts and the corresponding historical forecasts by the model used to provide price scenarios for the financial simulation model. The relative errors are mainly positive in both Figures, especially in Fig. 4. This already gives valuable insight that the spot price scenarios used in the financial simulation model have likely been historically too low.

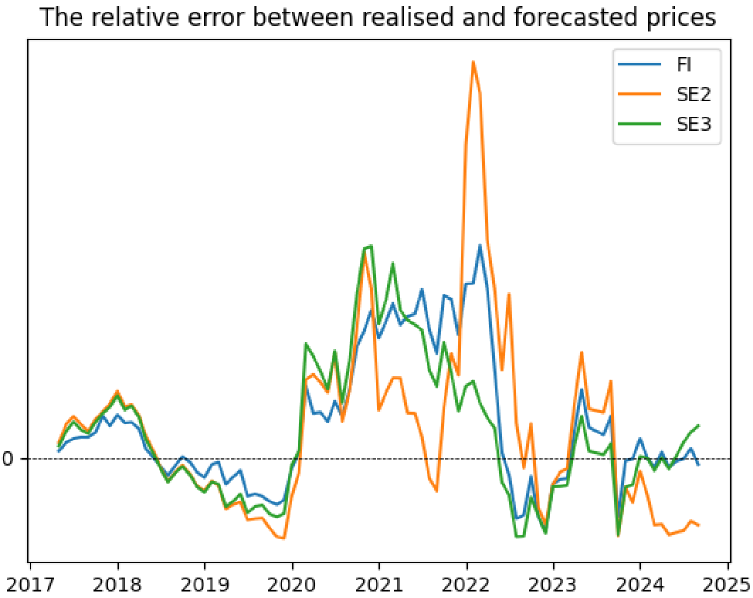

Figure 3: Time series of $E^{obs}_{a,f}$ defined in Eq. (16). Areas FI, SE2, and SE3 are considered.

The correlation of the adjacent errors is visible in both Figures. If the error at time

f is positive (negative), the error at the next time point is likely positive (negative). However, when predicting electricity prices at time point f, only the error at time $f-12$ is available because at each time point, the average price of the following 12 months is considered. Thus, it is not useful to try to predict the future errors using time series modelling.

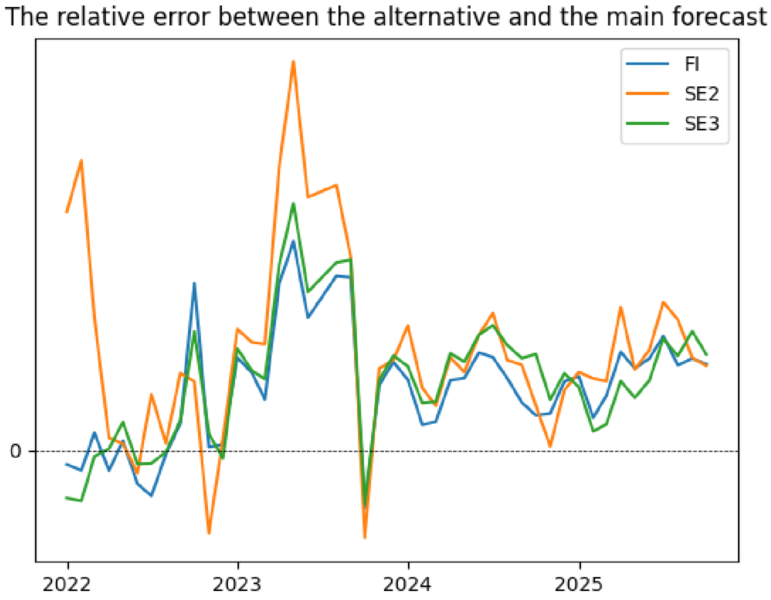

Figure 4: Time series of $E^{alt}_{a,f}$ defined in Eq. (16). Areas FI, SE2, and SE3 are considered.

