Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

Magnus A. Wendelborg

Sequencing of wholesale electricity markets (day-ahead and intraday) in a capacity expansion model under uncertainty

Development of a multi-horizon stochastic capacity expansion model containing both day-ahead and intraday markets under uncertainty

Master's thesis in Sustainable Energy Systems and Markets
Supervisor: Pedro Crespo del Granado
November 2020

NTNU
Norwegian University of Science and Technology

berlin

Magnus A. Wendelborg

Sequencing of wholesale electricity markets (day-ahead and intraday) in a capacity expansion model under uncertainty

Development of a multi-horizon stochastic capacity expansion model containing both day-ahead and intraday markets under uncertainty

Master's thesis in Sustainable Energy Systems and Markets
Supervisor: Pedro Crespo del Granado
November 2020

Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

NTNU
Norwegian University of
Science and Technology

Sequencing of wholesale electricity markets (day-ahead and intraday) in a capacity expansion model under uncertainty

Magnus A. Wendelborg

Supervisor: Pedro Crespo del Granado
Co-supervisor: Ruud Egging-Bratseth
Co-supervisor: Stian Backe

Dual-degree MSc Sustainable Energy Systems and Markets NTNU
Industrial Engineering and Managment - Energy and Resources TU Berlin

30.11.2020

Preface

This thesis marks my final work of my master's degree in Sustainable Energy Systems and Markets at NTNU and Industrial Engineering and Management - Energy and Resources at TU Berlin. It has been two great years, with much learning and various challenges that have resulted in this thesis.

I would like to like to express my deepest gratitude to my supervisors Pedro Crespo del Granado, Ruud Egging-Bratseth and Stian Backe for valuable advice, fruitful discussion and constructive feedback. A special thanks to Stian Backe for always being available to answer any question I had, be it programming or feedback on the thesis. Your guidance and helpful suggestions has been essential for the modelling and the results.

Many hours have been put into this thesis, possibly to the frustration of my partner, Sofie. I am forever grateful for your continuous support and running the household while I sat in the "office" writing. I would also like to thank my father for providing excellent help with Excel sharing ideas for the thesis. Lastly, I would like to thank my family and friends for supporting my work, being interested, and asking questions on the topic.

Sætersbø, 30.11.2020
Magnus A. Wendelborg

Magnus A. Wendelborg

Abstract

As the installed capacity of variable renewable energy sources [VRES] continues to expand worldwide due to the growing focus on climate change mitigation and improved economic conditions of VRES, the intraday market increases its importance in trading of electricity due to the uncertain nature of VRES. There is limited literature on how forecasting errors between market stages affect investment decisions in capacity expansion problem of a power system. This raises the following research question: How does an increased amount of uncertainty introduced by forecasting errors between a day-ahead and an intraday market affect investment decisions in the power system, including VRES investments?

To investigate how the investment decisions are affected by forecasting errors, a stochastic capacity expansion model was developed with two market stages, one day-ahead stage, and one intraday stage. The model emulates the European power system developments and aims to reduce emissions by restricting the emissions subject to the EU emission policy towards 2050. Three separate cases were analyzed to shed light on this issue. One case was selected to represent the standard approach to model investments in a power system. The second and third case represents cases with market sequencing, one stochastic and the other deterministic in order to investigate the impact of uncertainty in a capacity expansion problem. Four main conclusions can be drawn from the modelling results; 1) Forecasting error significantly impacts investment decisions and results in 10% less VRES investments and 40% more investments flexible capacity. 2) Cross-border transmission is a crucial contributor to flexibility and experiences a 10-20% increase in volume when accounting for forecasting errors. 3) Investments in storage capacity decreases significantly and are over-valued in the standard approach of capacity expansion models. 4) A deterministic approach significantly underestimates the total system costs and may even result in infeasible solutions if the conditions for VRES change from the expected conditions. These results imply that there are a significant differences between the standard approach and the approach developed in this thesis. We can therefore conclude that including forecasting errors between markets are of significant importance when analysing a capacity expansion problem. Considering the computational burden of adding a third stage, it increases significantly. Lastly, some considerations for future work was presented. These include research on market design, cost-recovery, demand-response and curtailment.

Sammendrag

De siste årene har andelen variable fornybare energikilder [VRES] økt betrakelig i verdens energimiks, mye grunnet det voksende fokuset på klimaendringer samt bedre økonomiske forhold for VRES. På grunn av usikkerheten tilknyttet prognosefeil fra VRES har ført til økt bruk av intradmarkeder. Det finnes begrenset literatur på hvordan prognosefeil for VRES mellom elektrisitetsmarkedet påvirker investeringsbeslutning i et kraftsystem. Dette peker behovet på forskning som kan svare på følgende spørsmål: Hvordan påvirker en økt grad av usikkerhet som følge av prognosefeil mellom et day-ahead marked og et intradag marked investeringsbesultninger i et kraftsystem, inkludert investeringer i VRES? For å undersøke hvordan investeringsbeslutninger i et energysystem påvirkes av disse prognosefeilene ble en stokastisk optimiseringsmodell utviklet i denne opgaven. Modellen består av tre steg. Ett investeringssteg og to operasjonelle steg; et operasjonelt steg for day-ahead markedet og et steg for intradag markedet. Modellen etterligner utviklingen av det Europeiske kraftsystemet og tar sikte på å redusere utslipp i tråd med utslippsmålene til EU frem mot 2050. Tre instanser av modellen ble testet for å belyse hvordan investeringsbeslutninger påvirkes av prognosefeil. Standard EMPIRE ble brukt for å teste den tradisjonelle måten å løse slike problemer. I tillegg ble utvidelsen av EMPIRE utviklet i denne opgaven brukt til å analsyre to instanser med to markedsteg, en stokastisk og en deterministisk, for å undersøke hvordan usikkerhet påvirker investeringsbeslutningene. Basert på resultatene, kan fire hovedresultater kan trekkes frem: 1) Prognosefeil mellom markeder påvirket investeringsbeslutninger betydelig og resulterte i 10% mindre VRES og 40% mer fleksibel kapasitet. 2) International kraftoverføring er en viktig bidragsyter til fleksibilitet og opplevde en volumøkning på 10-20% når det ble tatt hensyn til prognosefeil. 3) Investeringer i energilagring reduseres betydelig og er overvurdert i standardtilnærmingen til kapasitetsutvidelsesmodeller. 4) En deterministisk tilnærming undervurder de totale systemkostnadene, og kan resultere i umulige forhold dersom forholdene for VRES mellom markedene. Disse resultatene innebærer en betydlig forskjell mellom standardtilmærmingen og tilnærmingen utviklet i denne rapporten. Vi kan derfor konkludere med at inkludering av prognosefeil er av vesentlig betydning når et kapasitetsutvidelses problem analyseres. Derimot øker beregningsbyrden betraktelig når et tredje steg legges til. Fremtidig arbeid for å videreutvikle modellen inkluderer; markeds design, kostnadsgjennvinning, curtailment og demand-response.

Contents

Figures

Tables

Nomenclature

TSO	Transmission System Operator
RES	Renewable Energy Sources
VRES	Variable Renewable Energy Sources
W	Power
Wh	Energy
VSS	Value of Stochastic Solution
NO2	Node, representing the southern electricity zone in Norway

Sets, parameters and variables in the model

Sets

Supply technology sets

$$\begin{aligned} \mathcal{G}&: \text{Set of possible generator types,} \\ \mathcal{T}&: \text{Set of generator categories,} \\ \mathcal{B}&: \text{Set of possible storage types.} \end{aligned}$$

Temporal sets

$$\begin{aligned} \mathcal{I} = \{1, 2, ..., |\mathcal{I}|\}&: \text{Set of investment time periods,} \\ \mathcal{H} = \{1, 2, ..., |\mathcal{H}|\}&: \text{Set of operational time periods,} \\ \mathcal{S}&: \text{Set of seasons.} \end{aligned}$$

Spatial sets

$$\begin{aligned} \mathcal{N}&: \text{Set of nodes,} \\ \mathcal{L}&: \text{Set of bidirectional interconnectors,} \\ \mathcal{A}&: \text{Set of unidirectional arcs.} \end{aligned}$$

Stochastic sets

$$\Omega\text{: Set of scenarios.}$$

Sub-sets

$$
\begin{aligned}
\mathcal{G}_n \subseteq \mathcal{G}&\text{: Set of available generator types in node } n \in \mathcal{N},\\
\mathcal{G}_t \subset \mathcal{G}&\text{: Set of generator types in category } t \in \mathcal{T},\\
\mathcal{G}^{\text{Ramp}} \subset \mathcal{G}&\text{: Set of generator types limited by ramping,}\\
\mathcal{G}^{\text{RegHyd}} \subset \mathcal{G}&\text{: Set of regulated hydro generator types,}\\
\mathcal{G}^{\text{Hyd}} \subset \mathcal{G}&\text{: Set of all hydro generator types,}\\
\mathcal{G}^{\text{Flex}} \subset \mathcal{G}&\text{: Set of flexible generators,}\\
\mathcal{G}^{\text{Int}} \subset \mathcal{G}&\text{: Set of intermittent generators,}\\
\mathcal{G}^{\text{Inflex}} \subset \mathcal{G}&\text{: Set of inflexible generators,}\\
\mathcal{B}_n \subseteq \mathcal{B}&\text{: Set of available storage types in node } n \in \mathcal{N},\\
\mathcal{B}^{\dagger} \subseteq \mathcal{B}&\text{: Set of storage types with dependent ratio between energy and power,}\\
\mathcal{H}_s \subset \mathcal{H}&\text{: Set of operational time periods in season } s \in \mathcal{S}\ (\mathcal{H}_s = \{h_s^1, h_s^2, \ldots, |\mathcal{H}_s|\}),\\
\mathcal{H}_s^- \subset \mathcal{H}_s&\text{: Set of operational time periods except the first in season } s \in \mathcal{S},\\
\mathcal{A}_l \subset \mathcal{A}&\text{: Set of unidirectional arc pair on interconnection } l \in \mathcal{L},\\
\mathcal{A}_n^{\text{in}} \subset \mathcal{A}&\text{: Set of arcs flowing into node } n \in \mathcal{N},\\
\mathcal{A}_n^{\text{out}} \subset \mathcal{A}&\text{: Set of arcs flowing out from node } n \in \mathcal{N}.
\end{aligned}
$$

Input data

Costs

$$
\begin{aligned}
c_{g,i}^{\text{gen}}&\text{: Cost per unit of investing in generator type } g \in \mathcal{G} \text{ in period } i \in \mathcal{I},\\
c_{l,i}^{\text{tran}}&\text{: Cost per unit of investing in interconnection } l \in \mathcal{L} \text{ in period } i \in \mathcal{I},\\
c_{b,i}^{\text{storPW}}&\text{: Cost per unit of investing in power of storage type } b \in \mathcal{B} \text{ in period } i \in \mathcal{I},\\
c_{b,i}^{\text{storEN}}&\text{: Cost per unit of investing in energy of storage type } b \in \mathcal{B} \text{ in period } i \in \mathcal{I},\\
q_{g,i}^{\text{gen}}&\text{: Cost per unit of operating generator type } g \in \mathcal{G} \text{ in period } i \in \mathcal{I},\\
q_{g,i}^{\text{CO2}}&\text{: CO2 emission factor of generator type } g \in \mathcal{G} \text{ in period } i \in \mathcal{I},\\
q_{n,i}^{\text{ll}}&\text{: Value (cost) of lost load in node } n \in \mathcal{N} \text{ in period } i \in \mathcal{I},\\
Q_i^{\text{CO2}}&\text{: CO2 emission ceiling for all generators in period } i \in \mathcal{I},
\end{aligned}
$$

Technology limitations

Type dependent technology limitations

i_g^{gen}: Lifetime of investment in generator type $g \in \mathcal{G}$,
i_l^{tran}: Lifetime of investment in interconnector $l \in \mathcal{L}$,
i_b^{stor}: Lifetime of investment in storage type $b \in \mathcal{B}$,
γ_g: Ramping factor for generator type $g \in \mathcal{G}^{\text{Ramp}} \subset \mathcal{G}$,
ν_g: Variance factor for generator type $g \in \mathcal{G}^{\text{Flex}} \subset \mathcal{G}$,
η_a^{tran}: Efficiency factor for transmission losses along arc $a \in \mathcal{A}$, $\eta_a^{\text{tran}} \in (0,1)$,
η_b^{chrg}: Efficiency factor for charge losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{chrg}} \in (0,1)$,
η_b^{dischrg}: Efficiency factor for discharge losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{dischrg}} \in (0,1)$,
η_b^{bleed}: Efficiency factor for bleed losses with storage $b \in \mathcal{B}$, $\eta_b^{\text{bleed}} \in (0,1)$,
ρ_b: Capacity ratio between charge/discharge speed for storage type $b \in \mathcal{B}$,
β_b: Ratio between power and energy capacity for storage type $b \in \mathcal{B}^{\dagger} \subseteq \mathcal{B}$,
κ_b: Share of installed energy capacity initially available in storage type $b \in \mathcal{B}$ in each representative time period.

Node dependent technology limitations

$\bar{x}_{n,g,i}^{\text{gen}}$: Initial capacity of generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$\bar{x}_{l,i}^{\text{tran}}$: Initial capacity of interconnector $l \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$\bar{x}_{n,b,i}^{\text{storPW}}$: Initial capacity of power of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$\bar{x}_{n,b,i}^{\text{storEN}}$: Initial capacity of energy of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$\bar{X}_{t,n,i}^{\text{gen}}$: Max investments in generator category $t \in \mathcal{T}$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{X}_{l,i}^{\text{tran}}$: Max investments in interconnector $l \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$\bar{X}_{n,b,i}^{\text{storPW}}$: Max investments in power of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{X}_{n,b,i}^{\text{storEN}}$: Max investments in energy of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{V}_{t,n,i}^{\text{gen}}$: Max installed capacity of category $t \in \mathcal{T}$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{V}_{l,i}^{\text{tran}}$: Max installed capacity of interconnector $l \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$\bar{V}_{n,b,i}^{\text{storPW}}$: Max installed capacity of power of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{V}_{n,b,i}^{\text{storEN}}$: Max installed capacity of energy of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$.

Scenario input

π_{ω}: Probability of scenario $\omega \in \Omega$,

$\xi^{\text{gen,DA}}_{n,g,h,i,\omega}$: Availability of generator type in day-ahead market $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$, in hour $h \in \mathcal{H}$, in period $i \in \mathcal{I}$ and scenario $\omega \in \Omega$

$\xi^{\text{gen,ID}}_{n,g,h,i,\omega}$: Availability of generator type in intraday market $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$, in hour $h \in \mathcal{H}$, in period $i \in \mathcal{I}$ and scenario $\omega \in \Omega$

$\xi^{\text{load,DA}}_{n,h,i,\omega}$: Demand in node in day-ahead market $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$\xi^{\text{load,ID}}_{n,h,i,\omega}$: Demand in node in intraday market $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$\xi^{\text{RegHydLim}}_{n,s,i,\omega}$: Max output from regulated hydro in node $n \in \mathcal{N}$ in $s \in \mathcal{S}$, $i \in \mathcal{I}$ and $\omega \in \Omega$,

ξ^{HydLim}_{n}: Max expected annual output from total hydro in node $n \in \mathcal{N}$.

Variables

Investment decision variables

$x^{\text{gen}}_{n,g,i}$: Capacity investments in generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,

$x^{\text{tran}}_{l,i}$: Capacity investments in interconnector $l \in \mathcal{L}$ in period $i \in \mathcal{I}$,

$x^{\text{storPW}}_{n,b,i}$: Capacity investments in power of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,

$x^{\text{storEN}}_{n,b,i}$: Capacity investments in energy of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,

$v^{\text{gen}}_{n,g,i}$: Existing capacity of generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,

$v^{\text{tran}}_{l,i}$: Existing capacity of interconnector $l \in \mathcal{L}$ in period $i \in \mathcal{I}$,

$v^{\text{storPW}}_{n,b,i}$: Existing capacity of power of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,

$v^{\text{storEN}}_{n,b,i}$: Existing capacity of energy of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$.

Operational decision variables

$y^{\text{gen,inflex}}_{n,g,h,i,\omega}$: Output from inflexible generator type $g \in \mathcal{G}^{inflex}$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{gen,flexDA}}_{n,g,h,i,\omega}$: Output from Flexible generator type in day-ahead market $g \in \mathcal{G}^{Flex}$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{gen,interDA}}_{n,g,h,i,\omega}$: Output from intermittent generator type in day-ahead market $g \in \mathcal{G}^{inter}$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{gen,interID}}_{n,g,h,i,\omega}$: Output from intermittent generator type in intraday market $g \in \mathcal{G}^{inter}$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{gen,flexID}}_{n,g,h,i,\omega}$: Output from intermittent generator type in intraday market $g \in \mathcal{G}^{Flexible}$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{tranDA}}_{a,h,i,\omega}$: Power flow over unidirectional arc in day-ahead market $a \in \mathcal{A}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{tranID}}_{a,h,i,\omega}$: Power flow over unidirectional arc in intraday market $a \in \mathcal{A}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{chrgDA}}_{n,b,h,i,\omega}$: Charging of storage type in day-ahead market $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{chrg,ID}}_{n,b,h,i,\omega}$: Charging of storage type in intraday market $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{dischrg,DA}}_{n,b,h,i,\omega}$: Discharging of storage type in day-ahead market $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$y^{\text{dischrg,ID}}_{n,b,h,i,\omega}$: Discharging of storage type in intraday market $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$w^{\text{stor,DA}}_{n,b,h,i,\omega}$: Energy content of storage type in day-ahead market $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in hour $h \in \mathcal{H}$, in period $i \in \mathcal{I}$ and scenario $\omega \in \Omega$

$w^{\text{stor,ID}}_{n,b,h,i,\omega}$: Energy content of storage type in intraday market $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in hour $h \in \mathcal{H}$, in period $i \in \mathcal{I}$ and scenario $\omega \in \Omega$

$y^{\text{ll,ID}}_{n,h,i,\omega}$: Amoumt of load shed in intraday market in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$.

Chapter 1

Introduction

Electricity markets have traditionally had large shares of dispatchable energy sources such as coal, gas, and nuclear energy. However, recent years' development has shifted towards more renewable energy sources (RES) in the energy mix [1]. The development is driven by climate change concerns and more favorable economic conditions for RES than previously compared to its competitors in the power mix. In order to minimize the effect of climate change and stay below the 2°C target [2], this development is projected to continue [3].

As the share of variable renewable energy sources [VRES] in an energy mix grows, the uncertainty in relation to electricity production increases [4]. Weather conditions are susceptible to forecasting errors, and thus, the forecasts for the production of wind and solar might differ from actual production conditions. A key issue in a power system is to balance supply and demand. Energy sources such as wind and solar are intermittent by nature, and thus, matching supply with demand is increasingly difficult when the share of these energy sources grows [5]. Balancing mechanisms are therefore increasingly important in order to balance supply and demand of electricity. The electricity markets have traditionally handled the balancing with different market stages. The day-ahead market stage aims to use the available information to balance supply and demand until the day before actual delivery. Deviations from the scheduled plan are typically handled by the intraday market stage, which balances these deviations close to real-time. Multiple factors can contribute to the volume traded in the intraday market, such as weather forecasting errors, demand change, and line- and generator outage. Any deviations still remaining at the scheduled delivery time are typically handled by a transmission system operator (TSO) in a balancing market stage.

In the last five years, the installed capacity of solar and wind (onshore and offshore) in Europe have increased by 41% combined, as illustrated in figure 1.1 [6]. Wind offshore has had the most significant increase, having increased by 156%, from 20 GW installed in 2015 to 51 GW in 2019. Solar increased by 44%, from 200 GW to 287 GW, and wind onshore increased by 33% from 345 GW to 459

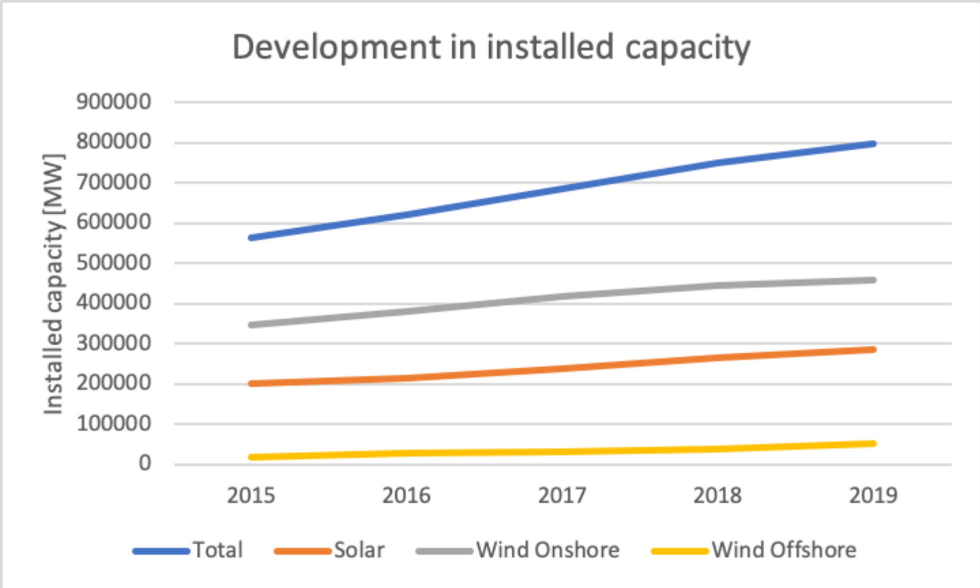

Figure 1.1: Installed capacity of wind onshore, wind offshore, and solar in Europe from 2015 to 2019. Data gathered from the ENTSO-e transparency platform using the SFTP protocol [6].

GW in the same period. As seen in figure 1.2 and table 1.1, an increase of VRES in the energy-mix entails that a larger volume of electricity was handled by the intraday volume, percentage-vise. With this in mind, it is likely that more VRES in the European energy mix increases the dependency on the intraday market to balance any discrepancies between the forecasts and actual available delivery.

In line with the development of the energy-mix in recent years and the projected increase in VRES capacity, three research questions are proposed in this thesis:

- How does an increased amount of uncertainty introduced by forecasting errors between a day-ahead and an intraday market affect investment decisions in the power system, including VRES investments?
- How are operational decisions affected when forecasting errors from market sequencing are included?
- What is the impact of including uncertainty when analyzing the developments in a power system?

The thesis is structured as follows; Chapter 2 gives an introduction to conducted research on related subjects and the lack of research related to the objective. Chapter 3 establishes the problem, while Chapter 4 provides the methodology to solve the problem. In Chapter 5, the methodology is utilized in test cases for proof of concept. In Chapter 6, large-scale cases representing the whole European power system are developed and solved to answer the research questions and illustrate the impact of the research conducted. Chapter 7 summarizes the findings

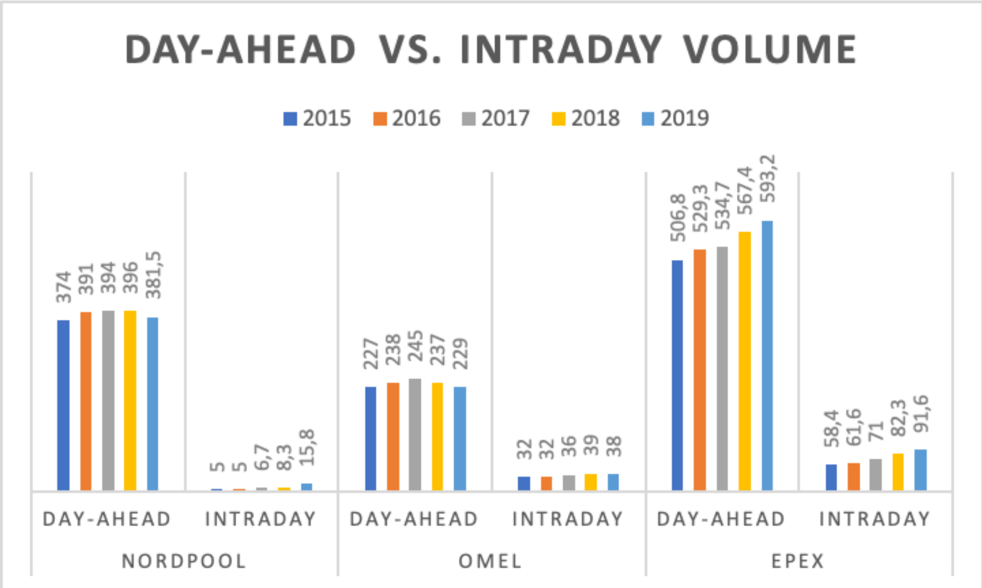

Figure 1.2: Intraday vs. Day-Ahead volumes for selected European electricity markets, data retrieved from [7–9].

Table 1.1: Overview of Day-Ahead and Intraday volume for selected markets from 2015-2019. Data adapted from [7–9]

Market			OMEL		
Year	2019	2018	2017	2016	2015
Day-Ahead Volume (TWh)	229	237	245	238	227
Intraday Volume (TWh)	38	39	36	32	32
Market			EPEX		
Year	2019	2018	2017	2016	2015
Day-Ahead Volume (TWh)	593,2	567,4	534,7	529,3	506,8
Intraday Volume (TWh)	91,6	82,3	71	61,6	58,4
Market			Nordpool		
Year	2019	2018	2017	2016	2015
Day-Ahead Volume (TWh)	381,5	396	394	391	374
Intraday Volume (TWh)	15,8	8,3	6,7	5	5

and propose recommendations for future work. Due to the limited research on the topic, the results was considered to be of contribution to the field. Therefore, a journal paper was written in parallel to the thesis. The draft of the paper is listed in Appendix B

Chapter 2

Literature Review

In recent years, more emphasis has been put into research on how VRES are influencing decision making in a power system, much due to climate change concerns. In addition, more powerful software has been developed, allowing for more computationally heavy models and analyses. This section will provide a review of current literature in relation to the research questions proposed in Chapter 1. The literature review will focus on research on investment and operational decisions in a power system and how VRES and its stochastic nature affect these decisions.

As the energy mix of the world moves towards a larger share of VRES, the level of uncertainty in a power system increases. To maintain a balance between supply and demand with high shares of VRES, flexible energy producers or consumers are required [10]. Several papers highlight the importance of flexibility in a power system with large shares of VRES, and the role that storage, transmission, flexible energy sources such as hydropower and gas, and demand-side flexibility, will have on the reliability and security of supply of such a power system [11–13]. An NREL study indicated that energy storage would be a key component to provide flexibility in a power system characterized by large shares of VRES penetration [14]. Denholm and Hand [15] also highlight the need for energy storage in the future and estimate storage capacity of about one day worth of load to meet the demand without a significant curtailment portion. Child et. al. [16] did an analysis on the flexibility requirements and benefits to allow for a high penetration on VRES. Their results indicated that, while energy storage and flexible generators would be key contributors to flexibility, transmission provided the most value for money flexibility vise. However, De Jonghe et. al. [17] did a similar study, which indicated that energy storage would be the most beneficial flexibility provider.

A common approach to analyze problems concerning investments and operational decisions in a power system is to utilize mathematical optimization models. Optimization models for power systems are typically divided into two categories: capacity expansion models and operational models. Capacity expansion models typically focus on investments and energy mix, while operational models typically focus on market aspects.

Multi-market modeling is usually done using operational models. Zipf and Möst [18] analyzed the direct and indirect costs of variable VRES in the German power system by utilizing a two-stage operational optimization model with day-ahead and intraday scheduling. Their results indicated that an increased amount of variable VRES in an power system leads to both increased direct and indirect cost due to the forecasting errors related to VRES. However, different studies on multi-stage operational optimization models without an investment stage [19, 20] have shown that an increased share of variable VRES is leading to a lower total cost than the current energy mix. Kulakov and Ziel [21] investigated how forecasting errors caused by VRES influenced electricity prices in the market stages. They found a non-linear correlation between intraday and day-ahead prices. Abrel and Kuntz [22] explored the impact of uncertainty from VRES on unit commitment power dispatch. They found that an increased amount of uncertainty triggers more unit commitment from inflexible energy sources. With the increased uncertainty, a more diverse energy portfolio was emphasized to balance the VRES forecasting errors between the market stages. Barth et. al. [23] also investigated the impact of wind uncertainty on a power system by creating a five-stage stochastic market model. The objective was to establish the reserves' role in such a power system and the cost associated with the reserves. The results indicated that the importance of reserves increased in such a system, and regulated hydropower was the main contributor to the reserve market. Morales et. al. [24] developed a model analyzing the issues with conventional market design due to VRES's stochastic nature. One issue they identified, was the lack of a cost-recovery guarantee for flexible producers. They proposed a solution where the day-ahead market is cleared while also factoring in the anticipated balancing cost resulting from forecasting errors. Borggrefe and Neuhoff [25] highlighted the need for a market design that facilitates potential improved conditions in the intraday market compared to the day-ahead market.

In addition to multi-market modeling, capacity expansion models are also of great interest to issues addressed in this thesis. Seljom and Tomasgaard [26] developed a model to analyze the investment decisions in the Danish power system. Both a deterministic and a stochastic approach were utilized, and they found significant differences between the approaches. They concluded that a stochastic approach was a more realistic and that this approach resulted in significantly lowered investments in VRES. Their results are also supported by Nagl et al. [27], who concluded that VRES is typically significantly overvalued and flexible providers the opposite. Ehremann and Smeers [28] developed a capacity expansion model addressing the issues with investment risks in a power system. They approached the issue by including stochastic properties in the discount rate to incorporate the risk of investing in VRES compared to dispatchable energy sources. The results indicated that by adding risk, i.e., considering the power system's uncertainty due to VRES's unpredictable nature, the system costs increased. Sun et al. [29] analyzed the US power system with a capacity expansion model focusing on transmission flow between different regions. They found that transmission might be an underestimated technology in capacity expansion models. In 2012, Giraldo et al. [30] investigated the impact of adding emission constraints to a capacity expansion model. Both an emission tax and an emission cap was included. They showed that adding such constraints increased the total costs somewhat, but that the investments and thus, the solution were applicable to a real-world scenario. Villavicencio [31] developed a capacity expansion model aiming to encapsulate some of the operational issues of VRES. It was concluded that proper modeling of the system- and operational requirements increase with a large penetration of VRES. Poncelet et al. [32] also developed a capacity expansion model aiming to integrate the challenges with large shares of VRES in an power system. Bermudez et. al. [33] highlights the need to consider the expected future development when planning for investments in a power system.

In addition to models focusing on capacity expansion and market modeling, there is some research on models combining capacity expansion and market sequencing. Pineda and Morales [34] developed a model with both an investment stage as well as market sequencing. Their results indicated that forecast errors had a major impact on investment decisions and that the installed capacity of VRES in a power system will decrease if considerations on forecasting errors between market stages are present. However, Pineda and Morales used a small model covering just the Danish power system, and the results did not include findings on transmission or energy storage. Table 2.1 lists the most relevant literature used to formulate the model developed in this thesis. The purpose of this literature review was to evaluate relevant research on capacity expansion model and the impact of forecasting errors. Much research has been conducted on capacity expansion model, but a better understanding on how forecasting errors affect such a problem is necessary. From the literature review, it can be expected that investigating the impact of market sequencing on investment decisions will significantly impact the results. Importantly, it is reasonable to assume that these systems will be more reliant on flexibility providers and that the total system costs will increase.

