Uncertainty in Long-Term Grid Planning

Approaching Transmission Expansion Planning through the Framework of Decision Making under Deep Uncertainty

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by

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Preface

Here it is; the long-awaited capstone project for the obtainment of my master degree in Engineering and Policy Analysis. The development of this thesis has been a much enjoyed journey that challenged me to further my understanding of exploratory modelling.

First of all, I want to thanks my supervisors for their constant support during the development of this thesis. Thank you Martti for your catching enthusiasm and thank you for the many people that you introduced me to within TenneT, thank you Emile for the critical thinking that you inspired during our meetings and thanks you Jan for patiently answering all my questions and allowing me to use your computer cluster.

Furthermore, I'd like to thank my colleagues at TenneT for the warm welcome that I've received. Before starting my internship I was convinced I knew a fair bit about the electricity sector and its current challenges. However, it didn't take me too long to realize that I had a lot to learn. Give me another year and I hope to finally be able to recognize all the different abbreviations.

Finally, I want to thank Minke for editing this thesis and naturally I want to thank my girlfriend Marloes for her patience during the development of this thesis. You supported me throughout the process and motivated me whenever I needed a little push.

Rob Calon
The Hague, March 2020

Summary

Motivations for sustainability are initiating an energy transition that is changing the European energy domain. The transition effectuated the adaptation of large volumes of wind and solar based generation capacity. The intermittent power-output of these Variable Renewable Energy Sources challenges the balancing operation of the electricity network in particular. Despite the availability of different solutions like storage, smart applications and infrastructure substitution, large investments in transmission capacity are inevitable.

While the need for additional transmission capacity is evident, the realization of transmission capacity has become increasingly complex due to the uncertainty surrounding the future landscape in which this expansion would take place. The many possible pathways towards a sustainable future make it increasingly difficult to predict the development of generation and load profiles and thereby complicate the identification of capacity requirements within the electricity network. This raises the need for new approaches that address the high degree of uncertainty present within the electricity domain.

Literature describes the framework of Decision Making under Deep Uncertainty as an alternative approach to addressing the role of uncertainty in Transmission Expansion Planning. In contrast to traditional scenario planning approaches, this approach focuses on the computational evaluation of large numbers of scenarios that are sampled from a constrained uncertainty space. The idea is to inform decision making by exploring the uncertainty space and identifying conditions under which certain outcomes occur. Consequently, decision makers are aware of the conditions under which interventions might succeed or fail and are therefor able to design strategies that perform in different futures.

The potential of the framework of Decision Making under Deep Uncertainty in the context of Transmission Expansion Planning is explored through a proof-of-concept approach that focuses on Transmission Expansion Planning in the context of The Netherlands. In this approach a simplified integrated market simulation and network model are used to explore the effects of different quantities of wind and solar based generation capacity on the required transmission capacity within the electricity network. Instead of using merely three traditional scenarios, this thesis has evaluated and analyzed 20,000 different scenarios.

The results of these analyses have been reviewed by domain experts during two

workshop sessions. These sessions established that approaches to Decision Making under Deep Uncertainty could provide useful insights in relation to model sensitivity, the reduction of dimensional complexity of the uncertainty space and the development of scenarios that describe areas within the uncertainty space. The sessions furthermore established that the application of Decision Making under Deep Uncertainty in relation to Transmission Expansion Planning requires further development in order to become a viable alternative to traditional scenario planning in a corporate environment.

Based on the assessment of the potential of the Decision Making under Deep Uncertainty framework in relation to Transmission Expansion Planning, this thesis recommends the further development of the approach within the policy domain by establishing different comprehensible use-cases to gain experience, and therewith confidence in the application of the framework. The potential of the framework exceeds the demonstrated proof-of-concept and provides opportunities to improve risk assessments of investment projects or to inform agile investment strategies that result a more robust transmission network configuration. The approach might further complicate the decision making process, while at the same time making the role of uncertainty in the decision making process more visible.

The scientific community is furthermore urged to research the relationship between the resolution of Transmission Expansion Planning models and the resolution of the outcomes in relation to Decision Making under Deep Uncertainty approaches. This research might help to reduce the required computing time in Decision Making under Deep Uncertainty approaches without having to necessarily resolve to an increase in allocated CPU hours. Thereafter, more research efforts could be directed towards the approach's accountability aspects related to regulated sectors, e.g. through the establishment of a framework that prescribes best practices, therewith guiding the appropriate application of Decision Making under Deep Uncertainty approaches. Thereafter, it is recommended that the scientific community invests in comparisons between Decision Making under Deep Uncertainty approaches and traditional scenario planning approaches to better understand the attitudes and mindsets of analysts and decision-makers towards the real-world application of Decision Making under Deep Uncertainty.

The application of Decision Making under Deep Uncertainty approaches within the context of Transmission Expansion Planning provides a unique opportunity to make the uncertainty space more visible for Transmission System Operators. The approach provides the building blocks to design adaptive investment strategies which in turn are geared towards facilitating the energy transition in a robust manner.

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List of Abbreviations

CPCA	Constrained Principal Component Analysis
DAP	Dynamic Adaptive Policy Pathways
DMDU	Decision Making Under Deep Uncertainty
EHV	Extra High voltage
EM	Exploratory Modelling
ENTSO-E	European Network of Transmission System Operators for Electricity
EU	European Union
HV	High Voltage
LP	Linear Programming
PCA	Principal Component Analysis
PEMMDB	Pan European Market Modelling Database
PRIM	Patient-Rule Induction Method
RES	Renewable Energy Source
SA	Sensitivity Analysis
SD	Scenario Discovery
TEP	Transmission Expansion Planning
TSO	Transmission System Operator
VRES	Variable Renewable Energy Source

Nomenclature

symbol	description
α	loading value of uncertainty parameter
A	line length
B	scenario bounds of principal component
c	capacity cost constant
d	length cost constant
E	total emissions
e	emission constant
f	overnight capital costs constant
G	generation costs
H	overload score
I	maximum rated current
J	investment impact score
K	loading capacity
L	Loading percentage
l	line element
M	Maximum loading percentage
m	collection of power elements
n	collection of line elements
P	Power output
Q	Maximum power output
R	dispatch revenue
T	Reference capacity
S	maximum overload score
U	uncertainty parameter in principal component
V	voltage level
W	installed capacity
X	dispatch costs
x	power element
Y	investment costs
Z	generation investment costs

Chapter 1

Introduction

1.1 Transmission expansion planning

The European Union (EU) supports motivations for sustainability which instigated an energy transition that is changing the European energy domain and the European electricity sector in particular. The large adaptation of Renewable Energy Sources (RES) has increased the share of renewable electricity in gross electricity consumption to 30.6% in 2017 (EEA, 2019). With an underlying compound growth rate of 6.3% in gross electricity consumption over the last decade, the share of renewable electricity is expected to grow even further and marked a change in the European energy domain, redefining how power systems are planned, operated and controlled (Pérez-Arriaga & Batlle, 2012).

1.1.1 Balancing electricity networks

The swift emergence of RES in the EU is primarily attributed to the accelerated adaptation of wind and solar powered RES capacity which represented 37.2% and 12.3% of the total installed RES capacity in 2017 respectively (EEA, 2019). Due to the spatio-temporal intermittent nature of their respective power output, wind and solar powered RES capacity are considered as Variable Renewable Energy Sources (VRES). This classification distinguishes these resources from their conventional fossil-based counterparts as they introduce the possibility of a mismatch between generation and load in different regions at different times (Rodriguez et al., 2014; Widén et al., 2015). This potential mismatch complicates the balance responsibility of Balance Responsible Parties and therefore has a potential impact on the availability performance of the electricity system as a whole (Van der Veen & Hakvoort, 2009).

Propitious options like storage, smart applications and infrastructure substitutions have been proposed to address the fluctuations in generation from VRES by enabling shifts in generation and/or load over time (Verzijlbergh et al., 2017). These options have demonstrated their potential to reduce the magnitude of imbalance and are expected to play an important role in the electricity system as the share of VRES increases over time. Their potential further improves in combination with investments in transmission capacity, as capacity investments address geographic variation between VRES production and electricity demand (Bove et al., 2012). Transmission investment, therefore, has the ability to decrease the magnitude of potential imbalance in the electricity system (Spiecker et al., 2013). The combined implementation of additional transmission capacity, together with generation and load shifting technologies therefore facilitate a cost-reducing effect on electricity prices. The resulting availability of transmission capacity enables electricity flows over long geographical distances. This reduces the amount of backup capacity that is required to balance transmission networks (Battaglini et al., 2009).

1.1.2 Contradicting investment incentives

Although investment in transmission capacity is desirable from a cost perspective, the regulatory structures that govern Transmission System Operators (TSOs) complicate network investment. This framework implicitly assumes that TSOs are able to decide on the optimal set of investments that ensure the current and future functioning of the transmission network (Van Blijswijk, 2017). Due to uncertainty inherent to future states, predicting 'the future' becomes a paradoxical process. Given the extensive lead times in Transmission Extension Planning (TEP), consistently deciding on the optimal set of investments in the face of substantial long-term uncertainty is therefore impossible (Blanco et al., 2011). The current regulatory framework does not acknowledge this implication of uncertainty, which leave TSOs at an impasse regarding their decision on the amount of risk that should be taken to meet future network requirements. As the regulatory framework penalizes overinvestment, TSOs seem to be incentivized to underinvest in transmission capacity, and to disregard the associated social costs (EPRI, 1978; Van Blijswijk, 2017).

While the prospect of a revision of the regulatory framework is probable in the long-term, in the short-term, TSOs are expected to find a balance between societal needs and the current regulatory incentives in order to facilitate the initiated energy transition (Van Blijswijk, 2017). A better understanding of uncertainty and its implications on TEP seems critical in the bid for TSOs to deliver the required network extensions.

1.2 Research problem

Uncertainty in relation to TEP has been extensively discussed in literature, especially in relation to the absence of information on generation extensions and load growth after the liberalization of the European electricity sector (EPRI, 1978; Van der Weijde & Hobbs, 2012; Van Blijswijk, 2017). The market liberalization unbundled ownership of generation and transmission activities, redistributing their responsibilities to energy producers and TSOs respectively. The separation of generation extension planning and TEP resulted in the fluctuation of generation and load profiles becoming less predictable. Therefore, anticipating future transmission capacity requirements became more complicated, marking the rigorous shift from deterministic to probabilistic approaches in TEP.

1.2.1 Modelling transmission expansion planning

Wu et al. (2006) describe how the shift to probabilistic TEP resulted in the emergence of more model-based decision making processes. As a result, different TEP models have been developed over time. These models aim to further TEP by focusing on different aspects in the context of network investment: Krause et al. (2006) evaluate the effects of strategic behavior of certain network users on the social costs related to network expansion, Jaehnert et al. (2013) researched profit-based investments strategies for the Northwest European transmission grid on the basis of congestion rents, while Van Blijswijk (2017) evaluated cross-regional and inter-regional TEP by modelling the individual perspectives of multiple TSOs.

In the context of uncertainty, Crousillat et al. (1993) were one of the first to address the role of uncertainty in a quantitative study by adapting a distinction between risk and uncertainty in their modelling approach. Oloomi Buygi et al. (2004) and Zhao et al. (2009) apply similar approaches in their respective models to what Van der Weijde & Hobbs (2012) describes as a single-stage approach to one-period investment problems. More advanced models apply Real Option Theory to address the limitations of the single-stage approach by introducing the possibility of taking and 'action', with the possibility of taking and 'option'. This 'option' can be reevaluated over time, as future changes might affect the underlying investment logic of the option (Hedman et al., 2005; Fletten et al., 2010). Van der Weijde & Hobbs (2012) expanded this idea by adding a game-theory dimension to their model that enabled gaming mechanisms between transmission and generation capacity planners. This resulted in a two-stage optimization approach to TEP which aims to capture the multistage nature of planning in uncertain environments.

1.2.2 An evolved understanding of uncertainty

As can be observed throughout the development of the different model-based approaches to TEP, the perceived significance of uncertainty evolved over time. The conceptual distinction between risk as a measurable and quantifiable unknown and uncertainty as a limit to knowledge and predictability is introduced by Knight in 1921. Quade (1989) expanded upon Knight's concept of uncertainty by distinguishing stochastic uncertainty from real uncertainty. Quade (1989) describes stochastic uncertainty as uncertainty that includes frequency-based and subjective probabilities, where real uncertainty includes uncertainty that results from the strategic behaviour of other actors. Lempert et al. (2003) and Ben-Haim (2006) refer to real uncertainty as deep uncertainty and severe uncertainty respectively. They both describe uncertainty as something that in principle is unknowable and thereby a source of disagreement. This contestation can derive from disagreements concerning anything from system functions, to general expectations, to the future state of the world and on the relative importance of different outcomes of interest.

Walker et al. (2003) build on the evolved understanding of uncertainty by proposing a framework that categorizes uncertainty, recognizing that different types of uncertainty require different types of approaches. Depending on the type and severity of the identified uncertainty, Walker et al. (2013) suggest suitable approaches to address the respective uncertainty and therewith link the evolved theoretical perception to uncertainty and the practical significance of uncertainty in a modelling context. Different tools are available Within the context of Decision Making under Deep Uncertainty (DMDU), e.g. scenario planning (Quade, 1989), Robust Decision Making (Lempert et al., 2006) and Dynamic Adaptive Policy Pathways (DAPP) (Haasnoot et al., 2013). To indicate the appropriate application of the different concepts in which the various approaches are founded, Kwakkel & Haasnoot (2019) propose a framework which allows analysts to design context-specific approaches to support DMDU.

1.2.3 Knowledge gap

The evolved understanding of uncertainty is also evident within the development of model-based TEP approaches as exemplified by Crousillat et al. (1993) who applied Knight's (1921) distinction between risk and uncertainty in their modelling approach. Over time, as the level of uncertainty increased, TEP models adopted scenario planning approaches in their models, which are similar to the approaches used in the models of Van der Weijde & Hobbs (2012) and Van Blijswijk (2017). Scenario planning, as an approach to deal with deep uncertainty, is also applied by different TSOs. This is demonstrated in the adoption of standardized scenarios in the 10-Year Network Development Plan of The European Network of Transmission System Operators for Electricity (ENTSO-E) (ENTSO-E, 2019b).

Therefore, the significance of uncertainty in TEP seems to be well-established. Within the domain of TEP, the presence of deep uncertainty is implicitly recognized, and scenario planning approaches are adopted in model-based decision-making processes. Simultaneously, the electricity sector is rapidly changing and TSOs are struggling to keep up with network extension investment which is required in an increasingly dynamic transmission network (ENTSO-E, 2015). The anticipated system integration between electricity and gas networks further increase the amount of uncertainty in an already deeply uncertain investment environment (ENTSO-E, 2018; Gasunie & TenneT, 2019). The combination of the different observed trends suggest a potential disconnect between the nature of uncertainty present in TEP and the established approach to decision making in TEP, i.e. the link between DMDU and the deeply uncertain nature of TEP is unestablished. Consequently, research is required to assess the value of DMDU approaches in the context of TEP.

1.2.4 Research question

This thesis aims to establish the link between DMDU and TEP by exploring the added value of DMDU approaches in the context of TEP. Through this objective, this thesis consequently aspires to contribute, however small, to the realization of a more sustainable energy system that is confided within the limits of our planet's carrying capacity. With these objectives in mind, this thesis seeks to address the following research question:

What are useful insights that Decision Making under Deep Uncertainty approaches can provide in the process of Transmission Expansion Planning?

In addressing the research question, different aspects of the research question are to be addressed. Therefore, the research question is broken down into three sub-questions. In order to understand how DMDU approaches can be applied in TEP, an understanding is required of the deep uncertain elements that affect TEP. This results in the following sub-question:

[1] *How is Transmission Expansion Planning affected by deep uncertainty?*

Given the role of deep uncertainty in the process of TEP, the framework of DMDU can be applied to examine how it addresses deep uncertainty in TEP. This results in the following sub-question:

[2] *How can Decision Making under Deep Uncertainty approaches be applied in the process of Transmission Expansion Planning?*

Provided that DMDU approaches can be applied in the TEP process, the usefulness of the resulting insights remains to be assessed. Within this assessment the practical application in decision making is considered as well. This results in the following sub-question:

[3] *How useful are Decision Making under Deep Uncertainty approaches in the process of Transmission Expansion Planning?*

Addressing the sub-questions provides insight in the deep uncertain elements that are present in TEP, approaches that can be used to address deep uncertainty in TEP and the (practical) usefulness of applying DMDU approaches in TEP. Therefore, addressing the sub-questions provides the insights required to address the research question.

1.3 Relevance

The relevance of the work presented in this thesis is twofold, it is rooted in a scientific as well as a societal field. The scientific relevance of this work is embedded in the application of the concept of DMDU in the context of TEP, whereas the societal relevance of this work is seen in its effort to improve the process of TEP.

1.3.1 Scientific relevance

This thesis explores the disconnect between the nature of uncertainty present in TEP and the established approaches in TEP. To that end, this thesis applies the framework of DMDU to TEP, and contrasts it to the current practice of traditional scenario planning. Although DMDU approaches have proven to be fruitful in different specific contexts, e.g. Popper et al. (2009) or Bloemen et al.

(2019), the framework of DMDU has yet to be applied in the context of TEP. The work presented in this thesis aims to address this knowledge gap.

Furthermore, literature that contrast the application of DMDU configurations to scenario planning approaches in expert environments is scarce, e.g. Gong et al. (2017). This thesis assess the usefulness of an open exploration oriented DMDU approach in workshop sessions with scenario domain experts in the field of TEP. This helps to better contrast the perceived advantages and disadvantages of a scenario planning approach versus DMDU approaches as perceived by domain experts and hereby helps to identify focus areas for the further development of DMDU.

1.3.2 Societal relevance

The previously described social costs resulting from imperfect TEP underline the societal relevance of research that aims to better inform TEP. This is especially relevant in the context of an energy transition in which the European electricity system requires enormous investments to realize the societal desire to become more sustainable. Through assessing the value of DMDU in TEP, TSOs might be able to improve their investment strategies and reduce the risk of inadequate TEP. The importance of these investments are for example underlined in the United Nation's Sustainable Development Goals (UN, 2018).

DMDU approaches are better suited to make the role of uncertainty visible in the TEP decision making processes. The framework fosters scenario thinking in terms of subspaces, rather than single points and hereby better addresses the complexity of the uncertainty that grasps TEP. The additional information gathered by approaching TEP through the framework of DMDU helps to optimize network investments in terms of robustness and thereby helps to formulate long-term investment strategies that are able to adapt as the future unfolds. In the long-term DMDU facilitates more robust investment decisions and thereby reduces the risk of underinvestment in the long-term.

1.4 Research methods

This thesis applies a mix of quantitative and qualitative approaches to address the research question. Within this mix, different methods are used to create, structure and analyze data and information. The methods applied in this thesis are described in subsequent sections.

1.4.1 Case study

This thesis aims to assess the value of DMDU in the specific context of TEP. The case study method is used to denote the context in which this analysis takes place; in this case TEP in The Netherlands. Although the method limits the ability to generally interpret the results of this thesis, a single case approach provides the context-specific details required to analyze TEP within a limited time schedule. The selection of the case is further specified in section 1.6. The case study therefore provides the context in which each of the research questions within this thesis is addressed.

1.4.2 Desk research

To address the first sub-question in the context of a specific catchment area, information is required on the specifics of the TEP process. TenneT TSO B.V. provided the opportunity of an internship during the execution of the work presented in this thesis. This presented the possibility to gather expert knowledge that is directly applied in this thesis. The desk research approach is used to address the first sub-question by detailing the TEP-process in The Netherlands.

1.4.3 Linear programming

Based on the locations of deep uncertainty in the TEP process that are described in chapter 2, this thesis applies Linear Programming (LP) as a method to model the physical network aspects in the TEP process. Linear programming is a method to solve mathematical models consisting of linear equations. LP is used to solve generation dispatch and load flow in the transmission model described in chapter 3. Therefore, the method is used to address the modelling aspect of the TEP-process in the second sub-question.

1.4.4 Exploratory modelling

Exploratory Modelling (EM) is used as a method for analyzing complex and uncertain systems through computation experimentation (Bankes, 1993). EM utilizes a comprehensive set of computationally generated what-if experiments to support reasoning and decision making (Kwakkel & Haasnoot, 2019). Consequently, this method facilitates searching through a vast set of possible model outcomes and allows the use of optimization algorithms, global sensitivity analysis techniques, multi-model use and computational experiment design. EM is used in combination with the LP-based TEP-model to approach the TEP-process through the framework of DMDU and is therefor used to address the DMDU aspect of the second sub-question.

1.4.5 Workshops

Workshops have been used as semi-structured interviews to asses the usefulness of the applied DMDU approaches to experts in within the TEP-domain. The workshop configuration was used as it facilitates active engagement resulting in more in-depth discussions as opposed to traditional, highly structured interviews. The input collected during the workshops is used in assessing the results of the application of DMDU approaches in the context of the TEP-process. The workshop method is therefore used to address the third sub-question.

1.5 Research tools and data

The application of the LP and EM methods require the use of programming and analytical tools to evaluate and analyze the multitude of computationally generated what-if scenarios. The required tools are described in the subsequent sections.

