Lars Skjelbred Nygaard

Investments in Low-Carbon Power Generation and Energy Storage under Uncertainty

Master's thesis in Energy and Environmental Engineering
Supervisor: Magnus Korpås
Co-supervisor: Emil Dimanchev
June 2023

Master's thesis

NTNU
Norwegian University of Science and Technology
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Abstract

The need for investment in new zero-emissions generation technologies is imminent, and after the Russian invasion of Ukraine, the transition is needed even faster than anticipated. Hence, policymakers are left with the challenging task of introducing the right climate policies, which strike a balance between reducing emissions and ensuring growth in electricity generation.

This Master's Thesis examines the impact of uncertainty and risk aversion on the decarbonization of the power system and investigates the effect of different policy options on investments in Renewable Energy Source (RES). A deterministic, risk-neutral stochastic, and risk-averse stochastic optimization models for Generation Expansion Planning (GEP) are made to conduct analysis of a multi-zonal grid in Northern Europe. The analysis examines the complex interplay between uncertainty, risk aversion, and climate policies and how it affects capacity expansion, carbon emissions, power prices, revenues, and Non-served Energy (NSE). Moreover, this thesis investigates the investment point for nuclear capacity in the context of a CO_2 Tax policy, and it explores how new profit taxes might affect the investment in renewable energy.

The findings made in this thesis indicate that the level of risk aversion affects the capacity mix. Under a CO_2 Tax policy, risk aversion results in greater investments in renewable energy. However, under a more stringent CO_2 Cap policy, a consistent capacity mix is observed across all levels of risk aversion. In contrast, investments in fossil generation capacity increase with risk aversion in the absence of climate policies.

This thesis also emphasizes the importance of a functional international transmission system and the development of offshore wind capacity in the North Sea to optimize the flexibility of the different Variable Renewable Energy Source (VRES) and reduce reliance on fossil generation technologies. Furthermore, the importance of including uncertainty and risk aversion in long-term Generation Expansion Planning (GEP) models is stressed to enable policymakers to facilitate informed decision-making. Additionally, policymakers are encouraged to carefully evaluate the effect of new taxes, such as the ground rent tax, which has shown a dampening effect of investments in wind capacity for the models used in this thesis. It is crucial to strike a balance between taxation and incentives for investments in Renewable Energy Source (RES) to be able to achieve the ambitious climate goals for 2050.

Sammendrag

Denne masteroppgaven analyserer hvordan usikkerhet, ulike grader av risikoaversjon og ulike klimatiltak påvirker investeringene i, og dermed dekarboriseringen av kraftsystemet. Store investeringer innen fornybar kraftproduksjon er nødvendig for å nå de ambisiøse klimamålene mot 2050. Med dagens geopolitisk utfordrende situasjon, blant annet Russlands invasjon av Ukraina, er behovet for en hurtig omstilling større enn noen gang. Politikerne står dermed overfor en betydelig utfordring med å utforme en klimapolitikk som stimulerer til reduserte klimagassutslipp, og samtidig gi insentiver som legger til rette for vekst i fornybar kraftproduksjon.

Tre ulike optimeringsmodeller benyttes for planlegging av investeringer i økt effekt i et Nordeuropeisk kraftsystem bestående av flere prissoner; en deterministisk modell, en risikonøytral stokastisk modell og en risikoavers stokastisk modell. Ved å analysere og sammenligne disse tre modellene vises det komplekse samspillet mellom usikkerhet, risikoaversjon og klimapolitikk, og hvordan dette påvirker utviklingen av ny kraftproduksjon, klimagassutslipp, kraftpriser, inntekter og evnen til å imøtekomme kraftetterspørselen.

Funnene i denne masteroppgaven antyder at nivået av risikoaversjon har en betydelig påvirkning på kraftmiksen. Modellene viser en vesentlig økning i investeringer i fornybar kraftproduksjon med økende risikoaversjon når det blir innført avgift på CO_2-utslipp. Til sammenligning er kraftmiksen stabil ved ulike grader av risikoaversjon når det settes et strengt tak for klimagassutslippene i kraftsystemet. På den andre siden, øker investeringene i fossil kraftproduksjon med økt risikoaversjon når systemet ikke er begrenset av klimapolitiske virkemidler. Masteroppgaven fremhever også betydningen av internasjonalt marked for kraftutveksling, for å best utnytte de volatile produksjonsmønstrene til ulik fornybar kraftproduksjon. Mer spesifikt, pekes det på hvordan havvind i Nordsjøen kan være avgjørende for å utnytte nettopp denne varierende kraftproduksjon i det Nordeuropeiske kraftsystemet. Dette vil føre til mindre avhengighet av fossil kraftproduksjon som kull og gass.

I tillegg påpekes viktigheten av at politikkutformingen hensyntar usikkerhet og risikoaversjon, og at dette bør inkluderes i langsiktige modeller for utviklingen av kraftsystemet. Dette vil bidra til at politikere kan ta mer velinformerte valg når klimapolitikk skal utformes. Det understrekes også at politikere ikke må undervurdere betydningen av nye skatter, slik som grunnrenteskatt på vindkraft. Denne oppgaven viser at slike skatter kan ha en betydelig dempende effekt på investeringsnivået innen fornybar kraftproduksjon. Viktigheten av å finne den riktige balansen mellom skatter og insentiver for videre investeringer påpekes. Alt dette er elementer som bidrar til å muliggjøre de betydelige utslippskuttene sektoren skal og må gjøre frem mot 2050 dersom de overordnede klimamålene skal nås.

Preface

This Master's Thesis is a conclusion of my Master in Science (MSc) in Energy and Environmental Engineering at the Department of Electric Energy at the Norwegian University of Science and Technology.

I want to express my gratitude to my supervisor Magnus Korpås and my co-supervisor Emil Dimanchev. The interesting meetings and discussions we have shared have given important guidance in exploring these significant and timely questions. I also want to thank Hanna Ek Fälth and Lina Reichenberg at Chalmers University for contributing with state-of-the-art capacity factor time series for my thesis.

Finally, I want to thank my parents for their continuous support and inspiration throughout my education, and I also want to thank all my friends for making my five years at NTNU highly enjoyable.

Trondheim, June 2023

Lars S. Nygaard

Lars Skjelbred Nygaard

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Acronyms

CCS Carbon Capture and Storage. 9

CRF Capital Recovery Factor. 23, 24

CVaR Conditional Value at Risk. 10, 15, 16, 22, 74, 79

DSO Distribution System Operator. 3

EEX European Energy Exchange. 21

ESI Electricity Supply Industry. 71

EU ETS EU Emission Trading System. 28, 76, 81

GCEP Generation Capacity Expansion Planning. 8

GDP Gross Domestic Product. 11

GEP Generation Expansion Planning. i, 1, 2, 7–9, 15, 16, 20–23, 27, 32, 45, 52, 75–77, 79–82

LNG Liquefied Natural Gas. 4

MIP Mixed-Integer Programming. 11

MSc Master in Science. iii

NSE Non-served Energy. i, viii, 2, 16, 21, 22, 31, 37, 41, 42, 45, 48, 52–55, 59, 66, 68–70, 79, 80

NVE The Norwegian Water Resources and Energy Directorate. 23, 24, 90

PV Photovoltaic. 5, 26, 29

PX Power Exchange. 3

RD&D Research, Development and Demonstration. 9

RES Renewable Energy Source. i, 1, 2, 5, 9, 15, 16, 25, 74–76, 79, 81, 82

RPS Renewable Portfolio Standard. 74, 79

SC-CO_2 Social Cost of Carbon Dioxide. 10, 11, 76

SO Stochastic Optimization. 7, 9, 15, 16, 22, 77

SW Social Welfare. 3, 14, 23

TEP Transmission Expansion Planning. 16

TSC Total System Costs. 21, 22, 41, 52, 64, 79, 80

TSO Transmission System Operator. 3, 4

TTC Total Transfer Capacity. 4

VaR Value at Risk. 10, 22, 45, 79, 80

VOLL Value of Lost Load. 67

VRES Variable Renewable Energy Source. i, x, 1, 9, 26, 29, 32, 34, 35, 38, 40–42, 45–47, 52–54, 57, 59, 61, 62, 64–68, 70, 74, 75, 77, 78, 80, 81

Z1 Price Zone 1: The Continent. 20, 25, 27–29, 32, 35, 36, 38, 43, 71–73, 75

Z2 Price Zone 2: United Kingdom. 20, 25, 27–29, 32, 35, 43, 46, 71–74

Z3 Price Zone 3: North Sea Offshore Grid. x, 20, 21, 23–25, 27, 29, 32, 36, 72, 73, 75, 91

Nomenclature

Sets

t $\in T$	Time steps [h]
r $\in R$	Resources
s $\in S$	Scenarios
i $\in I$	Resources i.e. Storage Technologies
z $\in Z$	Price Zones
l $\in L$	Transmission Lines

Parameters

α	Parameter for VaR
$\beta_{l,z}$	Transmission Zone Map
χ_r	CO2 Tax Rate
η	Power to Energy Ratio
γ	Degree of Risk Aversion
ν	Single-trip Efficiency
$\omega_{r,z}$	Binary Matrix for Ground Rent Tax
ψ_l	Maximum Transmission Capacity
ξ_r	CO2 Intensity Factor
$A_{t,r,z}$	Resource Availability
C^{cap}	Price Cap [€/MWh]
C_r^{inv}	Investment Cots [€/MW]
$C_{r,s}^{tax}$	Ground Rent Tax Cost [€/MW]
$C_{r,s}^{trans}$	Transmission Investment Cost [€/MW]
C_r^{var}	Variable Cost [€/MWh]
$D_{t,s,z}$	Demand [MWh]
E_r^{co2}	Emission Intensity [tCO_2/MWh]
P_s	Probability of Scenario s
C	Carbon Emission Cap [tCO2]

Decision variables

$\varphi_{t,l}$	Transmission Flow
$\zeta_{i,z}^{ch}$	Charge of Storage
$\zeta_{i,z}^{dch}$	Discharge of Storage
$d_{t,s,z}^{nse}$	Non-Served Energy [MWh]
$e_{i,t,s,z}$	State of Charge
$g_{r,t,s,z}$	Generation [MWh]

$x_{r,z}$ Capacity [MW]

Dual Variables

$\lambda_{t,s,z}$ Price of Electricity [$/MWh]

$\mu_{r,t,s,z}$ Shadow Price of Capacity

θ_s Risk Adjusted Probability

Auxiliary variables

u_s Loss Relative to VaR

VaR Value at Risk

1 Introduction

1.1 Background and Motivation

The European power system is progressively changing towards a more Renewable Energy Source (RES) intensive system. However, after the Russian invasion of Ukraine, the need for a rapid change towards more RES is increasingly urgent. Policymakers in European countries have set climate goals for 2030 and 2050 that require a rapid change towards RES. To incentivize a change towards more RES in the power system, policymakers have a lot of different policy options that can help drive this change, and some are already applied.

However, uncertainty about the future and investor return requirements are some of the main barriers to investments in RES [87] [70]. The liberalized electricity market includes a great number of short-term uncertainties about demand, intermittent generation, and equipment outages. Perhaps more importantly, market actors face long-term uncertainty in fuel prices, demand growth, construction cost, and political uncertainty [55]. Moreover, the already significant long and short-term uncertainty is expected to increase further in the coming years and decades as a result of the uncertainty of climate policies implemented, the uncertainty of the accessibility to fossil fuels, and the extent of RES in the power system. This can have an effect on the investments in new zero-emission generation capacity, as these are investments with a long lead time, and decisions made are not easily reversible [32] [5].

To better understand and include this uncertainty for Generation Expansion Planning (GEP), several stochastic models have been developed [87]. An issue with most of these models is that they often have the assumption of a risk-neutral central planner or investor. However, investigating the literature, empirical evidence on investments implies that both public investors and private investors are instead risk-averse [55]. Modeling with risk aversion can have an effect on how GEP models react to different uncertain parameters that include demand uncertainty and climate policies. This suggests that uncertainty and risk aversion should be considered when generation expansion is studied, and climate policies are made, enabling policymakers to make the best-informed decisions. Nonetheless, uncertainty and risk aversion are often not included in GEP modeling used to inform policy making.

For the past one and a half years, there has been an energy crisis in Europe as a result of the expiration of the import of Russian gas after the invasion of Ukraine. This situation has forced the prices of electricity to rise considerably. Consequently, there has been substantial growth in revenues by the power generation companies, especially for the RES. As a consequence of these high revenues, new taxation on RES has been introduced across Europe [81]. In Norway, there is a proposal by the current government to introduce a ground rent tax on existing and new onshore wind [62]. This has not received a positive response from investors already active in the market in Norway or from investors that want to invest in wind power in Norway [77] [41]. The unexpected taxes on wind power result in an increase in the political risks in Norway [35], which can result in under-investment in VRES in the coming years [75] [92]. This illustrates the importance of policymakers finding the right balance when introducing new policies to ensure a sufficient investment level in RES in the power system. Consequently, considering risk aversion is crucial to better understand how both public and private investors will react to the policies proposed.

1.2 Objective

This Master's Thesis aims to enhance the understanding of how uncertainty and risk aversion impact the decarbonization of the power system while also exploring the potential of how different policies affect investments in clean energy. To achieve this objective, the thesis compares and analyzes the deterministic and stochastic models under different levels of risk aversion and climate policy options for a multi-zonal grid in Northern Europe. Specifically, the thesis focuses on analyzing the capacity expansion decisions, emission levels, power prices, revenues, NSE, and the role of RES and storage technologies in the presence of uncertainty and risk aversion. Additionally, the thesis also investigates how a new tax policy on wind power can affect the investment done by the risk-neutral and risk-averse central planner.

The objective described above is achieved by following steps:

- Compare the capacity mix generated by a deterministic, risk-neutral stochastic, and a risk-averse stochastic optimization model for GEP for different climate policy options. Moreover, how carbon emissions, power prices, revenues, generation, and NSE are affected.
- Investigate the influence of different levels of risk aversion on the capacity mix. Consequently, generation, carbon emissions, power prices, revenue, and NSE.
- Examining the power prices and revenues from the solution of risk-averse models for different levels of risk aversion.
- Investigate the magnitude of the CO_2 Tax, which the risk-neutral and the risk-averse central planner would require to invest in nuclear capacity. To gain knowledge of when the upsides of nuclear power overcome the high investment costs.
- Analysis and comparison of the CO_2 Price for the deterministic model and the risk-averse model under different levels of risk aversion to better understand how the different policy options affect the models, hence, the technology mix selected for the system.
- The effect of a new ground rent tax on new and exciting wind power for the risk-neutral and for the risk-averse stochastic model. This is a tax option considered by several countries. Consequently, investigating how it affects the capacity mixes can facilitate more informed decision-making.

The findings in the Master's Thesis aim to improve the understanding of the complex interplay between uncertainty, risk aversion, and sustainable planning of the power system. Ultimately providing valuable insights for policymakers, central planners, and investors involved in the development of the power system, aiming to achieve the climate goals set for 2050. Hence, the thesis strives to contribute to advancing knowledge in the field of Stochastic Optimization models for Generation Expansion Planning (GEP) and energy politics, with the goal of facilitating informed decision-making.

2 Theory and Background

The information presented in subsection 2.1, 2.3 (except 2.3.3), 2.4, 2.5, 2.6, 2.7, and 2.10 was part of the project thesis related to the subject TET4510 [67], carried out in autumn 2022.

section 2 aims to outline important background knowledge needed for a better understanding of this Master's Thesis.

2.1 The European Electricity Market

The main objective for a single energy market in Europe is to ensure affordable energy, competitive prices, and provide better environmental sustainability [50]. The spot market is operated by the Power Exchange (PX), and the different Transmission System Operator (TSO) are responsible for network boundaries to ensure the feasibility and security of the system. The market is separated into different bidding areas, determined by national borders or bottlenecks in the system [6]. For instance, Norway has five bidding areas (NO1-NO5), but in EPEX Spot, there are only three: France, Germany/Austria, and Switzerland [6]. The different bidding areas reflect the conditions of the respective market area in terms of demand, production, and price. Different bidding areas may experience different prices due to bottlenecks between the bidding areas. When there is a price difference between two areas, the power will always flow from the low price area to the high price area [52].

The electricity market is divided into three main markets, Day-ahead Market, Intraday-Market, and Ancillary Service Market. The Day-ahead market is a closed auction where market participants can buy and sell power for the next 24 hours. Bids and orders are matched to maximize Social Welfare (SW) and simultaneously consider transmission constraints. The result is a market where the requested demand is met, and the price is set for each bidding area[59]. It is nearly impossible to forecast the coming day with 100% accuracy; hence the Intraday Market was created. The intraday markets help to ensure a balance between supply and demand, as power trading is closer to the physical delivery in the intraday market [60].

The purpose of the ancillary service is to use different resources for the security management of the electricity system and to ensure the system's quality. A constant equilibrium between power consumption and generation is needed to balance an electricity system. The result of not achieving this equilibrium is a frequency deviation and possibly a blackout. The TSO and the Distribution System Operator (DSO) are responsible for the ancillary services and ensuring that the different demands from the ancillary service market are met [95].

It is reasonable to believe that both the intraday and ancillary service markets will be even more important in the future. In addition, with an increasing share of variable renewable energy generation, the need for balancing in the market will grow.

The European Electricity system's power production is deregulated, but the state regulates and owns the transmission system. This is done because a neutral transmission system is needed to achieve an efficient power market. Electricity can not be stored in large amounts. Hence, access and control over the electricity transmission system can directly influence the electricity markets by determining where new transmission lines will be built, who is allowed to connect to the grid, and how to achieve an equilibrium in the system. Fair competition in the market requires a neutral TSO. Thus, it is required by law that the TSOs and DSOs are state-owned [22].

Another aspect of the liberalized market is that customers are free to choose their power distributor, which does not need to be a power producer or owner of the grid. Hence, the customer achieves better conditions due to the competition between the power distributors.

2.2 The Transmission System: The Zonal approach

There are different ways to structure the transmission grid, and the zonal approach is the most common method. The zonal model divides the grid into different zones/price areas. The division is based on a priory of the Total Transfer Capacity (TTC) from one area to another without exceeding the security constraints. All areas are considered as a single bus, and how the power flows between the zones is determined as a balance between generation and demand for each zone. The power will always flow to a zone with equal or higher price [49].

The main advantage of the zonal approach is that it is very simple and can find the market equilibrium efficiently. The simplicity of the model makes it understandable for the participants, which makes them understand the result and enables them to change their production and consumption to improve their profits. However, the fact that the zones are defined based on prior knowledge of congestion in the transmission system is not ideal. In an ideal system the zones would have been defined with respect to the most frequent congestion situation based on the TSOs experience [28].

2.3 The Technology Mix

2.3.1 Thermal: Nuclear, Coal, and Gas

Thermal power generation uses steam to rotate a steam or gas turbine connected to a generator that produces electricity. The steam is generated by burning oil, gas, coal, or other fuels. The working principle of a thermal power plant is advanced. It comes in different sizes and varieties, from a simple steam turbine to the more advanced and energy-efficient combined cycle steam turbine. The advantage of thermal power is that it delivers a steady amount of electricity and is very predictable. Thermal power generation is the primary source of electricity in Europe. The drawback is that gas and coal generation produces carbon dioxide emissions [12].

Nuclear power generation utilizes the heat produced when the uranium nucleus splits to create a high-temperature and high-pressure stream from water boiled inside the reactor. The steam drives the turbine, which is connected to the generator, producing electricity[96]. Nuclear power plants have very limited flexibility. Hence, it can not be adjusted to respond to changes in demand. Consequently, nuclear is often referred to as a base load. Even though nuclear power plants have zero CO2 emissions when producing electricity, the main drawback is the nuclear waste that needs to be taken care of.

Although delivering a constant and predictable power flow, thermal units also have some operational drawbacks. Coal power plants are similar to nuclear power plants in terms of how they operate. They deliver a steady energy amount around the clock and can not be easily adjusted to meet peaks or dips in demand or be shut on and off often. Gas power plants, like Liquefied Natural Gas (LNG) fired power plants, are more flexible, can adjust to daily fluctuations, and can be more easily turned on and off [97].

2.3.2 Onshore Wind

Wind power is one of the fastest-growing generation sources in the world. The windmills are grouped in farms in areas with good and steady wind resources. That can be both onshore and offshore. The wind turbine is connected to the generator through a driveshaft and a gearbox. The power is then transported down the tower to a transformer and distributed to the power grid [106].

The recent year's onshore wind power costs have dropped, and the price of building new wind farms is now lower than building new gas, coal, and nuclear power plants, according to Bjørn Mo Østgren, who is responsible for monitoring Statkrafts wind farms in Northwestern Europe [69]. As a result, the amount of wind power is expected to increase in the coming years to reduce emissions and meet new electricity demand. However, as wind power is a non-controllable renewable energy source, it will not always produce power.

2.3.3 Offshore Wind

Offshore wind farms are a rapidly growing generation technology but are less evolved compared to onshore wind. However, the potential of offshore wind is huge. The wind resources at sea are better than onshore due to more stable winds and no terrain obstacles. Additionally, at sea, the noise and size of the wind turbines do not affect people, which enables the option of larger wind turbines with greater production capacity [71].

There are two main offshore wind technologies; bottom fixed- and floating offshore wind. Fixed offshore wind turbines are connected to a structure that is installed on the seabed. Floating offshore wind turbines are mounted on a floating structure and are only connected to the seabed by anchors. While bottom fixed wind turbines are restricted to shallow waters with a maximum depth of around 60 meters, floating wind turbines enable wind power production in deep waters far from land [73].

2.3.4 Solar

Solar power is getting more competitive in the spectrum of electricity-generating technologies. The fact that the solar energy that enters the earth's atmosphere in a period of 40 minutes is enough energy to serve the whole world's energy demand for a year clearly illustrates the potential of solar power. A solar panel is made of several Photovoltaic (PV) cells. The PV cells are usually made of a silicon wafer. Electrons are knocked loose from the atoms when the sun hits the PV cells. These electrons are the forming a flow of electric current. The electricity generated from all the PV panels is then inverted to AC and distributed to the grid [94].

The same problem of production security occurs for solar power as for wind power. The solar power plants will only produce energy as there is daylight, and the amount of power produced depends on variables such as solar radiation, heat, and dirt on the PV panels.

2.3.5 Storage

With an increasing amount of RES in the electricity system, a more flexible grid is needed to make sure that these variable RES are integrated into the grid as efficiently as possible. Utility-scale batteries are a potential solution to increase the flexibility of the electricity system. Utility-scale battery storage systems are typically made to store electricity from around a few megawatt-hours up to hundreds of megawatt-hours. Several technologies like lithium-ion, lead acid, and sodium sulphur batteries have been used, but the greatest developments have been within lithium-ion batteries [43]. This is the type of battery storage used in the optimization model for this project.

Lithium-ion batteries are used in many technologies, from electric vehicles to phones. Due to this wide application, there has been rapid development in recent years. A lithium-ion battery used as a utility-scale battery consists of several lithium-ion cells. In the cell, lithium ions move between the electrodes of the cell internally through what's called a conductive electrolyte. At the same time, electrons move in an external grid in the opposite direction, from the anode to the cathode. These are the electrons that provide electricity for the load as depicted in Figure 1. When the battery is charged, the same process occurs, but in the opposite direction [104].

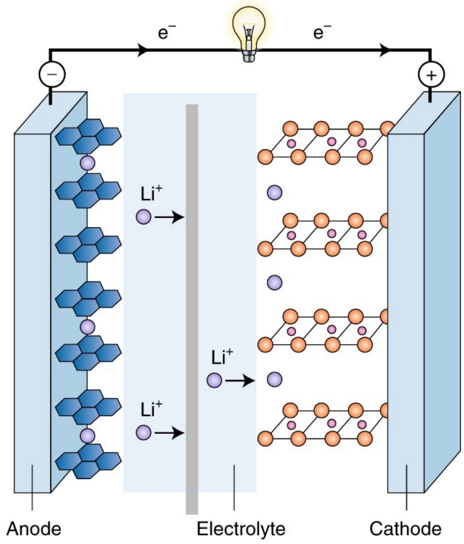


Figure 1: Lithium-ion Battery
[37]

There are several other storage technologies, including supercapacitors, flywheels, and superconducting magnetic energy storage. that can play a role in the power system. Either as normal storage or to work as an ancillary service.

2.4 Optimization and Stochastic Optimization Theory

The goal when using optimization is to find the best solution from a set of possible solutions. Optimality is determined by either maximizing or minimizing an objective function, which for example, can be the system costs. To find the optimal solution, the model undertakes a set of restrictions called constraints. Hence, the purpose of the optimization model is to minimize or maximize the objective function subject to a set of constraints. The constraints are expressed as equality or inequality constraints [40].

The basic mathematical formulation of an optimization problem is:
Objective function:

$$\min(\text{or}\max) : f(x_1, x_2, ..., x_N) \tag{1}$$

s.t.:
Inequality constraints

$$\begin{aligned} g_1(x_1, x_2, ..., x_N) &\leq 0 && (2)\\ g_2(x_1, x_2, ..., x_N) &\leq 0 && (3)\\ &\vdots && (4)\\ g_m(x_1, x_2, ..., x_N) &\leq 0 && (5)\end{aligned}$$

Equality constraints

$$\begin{aligned} h_1(x_1, x_2, ..., x_N) &= 0 && (6)\\ h_2(x_1, x_2, ..., x_N) &= 0 && (7)\\ &\vdots && (8)\\ h_E(x_1, x_2, ..., x_N) &= 0 && (9)\\ E &\leq N \end{aligned}$$

$x_1, x_2, ..., x_N$ are decision variables; simply put, these are the values that the model tries to determine [40].

The main advantage of using an optimization model is that it delivers a practical framework to solve large-scale problems, provides data that can be used to visualize the solution, and the mathematical formulation can provide a better understanding of the problem. Another key point is that it is easy to test the original problem for *what-if* scenarios, which can provide a better understanding of how different factors affect the end result of the model. However, a potential limitation of using a mathematical approach to address a problem is the possibility of encountering a local optimum solution rather than a global (the best possible) optimum solution when dealing with a non-convex problem. In contrast, convex problems may exhibit no solution, one global solution, or an infinite number of identical solutions [40].

Stochastic Optimization (SO) is a more advanced version of the standard optimization problem. The SO model has a similar goal: to minimize or maximize the value of the objective function. However, it also takes the uncertainty of the input parameters into account. The input parameters can be represented with different scenarios with respective weights. The weights describe how likely this scenario is to take place. Consequently, the result is a model that solves the objective function with respect to the constraints, some of which are scenario-specific [87].

Planning capacity expansion for a large-scale and highly renewable power system while accounting for renewable intermittency, broader uncertainty in the parameter space, and resource adequacy are very complex. Using SO models to solve GEP problems have shown very effective [107].

2.5 Generation Capacity Expansion Models

The energy system is quickly evolving, and the demand for electricity is growing. The global push for sustainability requires this new demand to be met by renewable power generation. Fortunately, technological innovations present an opportunity to achieve these ambitious sustainability goals. However, when a mix of renewables and non-renewables is implemented into the energy system, several societal objectives must be balanced concerning social, environmental, and economic outcomes. Consequently, a large number of energy policy analyses must be performed to find the best possible way to meet future demand. Generation Capacity Expansion Planning (GCEP) is therefore playing a vital role in the development of the energy system because it could represent the multiple objectives that need to be balanced as a combination of an objective function and constraints. [33].

GCEP, also called GEP, is the most fundamental part of the long-term planning of the electricity system because it determines what type of generation to build, where to install the generators and when to do it to satisfy the demand for the respective time horizon. A GEP model can be represented as a single-bus GEP and a multi-bus GEP, depending on whether the transmission system is defined or not[33]. The GEP model makes discussions based on minimizing an objective function consisting of two main parts.

$$Objective function = CapitalCosts + OperationalCosts \tag{10}$$

Capital costs are costs related to investment decisions, and operational costs are associated with the operating costs for the given time horizon. Furthermore, some of the most common constraints in the GEP model are the power demand satisfaction, generation limits for the units, reserve requirements and restrictions to the power productions due to the available generation capacity.

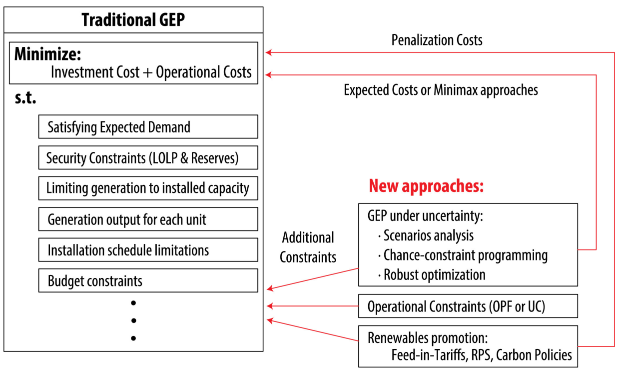


Figure 2: GEP model
[33]

Figure 2 is a general graphic representation of the optimization problem solving a generation expansion model. As seen under "New approaches," there is an ongoing development to make the GEP model more realistic. Facilitating the possibility of including uncertainty in modern GEP models, making them more robust and credible [33].

2.6 Risk and Risk Aversion

Several uncertainties, like energy prices CO_2 prices, fuel prices, and electricity demand, are present when working with GEP. With the ambitious climate goals for 2050, the electricity sector must take its share of the emission cut. In addition, a high share of renewable energy will lead to lower costs, which will benefit energy consumers. Due to the limited possibilities of building more hydro power and the political restrictions towards nuclear power [57], the European energy system will experience a high share of VRESs to achieve the emission goals for 2030 and reach net zero emission by 2050 [7]. The most dominant VRESs will be onshore and offshore wind power and solar power. The variability of VRESs will affect the power system's operation and, consequently, which technology mix can sufficiently meet several future demand scenarios. Consequently, a significant risk will be present for the governments and investors in the electricity sector [57]. As a result, many studies have been made in the past years on handling this in the best way possible. For example, studies made by both [83] and [88] state that the use of stochastic models for long-term energy modeling is recommended to sufficiently deal with these uncertainties.

Risk aversion is defined as the preference for receiving the expected outcome of a risk with certainty rather than the risk itself [78]. In other words, a risk-averse investor is only willing to accept a low level of risk on their investments and accept a lower but more certain return. Different investors have different levels of risk aversion. For instance, a private person can be willing to take significant risks in the stock market to fetch a major return. On the other hand, The Norwegian Government Pension Fund needs to be more risk-averse because it is managing public money, but at the same time, the Norwegian Pension Fund can accept a much lower return on the investment. The majority of the investors in the power system are expected to be risk averse[72]. Consequently, to make an investment in RES sustainable for the investor, it requires a stable return over several years [87]. Furthermore, the question of how risk aversion will affect investments in the energy sector, being aware of all the uncertainty parameters, is important and something that will be examined later in this thesis.

2.7 Policy Makers view on risk

The risk and uncertainty related to the power system are complex to manage. However, the power system is a natural place to start large downscaling of emissions because it can be done at a lower cost and with less dramatic changes than in other sectors [45]. Thus, policymakers need to ensure suitable and efficient funding of Research, Development and Demonstration (RD&D) to help less mature technologies, like Carbon Capture and Storage (CCS) and offshore wind, to a point where it is beneficial to invest in or where it is clear that they would not get profitable and should be abandoned [58]. However, this is easier said than done. Policymakers may seek to lower the risks of investing in RES to reach the set emission goals, meet electricity demand and obtain a more sustainable power system [87]. To make a sufficient choice in the jungle of policy options stimulating this transition, sophisticated simulation tools such as SO models should be adopted [87].

Different Renewable energy policies can have a dramatic effect on the energy transition.[70] investigate the potential risk of political recoil against high carbon prices, which endangers the transition to low carbon energy solutions. With a fast decreasing cost of RES, the policymakers want to reach a state of subsidy-free renewables. This could be sustainable for some situations. However, the revenues for the RES are still very uncertain due to factors such as demand risk and weather variations, which exposes investors to the risk that the profit margin may be too slim. Consequently, a lack of investments in RES can be experienced. This can be avoided by viewing these subsidies not as technology subsidies but as de-risking subsidies to keep the investment in RES at a sufficient level [70]. This is another example of how policymakers must consider risk when changing and adding policies related to the power system.

2.8 Value at Risk and Conditional Value at Risk

Value at Risk (VaR) is a method to quantify the extent of possible financial losses for an investment or a firm over a given time frame. An investor uses VaR to gauge the capital they need to cover potential losses. There are three components to a VaR measurement; a time frame, a confidence level, and a loss amount. By utilizing these three components, the VaR modeling determines the potential loss and the probability for that loss to occur. It is possible to either use the historical-, variance-covariance-, or the Monte Carlo method to compute the VaR [48]. For example, given a confidence level of 95%, what is the greatest amount that can be expected to be lost over the next year? This is a question that the VaR can give an answer to.

Conditional Value at Risk (CVaR) is also known as expected shortfall, and it quantifies the amount of tail risk associated with an investment or an investment portfolio. VaR represents the loss or profit at a given percentile of the distribution related to a probability and a time horizon. CVaR, on the other hand, represent the expected loss if the worst-case below a certain percentile of the distribution of outcomes is ever crossed. As Figure 3 shows, CVaR will give a greater loss compared to the cut-off point (VaR). If an investment portfolio shows to be stable over time, VaR may be sufficient to represent the risk. However, for a more unstable investment, the chances are great for VaR to be unable to give a satisfying picture of the risks because it is indifferent to all values beyond the set threshold. Thus, the utilization of CVaR for these investments is necessary, as it addresses the shortcomings of the VaR model [9].

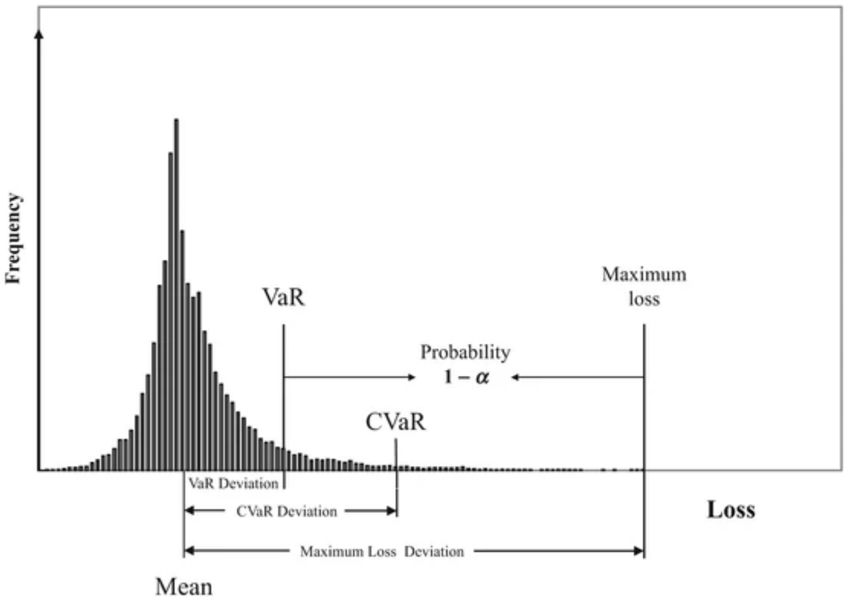


Figure 3: Value at Risk and Conditional Value at Risk
[89]

2.9 The Social Cost of Carbon

The Social Cost of Carbon Dioxide (SC-CO_2) determines the monetized value of the damage to society caused by one additional emitted tonne of CO_2 equivalent emissions. SC-CO_2 is an important tool for policymakers for cost-benefit analysis when evaluating different climate policies because the net benefit of a climate policy is the variety between the cost of the emission reduction, called the mitigation cost, and the value of preventing the damages related to the additional tonne of CO_2 emission [80]. In a world that acts like a perfect economic model, the optimal climate reduction would be when the cost of cutting one additional tonne of CO_2 is balanced with the benefits of limiting future global warming [74].

