Energy Supply Reliability-Based Optimisation for the Development of Energy Hubs

Graduation Thesis

Industrial Engineering & Management

L.H. van der Ploeg

06/2024

Master Industrial Engineering & Management

Production and Logistics Management

Energy Supply Reliability-Based Optimisation for the Development of Energy Hubs

Author:

L.H. van der Ploeg

Firan B.V.

Koningstraat 28-1

6811 DG Arnhem

(088) 542 6363 (Alliander)

Supervisor:

dr. A.J. Veldhuis (Hans)

University of Twente

Drienerlolaan 5

7522 NB Enschede

(053) 489 9111

Supervisor:

dr. A. Trivella (Alessio)

Preface

Enschede, June 2024

Dear reader,

In front of you lies the master thesis, ‘Energy Supply Reliability-Based Optimisation for the Development of Energy Hubs’. This research project was conducted at Firan as the final step in completing the Master of Industrial Engineering and Management, specialising in Production and Logistics Management.

It has been incredibly insightful to execute a project within the energy sector and contribute to facing the challenges of the energy transition we all hear and read about. Therefore, I want to express my gratitude towards Firan for taking me in and allowing me to design my own research project. With no prior experience in the sector, I learned a lot about various topics by joining team meetings with the department and hearing about all the work done to create a better future. Although generally working on my own project, everyone has been very welcoming and ready to help whenever possible. My special thanks go out to Hans Veldhuis, who guided me from the beginning until the end. Our discussions helped steer the research in the right direction while allowing me to express my thoughts.

Furthermore, I want to thank my university supervisor, Alessio Trivella. First, for helping me find a direction for potential projects in the energy sector and finding suitable companies to execute such a project, even before anything was official. Your close guidance in writing my project plan and every chapter afterwards made all the difference. You were always quick to answer any questions I had, and your feedback helped me in each step.

As I write this, I think about how this graduation project marks the end of my time studying in Enschede. It has been almost eight years since I started pursuing my bachelor's degree. With time spent living in Antwerp, a full- and part-time board year, a pre-master, and finally, doing a master's in IEM, I had the opportunity to experience many things. I made friends, discovered new hobbies, and grew into the person I am now. All those years, I lived in the same house and saw housemates come and go. To everyone I’ve lived with, thank you for making this place not only a house but also a home.

My final thanks go out to the dearest people in my life. Without the support of my parents, I could not have achieved the things I have. You believed in me while I sometimes doubted, and you always gave me the confidence to continue my studies. I cannot thank you both enough. Lastly, I want to thank my girlfriend for her support during these last months, and especially for the time we spent together after busy working days.

Enjoy reading!

Rens

Management Summary

This research was conducted at Firan under the umbrella of the Decentral Networks department. Firan is a daughter company of Alliander: One of the largest firms in the energy sector in The Netherlands. The decentralisation of our energy networks and the increased use of renewable energy sources are major developments driving the energy transition. However, capacity shortages and congestion on the electric power grid pose a great challenge. To address these issues, Firan specialises in developing, realising, and exploiting infrastructures for decentralised energy hubs, which aim to efficiently generate and distribute energy to consumers. To aid the development process for energy hubs, Firan developed the Energy Hub Configurator (EHC). The EHC is a powerful tool to analyse data and provide insights regarding the design of energy hubs, such that well-founded decisions are made. However, insights into the energy supply reliability and the effects of uncertainties posing a risk to supply reliability are currently limited, even though the highly uncertain nature of renewable energy sources and limited grid withdrawal capacity pose a significant challenge to overcome. For the development of the energy hubs, each consumer's trust in having a reliable energy supply is essential for broad participation. If the decision-making for the design of energy hubs takes the uncertainties affecting the energy supply at the consumer level into account, and if the trade-offs between making investments and improving supply reliability can be analysed, informed decisions can be made. For the objectives of this study, the following research question is formulated:

How can Firan improve the robustness in optimal decision-making for the design of Energy Hubs, considering its energy supply reliability?

A context analysis is performed to study the current design process and to identify to which aspect the research contributes. The research focuses on energy hubs for industrial consumers, with electricity as the implemented energy carrier and related technological assets such as wind and solar energy generation, as well as batteries for energy storage. The limitations in current energy hub modelling and optimisation processes, considering the energy supply reliability, are identified. A literature review is conducted to understand recent developments in energy hub modelling, practices, relevant parameters, and technological assets. Varying modelling approaches for energy hub optimisation are researched, and strategies discussed in the literature for modelling uncertainties are elaborated on. Furthermore, an analysis is made on methodologies for analysing energy supply reliability, and different performance indicators to quantify energy hub reliability are discussed.

Using the insights from the context analysis and the literature review, a two-stage stochastic optimisation model is developed for the design and operation of energy hubs, which incorporates the uncertainties posing a risk to the energy supply reliability and implements performance indicators to quantify the energy supply performance. In the first stage of the model, the strategic technological capacity investment decisions are taken. The second stage optimises the operation of the energy hub under uncertainty, using a scenario-based approach. The model's objective function minimises the costs associated with the design and operation of the energy hub and incorporates the fundamental cost/reliability trade-offs between making investments and energy supply reliability by setting a financial penalty for the occurrence of energy shortages within operational optimisation.

The optimisation model is used to conduct several experiments. First, the solvability and scalability of the model are assessed. Second, the merits of stochastic optimisation under uncertainty are analysed by evaluating deterministic model solutions under uncertainty compared the stochastic model solutions. The cost/reliability trade-offs in energy hub optimisation are studied in the third experiment. The optimal solution space in balancing costs and reliability is explored and visualised in a Pareto-front, and the consumer-level energy supply performance is analysed through the implemented reliability KPIs. Lastly, the impact of technological degradation on the energy supply performance in a multi-year operational planning horizon is studied.

The results of the experiments show that the importance of stochastic optimisation and incorporating uncertainty in decision-making for energy hub designs cannot be understated. While high energy supply performance is achieved under deterministic optimisation, the resulting capacity decisions from this model instance are insufficient to cover energy demands under uncertainty, for a range of analysed energy hub configuration variants. In the analysis of the cost/reliability trade-offs, it is observed that while improvements in energy supply reliability are made for each increase in capacity investments, not all solutions pose an efficient trade-off.

Using the minimum observed capacity investments totalling €67,896, 0.12% of all energy is expected to be unsupplied under uncertainty, with a probability of over 4% that an energy shortage occurs somewhere in the hub during each operational period of 15 minutes. By making additional investments, the performance can be improved iteratively, until the point at which no more shortages occur. For this, capacity investments totalling €195,326 are required. Lastly, it was found that the effects of technological degradation significantly affect the energy supply in the hub for each consumer. However, the extent to which the effects are visible is highly dependent on the configuration of the hub, as well as the specific demand profile of each consumer. The greatest decreases in energy supply performance are observed for the consumers with the largest demand.

Based on the findings of this research, several recommendations are made for the implementation of the studied concepts within the development of energy hubs at Firan:

- A stochastic approach in which the energy hubs are optimised under uncertainty and accounting for different scenarios is fundamental in decision-making for reliable energy hub designs. A range of uncertainty sources must be included, among which are the energy demands, the availability of renewable energy, and various technological uncertainties. Improvements of at least 1% to an observed maximum of 75% in the total minimised costs are achieved when comparing the deterministic model to the stochastic model solutions under uncertainty.
- The trade-offs between making investments and achieving energy supply reliability can be used to develop energy hub design variants. In consultation with stakeholders and given their requirements, reliability can be maximised within budget constraints, or the required budget for achieving a minimum reliability threshold can be found. Firan can communicate these insights with project stakeholders, and by identifying investment strategies that align with stakeholders' priorities in reliability and their financial constraints, well-founded decisions are made.
- Consumer-level reliability KPIs can be leveraged to provide stakeholders with elaborate insights into the performance of the energy hub. By analysing KPIs at the consumer level, Firan can offer stakeholders a detailed understanding of how collective or individual investments impact energy supply reliability. Having specific knowledge about the effects of making investments and operational uncertainties on the operation of the energy hub, tailored solutions can be developed to ensure reliability for all stakeholders at the consumer level, ultimately improving overall performance as well.
- By analysing the effects of technological degradation in multi-year operational planning horizons, energy supply issues and their severity are identified, such that mitigation strategies for the effects of technological degradation can be developed within the design process.

Reader's Guide

Chapter 1

The research and its goals are introduced in the first chapter. The company at which the project is executed and relevant topics about the research are introduced first, and the motivation for conducting this study is explained. Second, the problem identification and research objectives are explained, and the research questions are formulated.

Chapter 2

The second chapter elaborates on a descriptive context analysis explaining the current processes at the company, to identify how and where the research can contribute. The key elements in energy hub modelling and the uncertainties posing a risk to the energy supply in the hub are identified.

Chapter 3

A literature review is conducted to gain insight into recent developments in the field of energy hub modelling and optimisation. Various modelling approaches are studied, and methods to analyse energy supply reliability are introduced.

Chapter 4

The fourth chapter presents a two-stage stochastic optimisation model which incorporates the uncertainties posing a risk to energy supply reliability using a scenario-based approach. Consumer-level energy supply reliability indicators are implemented in this model, such that the operational performance of an optimised energy hub asset configuration can be quantified.

Chapter 5

A numerical study is performed by conducting several experiments. For this, a data sampling method is developed and implemented in the model, such that a time series is created which improves computational times while still ensuring the seasonality in consumer demands and renewable energy availability. In the experiments, model solvability and scalability are tested, the merits of stochastic optimisation under uncertainty compared to deterministic optimisation are examined, the cost/reliability trade-offs in strategic decision-making are explored, and the impacts of technological degradation on energy supply reliability in a multi-year planning horizon is analysed.

Chapter 6

In the last chapter, the main conclusions from the research are drawn. Several recommendations are provided based on the findings of this thesis. The contributions to the theoretical and practical fields are stated, and the chapter is finalised by acknowledging the limitations of this study and identifying opportunities for future research.

Table of Contents

Preface **iii**

Management Summary **iv**

Reader's Guide **vi**

Table of Contents **vii**

List of Figures **ix**

List of Tables **x**

Glossary of Terms **x**

1 Introduction **1**

1.1 Introducing the Company and Relevant Topics 1

1.1.1 The Company 1

1.1.2 Introducing Energy Hubs 1

1.1.3 The Energy Hub Configurator 2

1.2 Research Motivation 3

1.3 Problem Identification & Research Objectives 3

1.3.1 Problem Identification 3

1.3.2 Research Objectives 4

1.4 Research Questions 5

1.5 Research Design 6

1.5.1 Research Approach 6

1.5.2 Scope Definition 6

2 Context Analysis **7**

2.1 The Development of Energy Hubs 7

2.1.1 Steps in the Development Process 7

2.1.2 The Energy Hub Design Process 8

2.2 Details of Energy Hub Design and Optimisation 9

2.2.1 Configuring Energy Hubs 9

2.2.2 Energy Hub Assets 9

2.2.3 Decision Variables 10

2.2.4 A Basic Energy Hub Configuration 10

2.2.5 Key Constraints of Energy Hub Optimisation 11

2.3 Uncertainties and Risks Affecting Energy Supply Reliability 11

2.3.1 Current Methods 11

2.3.2 Sources of Uncertainty in Energy Hubs 12

2.3.3 Uncertainties Posing a Risk to Energy Supply 12

2.4 Conclusions 14

3 Literature Review **15**

3.1 Energy (Hub) Models 15
3.1.1 Model Types 15
3.1.2 Energy Hub Parameters 16
3.2 Energy Hub Optimisation 17
3.2.1 Optimisation Models 17
3.2.2 Related Works 17
3.3 Modelling Uncertainty 22
3.4 Energy Hub Reliability & Analysis 22
3.5 Conclusions 24
4 A Stochastic Model for Reliability-Based Energy Hub Optimisation 25
4.1 Mathematical Problem and Model Introduction 25
4.1.1 Problem definition 25
4.1.2 Two-Stage Stochastic Programming 26
4.1.3 Model Outline 26
4.1.4 Modelling Assumptions 28
4.2 Model Formulation 28
4.2.1 Sets 28
4.2.2 Parameters 29
4.2.3 Decision Variables 30
4.2.4 Objective Function 31
4.2.5 Constraints 31
4.3 Energy Supply Reliability Indicators 33
4.4 Conclusions 34
5 Numerical Study 35
5.1 Input Data, Preparation & Numerical Inputs 35
5.1.1 Data Availability & Manipulation 35
5.1.2 Data Sampling and Time Series 35
5.1.3 Numerical Inputs 37
5.1.4 Uncertainty Modelling 39
5.2 Experimental Design 40
5.3 Model Scalability and Solvability 41
5.4 Deterministic vs. Stochastic Optimisation 42
5.4.1 Experiment Setup 42
5.4.2 Experiment Results 43
5.5 Energy Hub Cost/Reliability Trade-Offs 45
5.5.1 Experiment Setup 45
5.5.2 Experiment Results 45

5.6 The Impact of Technological Degradation 48
5.6.1 Experiment Setup 48
5.6.2 Experiment Results 49
5.7 Conclusions 50
6 Conclusions, Recommendations & Future Research 51
6.1 Conclusions 51
6.2 Recommendations 51
6.3 Contributions 52
6.3.1 Theoretical Contributions 52
6.3.2 Practical Contributions 52
6.4 Limitations & Future Research 53
References 54
A: Optimisation Model Formulation 57
B: Observed Model Solving Times 60
C: Scenarios and Average Input Profiles 61
D: VSS Results 63
E: Cost/Reliability Trade-Offs 64
F: Cost/Reliability Trade-Offs; Investment Decisions 65
G: Cost/Reliability Trade-Offs; KPI Values 66
H: Generator Output Degradation 67
I: KPI Values Under Technological Degradation 68

List of Figures

Figure 1: Schematic Illustration of Energy Hubs 2
Figure 2: Steps in energy hub development projects 7
Figure 3: Steps in the energy hub design process 8
Figure 4: Steps in creating the energy hub model 9
Figure 5: A Basic Energy Hub Configuration 10
Figure 6: Uncertainties affecting energy supply reliability 13
Figure 7: Uncertain scenarios in a two-stage scenario fan 26
Figure 8: Schematic overview of energy hub modelling 27
Figure 9: Data sampling strategy implemented in the optimisation model 36
Figure 10: Observed solving times for varying model settings (years, total weeks, scenarios) 42
Figure 11: VSS and % improvement between deterministic and stochastic solutions 44
Figure 12: Energy hub cost/reliability trade-offs 46
Figure 13: Observed EENS values for all cost/reliability trade-offs 47
Figure 14: Observed LOLP values for all cost/reliability trade-offs 47
Figure 15: Observed AS values for all cost/reliability trade-offs 47
Figure 16: Technological degradation for renewable energy generators 49
Figure 17: EENS and LOLP at Consumer 1 for each configuration variant 49

List of Tables

Table 1: Description of energy hub components 9
Table 2: Optimisation decision variables 10
Table 3: Energy hub optimisation modelling approaches 20
Table 4: Reliability indicators discussed in the literature 23
Table 5: Identified research gap in the literature 24
Table 6: Grid capacity limitations and consumer contracts 37
Table 7: Cost parameter settings 38
Table 8: Battery performance specifications 38
Table 9: Uncertainty models incorporated in the optimisation model 40
Table 10: Optimal configurations set as inputs in the model 48

Glossary of Terms

Abb.	**Term**
AS	Adequacy of Supply
CAPEX	Capital Expenditures
DSO	Distribution System Operator
EENS	Expected Energy not Supplied
EHC	Energy Hub Configurator
KPI	Key Performance Indicator
LOLP	Loss of Load Probability
MTTR	Mean Time to Repair
OPEX	Operational Expenditures
PV	Photovoltaic
VSS	Value of Stochastic Solution

1 Introduction

This introductory chapter discusses the background of the research and its objectives. First, the company at which the project is executed and relevant topics to clarify for this thesis are introduced. Second, the motivation to conduct the research is explained. Next, the identification of the research problem and research objectives are elaborated on. The research questions are formulated, and the approach to solving the problem is provided. The chapter concludes with a concise definition of the research scope.