1.5.1 EM workbench

This thesis uses the Python language to model the physical network aspect in TEP. The model implementation leans heavily on the PandaPower package (Thurner et al., 2018). Thereafter, the programming language is used together with the Exploratory Modelling Workbench and its extensive library of analytical tools in the context of EM (Kwakkel, 2017). Furthermore, several other packages are utilized for numerical operations and visualization. These packages are listed in the README.md file in the GitHub distribution of the model.

1.5.2 Data

The model uses input data from several different sources. The static grid model representation of the transmission network of The Netherlands is available on the TenneT website (TenneT, 2019). Load profiles are available at the ENTSO-E data portal (ENTSO-E, 2019a). Capacity Factors are available at renewables.ninja (Renewables.ninja, 2019). External bidzone price time series, installed generation capacities and technical specifications of trafos are based on expert knowledge and on unpublished data sources. The generator types are based on the Pan European Market Modelling Database (PEMMDB).

1.6 Case selection

This thesis has selected TEP in the context of The Netherlands as the case of interest. Within this case, this research limits itself to the Extra High Voltage (EHV) network that is located within the catchment area of Dutch TSO TenneT. This selection includes the 380kV and 220kV network parts that are geographically located within The Netherlands. The selected demarcation includes interconnection and therefor cross-border power lines and electricity exchange.

With a targeted share of 70 percent renewable electricity production in 2030, The Netherlands is faced with the adaptation of large volumes of VRES generation capacity (Government of The Netherlands, 2019). TenneT is furthermore a member of ENTSO-E and is thereby committed to the European energy and climate agenda ENTSO-E (2020). The case of TEP in The Netherlands therefore represents a typical case of TEP within the European Union.

Furthermore, TEP in The Netherlands is well demarcated as the catchment area is geographically limited to the borders of The Netherlands, is operated by a single TSO, spans a single bidding zone and is topologically limited in relative complexity and size. In addition, the internship at TenneT provided access to expert knowledge related to the selected case. The accessibility of Dutch and English technical documents combined with the author's general understanding of the Dutch electricity sector make for a compelling and thorough analysis of TEP in the Netherlands.

1.7 Research scope

To focus on the research objective in the complex domain of TEP, this thesis and its results are confined within the limits of its bounded context. The preceding section described the main contextual limitations of the selected case, whereas the main quantitative limitations of this thesis are described in chapter 3. This thesis therefore evaluates the TEP process within a limited context. Therefore, the applied DMDU approaches are tailored to the specific context of The Netherlands. Although this limits the general applicability of the research results, this thesis attempts to approach TEP through the framework of DMDU as such, that it might be applied outside of the described research scope.

1.8 Thesis structure

This chapter described the increased significance of deep uncertainty in TEP and the subsequent investment dilemma it poses for TSOs. This thesis argues that research is required, linking TEP to modern approaches that address deep uncertainty, and develops the required research in subsequent chapters. Chapter 2 describes the theoretical concepts in which DMDU and TEP are embedded. Chapter 3 describes the TEP-model that has been applied in this thesis. Chapter 4 specifies the DMDU configuration that has been applied to the TEP-model. Chapter 5 presents the model results. Chapter 6 presents the workshop results and chapter 7 concludes this thesis by revisiting the research question. The coherence between the different chapters in this thesis is visualized in the research flow diagram in figure 1.1.

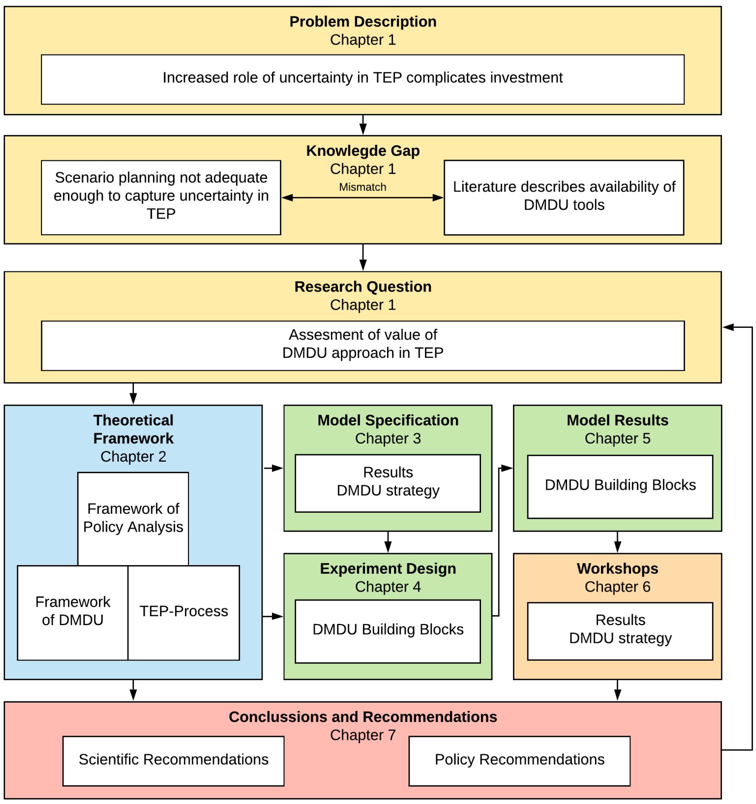

Figure 1.1: Research flow diagram

Chapter 2

Uncertainty in transmission expansion planning

2.1 Uncertainty in policy analysis

The notion of deep uncertainty is embedded in the policy domain within the framework of rational comprehensive policy analysis. Within this framework, modelling and simulation provide computer based learning approaches to deeply uncertain complex systems. The subsequent sections describe the link between deep uncertainty and the framework of rational comprehensive policy analysis in more detail.

2.1.1 Rational comprehensive policy analysis

Rational comprehensive policy analysis is an archetypal policy analysis style that is rooted in the hexagon model of Mayer et al. (2004). The style entails the consideration of possible consequences of different potential solution, i.e. it comprises the assessment of different alternatives in relation to a specific objective. Walker (2000) formalized this process into the framework that is visualized in figure 2.1.

The framework utilizes *system models* to describe systems in terms of its elements and the interactions among these elements. The system model is defined in relation to the boundaries, structures and operations of the system domain that are relevant in the context of the identified problem. The outcomes of the system model relevant to the considerations in the decision-making process are specified as *outcomes of interest*. The (relative) weights of the outcomes of interest are considered in relation to the *objectives* as agreed upon by the problem's decision-makers and stakeholders, thereby representing a subjective value trade-off in the decision domain.

Decision-makers influence the outcomes of interest through *policies*, which represent alternatives to the status quo. Policies affect the system of interest, aiming to affect the outcomes of the system in a desirable manner. Conjointly, the system is also affected by *external factors* that are outside the control of decision-makers. External factors therefore simultaneously have an impact on the outcomes of interest and thereby influence the effectiveness of policies.

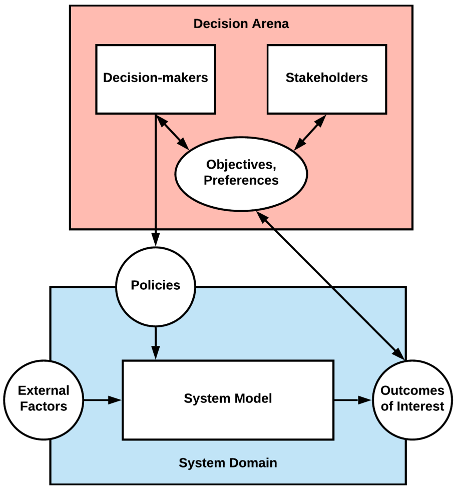

Figure 2.1: Rational comprehensive policy analysis. Adapted from Walker (2000).

2.1.2 Modelling and simulation

Proportional to the degree of complexity of a system domain, reasoning about the system model and the effects of policies becomes increasingly complex and thereby complicates the decision-making process. Decision making for complex systems therefore requires the use of modelling approaches to assess the effects of policies prior to implementing them.

Modelling approaches quantify system models by representing the relationships in the system as mathematical functions. Implementing these functions into computer code creates a simulation model which facilitates experimentation to test the effects of policies before implementation. Although simulation models are useful in the context of decision making for complex systems, the value of simulation models is limited by the Law of Requisite Variety (Ashby, 1968). This law entails that a model can only express something to the extent that the model has sufficient internal variety to represent it.

The different interpretation steps involved in modelling approaches by definition result in a limited representation of the real-world system. This is what Box (1976) referred to in his famous aphorism *"all models are wrong, some are useful"*, recognizing that, despite the inability of models to be true, models can be illuminating and useful. This means that a model's usefulness is defined in terms of its ability to help understand a problem rather than its ability to mimic aspects of the real-world.

2.1.3 Addressing deep uncertainty

To increase the usefulness of a model, its internal variety may be explored in order to assess the effects of uncertainty in the model. From the perspective of rational comprehensive policy analysis, locations of uncertainty are related to (1) the representation of the system itself, (2) the impact of external factors, (3) the outcomes of interest and (4) the weights attributed in the objective function. This thesis primarily focuses on uncertainty related to the impact of external factors.

Based on the framework of Walker et al. (2003), the level of uncertainty within the model may be assessed. The identified level of uncertainty is relevant in the context of the selected approach to address the uncertainty present in the model. Walker et al. (2003) argue that the required method to address the uncertainty is related to the level of uncertainty, specifying appropriate approaches based on the identified level of uncertainty. In the case of deep uncertainty, the framework of DMDU should be applied (Kwakkel & Haasnoot, 2019).

The framework of DMDU aims to facilitate learning about the understanding of the problem and potential solutions. In that aim, the paradigm strives to inform policy design in terms of adaptiveness and relative robustness, i.e. policies, by design, should be able to adapt to different circumstances, thereby ensuring performance over time. Policies therefore should consider different possible futures and contain a degree of flexibility in order to adequately respond to future events.

2.2 Decision making under deep uncertainty

The DMDU framework covers five building blocks which may be used in designing custom approaches to address deep uncertainty in policy problems. The building blocks in the framework are used to assess specific locations of uncertainty or to assess any given combination of different locations of uncertainty. The framework and its building blocks are visualized in figure 2.2. Each of the building blocks is described in individually in the subsequent sections.

2.2.1 Policy architecture

The unpredictable nature of deep uncertainty means that static policies are unlikely to succeed. This is due to the high costs required to protect them from failure and their inability to seize opportunities as time progresses (Kwakkel & Haasnoot, 2019). In order to facilitate flexibility in policies in terms of the implementation of actions, DMDU approaches are centered around the concept of adaptive policies.

Adaptive policies are policies that contain multiple actions. Actions within these policies are subsequently informed based on signals provided by monitoring data and the results of modelling and simulation studies. The signaling of these actions is structured around a policy architecture that is either of a protective-adaptive, or of a dynamic-adaptive nature (Kwakkel & Haasnoot, 2019). This

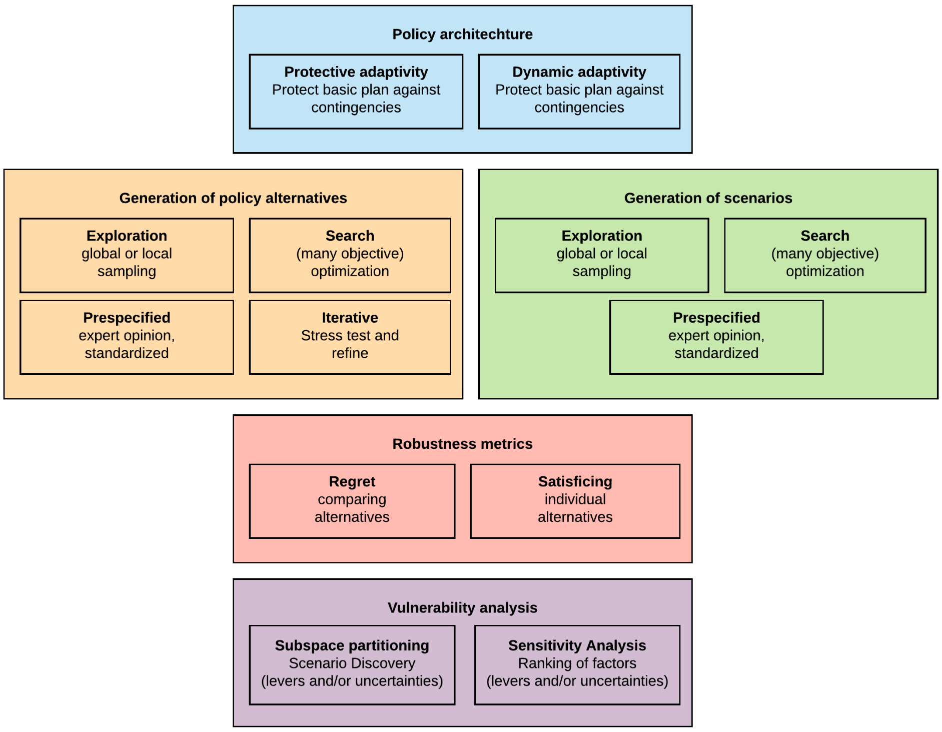

Figure 2.2: DMDU building blocks. Adapted from Kwakkel & Haasnoot (2019).

means that the policy architecture is either structured around a 'base' plan that is protected by contingency measures or is structured around a base plan that evolves as the future unfolds, i.e. a policy architecture that either consists of actions that protect the base plan or actions that change the base plan. Both architectures are visualized in figure 2.3.

2.2.2 Generation of scenarios and policy alternatives

In order to investigate the effects of uncertainties and policy interventions on the outcomes of the model, the specification of the uncertainty and policy space within the system domain is required. The generation of scenarios and policies determines the logic to cover scenario and policy combinations within the input space (Kwakkel & Haasnoot, 2019). There are multiple setups that can be deployed to cover different aspects within the input space, thereby addressing different types of analyses.

Exploration

Exploratory configurations systematically identify properties within the input space through the use of sampling techniques such as Monte Carlo sampling, Latin hypercube sampling or factorial designs. The configuration is therefore

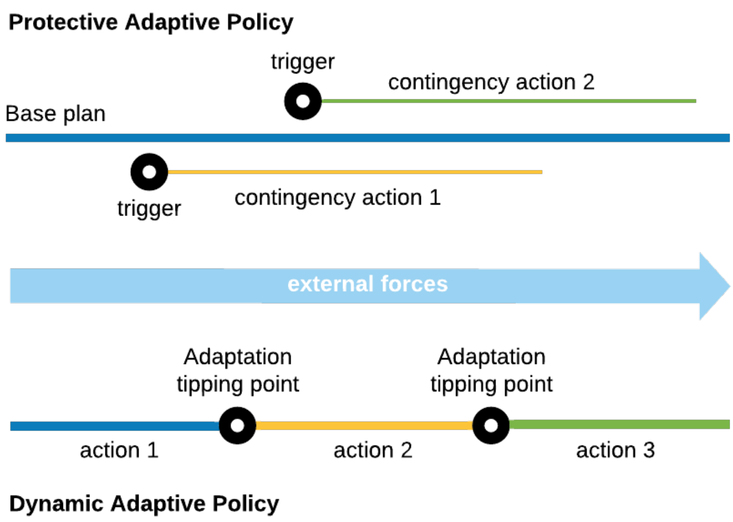

Figure 2.3: Protective actions versus dynamic actions. Adapted from Kwakkel & Haasnoot (2019).

used to provide insight into the global properties of the specified uncertainty and policy space.

Search

Search configurations use techniques to examine the uncertainty and policy space in a more directed fashion. The configurations relies on (many-objective) optimization techniques and is used to provide insight into particular points within the input space of the system model.

Prespecified

The prespecified configuration uses prespecified scenarios and/or policies to cover the uncertainty and/or policy space. In this type of analysis, pre-specified policies can be evaluated over a multitude of scenarios or visa versa. This configuration therefore aims to provide insight into the impact of the specified uncertainty or policy space of policies or scenarios respectively.

Iterative

An iterative configuration entails a mixed strategy in which different techniques are combined or deployed in an iterative fashion. Search could be used in combination with exploration to zoom-in on particular regions that have been discovered during the exploration phase. Subsequently, iterations could be used to design policies that perform under a wide range of scenarios within the identified region or entire uncertainty space.

2.2.3 Robustness metrics

The robustness metric determines how the performance of policy alternatives is measured in terms of robustness. There are different approaches to operationalize robustness that are derived from regret and satisficing definitions. The selection of an appropriate robustness definition depends on whether policies are scored individually or assessed in relation to one another and on the preferred manner in which one wants to describe the distribution of the policy scores (Kwakkel & Haasnoot, 2019).

Regret

Regret-based definitions consider the performance of policy options in relation to a reference option. In this case robustness is expressed robustness in terms of minimizing the maximum regret of a policy alternative over the different scenarios in the analysis.

Satisficing

Satisficing-based definitions consider the performance of policy option in relation to a minimum performance threshold. In this case robustness is operationalizes in terms of maximizing the number of scenarios in the analysis under which the policy option meets the performance threshold.

2.2.4 Vulnerability analysis

Vulnerability analysis covers the techniques that can be used to understand how vulnerable model outcomes are to the uncertainty and policy space of the system model's input parameters (Kwakkel & Haasnoot, 2019). These analyses cover sensitivity analysis techniques as well as subspace partitioning techniques.

Sensitivity analysis

Sensitivity analysis aims to establish the relative importance of uncertanties and/or policy levers. This type of analysis can be used to reduce the dimensionality of the uncertainty and policy space, therewith helping to focus on the key sources of uncertainty and the most influential policy levers.

Subspace partitioning

Subspace partitioning can be used to identify particular subspaces within the input space that results in particular model outcomes. The aim of most subspace partitioning techniques is to partition the uncertainty space into distinct regions that determine the success or failure of candidate policy options.

2.3 Transmission expansion planning

In The Netherlands, TEP is regulated in the Electricity Law 1998 and its subsidiary administrative measures, ministerial regulations and regulatory guidelines.

The framework prescribes mandatory elements within the TEP-process that TenneT details in its biennial investment plan (TenneT, 2017). This process is described in the subsequent subsections.

2.3.1 System outlook

Given the long lead times in TEP, TenneT's investment strategy should take into account network requirements over a time horizon of at least ten years. This requirement entails that TenneT has to consider factors that could affect future generation and load profiles. These factors include the high penetration rates of VRES, but also trends in adaptation rates of electrical vehicles, heat pumps or storage. As the electricity networks within Europe are interconnected, international trends have to be considered as well. For example, the German energiewende resulted in large transit flows that affected the operation of the Dutch electricity network.

Based on these trends, TenneT details scenarios that describe different load patterns and mixes of installed generation capacity. These scenarios are subsequently quantified based on estimate values that are derived from monitoring, reporting and research sources, e.g. sectoral and outlook reports. These data sources are primarily used to quantify trends within The Netherlands, whereas the quantification of foreign bidding zones is based on data that other European TSOs provided to ENTSO-E.

2.3.2 Market simulation

The scenarios are used in a market simulation model to evaluate hourly dispatch profiles for the different generation categories. Within the market simulation, dispatch profiles are approximated on a price-based optimization that minimizes dispatch costs given the technical properties of the different generation technologies and the limitations that apply to cross-border power exchange. Therefore, the market simulation aims to closely approximate the pricing-based dispatch allocation mechanism within the European electricity sector.

Provided that the market simulation does not take into account network limitations, the resulting dispatch profiles can be considered as 'optimal' market outcomes within the respective bidding zone. This means that generation dispatch is economically optimized and is unaffected by capacity constraints. However, in reality network congestion constrains optimal dispatch, resulting in sub-optimal market outcomes through redispatch interventions. Furthermore, it must be noted that constraints to interconnection are considered within the market simulation model.

2.3.3 Network calculations

Network bottlenecks can be identified in network simulations that evaluate load flows under optimal generation dispatch. Within the load flow calculations, a network model of the Dutch electricity network is subject to the load and dispatch profiles that are specified in each of the scenarios. Whenever a component within the network model overloads under the scenario input, the component causes congestion within the network and is therefore identified as a bottleneck.

Since the electricity network is subject to regulatory performance constraints, bottlenecks have to be considered under different network operation configurations. Due to these regulatory criteria, network congestion is considered under normal operation (n), single malfunction (n-1) and single malfunction during maintenance (n-2). The severity of a bottleneck is defined as a weighted score of the resultant of the frequency of overloading and the magnitude of overloading in each redundancy configuration.

2.3.4 Risk assessment

The congestion based severity scores are evaluated in a risk assessment. This assessment considers capacity bottlenecks together with other component related performance scores, e.g. component health, and assigns a weighed risk score that is based on different corporate values. These values include safety, quality of supply, finance and other indicators that represent corporate performance. The collection of the risk scores of all components form a risk profile that provides an indication of the performance and quality of the Dutch transmission network.

Risk scores within the risk profile that surpass a certain threshold initiate an investment process within TenneT's investment portfolio. This is a process that entails different phases in which mitigation measures are identified, selected and subsequently developed into detailed investment options. Within the investment portfolio there is a special group of projects that are labelled Large Cluster Projects and are coordinated by the central government. These projects are understood in terms of national or European interest and are characterized by their capital intensive and large scale scopes.