Several parameters and uncertainties are considered to measure the SC-CO_2. The most recent method to evaluate SC-CO_2 is called RFF-SPs and was developed by the research institute *Resurces* *of the Future* et al. [80]. RFF-SPs is designed to address the socioeconomic projections posed by the SC-CO_2 appraisal, and several aspects need to be considered to ensure an adequate result. The model has a 300-year time horizon to account for most discounted future damages and has geographically disaggregated estimates of GDP and population to assess damages at a regional scale. Additionally, accounting for uncertainty related to expected future changes in technology and policy, as the SC-CO_2 is calculated based on the best estimate of future emissions, assuming the implementation of all mitigation policies. Finally, to accurately estimate the SC-CO_2 RFF-SPs, careful consideration of the interdependence of future population, Gross Domestic Product (GDP), and greenhouse gas emissions trajectories [80].

In [80], the result is a preferred mean SC-CO_2 of $185 per tonne of CO_2 using a near-term risk-free discount rate of 2%. This is a value 3.6 times higher than the $51 value that the current US government uses (per September 2022). Consequently, a risk of underestimating the value of emission mitigation is present.

2.10 Julia and JUMP

Julia is a high-level, high-performance dynamic programming language well suited for numerical analysis. For this project, Julia is used for programming the optimization models [98]. This is done using the domain-specific modeling language JUMP [17]. It is a specific modeling language embedded in Julia made for mathematical optimization. JUMP is sufficient for an optimization problem that can be formulated using the language of mathematical programming [90].

2.11 Gurobi Optimizer

Gurobi is a commercial optimization solver that solves mathematical optimization problems. It uses state-of-the-art algorithms to solve everything from simple to complex optimization problems. It utilizes a powerful Mixed-Integer Programming (MIP) algorithm, enabling the user to add complexity to better represent the real world and solve the problem within a sufficient amount of time [39].

The Gurobi optimizer also uses advanced techniques such as branch-and-cut, branch-and-price, and branch-and-bound to solve optimization problems effectively. Combined, the Gurobi Optimizer is a broadly used tool for everything from finance to manufacturing and transportation [34].

3 Literature Review

3.1 Renewable energy supporting policy evaluation: The role of long-term uncertainty in market modeling

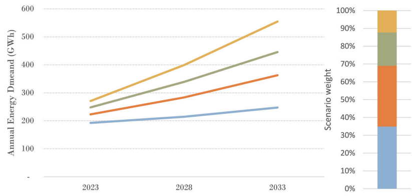
The literature review, in subsection 3.1, looking into [87] was done as a part of the specialization course *TET4565: Electricity Markets and Energy System Planning, Specialisation course*, and was a part of the project thesis, carried out in autumn 2022 [67].

"Renewable energy supporting policy evaluation: The role of long-term uncertainty in market modelling" by Ian J. Scott, Audun Botterud, Pedro M.S Carvalho and Carlos A. Santos Silva are investigated to better understand the effects of uncertainty in long-term market modeling [87].

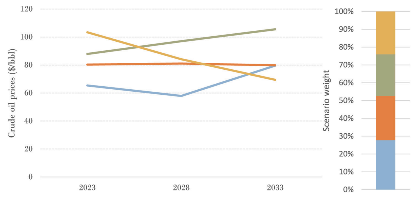
3.1.1 Introduction to the literature

Several studies on generation expansion planning have been made, but the inclusion of uncertainty is often ignored. The fact that investment decisions in the energy sector are complex and need a sufficient return over a long period makes these decisions particularly vulnerable to the effect of uncertainty. In this article, the importance of including uncertainty is presented by comparing different models and six different policy options. The case study selected was to model the island of Terceira in Portugal due to its beneficial characteristics. It is a small isolated system, with increasing demand and a need for investment in energy generation in the coming years [87].

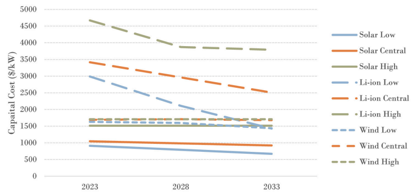
The three models reviewed in this report were a deterministic, a Scenario Average, and a Stochastic Optimisation model. The deterministic model minimizes the total system cost with respect to building costs, fixed operation costs, variable costs, and system costs for a single deterministic scenario. The Scenario Average model has the same minimization problem but is extended with several scenarios with respective weights (W). However, each of these scenarios is solved as an isolated deterministic problem with different sets of values. Finally, in the Stochastic optimization model, the uncertainty of the input parameters is considered in the attempt to minimize the expected value of the total system with respect to the system cost, summing over all the scenarios and considering their respective weights (W). The uncertainty in the model is related to the three inputs fuel price (b), annual energy demand (a), and operating costs as represented (c) in Figure 4 [87].



(a) Annual energy demand



(b) Crude oil price



(c) Construction costs

Figure 4: The uncertainties represented in the model
[87]

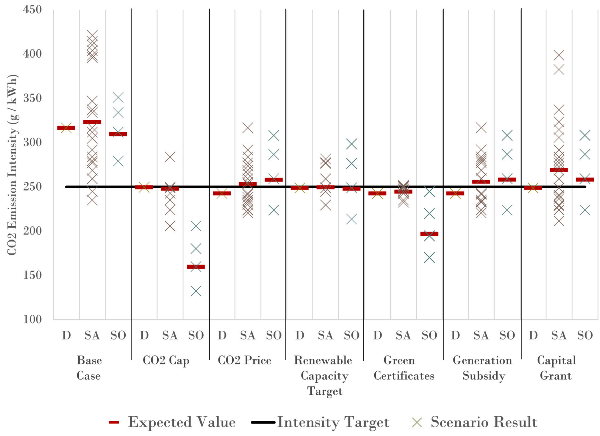
The model focuses on two categories of policy options; quantity-based policies and price-based policies. Quantity-based policies include CO2 Cap, Renewable capacity targets, and Green certificates, and price-based policies include CO2 price, Generation subsidies, and Capital grants [87].

Investing in the electricity market is highly intricate due to the complexity of transmission constraints, the difficulty of storing electricity, sizing constraints of new generators, the need for providing ancillary services, and the uncertainty related to production when using non-controllable renewable energy sources [87]. Thus, it was necessary to make some simplifications to get the model to work. Due to complexity limitations, the model is implemented as a two-stage stochastic optimization problem, where only the initial set of decisions is made without knowledge of the future. If a real optimization problem had been made, all decisions should have been taken with an uncertainty of the future. Hence, it is possible that this model underestimates the impact of uncertainty.

Additionally, it is important to bear in mind that this stochastic optimization model investigates the expected effect of different decarbonization policies when taking uncertainty into account, both in a competitive market and with a central planner. The model used for the studies relies heavily on the assumption of perfect competition. A next step in the research of uncertainty could be an extension of the model, including market power remains, as mentioned in the conclusion of the article [87].

3.1.2 Results and conclusion

The result of the Deterministic model and the scenario average model is similar, which indicates that the way the different scenarios are represented in the Scenario Average model has little effect on the policymaker compared to the Deterministic model. When the Scenario Average model and the Deterministic model are compared to the Stochastic Optimization model, which represents a competitive electricity market with different policy options where uncertainty is included, some significant differences are outlined.

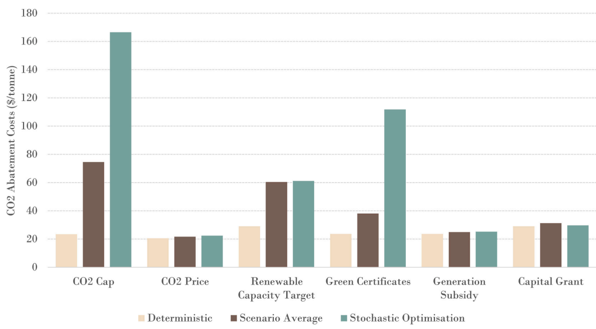


(a)

Figure 5: Expected carbon intensity levels for all scenarios for different policy options. [87]

The most significant difference appears when the CO2 Cap policy is adopted, depicted both in Figure 5 and 6. The CO2 Cap sets a limit of CO2 emissions for the whole system, and the model uses this to find the combination which maximizes SW and at the same time keeps within the limits of CO2 emissions. The higher demand scenarios require a significant growth of renewable generation which the Stochastic Optimization model is forced to build. This results in a carbon intensity level under the set limit of 250 $[g/kWh]$, which is remarkably lower than the Deterministic and the Scenario Average model. The same effect can be seen when employing Green Certificates but to a lesser extent.

In addition, it is important to notice that only the quantity-based policies achieve the wanted emission intensity (Figure 5). Hence, this reinforces the assumption that quantity-based policy options give better certainty on emission levels and price-based policy options give a better certainty of the costs.



(a)

Figure 6: Expected carbon abatement costs. [87]

Figure 6 represent the expected carbon abatement costs of the different policies applying the three models. To get a fair comparison, subsidy costs are accounted for. It is clear that both the Deterministic and the Scenario Average models underestimate the expected abatement costs. The difference from the Stochastic model varies from 2% in the case of Capital grant up to 86% in the case of CO2 Cap when comparing with the Deterministic model. Although the Scenario Average performs better, it is still far off. A noteworthy point, stated by the authors, is that the amount of renewable capacity the decision maker will consider economical and choose to build will not be the perfect amount for a given scenario. For example, for a low-demand scenario, renewable capacity is too high and thus is uneconomical for that specific scenario. However, the same amount of renewable capacity provides a lot of value for the scenarios when they are really needed (e.g. the high-demand scenarios where the CO2 Cap is binding). In short, the SO is meeting the emission constraint for the hardest scenarios leading to a large investment in renewables, which would not have been economical for certain other scenarios.

As stated in the conclusion by the authors, "In addition, we show that incorporating uncertainty as individual scenarios finds that in each individual scenario, where investors know the future costs and demand requirement, new onshore wind is typically the most cost-efficient technology to respond to decarbonization policies. However, in the real world, decision-makers in the market do not know the future and must decide what to build, given this uncertainty.

Overall, we find a strong case for including long-term uncertainty in electricity system models in the form of a stochastic optimization model. We find all outcomes of interest differ significantly when uncertainty is excluded, or modeled as individual scenarios, biasing the choice between different renewable energy policies." [87]

3.2 Existing Literature on Risk Averse Generation Planning

Several reports and studies have been carried out considering the effect of risk aversion on investments in GEP models. A general assumption often used is the setting of a perfectly competitive market [55]. In [56], Neuhoff et al. show that if you have a case with risk-averse investors, and the risks present can not be traded, an under-investment in power generation may be observed. This is because the risk is seen as an additional cost for the investor, increasing the generator costs and making the investment less lucrative. Additionally, [56] also point out that this risk pushes the generation mix towards less risky and intensive technologies, which will be unfavorable for RES.

However, the study carried out by [30] uses investors maximizing utility functions that contain an absolute risk aversion, and it points out that climate and carbon targets can affect the risk-averse investor considerably. [30] states that if carbon taxes, or similar climate initiatives, are expected in the model, a cleaner generation mix will be present to ensure against regulatory costs.

In contrast to the papers mentioned above focusing on project-based investments, [85] investigates how an investor would choose a portfolio of generation technologies using mean-variance optimization. [85] express the importance of the relationship between uncertainty variables. For instance, that the gas-prices and electricity prices are heavily related, making investments in gas power generation less risky because the high input price of gas generation will result in a high electricity price. Thus, gas power generation will be favorable for a risk-averse investor in this case, relative to coal or nuclear power generation. While electricity prices are exogenous in [85], a study carried out by [54] using a portfolio model with endogenous electricity prices shows similar interactions between the technologies as in [85]. Peaking capacities, like gas power generation, tends to increase with risk aversion because this will be the marginal unit determining the price in the market. This makes it useful to ensure a certain return on investment for the baseload capacity.

All the studies mentioned above share the simplification to ignore the effect of transmission constraints. In [47], on the other hand, a sensitivity analysis concerning transmission constraints is carried out. This sensitivity analysis shows that transmission constraints heavily impact the generator's earnings, thus, investment decisions and risk aversion. [47] is also introducing renewable energy sources as an investment option, which shows increasing investment in renewables with an increasing level of risk aversion, even though renewable energy sources have a high capital intensity. An additional study, carried out by [76], presents similar results using a model maximizing investor's weighted foreseen profits and CVaR. These results are based on the fact that there is no direct uncertainty related to fuel prices and a low operation cost. Consequently, the demand uncertainty can also be reduced or even ignored if the renewable generation levels are lower than the normal base demand. Even though the profitability is subject to the electricity price, which is still uncertain, as investment costs are not, it is less risky to invest in renewable energy sources. This is because the marginal costs of renewable energy sources are sufficiently low, ensuring the investor that the power generated will be sold on the market and with a low chance of being the marginal unit. Whether this is how the real world works are debatable, but [47] and [76] illustrate an important aspect of how investments may be chosen.

Additionally, it has been shown that the generation dispatch and generation expansion equilibrium is equivalent to the risk-adjusted cost minimization problem [55] [79], which is the model used for this thesis under some assumptions about the market equilibrium. Firstly, it assumes that generators aim to maximize expected profits and the CVaR of the lower tail of these profits need to be made, generation investments and dispatch levels need to be continuous and marginal costs need to be constant [55]. Secondly, it assumes perfect competition in the electricity market and complete financial markets [55].

3.3 Unanswered questions

This thesis aims to address not only how the capacity mix is affected by uncertainty and risk aversion but also how these affect other outcomes, including carbon emissions, power prices, revenues, NSE and the CO_2 price generated by emission cap policy. This is done for a large power system, including a relatively large variety of technology options. This is something not adequately addressed in the existing literature on how uncertainty and risk aversion affects Stochastic Optimization (SO) models for GEP.

The existing literature is mainly focused on small-scale systems, except [55]. However, [55] use a two-stage model where the decisions made for generation capacity are based on the results from the risk-averse stochastic Transmission Expansion Planning (TEP) model. Consequently, the effects of uncertainty and risk aversion in a large-scale risk-averse stochastic Generation Expansion Planning (GEP) model are still to be explored, which is the focus of this thesis.

How the risk-averse stochastic models weight the variables and outcomes of the models is also a question that the existing literature has not covered. This weighting is found and outlined in detail in the thesis. In addition, how to find the actual values for these parameters for extreme risk aversion ($\gamma = 1$) is also addressed.

Additionally, the existing literature does not address how other parameters, such as a profit tax on RES, can affect the investments made by the stochastic model for different levels of risk aversion. Moreover, how climate policies and risk aversion can affect the investment point of expensive climate-neutral technologies such as nuclear power generation is also an unanswered question.

4 Methodology

The methodology section provides a detailed explanation of the three optimization models used for this thesis. Furthermore, it outlines all input data and calculations involved in the model. Hence, facilitating a clear understanding of how the models work and which data serve as the foundation for the results obtained.

4.1 Model outline

4.1.1 Deterministic model

$$\begin{aligned}\min_{x_{r,z},g_{r,t,z},d_t^{nse}} & \sum_z\sum_r C_r^{inv}x_{r,z} + \sum_z\sum_r C_{r,z}^{trans}x_{r,z} + \sum_z\sum_t\sum_r C_r^{var}g_{r,t,z} \\ & + \sum_z\sum_t C^{cap}d_{t,z}^{nse} + \sum_z\sum_t\sum_r \chi_r\xi_r g_{r,t,z} + \sum_z\sum_r C_r^{tax}x_{r,z}\omega_{r,z}\end{aligned} \tag{11}$$

s.t.

$$x_{r,z} \geq 0 \quad \forall \quad x \in \mathbb{R}, r \in R, z \in Z \tag{12}$$

$$g_{r,t,z} \geq 0 \quad \forall \quad g \in \mathbb{R}, r \in R, t \in T, z \in Z \tag{13}$$

$$d_{t,z}^{nse} \geq 0 \quad \forall \quad d^{nse} \in \mathbb{R}, t \in T, z \in Z \tag{14}$$

$$\sum_r g_{r,t,z} + d_{t,z}^{nse} + \sum_i(\zeta_{i,t}^{dch} - \zeta_{i,t}^{ch}) + \sum_l \varphi_{t,l}\beta_{l,z} = D_{t,z} \quad \forall \quad t \in T, z \in Z-1 \tag{15}$$

$$\sum_r g_{r,t,z} + \sum_l \varphi_{t,l}\beta_{l,z} = D_{t,z} \quad \forall \quad t \in T, z = Z \tag{16}$$

$$g_{r,t,z} \leq x_{r,z}A_{t,r,z} \quad \forall \quad r \in R, t \in T, z \in Z \tag{17}$$

$$x_r \leq \bar{x} \tag{18}$$

$$e_{r,t=1,z} = e_{r,T,z} - \frac{1}{\nu^{down}}\zeta_{r,T,z}^{dch} + \nu^{up}\zeta_{r,T,z}^{ch} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{19}$$

$$e_{r,t,z} = e_{r,t-1,z} - \frac{1}{\nu^{down}}\zeta_{r,t-1,z}^{dch} + \nu^{up}\zeta_{r,t-1,z}^{ch} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{20}$$

$$e_{r,t,z} \leq \frac{1}{\eta}x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{21}$$

$$\zeta_{r,t,z}^{ch} \leq \frac{1}{\nu^{up}}x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{22}$$

$$\zeta_{r,t,z}^{ch} \leq \frac{1}{\eta}x_{r,z} - e_{r,t,z} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{23}$$

$$\zeta_{r,t,z}^{dch} \leq \nu^{down}x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{24}$$

$$\zeta_{r,t,z}^{dch} \leq e_{r,t,z} \quad \forall \quad r \in R \cap I, t \in T, z \in Z \tag{25}$$

$$\frac{1}{\nu^{down}}\zeta_{r,t,z}^{dch} + \nu^{up}\zeta_{r,t,z}^{ch} \leq x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{26}$$

$$e_{r,t,z} \geq 0, \quad \forall \quad r \in R \cap I, t \in T, z \in Z-1 \tag{27}$$

$$\sum_z g_{r,t,z}\xi_r \leq C \quad \forall \quad t \in T, z \in Z \tag{28}$$

$$-\psi_l \leq \varphi_{t,l} \leq \psi_l \quad \forall \quad l \in L, t \in T \tag{29}$$

4.1.2 Risk Neutral stochastic model

$$\min_{x_{r,z},g_{r,t,s,z},d^{nse}_{t,s,z}} \sum_z \sum_r C^{inv}_r x_{r,z} + \sum_z \sum_r C^{trans}_{r,z} x_{r,z} + \sum_z \sum_t \sum_s \sum_r P_s C^{var}_s g_{r,t,s,z} + \sum_z \sum_s \sum_t P_s C^{cap} d^{nse}_{t,s,z} + \sum_z \sum_t \sum_s \sum_r P_s \chi_r \xi_r g_{r,t,s,z} + \sum_z \sum_s \sum_r P_s C^{tax}_{r,s} x_{r,s} \omega_{r,z} \tag{30}$$

s.t.

$$x_{r,z} \geq 0 \quad \forall \quad x \in \mathbb{R}, r \in R, z \in Z \tag{31}$$

$$g_{r,t,s,z} \geq 0 \quad \forall \quad g \in \mathbb{R}, r \in R, t \in T, s \in S, z \in Z \tag{32}$$

$$d^{nse}_{t,s,z} \geq 0 \quad \forall \quad d^{nse} \in \mathbb{R}, t \in T, s \in S, z \in Z \tag{33}$$

$$\lambda_{t,s,z} \geq 0 \quad \forall \quad \lambda \in \mathbb{R}, t \in T, s \in S, z \in Z \tag{34}$$

$$\sum_r g_{r,t,s} + d^{nse}_{t,s} + \sum_i (\zeta^{dch}_{l,t,s} - \zeta^{ch}_{l,t,s}) + \sum_l \varphi_{t,l}\beta_{l,z} = D_{t,s,z} \quad \forall \quad t \in T, s \in S, z \in Z-1 \tag{35}$$

$$\sum_r g_{r,t,z} + \sum_l \varphi_{t,l}\beta_{l,z} = D_{t,z} \quad \forall \quad t \in T, s \in S, z = Z \tag{36}$$

$$g_{r,t,s,z} \leq x_{r,z} A_{t,r,z} \quad \forall \quad r \in R, t \in T, s \in S, z \in Z \tag{37}$$

$$x_r \leq \bar{x} \tag{38}$$

$$e_{r,t=1,s,z} = e_{r,T,s,z} - \frac{1}{\nu^{down}} \zeta^{dch}_{r,T,s,z} + \nu^{up} \zeta^{ch}_{r,T,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{39}$$

$$e_{r,t,s,z} = e_{r,t-1,s,z} - \frac{1}{\nu^{down}} \zeta^{dch_{r,t-1,s,z}} + \nu^{up} \zeta^{ch}_{r,t-1,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{40}$$

$$e_{r,t,s,z} \leq \frac{1}{\eta} x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{41}$$

$$\zeta^{ch}_{r,t,s,z} \leq \frac{1}{\nu^{up}} x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{42}$$

$$\zeta^{ch}_{r,t,s,z} \leq \frac{1}{\eta} x_{r,z} - e_{r,t,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{43}$$

$$\zeta^{dch}_{r,t,s,z} \leq \nu^{down} x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{44}$$

$$\zeta^{dch}_{r,t,s,z} \leq e_{r,t,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{45}$$

$$\frac{1}{\nu^{down}} \zeta^{dch}_{r,t,s,z} + \nu^{up} \zeta^{ch}_{r,t,s,z} \leq x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{46}$$

$$e_{r,t,s,z} \geq 0, \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{47}$$

$$\sum_z g_{r,t,s,z} \xi_r \leq C \quad \forall \quad t \in T, s \in S, z \in Z \tag{48}$$

$$-\psi_l \leq \varphi_{t,l} \leq \psi_l \quad \forall \quad l \in L, t \in T \tag{49}$$

4.1.3 Risk Averse stochastic model

$$
\begin{aligned}
\min_{x_{r,z},g_{r,t,s,z},d^{nse}_{t,s,z},VaR,u_s} \quad & \sum_z \sum_r C^{inv}_r x_{r,z} + \sum_z \sum_r C^{trans}_{r,z} x_{r,z} \\
& + (1-\gamma)[\sum_z \sum_t \sum_s \sum_r P_s C^{var}_r g_{r,t,s,z} + \sum_z \sum_t \sum_s P_s C^{cap} d^{nse}_{t,s,z} \\
& + \sum_z \sum_t \sum_s \sum_r P_s \chi_r \xi_r g_{r,t,s,z} + \sum_z \sum_s \sum_r P_s C^{tax}_{r,s} x_{r,s} \omega_{r,z}] \\
& + \gamma[VaR + \frac{1}{\alpha} \sum_s P_s u_s]
\end{aligned} \tag{50}
$$

s.t.

$$x_{r,z} \geq 0 \quad \forall \quad x \in \mathbb{R}, r \in R, z \in Z \tag{51}$$

$$g_{r,t,s,z} \geq 0 \quad \forall \quad g \in \mathbb{R}, r \in R, t \in T, s \in S, z \in Z \tag{52}$$

$$d^{nse}_{t,s,z} \geq 0 \quad \forall \quad d^{nse} \in \mathbb{R}, t \in T, s \in S, z \in Z \tag{53}$$

$$VaR \quad \forall \quad VaR \in \mathbb{R} \tag{54}$$

$$
\begin{aligned}
& u_s \geq \sum_r \sum_t \sum_z (g_{r,t,s,z} C^{var}_r + C^{tax}_{r,s} x_{r,s} \omega_{r,z} + \chi_r \xi_r g_{r,t,s,z}) + \sum_t \sum_z^{Z-1} C^{cap} d^{nse}_{t,s,z} \\
& - VaR \quad \forall \quad s \in S, z \in Z
\end{aligned} \tag{55}
$$

$$
\begin{aligned}
& \sum_r g_{r,t,s,z} + d^{nse}_{t,s,z} + \sum_i (\zeta^{dch}_{r,t,s,z} - \zeta^{ch}_{r,t,s,z}) + \sum_l \varphi_{t,l} \beta_{l,z} = D_{t,s,z} \\
& \quad \forall \quad l \in L, r \in R, t \in T, s \in S, z \in Z-1
\end{aligned} \tag{56}
$$

$$\sum_r g_{r,t,z} + \sum_l \varphi_{t,l} \beta_{l,z} = D_{t,z} \quad \forall \quad t \in T, s \in S, z = Z \tag{57}$$

$$g_{r,t,s,z} \leq x_{r,z} A_{t,r,z} \quad \forall \quad r \in R, t \in T, s \in S, z \in Z \tag{58}$$

$$x_r \leq \bar{x} \tag{59}$$

$$e_{r,t=1,s,z} = e_{r,T,s,z} - \frac{1}{\nu^{down}} \zeta^{dch}_{r,T,s,z} + \nu^{up} \zeta^{ch}_{r,T,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{60}$$

$$e_{r,t,s,z} = e_{r,t-1,s,z} - \frac{1}{\nu^{down}} \zeta^{dch}_{r,t-1,s,z} + \nu^{up} \zeta^{ch}_{r,t-1,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{61}$$

$$e_{r,t,s,z} \leq \frac{1}{\eta} x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{62}$$

$$\zeta^{ch}_{r,t,s,z} \leq \frac{1}{\nu^{up}} x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{63}$$

$$\zeta^{ch}_{r,t,s,z} \leq \frac{1}{\eta} x_{r,z} - e_{r,t,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{64}$$

$$\zeta^{dch}_{r,t,s,z} \leq \nu^{down} x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{65}$$

$$\zeta^{dch}_{r,t,s,z} \leq e_{r,t,s,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{66}$$

$$\frac{1}{\nu^{down}} \zeta^{dch}_{r,t,s,z} + \nu^{up} \zeta^{ch}_{r,t,s,z} \leq x_{r,z} \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{67}$$

$$e_{r,t,s,z} \geq 0, \quad \forall \quad r \in R \cap I, t \in T, s \in S, z \in Z-1 \tag{68}$$

$$g_{r,t,s,z} \xi_r \leq C \quad \forall \quad t \in T, s \in S \tag{69}$$

$$-\psi_l \leq \varphi_{t,l} \leq \psi_l \quad \forall \quad l \in L, t \in T \tag{70}$$

4.2 Model Description

The base for the model outlined in subsection 4.1 and shown in Figure 7 was originally developed by Emil Dimanchev and presented at [14]. In addition to the expansion of the model, the input data has been significantly upgraded. This is described in detail in subsubsection 4.5.1, subsubsection 4.5.2, and subsubsection 4.5.3. The CO_2 Tax policy option has also been introduced to the model, described in subsubsection 4.5.5.

Fixed offshore wind and floating offshore wind have been added as possible generation technologies for the GEP models. Further, it has also been extended to include three price zones with transmission lines between them instead of including one country as in the original model. Additionally, utility-scale storage has been updated to include stochasticity. The countries represented are the countries sounding the North Sea, and they are divided into the zones; Price Zone 1: The Continent (Z1), Price Zone 2: United Kingdom (Z2), and Price Zone 3: North Sea Offshore Grid (Z3). The Price Zone 1: The Continent (Z1) consists of Germany, Belgium, and Netherlands, Price Zone 2: United Kingdom (Z2) consists of the United Kingdom, and Z3 is an offshore grid in the North Sea, within the territorial area of Norway and Denmark. This offshore grid has no demand and only facilitates Z1 with renewable energy from fixed and floating offshore wind if the model finds it beneficial to invest. The rationale for this division of zones and how the transmission between the zones is determined are thoroughly described in subsubsection 4.5.4. In addition, the u expression constraint 55 has been modified to consider the CO_2 Tax option and the ground rent tax option, which is outlined in subsubsection 4.5.5 and subsubsection 4.5.9.

The assumption of perfect competition is made to reduce the complexity of the models. Another simplification is that hydropower is not a part of the technology options for the GEP models, even though it plays a vital part in the existing technology mix in today's power system. This is done to avoid the complexity of hydropower. Thus, utility-scale batteries represent the only storage option in the model.

All models (11 - 29, 30 - 49 and 50 - 70) have the perspective of a central planner or a well-functioned market with perfect competition as outlined in subsection 3.2, and all symbols used in the models are explained in the Nomenclature. The models are programmed using Julia, and the optimization code is displayed in Appendix C.

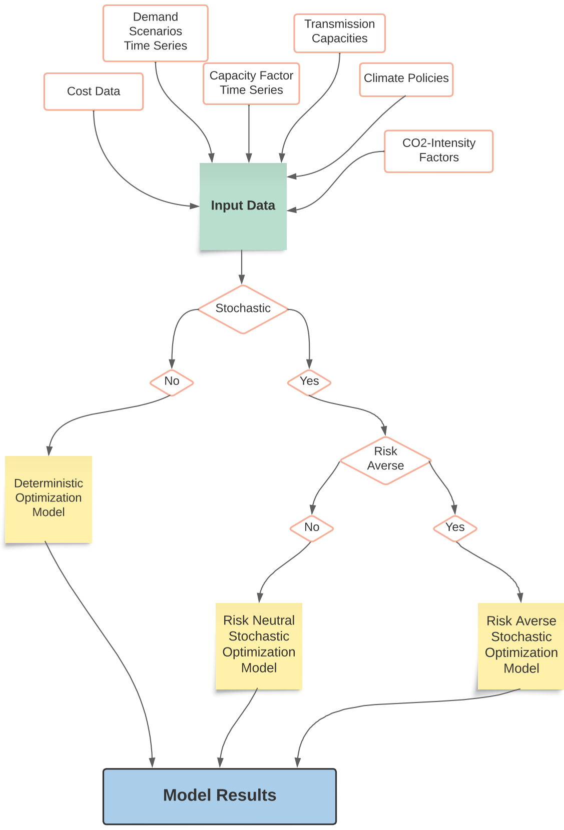


Figure 7: Simple representation of the models

4.3 Model Objective

The Deterministic optimization model is outlined in Equation 11 -29. The deterministic model is a GEP model that minimizes the Total System Costs (TSC) and simultaneously meets the electricity demand. To minimize the TSC, investment cost (C_r^{inv}), variable/operating cost (C_r^{var}), and the cost of NSE, represented in the three first terms of Equation 11 respectively, is considered for all zones $z \in Z$ and all hours $t \in T$. The cost of NSE is set to be equal to the system price cap at $C^{cap} = 3000$ [€/MWh], which corresponds to European Energy Exchange (EEX) technical price limit for European power [21]. The second term in the objective function represents a transmission capacity cost that is only applied to Z3. This is implemented to better represent the extra cost of building the offshore grid, and it is outlined in detail in subsubsection 4.5.1. The second to last term in Equation 11 is related to the possibility of introducing a carbon emission tax and is thoroughly described in subsubsection 4.5.5. Finally, the last term describes the ground rent tax, which can be used to evaluate the response to new profit-taxations on generation technologies, as further outlined in subsubsection 4.5.9 and subsection 5.6.

Equation 30 - 49 represents the Risk Neutral Stochastic optimization model. Similar to model 11 the risk-neutral stochastic model strives to minimize the TSC and meet electricity demand. However, as the model is extended to a stochastic optimization model, it incorporates all scenarios $s \in S$ for each zone $z \in Z$. Each scenario is a demand profile, described in subsection 4.5. The risk-neutral stochastic optimization model minimizes the TSC summing over all $s \in S$ for each $z \in Z$ and considering their respective weights (P_s). The TSC is the expected cost for the model. The expected cost consists of the first-stage investment cost and the second-stage operation cost. The investment costs consist of two costs, the investment for generation capacity [€/MW] and a transmission capacity cost [€/MW] that only applies to the capacity built in Z3. The operation costs are the variable costs for each resource. The costs are explained in detail in subsubsection 4.5.1.

The Risk Averse SO model represented in Equation 50 - 70 is based on the same stochastic model as the risk-neutral SO model, striving to minimize TSC summing over all $s \in S$ and $z \in Z$. Additionally, the objective function 50 introduces the effect of risk aversion. This is done by introducing VaR, γ, u_s and α in the SO model to represent CVaR, based on the method introduced by [84]. As thoroughly described in subsection 2.8 VaR is a parameter to quantify the extent of possible financial losses for an investment, which in this case is related to the investment in new power generation. γ represents the degree of risk aversion ranging from 0 (risk-neutral) to 1 (extreme risk aversion). u_s is the loss relative to VaR, which represents the net present value of the total cost of the generation expansion that exceeds the VaR threshold with a certain level of confidence. α is the CVaR threshold, also called tail definition, which sets the cut-off point for the VaR analysis. These parameters and auxiliary variables are used to represent CVaR, outlined in Equation 71 and described in subsection 2.8. CVaR measures the expected value of the worst-case scenarios, where α determines the extent of cases included. Put differently, for $\gamma = 0$ (Risk Neutral); the model strives to minimize all the costs presented in the model. For $\gamma = 1$ (extreme risk aversion), the objective is to minimize CVaR, shown in Equation 71, which is the expectation of the cost of the most costly $\alpha\%$ of the scenarios. Thus, the stochastic risk-averse optimization model aims to generate a more robust capacity mix less vulnerable to the risks related to the tail determined by α.

Additionally, for the model in this thesis, the risk-averse central planner trades the risk between the different technologies. Hence, the result of the model can also be interpreted as representing the equilibrium of a perfectly competitive market with different technologies as the market participants.

$$CVaR = [VaR + \frac{1}{\alpha}\sum_{s} P_s u_s] \tag{71}$$

4.4 Model Constraints

The constraints in the model represent the technical, economic, and environmental limitations that must be satisfied for all scenarios. All three models have similar constraints to represent these engineering features for the GEP models. However, the SO models (30 - 49) and model (50 - 70) consider all $s \in S$, and model (50 - 70) has some additional constraints related to the limitation of the CVaR. Consequently, the constraints related to the risk-averse stochastic model will be explained in detail below. However, it is important to bear in mind that most of these constraints also apply to model (11 - 29) and model (30 - 49).

The constraints represented in equation 51, 52, 53 and 68 are non-negative constraints, making sure the respective decision variables are equal or greater than zero.

Constraint 54 set VaR to be a real number. Following, constraint 55 sets the limit for loss relative to VaR. This constraint ensures that the expected loss is kept below a certain fraction of the VaR level, determined by the variable costs, the cost of NSE and cost related to the CO_2 Tax and the ground rent tax if these policy options are applied. Determining a limit of loss relative to VaR, the central planner is able to balance risk sufficiently. These constraints are only valid for the risk-averse SO model (50 - 70).

The power balance constraint is represented in Equation 56. The power balance constraint ensures that the demand is met in the model and is, therefore, essential to maintain a reliable and stable power system. However, to represent the reliability and stability realistic system 100% accurately, additional constraints would have been needed, but this is out of the scope of this thesis. The power balance constraint is an equality constraint operating within the principles of complementary slackness. Thus, the dual value will represent the marginal value of relaxing the constraint by one unit, which for the power balance constraint would represent the value of one additional unit of electricity for a given time step $t \in T$ for a price zone $z \in Z$. In other words, this will represent the price of electricity for a given time $t \in T$ in a price zone $z \in Z$ for a normal GEP model. However, the stochastic models weigh the dual values. Consequently, to find the actual power price, the dual value of the power balance needs to be unweighted. How this is done is outlined in detail in subsubsection 5.3.5 and subsubsection 5.4.5. Constraint 57 is added as an additional power balance constraint only for Z3 to ensure that all power produced in this zone is equal to the power transferred out of the zone.

In Equation 58 constrain the generation for each resource to be less or equal to the capacity multiplied with the capacity factor for each resource $r \in R$, time step $t \in T$ in each price zone $z \in Z$. Following, constraint 59 represents the capacity limits outlined in subsubsection 4.5.6. This is introduced to limit the model from building an unrealistic amount of capacities limited in the real world. For instance, Germany has a set phase-out policy for nuclear and countries as Norway has no history of nuclear power generation. The value for these constraints is described in subsubsection 4.5.6.

The following constraints are related to building and managing storage. Constraint 60 aligns the state of charge for the first and last time step for $t \in T$, and constraint 61 balance the state of charge for the remaining time steps $t \in T$. Both constraints consider the single-trip efficiency of the batteries. Following is the energy limit constraint 62, ensuring that the energy limit is not exceeded by multiplying the storage capacity with the power-to-energy ratio. The maximum charging limit is determined in constraint 63, and the free capacity possible to charge up is set in constraint 64. Constraint 65 and 66 represent the same only for discharging, determining the minimum discharging limit and energy available for discharge, respectively. To control the balance between charging and discharging, constraint 67 is utilized, determining the sum of charging and discharging to be within the capacity limit of the battery.