Table 2: Quantile and mean values of forecast errors in different areas

		Statistic		
Forecast error relative to	**Area**	**0.1 quantile**	**Mean**	**0.9 quantile**
Spot price history (E^{obs})	FI	-0.27	0.24	1.02
	SE2	-0.47	0.20	0.79
	SE3	-0.36	0.18	0.90
Alternative forecast model (E^{alt})	FI	-0.08	0.27	0.67
	SE2	0.03	0.44	1.08
	SE3	-0.05	0.30	0.63

Table 2 presents the quantiles and means of the relative errors presented in Figures 3 and 4. It is chosen that $\alpha = 0.1$ to give a higher weight for the expected price deviations and a smaller weight for the more extreme deviations. Thus, 0.1 and 0.9 quantiles are shown in Table 2. It should be noted that the mean relative errors with respect to both the spot price history and alternative forecasts are positive. Almost all quantiles and means in different areas of the E^{alt} distribution are higher than the corresponding numbers of the E^{obs} distribution. Only 0.9 quantiles of the distributions of relative errors with respect to the observed prices in FI and SE3 areas are higher than the same quantiles of the distributions of relative errors with respect to the alternative forecast prices.

To obtain the factors defined in Equations (20)-(22), the parameter λ that defines the relative importance of the spot history and the alternative forecasts needs to be determined. The spot history is considered to be a more reliable estimate of future electricity prices than the alternative forecast model, which is just a subjective model, as is also the forecast model used by the financial simulation model. On the other hand, the unusual price variations during the energy crisis in 2022 might distort the error distribution, as seen in Figure 3.

At every time point f, the alternative forecast model has access to the same information as the forecast model used by the model. The alternative forecast model predicting most of the time higher prices than the main forecast model indicates that there might be some systematic error in the main forecast model that causes the forecast values to be too low. It is also possible that the alternative forecast model predicts too high prices. The choice of the parameter λ is subjective and $\lambda = 0.6$ is chosen to give a bit more weight to the spot history compared to the alternative forecasts.

Table 3: Factors $k_a^{(low)}$, $k_a^{(mean)}$, and $k_a^{(high)}$ for electricity price areas FI, SE2, and SE3

	Area		
Scenario	FI	SE2	SE3
low	0.81	0.73	0.76
mean	1.25	1.30	1.23
high	1.88	1.91	1.79

Table 3 presents the factors that are used to multiply the original spot price scenarios of S^0 to obtain *low*, *mean*, and *high* spot price scenarios as shown in Equations (23)-(25). The financial simulation model is run in August 2025, denoted by f^*. Consider a scenerio $s_{i,FI,f*} \in S^0$. In the *low* scenario, the scenario is multiplied by $k_{FI}^{(low)} = 0.81$. Each monthly price inside the scenario is multiplied with the same multiplier. Thus, the mean price of $s_{i,FI,f*}$ over the 12-month period is also reduced by 19%. The mean price of all scenarios in $S^{(low)}$ is also 19% lower than the mean price of scenarios in S^0. As explained in Section 3.1.1, the probabilities of *low* and *high* scenarios are $p_{S^{(low)}} = p_{S^{(high)}} = 0.10$ due to the use of 0.1 and 0.9 error quantiles. It follows that the probability of the *mean* scenario is $p_{S^{(mean)}} = 0.8$.

The default scenarios $D^{(low)}$ and $D^{(high)}$ are created as explained in Section 3.1.2. Table 4 presents the number of bilateral counterparties in each rating class in those scenarios. The PDs of FIR levels vary based on the home country of the counterparty.

Table 4: Number of counterparties in each FIR class in the three different scenarios

FIR	Default scenario		
	$D^{(low)}$	D^0	$D^{(high)}$
5	153	61	0
4	58	92	61
3	6	58	92
2	3	6	58
1	0	3	9

4.2 Scenario analysis results

In this Section, the results of the scenario analysis are presented. First, the effect of each input perturbation on the maximum CapEx investment is shown. Finally, the maximum CapEx investment amount is suggested based on the perturbed output distribution that combines the outputs related to each of the input perturbations.