2.3.5 Strategy formulation

Aside from capacity related investments, TenneT's investment portfolio also includes projects that are related to network quality, client connections and network reconstructions. Given that the resources available to TenneT are limited and the quantity of identified investments is substantial, the investments within the investment portfolio are prioritized. This is a process that takes into account the network's risk profile and investment dependencies in order to formulate an investment strategy aimed at optimizing network performance under the limited availability of production factors.

2.4 Analysis

TenneT addresses the role of uncertainty within the TEP-process through the development of traditional scenarios. This approach can be characterized as scenario planning and to a certain degree addresses deep uncertainty within

TEP. However, within the deep uncertain context of TEP, a scenario-planning-based approach is considered to be too limited to adequately address the complexity introduced by the uncertain context.

The development of investment strategies within TEP are thereafter based on a system outlook that includes a limited number of discrete scenarios and therewith resulting in the limited coverage of the uncertainty space. Thereafter, as the quantification of scenarios is based on educated extrapolations of historic data, the interval variety represented in the specified scenarios of the traditional scenarios is fairly small as well. The scenarios used in the traditional scenario planning approach therefore only cover a small and limited area within the uncertainty space, thereby leaving many possible futures unexplored.

Furthermore, the specification of scenarios is primarily centered around expert knowledge. The quantification of the different scenarios involves a number of assumptions about, for example technology maturing curves, load development patterns and economic forecasts. Given this prominent role of expert knowledge, social dynamics between experts might result in processes that introduce blind spots in either the development of scenarios or in the assessment of scenario-based model analyses.

2.5 Discussion

Since the scenario planning approach is limited in the extend to which it can address the uncertainty space in TEP, DMDU approaches to TEP could provide additional insights. With regard to the specification of scenarios, exploratory configurations might prove especially fruitful in order to better understand the uncertainty space in TEP. The resulting insights could subsequently be used to specify more diverse scenario narratives, to evaluate the robustness of investment options or even to inform the design of adaptive investment strategies.

The uncertainty space addressed by DMDU approaches in the context of TEP would primarily address the uncertainty related to market developments, as these developments constitute the largest source of uncertainty within the TEP-process. The availability of transmission capacity facilitates electricity markets to connect generation and load in a market environment, whereas network congestion constrains optimal dispatch and results in sub-optimal market outcomes due to redispatch interventions. Therefore, to facilitate the realization of the adequate availability of transmission capacity in the right place on the right moment in time, generation capacities and the development of load profiles are considered to be the main uncertainties within TEP.

Chapter 3

Model Specification

3.1 Modelling objective

The role of uncertainty in the TEP-process can be primarily attributed to the uncertain development of load profiles and generation portfolios. Within the TEP-processs, these developments are translated into scenarios that are used as input in the market simulation and the subsequent network calculations. The combination of the market and network models are hereby describing the relationship between uncertainty and the identification of network bottlenecks.

Given that the deployment of industry standard models in combination with EM would prove to be a rather time-consuming and impractical approach in the development of this thesis, another modelling approach is required to assess the relation between uncertainty and bottleneck identification from the perspective of DMDU. Therefore, in relationship to the objectives of this thesis, a python model was developed in order to describe a simplified relationship between a scenario configuration and the identification of network bottlenecks. The remainder of this chapter describes the functioning of the model itself, whereas chapter 4 describes how the model is used in relation to the framework of DMDU.

3.2 Model description

The model represents the EHV network of the Netherlands that consists of two network parts operating at 380kV and 220kV respectively. These network parts are represented as a collection of buses that are interconnected by power lines. To include geographic variations in load and generation in the model, regional aggregations representing the 150kV and 110kv HV networks are included as single buses in the model. The network parts that operate at different voltage levels are interconnected through transformers that are present at a select number of stations.

Load flows are determined by the location of generation and load volumes within a network. An imbalance between load and generation at any location within the network causes power to flow from a generator source to the load location in accordance with Kirchhoff's circuit laws. The requested power volumes in the load and generation elements are time dependent; within the model these are derived from different time series. Loads within the model are derived from an exogenous time series, whereas generation is evaluated by a simplified endogenous allocation mechanism. The allocation mechanism minimizes the costs of the generation volumes that are required to balance the network and therewith provide the requested load.

The time dependent nature of the load and generation volumes within the model result in line loads that are time dependent as well. When the quantities and geographic locations of load and generation volumes vary over time, the center point and magnitude of line loads vary as well. The combination of load, generation and the technical specification network lines is used to calculate load flows which are in turn used to identify lines that are overloaded. Due to the dynamic nature of the line loads, the severity is assessed by a metric that includes the frequency and magnitude of line overloads over the year.

Exchange between different bidding zones through interconnection capacity is also implemented in the model. The electricity prices in foreign bidding zones are taken into account in the generation allocation mechanism. The exchange volumes are limited based on the available interconnection capacity and are represented as load and generation elements for export and import respectively. The model's network layout is visualized in figure 3.1.

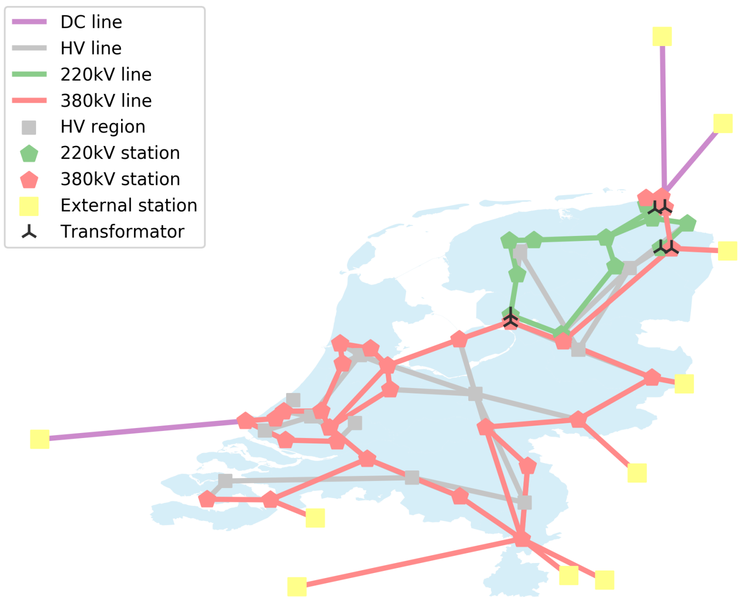

Figure 3.1: Modelled network layout

3.3 Model components

The physical building blocks of the model include load and generation elements, buses, lines and transformers. Due to the different network parts operating at different voltage levels, variations of the core building blocks are used to represent different components in the model. These variations represent the components that are present in the structure of the model and are visualised in figure 3.2. The individual components are described in the subsequent subsections, whereas the values used in the parameterization of the components are described in appendix A.

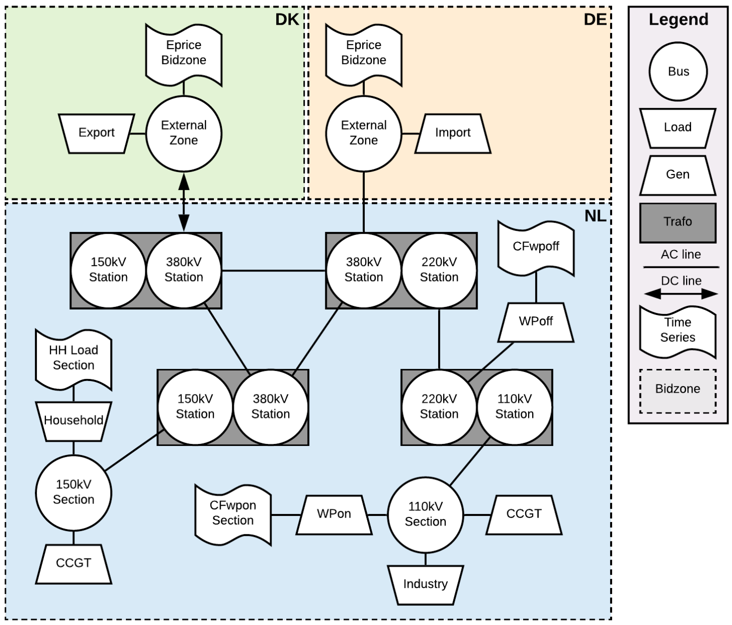

Figure 3.2: Model components

3.3.1 Buses

Buses are the physical nodes in the network to which all other physical components are connected. Each bus has its own voltage level at which it is operating. The model differentiates three categories of buses that can be operated at different voltage levels.

Stations

Nodes represent station in the EHV network and are thereby the most simple form of bustype present in the model. The model includes stations operating at 380, 220, 150 and 110kV. Stations operating at different voltage levels can only be connected through a transformer.

Network parts

Network parts in the HV network are depicted as buses in the model to reduce the complexity of the modelled transmission network. The underlying structure of a HV network part is aggregated to a single bus to which all model components operating at HV voltage levels are connected. The inclusion of these network parts enables the model to take transit flows into account. These network parts are not modelled in detail and therefore the loading of the lines in the HV network parts are not evaluated within this thesis.

External stations

External stations are bused in the EHV network that are connected to the Dutch EHV network, while being located outside the borders of the Dutch bidzone. These buses denote an aggregated representation of interconnected foreign transmission networks in an effort to reduce the complexity of the modelled transmission network. These buses are special cases as import and export volumes are sourced or sinked at these network nodes. Furthermore, it must be noted that the term 'external stations' is a non-conventional classification within electricity market modelling and is only used in the context of this thesis to limit the extend into which foreign bidding zones are depicted in the model.

3.3.2 Lines

Power lines are the edges in the network which connect the different buses to each other, thereby creating the network structure. Each line has its own length and a set of technical parameters determining its performance. There are two categories of lines included in the model:

AC lines

AC lines represent the most used line category in the model. The technical parameters of the line category includes the line's resistance, reactance and maximum current. The former three are considered in the load flow calculation, whereas the latter is considered in relation to the loading of the line.

DC lines

DC lines are a line category used for interconnection. The line category allows long distance load flows and transfers power in a single configured direction. Due to its configurable nature, the line cannot be overloaded as it only operates up to its maximum capacity. Its technical parameters include a capacity and a loss factor. By default, the lines are configured in an export direction within the model, which can also be reversed in the model. The specification of the directional orientation of these lines is due to current limitations in the PandaPower implementation.

3.3.3 Transformers

Transformers are network components that connect buses operated at different voltage levels. A transformer is thereby a conversion component of which its technical parameters primarily consists of loss-related factors.

The rated apparent power of a transformer, however, is considered in the load flow calculation. This factor is considered in relation to other transformers that converge from and to the same voltage levels and determines the relative power volume convergence at the respective transformers. Therefore, the technical specification of HV to EHV transformers is used to determine the transformation of load flows from and to network parts operating at different voltage levels.

3.3.4 Load

Load is a network component that represents a power demand in MW at a given point in time. Within the model, each network part has its own load element to express the power demand within the network part. This enables the allocation of different load volumes and/or patterns in different parts of the network. The load patterns within the model are expressed as time series that are based on historical Dutch load patterns. The total load is proportionally distributed over the network parts based on allocation ratios used within TenneT.

3.3.5 Generation

Generation is represented through generator elements that have a power output in MW at a given point in time. There are 13 different generator categories included in the model which are connected to the different (E)HV network parts. The default installed capacities of each of the generator categories are derived from the scenarios used in TenneT's latest investment plan (TenneT, 2017). The 13 generator categories are adapted from the PEMMDB generator classes and represent the following 10 generation technologies:

- nuclear
- hard coal
- open cycle gas turbine
- combined cycle gas turbines
- solar photovoltaic
- onshore wind power
- offshore wind power
- other RES
- other non-RES
- back-up

3.3.6 Capacity factors

Since the power output of VRES generators is dependent on weather related factors, the available capacity in MW at a given point in time is determined based on capacity factors. A capacity factor expresses the capacity utilization of a VRES generators based on a combination of weather conditions and the technological state of the installed technology (Pfenninger & Staffel, 2016; Staffel & Pfenninger, 2016).

The capacity factors for onshore wind and solar based generation capacity used in the model, geographically distinguishes the 12 provinces in The Netherlands, providing resolution at a NUTS-2 level with 12 different time series. The offshore wind time series expresses an average capacity factor for the North Sea area in The Netherlands. The technological state expressed in all capacity factors is based on current generation technology. The technological state of the capacity factors used in the model do not match with the state of technology in the year analyzed in this thesis. The power output of VRES generation, which is based on the state of technology in 2016, is therefore lower than could be expected in 2030. Furthermore, the NUTS-2 regions do not fully match with the HV network parts and therefore the capacity factors in the HV network parts are expressed as the mean value of the geographically covered NUTS-2 regions of the HV network part.

3.3.7 Bidding zones

Different foreign bidding zones are implemented in the model to include import and export flows in the network calculation. The external bidding zones included in the model are Belgium, Denmark, Germany, Norway and The United Kingdom. Each of these zones has a time series based electricity price that is considered in the allocation mechanism to determine if power is imported or exported in the model. This mechanism is described in more detail in Van Blijswijk (2017). The import and export volumes to and from the external bidding zones are maximized to respectively 60 and 100 percent of the maximum capacity respectively, concerning the interconnected AC and DC lines (TenneT, 2020).

3.4 Model functions

To determine the loading percentages of the lines in the network, the loads of the component are to be set before evaluating the network flow. This process consists of three steps: dispatch calculation, dispatch allocation and load flow calculation. Each of these function evaluations is explained in detailed in the subsequent sections.

3.4.1 Dispatch

A dispatch calculation is required to determine which generator classes are called upon to supply the requested load. In line within the current practice within the electricity market, the objective of the mechanism is to supply load at the lowest generation costs. The allocation of generation capacity is based on the costs function and the available generation power of each generator class during each time-step in the model.

Generation is allocated through a linear solver that uses a static costs function for all generation units within the Dutch bidding zone and a time series based electricity price for generation and/or load requirements in external zones. The solver takes into account the total required power volume of each load and/or generation related power element. This is expressed as the sum of all elements in of each category and is mathematically represented in equation 3.1.

$$P_m(t) = \sum_{x \in m} P_x(t) \tag{3.1}$$

where:

P = power output

x = power element

m = collection of power elements

The solver constraints the maximum volumes of each category to the maximum volumes of the generators in the network and the total sum of capacities within the interconnected lines for each external bidding zone. Subsequently, the solver sums each load, generation, import and export category to constrain the solution space. This is expressed in equation 3.2.

$$P_{load}(t) + P_{exp}(t) = P_{gen}(t) + P_{imp}(t) \tag{3.2}$$

where:

P = power output

m = collection of power elements

To determine the costs associated with generation dispatch and power exchange, the costs of each generation category, as well as the costs and revenue of exchange from each bidding zone are evaluated by multiplying the power volume with the associated costs of a single power unit. This is expressed in equation 3.3.

$$X_m(t) = \sum_{x \in m} P_x(t) * G_m(t) \tag{3.3}$$

where:

P = power output

X = dispatch costs

G = generation costs

x = power element

m = collection of power element

This implementation ignores cross-bidding-zone transit flows and assumes that imports do not influence the electricity price in other bidding zones. Exchange volumes are thereby optimized based on the time-series-based electricity prices in the different bidding zones and the available exchange capacity.

The objective function of the solver is defined as the sum of all costs minus the revenue from exports. The objective of the solver is to minimize the total costs of dispatch and return a combination of power volumes per generation category, including import and export volumes, within the specified constraints. The dispatch cost function is expressed in equation 3.4.

$$X(t) = X_{gen}(t) + X_{imp}(t) - R_{exp}(t) \tag{3.4}$$

where:

X = dispatch costs

R = dispatch revenue

m = collection of power element

It is important to note that the implementation of the dispatch mechanism is fairly limited. Since all generation elements within a generation category have the same standardized properties, dispatch is determined based on a generation category instead of a single generation unit. In reality, the price functions of generation capacity is dynamic, whereas the model assumes these are static. Both limitations affect the magnitude of dispatch within the price-clearing generation category and thereby affect the accuracy of load dispatch within the model.

3.4.2 Dispatch allocation

Based on the returned dispatch per category, the power volumes of the individual generators and external stations have to be set. This step requires the allocation of the dispatched power volume per category to the dispatched power volume per generator and external station. Within the model, it is assumed that, the load per generator is calculated by the division of the product of the total dispatch of a generation category and maximum output of the respective generator by the maximum generation volume of the category. This is expressed in equation 3.5.

$$P_x(t) = \frac{P_m(t) * Q_x(t)}{Q_m(t)} \tag{3.5}$$

where:

$$P = \text{power output}$$
$$Q = \text{maximum power output}$$
$$x = \text{power element}$$
$$m = \text{collection of power element}$$

Equation 3.5 ensures that all fully utilised generation categories have generation units dispatching at maximum output and that the generation units within the market-clearing category are operating at output levels proportional to the utilization level of that category. Generation units that are not called upon by the allocation mechanism are set to have a power output equal to zero. Import and export volumes are set in a similar fashion at the external nodes. When bidding zones connected through DC lines are exporting to the Dutch bidding zone, the orientation of the DC line is inverted.

The solver is configured to favour domestic generation over import when the price of cross-zonal power exchange and generation are equal. This is implemented by introducing a small wheeling charge, making import and export a bit more expensive than domestic generation. Whenever price levels between different categories within the solver are equal, the solver allocates power volumes proportionally based on the available capacity within the category. In cases of cross-bidding-zone power exchange, the solver only considers the net exchange position of the respective bidding zones, thereby excluding simultaneous import and export over different exchange nodes within the network.

3.4.3 Network calculations

The dispatch procedures ensure that the network is balanced and the sum of all power elements equals zero. Based on this state, the load flow calculation in the network can be evaluated to determine the line loading percentages of the power lines in the network. To evaluate the load flow, the model uses a lossless DC load flow calculation. The DC load flow calculation is chosen over an AC load flow calculation due to the latter's computational intensity. AC load flow calculation for a network of N nodes, requires the iterative solving of 2N non-linear power equations (Van den Bergh et al., 2014). Large numbers of AC calculations also increase the probability of non-converging power equations, interrupting the model evaluation. Van den Bergh et al. (2014) concluded that for high voltage grids, the accuracy of DC load flows calculations introduces an average error of around 5 percent compared to DC load flow calculations. However, deviations in individual lines can be larger, making it harder to draw conclusions about single lines in the network.

3.5 Input parameters

The model is configured to accept a limited number of input parameters to change properties of the different model components. Provided that the model evaluates network bottlenecks over a scenario, the input parameters are configured to describe configure a single scenario based on installed generation capacity and variations to the default load profile.

3.5.1 Installed generation capacity

In its default state, the model uses the default generation categories and capacities described in appendix A. The model's input parameters, however, accepts custom values that describe the installed generation capacities of different generation categories in different network parts.

3.5.2 Load profiles

The default load profiles in the model can be modified through the specification of load variation values. These specifications add the specified variation value to each hour in the default load profile. The model accepts the specification of load variation values for the load profiles present in the different network parts.

3.6 Outcomes of Interest

The primary goal of the model is to evaluate the network flow and assess the loading percentages of the individual power lines and the network in order to gain insight in the required network investments. The assessment of required network investments are based on different contextual aspects. The subsequent sections specifies these contextual outcomes of interest and describes the network aspect that they aim to capture.

3.6.1 Overload scores

The equation to determine the overload of an individual line is specified in equation 3.6. Overloading at a single point in time is given by the magnitude of overload, which is expressed as the loading percentage that exceeds the maximum loading percentage of the line. Therefore, whenever the line loading does not exceed the maximum loading of the line, the overload of the line equals zero. As the model evaluates the line loading in every time step, the overload score is the sum of the overload scores of the line in every time step. The outcomes of the each line can be considered in relation to each other, indicating the relative position of a line in term of overloading.

$$H_l(t) = a_x(t) - 1, \quad a_x(t) = \begin{cases} \frac{L_l(t)}{M_l}, & \text{if } L_l(t) > M_l \\ 1, & \text{otherwise} \end{cases} \tag{3.6}$$

$$H_n = \sum_{l \in n} \sum_{t=1}^{t_{max}} H_l(t) \tag{3.7}$$

where:

H = overload score
L = loading percentage
M = maximum loading percentage
l = line element
n = collection of line elements
a_x = dummy variable

Provided that different experiments are considered in relation to each other, the overloading scores of the lines are aggregated to the network level by taking the sum of the overload scores of the lines in the network. This aggregated score makes it possible to assess the relative overloading of a network in comparison with other networks configurations as is expressed in equation 3.7.