To enable the CO_2 Cap policy option, constraint 68 is utilized. It ensures that the carbon emission cap is met by constraining the generation multiplied with the CO_2 intensity factor to be less than the set CO_2 Cap.

Constraint 69 ensures that the capacity of all the transmission lines $l \in L$ does not exceed their set transmission capacity for each time step $t \in T$. It also ensures that power only flows in one direction on each line $l \in L$ for each time step $t \in T$.

4.5 Input Data

4.5.1 Resource Cost Data

It is important to have trustworthy cost estimations for the different resource technologies to enable the GEP models to estimate a sufficient technology mix. The investment costs, fixed operation and maintenance costs and variable non-fuel costs, shown in Table 1, are all from the European Commissions technology assumptions for the *EU Reference Scenario 2020* report [29], except for Utility-scale battery storage where the *2022 Annual Technology Baseline* from NREL is utilized [68]. The fuel costs are based on data from [53], and the technical lifetime is based on data from the technology assumptions in [29].

As the model has the view of a central planner and perfect competition is assumed, the model will maximize SW. Consequently, it is reasonable to use the same discount rate as The Norwegian Water Resources and Energy Directorate (NVE) for socio-economic projects, which is set to 4% [86].

Capital recovery refers to how to recover the funds originally invested at the start of an investment [105]. Consequently, adding the Capital Recovery Factor (CRF) to the costs is important to ensure that the investments are sustainable. NVE uses technical lifetime in their analysis for socio-economic projects [86]. Thus, the same approach is utilized for this model. The CRF is calculated using Equation 72, where n is the technical lifetime and i is the discount rate. This results in the CRF shown in Table 1.

$$CRF = \frac{i(1+i)n}{(1+i)n-1} \tag{72}$$

Technology	Investment Cost [EUR/kW]	Fixed Operation and Maintenance Cost [EUR/kW]	Variable non-Fuel Cost [EUR/MWh]	Fuel Cost [EUR/MWh]	Technical Lifetime [Years]	Discount Rate	Critical Recovery Factor (CRF)
Nuclear	4500	108	7.6	3.6	60	0.04	0.044201845
Coal	1450	25.6	2.4	11	40	0.04	0.050523489
Gas	533	20	2.31	22	30	0.04	0.057830099
Onshore Wind	950	12	0.15	0	30	0.04	0.057830099
Offshore wind Bottom Fixed	1513	26	0.39	0	30	0.04	0.057830099
Offshore Wind Floating	2282	40	0.39	0	30	0.04	0.057830099
Solar PV	371	9.5	0	0	30	0.04	0.057830099
Utility Scale Battery Storage	744.633	19.02	0	0	30	0.04	0.057830099

Table 1: Technical data for all resources

Furthermore, the investment, fixed operation, and maintenance costs are converted from kW to MW. The investment, fixed operation and maintenance, and variable non-fuel costs are multiplied by the CRF. The investment and fixed operation and maintenance costs are added together to represent the Investment costs and the variable non-fuel and fuel costs are added together to represent the variable/operating costs, shown in Table 2.

Technology	Investment Costs [EUR/MW/Year]	Variable Costs [EUR/MWh]
Nuclear	203682.102	11.20
Coal	74552.461	13.40
Gas	31980.045	24.31
Onshore wind	55632.555	0.15
Offshore Wind Bottom Fixed	89000.523	0.39
Offshore Wind Floating	134281.490	0.39
Solar PV	22004.353	0.00
Utility Scale Battery Storage	44162.129	0.00

Table 2: Investment Costs and Variable Costs for all resources

The cost data from Table 2 is assumed equal for all price zones $z \in Z$.

However, to better represent the costs related to building an offshore grid in the North Sea, an additional transmission investment cost has been added to the investment costs for fixed and floating offshore wind in Z3. To calculate a fair estimation of this additional cost, the length- and power-dependent cost for building a branch in the NorthSeaGrid outlined in [103] is utilized. [103] sets a cost of 0.35 [M€/GW km]. Further, it is reasonable to assume that an offshore hub/electrical island will exist in 2040, and plans of electrical islands at the DoggerBank, among other areas in the North Sea, are already outlined [24]. By analyzing the distance from the north part of the Dogger Bank field, stretching through the UK, German, Dutch and Danish part of the North Sea [15], to some of the possible offshore wind farms introduced by NVE in [66] in the southern part of the Norwegian part of the North Sea, it is found that an approximate distance of 100km is a sufficient assumption. Locating the ideal site for an electricity island is outside the scope of this thesis. However, a sensitivity analysis is carried out in Appendix subsection B to see how this distance affects the results. It shows that the length of the cable can affect the capacity mix built by the model. However, it is out of scope to forecast the exact length of this cable.

Following, using these assumptions, the additional transmission cost for fixed and floating offshore wind in Z3 are shown in Table 3. This transmission investment cost represents a 39% and a 26% increase in the total investment cost for fixed and floating offshore wind, respectively, in Z3.

	Investment Cost Transmission [€/MW] Zone 3
Offshore Wind Bottom Fixed	35000
Offshore Wind Floating	35000

Table 3: Transmission investment cost in Z3.

4.5.2 Electricity Demand

The electricity demand is represented as annual electricity demand with hourly time steps. In other words, 8760-time steps of electricity demand. The *TYNDP 2022 Scenarios Report - Version April 2022* is used to represent the electricity demand for the base scenario [27], which is the electricity demand for the year 2040. The model has three price zones, shown below. The reasoning for division is thoroughly described in subsubsection 4.5.4.

- Continental (Zone 1): Germany, Netherlands, and Belgium
- United Kingdom (Zone 2): United Kingdom
- North Sea Offshore Grid (Zone 3): Norway and Denmark

Consequently, the electricity demand for the base scenario for Z1 is the combined electricity demand of Germany, Netherlands, and Belgium for 2040. The base scenario electricity demand 2040 for Z2 is the combined demand for the United Kingdom for 2040. For Z3, the demand is set to be zero for all hours as this an offshore grid with no demand. The demand time series for Z1 and Z2 are based on the Global Ambition scenario for the year 2040. The Global Ambition scenario is one of the COP 21 scenarios. It represents an electricity demand meeting the goal of at least a 55% reduction in emissions by 2030 and climate neutrality by 2050. It presupposes a global economy with centralized low-carbon and RES options, focusing on large-scale technologies such as offshore wind and large storage [25].

Several climatic years are considered when building the electricity demand time series. [25] performed a statistical analysis on the last 35 years to find the most repressive combination of years. This analysis ended up with a weighted average of the climate years 1995 (23%), 2008 (37%), and 2009 (40%). These are also the weights used in this thesis to establish one demand profile from the weighted average of these climatic years. This resulted in hourly demand profiles for each zone with a total electricity demand as shown in Table 4.

	Continent (Zone 1)	United Kingdom (Zone 2)	The North Sea Grid (Zone 3)
Electricity Demand Base Scenario [TWh]	1077.17	551.65	0.0

Table 4: Annual electricity demand for the base scenario for all zones [27]

The electricity demand represents the uncertainty in the model. The demand scenarios outlined in [38] establish a sufficient set of demand scenarios. This results in three additional demand scenarios using the base scenario as a reference. The first additional scenario is a low-demand scenario with a 15% reduction in demand compared to the base-demand scenario. This scenario weights a low increase in demand from today, based on more political governance, more energy efficiency, and low growth in power-intensive industries [38]. The high-demand and very high-demand scenarios are based on the assumption of growth within green power-intensive industries, assuming that technologies like floating offshore wind power will become affordable and competitive [38]. The high-demand scenario represents a 15% increase from the base scenario, and the very high demand scenario represents a 30% increase from the base scenario.

4.5.3 Capacity Factor Time Series

The assumptions for hourly capacity factors for onshore wind, offshore wind, and PV are obtained with the GIS model developed by [53]. Table 5 shows the energy density and available land for each VRES used in [53]. The available land refers to a portion of suitable land, defined as the total area excluding populated regions, natural parks, lakes, mountains, and other areas. The technologies are categorized into five groups based on resource quality. This is done to improve the accuracy of the capacity factors for wind and solar. The capacity factors for wind speed are based on the power curve of a typical wind-power farm equipped with Vestas 112 3.075 MW turbines. The capacity factor profiles for solar irradiation are calculated by assuming fixed-latitude-tilted PV technology. The Global Wind Atlas [36], and the ECMWF ERA5 database [10] are both used to make the capacity factor time series, and all VRES data are based on the year 2018.

	Onshore Wind	**Offshore Wind**	**Solar PV**
Density [W/M2]	5	8	45
Available land [%]	10	33	6

Table 5: Energy density and available land for all VRESs.
[53]

In [53], several zones are used, which have different capacity factor time series and different installed capacity potential. To make one general capacity factor time series for each VRES technology in each price zone, the different capacity factor time series are weighted by the installed capacity potential. Consequently, a general capacity factor time series are achieved for each region. Further, the same procedure is utilized to make the data fit the price zones for this model. The time series for Germany, Belgium, and the Netherlands are weighted and combined for Zone 1, and the UK data is used for Zone 2. The capacity factor time series for offshore wind in Norway and Denmark are weighted and combined to represent the capacity factor time series for offshore wind in the North Sea offshore grid, Zone 3.

Consequently, one general capacity factor time series are achieved for each VRES for each price zone. The average annual capacity factor for each VRES in each price zone is outlined in Table 6.

	Onshore Wind	**Offshore Wind**	**Solar PV**
Average Capacity Factor [%] Zone 1	22.84 %	50.95 %	16.68 %
Average Capacity Factor [%] Zone 2	41.23 %	52.15 %	13.97 %
Average Capacity Factor [%] Zone 3	-	50.07 %	-

Table 6: Annual average capacity factor for all VRESs.

The availability of the other generation technology options is shown in Table 7. The capacity factor for nuclear is set to 100%, which is a small simplification. According to [101], the capacity factor for nuclear in the US in 2022 was 92.6%. Thus, using a capacity factor of 100% is an acceptable assumption. For coal and gas power plants, downtime due to rehabilitation, etc., is not considered. These power generation capacities are considered to be flexible in the model. Thus it is an acceptable simplification to set the capacity factor to 100% to enable the model to determine when the coal and gas power plants need to generate power. Storage is set to 100% because if storage capacity is built, it is up to the model when to use it.

	Nuclear	Coal	Gas	Storage
Average Annual Capacity Factor [%]	100%	100%	100%	100%

Table 7: The capacity factor for thermal generation technologies and for storage.

4.5.4 Transmission Capacities and Price Zones

The transmission capacity between the different price zones is represented as a single transmission line. The transmission capacity for the line between Z1 and Z2 is the sum of all already exciting transmission capacities between the countries represented in one zone i and a country in another zone j. Maximum transmission capacity for each line (ψ_l) from a zone i to another zone j can be calculated using data from [27] and Equation 73. The resulting transmission capacities are displayed in Table 8.

$$\psi_l = \sum_{countries} \psi_{li,lj} \tag{73}$$

The reason why the capacity between Z1 and Z3 is set to ∞ in Table 8, is because the amount of transmission capacity is an investment decision represented as an additional transmission investment cost only present the offshore technologies in Z3. This transmission investment cost is carefully described in subsubsection 4.5.1. This is done to avoid the transmission capacity constraining the model from expanding the capacity in the North Sea (Z3). All transmission losses are neglected. This is a common assumption for GEP models made in several acknowledged studies like [91].

From Zone	To Zone	Transmission Capacity [MW]
United Kingdom (Z2)	Continent (Z1)	4800
North Sea Grid (Z3)	Continent (Z1)	∞
North Sea Grid (Z3)	United Kingdom (Z2)	0

Table 8: Transmission capacities.
[25]

This model aims to investigate the power market in and between the countries surrounding the Northern Sea. The price zones, shown in Figure 8, are determined based on which countries have the best transnational transmission connections and part of the same European markets under the common power market Euronext [3].

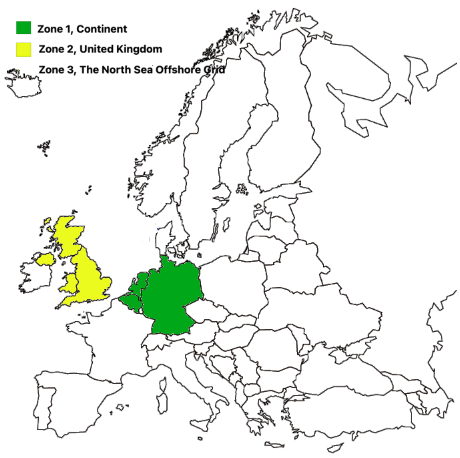


Figure 8: The price zones represented in the model
[61]

4.5.5 Policy Options

The model has two policy options; a CO_2 Cap Policy and a CO_2 Tax policy. The CO_2 Cap policy is a quantity-based climate policy that sets a carbon emission limit for the whole system. The carbon emission cap is determined by taking a 90% reduction of the combined carbon emissions related to the energy supply in the countries represented in Z1 and Z2 in the year 2005, shown in Table 9. The carbon emissions for 2005 for the countries in Z1 are all from [20], and the 2005 emissions for Z2 are from [2]. All the data in Table 9 represent the carbon emissions from the energy supply industry. Ideally, only the carbon emissions related to electricity production should be used. However, this is a sufficient value to use because the value for only electricity production is not specified, and for this thesis, it is not required for the cap to be 100% accurate. It serves the purpose of this thesis of showing the effect of a CO_2 Cap roughly indicative of the level of ambition of EU climate policy.

The data from [20] states that it was a 37% reduction in carbon emission related to the energy supply industry from 2005 to 2021. Additionally, the EU Emission Trading System (EU ETS) cap was updated in the spring of 2023 and is now aiming for a 62% reduction in emissions with respect to the 2005 levels [1] to be in line with the EU *Fit for 55* goals. To achieve this reduction of 62% in carbon emissions in the energy supply industry by 2030, an annual reduction of $\frac{62\%-37\%}{9years} = 2.78\%/year$ is required each from the year 2021. Assuming the ambition to maintain this reduction in emissions levels gives a total reduction of approximately 90% from the 2005 emission levels is required, as shown in Equation 74. This results in a carbon emission cap equal to 72.78 [MtCO2], as elaborated in Table 9.

$$62\% + 2.78\%/year \cdot 10years = 89.8\% \approx 90\% \tag{74}$$

The CO_2 Cap policy may generate a CO_2 price when the Cap is binding, for instance, in a high-demand scenario. Consequently, a non-zero dual value will be present as the shadow price on the system, i.e. the carbon price. This is based on the principles of complementary slackness. The carbon price is weighted the same way as power prices as outlined in Figure 19 and must be unweighted to represent the actual value, shown in subsubsection 5.4.8.

Country	**CO2 Emissions [MtCO2] Energy Supply**	**90% reduction [MtCO2]**
Germany	398.89	39.89
Belgium	29.81	2.98
Netherlands	70.35	7.04
United Kingdom	228.70	22.87
Sum	727.76	72.78

Table 9: Calculation of the carbon emission cap.
[20] [2]

The CO_2 Tax policy is a price-based policy setting a fixed price per ton of CO_2 equivalent emissions. The CO_2 Tax is set to 120 [$€/tCO_2$] for the model in the year 2040 because this is the base scenario for Statnett's Long-term Market Analysis report [38]. This report [38] uses the predictions made by the European Commission for the EU ETS in combination with the EU's Fit for 55-goals [11] to projects this CO_2 Tax value. [38] also have low-price and high-price scenarios in their analysis. However, as the CO_2 Tax is not a part of the uncertainty in the model, only the base scenario will be considered.

4.5.6 Resource Capacity Limits

To ensure a realistic result, it is necessary to constrain nuclear capacity in case of CO_2 Cap and Tax policy. The construction time for a nuclear power plant can be up to 25 years, affected by the plant size, location, and regulatory framework [100]. Additionally, the current political climate in certain countries represented in the model, such as Germany, where new power plants face opposition [99], necessitates the need to constrain the nuclear capacity in the model to ensure a realistic outcome.

The nuclear constraint for each price zone is based on the present nuclear capacity (before April 15, 2023) displayed in Table 10. The figures presented in the model have been rounded for ease of use. For Z1, the nuclear capacity is derived from the combined capacity of Germany (4000 MW) [64], Belgium (4000 MW) [63], and the Netherlands (500 MW) [65]. In Z3, The United Kingdom (6000 MW) [102] is used to represent the capacity for Z3. As a consequence of Z2 being an offshore grid, the nuclear capacity is zero for this zone. These values restrict the model from building unrealistic amounts of nuclear capacity, which is further elaborated and discussed in section 5.

	Zone 1	**Zone 2**	**Zone 3**
Existing Nuclear Capacity	8500 MW	6000 MW	-

Table 10: Existing nuclear capacity rounded.

As elaborated in subsubsection 4.5.3, the capacity factors for onshore wind, offshore wind, and PV are obtained with the GIS model developed by [53]. In [53], the available land for each VRES, and consequently the maximal capacity for each VRES, are accounted for. The model [53] only considers bottom fixed offshore wind technologies and not floating offshore wind. It also operates with a maximum depth of 40 meters for the bottom fixed offshore wind, although new fixed offshore wind already has been installed at 59 meters [51]. Even though this estimation may seem a bit conservative, the available maximum capacity, shown in Table 11, seems to be reasonable according to calculations described in Appendix subsection A.

	Zone 1	**Zone 2**	**Zone 3**
Onshore Wind [GW]	108.05	80.17	-
Offshore Wind Bottom Fixed[GW]	43.91	88.53	85.78
Offshore Wind Floating[GW]	0	∞	∞
Solar[GW]	423.70	371.75	-

Table 11: Maximum installed capacity for the different VRES in the different zones [53]

The capacity for floating offshore wind in Z1 is set to zero because the North Sea area inherited by Germany, Belgium, and the Netherlands is heavily dominated by shallow waters ($\leq$ 60 meters of depth) [16], as shown in Figure 9. The floating offshore wind capacity is set to ∞ for Z2 and Z3 because both zones possess large areas where it is possible to build floating offshore wind, clearly depicted in Figure 9, and the capacity limitation is something that has to be politically determined or simply determined by the demand versus costs. PV and onshore wind capacity are not relevant for Z3, because this is an offshore grid.

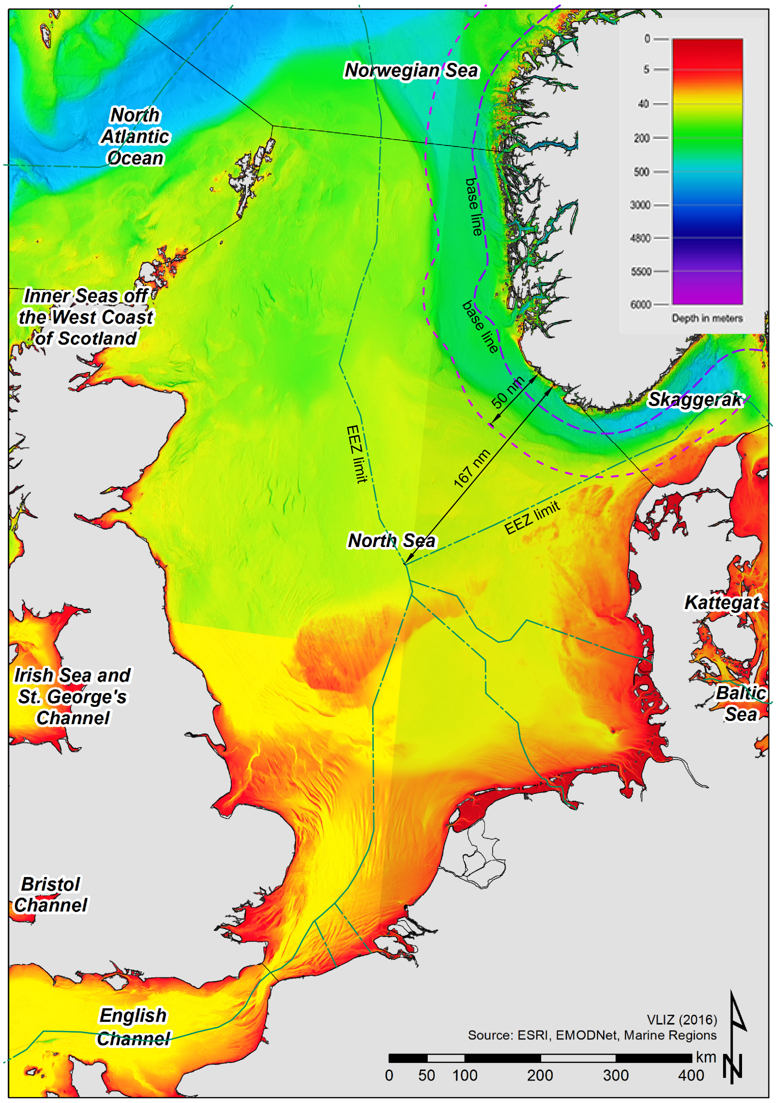


Figure 9: The depth of the sea bed in the North Sea
[16]

4.5.7 Calculation of Carbon Emissions

The carbon emissions are determined by multiplying the generation by the CO_2-intensity factor for each resource, respectively. Each resource's CO_2-intensity factors are displayed in Table 12. The numbers representing coal and gas are based on numbers from [19]. The CO_2-intensity factor for gas-turbine power plants is $0.486[tCO2/MWh]$ and it is $0.352[tCO2/MWh]$ for combined cycle gas-turbines [19]. Thus, an average of $\frac{0.486+0.352}{2} = 0.419[tCO2/MWh]$ is used.

	Nuclear	Coal	Gas	Onshore Wind	Offshore wind Bottom Fixed	Offshore Wind Floating	Solar	Storage
CO2 Intensity Factor	0	0.986	0.419	0	0	0	0	0

Table 12: CO_2-Intensity Factors

This model does not consider carbon emissions related to building the power plants or producing the components.

4.5.8 Calculation of Revenues

The revenues can be calculated using different methods. It is to use the dual value of the power balance to calculate the revenues, as described in Equation 75. The power balance constraint ensures the balance between demand, generation, power flows, and NSE. This constraint also follows the principles of complementary slackness. Consequently, the dual value of the power balance will represent the cost of adding one more MWh of demand. In other words, the power price. The power price multiplied with the generation for each time step $t \in T$, in each demand scenario $s \in S$, for each resource $r \in R$ gives the revenues for each resource.

$$Revenues_{r,s,z} = \sum_t \lambda_{t,s,z} g_{r,t,s,z} \tag{75}$$

Another way to calculate the revenues is to use the dual value of the capacity limit constraint (58) multiplied by the generation to calculate the revenues plus the variable cost, shown in Equation 76. The variable cost is added because the variable cost for each resource is subtracted from $\mu_{r,t,s,z}$. Consequently, to represent revenues equally as in Equation 75, the variable costs have to be added. Additionally, $\mu_{r,t,s,z}$ is a negative number because it shows how an increase in capacity would affect the objective function. Consequently, when $\mu_{r,t,s,z} \neq 0$, it means that an increase in capacity would decrease the objective function. Thus, the shadow price of capacity is multiplied by -1. This value, multiplied by the generation and minus one plus the variable costs, will represent the revenues for each resource $r \in R$.

$$Revenues_{r,s,z} = \sum_t (\mu_{r,t,s,z} g_{r,t,s,z} * -1 + C_r^{var} g_{r,t,s,z}) \tag{76}$$

To calculate the revenues for the storage technologies, Equation 77 is utilized. The revenues equal the revenue of selling power and discharging the battery and the cost of charging the battery. The single-trip efficiency is also considered in the calculations.

$$Revenues_{r,s,z} = \sum_t (\zeta^{dch}_{r,t,s,z} \nu_{down} \lambda_{t,s,z} - \zeta^{ch}_{r,t,s,z} \nu^{up} \lambda_{t,s,z}) \tag{77}$$

For the stochastic models, the revenues are weighted as a result of the weighting of the dual values. Consequently, $\lambda_{t,s,z}$ and $\mu_{r,t,s,z}$ have to be weighted back to represent the actual power prices which can be used to calculate the revenues. How this is done is further elaborated in subsubsection 5.3.5 and subsubsection 5.4.5.

4.5.9 Calculation of Ground Rent Tax

A simplified representation of ground rent tax on wind power is calculated using Equation 78 and Equation 79.

$$NetProfit_{r,s,z} = \sum_t \lambda_{t,s,z} g_{r,t,s,z} - x_{r,z} C_r^{inv} - \sum_t C_r^{var} g_{r,t,s,z} - x_{r,z} C_{r,z}^{trans} \tag{78}$$

$$C^{tax}_{r,s} = \frac{\sum_z NetProfit_{r,s,z} \cdot TaxRate}{\sum_z x_{r,z}} \tag{79}$$

The Net profit, Equation 78, is the remaining revenues after investment costs and variable costs are covered. An average ground rent tax for each technology $r \in R$ for each demand scenario $s \in S$ is then generated using Equation 79. The tax rate represents how much of the net profit that is to be taxed. The average value for the tax is determined by weighing the tax by the capacities in each zone.

5 Results

Several simulations are conducted using the deterministic, risk-neutral stochastic, and risk-averse stochastic optimization models for GEP.In this section, the results from these models are examined and compared to examine the impact of uncertainty, risk aversion, and different policy options.

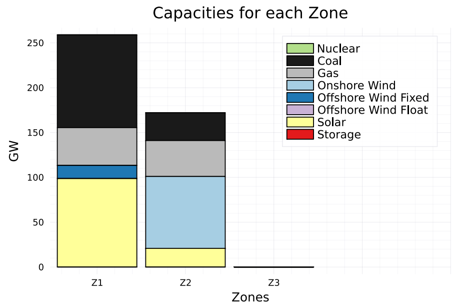
The results are briefly presented and explained in this section. The deeper analysis and discussion are done in section 6.

5.1 Deterministic model

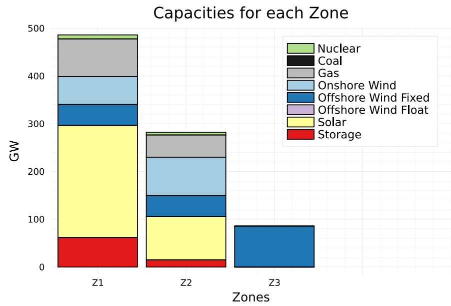
The deterministic model only has the base demand scenario as demand input. Consequently, having no demand uncertainty.

5.1.1 Technology Capacities

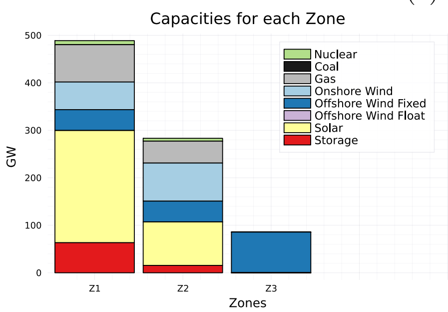
The resulting capacity mix for the deterministic model simulations with and without climate policies are shown in Figure 10 and in Table 13.



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax policy

Figure 10: Capacities for the deterministic model under different climate policies.

As shown in Figure 10a, the deterministic model heavily relies on coal and gas when there are no climate policies. This is as expected as the investment costs (Table 2) are relatively low, and the availability is always 100% (Table 7). However, a large investment in solar in Z1 and onshore wind in Z2 can also be observed. This indicates that solar and onshore wind power production are competitive technologies even without any climate policies.

When the CO_2 Cap policy is introduced in Figure 10b, a vast change in the technology mix can be seen. Firstly, it is important to notice that the total installed capacities over all three price zones have increased by over 95% in comparison to Figure 10a. Such a vast increase in capacity is necessary to cover the demand using mainly VRES because the availability varies throughout the year. The deterministic model also builds fixed offshore wind in Z3 to cover the demand in Z1 with renewable energy.

The model also builds nuclear generation capacity equal to the capacity limit constraint described in Table 10. This is because the model looks at nuclear as a renewable flexible generation technology that can be tuned hourly to meet the demand. This is a result of the simplification that real-world issues like the unit commitment problem with start-up time and costs are not considered. This may have affected the investments in nuclear power generation.

The technology mix built by the deterministic model when the CO_2 Tax policy, depicted in Figure 10c, is introduced is similar to the technology mix achieved with a CO_2 Cap policy. This is because of the CO_2 price, which is a part of the CO_2 Cap policy constraint, explained in subsubsection 4.5.5. Under the CO_2 Cap, an additional CO_2 price equal to 118.6 [€/tCO2] was added. This is close to the CO_2 Tax equal to 120 [€/tCO2] used for the technology mix in Figure 10c. Hence, a similar technology mix is achieved.

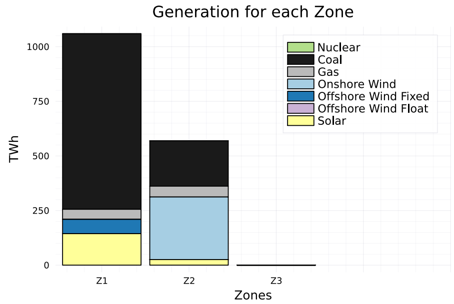
	Capacities [GW] No Climate Policies			**Capacities [GW] CO2 Cap Policy**			**Capacities [GW] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	8.5	6.0	0.0	8.5	6.0	0.0
Coal	103.4	31.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	42.1	40.0	0.0	78.8	46.3	0.0	78.6	46.1	0.0
Onshore Wind	0.0	80.2	0.0	58.4	80.2	0.0	58.3	80.2	0.0
Offshore Wind Bottom Fixed	14.7	0.0	0.0	43.9	43.8	85.4	43.9	43.8	85.6
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Solar	98.6	20.8	0.0	234.4	90.9	0.0	236.2	91.6	0.0
Storage	0.0	0.0	0.0	62.0	15.1	0.0	63.3	15.5	0.0

Table 13: Capacities for the different technologies under different policy options for the deterministic model.

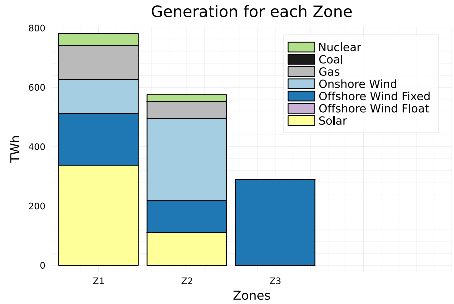
	Base Demand Scenario
CO2 Price [€/tCO2]	118.57

Table 14: CO2 Price in the base-demand Scenario for the deterministic model.

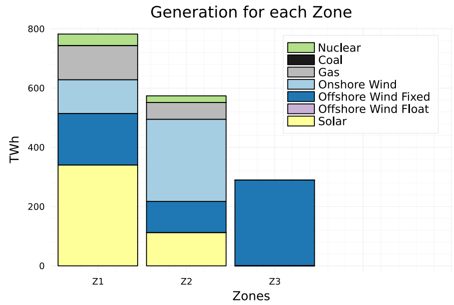
5.1.2 Power Generation



(a) Deterministic model without climate policies



(b) Deterministic model with CO2 Cap policy



(c) Deterministic model with CO2 Tax and Nuclear constraint

Figure 11: Power Generation for the given capacity mix

Figure 11 and Table 15 shows the generation for the given technology mixes. It is eye-catching how huge the change in the generation-mix is from the model with no climate policies, Figure 11a, in comparison to the model with climate policies Figure 11b and Figure 11c. Another result worth noticing is the change in power generated in each zone. When no climate policies are implemented, each zone serves its own demand. However, when more VRES are introduced as a result of the climate policies, the system needs to maximize the effect of the trans-zonal transmission cables with the varying production patterns of the VRES.

	Generation [TWh] No Climate Policies			**Generation [TWh] CO2 Cap Policy**			**Generation [TWh] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0	0	0	39.4	22.7	0	39.1	22.6	0.0
Coal	803.5	207.9	0	0	0	0	0.0	0.0	0.0
Gas	46.2	49.5	0	116.0	57.7	0	115.2	56.8	0.0
Onshore Wind	0	286.6	0	114.4	277.2	0	114.0	277.1	0.0
Offshore Wind Bottom Fixed	65.5	0	0	174.0	106.5	288.9	173.9	105.6	289.4
Offshore Wind Floating	0	0	0	0	0	0	0.0	0.0	0.0
Solar	144.1	25.5	0	337.5	111.0	0	340.1	111.9	0.0

Table 15: Generation for the different technologies under different policy options for the deterministic model.

5.1.3 Carbon Emissions

The carbon emissions are calculated using the method described in subsubsection 4.5.7, resulting in the carbon emissions described in Table 16. The outcome is an over 1425% reduction in carbon emissions from the model without climate policies to the models with climate policies. The emissions for the model with CO_2 Cap and CO_2 Tax policy are very similar as a result of a similar capacity mix and generation pattern.

	Carbon Emissions [MtCO2] No Climate Policies			**Carbon Emissions [MtCO2] CO2 Cap Policy**			**Carbon Emissions [MtCO2] CO2 Tax Policy**		
	Coal	**Gas**	**Total**	**Coal**	**Gas**	**Total**	**Coal**	**Gas**	**Total**
Base Demand Scenario	997.27	40.08	1037.35	0.0	72.78	72.78	0.0	72.06	72.06

Table 16: Carbon emissions under different climate policies for the deterministic model.

5.1.4 Power Price

The power prices are determined as the dual value of the power balance constraint and are given for each time step $t \in T$. Even though the maximum price decreases when climate policies are introduced, an increasing average power price can be observed in Table 17. The deterministic models with climate policies struggle to meet the demand for all hours because of the varying availability of the VRES. This forces the model to increase the power price for more hours to make it more lucrative to meet the demand, resulting in a higher average power price.

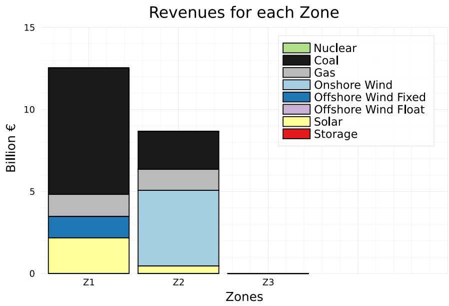
The power price in Z1 and Z2 will be equal, as there are no bottlenecks or transmission constraints on the cable between these zones.

	Power Price [€/MWh] No Climate Policies			**Power Price [€/MWh] CO2 Cap Policy**			**Power Price [€/MWh] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Average Price	21.91	21.22	-	39.69	33.59	39.69	39.76	33.68	39.76
Max Price	3000	3000	-	1727.92	3000	1727.92	1723.72	2838.43	1723.72

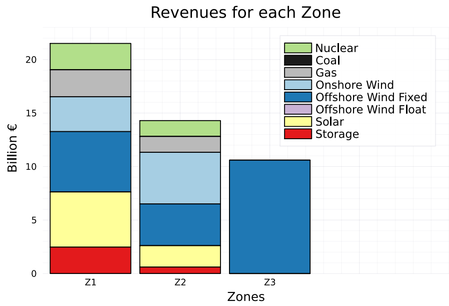
Table 17: The average and maximum power prices in each price zone under the different policy options.

5.1.5 Revenues

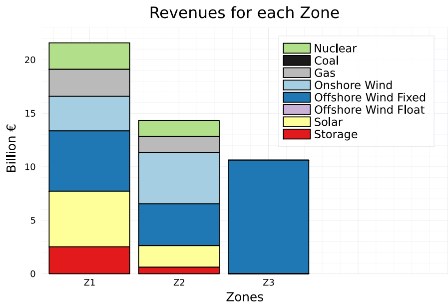
The revenues are calculated using the dual value of the capacity limit, as described in subsubsection 4.5.8.



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax policy

Figure 12: Revenues for each technology in each price zone for the base demand scenario

Figure 12 and Table 18 shows the revenues for the deterministic model under different climate policies. It is noteworthy that the offshore wind power generation in Z3 under the CO_2 Cap and CO_2 Tax policies gain a significant amount of revenue. As there are no bottlenecks on the transmission between Z1 and Z3, the price will be identical. The marginal unit sets the price, and this will often be gas or nuclear power generation in Z1 with high variable cost, resulting in high prices. Thus, sufficient revenue is achieved for the offshore wind capacity in Z3.