1.1 Introducing the Company and Relevant Topics

1.1.1 The Company

This research project is executed at Firan. This company is part of Alliander N.V., one of the largest firms in the energy sector in The Netherlands. The Alliander group consists of multiple firms operating in different areas, among which is the management and maintenance of the power grid in large parts of the country, as well as grid development activities through the New Business section of companies. Companies within New Business aim to address the current questions from the energy sector and contribute to tackling the challenges of the energy transition. Along with several sister companies, Firan is one of the firms within New Business.

This thesis project takes place under the supervision of the Decentral Networks department of Firan. This department focuses on developing novel and future-proof solutions for the increasing demand for green energy. One such solution is developing, realising, and exploiting infrastructures for energy hubs. Energy hubs help organisations and businesses realise smart and efficient solutions for their energy requirements, by optimally generating and distributing renewable energy. The technical solutions offered by Firan make the company a suitable sparring partner for the different stakeholders in development projects, such as the provinces, municipalities, and business owners.

1.1.2 Introducing Energy Hubs

First, energy hubs must be introduced in more detail. Energy hubs aim to make optimal use of locally generated renewable energy and to efficiently control the production, storage, and consumption of this energy. Modern energy hubs may provide solutions for the energy demand satisfaction of different energy carriers such as electricity, heat, hydrogen, and other natural gases. The energy hub leverages the capabilities of various technological assets to optimally operate the system and meet all consumer energy demands.

An energy hub can consist of a mix of different technological assets. These technologies' exact configurations and capacities vary between each energy hub, and each configuration is influenced by specific energy demands and stakeholder requirements, and the opportunities and limitations within each development project. The most well-known examples of these assets are the production capacity of wind- and solar energy, and the storage of excess production using battery devices such that the energy can be used at a later point in time. Additionally, other technologies and systems can be implemented as well. Combined heat and power systems, electric vehicle charging stations, vehicle-to-grid technologies, and electrolysers for hydrogen production are some examples of the wide variety of options for configuring an energy hub. The consumers in the energy hub are, in principle, connected to the power grid, and they have access to the additional energy supply from a mix of different sources. Figure 1 depicts a schematic overview of the energy hubs developed at Firan. Depending on the energy supply challenges faced at the location of a potential energy hub, or the opportunity to make improvements in energy efficiency, a selection is made for the technologies to implement. This way, a tailored solution is designed which meets all stakeholder requirements and wishes.

Generally, the energy hubs developed at Firan relate to business parks with office buildings and/or industrial areas with factories. Relevant stakeholders in such an energy hub are first and foremost the consumers in the energy hub who have specific energy demands and load profile characteristics, but also the project developers, property owners, and governmental authorities such as the municipalities and provinces affect the design processes at Firan.

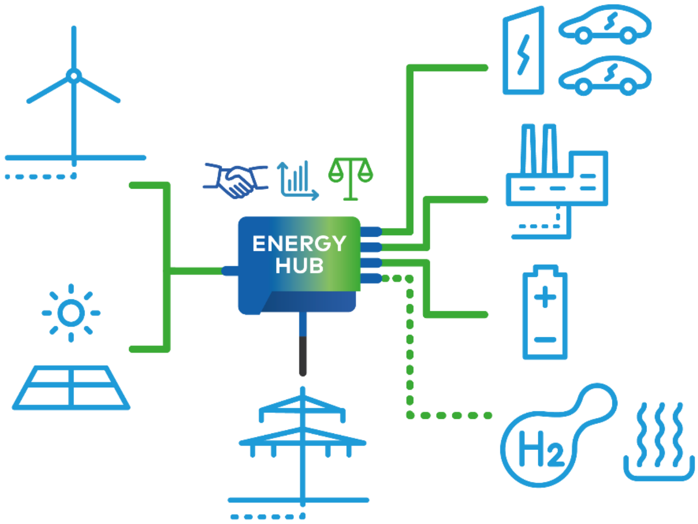


Figure 1: Schematic Illustration of Energy Hubs

1.1.3 The Energy Hub Configurator

In the design process for these energy hubs, Firan utilises the Energy Hub Configurator (EHC). The EHC has been developed at Firan and provides engineers with a powerful tool that can be used to analyse data and provide practical insights into the performance of potential energy hub configurations, ensuring informed decisions are made for all aspects of the design. Using the EHC, energy hubs can be modelled and optimised, taking into account the ever-changing requirements of project stakeholders.

The EHC utilises energy demand profiles from clients as its core inputs and it models different assets with which energy hub configurations can be built. Among these assets are wind turbines, photovoltaic (PV) systems, and batteries. Engineers can create different variations of a configuration for the energy hub using the EHC, to account for specific client requirements and project-specific constraints such as the budget, area limitations, and regulations.

In the EHC, potential designs for energy hubs are tested and compared based on several performance objectives, for which the assets included in the configuration are optimised. These objectives relate to minimising energy hub costs, maximising its profits, maximising the use of renewable energy, and maximising the energy hubs' autonomy from the power grid in its energy supply. Logically, in all cases, the energy demands of the consumers in the hub must be met fully. A computational core is the backbone of the EHC, which utilises mathematical optimisation to find the best solution for the selected performance objective. An optimised dimensioning of assets and their operation is calculated accordingly, ensuring a well-founded design proposal for the energy hub is made.

1.2 Research Motivation

The topics discussed in the previous sections all have a place in and apply to the energy sector in The Netherlands. The energy sector is a fast-moving industry with many stakeholders and uncertain, continuously changing elements to account for. Larger populations, increasing energy demands, and the intermittency of renewable energy sources are, among others, important factors at play. In recent times, the energy transition has been driving major changes within the industry. A greater proportion of our energy must come from renewable sources, moving away from the use of non-sustainable energy, the efficiency of our energy use must be improved, and the electrification of our industries has increased the overall demand. Along with these changes, the load on the power grid has increased drastically.

In The Netherlands, capacity shortages for new connections and congestion on the power grid pose a great challenge in ensuring power supply now, and in the future. Businesses that aim to settle or existing businesses that want to expand their activities cannot be accommodated in their energy requirements. The current available capacity on the power grid for energy withdrawal is unable to match the recent increase in demand (Koster, 2023), and development projects suffer delays due to the necessity of waiting lists for the allocation of grid capacity (Voorhoeve, 2022). Household consumers may also experience the negative effects of these issues. Longer waiting times to make homes more sustainable, an inability to feed solar energy into the grid, and possibly even electric outages could occur. Currently, energy suppliers have started to incur costs for returned electricity to compensate for increased processing expenses and to balance the surplus on the grid (Blotenburg, 2023; Gestel, 2023).

The decentralisation of our energy networks and increased use of renewable sources are major developments driving the energy transition. When new businesses emerge and business parks are developed, a crucial decision must be made for the allocation of new grid connections, the division of available capacity, and the use of energy-related assets to ensure a future-proof solution is delivered. These developments have sparked an increase in recent academic research as well, with evident relevance for implementation in real-world projects, where energy hubs are one of the main solutions to address these challenges and aid in making the difficult decisions at hand.

Optimisation of the design and operation of energy hubs is an essential part of their development before real-world implementation and exploitation can be achieved. Energy hub performance objectives and stakeholder requirements vary between projects, and many strategic decisions are made along the way. By realising an energy hub with renewable energy production and storage capacity, the grid congestion and capacity issues can be addressed, and greater independence on energy supply from the power grid can be achieved. Conducting research regarding the development and optimisation of energy hubs is a significant opportunity to make a contribution to the design process at Firan and to develop new ideas for the academic field.

1.3 Problem Identification & Research Objectives

1.3.1 Problem Identification

Currently, the EHC can incorporate some uncertainty within the mathematical optimisation of energy hubs within the energy demand profiles of consumers. This is achieved by including a set of possible demand profiles for a consumer if, for example, no historical data is available, or the exact profile of a new consumer is not yet known. The energy hub is optimised taking the different possible demand profiles into account, such that the strategic decisions for the energy hub design consider all possibilities.

This method increases the robustness of decision-making by ensuring the energy supply is ensured for all the included demand profiles. However, even though the main objective of the energy hub is to meet all consumers effectively and efficiently in their energy demands, insights into other uncertainties posing a risk to the energy supply in the hub are limited. Energy supply reliability can be compromised if the power-grid withdrawal capacity is limited and insights into risks affecting the energy supply are not available. Especially if the capacity of the power grid is insufficient to meet consumer demands at their load peaks and hence, a dependence on renewable energy generation exists, unavailability of additional energy production is detrimental to the supply reliability. Then, any reduction in energy supply capacity will cause shortages in meeting demand.

Considering the energy supply challenges faced in energy hubs, the trust stakeholders must have in the system's ability to meet their energy demands during operation cannot be understated. For broad participation among stakeholders in potential energy hubs, the reliability of ensured energy supply is essential. However, the mathematical optimisation of energy hubs using the EHC currently does not account for the uncertainties posing a risk to the energy supply reliability, nor does it provide specific insights into or quantify the supply performance of a configuration under these uncertainties.

The research problem concerning the current design process for energy hubs lies in the limited implementation of optimisation under uncertainties which affect the energy supply reliability during operation, and the lack of insight into the specific energy supply performance for the consumers in the energy hub. The effects of these uncertainties on the energy hub and its operation may necessitate the evaluation of design decisions to overcome supply risks and improve reliability. Hence, the optimisation of energy hubs ideally incorporates a variety of uncertain elements to ensure robust decision-making in the design process for the development of reliable energy hubs.

The research problem is defined as follows: The Energy Hub Configurator does not adequately incorporate the key uncertainties affecting energy supply reliability in its optimisation, limiting the robustness of decision-making. Furthermore, the current methods do not provide the essential measures to quantify the energy supply performance for consumers in the hub.

1.3.2 Research Objectives

By addressing the research problem, a contribution to the energy hub design process is made and the robustness of decision-making for the design of energy hubs can be improved. The uncertainties inherent to energy hubs and how these affect the energy supply reliability must be identified, such that strategies for improving reliability can be developed. Here, the trade-offs between making investments and achieving reliable supply performance are crucial. The extent to which supply reliability can be ensured for each consumer in the energy hub must be known, and the benefits of making additional investments must be made clear.

Hence, the main objective of this research is to develop a method for energy hub strategic design and operational optimisation under the uncertainties posing a risk to energy supply reliability, which considers this reliability as a key performance objective. For this, the uncertainties affecting the energy supply must be identified and modelled such that the energy hub configuration and its operation can be optimised.

In addition to the main objective, this research aims to generate insight into the investment costs and energy supply reliability trade-offs. This trade-off is essential in strategic decision-making, as the potential improvements in energy supply reliability must be considered about the potential technological investments in the energy hub. Lastly, the research aims to develop a strategy to quantify the operational energy supply performance in the optimisation process. In conducting this research, new strategies and insights for the energy hub design and optimisation processes at Firan are developed.

1.4 Research Questions

Based on the problem identification and research objectives discussed in Section 1.3, the main research question is formulated:

How can the robustness in optimal decision-making for the design of energy hubs be improved, considering its operational energy supply reliability?

A set of sub-questions is formulated for each step in executing this thesis project. The first two sets focus on analysing the research problem context and elaborating on relevant studies in the literature. These questions are answered in the preliminary research phase, and the results provide the insights needed to solve the research problem. For the project execution phase, the development of the model and experimentation are considered, and these sub-questions are included in sets 3 and 4 respectively.

1. ***What is the problem context, and what does the energy hub design process look like?***

    - How are energy hub development projects executed at Firan?
    - How are the EHC and design optimisation implemented in this process?
    - Which assets, parameters, and (decision) variables are relevant in the optimisation?
    - Which uncertainties and risks exist within energy hub operation?

2. ***What are, according to the literature, suitable modelling approaches for energy hub optimisation and reliability assessment?***

    - How are energy hubs modelled and optimised?
    - Which approaches are used to model and represent uncertainty?
    - Which performance indicators for hub reliability are proposed?

3. ***How is the reliability-based stochastic optimisation model for energy hub design formulated?***

    - What is the outline of the optimisation model?
    - How are the stochastic model decision stages and scenarios structured?
    - Which assumptions are made in the modelling approach?
    - Which sets, parameters and constraints are included in the model?
    - How is the objective function formulated?
    - Which reliability performance indicators are implemented?

4. ***Which experiments are conducted to test the model and analyse energy supply reliability-based optimisation?***

    - Which input data is required, and how is it used in the model?
    - How are the input parameters and values defined?
    - How are the uncertainties affecting energy supply reliability modelled?
    - Which experiments are conducted?
    - What are the results of the conducted experiments?
    - Which conclusions can be drawn from the experiment results?

1.5 Research Design

1.5.1 Research Approach

Several steps are taken to solve the research problem and to address the research objectives:

The first part of the preliminary research discusses the problem context and activities of the design process for energy hubs. This enables the identification of the steps in this process to which the research can contribute. Using available documentation and knowledge gathered from interviews, a descriptive study presents a detailed analysis of the current situation at the company. The results of this study are elaborated on in Chapter 2.

A literature review is conducted in the second part of the preliminary research. Both energy hub modelling and optimisation, as well as associated topics in the field, are discussed. Different approaches and their potential suitability for the research project are assessed, and strategies for energy hub reliability analysis are elaborated on. The results of the literature review and identified research gaps in the available literature are discussed in Chapter 3.

Chapters 4 and 5 discuss the project execution phase. The knowledge gathered in the context analysis and literature review is used to develop a model for energy hub design and operational optimisation under uncertainty. In Chapter 4, the model is introduced, and its outline is explained. Next, the complete model formulation is presented. The fifth chapter elaborates on a numerical study conducted using the model. All input parameters of the model are defined, and several experiments are performed to gather results.

The research is concluded in Chapter 6, in which recommendations for the company and the theoretical and practical contributions are also explained. Lastly, the limitations of this research are acknowledged, and opportunities for future research are explained.

1.5.2 Scope Definition

As energy hubs and their development are highly complex, the achievability of several aspects within the project execution is discussed, considering the existing time limits. Because of this, a project scope is defined and agreed upon by the supervisors at the University of Twente and Firan.

The results of the project and the gathered insights should apply to the existing development process of energy hubs at Firan. However, the objective of this research is not to develop a directly applicable solution for implementation in the Energy Hub Configurator used at Firan. Rather, the research is conducted to develop concepts for the energy supply reliability-based optimisation of energy hubs, such that recommendations can be made about the possibilities and benefits of implementing these concepts in the design process.

Furthermore, a selection is made for the energy hub components and technological assets to incorporate into the scope of this research. Modern energy hubs usually consist of multiple energy carriers, such as electricity, heat, hydrogen, and other (natural) gases. Considering this, an extensive set of energy hub assets for different energy carriers may be modelled, with many different parameters, variables, and characteristics.

However, it is infeasible to develop such a complete model with a high degree of detail for each asset and all energy carriers within the scope of a thesis project. Hence, the focus of this study is on implementing electricity as the modelled energy carrier, with related assets to incorporate being wind- and solar power generation technologies and energy storage capabilities using batteries.

2 Context Analysis

Through a descriptive study, an analysis of energy hub development and the use of the EHC at Firan is discussed. The components, assets, decision variables, modelling constraints, and uncertainties considered within energy hub modelling and optimisation are explained. The gathered insights aiding further execution of the research are summarised at the end of the chapter. The following research questions are answered:

What is the problem context, and what does the current development process at Firan look like?

- How are energy hub development projects executed at Firan?
- How are the EHC and design optimisation implemented in this process?
- Which assets, parameters, and (decision) variables are relevant in the optimisation?
- Which uncertainties and risks exist within energy hub operation?

2.1 The Development of Energy Hubs

2.1.1 Steps in the Development Process

The development of energy hubs for business- and industrial areas is one of the main product propositions at Firan. The complete process, from identifying market opportunities to final exploitation, is conducted at the company. In this process, several crucial steps are taken.

The first step is to identify lead opportunities in the market. Areas with a high degree of grid congestion and limited capacity for new grid connections offer the opportunity to implement an energy hub to improve energy-use efficiencies and reduce grid congestion. Additionally, areas in which entirely new business- and industrial parks are developed may provide the possibility to implement energy hubs as well, as a key part of local area development projects.

Within the development process, several iterations of the energy hub configuration design are created. The draft design comprises a first general idea of what the hub may look like. The preliminary and final designs are logical continuations of this and propose further developed iterations as more details become known. In these phases, communication with clients is crucial, such that each new design iteration is evaluated considering project requirements and stakeholder demands. Here, also the addition of or withdrawals from stakeholders and changing requirements for the design highlight the importance of flexibility in project execution.