This thesis aims to fill a gap in the current literature concerning capacity expansion models with market sequencing. Capacity expansion models with market sequencing is currently rarely done, and only on relatively small power systems with limited transmission opportunities and energy storage systems. Therefore, this paper aims to establish what the impact market sequencing has, both on installed capacity, transmission capacity, and storage capacity, in order to provide a more accurate representation of the ideal developments in a power system.

Table 2.1: Table of relevant literature on capacity expansion models or market sequencing models which are similar to the model developed in this thesis.

Author and source	Investments	Markets
Zipf and Most [18]	No	Day-Ahead and Intraday
Abrell and Kunz [22]	No	Day-Ahead and Intraday
Kannavou et. al. [20]	No	Day-ahead, Intraday and Reserve
Barth et. al. [19]	No	5: Day-ahead, Intraday, Day-ahead for reserves, Intraday for spinning, Heat
Morales et. al. [24]	No	Day-Ahead and Intraday
Pineda and Morales [34]	Yes	Day-Ahead and Intraday
Seljom and Tomasgard [26]	Yes	Operational
Poncelet [32]	Yes	Operational
Villavicencio [31]	Yes	Operational
Giraldo et. al. [30]	Yes	Operational
Sun et. al. [29]	Yes	Operational
Ehremann and Smeers[28]	Yes	Operational

Chapter 3

Problem Description

This section describes the problem of investments and operational decisions in a power system with market sequencing under uncertainty. We specifically consider the impact of forecasting errors in optimal investments

3.1 Problem Definition

Let us take the perspective of a capacity expansion problem in a power system. The purpose of a power system is to facilitate delivery of electricity to potential consumers at all times. In order to supply electricity, producers of electricity are needed. In addition to production capacity, other infrastructure components such as transmission and possibly energy storage systems, are important parts of a power system. Long-term investment decisions in these infrastructure components are important in order to ensure sufficient installed capacity and guarantee security of supply.

The delivery of electricity is normally scheduled and decided in electricity markets. Typically, these are classified as forward markets, day-ahead markets and intraday/balancing markets. In this report, we ignore forward markets. Day-ahead markets schedule the production and delivery of electricity in order to meet a demand, the day before actual delivery. Day-ahead markets are important parts in a power system as they allow producers to anticipate and plan their operations including the production of electricity. However, the actual demand and production conditions may deviate from the projected conditions in the day-ahead market. Load as well as production from VRES are susceptible to forecasting errors, due to the intrinsic short-term uncertainty in weather conditions and user behavior. In order to be able to supply the demand, an intraday market is used to balance the deviations resulting from the forecasting errors between the market stages, or shed load if necessary.

A capacity expansion problem in a power system aims to plan the minimal cost investments in a power system given future demand levels and various uncertainties. To decide on the best investments in a power system, it is important to include both the intrinsic uncertainty of VRES and load and the forecasting errors between electricity markets. The problem can therefore be separated into three distinct types of stages, strategic stages and two types of operational stages. In strategic stages, the long-term investments in the power system are decided, while the two operational stages are the day-ahead and intraday market, respectively. As the forecasting errors largely depend on the energy-mix, it is particularly important to consider the forecasting errors when analysing a capacity expansion problem.

3.2 Objective

The objective is to identify the optimal investment decisions in a power system with market sequencing under uncertainty at minimal costs. This implies that power system operation must be considered. The strategic investment decisions must take into account the operational decisions, and thereby account for the uncertainty in VRES and load, in addition to the forecasting errors introduced by the market stages. Given the consideration of uncertainty in a multi-stage setting for a long planning horizon, the aim is to mimimize expected discounted system costs. Investment costs include investment costs for all infrastructure, i.e., generation, transmission and energy storage. Operational costs include fuel costs, operations and maintenance costs and other variable costs.

3.3 Decisions

The decisions in a power system can be separated into strategic and operational decisions. Strategic decisions are investments in technologies, such as generators, transmission capacity and energy storage. The strategic decisions state what is invested in and the level of the investments in each strategic stage. The operational decisions plan respectively how all available capacity is utilized to serve the demand based on information available in the specific operational stage. Specifically these concern generation, transmission flows, battery charging and discharging, and load shedding in the intraday stage. The operational decisions in the day ahead market are based on forecasts for load and VRES generation. The operational decisions in the intraday market have to adjust the decisions made in the day-ahead market, if these turn out to be inaccurate. As such, three separate groups of decisions are made. First, strategic investment decisions are made, second operational decisions for the day-ahead market based on the best available information (the forecast), and third, operational decisions in the intraday market when actual information is revealed. These decisions drive the costs of operating a power system.

3.4 Assumptions

It is assumed that technology costs and location availability is known. For technology costs, this refers to both variable and fixed costs for all technologies, in all strategic periods analysed. Location availability implies which technology is available in each location, and which nodes can by connected by inter-connectors. The system is reliable, and thus, generator- and line outage is assumed to be not present. Operational decisions are made based on the assumption of perfect competitive markets. Information concerning actual conditions for VRES and load are always revealed one hour prior to the actual delivery. Lastly, the cross-border intraday market project (XBID) is fully operational, and thus, allow for additional trading of transmission capacity in the intraday market.

A crucial assumption is the market design. It is assumed that both the day-ahead and intraday markets will balance the full load. This implies that the intraday market will not balance just the deviations from the day-ahead market, but a complete re-balance. This results in the assumption that the day-ahead market is not completely binding in its decisions, and thus potential poor decision making in the day-ahead market can be improved.

3.5 Restrictions

This section will first present the restrictions concerning investments before the restriction concerning operations are presented.

The investments are restricted by maximum installed capacity, maximum build capacity and location availability. Maximum installed capacity refers to how much capacity can be installed in a given node of a given technology. Maximum build capacity refers to how much capacity can be built in a single strategic period, and location availability restrict investments of certain components in certain nodes. The location availability also includes which nodes can be interconnected to each other. Additionally, some energy storage technologies have restrictions on the relationship between power and energy investments.

In the day-ahead market, the supply has to be equal to the demand in a given node. In the intraday market, there is a possibility for load shedding at an additional cost. As it assumed that actual information on VRES and load is revealed one hour prior to actual delivery, flexible generators are able to ramp up or down their production subject to technological ramping restrictions in one hour. However, only flexible generators are able to ramp in between markets. The VRES generators are subject to the weather conditions, and the inflexible generators are committed by the decisions made in the day-ahead market. Ramping of generators are also restricted between operational time steps in both markets. All generator output are limited by the installed capacity and generator availability for each operational point. Transmission and storage operations are also limited by the installed capacity. The energy level of the storage is limited by the installed capacity and the discharge- and charge volume of an operational point. Charging and discharging are, therefore, also limited by the energy level. The energy level is also restricted by a bleed factor, resulting in a minor loss of energy between operational points. Hydroelectric generators are limited by the volume of the reservoir. Transmission- and discharge/charge volume are also restricted by losses due to efficiency factors. Lastly, all operations are limited by an emission cap which span over each strategic period.

3.6 Summary

This section has described the problem of capacity expansion of a power system considering forecasting errors between market stages. The objective is to establish ideal investments in a power system with market sequencing restricted by technological limitations while also considering uncertainty from VRES and load.

Chapter 4

Method

This chapter describes the methodology used on the problem. It is divided into five separate sections. The first section gives a brief introduction to the EMPIRE (European Model for Power System Investment with Renewable Energy) model, serving as the framework for the model formulation. The second section describes the additional module that was developed in this thesis. Section three describes the model formulation while section four reflects on potential shortcomings in the model. Finally, section five presents the method for the intraday volume calculation.

4.1 EMPIRE

The model developed in this thesis is based on the EMPIRE model, described in [35]. Existing data for the EMPIRE model is used in this project. EMPIRE is an existing model containing two stages: one investment stage and one operational stage, thereby characterizing it as a capacity expansion model. Figure 4.1 illustrates EMPIRE graphically. EMPIRE has been used in a number of different publications [36–39]. The model represents the EU countries in addition to Switzerland and Norway. In total, there are 35 nodes present. Norway is also split into five zones, according to Nordpools trading zones [40]. Export and import of electricity is possible in neighbouring countries and zones. Investment decisions in generator capacity, energy storage and transmission are done in EMPIRE to facilitate production in order to meet the demand in each node on an hourly basis without exceeding an emission cap. Electricity demand, technology costs, technology options and operational characteristics are inputs [37]. The output is given as investments in technologies and operational decisions assuming a perfect competition market. EMPIRE is a linear capacity expansion model, spanning over 8 periods of 5 years each. Each period is composed of 4 regular seasons, representing winter, spring, summer and autumn, and two peak seasons representing extreme conditions. Each regular season has 168 hours and each peak season has

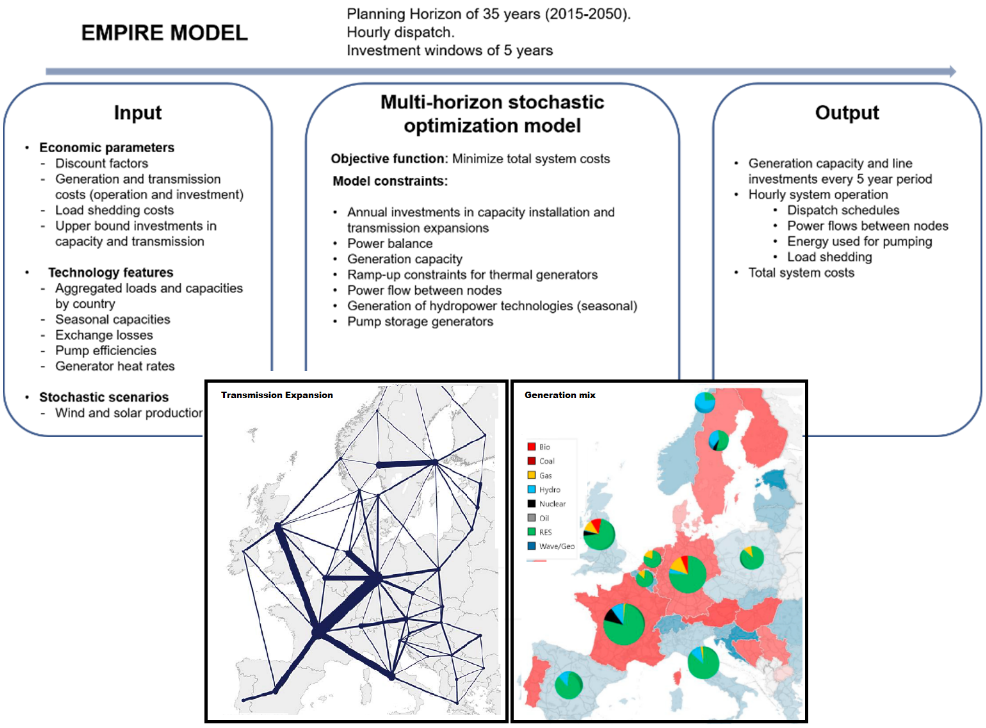

Figure 4.1: Illustration of the EMPIRE model, illustrating its input data, objective and constraints, and output. Adapted from [41]

24 hours. Uncertainty is included in every hour for load and generator availability for VRES. Additionally, regulated hydro has uncertainty concerning available capacity on a per period basis.

4.2 Explanation of the model

The existing framework for EMPIRE was used to create a three-stage stochastic optimization model [42] with one investment stage and two operational stages, simulating two electricity markets in order to solve the problems stated in Chapter 3. The investment stage makes investments in technologies such as generators, transmission capacity and energy storage. The operational stages emulates a day-ahead market and an intraday market. Both markets supply a load assuming perfect competition. The day-ahead market is cleared based on a best guess forecast for load and production conditions for VRES, which is similar to the approach used in [22]. In the intraday market, actual information on load and production conditions are revealed, and the system re-balances based on the updated information subject to the relationship between the market stages. As not every generator type can change its output on short notice, these generators are committed to the production decided in the day-ahead market. Generators that cannot alter their scheduled production in the day-ahead market are referred to as inflexible generators. Generators that are able to alter their output on a short notice are referred to as flexible generators.

It is assumed that energy storage systems are fully flexible between the two markets as the ramping time of energy storage's typically are very low [14]. Figure 4.2 illustrates the two markets graphically and how the markets are dependant on each other. As depicted by the figure, the output from the inflexible generators is a committed decision made in the day-ahead market while flexible generators are dependant on the decision made in the day-ahead market by the flexibility factor. Transmission is connected as well. The connection between the investment stage and the operational stages are limited by the installed capacity of each generator type in each node. Production in any of the markets are thus limited by what is available at that specific point in time.

The generator availability is defined as a constant value for all generators except for intermittent energy sources as described in [35]. The generator availability for intermittent generators is calculated by using a normalized value of production per installed capacity, as shown in equation (4.1). The normalized value ensures scalability of production per installed capacity, thus allowing for analysis of the impact VRES has on investment- and operational decisions when and if the energy mix changes.

$$\frac{Production_{n,g,h,i}}{InstalledCapacity_{n,g,i}} = \xi^{\text{gen}}_{n,g,h,i} \tag{4.1}$$

4.3 Model Formulation

This section will describe the model formulation. For an explanation of the parameters, sets, and variables, please refer to the nomenclature.

4.3.1 Objective function

$$\begin{aligned}\min z = &\sum_{i\in\mathcal{I}}(1+r)^{-5(i-1)}\times \\ &\Big[\sum_{n\in\mathcal{N}}\sum_{g\in\mathcal{G}_n} c^{\text{gen}}_{g,i}x^{\text{gen}}_{n,g,i} + \sum_{l\in\mathcal{L}} c^{\text{tran}}_{l,i}x^{\text{tran}}_{l,i} + \sum_{n\in\mathcal{N}}\sum_{b\in\mathcal{B}_n}\big(c^{\text{storPW}}_{b,i}x^{\text{storPW}}_{n,b,i} + c^{\text{storEN}}_{b,i}x^{\text{storEN}}_{n,b,i}\big) + \\ &\vartheta\sum_{\omega\in\Omega}\pi_\omega\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\Big(\sum_{g\in\mathcal{G}_n} q^{\text{gen}}_{g,i}(y^{\text{gen,inflex}}_{n,g,h,i,\omega} + y^{\text{gen,flexID}}_{n,g,h,i,\omega} + y^{\text{gen,InterID}}_{n,g,h,i,\omega}) + q^{\text{ll}}_{n,i}y^{\text{ll,ID}}_{n,h,i,\omega}\Big)\Big]\end{aligned} \tag{4.2}$$

The objective function (4.2) discounts all costs at an annual rate of r, and the investment periods are given as five year blocks. The factor $\vartheta = \sum_{j=0}^{4}(1+r)^{-j}$ scales annual operational costs to the five year investment periods.

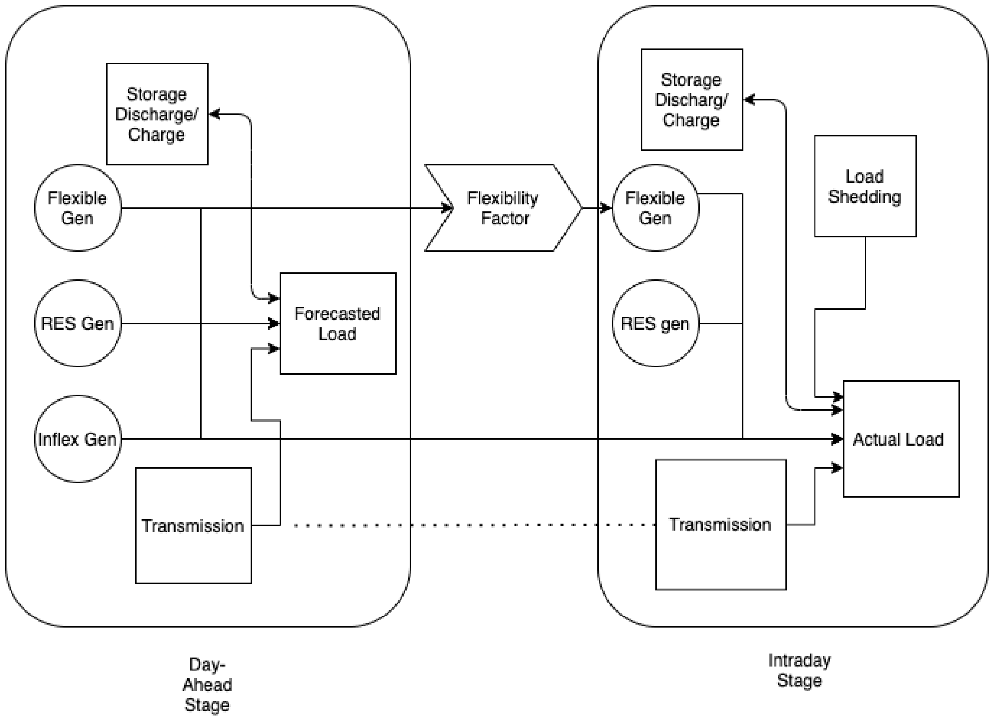

Figure 4.2: Illustration of day-ahead stage and intraday stage and its connection.

The first four terms of (4.2) relate to investment costs of the additional capacity of generation, transmission and storage. The last four terms relate to operational costs of generation and costs of load shedding. The terms for operational costs are scaled with the scenario probability π_ω and the seasonal scaling factor α_s, where α_s make sure the seasonal costs are scaled up to the length of each season. The total generation output is calculated by summing the committed generation schedule from the day-ahead market and the actual delivery of energy from the intraday market.

4.3.2 Constraints

Operational constraints

Constraint (4.3) balances the anticipated load with the expected generator availability. Storage discharge volume, as well as transmission, can contribute to serving the demand. Storage can also be charged for later use, and transmission volume can be exported. In the day-ahead market, no load shedding is allowed due to the characteristics of a day-ahead market.

$$\sum_{g\in\mathcal{G}_n}(y^{\text{gen,inflex}}_{n,g,h,i,\omega}+y^{\text{gen,FlexDA}}_{n,g,h,i,\omega}+y^{\text{gen,interDA}}_{n,g,h,i,\omega})+\sum_{b\in\mathcal{B}_n}\eta^{\text{dischrg}}_{b}y^{\text{dischrg,DA}}_{n,b,h,i,\omega}+\sum_{a\in\mathcal{A}^{in}_n}\eta^{\text{tran}}_{a}y^{\text{tran,DA}}_{a,h,i,\omega}=$$
$$\xi^{\text{load,DA}}_{n,h,i,\omega}+\sum_{b\in\mathcal{B}_n}y^{\text{chrg,DA}}_{n,b,h,i,\omega}+\sum_{a\in\mathcal{A}^{out}_n}y^{\text{tran,DA}}_{a,h,i,\omega},\;\; n\in\mathcal{N},\; h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.3)$$

Constraint (4.4) re-balances the operations of the system after the new information on generator availability and actual electrical load are available. The committed decisions concerning output from inflexible generators made in the day-ahead market are present due to the characteristics of these generators not being able to alter its output in the period between the two markets. Transmission and storage decisions are also influencing the decisions on how the load is met.

$$\sum_{g\in\mathcal{G}_n}(y^{\text{gen,inflex}}_{n,g,h,i,\omega}+y^{\text{gen,FlexID}}_{n,g,h,i,\omega}+y^{\text{gen,interID}}_{n,g,h,i,\omega})+\sum_{b\in\mathcal{B}_n}\eta^{\text{dischrg}}_{b}y^{\text{dischrg,ID}}_{n,b,h,i,\omega}+\sum_{a\in\mathcal{A}^{in}_n}\eta^{\text{tran}}_{a}y^{\text{tran,ID}}_{a,h,i,\omega}+y^{\text{ll,ID}}_{n,h,i,\omega}=$$
$$\xi^{\text{load,ID}}_{n,h,i,\omega}+\sum_{b\in\mathcal{B}_n}y^{\text{chrg,ID}}_{n,b,h,i,\omega}+\sum_{a\in\mathcal{A}^{out}_n}y^{\text{tran,ID}}_{a,h,i,\omega},\;\; n\in\mathcal{N},\; h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.4)$$

Constraints (4.5), (4.6), and (4.7) state the maximum allowed difference between the day-ahead and intraday market in terms of generation output and transmission for every hour in every period, for all scenarios, and in all nodes. The parameter, ν_g, is based on variance per hour for flexible generators and is identical to the ramping parameter.

$$(1+\nu_g)*y^{\text{gen,FlexDA}}_{n,g,h,i,\omega}\leq y^{\text{gen,FlexID}}_{n,b,h,i,\omega}$$
$$g\in\mathcal{G}^{\text{Flex}}, n\in\mathcal{N},\; h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.5)$$

$$y^{\text{gen,FlexID}}_{n,b,h,i,\omega}\leq(1-\nu_g)*y^{\text{gen,FlexDA}}_{n,g,h,i,\omega}$$
$$g\in\mathcal{G}^{\text{Flex}}, n\in\mathcal{N},\; h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.6)$$

$$y^{\text{tran,DA}}_{a,h,i,\omega}\leq y^{\text{tran,ID}}_{a,h,i,\omega}$$
$$a\in\mathcal{A},\; h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.7)$$

Production from generators are limited by the available installed capacity:

$$y^{\text{gen,inflex}}_{n,g,h,i,\omega}\leq\xi^{\text{gen,DA}}_{n,g,h,i,\omega}v^{\text{gen}}_{n,g,i},\quad g\in\mathcal{G}^{\text{Inflex}},\; n\in\mathcal{N}$$
$$h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.8)$$

$$y^{\text{gen,FlexDA}}_{n,g,h,i,\omega}\leq\xi^{\text{gen,DA}}_{n,g,h,i,\omega}v^{\text{gen}}_{n,g,i},\quad g\in\mathcal{G}^{\text{Flex}},\; n\in\mathcal{N}$$
$$h\in\mathcal{H},\; i\in\mathcal{I},\; \omega\in\Omega. \quad (4.9)$$

$$y^{\text{gen,interDA}}_{n,g,h,i,\omega} \leq \xi^{\text{gen,DA}}_{n,g,h,i,\omega} v^{\text{gen}}_{n,g,i}, \quad g \in \mathcal{G}^{\text{Inter}},\ n \in \mathcal{N}$$
$$h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.10}$$

$$y^{\text{gen,FlexID}}_{n,g,h,i,\omega} \leq \xi^{\text{gen,ID}}_{n,g,h,i,\omega} v^{\text{gen}}_{n,g,i}, \quad g \in \mathcal{G}^{\text{Flex}},\ n \in \mathcal{N}$$
$$h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.11}$$

$$y^{\text{gen,interID}}_{n,g,h,i,\omega} \leq \xi^{\text{gen,ID}}_{n,g,h,i,\omega} v^{\text{gen}}_{n,g,i}, \quad g \in \mathcal{G}^{\text{Inter}},\ n \in \mathcal{N}$$
$$h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.12}$$

Constraints (4.8)-(4.12) establish the maximum amount of generator output as its installed capacity multiplied with its generator availability. The constraints ensure that, for any hour, in any period, in any scenario, no more than the available output can be produced. The available output is based on the endogenous decision of installed capacity of each generator type in a node and period. The generator availability is exogenous input based on a normalized percentage value specific for its generator type. For intermittent generators, the generator availability may vary from one hour to the next due to the uncertain nature of these generators. For all other generators, the generator availability is constant across all periods, scenarios and hours. The generator availability for the intermittent generators are established using the method described in section 4.4

For thermal generators, ramping up load in between hours is limited:

$$y^{\text{gen,inflex}}_{n,g,h,i,\omega} - y^{\text{gen,inflex}}_{n,g,h-1,i,\omega} \leq \gamma^{\text{gen}}_{g} v^{\text{gen}}_{n,g,i}, \quad g \in \mathcal{G}^{\text{Ramp}} \cap \mathcal{G}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},$$
$$h \in \mathcal{H}^{-}_{s},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.13}$$

$$y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} - y^{\text{gen,FlexDA}}_{n,g,h-1,i,\omega} \leq \gamma^{\text{gen}}_{g} v^{\text{gen}}_{n,g,i}, \quad g \in \mathcal{G}^{\text{Ramp}} \cap \mathcal{G}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},$$
$$h \in \mathcal{H}^{-}_{s},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.14}$$

$$y^{\text{gen,FlexID}}_{n,g,h,i,\omega} - y^{\text{gen,FlexID}}_{n,g,h-1,i,\omega} \leq \gamma^{\text{gen}}_{g} v^{\text{gen}}_{n,g,i}, \quad g \in \mathcal{G}^{\text{Ramp}} \cap \mathcal{G}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},$$
$$h \in \mathcal{H}^{-}_{s},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.15}$$

The ramping constraints (4.13)-(4.15) ensure that all generators are subject to their respective technological restrictions concerning a change in output. The constraints state that the difference in output in a generator between two consecutive hours can not exceed the installed capacity multiplied by the ramping factor.

All storages start with an initial energy level available as a percentage of installed capacity and runs a full cycle over each representative time period in each season:

$$\kappa_b v^{\text{storEN}}_{n,b,i} + \eta^{\text{chrg}}_b y^{\text{chrg,DA}}_{n,b,h^1_s,i,\omega} - y^{\text{discrg,DA}}_{n,b,h^1_s,i,\omega} = w^{\text{stor,DA}}_{n,b,h^1_s,i,\omega}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.16}$$

$$\kappa_b v^{\text{storEN}}_{n,b,i} = w^{\text{stor,DA}}_{n,b,|\mathcal{H}_s|,i,\omega}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N}, s \in \mathcal{S}\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.17}$$

$$\kappa_b v^{\text{storEN}}_{n,b,i} + \eta^{\text{chrg}}_b y^{\text{chrg,ID}}_{n,b,h^1_s,i,\omega} - y^{\text{discrg,ID}}_{n,b,h^1_s,i,\omega} = w^{\text{stor,ID}}_{n,b,h^1_s,i,\omega}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.18}$$

$$\kappa_b v^{\text{storEN}}_{n,b,i} = w^{\text{stor,ID}}_{n,b,|\mathcal{H}_s|,i,\omega}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N}, s \in \mathcal{S}\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.19}$$

Constraints (4.16)-(4.19) gives the initial energy level of a storage type based on the installed capacity in that period. In addition, the charging and discharging volumes are considered. It is repeated for every season in each period for all scenarios.

The balance of storage is ensured between operational time steps:

$$w^{\text{stor,DA}}_{b,n,h-1,i,\omega} + \eta^{\text{chrg}}_b y^{\text{chrg,DA}}_{b,n,h,i,\omega} - y^{\text{discrg,DA}}_{b,n,h,i,\omega} = \eta^{\text{bleed}}_b w^{\text{stor,DA}}_{b,n,h,i,\omega}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},\ h \in \mathcal{H}^-_s,\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.20}$$

$$w^{\text{stor,ID}}_{b,n,h-1,i,\omega} + \eta^{\text{chrg}}_b y^{\text{chrg,ID}}_{b,n,h,i,\omega} - y^{\text{discrg,ID}}_{b,n,h,i,\omega} = \eta^{\text{bleed}}_b w^{\text{stor,ID}}_{b,n,h,i,\omega}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ s \in \mathcal{S},\ h \in \mathcal{H}^-_s,\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.21}$$

Constraints (4.20) and (4.21) balance the energy content of each storage type every hour of every scenario in each period subject to technological restrictions of the storage type. The constraints are essentially an inventory constraint ensuring that what was available in the storage unit at the previous time step, the energy coming into the storage unit at the current time step, and the energy discharged from the storage unit in the current time step has to be equal to the energy content of the storage unit in the current time step.

The energy content of storage is limited by capacity:

$$w^{\text{stor,DA}}_{n,b,h,i,\omega} \le v^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.22}$$

$$w^{\text{stor,ID}}_{n,b,h,i,\omega} \le v^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.23}$$

Constraints (4.22) and (4.22) ensure that the energy content of a storage type in a node for every hour and scenario does not exceed the maximum storage capacity for that particular node, storage type and period.

The amount of charging and discharging per hour is also limited by capacity:

$$y^{\text{chrg,DA}}_{n,b,h,i,\omega} \leq v^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega, \tag{4.24}$$

$$y^{\text{dischrg,DA}}_{n,b,h,i,\omega} \leq \rho_b v^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.25}$$

$$y^{\text{chrg,ID}}_{n,b,h,i,\omega} \leq v^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega, \tag{4.26}$$

$$y^{\text{dischrg,ID}}_{n,b,h,i,\omega} \leq \rho_b v^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.27}$$

Constraints (4.24)-(4.27) limits the charge- and discharge volume subject to the installed capacity of the storage type in each node and period. The charging and discharge limits are enforced for all hours in each period and are also subject to technological limitations of the storage types in the form of discharge efficiency.

For hydroelectric generators, the energy available is restricted by season and node:

$$\sum_{h \in \mathcal{H}_s} y^{\text{gen,FlexDA}}_{g,n,h,i,\omega} \leq \xi^{\text{RegHydLim}}_{n,i,s,\omega}, \ n \in \mathcal{N},\ g \in \mathcal{G}^{\text{Flex}} \cap \mathcal{G}_n,$$
$$s \in \mathcal{S},\ i \in \mathcal{I},\ \omega \in \Omega, \tag{4.28}$$

$$\sum_{\omega \in \Omega} \pi_\omega \sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}^{\text{Hyd}} \cap \mathcal{G}_n} y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} \leq \xi^{\text{HydLim}}_{n}, \ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{4.29}$$

$$\sum_{h \in \mathcal{H}_s} y^{\text{gen,FlexID}}_{g,n,h,i,\omega} \leq \xi^{\text{RegHydLim}}_{n,i,s,\omega}, \ n \in \mathcal{N},\ g \in \mathcal{G}^{\text{Flex}} \cap \mathcal{G}_n,$$
$$s \in \mathcal{S},\ i \in \mathcal{I},\ \omega \in \Omega, \tag{4.30}$$

$$\sum_{\omega \in \Omega} \pi_\omega \sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}^{\text{Hyd}} \cap \mathcal{G}_n} y^{\text{gen,FlexID}}_{n,g,h,i,\omega} \leq \xi^{\text{HydLim}}_{n}, \ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{4.31}$$

Constraints (4.28) and (4.30) ensures the maximum available production from regulated hydro does not exceed available hydro capacity for a given year. This is done by summing the production of every hour of regulated hydro generators for every scenario, period and node and ensuring that the sum of the production is less than or equal to the available generator capacity. The maximum hydro capacity is generated as described in 4.4. In essence, these constraints further restrict the production from regulated hydro as regulated hydro is also affected by constraints (4.9) and (4.11). Constraints (4.29) and (4.31) limits the total production in a year by ensuring that production for a given year does not exceed the available hydro resources for a given node. In contrast to the two previous constraints, these constraints do not consider the unpredictability concerning rainfall, and thus, these constraints are a max production constraints which hold true for all scenarios and periods.