	Revenues [Billion €] No Climate Policies			**Revenues [Billion €] CO2 Cap Policy**			**Revenues [Billion €] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.00	0.00	0.00	2.47	1.49	0.0	2.48	1.49	0.0
Coal	7.71	2.31	0.00	0.0	0.0	0.0	0.0	0.0	0.0
Gas	1.35	1.28	0.00	2.52	1.48	0.0	2.51	1.48	0.0
Onshore Wind	0.00	4.61	0.00	3.25	4.83	0.0	3.24	4.82	0.0
Offshore Wind Bottom Fixed	1.31	0.00	0.00	5.65	3.90	10.6	5.64	3.90	10.6
Offshore Wind Floating	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0
Solar	2.17	0.46	0.00	5.16	2.00	0.0	5.20	2.02	0.0
Storage	0.00	0.00	0.00	2.47	0.60	0.0	2.52	0.61	0.0

Table 18: Revenues for the different technologies under different policy options for the base demand scenario for the deterministic model.

5.1.6 Non Served Energy

Table 19 shows the NSE for the deterministic model under different climate policies. The NSE decrease drastically when climate policies are introduced.

Non-Served Energy [MWh] No Climate Policies	**Non-Served Energy [MWh] CO2 Cap Policy**	**Non-Served Energy [MWh] CO2 Tax Policy**
43842.86	16.00	0.0

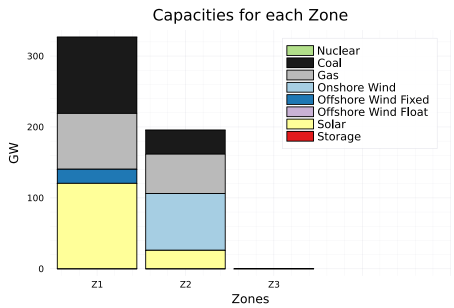
Table 19: Non-Served Energy for the deterministic model under the different policy options.

5.2 Risk Neutral Stochastic model

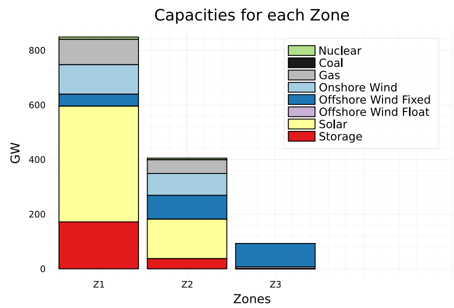
The calculations made in subsubsection 5.2.2 and subsubsection 5.2.6 are based on the base demand scenario.

5.2.1 Technology Capacities

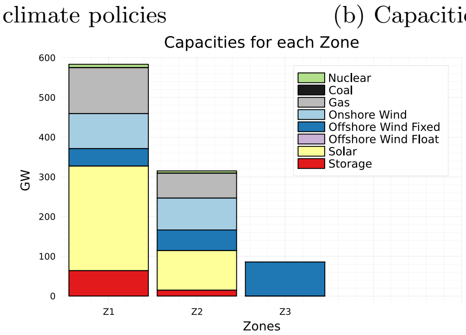
Performing simulations using the risk-neutral model with the different policy options gives the capacity mixes shown in Figure 13 and Table 20.



(a) Capacities with no climate policies



(b) Capacities with CO2 Cap policy



(c) Capacities with CO2 Tax and Nuclear constraint

Figure 13: Capacities for the Risk Neutral model for different climate policy options.

For the simulation of the risk-neutral stochastic model with no climate policies (Figure 13a), it is an overall increase in capacity compared to the deterministic model. The increase in gas capacity stands out with an enlargement of over 52 GW. This is a result of the risk-neutral stochastic model finding the optimal capacity mix summing over all the demand scenarios. Gas capacity has lower investment costs compared to coal capacity, but coal capacity has lower variable costs compared to gas capacity. However, the result is driven by the optimal combination of the costs, which results in the risk-neutral central planner favoring gas under uncertainty.

In contrast to the deterministic model where the capacity mix for CO_2 Cap and CO_2 Tax policy was very similar. One reason for this is the CO_2 Price generated as a complementary policy by the CO_2 Cap in the high demand scenario, shown in Table 21. The CO_2 price for the very high demand scenario is over 750 [€/tCO2] higher than the CO_2 Tax value of 120 [€/tCO2]. Consequently, the capacity mix for the CO_2 Cap policy has a much greater amount of VRES and storage compared to the capacity mix for the CO_2 Tax policy.

The risk-neutral central planner maximizes the capacity of solar power in Z1 in relation to the set maximum capacity limits, elaborated in subsubsection 4.5.6 when the CO_2 Cap is introduced. This is to ensure meeting the demand in the very high demand scenario and minimizing the costs if the low demand scenario occurs because of the low investment cost of solar capacity, and at the same time, meeting the carbon emission cap. The large investments in solar power make the investment in storage more lucrative as it helps to even out the large amount of power produced by the solar power in the hours with sunlight. Thus, a great amount of storage capacity is present in the capacity mix built under the CO_2 Cap.

Another interesting result for the risk-neutral model with CO_2 Cap is that it finds it economical to invest in some floating offshore wind capacity. This is a very expensive technology. However, this shows that it can be a sufficient and economically beneficial solution under strict climate policies.

	Capacities [GW] No Climate Policies			Capacities [GW] CO2 Cap Policy			Capacities [GW] CO2 Tax Policy		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	8.5	6.0	0.0	8.5	6.0	0.0
Coal	107.7	33.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	78.8	55.5	0.0	92.7	50.2	0.0	115.7	62.6	0.0
Onshore Wind	0.0	80.2	0.0	108.0	80.2	0.0	88.2	80.2	0.0
Offshore Wind Bottom Fixed	19.9	0.0	0.0	43.9	87.4	85.8	43.9	52.0	85.8
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	6.9	0.0	0.0	0.0
Solar	120.4	26.0	0.0	423.7	144.3	0.0	263.3	99.7	0.0
Storage	0.0	0.0	0.0	171.7	37.2	0.0	63.9	14.7	0.0

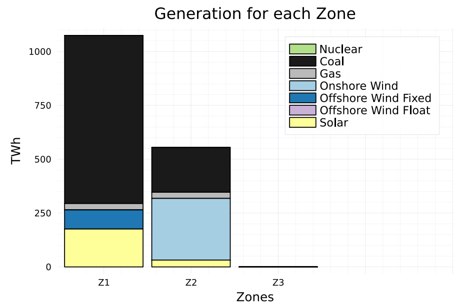
Table 20: Capacities for the different technologies under different policy options for the risk-neutral stochastic model, Figure 13.

Table 21 shows that the unweighted CO_2 Price is only present in the very high demand scenario because this is the only scenario where the model struggles to meet the CO_2 Cap. Consequently, a price for additional emissions is generated after the principles of complementary slackness.

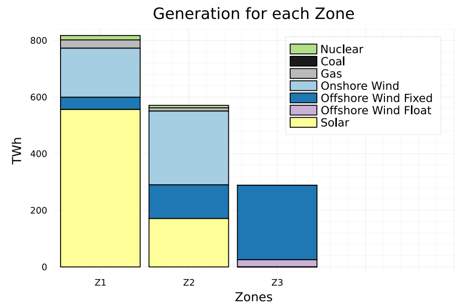
	Base Demand Scenario	Low Demand Scenario	High Demand Scenario	Very High Demand Scenario
CO2 Price [€/tCO2]	0	0	0	872.44

Table 21: CO2 Price generated as a part of the CO2 Cap policy.

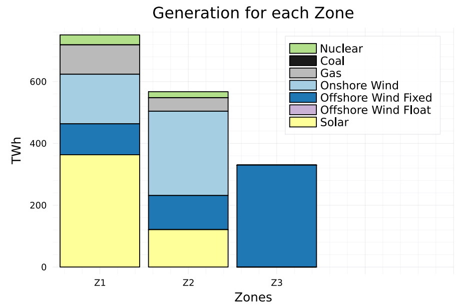
5.2.2 Power Generation



(a) Power generation with no climate policies



(b) Power generation under CO2 Cap policy



(c) Power generation under CO2 Tax policy

Figure 14: Power Generation for the given capacity mix for the base demand scenario

Figure 14 and Table 22 shows the generation for the risk-neutral model under the different policy options for the base demand scenario. Increasing power production by VRES, compared to the deterministic model, can be observed, even when no climate policies are introduced. This is a result of the risk-neutral model being stochastic, finding the optimal solution summing over several demand scenarios. Thus, a greater capacity of VRES is built to be able to meet demand in the highest demand scenarios. VRESs has low variable costs, making them prioritized over the thermal capacity to supply the demand to minimize the costs.

The same pattern can be spotted for the models with climate policies. The model with a CO_2 Cap has the greatest amount of VRES, leading to very little thermal power generation. The model with CO_2 Tax has a lower share of VRES. Thus, a greater amount of thermal power production with higher variable costs is needed to cover the demand for the base scenario.

	Generation [TWh] No Climate Policies			**Generation [TWh] CO2 Cap Policy**			**Generation [TWh] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	15.44	8.61	0.0	32.29	19.49	0.0
Coal	780.14	207.74	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	29.62	28.56	0.0	29.30	11.59	0.0	94.96	43.59	0.0
Onshore Wind	0.0	286.35	0.0	173.13	260.70	0.0	160.40	272.66	0.0
Offshore Wind Bottom Fixed	88.65	0.0	0.0	43.35	118.97	262.98	100.03	110.48	329.72
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	25.28	0.0	0.0	0.0
Solar	175.94	31.81	0.0	556.04	170.78	0.0	363.27	120.93	0.0

Table 22: Generation for the different technologies under different policy options for the risk-neutral stochastic model.

5.2.3 Carbon Emissions

Table 23 clearly shows the effect of the climate policies and demand uncertainty. Higher VRES capacity results in lower carbon emissions for the risk-neutral model compared to the deterministic for the base demand scenario with no climate policies.

It is also interesting to observe the difference in carbon emissions for the model with CO_2 Cap and CO_2 Tax policy. The model with CO_2 Cap policy has over 70% lower carbon emissions for the base demand scenario and 55% lower carbon emissions in the very high demand scenario compared to the CO_2 Tax model. This aligns well with the conclusion in [87] that quantity-based policies give better knowledge about emission intensity and price-based policies give better knowledge about costs.

	Carbon Emissions [MtCO2] No Climate Policies			**Carbon Emissions [MtCO2] CO2 Cap Policy**			**Carbon Emissions [MtCO2] CO2 Tax Policy**		
	Coal	**Gas**	**Total**	**Coal**	**Gas**	**Total**	**Coal**	**Gas**	**Total**
Base Demand Scenario	974.05	24.38	998.43	0.0	17.14	17.14	0.0	58.05	58.05
Low Demand Scenario	790.50	3.73	794.23	0.0	5.07	5.07	0.0	27.59	27.59
High Demand Scenario	1096.81	73.53	1170.34	0.0	39.04	39.04	0.0	102.60	102.60
Very High Demand Scenario	1163.75	147.07	1310.82	0.0	72.78	72.78	0.0	161.24	161.24

Table 23: Carbon emissions under different climate policies for the risk-neutral stochastic model.

5.2.4 Non Served Energy

Table 24 shows the NSE for the different demand scenarios under the different policy options. All models are able to meet the demand for all scenarios except the very high demand scenario. For the very high demand scenario, all models find it sufficient to have a certain amount of NSE. As the probability for each scenario is uniform, the costs of NSE will also be weighted with this probability. Thus, the risk-neutral central planner considers the cost of covering all the demand in the very high demand scenario too high with the given probability for this scenario to occur. Consequently, some NSE is considered optimal to minimize the TSC.

The NSE for the model with CO_2 Cap policy is significantly higher than for the other policy options. To be within the emission goals of the *Fit-For-55* report by the European Commission, outlined in subsubsection 4.5.5, the set carbon emission cap is quite strict. Consequently, it is not possible for the model to include flexible thermal energy sources such as coal or gas to reduce the cost related to NSE. Implementing more VRES could be an option. However, as all price zones are related in the same part of Europe, with similar wind and solar capacity time series. The extent of VRES capacity needed to serve this demand is so high that the risk-neutral central planner considers the cost of NSE to be the better option with a probability of 25% for the very high demand scenario to occur.

	Non-Served Energy [MWh] No Climate Policies	**Non-Served Energy [MWh] CO2 Cap Policy**	**Non-Served Energy [MWh] CO2 Tax Policy**
Base Demand Scenario	0.0	0.0	0.0
Low Demand Scenario	0.0	0.0	0.0
High Demand Scenario	0.0	0.0	0.0
Very High Demand Scenario	284578.6	416372.5	299338.7

Table 24: Non-Served Energy for each demand scenario under different climate policies for the risk-neutral model.

5.2.5 Power Price

The power prices in Table 25 reflect the variable costs of the producing technologies. For the model with CO_2 Cap, there is a high installed capacity of VRES with low variable costs. The VRESs are able to serve much of the demand in the base, low and high demand scenario, resulting in a low average and maximum power price. However, in the very high demand scenario, the prices get high as the model struggles to meet demand. The power price is determined as the dual value of the power balance constraint, showing how much one additional MWh is worth trying to meet the demand. For the very high demand scenario where the CO_2 price is high, and the NSE is high, the power price is dramatically increased to endeavor to meet more demand.

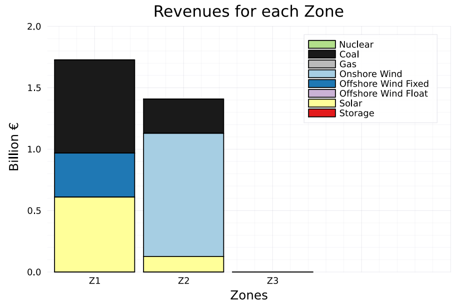
The model with CO_2 Tax policy has overall higher power prices in the base, low, and high demand scenarios. This is a result of the CO_2 tax adding to the variable cost of the emitting generation technologies. This leads to higher variable costs, thus, a higher power price when these generation technologies serve as marginal units in the system. Additionally, the capacity mix for the model with CO_2 Tax contains a greater amount of gas capacity and less VRES than for the model with CO_2 Cap. Thus, gas has to serve more hours as the marginal unit, forcing the power price to rise.

The max price in the very high demand scenario is 750 €/MWh for all zones and policy options. The maximum price cap of the model is set to 3000 €/MWh, outlined in subsection 4.3. The risk-neutral central planner considers the probability of ending up in the very high demand scenario and not being able to sufficiently serve the demand, to be 25% due to the uniform scenario probability. Thus, the maximal power price in the very high demand scenario is equal to 25% of the price cap, resulting in a maximum power price of 750 €/MWh.

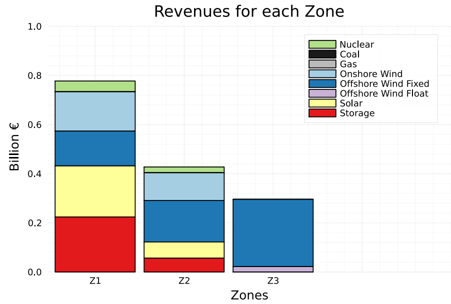
		Power Price [€/MWh] No Climate Policies			Power Price [€/MWh] CO2 Cap Policy			Power Price [€/MWh] CO2 Tax Policy		
		Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Base Demand Scenario	**Average Price**	4.15	4.10	4.15	1.27	1.07	1.27	7.69	6.34	7.69
	Max Price	6.08	6.08	6.08	6.08	6.08	6.08	18.65	18.65	18.65
Low Demand Scenario	**Average Price**	3.45	3.16	3.45	0.63	0.60	0.63	4.81	4.19	4.81
	Max Price	6.08	6.08	6.08	6.08	6.08	6.08	18.65	18.65	18.65
High Demand Scenario	**Average Price**	5.03	4.85	5.03	2.03	1.59	2.03	10.40	8.33	10.40
	Max Price	6.08	6.08	6.08	6.08	6.08	6.08	18.65	18.65	18.65
Very High Demand Scenario	**Average Price**	9.23	9.04	9.23	47.00	34.29	47.00	16.87	14.09	16.87
	Max Price	750	750	750	750	750	750	750	750	750

Table 25: Power price for each zone under different climate policies for the different demand scenarios for the risk-neutral model.

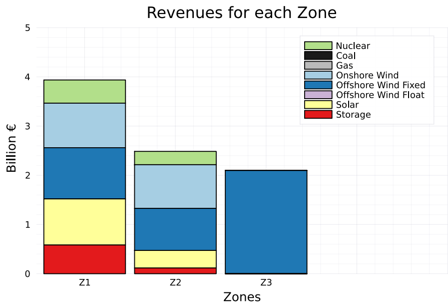
5.2.6 Revenues



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax policy

Figure 15: Weighted revenues for each technology in each price zone for the base demand scenario

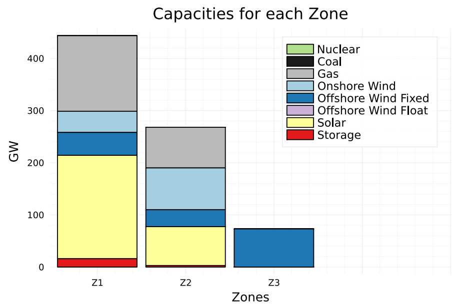
The weighted revenues are shown in Figure 15 and Table 26, which are based on the base demand scenario. The revenues are closely linked to the generation and power price. The revenues for the risk-neutral stochastic model significantly lower than the revenues for the deterministic model (Table 18). However, this is because the risk-neutral stochastic model has a higher share of VRES and no NSE for the base demand scenario, contributing to keep the power price low.

	Revenues [Billion €] No Climate Policies			Revenues [Billion €] CO2 Cap Policy			Revenues [Billion €] CO2 Tax Policy		
	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3
Nuclear	0.0	0.0	0.0	0.04	0.02	0.0	0.47	0.27	0.0
Coal	0.76	0.28	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Onshore Wind	0.0	1.0	0.0	0.16	0.11	0.0	0.91	0.89	0.0
Offshore Wind Bottom Fixed	0.36	0.0	0.0	0.14	0.17	0.27	1.04	0.85	2.10
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	0.02	0.0	0.0	0.0
Solar	0.61	0.13	0.0	0.21	0.07	0.0	0.94	0.36	0.0
Storage	0.00	0.00	0.00	0.22	0.06	0.0	0.58	0.12	0.0

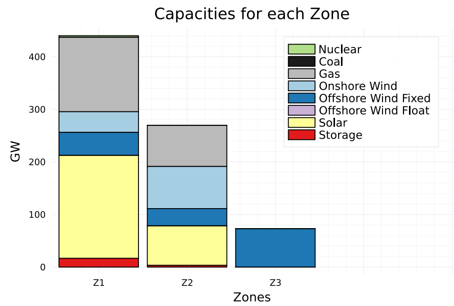
Table 26: Weighted revenues for the different technologies under different policy options for the base demand scenario for the risk-neutral stochastic model.

5.2.7 Starting Point for Investments in Nuclear Power with CO2 Tax

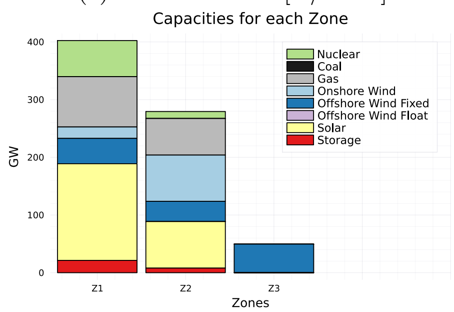
As mentioned earlier in section 5 and in subsubsection 4.5.6, it was necessary to implement a constraint on nuclear power generation to make the results realistic for the models with a CO_2 Tax and CO_2 Cap policy. However, looking into what level of CO_2 Tax sets the breakpoint for profitable investments in nuclear power generation can be valuable. For these simulations, there is no capacity limit on nuclear capacity in Z1 and Z2. As shown in Figure 16 and Table 27, the risk-neutral stochastic model starts investing in nuclear power for a CO_2 tax of 32 €/tCO2. The model has also been run for a CO2 Tax of 80 €/tCO2, which is approximately the current CO2 price (May 2023) [8], and for a CO2 Tax of 120 €/tCO2, which is the value used for the year 2040, elaborated in subsubsection 4.5.5.



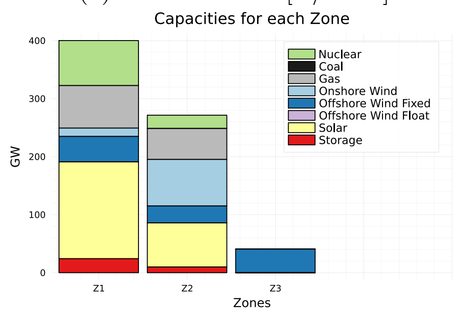
(a) CO2 Tax = 31 [€/tCO2]



(b) CO2 Tax = 32 [€/tCO2]



(c) CO2 Tax= 80 [€/tCO2]



(d) CO2 Tax = 120 [€/tCO2]

Figure 16: Capacities for the Risk Neutral model for different levels of CO2 Tax

The risk-neutral central planner starts to invest in nuclear power capacity for a CO_2 Tax = 32 €/tCO2. However, even for a CO_2 Tax equal to 120 €/tCO2, gas is the dominant thermal capacity with 126.6 GW compared to 100.5 GW of nuclear capacity. This is due to the huge investment costs of nuclear capacity.

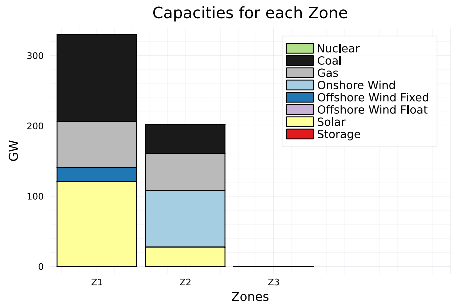
	CO2 Tax = 31 €/tCO2	**CO2 Tax = 32 €/tCO2**	**CO2 Tax = 80 €/tCO2**	**CO2 Tax = 120 €/tCO2**
Nuclear Capacity for Risk Neutral model	0 MW	3029.2 MW	74682.4 MW	100529.0 MW

Table 27: Total nuclear capacity for all zones under different CO2 Tax levels.

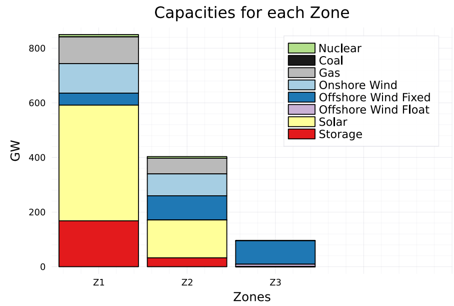
5.3 Risk Averse Stochastic model

All simulations in subsection 5.3 are done for the risk-averse stochastic model with $\alpha = 0.25$ and $\gamma = 0.5$.

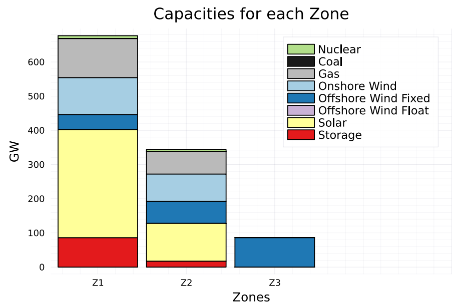
5.3.1 Generation Capacities



(a) Capacities with no climate policies



(b) Capacities with CO2 Cap policy



(c) Capacities with CO2 Tax and Nuclear constraint

Figure 17: Capacities for the Risk Averse model for different climate policy options

There are several interesting differences between the capacity mix generated by the risk-neutral stochastic model (subsection 5.2) and the capacity mix generated by the risk-averse stochastic model, outlined in Figure 17 and Table 28. As elaborated in subsection 4.4, the risk-averse model strives to minimize the variable costs, additional tax costs, and the costs of NSE relative to VaR, expressed in constraint 55. This is to satisfyingly minimize the tail risk associated with the investment by the risk-averse stochastic GEP model with respect to the set level of risk-aversion (γ).

The capacity mix for the risk-averse model with no climate policies builds more coal capacity and less gas and VRES capacity, even though the investment cost for coal is significantly higher than for gas. The risk-averse central planner strives to minimize the costs for the worst-case scenario, which is the very high demand scenario for this model. As coal capacity has low variable costs compared to gas capacity, this will result in lower costs if the worst-case scenario were to happen. The overall growth in thermal capacity compared to the risk-neutral model will also contribute to avoiding the cost of NSE.

For the risk-averse model with CO_2 Cap policy, there are only small differences compared to the risk-neutral model. This is because the model has fewer degrees of freedom when the CO_2 Cap is introduced. However, a slight increase in gas capacity and a decreased storage capacity in comparison to the risk-neutral model. The risk-averse central planner also builds about 35% more floating offshore wind under the CO_2 Cap policy. Both the investment in more gas and floating offshore wind capacity is to avoid some of the high costs of NSE in the very high demand scenario.

For the CO_2 Tax policy, the risk-averse central planner builds less gas capacity and increases the solar capacity by over 17% and onshore wind by over 11% compared to the risk-neutral central planner. Additionally, the offshore wind increases slightly in Z2 for fixed offshore wind. This change in the capacity mix is a result of the risk-averse central planner striving to lower the risk of high CO_2 Tax costs for the higher demand scenarios. By increasing the amount of VRES the risk-averse central planner relies less on gas capacity to meet the demand. Hence, the risk of high CO_2 Tax costs is reduced.

	Capacities [GW] No Climate Policies			**Capacities [GW] CO2 Cap Policy**			**Capacities [GW] CO2 Cap Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	8.5	6.0	0.0	8.5	6.0	0.0
Coal	123.7	41.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	65.2	53.0	0.0	97.8	57.3	0.0	114.4	65.7	0.0
Onshore Wind	0.0	80.2	0.0	108.0	80.2	0.0	108	80.2	0.0
Offshore Wind Bottom Fixed	19.8	0.0	0.0	43.9	88.5	85.8	43.9	64.2	85.8
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	9.3	0.0	0.0	0.0
Solar	120.9	27.6	0.0	423.7	138.6	0.0	316.6	110.5	0.0
Storage	0.0	0.0	0.0	168.0	32.5	0.0	85.6	17.1	0.0

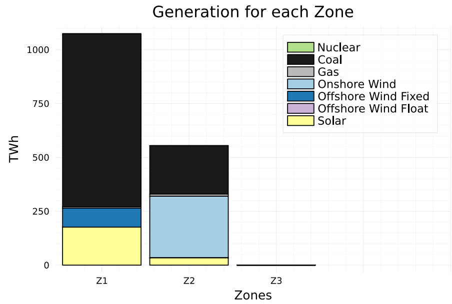
Table 28: Capacities for the different technologies under different policy options for the risk-averse stochastic model.

Table 29 displays a decrease in CO_2 price for the risk-averse model compared to the risk-neutral model. This suggests that the risk-averse central planner struggles less to meet the emission cap in the very high demand scenario because of the overall increase in generation capacity.

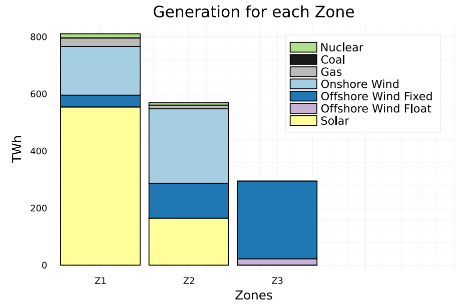
	Base Demand Scenario	**Low Demand Scenario**	**High Demand Scenario**	**Very High Demand Scenario**
CO2 Price [€/MWh]	0	0	0	274.37

Table 29: CO2 Price generated as a part of the CO2 Cap policy.

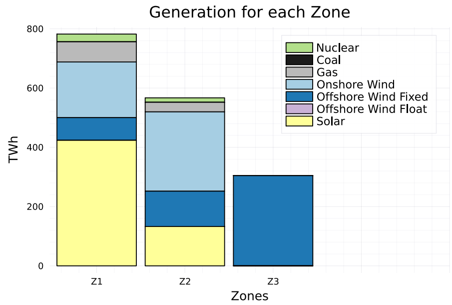
5.3.2 Power Generation



(a) Power generation with no climate policies



(b) Power generation under CO2 Cap policy



(c) Power generation under CO2 Tax policy

Figure 18: Power Generation for the given capacity mix for the base demand scenario

The power generation for the risk-averse stochastic model, shown in Figure 18 and Table 30, is for the base demand scenario. Hence, it is similar to the generation in the risk-neutral stochastic model. However, some differences related to the difference in the capacities can be identified. When no climate policies are present, the coal generation increase by over 4%, and gas generation is decreased by over 72%. The power generation from offshore wind also decreased as a result of less capacity installed.

For the model with CO_2 Cap, the differences from the risk-neutral model are less because the technology mix is similar, and the VRESs stands for most of the power generated in the base-demand scenario.

As a result of the increased investment in VRES for the risk-averse central planner under CO_2 Tax policy, the power generation from gas is reduced notably. Consequently, an increasing amount of VRES power generation can be observed.

	Generation [TWh] No Climate Policies			**Generation [TWh] CO2 Cap Policy**			**Generation [TWh] CO2 Cap Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	15.3	8.8	0.0	26.09	15.13	0.0
Coal	802.80	224.90	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	6.36	9.91	0.0	29.01	12.79	0.0	68.00	32.25	0.0
Onshore Wind	0.0	286.24	0.0	170.92	261.19	0.0	187.93	267.74	0.0
Offshore Wind Bottom Fixed	88.31	0.0	0.0	41.82	122.38	272.50	76.60	119.13	304.38
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	21.78	0.0	0.0	0.0
Solar	176.61	33.74	0.0	553.63	164.16	0.0	423.64	132.84	0.0

Table 30: Generation for the different technologies under different policy options for the risk-averse stochastic model.

5.3.3 Carbon Emissions

Table 31 shows the carbon emissions for the risk-averse stochastic model for the different policy options and demand scenarios. One aspect worth noticing is that emissions increase for the risk-averse central planner compared to the risk-neutral central planner for no climate policies. A significant reduction in emissions can be observed for the risk-averse central planner under CO_2 Tax compared to the risk-neutral central planner. The carbon emissions in the very high demand scenario increase by over 6.3% for no climate policies, compared to Table 23. One can also observe that the risk-averse central planner emits 74.9% more CO_2 than the European Commission's target for 2055 when the CO_2 Tax policy is utilized for the very high demand scenario. However, for the CO_2 Cap policy, the emission target is met for all demand scenarios.

	Carbon Emissions [MtCO2] No Climate Policies			**Carbon Emissions [MtCO2] CO2 Cap Policy**			**Carbon Emissions [MtCO2] CO2 Cap Policy**		
	Coal	**Gas**	**Total**	**Coal**	**Gas**	**Total**	**Coal**	**Gas**	**Total**
Base Demand Scenario	1013.26	6.81	1020.07	0.00	17.51	17.51	0.00	42.00	69.37
Low Demand Scenario	795.86	0.65	796.52	0.00	5.28	5.28	0.00	18.55	35.08
High Demand Scenario	1191.29	32.45	1223.74	0.00	39.31	39.31	0.00	77.83	77.83
Very High Demand Scenario	1308.26	84.81	1393.06	0.00	72.78	72.78	0.00	127.26	127.26

Table 31: Carbon emissions under different climate policies for the risk-averse stochastic model.

5.3.4 Non Served Energy

Because the risk-averse stochastic model strives to minimize the cost of NSE, a major decrease in NSE is displayed in Table 32 compared to the risk-neutral stochastic model. The magnitude of NSE is reduced by 72.7% for the model with no climate policies, 100% for the model with CO_2 Cap, and by almost 100% for the model with CO_2 Tax.

	Non-Served Energy [MWh] No Climate Policies	**Non-Served Energy [MWh] CO2 Cap Policy**	**Non-Served Energy [MWh] CO2 Cap Policy**
Base Demand Scenario	0.00	0.0	0.00
Low Demand Scenario	0.00	0.0	0.00
High Demand Scenario	0.00	0.0	0.00
Very High DemandScenario	77807.87	0.0	4.19

Table 32: Non-Served Energy for each demand scenario under different climate policies for the risk-averse model.

5.3.5 Power Price

At first, one may think that the power prices decrease significantly compared to the risk-neutral model. However, as a consequence of the model being risk-averse, weighting the importance of the different parameters and variables affects the power prices generated. The risk-averse and the risk-neutral central planner weight the power price in the base, low and high demand as less important. Consequently, when the power prices are generated as the dual value to the power balance constraint, they will be weighted in the base, low, and high demand scenarios. Thus, they will not reflect the actual power price in the respective scenarios. However, it is possible to re-calculate this weighting to achieve the actual power price for these scenarios. Equation 80 shows how the power price is weighted for the risk-averse and the risk-neutral stochastic models.

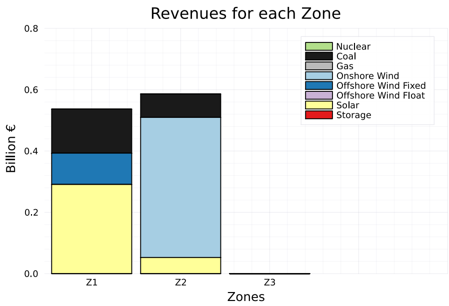
$$\lambda_{t,s,z}^{weighted} = \theta_s \cdot \lambda_{t,s,z} + (1-\gamma) \cdot P_s \cdot \lambda_{t,s,z} \tag{80}$$

$\lambda^{weighted}_{t,s,z}$ represent the weighted power prices, $\lambda_{t,s,z}$ is the actual power price, γ is the level of risk-aversion (0.5 in this case), P_s is the probability for each scenario, and θ_s is the risk-adjusted probability which is the dual value to u_s from constraint 55. Consequently, the actual power price can be found using Equation 81.

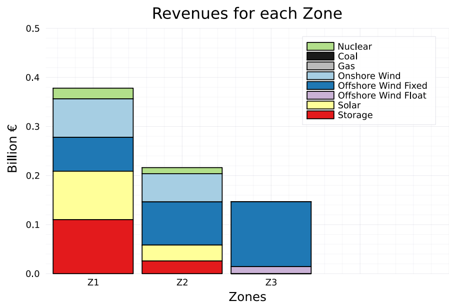
$$\lambda_{t,s,z} = \frac{\lambda^{weighted}_{t,s,z}}{\theta_s + (1-\gamma) \cdot P_s} \tag{81}$$

Further analysis on the behavior of the power price with risk aversion and climate policies are elaborated in subsubsection 5.4.6.

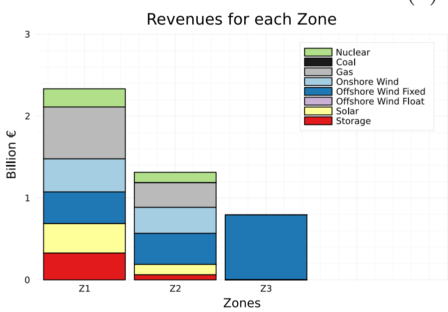
5.3.6 Revenues



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax policy

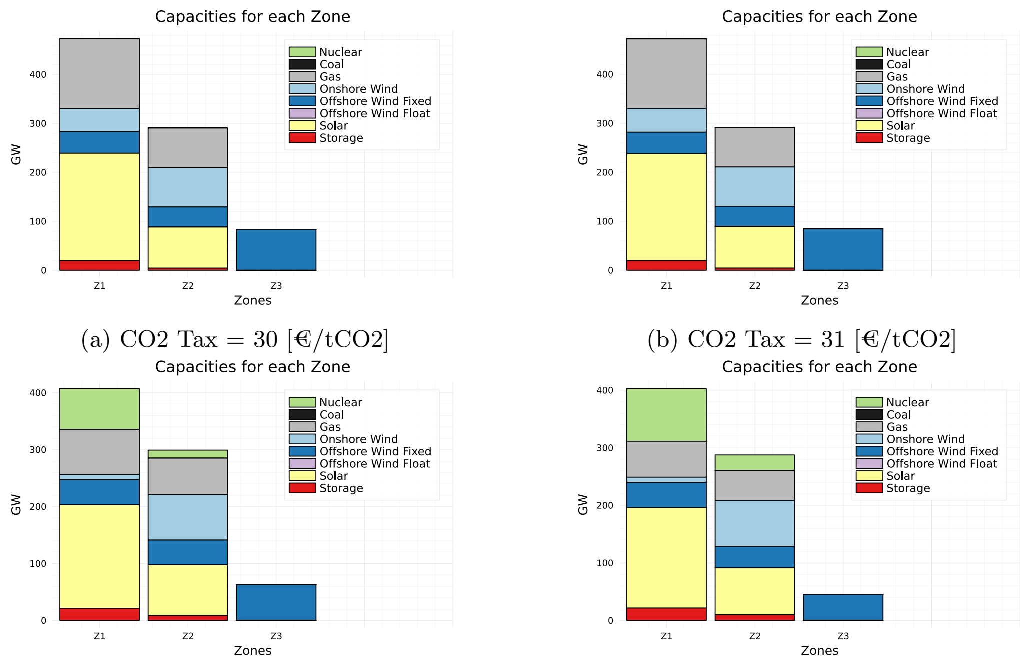
Figure 19: Weighted revenues for each technology in each price zone for the base demand scenario

The revenues showed in Figure 19 and Table 33 are for the base demand scenario. The revenues are calculated using the dual value of the power balance, as outlined in subsubsection 4.5.8. However, this variable is weighed, as previously discussed in subsubsection 5.3.5. Consequently, the revenues outlined in Figure 19 will not be the actual revenues if this scenario were to happen. However, it represents how the risk-averse central planner values the revenues for this scenario when making the investment decision. To determine the actual revenues in the base, low, and high demand scenarios, the weighting described in Equation 81 can be utilized, and this is explained in detail in subsubsection 5.4.5.