If the final design is agreed upon by all parties involved in the project, local implementation of the energy hub and its exploitation are the last steps in the development process (Figure 2).

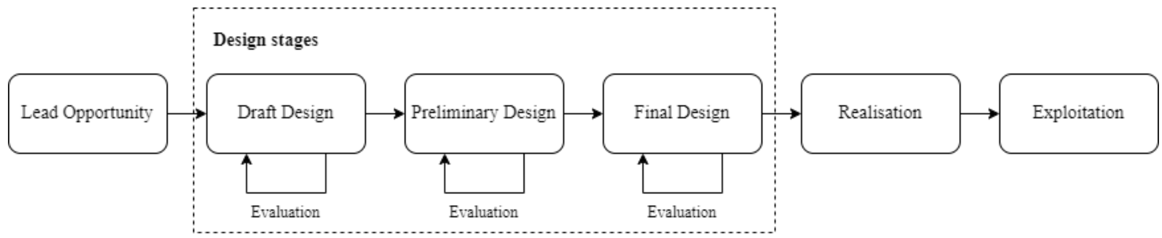


Figure 2: Steps in energy hub development projects

2.1.2 The Energy Hub Design Process

Within the energy hub development process, the design stages comprise several distinct steps as well. In these steps, the EHC is primarily used in making draft and preliminary design proposals. Its use in both stages is comparable, but the inputs for the model are updated as more details of the energy hub become known as the project progresses. The most labour-intensive efforts are made in developing a draft design where, from a business opportunity, an initial proposal is made for the configuration of the energy hub. In this process, the Energy Hub Configurator is used for initial problem analysis, energy hub configuration building, and mathematical optimisation of this configuration.

First, an 'energy scan' is performed. This procedure covers data collection for the project, followed by preparation and validation of this data such that it is usable in the EHC in the next steps of the design process. Initial calculations are conducted to identify existing bottlenecks in energy supply, and a baseline is defined from which the energy hub configuration can be designed.

After identifying the main bottlenecks in operational performance, their causes are analysed, and potential solutions are discussed. Engineers use available assets and consider the requirements of project stakeholders to adapt the energy hub configuration accordingly. The EHC is deployed to analyse the performance of configuration variants, make changes in the configuration, and optimise the asset capacities and operational planning of assets.

The mathematical optimisation in this part of the process can be conducted for four objectives. First, the total costs of the energy hub can be minimised. Second, the profits of the energy hub can be maximised. Third, the use of renewable energy to meet consumer demands can be maximised. Fourth, the autonomy of the energy hub can be maximised. For the latter, the autonomy of the energy hub relates to its independence from the power grid in energy supply during operation. Based on the potential configuration variants developed in this process, the optimal solution for each specific project is determined, to define what is called the energy hub model. The energy hub model formulates a detailed proposal for the entire energy hub configuration, including all project stakeholders, with a complete implementation of asset investments.

After the energy hub model is defined, an impact analysis is conducted, which examines the organisational structure of the energy hub, including financial responsibilities and legal implications. While this analysis is not implemented in the mathematical model of the EHC, it is a crucial step, as its findings significantly influence the feasibility of the project's realisation.

The steps of the design process are visualised in Figure 3. Only if each step is completed and agreed upon by all stakeholders, further progress towards energy hub realisation and exploitation can be made.

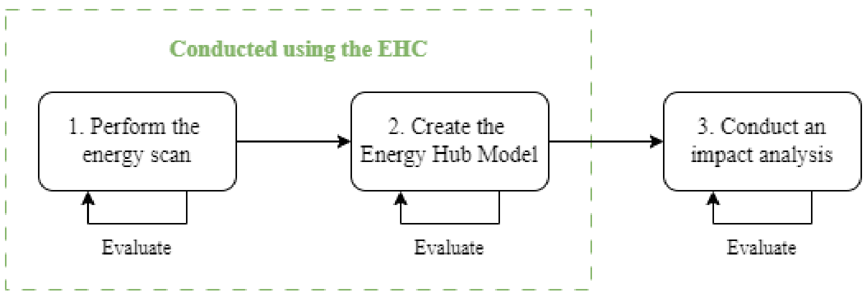


Figure 3: Steps in the energy hub design process

2.2 Details of Energy Hub Design and Optimisation

2.2.1 Configuring Energy Hubs

In this section, the specific activities for creating an optimised energy hub model using the EHC are explained.

The first step in configuring energy hubs is to add project-specific stakeholders and assets to the EHC. This means that all energy consumers and accompanying demand profiles, the technological assets, and the components allowing energy flows are set as inputs. A base configuration which represents the real-world situation is hence defined, which can then be mathematically optimised. In this process, the EHC is utilised as a building tool to iteratively set configuration variants, to test and optimise for different performance objectives.

The optimisation process results in the optimal dimensioning of the incorporated asset capacities and operational profiles of these assets. The results of the optimisation are evaluated, and a sensitivity analysis is performed (Figure 4).

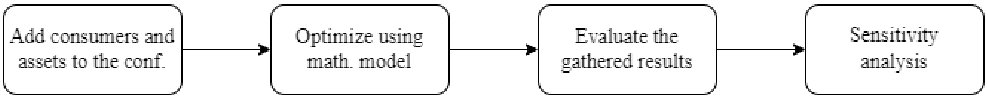


Figure 4: Steps in creating the energy hub model

2.2.2 Energy Hub Assets

Several assets are available for building configurations. Generators are renewable energy sources and consist of wind turbines and photovoltaic (PV) systems. Batteries store energy in case of an energy surplus and deploy energy in case of a deficit. The generator and storage technologies are attached to the buses in the configuration. Companies are the energy consumers in the hub, who all have specific electricity requirements which vary over time. They may or may not own assets, are connected to the power grid, and have a contract with the distribution system operator (DSO) concerning their energy withdrawal and injection limits.

Table 1 describes all the components included in a basic energy hub configuration with electricity as the main energy carrier.

Asset	Description
Battery	Battery that can charge and discharge energy
Bus	Location to which assets are attached
Company	Location where energy is consumed
DSO	Modelling contractual bounds between companies and grid
Line	Distribution line allowing energy flows
PV System	Photovoltaic power generator
Substation	Gateway to the power grid with bounds on energy flows
Wind Turbine	Wind turbine power generator

Table 1: Description of energy hub components

2.2.3 Decision Variables

Within energy hub optimisation, decisions are made to find the optimal dimensioning of assets and their operation. Table 2 lists the key decisions regarding capacities and operations for each of the configurable assets included in Table 1.

Asset	Variables	Purpose	Description
Battery	Capacity	Design	Storage capacity of a battery
	Charge	Operation	Charging of the battery
	Discharge	Operation	Discharging of the battery
	SOC	Operation	State of charge of the battery
Bus	Slack	Operation	Shortage or excess of power
Generator	Capacity	Design	Optimal capacity of a wind or solar generator
	Generate	Operation	Power supplied by a generator
Line	Flow	Operation	Energy flows through distribution lines
Substation	Withdrawal	Operation	Energy obtained from the power grid
	Injection	Operation	Energy supplied to the power grid

Table 2: Optimisation decision variables

2.2.4 A Basic Energy Hub Configuration

Figure 5 gives an example of a basic configuration showing how the assets in an energy hub can be connected. The blue arrows indicate the possible energy flows in the hub. Energy flows are bi-directional to allow energy withdrawal from and injection into the power grid, as well as to allow the charging and discharging of a battery. Logically, there is no need to transmit electricity in the direction of renewable energy generators, so here, only distribution away from the technologies is possible. In all cases, the energy balance must be kept in the energy hub, meaning that the total incoming and outgoing energy flows at the bus are equal.

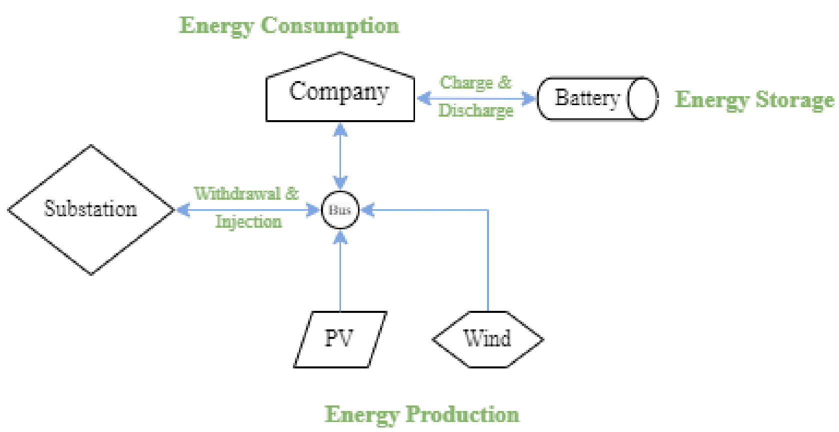


Figure 5: A Basic Energy Hub Configuration

2.2.5 Key Constraints of Energy Hub Optimisation

Constraints for the optimisation of energy hubs relate to the operational capabilities of technological assets in a configuration, their parameters, possible energy flows, the limitations of the power grid, and the contractual bounds of consumers. The following constraints are considered:

- Injection or withdrawal of energy to or from the power grid via the substation is limited to a specified maximum bound.
- For the DSO connection, the collective energy injection and withdrawal from all consumers in the energy hub is compared with the collective sum of the contractual bounds to check capacity limits.
- Renewable energy production quantities equal the *availability* × *capacity*. The capacity of the generator technology is either optimally determined by the model or pre-established within the model input.
- Battery charging and discharging rates are limited by specified bounds.
- Charging and discharging activities of batteries are modelled as energy flows, and charging and discharging efficiencies limit these energy flows.
- Storage capacities of batteries optimally determined by the model lie between a user-specified minimum and maximum value.
- A specified capacity limits the flow of energy through distribution lines installed between components of the energy hub.
- Incoming and outgoing energy flows are kept in balance. A slack variable is introduced to ensure energy balance and a feasible model in case the balance cannot be kept within normal operational optimisation.

2.3 Uncertainties and Risks Affecting Energy Supply Reliability

2.3.1 Current Methods

Currently, uncertainty is addressed in energy hub design optimisation by generating scenarios for the demand profiles of consumers. If the exact load profile of a consumer is not yet known or potentially differs from available historical data, a set of scenarios can be generated to represent variants of the load profile of that consumer. In such cases, for example, a combination of low-, mid-, and high-load scenarios of consumer demand can be included within the optimisation process. To reduce the computational load of this scenario-based strategy for uncertain consumer demands, a time aggregation method is used to determine typical weeks within available data, and the scenarios are generated for these typical weeks. Optimal decisions are based on these scenarios, increasing the robustness of the technology capacity decisions in the solution.

This strategy does not explicitly incorporate uncertainties directly affecting the energy supply reliability in the hub, nor does it provide measures to analyse the supply performance. It has been discussed how ensuring energy supply for each consumer in the energy hub is essential for broad participation in development projects (Section 1.3.1). The current methods and incorporated uncertainties, however, do not address the supply reliability in the energy hub, the effects of making investments on the improved energy supply and accompanying costs/reliability trade-offs, and measures to quantify the energy supply performance.

For the energy supply reliability of the energy hub, uncertain demand profiles are not the only factors affecting potential energy supply issues. Evidently, consumer demand profiles do affect the ability of the energy hub to meet demands if the consumption differs from the expected profiles used in optimisation model inputs, but various other uncertainty sources and characteristics of the energy hub influence its ability to ensure energy supply for all consumers.

2.3.2 Sources of Uncertainty in Energy Hubs

Trivella (2018) categorises six different sources of uncertainty present within energy hubs. These are classified in market, weather, energy supply/demand, regulatory, behavioural, and technological uncertainty. The uncertainties affect decision-making in energy hub design and optimisation, and identifying relevant uncertainties is an important step in developing an optimisation model.

1. Market uncertainty consists of, e.g., short-term uncertainty in energy prices, but also uncertainty in the long-term evolution of the prices and contracts.
2. Weather uncertainty is especially important for the (availability of) renewable energy generation from wind turbines and PV systems. Uncertainty in the forecasts for the expected availability of wind- and solar energy is an important aspect in case these technologies are incorporated into the energy supply mix of an energy hub, especially when consumers are dependent on renewable energy production to meet their energy demands. This source of uncertainty also relates to the supply-side uncertainty of the energy hub.
3. Uncertainty in energy supply and demand is crucial for each consumer in the energy hub. The relationship between energy supply and demand is the defining element for energy supply reliability, as a shortage in supply creates the inability to meet demands. Uncertainty in demand profiles and unexpected peak loads, as well as the energy supply from assets, is highly important to consider.
4. Regulatory uncertainty considers, for example, the unknown elements in governmental policies and regulations, support schemes, and subsidies.
5. Behavioural uncertainty is associated with the uncertain nature of human behaviour, concerning, for example, energy end-use and competitor strategy. Here, energy end-use relates to demand uncertainty. While uncertainty in the expected demand profiles can be explicitly included in the inputs for energy hub optimisation, uncertainty in end-use behaviour is more challenging to incorporate, as this is only truly revealed once the energy hub is realised in the real world. While the expectation is that consumers keep their energy consumption within the limits stated in their contracts, real-world situations might prove otherwise.
6. Technological uncertainty relates to, for example, the unexpected unavailability of assets and technological degradation. This uncertainty source also directly relates to the energy supply of the energy hub. Random unit failures and the extent to which assets in the energy hub degrade affect the available capacity of renewable energy generator outputs.

2.3.3 Uncertainties Posing a Risk to Energy Supply

Using Section 2.3.2, the uncertainties affecting energy supply reliability can be identified. For a high level of performance in energy supply reliability, the relation between supply and demand is crucial. If the supply from a mix of different energy sources is insufficient to cover the demand of each consumer and shortages occur, the energy supply reliability is compromised. Considering the relation between energy supply and demand, several uncertainty sources affect this characteristic of the energy hub's operation.

It was discussed how the uncertainty sources relate to and affect each other. Weather, technological, and behavioural uncertainties are key sources of uncertainty affecting the reliability of the energy hub. Here, weather, and technological uncertainties affect the energy supply in the hub. Behavioural uncertainty may affect the demand-side uncertainty in the energy hub (Figure 6). It is noted how these three core sources of uncertainty affect the energy supply and demand relation in different ways, and ultimately affect the operational performance of the hub to varying extents of severity. While asset failures lead to a complete loss of supply, technological degradation causes a partial decline in available capacity. Moreover, the degree to which actual consumer demands and renewable energy availability differentiate from the expected profiles affects the ability of the energy hub to meet demands.

Market and regulatory uncertainties do not directly affect the operational performance of the hub in its energy supply reliability. Although uncertain electricity prices and technological investment costs may affect optimal decision-making for the energy hub, these factors do not directly affect the energy supply reliability of the hub. The same holds for regulatory uncertainties. While support schemes, subsidies and uncertain development project approvals may affect the development of energy hubs, it has no relation to the energy supply reliability of an energy hub during its operation. These uncertainty sources are therefore not considered in this research.

Considering the discussed uncertainty sources, the following is concluded: The energy demands in a business park-oriented energy hub are satisfied using three main sources, these being the power grid, and wind- and solar energy production. Hence, this research must take into account the intermittency in the availability of renewable energy using these generator assets.

Furthermore, energy demands have an uncertain nature and must be incorporated as well. Demand uncertainty affects the energy hub at multiple levels. First, the energy hub may be considered in its entirety. The total demand of all consumers influences the required capacity of renewable production within the hub, as well as the required power withdrawal from the grid. Second, the uncertainty in demands at the consumer level must be considered. Here, unexpected peak loads in energy end-use pose a risk to ensuring supply and a high level of system performance.

The availability of assets within the energy hub is not guaranteed. In case of a failure or any event which causes the unavailability of an asset, supply capacity is lost. If no energy can be retrieved from renewable sources, the consumer must rely on the power grid, which has a limited capacity. Additionally, due to technological degradation, the performance of assets will decrease over time. This means that as the system is in the exploitation phase, it may rely less on the assets than initially accounted for.