Table 5: Maximum CapEx investment individually for each set of perturbed input scenarios. The first row with unmodified price and default scenarios is the reference level for the CapEx investment. In other rows, the relative difference of the CapEx investment with respect to the same quantile (or mean) of the original output distribution is shown.

The set of price scenarios	The set of default scenarios	Maximum CapEx investment relative to the original scenarios		
		0.05 quantile	**mean**	**0.95 quantile**
S^0	D^0	0	0	0
S^0	$D^{(\text{low})}$	0.015	0.008	0.001
S^0	$D^{(\text{high})}$	-0.047	-0.019	0.002
$S^{(\text{low})}$	D^0	-0.216	-0.219	-0.234
$S^{(\text{mean})}$	D^0	0.227	0.238	0.258
$S^{(\text{high})}$	D^0	0.761	0.793	0.864

In Table 5 the summary statistics are shown individually for each set of the perturbed scenarios. The perturbed default scenarios are combined with the original price scenarios, and likewise, the perturbed price scenarios are combined with the original default scenarios. The leverage ratio distribution is transformed to CapEx investment distribution as explained in Section 3.2. Only the relative differences of the maximum CapEx investments are shown to protect company's sensitive information.

The 0.05 quantile reflects the unfavourable situation in which only a small CapEx investment can be made until the limit of 3.0 is reached for the leverage ratio. An investment recommendation for the risk-averse decision maker is given based on the 0.05 quantile as the risk-averse decision maker wants to be certain that the real leverage ratio in one year remains below the limit. Similarly, the risk-seeking decision maker is recommended to invest based on a higher quantile, such as 0.95.

As shown in Table 5, the effect of the default scenario perturbations is small compared to the effect of the price scenario perturbations. CapEx investments within both sets of perturbed default scenarios (rows 2 and 3), in both quantiles and mean, remain within 5% of the results obtained with the original input scenarios. The results obtained with scenarios $S^{(low)}$ and $S^{(mean)}$ (rows 4 and 5) are within 26% of those obtained with the original scenarios. The scenario $S^{(high)}$ suggests investing approximately 80% more than the original scenarios.

It is also interesting that the effect of $D^{(high)}$ in absolute terms on the 0.05 quantile is approximately three times greater than the effect of the scenario $D^{(low)}$. The main reason is likely that many of the counterparties are already in the best FIR rating in the D^0 scenario, and thus $D^{(low)}$ does not improve their PDs, while almost all counterparties have their PD worsened in the $D^{(high)}$ scenario. In addition, improving the FIR rating by one level usually has a smaller absolute effect on the PD than worsening the rating by one level.

The perturbed default scenarios impact the output distribution most on the 0.05 quantile from the chosen metrics. For the mean and the 0.95 quantile, the CapEx investments are closer to those of the original scenarios. The explanation is that the most unfavourable outcomes associated with low maximum CapEx investments have low spot price forecasts, and if the hedges are lost due to defaulting counterparties, electricity is sold at low prices in the spot market, which further worsenes the result.

On the other hand, the perturbed default scenarios have little impact on the most favourable outcomes, which are represented by the 0.95 quantile. This is due to those outcomes having high spot prices, and if the counterparties default, the electricity is sold on the spot market at higher profit, but the profit is at least partly offset by the termination payment. Thus, the number and severity of defaults in those outcomes has little effect on the results. The 0.95 quantiles of the CapEx distributions corresponding to $D^{(low)}$ and $D^{(high)}$ are both slightly above the 0.95 quantile of the original CapEx distribution. This behaviour was not expected, and it probably relates to some undesired feature of the model that should be analysed more thoroughly in the future.

The price scenario perturbations have larger effect on the 0.95 quantile than the 0.05 quantile, unlike the default scenario pertubations. The relative differences between the 0.05 quantile of the original CapEx distribution and the 0.05 quantiles of the CapEx distributions obtained with the perturbed price scenarios are smaller than the relative differences between the 0.95 quantiles of the same distributions. The relative difference in the relative differences is not as significant as it is with default scenario perturbations. The most favourable outcomes involve counterparties defaulting, because in that case, electricity can be sold at a higher price on the spot market.