	Revenue [Billion €] No Climate Policies			Revenue [Billion €] CO2 Cap Policy			Revenue [Billion €] CO2 Cap Policy		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	0.022	0.012	0.0	0.222	0.128	0.0
Coal	1.484	0.452	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	0.019	0.030	0.0	0.0	0.0	0.0	0.634	0.301	0.0
Onshore Wind	0.0	0.459	0.0	0.078	0.057	0.0	0.403	0.317	0.0
Offshore Wind Bottom Fixed	0.159	0.0	0.0	0.069	0.088	0.132	0.387	0.379	0.793
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	0.014	0.0	0.0	0.0
Solar	0.294	0.057	0.0	0.099	0.032	0.0	0.359	0.127	0.0
Storage	0.0	0.0	0.0	0.110	0.026	0.0	0.327	0.062	0.0

Table 33: Weighted revenues for the different technologies under different policy options for the base demand scenario for the risk-averse stochastic model.

5.3.7 Starting Point for Investments in Nuclear Power with CO2 Tax



(a) CO2 Tax = 30 [€/tCO2]

(b) CO2 Tax = 31 [€/tCO2]

(c) CO2 Tax= 80 [€/tCO2]

(d) CO2 Tax = 120 [€/tCO2]

Figure 20: Capacities for the risk-averse stochastic model for different levels of CO2 Tax

Figure 20 and Table 34 outlines for which level of CO_2 Tax the risk-averse stochastic model finds it profitable to invest in nuclear capacity. The risk-averse central planner starts to invest in nuclear capacity for a CO_2 Tax of 31 €/tCO2. This is very similar to the investment point for the risk-neutral stochastic model, outlined in subsubsection 5.2.7. The risk-averse central planner also invests more in nuclear capacity for today's taxation level of 80 €/tCO2 [8] and the level for 2040 at 120 €/tCO2 used in the model, compared to the risk-neutral central planner. It is also noteworthy that gas is the predominant thermal generation technology even for a CO_2 Tax of 80 €/tCO2. Thus, the risk-averse central planner considers paying the taxation for the carbon emissions related to gas power production as the better option, rather than the high investment costs of nuclear capacity. However, for a CO_2 Tax of 120 €/MWh, nuclear becomes the predominant capacity with 3669 MW more installed capacity compared to gas.

	CO2 Tax = 30 €/tCO2	**CO2 Tax = 31 €/tCO2**	**CO2 Tax = 80 €/tCO2**	**CO2 Tax = 120 €/tCO2**
Nuclear Capacity for Risk Averse model	0 MW	881.9 MW	85280.6 MW	118081.1 MW

Table 34: Total nuclear capacity for all zones under different CO2 Tax levels.

5.4 Different Levels of Risk Aversion

subsection 5.4 aims to investigate how the stochastic GEP optimization model changes the investments for different levels of risk-aversion under the different policy options outlined in subsubsection 4.5.5. Consequently, how NSE, revenues, power prices, emissions, CO_2 price, and TSC are affected.

5.4.1 Capacity Mix with No Climate Policies

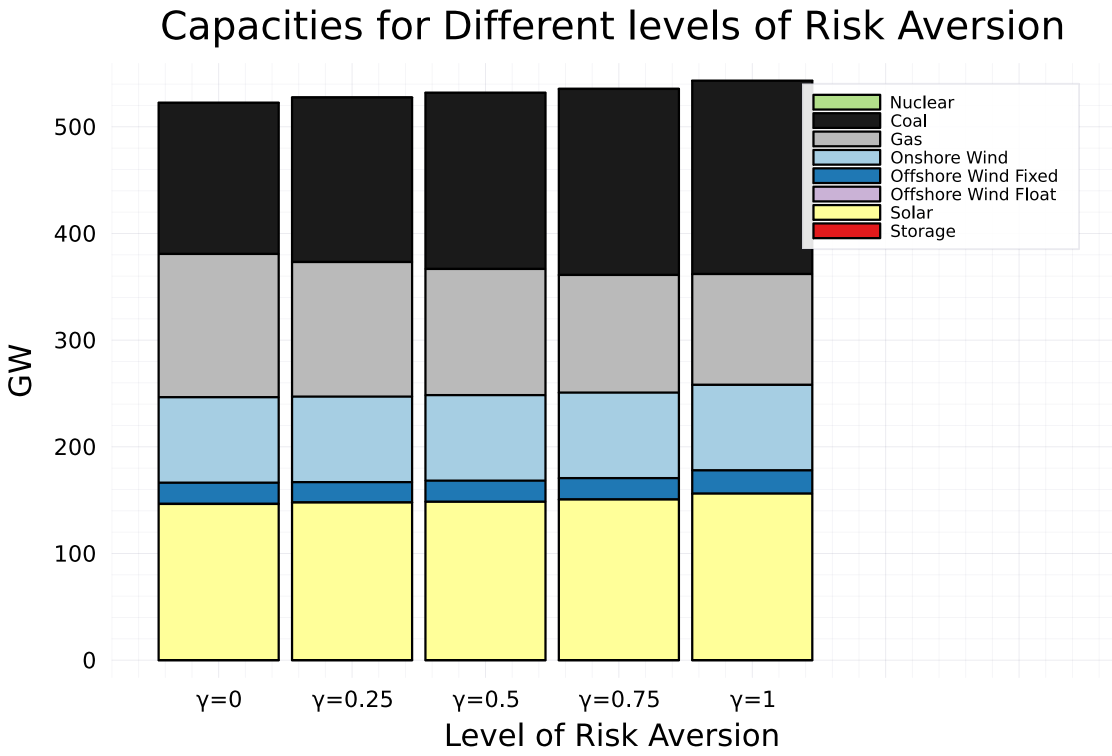


Figure 21: Capacity mix for increasing risk aversion with no climate policies

Investigating the capacity mixes depicted in Figure 21 and described in Table 35, some trends can be observed. The amount of gas capacity decrease, and the amount of coal capacity increase with an increasing level of risk aversion. Even though the gas capacity decrease, the total installed thermal capacity increase with an increasing level of risk aversion.

When examining the VRES, fewer changes can be observed. Onshore wind is stable at around 80 GW. A slight increase in solar and offshore wind power can be observed. The risk-averse central planner wants to cover the demand for the very high demand scenario. Thus, the overall installed capacity increase by approximately 4% from $\gamma = 0$ to $\gamma = 1$, enabling the central planner to meet more of the demand in the worst-case scenario.

	Capacities [GW] $\gamma = 0$	Capacities [GW] $\gamma = 0.25$	Capacities [GW] $\gamma = 0.5$	Capacities [GW] $\gamma = 0.75$	Capacities [GW] $\gamma = 1$
Nuclear	0.0	0.0	0.0	0.0	0.0
Coal	141.6	154.2	165.1	174.4	181.2
Gas	134.3	126.2	118.3	110.3	103.9
Onshore Wind	80.2	80.2	80.2	80.2	80.2
Offshore Wind Bottom Fixed	19.9	19.1	19.8	20.0	21.8
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0
Solar	146.4	147.8	148.5	150.6	156.1
Storage	0.0	0.0	0.0	0.0	0.0

Table 35: Capacities for different levels of risk-aversion for the risk-averse model with no climate policies.

5.4.2 Capacity Mix with CO2 Cap Policy

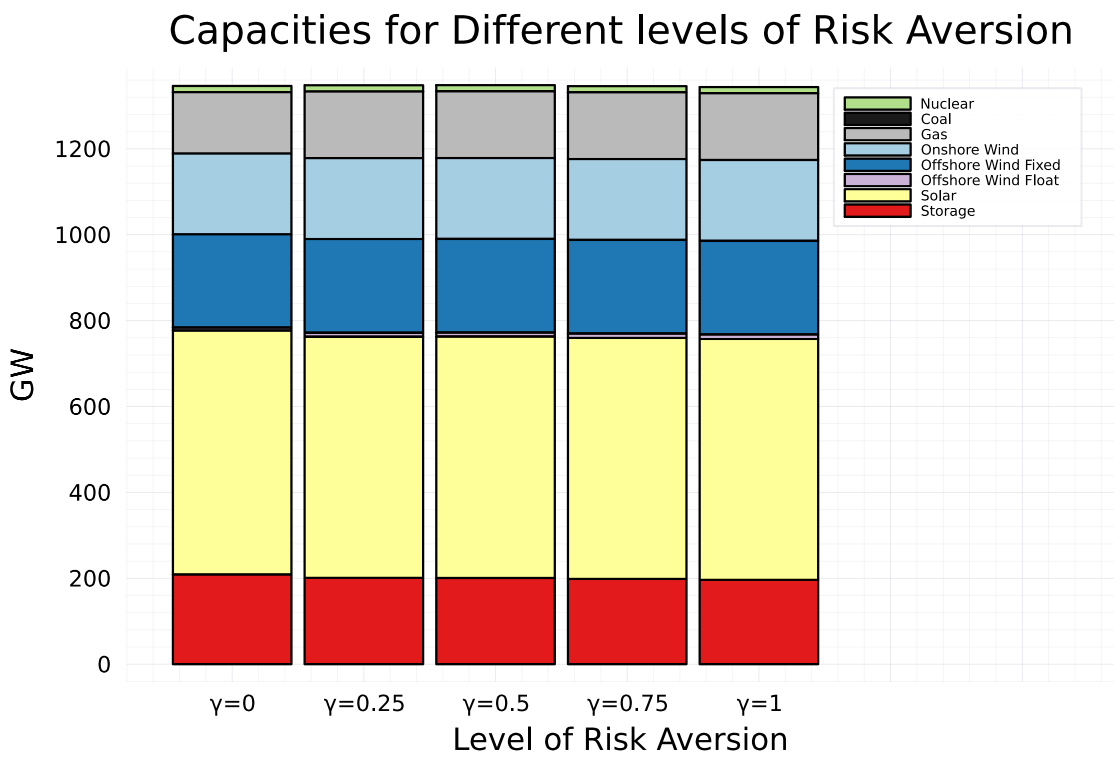


Figure 22: Capacity mix for increasing risk aversion with CO2 Cap policy

Figure 22 and Table 36 outlines the capacity mix for different levels of risk aversion under CO_2 Cap policy. The capacity mix is very stable under the CO_2 Cap policy. The emission cap, outlined in subsubsection 4.5.5, is strict, leaving the model with less degree of freedom. Hence, few changes can be observed.

However, a small increment in gas capacity can be observed. When the model is risk-averse ($\gamma > 0$), it increases the gas capacity to gain flexible capacity, to easier meet demand in the hours where the VRES availability is not sufficient. Additionally, as the capacity limit is met for onshore wind, fixed offshore wind, and solar capacity, a small increment in floating offshore wind is presented with an increasing level of risk aversion. In spite of floating offshore wind having high investment costs, the central planner with a high level of risk aversion sees it as more sufficient to increase the floating offshore wind capacity than to struggle to meet demand and pay the price of NSE.

	Capacities [GW] $\gamma = 0$	Capacities [GW] $\gamma = 0.25$	Capacities [GW] $\gamma = 0.5$	Capacities [GW] $\gamma = 0.75$	Capacities [GW] $\gamma = 1$
Nuclear	14.5	14.5	14.5	14.5	14.5
Coal	0.0	0.0	0.0	0.0	0.0
Gas	142.9	155.1	155.2	155.2	155.3
Onshore Wind	188.2	188.2	188.2	188.2	188.2
Offshore Wind Bottom Fixed	217.0	218.2	218.2	218.2	218.2
Offshore Wind Floating	6.9	9.3	9.3	10.0	10.6
Solar	568.0	561.6	562.3	561.5	560.7
Storage	208.8	201.0	200.5	198.4	196.3

Table 36: Capacities for different levels of risk-aversion for the risk-averse model with CO2 Cap policy.

5.4.3 Capacity Mix with CO2 Tax Policy

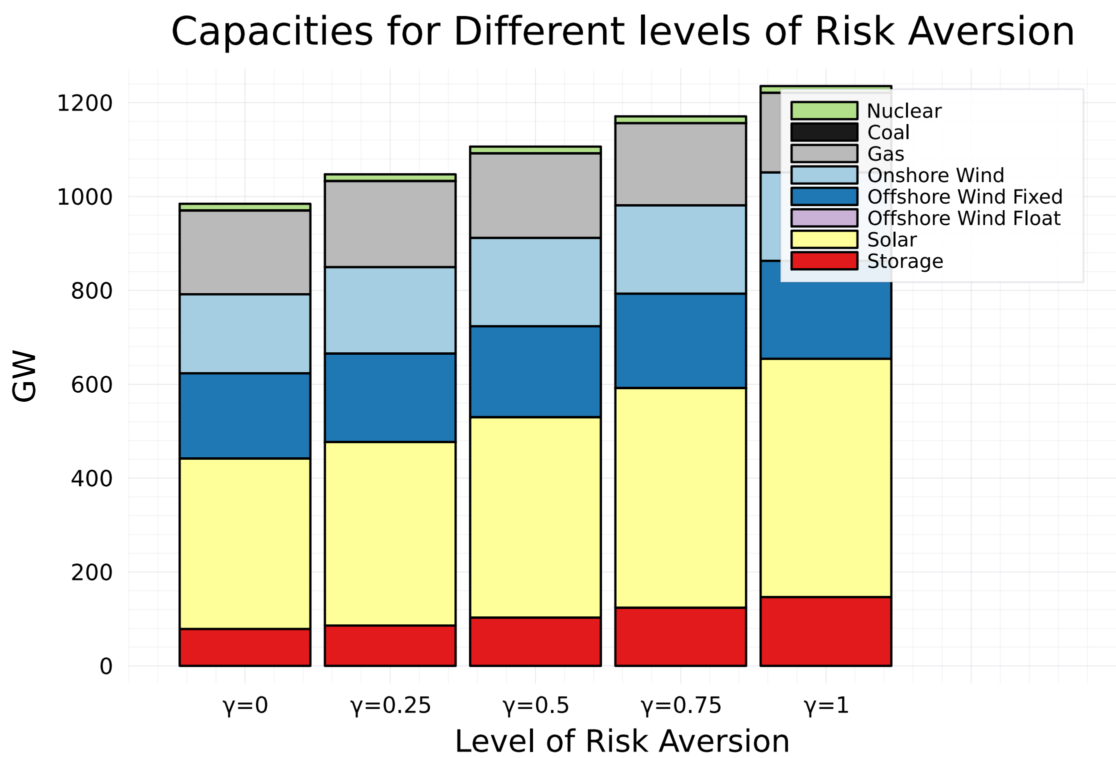


Figure 23: Capacity mix for increasing risk aversion with CO2 Tax policy

The capacity mix for different levels of risk aversion under the CO_2 Tax policy is shown in Figure 23 and Table 37. Firstly, a great change in the capacity mix with risk aversion can be observed. As the model gets more risk-averse, it strives to reduce the risk of paying the cost of the CO_2 Tax. Consequently, the investments in VRES increase notably. The solar capacity increased by almost 40% from $\gamma = 0$ to $\gamma = 1$, and onshore and fixed offshore wind both increased by over 14% in the same interval. Consequently, the risk-averse stochastic model can rely less on gas power generation.

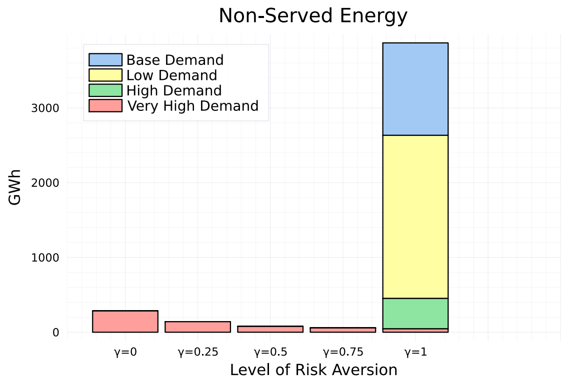
As a result of the increase in VRES capacity, the risk-averse stochastic model also builds more storage capacity with risk aversion. This is to exploit the production from VRES sources better.

The gas capacity increase from $\gamma = 0$ to $\gamma = 0.25$ before decreasing towards extreme risk aversion ($\gamma = 1$). This happens as a result of the cost of NSE being weighted more than the cost of the CO_2 Tax. Hence, the risk-averse central planner finds it most important to reduce NSE due to its high costs. Subsequently, the cost of the CO_2 Tax is more and more weighted with risk aversion resulting in a decrease in gas capacity.

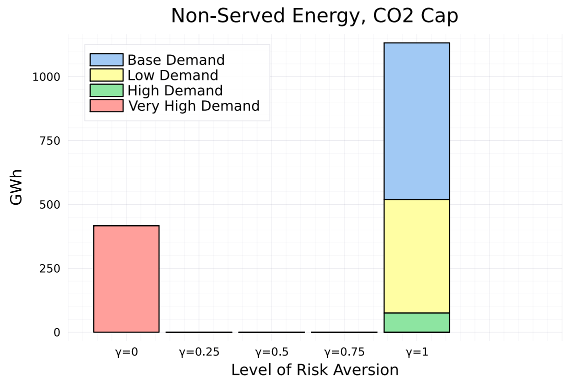
	Capacities [GW] $\gamma = 0$	Capacities [GW] $\gamma = 0.25$	Capacities [GW] $\gamma = 0.5$	Capacities [GW] $\gamma = 0.75$	Capacities [GW] $\gamma = 1$
Nuclear	14.5	14.5	14.5	14.5	14.5
Coal	0.0	0.0	0.0	0.0	0
Gas	178.3	183.3	180.1	175.1	169.7
Onshore Wind	168.4	184.1	188.2	188.2	188.2
Offshore Wind Bottom Fixed	181.7	188.5	193.9	201.1	208.7
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0
Solar	363.0	390.9	426.8	468.0	507.6
Storage	78.6	85.9	102.8	123.7	146.5

Table 37: Capacities for different levels of risk-aversion with CO2 Tax policy.

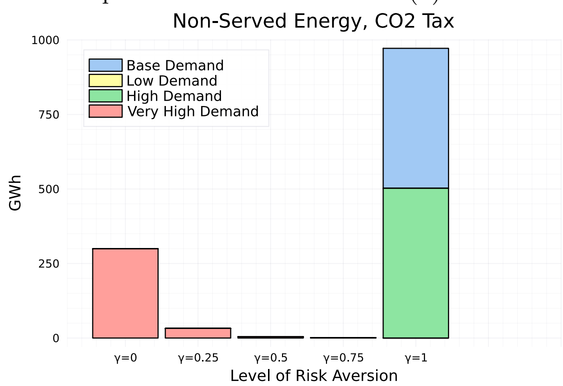
5.4.4 Non-Served Energy



(a) NSE with no climate policies



(b) NSE with CO2 Cap policy



(c) NSE with CO2 Tax

Figure 24: NSE for each demand scenario for different levels of risk aversion

The risk-averse central planner strives to avoid the high cost of NSE, and this is clearly shown in Figure 24 and in Table 38, Table 39 and Table 40. However, some odd results appear for the base-, low-, and high-demand scenarios for extreme risk-aversion under all the different policy options. The actual NSE in these demand scenarios will be zero. Nevertheless, great amounts of NSE can be seen in these scenarios in Figure 24. For extreme risk-aversion, the model only focuses on avoiding the cost of NSE in the worst-case scenario, ergo the very high demand scenario. Consequently, a non-existent NSE will appear in the lower demand scenarios. To ensure that the NSE actually is zero for the lower demand scenarios as well, the deterministic model was run for all demand scenarios, constrained to the capacities determined by the extreme risk-averse models. This resulted in zero NSE for the base-, low-, and high-demand scenarios for all the policy options for the extreme risk-averse model.

	Non-Served Energy [GWh] $\gamma = 0$	Non-Served Energy [GWh] $\gamma = 0.25$	Non-Served Energy [GWh] $\gamma = 0.5$	Non-Served Energy [GWh] $\gamma = 0.75$	Non-Served Energy [GWh] $\gamma = 1$
Base Demand Scenario	0.00	0.00	0.00	0.00	1235.97
Low Demand Scenario	0.00	0.00	0.00	0.00	2181.44
High Demand Scenario	0.00	0.00	0.00	0.00	406.17
Very High DemandScenario	284.58	141.14	77.81	57.56	45.42

Table 38: Non-Served Energy for different levels of risk-aversion with no climate policies.

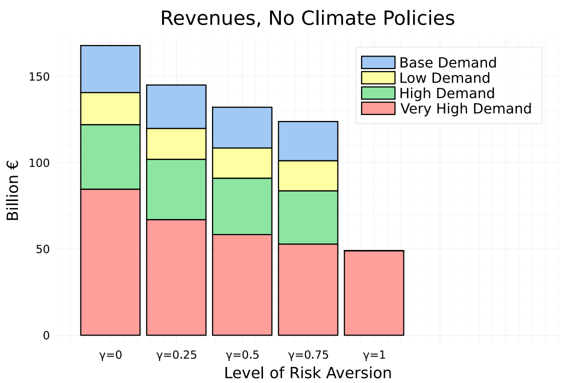
	Non-Served Energy [GWh] $\gamma = 0$	Non-Served Energy [GWh] $\gamma = 0.25$	Non-Served Energy [GWh] $\gamma = 0.5$	Non-Served Energy [GWh] $\gamma = 0.75$	Non-Served Energy [GWh] $\gamma = 1$
Base Demand Scenario	0.00	0.00	0.00	0.00	613.60
Low Demand Scenario	0.00	0.00	0.00	0.00	443.34
High Demand Scenario	0.00	0.00	0.00	0.00	75.28
Very High Demand Scenario	416.37	0.00	0.00	0.00	0.00

Table 39: Non-Served Energy for different levels of risk-aversion with CO2 Cap policy.

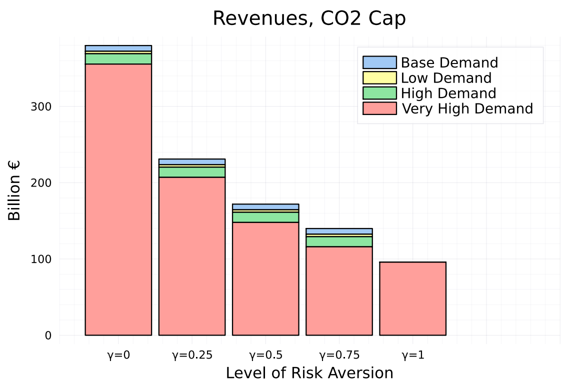
	Non-Served Energy [GWh] $\gamma = 0$	Non-Served Energy [GWh] $\gamma = 0.25$	Non-Served Energy [GWh] $\gamma = 0.5$	Non-Served Energy [GWh] $\gamma = 0.75$	Non-Served Energy [GWh] $\gamma = 1$
Base Demand Scenario	0.00	0.00	0.00	0.00	469.59
Low Demand Scenario	0.00	0.00	0.00	0.00	0
High Demand Scenario	0.00	0.00	0.00	0.00	502.4
Very High Demand Scenario	299.34	32.26	4.18	0.99	0.00

Table 40: Non-Served Energy for different levels of risk-aversion with CO2 Tax policy.

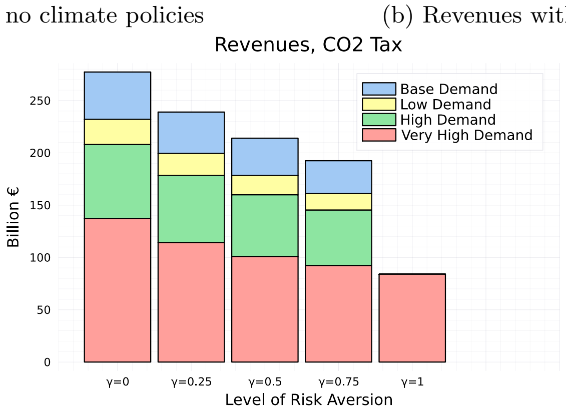
5.4.5 Revenues



(a) Revenues with no climate policies



(b) Revenues with CO2 Cap policy



(c) Revenues with CO2 Tax

Figure 25: Unweighted Revenues for each demand scenario for different levels of risk aversion

The risk-averse weights the importance of the revenues for the different demand scenarios differently. This is clearly shown in Appendix subsection A in Table A.50, Table A.51 and Table A.52 , as the base-, low-, and high-demand scenarios encounter a decreasing amount of the revenue with an increasing level of risk aversion. However, this is due to the weighting of the revenues, outlined in subsubsection 5.3.6, and can be re-weighted by using Equation 81 to represent the actual revenues for these demand scenarios.

Furthermore, for extreme risk aversion ($\gamma = 1$), the revenues are considered to be zero for all demand scenarios except the very high demand scenario, shown in Table A.50, Table A.51 and Table A.52. This can not be correct because in all these scenarios, power is generated, and thus, a price is paid for the power produced. As the values for the electricity price ($\lambda_{t,s,z}$) and the shadow price of electricity ($\mu_{r,t,s,z}$) are both set to zero for $\gamma = 1$, Equation 81 can not be utilized. This shows that the dual value of the power balance and the dual value of the capacity limit can no longer be used to represent the revenues for the risk-averse stochastic optimization model with $\gamma = 1$.

To determine the actual revenues in the base-, low-, and high-demand scenarios for extreme risk aversion, the following method can be utilized:

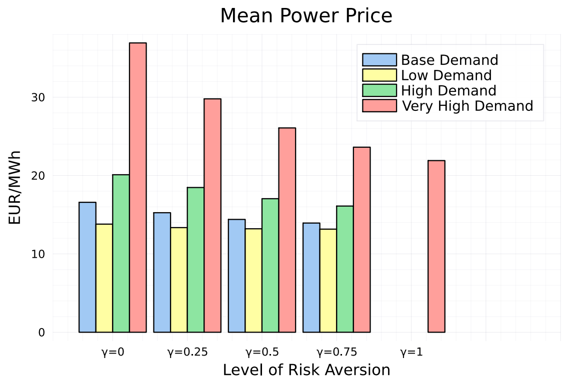
- Store the capacities determined by the risk-averse stochastic model with $\gamma = 1$.
- Constrain the deterministic model to the capacity mix determined by the risk-averse stochastic model.
- Run the deterministic model for each demand scenario.
- The actual values for $\lambda_{t,s,z}$ and $\mu_{r,t,s,z}$ can then be used to find the revenues for the base-, low-, and high-demand scenario for the extreme risk-averse capacity mix.

The revenues outlined in Figure 25 are unweighted using Equation 81. In Appendix subsection B, in Table B.53, Table B.54, and Table B.55 the revenues weighted back to the actual values for all demand scenarios using the method above. The risk-averse stochastic models with $\gamma < 1$ utilize Equation 81 to determine the actual power prices, further elaborated in subsubsection 5.4.6. These power prices are again used to calculate the revenue as described in subsubsection 4.5.8, Equation 75. How risk aversion and different policy options affect the revenues are further elaborated in section 6.

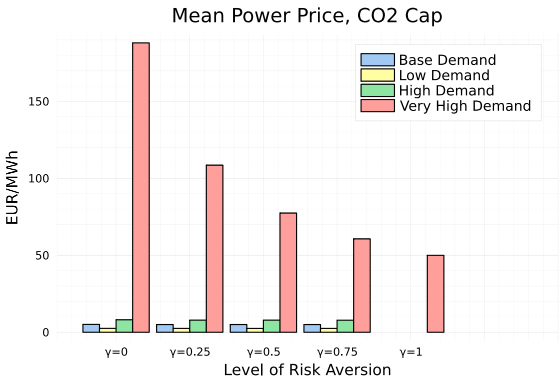
It is worth noticing that all revenues decrease with risk aversion in the very high demand scenario. This is closely linked to the power prices described in subsubsection 5.4.6. Furthermore, the revenues are found to be greater in the lower demand scenarios under no climate policies and under the CO_2 Tax policy. None of the models will struggle to meet demand in these scenarios, but the prices will be sufficient for the generators to gain revenues, as the price is set by the marginal unit, and the CO_2 Tax adds on to the marginal cost of the emitting units. In contrast, the model with the CO_2 Cap policy has such a great amount of VRES with low marginal costs that these will cover most of the demand in the lower demand scenarios, resulting in a low power price and, therefore, a low revenue.

5.4.6 The Affect of Risk Aversion on Power Prices

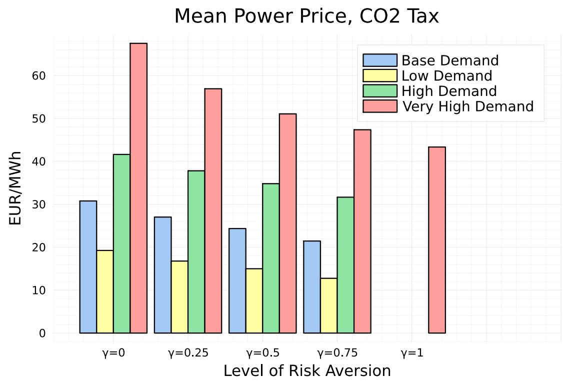
As earlier discussed in subsubsection 5.3.6, the power prices ($\lambda_{t,s,z}$) are weighted by the risk-averse model and can be weighted back using Equation 81 to display the actual power price. For the simulations with extreme risk aversion, the method described in subsubsection 5.4.5 is utilized.



(a) Average power price with no climate policies



(b) Average power price with CO2 Cap policy



(c) Average power price with CO2 Tax

Figure 26: Average unweighted power price for each demand scenario for different levels of risk aversion for price zone 1

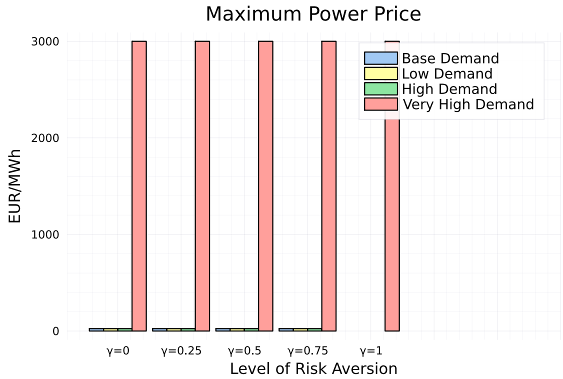
For the weighted average power prices are shown in Appendix subsection C, in Table C.56, Table C.57 and Table C.58, some trends can be observed. For the very high demand scenario under all the different policies, the average power price increase with risk aversion. However, the magnitude of the increment differs between the different policy options. For the other demand scenarios, the opposite can be observed. The average power price in the base-, low-, and high-demand scenario decreases with risk aversion. This is a result of the weighting of the power prices described in Equation 80. The risk-averse central planner values the power price in the lower demand scenarios less with an increasing level of risk aversion. For high levels of risk aversion, the central planner focus on the costs and revenues in the worst-case scenario. Thus, the prices in the lower demand scenarios are valued less with risk aversion.

However, investigating the actual average power prices calculated using Equation 81, outlined in Figure 26, and in Appendix subsection D, in Table D.59, Table D.60, and Table D.59, presents some different results. Firstly, the prices are now higher due to the recalculations in all demand scenarios and for all levels of risk aversion. One exception is for the very high demand scenario for extreme risk aversion, where the price is the same as is in Figure 26, as the extreme risk-averse central planner weights this scenario 100%.

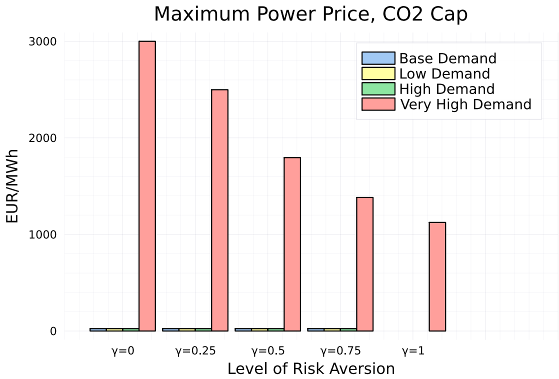
Following, the results indicate that an increasing level of risk aversion tends to decrease the average power prices for all demand scenarios under all climate policy options. The model under CO_2 Cap policy tend to have the lowest prices for the lower demand scenarios due to a great amount of

VRES in the capacity mix with low marginal costs. However, for the very high demand scenario, the average price is the highest for the model with a CO_2 Cap. This happens because, for this scenario, the model struggles more to meet the demand for all hours and, at the same time, keep within the carbon emission cap. Thus, the power price is increased to ensure power generation.

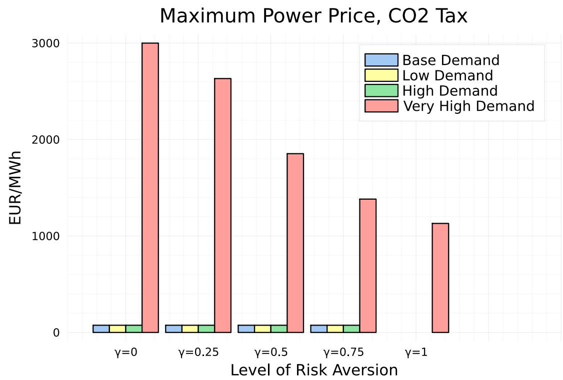
The power prices under the CO_2 Tax policy are high because the cost of the CO_2 Tax adds on to the marginal cost of the emitting units. When the installed gas capacity is needed and generates power, it will serve as the marginal unit as it has the highest marginal cost, shown in subsubsection 4.5.1. The CO_2 Tax cost of power generation will add to the marginal costs resulting in an overall higher power price. The power price decrease with risk aversion as a result of more VRES and storage capacity being built, making the system less dependent on gas power generation.



(a) Maximum power price with no climate policies



(b) Maximum power price with CO2 Cap policy



(c) Maximum power price with CO2 Tax

Figure 27: Maximum power price for each demand scenario for different levels of risk aversion for price zone 1

The weighted maximum power prices also decrease with risk aversion in the base-, low-, and high-demand scenario, as displayed in Appendix subsection E, in Table E.62, Table E.63, and Table E.64. Similarly, as for the average power price this is because the central planner values the very high demand scenario more with an increasing level of risk aversion.

The actual maximum power prices are presented in Figure 27, and in Appendix subsection F in Table F.65, Table F.66, and Table F.67. For $\gamma < 1$, the maximum power price is determined using Equation 81, and for $\gamma = 1$, the method described in subsubsection 5.3.6 is utilized. These tables present some interesting results that ensure that the model works as expected.

First of all, the maximum cost in the models with no climate policy and with CO_2 Cap policy has maximum prices equal to the variable cost of gas capacity or coal capacity in the base-, low-, and high-demand scenario. As known from Figure 24, there are no NSE in these scenarios, implying that the model has enough capacity to serve the demand for all hours $t \in T$. Consequently, the maximum price will be equal to the highest variable cost of the technologies generating power, which mainly is gas. However, for the model with no climate policy, a sufficient amount of coal capacity is built for $\gamma > 0.5$ to serve the low-demand scenario without gas, resulting in a lower maximum power price.