Transmission operation is in a net transfer capacity (NTC) representation:

$$y^{\text{tran,DA}}_{a,h,i,\omega} \leq v^{\text{tran}}_{l,i}, \quad l \in \mathcal{L},\ a \in \mathcal{A}_l,\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.32}$$

$$y^{\text{tran,ID}}_{a,h,i,\omega} \leq v^{\text{tran}}_{l,i}, \quad l \in \mathcal{L},\ a \in \mathcal{A}_l,\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.33}$$

Constraints (4.32) and (4.33) establishes the rules for transmission volume. The constraints ensures that the net transfer volume for each hour in each scenario in each period does not exceed the installed transmission capacity of the particular interconnector.

All annual emissions are limited by an emission cap:

$$\sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in \mathcal{N}} \sum_{g \in \mathcal{G}_n} q^{\text{CO2}}_{g,i} * (y^{\text{gen,inflex}}_{n,g,h,i,\omega} + y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} + y^{\text{gen,interDA}}_{n,g,h,i,\omega}) \leq Q^{\text{CO2}}_i,\ \ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.34}$$

$$\sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in \mathcal{N}} \sum_{g \in \mathcal{G}_n} q^{\text{CO2}}_{g,i} * (y^{\text{gen,inflex}}_{n,g,h,i,\omega} + y^{\text{gen,FlexID}}_{n,g,h,i,\omega} + y^{\text{gen,interID}}_{n,g,h,i,\omega}) \leq Q^{\text{CO2}}_i,\ \ i \in \mathcal{I},\ \omega \in \Omega. \tag{4.35}$$

The emission constraints, (4.35) and (4.34), limits the total emissions for a given period. The emissions for every hour for every generator in every node and scaling it with the seasonal scale is summed and restricted by the maximum allowed emissions in each period. The constraints apply for every scenario. The total emission for in each scenario and period can not exceed the maximum allowed emissions stated by the EU emission policy [43].

Investment constraints

Every generator, transmission line and storage unit have existing capacitiy available in each period:

$$v^{\text{gen}}_{n,g,i} = \bar{x}^{\text{gen}}_{n,g,i} + \sum_{j=i'}^{i} x^{\text{gen}}_{n,g,j}, \quad g \in \mathcal{G}_n,\ n \in \mathcal{N},\ i \in \mathcal{I},$$
$$i' = \max\{1, i - i^{\text{gen}}_g\}, \tag{4.36}$$

$$v^{\text{tran}}_{l,i} = \bar{x}^{\text{tran}}_{l,i} + \sum_{j=i'}^{i} x^{\text{tran}}_{l,j}, \quad l \in \mathcal{L},\ i \in \mathcal{I},$$
$$i' = \max\{1, i - i^{\text{tran}}_l\}, \tag{4.37}$$

$$v^{\text{storPW}}_{n,b,i} = \bar{x}^{\text{storPW}}_{n,b,i} + \sum_{j=i'}^{i} x^{\text{storPW}}_{n,b,j}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I},$$
$$i' = \max\{1, i - i^{\text{stor}}_b\}, \tag{4.38}$$

$$v^{\text{storEN}}_{n,b,i} = \bar{x}^{\text{storEN}}_{n,b,i} + \sum_{j=i'}^{i} x^{\text{storEN}}_{n,b,j}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I},$$
$$i' = \max\{1, i - i^{\text{stor}}_b\}. \tag{4.39}$$

Constraints (4.36)-(4.39) ensures that both existing capacities, as well as invested capacity, is counted for total capacity. It is repeated for every generator, storage or transmission type in each node and for every period.

There are restrictions on investments and available capacity the technologies have in each node:

$$\sum_{g \in \mathcal{G}_t} x^{\text{gen}}_{n,g,i} \leq \bar{X}^{\text{gen}}_{t,n,i}, \quad t \in \mathcal{T},\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{4.40}$$
$$x^{\text{tran}}_{l,i} \leq \bar{X}^{\text{tran}}_{l,i}, \quad l \in \mathcal{L},\ i \in \mathcal{I}, \tag{4.41}$$
$$x^{\text{storPW}}_{n,b,i} \leq \bar{X}^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{4.42}$$
$$x^{\text{storEN}}_{n,b,i} \leq \bar{X}^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{4.43}$$
$$\sum_{g \in \mathcal{G}_t} v^{\text{gen}}_{n,g,i} \leq \bar{V}^{\text{gen}}_{t,n,i}, \quad t \in \mathcal{T},\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{4.44}$$
$$v^{\text{tran}}_{l,i} \leq \bar{V}^{\text{tran}}_{l,i}, \quad l \in \mathcal{L},\ i \in \mathcal{I}, \tag{4.45}$$
$$v^{\text{storPW}}_{n,b,i} \leq \bar{V}^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{4.46}$$
$$v^{\text{storEN}}_{n,b,i} \leq \bar{V}^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{4.47}$$

Constraints (4.40)-(4.47) limit the maximum allowed capacity of a technology in each node. For generators, this is done by summing the installed generator capacity in its technology group, e.g. ‘fossil gas’, in every node and period.

Some storage technologies $b \in \mathcal{B}^{\dagger} \subseteq \mathcal{B}$ have dependencies between power and energy capacity:

$$v_{n,b,i}^{\text{storPW}} = \beta_b v_{n,b,i}^{\text{storEN}}, \quad b \in \mathcal{B}^{\dagger} \cap \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{4.48}$$

Constraint (4.48) states the dependencies between power and energy capacity for some of the storage technologies. The constraint is implemented to capture the technological limitations of storage technologies that are subject to these limitations.

4.4 Scenario Generation

In order to include the unpredictable nature of VRES and load, different scenarios are generated. The scenario data is based on historical data for load, generator availability, and maximum hydro allowance. All data is collected from the ENTSO-e database using the SFTP protocol [6]. Data for both day-ahead and intraday, named forecast and actual from ENTSO-e, respectively, are collected. The data is then put into to a scenario-generation routine. The scenario-generation routine divides the historical data into seasons according to hours of the year. Then, for every scenario and every season, a random hour is sampled. The hours are then sorted, to start on Monday 00:00. In addition, any hour later than the length of the operational period could not be selected, because the chronology is preserved and we would not get a sufficient amount of data. All parameters generated from the scenario routine are sampled based on the same hour for each season and scenario, ensuring correlation between the different parameters, such as wind-PV correlation.

Since only a small portion of the historical data sets are randomly generated, there was a need to ensure a correlation between historical trends and the trend generated by the scenario-generation. Securing a correlation was done by utilizing moment matching. The moment matching routine analyzes the generated scenarios to find the best collection of scenarios that match the statistical moments of the historical data. The procedure is as follows: First, a realization of the stochastic data is created based on the historical data sets for each hour, season, scenario and period. The first step is then repeated U times to generate U different collections of scenarios, or scenario trees. Then, the first four moments (expectation, variance, skewness, and kurtosis) was calculated for each season for all U scenario trees. The seasonal moments of each scenario tree are further compared to the seasonal moments of all historical data.

The scenario tree with the best match to the original data was identified based on equation (4.49):

$$d_{u,s} = \sum_{n \in \mathcal{N}} w_n \sum_{v \in \mathcal{V}} \frac{|m^{\text{all}}_{v,s,n} - m^{\text{tree}}_{v,s,n,u}|}{|m^{\text{all}}_{v,s,n}|}, \tag{4.49}$$

where u is the scenario tree, s is the seasons, n is the nodes, and v is the moment order. The nodal weight, w_n, represents how much node n should contribute to the tree score. The values $m^{\text{all}}_{v,s,n}$ represent moment v in season s and node n for all data, and $m^{\text{tree}}_{v,s,n,u}$ represent the moment value specific to tree u. The minimum value of $\sum_{s \in \mathcal{S}} d_{u,s}$ yields the tree u which has moments matching best with all historical data.

In this thesis, the seasonal moments for each scenario tree and all historical data are calculated based on all actual load realizations as a univariate distribution of hourly values. The nodal weight is calculated based on the nodal share of the total actual load in the whole system. Therefore, the hours best represented in the scenario tree compared to the actual load was also used in the forecasted load, forecasted generator availability, generator availability, and hydro availability. By using the same hours for all parameters, we preserve the cross-correlation between load and production, and thus, create a likely future scenario tree. In addition, nodes are weighted differently to make sure that a correlation in larger nodes is more important than a correlation in smaller nodes. The scenario generation approach is based on [26].

4.5 Shortcoming of the model

In order to not make a too complex and computational heavy model, some assumptions were made which results in a simplification of a real-world power system. The model presented in this thesis is a linear three-stage optimization model. However, some components, such as transmission and power generation, are inherently nonlinear but converted to linear to reduce the computational efforts. The model also utilizes a perfect market, leading to a minimization of the costs of operating the markets at each hour. The market is cleared so that the electricity price is set at the point where the last contributing generator is meeting the demand, illustrated in figure 4.3. The traditional approach does not consider the fixed costs of production, which studies have shown is leading to unprofitable operations of key generators in a power system [44]. In addition, by modelling the markets as perfect competition, regulatory and technological limitations are prevalent. For instance, generators typically have a start/stop cost, minimum running time or commitment to produce power due to regulatory responsibilities [45]. These problems are not included in this model in order to reduce computational efforts. Another factor is the assumed perfect system development. The model chooses the investments based on an objective to minimize the system costs. By choosing the investments purely based on cost aspects, issues such as reliability on long term investments due to the unpredictable nature of VRES and load may arise [46]. This means that dedicated reserve capacity is not included in the investments, and the model does also not consider maintenance and drop-out of the components. This may lead to the investments in the power system being at the absolute minimum, and in extreme cases or malfunctions on the power system, the demand may not be met.

There is also the issue of cost recovery. The cost recovery issue is prevalent in the generators that are required to reduce the output between the market stages. As the generators are only paid what they are actually delivering, and not what was planned, there might be a difference in income for these generators. This means that if a generator is reducing its output made in the planning stage to the delivery, there is no compensation for the change. If for instance, a fuel-driven generator uses less fuel than what was scheduled in the day-ahead market, the marginal cost of that generator will in fact not necessarily be covered, dependant on the electricity price. There are difficulties establishing how the generators providing flexibility, should be compensated due to market design, leading to this feature not being implemented. An additional point is the generator availability data derived from ENTSO-e. The data is based on the forecasted production and actual production from 2015-2020. The data does, therefore, not use actual wind speeds and solar irradiation, and are thus susceptible to different bidding strategies in the markets. However, it assumed that a VRES producer would bid what the producers predict is available for the day-ahead market.

4.6 Intraday Volume

A method for calculating the intraday volume is explained in the following section. The intraday volume can be defined as the excess trading that is needed or beneficial in order to supply the demand according to the actual conditions. It is therefore based on the difference in decisions between the two market stages. The method determines the difference between the decisions made in the day-ahead market and intraday market for energy storage, transmission, intermittent generators, and flexible generators. First, lets define a set of components, $\mathcal{D}$, that are subject to altered decisions or conditions between the market stages:

$$\mathcal{D} = \{\text{Flex}, \text{Inter}, \text{storDischrg}, \text{storChrg}, \text{tran}, \text{load}\}$$

Equation (4.50) - (4.55) illustrates how the difference in production volume changes between the markets for each period, where δ_i^d is the difference in output between the market stages in each period for the components that are able to alter the output between market stages:

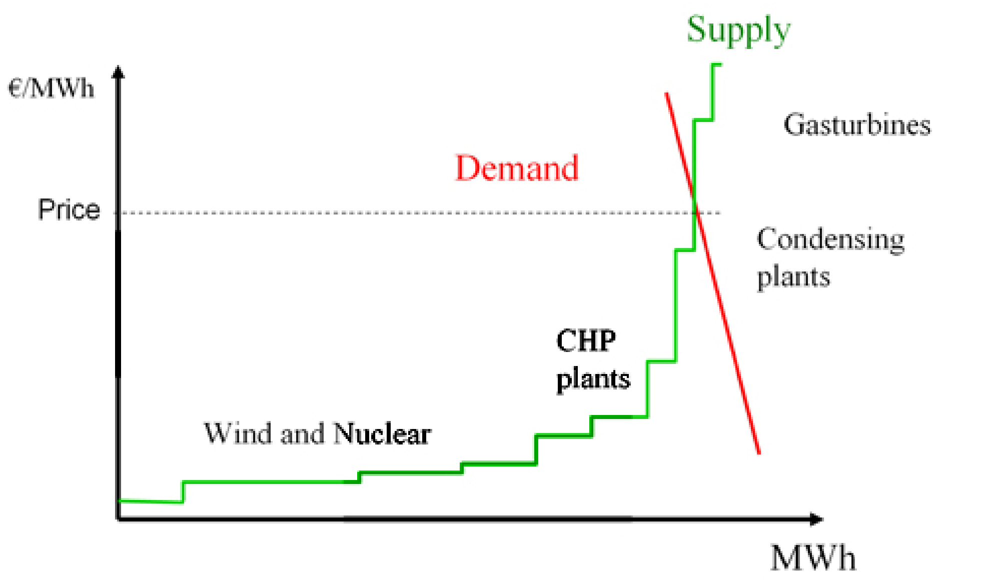

Figure 4.3: Illustration of market clearing based on marginal costs in a electricity market adapted from [47].

$$\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\sum_{g\in\mathcal{G}_n}\pi_\omega\sum_{\omega\in\Omega}(y^{\text{gen,FlexID}}_{n,g,h,i,\omega}-y^{\text{gen,FlexDA}}_{n,g,h,i,\omega})=\delta^{\text{Flex}}_i,\ \ i\in\mathcal{I} \tag{4.50}$$

$$\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\sum_{g\in\mathcal{G}_n}\pi_\omega\sum_{\omega\in\Omega}(y^{\text{gen,InterID}}_{n,g,h,i,\omega}-y^{\text{gen,InterDA}}_{n,g,h,i,\omega})=\delta^{\text{Inter}}_i,\ \ i\in\mathcal{I} \tag{4.51}$$

$$\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\sum_{b\in\mathcal{B}_n}\pi_\omega\sum_{\omega\in\Omega}(y^{\text{dischrg,ID}}_{n,b,h,i,\omega}-y^{\text{dischrg,DA}}_{n,b,h,i,\omega})=\delta^{\text{stor,Dischrg}}_i,\ \ i\in\mathcal{I} \tag{4.52}$$

$$\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\sum_{b\in\mathcal{B}_n}\pi_\omega\sum_{\omega\in\Omega}-(y^{\text{Chrg,ID}}_{n,b,h,i,\omega}-y^{\text{Chrg,DA}}_{n,b,h,i,\omega})=\delta^{\text{stor,Chrg}}_i,\ \ i\in\mathcal{I} \tag{4.53}$$

$$\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{a\in\mathcal{A}}\pi_\omega\sum_{\omega\in\Omega}(y^{\text{tran,ID}}_{a,h,i,\omega}-y^{\text{tran,DA}}_{a,h,i,\omega})=\delta^{\text{tran}}_i,\ \ i\in\mathcal{I} \tag{4.54}$$

$$\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\pi_\omega\sum_{\omega\in\Omega}(\xi^{\text{load,ID}}_{n,h,i,\omega}-\xi^{\text{load,DA}}_{n,h,i,\omega}=\delta^{\text{load}}_i,\ \ i\in\mathcal{I} \tag{4.55}$$

From these equations, we can calculate the total difference between the decisions in the day-ahead stage and the intraday stage, ref equation (4.56):

$$ID_i^{\text{volume}} = \begin{cases} \sum_{d \in \mathcal{D}} \delta_i^d & \delta_i^d \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.56}$$

Note that we only consider output that has increased from the day-ahead markets in order to not double count the volumes. If a generator increases its output between the markets, another generator has to decrease its output subject to the deviations in load and potential losses in transmission or storage if these are utilized. Therefore, it is important to only sum the components that increases its output compared to the day-ahead stage as it is a zero-sum issue.

From the intraday volume, the percentage intraday volume can be calculated as a share of the total load that is delivered, ref equation (4.57)

$$ID_i^{\%} = \frac{ID_i^{\text{volume}}}{\sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in \mathcal{N}} \pi_\omega \sum_{\omega \in \Omega} \xi_{n,h,i,\omega}^{\text{load,ID}}}, \tag{4.57}$$

The method to calculate the intraday volume shown here does not necessarily correlate with the historical intraday volumes illustrated in Chapter 1 due to the market design. However, the intraday volume can still be used to illustrate the importance of an intraday market, as it illustrates the difference in the operational decision between the market stages.

Chapter 5

Simplified Test Case

In this chapter, three cases are investigated in order to prove the concept and how the new additions to the EMPIRE model functions. The standard version of EMPIRE will also be analysed to establish the impact of adding market sequencing to the pre-existing EMPIRE model. The cases used in this chapter uses a simplified version of EMPIRE in order to present the key results from the implementation of market sequencing. The cases studied in this chapter uses a three node system, with fewer periods, operational hours and scenarios. For a full explanation of the input data, see section 5.2. Chapter 6 will present a larger case study, focusing on the European power system.

5.1 Description of cases

5.1.1 Case 0: Reference case, Standard EMPIRE

The reference case will use the standard version of EMPIRE as described in [35]. The standard version consists of two stages, one investment stage and one operational stage. The case is run in order to be able to compare the decisions made in each of the different cases to the reference case and investigate the impact the modifications has on the optimal solutions.

5.1.2 Case 1: Basecase

The basecase consists of an intraday market, a day-market, and an investment stage. The investment stage is followed by the day-ahead stage, which has three scenarios. The day-ahead stage is followed by an intraday stage with one scenario for each scenario in the day-ahead stage, as illustrated in figure 5.1. The connection between the market stages is based on figure 4.2 and the constraints 4.5, 4.6, and 4.7. As seen by the transmission connection constraint, it is only allowed to increase or remain at its scheduled operation decided in the day-ahead market. Historically, cross-border transmission re-dispatch has not been allowed in the intraday market. However, in 2018, the cross-border intraday market project (XBID)

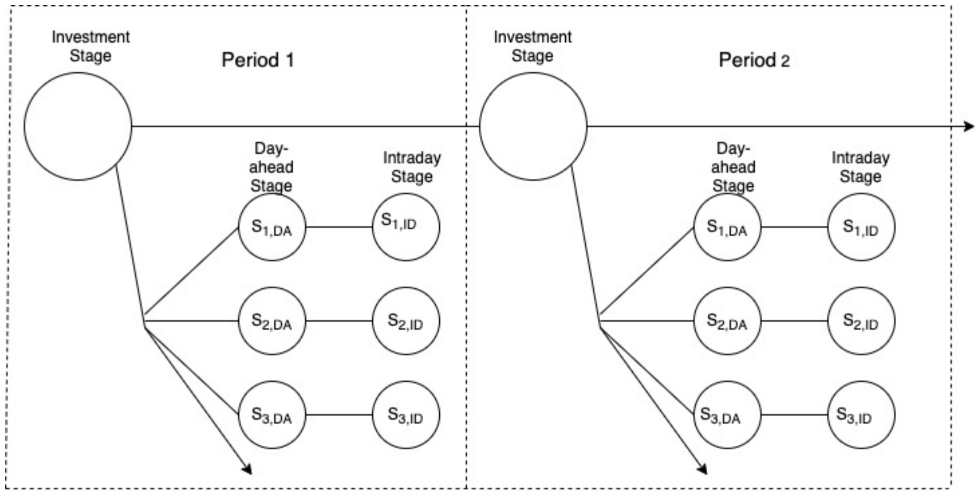

Figure 5.1: Illustration of scenario-tree in the model.

went live. The XBID project is aiming to allow for cross-border transmission trading in the intraday market [48]. Currently, only some of the European energy markets are participating in the project, but the plan is to incorporate all of the European power market zones shortly [48]. Therefore, it was decided to allow excess trading of transmission capacity between all nodes with an interconnector in the intraday market in this thesis.

5.1.3 Case 2: No transmission case

The objective of the no transmission case is to analyse how the energy markets have operated up until the XBID project was implemented, and thus analyze the impact of intraday transmission trading on the flexibility needs of a power system. Therefore, this case does not allow for excess trading of transmission capacity in the intraday market, and thus constraint 4.7 is slightly altered. In this case, the constraint is altered to ensure that no excess transmission volume can be traded in intraday market as presented in equation 5.1:

$$y^{\text{tran,DA}}_{a,h,i,\omega} = y^{\text{tran,ID}}_{a,h,i,\omega}, \quad a \in \mathcal{A},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \tag{5.1}$$

5.1.4 Case 3: Less flexibility case

The less flexibility case aims to analyse the impact of having shorter time between the intraday trading and the actual operation. In case 1 and 2, the actual load and generator availability is revealed one hour before delivery, meaning that the generators have one hour to alter their output. In case 3, however, the time between the trading and delivery is changed to only 15 minutes. With only 15 minutes to change generation output, generators becomes less flexible, and it is of interest to investigate how this impacts investments and operational decisions. In equation

4.5 and 4.6, the parameter V_g changes to 25% of its original value. Here, it is assumed a linear ramping factor of the generators, which is supported by [49].

$$(1+\frac{v_g}{4})*y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} \leq y^{\text{gen,FlexID}}_{n,b,h,i,\omega} \qquad g \in \mathcal{G}^{\text{Flex}}, n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \quad (5.2)$$

$$y^{\text{gen,FlexID}}_{n,b,h,i,\omega} \leq (1-\frac{v_g}{4})*y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} \qquad g \in \mathcal{G}^{\text{Flex}}, n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \quad (5.3)$$

5.2 Input Data

The same input data is used across all of the cases. Three nodes are analysed in these cases representing Germany, Denmark, and France. The emission cap is low, referencing the EU policy on carbon emissions (see table 5.1) [43]. The emission cap is scaled linearly down to account for just the nodes included in the case. In addition, cost parameters represent projected costs in 2050, 2055, and 2060 to simulate future conditions for costs. Three periods of 10 years are analysed, each with two regular seasons and two peak seasons. In order to evaluate investment decisions, no initial installed capacity was assumed. The initial capacity includes generators, storage and transmission. Scenarios are generated based on the procedure explained in chapter 4.4. Three scenarios are generated for each hour, season, and period. For every period, season, and scenario, a random hour was sampled. The same hour was sampled in both the intraday and day-ahead stage, for generator availability and load. By sampling the same hour, the correlation between the stochastic parameters and market stages are preserved. Table 5.2 presents the different generator types sorted into the new generator sets. For case 0, the model resulted in 122 000 constraints and 76 000 variables. The cases with market sequencing have 545 000 constraints and 319 000 variables. As seen by the increased amount of variables and constraints in the cases with market sequencing, the computational effort of solving the model increases significantly.

5.2.1 Data Gathering

The input data for both day-ahead and intraday parameters are gathered from the ENTSO-e database using the Secure File Transfer Protocol (SFTP) [6]. The day-ahead data is assumed to be forecasted data, while the intraday data is assumed to be actual data. The data consists of hourly measures from 2015 to the end of 2019. Some countries represented in the model are not included in various datasets in the ENTSO-e database. These countries were therefore represented using neighbouring countries with an assumption that conditions were similar in the countries. This issue was only prevalent in generator availability parameters. Another issue in the datasets from ENTSO-e is missing data for certain hours or

Table 5.1: Total emission cap in Mton CO_2 equivalent in each period

Period	CO_2Cap [in Gton CO_2eq]
2020-2030	1.2
2030-2040	0.6
2040-2050	0.24

values that are assumed to be incorrect. In order to combat this issue, a smoothing algorithm was used on the datasets. The purpose of the smoothing algorithm was to calculate a median value based on hour-day-month to replace the incorrect or missing values. For the generator availability parameters, the generator availability was calculated by 4.1, where the production is the smoothed datasets from ENTSO-e for the production from the generators, and the installed capacity is the capacity installed at the start of the given year. The procedure was applied on wind onshore and solar, and both the forecasted production and the actual production. The reason why offshore wind was not include was due to a lack of data, as only a few countries have offshore wind installed. It was therefore decided to use onshore data for offshore as well to get representative data for all countries. The identical onshore and offshore wind data is basically resulting in offshore wind being a more expensive energy source pr installed capacity than onshore wind. By calculating the generator availability like this, it assumed that the correlation between production and installed capacity is representative if the installed capacity changes. The electric load parameters were also gathered from the ENTSO-e database and put through the smoothing algorithm to get a complete dataset ranging from 2015-2019. Both forecasted and the actually delivered load was collected from ENTSO-e using the SFTP protocol [6].

5.3 Results

This section will present the key results from the case studies in order to showcase the developed model.

5.3.1 Objective function value

The four cases yielded significant differences in objective value. Case 2 was the most expensive case, followed by case 3. Case 0 yielded an objective value significantly lower than the cases with market sequencing. Table 5.3 lists the key results derived from the test cases. As seen by the objective value, adding market sequencing, and thus introducing forecasting errors, results in significantly higher costs. These results are also supported by [19] and [34]. Additionally, it appears that transmission is a key contributor to help balance the forecast errors and provide flexibility as case 2 is the most expensive. It is also worth noting that as the installed capacity of VRES increases, so does the intraday volume. Concerning the intraday volume, transmission is contributing a significant amount to the

Table 5.2: Overview over generators and sets

Inflexible Generators	
	Lignite
	Coal
	Nuclear
	Wave
Flexible Generators	
	Bio 10 cofiring
	Geo
	Hydro regulated
	Bio
	Waste
	Gas OCGT
	Gas CCGT
Intermittent Generators	
	Hydro run-of-the-river
	Wind onshore
	Wind offshore
	Solar

intraday volume, indicated by the relatively small intraday volume in case 2 compared to the other cases. Other studies have also highlighted transmissions role in providing flexibility in a power system with a lot of uncertainty [11–13, 29].

5.3.2 Investments in generator capacity

Figure 5.2 highlights the installed capacity by generator type and period across all nodes. The results are similar across case 1-3, with only a 4% difference in investments per generator type. The difference is largest in flexible generators, with case 3 investing 3 GW less than the other cases. As seen by the figure, the amount of flexible and inflexible generators is stable over the period. Due to limitations in the model on maximum installed capacity and emissions, the installed capacity of nuclear, bio, and gas (CCGT and OCGT) are at its effective maximum installed capacity. From 2040 to 2050, there is a drop in installed capacity. The reason for this drop is due to a mixture of the lifetime of generators and period length as well as an 'end-of-horizon' effect. Due to the lifetime of the VRES, re-investments are needed at some point in the time horizon. In order to get more value out of the investment, it is beneficial to invest earlier than required. Investing earlier allows for the possibility to utilize more of the RES resources over the remaining period. Additionally, the model does not consider anything beyond the scope of the horizon. Therefore, the actual value of investments that have a lifetime beyond the horizon are underestimated. This combined leads to more favourable re-investments options by 2040 rather than by 2050.

Table 5.3: Overview of key results from all four cases

Cases	Case 0	Case 1	Case 2	Case 3
Obj Value in billion Euros	1 635	1 805	1 822	1 810
Installed capacity of inflexible generators in 2050 [%]	6	3.9	3.9	3.9
Installed capacity of flexible generators in 2050 [%]	8.2	5	5	4.8
Installed capacity of intermittent generators in 2050 [%]	85.8	91.1	91.1	91.3
Installed transmission cap in 2050 [GW]	50.6	59	57.5	58.7
Day-ahead demand in 2050 [TWh]	163.7	163.7	163.7	163.7
Intraday demand in 2050 [TWh]	163.8	163.8	163.8	163.8
Intraday volume in period 1 [%]	-	7.9	4.8	7.6
Intraday volume in period 2 [%]	-	21.1	11.1	21.4
Intraday volume in period 3 [%]	-	24.2	3.1	24.5
Curtailment in 2050 [TWh]	39	166.8	170.5	169.5

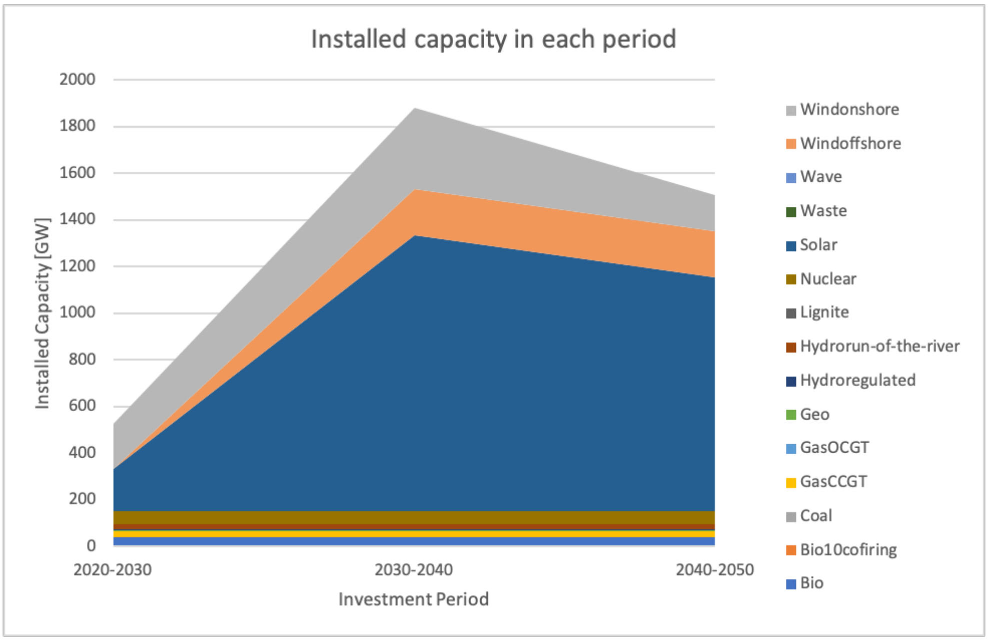

Figure 5.2: Installed generator capacity for each period in case 1 of the test cases for all nodes

Figure 5.3 illustrates the installed capacity per generator type in case 0. The investments differ significantly when compared to the market sequencing cases. The hypothesis of the thesis was that there will be an increased amount of investments in flexible generators when market sequencing is present. The reason why this was not experienced in case 1-3 is likely due to the restriction concerning maximum installed capacity and emission cap in all cases. As the cost-efficient flexible generators (Bio, Gas) are at its maximum capacity, the model has to account for the differences between the markets by providing electricity from other sources. However, due to both investment- and operational costs, VRES are preferred over other flexible generators even though this leads to massive curtailment from VRES. When comparing the results with results from existing literature, it is clear that there are some differences. Existing literature highlights the need for flexible generators and additional generator capacity in a power system characterized by large amounts of uncertainty [26, 34]. However, due to the limitations of flexible generators in these cases, the current literature is comparable with the results of the cases analysed in this report.