3.6.2 Costs of network investment

Similar to the approximation of the investment costs of generation capacity, the investment costs of network expansion can be approximated. Based on the magnitude of overload, different types of capacity measures can be considered. The costs of addressing small overloads of a short, low capacity line are significantly lower than the costs to address large overloads on long, high capacity lines. Both the required length of the line and the required additional capacity of the line have to be considered in order to approximate the required line investment costs. To calculate the capacity requirement of a single line, the maximum capacity of a single line must be determined. The calculation of the maximum capacity of a line is expressed in MVA in equation 3.8.

$$K_l = V_l * I_l * \sqrt{3} \tag{3.8}$$

where:

K = loading capacity
V = voltage level
I = maximum rated current
l = line element

Through the subsequent multiplication of the maximum line capacity and the maximum overload score of a line, the required additional capacity of the line can be calculated. Together with the length of the line, the associated investment costs can be approximated based on capacity and length related costs constants. The line investment costs are expressed in equation 3.9. Similar to the overload score, the line investment cost can be aggregated to the network level by taking the sum over all the individual lines.

$$Y_l = S_l * K_l * c + A_l * d \tag{3.9}$$

where:

$Y =$ investment costs
$S =$ maximum overload score
$K =$ loading capacity
$A =$ line length
$l =$ line element
$c =$ capacity cost constant
$d =$ length cost constant

3.6.3 Investment impact score

In an investment assessments, more factors are considered than the overloading score of the line alone. Lines can run through densely populated areas or through protected natural environments. In a trade-off between investment locations, the impact of these aspects are relevant to consider as well. Therefore the model allocates an impact score to each line representing social and environmental impact per line; this is based on the line requirement expressed in MWkm (Van Blijswijk, 2017). The investment impact score is expressed in equation 3.10. The investment impact score cannot be summed due its non-numeric nature. Therefore, when aggregating, the score has to be interpreted in terms of frequency counts. The described impacts scores are not based on real data and are hereby not representative.

$$J_l = b_x, \quad b_x = \begin{cases} \text{none}, & \text{if } 0 < S_l * K_l * A_l \leq 0.5 \\ \text{low}, & \text{if } 0.5 < S_l * K_l * A_l \leq 5 \\ \text{medium}, & \text{if } 5 < S_l * K_l * A_l \leq 50 \\ \text{large}, & \text{otherwise} \end{cases} \tag{3.10}$$

where:

$$J = \text{investment impact score}$$
$$S = \text{maximum overload score}$$
$$K = \text{loading capacity}$$
$$A = \text{line length}$$
$$l = \text{line element}$$
$$b_x = \text{dummy variable}$$

3.6.4 Generation-related emissions

Based on the installed capacity in each generation category, it is possible to assess the emissions related to the dispatch of generation capacity within the network. The total emission per category is represented by the sum of all emissions per generation unit within the category summed over the different time steps in the model. The equation to calculate the emissions per generation class is expressed in equation 3.11.

$$E_m = \sum_{x \in m} \sum_{t=1}^{t_{max}} (P_x(t) * e_m) \tag{3.11}$$

where:

$$E = \text{total emissions}$$
$$P = \text{power output}$$
$$e = \text{emission constant}$$
$$x = \text{power element}$$
$$m = \text{collection of power elements}$$

In order to determine the emissions on the network level, the sum of the emissions for all emission categories must be calculated. The emission on the network level can be used to assess the sustainability of a network and is mainly considered in relation to other outcomes of interest.

3.6.5 Costs of generation capacity

The additional required generation capacity per generation category can be calculated as the difference between the generation capacity per generation category in the network and the generation capacity per generation category in a reference situation. Based on these differences, the costs associated with the additional generation capacity can be approximated by the multiplication of the required additional generation capacity with the corresponding overnight capital costs of the generation category. This calculation provides an rough insight into the investment involved with the generation side of the electricity system and is expressed in equation 3.12.

$$Z_m = \sum_{x \in m} (W_x - T_x) * f_m \tag{3.12}$$

where:

Z = generation investment costs
W = installed capacity
T = reference capacity
f = overnight capital costs
x = power element
m = collection of power elements

Based on the costs per category, it is possible to determine the costs of the additional generation capacity for the entire network by taking the sum of the different costs of each category.

3.7 Exploratory modelling workbench

The EM workbench is used to perform different experiments on the model. In this setup, the workbench is configured to sample experiment configurations from the input space that is specified in chapter 4. Each of the sampled experiments details the configuration of the input parameters under which the workbench calls upon the model. After evaluating the model under the configuration of the experiment, the workbench stores both the experiment configuration and the model's outcomes of interest. This process is repeated until all experiments have been evaluated, resulting in a dataset that links points in the model's input space to points in the model's output space.

3.8 Representative days

To limit the evaluation time of the model, the model evaluates a limited number of hours in relation to the selected reference year. Given the large number of experiments that are inherent to the experiment design described in chapter 4, the time required to evaluate the experiments would exceed the time budget that is available for this research.

To reduce the number of evaluated hours, weighted representative days have been selected to describe typical hours within the time series of the selected reference year. Since the model uses different time series, the identification of representative days requires an advanced approach that is able to capture interaction effects between different time series. Therefore, the selection of reference days within this thesis is based on the hybrid reference day selection approach described by Poncelet et al. (2017). This approach randomly selects a prespecified number of reference days that is followed by an optimization of the relative weight that is assigned to each of the selected days. Based on the method described by Poncelet et al. (2017), five weighted reference days have been selected to represent the selected reference year. The selection process and the resulting time series are described in appendix B.

3.9 Network redundancy

The calculations involving the assessment of the regulatory redundancy requirements described in chapter 2 scales exponentially over the different redundancy criterion. Even under a limited number of scenarios, the redundancy requirement would introduce numerous of model evaluations that would each have to be evaluated over the duration of a entire reference year.

To reduce the number of model evaluations within a single model configuration, the redundancy calculations are limited to a simplified representation of the normal operation criterion. The maximum line loading of each of the AC lines in the model is set to 60 percent of the thermal capacity of the line to approximate network operation under the normal operation criterion. By excluding the 'single malfunction' and 'single malfunction during maintenance' redundancy criterion, the network model is evaluated only once per configuration, reducing the required computation time by $n + n^2$ times, where n represents the number of lines.

3.10 Verification and validation

Please note that the verification of the described model is limited to the assessment of power volume balances. Based on the assessment of the power volumes the model functions as intended. Barring small rounding errors, the summed volumes of all power elements equals zero during each time step of a model evaluation. Thereafter, the power allocation mechanism allocates the appropriate power volumes to the model's generation, import and export elements given the capacity factor, load and exchange related constraints in each time step.

The model is able to identify network bottlenecks through a simplified process that resembles the market simulation and network calculation aspects of the TEP-process as described in chapter 2. The system outlook aspect of the TEP-process is an integral part of the DMDU and is addressed in chapter 4, while the risk assessment and strategy formulation aspects are the results of the analyses that are based on the model results. The latter two aspects, however, are not the primary focus of this thesis. Even though the model has not been historically validated, the model is able to conceptually represent the aspects of the TEP-process that are relevant in the context of this thesis. The model is therefore considered valid for the purpose of this thesis.

Chapter 4

Experiments

4.1 Objective

The TEP-model described in chapter 3 provides the possibility to evaluate network bottlenecks in relation to a prespecified scenario. However, within the framework of DMDU the aim is to evaluate a model under a multitude of different configurations. In the case of bottleneck identification this in done by exploring the uncertainty space through the evaluation of different unique scenarios.

This chapter therefore describes the configuration of the selected DMDU approach under which the model described in chapter 3 is evaluated. The EM workbench is used to evaluate the described DMDU configuration and to subsequently explore the effects of the specified uncertainty space in relation to the identification of network bottlenecks. To reduce the dimensional complexity of the analysis, the defined uncertainty space is limited to only include uncertainties related to the development of installed VRES generation capacity and the development of load profiles.

4.2 Uncertainty space

The main category of uncertainty within the TEP-model encompasses the installed capacity of VRES generation at different stations or network parts in the (E)HV network. The model contains a total of 72 VRES parameters that are related to installed generation capacity of which 42 are regarded to be uncertain. The remaining 30 parameters represent stations or network parts that are presumed unlikely to function as access points for certain VRES categories, e.g. an offshore wind park that is connected to an HV network station in the province of Limburg.

The different load profiles of the 12 network parts in the HV network are furthermore regarded as uncertainties. The uncertainty related to these profiles is expressed in the load variation input parameter of the TEP-model. Within the TEP-model, there are no load profiles specified that are directly connected to stations in the EHV network itself. Therefore, there are no load variation parameters specified for stations in the EHV network.

In total, the uncertainty space covers 54 uncertainty parameters. Each of the parameter values is expressed in the number of MW on an integer-based ratio scale. The uncertainty ranges of each uncertainty parameter are detailed in appendix A and is briefly described in table 4.1. The ranges of the installed capacity of VRES generation are specified as a 50 to 200 percent bandwidth of their respective default parameter values.

Table 4.1: Summed uncertainty bounds in MW

Uncertainty Bound	**Solar Photovoltaic**	**Wind Offshore**	**Wind Onshore**	**Load Variation**
Lower	15136	5628	3924	-998
Upper	60546	22513	15692	998

The uncertainty bandwidth spans an arbitrary range that covers extremes in the uncertainty space of what is deemed possible in the realization of VRES capacity towards 2030. Increasing or decreasing the range, or even the specification of individual bandwidths per uncertainty parameter affect the degree in which extremes in the uncertainty space are considered within the experiment. Given the exploratory nature of the analysis, the initially analyzed uncertainty space is specified over a relatively large range.

4.3 Open exploration

Given that the TEP-process aims to assess the effects of uncertainty, an open exploration configuration is selected to explore the defined uncertainty space. To this end, the selected open exploration approach combines the DMDU building blocks of 'generation of scenarios' and 'vulnerability analysis'. The subsequent sections describe the configuration of the individual building blocks.

4.3.1 Generation of scenarios

The exploratory nature of the open exploration configuration aims to provide insight in the global properties of the entire uncertainty space. Therefore Latin hypercube sampling is selected as a method to sample scenario configurations from the uncertainty space. The selection of Latin hypercube sampling ensures that the set of sampled scenarios is representative of the real variability in the uncertainty space and thereby also covers the 'extremes' or 'edges' within the uncertainty space (McKay et al., 1979). A two-dimensional example of a Latin hypercube sampled set is visualized in figure 4.1.

Establishing the required number of scenario configurations is somewhat of an educated guess. Whether an appropriate number of scenarios has been evaluated is retrospectively assessed in the different vulnerability analyses. Specifying the

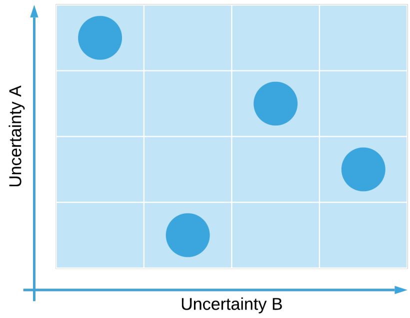

Figure 4.1: Example of Latin hypercube sampling

number of scenarios is therefore based on experience and trail-and-error. In this thesis, a sample size of 20.000 scenarios is selected as a starting point.

4.3.2 Sensitivity analysis

Sensitivity Analysis (SA) is used to identify model uncertainties that have the largest impact on the outcomes of interest. Therefore, SA is used to reduce the number of uncertain input parameters and thereby to reduce the dimension complexity of the uncertainty space. The reduced number of uncertain input parameters can subsequently be used to specify scenarios during subspace partitioning.

Global sensitivity analysis

To determine the importance of each input parameter across the domains of all other model parameters, a global SA approach is regarded as the most appropriate (Liu & Homma, 2009). Due to the large number of input parameters that span the uncertainty space, a full variance-based Sobol analysis is too computationally expensive. Screening methods like Morsis' elementary effects and feature scoring inspired by machine learning provide computationally less expensive alternatives. Based on Jaza-Rozen & Kwakkel (2017), the use of the extremely randomized trees (Extra-Trees) configuration is selected to be used as a global SA method. The decision-trees-based feature scoring method represents an adequate trade-off between the number of uncertainties to be evaluated and the provided accuracy that can be achieved within a limited time budget.

Factor prioritization

The global SA provides the relative importance for each of the uncertainty parameters but does not specify which uncertainty parameters can be excluded to reduce the dimensional complexity of the uncertainty space. To determine the cut-off point between significant and insignificant uncertainty parameters, this thesis uses the 'knee-point' to classify the uncertainties in the respective categories. The knee-point represents the point where the addition of another uncertainty parameter would result in a relatively small increase in explanatory power. The point is based on the maximum curvature in a graph and therefore represents an extreme point of the second derivative.

4.3.3 Scenario Discovery

Scenario discovery (SD) is used as a subspace partitioning technique. The technique is used to partition the uncertainty space into distinct regions that determine a specific type of model outcome. These regions within the uncertainty space represent the scenario conditions under which a desired or undesired outcome occurs.

Regional sensitivity analysis

Based on the specified region of interest within a model outcome, the relative sensitivity of the remaining uncertainty parameters can be assessed through a regional SA (Pianosi et al., 2016). In the regional SA, the outcomes within the model outcome are divided into two binary sets; a set that contains the outcomes inside the region of interest, and a set that contains the remaining outcomes, i.e. a 'behavioural' and a 'non-behavioral' set. The comparison of the sets provides insight into the behaviour of the uncertainty parameter and helps to assess the relative importance in relation to the specified region of interest. An uncertainty parameter can thus be relevant to describe the model outcome in the global SA, while being irrelevant when describing the region of interest within the model outcome in a regional SA.

Patient-Rule Induction Method

The identification of subspaces within the uncertainty space requires a partitioning method that is able to find the conditions under which a certain range of model outcomes occurs. One of these methods is the Patient-Rule Induction Method (PRIM). The method aims to identify concentrations of parameter configurations within the uncertainty space that are within the region of interest (Bryant & Lempert, 2010). The PRIM algorithm sacrifices 'coverage' of the specified outcomes of interest in that are inside the uncertainty space in a trade-off resulting in an increase in 'density' of outcomes of interest inside the identified subspace by incrementally reducing the size off the subspace. This results in a trade-off trajectory in which one can select a subspace that represents a desired trade-off. The parameter ranges of the selected subspace describe the scenarios under which the outcomes of interest are most likely to occur.

Chapter 5

Model results

5.1 Model evaluation

The experimental design is evaluated on a high performance cluster. The generated dataset contains the configuration of each of the 20,000 sampled scenarios and the model's outcomes of interest in each configuration. The overload score, the investment costs and the investment impacts scores are evaluated on a per-line basis, whereas the carbon emissions and costs of generation capacity are evaluated on a per-scenario basis. Since several of the outcomes of interest are evaluated on a per-line basis, the generated dataset provides the possibility to analyze the EHV network in various levels of detail.

Within this chapter, three levels of detail are discussed: a global network perspective, a station perspective and a line segment perspective. To demonstrate the EM-process, the results of the analyses on the network level are discussed in detail, whereas the results of the analyses on the remaining two levels are discussed in a more concise manner. Furthermore, the analyses in this chapter primarily focuses on the overload score as a means to demonstrate the analytical possibilities of the different analyses, rather than providing a repetition of steps for each individual outcome of interest.

5.2 Outcomes of interest

The bandwidths of the outcomes of interest can be visualized in box plots. A box plot is represents data in terms of quartiles, in which the colored and whiskered areas respectively represents 50 and 99.3 percent of the confidence interval of the probability density function of the data. The line in the colored area represents the median of the data and the points outside the whiskers represents the 0.7 percent of the data points that are considered to be outliers. Each box plot in this chapter contains 20,000 data points that are based on the line information of the evaluated dataset of 20,000 scenarios.

5.2.1 Line scores

The results of the outcomes of interest that are related to the lines in the network are visualized in figure 5.1. The results are based on the sum or frequency of the different types of outcomes of the individual lines. The spreads in the box plots seem relatively narrow given the large spread in the uncertainty parameters with high probability densities around their median values. Notable are the investment impact scores of the lines, where around 25 lines seem to explain the capacitylength demand in the results. Most lines require no capacitylength, whereas there is a negligible amount of lines that requires small or medium amounts of capacitylength. These outcomes would suggest that a select few lines are being overloaded in the model.

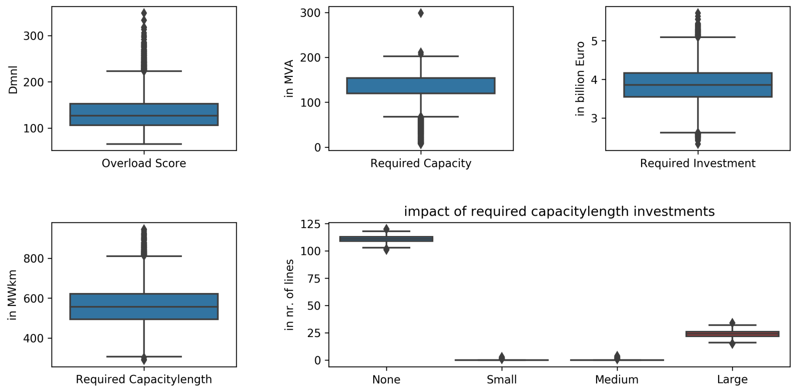

Figure 5.1: Line scores

5.2.2 Carbon emissions

The cumulative carbon emissions of the carbon-emitting generation categories in the model is visualized in figure 5.2. Only the newest gas-based generation plants within the model are responsible for emissions in the different scenarios, meaning that the other generation categories are not being dispatched. The spreads in the box plots suggest that the generation category is only dispatched as a market-clearing generation category.

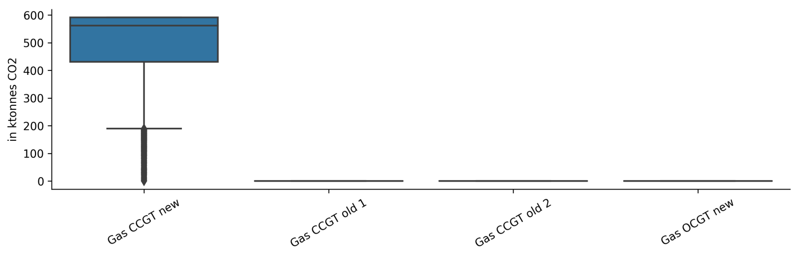

Figure 5.2: Carbon emissions

5.2.3 Overnight capital costs

The generation investment costs over the different scenarios are visualized in figure 5.3. The results show that only the VRES categories within the uncertainty space are varied over the different scenarios. Furthermore, there is no technological investment between 2020 and 2030 other than 'gas CCGT new', thereby confirming the generation portfolio configuration detailed in appendix A. Thereafter, the figure visualizes the distribution of installed VRES generation capacity samples as the outcomes are linearly scaled to the overnight capital costs factors.

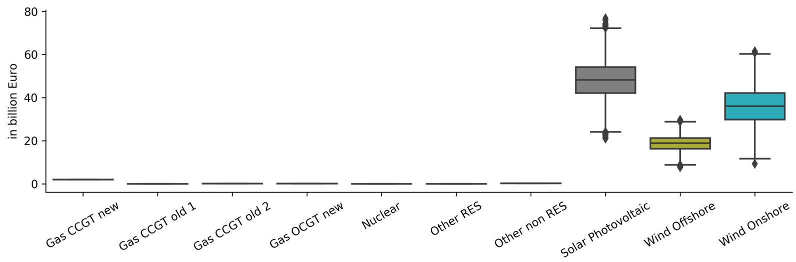

Figure 5.3: Overnight investment costs

5.3 Topological overview

The line related outcomes are visualized based on the network configuration. These types of visuals help to locate the geographic location of overloads and help to identify whether multiple neighboring lines are affected as well. Within the visualizations, the DC lines are depicted although their outcomes are not considered, as it is impossible in the model to overload DC-lines. The overload scores of the network are colour coded based on relative performance. The darker coloured lines represent the relatively highest scoring lines. In order to compare different topological overviews it is important to consider the absolute line scores as well. The absolute scores of the lines can be derived from the colourbars on the right side of the respective figures.

5.3.1 Average overload score

The calculated average overload scores is visualized in figure 5.4. The average score of each line is calculated as the average of the maximum overload score in each of the evaluated scenarios. The overload scores depicted in the colourbar of the figure concerns the overload fraction. The overload scores in the network are therefore on average mostly constrained within the range of 0 to 100 percent. There are several outliers with high overload scores; these outliers are between Ens and Diemen, between Dodewaard and Boxmeer, around station Dodewaard and between Maasbracht and Eindhoven.

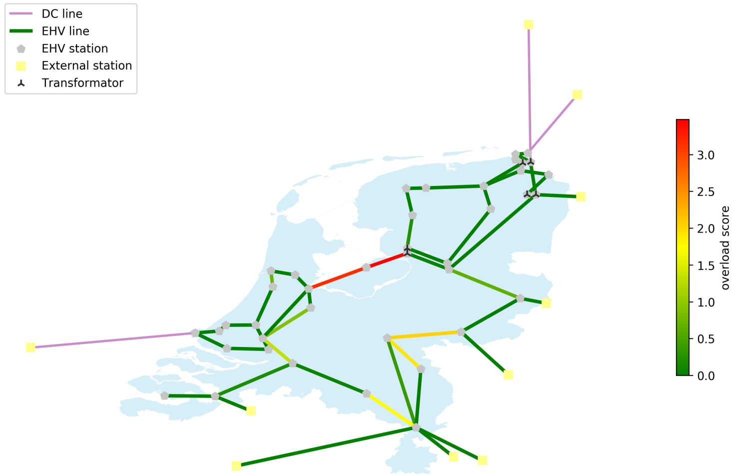

Figure 5.4: Average line overload scores

5.3.2 Maximum overload score

Figure 5.5 depicts the maximum overload scores of each line. The maximum overload score of each line is calculated as the maximum overload score of the maximum overload score in each scenario. The maximum overload scores represent the worst-case scenario of each line; note that the selected maximum does not include simultaneity of the score for each line. Notable areas with extremely high overload scores are the lines between Geertruidenberg and Krimpen a/d IJssel, the lines between Ens, Lelystad and Diemen and the lines between Maasbracht and Eindhoven. Furthermore it is noteworthy that the absolute overload scores go up to 800 percent with the (light) green areas representing overload scores up to 300 percent.