The reason for the high maximum prices for the model with CO_2 Tax is that the tax paid for emitting CO_2 is added to the variable costs in the model, outlined in subsubsection 5.3.5. Thus, the cost of the marginal unit, which is gas, will increase.

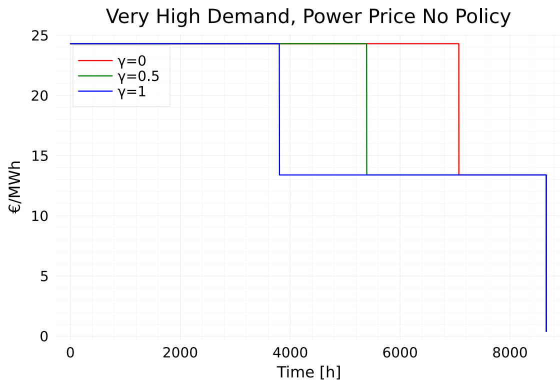
For the base-, low-, and high-demand scenarios for the model with CO_2 Tax, Table F.67, a significantly higher maximum power price is presented. This is because the CO_2 Tax works as an additional variable cost, adding to the variable cost presented in Table 2. The new marginal cost for the different generation technologies under CO_2 Tax policy can be calculated using Equation 82.

$$C_r^{var} + \xi_r \chi_r \tag{82}$$

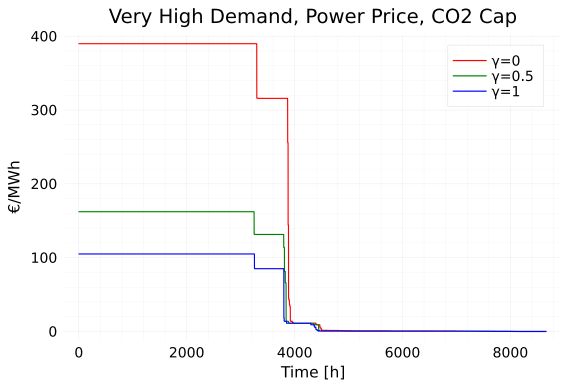
This results in the following variable costs for coal and gas shown in Equation 83 and Equation 84, respectively. This explains why higher prices can be observed in the lower demand scenarios for the models with CO_2 Tax policy.

$$C_{coal}^{var} = 13.4 + 120[/tCO2] \cdot 0.986[tCO2/MWh] = 131.72[/MWh] \tag{83}$$

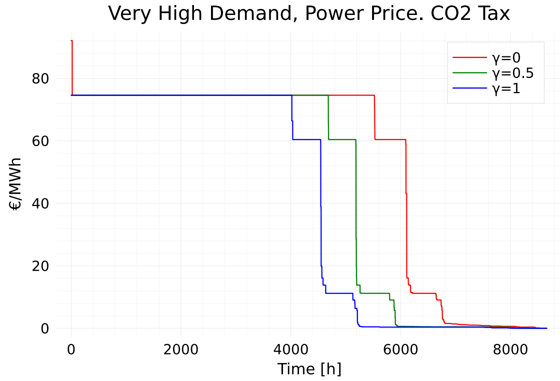
$$C_{coal}^{var} = 24.31 + 120[/tCO2] \cdot 0.419[tCO2/MWh] = 74.59[/MWh] \tag{84}$$



(a) No climate policy



(b) CO2 Cap

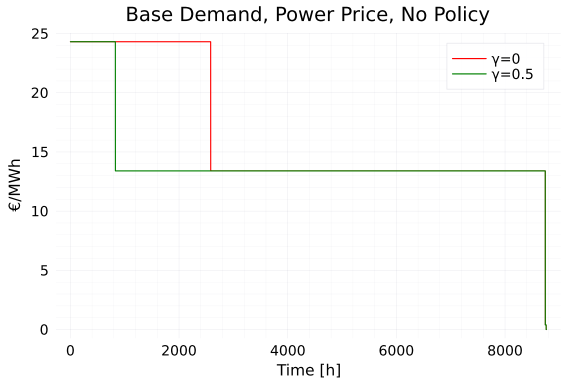


(c) CO2 Tax

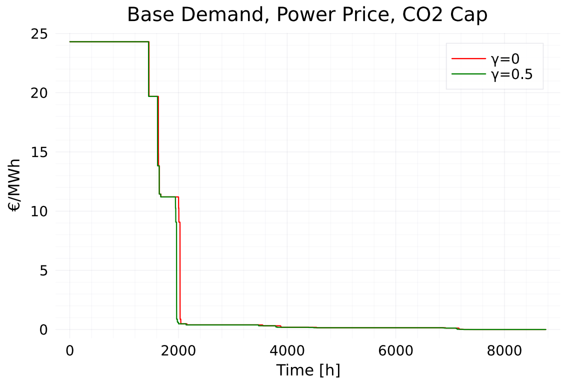
Figure 28: Duration Curve for the power price from hour 100 to 8760 for the very high demand scenario, for different policy options and different levels of risk aversion.

Figure 28 show the duration curve of the actual power price in the very high demand scenario for the models with $\gamma = 0$, $\gamma = 0.5$, and $\gamma = 1$. The first hours are excluded from the duration curve because some of these hours have a power price of 3000 €/MWh. Leaving out these peak hours enables analyzing the remaining hours in more detail.

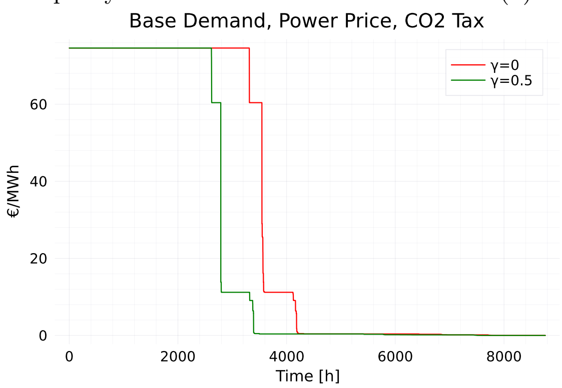
All these curves show the trend that the power price decrease with risk aversion under all policy options. It is also worth noticing that the reduction in the price is non-linear with risk aversion.



(a) No climate policy



(b) CO2 Cap

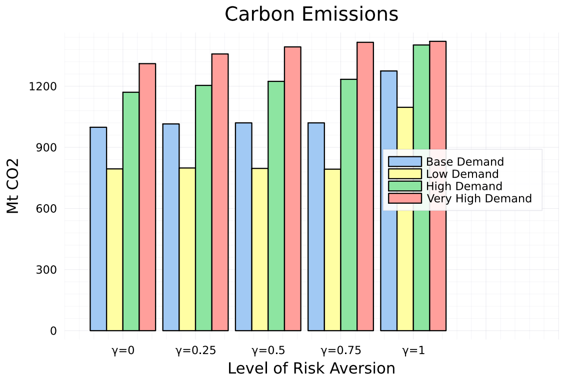


(c) CO2 Tax

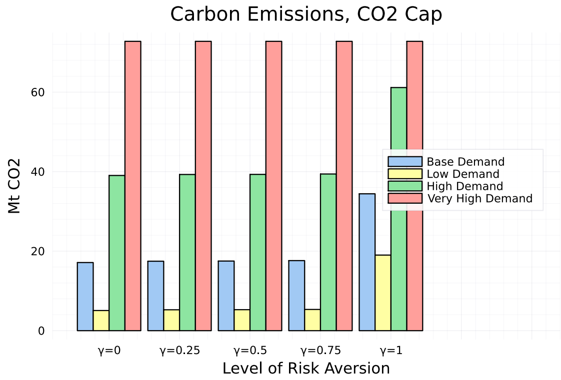
Figure 29: Duration Curve for the power price from hour 1 to 8760 for the Base demand scenario, for different policy options and different levels of risk aversion.

Figure 29 show the duration curve for the actual power price in the base-demand scenario for $\gamma = 0$ and $\gamma = 0.5$ for all hours $t \in T$. The same trend as in Figure 28 is present, with a reduction of the power price with risk aversion. However, the differences here a minor as the models does not struggle to meet demand. The reduction in power price consequence of the increasing VRES capacity with a lower marginal cost from $\gamma = 0$ to $\gamma = 0.5$.

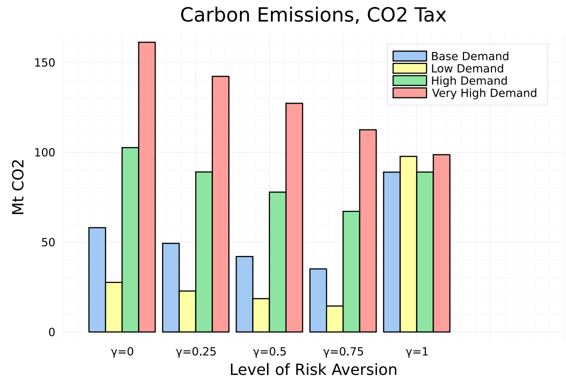
5.4.7 Carbon Emissions



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax

Figure 30: Carbon emissions for each demand scenario for different levels of risk aversion

The carbon emissions are closely linked to the capacity mix and generation pattern. Thus, risk aversion will affect carbon emissions. For the risk-averse stochastic model with no climate policies, shown in Figure 30a and Table 41, the carbon emissions increase with risk-aversion for all demand scenarios. This is a result of the increasing investment in coal capacity with increasing levels of risk aversion. Consequently, leading to more carbon emissions.

When the CO_2 Cap policy is introduced to the risk-averse stochastic model, the carbon emissions drop dramatically compared to Figure 30a. Following, as shown in Figure 24b and Table 42, all models have emissions equal to the cap at 72.78 MtCO2 in the very high demand scenario. This aligns well with Table 44, as the models only generate a CO_2 price for the very high demand scenarios, which means that it is only in these scenarios the model struggles to meet the cap. Additionally, it is possible to observe a slight increase in carbon emissions for the other demand scenarios with an increasing level of risk aversion. This agrees well with the fact that the risk-averse central planner weights the very high demand scenario 100% for extreme risk aversion. Consequently, the actual emissions in the lower demand scenarios could be determined by running the model deterministically for each of the lower demand scenarios with the capacity mix presented by the extreme risk-averse central planner under the CO_2 Cap policy.

The carbon emissions are higher for all demand scenarios and for all levels of risk aversion compared to the model with the CO_2 Cap policy. However, it decreases more with risk aversion as more VRES capacity is introduced. The same issue is present here for the lower demand scenarios for extreme risk aversion and can be solved equally, as described in the paragraph above.

	Emissions [MtCO2] $\gamma = 0$	Emissions [MtCO2] $\gamma = 0.25$	Emissions [MtCO2] $\gamma = 0.5$	Emissions [MtCO2] $\gamma = 0.75$	Emissions [MtCO2] $\gamma = 1$
Base Demand Scenario	998.43	1014.82	1020.07	1020.02	1274.86
Low Demand Scenario	794.23	798.61	796.52	792.79	1096.37
High Demand Scenario	1170.34	1203.99	1223.74	1233.81	1402.40
Very High DemandScenario	1310.82	1358.36	1393.06	1415.45	1420.22

Table 41: Carbon emissions for different levels of risk-aversion with no climate policy

	Emissions [MtCO2] $\gamma = 0$	Emissions [MtCO2] $\gamma = 0.25$	Emissions [MtCO2] $\gamma = 0.5$	Emissions [MtCO2] $\gamma = 0.75$	Emissions [MtCO2] $\gamma = 1$
Base Demand Scenario	17.14	17.47	17.51	17.62	34.43
Low Demand Scenario	5.07	5.26	5.28	5.34	19.01
High Demand Scenario	39.04	39.29	39.31	39.41	61.16
Very High DemandScenario	72.78	72.78	72.78	72.78	72.78

Table 42: Carbon emissions for different levels of risk-aversion with CO2 Cap policy

	Emissions [MtCO2] $\gamma = 0$	Emissions [MtCO2] $\gamma = 0.25$	Emissions [MtCO2] $\gamma = 0.5$	Emissions [MtCO2] $\gamma = 0.75$	Emissions [MtCO2] $\gamma = 1$
Base Demand Scenario	58.05	49.31	42.00	35.10	88.95
Low Demand Scenario	27.59	22.80	18.56	14.45	97.71
High Demand Scenario	102.60	89.95	77.83	67.10	89.00
Very High DemandScenario	161.24	142.26	127.26	112.54	98.68

Table 43: Carbon emissions for different levels of risk-aversion with CO2 Tax policy

5.4.8 CO2 Price, A Part of the CO2 Cap

Table 44 outline the CO_2 Price generated as a part of the CO_2 Cap in each demand scenario for different levels of risk aversion. A CO_2 Price is presented for all levels of risk aversion in the very high demand scenario, which aligns well with the results presented in Table 42. The models struggles to meet the carbon emission cap in the very high demand scenario. Thus, a CO_2 price is added as an additional policy, striving to keep the carbon emission within the limits of the cap. However. similarly to the power price, the CO_2 price is weighted by the model. Consequently, Equation 81 can be used to find the actual CO_2 Price, shown in Table 44. This show that the CO_2 Price decrease in the very high demand scenario for an increasing level of risk aversion.

	CO2 Price [€/tCO2] $\gamma = 0$	CO2 Price [€/tCO2] $\gamma = 0.25$	CO2 Price [€/tCO2] $\gamma = 0.5$	CO2 Price [€/tCO2] $\gamma = 0.75$	CO2 Price [€/tCO2] $\gamma = 1$
Base Demand Scenario	0.00	0.00	0.00	0.00	0.00
Low Demand Scenario	0.00	0.00	0.00	0.00	0.00
High Demand Scenario	0.00	0.00	0.00	0.00	0.00
Very High Demand Scenario	872.44	483.56	274.37	246.08	192.63

Table 44: CO2 price as a complementary policy to the CO2 Cap for different levels of risk-aversion.

5.4.9 Total System Cost

The Total System Costs (TSC) for the different levels of risk aversion under different policy options are described in Table 45. It shows the cost of evolving the generation technology mix toward a mainly renewable technology mix, enabling the power sector to reach the ambitious climate goals set for 2050. However, this transformation is expensive. Comparing the risk-neutral model with no climate policy and with CO_2 Cap, the TSC increase by over 57%. This is a consequence of the great amount of VRES capacity installed to cover the power generated from coal and gas in the model with no climate policies.

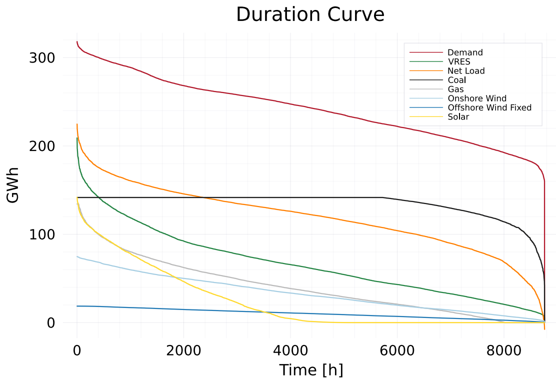
Furthermore, the TSC increase with risk aversion under all climate policy options. The increment is most prominent for the model with CO_2 Tax policy, with an increase in the TSC of 7.98 billion euros from $\gamma = 0$ to $\gamma = 1$. The main driver for this increment in TSC is the enlargement in VRES capacity with risk aversion, which has high investment costs. The increment for the model with CO_2 Cap is 2.7 billion euros from $\gamma = 0$ to $\gamma = 1$. This is a result of fewer degrees of freedom as the model is constrained by the carbon emission cap. Consequently, fewer changes are made to the model.

	Total System Cost $\gamma = 0$	**Total System Cost** $\gamma = 0.25$	**Total System Cost** $\gamma = 0.5$	**Total System Cost** $\gamma = 0.75$	**Total System Cost** $\gamma = 1$
No Climate Policy [Billion €]	41.88	43.71	45.38	46.94	48.43
CO2 Cap [Billion €]	66.09	66.85	67.50	68.14	68.79
CO2 Tax [Billion €]	68.71	65.19	71.62	74.29	76.69

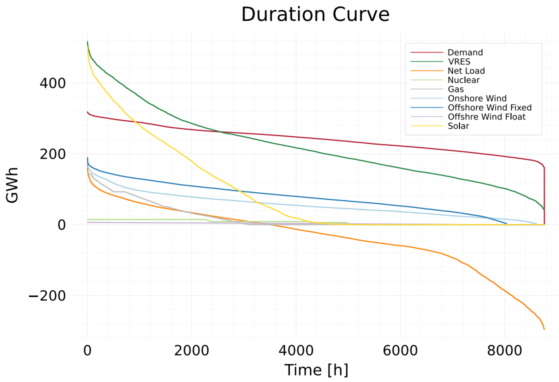
Table 45: Total System Cost for different levels of risk aversion and different policy options.

5.5 Cover of the Demand

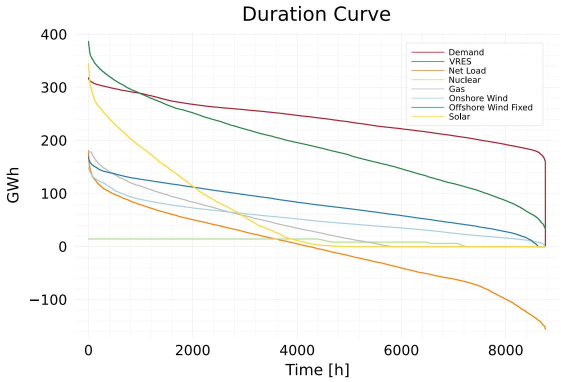
5.5.1 Duration Curves, Risk Neutral Stochastic Model



(a) No climate policy



(b) CO2 Cap



(c) CO2 Tax

Figure 31: Duration Curve for the risk-neutral stochastic model for the very high demand scenario

The duration curves in Figure 31 show how the demand in the very high demand scenario is covered by the generation sources. The *Net Load*, represented with the orange line in the charts, is the demand minus the power generated from VRESs, as outlined in Equation 85.

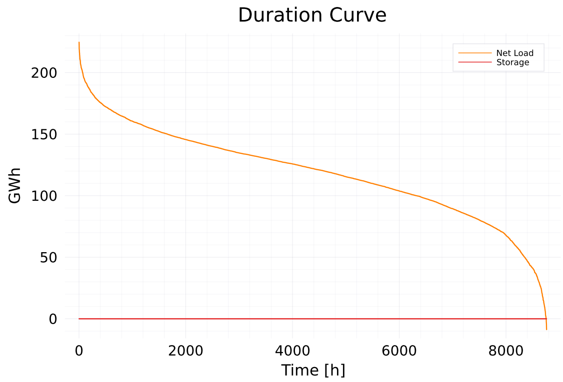
$$NetLoad = Demand - VRES \quad Generation \tag{85}$$

Figure 31a display how the demand is covered for the risk-neutral model with no climate policies. The Coal power generation is stable at around 140 GW for almost 6000 hours, as the high demand hours get covered by gas and VRES. It is interesting to notice that solar only are able to generate power for approximately 4000 hours throughout the time series, and of these hours, less than 50% are over 50 GW even though the installed capacity is 120.4 GW.

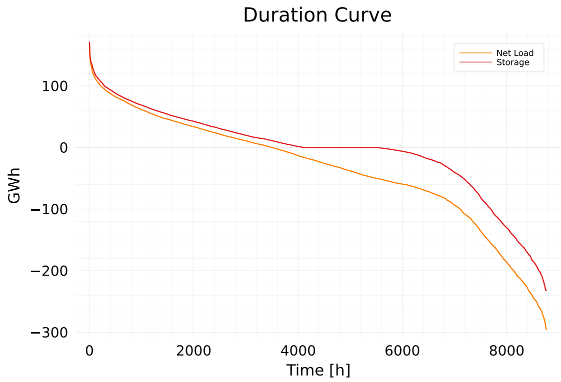
The behavior of the risk-neutral model with CO_2 Cap is outlined in Figure 31b. As the model strives to keep within the limit of the CO_2 Cap, a great magnitude of VRES capacity is built. Consequently, the production from VRES will be greater than the demand for several hours. This is clearly shown as the *Net Load* (orange line) is negative for over 50% of the year represented. However, all the produced power that exceeds the demand, represented as negative *Net Load*, does not go to waste. There is also a great storage capacity of 208.9 GW represented in the capacity mix. Figure 32b show how the model utilizes the storage capacity to store most of the excess power and employs this in hours where the VRES are not able to cover the demand. Thus, making the need for flexible thermal power production less intrusive.

The same characteristics can be observed in Figure 31c and Figure 32c. However, as the capacity mix for the risk-neutral model with CO_2 Tax has less VRES, the *Net Load* are negative for fewer hours and for less extent of capacity. Thus, less capacity of storage is installed to cover the excess power generated from VRESs.

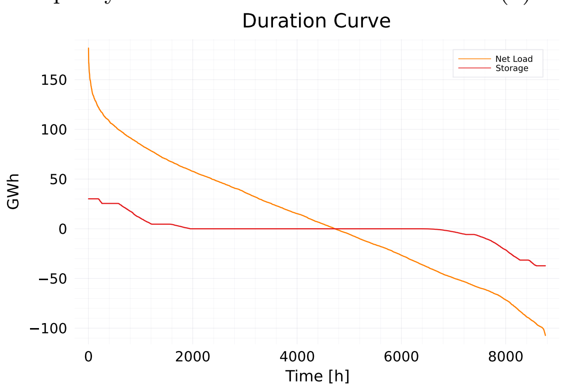
Both Figure 31 and Figure 32 help to ensure that the model works as intended.



(a) No climate policy



(b) CO2 Cap



(c) CO2 Tax

Figure 32: Duration Curve describing the relationship between Net-load and Storage for the risk-neutral stochastic model.

5.5.2 Demand Covered by VRES, Risk Neutral Stochastic Model

The week represented is week number 2 in the very high demand time series, represented as hour 168 to hour 336. This specific week is selected because it is the week throughout the whole time series that contains the most NSE, shown in Figure 33.

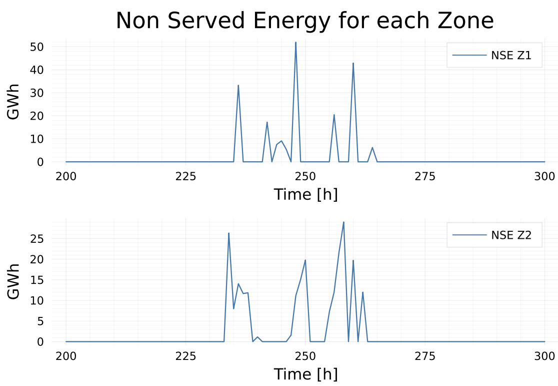
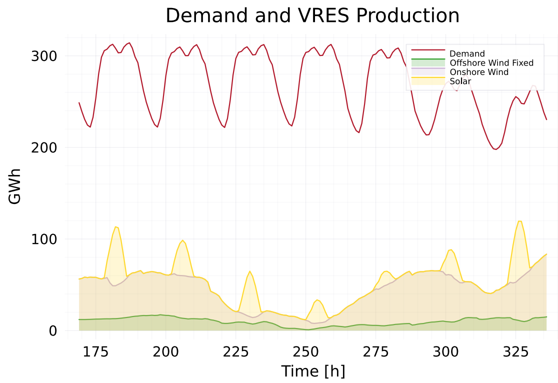
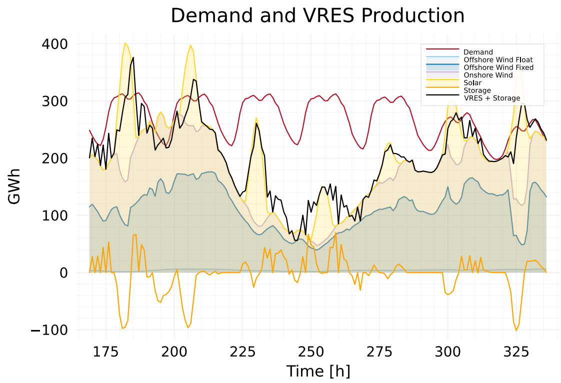


Figure 33: NSE for hours 200 to 300 for the risk-neutral model with CO2 Cap policy.

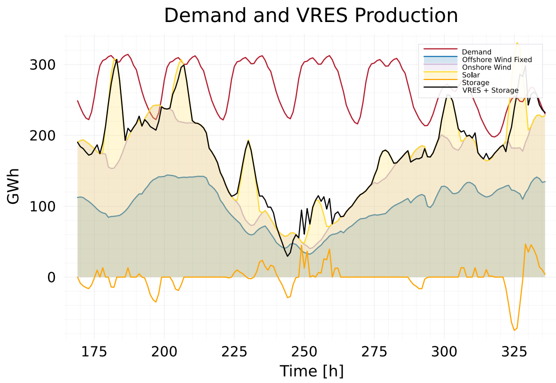
Figure 34a displays how the risk-neutral central planner utilizes the VRESs to cover a share of the load in the very high demand scenario when no climate policy is present. The main part of the load shedding occurs around hour 250, as outlined in Figure 33. Even though the VRES capacity represented in the risk-neutral model with no climate policies are relatively small, it is possible to observe a significant drop in VRES production for hours before and after hour 250. This phenomena is also present in Figure 34b and Figure 34c. The low production from VRES is a result of lacking availability of solar, onshore wind, and offshore wind occurring simultaneously. The amount of VRES capacity needed to ensure a normal power generation from the renewable resources for these hours is so high that the risk-neutral central planner considers the Value of Lost Load (VOLL) cheaper than the expense of building more capacity.



(a) No climate policy



(b) CO2 Cap



(c) CO2 Tax

Figure 34: How the VRES and Storage cover the demand in the very high demand scenario for one week for the risk-averse stochastic model.

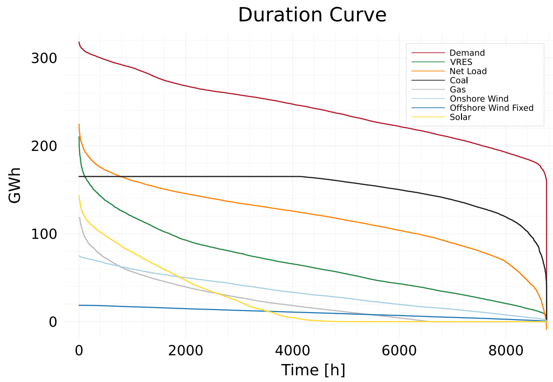
Investigating Figure 34b, it is clear how the risk-neutral central planner under the CO_2 Cap policy utilizes the storage in combination with VRES power generation to minimize the need for emitting generation technologies. For the first 48 hours of the week represented, a normal availability of solar, onshore wind, and offshore wind is present. The storage, represented with the orange line, discharges in periods when the VRES production is not sufficient to meet demand and charges in periods where the VRES production exceeds the demand. Hence, the storage works as intended.

Furthermore, it is striking how few hours the risk-neutral central planner is able to cover the demand with VRES generation under CO_2 Tax policy, shown in Figure 34c. This is due to less installed VRES and storage capacity. As a result of less excessive renewable power generation, the use of storage is reduced, as shown in Figure 34c compared to Figure 34b.

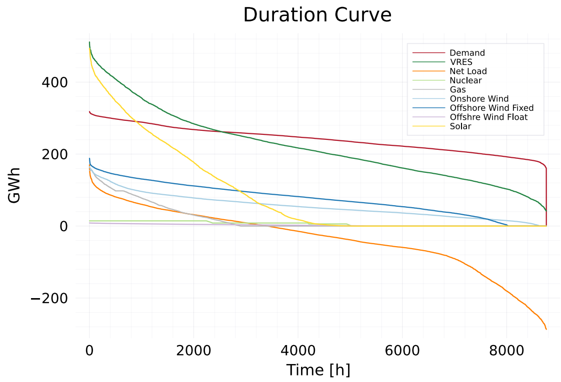
It is worth noticing that the discharge line from the storage is jagged, which can seem odd. However, as the storage for this model is constrained similarly as in the *GenX model* [44], and it works as intended, the jagged discharge is not further investigated as it is out of scope for this thesis.

5.5.3 Duration Curves, Risk Averse Stochastic Model

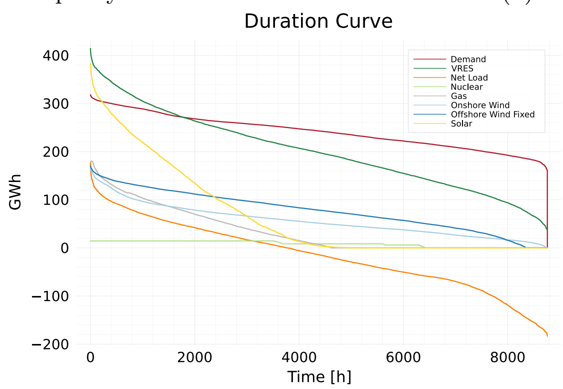
All duration curves for the risk-averse stochastic model have $\gamma = 0.5$ and are plotted for the very high demand scenario.



(a) No climate policy



(b) CO2 Cap



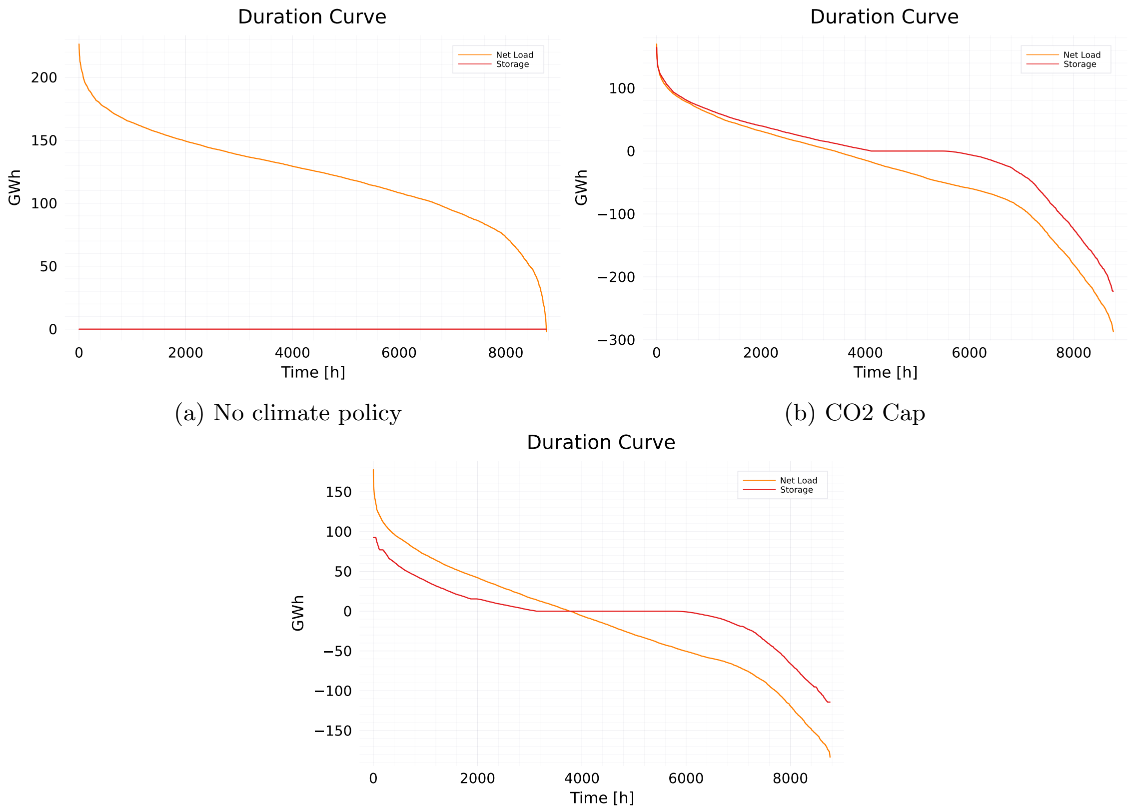
(c) CO2 Tax

Figure 35: Duration Curve for the risk-averse stochastic model for the very high demand scenario

The risk-averse model under no climate policy, Figure 35a, has a higher coal power generation compared to the risk-neutral model, Figure 31a. The risk-averse central planner builds a greater amount of coal capacity to avoid the high cost of NSE, resulting in only 77.8 GWh of NSE compared to 284.5 GWh for the risk-neutral model with no climate policies.

The duration curve for the risk-averse stochastic model with CO_2 Cap shown in Figure 35b is very similar to Figure 31b because the capacity mix for the two models is very similar. Consequently, the relationship between the *Net Load* and the storage in Figure 36b are very similar to Figure 32b.

As observed earlier in subsection 5.4, the cost of the CO_2 Tax results in less VRES and storage capacity compared to the model with CO_2 Cap. This is displayed in Figure 35c, as the gas capacity is higher and it is generating power for more hours. This also affects the behavior of the storage. As the storage capacity for the risk-averse model has increased compared to the risk-neutral, it is capable of covering more of the excess power produced, shown in Figure 36c. Consequently, it can avoid load shedding and the high cost of the CO_2 Tax from using gas power generation.



(a) No climate policy

(b) CO2 Cap

(c) CO2 Tax

Figure 36: Duration Curve describing the relationship between Net load and Storage for the risk-averse stochastic model.

5.5.4 Demand Covered by VRES, Risk Averse Stochastic Model

There are a very low amount of NSE present in the risk-averse stochastic models. However, some load shedding occurs for the model with no climate policy in the same week as for the risk-neutral stochastic model, shown in Figure 37. Thus, the same week as in subsubsection 5.5.2 is used for Figure 38 spanning from hour 168 to hour 336.

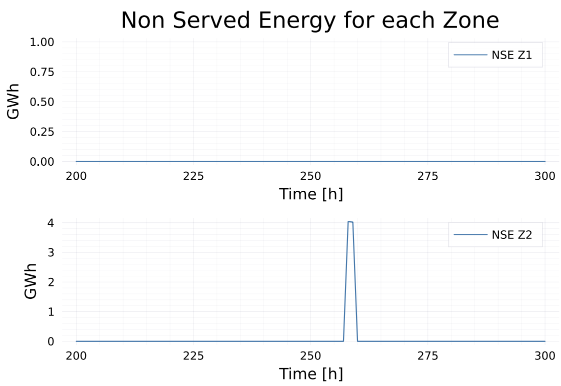
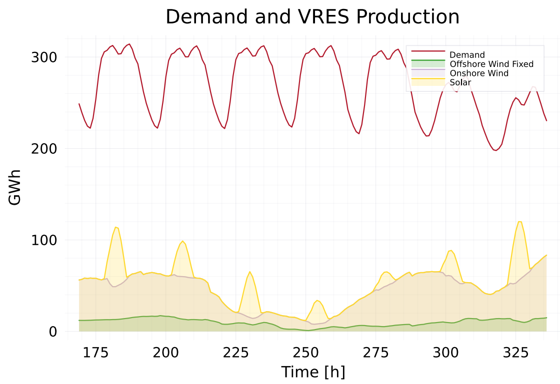
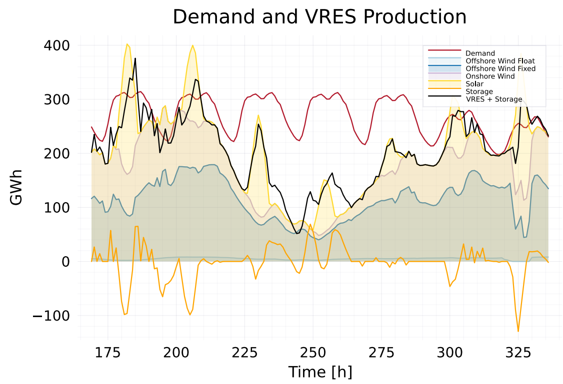


Figure 37: NSE for hours 200 to 300 for the risk-averse model with no climate policy.

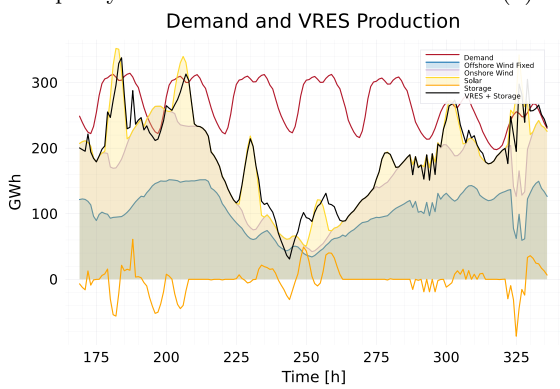
The same phenomenon, as in Figure 34, is present in Figure 38, as the availability for solar, offshore wind, and onshore wind drops in the same time period. However, this does not lead to a great amount of load shedding as the risk-averse central planner strives to avoid the high cost of NSE.