The reason for price perturbations having larger effect on the 0.95 quantile than on the 0.05 is most likely that the size of the termination payment is determined based on the forward prices, which in this model are not affected by the spot price perturbations. Thus, in the $S^{(low)}$ scenario, the forward prices are higher than the spot prices, increasing the size of the termination payment at 0.95 quantile relative to the profit that will be obtained from the spot market in case a counterparty defaults. Similarly, in the $S^{(high)}$ scenario, the forward prices are lower than the spot prices, and thus the termination payment at 0.95 quantile is smaller than the profits from the spot market. If the forward prices for each input scenario were perturbed similarly to the spot prices, defaults would not significantly affect the outcomes at the 0.95 quantile, and the impact of price perturbations on the 0.95 quantile would be closer to that of the 0.05 quantile.

Table 6: Probabilities of the different price and default scenario perturbations, and the probabilities for each combination of price and default scenario perturbations

Perturbation probabilities		
Price perturbation	**Default perturbation**	**Price and default perturbation combined**
$p_{S^{(\mathrm{low})}} = 0.1$	$p_{D^{(\mathrm{low})}} = 0.025$	$p_{S^{(low)},D^{(low)}} = 0.0025$
$p_{S^{(\mathrm{low})}} = 0.1$	$p_{D^0} = 0.925$	$p_{S^{(low)},D^0} = 0.0925$
$p_{S^{(\mathrm{low})}} = 0.1$	$p_{D^{(\mathrm{high})}} = 0.05$	$p_{S^{(low)},D^{(high)}} = 0.0050$
$p_{S^{(\mathrm{mean})}} = 0.8$	$p_{D^{(\mathrm{low})}} = 0.025$	$p_{S^{(mean)},D^{(low)}} = 0.0200$
$p_{S^{(\mathrm{mean})}} = 0.8$	$p_{D^0} = 0.925$	$p_{S^{(mean)},D^0} = 0.7400$
$p_{S^{(\mathrm{mean})}} = 0.8$	$p_{D^{(\mathrm{high})}} = 0.05$	$p_{S^{(mean)},D^{(high)}} = 0.0400$
$p_{S^{(\mathrm{high})}} = 0.1$	$p_{D^{(\mathrm{low})}} = 0.025$	$p_{S^{(high)},D^{(low)}} = 0.0025$
$p_{S^{(\mathrm{high})}} = 0.1$	$p_{D^0} = 0.9250$	$p_{S^{(high)},D^0} = 0.0925$
$p_{S^{(\mathrm{high})}} = 0.1$	$p_{D^{(\mathrm{high})}} = 0.05$	$p_{S^{(high)},D^{(high)}} = 0.0050$

Table 6 shows the probabilities $p_{S,D}$ for all perturbations $(S, D) \in C$. Most weight is given to the perturbed input scenario $(S^{(mean)}, D^0)$, which has the original non-perturbed default scenarios, and the spot price perturbations based on the means of the error distributions as defined in Equations (21) and (24). The probabilities presented in Table 6 are used to scale the individual perturbed output distributions to obtain the perturbed output distribution Y_{com} as presented in (26).

Figure 5 shows the perturbed output distribution Y_{com} compared to the original output distribution Y_{S^0,D^0} which does not involve input perturbations. The horizontal axis containing absolute CapEx values is hidden to protect sensitive information. The cumulative distribution function of Y_{com} is mainly above that of Y_{S^0,D^0}, indicating that when perturbed input scenarios are used, the maximum allowed CapEx investment for the following year is likely to be higher than the maximum investment when the financial status is simulated using only the original inputs. Especially in the best-case scenarios, perturbing the model inputs allows significantly higher maximum CapEx investment than the results with the original inputs. The maximum CapEX investment that can be made in the 0.95 quantile, while respecting the leverage ratio constraint, is 35% higher than that of the original scenarios.