5.3.3 Generator output

In addition to the installed capacity being similar across the cases, the generator output is also comparable and varies at most by 1% between the cases for every period. Figure 5.4 illustrate the share of output between the generator types. Im-

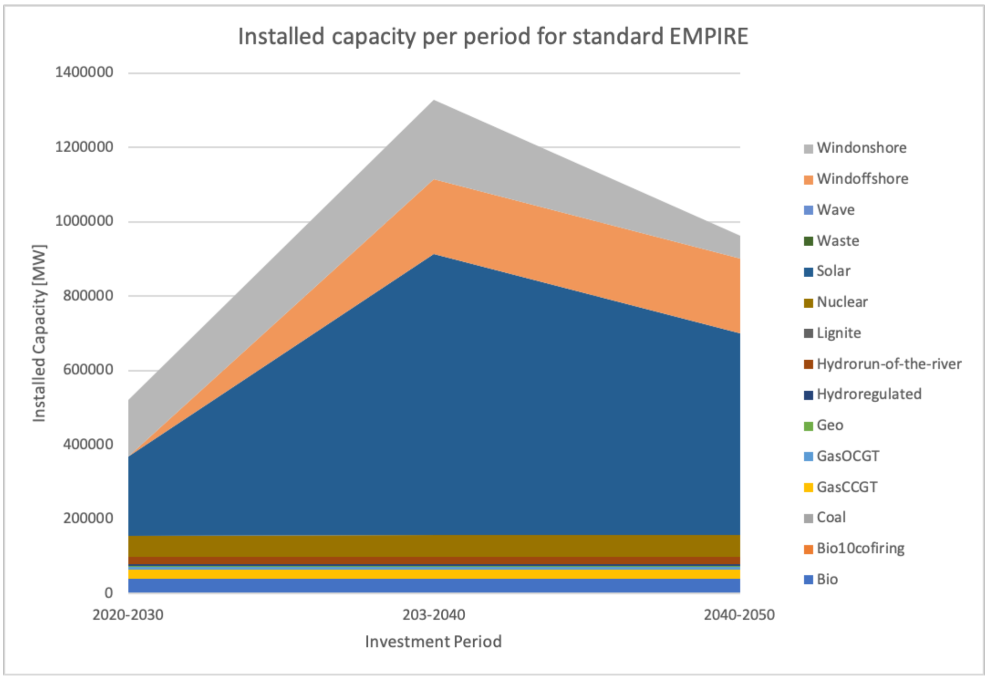

Figure 5.3: Installed generator capacity for each period in case 0 of the test cases fo all nodes

portantly, VRES is dominating the generation, followed by inflexible generators. However, there is more installed capacity of flexible than inflexible generators. As the amount of inflexible production increases, so does the flexible production. This may indicate that inflexible generators are harder to regulate than intermittent generators, and not the other way around.

There are significant differences across the cases when analyzing the differences between the output in the day-ahead market versus the intraday market. All of the cases reduce output from flexible generators between the market stages and increases the VRES output. The reduction in flexible output may indicate better conditions for VRES in the intraday stage than the day-ahead stage. It may also indicate conservative scheduling for flexible and inflexible generators in the day-ahead stage to make sure that the load in the intraday stage will be met. The degree of change between intraday and day-ahead decisions varies slightly, with case 2 having the largest deviations. The high deviations in case 2 is to be expected as this case is restricting the transmission dispatch between the stages, which leaves only storage and generators to contribute to the needed balancing. Therefore, case 2 has to alter its generators the most. The opposite result is observed in case 3. As this case restricts the response time of generators, the degree of change in flexible generators is reduced. Thus, there is a lower difference in generator output between the day-ahead and the intraday markets than in the other cases.

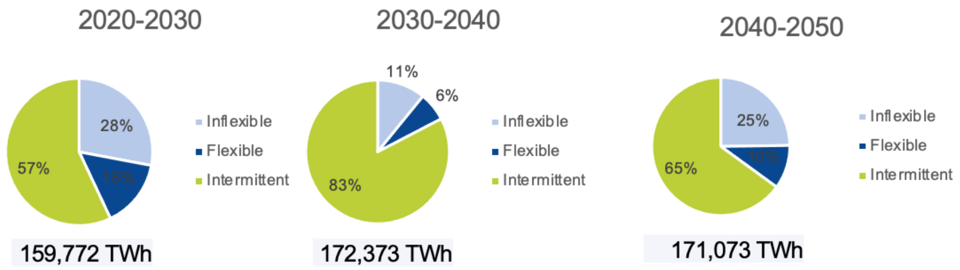

Figure 5.4: Generator output in all three periods in the case 1

5.3.4 Transmission and Storage in case 0

Transmission investments in standard EMPIRE is significantly lower than in the cases with market sequencing, even though one of the interconnectors are still at max install capacity in case 0. Investments in case 0 invest 9 GW less in transmission capacity than case 1, which further supports the importance of transmission in regards to flexibility in a power system. Additionally, case 1 delivers 40% more volume than case 0. It is also worth noting that case 2 is significantly more reliant on transmission than case 0 even though there are no options to deviate from the dispatch decisions made in the day-ahead market.

Concerning storage, case 0 is investing in more storage capacity than the other cases. However, volume delivered by storage is significantly lower compared to the cases with market sequencing. The reason for these results may be that with scarcer investments in transmission, storage has to cover peak load within nodes, thus increasing investments in storage capacity.

5.3.5 Storage

Regarding storage capacity, the three cases are similar with some minor exceptions. Case 1 and 3 invests in 10% less power capacity than case 2 (20 GW difference). Investments in energy storage vary by a smaller degree, with a 1% difference between the cases and case 1 having the highest investments. For reference, the investments in power and energy are 242 GW and 1193 GWh, respectively, for case 1. The discharge volume from storage varies between the cases. Case 3 delivers the greatest amount of energy with a total of 79 TWh over all the periods. Case 2 delivers the least amount of energy with 75 TWh across the periods. In all of the cases, the discharge volume follows the trend of output from the intermittent generators in that when the total output from VRES increases, so does the total discharge volume. In period two, when VRES has the greatest share of production, storage covers around 30% of the total load. The results concerning storage are in line with what is expected based on the input of the model. Case 3 is less reliant on generators to balance the forecast errors from VRES and load, and thus, it is reasonable to expect a greater amount of output from storage in this case. Concerning case 2, with restricted transmission opportunities, storage is only able to provide flexibility within a node. The limitation of intraday trading of transmission capacity is likely leading to scarcer investments in storage and less discharge volume due to the forecasting errors concerning load and VRES between the nodes.

5.3.6 Transmission

Transmission show the greatest differences between the cases. Case 2, with restricted transmission between the markets, has the least amount of investments in transmission at 3% less investments than case 1. One of the two interconnectors are at max installed capacity in all three cases. Concerning load coverage by transmission, there are significant differences across the cases. Case 1 and 3 covers more of the load than case 2, ranging from 2 to 13% less load coverage in case 2. For reference, case 3 covers 16%, 25%, and 42% of the load by transmission. The reduced load coverage by transmission in case 2 supports the claim that transmission is playing a crucial role in balancing and providing flexibility of a power system. As mentioned in section 5.3.1, a lot of existing literature highlights the need for additional transmission capacity when adding uncertainty to an energy model.

5.4 Conclusion

This chapter has shown that by sequencing markets in the EMPIRE model, the solution gets more expensive due to the need for additional generator capacity, storage, and transmission. Transmission is the key contributor to flexibility in a power system with uncertainty from VRES and load, illustrated by both the high objective value of case 2 and investments in transmission in the other cases. Restrictions on transmission also have consequences for storage, as, without the ability to change transmission dispatch, shorts bursts of power from storage is important, however, the total energy delivered by storage decreases due to not being to benefit from changing conditions in neighbouring nodes. When limiting transmission, the flexible generators also gain importance, and there are greater deviations between the generator output in the two markets. As seen by the results, it is clear that forecasting errors originating from market sequencing do have a significant impact on investment decisions. Furthermore, we experience change in operational decisions due to the significantly increased transmission volume in all three cases with market sequencing.

From the results, it is clear that existing literature supports the findings. By adding a 3rd stochastic stage to the model, the level of uncertainty increases, which is leading to higher system costs, which is also supported by [19]. The results yielded significantly higher investments in transmission, which several other studies also highlighted [11–13]. Besides, only one other has utilized a capacity expansion model with two market stages [34]. Their results are similar to those presented from the test case in that operations and investments are significantly impacted by forecasting errors. The differences in investments are easily explainable by investigating the maximum allowed capacity in a node, and therefore also has a great impact on operations. To conclude, by adding forecasting errors to a capacity expansion model, flexible energy sources increases its value compared to stochastic energy sources. Due to the cost-related aspects of the different generator types and its altered valuation in a three-stage model, the overall cost of operating a power system increases significantly and it gives a better representation of how modelling of capacity expansion problem should be solved. However, the major downside with a three-stage approach is the computational burden due to the significantly increased number of variables and constraints.

Chapter 6

European Case Study

This chapter presents a full-scale analysis of the model to answer the research question stated in Chapter 1. Two different cases, as well as a deterministic case to highlight the importance of uncertainty, are presented. The cases consists of 35 nodes representing the European power system over eight periods of five years each. Each period consists of four seasons and two peaks seasons of 168 and 24 hours, respectively. Four scenarios per investment period are generated with the routine described in 4.4. The data used in this thesis is the same as used in previous studies utilising EMPRIE [36, 37]. For a complete overview of the numerical results, see Appendix A.

6.1 Description of Cases

6.1.1 Case 0: Standard EMPIRE

The standard EMPIRE case is EMPIRE without market sequencing. The model is identical to the one developed by Christian Skar in [35]. This case represents the traditional way of analysing the development of power systems, considering investments and operations without market sequencing. Case 0 consists of 37 million constraints and 24 million variables.

6.1.2 Case 1: EMPIRE with market sequencing

Case 1 represents the European power system with market sequencing. The input data is the same as in case 0, but additional parameters are added for the day-ahead market. These include generator availability for the day-ahead market as well as the expected demand. Case 1 provides the baseline of how investment decisions may change when the forecasting errors between electricity markets are included. The model formulation is described in Chapter 4. Case 1 consists of 158 million constraints and 94 million variables

6.1.3 Case 2: Deterministic market sequencing

Case 2 is a deterministic approach, focusing on the development of the European power system based on the expected conditions. In this case, the scenarios generated for the other two cases were used to calculate the expected scenario for each hour, season, and period. The parameters calculated in case 2 is the average parameter value of case 1. The model used is otherwise identical to case 1. Case 2 also forms the basis when analysing the impact of uncertainty. Case 2 consists of 39 million constraints and 24 million variables. The reason why it is more computational heavy than the stochastic case 0 is due to the implementation of market sequencing, and the number of scenarios in case 0. However, it is difficult to compare the computational burden of case 0 and 2 directly since case 0 is stochastic and without market sequencing, while case 2 is deterministic with market sequencing. Thus, the computational burden heavily depends on the number of scenarios used in a stochastic approach.

6.2 Results and Discussion

This section presents the results and discussion of the three different cases. The section is structured as follows: First, both generator investments and expected production are analysed for all three cases. Then, storage and transmission results are presented and discussed. Finally, a spring week in Norway and Germany for the investment period 2045-2050 is analysed to investigate how operations are impacted in the European power system in the different cases.

6.2.1 General Results and Objective Value

The objective value, or the total system costs, varied significantly between the cases. Table 6.1 lists the objective value in billion Euros, the number of constraints and variables. As depicted by the table, the deterministic approach is the cheapest, followed by the standard case without market sequencing. The deterministic case is 7.3% cheaper than the standard, while case 1 is 2.1% more expensive. The reason for the difference in costs can be attributed to the different levels of uncertainty in each case, resulting in a more expensive solution the more uncertainty is present [50]. These results imply that the implementation of market sequencing when the forecasting errors are known for certain seems to be cheaper than considering uncertainty without market sequencing.

The differing objective values between case 0 and 2 may elucidate whether uncertainty or market sequencing is the most important factor to include in a capacity expansion model, if only one can be included. These issues will be further dissected in later sections, that address the impact of uncertainty. Additionally, our findings suggests that market sequencing significantly increases the computational burden of the problem, considering the number of constraints and variables

Table 6.1: Overview of objective value, number of constraints and variables

	Case 0	Case 1	Case 2
Objective Value [Billion €]	2788	2847	2585
Number of constraints in million	37	158	39
Number of variables in million	24	94	24

in case 0 and 2. The computational burden is even further elevated by the addition of stochastic parameters in case 1 compared to case 2.

6.2.2 Investments in generation

The general trend across all three cases is the growth of VRES over the periods. However, there are significant differences between the cases when it comes to investments in generation capacity. Figure 6.1 highlights the total capacity expansion by generator type over the entire horizon. As seen from the figure, investments in inflexible capacity are similar for the three cases, but slightly lower in case 1 and 2 compared to case 0. Regarding flexible generators, case 1 invests in significantly more capacity than the other two cases, and case 2 is investing slightly less than case 0. In terms of intermittent generators, case 0 invests the most, and case 2 invests slightly more than case 1. In total, case 2 invests the least in generator capacity (-10% compared to case 0), followed by case 1 (-6% compared to case 0).

Figures 6.3 and 6.2 illustrates the development of installed generator capacity over the entire period for case 1 and 0, respectively. As depicted from the figures, there are significant differences in the investment decisions between the three cases, both in terms of total installed generation capacity and in generator type preference.

In case 1, the total installed capacity is about 4% lower than case 0. The reduced installed capacity is mostly due to the significant decrease in intermittent capacity compared to case 0. In addition, the installed capacity of flexible generators is significantly higher in case 1 than case 0 (+41%), mainly due to increased investments in bio and gas. All cases have the same demand to supply and the same conditions to supply the demand. However, the generator availability of VRES and the flexible generators are different, leading to flexible generators being able to generate more electricity per installed capacity than VRES. The differing generator availability imply that if there is an increase in flexible generators, there can be an even larger reduction in VRES.

Regarding case 2, there are even less capacity expansion than case 0 (-10%). Being a deterministic approach, case 2 does not have to account for extreme scenarios which may occur in the other cases. In turn, this is likely leading to less in-

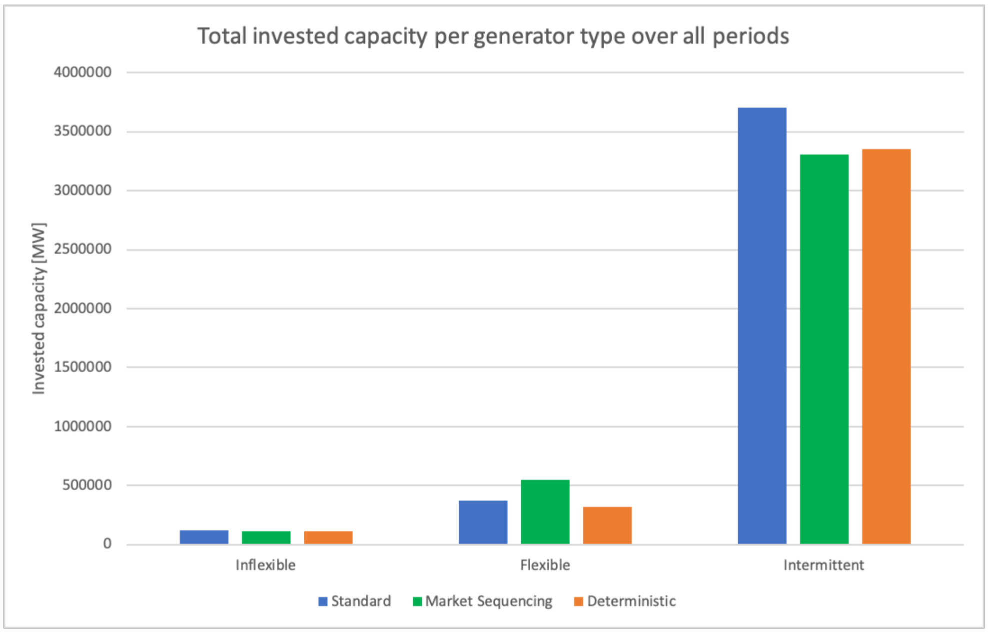

Figure 6.1: Invested capacity for each generator type over all periods for the three cases

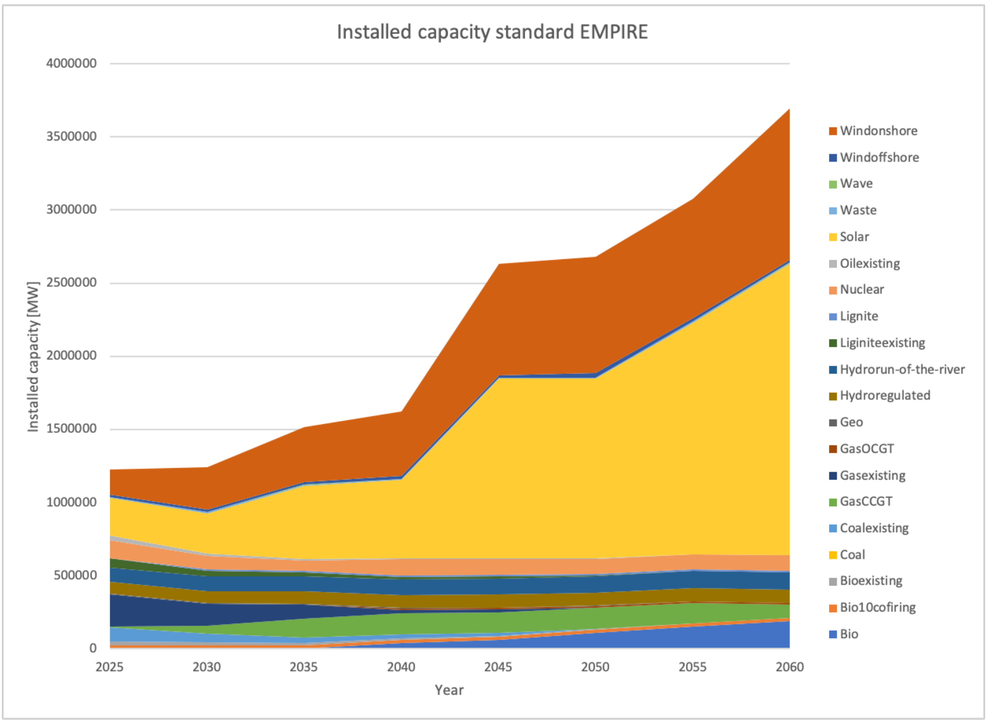

Figure 6.2: Installed capacity over the period for case 0

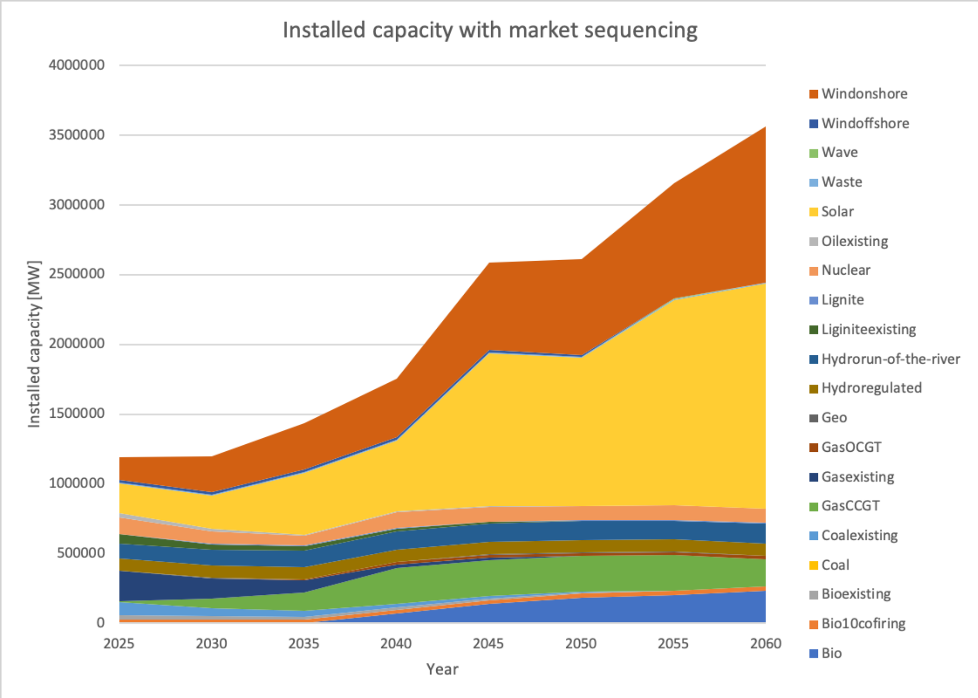

Figure 6.3: Installed capacity over the period for case 1

vestments, as the model supply the expected demand with less installed capacity. In general, we observed a decrease in installed capacity when including market sequencing. This was especially prominent for VRES, driven by the switch from intermittent energy sources towards flexible energy sources. The decrease in installed capacity when including market sequencing is also supported by [34].

The reason why the installed capacity is increasing over the periods is twofold. Firstly, the demand is increasing slightly over the periods, entailing that more capacity is needed in order to supply the demand. The increase in demand does, however, only slightly impact the installed capacity. The increase in installed capacity can be attributed to how the electricity generated is being used. In the later period, more volume is used for both storage and transmission. How the electricity is used will be addressed in more detail later. Additionally, as described previously, the capacity factor for VRES is generally lower than for the competitors meaning that in order to produce the same output, more installed capacity is needed.

6.2.3 Generator output

Even though case 1 has slightly less (4GW) installed capacity of inflexible generators compared to case 0, the production from these generators are practically identical between all cases. The reason why the output is similar is likely tied to uncertainty and market sequencing, which leads to a more flexible portfolio [22].

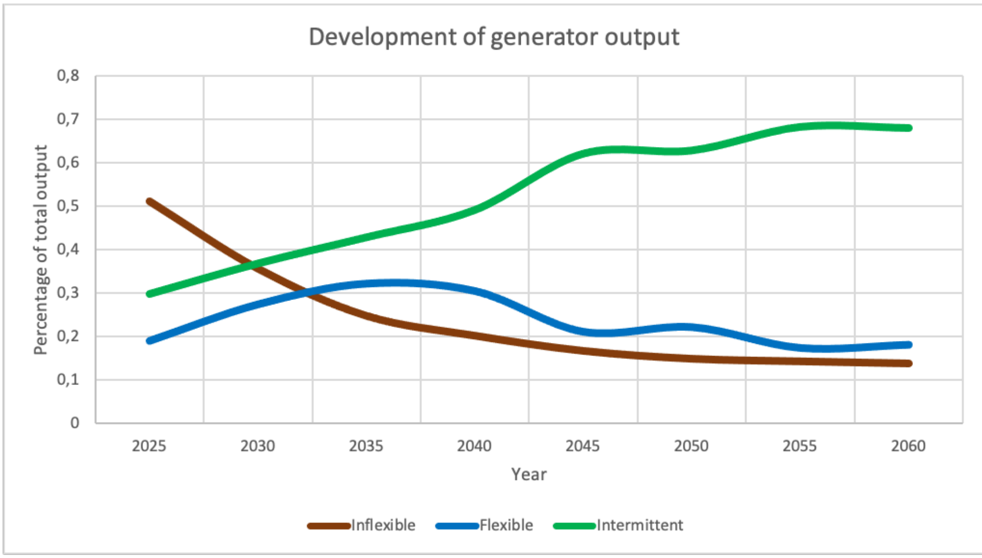

Figure 6.4: Development of generator output in percentage over the investment periods

The deterministic case is the case that values intermittent generators the most, followed by standard EMPIRE. Case 2 generates 51 TWh more from VRES than case 0, which is a significant amount. The relatively large difference in terms of generator output is likely due to the stochastic nature of VRES, and when this is not considered, we can experience an over-evaluation of these energy sources [26, 51]. In case 1, there are 219 TWh less production from the intermittent energy sources, probably explained by the decreased installed capacity. Case 2 produces the least amount of electricity from flexible generators, followed by case 0. Again, this is tied to the uncertainty of the problem, as less uncertainty leads to an over-evaluation of stochastic energy sources. Furthermore, it is tied to the fact that these cases have less installed capacity of flexible generators than case 1. Figure 6.4 illustrates the development of output from the different generator types over the period for case 1.

Concerning the differences in output between the market stages, there are some minor differences. Since case 0 does not have market sequencing, case 0 will not be discussed here. The other cases have very similar differences in output between the market stages. In general, flexible producers decrease their output from the day-ahead market, while intermittent generators increase their output. This can be justified by the need to balance the different conditions at the two market stages. Figure 6.5 illustrates the generator availability for a week in Denmark in winter of 2040. As depicted by the figure, there are clear fluctuations between the forecasted and actual availability of solar and wind. Thus, there is a need to re-balance the decisions from the day-ahead stage, resulting in different operations than scheduled. Two rationales can explain the increased production from

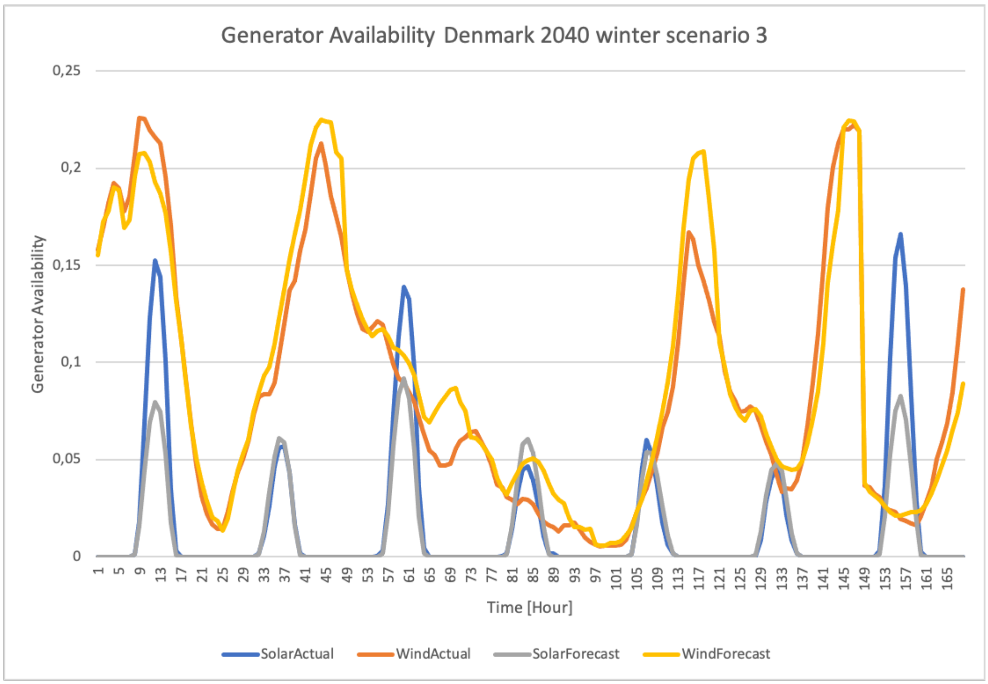

Figure 6.5: Generator availability for onshore wind and solar for a week in Denmark, winter 2040

intermittent generators in the intraday market compared to the day-ahead market. First, there is no consequences or benefits to changing the generation output from flexible generators, which may result in over-dispatching of these in order to ensure that the intraday demand is supplied. Second, conditions from VRES may improve between the market stages. However, as seen by the figure 6.5, both solar and wind availability are similar in the two markets and are not significantly better or worse in either market. Still, with just slightly better conditions in the intraday market, and with a significant amount of VRES installed, the overall conditions in the intraday stage could improve significantly and thus be a plausible explanation. Besides, VRES can also contribute to the balancing requirements in an intraday market [52]. Borggrefe and Neuhoff [25] also highlight the need for a market design that facilitates possible improved conditions for VRES between market stages.

6.3 Storage investments and operational decisions

Figure 6.6 shows the development in installed energy capacity for case 0 and 1. Case 1 and 2 are very similar in terms of investments in storage capacity with less than 1% difference in investments in both power and energy capacity. However, case 0 invests significantly more in both power and energy with 42% and 16% more investments, respectively. In case 1, less VRES are installed, and the need

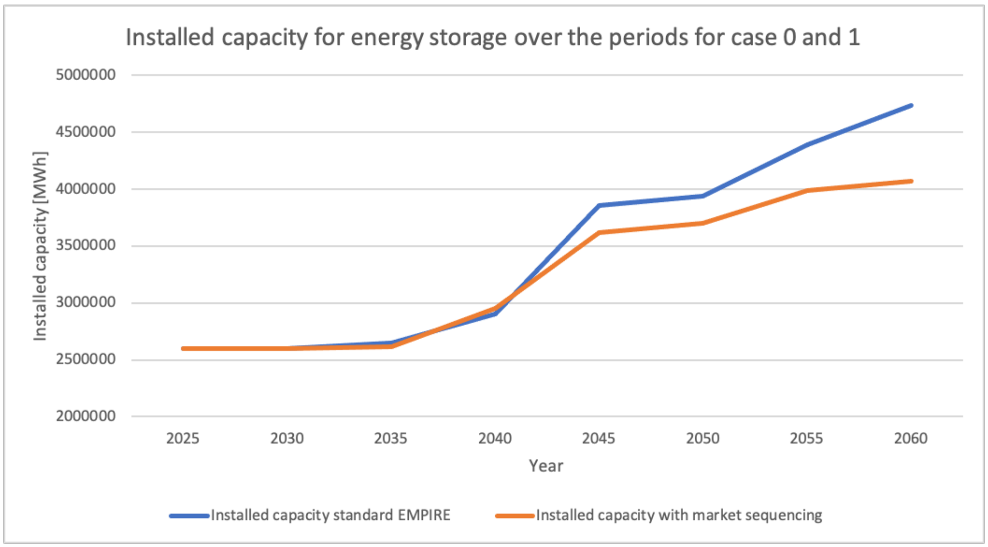

Figure 6.6: Development of installed energy capacity for energy storage for case 0 and 1

for storage is reduced in this case as storage is often used as a direct balancing mechanism for VRES [53]. With regards to case 2, the lack of uncertainty is likely leading to less investments in storage capacity since case 2 knows the future conditions for certain.

These results demonstrates that without the considerations of forecasting errors due to market sequencing, energy storage is significantly overvalued. The reason for the over-evaluation can be explained by more flexible producers with market sequencing, which are able to deliver power instead of energy storage systems. Research on investments in energy storage indicates that it will likely increase significantly [14, 15, 54], and is supported by the findings presented in this thesis. However, we deduce that energy storage will play a less significant role in the future power system than predicted previously. This is caused by the reduced amount of VRES, as storage investments are linked to VRES investments, and more flexible energy producers which can fulfill parts of the role storage has in a power system. However, there are no penalties for curtailment in the model. If there was mechanisms to reduce or minimize curtailment, storage could contribute significantly to solve this issue.

6.3.1 Operational decisions for energy storage

When evaluating discharge volume from energy storage, it is similar to that of investments in that case 0 has significantly more discharge volume than case 1 (37%). The reduced discharge volume in case 1 supports the argument that energy storage has traditionally been overvalued when analysed in a capacity expansion

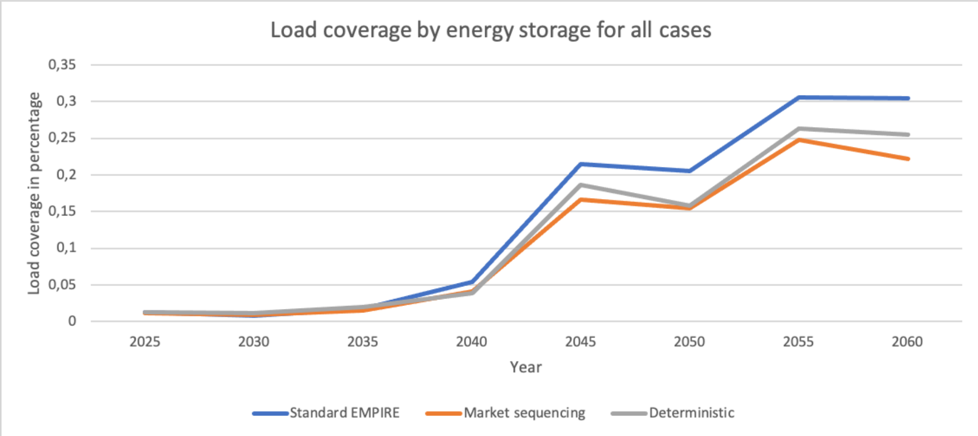

Figure 6.7: Load coverage by storage for the different cases.

model. The results from the deterministic case indicates a 15% higher discharge volume than in case 1 in 2050. The higher discharge volume in case 2 is likely explained by the lack of uncertainty in case 2, leading to a higher valuation of storage. Figure 6.7 illustrates the load coverage in each period for all three cases. As depicted by the figure, storage is contributing to a significant amount of the supply, mainly driven by the high installed capacity of VRES, especially solar.