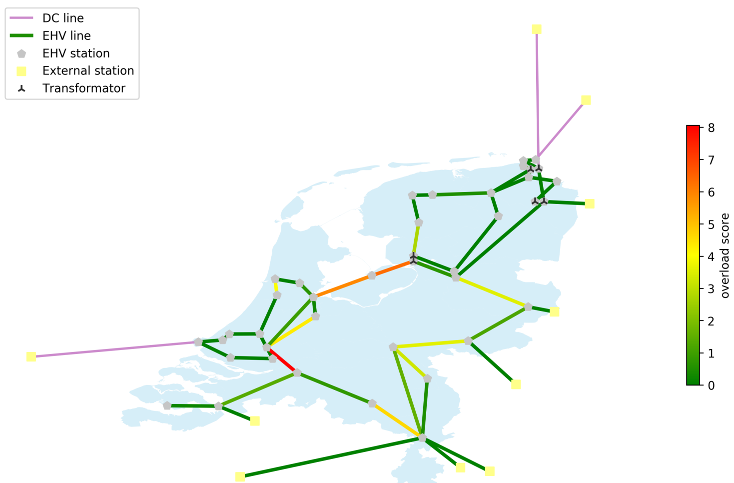

Figure 5.5: Maximum line overload scores

5.4 Network Sensitivity

The sensitivity of the model's outcomes of interest in relationship to the specified uncertainty space is expressed in feature scores. The feature score describes the amount in which a parameter contributes to the specified outcome of interest. The score is defined as a fraction of the total outcome of interest and therewith represents a percentage score. Since the score is based on a statistical learning algorithm, the reliability of the score is assessed based on replications. The calculation of the feature score is replicated 100 times and visualized in box plots to visualize the confidence intervals of the feature scores.

5.4.1 Aggregated feature scores

The aggregated feature scores of the different uncertainty categories is visualized in figure 5.6. With a score of around 70 percent, the offshore wind power uncertainty category explains most of the overload scores observed in the different scenarios. The contribution of photovoltaic capacity is situated at around 20 percent, whereas installed onshore wind power volumes and load variations seem to contribute almost nothing to the overload score. The small confidence intervals of the box plots furthermore suggests an adequate number of samples to produce reliable SA results.

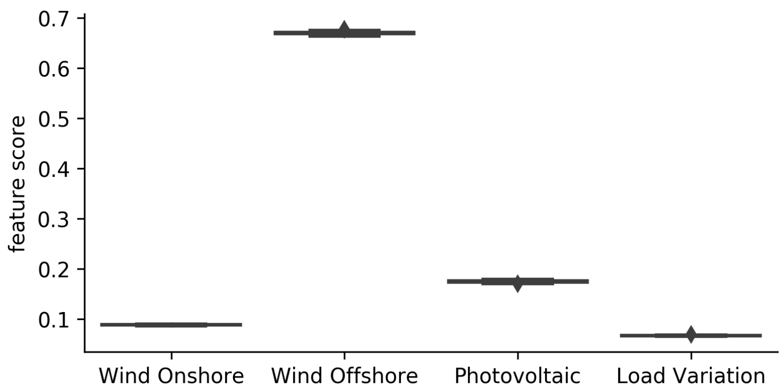

Figure 5.6: Aggregated feature scores

The high feature score of offshore wind power means that the magnitude of the overload score is primarily attributed to offshore wind related power volumes. Based on figures 5.4 and 5.5 this might be a rather surprising result, as the high overload scores are not observed around the coastal offshore wind feed-in point within the network. To further investigate the origin of the high feature score attributed to the offshore wind category, one can look at the individual feature scores of each uncertainty parameters.

5.4.2 Individual feature scores

The individual feature scores of the different uncertainty parameters are visualized in figure 5.7. The results show that the overload score can almost entirely be contributed to the installed offshore wind capacities that are connected to the 380kV stations in Beverwijk and Borssele at 30 and 25 percent respectively. The remaining 45 percent is distributed more evenly over the other uncertainty parameters with small peaks for offshore wind at the 380kV station in Maasvlakte and for solar photovoltaic in regional networks of Noord-Holland and Limburg.

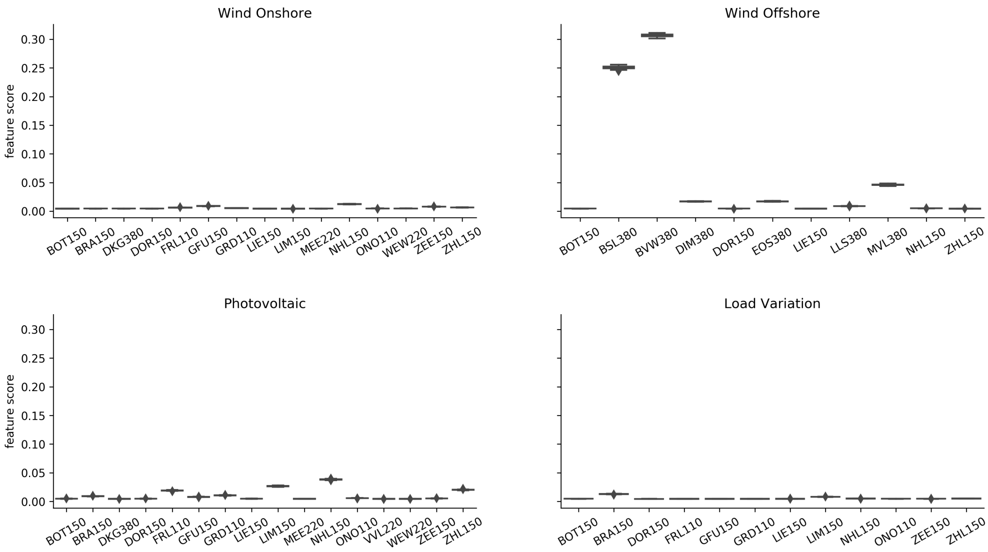

Figure 5.7: Individual feature scores

The high feature score of offshore wind capacity in Borssele is especially notable when considered in relation to the location of high overload scores in figures 5.4 and 5.5. The capacity connected to Borssele is not causing high overloads in the power lines within the station's immediate proximity, but rather elsewhere in the network. Furthermore, the number of high impact uncertainty parameters is limited, meaning that there are a lot of uncertainty parameters that can be ignored when considering network overloading. Factor prioritization can thus be applied to reduce the number of uncertainty parameters considered in relation to overload scores within the network.

5.4.3 Factor prioritization

The application of the knee point criterion in relation to factor prioritization is visualized in figure 5.8. This results in a cut-off point after 5 uncertainty parameters, thereby reducing the uncertainty space with 49 uncertainty parameters, i.e. the uncertainty space is constrained to only include 5 dimensions. The five relevant uncertainty scores are the five notable uncertainty parameters discussed in the previous subsection, representing a cumulative feature score over 65 percent.

The combination of global SA applied in this section demonstrate how the significant uncertainty parameters within the specified uncertainty space are identified. This information can in turn be used to reduce the dimensional complexity

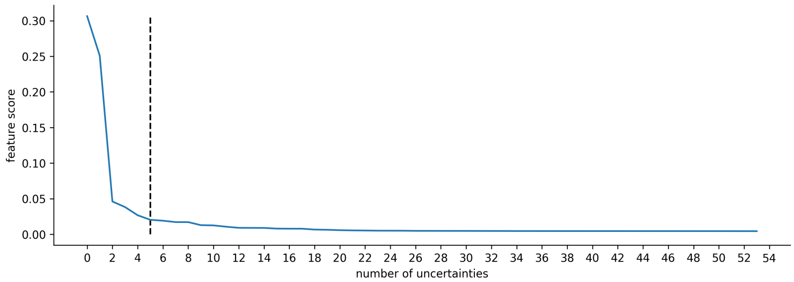

Figure 5.8: Uncertainty cut-off point

of bottleneck identification can be reduced with factor prioritization and help to focus an analysis. The global SA method therefore provides the tools to identify relevant uncertainty parameters based on the effects observed in the model, rather than on their estimated importance in traditional scenario planning approaches.

5.5 Scenario discovery

The reduced dimensional complexity of the uncertainty space reduces the number of uncertainty parameters that can be used to describe scenarios under which certain types of outcomes occur. To eliminate the noise that is introduced to the model evaluation dataset, the model is reevaluated under the reduced number of uncertainty parameters, fixing the irrelevant uncertainty parameters at their default values. However, due to time limitations, the results in the subsequent sections are based on the original dataset and include the aforementioned noise.

5.5.1 Cases of interest

This section describes the identification of a worst-case scenario and is thereby interested in the worst-case overload scores. The worst-case overload scores are defined as the scores that are greater or equal to the 90th percentile value of the overload score and represent the tale of the distribution plot. The distribution plot and the 90th percentile are visualized in figure 5.9.

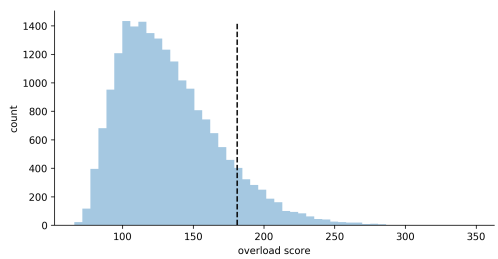

Figure 5.9: Distribution plot of overload score

5.5.2 Regional parameter sensitivity

The regional sensitivity of the remaining uncertainty parameters is visualized in figure 5.10. The results show that the outcomes of interest are most sensitive to the scores of offshore wind power uncertainties and to a lesser degree to the scores of photovoltaic-related uncertainties. The contributing effects of offshore wind in Beverwijk and Borssele are almost completely opposite to each other. This suggests that there might be an interaction effect between the two parameters that results in worst-case outcomes.

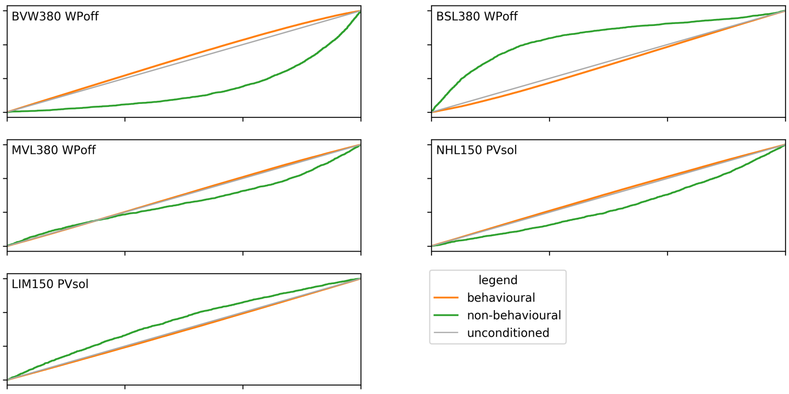

Figure 5.10: Regional sensitivity of uncertainty parameters

The interaction effects suggest a conditional overload in a single, or indeed within in multiple lines in the network. The results in figure 5.10 suggest that a high volume of installed offshore wind capacity in Beverwijk in combination with a low volume of installed offshore wind capacity in Borssele might result in a high network overload score. The relationship between both parameters can be further explored through subspace partitioning helping to identify the conditions under which the parameters result in high overload scores.

5.5.3 Subspace partitioning

The trade-off trajectory of the PRIM algorithm is visualized in figure 5.11. The trade-off in the trajectory is fairly steep, as the algorithm was unable to identify boxes with both relative high coverage and high density. The unfavorable trade-off curve is potentially related to the noise introduced by the excluded uncertainty parameters or to the relative orientation of uncertainty parameters and PRIM's ability to capture the outcomes of interest in a squared shape.

To explore the relative orientation of the uncertainty parameters, a box within the trade-off trajectory of the PRIM algorithm is selected. The parameters inside the box are plotted against each other in figure 5.12, where the red box in the pair plots represents the dimensions of the selected PRIM-box, and the orange dots the cases of interest.

Based on visual inspection, the orientation of the uncertainty parameters seems not to favor being captured in a square shape. This means that the PRIM-

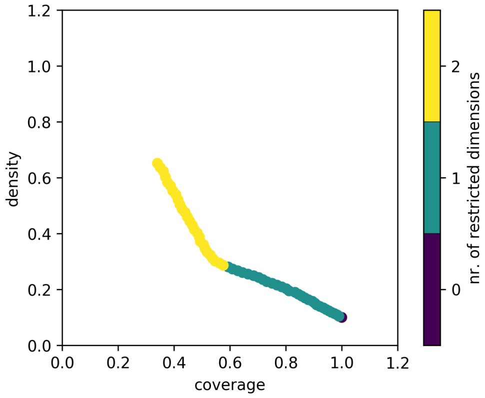

Figure 5.11: PRIM trade-off trajectory

algorithm is unable to capture high concentrations of parameter configurations that represent cases of interest. An alternative approach is required to better orient the uncertainty parameters, and thereby improving the ability of the PRIM-algorithm to identify boxes with higher concentrations of cases of interest.

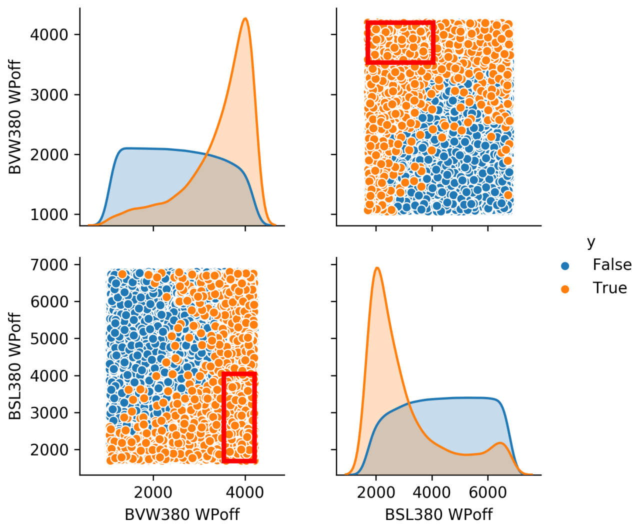

Figure 5.12: Pair plots of a random PRIM-box

5.5.4 Dimensional rotation

Rotation of the uncertainty parameters can help to improve the orientation of the uncertainty parameters. Dalal et al. (2013) describes how the Principle Component Analysis (PCA) rotation based pre-processing of the uncertainty parameters helps to improve the quality of the PRIM-algorithm. They furthermore suggest constraining rotations to groups of similar parameters in order to improve the interpretability of resulting scenarios. Figure 5.13 visualizes the constrained PCA (CPCA) PRIM trade-off trajectory.

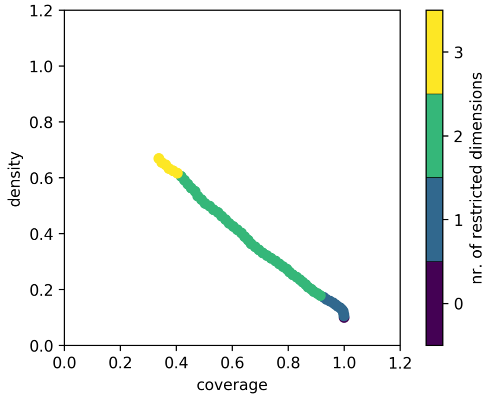

Figure 5.13: CPCA PRIM trade-off trajectory

Within the CPCA PRIM trajectory, the uncertainty parameters are grouped based on their uncertainty categories: offshore wind power and photovoltaic. Although still not representing an ideal trade-off, the trade-off trajectory improved in comparison to the regular PRIM trade-off trajectory. As visualized in figure 5.14, the orientation of the uncertainty parameters improved after the CPCA rotation.

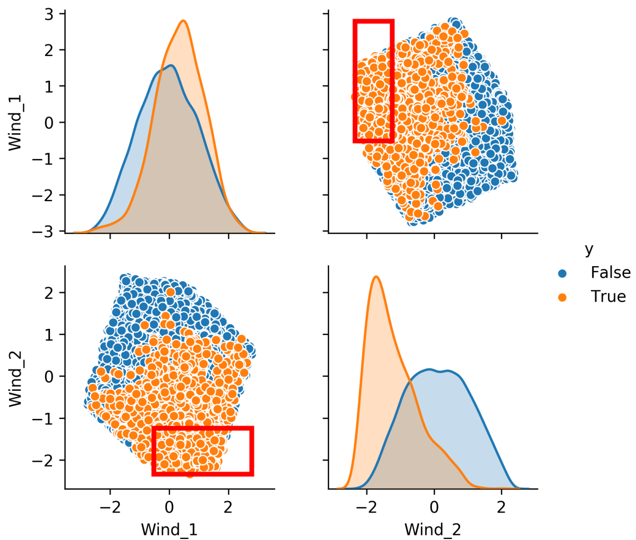

Figure 5.14: Pair plots of a random CPCA PRIM-box

The two principal components visualized in figure 5.14 show that especially the second wind component is able to capture a relatively large concentration of cases of interest. The distribution curve of the first wind component is almost identical to the distribution curve of the remaining cases, showing a relatively small deviating peak.

5.5.5 Network scenarios

Based on the improved CPCA PRIM trade-off trajectory, a coverage versus density trade-off is made by selecting a box in the middle of the trajectory. The selected box has a coverage and density score of 63 and 49 percent respectively. Sacrificing more coverage for the purpose of increasing density would result in more precise parameter bounds, while decreasing the number of cases of interest that are described. The bounds of the selected box are visualized in figure 5.15.

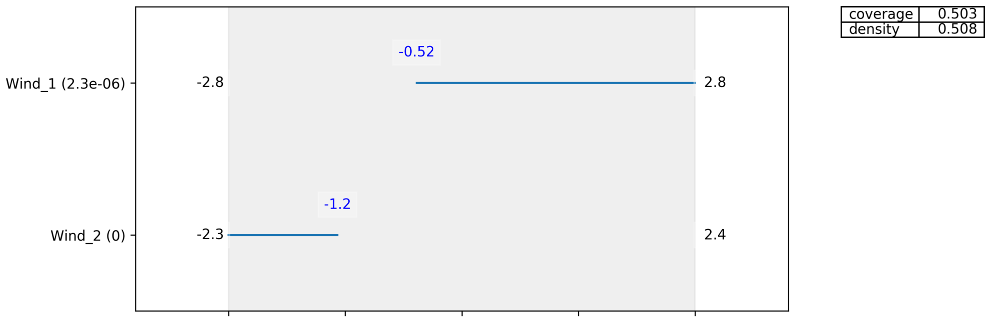

Figure 5.15: Worst-case scenario bounds

The resulting scenarios consists of two principal components that are based on the grouped wind parameters. Both principal components are described in table 5.1. The first principle component primarily consists of the installed offshore wind capacity that is connected to Borssele, whereas the second component primarily consists of the installed offshore wind capacity that is connected to Beverwijk.

Table 5.1: Loading values of principal components

Station	Wind PC1	Wind PC2
BVW380	-0.394	-0.885
BSL380	-0.709	0.464
MVL380	0.585	-0.035

The scenario boundaries of each principle component are interpreted as a linear functions that consists of the uncertainty parameters and their respective loading values. This function is described in equation 5.1. All parameter configurations within the range of each scenario boundary describe the specified cases of interest. The range of an uncertainty parameters is therefore described in relation to other uncertainty parameters. A scenario is thus best explained in terms of the parameter interactions that it describes.

$$B_{lower} < \alpha * U_1 + \beta * U_2 \dots \nu * U_n < B_{upper} \tag{5.1}$$

where:

$$\alpha = \text{loading value of uncertainty parameter}$$
$$B = \text{scenario bounds of principal component}$$
$$U = \text{uncertainty parameter in principal component}$$

5.5.6 Scenario interpretation

To interpret the scenario visualized in figure 5.15, the directions and magnitudes of the loading values in table 5.1 have to be considered. The first principle component describes a relationship between the direction of installed offshore wind capacity in Beverwijk and Borssele versus the installed offshore wind capacity in Maasvlakte. Worst-case outcomes occur whenever the volumes of offshore wind capacity in Beverwijk and Borssele increase in combination with a relative decrease of installed offshore wind capacity in Maasvlakte or vise versa. The precise relationship depends on the rotation and the scenario boundaries of the principal component. The second principle component describes a relationship between the installed offshore wind capacity in Beverwijk versus the installed offshore wind capacity in Borssele, where the loading factor of offshore wind capacity in Maasvlakte is considered too small to be significant. Therefore, worst-case outcomes are also characterized by a correlation between the installed offshore wind capacity in Beverwijk and the installed offshore wind capacity in Borssele.