However, the worst-case scenarios simulated with the perturbed and original input scenarios are almost similar. The 0.05 quantile of the maximum CapEx investment distribution with the perturbed scenarios is only 2% lower than the 0.05 quantile of the corresponding distribution with the original inputs. Compared to the accuracy of our data and methods, the CapEx investment in the 0.05 quantile does not differ significantly depending on whether the input uncertainty is taken into account or not.

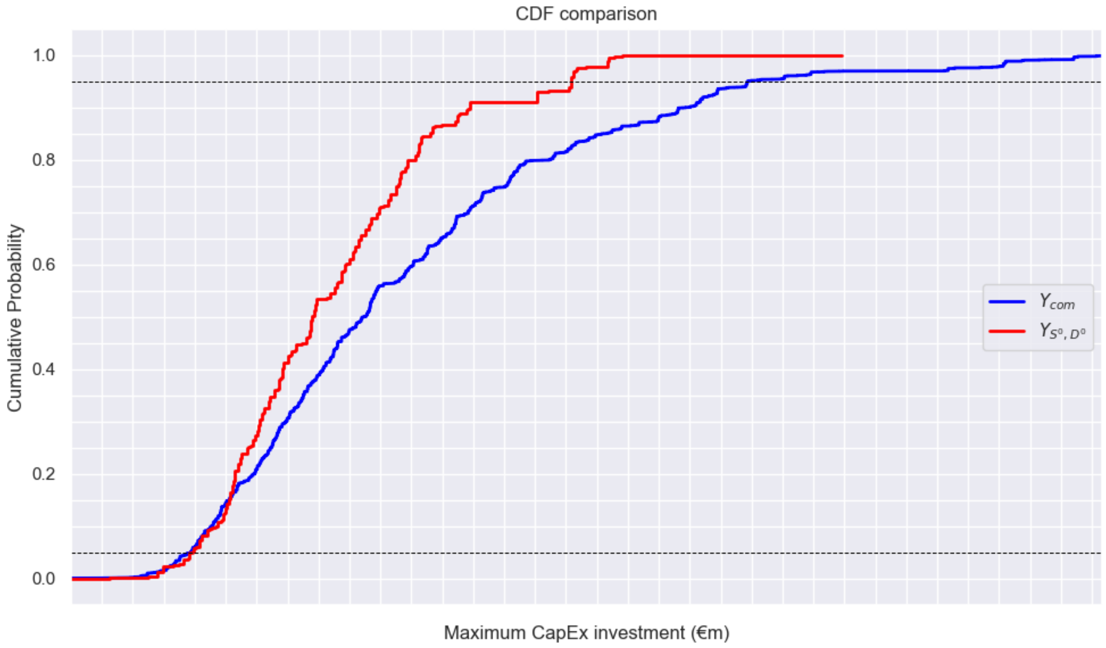

Figure 5: Cumulative maximum CapEx investment distributions of Y_{com} and the original distribution Y_{S^0,D^0}. The dashed lines show the 0.05 and 0.95 quantiles.

The overall higher allowed maximum CapEx investment indicated by the perturbed scenarios is mainly explained by the high weight of the scenario $(S^{(mean)}, D^0)$, which increases the spot price scenarios to better align with the spot price history and the alternative forecast model. The slightly lower maximum CapEx investment in the 0.05 quantile is likely caused by the scenarios included in the set $S^{(low)}$. The 0.05 quantile of the output distribution produced with the perturbed inputs reflects the possibility that the already low spot prices could be even lower.

Table 7 shows the maximum recommended CapEx investments relative to the same recommendations produced with the original inputs for different decision makers. Traditionally, risk aversion and risk seeking are defined through the shape of the utility function, as discussed in Section 2.3.3. Risk-averse and risk-seeking decision makers are characterised by concave and convex utility functions, respectively. In this thesis, risk-attitudes are defined through the choice of quantiles of the output distribution. These quantiles can also be different from the chosen 0.05 and 0.95 quantiles, which would reflect a different level of risk aversion and risk seeking. Thus, the results in Table 7 do not apply to all risk-averse or risk-seeking decision makers, but to those whose preferences can be presented by the selected quantiles. The investment recommendation for risk-neutral decision makers is accurate because it is based on the expected value of the output distribution.