6.4 Transmission investments and operational decisions

Investments in transmission capacity are very similar across the cases with less than 1% difference in installed capacity between case 0 and 1. Case 2 invests the least in transmission with 4% less than case 0. The observation that the deterministic case invests the least in transmission is expected due to the perfect foresight. In all three cases, there is an increase in installed transmission capacity over the periods. It is reasonable to explain these results by highlighting the increased VRES capacity in the later periods, which contributes to more emphasis on transmission [11, 16].

Operational transmission decisions differ significantly between the cases. Case 1 has 10-20% more transmission volume than case 0 in the different periods in the intraday market, despite a very similar capacity. Case 2 also delivers from 10-20% more transmission volume, although there are differences for each period between case 1 and 2. These results indicate that transmission is significantly contributing to flexibility in a power system by balancing the forecasting errors between nodes. Our findings appear to be well supported by existing literature [13, 16, 29, 55]. There is also a significant increase in transmission volume in the intraday market compared to the day-ahead market. The increase in transmission volume is likely driven by changing forecasts between the nodes, and transmission

Table 6.2: Overview of intraday volume in percentage of actual load

Period	Case 1 (stochastic)	Case 2 (deterministic)
2025	11	11.6
2030	12.5	13.9
2035	14.9	16.3
2040	17.3	17.5
2045	33.5	39.5
2050	27.1	29.4
2055	37.6	35.6
2060	32.4	34.8

is a key balancing component to solve this issue cost-effectively.

6.5 Curtailment

Concerning curtailment, there is a similar amount of electricity being curtailed in each period in all three cases. The curtailment percentage is calculated as the curtailed electricity in each period divided by the total possible production from VRES. In general, case 2 curtails the least amount of electricity, except for the last two periods. Since case 2 does not consider uncertainty, these results are justifiable. The reason why case 2 curtails a larger amount in the last two periods is probably due to the conditions and the installed VRES capacity in these periods. Case 1 is similar to case 2 in terms of curtailment percentage. In the first six periods, it curtails slightly more (2-3%) than case 2, while in the last two periods, a slightly lower amount is curtailed (3-4%). Case 0 curtails slightly more electricity over all the periods compared to the other case 1. These finding can be attributed the installed capacity being lower, and thus, a higher share of the available VRES resources has to be utilised to supply the load, even though case 1 also utilises more flexible energy sources.

6.6 Intraday Volume

In Chapter 1, the importance of the intraday market was demonstrated. Based on the historical development of some of the European electricity markets, it could be argued that the importance of the intraday market would increase due to the growing share of VRES in the energy mix. In order to analyse the future development of the intraday market, the intraday volume was calculated for the cases with market sequencing in each period. For an in depth explanation of the method used to calculate the intraday volume, see section 4.6. The results from the intraday volumes are shown in Table 6.2.

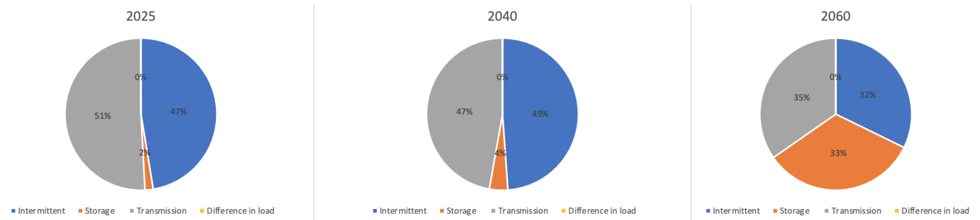

Figure 6.8: Contribuitions to intraday volume from load, transission, intermittent generators and storage in percentage.

As seen by table 6.2, the intraday volume increases significantly over the periods. Intermittent generators and transmission contribute to the majority of the volume, followed by energy storage. In addition, storage contributions grow significantly over the time horizon. Figure 6.8 illustrates the intraday volume contributions for three periods in case 1. The high transmission share in the intraday market gives further merit to the importance of transmission for efficient market clearing by providing flexibility between nodes. The table demonstrates a clear correlation of the intraday volume and installed capacity of VRES. The results are supported by [56, 57]. These findings are consistent with Ehrenmann et al. [56], who also highlights the likelihood of cross-border intraday trading due to the implementation of the XBID project. The higher share of transmission volume in case 2 compared to case 1 can be attributed to the lack of uncertainty, thus being able to utilise more of the available VRES resources.

6.7 Hourly operations in Germany and Norway

This section presents the results of one operation week for Germany and the southern part of Norway, NO2,in order to analyse how the energy markets and the operational decisions functions. The results for each case is presented individually before a comparison and discussion of the results are presented.

6.7.1 Choice of nodes and operational week

One operational week in all three cases is analysed, and both markets are analysed for case 1 and 2. The week analysed is in the spring season and in the period 2045-2050 and was randomly selected. The same operational scenario is used for case 0 and 1, while the expected scenario is used for case 2. In all three cases, NO2 is characterized by large shares of regulated hydro and wind, while large shares of VRES characterise Germany. Furthermore, both nodes have other, smaller generators contributing to the production. NO2 was chosen as a node of interest due to the large shares of flexible generators. NO2 exports large volumes of electricity, and Germany is among the nodes where NO2 is exporting the most. Moreover, Germany is a node with a lot of VRES, so these two nodes and their relations in the markets are of great interest in order to analyse the impact of market sequencing and uncertainty.

6.7.2 Standard EMPIRE

Figure 6.9 and 6.10 illustrates the production by generator type in a week in addition to load, net charging, and net transmission flow out. As seen by the figures, NO2 is dominated by regulated hydro, hydro run-of-river, and onshore wind, while Germany is dominated by solar and onshore wind. Due to the large share of PV in Germany, Germany may have trouble being self-sufficient during night hours, illustrated by the load curve in figure 6.10. In night hours, Germany is therefore reliant on contributions from storage, other generator output, and/or imports from other nodes. On the other side, when the solar conditions are good, Germany is exporting a significant volume of power as well as charging storage systems. From figure 6.10, it is observed that transmission and storage operations closely follow the trend for solar production. Bio energy is also contributing significantly to flexibility at nighttime.

For NO2, the production is dominated by regulated hydro, followed by VRES. The electricity generation in NO2 is correlating with the production and load in Germany. In NO2, regulated hydro is producing a significant amount of electricity during the night due to the large share of solar power, both in the German system as well as the whole European power system. The large transmission volume during these hours also supports Norway's role as a flexibility provider in the European power system [58]. From the results, it is observed that NO2, with its larges share of flexible generators, are providing flexibility to other nodes with larges shares of VRES. Norway's role as a flexibility provider is also supported by [59, 60]

6.7.3 Market sequencing

Figure 6.11 and 6.12 illustrate the same week as presented in section 6.7.2 in the day-ahead stage. The results are very similar to standard EMPIRE, with production in Norway dominated by regulated hydro and high transmission volumes during the hours of the night, providing flexibility for nodes with high shares of solar production. However, there are some differences between the market stages. Figure 6.13 illustrates the intraday market in NO2 in the same week. When comparing figure 6.11 and figure 6.13, it can be observed that flexible resources (regulated hydro) contribute significantly to balance forecast errors, as regulated hydro is increasing its production between the market stages for a significant portion of the hours. The altered production is also reflected in the net transmission since the transmission volume is increasing during the same hours. Also, NO2 is importing some electricity in the intraday stage which had not been scheduled in the day-ahead market. The imports in NO2 is likely due to better conditions for VRES generation than predicted in neighbouring nodes, and VRES can therefore

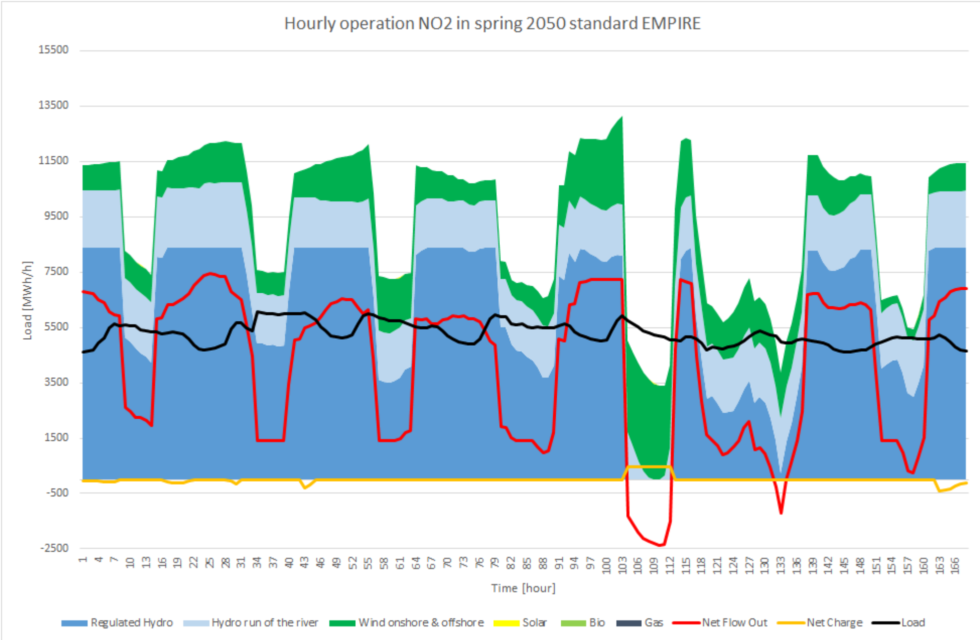

Figure 6.9: Operational week of NO2 in standard EMPIRE.

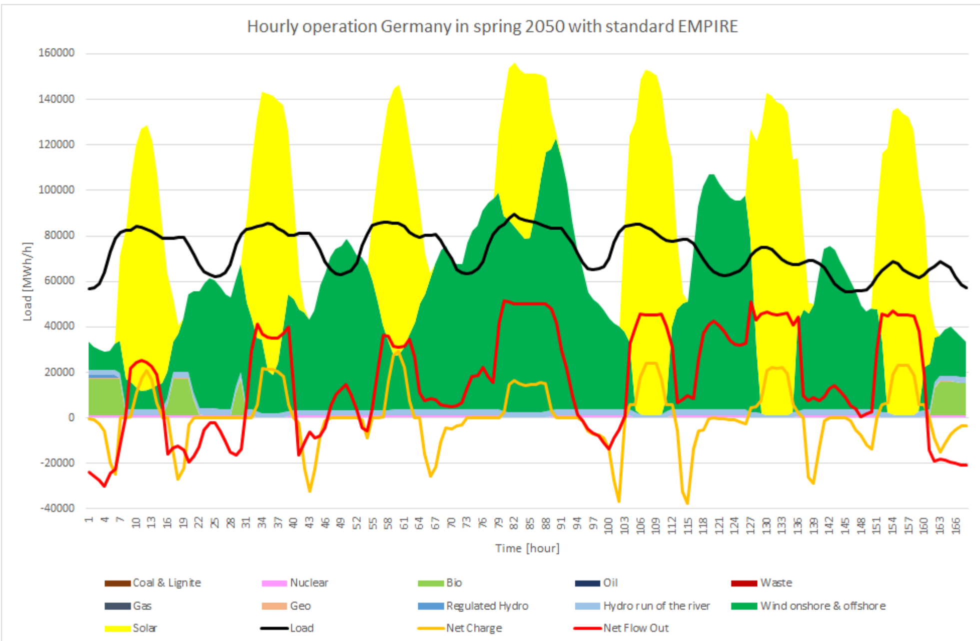

Figure 6.10: Operational week of Germany in standard EMPIRE.

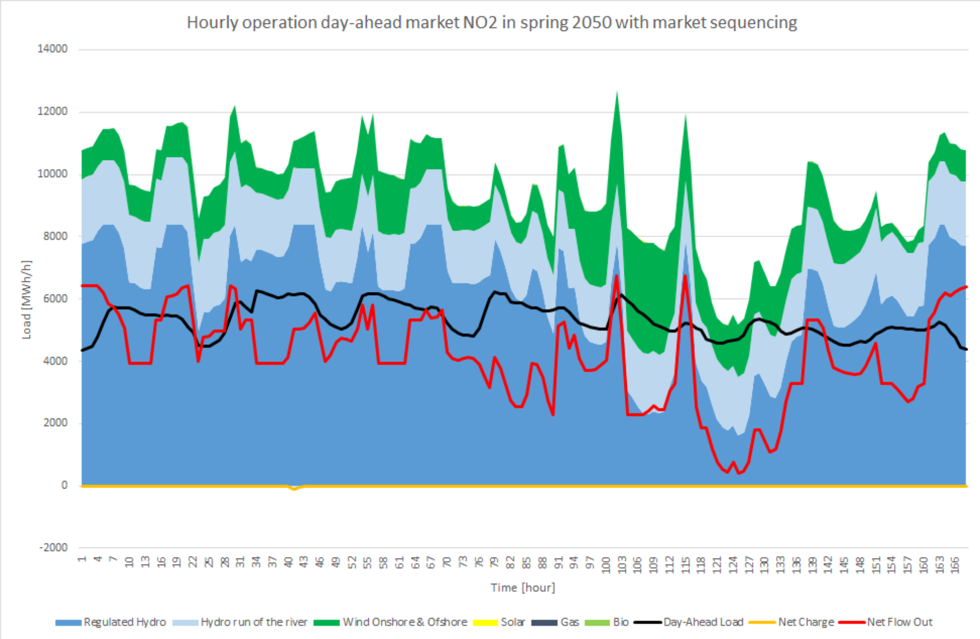

Figure 6.11: Operational week of NO2 in EMPIRE with market sequencing, day-ahead.

be used instead of a resource-limited generator like regulated hydro. Net charging in NO2 is also different in the market stages. There is generally charging during the day and discharging during the night. The increased charging is likely tied to the installed solar capacity in Europe, allowing for more transmission volume from NO2 when energy storages are utilised.

In Germany, the situation is a bit more nuanced as there is a wider scope of generators in the German market. Figure 6.14 illustrates the intraday market for Germany. Importantly, bio is the major flexible generator in Germany. Furthermore, bio is reducing its output significantly between the day-ahead market and the intraday market. The reduction in flexible production is generally covered by an increase in intermittent production or an increase in imports from transmission. The results from Germany are also in line with the results from NO2. From figure 6.12 and figure 6.14 , it is observed that the intraday market re-balances the production and transmission in order to achieve the best possible production scheme for the intraday market, subject to the decisions made in the day-ahead market. When evaluting differences in net charging between the two German markets, there are some minor changes both in volume and time of charging and discharging. These are likely driven by the slightly altered VRES output in the intraday market compared to the day-ahead market.

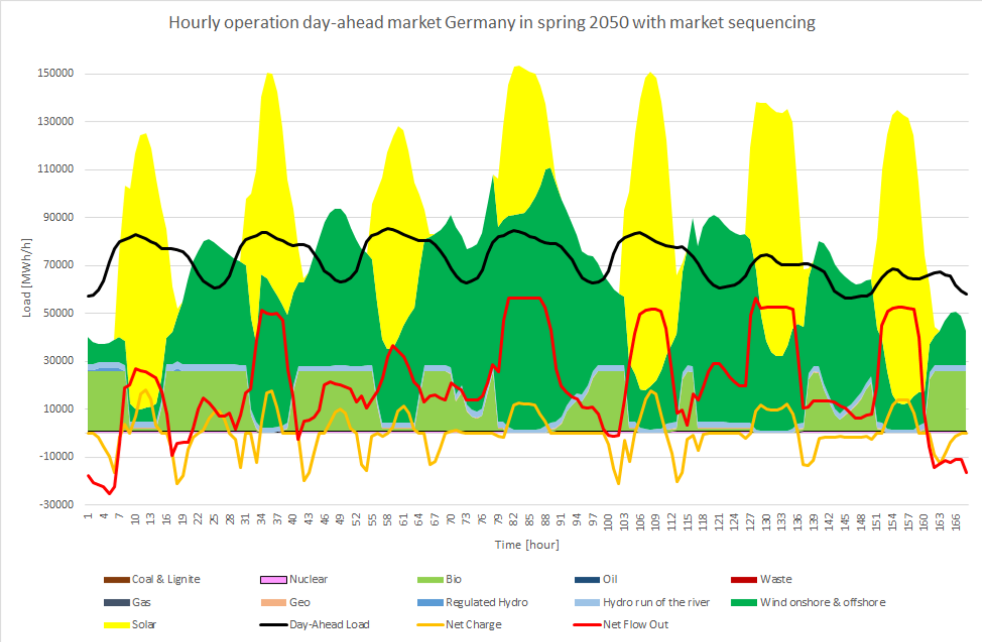

Figure 6.12: Operational week of Germany in EMPIRE with market sequencing, day-ahead.

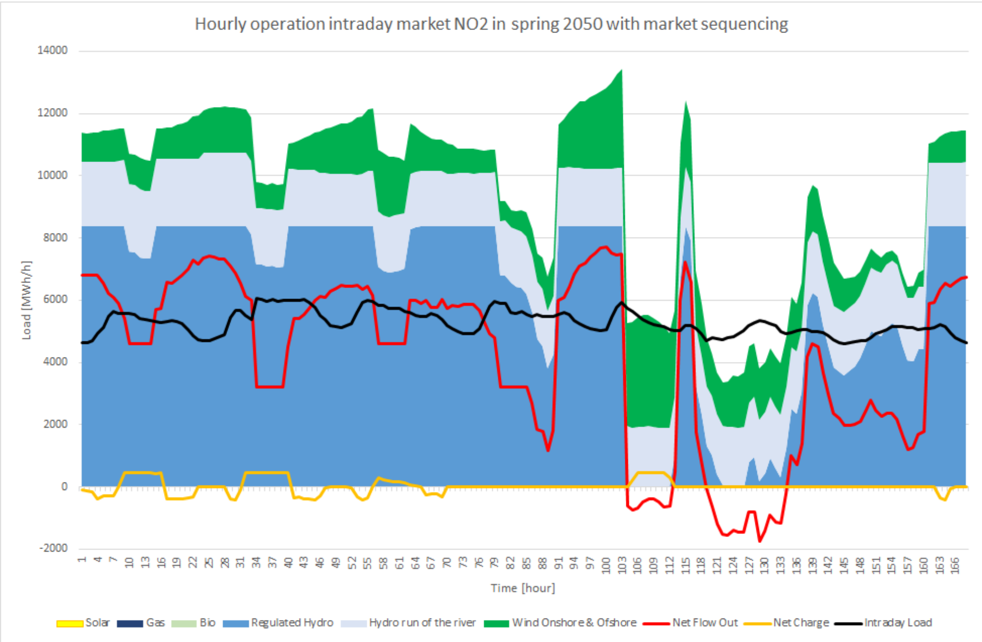

Figure 6.13: Operational week of NO2 in EMPIRE with market sequencing, intraday.

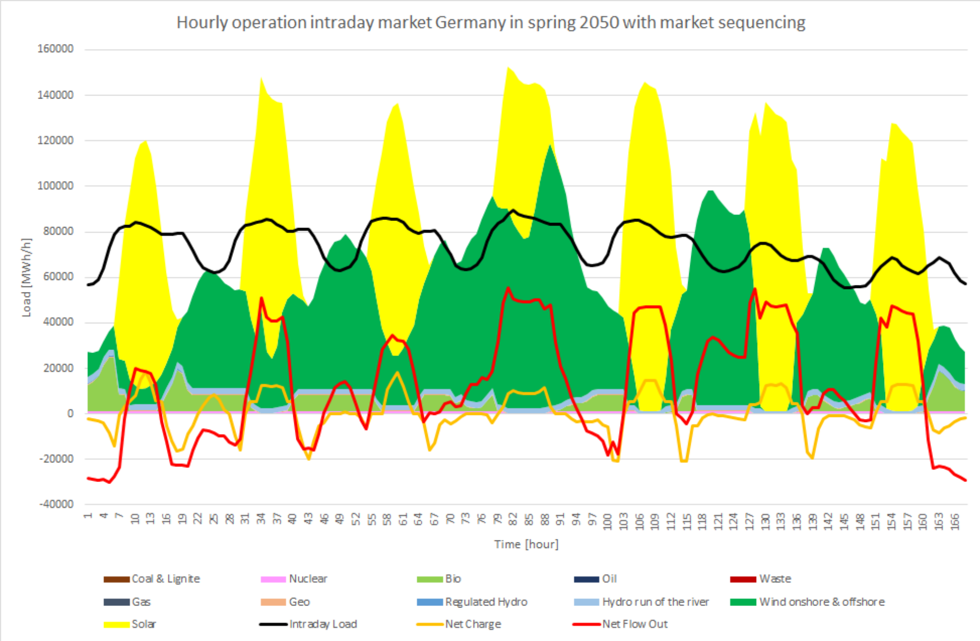

Figure 6.14: Operational week of Germany in EMPIRE with market sequencing, intraday.

6.7.4 Deterministic

Figure 6.15 illustrates the operational decisions for the day-ahead market in NO2. Once again, regulated hydro is used during the night hours to facilitate the supply of load in nodes with large shares of solar capacity installed. The load in NO2 is mostly covered by VRES, with small shares of regulated hydro in some hours and a tiny part of imports from other nodes. Figure 6.17 illustrated the operational decisions in the intraday market for NO2. As seen by this figure, there are some minor differences, mostly driven by changing conditions for VRES production. When comparing the figure 6.15 and figure 6.17, the major trends from the other cases continues. Regulated hydro produce during the night and mostly export to neighbouring nodes. However, the volumes are slightly different between the markets. The change in net flow out is driven by the changing weather conditions between the market stages in the neighbouring nodes. It is especially noticeable in hours 127-136 and hours 151-160 in figure 6.15 and figure 6.17, where the transmission plan is changed from exports to imports. Since these hours are during the day when there is solar production, these changes are most likely driven by better conditions for solar production than what was forecasted in neighboring nodes. However, wind energy could also contribute to the change in transmission volume. In hours 106-115, the opposite is true. Here, there is an increase in exports compared to day-ahead scheduling, probably due to worse conditions for VRES in some neighbouring nodes.

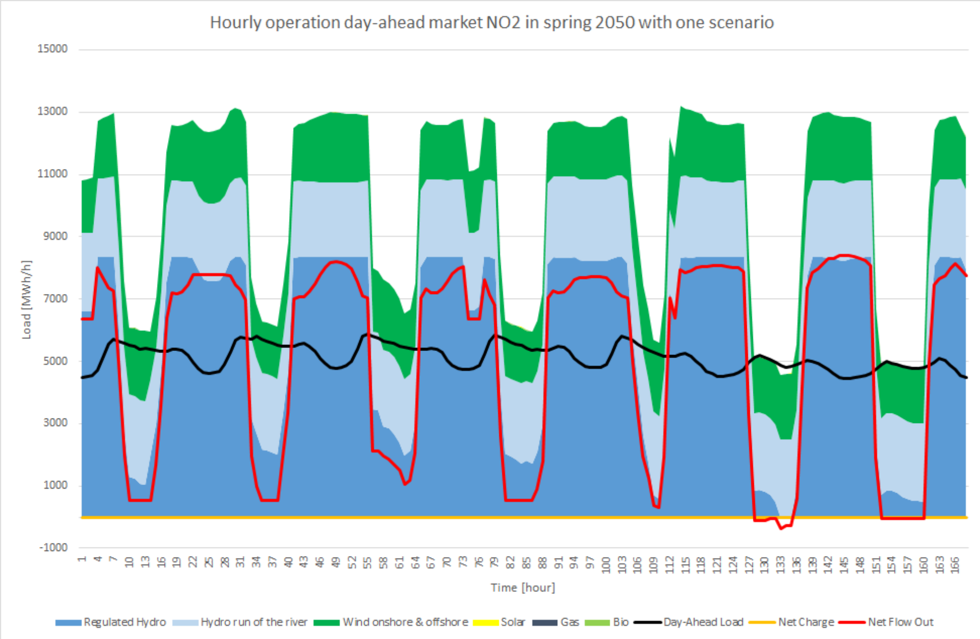

Figure 6.15: Operational week of NO2 in Deterministic, day-ahead.

Figure 6.16 and 6.18 illustrate an operational week in Germany for the day-ahead market and intraday market, respectively. Once again, Germany is decreasing output from flexible generators between the market stages. In the intraday market, there is also generally an increase in production from solar, indicating that the conditions improved from the day-ahead market. Concerning wind generation, there are improved conditions in some hours and a worse in conditions in other hours. Transmission generally follows the same trend as the solar production. In periods with solar generation, there are a lot more exports than in the hours without solar generation. Net charging is also following the trend of solar production. Concerning the difference in transmission and storage volumes between the markets, there is generally a slight increase, although a minor one.

6.7.5 Comparison of the cases

Day-ahead analysis for Norway

By comparing figure 6.11 and 6.15, there are significant differences in the planning by using a deterministic approach versus a stochastic approach in NO2. In a deterministic approach, there is less variation between different days in a week compared to a stochastic approach. Another difference is seen in the relation of production between the day and night between the cases, resulting in a stochastic approach having a more stable production throughout the week. There is also a significant difference in terms of planned transmission volume. In the deterministic case, it is generally planned to export almost all of the production from

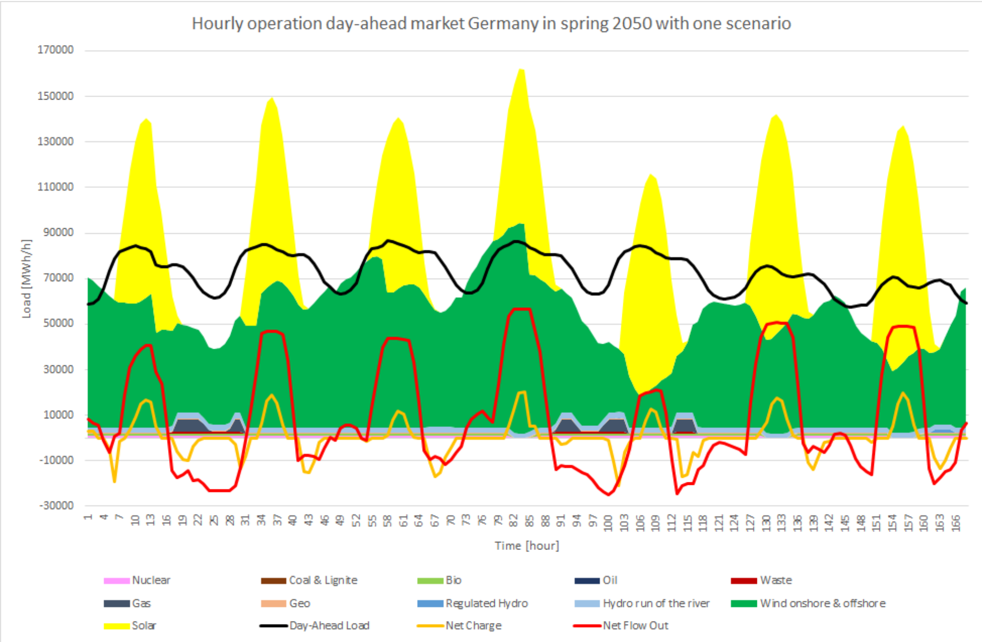

Figure 6.16: Operational week of Germany in Deterministic, day-ahead.

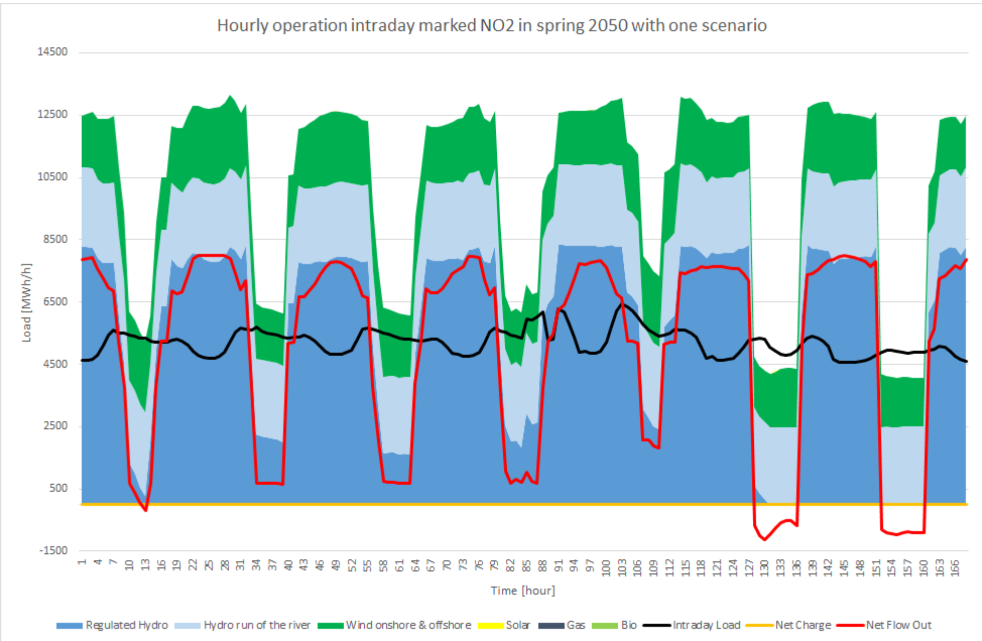

Figure 6.17: Operational week of NO2 in Deterministic, intraday.

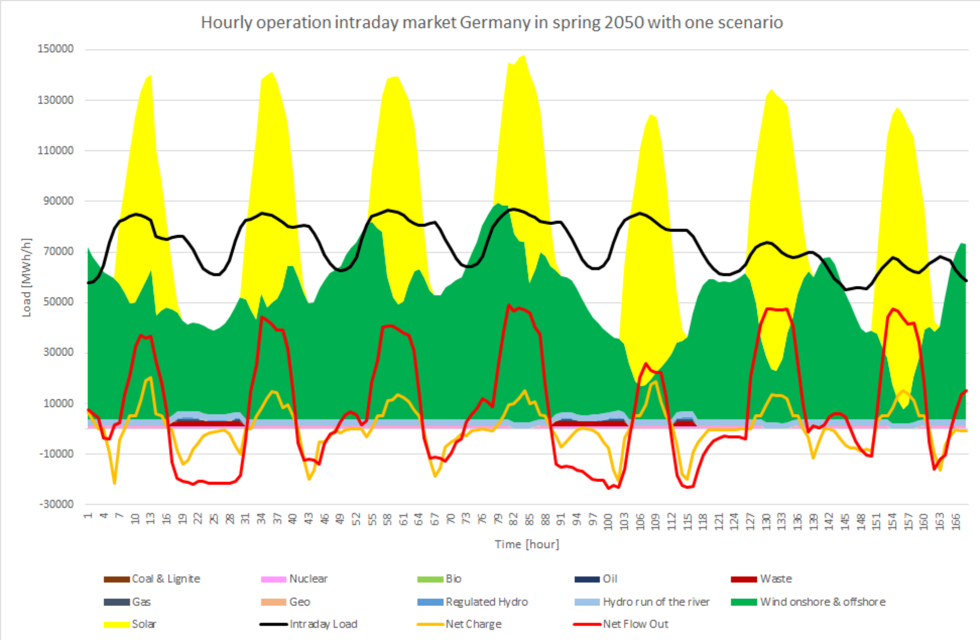

Figure 6.18: Operational week of Germany in Deterministic, intraday.

regulated hydro, while in a stochastic approach, a smaller portion of the production from regulated hydro is scheduled for transmission. In both cases, there is an insignificant amount of scheduled storage usage in NO2.