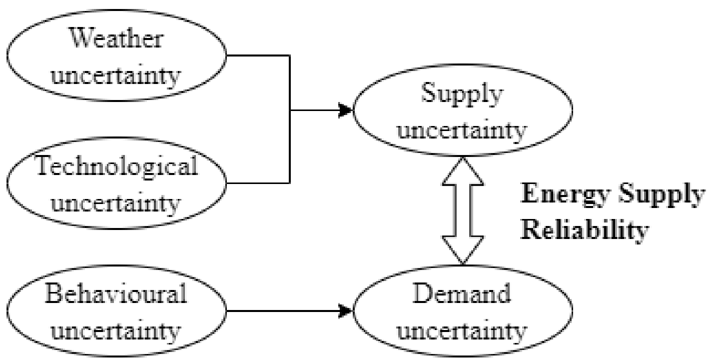


Figure 6: Uncertainties affecting energy supply reliability

2.4 Conclusions

Chapter 2 presented a descriptive context analysis to elaborate on several aspects related to the research problem. The first objective of the context analysis was to discuss the relevant details of energy hub development projects at Firan, such that it is assessed where in these projects the results from this research can contribute. The second objective was to collect essential knowledge about energy hub modelling and optimisation, such that it is known which elements to incorporate in this research. The analysis was performed while considering the research problem and the formulated research objectives.

The entire energy hub development process, from identifying lead opportunities in the market to final exploitation was elaborated on. In this process, several design stages are conducted iteratively after which a final design that covers all parts of the energy hub can be proposed. During these design stages, the energy hub configurator is deployed in both configuring energy hubs, as well as their mathematical optimisation. Next, the energy hub configuration building and optimisation processes were analysed. For the energy hubs considered within the scope of this research, the assets, decision variables for optimisation, and essential modelling constraints were defined.

Section 2.3 discussed the current methods of incorporating uncertainty within the energy hub optimisation. It was found that the energy supply reliability of configured energy hubs is not explicitly considered in the design process, and specific uncertainties affecting the energy supply during operation are not taken into account in (operational) optimisation. Incorporating these elements into the design of energy hubs is, however, essential. Using a characterisation of different sources of uncertainty within energy hubs, the specific uncertainties posing a risk to energy supply reliability were identified, and the way the relevant uncertainty sources affect each other was elaborated on.

In the next chapter, a literature review is conducted to provide an in-depth discussion on techniques for energy hub modelling and optimisation.

3 Literature Review

A literature review is conducted to elaborate on recent developments and practices in the field of energy hub modelling. The chapter specifically focuses on discussing research concerning the optimisation of strategic and operational decision-making for energy hubs, the uncertainties relating to the stochastic nature of energy hubs, and strategies for assessing energy supply reliability.

General practices of energy hub modelling are introduced in Section 3.1, and the parameters defining the relevant inputs of energy hub models are elaborated on. In Section 3.2, the state of the art in the development of optimisation models for energy hubs is analysed. A specific focus on energy hub optimisation under uncertainty is considered. Additionally, the explicit modelling of uncertainties within energy hubs is discussed in Section 3.3. Section 3.4 elaborates on the analysis of energy supply reliability. Different performance indicators for energy hubs used in the literature are introduced, and the relevant indicators for this thesis are identified. The chapter is concluded in Section 3.5, where the key insights from the literature review are collected, and the research gap in the literature is discussed. The following research questions are answered:

What are, according to the literature, suitable modelling approaches for energy hub optimisation and reliability analysis?

- How are energy hubs modelled and optimised?
- Which approaches are used to model and represent uncertainty?
- Which performance indicators for hub reliability are proposed?

3.1 Energy (Hub) Models

3.1.1 Model Types

An extensive number of research papers presenting (mathematical) models for purposes concerning the energy market and the development of energy hubs and related technological solutions are available. Energy models exist for varying purposes. Some are used to generate energy demand forecasts (Hayes & Prodanovic, 2016), while others are aimed at simulating technological, strategic, operational, and policy choices for, e.g., the design of energy hubs. A distinction for energy models is made between top-down and bottom-up models (Herbst et al., 2012). Top-down models depict the whole energy market on a regional or national level, to assess the effect of policies in monetary units. Contrary to bottom-up models, top-down models consider an aggregated view of the energy sector when simulating for example energy supply and demand processes, omitting technical details. Bottom-up energy models use a business economics approach for the evaluation of the technologies simulated within the model.

Generally, engineers construct and use bottom-up models to assess energy supply and demand leveraging their high degree of technological detail. Bottom-up modelling approaches do, however, have drawbacks. For example, bottom-up models do not consider the macroeconomic impacts of policies, making them unsuitable for very long-term analysis. Optimisation, simulation, and multi-agent energy hub models are examples of bottom-up modelling techniques. Nevertheless, even though their drawbacks are noted, bottom-up models generally pose the most suitable approach for the development and optimisation of energy hubs.

Energy hub models may be developed to find solutions for the energy supply of a single consumer, but energy hubs aimed at satisfying the demands for buildings, neighbourhoods, districts, or entire countries are discussed as well (Hiremath et al., 2007). The terminology used in research on energy hubs is inconsistent. Among others, energy systems, energy hubs, energy-hub systems, and multi-energy systems are discussed. For consistency, the term energy hub(s) is used in the remainder of this literature review.

Related to the modelling of energy hubs is the modelling of microgrids. Varying definitions to describe microgrids are found in the literature. Nevertheless, in a similar fashion to energy hubs, microgrids propose a technological solution for decentralised energy supply and demand, using assets for renewable energy production and storage, as well (Hirsch et al., 2018). A microgrid can operate both in a grid-connected setting as well as independently. Despite the similarities between energy hubs and microgrids, several key differences must be noted as well. Usually, energy hubs manage flows and conversion of multiple types of energy carriers, whereas microgrids primarily focus on electrical power. Additionally, energy hubs aim to optimise these different energy flows for improved efficiency and sustainability, while microgrids generally aim to provide a reliable energy supply to a specific area. Furthermore, energy hubs can operate at different (larger) scales, while microgrids are typically focused on localised energy generation and distribution.

Considering the characteristics of energy hubs and microgrids within the context of this research, a key observation is made. While the energy hubs considered within the scope of this thesis are not required to be independent of the power grid as is common with microgrids, the similarities between energy hubs and microgrids regarding their capacities for energy production and storage for reliable energy supply must be noted. Nevertheless, despite these similarities, the difference between the core purpose of the two energy solutions is significant. While a multi-energy system is outside the scope of this thesis, the optimisation of energy flows and the operation of assets for efficient energy use in the energy hub is, contrary to the main objectives of microgrids, still an important aspect of this research.

3.1.2 Energy Hub Parameters

Mavromatidis and Petkov (2021) categorise the different (input) parameters commonly included in energy hub models. These are energy demand profiles, availability profiles of renewable energy sources, and economic, technological, and miscellaneous parameters.

Generally, an extensive set of parameters is included in energy hub models for the most detailed and realistic results, and several parametric uncertainties should be considered for this research. The following list highlights the most important characteristics of each parameter category:

- Demand profiles of consumers in the energy hub should reflect short-term variability and long-term developments. It is essential to consider the different energy loads of each consumer in the hub, peaks, and the times at which they occur for optimal operation of the energy hub.
- The availability profiles of renewable sources should reflect short-term variability and long-term patterns to create a realistic representation of the availability of these sources.
- Economic parameters include energy prices and the technology costs of components and assets in the energy hub. Essential are the investment, maintenance, and operational costs of each asset included in the energy hub. These cost factors are commonly analysed within the optimisation objectives, dependent on the model goals and formulation.
- Technical parameters of the energy hub define the performance and operation of technologies, such as their efficiencies, self-discharge losses, and the technology lifetimes.
- Due to case-specific characteristics and limitations within energy hub development projects, other parameters may be necessary to implement in the energy hub optimisation model as well.

3.2 Energy Hub Optimisation

3.2.1 Optimisation Models

The development of optimisation models for energy hubs is a prevalent topic within the literature. Energy hub optimisation models are characterised as technology-rich models covering the entire energy supply and demand system for one or more consumers (Yue et al., 2018). The distinction made by Pfenninger et al. (2014) between planning and operational optimisation for energy hubs is relevant to address. Some studies focus on strategic design optimisation, while others specifically analyse the operational aspect of the energy hub (Ren et al., 2010). Methodologies combining both strategic design and operational optimisation of energy hubs are studied within the literature as well (Evins, 2015). Storage system design, sizing objectives of renewable energy generation assets (Geng et al., 2020), operational management and energy flow optimisation (Geidl & Andersson, 2007), and expansion planning (Cho et al., 2022) are some examples for which an optimisation model may be used.

Varying mathematical approaches to formulate energy hub optimisation models are studied. Common approaches include deterministic strategies such as linear programming, mixed-integer linear programming, and dynamic programming. In linear programming, the operational aspect of the energy hub can be described and optimised using linear mathematical functions. Integer linear programming approaches are useful when, for example, the optimal installation quantity of technological assets must be determined if the capacities of these technologies are fixed. Mixed-integer linear programming approaches are studied in the literature as well, using the technique, for example, to combine both strategic and operational decision-making aspects for energy hubs in a single model. Non-linear relations may be treated using a dynamic programming approach, splitting the problem into sub-problems, and storing intermediate results.

Besides the development of novel solutions for the optimisation of energy hubs, publicly available software tools exist, and the use of algorithms for energy hub optimisation is discussed as well (Fathima & Palanisamy, 2015). Stochastic programming models are also commonly used. In contrast to deterministic models, which assume all parameters are known and fixed, stochastic models incorporate uncertainties and variability in input data. Additionally, artificial intelligence-based approaches for energy hub optimisation are studied (Klemm & Vennemann, 2021).

3.2.2 Related Works

In this section, a review of relevant related works in the field of energy hub optimisation is conducted. Recent developments in research, modelling techniques, and strategies to optimise the design and operation of energy hubs are elaborated on. Deterministic modelling approaches, as well as optimisation models incorporating uncertainty, are considered in this section.

First, several examples of deterministic modelling approaches are analysed. Cano et al. (2014) propose a mixed-integer linear optimisation model combining both the strategic and operational decision-making for energy hubs. The model deals with strategic decisions relating to which specific assets to install and/or decommission, and short-term decisions are embedded within the constraints of the model to take into account operational decisions for the installed assets.

In case both strategic and operational decisions are considered, potential interference in the model objective leading to unrealistic outcomes must be taken into account because of the different time scales in which decisions are made. To illustrate, the strategic design decisions for the installation of assets are usually made for a multi-year planning horizon. On the other hand, the operational decisions concerning energy flows and the operational schemes of these assets are made for a short-term time scale relating to operational periods, for example, in each hour. If the costs for both the strategic and operational decisions are included in the optimisation model objective, they must be normalised to an equal timescale to prevent the generation of unrealistic outcomes. This can be achieved by, for example, annualising both the strategic and operational cost components.

Mixed-integer linear programming models to optimise both the strategic design and operational decision-making for energy hubs are often hindered by their complexity (Gabrielli et al., 2018). The complexity is mainly caused by the inclusion of binary variables, which for example describe the operational status of technologies, or the asset installation and decommissioning decisions as proposed by Cano et al. (2014). To address this limitation, two methods are developed to reduce the model complexity while retaining model accuracy.

The first method proposes the coupling of operational days. A sequence of typical design days from a year-long planning horizon are coupled into a sequential series, and technological states at the end of one day are connected to the start of the next. The second method takes into consideration that the complexity of the model is mainly caused by the binary variables. In this method, the operational decision variables are divided into those related to binary variables and those unrelated to binary variables. The computational complexity is reduced by modelling the group of operational binary variables for typical days, and the non-binary operational variables for each hour in a year. The specific optimisation decisions in the model proposed by Gabrielli et al. (2018) concern the dimensioning of installed technologies, the (binary) on/off status of energy conversion technologies, input and output energy, stored energy, and power-grid energy withdrawal. The model is deployed for optimising a multi-energy supply/demand system for the collective of consumer households in a neighbourhood-scale area.

A multi-stage MILP optimisation model for long-term system planning is proposed by Mavromatidis and Petkov (2021). The dynamic and evolving nature of energy hub parameters and flexible, multi-stage investment strategies are implemented. The model is used to develop a six-stage design plan within a thirty-year planning horizon. Perfect knowledge is assumed for all parameters, i.e., there are no uncertainties included in the model. Due to the optimisation of a multi-year, multi-location energy hub structure, the computational effort of this MILP is considerably higher compared to other deterministic approaches.

Besides these deterministic modelling approaches, stochastic models are also frequently studied, and recent literature is generally moving towards the development of stochastic optimisation approaches (Zakaria et al., 2020). Stochastic optimisation approaches are not limited to the use of fixed parameters, which allows for the optimisation of energy hubs under uncertainty. Deterministic models can be extended to their stochastic version by approximation of the probabilistic distributions and stochastic parameters through a finite set of scenarios, requiring constraints to be fulfilled for all scenarios and optimising the mathematical expectation of the objective (Cano et al., 2016). Optimising over a set of future outcomes allows the engineer to take recourse action as uncertainty is resolved (DeCarolis et al., 2017; Loulou & Kanudia, 1999). Uncertainties concerning, e.g., energy demands, renewable energy generation profiles, energy prices, and operational costs are commonly addressed.

Both the strategic and operational decisions for energy hub optimisation are commonly embedded within stochastic models. The difference between two-stage and multi-stage stochastic optimisation models must be noted. In a two-stage model, all strategic variables are first-stage decisions made before uncertainty is resolved. Hence, this stage commonly optimises the investment decisions for the installation of technologies in the energy hub. The operational decisions for the energy hub are made in the second stage, incorporating the available technologies defined in the first stage in the operational planning of the hub. In a multi-stage formulation, both strategic and operational decisions to be made before the first-tree branch are first-stage decisions. In contrast to two-stage models for energy hub optimisation, both strategic and operational decisions are already included in the first stage at the beginning of the time horizon. Second- and higher-stage decisions are the decisions made when new information concerning uncertainties is revealed. In principle, multi-stage optimisation models are more complex compared to two-stage models, both in terms of mathematical complexity and the interpretation of results. Both two-stage and multi-stage models for energy hub optimisation purposes are studied in the literature, but two-stage models are more common. In a stochastic program, the evolution of scenarios is approximated by a discrete-state scenario process using different techniques, such as a scenario tree, or a scenario fan. A scenario tree in a stochastic optimization model represents a branching structure of possible future events with discrete outcomes at each node. A node represents a specific point in time where a decision is made or an event occurs, leading to different possible future outcomes or branches. A scenario fan displays continuous paths of possible future values spreading out from a single point, often used for visualizing uncertainty over time.

Mansouri et al. (2020) propose a two-stage stochastic model for energy hub planning and operation. The first stage of the model optimises the sizing problem of technologies in the energy hub, and the second stage optimises the operation of the energy hub. It is noted that their approach considers a framework in which the first stage utilises an algorithm-based approach for the optimisation of technological capacities in the energy hub. The second stage of the model considers the operational optimisation problem of the energy hub. The outputs of the first stage defining the optimal capacities of installed assets are used as inputs for optimising the operation of the energy hub using these assets. Contrary to common methods found in the literature considering integer values for the number of units of an asset to install, capacity decisions for assets in this model are continuous to allow for precise decision-making for the energy hub design. In the model, operational uncertainty in energy demands and the intermittency of renewable power generation from photovoltaic systems are considered. Scenarios of these uncertain parameters in the model are generated using Monte Carlo simulation.

Another two-stage stochastic modelling approach is proposed by Cano et al. (2013), which finds a combination of installed technologies in the energy hub that minimises investment, equipment maintenance, and stochastic operational costs. The first stage includes investment decisions made before uncertainty is resolved. The second stage consists of decisions taken once the uncertainty is revealed. A multi-stage stochastic modelling extension on the deterministic model proposed by Cano et al. (2014) is presented as well (Cano et al., 2016). This approach includes a risk factor within the model formulation. Optimisation models in which risks are not explicitly modelled are risk-neutral. Ignoring risk management results in an optimal average value for the objective function but might lead to very bad outcomes in the case of extreme scenarios. Strategies can be implemented in an optimisation model to mitigate the risks of such extreme scenarios. The uncertain parameters considered in this risk-management model are energy demands, energy purchasing costs, and technology installation costs.