The answer to the research question of how uncertainties in model inputs over a one-year horizon impact the size of a CapEx investment an electricity producer can make without violating financial constraints depends on the decision maker's risk attitude. For a risk-averse decision maker focusing on the 0.05 quantile, the

Table 7: Maximum CapEx investment recommendations for decision makers with different risk attitudes when input uncertainty is taken into account.

Risk attitude	**Maximum CapEx investment relative to results of the original scenarios**
Risk averse (0.05 quantile)	-0.02
Risk-neutral (expected value)	0.21
Risk-seeking (0.95 quantile)	0.35

uncertainties in the model inputs do not significantly affect the size of the maximum CapEx investment. On the other hand, a risk-seeking decision maker focusing on the 0.95 quantile and a risk-neutral decision maker have more flexibility in the financial planning as the current inputs may underestimate the future spot prices leading to too conservative leverage ratio estimates.

4.3 Discussion

The results of the case study should be analysed critically. Multiple sources might have given rise to inaccuracies in the results. First of all, the fact that the price forecast model has historically forecasted low spot prices compared to realised spot prices and to those produced by the alternative forecast model does not guarantee that the same trend would persist in the future. Also, the size of the default scenario perturbations and the probabilities for those perturbations are loose approximations that can be far from the true uncertainty. In addition, the methodology used to create the price scenario perturbations could be strengthened, for example, by taking into account the correlations in the error distributions.

However, the intention of the results is not to directly suggest that a risk-seeking decision maker should allocate 35% more capital to CapEx investments compared to the previous model-based recommendation that does not account for the input uncertainty. Instead, the main purpose of the results is to increase decision makers' awareness of potential risks and opportunities when allocating investments for the next one-year period. In this setting, a risk-averse decision maker focusing on the 0.05 quantile of the output distribution can be confident that if they invest in CapEx as much as suggested by the model run with the original inputs, the leverage ratio in one year will likely remain below the predefined threshold. This is because the uncertainty in spot price forecasts and counterparty PDs does not have a significant effect on the maximum CapEx investment size for the risk-averse decision maker.

Considering a risk-seeking decision maker that accepts breaching the leverage ratio with a probability of 95% in order to be able to allocate enough capital for an important business opportunity, it is possible that they could invest even 35% more due to model's input uncertainty. Thus, if the input uncertainty is not considered, a valuable opportunity is missed while investing less than the chosen risk attitude would allow in reality.

The results indicate that the input uncertainty is not significant for the risk-averse decision maker, while the risk-seeking decision maker can allow significantly higher CapEx investments if the input uncertainty is taken into account. The reason for this is likely the fact that the spot price perturbations both shifted and stretched the output distribution. The use of 0.1 and 0.9 quantiles of the error distributions to create the $S^{(low)}$ and $S^{(high)}$ scenarios made the perturbed output distribution more spread out, while the $S^{(mean)}$ scenario shifted the perturbed output distribution towards higher CapEx figures. In the final results, the upward shift appeared to balance the downward stretch, as the original and the perturbed output distribution both indicate similar maximum CapEx investment levels for the risk-averse decision maker.

The 2022 energy crisis probably impacts the results by increasing the relative errors between realised and historical forecasted prices, as seen in Figure 3. That increase in relative errors contributes to higher prices in the $S^{(mean)}$ and $S^{(high)}$ scenarios, resulting in a greater difference from the original output distribution. This is an important aspect of risk analysis; when an extraordinary event occurs, it is easier to believe that it can happen in the future as well. If increased prices due to the energy crisis had not occurred, this method would have produced lower estimates of input uncertainty. This highlights the difficulty in estimating possible future developments.

Since the hypothesis that the input uncertainty does not have a significant effect on the output is rejected, it is reasonable to consider whether the input uncertainty should be tried to decrease in the future. The spot price forecasts used in the model have been on average significantly lower than the realised prices and the alternative forecasts on every price area, as seen in Table 2. Thus, it is suggested to improve the methodology of the model used to forecast prices, which would further decrease the input uncertainty and its effect on investment headroom, which is part of financial planning. Measuring the accuracy of counterparty credit risk modelling is challenging, and this thesis did not aim to evaluate the accuracy of Fortum's counterparty credit risk modelling or justify the need to improve it.