The locations of high overloads visualized in figures 5.4 and 5.5 help to formulate a hypothesis about the aforementioned dynamics between the principal components. The consistent high overloads of the lines between Ens, Lelystad and Diemen is the result of the transmission of high volumes of electric power and thereby a relationship between the location of load and the location of generation in the network. The DC line in Maasvlakte is historically an export oriented line, which explains the negative impact of low volumes of offshore wind capacity that are connected to this station. Export volumes thus have to be transported in the network, causing overloads whenever offshore wind parks output large power volumes. Thereafter, offshore wind capacity in Beverwijk is probably exported towards Ens to be absorbed elsewhere in the network. A relative small percentage of installed offshore wind capacity in Beverwijk would then be compensated by offshore wind output that is generated in Borssele. Transmitting these large power volumes over a relative large distance in the network subsequently results in overloads throughout the network.

5.6 Local aggregation

Provided that the model evaluates the overload scores of each individual line, it is possible to assess individual lines as well as aggregations of custom regions.

Based on the results visualized in figure 5.4 and 5.5, the lines that are connected to Dodewaard and the line segment Ens-Lelystad-Diemen are interesting candidates to further explore and assess the validity of the scenario hypothesis formulated in the previous section. Exploring the line segments helps to verify which power sources contribute to the overloads, whereas analyzing Dodewaards helps to assess whether the overloads in that region can also be contributed to offshore wind power load flows.

5.6.1 Station Dodewaard

There are four different 380 kV lines connected to station Dodewaard within the TEP-model. The results of these lines have been aggregated to represent the Dodewaard station perspective.

Regional sensitivity

The results of the global SA are similar to the results of the global SA of the network level. The knee point criterion, however, reduced the number of relevant uncertainties even further to only include the three offshore wind related uncertainty parameters. However, as can be observed in figure 5.16, the regional SA of station Dodewaard resulted in different outcomes. The regional sensitivity effects of Borssele and Beverwijk are now no longer opposite to each other.

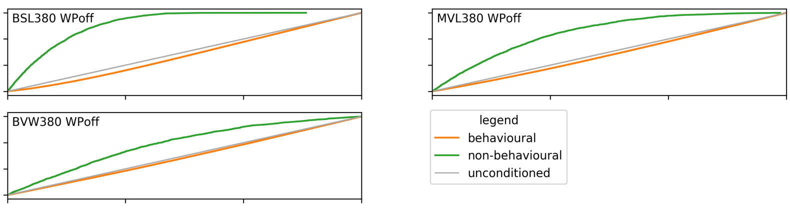

Figure 5.16: Regional sensitivity of uncertainty parameters

The presence of larger volumes of offshore wind capacities result in higher overloads around station Dodewaard. The relative spreads in the parameter scores demonstrates that the installed capacity in Borssele has the largest effect on the overload scores. The impact of Maasvlakte could be related to the degree in which power flows from the offshore wind capacity in Borssele is absorbed in the western region of The Netherlands, thereby decreasing the magnitude of line overloads around Dodewaard. This relationship can again be further explored through subspace partitioning.

Subspace partitioning

The trade-off trajectory in the subsequent worst-case PRIM analysis resulted in a much more desirable outcomes in comparison with the network level trade-off trajectory in figures 5.11 and 5.13. The trade-off trajectory could be further improved through PCA pre-processing of the data. The resulting trajectory is visualized in figure 5.17. Since the trade-off trajectory is less steep, it is now possible to select a box that has both a high coverage value and a high density value.

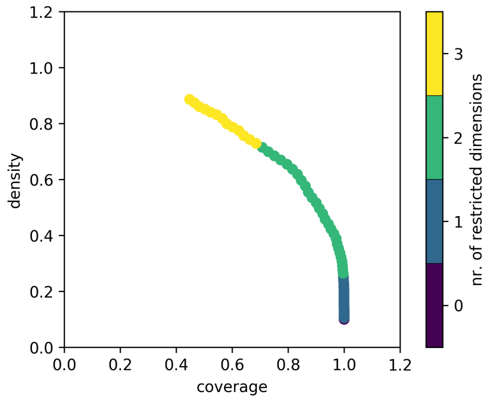

Figure 5.17: PCA PRIM trade-off trajectory

Scenario selection

Within the trade-off trajectory, a box was selected with a coverage and density score of 0.708 and 0.715 respectively. Both the coverage and the density are relatively high and thereby describe a unique scenario that covers a high shares of the worst-case outcomes. The uncertainty parameter boundaries that describe the scenario are depicted in figure 5.18.

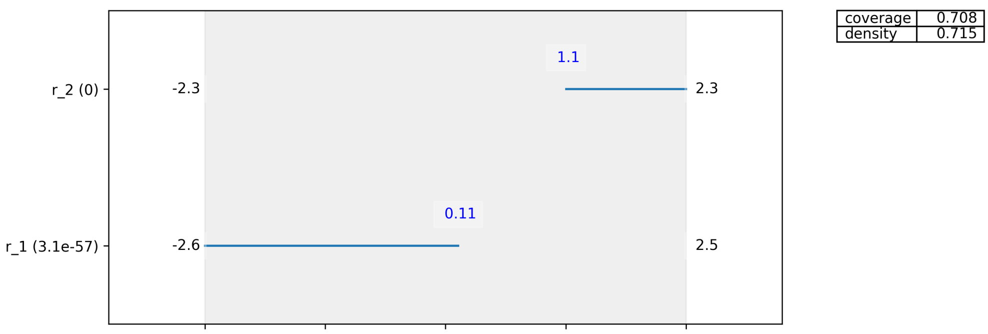

Figure 5.18: Worst-case scenario bounds

The resulting scenario again consists of two principal components and are described in table 5.2. The loads of both principle components describe the connected capacity of offshore wind power, where the first component is predominantly attributed to the volume connected to station Maasvlakte and the second component is predominantly attributed to the volume connected to station Borssele.

Table 5.2: Loading values of principal components

Station	**PC1**	**PC2**
BSL380	-0.279	-0.952
BVW380	0.319	-0.154
MVL380	0.906	-0.241

Scenario interpretation

Based on equation 5.1, the principal components describe where large volumes of offshore wind capacity in Maasvlakte in combination with small volumes of offshore wind capacity in Borssele result in worst-case outcomes. The availability of offshore wind capacity in the western part of The Netherlands seems to redirect offshore wind capacity power flows in Borssele via the power lines connected to station Dodewaard. Whenever the volume of offshore wind capacity in Borssele increases, the overloads in Dodewaard increase as well. This explanation strengthens the network scenario hypothesis, as it confirms that there is a relationship between the ability of the western part of The Netherlands to supply its demand, and the location where overloads in the network occur.

5.6.2 Line segment ENS-LLS-DIM

The line segment between Ens, Lelystad and Diemen consists of two segments of two parallel lines. The results of these lines have been aggregated to represent the ENS-LLS-DIM perspective.

Global sensitivity

The aggregated overview of the model sensitivity to the different uncertainty categories resulted in a similar pattern in comparison to the network level overview. Offshore wind is the primary contributing factor that explains the overload scores in the network. However, the individual feature scores in the ENS-LLS-DIM line segment show much lower feature scores for the offshore wind capacity that is connected to the stations Borssele and Beverwijk. Simultaneously, the features scores for offshore wind capacity connected to the stations Maasvlakte and Eemshaven Oude Ship have increased. The individual feature scores can be seen in figure 5.19.

The feature scores suggest a relationship between the available capacity north of ENS and the available capacity south of Diemen. Since the role of the installed offshore wind capacity in Borssele is already associated with the availability of generation surplus in the western part of The Netherlands, the high feature scores for Maasvlakte and Beverwijk suggest that surplusses are exported north through line segment ENS-LLS-DIM. The feature score of offshore wind capacity in Eemshaven Oude Schip would then be related to the degree of generation shortage in the northern part of The Netherlands. To further examine the relationship between these parameters, the number of non-significant uncertainty

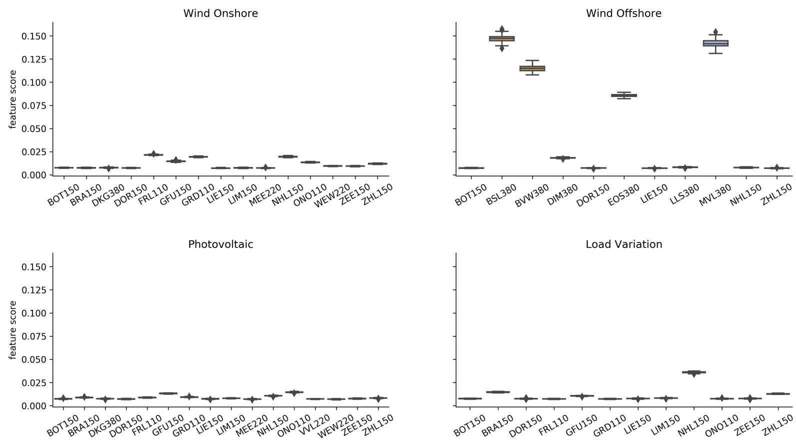

Figure 5.19: Individual feature scores

parameters can again be reduced through factor prioritization.

Factor prioritization

Based on the application of the knee point criterion, the cut-off point of the relevant uncertainties remains at 5 uncertainty parameters. The combined explanatory power, however, decreased to just over 50 percent. The relevant uncertainty parameters include the offshore wind parameters in Borssele, Beverwijk, Maasvlakte and Eemshaven Oude Ship and the load variation parameter of the regional network in Noord-Holland. The application of the knee point criterion is visualized in figure 5.20.

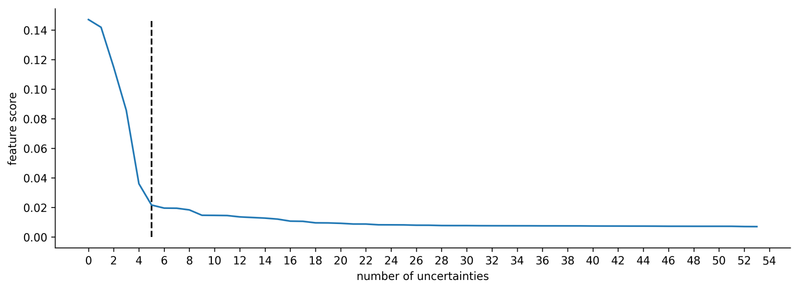

Figure 5.20: Uncertainty cut-off point

With a reduced number of uncertainty parameters, the model can be reevaluated to increase the resolution of the outcomes that relate to the high overload scores in the line segment. However, due to time constraints, the results have not been reevaluated. Based on the original data, the contribution of each significant uncertainty parameter can still be assessed through a regional SA.

Regional sensitivity

The regional SA of the remaining uncertainty parameters can be seen in figure 5.21. The results demonstrate that the difference between the cases of interest and the other cases is not very large. This is also observed in the trade-off trajectories and has resulted in very low density scores. Therefore it was impossible to subspace the uncertainty space and identify a meaningful scenario. Reevaluating the experimental design with only the five uncertainties could help to reduce the noise that is present in the dataset.

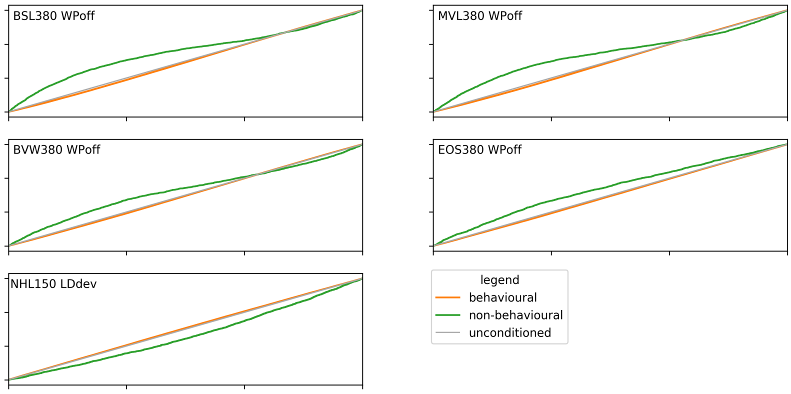

Figure 5.21: Regional sensitivity

As a result of the inability to identify a meaningful scenario, it is not possible to verify the relationship between the different offshore wind parameters and the load deviation in Noord-Hollland. It can be observed that the direction of the load deviation in Noord-Holland is opposite to the direction of the offshore wind parameters, which would make sense given the hypothesis that electricity is transported from the western part of The Netherlands to the northern part of The Netherlands. Even though the spread is fairly small, offshore wind capacity in Eemshaven Oude Schip spreads in the same direction as the other offshore wind parameters. An opposite spread would have been expected if Eemshaven Oude Schip would reduce the import of electricity from the western part of The Netherlands. It might be that the power volumes in the western part of The Netherlands are exported to Denmark, Norway or even Germany. This adjusted hypothesis could be tested through similar analyses focused on the stations near the interconnection capacity of the respective foreign bidding zones.

5.7 Scenario Narrative

Based on the results of the different analyses described in this chapter, a narrative can be formulated that describes a worst-case scenario in terms of the overload score in the network, e.g. as has been demonstrated in Greeven et al. (2016). The narrative for the worst-case scenario can therefore be based on the results observed in the worst-case subspace, which has been analyzed in the preceding sections. These analyses demonstrated that the adaptation of large volumes of offshore wind power is able to result in high overload scores in the EHV network. The interpretation of the scenario results revealed that there are interaction effects between the installed offshore wind capacities in different locations in the southwestern and western parts of The Netherlands.

A scenario narrative based on these results could be formulated in the following sense:

Large volumes of offshore wind in the southwestern and western regions of The Netherlands result in large volumes of offshore wind power related load volumes that have to be transported to the northern part of The Netherlands. These power flows are the result of the export oriented position of the Dutch electricity market in relation to Denmark, Norway and Germany. As a result of the transmission of high volumes of offshore wind power, the power lines that connect the southern and northern parts of the Dutch transmission network are severely overloaded.

Chapter 6

Workshops

6.1 Objective

The main objective during the workshop sessions is to gather feedback from the participating experts with regards to the perceived usefulness of an open exploration approach in the context of TEP. Therefore, the workshops serve as an assessment of the usefulness of DMDU configuration that was selected in this thesis. Assessing the usefulness of DMDU configurations in contrast to scenario planning approaches in expert environments is a topic that has been rarely addressed in literature. Furthermore, the workshop sessions serve as an introduction to DMDU and were meant to provide a demonstration of a practical application of EM within the domain of TEP.

6.2 Design

Two workshop sessions were conducted with domain experts at TenneT in Arnhem. Each workshop covered a duration of three hours during which results where presented and discussed in different rounds. The participating experts were selected based on their roles within the TEP-process, spanning different departments that covered different aspects of the TEP-process described in chapter 2. The experts that attended during each sessions are listed in tables 6.1 and 6.2. Both workshop sessions were assisted by Martti van Blijswijk, in which he helped to streamline the plenary discussions.

6.3 Results

The results of both workshop sessions were merged and structured based on content. As agreed upon with the participants, the workshop results are discussed in accordance with the Chatham House Rule and direct quotes are indicated by quotation marks. Since the workshop sessions were held in Dutch, quotes are translations and therefore might include minor translation errors.

Table 6.1: Participants first workshop session

Name	Department
Andres Christoforidis	Grid Development & Strategy
Bart van Hulst	Grid Development & Strategy
Robert Kuik	Grid Development & Strategy
Arno Haverkamp	Long-term Grid Planning
Gert van der Lee	Long-term Grid Planning
Rutger van Houtert	Long-term Grid Planning
Willian Zappa	Long-term Grid Planning

Table 6.2: Participants second workshop session

Name	Department
Micha Weijnen	Asset Owner
Alan Croes	Long-term Grid Planning
Gerjan Emsbroek	Long-term Grid Planning
Koen Gorrissen	Long-term Grid Planning
Patrick van de Rijt	Long-term Grid Planning
Bryan Brard	North-Sea Infrastructure

6.3.1 Opportunities

In general, the potential to identify relevant uncertainties and narrow down uncertainty ranges were perceived to be interesting options. The subsequent sections describe the different opportunities that were identified during the workshop sessions.

Scenario building

A more promising application of open exploration was attributed to scenario building. "It would be helpful to know about high impact variables while constructing scenarios". Feature scoring and subspace partitioning are methods that help to focus the scenario building process and result in more 'stable' scenarios, i.e. scenarios which are embedded within a known area of the uncertainty space. This helps to strengthen the development of the scenario narratives that are used during the TEP-process.

Vulnerability assessment

Given specific network calculation related sub-problems, the open exploration approach could prove to be an interesting alternative to explore vulnerability within (parts of) the electricity network. However, in relation to the specified problem, the scenarios were not perceived as an approach that could result in additional knowledge. The results of the global SA demonstrated a relationship between generation volumes and line congestion that was already obvious to the participants of the workshop sessions.

Risk assessment

More diverse sets of scenarios were described to be potentially useful during investment related risk assessments. Since the number of required investments is often larger than the size of the available investment resources, the realization of investments has to be prioritized. Assessing potential investments in relation to scenarios could help to identify relative robust investment options and inform investment strategies that consider interdependence and timing in relation to investment options.

Validating expert knowledge

Participants recognized that exploratory modelling, whether or not in an open exploration configuration, could help to validate expert knowledge. This process could help to identify blind-spots that require attention. In this case, exploratory modelling could be used in a more selective manner during the TEP-process and other network or market related studies. The relation between different scenarios is often presumed to be linear, whereas the identification of subspaces helps to embed this assumption to specific parameter ranges.

6.3.2 Challenges

Participants also expressed reservations towards certain aspects of the DMDU framework and the selected application of the framework. The subsequent sections describe each of the expressed reservations and are each followed by a brief reflection in italics on how their hesitations could be addressed.

Uncertainty specification

It was noted that the specification of uncertainties and uncertainty ranges might prove to be challenging due to the long lead times in the realization of TEP investments. "A decade ago, nobody would have presumed the large quantities of installed offshore wind power that the network is currently facing". Therefore, the identification and specification of uncertainties was considered problematic. The specification of "extreme" uncertainty ranges was furthermore considered to impact the analysis due to over-representation of certain parameters in the subsequent analyses, e.g. the feature scores of the uncertainty parameters that were used to reduce the number of uncertainties.

The core aspect of the applied open exploration configuration is to explore the uncertainty space and identify subspaces that result in desirable or undesirable outcomes. The idea is that infrastructure investment requirements related to large quantities of offshore wind capacities would have been identified in an earlier stage, providing the opportunity for an earlier intervention or response. Exploring extremes that are regarded as infeasible by experts is therefor inherent to open exploration. This reasoning also applies to the perceived danger of parameter over-representation, as these parameters should incentivize further exploration that helps to understand the high feature scores.

Uncertainty sampling

It was noted that the configuration of the uncertainty ranges might result in sets of input parameters that are unrealistic, e.g. scenarios in which generation capacity consistently exceeds the total load in the network. These scenarios are considered implausible within liberalized markets and introduce noise in the data. It was suggested to scrub these data points from the data after the experiment evaluation or by constraining the uncertainty sampling itself. Alternative suggestions included an intermediate step which splits the market simulation from the network calculation to limited the number of evaluated scenarios in the load flow calculations.

The suggested approaches provide possibilities to remove infeasible samples from the analyses. However, it is not ideal to evaluate configurations that are subsequently removed from the dataset. An alternative possibility would be to check the configuration of a sample before subsequent evaluations and determine whether it is feasible or not. This could be done within the model through an investment module or possibly within the sampling algorithm itself. However, the author is unaware of methods that constrains sample configurations of sampling algorithms, providing a window for further research.

Required resources

Several participants questioned the usefulness of an exploratory modelling approach based on the required computational resources. Models that reflect higher precision regarding market simulation and network calculations are likely to require more computing power. This becomes even more apparent when considering resilience calculations based on component redundancy as well. Within the time constrained TEP-process, the trade-off between the desired model resolution and the required number of model evaluations is perceived to become to steep to consider EM as a viable addition to the TEP-process.

In contrast to the perceived computational bottleneck, additional computing power could resolve the trade-off problem and provide the possibility to increase both model resolution and the number of model evaluations. The availability of cloud platforms have reduced the costs per cpu hour significantly and have provided flexible and scalable computing solutions (AWS, 2020). The costs associated with the required cloud configuration are expected to be negligible in an investment portfolio that covers network investments costing billions of euros. Another option could be to assess the desired resolution of network models in relation to the long-term scope of the investment problem. It might not be necessary to use the highest possible model resolution in exploratory setups that examine long-term effects (Walker et al., 2013).

Limited impact

Given the required resources, the upfront costs of the exploratory modelling approach were considered high. It was questioned whether these efforts would have a large enough impact on the realization of network capacity. The TEP objective set-out in the regulatory framework is clear and does not provide much flexibility in approaching bottleneck resolution in manners other than additional capacity investments. Furthermore, it was mentioned that based on traditional scenarios and expert knowledge, most uncertainties could already be sufficiently explained.

This reservation relates to the reservation on uncertainty specification. DMDU approaches can be used to explore the uncertainty space and identify under which conditions certain network investments might fail or succeed. In the current scenario planning approach, network investment is optimized over a limited number of scenarios of which it is unknown which area within the uncertainty space they cover, the conditions under which investments succeed or fail are therefor unknown. Thereafter it was mentioned that nobody could have foreseen the large shares of offshore wind adaptation; an open exploration approach would at least have been included as a sample in the uncertainty space.