Yang et al. (2017) present a two-stage stochastic model for the design of energy hubs under uncertainty in energy demands, energy prices, and renewable energy intensity. The renewable energy intensity in this study defines solar radiation and wind density. In this model, strategic decisions in the first stage consider the number of units to install a certain technology, and the second stage determines the optimal operation. To stochastic model is transformed into its deterministic equivalent mixed-integer linear programming problem to solve it. Random sampling is used to generate a finite number of scenarios for the uncertainties incorporated in the model, and the model is solved to satisfy the operational constraints in the second stage for all scenarios.

Table 3 provides an overview of different deterministic and stochastic optimisation models discussed in this section, as well as relevant additional research papers found in the literature which were not explicitly elaborated on. If applicable, the uncertainties included in the models are stated, and the modelling approach of each study is included.

Table 3: Energy hub optimisation modelling approaches

Author(s)	Problem/context	Uncertainties	Uncertainty model	Optimisation model
Ren et al. (2010)	Operational optimisation of multi-energy hubs	n/a	Deterministic model	Multi-objective linear programming
Cano et al. (2013)	Building-level energy hub design problem	Demand, prices, operational costs, technology lifetimes	Probabilistic scenarios of parameters	Two-stage stochastic optimisation
Cano et al. (2014)	Building-level energy hub design problem	n/a	Deterministic model	Mixed-integer linear programming
Evins (2015)	Design and operation of multi-energy hubs	n/a	Deterministic model	Genetic algorithm (design) & MILP (operation)
Cano et al. (2016)	Building-level energy hub design optimisation	Prices, demands, asset installation costs	Yearly probabilistic increase in uncertain parameters	Multi-stage stochastic optimisation
Yang et al. (2017)	Asset selection and operation in a multi-energy hub	Energy demands, energy prices, renewable energy intensity	Use of a finite set of scenarios with probabilistic modelling of the uncertainties	Two-stage stochastic optimisation
Gabrielli et al. (2018)	Optimal design and operation of energy hubs	n/a	Deterministic model	Mixed-integer linear programming
Sanajaoba Singh and Fernandez (2018)	Remote hybrid energy hub size optimisation	Random failures of wind- and PV systems	Probabilistic modelling of asset capacities	Meta-heuristic optimisation algorithm
Mavromatidis et al. (2018)	Optimal design and operation of energy hubs under uncertainty	Energy prices, emission factors, demands, solar radiation	Probability distribution functions for the uncertain parameters	Two-stage stochastic mixed-integer linear program
Su et al. (2020)	Energy hub with electric power and natural gas	Energy demands, random unit failures, renewable energy production	Stochastic process models and probability distributions	Two-stage optimisation framework using multiple (algorithmic) methods

Author(s)	Problem/context	Uncertainties	Uncertainty model	Optimisation model
Mansouri et al. (2020)	Multi-energy hub design optimisation	Energy demands, PV-system energy production	Scenario generation using Monte Carlo simulation	Two-stage stochastic optimisation
Geng et al. (2020)	Isolated hub capacity design and operation	Energy production, electrical load	Probabilistic formulation of model constraints	Chance-constrained optimisation
Mavromatidis and Petkov (2021)	Multi-stage investment and hub design optimisation	n/a	Deterministic model	Mixed-integer linear programming
Wu et al. (2021)	Reliability-based operational optimisation	Random technological failures	Probabilistic modelling of random failure events	Linear programming
Faraji et al. (2021)	Operational optimisation of energy hubs under uncertainty	Uncertainty in renewable energy sources	Probability distribution for uncertainty in wind speed and solar radiation	Scenario-based stochastic programming
Abdulnasser et al. (2022)	Multi-objective optimisation of energy hub operation	Energy demands, renewable energy production	Probability distribution functions for the uncertain parameters	Multi-objective scenario-based stochastic programming
Ebrahimi and Sheikhi (2023)	Operational optimisation of multiple energy hubs in a local energy market	Renewable energy production	Probability distribution for uncertainty in wind speed and solar radiation	Mixed-inter linear program
Seyednouri et al. (2023)	Optimal day-ahead scheduling of multi-energy hubs	Renewable energy production, electricity demands, heat demands	Probability distribution for the uncertain parameters	Multi-objective scenario-based stochastic programming
Vera et al. (2023)	Optimal design and operation of a multi-microgrid system	Electricity demand, renewable energy sources	Probability distribution functions for the uncertain parameters	Two-stage stochastic optimisation

3.3 Modelling Uncertainty

The uncertainties inherent to energy hubs have a significant effect on the optimal strategic and operational decisions in the design process. Without adequately addressing these uncertainties, modelling insights may be limited and lack robustness. Representing the uncertainties in such a way that it is suitable for an optimisation approach usually involves model selection, parameter calibration, and scenario generation (Trivella, 2018).

In Section 3.2.2, varying models incorporating some form of energy hub optimisation under uncertainty have been discussed. However, the distinction between these stochastic optimisation models and the implementation of models to represent specific uncertainties is relevant to explain. Models of uncertainty focus on characterizing and representing uncertain elements within processes or systems. On the other hand, stochastic optimisation models are models designed to make optimal decisions under uncertainty. These models integrate the representation of uncertainty directly into the optimization process. So, while models of uncertainty aim to specifically represent the uncertainty, stochastic optimisation models aim to make the best decisions while accounting for these uncertainties.

For this research, varying models of uncertainty are required to represent the uncertainties posing a risk to the supply reliability of the energy hub. By developing a stochastic optimisation model, the strategic and operational decisions can be optimised for the energy hub while accounting for these uncertainties.

A suitable uncertainty model must be selected to represent each uncertainty considered within this research. To recall, these are the weather and technological uncertainties affecting the energy supply, and behavioural uncertainties affecting the consumer demands.

For the parametric energy supply- and demand-related uncertainties in energy hubs, probability distributions are most often used in the literature. The stochasticity of environmental circumstances significantly influences power generation from renewable sources, which affects the stability of the energy supply in the hub (Su et al., 2020). Probability distributions commonly describe the randomness of wind speed and the uncertainty in solar radiation. (Sedighizadeh et al., 2018; Shoaib et al., 2019). Such modelling approaches are especially relevant for the detailed modelling of these specific energy generation assets, but highly detailed modelling of assets is outside the scope of this thesis project. Hence, a more suitable approach for this research is to represent generator output uncertainty within expected output profiles from established data sets. However, very limited research into such an approach is available.

Wind turbines and PV systems can fail and will degrade over time, decreasing available power generation capacity. Failures of assets are often assumed to follow a binomial distribution (Sanajaoba Singh & Fernandez, 2018). In the study by Wu et al. (2021), several assumptions are made regarding unit failures of generator assets. A component is assumed to be either in a fully operational or failed state. Times to failure and times to repair are exponentially distributed with a constant failure rate and constant repair rate. The power output of a wind turbine generator is modelled considering two possible operating states, either fully available or unavailable, to represent the effect of forced outages.

3.4 Energy Hub Reliability & Analysis

The basic function of an energy hub is to supply its consumers with energy as economically as possible, with a reasonable degree of reliability (Billinton & Allan, 1990). To measure and quantify the reliability of energy hubs, performance indicators are used. These indicators are used to evaluate the impact of failures and interruptions in an energy hub (Son et al., 2021). The literature considers the implementation of reliability indicators for overall system performance, as well as energy carrier- and component-specific reliability indicators.

Among others, Wu et al. (2021) describe two distinct reliability indicators. The Expected Energy Not Supplied (EENS) calculates the amount of energy not delivered to meet the demand requirements of consumers each year due to the failure of a component or any other event interrupting the supply of energy. The Uninterrupted Supply Time (UST) measure enables analysis of the reaction to failures within the energy hub.

The Loss of Load Probability (LOLP) is a measure to determine the probability that the load in the system exceeds the energy generation level (Bao et al., 2019; Yang et al., 2003; Zeng et al., 2020). The loss of Load Expectation (LOLE) determines the expected energy deficit in hours per year for the operation of the energy hub (Dolatabadi et al., 2017).

Two consumer-level reliability indicators are proposed by Su et al. (2020). Their analysis is performed at the system- and consumer levels. The system-level analysis provides an overall measure of the ability of the energy hub to supply all consumers with the required energy under different uncertain conditions. Consumer-level analysis is used to assess the reliability of energy supply to individual stakeholders. The Probability of Shortage (POS) measures the system's ability to satisfy each energy consumer's demand. The Adequacy of Supply (AS) measures the severity of energy shortages for each consumer. It is quantified by the average value of the shortage for all events for each consumer. The Influence of Energy Shortage (INFL) is quantified by the total number of shortages and consumers affected by each.

Author(s)	**KPI**	**Description**
Wu et al. (2021), Zeng et al. (2020)	EENS	Expected Energy Not Supplied in % of Demand
Wu et al. (2021)	UST	Uninterrupted Supply Time in hours for an asset
Bao et al. (2019), Zeng et al. (2020), Yang et al. (2003)	LOLP	Loss of Load Probability in %
Dolatabadi et al. (2017)	LOLE	Loss of Load Expectation in hours per year
Su et al. (2020)	POS	Probability of Shortage of each consumer in %
Su et al. (2020)	AS	Measure for the severity of the energy shortage
Su et al. (2020)	INFL	Measure for the influence of each shortage

Table 4: Reliability indicators discussed in the literature

Using these concepts for the implementation of supply reliability indicators, those relevant to the objectives of this thesis can be determined. The expected energy not supplied (EENS) and the loss of load probability (LOLP) measures are important indicators to analyse the losses in energy supply and the probability an energy shortage occurs during an operational period of the energy hub. Additionally, the average quantity of energy deficit in a shortage occurrence is important to consider, as it provides potential insight into which investment strategies may be beneficial to overcome or mitigate the effects of the shortage by increasing energy supply capacities based on this measure. Furthermore, implementing performance indicators at the consumer level provides the necessary knowledge on specifically how and where the effects of uncertainties affecting energy supply are most severe.

3.5 Conclusions

In the literature review, research into the field of energy hub modelling and optimisation was conducted. First, the types of energy hub models, key parameters, and characteristics of the assets included within the scope of this research have been discussed. Second, an in-depth analysis of energy hub optimisation and related works was presented. Third, the distinction between uncertainty modelling within energy hub optimisation, and models of uncertainty models to represent specific uncertainties inherent to energy hubs is made. Fourth, relevant energy hub reliability performance indicators to integrate in this research were identified.

Using the gathered knowledge from the conducted literature review, the research gap to which this study contributes can be identified. For this, the research papers discussed in the literature review in which explicitly a strategy for energy hub optimisation is proposed are categorised (Table 5).

<table>
<tr><td colspan="2"></td><td colspan="3">Decisions</td></tr>
<tr><td colspan="2"></td><td>Strategic</td><td>Operational</td><td>Both</td></tr>
<tr><td rowspan="3">Approaches</td><td>Deterministic</td><td>Mavromatidis and Petkov (2021)</td><td>Ren et al. (2010)</td><td>Cano et al. (2014),
Evins (2015),
Gabrielli et al. (2018)</td></tr>
<tr><td>Stochastic</td><td>n/a</td><td>Faraji et al. (2021),
Abdulnasser et al. (2022),
Ebrahimi and Sheikhi (2023),
Seyednouri et al. (2023)</td><td>Cano et al. (2013),
Cano et al. (2016),
Yang et al. (2017),
Mavromatidis et al. (2018),
Mansouri et al. (2020)</td></tr>
<tr><td>Stochastic & Reliability Analysis</td><td>n/a</td><td>Zeng et al. (2020),
Wu et al. (2021)</td><td>Dolatabadi et al. (2017),
Su et al. (2020),
This thesis</td></tr>
</table>

Table 5: Identified research gap in the literature

Most of the analysed literature considers research into the development of models in which both strategic and operational decision-making processes are combined. Both deterministic and stochastic approaches are common. This thesis project aims to develop a stochastic optimisation model in which uncertainties posing a risk to energy supply reliability are incorporated within the operational decision-making process, with the additional implementation of relevant indicators to assess the energy supply performance of the energy hub defined by the strategic decisions.

In the literature, the studies by Dolatabadi et al. (2017) and Su et al. (2020) propose a similar objective. However, the first paper does not consider photovoltaic renewable energy generation within the studied model, which this thesis aims to include. The latter includes a more complete approach including both wind and photovoltaic power generation, but no energy storage capacities are modelled. Furthermore, although proposing a systematic framework with methods for the strategic and operational optimisation of energy hubs under uncertainty and evaluating the energy supply, the strategic and operational decision-making processes and evaluation methods are not included in a single mathematical model. Additionally, neither of these studies incorporates energy supply reliability performance as the main objective of the model. Rather, in the first study, costs are minimised, and reliability indicators are included as constraints, and in the second study, energy supply performance is only assessed after simulating energy hub operation. It is concluded that research into the development of stochastic models combining both strategic and operational optimisation which integrate energy supply reliability into the model objective is limited, and a relevant contribution can be made in this regard.

4 A Stochastic Model for Reliability-Based Energy Hub Optimisation

This chapter presents the stochastic optimisation model developed for this research. The uncertainties posing a risk to energy supply reliability are incorporated in this model using a scenario-based approach. First, the problem which is solved with this model and its outline are explained, and the assumptions made within the modelling approach are elaborated on. Next, the complete model formulation is presented, detailing the sets, parameters, decision variables, the objective function, and its constraints. The equations for the implemented performance indicators are defined, and the chapter is concluded in the last section. The following research questions are answered:

How is the reliability-based stochastic optimisation model for energy hub design formulated?

- What is the outline of the optimisation model?
- How are the stochastic model decision stages and scenarios structured?
- Which assumptions are made in the modelling approach?
- Which sets, parameters and constraints are included in the model?
- How is the objective function formulated?
- Which reliability performance indicators are implemented?

4.1 Mathematical Problem and Model Introduction

4.1.1 Problem definition

This section describes the specific problem that is modelled and solved in this research. To define the problem, the insights from the context analysis and literature review are used. The foremost objective of the model is to optimise the design and operation of an energy hub, taking into account its energy supply reliability. The trade-offs between making or not making strategic investments for the installation of technological assets and the effects on the energy supply reliability are explicitly considered within the optimisation.

In principle, the energy hubs that can be configured using the optimisation model contain a set of consumers with electric energy demands who are all connected to the main power grid, and there is the possibility to invest in wind- and solar energy production, as well as energy storage capacity. Power grid withdrawal in the energy hub is limited, hence a mix of energy supply sources is required to meet all consumer demands. For the assets, the investment strategy is defined by optimising the specific capacity of the technologies to be installed at each location if it is required. The operation of these assets and the energy flows in the hub are optimised under uncertainty.

To incorporate these elements in the optimisation model, an extensive collection of sets and parameters is required. Sets are formulated for the consumers, the technologies, the modelling of strategic and operational time scales for the accompanying strategic and operational decision variables, and the scenarios in which the stochastic outcomes of the uncertainties are generated and represented. The parameters relate to the energy demand profiles of each consumer, the output profiles of wind- and solar generator assets, economic (financial) parameters for the investment and operation of assets and the cost of energy withdrawal, the constraints of the power grid and contractual bounds for consumers, and technological parameters for the operation of batteries.

The model aims to find the optimal investment strategy for assets at each location in the energy hub, as well as their optimal operation to supply energy and meet consumers' demands. In the model, reliability indicators are implemented, through which the operational performance of the energy supply in the hub is quantified at the consumer level, providing detailed insights.

4.1.2 Two-Stage Stochastic Programming

To optimise both the strategic design decisions relating to the energy hub, as well as the operational decisions under uncertainty, a two-stage stochastic programming approach is used. In this section, the idea behind the setup of the stochastic model formulation is explained.

In a two-stage stochastic program, the uncertainties are represented using a scenario-based approach. In each scenario, a different outcome of the uncertainties is revealed, and the operation of the energy hub is optimised under these revealed uncertainties. Logically, the optimisation model is bound by the same constraints in each scenario. I.e., the model optimises the expected operational performance of the energy hub under the uncertainties posing a risk to system reliability.