Day-ahead analysis for Germany

The analysis of the operational decisions in the day-ahead markets for Germany, illustrated by figure 6.12 and 6.16, further supports the differences between a stochastic and a deterministic approach. In a deterministic approach, there is significantly less planned generation from flexible generators compared to a stochastic approach. Notably, bio is not used nearly as much as in a stochastic approach. The reason for the reduced contributions from bio is tied to the installed capacity of flexible generators between the two approaches. Transmission and storage trends are similar in the two approaches. However, the stochastic approach generally has slightly more variance in transmission and storage than the deterministic approach. Similarly, case 1 is scheduling for more exports than case 2. Note that the VRES availability is different between the cases as case 2 only uses expected availability. In some hours, the availability is significantly better in one case compared to the other, while in other hours it is worse.

Intraday Analysis for Norway

The are also evident differences in the intraday market between the cases. Figure 6.13, 6.9, and 6.17 illustrate the operational decisions for actual delivery in NO2. The main difference between case 0 and case 1 is the increased output of regulated hydro in the hours mid-day. The increased hydro production is likely the reason why the transmission volume exported are increasing in these hours. Storage is also used significantly more in case 1 than in case 0, likely due to an increase in exports. In hours 103-112, there are imports to NO2, likely driven by good solar conditions in neighbouring nodes. In case 2, there are even larger differences compared to the other two cases. In contrast to the other two cases, the deterministic case is delivering power in a very stable cycle over the week. Furthermore, in case 2, even more of the electricity generated by regulated hydro is exported, and a negligible amount of energy is used for storage. An interesting observation is the lower regulated hydro production in the hours 140-160 in case 1 compared to case 0. It is difficult to state a clear conclusion on this, but one factor may be the availability of hydro resources as there is a higher production from hydro in the other hours. Another explanation could be that neighbouring nodes are utilising more of their flexible and VRES resources in these hours, as the export volume in these hours from NO2 are lower in case 1 than case 0.

Intraday Analysis for Germany

Concerning Germany, there are also significant differences in the operational decisions in the intraday market. Case 1 values flexible energy sources more than case 0, which is illustrated by the increase in generator output for these energy sources in figure 6.14 and 6.10. Moreover, it appears that production from intermittent energy sources is slightly lower in case 1 than case 0. This is also reflected by the decreased charging and discharging volumes throughout the week. In case 2, there are generally more imports of electricity to Germany than the other cases. The increased imports is driven by the reduction in flexible energy sources and, therefore, more utilisation of the intermittent energy sources, both in Germany and neighbouring nodes illustrated by the significantly higher production from wind in the first 15 hours. In case 2, the charging volumes are very similar to those of case 1. These results illustrates that a deterministic approach can utilise a higher portion of the installed intermittent capacity.

6.8 The Importance of Considering Uncertainty

This section demonstrates the importance of considering uncertainty in a capacity expansion problem. A value of stochastic solution [VVS] test was conducted in order to investigate the impact of including uncertainty.

Value of stochastic solution test is a test that establishes the value of using stochastic programming as opposed to deterministic programming [61]. The VSS test is performed by calculating the difference in objective value between using first stage decisions optimized for an expected deterministic scenario and using a stochastic multi-stage optimization model, ref equation 6.1. To establish the VSS, the results from case 2 concerning the first stage variables were used as input parameters in case 1. This allowed us to investigate the impact of having uncertainty concerning load and the generator availability in both markets when the installed capacity is optimized for different scenarios as opposed to being optimized for a single expected operational scenario. As shown in table 6.1, a deterministic solution is a seemingly cheaper solution. Furthermore, a deterministic approach invests in significantly less generator capacity.

$$VSS = z_{exp} - z_{stoc} \tag{6.1}$$

The results of the run of case 1 with input from case 2 yielded an infeasible model. There are many explanations why the VSS test yielded an infeasible solution. First, by performing a deterministic run based on the expected outcome, investments are smaller across the technologies. This leads to more stress on the operational energy balance constraints, (4.3) and (4.4), when a scenario with poorer conditions than the expected occurs. In the intraday market, this is not a problem in terms of infeasibility, due to the ability to shed load that is not possible to cover. However, this is not an option in the day-ahead market. Therefore, due to the inability to shed load or otherwise not meet the demand in the day-ahead market, the result is infeasible giving a seemingly infinite value to the stochastic solution.

Different market designs were tested to accommodate the infeasible solution of the VSS test. First, the equality of constraint 4.3 was changed to an inequality, meaning that the supply does not have to meet the demand. The change yielded a feasible model, but due to the changed energy balance constraint and the impact this had on the results, the results were deemed not comparable and not realistic in terms of how a day-ahead market operates. As the objective function only factors the actual delivery cost-wise and not the scheduled planning, there is a lack of incentive to meet the demand in the day-ahead stage. This results in a significant lack of supply in the day-ahead stage, which is not realistic in a real-world day-ahead market. A minimum of supply was scheduled in the day-ahead market, just so the intraday demand could be met with limited load shedding. It was also tested to allow load shedding in the day-ahead market. Allowing for load shedding in the day-ahead market without a cost associated yielded very similar results to that of creating an inequality instead of an equality. This is to be expected, as making it an opportunity to shed load without a cost associated is adding slack to the constraint, which is basically the same as changing the constraint from equality to inequality. A possibility is also to allow for load shedding in the day-ahead stage, but with a cost associated. It would be expected that a similar amount of load would be shed in both markets, which would mean that load shedding would essentially be twice as expensive. This approach would likely lead to a feasible model, but it would be difficult to compare the results to the other cases. Lastly, it could be possible to calculate the difference in load shedding between the markets and give a cost to the absolute total load shed. However, this is challenging to implement in the model and would increase the computational burden. Therefore, this last option was discarded.

Even though a result for the VSS test was not achievable, the results can still be used to estimate the error of not considering uncertainty [62], which for the cases analysed in this thesis is significant. As seen from the objective value for case 1 and 2, there is roughly a 10% difference in objective value. The reason for this difference is due to an under-estimation of the need for capacity in case 2, as this case invests based on perfect information. Thus, case 2 does not account for the unpredictable nature of VRES and load. In addition, case 2 invests the least in inflexible and flexible generators. When conditions are poorer than expected, the deterministic approach is not able to supply the demand due to the limited installed capacity, and additional capacity is needed for these hours in order to supply the load. Therefore, we can say that a stochastic approach to a capacity expansion problem is more robust, as the likelihood of supplying the demand increases significantly. By utilising a deterministic approach, the investment costs would be lower, but the costs of not supplying the load in hours with poor conditions are much higher. We can therefore conclude that the costs saved on capacity is significantly lower than the costs of not having sufficient capacity.

Chapter 7

Conclusion

This thesis presents a method to analyse the long-term developments in a power system while considering forecast errors from intermittent energy sources between market stages. A capacity expansion model with one investment stage and two market stages was developed to include forecast errors and the uncertainty from VRES in order to elucidate how this impacts investment decisions. The approach utilised is not commonly used, but it may provide better insights into how the future power system may develop. A simplified case study was conducted to prove that the model is functional. In order to answer the research questions stated in Chapter 1, three distinct cases was tested. Case 0 was used as a reference case illustrating the traditional way to model capacity expansion of a power system. Case 1 implements a second market stage to represent a day-ahead market and an intraday market. Case 2 is a deterministic version of case 1, aiming to demonstrate the impact of not considering uncertainty when modelling a capacity expansion problem. Below, the three research question introduced in Chapter 1 are presented and answered.

How does an increased amount of uncertainty introduced by forecasting errors between a day-ahead and an intraday market affect investment decisions in the power system, including VRES investments?

Our findings demonstrate a significant difference in investment decisions between the cases. An addition of market sequencing increases the total system costs by 2.1%. Additionally, there is a steep increase in intraday volume over the analysed period due to the increased installed capacity of intermittent energy sources. When accounting for forecasting errors, there is a decrease in 10% of investments in intermittent energy sources and an increase of 40% in investments of flexible generators. Intermittent generators still dominates the installed capacity with a share of 80% when including forecasting errors. The findings from this study indicates a decreased importance of energy storage in the future power system, reducing the installed capacity by 16%. The reduction in energy storage can be attributed to the lower investments in intermittent energy sources, but also implies that energy storage is over-valued when not considering forecasting errors. Investments in cross-border transmission capacity are almost unchanged (<1% difference) between the cases. Our findings supported by existing literature [26, 31, 34].

How are operational decisions affected when forecasting errors from market sequencing are included?

Operational decisions differ significantly between the cases. Concerning storage and generation, the output follows the same trend as the installed capacity. However, when accounting for forecast errors, transmission utilisation increases with 10-20%. Transmission serves therefore as major flexibility provider to help balance the forecast errors that occur between the market stages. Cross-border transmission have previously been assumed to be a crucial part of providing flexibility in power systems characterised by large shares of VRES [11, 16, 29].

What is the impact of including uncertainty when analyzing the developments in a power system?

The deterministic approach is compared to a stochastic program to identify the value of considering uncertainty. The VSS test yielded an infeasible model, indicating that in order to operate a power system in a capacity expansion model, it is crucial to consider uncertainty. Furthermore, the deterministic approach yielded a 7.3% lower total system cost, and we can therefore conclude that the lower costs due to the reduced installed capacity does not cover the costs for potential load shedding, should the conditions deviate from the expectations. Moreover, our findings has led us to conclude that a deterministic approach significantly undervalues installed capacity, and thus, is not able to supply the demand if conditions change to the worse compared to the expected conditions.

In summary, four main conclusions can be drawn from this study:

- Investments in intermittent energy sources are significantly decreased when accounting for forecast errors.
- Transmission will be a pivotal contributor to balance the future power system.
- Investments in storage has traditionally been overvalued and are likely to play a less important role than anticipated.
- Considering short-term uncertainty from forecasting errors between market stages and uncertainty of VRES is crucial when planning for investments in a power system.

This thesis has highlighted the importance of considering forecasting errors when analysing a capacity expansion problem. The results proves significant differences in investments and operational decisions compared to the traditional approach. It should be noted that adding a third stage to the EMPIRE model, as done in this thesis, entails a significant increase to the computational burden.

7.1 Future Work

This section will briefly state some considerations regarding future work.

Cost-recovery

A method to consider cost-recovery should be developed in order to solve the cost-recovery issue. In the presented model, generators that are reducing their output between the market stages are not compensated. This could imply that a generator relying on fuel purchases does not cover its costs. An excess cost for producing more than scheduled is also possible. As intraday prices are typically higher than day-ahead prices for various reasons, the model could reflect this in a better manner.

Market design

A different and more realistic real-world market design could improve the model. The current model involves a complete system balance in each market. However, intraday markets usually function by just balancing the errors that occur from the day-ahead market, not a complete re-balance only limited by the flexibility from the flexible generators. The standard market design leaves little room to improve the decision making from the day-ahead market should the conditions for the intermittent energy sources improve. Hence, a study on improved market design could prove beneficial.

Demand Response

Demand response is an issue which has been implemented and tested in EMPIRE previously [36, 39]. Thus, demand side flexibility is already present in some versions of EMPIRE. It could be of major interest to investigate how demand-side flexibility can contribute to balance the deviations between the energy markets due to forecasting errors, by combining the demand response module and the model developed in this thesis. In this paper, we experienced reduced investments in storage with market sequencing. Demand response, may have similar results, as the purpose of both demand response and energy storage is to provide flexibility [63]. However, it is of interest to investigate how demand response could be affected by market sequencing due to the increased need for flexibility introduced by the forecasting errors.

Curtailment

As the model is currently, there are no mechanisms to reduce or minimize curtailment and the amount of curtailment is high. Therefore, research on how to solve this issue could be very beneficial. An idea could be a cap or a cost associated with curtailment. By implemented a way to handle curtailment, the results may provide better conditions for energy storage and transmission.

Branching on the intraday stage

Lastly, it could be beneficial to branch on the intraday stage as well. Branching was not done in this thesis, due to the lack of both a method and computational requirements. An idea for a method could be to add two more scenarios to the intraday, with + or - a percentage difference from the actual conditions. However, this would significantly increase the computational burden of the problem.

Bibliography

[1] European Environmental Agency, 'Overview of electricity production and use in europe', p. 42, 2015, Accessed: 18.08.2020, Available at:"https://www.eea.europa.eu/data-and-maps/indicators/overview-of-the-electricity-production-2/assessment-4".

[2] C. A. Horowitz, 'Paris agreement', *International Legal Materials*, vol. 55, no. 4, pp. 740–755, 2016. DOI: 10.1017/S0020782900004253.

[3] D. Gielen, F. Boshell, D. Saygin, M. D. Bazilian, N. Wagner and R. Gorini, 'The role of renewable energy in the global energy transformation', *Energy Strategy Reviews*, vol. 24, pp. 38–50, 2019, ISSN: 2211-467X. DOI: https://doi.org/10.1016/j.esr.2019.01.006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2211467X19300082.

[4] M. H. Athari and Z. Wang, 'Modeling the uncertainties in renewable generation and smart grid loads for the study of the grid vulnerability', Sep. 2016. DOI: 10.1109/ISGT.2016.7781265.

[5] L. Gan, P. Jiang, B. Lev and X. Zhou, 'Balancing of supply and demand of renewable energy power system: A review and bibliometric analysis', *Sustainable Futures*, vol. 2, p. 100 013, 2020, ISSN: 2666-1888. DOI: https://doi.org/10.1016/j.sftr.2020.100013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S266618882030006X.

[6] ENTSO-E, 'Entso-e transparancy platform', 2020, Accessed: 18.08.2020, Available at:"https://transparency.entsoe.eu/content/static_content/Static%20content/knowledge%20base/SFTP-Transparency_Docs.html".

[7] Nordpool, 'Annual report', 2015-2019, Accessed: 18.08.2020, Available at:"https://www.nordpoolgroup.com/message-center-container/Annual-report/".

[8] EPEX, 'Annual report', 2015-2019, Accessed: 18.08.2020, Available at:"https://www.eex-group.com/en/about/annual-reports/".

[9] OMEL, 'Annual report', 2015-2019, Accessed: 18.08.2020, Available at:"https://www.omie.es/en/publications/annual-report".

[10] M. Alizadeh, M. Parsa Moghaddam, N. Amjady, P. Siano and M. Sheikh-El-Eslami, 'Flexibility in future power systems with high renewable penetration: A review', *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 1186–1193, 2016, ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2015.12.200. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S136403211501583X.

[11] P. D. Lund, J. Lindgren, J. Mikkola and J. Salpakari, 'Review of energy system flexibility measures to enable high levels of variable renewable electricity', *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 785–807, 2015, ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2015.01.057. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1364032115000672.

[12] H. Marañón-Ledesma and A. Tomasgard, 'Long-Term Electricity Investments Accounting for Demand and Supply Side Flexibility', University Library of Munich, Germany, MPRA Paper 93341, Mar. 2019. [Online]. Available: https://ideas.repec.org/p/pra/mprapa/93341.html.

[13] H. Kondziella and T. Bruckner, 'Flexibility requirements of renewable energy based electricity systems – a review of research results and methodologies', *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 10–22, 2016, ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2015.07.199. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1364032115008643.

[14] A. Schreider and R. Bucher, 'An auspicious combination: Fast-ramping battery energy storage and high-capacity pumped hydro', *Energy Procedia*, vol. 155, pp. 156–164, Nov. 2018. DOI: 10.1016/j.egypro.2018.11.059.

[15] P. Denholm and M. Hand, 'Grid flexibility and storage required to achieve very high penetration of variable renewable electricity', *Energy Policy*, vol. 39, pp. 1817–1830, Mar. 2011. DOI: 10.1016/j.enpol.2011.01.019.

[16] M. Child, C. Kemfert, D. Bogdanov and C. Breyer, 'Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in europe', *Renewable Energy*, vol. 139, pp. 80–101, 2019, ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2019.02.077. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0960148119302319.

[17] C. De Jonghe, E. Delarue, R. Belmans and W. D'haeseleer, 'Determining optimal electricity technology mix with high level of wind power penetration', *Applied Energy*, vol. 88, no. 6, pp. 2231–2238, 2011, ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2010.12.046. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261910005660.

[18] M. Zipf and D. Möst, 'Impacts of volatile and uncertain renewable energy sources on the german electricity system', pp. 1–8, 2013.

[19] R. Barth, H. Brand, P. Meibom and C. Weber, 'A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power', *2006 9th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS*, 2006. DOI: 10.1109/PMAPS.2006.360195.

[20] M. Kannavou, M. Zampara and P. Capros, 'Modelling the EU internal electricity market: The PRIMES-IEM model', *Energies*, vol. 12, no. 15, 2019, ISSN: 19961073. DOI: 10.3390/en12152887.

[21] S. Kulakov and F. Ziel, 'The impact of renewable energy forecasts on intraday electricity prices', Mar. 2019.

[22] J. Abrell and F. Kunz, 'Integrating Intermittent Renewable Wind Generation - Insights from the Stochastic Electricity Market Model (stELMOD)', *SSRN Electronic Journal*, no. May, 2012, ISSN: 1556-5068. DOI: 10.2139/ssrn.2069935.

[23] R. Barth, H. Brand, P. Meibom and C. Weber, 'A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power', Jul. 2006, pp. 1–8. DOI: 10.1109/PMAPS.2006.360195.

[24] J. M. Morales, M. Zugno, S. Pineda and P. Pinson, 'Electricity market clearing with improved scheduling of stochastic production', *European Journal of Operational Research*, vol. 235, no. 3, pp. 765–774, 2014, ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2013.11.013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0377221713009120.

[25] F. Borggrefe and K. Neuhoff, 'Balancing and intraday market design: Options for wind integration', *SSRN Electronic Journal*, Oct. 2011. DOI: 10.2139/ssrn.1945724.

[26] P. Seljom and A. Tomasgard, 'Short-term uncertainty in long-term energy system models — a case study of wind power in denmark', *Energy Economics*, vol. 49, pp. 157–167, 2015, ISSN: 0140-9883. DOI: https://doi.org/10.1016/j.eneco.2015.02.004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140988315000419.

[27] S. Nagl, M. Fürsch and D. Lindenberger, 'The costs of electricity systems with a high share of fluctuating renewables: A stochastic investment and dispatch optimization model for europe', *The Energy Journal*, vol. 34, Jan. 2012. DOI: 10.5547/01956574.34.4.8.

[28] A. Ehrenmann and Y. Smeers, 'Stochastic equilibrium models for generation capacity expansion', in. Jul. 2011, pp. 273–310, ISBN: 978-1-4419-9585-8. DOI: 10.1007/978-1-4419-9586-5_13.

[29] Y. Sun, W. Cole and V. Krishnan, 'Comparing power flow approximations for electricity infrastructure capacity expansion models with high spatial resolution', in *2018 IEEE/PES Transmission and Distribution Conference and Exposition (T D)*, 2018, pp. 1–5. DOI: 10.1109/TDC.2018.8440480.

[30] D. Giraldo, J. López-Lezama and L. Pareja, 'Power system capacity expansion planning model considering carbon emissions constraints', *Revista Facultad de Ingeniería Universidad de Antioquia*, vol. 62, pp. 114–125, Mar. 2012.

[31] M. Villavicencio, 'A capacity expansion model dealing with balancing requirements, short-term operations and long-run dynamics', *CEEM Working Papers*, Feb. 2017.

[32] K. Poncelet, A. van Stiphout, J. Meus, E. Delarue and W. D'haeseleer, 'Lusym invest: A generation expansion planning model with a high level of temporal and technical detail', May 2018.

[33] J. Gea-Bermúdez, L.-L. Pade, M. J. Koivisto and H. Ravn, 'Optimal generation and transmission development of the north sea region: Impact of grid architecture and planning horizon', *Energy*, vol. 191, p. 116 512, 2020, ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2019.116512. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544219322078.

[34] S. Pineda and J. M. Morales, 'Capacity expansion of stochastic power generation under two-stage electricity markets', *Computers Operations Research*, vol. 70, pp. 101–114, 2016, ISSN: 0305-0548. DOI: https://doi.org/10.1016/j.cor.2015.12.007. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0305054815002932.

[35] C. Skar, G. Doorman, G. A. Pérez-Valdés and A. Tomasgard, 'A multi-horizon stochastic programming model for the european power system', 2016.

[36] H. Marañón-Ledesma, 'Analyzing demand response in a dynamic capacity expansion model for the european power market', *Energies*, vol. 12, Aug. 2019. DOI: 10.3390/en12152976.

[37] S. Backe, D. Pinel, P. Crespo Del Granado, M. Korpås, A. Tomasgard and K. Lindberg, 'Towards zero emission neighbourhoods: Implications for the power system', Sep. 2018. DOI: 10.1109/EEM.2018.8469976.

[38] P. Crespo Del Granado, C. Skar, H. Doukas and G. Trachanas, 'Investments in the eu power system: A stress test analysis on the effectiveness of decarbonisation policies', in. Jan. 2019, pp. 97–122, ISBN: 978-3-030-03151-0. DOI: 10.1007/978-3-030-03152-7_4.

[39] S. Backe, M. Korpås and A. Tomasgard, 'Heat and electric vehicle flexibility in the european power system: A case study of norwegian energy communities', *International Journal of Electrical Power Energy Systems*, vol. 125, p. 106 479, 2021, ISSN: 0142-0615. DOI: `https://doi.org/10.1016/j.ijepes.2020.106479`. [Online]. Available: `http://www.sciencedirect.com/science/article/pii/S0142061520322079`.

[40] *Bidding areas*, `https://www.nordpoolgroup.com/the-power-market/Bidding-areas/`, Accessed: 2020-11-25.

[41] *European model for power system investment with renewable energy*, `https://www.ntnu.edu/web/iot/energy/energy-models-hub/empire`, Accessed: 2020-11-25.

[42] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. New York, NY, USA: Springer-Verlag, 1997.

[43] European Commission, 'COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE EUROPEAN COUNCIL, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE, THE COMMITTEE OF THE REGIONS AND THE EUROPEAN INVESTMENT BANK A Clean Planet for all A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy COM/2018/773 final', 2018.

[44] M. Keay, 'Electricity markets are broken – can they be fixed?', 2016.

[45] P. Chauve and M. Godfried, 'Modelling competitive electricity markets: Are consumers paying for a lack of competition? (1)', *DG Competition, Competition Policy Newsletter, 2007(2)*, 2007.

[46] P. Cramton, 'Electricity market design', *Oxford Review of Economic Policy*, vol. 33, no. 4, pp. 589–612, Nov. 2017, ISSN: 0266-903X. DOI: `10.1093/oxrep/grx041`. eprint: `https://academic.oup.com/oxrep/article-pdf/33/4/589/21515797/grx041.pdf`. [Online]. Available: `https://doi.org/10.1093/oxrep/grx041`.

[47] Wind Energy The Facts. (). Power markets, [Online]. Available: `https://www.wind-energy-the-facts.org/power-markets-7.html` (visited on 16/11/2020).

[48] Cross-border intraday market project, 'Xbid launch information package', 2018.

[49] IRENA, 'POWER SYSTEM FLEXIBILITY FOR THE ENERGY TRANSITION PART II: IRENA FLEXTOOL METHODOLOGY', 2018.

[50] A. Kann and J. Weyant, 'Approaches for performing uncertainty analysis in large-scale energy/economic policy models', *Environmental Modeling and Assessment*, vol. 5, pp. 29–46, Jan. 2000. DOI: `10.1023/A:1019041023520`.

[51] I. J. Scott, A. Botterud, P. M. Carvalho and C. A. S. Silva, 'Renewable energy support policy evaluation: The role of long-term uncertainty in market modelling', *Applied Energy*, vol. 278, p. 115 643, 2020, ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2020.115643. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261920311430.

[52] J. Chaves-Ávila and C. Fernandes, 'The spanish intraday market design: A successful solution to balance renewable generation?', *Renewable Energy*, vol. 74, pp. 422–432, Feb. 2015. DOI: 10.1016/j.renene.2014.08.017.

[53] L. Komay Maia and E. Zondervan, 'Optimization of energy storage and system flexibility in the context of the energy transition: Germany's power grid as a case study', *BMC Energy*, vol. 1, Dec. 2019. DOI: 10.1186/s42500-019-0009-2.

[54] H. Teichgraeber and A. Brandt, 'Identifying and evaluating new market opportunities with capacity expansion models', Nov. 2017.

[55] K. Uehara, C. Kern and J. L. Koepfinger, 'Future vision of transmission and distribution 2030', 2015.

[56] A. EHRENMANN, P. HENNEAUX, G. KÜPPER, J. BRUCE, B. KLASMAN and L. SCHUMACHER, 'The future electricity intraday market design', 2019. DOI: 10.2833/004191.

[57] C. Koch and L. Hirth, 'Short-term electricity trading for system balancing - an empirical analysis of the role of intraday trading in balancing germany's electricity system', *SSRN Electronic Journal*, Dec. 2018. DOI: 10.2139/ssrn.3284262.

[58] I. Graabak, M. Korpås, S. Jaehnert and M. Belsnes, 'Balancing future variable wind and solar power production in central-west europe with norwegian hydropower', *Energy*, vol. 168, pp. 870–882, 2019.

[59] R. Egging and A. Tomasgard, 'Norway's role in the european energy transition', *Energy Strategy Reviews*, vol. 20, pp. 99–101, 2018, ISSN: 2211-467X. DOI: https://doi.org/10.1016/j.esr.2018.02.004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2211467X18300075.

[60] L. Emelie, B. Mo and I. Graabak, *Electricity prices and value of flexible generation in northern europe in 2030*, Sep. 2019. DOI: 10.1109/EEM.2019.8916390.

[61] M. Avriel and A. Williams, 'The value of information and stochastic programming', *Operations Research*, vol. 18, pp. 947–954, Oct. 1970. DOI: 10.1287/opre.18.5.947.

[62] P. Crespo Del Granado, S. Wallace and Z. Pang, 'The impact of wind uncertainty on the strategic valuation of distributed electricity storage', *Computational Management Science*, vol. 13, pp. 5–27, Aug. 2015. DOI: 10.1007/s10287-015-0235-0.

[63] A. Ghasemi, S. S. Mortazavi and E. Mashhour, 'Hourly demand response and battery energy storage for imbalance reduction of smart distribution company embedded with electric vehicles and wind farms', *Renewable Energy*, vol. 85, pp. 124–136, 2016, ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2015.06.018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0960148115300409.