(a) No climate policy



(b) CO2 Cap



(c) CO2 Tax

Figure 38: How the VRES and Storage cover the demand in the very high demand scenario for one week for the risk-averse stochastic model.

For the risk-averse model with no climate policies, displayed in Figure 38a, it is possible to locate a small decrease in power generated from the VRES, as a result of less installed VRES capacity. Furthermore, Figure 38b show only small differences compared to the risk-neutral model displayed in Figure 34b. The most noteworthy difference is how the storage is managed differently by the risk-averse central planner compared to the risk-neutral central planner. The risk-averse central planner has to make changes in the utilization of the storage capacity to more efficiently meet the demand and avoid the cost of NSE.

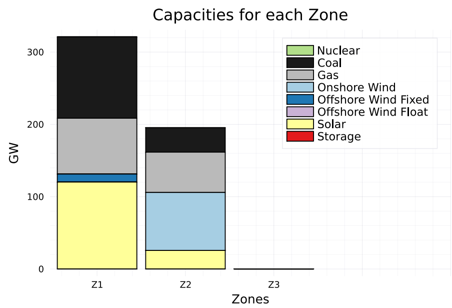
Figure 38c show that the installed VRES capacity only are able to serve the demand 100% for a couple of hours with a small amount of excess power. Consequently, the remaining demand has to be covered by the gas capacity to avoid the cost of NSE. The increased storage capacity, compared to the risk-neutral model, makes the effect of the storage greater than in Figure 34c.

5.6 Effect of New Ground Rent Tax on Existing Capacity

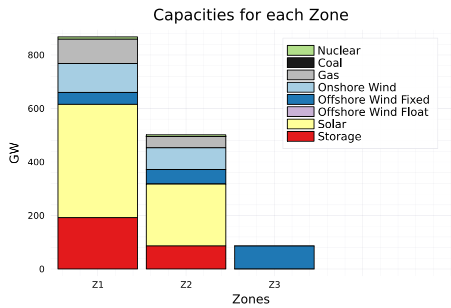
All over Europe, new taxes on wind power have been introduced as a result of the high prices of electricity due to the lack of gas after Russia invaded Ukraine. All over Europe the new *Windfall-Tax* is introduced in the Electricity Supply Industry (ESI), as a result of the significantly above average revenues experienced in the sector due to the high electricity prices [46]. However, the *Windfall-Tax* can vary from one county to another [81]. In Norway, there is a suggestion to introduce a Ground Rent Tax on new and existing onshore wind power plants pf 40% [62].

To better understand the effect that new taxation on existing wind power may have, an additional tax is introduced in the model. It is based on the ground principles of the ground rent tax, only taxing the net profit for those scenarios that a net profit is present. To calculate the cost of the tax, the risk-neutral stochastic model and the risk-averse ($\gamma = 0.5$) stochastic model is run for all climate policy options excluding the ground rent tax cost ($C^{tax}_{r,s}$). The ground rent tax is calculated using the method described in subsubsection 4.5.9, with a $TaxRate = 40\%$ for all the wind technologies in all the scenarios where net profit is generated. Following, the model is run again with the ground rent tax ($C^{tax}_{r,s}$) included, enabling an investigation of the effects of the taxation.

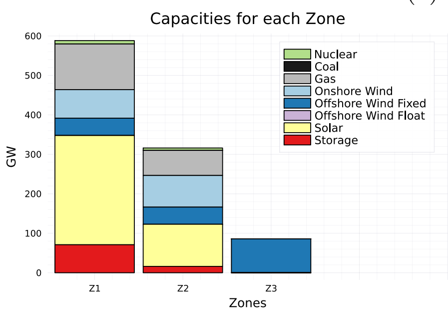
5.6.1 Capacities for The Risk Neutral Stochastic Model



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax

Figure 39: Capacities for the Risk Neutral model with Ground Rent Tax for the different climate policy options.

The effect of the ground rent tax for the risk-neutral stochastic model is outlined in Figure 39 and Table 46. For the model with no climate policies, only small differences can be found compared to the risk-neutral stochastic model without ground rent tax, outlined in subsection 5.2 Table 20. The coal capacity increased by 4.5% in Z1 to cover for the 44.22% (8.8 GW) decrease of offshore wind capacity in Z1.

More significant impacts can be found when the CO_2 Cap policy is introduced. In Z2, the offshore wind decreased by 37% from 87.4 GW to 55.1 GW after the introduction of the tax. Simultaneously, to cover this loss in generation capacity, a great increase of 60% in solar capacity and 131% in storage capacity is introduced. Surprisingly, the gas capacity decreased by almost 15% in Z2 compared to Table 20.

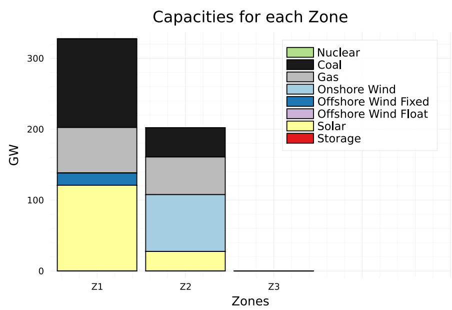
In Z3 for the risk-neutral stochastic model with CO_2 Cap, the model doesn't invest in floating offshore wind when the ground rent tax is introduced. This implies a capacity reduction of 6.9 GW in Z3, as the fixed offshore wind capacity does not get affected by the ground rent tax.

For the risk-neutral stochastic model with CO_2 Tax, a different reaction can be observed. The onshore wind capacity is reduced by 18% in Z1, from 88.2 GW to 72.3 GW. The fixed offshore wind capacity in Z2 is reduced by over 16% in Z2 from 52.0 GW to 43.5 GW. To cover for this reduction in capacity, the solar capacity increased by 5% and 6.6% in Z1 and Z2, respectively. The total amount of storage capacity also increased by 10.8% for all zones combined, compared to Table 20.

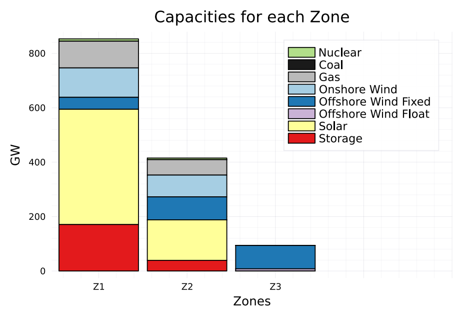
	Capacities [GW] No Climate Policies			**Capacities [GW] CO2 Cap Policy**			**Capacities [GW] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	8.5	6.0	0.0	8.5	6.0	0.0
Coal	112.5	33.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	77.3	55.8	0.0	91.5	42.7	0.0	115.7	63.6	0.0
Onshore Wind	0.0	80.2	0.0	108.0	80.2	0.0	72.3	80.2	0.0
Offshore Wind Bottom Fixed	11.1	0.0	0.0	43.9	55.1	85.8	43.9	43.5	85.8
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Solar	120.2	25.7	0.0	423.7	231.4	0.0	276.8	106.8	0.0
Storage	0.0	0.0	0.0	192.0	86.0	0.0	71.0	16.1	0.0

Table 46: Capacities for the risk-neutral stochastic model with Ground Rent Tax.

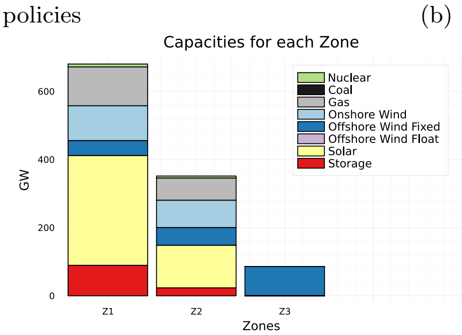
5.6.2 Capacities for The Risk Averse Stochastic Model



(a) No climate policies



(b) CO2 Cap policy



(c) CO2 Tax

Figure 40: Capacities for the Risk Averse model with Ground Rent Tax for the different climate policy options.

When the ground rent tax is introduced to the risk-averse central planner, some changes can be observed in Figure 40 and in Table 47 in comparison to Table 28 in subsubsection 5.3.1. Firstly, the fixed offshore wind in Z1 is reduced by over 13% in Figure 40a compared to **??**, and an additional 1.3 GW of coal capacity is added to cover the loss in wind capacity.

Two slight changes in wind capacity can also be observed for the risk-averse stochastic model with a CO_2 Cap policy. The fixed offshore wind capacity in Z2 is reduced by 4.6% from 88.5 GW to 84.4 GW, and the floating offshore wind in Z3 is reduced by 14% from 9.3 GW to 8 GW. To cover this reduction, an increase in solar and storage capacity of 7.4% and 4.6% is presented in Z2. Only small changes in the capacity mix are observed for the model with CO_2 Cap, compared to Table 28. This is because the model has few degrees of freedom under the carbon emission cap policy. Consequently, wind capacity has to be part of the capacity mix to meet demand and simultaneously keep within the limits of the cap, even though the costs increase.

Onshore wind capacity in Z1 is reduced by 5.4%, and fixed offshore wind in Z2 is reduced by 18.7% compared to Table 28 under the CO_2 Tax policy. The gas capacity is reduced by 0.8 GW. The solar capacity in Z1 increased by 1.8% or 5.6 GW, while in Z2, it is observed a more significant rise of 12.8 % or 14.2 GW. This additional solar capacity, in combination with a total increment of 9.9 GW of storage capacity, helps to cover for the lost wind capacity.

	Capacities [GW] No Climate Policies			**Capacities [GW] CO2 Cap Policy**			**Capacities [GW] CO2 Tax Policy**		
	Zone 1	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 1**	**Zone 2**	**Zone 3**
Nuclear	0.0	0.0	0.0	8.5	6.0	0.0	8.5	6.0	0.0
Coal	125.0	41.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gas	64.3	53.1	0.0	98.3	56.7	0.0	114.1	65.2	0.0
Onshore Wind	0.0	80.2	0.0	108.0	80.2	0.0	102.2	80.2	0.0
Offshore Wind Bottom Fixed	17.2	0.0	0.0	43.9	84.4	85.8	43.9	52.2	85.8
Offshore Wind Floating	0.0	0.0	0.0	0.0	0.0	8.0	0.0	0.0	0.0
Solar	121.0	27.6	0.0	423.7	148.9	0.0	322.23	124.73	0.0
Storage	0.0	0.0	0.0	170.7	39.1	0.0	89.3	23.3	0.0

Table 47: Capacities for the risk-averse stochastic model with Ground Rent Tax.

6 Discussion

The discussion addresses the most important findings of the thesis and put them in the context of existing literature and the challenges of the power system.

6.1 The Effect of Risk Aversion and Uncertainty on the Capacity Mix

The capacity mix for the risk-averse stochastic model with no climate policies, shown in Table 35, tends to increase the coal capacity and decrease gas and VRES capacity with risk aversion relative to the risk-neutral stochastic model. The risk-neutral ($\gamma = 0$) central planner weighs the different demand scenarios equally. The extreme risk-averse ($\gamma = 1$) central planner only values to minimize the costs and the CVaR in the worst-case scenario, which for a central planner is the very high demand scenario. Although the investment cost for coal capacity is over 130% of the investment cost for gas capacity, the lower variable costs for coal make it the better choice for the risk-averse central planner when no climate policies are present. This is due to the risk-averse central planner striving to minimize the costs in the very high demand scenario, consequently valuing coal as it has low variable cost making it the better solution if this scenario were to happen. On the other hand, the risk-neutral central planner weights all the demand scenarios equally, making gas more favorable due to lower investment costs, as this ensures lower costs if the very high demand scenario were not to happen.

Moreover, all the VRES are relatively unchanged with an increasing level of risk aversion under no climate policy. This is because the interplay between these VRES works sufficiently to serve an amount of the demand with very low variable costs. Additionally, solar power and onshore wind power are affordable due to acceptable investment costs. Solar has the lowest investment costs and variable costs of all the technologies available, making it a good investment even if the average capacity factor for solar is the lowest. The onshore wind capacity is mainly built in Z2 when no climate policies are present. This is because this zone inhabits a good availability for onshore wind with an average capacity factor of 41.23%. Investments in fixed offshore wind tend to be stable with risk aversion. This is a result of the low variable costs and the good average capacity factor of 52.15% in Z2. The latter shows that the interplay between different VRES is cost-efficient even when no climate policies are present and serve a substantial portion of the demand.

Table 36 shows that when the CO_2 Cap policy is introduced, the effect of increasing risk aversion is less significant. The carbon emission cap is so strict that the model is left with few degrees of freedom. Hence, the room for changes in the capacity mix is slim, even for high levels of risk aversion. The only considerable difference is the slight increase in gas capacity of 8.5%, and in floating offshore wind 35% (2.4 GW) from $\gamma = 0$ to $\gamma = 0.25$. This shows that a strict climate policy reduces the effect of risk aversion on the central planner. Nevertheless, the relatively small group of possible RES presented in the mix can have affected the result. Hence, the lack of change in the capacity mix can therefore stem from the fact that there is a limited combination of technologies being modeled. It also raises the question if the model would shift towards nuclear capacity if the maximum capacity was higher or the investment cost was lower, as the model with no climate policies tends to prefer a high amount of capacity with an average capacity factor of 100%, more specifically, thermal capacity.

In [55], it is found that higher levels of risk aversion lead to higher investments in wind and solar and less investment in gas. This is because in [55], the worst-case scenarios are those with high Renewable Portfolio Standards (RPSs) and high fuel prices. Consequently, investments in RES will help to meet the RPS target and reduce the fuel price risk. In this thesis, a stable and slightly increasing investment in the RES is observed when the strict CO_2 Cap climate policy is introduced. However, as fuel prices are not part of the uncertainty in this model, the investments in gas are stable with risk aversion under climate policies. If fuel price uncertainty had been included in the model, it is possible that the same reduction in gas capacity investment could have been observed as in [55] for this CO_2 Cap policy.

This model has no extra support for renewables, such as feed-in tariffs or other tools that affect the marginal profits of the RES generators. Not having mechanisms like that can increase the risk of investing in RES, and investments could decrease with risk aversion [88]. This can explain why the capacity mix is very stable under the CO_2 Cap policy and why more investments in, for instance, floating offshore wind is present.

Although only slight changes can be observed in the capacity mix for the model with CO_2 Cap policy, the changes in power prices and CO_2 prices are more severe, which will be discussed in the following sections. Thus, this shows that risk aversion does not affect the outcome in the presence of a strict CO_2 Cap policy, but it impacts the cost of the outcome, more specifically, the power price and the CO_2 price.

For this thesis, it is observed that the gas capacity decreases with risk aversion under the CO_2 Tax policy. Simultaneously, the VRES capacities increase. The best way to hedge against the cost of the CO_2 Tax in the very high demand scenario is to invest in capacities where the variable costs do not depend on the CO_2 Tax. Hence, a growth in VRES capacity is observed, similar to the results in [55].

Table 37 show the effect of a CO_2 Tax policy with an increasing level of risk aversion. The risk-averse stochastic model tends to increase the investment in VRES and storage capacity with risk aversion. This is to hedge against the risk of high CO_2 Tax costs in the worst-case scenario. This is a pattern that aligns well with existing literature [55] [87]. By introducing more VRES and reducing gas capacity, the risk-averse central planer hedge against the political risk of the CO_2 Tax. This aligns well with [55] stating that US investors are looking at RES for these purposes.

Both this thesis and [55] show that the effects on the capacity mix from risk aversion are non-linear. In [55], a larger model with transmission investment is used. However, this thesis shows that the same effect of risk aversion can be found in a risk-averse stochastic GEP model. The effect of risk aversion is non-linear because of the complex interplay between RES and generation investments. This implies that a small change in the model input can result in a larger change in the model outcome. One of the outcomes that shows this well is for the power price, outlined in subsubsection 5.4.6. Consequently, investigating these interactions before a policy is made is very important to avoid unintended effects on the power system.

The effect of the Price Zone 3: North Sea Offshore Grid (Z3) is also shown to be significant under the CO_2 Cap and the CO_2 Tax policy. Z1 does not have a sufficient amount of wind capacity to meet the demand. Consequently, substantial investments in Z3 are made, regardless of the extra cost of transmission present for the offshore wind technologies in Z3. The sensitivity analysis made related to the transmission cost in Appendix subsection B shows a great investment in Z3 even with a remarkably higher transmission cost. This emphasizes the importance of cooperation in electricity transmission between countries to achieve the ambitious climate goals set for 2050. Additionally, it emphasizes the importance of developing the offshore grid in the North Sea specifically. This is an area with great wind resources and major areas of shallow water, which makes it suitable for a great expansion in offshore wind capacity. VRES have volatile production profiles. Thus, the need for a transnational grid where the interaction between the various VRES is exploited is crucial to maximizing the effect and the interplay of the VRES. Having sufficient transmission connections will enable zones with excess electricity to export and zones with energy deficit to import, leading to an electricity grid less dependent on coal and gas generation.

Significant changes in the capacity mix can be observed between the deterministic model and the risk-neutral and risk-averse stochastic models. The deterministic model does not consider demand uncertainty. Consequently, the capacity mix presented by the deterministic model has less total capacity installed because it only needs to meet the demand in the base-demand scenario. This difference is most significant when the CO_2 Cap policy is present. The carbon emission cap policy is stringent, making it hard for the stochastic models to meet demand sufficiently in all demand scenarios and keep within the cap simultaneously. Thus, substantial differences in VRES and storage capacity between the deterministic model and the stochastic models can be observed in Table 13, Table 20, and Table 28, with the most dramatic difference to be an expansion of 189.3 GW of solar capacity between the deterministic model and the stochastic models.

Europe needs significant expansion in the generation capacity to cope with the electrification of society. However, to what extent is unknown because it depends on several factors, including growth in power-intensive industries and the evolution of energy efficiency [38]. Thus, using deterministic GEP models enables the possibility of underestimating the need for capacity. Consequently, struggling to meet the demand in higher-demand scenarios. Another issue with the deterministic model is that it assumes that the central planner has perfect foresight. This will never be the case, as it is not possible to foresight the future in long-term GEP with a 100% accuracy. The uncertainty of several parameters will always be present and affect the investment decisions in the power system.

6.2 Risk Aversions Effect on Emissions

The carbon emissions presented in subsubsection 5.1.3 and subsubsection 5.4.7 show several patterns for the emission related to risk aversion and the different policy options. Firstly, the model with no climate policy experience a significant growth in carbon emissions with an increasing level of risk aversion. This is because risk aversion makes coal generation more valuable in the very high demand scenario. In contrast, only minor changes in emissions can be observed for the model with CO_2 Cap policy as a consequence of the strict cap and small changes in the capacity mix with risk aversion.

Additionally, the difference in carbon emissions between the model with CO_2 Cap and the model with CO_2 Tax is noteworthy. These are two comparable policies, as outlined in subsection 6.4. The model with CO_2 Tax emits more than the model with CO_2 Cap for all demand scenarios. This finding aligns well with the conclusion in [87], stating that quantity-based policy options give better certainty of emission levels.

The deterministic model has significantly higher carbon emissions under all climate policies in the base-demand scenario than the risk-neutral stochastic model. The deterministic model also has more significant carbon emissions than the risk-averse stochastic models.

The European Commission has presented a strategy to make the EU climate-neutral by 2050 [1]. However, when the CO_2 price predicted in [38] is utilized as a CO_2 Tax in the model in this thesis, the emission goal calculated in subsubsection 4.5.5 is not met for all demand scenarios. Only the models with the CO_2 Cap policy are within the acceptable carbon emission level in all demand scenarios. Due to the electrification of industries and a reduction in the use of fossil fuels, substantial growth in electricity demand is forecasted for the coming years [26] [38]. However, exactly how much is unknown. Consequently, it can be problematic for policymakers to use deterministic GEP models, as it can result in a power system not suited to meet the demand in cases of larger growth in demand. If this situation occurs and the electricity demand rise above the installed generation capacity, it is likely that decommissioned power plants, like coal power plants, will get reopened to be able to meet the demand. This happened as recently as in 2022 when Germany reopened coal power plants to cope with the electricity demand after gas from Russia could no longer be purchased as a result of the Russian invasion of Ukraine [82] [18]. This demonstrates the importance of including uncertainty in GEP to be suited for several scenarios and be able to meet the emission levels necessary to be in line with the EU emission targets, regardless of which scenario occurs.

An economic motivation to ensure that the climate goals are met is to avoid the Social Cost of Carbon Dioxide (SC-CO_2), elaborated in subsection 2.9. [80] estimates the SC-CO_2 to be 185 \$/tCO2. Consequently, greater emissions than expected can lead to a huge social-economic cost. This is a cost that the governments will need to cover. Thus, to ensure investments in RES reducing carbon emissions can be economically beneficial, even if the RES needs to be subsidized.

The results presented in subsubsection 5.4.8 show how the CO_2 price related to the CO_2 Cap policy change with risk aversion. The CO_2 price decrease with risk aversion in the very high demand scenario by over 77% from the risk-neutral stochastic model to the extreme risk-averse model. This indicates that the prices in the cap and trade market (EU ETS) will decrease with increasing risk aversion. This suggests that the market demand for carbon emission allowances has weakened. This price reduction can have several implications, such as lowering the financial burden for companies that need to purchase these allowances. It also indicates a decreased incentive for the companies to reduce their carbon emissions because the cost of emitting CO_2 becomes relatively cheaper. Additionally, it is also noteworthy that the stochastic models react non-linear to the increasing risk aversion. This emphasizes the importance of investigating these interactions between risk aversion and the model outcomes before a policy is made to avoid unintended effects on the power system or, in this case, carbon emissions.

6.3 Risk Aversion and Climate Policies Effect on the Power Price

The risk-averse central planner weights the power price, and it can be weighted back to the actual power price using Equation 81. The weighted power prices reflect how the risk-averse central planner values the price in the different demand scenarios. Consequently, the weighted power prices, presented in subsubsection 5.4.5, decrease for the base-, low-, and high-demand scenarios with increasing levels of risk aversion. The power prices in the base-, low-, and high-demand scenarios are all zero for extreme risk aversion. However, this can not be true. Power is produced in all these scenarios, and consequently, it is paid a price for this power. To find the actual power price in these scenarios, the capacity mix can be constrained, and the model can be run deterministic for each demand scenario, as described in subsubsection 5.4.5.

Some tendencies can be observed when examining the actual power prices presented in subsubsection 5.4.6. The average power price tends to decrease with risk aversion in all demand scenarios under all climate policies. However, the differences for the model with CO_2 Cap with increasing levels of risk aversion are slim. This is a result of the capacity mix being very stable for this model regardless of how risk-averse the central planner is. The power price for the model with CO_2 Tax policy is significantly higher because the cost of the CO_2 Tax adds to the marginal cost of the emitting generation technologies, which for this model is gas capacity. Figure 29 clearly show the latter, as the line for $\gamma = 0$ is clearly at a higher level compared to the $\gamma = 0.5$ line for no climate policy and CO_2 Cap policy. What also can be observed from Figure 28 and Figure 29 is that the power price reacts non-linear to risk aversion. This is also discussed earlier in section 6 and shows, once again, the importance of policymakers carefully examining these interactions.

By contrast, the power prices for the deterministic model, presented in Table 17, are significantly higher than the actual power prices in the base-demand scenario for the stochastic optimization models. The greatest contrast is between the deterministic model and the stochastic optimization models with the CO_2 Cap policy. The price for the deterministic model is over 680% higher in the deterministic model compared to the SO model.

The latter is also important when it comes to the deployment of new VRES capacity. If governments or policymakers use deterministic models for GEP, the risk of forecasting a too high power price is present. Several VRESs need government subsidies to become realizable and sustainable. However, if the power price predicted by the policymakers is too high, it can contribute to the risk of establishing a too-low subsidy level, which can result in a decrease in new VRES capacity or the investors can experience a shortage in expected revenues. This can be critical for investors in, for example, wind power, which is already experiencing a reduction in new investments [42].

The revenues for the different technologies under the different policy options reflect the power price changes discussed above. In subsubsection 5.4.5, it is shown that revenues decrease with risk aversion as a result of decreasing power prices.

6.4 The CO2 Price in Comparison to the CO2 Tax

As described earlier, the CO_2 Price is a part of the CO_2 Cap policy constraint for the demand scenarios where the system struggles to meet the strict emission cap calculated in subsubsection 4.5.5. The cap generated for the base scenario by the deterministic model equal to 118.57 €/tCO2, shown in Table 14, is very consistent with the result of Statnett's analysis in [38] using a 120 €/tCO2 in 2040 as a base for their analysis. This is also the value utilized for the CO_2 Tax, elaborated in subsubsection 4.5.5.

The stochastic models under the CO_2 Cap policy have significantly higher CO_2 Prices, outlined in Table 44, in the highest demand scenario compared to the prices presented in [38] and Table 14. [38] operates with a CO_2 Price ranging from 95 €/tCO2 to 160 €/tCO2 for 2040, depending on which demand scenario that occurs. However, all these are far below the CO_2 price generated by the stochastic model for all levels of risk aversion. For extreme risk aversion, the price is 20% higher than the highest price estimation in [38], and for the risk-neutral, it is 445% higher. Although these are two different models serving different purposes, it can suggest that the CO_2 price estimated in [38] may be too low to meet the ambitious goal set by the European Commission [1].

Nonetheless, it is also possible that the model in this thesis overestimates the CO_2 Price. Many of the new electricity-intensive industries developing, like hydrogen, are energy-flexible sectors. Meaning that they can schedule demand to non-peak hours, reducing the stress on the power system. This will reduce the need for emitting thermal generation to cover this extraordinarily high demand. Consequently, it is easier for the system to keep within the set emission cap, and the CO_2 Price will decline.

6.5 Investment Point in Nuclear Capacity

Nuclear capacity has a major investment cost in comparison to the other generation technologies. However, there are no carbon emissions related to nuclear power production, and the availability is set to be 100% for all the models. Additionally, the problems related to the unit commitment problem are also neglected. However, the model does not invest in nuclear capacity unless a climate policy is introduced. Thus, the question of when the central planner finds it sustainable to invest in nuclear capacity is investigated in subsubsection 5.2.7 and subsubsection 5.3.7.

Comparing the results presented in subsubsection 5.2.7 and subsubsection 5.3.7, it is evident that risk aversion has a significant effect on investments in nuclear capacity. The risk-neutral stochastic model starts to invest in nuclear capacity for a CO_2 Tax of 32 €/tCO2. This is the point where the risk-neutral central planner finds the benefits of nuclear to overcome the great investment cost. The risk-averse central planner exhibits a similar investment threshold, requiring a CO_2 Tax equal to 31 €/tCO2 to start investing.

The risk-averse central planner invests more in nuclear capacity. For both the current tax level of 80 €/tCO2 and the projected level of 120 €/tCO2 for 2040, outlined in subsubsection 4.5.5, the risk-averse central planner allocates more capacity to nuclear compared to the risk-neutral central planner. This suggests that the risk-averse central planner weights the high investment costs of nuclear power less and the cost of the CO_2 Tax more compared to the risk-neutral model. This reflects that the nuclear capacity is an efficient way for the risk-averse model to hedge against the political risk of the CO_2 Tax policy. The risk-neutral central planner has a more restrained approach to nuclear power investments.

It is worth noting that the discussion around nuclear energy is an ongoing topic in today's energy transition debate [31]. Technological advancements, public perceptions, policy changes, and development of other VRES are all part of shaping the landscape for new investments in nuclear capacity. Thus, while the risk-neutral stochastic model results in a more cautious stance towards nuclear investments and the risk-averse stochastic model invest more, it does not provide a definite answer, as several factors have not been considered in the model.

6.6 The effect of Ground Rent Tax on Exciting Wind Capacity

In subsection 5.6, the effects of the ground rent tax on existing wind capacity are highlighted for the risk-neutral and the risk-averse stochastic model. For the risk-neutral stochastic model, a significant reduction in the offshore wind under the CO_2 Cap policy, which was partially covered by greater solar and storage capacities. Similarly, a reduction in onshore and offshore wind is also observed for the risk-neutral model with CO_2 Tax, which is also mainly covered by solar and storage capacity. For the model with no climate policies, a slight decrease in offshore wind can be observed, which is covered by a slight increase in gas capacity.

The ground rent tax affects the risk-averse stochastic model differently. For the model with no climate policy, it resulted in the elimination of offshore wind, necessitating the addition of coal capacity to cover for this loss in wind capacity. Under the CO_2 Cap policy, only slight changes in wind capacity are observed, which is covered by an increase in solar and storage capacity. This is due to the few degrees of freedom for the model under the strict CO_2 Cap policy. The CO_2 Tax policy had more significant impacts. Both offshore and onshore wind capacities are significantly reduced. However, the solar capacities are increased together with storage to cover for the lost capacity.

The findings presented in subsection 5.6 highlight the complex interplay between taxes, climate policies, and investment decisions for wind capacity. While the ground rent tax affected the amount of wind capacity built, the effects were not uniform across all policy options and levels of risk aversion. Moreover, the results presented suggest that taxes on exciting wind power, like the ground rent tax presented in this model, could have a considerable impact on the investment choices made for the overall capacity mix and how the resources are allocated.

In Europe today, where the need for investments in RES is substantial, the impact of taxes that can affect the investment in new wind capacity, like the windfall tax [46] and the ground rent tax suggested in Norway [62], needs to be critically considered. While taxes can serve as mechanisms to generate state revenue and promote fairness, they must be carefully designed and implemented to avoid unintended consequences. Taxes on wind power, such as the ground rent tax utilized in this model, can make exciting wind power lose important profit margins, it can discourage new investments, and hinder the further expansion of RES [4]. The urgency for a transition to a more climate-neutral power system is unmistakable. Thus, policymakers need to strike a balance between taxation and incentivization to ensure that RES receive adequate support enabling the needed growth to meet the climate goals.

6.7 Relevant Literature

Analysis has been carried out on the effect of relaxing risk-neutrality assumptions in GEP models. Most of the exciting literature about the effect of risk aversion on GEP models uses equilibrium models aiming to maximize the profits for an investor. However, these are generally very small models which are not able to represent real-world issues satisfyingly [56] [30]. In contrast, the study made by Munzo et al. [55] attempts to investigate the impact of risk aversion on large-scale electricity planning using an equilibrium model.

The model used in [55] is a two-stage model concerning transmission expansion and utilizing this transmission expansion to optimize the generation expansion for the system. Hence, [55] encounters transmission expansion uncertainty. In contrast, the model developed in this thesis only encounters generation expansion. The model made for this thesis, presented in subsubsection 4.1.3, is therefore similar to the lower level of the two-stage model used in [55]. Both models use a linearized formulation of CVaR, where the model strives to minimize the VaR and the u-expression outlined in Equation 55. As outlined in subsection 4.3, for $\gamma = 0$, the model aims to minimize all the TSC, but for $\gamma = 1$, the objective is to minimize CVaR in addition to the first-stage investment cost for the most costly scenario. Which scenario is the most costly is endogenously defined, hence, it being the highest demand scenario for the model in this thesis, and the demand scenarios with high RPS levels, high demand, and high fuel prices in [55].

[55] find that investments in zero-emissions generation technologies increase with increasing risk aversion. The worst-case scenario for the model in [55] are the scenarios with high RPS levels, high demand growth, and high fuel prices. Consequently, [55] experience growth in low-carbon technologies with risk aversion, especially wind, and solar. The most carbon-intensive technologies decrease significantly with risk aversion. Hence, for the model under CO_2 Tax policy presented in this thesis, the results align well with the results in [55]. In contrast, the investments in coal and gas tend to increase with risk aversion for the model with no climate policies. However, this is reasonable because if no climate policy is present, the risk-averse stochastic model will strive to avoid the high cost of NSE. The model presented in subsection 4.3 strives to minimize the costs in the worst-case scenario, which is the very high demand scenario. For the central planner, the

need to avoid the high costs of NSE increases with risk aversion. Thus, coal and gas are preferred because of an acceptable investment cost and 100% availability. However, if uncertainty related to the fuel price had been included in the model developed for this thesis, it could have an effect similar to the result presented in [55], with a more significant increase in VRES capacity with risk aversion also for the model with no climate policies.

Both [55] and [87] urge the importance of including uncertainty and risk aversion in GEP models, particularly for policy-making purposes. The results presented in this thesis can build up under this statement, as considerable non-linear changes in capacity mix, emissions, revenues, and power prices are some of the effects found after the introduction of risk aversion.

This risk-averse stochastic model used in this thesis shares the same assumption as in [55] regarding complete financial markets where all types of risk can be traded. Not all types of risk can be traded in the real world. It is possible to trade risks as price risks, for instance, electricity futures, forwards, and options [13]. However, some systematic risks can not be traded. These risks are unique to a circumstance of a specific electricity asset or investment and are hard to diversify or hedge against [55]. However, it is complex to include this in large investment models. Consequently, a sufficient solution is to assume that all risks can be traded [23]. A consequence can be an overestimation of the investment in the system and an underestimation of strategic interactions between market participants [55].

This thesis demonstrates how risk aversion affects the capacity mix from the point of view of a central planner under no climate policy, a CO_2 Cap policy, and a CO_2 Tax policy. Furthermore, how the risk-averse central planner weights the power prices are outlined in Equation 81. The dual value of the power balance or the dual value of the capacity limit can not be used to represent the power prices, thus, not to calculate the revenues in the event of extreme risk aversion. For the demand scenarios not included by the parameter for VaR (α), because in this case, these dual values for these demand scenarios are weighted to zero. To get around this problem, a method of calculating the power prices and revenues is presented in subsubsection 5.4.5. The latter are technical contributions to the existing literature about risk-averse GEP models.

Additional to the power prices and revenues, this thesis also has findings related to emissions. It is presented that the central planner tends to emit more carbon emissions with an increasing level of risk aversion. This is a consequence of the more risk-averse central planner striving to avoid NSE and simultaneously keep the cost down. However, when strict quantity-based climate policies are introduced, the degree of freedom is reduced to a level where the effect of risk aversion is minimal.

The TSC tend to increase slightly with risk aversion for all climate policies as a result of a general growth in installed capacity and a transition towards technologies with higher investment costs. Thus, the investments increase with risk aversion. This aligns well with the findings in [55].

7 Conclusion

This Master's Thesis provides insight into how uncertainty and risk aversion impacts the decarbonization of the power system. This has been done to a comprehensive analysis comparing a deterministic, a risk-neutral stochastic, and a risk-averse stochastic optimization model for GEP. Hitherto, most studies are based on small test cases, which can struggle to capture the effect of risk aversion. Thus, the approach used for this thesis with a multi-zonal North European power system, including an offshore grid in the North Sea, was needed.

This thesis finds that the investment in coal capacity tends to increase with risk aversion when no climate policies are present. However, when climate policies are introduced, the investments shift towards VRES. In the presence of the CO_2 Tax policy, the investment in VRES and storage increase with risk aversion, for the risk-averse stochastic model better to hedge against the political risk imposed by the CO_2 Tax policy. With a greater amount of renewable power generation, the cost of the CO_2 Tax is sufficiently reduced. In contrast, when the strict CO_2 Cap policy is introduced, the effect of risk aversion is small, which results in a stable capacity mix across all levels of risk aversion, meeting the emission cap for all demand scenarios. However, with great changes in the resulting power prices and CO_2 prices under the CO_2 Cap policy, it is found that the cost of the outcome is heavily affected by risk aversion under this policy option. An additional takeaway is that the model responds non-monotonic to risk aversion under different policy options. This can complicate the task of making climate policies. Hence, investigating these interactions before a policy is made is important to avoid unintended effects on the power system.

The results presented in the thesis emphasize the importance of cooperation between countries related to electricity transmission to maximize the interplay between the different VRES. Additionally, the importance of developing the North Sea offshore grid to enable the countries surrounding the North Sea can reduce their dependence on fossil generation sources.