A scenario fan of the stage one strategic and stage two operational decisions represents the structure of the model (Figure 7). In the figure, each *t* represents a time step in the optimisation. Time 0 concerns the first stage, in which the strategic capacity investment decisions for the energy hub are taken before uncertainty is revealed. So, in the first stage, the complete set of investment decisions for all available assets at each location is defined. After the first stage, the uncertainty is revealed, and the operational decisions are considered for each generated scenario and each sequential time step. The nodes in the figure in the second stage represent an operational time step in a scenario for which the operational decisions for the assets and energy flows are defined. The objective is to determine the initial strategic investment decisions such that the maximum achievable reliability of the energy hub is ensured for all scenarios in the operational stage.

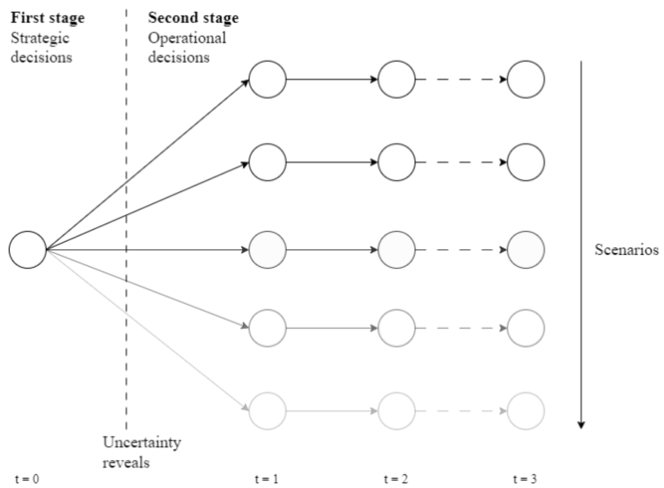


Figure 7: Uncertain scenarios in a two-stage scenario fan

4.1.3 Model Outline

The model is formulated as a two-stage mixed-integer stochastic linear program. The model optimises energy hub design and operation by minimising the total investment and expected operational costs under uncertainty for a specified planning horizon. The objective function includes a financial penalty for the occurrence of energy shortages, which poses a trade-off between making investments and energy supply reliability. By varying the value of the penalty, the solution space for this trade-off can be explored.

In principle, any energy supply reliability performance indicator can be included in the objective of the model, but for simplicity, the cumulative energy shortage for all consumers in the energy hub is considered as this value is already embedded in the model formulation. Intuitively, as reliability indicators are not conflicting, improving one consequently also improves the others. It is therefore expected that by including the cumulative shortage in the model objective and making improvements here, other performance indicators improve as well.

Generally, any number of consumers may be included in the energy hub. Energy flows can exist between all network components, but no specific energy market allowing consumers to trade energy amongst each other is incorporated. In addition to the consumers in the model, a consumer called ‘hub’ is used. Although it is included as a consumer, the hub has no energy demand to be met and serves as a generic system component at which assets can be installed and from which energy can be transferred to the other consumers. Time is modelled according to long-term periods and short-term periods. Long-term periods are used for strategic decisions, while short-term periods are used for operational decisions.

Figure 8 provides an example of a configuration for the consumers and the hub. It is noted that this figure does not illustrate a specific optimised configuration or existing case that is considered in this research, rather, its purpose is to show the capabilities of the model in configuring energy hubs.

The consumers are connected to the electric power grid and the energy available from assets installed at the hub can used to cover the demands of all consumers. Assets installed at a consumer can only supply energy to that specific consumer. Assets are not modelled separately. In principle, the investment decision describes a certain unit capacity of one or more assets at each specific location in the hub. For renewable energy generators, this means that the output profile at a specific location is a single profile based on the installed capacity and available data, as was discussed in the constraints in Section 2.2.5.

Strategic decisions are made at the start of the planning horizon, after which the operational decisions are optimised for the entire planning horizon. The model offers flexibility in how it is used. First, a situation may be considered in which there are no assets at the current time. In that case, decisions are made about which assets to invest in at which location, based on an empty hub with only consumers connected to the power grid. Second, assets may already be present. In that case, a configuration of asset capacities may be set as model input, pre-defining these decisions, and only optimising the operational planning of the hub.

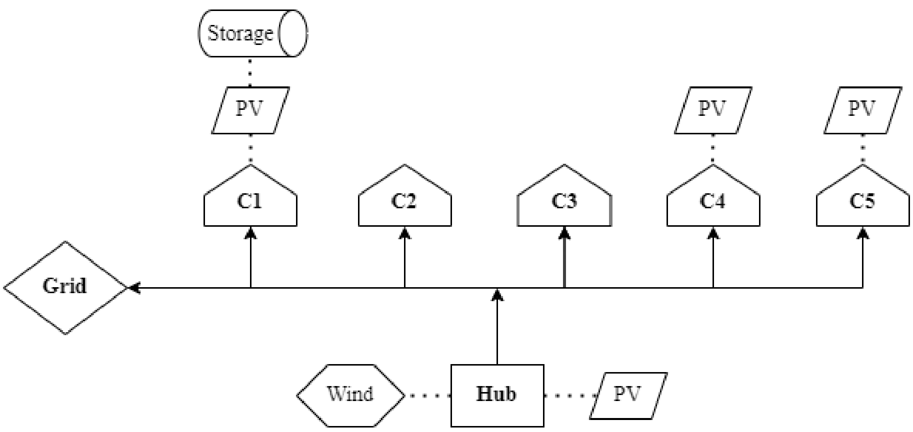


Figure 8: Schematic overview of energy hub modelling

4.1.4 Modelling Assumptions

Several assumptions are made, relating to the modelling complexity of certain aspects of technological assets, energy hub design, and its operation.

The model utilises a pre-defined profile for the outputs of renewable energy generators, and in the modelling of the assets, no technical limitations such as inefficiencies are considered. For all generator assets installed in an energy hub, the output profile is based on equal data for wind or solar energy production. No output efficiencies and losses are defined based on specific technological parameters.

Within energy hub operation, surpluses might occur in renewable energy production as they exceed demands. In such cases, curtailment of one or more generator assets is required. In principle, curtailment is only required in case energy production exceeds both the demand of consumers in the energy hub and the power grid injection capacity for selling energy. The curtailment decision is modelled to allow a perfect reduction in output to remove the surplus. Curtailment is embedded within the constraints by specifying energy generator outputs in each short-term operational period.

On the contrary, in case of energy deficits, the option to supply emergency energy generation is used. This essentially concerns a slack variable in the model which provides energy if the supply capacity from the power grid, renewable generators, and batteries, is insufficient to meet consumer demands. In that case, the deficit is supplied through emergency generation, which in turn indicates a shortage and the size of each specific shortage. It is also required to ensure model feasibility, as otherwise, energy balances cannot hold in case of a shortage.

The location of energy hubs is assumed to be generic and unrestricted in the model. No area-specific boundaries or limitations exist, and no distances between companies and assets in the network are considered. Hence, no distribution line losses are included, and energy transfer from one place to another is instantaneous. Using a generic location also omits the inclusion of available space to install assets and the use of weather data for the power outputs of generators.

Lastly, several assumptions are made regarding the possible strategic capacity investments for assets in the configured energy hub. While in principle, the model can be entirely free in the decision-making for the capacities of assets to be installed at each location, the logicality of these decisions must be taken into account as well. First, it is assumed that any wind energy generator capacity can only be installed at the hub location, not at any of the consumers. A consumer is considered a stakeholder who cannot own and have exclusive access to the energy supply of a wind turbine, rather, wind turbine supply is aimed at providing any of the consumers in the hub with energy. Second, for PV and battery capacity, it is assumed that there are no such restrictions. For PV systems, this represents how, e.g., a solar park can be installed near the industrial area where the energy hub is realised, while individual consumers may also have rooftop installed PV capacity. For the batteries, the same logic holds.

4.2 Model Formulation

4.2.1 Sets

Several sets are defined for the optimisation model. The consumer set consists of all consumers with energy demand, as well as the hub, at which assets may be installed, but no energy is required. To avoid ambiguity, the technology set is divided into two subsets, representing wind- and solar generators, and batteries. Time is modelled according to long- and short-term periods, representing the strategic and operational decision-making levels, respectively. Lastly, a set representing each scenario included in the optimisation is defined.

Sets	Description	Indices
C	Set of energy consumers	$c \in C$, $hub \in C$
T	Set of technologies	$t \in T$
$T_g \subseteq T$	Subset of generators	$t_g \in T_g$
$T_b \subseteq T$	Subset of batteries	$t_b \in T_b$
Y	Set of strategic-level periods	$y \in Y$
H	Set of operational-level periods	$h \in H$
S	Set of scenarios	$s \in S$

4.2.2 Parameters

The parameters define energy demand and energy generator output profiles, technological inputs, economic inputs relating to energy prices and the fixed costs of assets, the power grid capacity bounds, and battery specifications. Additionally, the penalty for energy shortages in meeting demand, and the discount rate and annualization factor used in the objective function are included.

Parameters	Description
$D_c^{y,h,s}$	Energy demand for consumer c, at time y, h in scenario s [kWh]
$P_{t_g}^{y,h,s}$	Output profile of a generator at time y, h in scenario s [kWh]
$DF_{t_g}^{y,s}$	Technology degradation factor in each year in scenario s [%]
$FP_{t_g}^{y,h}$	Renewable energy generator failure probability [%]
$DT_{t_g}^{s}$	Downtime of failed generator assets in scenario s (in hours)
PR^s	Probability of scenario s [%]
WC	Power-grid energy withdrawal cost [€/kWh]
IP	Power-grid energy injection profit [€/kWh]
IC_t	Technology investment cost [€]
MC_t	Technology maintenance cost [€/Year]
OC_t	Technology operation cost [€/Year]
WCap	Collective power grid withdrawal capacity [kW]
ICap	Collective power grid injection capacity [kW]
$MaxW_c$	Maximum withdrawal limit for consumer c [kW]
$MaxI_c$	Maximum injection limit for consumer c [kW]
$MaxT_{c_{from},c_{to}}$	Maximum energy that can be transferred between locations [kW]

SL_{t_b}	Fraction of storage lower limit [kWh]
SU_{t_b}	Fraction of storage upper limit [kWh]
SC_{t_b}	Battery charging efficiency [%]
SD_{t_b}	Battery discharging efficiency [%]
SX_{t_b}	Maximum battery charge rate [-]
SY_{t_b}	Maximum battery discharge rate [-]
P	Penalty cost for shortages in meeting energy demands [€/kWh]
DR	Discount rate
AF	Annualization factor

4.2.3 Decision Variables

Strategic decisions concern the installed capacities of renewable energy generators and batteries at each location in the energy hub. These decisions are made in the investment year at the start of the planning horizon. No further investments can be made after. Operational decisions include all energy flows in the hub and the operation of batteries.

Variables	**Description**
$GC_{t_g,c}$	Capacity of an energy generator installed at c [kW]
$BC_{t_b,c}$	Capacity of a battery installed at c [kWh]
$O_{t_g,c}^{y,h,s}$	Generator output at c, at time y, h in scenario s [kWh]
$CT_{t_g,c}^{y,h,s}$	Generator curtailment at c, at time y, h in scenario s [kWh]
$T_{c_{from},c_{to}}^{y,h,s}$	Transfer of energy at time y, h in scenario s [kWh]
$W_c^{y,h,s}$	Energy withdrawal by c, at time y, h in scenario s [kWh]
$I_c^{y,h,s}$	Energy injection by c, at time y, h in scenario s [kWh]
$E_c^{y,h,s}$	Emergency generation at c, at time y, h in scenario s [kWh]
$C_{t_b,c}^{y,h,s}$	Charging of a battery at c, at time y, h in scenario s [kWh]
$D_{t_b,c}^{y,h,s}$	Discharging of a battery at c, at time y, h in scenario s [kWh]
$SOC_{t_b,c}^{y,h,s}$	State of charge of a battery at c, at time y, h in scenario s [kWh]
$CS_{t_b,c}^{y,h,s} \in \{0, 1\}$	Charge state indicator at c, at time y, h in scenario s
$DS_{t_b,c}^{y,h,s} \in \{0, 1\}$	Discharge state indicator at c, at time y, h in scenario s

4.2.4 Objective Function

The objective function minimises the strategic investment and fixed technological costs and the expected value of the annual operational costs under uncertainty. For this, the scenario probability PR^s is included. The operational costs are annualised to the strategic (yearly) level using factor AF.

$$\text{Minimize} \sum_{y} (1+\mathrm{DR})^{-y} * \Big(\sum_{t_g}\sum_{c} \mathrm{IC}_{t_g,c} * \mathrm{GC}_{t_g,c} + \sum_{t_b}\sum_{c} \mathrm{IC}_{t_b,c} * \mathrm{BC}_{t_b,c}$$

$$+ \sum_{t_g}\sum_{c} \mathrm{MC}_{t_g} * \mathrm{GC}_{t_g,c} + \mathrm{OC}_{t_g} * \mathrm{GC}_{t_g,c} + \sum_{t_b}\sum_{c} \mathrm{OC}_{t_b,c} * \mathrm{BC}_{t_b,c} + \mathrm{E}[\mathrm{Ann.\,Op.}]\Big)$$

Where:

$$\mathrm{E}[\mathrm{Ann.\,Op.}] = \sum_{s} \mathrm{PR}^{s} * \Big(\mathrm{AF} * \sum_{h}\sum_{c} \mathrm{W}_{c}^{y,h,s} * \mathrm{WC} - \mathrm{I}_{c}^{y,h,s} * \mathrm{IP} + \mathrm{E}_{c}^{y,h,s} * \mathrm{P}\Big)$$

4.2.5 Constraints

The main equations modelling energy flows are the energy balance constraints formulated explicitly for consumers (4.1) and the hub location (4.2). This balance is ensured for each location and each operational period. The left-hand side of the balance constraint defines the available energy in each period h, and the right-hand side sets the energy demand to be met. For the hub, at which no demand is to be satisfied, the energy balance constraint is formulated such that all available energy is transferred to the consumers. At the hub, no energy can be withdrawn from the grid, and it cannot receive energy transferred from consumers.

$$\sum_{t_g} \mathrm{O}_{t_g,c}^{y,h,s} + \mathrm{D}_{t_b,c}^{y,h,s} - \mathrm{C}_{t_b,c}^{y,h,s} + \mathrm{W}_{c}^{y,h,s} - \mathrm{I}_{c}^{y,h,s} + \mathrm{T}_{hub,c}^{y,h,s} + \mathrm{E}_{c}^{y,h,s} = \mathrm{D}_{c}^{y,h,s} \quad y \in Y,\ h \in H,\ s \in S,\ c \in C \tag{4.1}$$

$$\sum_{t_g} \mathrm{O}_{t_g,hub}^{y,h,s} + \mathrm{D}_{t_b,hub}^{y,h,s} - \mathrm{C}_{t_b,hub}^{y,h,s} - \mathrm{I}_{hub}^{y,h,s} = \sum_{c_{to} \neq hub} \mathrm{T}_{hub,c_{to}}^{y,h,s} \quad \forall\, y \in Y,\ h \in H,\ s \in S \tag{4.2}$$

The usable outputs of renewable generators are equal to the output of the installed technology from the input data multiplied by the installed capacity (4.3). A year-specific degradation factor is included, and curtailment on the output is subtracted. In case of failures, the output is set to 0 for the duration DT_{t_g}.

$$\mathrm{O}_{t_g,c}^{y,h,s} = \begin{cases} \mathrm{P}_{t_g,c}^{y,h,s} * \mathrm{GC}_{t_g,c} * \mathrm{DF}_{t_g}^{y,s} - \mathrm{CT}_{t_g,c}^{y,h,s} & \text{if operational} \\ 0 \text{ if failed, for duration } \mathrm{DT}_{t_g}^{s} \end{cases} \quad \forall\, y \in Y,\ h \in H,\ s \in S,\ t_g \in T_g,\ c \in C \tag{4.3}$$

The initial state of the battery is assumed to be at minimum charge capacity (4.4). For the transition between operational periods, the state of charge $SOC_{t_b,c}^{y,h+1}$ is set based on the previous state and the energy-charged or discharged during that time, limited by battery efficiencies (4.5). Additionally, the operational transition between the sequential strategic-level periods is ensured. Constraint (4.6) sets the state of charge in operational period 0 of the next year y+1 based on the state of charge in the last operational period max(H) of the previous year. The SOC is constrained by the fraction of storage lower and upper bounds (4.7) and the energy charged to and discharged from the battery cannot exceed the charge and discharge rates (4.8), and (4.9). Additionally, binary state indicators are included, ensuring that either a charging or discharging decision is taken (4.10).