Appendix A

Results from European case study

Table A.1: Production of generators by generator type in each period in GWh

Standard EMPIRE	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Inflexible	1727760,22	1248227,34	909511,332	755741,787	676665,276	652149,493	622085,627	652631,845
Flexible	611549,987	865992,858	1071101,1	1103847,52	658292,442	741231,246	629545,97	663613,992
Intermittent	964653,362	1286752,64	1503271,37	1790640,37	2688252,72	2860926,5	3170260,91	3402010
Total output	3303963,57	3400972,83	3483883,81	3650229,67	4023210,44	4254307,24	4421892,51	4718255,83
Market sequencing	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Inflexible	1690690,64	1212961,67	865703,215	739222,299	671792,842	633323,175	632643,281	650082,103
Flexible	627784,589	934055,618	1125314,05	1114484	845011,412	938800,03	763692,809	846502,835
Intermittent	987111,581	1253997,91	1495377,65	1793606,11	2487368,16	2659817,69	3004850,22	3183291,2
Total output	3305586,81	3401015,2	3486394,91	3647312,41	4004172,42	4231940,9	4401186,31	4679876,13
Deterministic	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Inflexible	1728358,29	1254437,61	926138,574	734752,606	676113,389	646093,143	653075,422	653909,177
Flexible	572816,168	788287,376	956099,712	1037748,54	655158,681	717565,564	637622,006	592391,961
Intermittent	1005664,19	1361152,75	1606845,66	1872219,29	2683466,77	2870659,86	3117422,01	3453275,27
Total output	3306838,65	3403877,73	3489083,94	3644720,44	4014738,85	4234318,57	4408119,43	4699576,4

Table A.2: Installed capacity of generator type for each period in MW

Standard EMPIRE	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Inflexible	283190,002	196989,406	147276,524	169915,791	153646,019	125574,554	115409,879	118102,769
Flexible	400224,845	359438,553	367843,71	351343,9	361074,486	384988,225	419855,247	408889,82
Intermittent	540019,199	682913,698	997530,479	1099750,56	2118589,87	2169670,58	2542903,91	3169862,5
	1223434,05	1239341,66	1512650,71	1621010,25	2633310,37	2680233,36	3078169,03	3696855,09
Market Sequencing	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Inflexible	283190,002	191976,951	142349,728	162655,118	146397,333	118325,869	110761,372	114360,905
Flexible	403693,482	375859,997	378796,748	515159,013	572258,954	596534,081	605472,839	577709,35
Intermittent	501291,518	629533,51	914647,621	1077214,63	1864667,27	1894720,91	2439707,63	2872727,43
	1188175	1197370,46	1435794,1	1755028,76	2583323,56	2609580,86	3155941,84	3564797,69
Deterministic	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Inflexible	283190,002	196756,037	147031,154	165769,926	149114,297	121834,363	114657,501	115592,787
Flexible	398837,474	344373,702	347171,517	346004,643	395185,955	383401,296	412417,452	386277,795
Intermittent	504988,486	672642,651	962044,009	1061412,94	1877373,33	1904997,82	2531445,15	2881372,62
	1187015,96	1213772,39	1456246,68	1573187,51	2421673,59	2410233,48	3058520,1	3383243,2

Table A.3: Installed capacity of power and energy for storage systems in each period and discharge volume for storage systems

Installed Storage Capacity								
Standard EMPIRE	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Sum of storPWInstalledCap_MW	48733,0023	48733,0053	69347,6681	199493,162	677481,249	719208,297	945041,545	1118967,59
Sum of storENInstalledCap_MWh	2601010,8	2601010,81	2646359,06	2903941,55	3853350,98	3936524,07	4386591,57	4734383,03
Market Sequencing	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Sum of storPWInstalledCap_MW	47361,0058	47638,4998	54628,9426	223528,76	556457,043	599657,048	744733,153	785912,311
Sum of storENInstalledCap_MWh	2601010,81	2601565,8	2616815,2	2952821,42	3617043,1	3703515,75	3986637,15	4068095,46
Deterministic	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Sum of storPWInstalledCap_MW	47491,9696	47491,9815	58129,0689	135517,849	518166,162	524635,131	683141,184	789199,641
Sum of storENInstalledCap_MWh	2601010,81	2601010,83	2623815,45	2779070,94	3544136,98	3557074,92	3864037,87	4075723,53
Discharge Volume								
Standard EMPIRE	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Volume GWh	41099,703	29290,021	60301,8378	194253,1	835991,561	848259,522	1292949,95	1378933,68
Market Sequencing	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Volume GWh	37302,5116	29840,6325	51511,7569	147975,372	647946,37	635683,478	1051099,77	1001157,65
Deterministic	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Volume GWh	41076,9117	37845,9009	68877,2151	138417,749	726079,603	653187,363	1113000,7	1151522,99

Table A.4: Installed transmission capacity and transmission volume

Transmission Installed capacity								
Standard EMPIRE	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Installed Capacity MW	99575,5732	149173,378	164161,09	172362,415	182397,376	184553,332	186061,357	186365,808
Basecase	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Sum of transmisionInstalledCap_MW	99806,0134	142636,677	164877,575	174082,711	180531,441	181180,402	185358,047	185358,047
OneScenario	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Installed Cap	96155,7926	133193,809	150356,845	163478,086	177106,001	179169,289	179785,001	180549,864
Transmission Volume								
Standard EMPIRE	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Transmission Volume GWh	498575,199	603740,4	620971,865	724948,987	947141,081	996111,836	999384,558	1054565,86
Basecase	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Sum of transmisionExpectedAnnualVolumeActual_GWh	584495,61	607303,321	704668,988	811973,991	1058663,41	1077976,56	1194525,48	1175254,24
OneScenario	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Sum of transmisionExpectedAnnualVolumeActual_GWh	594601,377	629271,347	672936,61	745407,875	1085595,49	1059847,49	1147923,08	1270711,55

Table A.5: Load coverage by storage and transmission

Load Coverage by storage	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Standard EMPIRE	0,01253525	0,00867714	0,01746188	0,05394013	0,2149304	0,20592431	0,30539111	0,30506247
Market Sequencing	0,01137712	0,00884026	0,01491649	0,04108975	0,16658467	0,15431914	0,24826678	0,22148681
Deterministic	0,01252829	0,01121181	0,01994509	0,03843579	0,18667244	0,1585684	0,26288761	0,25475224
Load Coverage by transmission	**2020-2025**	**2025-2030**	**2030-2035**	**2035-2040**	**2040-2045**	**2045-2050**	**2050-2055**	**2055-2060**
Standard EMPIRE	0,15206345	0,17885753	0,17981764	0,20130357	0,24350654	0,24181708	0,2360518	0,23330235
Market Sequencing	0,17826883	0,17991304	0,20405419	0,22546864	0,27217853	0,26169064	0,28214353	0,26000233
Deterministic	0,18135105	0,18642105	0,1948653	0,20698458	0,27910267	0,25728961	0,27113618	0,28112041

Table A.6: Difference in volume from the day-ahead market

Market Sequncing	2020-2025	2025-2030	2030-2035	2035-2040	2040-2045	2045-2050	2050-2055	2055-2060
Intermittent	171861,291	199053,583	235024,226	305882,541	460829,996	434777,012	467532,337	472297,845
Flexible	-164618,72	-197587,53	-224784,92	-295197,8	-396751,67	-388334,88	-376336,74	-400435,21
Storage	6344,04907	-21324,611	9040,98383	24464,9199	416435,12	302108,475	621186,673	485261,047
Transmission	184156,23	224268,663	270332,014	295473,031	428030,195	381137,176	505280,845	507928,404
Difference in load	131,875179	38,074408	49,3645724	15,2627083	1,9890444	75,5860364	135,055938	89,0182577
SUM	362493,445	423322,246	514397,224	625820,491	1305295,31	1118022,66	1593999,85	1465487,3
Deterministic	2020-2025	2025-2030	2030-2035	2035-2040	2040-2045	2045-2050	2050-2055	2055-2060
Intermittent	187745,276	206859,366	258581,671	309190,142	533622,869	448000,616	415258,015	464402,271
Flexible	-178866,23	-198033,8	-244123,13	-294344,89	-451081,27	-386128,12	-321840,28	-375882,36
Storage	13565,2849	4179,13033	26143,4388	57362,7993	546824,884	417179,105	663449,982	634469,526
Transmission	178528,306	258090,349	278948,681	262071,707	454620,159	347294,922	430285,286	475914,468
Difference in load	131,875179	38,0744079	49,3645723	15,2627092	1,9890446	75,5860352	135,055938	89,0182572
SUM	379970,742	469166,92	563723,155	628639,911	1535069,9	1212550,23	1509128,34	1574875,28

Table A.7: Day-ahead and intraday load for each period

	Intraday Load	Day-Ahead Load
2020-2025	3278731,39	3278599,51
2025-2030	3375538,12	3375500,04
2030-2035	3453342,37	3453293
2035-2040	3601272,45	3601257,18
2040-2045	3889591,92	3889589,93
2045-2050	4119278,2	4119202,61
2050-2055	4233751,07	4233616,02
2055-2060	4520168,202	4520079,183

Table A.8: Curtailment in percantage compared to total production from VRES

	Deterministic	Market sequencing	Standard
2020-2025	0,0144521	0,02004415	0,08054671
2025-2030	0,00883346	0,01635624	0,043715
2030-2035	0,04670292	0,06012463	0,0960002
2035-2040	0,05684638	0,06394692	0,09665971
2040-2045	0,11993638	0,14063926	0,16192179
2045-2050	0,09449687	0,12493633	0,15992754
2050-2055	0,26204119	0,20226421	0,20980723
2055-2060	0,21449895	0,1818388	0,21906594

Appendix B

Paper:Designing Day-ahead and Intraday Electricity Markets in a Capacity Expansion Model Applied to the European Power System

Designing Day-ahead and Intraday Electricity Markets in a Capacity Expansion Model Applied to the European Power System

Magnus A. Wendelborg[a,b]

[a] *Dept. of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway*
[b] *Technische Universität Berlin (TU Berlin), Berlin, Germany.*

Abstract

The European Energy Transition envisions a high degree of deployment of variable renewable energy sources (VRES) by 2050. Some estimates expect that 60-to-70% of power generation will be entirely covered by VRES technologies (i.e. solar and wind). This creates challenges on balancing VRES with conventional and flexible generations (e.g. gas and storage). That is, VRES is transforming the way electricity markets will operate and coordinate the balancing needs between day-ahead and intraday electricity markets. In this regard, intraday markets will grow in importance due to the uncertain short-term nature of VRES. However, there is limited research on how forecasting errors between market stages affect investment decisions in capacity expansion problems. In this paper, we investigate: How does an increased amount of VRES uncertainty (forecasting errors) between a day-ahead and an intraday market affect investment decisions in the power system? To address this research question, we developed a multi-horizon stochastic capacity expansion model containing both day-ahead and intraday markets under uncertainty. The model emulates the European power system developments and aims to reduce emissions by restricting the emissions subject to the EU emission policy towards 2050. Main results indicate that when comparing a standard single market approach to a market sequencing case, we observe that: i) Forecasting error significantly impacts investment decisions in 10% less VRES investments and 40% more investments flexible capacity, ii) Cross-border transmission is a crucial contributor to flexibility and experiences a 10-20% increase in volume when accounting for forecasting errors, and iii) investments in storage capacity decreases significantly and are over-valued in the standard approach of capacity expansion models. The approach and findings in the paper imply that including forecasting errors between markets are of significant importance when analysing a capacity expansion problem.

Keywords: Capacity Expansion, Electricity markets, Energy transition, System flexibility, power system

1. Introduction

Electricity markets have traditionally had large shares of dispatchable energy sources such as coal, gas, and nuclear energy. However, recent years' development has shifted towards more renewable energy sources (RES) in the energy mix [49]. The development is driven by climate change concerns and more favorable economic conditions for RES than previously compared to its competitors in the power mix. In order to minimize the effect of climate change and stay below the 2°C target [28], this development is projected to continue [26].

As the share of variable renewable energy sources [VRES] in an energy mix grows, the uncertainty in relation to electricity production increases [5]. Weather conditions are susceptible to forecasting errors, and thus, the forecasts for the production of wind and solar might differ from actual production conditions. A key issue in a power system is to balance supply and demand. Energy sources such as wind and solar are intermittent by nature, and thus, matching supply with demand is increasingly difficult when the share of these energy sources grows [24]. Balancing mechanisms are therefore increasingly important in order to balance supply and demand of electricity. The electricity markets have traditionally handled the balancing with different market stages. The day-ahead market stage aims to use the available information to balance supply and demand until the day before actual delivery. Deviations from the scheduled plan are typically handled by the intraday market stage, which balances these deviations close to real-time. Multiple factors can contribute to the volume traded in the intraday market, such as weather forecasting errors, demand change, and line- and generator outage. Any deviations still remaining at the scheduled delivery time are typically handled by a transmission system operator (TSO) in a balancing market stage.

In the last five years, the installed capacity of solar and onshore and offshore wind have increased by 41%, resulting in significantly more volume traded in the intraday markets [23]. With this in mind, it is likely that more VRES in the European energy mix increases the dependency on the intraday market to balance any discrepancies between the forecasts and actual available delivery.

In line with the development of the energy-mix in recent years and the projected increase in VRES capacity, the scope of this paper is to address these research questions:

- How does an increased amount of uncertainty introduced by forecasting errors between a day-ahead and an intraday market affect investment decisions in the power system?
- How are operational decisions affected when forecasting errors from market sequencing are included?
- What is the impact of including uncertainty when analyzing the developments in a power system?

These questions are addressed by implementing a multi-horizon stochastic model based on the EMPIRE model. The EMPIRE (European Model for Power System Investment with Renewable Energy) model has been used in multiple European Union and national research projects [1]. The model represents hourly power system decisions of the European countries while accounting for long-term investment decisions. In this paper, we introduce a novel model extension that takes into consideration the split between day-ahead and intraday markets. That is, it includes the uncertainty on information among markets (forecast errors). This method is then compared with the standard capacity expansion model as well as the deterministic version of it.

The paper is structured as follows; Chapter 2 gives an overview on related literature. Chapter 3 provides the methodology for the capacity expansion model containing wholesale market sequencing. In Chapter 4, the model is applied to the European power systems and analysed to answer the research questions and illustrate the impact of the research conducted. Chapter 5 summarizes the findings.

2. Related literature

As the energy mix of the world moves towards a larger share of VRES, the level of uncertainty in a power system increases. To maintain a balance between supply and demand with high shares of VRES, flexible energy producers or consumers are required [4]. Several papers highlight the importance of flexibility in a power system with large shares of VRES, and the role that storage, transmission, flexible energy sources such as hydropower and gas, and demand-side flexibility, will have on the reliability and security of supply of such a power system [36, 38, 34]. An NREL study indicated that energy storage would be a key component to provide flexibility in a power system characterized by large shares of VRES penetration [43]. Denholm and Hand [20] also highlight the need for energy storage in the future and estimate storage capacity of about one day worth of load to meet the demand without a significant curtailment portion. Child et. al. [15] did an analysis on the flexibility requirements and benefits to allow for a high penetration on VRES. Their results indicated that, while energy storage and flexible generators would be key contributors to flexibility, transmission provided the most value for money flexibility vise. However, De Jonghe et. al. [19] did a similar study, which indicated that energy storage would be the most beneficial flexibility provider.

A common approach to analyze problems concerning investments and operational decisions in a power system is to utilize mathematical optimization models. Optimization models for power systems are typically divided into two categories: capacity expansion models and operational models. Capacity expansion models typically focus on investments and energy mix, while operational models typically focus on market aspects.

Multi-market modeling is usually done using operational models. Zipf and Möst [53] analyzed the direct and indirect costs of variable VRES in the German power system by utilizing a two-stage operational optimization model with day-ahead and intraday scheduling. Their results indicated that an increased amount of variable VRES in an power system leads to both increased direct and indirect cost due to the forecasting errors related to VRES. However, different studies on multi-stage operational optimization models without an investment stage [9, 30] have shown that an increased share of variable VRES is leading to a lower total cost than the current energy mix. Kulakov and Ziel [35] investigated how forecasting errors caused by VRES influenced electricity prices in the market stages. They found a non-linear correlation between intraday and day-ahead prices. Abrel and Kuntz [3] explored the impact of uncertainty from VRES on unit commitment power dispatch. They found that an increased amount of uncertainty triggers more unit commitment from inflexible energy sources. With the increased uncertainty, a more diverse energy portfolio was emphasized to balance the VRES forecasting errors between the market stages. Barth et. al. [10] also investigated the impact of wind uncertainty on a power system by creating a five-stage stochastic market model. The objective was to establish the reserves' role in such a power system and the cost associated with the reserves. The results indicated that the importance of reserves increased in such a system, and regulated hydropower was the main contributor to the reserve market. Morales et. al. [39] developed a model analyzing the issues with conventional market design due to VRES's stochastic nature. One issue they identified, was the lack of a cost-recovery guarantee for flexible producers. They proposed a solution where the day-ahead market is cleared while also factoring in the anticipated balancing cost resulting from forecasting errors. Borggrefe and Neuhoff [12] highlighted the need for a market design that facilitates potential improved conditions in the intraday market compared to the day-ahead market.

In addition to multi-market modeling, capacity expansion models are also of great interest to issues addressed in this paper. Seljom and Tomasgaard [45] developed a model to analyze the investment decisions in the Danish power system. Both a deterministic and a stochastic approach were utilized, and they found significant differences between the approaches. They concluded that a stochastic approach was a more realistic and that this approach resulted in significantly lowered investments in VRES. Their results are also supported by Nagl et al. [40], who concluded that VRES is typically significantly overvalued and flexible providers the opposite. Ehremann and Smeers [21] developed a capacity expansion model addressing the issues with investment risks in a power system. They approached the issue by including stochastic properties in the discount rate to incorporate the risk of investing in VRES compared to dispatchable energy sources. The results indicated that by adding risk, i.e., considering the power system's uncertainty due to VRES's unpredictable nature, the system costs increased. Sun et al. [47] analyzed the US power system with a capacity expansion model focusing on transmission flow between different regions. They found that transmission might be an underestimated technology in capacity expansion models. In 2012, Giraldo et al. [27] investigated the impact of adding emission constraints to a capacity expansion model. Both an emission tax and an emission cap was included. They showed that adding such constraints increased the total costs somewhat, but that the investments and thus, the solution were applicable to a real-world scenario. Villavicencio [51] developed a capacity expansion model aiming to encapsulate some of the operational issues of VRES. It was concluded that proper modeling of the system- and operational requirements increase with a large penetration of VRES. Poncelet et al. [42] also developed a capacity expansion model aiming to integrate the challenges with large shares of VRES in an power system. Bermudez et. al. [25] highlights the need to consider the expected future development when planning for investments in a power system.

In addition to models focusing on capacity expansion and market modeling, there is some research on models combining capacity expansion and market sequencing. Pineda and Morales [41] developed a model with both an investment stage as well as market sequencing. Their results indicated that forecast errors had a major impact on investment decisions and that the installed capacity of VRES in a power system will decrease if considerations on forecasting errors between market stages are present. However, Pineda and Morales used a small model covering just the Danish power system, and the results did not include findings on transmission or energy storage. The purpose of this literature review was to evaluate relevant research on capacity expansion model and the impact of forecasting errors. Much research has been conducted on capacity expansion model, but a better understanding on how forecasting errors affect such a problem is necessary. Therefore, this paper aims to develop a three-stage mathematical optimization model in order to encapsulate the impact forecasting errors has on investment decisions .

3. Model and methods

3.1. The EMPIRE model

The model developed in this paper is based on the EMPIRE model, described in [46]. Existing data for the EMPIRE model is used in this project. EMPIRE is an existing model containing two stages: one investment stage and one operational stage, thereby characterizing it as a capacity expansion model. Figure 1 illustrates EMPIRE graphically. EMPIRE has been used in a number of different publications [37, 7, 18, 8]. The model represents the EU countries in addition to Switzerland and Norway. In total, there are 35 nodes present. Norway is also split into five zones, according to Nordpools trading zones [2]. Export and import of electricity is possible in neighbouring countries and zones. Investment decisions in generator capacity, energy storage and transmission are done in EMPIRE to facilitate production in order to meet the demand in each node on an hourly basis without exceeding an emission cap. Electricity demand, technology costs, technology options and operational characteristics are inputs [7]. The output is given as investments in technologies and operational decisions assuming a perfect competition market. EMPIRE is a linear capacity expansion model, spanning over 8 periods of 5 years each. Each period is composed of 4 regular seasons, representing winter, spring, summer and autumn, and two peak seasons representing extreme conditions. Each regular season has 168 hours and each peak season has 24 hours.

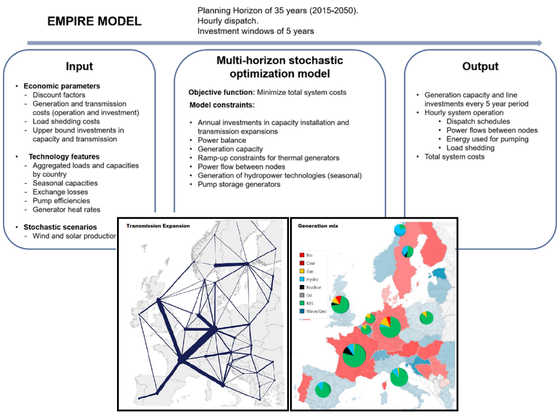

Figure 1: Illustration of the EMPIRE model, illustrating its input data, objective and constraints, and output. Adapted from [1]

Uncertainty is included in every hour for load and generator availability for VRES. Additionally, regulated hydro has uncertainty concerning available capacity on a per period basis.

3.2. Adding Day-ahead and intraday markets

The existing framework for EMPIRE was used to create a three-stage stochastic optimization model [11] with one investment stage and two operational stages, simulating two electricity markets in order to solve the problems stated in Chapter 1. The investment stage makes investments in technologies such as generators, transmission capacity and energy storage. The operational stages emulates a day-ahead market and an intraday market. Both markets supply a load assuming perfect competition. The day-ahead market is cleared based on a best guess forecast for load and production conditions for VRES, which is similar to the approach used in [3]. In the intraday market, actual information on load and production conditions are revealed, and the system re-balances based on the updated information subject to the relationship between the market stages. As not every generator type can change its output on short notice, these generators are committed to the production decided in the day-ahead market. Generators that cannot alter their scheduled production in the day-ahead market are referred to as inflexible generators. Generators that are able to alter their output on a short notice are referred to as flexible generators.

It is assumed that energy storage systems are fully flexible between the two markets as the ramping time of energy storage's typically are very low [43]. Figure 2 illustrates the two markets graphically and how the markets are dependant on each other. As depicted by the figure, the output from the inflexible generators is a committed decision made in the day-ahead market while flexible generators are dependant on the decision made in the day-ahead market by the flexibility factor. The flexibility factor states to what degree a flexible generator is able to alter its output between market stages. Transmission is connected as well. The connection between the investment stage and the operational stages are limited by the installed capacity of each generator type in each node. Production in any of the markets are thus limited by what is available at that specific point in time. The model uses four different scenarios for each operational step in the day-ahead market, and one scenario in the intraday market for each of the four scenarios in the day-ahead market, as illustrated by figure 3.

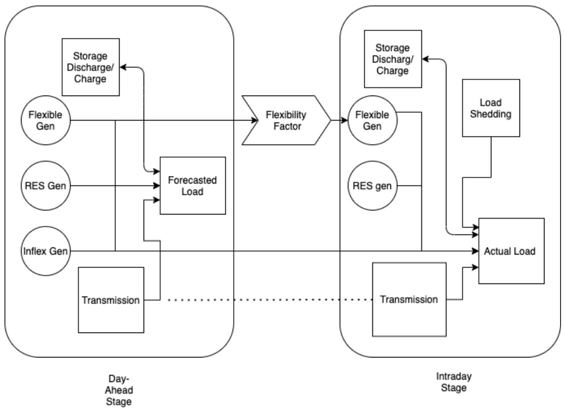

Figure 2: Illustration of day-ahead stage and intraday stage and its connection.

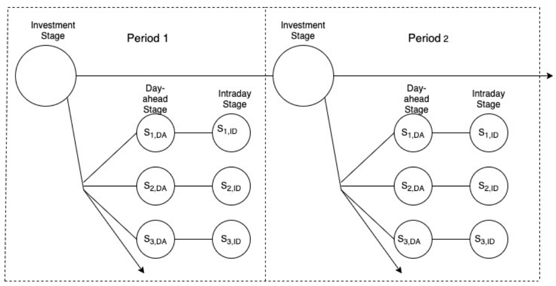

Figure 3: Illustration of scenario-tree in the model.

The generator availability is defined as a constant value for all generators except for intermittent energy sources as described in [46]. The generator availability for intermittent generators is calculated by using a normalized value of production per installed capacity. The normalized value ensures scalability of production per installed capacity, thus allowing for analysis of the impact VRES has on investment- and operational decisions when and if the energy mix changes. For a full description of the model formulation, refer to [52]

Shortcoming of the model

In order to not make a too complex and computational heavy model, some assumptions were made which results in a simplification of a real-world power system. The model presented in this paper is a linear three-stage optimization model. However, some components, such as transmission and power generation, are inherently nonlinear but converted to linear to reduce the computational efforts. The model also utilizes a perfect market, leading to a minimization of the costs of operating the markets at each hour. The market is cleared so that the electricity price is set at the point where the last contributing generator is meeting the demand. The traditional approach does not consider the fixed costs of production, which studies have shown is leading to unprofitable operations of key generators in a power system [31]. Additionally, by modelling the markets as perfect competition, regulatory and technological limitations are prevalent. For instance, generators typically have a start/stop cost, minimum running time or commitment to produce power due to regulatory responsibilities [13]. These problems are not included in this model in order to reduce computational efforts. Another factor is the assumed perfect system development. The model chooses the investments based on an objective to minimize the system costs. By choosing the investments purely based on cost aspects, issues such as reliability on long term investments due to the unpredictable nature of VRES and load may arise [16]. This means that dedicated reserve capacity is not included in the investments, and the model does also not consider maintenance and drop-out of the components. This may lead to the investments in the power system being at the absolute minimum, and in extreme cases or malfunctions on the power system, the demand may not be met. There is also the issue of cost recovery. The cost recovery issue is prevalent in the generators that are required to reduce the output between the market stages. As the generators are only paid what they are actually delivering, and not what was planned, there might be a difference in income for these generators. This means that if a generator is reducing its output made in the planning stage to the delivery, there is no compensation for the change. If for instance, a fuel-driven generator uses less fuel than scheduled, the marginal cost of that generator will in fact not necessarily be covered, dependant on the electricity price. There are difficulties establishing how the generators providing flexibility, should be compensated due to market design, leading to this feature not being implemented. An additional point is the generator availability data derived from ENTSO-e. The data is based on the forecasted production and actual production from 2015-2020. The data does, therefore, not use actual wind speeds and solar irradiation, and are thus susceptible to different bidding strategies in the markets. However, it assumed that a VRES producer would bid what the producers predict is available for the day-ahead market.

Intraday Volume

A method for calculating the intraday volume is explained in the following section. The intraday volume can be defined as the excess trading that is needed or beneficial in order to supply the demand according to the actual conditions. It is therefore based on the difference in decisions between the two market stages. The method determines the difference between the decisions made in the day-ahead market and intraday market for energy storage, transmission, intermittent generators, and flexible generators. First, lets define a set of components, $\mathcal{D}$, that are subject to altered decisions or conditions between the market stages:

$\mathcal{D} = \{\text{Flex}, \text{Inter}, \text{storDischrg}, \text{storChrg}, \text{tran}, \text{load}\}$

For each of these components, the difference in output between the market stages is calculated, δ_i^d. By summing the differences, we can obtain the intraday volume:

$$ID_i^{\text{volume}} = \begin{cases} \sum_{d \in \mathcal{D}} \delta_i^d & \delta_i^d \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Note that we only consider output that has increased from the day-ahead markets in order to not double count the volumes. If a generator increases its output between the markets, another generator has to decrease its output subject to the deviations in load and potential losses in transmission or storage if these are utilized. Therefore, it is important to only sum the components that increases its output compared to the day-ahead stage as it is a zero-sum issue. From the intraday volume, the parentage can by calculated as the difference in volume divided by the actual load in a specific strategic period. The method to calculate the intraday volume shown here does not necessarily correlate with the historical intraday volumes illustrated in Chapter 1 due to the market design. However, the intraday volume can still be used to illustrate the importance of an intraday market, as it illustrates the difference in the operational decision between the market stages.

4. Results

4.1. European case study

This chapter presents a full-scale analysis of the model to answer the research question stated in Chapter 1. Two different cases, as well as a deterministic case to highlight the importance of uncertainty, are presented. Four scenarios per investment period are generated with the routine described in the Appendix A. The data used in this paper is otherwise the same as used in previous studies utilising EMPRIE [7, 37].

Case 0: Standard EMPIRE

The standard EMPIRE case is EMPIRE without market sequencing. The model is identical to the one developed by Christian Skar in [46]. This case represents the traditional way of analysing the development of power systems, considering investments and operations without market sequencing. Case 0 consists of 37 million constraints and 24 million variables.

Case 1: EMPIRE with market sequencing

Case 1 represents the European power system with market sequencing. The input data is the same as in case 0, but additional parameters are added for the day-ahead market. These include generator availability for the day-ahead market as well as the expected demand. Case 1 provides the baseline of how investment decisions may change when the forecasting errors between electricity markets are included. Case 1 consists of 158 million constraints and 94 million variables

Case 2: Deterministic market sequencing

Case 2 is a deterministic approach, focusing on the development of the European power system based on the expected conditions. In this case, the scenarios generated for the other two cases were used to calculate the expected scenario for each hour, season, and period. The parameters calculated in case 2 is the average parameter value of case 1. The model used is otherwise identical to case 1. Case 2 also forms the basis when analysing the impact of uncertainty. Case 2 consists of 39 million constraints and 24 million variables. The reason why it is more computational heavy than the stochastic case 0 is due to the implementation of market sequencing, and the number of scenarios in case 0. However, it is difficult to compare the computational burden of case 0 and 2 directly since case 0 is stochastic and without market sequencing, while case 2 is deterministic with market sequencing. Thus, the computational burden heavily depends on the number of scenarios used in a stochastic approach.

General Results and Objective Value

The objective value, or the total system costs, varied significantly between the cases. Table 1 lists the objective value in billion Euros, the number of constraints and variables. As depicted by the table, the deterministic approach is the cheapest, followed by the standard case without market sequencing. The deterministic case is 7.3% cheaper than the standard, while case 1 is 2.1% more expensive. The reason for the difference in costs can be attributed to the different levels of uncertainty in each case, resulting in a more expensive solution the more uncertainty is present [29].

Table 1: Overview of objective value, number of constraints and variables

	Case 0	Case 1	Case 2
Objective Value [Billion Euro]	2788	2847	2585
Number of constraints in million	37	158	39
Number of variables in million	24	94	24

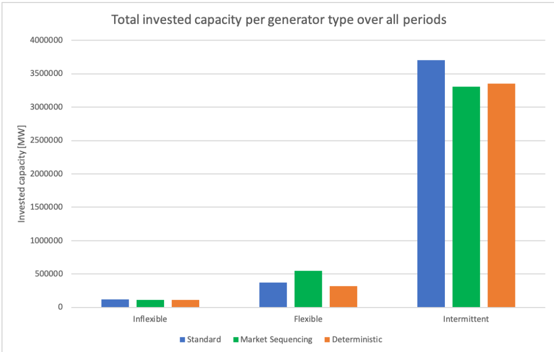

Figure 4: Invested capacity for each generator type over all periods for the three cases

Generator investments and operational decisions

The general trend across all three cases is the growth of VRES over the periods. However, there are significant differences between the cases when it comes to investments in generation capacity. Figure 4 highlights the total capacity expansion by generator type over the entire horizon. As seen from the figure, investments in inflexible capacity are similar for the three cases, but slightly lower in case 1 and 2 compared to case 0. Regarding flexible generators, case 1 invests in significantly more capacity than the other two cases, and case 2 is investing slightly less than case 0. In terms of intermittent generators, case 0 invests the most, and case 2 invests slightly more than case 1. In total, case 2 invests the least in generator capacity (-10% compared to case 0), followed by case 1 (-6% compared to case 0). Figure 5 illustrates the installed capacity per generator type over the analysed period for case 1.

In case 1, the total installed capacity is about 4% lower than case 0. The reduced installed capacity is mostly due to the significant decrease in intermittent capacity compared to case 0. In addition, the installed capacity of flexible generators is significantly higher in case 1 than case 0 (+41%), mainly due to increased investments in bio and gas. All cases have the same demand to supply and the same conditions to supply the demand. However, the generator availability of VRES and the flexible generators are different, leading to flexible generators being able to generate more electricity per installed capacity than VRES.

Regarding case 2, there are even less capacity expansion than case 0 (-10%). Being a deterministic approach, case 2 does not have to account for extreme scenarios which may occur in the other cases. In turn, this is likely leading to less investments, as the model supply the expected demand with less installed capacity. In general, we observed a decrease in installed capacity when including market sequencing. This was especially prominent for VRES, driven by the switch from

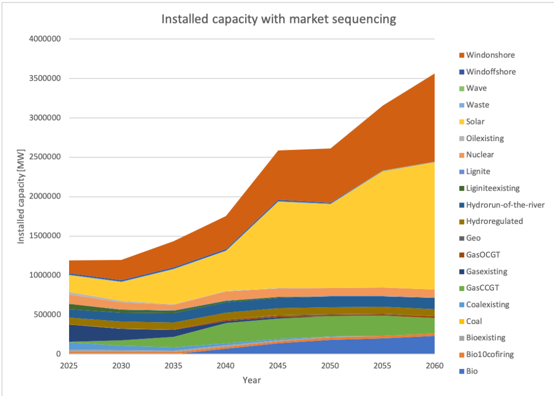

Figure 5: Installed capacity over the period for case 1

intermittent energy sources towards flexible energy sources. The decrease in installed capacity when including market sequencing is also supported by [41]

Even though case 1 has slightly less (4GW) installed capacity of inflexible generators compared to case 0, the production from these generators are practically identical between all cases. The reason why the output is similar can be attributed to the uncertainty and market sequencing, which leads to a more flexible portfolio [3]. The deterministic case is the case that values intermittent generators the most, followed by standard EMPIRE. Case 2 generates 51 TWh more from VRES than case 0. The relatively large difference in terms of generator output is likely due to the stochastic nature of VRES, and when not considered, we can experience an over-evaluation of these energy sources [44, 45]. In case 1, there are 219 TWh less production from the intermittent energy sources, probably explained by the decreased installed capacity. Case 2 produces the least amount of electricity from flexible generators, followed by case 0. Again, this is tied to the uncertainty of the problem, as less uncertainty leads to an over-evaluation of stochastic energy sources. Furthermore, it is tied to the fact that these cases have less installed capacity of flexible generators than case 1. Case 1 and 2 have very similar differences in output between the market stages. In general, flexible producers decrease their output from the day-ahead market, while intermittent generators increase their output. This can be justified by the need to balance the different conditions at the two market stages. Figure 6 illustrates the generator availability for a week in Denmark in winter of 2040. As depicted by the figure, there are clear fluctuations between the forecasted and actual availability of solar and wind. Thus, there is a need to re-balance the decisions from the day-ahead stage, resulting in different operations than scheduled. Two rationales can explain the increased production from intermittent generators in the intraday market compared to the day-ahead market. First, there is no consequences or benefits to changing the generation output from flexible generators, which may result in over-dispatching of these in order to ensure that the intraday demand is supplied. Second, conditions from VRES may improve between the market stages. However, as seen by the figure 6, both solar and wind availability are similar in the two markets and are not significantly better or worse in either market. Still, with just slightly better conditions in the intraday market, and with a significant amount of VRES installed, the overall conditions in the intraday stage could improve significantly and thus be a plausible explanation. Besides, VRES can also contribute to the balancing requirements in an intraday market [14]. Borggrefe and Neuhoff [12] also highlight the

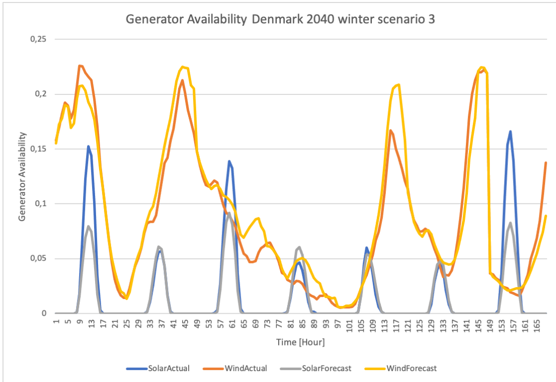

Figure 6: Generator availability for onshore wind and solar for a week in Denmark, winter 2040

need for a market design that facilitates possible improved conditions for VRES between market stages.