Informing decision making

Participants mentioned that it was unclear how the presented results would facilitate a decision-making process, as knowledge about exploratory modelling would be required to interpret the results. "How can data be transformed into information that facilitates the decision-making process?". However, it was recognized that more knowledge about the network might be required to translate sensitivity scores and different scenarios into investment options that could be considered in further (EM) analyses.

The application of DMDU approaches within the context of TEP definitely requires further development. The open exploration configuration is a relatively small setup that should be part of a broader analysis. Configurations in which multiple investment options are compared would already result in an analysis that relates more to policy analysis and decision making.

Accountability and transparency

The extensive and theoretical nature of the method raised concerns with regard to accountability towards shareholders, regulatory bodies and other stakeholders. Participants noted that they themselves already had a hard time understanding the method and wondered how to build trust in the method. "How are we expected to convince our stakeholders of an approach that by many would be considered to be a black-box?".

There is definitely a learning curve in understanding the DMDU paradigm. This is a process that requires time to familiarize oneself with the framework. The same reasoning naturally also applied to the adaptation of what is now called traditional scenario planning. Developing different use-cases might help to further understanding of DMDU and thereby build confidence in the method.

6.3.3 Other applications

During the workshop sessions, participants identified several applications of DMDU that are not directly related to TEP. These applications are detailed in the subsequent sections.

Advocacy

The possibility to assess different governance structures is another exploratory modelling application that was often mentioned by participants. These exploratory studies would help to assess the adequacy of the current regulatory framework(s) and inform policy positions that investigate different regulatory configurations. Studies could for example assess more integrated approaches of generation and transport capacity implementation in relation to system costs. Other options could review bidding zones, capacity mechanisms or other market organization related aspects.

Offshore wind projects

Participants also mentioned that offshore projects might be an interesting domain to apply exploratory modelling. Government control on offshore wind projects is decreasing as offshore wind projects are increasingly tendered without government subsidies. This introduces uncertainty with regard to the realization of offshore projects, as it becomes uncertain whether and when projects will be (completely) realized. This uncertainty impacts network planning related to the feed-in of offshore wind generation capacity in the electricity network. An open exploration configuration that combines policy and scenario sampling could be useful to inform feed-in strategies for offshore wind projects.

6.3.4 Observations

While observing the discussions during the workshop, several notable observations were made. These observations are described in the following subsections.

Theoretical dimension

The presented results are embedded in the extensive framework that described DMDU. This research presents only a limited configuration within this framework which is hard to position without knowledge of the DMDU framework and the concept and role of exploratory modelling within this framework. It is relatively hard to introduce participants to the framework while maintaining focus on the open exploration configuration within the three hour duration of a session as participants felt a bit overwhelmed at some points.

Model versus method

The results presented in the sessions were based on a network model that was not validated. It proved hard to distinguish the model from the EM results as the EM results were often contested based on the expert knowledge of participants on the electricity network. Although this underlined the importance of the role of expert knowledge in the interpretation phase of the EM results, it simultaneously distracted from the more theoretical objective set out in the workshops, i.e. participants were sometimes inclined to validate the EM results, rather than to assess their usefulness.

Complex nature of uncertainty

Participants were perceived to be critical with regard to addressing uncertainty through modelling, as they were skeptical whether more model evaluations would suffice to capture the complex nature of uncertainty. Since the TEP-process is already substantial, participants doubted how evaluating more scenarios in itself would facilitate the TEP-process. Reverting to expert knowledge therefore was perceived to serve as an imperfect but adequate coping mechanism. It however remained unclear whether the limitations in the current scenario planning-bases approach therefor sufficiently recognizes and 'owns' the consequences of uncertainty in the TEP-process.

Complementary configurations

During the workshops, the role of exploratory modelling was often contrasted with the role of expert knowledge. It is notable that complementary or supplementary properties were often overlooked. Expert opinions could be based on insight in the electricity system that have been fostered through DMDU approaches. Thereafter, as mentioned by participants, DMDU approaches can be used to test expert knowledge and help to identify blind spots.

Genuine interest

Participants were genuinely interested in the DMDU framework with a particular interest in EM. Some participants were already somewhat familiar with potential applications relating to scenario building and adaptive policy architectures. This genuine interest translated to active participation during the discussions and thereby helped to better position the DMDU framework in relation to the TEP-process.

6.4 Analysis

The main aim of the workshops was to establish the usefulness of an open exploration approach within the TEP-process. During the workshops the participants recognized the type of results and were able to relate the results to their own role within the TEP-process. The usefulness of the open exploration approach, however, depended on the context in which the configuration was applied. The usefulness of the analyses is thus recognized provided that certain surmountable reservation were expressed.

Furthermore, the workshops reconfirmed that the role of uncertainty within the TEP-process is widely recognized. However, opinions differed concerning the extend to which uncertainty should and could be addressed. This was voiced in several reservations that related to the ability of modelling approaches to capture the complex nature of uncertainty. The more fathomable but limited nature of the scenario planning approach was preferred over the increased complexity introduced in a DMDU approach. This is especially interesting in relation to the results described in Gong et al. (2017), where participants tended to opt for robuster interventions in scenario approaches versus probabilistic oriented forecasting approaches. The human tendency to ignore the consequences of smaller risks could prove to be a hazardous approach in terms of effectuating the adequate long-term functioning of the transmission network.

The workshops did furthermore establish several use-cases for DMDU approaches within the domains of TSOs. However, the number of identified use-cases within the process of the investment plan were fairly limited as a result of a regulatory framework that constrains TenneT's policy space. These constraints affect the impact of DMDU approaches as opportunities to divert from scenario-planning-based investment strategies are limited. The adaptive nature of DMDU-informed strategies can therefore not be well reflected in network investment strategies within TenneT's biennial investment plan. The framework needs to be adapted to fully utilize the strengths of DMDU approaches, although the framework can already be deployed to analyze sub-problems within the process. The aforementioned development of bottom-up scenario narratives as described in Greeven et al. (2016) would already help to embed the 'traditional' scenarios within the uncertainty space.

Thereafter, the workshops indicated that more developed use-cases are required to build trust and confidence in the DMDU framework. The tooling used in EM is based on advanced computer and data science applications that tend to resemble 'black-boxes'. Use-cases should aim to unpack these black-boxes in order to demonstrate their functionality and build experience in the adequate application of the tooling. This active effort for transparency helps to build trust in the application of these advanced applications and thereby the confidence to apply them within the context of TEP. As such, this thesis is already an attempt to provide insights into the black-boxes and demonstrate how these tools can be used in the context of TEP.

6.5 Discussion

Based on the provided feedback it could be concluded that DMDU approaches provide useful insights in the context of TEP. The limitations of the scenario planning approach are recognized, as well as the potential of DMDU approaches to overcome these limitations. This was especially recognized in the possibility of the open exploration configuration to develop scenario narratives in relation to subspaces within the uncertainty space. More advanced configurations of the DMDU framework would help to better understand the robustness of investment options in relation to these scenario narratives and thereby improve the risk assessment of the respective investment. As a result, it becomes possible to develop an investment portfolio in terms of robust investments or even in terms of adaptive investment strategies.

Although the traditional scenario planning approach might be considered a more fathomable approach to address uncertainty, the risks resulting from this approach are not always explicitly expressed or 'owned'. DMDU approaches are better suited to make the role of uncertainty visible within the decision making process, while simultaneously making the process more complicated. The limited context that is provided in scenario planning approaches should be more explicitly expressed to foster thinking in terms of subspaces, rather than single points, i.e. the uncertainty in which TEP is embedded cannot be adequately captured in merely three discrete scenarios. Failing to recognize the full uncertainty space is doing an injustice to the complexity that grasps TEP.

There are furthermore several 'hurdles' that have to be overcome to fully utilize the potential of DMDU approaches within the TEP-process. Linking the many analytical steps within the process in an overarching DMDU informed investment strategy requires a long-term commitment during which the method is increasingly applied in TEP related analyses. This could also help to overcome the regulatory limitations to fully utilizing the potential of DMDU approaches within the development of the biennial investment plan. The development of use-cases helps to build the required trust and confidence that is required to convince regulators and lawmakers of the added value of DMDU approaches in comparison to traditional scenario planning.

Lastly, more resources should be allocated towards the adaptation of (hybrid) cloud solutions that would facilitate the approach of TEP through the framework of DMDU. At a rate of 0.224 dollar per cpu hour, a cloud setup of the TEP-model detailed in chapter 3 would cost 56 cores * 18 hours * 0.224 dollar = 226 dollar (AWS, 2020). The model would probably even need less computing time provided that High Performance Cluster used in this thesis runs on older hardware. Even when considering models that run at higher resolutions, requiring a thousand times more CPU power and a thousand times more run hours, the associated computing costs in the context of an investment portfolio concerning billions of Euros. The costs of realizing inadequate network investments are therefor far higher than the costs of the required computing power.

Chapter 7

Conclusion and recommendations

7.1 Conclusion

This thesis established a proof-of-concept approach to assess the potential of the DMDU framework in the context of TEP in The Netherlands. In this approach, a simplified integrated market simulation and network model are used to explore the effects of different quantities of wind and solar based generation capacity in relation to the identification of bottlenecks within the electricity grid. A dataset containing 20.000 data points is evaluated and analysed the results of which have been reviewed by domain experts in two workshop sessions. In this approach this thesis aims to answer the research question:

What are useful insights that Decision Making under Deep Uncertainty approaches can provide in the process of Transmission Expansion Planning?

Given the increased significance of uncertainty within the energy domain, DMDU approaches provide useful insight in the TEP-process. As established in chapter 2, the scope of scenarios in traditional scenario planning approaches are limited when attempting to meaningfully address the role of uncertainty in TEP. Therefore, scenario planning approaches when exploring the criteria under which network investments succeed in addressing long-term network capacity requirements. In contrast, the inherent exploratory scope of DMDU approaches addresses these limitations by considering investments in relation to the full uncertainty space in which TEP is embedded, thereby providing the possibility to inform more robust investment strategies that specify boundary conditions in advance.

The development of the research question confirms the potential of DMDU approaches in the context of TEP. DMDU approaches have provided the opportunity to address uncertainties within the domain of TEP through a modelling approach that explores the uncertainty space of the model's input parameters. An open exploration oriented DMDU configuration is able to establish model sensitivity, reduce the dimensional complexity of the uncertainty space and identify subspaces within the uncertainty space that are described as scenarios. The results thereby provide a broader understanding of the uncertainty space in comparison to scenario planning approaches. This potential is furthermore recognized by experts in the field of TEP and can be further utilized through the development of additional use-cases in the context of TEP.

[1] *How is Transmission Expansion Planning affected by deep uncertainty?*

The role of uncertainty in the context of TEP is, as established in chapter 2, primarily embedded in the assessment of market developments. The availability of transmission capacity facilitates electricity markets to connect generation and load in a market environment, whereas network congestion constrains optimal dispatch and results in sub-optimal market outcomes due to redispatch interventions. Therefore, to facilitate the realization of the adequate availability of transmission capacity in the right place at the right time, generation capacities and the development of load profiles are considered to be the main uncertainties within the process of TEP.

[2] *How can Decision Making under Deep Uncertainty approaches be applied in the process of Transmission Expansion Planning?*

It is feasible to apply DMDU approaches in the context of TEP. The application of the proof-of-concept approach described in chapters 3 and 4 demonstrates how uncertainty with regard to the development of VRES generation capacity and load profiles can be linked to the identification of capacity bottlenecks within the electricity network. Latin hypercube sampling techniques can be used to sample scenarios from the vast uncertainty space in which TEP is embedded, while screening techniques like Extra-Trees in combination with factor prioritization can subsequently be used to process the large number of uncertainty parameters and reduce the dimensional complexity of the transmission capacity investment problem. The use of regional SA in combination with CPCA PRIM thereafter provided the possibility of identifying subspaces within the uncertainty space that can be used to develop scenario narratives. The applied methods are fully scalable and can thereby be applied in larger models with higher model resolutions. Together with the availability of large amounts of affordable computing power through (hybrid) cloud platform solutions, there are no inherent technical barriers that prevents the adaptation of DMDU approaches in relation to real-world TEP processes.

[3] *How useful are Decision Making under Deep Uncertainty approaches in the process of Transmission Expansion Planning?*

The domain expert review of the results described in chapter 3 confirmed the usefulness of DMDU approaches in the context of TEP. The TEP-experts were able to identify different use-cases for DMDU approaches that are related to TEP, offshore wind projects, advocacy and outlook studies. They recognized the potential of DMDU approaches in constructing scenario narratives, performing vulnerability and risks assessments and in validating expert knowledge. However, as discussed in chapter 6, the application of the framework of DMDU within the context of TEP requires further development to overcome several reservations expressed by the experts.

Domain experts perceived traditional scenario planning to be a more comprehensible approach in addressing deep uncertainty. In combination with expert knowledge, traditional scenario planning was perceived to provide an adequate enough understanding of the complexity in which infrastructure investment decision should be made. This perception overestimates the robustness of current investment options and underestimates the consequences of overlooking scenarios that are perceived to have lower risks, thereby marking a hazardous approach to addressing deep uncertainty. To effectuate the ambition of ensuring the long-term robust functioning of the transmission network, this hazardous mindset should be reconsidered and aim to do more justice to the complexity of the uncertain environment in which TEP is embedded. In this reconsideration DMDU approaches could actually help identify blind-spots of domain experts.

Other reservations relate to the more practical application of DMDU in the context of TEP. The utilization of the full potential of the DMDU framework is, in some cases, constrained by the regulatory framework, e.g. in the development of the biennial investment plan. Thereafter, the adaptation of DMDU approaches requires the establishment of trust and confidence in order to further the scopes of the different analyses and DMDU configurations. Experimentation with the actual application of DMDU approaches in more use-cases would help to overcome these practical reservations and build the trust and confidence to convince regulators and policy makers to change the regulatory framework, while simultaneously gaining the required experience in the deployment of (hybrid) cloud computing solutions.

7.2 Recommendations

The conclusions provide the foundation required to recommend further research. The recommendations are grouped under policy recommendations and scientific recommendations.

7.2.1 Policy recommendations

The implementation of DMDU approaches within the TEP process requires a long-term effort that requires extensive experimentation. The development of different comprehensible use-cases would help deepen the knowledge about the method by providing learning opportunities. The experience gained during the development of these use-cases would therewith help to establish trust in the underlying methods of DMDU approaches and thereby open up the 'black box'. This gradual approach would thereafter help TSOs to acquire more experience with cloud platform based computing solutions to support the underlying analyses within TEP-processes.

The experience that TSOs would gain during the development of different use-cases could also be deployed towards more advanced DMDU configurations. Open exploration is a relatively small DMDU configuration, whereas the framework of DMDU can also be used to assess investment decisions and thereby improve, for example, risk assessment. Knowing under which conditions certain investments succeed or fail could inform investment strategies that are able to respond to developments that deviate from expected transition paths. This would make the network investment portfolio more agile and thereby result in a network design that is more robust when faced with 'unexpected' outcomes. The scenario narrative described in chapter 5 already demonstrated an interaction effect between the realization of different offshore wind parks and the location of network overload in the EHV.

Lastly, the impact of uncertainty in the decision making process in TEP should be recognized more explicitly. Exploring scenarios through either scenario planning, or through the framework of DMDU does not eliminate the presence of uncertainty. The framework of DMDU should therefore not be used to make decision making more convenient, but rather to make the role of uncertainty in the decision making process more visible. Formulating the right investment strategy might therefore become even more difficult as the uncertain context in which the decision becomes much more visible. As is described in chapter 6, failing to recognize the full extend of the uncertainty space is doing an injustice to the complexity in which the TEP-process is embedded. Investment decisions should therefore better recognize the role of uncertainty in reflecting the conditions under which the decision is considered a viable option.

7.2.2 Scientific recommendations

During the development of the TEP-model used in this thesis, several trade-offs were made to reduce the computing time that was required to evaluate the model. Based on the low costs of CPU hours, cloud computing platforms are often recommended as options to improve the trade-off between resolution and number of runs. However, the trade-off between the (minimal) required model resolution in relation to the number of runs has not been explored in the context of TEP. In the current TEP practices, the resolution in the network models is often very high, whereas it can be doubted whether this resolution is required in exploratory settings. Therefore, research efforts should be directed towards informing this trade-off, e.g. through a comparison of DMDU results in the context of multi-resolution models. As a result, TSOs would be able to better inform the selection of a certain model resolution in the context of a given (sub-)problem within the TEP-process.

Furthermore, research efforts could be directed towards the accountability aspect of the application of the framework of DMDU in relation to the decision making processes. While the methods within the framework itself are scientifically validated, communicating the adequate application of the methods can be quite challenging. It might prove especially hard to convince a regulator that the tooling has been used correctly and that the resulting investment decision(s) are adequately justified. This complexity is naturally inherent in the process of making uncertainty more visible, but could possibly be structured around a framework of 'best practices'. More research that compares DMDU approaches to traditional scenario planning approaches is hereby also desirable. This research would help to better understand the mindsets of analysts and decision-makers and thereby help to pinpoint errors or fallacies in the application of uncertainty addressing approaches.

Lastly, research could be directed towards conditional sampling possibilities. The possibility of sampling configurations in which the Dutch electricity market would be severely oversaturated did not represent viable extremes. These oversatured samples were caused by the bottom-up samples of capacity volumes that described the overall generation portfolio of The Netherlands. The local differences between the sampled capacity volumes were an essential aspect of the uncertainty space in the context of the developed TEP-problem and therefore cannot be aggregated to resolve the problem. Introducing an investment module could bypass the problem, but might introduce other conceptual or conditional difficulties. It would be convenient to consider the sampling of individual parameter values in consideration with already sampled parameter values in order to reflect constraints in the overall scenario configuration.

7.3 Reflection

Through its mandate and as the 'guardian' of the electricity sector, TenneT is confronted with the complexity of this problem. Internally, numerous problems are studied at TenneT, aimed at providing the information that players within the electricity sector require to understand the landscape in which they operate. I have come to know TenneT as an organisation that faces these challenges with an open mind, while also realising that change requires a long-term commitment.

The most striking observation during the internship relates to the level of detail in which TenneT addresses mid-term and long-term studies. The drive to understand every aspect of the electricity sector fascinated me; though I did wonder whether the level of detail was relevant given the large amount of uncertainty in which the resulting outcomes have to be interpreted. Given the complex nature of the challenge that TenneT is currently facing, I initially expected TenneT to be more conceptually conscious of the uncertainty aspects of the problem and the conditionality under which the resulting outcomes could be interpreted.

I expected analyses that addressed the uncertainty space in a broader sense, as this type of analyses would bring forward the position of the sector's regulatory framework in relation to its uncertainty space. Through these insights, a better understanding of the different positions of the players within the electricity sector would be gained, thereby informing discussions about the conditions under which they could contribute to facilitating the energy transition. Through this approach, the logical assumptions about expected developments and responses could thereby be assessed and validated. Through interventions in the regulatory framework, the uncertainty space could subsequently be reduced.

The framework presented in this these facilitates these kinds of these kinds of discussions. Even though the implementation of the method requires high upfront investment costs in terms of learning processes and development of the required scripts and model code, the adaptation of DMDU approaches are the next natural evolutionary step in approaching uncertainty in TEP. Thereafter, the development of a TSO specific workbench could also be deployed in other infrastructural network configuration in collaboration with Distribution System Operators, ENTSO-E or even GasUnie. The required tools and potential use-cases are readily available to be adapted by TSOs.

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Appendix A

Model parameters

A.1 Lines

The assumed cost components of network investment are specified in table A.1 (Van Blijswijk, 2017).

Table A.1: Cost components in billion of euros

Component	**Costs**
Cost of additional capacity	0.15
Cost of addition length	1.50

A.2 Generators

The assumed technical properties of each generator class are specified in table A.2 (U.S. Energy Information Services, 2020). The default values of installed generation capacity per generation category are specified in table A.3. The 2020 reference values for installed generation capacity per generation category are specified in table A.4.