$$SOC_{t_b,c}^{0,0,s} = SL_{t_b,c} * BC_{t_b,c} \ \forall\, s \in S,\ t_b \in T_b, c \in C \tag{4.4}$$

$$SOC_{t_b,c}^{y,h+1,s} = SOC_{t_b,c}^{y,h,s} + SC_{t_b} * C_{t_b,c}^{y,h,s} - SD_{t_b} * D_{t_b,c}^{y,h,s} \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C \tag{4.5}$$

$$SOC_{t_b,c}^{y+1,0,s} = SOC_{t_b,c}^{y,\max(H),s} + SC_{t_b} * C_{t_b,c}^{y,\max(H),s} - SD_{t_b} * D_{t_b,c}^{y,\max(H),s} \ \forall\, y \in Y,\ s \in S,\ t_b \in T_b, c \in C \tag{4.6}$$

$$SL_{t_b,c} * BC_{t_b,c} \le SOC_{t_b,c}^{y,h,s} \le BC_{t_b,c} * SU_{t_b,c} \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C \tag{4.7}$$

$$C_{t_b,c}^{y,h,s} \le SX_{t_b} * CS_{t_b,c}^{y,h,s} \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C \tag{4.8}$$

$$D_{t_b,c}^{y,h,s} \le SY_{t_b} * DS_{t_b,c}^{y,h,s} \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C \tag{4.9}$$

$$CS_{t_b,c}^{y,h,s} + DS_{t_b,c}^{y,h,s} = 1 \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C \tag{4.10}$$

Energy transfers from the hub to consumers are bound through (4.11) and no energy can be transferred to the hub (4.12). The collective of consumers cannot withdraw or inject energy beyond the capacity of the power grid (4.13), (4.14) and contractual bounds limit the energy consumers can withdraw and inject during each operational period (4.15), (4.16).

$$\sum_{c_{to} \neq hub} T_{hub,c_{to}}^{y,h,s} \le MaxT_{hub,c_{to}}^{y,h,s} \ \forall\, y \in Y,\ h \in H,\ s \in S \tag{4.11}$$

$$\sum_{c_{from} \neq hub} T_{c_{from},hub}^{y,h,s} = 0 \ \forall\, y \in Y,\ h \in H,\ s \in S \tag{4.12}$$

$$\sum_{c \neq hub} W_c^{y,h,s} \le WCap \ \forall\, y \in Y,\ h \in H,\ s \in S \tag{4.13}$$

$$\sum_{c} I_c^{y,h,s} \le ICap \ \forall\, y \in Y,\ h \in H,\ s \in S \tag{4.14}$$

$$W_c^{y,h,s} \le MaxW_c \ \forall\, y \in Y, h \in H,\ s \in S,\ c \in C,\ c \neq hub \tag{4.15}$$

$$I_c^{y,h,s} \le MaxI_c \ \forall\, y \in Y,\ h \in H,\ s \in S,\ c \in C \tag{4.16}$$

A positive, continuous value decision is taken for the capacities of assets installed at each location (4.17), (4.18). Constraints (4.19) relate to the binary variables. All other variables are continuous and nonnegative (4.20).

$$GC_{t_g,c} \geq 0 \; \forall \; t_g \in T_g, c \in C \tag{4.17}$$

$$SC_{t_b,c} \geq 0 \; \forall \; t_b \in T_b, c \in C \tag{4.18}$$

$$CS_{t_b,c}^{y,h,s}, \; DS_{t_b,c}^{y,h,s} \in \{0,1\} \;\; \forall \;\; t_b \in T_b, \; y \in Y, \; h \in H, \; s \in S, \; c \in C \tag{4.19}$$

$$\text{All other variables} \geq 0 \tag{4.20}$$

4.3 Energy Supply Reliability Indicators

Performance indicators are implemented in the optimisation model to analyse the operational reliability of the energy supply. The concepts and insights gathered in the literature review (Section 3.4) are used to define the implemented indicators. The indicators are scenario-independent and provide insight into the expected energy supply performance in meeting demands under uncertainty, by measuring the reliability of the energy supply and the severity of the observed shortages. It is noted that these performance indicators are only relevant to the actual consumers: The hub component in the configuration, at which assets are installed to transfer energy to consumers, does not require any energy; thus, it cannot have shortages and, in terms of reliability, does not affect operational performance.

The variable $E_c^{y,h,s}$ in the optimisation model represents emergency energy generation in case of a shortage. Its main purpose is to ensure energy balance in case of a shortage, but it is also used to compute the cumulative energy shortage that occurred during operational optimisation (5.21). Additionally, the number of shortage occurrences can logically be computed from this variable by counting the number of times the value $E_c^{y,h,s} > 0$. The cumulative shortage value and the number of shortage occurrences are used to compute the performance indicators included in the model.

$$\text{Cumulative Short}_c = \textstyle\sum_y \sum_h \sum_s E_c^{y,h,s} \tag{5.21}$$

The Expected Energy Not Supplied ($EENS_c$) computes the percentage of unsupplied demand at the consumer level (5.23). The Adequacy of Supply (AS_c) measures the severity of shortages at each consumer (5.24). It is quantified by the average value of the shortages during the operational planning horizon. The Loss of Load Probability ($LOLP_c$) computes the probability an energy deficit will occur in an operational period for each consumer (5.25). The total number of operational periods is quantified by the size of the sets of long- and short-term periods and all scenarios.

$$EENS_c = \frac{\text{Cumulative Short}_c}{\sum_y \sum_h \sum_s D_c^{y,h,s}} * 100\% \tag{5.23}$$

$$AS_c = \frac{\text{Cumulative Short}_c}{\text{No. of Shortages}_c} \tag{5.24}$$

$$LOLP_c = \frac{\text{No. of Shortages}_c}{|Y| * |H| * |S|} * 100\% \tag{5.25}$$

4.4 Conclusions

In Chapter 4, the developed modelling approach for the optimisation of energy hub design and operation was presented. The purpose of this model is to ensure the energy supply for the consumers in the energy hub, in a context where limited power grid capacity is available for the withdrawal of energy, and additional energy supply using renewable energy production and energy storage is incorporated.

The specific problem solved using the model, the model outline and the assumptions made within the modelling approach were discussed first. Additionally, the set-up of the scenario-based stochastic programming approach was described, such that the uncertainties posing a risk to the energy supply reliability can be incorporated within the operational optimisation. For this, a two-stage modelling approach was chosen, in which the strategic design decisions concerning the capacities of technologies installed at each location are made in the first stage, and in which the operational decisions for the use of these assets and energy flows are optimised in the second stage.

The objective function of the model minimises the strategic and expected operational costs under uncertainty for the configured energy hub. By setting a financial penalty for the occurrence of energy shortages in meeting consumer demands and minimising operational costs, the operational energy supply reliability can be addressed: As the objective function aims to minimise the overall costs related to the energy hub, the model consequently aims to minimise the incurrence of the penalty, reducing the occurrence of energy shortages during operation. This inherently improves the energy supply reliability as energy shortages are minimised. Additionally, by varying the specific value of the financial penalty incurred for energy shortages, the solutions space for the costs/reliability trade-offs can be explored. As a higher penalty is set, more strategic investments for energy generation or storage are expected to be made. The opposite is expected to be true as well.

In Section 4.3, the implemented performance indicators were described. For this, the concepts discussed in the literature review were used, and the equations to compute these indicators were developed based on the sets and variables included in the model formulation. In principle, these performance indicators could also be incorporated into the model objective, but as it is expected that the implemented indicators are not conflicting, it is assumed that the values of the indicators are improved as the minimisation of energy shortages included in the objective is improved as well.

In the next chapter, a numerical study is conducted in which several experiments are performed using the presented model. These experiments are aimed at testing the model and generating relevant insights into energy supply reliability-based optimisation for the design and operation of energy hubs.

5 Numerical Study

This chapter focuses on performing a numerical study using the stochastic optimisation model that was presented in Chapter 4. First, the required input data and parameter settings are explained, including the development of a time sampling strategy. Next, the experimental design is elaborated on. In the experiments, model solvability, the merits of stochastic optimisation, cost/reliability trade-offs, and the effects of technological degradation on energy supply reliability are assessed. The chapter concludes with a summary of the results and the gathered insights. The following research questions are answered:

Which experiments are conducted to test the model and analyse energy supply reliability-based optimisation?

- Which input data is required, and how is it used in the model?
- How are the input parameters and values defined?
- How are the uncertainties affecting energy supply reliability modelled?
- Which experiments are conducted?
- What are the results of the conducted experiments?
- Which conclusions can be drawn from the experiment results?

5.1 Input Data, Preparation & Numerical Inputs

5.1.1 Data Availability & Manipulation

A dataset provided by the company is used for the demand profiles and the available outputs from wind turbines and PV systems. It includes anonymous demand profiles of five companies with varying loads. Additionally, it defines the output profiles of wind turbines and PV systems. The dataset consists of the calendar year 2021 and has a data point for each 15-minute period from January 1st to December 31st. It accurately represents the energy load between working days and weekends, holidays, and the seasonality in wind- and solar energy production.

For effective use in the model, the dataset is manipulated such that it starts at the beginning of a Monday. Additionally, the last day included in the data, this specific day being a weekend, is omitted. As energy demands in the data are observed to be significantly reduced at weekends compared to normal working days, they are less relevant for optimal strategic and operational decision-making and, consequently, their influence on energy supply reliability. Therefore, it is assumed this specific Sunday may be omitted without affecting optimisation results. Applying this procedure, the remaining data can be segmented into 52 week-long periods of equal length, each starting at the beginning of a Monday and ending at the last operational period on Sunday. This enables the specific sampling of different weeks from the dataset to extract week-long operational profiles which are added sequentially to create a computationally easier time series to optimise.

5.1.2 Data Sampling and Time Series

To reduce computational complexity, a time series is created for each scenario in the optimisation model, consisting of randomly sampled years and weeks in a pre-established time horizon. A specific number of weeks is selected for each sampled year. The probability of sampling a specific year or week is equal for all instances. In each scenario of the stochastic model, an equally long time series containing a different set of years and weeks is included. It is noted that the sampling, in principle, always includes the investment year 0, after which any of the others can be added. The time series is ordered from the investment year to the latest, and the weeks sampled in each year are also ordered.

Figure 9 depicts how a time series is sampled from the full data. Year *x* represents the latest possible year that can be considered. As there is one year of data available, the data from that year is copied for the other years in case a multi-year planning horizon is considered. In that case, any year-dependent parameter or factor included in the model is applied to the available single-year data and sequentially added to the time series. Then, for each sampled year, a random set of weeks is selected, for which the accompanying set of operational periods is added. A 15-minute granularity is available, so there are 672 decision-making periods added to the time series for each sampled week.

By enabling the sampling of a varying number of years and weeks from the planning horizon, the model's flexibility and scalability are improved. Furthermore, by limiting the amount of data used in the optimisation procedure, the mathematical complexity of the model is reduced, and the computational time to generate optimal solutions is improved. On the contrary, if completely random sampling is applied, it is uncertain whether the included data is representative of all seasons.

In an ideal case, at least one week is sampled from each season, such that the seasonality in demand and production is represented. Therefore, it is decided that the sampling of weeks always includes at least a specific number of weeks from each of the seasons. To illustrate, if one week is sampled from each season, four weeks are added to the time series for each year. If two weeks are sampled for each season, eight weeks are added to the time series for each year, and so on. Although this limits the flexibility of the model in the number of weeks that can be selected to sample, this strategy removes some randomness in the results and ensures seasonality is represented in an optimised solution.

To illustrate, the sampling strategy works as follows: There are three choices the model user can make, namely the last possible year to include in the planning horizon, the number of years to sample from that planning horizon, and the number of weeks to sample from each season in the sampled years. Suppose the model is set to sample four years from a planning horizon of 10 years, and one week from each season. In that case, the investment year 0, and three randomly selected other years are added, where each year is based on the same available single-year data. However, the accompanying year-dependent factors are applied affecting the operational optimisation for those years. Next, for each of the four years, one week is randomly sampled from each season, and these selected weeks may vary between each year. Ultimately, using this example, the sampling process generates an ordered time series of 16 weeks indexed by the year numbers and operational decision-making periods in each week.

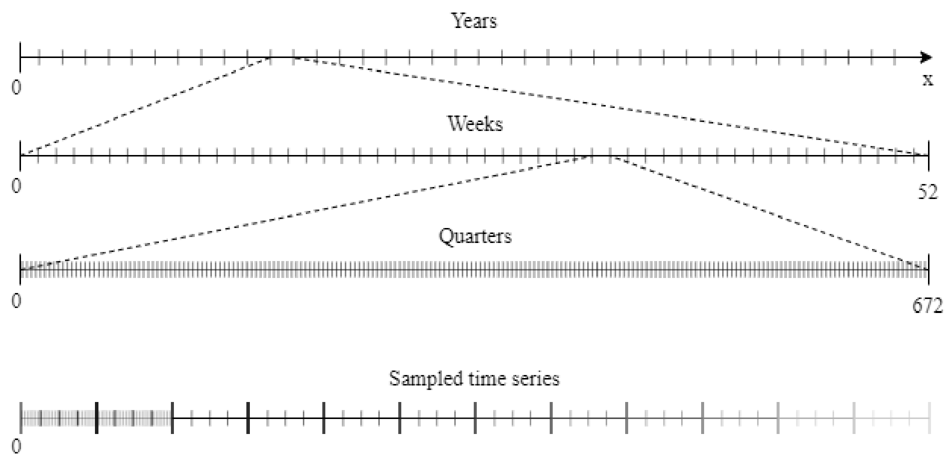


Figure 9: Data sampling strategy implemented in the optimisation model

5.1.3 Numerical Inputs

The model inputs for consumer demands are based on the profiles in the dataset but scaled to be representative of an industrial energy hub with middle- to large-sized firms in The Netherlands (Dekker et al., 2022). The total demand of all consumers for the entire year is expected to be approximately 925,000 kWh, with peak loads of 224 kW for the collective in a single operational period during regular working days. The actual demand profiles, however, vary between the scenarios due to the uncertainty incorporated into the input data. Based on this knowledge, grid withdrawal and injection capacities and the contractual bounds for individual consumers are specified. It is assumed that 80-90% of the expected energy demand of each consumer can be supplied through grid withdrawal. Energy transfers are included to share energy produced at the hub with the consumers. The maximum energy that can be transferred during each operation period from the hub to the collective of consumers is set to the same value as the grid withdrawal capacity. Table 6 provides an overview of all the network-related parameter capacities set in the model.

Parameter	**Description**	**Value**
WCap	Collective withdrawal capacity	224.0 kW
ICap	Collective injection capacity	60.0 kW
MaxW_1	Max. withdrawal consumer 1	116.0 kW
MaxW_2	Max. withdrawal consumer 2	28.0 kW
MaxW_3	Max. withdrawal consumer 3	16.0 kW
MaxW_4	Max. withdrawal consumer 4	24.0 kW
MaxW_5	Max. withdrawal consumer 5	40.0 kW
$\mathrm{MaxIn}_\mathrm{c}$	Max. injection per consumer	8.0 kW
MaxIn_{hub}	Max. injection from the hub	20.0 kW
$\mathrm{MaxTr}_{\mathrm{hub},\mathrm{c}_\mathrm{to}}$	Energy transfers from hub to c	224.0 kW

Table 6: Grid capacity limitations and consumer contracts

Costs included in the optimisation model define the capital expenditures (CAPEX) and operational expenditures (OPEX) related to the energy hub. This includes the investment, maintenance, and operational costs of assets, as well as energy withdrawal costs.

For the technology investment and yearly incurred fixed costs, the values are given per installed unit capacity as resulting from the optimisation model. Based on the approximate real-world investment costs per MW of production capacity, the expected yearly kWh output of these technologies, and the yearly expected power output of the generators included in the data, the investment costs are scaled and defined accordingly.

Injection profits generated by selling energy are subtracted from the overall OPEX. Real-world costs vary significantly depending on technology types, location, and subsidies. These factors are not accounted for in the model. Maintenance and operational costs for wind turbines and PV systems are incurred annually and are equal across all assets. Energy withdrawal and injection costs are assumed to be constant and equal for all consumers. The discount rate for the investments and operational costs is assumed to be 2.5%, and the annualization factor for operational costs is dependent on the number of operational periods included in the sampled time-planning horizon.