Storage investments and operational decisions

Case 1 and 2 are very similar in terms of investments in storage capacity with less than 1% difference in investments in both power and energy capacity. However, case 0 invests significantly more in both power and energy with 42% and 16% more investments, respectively. In case 1, less VRES are installed, and the need for storage is reduced in this case as storage is often used as a direct balancing mechanism for VRES [33]. With regards to case 2, the lack of uncertainty is likely leading to less investments in storage capacity since case 2 knows the future conditions for certain.

These results demonstrates that without the considerations of forecasting errors due to market sequencing, energy storage is significantly overvalued. The reason for the over-evaluation can be explained by more flexible producers with market sequencing, which are able to deliver power instead of energy storage systems. Research on investments in energy storage indicates that it will likely increase significantly [43, 20, 48], and is supported by the findings presented in this paper. However, we deduce that energy storage will play a less significant role in the future power system than predicted previously. This is caused by the reduced amount of VRES, as storage investments are linked to VRES investments, and more flexible energy producers which can fulfill parts of the role storage has in a power system. However, there are no penalties for curtailment in the model. If there was mechanisms to reduce or minimize curtailment, storage could contribute significantly to solve this issue. Concerning operational decision, case 1 and 2 utilizes storage significantly less than case 0, which are in line with the investments. However, case 2 utilises slightly more storage than case 1, which may indicate that storage benefits from a deterministic approach.

Transmission investments and operational decisions

Investments in transmission are very similar across the cases with less than 1% difference in installed capacity between case 0 and 1. Case 2 invests the least in transmission with 4% less than case 0. The fact that the deterministic case invests the least in transmission is expected due to the perfect foresight. In all three cases, there is an increase in installed transmission capacity over the periods. Again, it is reasonable to explain this by highlighting the increased VRES capacity

Table 2: Overview of intraday volume in percentage of actual load

Period	Case 1 (stochastic)	Case 2 (deterministic)
2025	11	11.6
2030	12.5	13.9
2035	14.9	16.3
2040	17.3	17.5
2045	33.5	39.5
2050	27.1	29.4
2055	37.6	35.6
2060	32.4	34.8

in the later periods, which contributes to more emphasis on transmission [15, 36]. Operational transmission decisions differ significantly between the cases. Case 1 has 10-20% more transmission volume than case 0 in the different periods in the intraday market, despite a very similar capacity. Case 2 also delivers from 10-20% more transmission volume, although there are differences for each period between case 1 and 2. The results of transmission volume indicate that transmission is significantly contributing to flexibility in a power system by balancing the forecasting errors between nodes. Our finding appear to be well supported by existing literature [34, 15, 47, 50].

4.2. Intraday Volume

In Chapter 1, the importance of the intraday market was highlighted. Based on the historical development of some of the European electricity markets, it could be argued that the importance of the intraday market would increase due to the growing share of VRES in the energy mix. In order to analyse the future development of the intraday market, the intraday volume was calculated for the cases with market sequencing in each period. For an in depth explanation of the method used to calculate the intraday volume, see section 3.2. The results from the intraday volumes are shown in Table 2.

Intermittent generators and transmission contribute to the majority of the volume, followed by energy storage. In addition, storage contributions grow significantly over the time horizon. The high transmission share in the intraday market gives further merit to the importance of transmission for efficient market clearing by providing flexibility between nodes. The table demonstrates a clear correlation of the intraday volume and installed capacity of VRES. The results are supported by [22, 32]. These findings are in line with Ehrenmann et al. [22], who also highlights the likelihood of cross-border intraday trading due to the implementation of the XBID project. The higher share of transmission volume in case 2 compared to case 1 can be attributed to the lack of uncertainty, thus being able to utilise more of the available VRES resources.

4.3. Analysis of an operational week in Germany and Norway

One operational week in all three cases is analysed, and both markets are analysed for case 1 and 2. The week analysed is in the spring season and in the period 2045-2050 and was randomly selected. The same operational scenario is used for case 0 and 1, while the expected scenario is used for case 2. In all three cases, the southern zone of Norway, NO2, is characterized by large shares of

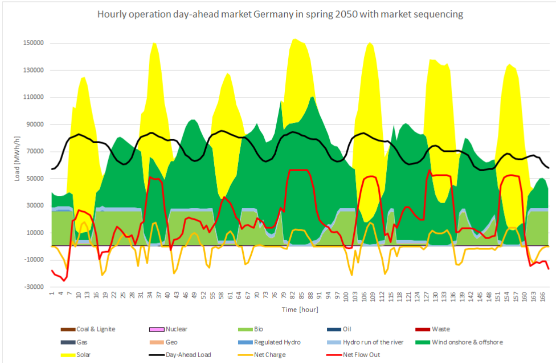

Figure 7: Operational week of Germany in EMPIRE with market sequencing, day-ahead.

regulated hydro and wind, while large shares of VRES characterise Germany. Furthermore, both nodes have other, smaller generators contributing to the production. NO2 was chosen as a node of interest due to the large shares of flexible generators. NO2 exports large volumes of electricity, and Germany is among the nodes where NO2 is exporting the most. Moreover, Germany is a node with a lot of VRES, so these two nodes and their relations in the markets are of great interest in order to analyse the impact of market sequencing and uncertainty. Figure 7 and 8 illustrates an operational week in the day-ahead market and the intraday for Germany in case 1. The result from the analysis indicates that flexible generators is of significant importance when forecasting errors are included. Specifically, flexible generators provide electricity in large shares during the night hours, when solar production is non-existent. Transmission volumes are also high during these hours. Additionally, there are clear deviations in the operational decisions between the market stages. These changes can be attributed to changing conditions for VRES. Generally, the scheduled output from flexible generators are reduced in Germany, while intermittent generators increase their output. In NO2, there are some hours with increased production from flexible generators likely due to the differing conditions in VRES conditions in neighboring nodes. Considering the three cases, there are significant differences in the operational decisions. Case 0 schedules significantly less flexible generation, and are relying on intermittent production to a larger degree. Being a deterministic case, case 0 have significantly less variation in production between the different days in a week. Similarly to case 0, case 2 also utilises VRES, at the expense of flexible production.

4.4. The Importance of Considering Uncertainty

This section illustrates the importance of considering uncertainty in a capacity expansion problem. A Value of stochastic solution [VVS] test was conducted.

Value of stochastic solution test is a test that establishes the value of using stochastic programming as opposed to deterministic programming [6]. The VSS test is performed by calculating the difference in objective value between using first stage decisions optimized for an expected deterministic scenario and using a stochastic multi-stage optimization model, ref equation 2. To establish the VSS, the results from case 2 concerning the first stage variables were used as input parameters in case 1. This allowed us to investigate the impact of having uncertainty concerning load and the generator availability in both markets when the installed capacity is optimized for different scenarios as opposed to being optimized for a single expected operational scenario. As shown in table

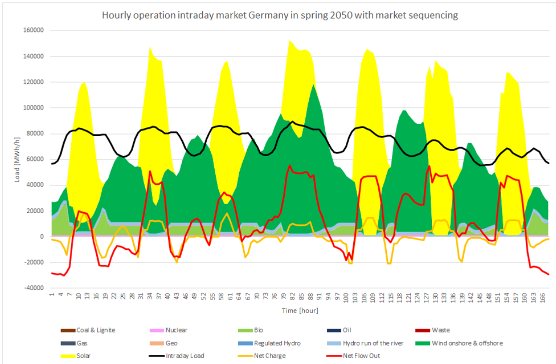

Figure 8: Operational week of Germany in EMPIRE with market sequencing, intraday.

1, a deterministic solution is a seemingly cheaper solution. Furthermore, a deterministic approach invests in significantly less generator capacity.

$$VSS = z_{exp} - z_{stoc} \tag{2}$$

The results of the run of case 1 with input from case 2 yielded an infeasible model. There is a combination of reasons why that yielded an infeasible solution. First, by performing a deterministic run based on the expected outcome, investments are smaller across the technologies. This leads to more stress on the operational energy balance constraints, when a scenario with poorer conditions than the expected occurs. In the intraday market, this is not a problem in terms of infeasibility, due to the ability to shed load that is not possible to cover. However, this is not an option in the day-ahead market. Therefore, due to the inability to shed load or otherwise not meet the demand in the day-ahead market, the result is infeasible giving a seemingly infinite value to the stochastic solution.

Different market designs were tested to accommodate the infeasible solution of the VSS test. First, the equality of constraint in the day-ahead energy balance constraint was changed to an inequality, meaning that the supply does not have to meet the demand. The change yielded a feasible model, but due to the changed energy balance constraint and the impact this had on the results, the results were deemed not comparable and not realistic in terms of how a day-ahead market operates. As the objective function only factors the actual delivery cost-wise and not the scheduled planning, there is a lack of incentive to meet the demand in the day-ahead stage. This results in a significant lack of supply in the day-ahead stage, which is not realistic in a real-world day-ahead market. A minimum of supply was scheduled in the day-ahead market, just so the intraday demand could be met with limited load shedding. It was also tested to allow load shedding in the day-ahead market. Allowing for load shedding in the day-ahead market without a cost associated yielded very similar results to that of creating an inequality instead of an equality. This is to be expected, as making it an opportunity to shed load without a cost associated is adding slack to the constraint, which is basically the same as changing the constraint from equality to inequality. A possibility is also to allow for load shedding in the day-ahead stage, but with a cost associated. It would be expected that a similar amount of load would be shed in both markets, which would mean that load shedding would essentially be twice as expensive. This approach would likely lead to a feasible model, but it would be difficult to compare the results to the other cases. Lastly, it could be possible to calculate the difference in load shedding between the markets and give a cost to the absolute total load shed. However, this is challenging to implement in the model and would increase the computational burden. Therefore, this last option was discarded.

Even though a result for the VSS test was not achievable, the results can still be used to estimate the error of not considering uncertainty [17], which for the cases analysed in this paper is significant. As seen from the objective value for case 1 and 2, there is roughly a 10% difference in objective value. The reason for this difference is due to an under-estimation of the need for capacity in case 2, as this case invests based on perfect information. Thus, case 2 does not account for the unpredictable nature of VRES and load. In addition, case 2 invests the least in inflexible and flexible generators. When conditions are poorer than expected, the deterministic approach is not able to supply the demand due to the limited installed capacity, and additional capacity is needed for these hours in order to supply the load. Therefore, we can say that a stochastic approach to a capacity expansion problem is more robust, as the likelihood of supplying the demand increases significantly. By utilising a deterministic approach, the investment costs would be lower, but the costs of not supplying the load in hours with poor conditions are much higher. We can therefore conclude that the costs saved on capacity is significantly lower than the costs of not having sufficient capacity.

5. Conclusions

The paper has presented a methodology to analyse the long-term developments in a power system while considering forecast errors from intermittent energy sources between market stages. A capacity expansion model with one investment stage and two market stages was developed to include forecast errors and the uncertainty from VRES in order to elucidate how this impacts investment decisions. The approach utilised is not commonly used, but it may provide better insights into how the future power system may develop. In order to answer the research questions stated in Chapter 1, three distinct cases was tested. Case 0 was used as a reference case illustrating the traditional way to model capacity expansion of a power system. Case 1 implements a second market stage to represent a day-ahead market and an intraday market. Case 2 is a deterministic version of case 1, aiming to illustrate the impact of not considering uncertainty when modelling a capacity expansion problem.

Our findings demonstrate a significant difference in investment decisions between the cases. An addition of market sequencing increases the total system costs by 2.1%. Additionally, there is a steep increase in intraday volume over the analysed period due to the increased installed capacity of intermittent energy sources. When accounting for forecasting errors, there is a decrease in 10% of investments in intermittent energy sources and an increase of 40% in investments of flexible generators. Intermittent generators still dominates the installed capacity with a share of 80% when including forecasting errors. The findings from this study indicates a decreased importance of energy storage, reducing the installed capacity by 16%. The reduction in energy storage can be attributed to the lower investments in intermittent energy sources, but also implies that energy storage is over-valued when not considering forecasting errors. Investments in cross-border transmission capacity are almost unchanged (1% difference) between the cases. Our findings are supported by existing literature [41, 45, 51].

Operational decisions differ significantly between the cases. Concerning storage and generation, the output follows the same trend as the installed capacity. However, when accounting for forecast errors, transmission utilization increases with 10-20%. Transmission is therefore a major flexibility provider to help balance the forecast errors that occur between the market stages. Cross-border transmission have previously been assumed to be a crucial part of providing flexibility in power systems characterised by large shares of VRES [36, 47, 15].

The deterministic approach is compared to a stochastic program to identify the value of considering uncertainty. A VSS test yielded an infeasible model, indicating that in order to operate a power system in a capacity expansion model, it is crucial to consider uncertainty. Furthermore, the deterministic approach yields a 7.3% lower total system cost, and we can therefore conclude that the lower costs due to the reduced installed capacity does not cover the costs for potential load shedding, should the conditions deviate from the expectations. Moreover, it is concluded that a deterministic approach significantly under-values installed capacity, and thus, is not able to supply the demand if conditions change to the worse compared to the expected conditions.

In summary, four main conclusions can be drawn:

- Investments in intermittent energy sources are significantly decreased when accounting for forecast errors.
- Transmission will be a pivotal contributor to balance the future power system.
- Investments in storage has traditionally been overvalued and are likely to play a less important role than anticipated.
- Considering short-term uncertainty from forecasting errors between market stages and uncertainty of VRES is crucial when planning for investments in a power system.

This paper has highlighted the importance of considering forecasting errors when analysing a capacity expansion problem. The results proves significant differences in investments and operational decisions compared to the traditional approach. It should be noted that adding a third stage to the EMPIRE model, as done in this paper, entails a significant increase to the computational burden.

References

[1] European model for power system investment with renewable energy. https://www.ntnu.edu/web/iot/energy/energy-models-hub/empire. Accessed: 2020-11-25.

[2] Bidding areas. https://www.nordpoolgroup.com/the-power-market/Bidding-areas/. Accessed: 2020-11-25.

[3] Jan Abrell and Friedrich Kunz. Integrating Intermittent Renewable Wind Generation - Insights from the Stochastic Electricity Market Model (stELMOD). *SSRN Electronic Journal*, (May), 2012. ISSN 1556-5068. doi: 10.2139/ssrn.2069935.

[4] M.I. Alizadeh, M. Parsa Moghaddam, N. Amjady, P. Siano, and M.K. Sheikh-El-Eslami. Flexibility in future power systems with high renewable penetration: A review. *Renewable and Sustainable Energy Reviews*, 57:1186 – 1193, 2016. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2015.12.200. URL http://www.sciencedirect.com/science/article/pii/S136403211501583X.

[5] Mir Hadi Athari and Zhifang Wang. Modeling the uncertainties in renewable generation and smart grid loads for the study of the grid vulnerability. 09 2016. doi: 10.1109/ISGT.2016.7781265.

[6] Mordecai Avriel and A. Williams. The value of information and stochastic programming. *Operations Research*, 18:947–954, 10 1970. doi: 10.1287/opre.18.5.947.

[7] Stian Backe, Dimitri Pinel, Pedro Crespo Del Granado, Magnus Korpås, Asgeir Tomasgard, and Karen Lindberg. Towards zero emission neighbourhoods: Implications for the power system. 09 2018. doi: 10.1109/EEM.2018.8469976.

[8] Stian Backe, Magnus Korpås, and Asgeir Tomasgard. Heat and electric vehicle flexibility in the european power system: A case study of norwegian energy communities. *International Journal of Electrical Power Energy Systems*, 125:106479, 2021. ISSN 0142-0615. doi: https://doi.org/10.1016/j.ijepes.2020.106479. URL http://www.sciencedirect.com/science/article/pii/S0142061520322079.

[9] R. Barth, H. Brand, P. Meibom, and C. Weber. A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power. *2006 9th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS*, 2006. doi: 10.1109/PMAPS.2006.360195.

[10] R. Barth, Heike Brand, Peter Meibom, and Christoph Weber. A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power. pages 1 – 8, 07 2006. doi: 10.1109/PMAPS.2006.360195.

[11] John R. Birge and François Louveaux. *Introduction to Stochastic Programming*. Springer-Verlag, New York, NY, USA, 1997.

[12] Frieder Borggrefe and Karsten Neuhoff. Balancing and intraday market design: Options for wind integration. *SSRN Electronic Journal*, 10 2011. doi: 10.2139/ssrn.1945724.

[13] Philippe Chauve and Martin Godfried. Modelling competitive electricity markets: are consumers paying for a lack of competition? (1). *DG Competition, Competition Policy Newsletter, 2007(2)*, 2007.

[14] José Chaves-Ávila and C. Fernandes. The spanish intraday market design: A successful solution to balance renewable generation? *Renewable Energy*, 74:422–432, 02 2015. doi: 10.1016/j.renene.2014.08.017.

[15] Michael Child, Claudia Kemfert, Dmitrii Bogdanov, and Christian Breyer. Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in europe. *Renewable Energy*, 139:80 – 101, 2019. ISSN 0960-1481. doi: https://doi.org/10.1016/j.renene.2019.02.077. URL http://www.sciencedirect.com/science/article/pii/S0960148119302319.

[16] Peter Cramton. Electricity market design. *Oxford Review of Economic Policy*, 33(4):589–612, 11 2017. ISSN 0266-903X. doi: 10.1093/oxrep/grx041. URL https://doi.org/10.1093/oxrep/grx041.

[17] Pedro Crespo Del Granado, Stein Wallace, and Zhan Pang. The impact of wind uncertainty on the strategic valuation of distributed electricity storage. *Computational Management Science*, 13:5–27, 08 2015. doi: 10.1007/s10287-015-0235-0.

[18] Pedro Crespo Del Granado, Christian Skar, H. Doukas, and Georgios Trachanas. *Investments in the EU Power System: A Stress Test Analysis on the Effectiveness of Decarbonisation Policies*, pages 97–122. 01 2019. ISBN 978-3-030-03151-0. doi: 10.1007/978-3-030-03152-7_4.

[19] Cedric De Jonghe, Erik Delarue, Ronnie Belmans, and William D'haeseleer. Determining optimal electricity technology mix with high level of wind power penetration. *Applied Energy*, 88(6):2231 – 2238, 2011. ISSN 0306-2619. doi: https://doi.org/10.1016/j.apenergy.2010.12.046. URL http://www.sciencedirect.com/science/article/pii/S0306261910005660.

[20] Paul Denholm and Maureen Hand. Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. *Energy Policy*, 39:1817–1830, 03 2011. doi: 10.1016/j.enpol.2011.01.019.

[21] Andreas Ehrenmann and Yves Smeers. *Stochastic Equilibrium Models for Generation Capacity Expansion*, pages 273–310. 07 2011. ISBN 978-1-4419-9585-8. doi: 10.1007/978-1-4419-9586-5_13.

[22] Andreas EHRENMANN, Pierre HENNEAUX, Gerd KÜPPER, Johan BRUCE, Björn KLASMAN, and Linda SCHUMACHER. The future electricity intraday market design. 2019. doi: 10.2833/004191.

[23] ENTSO-E. Entso-e transparancy platform. 2020, Accessed: 18.08.2020, Available at:"https://transparency.entsoe.eu/content/static_content/Static%20content/knowledge%20base/SFTP-Transparency_Docs.html".

[24] Lu Gan, Pengyan Jiang, Benjamin Lev, and Xiaoyang Zhou. Balancing of supply and demand of renewable energy power system: A review and bibliometric analysis. *Sustainable Futures*, 2:100013, 2020. ISSN 2666-1888. doi: https://doi.org/10.1016/j.sftr.2020.100013. URL http://www.sciencedirect.com/science/article/pii/S266618882030006X.

[25] Juan Gea-Bermúdez, Lise-Lotte Pade, Matti Juhani Koivisto, and Hans Ravn. Optimal generation and transmission development of the north sea region: Impact of grid architecture and planning horizon. *Energy*, 191:116512, 2020. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2019.116512. URL http://www.sciencedirect.com/science/article/pii/S0360544219322078.

[26] Dolf Gielen, Francisco Boshell, Deger Saygin, Morgan D Bazilian, Nicholas Wagner, and Ricardo Gorini. The role of renewable energy in the global energy transformation. *Energy Strategy Reviews*, 24:38–50, 2019. ISSN 2211-467X. doi: https://doi.org/10.1016/j.esr.2019.01.006. URL http://www.sciencedirect.com/science/article/pii/S2211467X19300082.

[27] Diego Giraldo, Jesús López-Lezama, and Luis Pareja. Power system capacity expansion planning model considering carbon emissions constraints. *Revista Facultad de Ingeniería Universidad de Antioquia*, 62:114–125, 03 2012.

[28] Cara A. Horowitz. Paris agreement. *International Legal Materials*, 55(4):740–755, 2016. doi: 10.1017/S0020782900004253.

[29] Antje Kann and John Weyant. Approaches for performing uncertainty analysis in large-scale energy/economic policy models. *Environmental Modeling and Assessment*, 5:29–46, 01 2000. doi: 10.1023/A:1019041023520.

[30] Maria Kannavou, Marilena Zampara, and Pantelis Capros. Modelling the EU internal electricity market: The PRIMES-IEM model. *Energies*, 12(15), 2019. ISSN 19961073. doi: 10.3390/en12152887.

[31] Malcolm Keay. Electricity markets are broken – can they be fixed? 2016.

[32] Christopher Koch and Lion Hirth. Short-term electricity trading for system balancing - an empirical analysis of the role of intraday trading in balancing germany's electricity system. *SSRN Electronic Journal*, 12 2018. doi: 10.2139/ssrn.3284262.

[33] Leonardo Komay Maia and Edwin Zondervan. Optimization of energy storage and system flexibility in the context of the energy transition: Germany's power grid as a case study. *BMC Energy*, 1, 12 2019. doi: 10.1186/s42500-019-0009-2.

[34] Hendrik Kondziella and Thomas Bruckner. Flexibility requirements of renewable energy based electricity systems – a review of research results and methodologies. *Renewable and Sustainable Energy Reviews*, 53:10 – 22, 2016. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2015.07.199. URL http://www.sciencedirect.com/science/article/pii/S1364032115008643.

[35] Sergei Kulakov and Florian Ziel. The impact of renewable energy forecasts on intraday electricity prices. 03 2019.

[36] Peter D. Lund, Juuso Lindgren, Jani Mikkola, and Jyri Salpakari. Review of energy system flexibility measures to enable high levels of variable renewable electricity. *Renewable and Sustainable Energy Reviews*, 45:785 – 807, 2015. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2015.01.057. URL http://www.sciencedirect.com/science/article/pii/S1364032115000672.

[37] Hector Marañón-Ledesma. Analyzing demand response in a dynamic capacity expansion model for the european power market. *Energies*, 12, 08 2019. doi: 10.3390/en12152976.

[38] Hector Marañón-Ledesma and Asgeir Tomasgard. Long-Term Electricity Investments Accounting for Demand and Supply Side Flexibility. MPRA Paper 93341, University Library of Munich, Germany, March 2019. URL https://ideas.repec.org/p/pra/mprapa/93341.html.

[39] Juan M. Morales, Marco Zugno, Salvador Pineda, and Pierre Pinson. Electricity market clearing with improved scheduling of stochastic production. *European Journal of Operational Research*, 235(3):765 – 774, 2014. ISSN 0377-2217. doi: https://doi.org/10.1016/j.ejor.2013.11.013. URL http://www.sciencedirect.com/science/article/pii/S0377221713009120.

[40] Stephan Nagl, Michaela Fürsch, and Dietmar Lindenberger. The costs of electricity systems with a high share of fluctuating renewables: A stochastic investment and dispatch optimization model for europe. *The Energy Journal*, 34, 01 2012. doi: 10.5547/01956574.34.4.8.

[41] Salvador Pineda and Juan M. Morales. Capacity expansion of stochastic power generation under two-stage electricity markets. *Computers Operations Research*, 70:101 – 114, 2016. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2015.12.007. URL http://www.sciencedirect.com/science/article/pii/S0305054815002932.

[42] Kris Poncelet, Arne van Stiphout, Jelle Meus, E Delarue, and W D'haeseleer. Lusym invest: a generation expansion planning model with a high level of temporal and technical detail. 05 2018.

[43] Achim Schreider and Ralf Bucher. An auspicious combination: Fast-ramping battery energy storage and high-capacity pumped hydro. *Energy Procedia*, 155:156–164, 11 2018. doi: 10.1016/j.egypro.2018.11.059.

[44] Ian J. Scott, Audun Botterud, Pedro M.S. Carvalho, and Carlos A. Santos Silva. Renewable energy support policy evaluation: The role of long-term uncertainty in market modelling. *Applied Energy*, 278:115643, 2020. ISSN 0306-2619. doi: https://doi.org/10.1016/j.apenergy.2020.115643. URL http://www.sciencedirect.com/science/article/pii/S0306261920311430.

[45] Pernille Seljom and Asgeir Tomasgard. Short-term uncertainty in long-term energy system models — a case study of wind power in denmark. *Energy Economics*, 49:157 – 167, 2015. ISSN 0140-9883. doi: https://doi.org/10.1016/j.eneco.2015.02.004. URL http://www.sciencedirect.com/science/article/pii/S0140988315000419.

[46] Christian Skar, Gerard Doorman, Gerardo A. Pérez-Valdés, and A. Tomasgard. A multi-horizon stochastic programming model for the european power system. 2016.

[47] Y. Sun, W. Cole, and V. Krishnan. Comparing power flow approximations for electricity infrastructure capacity expansion models with high spatial resolution. In *2018 IEEE/PES Transmission and Distribution Conference and Exposition (T D)*, pages 1–5, 2018. doi: 10.1109/TDC.2018.8440480.

[48] Holger Teichgraeber and Adam Brandt. Identifying and evaluating new market opportunities with capacity expansion models. 11 2017.

[49] European Environmental Agency. Overview of electricity production and use in europe. page 42, 2015, Accessed: 18.08.2020, Available at:"https://www.eea.europa.eu/data-and-maps/indicators/overview-of-the-electricity-production-2/assessment-4".

[50] K. Uehara, C. Kern, and Joseph L. Koepfinger. Future vision of transmission and distribution 2030. 2015.

[51] Manuel Villavicencio. A capacity expansion model dealing with balancing requirements, short-term operations and long-run dynamics. *CEEM Working Papers*, 02 2017.

[52] Magnus A. Wendelborg. Sequencing of wholesale electricity markets (day ahead and intra-day) in a capacity expansion model under uncertainty. Master's thesis, 2020.

[53] M. Zipf and D. Möst. Impacts of volatile and uncertain renewable energy sources on the german electricity system. pages 1–8, 2013.

Appendix

Appendix A: Scenario Generation

In order to include the unpredictable nature of VRES and load, different scenarios are generated. The scenario data is based on historical data for load, generator availability, and maximum hydro allowance. All data is collected from the ENTSO-e database using the SFTP protocol [23]. Data for both day-ahead and intraday, named forecast and actual from ENTSO-e, respectively, are collected. The data is then put into to a scenario-generation routine. The scenario-generation routine divides the historical data into seasons according to hours of the year. Then, for every scenario and every season, a random hour is sampled. The hours are then sorted, to start on Monday 00:00. In addition, any hour later than the length of the operational period could not be selected, because the chronology is preserved and we would not get a sufficient amount of data. All parameters generated from the scenario routine are sampled based on the same hour for each season and scenario, ensuring correlation between the different parameters, such as wind-PV correlation.

Since only a small portion of the historical data sets are randomly generated, there was a need to ensure a correlation between historical trends and the trend generated by the scenario-generation. Securing a correlation was done by utilizing moment matching. The moment matching routine analyzes the generated scenarios to find the best collection of scenarios that match the statistical moments of the historical data. The procedure is as follows: First, a realization of the stochastic data is created based on the historical data sets for each hour, season, scenario and period. The first step is then repeated U times to generate U different collections of scenarios, or scenario trees. Then, the first four moments (expectation, variance, skewness, and kurtosis) was calculated for each season for all U scenario trees. The seasonal moments of each scenario tree are further compared to the seasonal moments of all historical data.

The scenario tree with the best match to the original data was identified based on equation (3):

$$d_{u,s} = \sum_{n \in \mathcal{N}} w_n \sum_{v \in \mathcal{V}} \frac{|m^{\text{all}}_{v,s,n} - m^{\text{tree}}_{v,s,n,u}|}{|m^{\text{all}}_{v,s,n}|}, \tag{3}$$

where u is the scenario tree, s is the seasons, n is the nodes, and v is the moment order. The nodal weight, w_n, represents how much node n should contribute to the tree score. The values $m^{\text{all}}_{v,s,n}$ represent moment v in season s and node n for all data, and $m^{\text{tree}}_{v,s,n,u}$ represent the moment value specific to tree u. The minimum value of $\sum_{s \in \mathcal{S}} d_{u,s}$ yields the tree u which has moments matching best with all historical data.

In this thesis, the seasonal moments for each scenario tree and all historical data are calculated based on all actual load realizations as a univariate distribution of hourly values. The nodal weight is calculated based on the nodal share of the total actual load in the whole system. Therefore, the hours best represented in the scenario tree compared to the actual load was also used in the forecasted load, forecasted generator availability, generator availability, and hydro availability. By using the same hours for all parameters, we preserve the cross-correlation between load and production, and thus, create a likely future scenario tree. In addition, nodes are weighted differently to make sure that a correlation in larger nodes is more important than a correlation in smaller nodes. The scenario generation approach is based on [45].

Magnus A. Wendelborg

Capacity expansion with market sequencing under uncertainty

NTNU
Norwegian University of
Science and Technology