It is found how the risk-averse stochastic model weights several outcomes, such as the power price, the CO_2 price, and the shadow price of capacity, and how to obtain the unweighted revenues for all levels of risk aversion. This finding is a contribution to the existing literature on stochastic optimization models for Generation Expansion Planning (GEP). Understanding the relationship between risk aversion and financial outcomes is essential for policymakers when designing taxation and climate policies to promote a sustainable and resilient power system that facilitates investments in renewable energy.

The results in this thesis reveal that the CO_2 price, generated from the carbon emission cap constraint, is found to be higher than the estimated CO_2 price for the EU ETS in 2040. This suggests that the forecasted price for CO_2 in the EU ETS may not be sufficient to meet the ambitious climate goals for 2050. Although the model in this thesis potentially overestimates the CO_2 price as a result of not including energy-flexible sectors, it is important to delve deeper into the effects of introducing a more strict cap in the EU ETS cap and trade market. Policymakers must acknowledge the significance of uncertainty in GEP models to ensure a resilient grid suited to meet the demand for several possible demand scenarios while simultaneously meeting the emission goals set. Further investigation into policy adjustment is necessary to ensure that the power system is composed sufficiently to meet the cap set in EU ETS and the power demand. This type of adjustment could, for instance, be adjustments on VRES subsidies.

The examination of the ground rent tax sheds light on what impact new taxation can have on investments in wind capacity. Taxation tends to have a dampening effect on the investment in wind capacity. The central planners in both models tend to be more cautious in the wind capacity investment when faced with the increased financial burden of the ground rent tax. These insights provide some noteworthy aspects for policymakers to carefully assess the potential implications when introducing additional taxes on this emerging sector. While taxation can be an important tool to generate state revenue and promote fairness, policymakers need to be mindful of the potential for investor behavior and the overall growth of RES. Striking the right balance between taxation and incentives for continued investment in RES is crucial to meet the climate goals of 2050. The findings presented in this thesis show a possible effect of the ground rent taxation on wind power under different policy options. Consequently, it can help policymakers take more informed decisions and design policies that encourage development and profitable investments in RES.

In conclusion, this Master's Thesis aims to illustrate some of the consequences of the complex interplay between uncertainty, risk aversion, and climate policy, providing valuable insights to policymakers, central planners, and investors. This thesis aims to facilitate well-informed decision-making by policymakers striving to find the best combination of climate policies and taxation and simultaneously enable incentives to invest in renewable energy capacity. The results achieved are consistent with anecdotal evidence and theory. Additionally, several findings have also been added to the existing knowledge on risk-averse stochastic optimization for Generation Expansion Planning (GEP) models. Finally, the results of this Master's Thesis highlight that policymakers should include uncertainty and risk aversion in long-term GEP models, as it is not possible to have a 100% accurate foresight in long-term GEP. It has been shown that the models have a non-linear reaction to risk aversion for several outcomes. Thus, investigating these interactions before a climate or taxation policy is made is important to avoid unintended effects on the power system. By considering uncertainty and risk aversion, policymakers can effectively adapt to various scenarios, encouraging investments in RES and fostering the development of a sustainable power system.

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Appendix

A Calculations

A Calculation of Norwegian Fixed Offshore Capacity

The maximum capacity for fixed offshore wind in Norway generated by the GIS model from [53] shows a capacity of 18.42 GW. Knowing that the maximum depth for fixed offshore wind in the GIS model by [53] is only 40 meters, an additional calculation has been made to ensure that the capacity limit presented is a realistic figure. To make this calculation, the most recent data from NVE on possible offshore wind areas in Norway [66]. Only three areas are suited for fixed offshore wind with a depth of 60 meters or shallower. The energy density of 8 $[W/m^2]$ is used, which is the same energy density as in [53]. This results in the capacities shown in Table A.48.

Offshore Wind Area	**Areal [km^2]**	**Capacity [MW]**
Sørvest B	2179	17432
Sørvest C	1766	14128
Sørvest F	2702	21616
Sum		53176
33% available land		17707.608

Table A.48: Capacity calculations for fixed offshore wind in Norway

The model from [53] uses 33% of the available land for offshore wind as elaborated in subsubsection 4.5.3, and, as shown in Table A.48, using this percentage of available land gives a capacity of 17.71 GW. This is a fairly small difference from the results from the model in [53]. Hence, using the numbers from [53] is sufficient even though they operate with a maximum depth of 40 meters for fixed offshore wind.

B Sensitivity Analysis: Cable length between Zone 1 and Zone 3

The results presented in section 5 are made with an assumption of the existence of an offshore electricity hub with an average distance of 100km to the built offshore capacity in Z3. However, this may affect the results and how much capacity that is found economically to build in Z3. Thus, to get a picture of how this affects the result, a sensitivity analysis is performed where the cable length is equal to the distance between the southern part of the Norwegian offshore field *Sørvest D* [93] and the German town of Flensburg, which is approximately 400km. This results in an additional transmission cost for the offshore wind technologies in Z3 of 140000 [€/MW], calculated using the same method as shown in subsubsection 4.5.1.

In subsection 5.3, the risk-averse stochastic optimization model, with $\gamma = 0.5$ builds 85.8 GW of fixed offshore wind and 9.3 GW of floating offshore wind in Z3. To see the effect of a longer cable, the same simulation is executed with a transmission cost of 140000 [€/MW] for the offshore wind in Z3. This results in a slight decrease in fixed offshore wind to 79.2 GW and no floating offshore wind in Z3, shown in Figure 41 and Table B.49. Consequently, it is possible to say that the assumed length of the cable may affect the resulting capacity mix of the model.

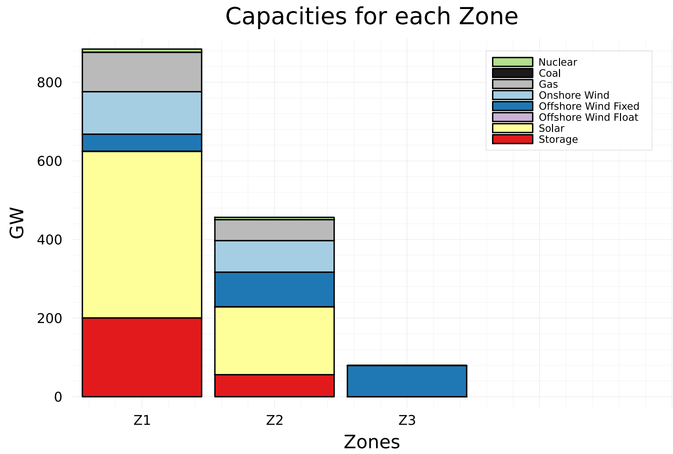

Figure 41: Capacity mix for risk-averse model ($\gamma = 0.5$) with CO2 Cap and transmission cost in Z3 of 140000€/MW

	Capacities [GW] Zone 1	**Capacities [GW] Zone 2**	**Capacities [GW] Zone 3**
Nuclear	8.5	6.0	0.0
Coal	0.0	0.0	0.0
Gas	100.1	53.3	0.0
Onshore Wind	108.1	80.2	0.0
Offshore Wind Fixed	43.9	88.5	79.2
Offshore wind Float	0.0	0.0	0.0
Solar	423.7	172.3	0.0
Storage	200.3	56.1	0.0

Table B.49: Capacity mix for risk-averse model ($\gamma = 0.5$) with CO2 Cap and transmission cost in Z3 of 140000€/MW, Figure 41

B Results

A Weighted Revenus for Different Levels of Risk Aversion

	Revenues [Billion €] $\gamma = 0$	**Revenues [Billion €]** $\gamma = 0.25$	**Revenues [Billion €]** $\gamma = 0.5$	**Revenues [Billion €]** $\gamma = 0.75$	**Revenues [Billion €]** $\gamma = 1$
Base Demand Scenario	6.82	4.73	2.96	1.42	0.00
Low Demand Scenario	4.66	3.36	2.20	1.09	0.00
High Demand Scenario	9.36	6.56	4.08	1.93	0.00
Very High DemandScenario	21.15	29.30	36.48	42.91	48.90

Table A.50: The sum of the weighted revenues in the different demand scenarios for different levels of risk-aversion with no climate policies.

	Revenue [Billion €] $\gamma = 0$	**Revenue [Billion €]** $\boldsymbol{\gamma = 0.25}$	**Revenue [Billion €]** $\boldsymbol{\gamma = 0.5}$	**Revenue [Billion €]** $\boldsymbol{\gamma = 0.75}$	**Revenue [Billion €]** $\boldsymbol{\gamma = 1}$
Base Demand Scenario	1.87	1.39	0.93	0.46	0.0
Low Demand Scenario	0.81	0.61	0.41	0.20	0.0
High Demand Scenario	3.40	2.50	1.67	0.83	0.0
Very High Demand Scenario	88.87	90.56	92.43	94.23	95.74

Table A.51: The sum of the weighted revenues in the different demand scenarios for different levels of risk-aversion with CO2 Cap policy.

	Revenues [Billion €] $\gamma = 0$	**Revenues [Billion €]** $\gamma = 0.25$	**Revenues [Billion €]** $\gamma = 0.5$	**Revenues [Billion €]** $\gamma = 0.75$	**Revenues [Billion €]** $\gamma = 1$
Base Demand Scenario	11.31	7.42	4.44	1.95	0.00
Low Demand Scenario	6.02	3.93	2.33	1.00	0.00
High Demand Scenario	17.65	12.06	7.36	3.31	0.00
Very High Demand Scenario	34.34	49.97	63.09	75.00	83.98

Table A.52: The sum of the weighted revenues in the different demand scenarios for different levels of risk-aversion with CO2 Tax policy.

B Revenues for Different Levels of Risk Aversion

	Revenue [Billion €] $\gamma = 0$	**Revenue [Billion €]** $\gamma = 0.25$	**Revenue [Billion €]** $\gamma = 0.5$	**Revenue [Billion €]** $\gamma = 0.75$	**Revenue [Billion €]** $\gamma = 1$
Base Demand Scenario	27.27	25.24	23.65	22.76	22.17
Low Demand Scenario	18.65	18.00	17.57	17.46	17.30
High Demand Scenario	37.42	34.99	32.60	30.86	29.46
Very High Demand Scenario	84.60	66.96	58.37	52.82	48.90

Table B.53: Actual revenues for the risk-averse stochastic optimization model with no climate policies.

	Revenue [Billion €] $\gamma = 0$	**Revenue [Billion €]** $\gamma = 0.25$	**Revenue [Billion €]** $\gamma = 0.5$	**Revenue [Billion €]** $\gamma = 0.75$	**Revenue [Billion €]** $\gamma = 1$
Base Demand Scenario	7.47	7.41	7.42	7.41	7.49
Low Demand Scenario	3.24	3.24	3.24	3.26	3.42
High Demand Scenario	13.58	13.34	13.33	13.26	13.29
Very High Demand Scenario	355.49	207.00	147.89	115.98	95.81

Table B.54: Actual revenues for the risk-averse stochastic optimization model with CO2 Cap policy.

	Revenue [Billion €] $\gamma = 0$	**Revenue [Billion €]** $\gamma = 0.25$	**Revenue [Billion €]** $\gamma = 0.5$	**Revenue [Billion €]** $\gamma = 0.75$	**Revenue [Billion €]** $\gamma = 1$
Base Demand Scenario	45.26	46.94	49.22	52.53	18.53
Low Demand Scenario	24.10	26.75	28.36	32.11	8.78
High Demand Scenario	70.60	73.30	75.86	79.73	32.66
Very High Demand Scenario	137.37	95.71	79.02	70.98	66.28

Table B.55: Actual revenues for the risk-averse stochastic optimization model with CO2 Tax policy.

C Weighted Average Power Prices for Different Levels of Risk Aversion

	Average Price [€/MWh] $\gamma = 0$	**Average Price [€/MWh]** $\gamma = 0.25$	**Average Price [€/MWh]** $\gamma = 0.5$	**Average Price [€/MWh]** $\gamma = 0.75$	**Average Price [€/MWh]** $\gamma = 1$
Base Demand Scenario	4.15	2.86	1.80	0.87	0.00
Low Demand Scenario	3.45	2.50	1.65	0.82	0.00
High Demand Scenario	5.03	3.46	2.13	1.01	0.00
Very High DemandScenario	9.23	13.03	16.30	19.19	21.91

Table C.56: Average weighted power prices in zone 1 for different levels of risk-aversion with no climate policies.

	Average Price [€/MWh] $\gamma = 0$	**Average Price [€/MWh]** $\gamma = 0.25$	**Average Price [€/MWh]** $\gamma = 0.5$	**Average Price [€/MWh]** $\gamma = 0.75$	**Average Price [€/MWh]** $\gamma = 1$
Base Demand Scenario	1.27	0.93	0.62	0.31	0.00
Low Demand Scenario	0.63	0.47	0.31	0.16	0.00
High Demand Scenario	2.03	1.48	0.99	0.49	0.00
Very High Demand Scenario	47.00	47.52	48.43	49.30	50.06

Table C.57: Average weighted power prices in zone 1 for different levels of risk-aversion with CO2 Cap policy.

	Average Price [€/MWh] $\gamma = 0$	**Average Price [€/MWh]** $\gamma = 0.25$	**Average Price [€/MWh]** $\gamma = 0.5$	**Average Price [€/MWh]** $\gamma = 0.75$	**Average Price [€/MWh]** $\gamma = 1$
Base Demand Scenario	7.69	6.29	4.74	2.91	0.00
Low Demand Scenario	4.81	4.34	3.40	2.16	0.00
High Demand Scenario	10.40	8.50	6.17	3.55	0.00
Very High DemandScenario	16.87	18.81	20.80	23.12	21.91

Table C.58: Average weighted power prices in zone 1 for different levels of risk-aversion with CO2 Tax policy.

D Average Power Prices for Different Levels of Risk Aversion

	Average Price [€/MWh] $\gamma = 0$	Average Price [€/MWh] $\gamma = 0.25$	Average Price [€/MWh] $\gamma = 0.5$	Average Price [€/MWh] $\gamma = 0.75$	Average Price [€/MWh] $\gamma = 1$
Base Demand Scenario	16.59	15.26	14.40	13.94	13.66
Low Demand Scenario	13.80	13.36	13.21	13.16	13.09
High Demand Scenario	20.10	18.48	17.05	16.11	15.43
Very High Demand Scenario	36.93	52.13	43.46	30.71	21.91

Table D.59: Actual average power prices in Zone 1 for the risk-averse stochastic optimization model with no climate policies.

	Average Price [€/MWh] $\gamma = 0$	Average Price [€/MWh] $\gamma = 0.25$	Average Price [€/MWh] $\gamma = 0.5$	Average Price [€/MWh] $\gamma = 0.75$	Average Price [€/MWh] $\gamma = 1$
Base Demand Scenario	5.08	4.98	4.99	4.98	5.06
Low Demand Scenario	2.51	2.49	2.47	2.48	2.65
High Demand Scenario	8.11	7.91	7.91	7.86	7.87
Very High Demand Scenario	188.01	190.08	129.13	78.88	50.06

Table D.60: Actual average power prices in Zone 1 for the risk-averse stochastic optimization model with CO2 Cap policy.

	Average Price [€/MWh] $\gamma = 0$	Average Price [€/MWh] $\gamma = 0.25$	Average Price [€/MWh] $\gamma = 0.5$	Average Price [€/MWh] $\gamma = 0.75$	Average Price [€/MWh] $\gamma = 1$
Base Demand Scenario	32.95	31.91	37.64	46.28	18.00
Low Demand Scenario	21.81	21.78	27.12	34.08	9.99
High Demand Scenario	45.16	43.32	49.20	57.06	27.03
Very High Demand Scenario	75.38	46.95	55.64	37.12	21.90

Table D.61: Actual average power prices in Zone 1 for the risk-averse stochastic optimization model with CO2 Tax policy.

E Maximum Weighted Power Prices for Different Levels of Risk Aversion

	Max Price [€/MWh] $\gamma = 0$	Max Price [€/MWh] $\gamma = 0.25$	Max Price [€/MWh] $\gamma = 0.5$	Max Price [€/MWh] $\gamma = 0.75$	Max Price [€/MWh] $\gamma = 1$
Base Demand Scenario	6.08	4.56	3.04	1.52	0.00
Low Demand Scenario	6.08	4.56	3.04	1.52	0.00
High Demand Scenario	6.08	4.56	3.04	1.52	0.00
Very High DemandScenario	750.00	1312.50	1875.00	2437.50	3000.00

Table E.62: Weighted maximum power prices in zone 1 for different levels of risk-aversion with no climate policies.

	Max Price [€/MWh] $\gamma = 0$	Max Price [€/MWh] $\gamma = 0.25$	Max Price [€/MWh] $\gamma = 0.5$	Max Price [€/MWh] $\gamma = 0.75$	Max Price [€/MWh] $\gamma = 1$
Base Demand Scenario	6.08	4.56	3.04	1.52	0.00
Low Demand Scenario	6.08	4.56	3.04	1.52	0.00
High Demand Scenario	6.08	4.56	3.04	1.52	0.00
Very High Demand Scenario	750.00	1093.14	1122.17	1123.52	1124.47

Table E.63: Weighted maximum power prices in zone 1 for different levels of risk-aversion with CO2 Cap policy.

	Max Price [€/MWh] $\gamma = 0$	Max Price [€/MWh] $\gamma = 0.25$	Max Price [€/MWh] $\gamma = 0.5$	Max Price [€/MWh] $\gamma = 0.75$	Max Price [€/MWh] $\gamma = 1$
Base Demand Scenario	18.65	13.99	9.32	4.66	0.00
Low Demand Scenario	18.65	13.99	9.32	4.66	0.00
High Demand Scenario	18.65	13.99	9.32	4.66	0.00
Very High DemandScenario	750.00	1312.50	1875.00	2437.50	3000.00

Table E.64: Weighted maximum power prices in zone 1 for different levels of risk-aversion with CO2 Tax policy.

F Maximum Power Prices for Different Levels of Risk Aversion

	Max Price [€/MWh] $\gamma = 0$	Max Price [€/MWh] $\gamma = 0.25$	Max Price [€/MWh] $\gamma = 0.5$	Max Price [€/MWh] $\gamma = 0.75$	Max Price [€/MWh] $\gamma = 1$
Base Demand Scenario	24.31	24.31	24.31	24.31	24.31
Low Demand Scenario	24.31	24.31	24.31	13.4	13.4
High Demand Scenario	24.31	24.31	24.31	24.31	24.31
Very High Demand Scenario	3000	3000	3000	3000	3000

Table F.65: The actual maximum power prices in Zone 1 for the risk-averse stochastic optimization model with no climate policy.

	Max Price [€/MWh] $\gamma = 0$	Max Price [€/MWh] $\gamma = 0.25$	Max Price [€/MWh] $\gamma = 0.5$	Max Price [€/MWh] $\gamma = 0.75$	Max Price [€/MWh] $\gamma = 1$
Base Demand Scenario	24.31	24.31	24.31	24.31	24.31
Low Demand Scenario	24.31	24.31	24.31	24.31	24.31
High Demand Scenario	24.31	24.31	24.31	24.31	24.31
Very High Demand Scenario	3000	2498.62	1795.48	1382.79	1124.47

Table F.66: The actual maximum power prices in Zone 1 for the risk-averse stochastic optimization model with CO2 Cap.

	Max Price [€/MWh] $\gamma = 0$	Max Price [€/MWh] $\gamma = 0.25$	Max Price [€/MWh] $\gamma = 0.5$	Max Price [€/MWh] $\gamma = 0.75$	Max Price [€/MWh] $\gamma = 1$
Base Demand Scenario	74.59	74.59	74.59	74.59	74.59
Low Demand Scenario	74.59	74.59	74.59	74.59	74.59
High Demand Scenario	74.59	74.59	74.59	74.59	74.59
Very High Demand Scenario	3000	2632.64	1853.70	1382.71	1130.43

Table F.67: The actual maximum power prices in Zone 1 for the risk-averse stochastic optimization model with CO2 Tax.

C Generation Expansion Planning model - Julia

```
using DataFrames
using JuMP
using CSV
using Gurobi
using Random
using Statistics
import Plots
using Plots; theme(:bright)
using RDatasets
using GR
using PyPlot
using Pkg

# ~~~
# Settings
# ~~~

# Choose stochastic or deterministic
stochastic = true
risk_aversion = true
# Policy
# Carbon constraint
co2_cap_flag = false
#CO2-tax policy
CO2_tax_flag = true

#Choose Ground Rent tax
Ground_rent_tax = true
# ~~~
# Folder paths
# ~~~

if Sys.isunix()
    sep = "/"
elseif Sys.iswindows()
    sep = "\U005c"
end

working_path = pwd()

# Define input and output paths
inputs_path = string(working_path, sep, "Inputs", sep,
↪  "Inputs_course_all_techs_annual_2041")
inputs_path_tax_cost = string(working_path, sep, "Results", sep,
↪  "Results_stochastic_031422")
results_path = string(working_path, sep, "Results", sep,
↪  "Results_stochastic_031422")

if !(isdir(results_path))
    mkdir(results_path)
end

# ~~~
# Load data
```

```
# ~~~

if stochastic
    demand_input_z1 = CSV.read(string(inputs_path,sep,"Demand_z1.csv"),
    ↪  DataFrame, header=true)
    demand_input_z2 = CSV.read(string(inputs_path,sep,"Demand_z2.csv"),
    ↪  DataFrame, header=true)
    demand_input_z3 = CSV.read(string(inputs_path,sep,"Demand_z3.csv"),
    ↪  DataFrame, header=true)
else
    demand_input_z1 = CSV.read(string(inputs_path,sep,"Demand_z1.csv"),
    ↪  DataFrame, header=true, select=["Time_index", "Load"])
    demand_input_z2 = CSV.read(string(inputs_path,sep,"Demand_z2.csv"),
    ↪  DataFrame, header=true, select=["Time_index", "Load"])
    demand_input_z3 = CSV.read(string(inputs_path,sep,"Demand_z3.csv"),
    ↪  DataFrame, header=true, select=["Time_index", "Load"])
end

resources_input = CSV.read(string(inputs_path,sep,"Resources_updated.csv"),
↪  DataFrame, header=true)
resource_avail_input_z1 =
↪  CSV.read(string(inputs_path,sep,"Resources_availability_z1.csv"), DataFrame,
↪  header=true)
resource_avail_input_z2 =
↪  CSV.read(string(inputs_path,sep,"Resources_availability_z2.csv"), DataFrame,
↪  header=true)
resource_avail_input_z3 =
↪  CSV.read(string(inputs_path,sep,"Resources_availability_z3.csv"), DataFrame,
↪  header=true)

time_index = demand_input_z1[:,1]

#Tax costs input values
if Ground_rent_tax
    GRtax_cost_input = CSV.read(string(inputs_path_tax_cost,sep,
    "High_profit_tax_avg_RA_co2_tax_and_Nuclear_const.csv"), DataFrame,
    ↪  header=true)
    GR_tax_map = CSV.read(string(inputs_path,sep,"GR_Tax_MAP.csv"), DataFrame,
    ↪  header=true)
else
    GRtax_cost_input = zeros(S,R_all)
    GR_Tax_map = zeros(R_all,Z)
end

#Transmission and zone input values
transmission_input = CSV.read(string(inputs_path,sep,"trans_cap_and_zones.csv"),
↪  DataFrame, header=true)

# ~~~
# Model
# ~~~

## Sets
T = size(demand_input_z1)[1] # number of time steps
if stochastic
    S = size(demand_input_z1[:,2:end])[2] # number of scenarios
else
    S = 1
```

```
end
R_all = size(resources_input)[1] #All technologies
R =  length(resources_input[(resources_input[!,:Generation].==1),:][!,:Index_ID])
↪  #All generation technologies
resources = resources_input[:,1:5]

#Number of storage technologies
R_S = length(resources_input[(resources_input[!,:Storage].==1),:][!,:Index_ID])
↪  #All storage technologies
#transmission and zones
L = size(transmission_input[:,3])[1]
Z = size(transmission_input[:,2])[1]

## Parameters
cost_inv = resources_input[1:R_all,"Investment cost"] # €/MW-336days
cost_var = resources_input[1:R_all, "Operating cost"] # €/MWh
CO2_Tax = resources_input[1:R_all, "CO2_tax_per_ton_CO2"]

#Cost variables for transmission investemnet in the north sea grid Z3
cost_inv_transmission = zeros(R_all,Z)
cost_inv_transmission[:,1] =
↪  resources_input[1:R_all,"Investment cost transmission z1"]
cost_inv_transmission[:,2] =
↪  resources_input[1:R_all,"Investment cost transmission z2"]
cost_inv_transmission[:,3] =
↪  resources_input[1:R_all,"Investment cost transmission z3"]

availability = zeros(T,R_all,Z)
availability[:,:,1] = Matrix(resource_avail_input_z1[:, 2:9])
availability[:,:,2] = Matrix(resource_avail_input_z2[:, 2:9])
availability[:,:,3] = Matrix(resource_avail_input_z3[:, 2:9])

#define tax costs
GR_tax_cost = zeros(R,S)
GR_tax_cost[:,:] = Array(GRtax_cost_input[:,2:end])
GR_Tax_map = zeros(R_all,Z)
GR_Tax_map[:,:] = Array(GR_tax_map[:,:])

co2_factors = resources_input[:,"Emissions_ton_per_MWh"] # ton per MWh
price_cap = 3000 # €/MWh
carbon_cap = 72775794.4  # tCO2, -90% from 2005 emission levels

# Storage
# Current parameters assume battery storage
p_e_ratio = 1/4 # Power to energy ratio
# Single-trip efficiecy
eff_down = 0.9
eff_up = 0.9

if risk_aversion
    # CVaR
    # Define parameters
     = 1/4 # parameter for VaR set to 1/4 to look at worst case scenario which is
    ↪  the high demand scenario
     = 0.5 # parameter for degree of risk aversion, 1 means max/perfect risk
    ↪  aversion
else
     = 0
```

```
end

demand = zeros(T,S,Z)
demand[:,:,1] = Array(demand_input_z1[:,2:end])
demand[:,:,2] = Array(demand_input_z2[:,2:end])
demand[:,:,3] = Array(demand_input_z3[:,2:end])

# Define scenario probabilities
P = ones(S)*1/S # uniform distribution

#Transmission parameters
MaxTransCapacity = transmission_input[:,8]
MinTransCapacity = transmission_input[:,9]
LineLoss = transmission_input[:,10]
ZoneMap = transmission_input[:,5:7]


gep = Model(Gurobi.Optimizer)

# Supply
# Power supply, aka generation but could also be from storage in the future
@variable(gep, g[r in 1:R, t in 1:T, s in 1:S, z in 1:Z] >= 0) # amount of power
↪  supply, MW

# Capacity
@variable(gep, x[r in 1:R_all, z in 1:Z] >= 0) # Capacity, MW

# Non-served energy
@variable(gep, nse[t in 1:T, s in 1:S, z in 1:Z-1] >= 0)

# Storage
@variable(gep, discharge[r in 1:R_all, t in 1:T, s in 1:S, z in 1:Z-1] >= 0)
@variable(gep, charge[r in 1:R_all, t in 1:T, s in 1:S, z in 1:Z-1] >= 0)
# State of charge
@variable(gep, e[r in R:R_all, t in 1:T, s in 1:S, z in 1:Z-1] >= 0)

##Variables, Zones and Transmission
@variable(gep, MaxTransCap[l in 1:L] >= 0)
#PF for every Transmission line for every time step t
@variable(gep,Flow[t in 1:T, l in 1:L])

# Risk aversion
if risk_aversion
    # Auxiliary varliables for CVaR
    @variable(gep, u[s in 1:S] >= 0) # loss relative to VaR, €/MW
    @variable(gep, VaR) # VaR variable, €/MW
    @constraint(gep, u_expression[s in 1:S], u[s] >= sum(g[r,t,s,z]*cost_var[r]
    ↪  for r in 1:R, t in 1:T, z in 1:Z) + sum(price_cap*nse[t,s,z] for t in
    ↪  1:T, z in 1:Z-1) + sum(CO2_Tax[r]*co2_factors[r]*g[r,t,s,z] for r in 1:R,
    ↪  t in 1:T, z in 1:Z) + sum(GR_tax_cost[r,s]*x[r,z]*GR_Tax_map[r,z] for r
    ↪  in 1:R, z in 1:Z)  - VaR)
end

# Objective function
if CO2_tax_flag
    if risk_aversion
```

```
        @objective(gep, Min,
        ↪   sum(x[r,z]*cost_inv[r]+x[r,z]*cost_inv_transmission[r,z] for r in
        ↪   1:R_all, z in 1:Z) +(1-)*(sum(P[s]*g[r,t,s,z]*cost_var[r] for r in
        ↪   1:R, t in 1:T, s in 1:S, z in 1:Z) + sum(P[s]*price_cap*nse[t,s,z]
        ↪   for t in 1:T, s in 1:S, z in 1:Z-1)+
        ↪   sum(P[s]*CO2_Tax[r]*co2_factors[r]*g[r,t,s,z] for r in 1:R, t in 1:T,
        ↪   s in 1:S, z in 1:Z)+sum(P[s]*GR_tax_cost[r,s]*x[r,z]*GR_Tax_map[r,z]
        ↪   for s in 1:S, r in 1:R, z in 1:Z)) + *(VaR + 1/*sum(P[s]*u[s] for s
        ↪   in 1:S)))
    else
        # Risk neutral
        @objective(gep, Min,
        ↪   sum(x[r,z]*cost_inv[r]+x[r,z]*cost_inv_transmission[r,z] for r in
        ↪   1:R_all, z in 1:Z) + sum(P[s]*g[r,t,s,z]*cost_var[r] for r in 1:R, t
        ↪   in 1:T, s in 1:S, z in 1:Z) + sum(P[s]*price_cap*nse[t,s,z] for t in
        ↪   1:T, s in 1:S, z in 1:Z-1)+
        ↪   sum(P[s]*CO2_Tax[r]*co2_factors[r]*g[r,t,s,z] for r in 1:R, t in 1:T,
        ↪   s in 1:S, z in 1:Z)+sum(P[s]*GR_tax_cost[r,s]*x[r,z]*GR_Tax_map[r,z]
        ↪   for s in 1:S, r in 1:R, z in 1:Z))
    end
else
    if risk_aversion
        @objective(gep, Min,
        ↪   sum(x[r,z]*cost_inv[r]+x[r,z]*cost_inv_transmission[r,z] for r in
        ↪   1:R_all, z in 1:Z) +(1-)*(sum(P[s]*g[r,t,s,z]*cost_var[r] for r in
        ↪   1:R, t in 1:T, s in 1:S, z in 1:Z) + sum(P[s]*price_cap*nse[t,s,z]
        ↪   for t in 1:T, s in 1:S, z in
        ↪   1:Z-1)+sum(P[s]*GR_tax_cost[r,s]*x[r,z]*GR_Tax_map[r,z] for s in 1:S,
        ↪   r in 1:R, z in 1:Z)) + *(VaR + 1/*sum(P[s]*u[s] for s in 1:S)))
    else
        # Risk neutral
        @objective(gep, Min,
        ↪   sum(x[r,z]*cost_inv[r]+x[r,z]*cost_inv_transmission[r,z] for r in
        ↪   1:R_all, z in 1:Z) + sum(P[s]*g[r,t,s,z]*cost_var[r] for r in 1:R, t
        ↪   in 1:T, s in 1:S, z in 1:Z) + sum(P[s]*price_cap*nse[t,s,z] for t in
        ↪   1:T, s in 1:S, z in
        ↪   1:Z-1)+sum(P[s]*GR_tax_cost[r,s]*x[r,z]*GR_Tax_map[r,z] for s in 1:S,
        ↪   r in 1:R, z in 1:Z))
    end
end

#Power Balance Constraint
@constraint(gep, PowerBalance[t in 1:T, s in 1:S, z in 1:Z-1], sum(g[r,t,s,z] for
↪   r in 1:R) + nse[t,s,z]+ sum(discharge[r,t,s,z] - charge[r,t,s,z] for r in
↪   (resources_input[(resources_input[!,:Storage].==1),:][!,:Index_ID]))  +
↪   sum(Flow[t,l]*ZoneMap[l,z] for l in 1:L) == demand[t,s,z])
#Power Balance in Zone 3
@constraint(gep, PowerBalance_z3[t in 1:T,s in 1:S,z in Z], sum(g[r,t,s,z] for r
↪   in 1:R) + sum(Flow[t,l]*ZoneMap[l,z] for l in 1:L) == demand[t,s,z])
#Capacity Limit Constraint
@constraint(gep, CapacityLimit[r in 1:R, t in 1:T, s in 1:S, z in 1:Z],
↪   g[r,t,s,z] <= x[r,z]*availability[t,r,z])


#CAPACITY CONSTRAINTS ZONE 1
@constraint(gep, x[1,1] <= 8500)
@constraint(gep, x[4,1] <= 108045.33)
@constraint(gep, x[5,1] <= 43906.825)
```

```
@constraint(gep, x[6,1] == 0)
@constraint(gep, x[7,1] <= 423697.5)

#CAPACITY CONSTRAINTS ZONE 2 NOW REPRESENTIN UK
@constraint(gep, x[1,2] <= 6000)
@constraint(gep, x[4,2] <= 80170.994)
@constraint(gep, x[5,2] <= 88526)
@constraint(gep, x[7,2] <= 371750)

#CAPACITY CONSTRAINTS ZONE 3 NOW REPRESENTING THE OFFSHORE GRID
@constraint(gep, x[1,3] == 0)
@constraint(gep, x[2,3] == 0)
@constraint(gep, x[3,3] == 0)
@constraint(gep, x[4,3] == 0)
@constraint(gep, x[5,3] <= 85779.12)
@constraint(gep, x[7,3] == 0)
@constraint(gep, x[8,3] == 0)



#Storage constraints
# Loop through storage technologies
for r in (resources_input[(resources_input[!,:Storage].==1),:][!,:Index_ID])
    # Wrap first and last periods
    @constraint(gep, state_of_charge_start[t in 1:1, s in 1:S, z in 1:Z-1],
    ↪ e[r,t,s,z] == e[r,T,s,z] - (1/eff_down)*discharge[r,T,s,z] +
    ↪ eff_up*charge[r,T,s,z])
    # Energy balance for the remaining periods
    @constraint(gep, state_of_charge[t in 2:T, s in 1:S,z in 1:Z-1], e[r,t,s,z]
    ↪ == e[r,t-1,s,z] - (1/eff_down)*discharge[r,t-1,s,z] +
    ↪ eff_up*charge[r,t-1,s,z])
    @constraint(gep, energy_limit[t in 1:T, s in 1:S, z in 1:Z-1], e[r,t,s,z] <=
    ↪ (1/p_e_ratio)*x[r,z])
    @constraint(gep, charge_limit_total[t in 1:T, s in 1:S, z in 1:Z-1],
    ↪ charge[r,t,s,z] <= (1/eff_up)*x[r,z])
    @constraint(gep, charge_limit[t in 1:T, s in 1:S, z in 1:Z-1],
    ↪ charge[r,t,s,z] <= (1/p_e_ratio)*x[r,z] - e[r,t,s,z])
    @constraint(gep, discharge_limit_total[t in 1:T, s in 1:S, z in 1:Z-1],
    ↪ discharge[r,t,s,z] <= eff_down*x[r,z])
    @constraint(gep, discharge_limit[t in 1:T, s in 1:S, z in 1:Z-1],
    ↪ discharge[r,t,s,z] <= e[r,t,s,z])
    @constraint(gep, charge_discharge_balance[t in 1:T, s in 1:S, z in 1:Z-1],
    ↪ (1/eff_down)*discharge[r,t,s,z] + eff_up*charge[r,t,s,z] <= x[r,z])
end

# Climate policy
if co2_cap_flag
    @constraint(gep, emissions_cap[s in 1:S], sum(g[r,t,s,z]*co2_factors[r] for r
    ↪ in 1:R, t in 1:T, z in 1:Z) <= carbon_cap)
end

## Constraints, Transmission and zones
@constraint(gep, MaxFlowPos[l in 1:L,t in 1:T], Flow[t,l] <= MaxTransCapacity[l])
@constraint(gep, MaxFlowNeg[l in 1:L,t in 1:T], Flow[t,l] >= MinTransCapacity[l])


JuMP.optimize!(gep)
```

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