Table A.2: Technical properties per MW generation

Category	**Carbon emissions**	**Overnight capital costs**	**Generation costs**
Nuclear	0	6.00	2
Hard coal new	94	3.80	35
Hard coal old 2	94	3.50	25
Gas CCGT old 1	57	1.00	62
Gas CCGT old 2	57	1.00	59
Gas CCGT new	57	1.00	55
Gas OCGT new	57	0.85	80
Other non RES	0	1.50	0
Other RES	0	1.50	0
Solar Photovoltaic	0	1.80	0
Wind Offshore	0	1.60	0
Wind Onshore	0	6.50	0
Backup	0	0.00	1000

Table A.3: Default generation capacities

Region	Gas CCGT new	Gas CCGT old 1	Gas CCGT old 2	Gas OCGT new	Hard coal new	Hard coal old 2	Nuclear	Other non-RES	Other RES	Solar Photovoltaic	Wind Offshore	Wind Onshore	Backup
FRL110	0	0	0	71	0	0	0	0	0	2391	0	648	50
GRD110	126	0	0	77	0	0	0	204	50	2659	0	677	50
ONO110	0	72	0	195	0	0	0	66	0	2312	0	539	50
NHL150	440	0	249	391	0	0	0	342	29	3497	228	805	50
GFU150	415	50	467	294	0	0	0	67	0	8017	0	2444	50
ZHL150	0	156	506	556	0	0	0	527	0	2372	81	736	50
LIE150	0	31	101	111	0	0	0	105	0	474	16	147	50
DOR150	0	31	101	111	0	0	0	105	0	474	16	147	50
BOT150	0	31	101	111	0	0	0	105	0	474	16	147	50
BRA150	426	52	0	352	0	0	0	308	0	3645	0	276	50
LIM150	495	0	0	212	0	0	0	67	0	1804	0	36	50
ZEE150	0	440	0	104	0	0	493	47	0	1661	0	698	50
BSL380	850	0	0	0	0	0	0	0	0	0	3400	0	50
BVW380	0	0	0	0	0	0	0	0	0	0	2100	0	50
EOS380	0	0	0	0	0	0	0	0	0	0	1300	0	50
MVL380	1290	0	0	0	0	0	0	0	0	0	2700	0	50
MEE220	0	0	0	0	0	0	0	0	0	296	0	72	50
VVL220	0	0	0	0	0	0	0	0	0	51	0	0	50
DKG380	0	0	0	0	0	0	0	0	0	18	0	144	50
WEW220	0	0	120	0	0	0	0	0	0	126	0	329	50
EHA220	1410	0	0	0	0	0	0	0	0	0	0	0	50
LLS380	431	0	0	0	0	0	0	0	0	0	700	0	50
DIM380	435	0	0	0	0	0	0	0	0	0	700	0	50
MBT380	810	0	0	0	0	0	0	0	0	0	0	0	50

Table A.4: Reference generation capacities

Region	Gas CCGT new	Gas CCGT old 1	Gas CCGT old 2	Gas OCGT new	Hard coal new	Hard coal old 2	Nuclear	Other non-RES	Other RES	Solar Photovoltaic	Wind Offshore	Wind Onshore	Backup
FRL110	0	0	0	71	0	0	0	0	0	1377	0	285	50
GRD110	0	28	0	121	0	0	0	160	49	290	0	162	50
ONO110	0	62	0	195	0	0	0	2	64	746	0	494	50
NHL150	440	869	243	379	0	0	0	342	26	1441	228	796	50
GFU150	415	50	474	262	0	0	0	67	0	3887	0	1212	50
ZHL150	0	278	644	746	0	0	0	617	0	956	81	417	50
LIE150	0	56	129	149	0	0	0	123	0	191	16	83	50
DOR150	0	56	129	149	0	0	0	123	0	191	16	83	50
BOT150	0	56	129	149	0	0	0	123	0	191	16	83	50
BRA150	0	50	0	352	0	620	0	308	0	1024	0	276	50
LIM150	495	0	245	212	0	0	0	42	0	360	0	12	50
ZEE150	0	440	0	91	0	0	493	47	0	375	0	420	50
BSL380	850	0	0	0	0	0	0	0	0	0	1400	0	50
BVW380	0	0	0	0	0	0	0	0	0	0	0	0	50
EOS380	0	0	0	0	0	0	0	0	0	0	600	0	50
MVL380	1290	0	1082	0	3411	0	0	0	0	0	0	0	50
MEE220	0	0	0	0	0	0	0	0	0	17	0	0	50
VVL220	0	0	0	0	0	0	0	0	0	21	0	0	50
DKG380	1410	0	0	0	0	0	0	0	0	0	0	0	50
WEW220	0	120	0	0	0	0	0	0	0	41	0	80	50
EHA220	0	0	0	0	0	0	0	0	0	3	0	144	50
LLS380	431	0	0	0	0	0	0	0	0	0	0	0	50
DIM380	435	0	0	0	0	0	0	0	0	0	0	0	50
MBT380	810	0	0	0	0	0	0	0	0	0	0	0	50

A.3 Uncertainty bounds

The uncertainty bounds of the experimental design are specified in table A.5.

Table A.5: Uncertainty bounds

Region	**Solar Photovoltaic**		**Wind Offshore**		**Wind Onshore**		**Load Variation**	
code	***lower***	***upper***	***lower***	***upper***	***lower***	***upper***	***lower***	***upper***
FRL110	1195	4782	0	0	324	1297	-32	32
GRD110	1330	5318	0	0	338	1353	-53	53
ONO110	1156	4624	0	0	270	1078	-69	69
NHL150	1749	6995	114	456	403	1610	-188	188
GFU150	4008	16034	0	0	1222	4887	-179	179
ZHL150	1186	4744	40	161	368	1473	-103	103
LIE150	237	949	8	32	74	295	-34	34
DOR150	237	949	8	32	74	295	-34	34
BOT150	237	949	8	32	74	295	-34	34
BRA150	1823	7291	0	0	138	553	-157	157
LIM150	902	3608	0	0	18	72	-78	78
ZEE150	831	3322	0	0	349	1396	-37	37
BSL380	0	0	1700	6800	0	0	NaN	NaN
BVW380	0	0	1050	4200	0	0	NaN	NaN
EOS380	0	0	650	2600	0	0	NaN	NaN
MVL380	0	0	1350	5400	0	0	NaN	NaN
MEE220	148	592	0	0	36	144	NaN	NaN
VVL220	25	102	0	0	0	0	NaN	NaN
DKG380	9	35	0	0	72	287	NaN	NaN
WEW220	63	252	0	0	164	657	NaN	NaN
EHA220	0	0	0	0	0	0	NaN	NaN
LLS380	0	0	350	1400	0	0	NaN	NaN
DIM380	0	0	350	1400	0	0	NaN	NaN
MBT380	0	0	0	0	0	0	NaN	NaN

A.4 Time Series

The time series of the selected reference days are visualized in figures A.1, A.2, A.3, A.4 and A.5.

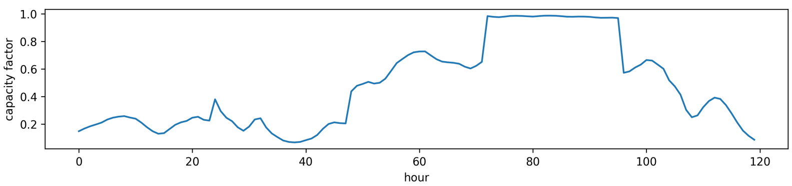

Figure A.1: Offshore wind power curve of reference days

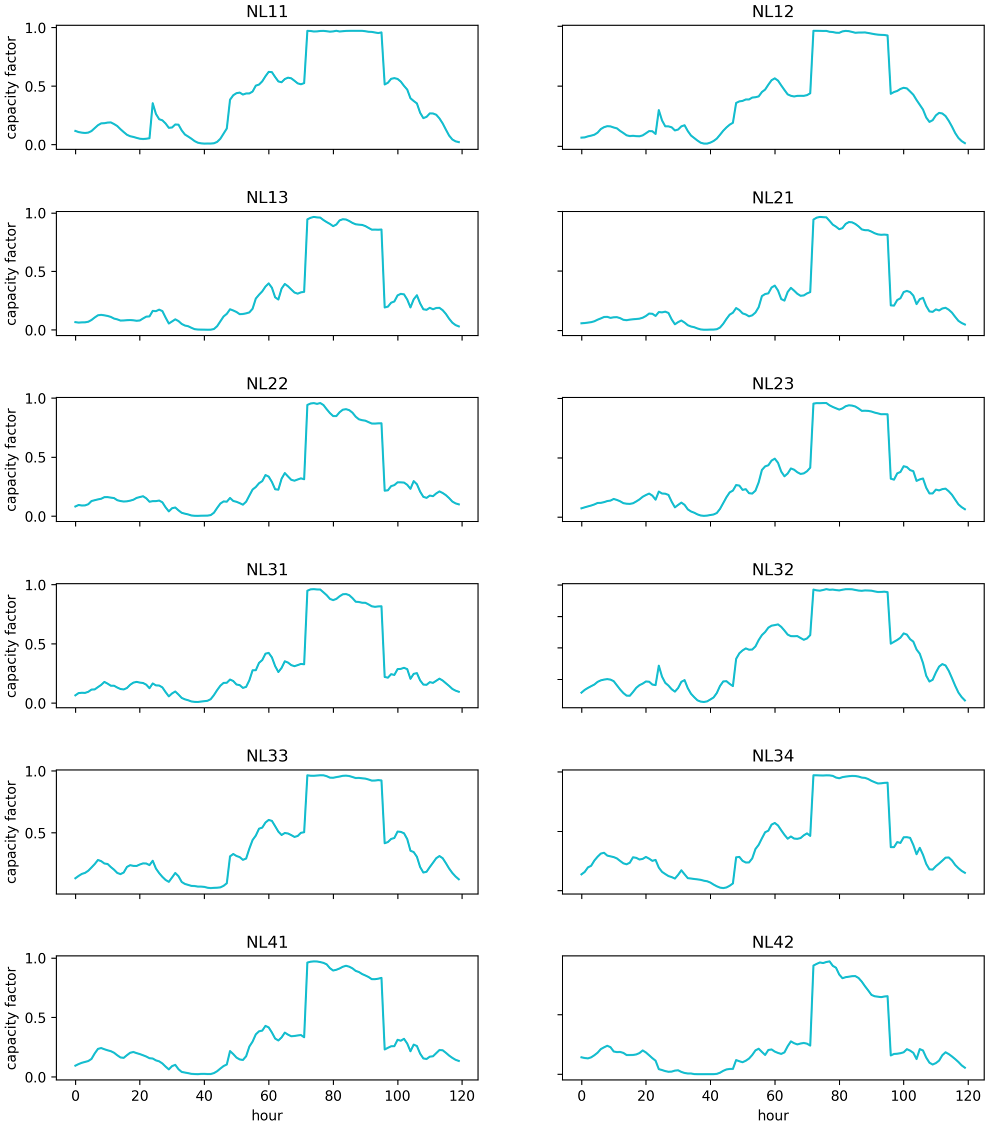

Figure A.2: Onshore wind power curves of reference days

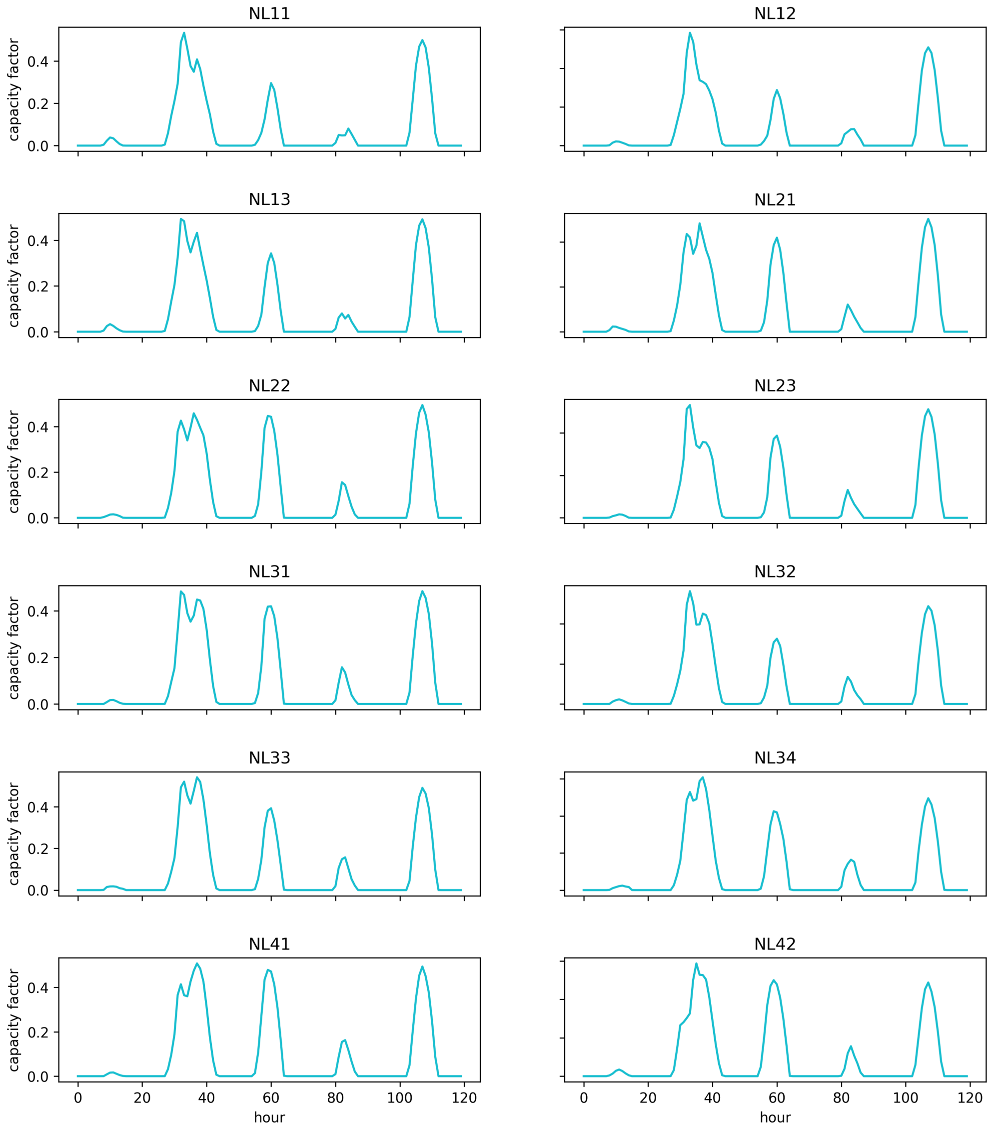

Figure A.3: Solar photovoltaic power curves of reference days

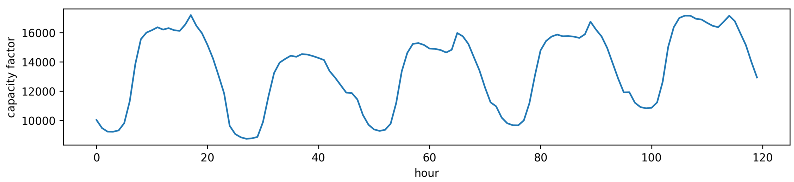

Figure A.4: Load curve of reference days

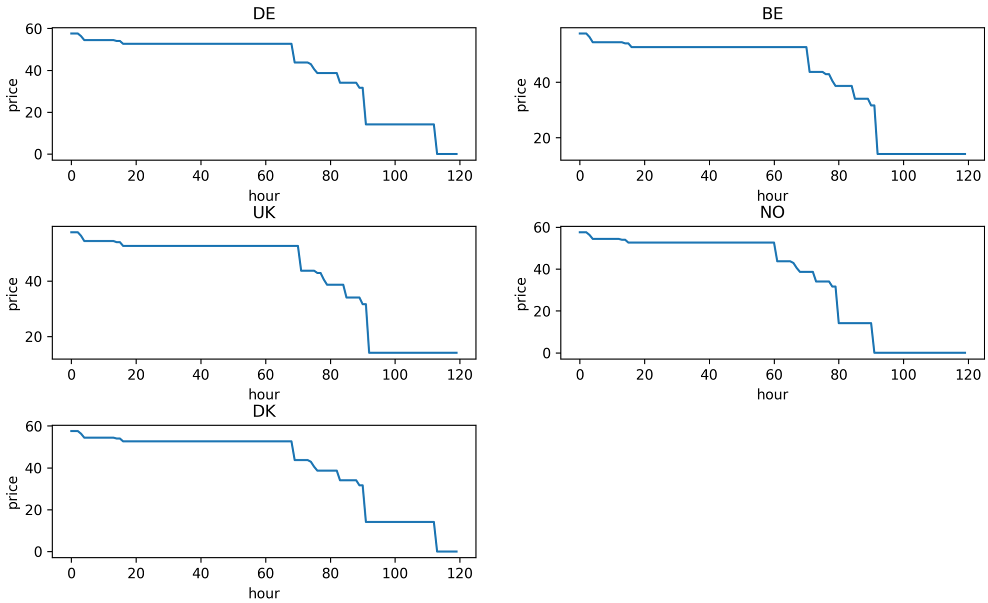

Figure A.5: Electricity exchange price curves of reference days

Appendix B

Reference Days

B.1 Objective

To limit the evaluation time of the model, the model evaluates a limited number of hours in relation to the selected reference year. Given the large number of experiments that are inherent to the experiment design described in chapter 4, the time required to evaluate the experiments would exceed the time budget that is available for this research.

To reduce the number of evaluated hours, weighted representative days have been selected to describe typical hours within the time series of the selected reference year. Since the model uses different time series, the identification of representative days requires an advanced approach that is able to capture interaction effects between different time series. Therefore, the selection of reference days within this thesis is based on the hybrid reference day selection approach described by Poncelet et al. (2017). The hybrid approach randomly selects a prespecified number of reference days that is followed by an optimization of the relative weight that is assigned to each of the selected days.

B.2 Implementation

The hybrid method described by Poncelet et al. (2017) is implemented in python scripts. These python scripts are included in the model repository described in appendix C. The scripts select a fixed number of random days and extracts the corresponding time series values from all the available time series. Both the sampled time series as the original time series are subsequently binned in a fixed number of bins. Thereafter, the data is normalized, making it possible to compare each of the subsetted datasets to the original time series dataset.

The goal of the optimization is to find relative weights for each of the reference days, such that the total error resulting from the comparison is minimized. This is achieved through an LP-based optimization that determines the relative weight. However, as the number of days and the number of bins are user-selected the optimization might not be optimal. Increasing the number of bins, increases the accuracy of the calculated error, whereas the selected number of days provides the weight optimization with more combinations to weigh the selected reference days. Thereafter, the sampled reference days might not be suitable, where the total error could be reduced by selecting a different sample of reference days.

To address the sampling issue, the pseudo-optimization in the hybrid approach prescribes replication of the weight optimization under different samples of an equal number of reference days and bins. Based on the replications it is possible to select the reference day sample that has the lowest error score and therewith most accurately describes the different time series. An optimal outcome is achieved by evaluating all possible samples, but is computationally very expensive, whereas the pseudo-optimization should approach the optimal result.

B.3 Optimization configuration

Since the selection of the number of reference days and the number of bins is user-specified, selecting an appropriate configuration requires a bit of trail-and-error. To make a more informed decision, the trade-off for the time series used in this thesis is visualized in figure B.1. In the set-up, the number of bins has been varied between 5 and 10 bins and the number of sampled number of reference days has been varied between 1 and 30 days, resulting in 180 experiments. Each of the experiments has subsequently been replicated 1000 times to approximate the minimal error.

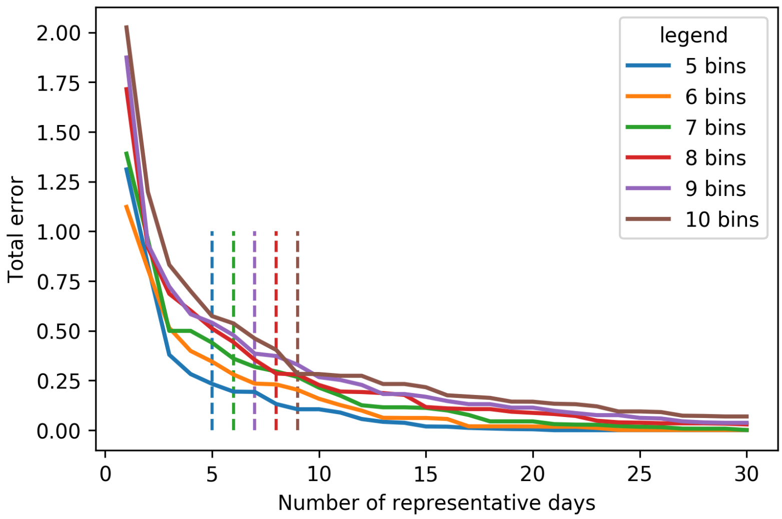

Figure B.1: Trade-off between number of bins and number of reference days

Based on the results in figure B.1 it is concluded that an increase in the number of reference days results in a lower total error score, whereas an increase in the number of bins results in a lower total error score. Therefore an increase in the number of bins requires an increase in the number of reference days to achieve a similar total error score in comparison to a lower number of bins. The 'ideal' number of reference days is determined based on the knee point of the lines in the graph, visualized as dotted lines. The knee point criterion is discussed in more detail in chapter 4.

Given that the objective of the selection of reference days is to reduce the computation time of the TEP-model, selecting a minimum number of reference days most significantly reduces the computation time. Therefore, the number of reference days has been set to 5 days and the number of bins to 10. In this trade-off the total error is relatively low compared to fewer days, while being optimized under a stricter 10 bin accuracy criteria. The reference day configuration is optimized over 10.000 unique samples.

B.4 Results

The results of the optimization configuration are described in table B.1. The resulting time series profiles are visualized in appendix A. The optimization resulted in a total error of 0,530, therewith performing slightly better than was expected based on figure B.1. The resulting reference days represent 120 hours, reducing the total number of hours that has to be evaluated in a single model evaluation with 98,6 percent.

Table B.1: Reference days and relative weights

Reference day	**Relative weight**	**Representative days**
84	0,223	82
101	0,294	107
108	0,126	46
172	0,192	70
359	0,165	60
Total	**1,000**	**365**

Appendix C

Model Repository

The model repository is available on GitHub under the MIT license via `https://github.com/robcalon/transmission-expansion-planning`.

The repository contains the code for the model itself, as well as several scripts and notebooks that have been developed to perform the different analyses described in this thesis. It is possible to contact me for any further questions via `https://www.linkedin.com/in/robcalon/`.