The results indicate that, for Fortum, the uncertainty in spot prices has a significantly larger effect on financial planning than the uncertainty in counterparties' default probabilities. This is expected for an electricity producer whose main business is to sell electricity which involves significant price risk. The impact of uncertainty in price risk can also be decreased by increasing the share of long-term contracts, thereby reducing exposure to spot prices.

The uncertainty in counterparty PDs having a small impact on financial planning may also be a sign of a properly managed counterparty credit risk. The portfolio of bilateral contracts is naturally diversified across many companies, as Fortum generates enough electricity to supply a large number of corporate customers. The portfolio mainly contains counterparties with strong credit ratings, as seen in Table 4, which lowers the counterparty credit risk. Under or overestimating counterparty credit risk is not very critical as it does not significantly affect financial planning. Due to the small effect of the counterparty credit risk on financial planning, there might even be room for accepting slightly less reliable counterparties when it would create business opportunities that outweigh the increased risks.

5 Conclusions

This thesis investigated the effect of input uncertainty on the financial planning, specifically investment headroom, of an electricity producer. Investment headroom is defined as the maximum size of CapEx investment that can be made while respecting the constraint imposed on company's leverage ratio. Scenario analysis was conducted by changing the spot price and counterparty default scenarios, which are inputs into the financial simulation model used by Fortum. For each scenario, the financial simulation model estimates the financial status of Fortum, for example, leverage ratio, one-year after the modelling date. Although these input scenarios are originally used to take uncertainty into account, it is still possible that they are biassed, resulting in a leverage ratio distribution different from the true distribution.

Then, if a decision maker chooses, for example, the 95% VaR of leverage ratio, the true quantity can be either under- or overestimated. This can lead the decision maker to either invest too much, which can cause the leverage ratio to raise more than expected, or miss opportunities by being too cautios. To address this problem, scenarios with different input assumptions were created by perturbing the spot price and default scenarios. The sizes for spot price scenario perturbations were determined using historical spot prices and an alternative forecast model as references. Default scenario perturbations were done either by upgrading or downgrading the credit rating of each counterparty by one level, which changes the counterparty's probability of default.

The results of the scenario analysis indicate that the input uncertainty does not significantly affect the 5% Value-at-Risk of the maximum CapEx investment distribution, which the risk-averse decision maker uses. The maximum CapEx investment indicates the amount that can be invested in CapEx without the leverage ratio exceeding the threshold of 3.0 in one year. This thesis does not take a stance on what investments should be made but sets a leverage ratio based limit on CapEx increase and therefore limits the size and number of investments. Thus, the uncertainty in spot prices and counterparty defaults affects which investments will be made.

For risk-neutral and risk-seeking decision makers, taking into account the input uncertainty allows significantly higher CapEx investments. The asymmetry on the effect of input uncertainty between risk-seeking and risk-averse decision makers is mainly due to the bias found in the spot price scenarios. The spot price scenarios used as input have historically been below realised prices and the alternative spot price forecasts. Thus, the spot price scenarios were shifted towards higher prices. Since the output distribution is also widened, the 5% VaR of the maximum CapEx investment distribution does not change significantly when perturbed inputs are used. Shifting and widening the inputs both improve the best-case scenarios. Thus, the risk-seeking decision maker who uses the 95% VaR of the maximum CapEx investment distribution could invest even 35% more in CapEx when the input uncertainty is taken into account.

In the future, the accuracy of the spot price forecast model could be refined as from the model inputs it had the greatest impact on financial planning and the spot price forecast model has been systematically underestimating spot prices. Also, decision makers are advised to take into account the input uncertainty, as it can significantly affect financial planning. In the future, the accuracy of the financial simulation model could be studied, as in this thesis the financial simulation model was assumed to be fully accurate.

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