Where possible, these costs are based on recent, real-world values, but no historical data from projects is available, hence some assumptions are made in defining these parameters. Including real-world data for precise parameter tuning is, in principle, straightforward in case this data is available. An overview of the cost parameters is detailed in Table 7.

Parameter	**Description**	**Value**
$\mathrm{WC_c}$	Energy withdrawal cost	0.30 €/kWh
$\mathrm{IP_c}$	Energy injection profit	0.05 €/kWh
$\mathrm{IC_{wind,c}}$	Wind turbine investment cost	37,500 €/Unit Capacity
$\mathrm{IC_{pv,c}}$	PV system investment cost	25,000 €/Unit Capacity
$\mathrm{IC_{battery,c}}$	Battery investment cost	5,000 €/Unit Capacity
$\mathrm{MC_{wind,c}}$	Maintenance cost of wind turbines	1,000 €/Unit Capacity/Year
$\mathrm{MC_{pv,c}}$	Maintenance cost of PV systems	250 €/Unit Capacity/Year
$\mathrm{OC_{wind,c}}$	Operation cost wind turbines	500 €/Unit Capacity/Year
$\mathrm{OC_{pv,c}}$	Operation cost PV systems	250 €/Unit Capacity/Year
$\mathrm{OC_{battery,c}}$	Operational cost batteries	50 €/Unit Capacity/Year
DR	Discount rate	0.025
AF	Annualization factor	Dependent on $\lvert \mathrm{H} \rvert$

Table 7: Cost parameter settings

For storage technologies, uniform performance specifications are used for all batteries if included in an optimised energy hub configuration (Table 8). As there is no data on a specific type of battery with accompanying performance specifications, the following values are assumed:

Battery parameter	**Description**	**Value**
$\mathrm{SL_{t_b}}$	Storage fraction lower limit	10% of Capacity
$\mathrm{SU_{t_b}}$	Storage fraction upper limit	95% of Capacity
$\mathrm{SC_{t_b}}$	Charging efficiency	90%
$\mathrm{SD_{t_b}}$	Discharging efficiency	90%
$\mathrm{SX_{t_b}}$	Maximum charge rate	6 kW/Quarter
$\mathrm{SY_{t_b}}$	Maximum discharge rate	10 kW/Quarter

Table 8: Battery performance specifications

5.1.4 Uncertainty Modelling

Uncertainty in demand profiles is included by applying a uniformly distributed random change for each operational period, generating variation in the input profile for each scenario. A similar approach is used to represent uncertainty in the energy production profiles. The greatest risk for energy supply reliability is greater energy use and less energy production than the expected value in the data. Using this logic, a worst case of energy consumption more than 2.5% over the expected value during an operational period and a 5% decrease in expected production output is assumed. On the contrary, as the risks for supply reliability are lower in the case of less demand and more production, 1% less demand and 2.5% more production than the given values in the data profiles are assumed.

The occurrence of technological failures follows a binomial distribution with probability FP. In the model, each short-term period represents an individual trial *n* during which a failure can occur. The failure probability of wind turbines is set using insights from the study by Anderson et al. (2023). An expected failure rate of 7.47 failures per year is determined when failures are restricted to those related to the failure of a particular component in the wind turbine. The PV system failure rate depends on several factors, the foremost being system size (Lillo et al., 2018). Additionally, it is noted that in a PV system, not all failures directly cause a direct loss in energy production, such as monitoring system irregularities. Based on this knowledge and observed failure rates, an expectation of 3.20 failures/per year is assumed for the numerical study. The actual failure probability during each operational period within the model is scaled according to the length of the sampled times series using (5.1). Periods/Year indicates the number of operational periods in a full year, and |H| is the number of operational periods in the sampled time series. In case of a failure, the output is assumed to be 0.

$$\mathrm{FP}_{t_{\mathrm{gen}}}^{y,h} = \frac{\mathrm{Failures/Year}}{\mathrm{Periods/Year}} * \frac{|\mathrm{H}|}{\mathrm{Periods/Year}} \tag{5.1}$$

Real-world observed downtimes depend on specific technological causes, the time at which the failure occurs, the location of the energy hub, or any unforeseen circumstance affecting the repair time. Different studies on the operational metrics for wind farms are available, providing estimates for the mean time to repair (MTTR) for minor incidents and major repairs from the time a wind turbine fails until it functions again (Anderson et al., 2021; Li et al., 2022). The observed values vary significantly depending on required repairs or services, ranging from several hours to multiple days. Additionally, the time for scheduled maintenance activities leads to downtime of assets within the hub. Based on this information, for this numerical study, an expected MTTR of 72 hours is assumed. The MTTR for PV systems is dependent on the specific system and type of failure as well (Spertino et al., 2021). For PV systems, an expected MTTR of 96 hours is assumed in the numerical study. For wind- and solar production capacities, the MTTR is assumed to follow an exponential distribution (Wu et al., 2021). Furthermore, the downtime duration is adapted to correctly cover the number of operational periods in the model for which the output of generators must be 0 in case of failures.

In the study by Staffell and Green (2014), wind turbines are found to lose 1.6±0.2% of their output each year. The degradation rate of PVs is lower, with a mean of 0.8% per year (Jordan & Kurtz, 2013). As the exact degradation rate is unknown, a uniform distribution generates the actual degradation rate for each year.

The outcomes of these uncertainties are incorporated into the optimisation through different scenarios. Each scenario is assumed to occur with equal probability.

Uncertainty	Modelling Approach
Demand	$X \sim U(-0.01, 0.025)$
Production	$Y \sim U(-0.05, 0.025)$
Asset failures	$F^{s}_{t_g} \sim B\left(n,\ FP^{y,h}_{t_g}\right)$ where $FP^{y,h}_{t_{gen}}$ = (5.1)
Wind downtime	$DT^{s}_{wind} \sim Exp(MTTR_{wind}), MTTR_{wind} = 72$ hours
PV downtime	$DT^{s}_{pv} \sim Exp(MTTR_{pv}), MTTR_{pv} = 96$ hours
Wind degradation	$DF^{y,s}_{wind} \sim U(0.014,\ 0.018)$
PV degradation	$DF^{y,s}_{pv} \sim U(0.007,\ 0.009)$

Table 9: Uncertainty models incorporated in the optimisation model

5.2 Experimental Design

In this section, the experiments conducted to test model performance and to generate results are introduced. The optimisation model presented in Chapter 4, the time sampling strategy discussed in Section 5.1.2, and all the input parameters defined in Sections 5.1.3 and 5.1.4 are implemented in Python code. In principle, for all experiments, the same input parameters and data are used. The Gurobi Optimiser (Version 11.0.2) is used to solve the model.

In Gurobi, two main algorithms are available to solve the continuous relaxations of mixed-integer models, which is required for solving the developed model and conducting the experiments. These are the simplex (primal and dual) and barrier algorithms. The barrier algorithm is often the fastest for large, difficult models, but it is also numerically sensitive, meaning that results from the optimisation using this algorithm can be highly affected by numerical issues such as rounding errors or precision limitations. The simplex algorithm is generally less numerically sensitive, hence posing a good alternative. However, choosing simplex exclusively may prevent taking advantage of the performance advantages of the barrier algorithm in numerically good instances. Using Gurobi, the algorithm that is used to solve the model can be set to be a specific method. Alternatively, Gurobi can utilise the three algorithms concurrently and dynamically choose the most suitable algorithm based on the problem characteristics and algorithm performance.

The first experiment analyses the solvability and scalability of the model (Section 5.3). This relates to the size of the optimised time series that is sampled from the data, as well as the scenarios that are generated. The quantity of data significantly influences the solvability of the model, but it also affects the results and solution quality. In principle, for this experiment, the investment year is considered, and by iteratively increasing the number of weeks sampled for this year and the included scenarios, the effects on the solving time and the strategic capacity decisions for each sampling variation are analysed. The model's limits are explored to conclude the possibilities of further experimentation.

In the second experiment, the differences between the deterministic and stochastic optimisation approaches are examined, and the merits of stochastic optimisation are quantified (Section 5.4). This is achieved by computing the value of the stochastic solution (VSS). First, the deterministic instance of the model is optimised by replacing the uncertainties with their expectation. The resulting first-stage strategic capacity decisions are then used as input for the stochastic model for evaluation, which incorporates the original scenarios. The results are compared to the original model to analyse the differences between deterministic and stochastic solutions.

The third experiment analyses the cost/reliability trade-offs included in the model objective by varying the incurred penalty for energy shortages such that the effects on the strategic investment decisions and reliability KPIs are visible (Section 5.5). The resulting optimised solutions are visualised in a Pareto-front. The benefits of making additional investments to improve system reliability are discussed.

In the fourth experiment, the effects of technological degradation on the energy supply performance are analysed (Section 5.6). Configuration variants are set as inputs in the model, and the operational planning of the energy hub is optimised for a multi-year horizon with and without degradation on generator outputs, such that the effects on supply reliability can be analysed according to the implemented KPIs.

5.3 Model Scalability and Solvability

The model is formulated such that there is flexibility in the sampled number of years and weeks, as well as the number of generated scenarios. Using the highest possible granularity provides a higher quality solution that more accurately represents the characteristics of the data but at the cost of longer computational times. The model's limits in terms of scalability and accompanying solvability are explored through experimentation with the sampling and scenario generation inputs. The solving times and resulting strategic capacity decisions are compared, to define which settings are suitable for further experimentation.

The concurrent solver setting is used, so the Gurobi optimiser dynamically chooses the most suitable algorithm to solve the model. The solver is observed to always find an optimal solution for the model the fastest using the barrier algorithm, for each tested sampling and scenario generation setting. Hence, the found solving times are those of the optimal solution found using the barrier algorithm.

Ideally, the highest possible granularity of the data is used such that strategic decisions are taken based on the most precise operational profiles. Especially peak loads during operational periods are of importance, which may get lost in aggregated profiles. As the highest possible granularity is preferred, model solvability and scalability are examined using the 15-minute granularity available in the data.

Only the investment year is considered, to be able to compare the solutions between different runs of the model in the experiment. In doing so, strategic capacity decisions are not influenced by the randomness of sampled years near or far away in a long-term planning horizon between each test, such that the effects of technological degradation do not affect the results and the capacity decisions can be compared accurately. The model is tested by iteratively changing the number of weeks and scenarios included in the optimisation, starting with the smallest possible instance, and increasing these values until the limits of computational time are reached and converging model solutions are observed.

Figure 10 visualises the observed solving times for various model settings. In each setting, an equal number of weeks is sampled from each season. It is observed that with each increase in the number of scenarios, the solving time increases substantially.

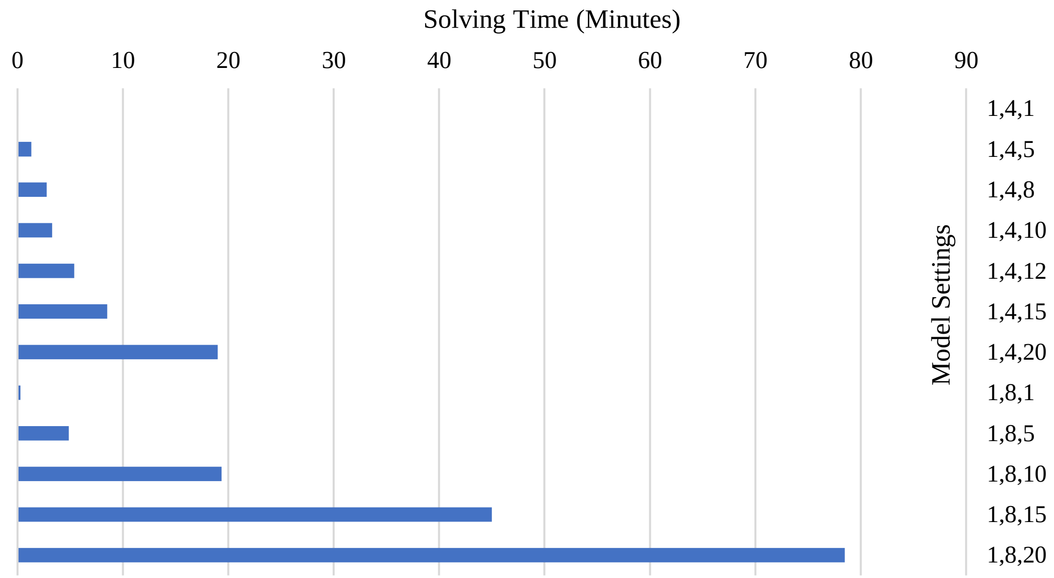


Figure 10: Observed solving times for varying model settings (years, total weeks, scenarios)

The investment decisions observed for the various model settings show approximately equal characteristics regarding which technologies are invested at which location. Generally, the capacities increase as more weeks and scenarios are included in the optimisation. The model results converge for larger instances, but the model becomes increasingly more difficult to solve if eight weeks and ten or more scenarios are included, without significantly improving the objective value compared to the test where four weeks are sampled for the same number of scenarios, which has a much faster solving time. Therefore, it is decided to sample one week per season and generate twelve scenarios in the next experiments.

Two things are noted from the experiment results. First, it is observed that while the results do converge towards similar values, differences remain. This highlights the importance of performing multiple runs of the model in further experimentation and considering the averages of all runs for higher-quality results. Furthermore, it must be noted that the penalty for shortages in this experiment is set arbitrarily to a value of 500 €/kWh, which logically influences the capacity decisions. The effects of the penalty value on the capacity decisions and accompanying costs/reliability trade-offs are explored in a different experiment. The complete set of results for each tested model setting is included in Appendix B: Observed Model Solving Times.

5.4 Deterministic vs. Stochastic Optimisation

5.4.1 Experiment Setup

In this experiment, the value of accounting for stochasticity when making decisions is analysed. For this, a deterministic instance of the model is evaluated and compared against the stochastic model to determine the value of the stochastic solution (VSS).

In the context of this research, this means that by determining the value of the stochastic solution, it is assessed which improvement can be achieved in the minimisation of costs, if the optimisation accounts for the uncertainties affecting the energy supply in the hub. To recall, the objective value function of the model minimises the total investment and operational costs, where the operational costs include the incurred penalty for the occurrence of energy shortages in meeting demand.

First, the deterministic problem is solved, in which the uncertain parameters are replaced by their expectation. The (first stage) strategic capacity decisions for technology investments are then used as input for the stochastic optimisation model, such that the results of the deterministic solution can be evaluated under the ‘real’ scenarios. The original stochastic problem is solved next, and the results of both solutions, i.e., the deterministic evaluation under the real scenarios and the original stochastic problem, are analysed. In this comparison, the VSS is computed through (5.2).

$$\mathrm{VSS} = \text{ Minimal cost without uncertainty } z^{D,*} - \text{Minimal cost under uncertainty } z^{*} \qquad (5.2)$$

In the deterministic problem instance, the uncertain parameters are substituted by their expectation using the following method: For consumer demands and the outputs of wind and solar generation technologies, a single average profile is created from those generated in each scenario. The single profiles are then used as input for the deterministic model. Additionally, the expectation in technology availability is that no failures occur; hence, no downtime is included. An example of the input profiles for consumer demands and renewable generator outputs generated in different scenarios and their aggregated average profiles are included in Appendix C: Scenarios and Average Input Profiles.

In the experiment, one week is sampled from each season and 12 scenarios are generated. For the deterministic model, this means that single average input profiles are based on 12 scenarios as well. For the stochastic model, the model is solved as normal, sampling one random week for each season between the different scenarios. Only the investment year is considered; hence, technological degradation is not included, and the potential risk of overinvesting in technological capacities in the stochastic model is mitigated. As the observed value of the stochastic solution is highly dependent on the specific penalty value set in the model, a set of penalty variations is set in the model, and the effects of the penalty value on the observed VSS are examined. The following set of penalties is used:

$$\mathrm{P}\ (€/\mathrm{kWh}) \in \{25, 50, 75, 150, 250, 500, 750, 1000, 1250, 1500, 1750, 2000\}$$

In the previous experiment, it was observed how for large problem instances, the concurrent solver setting with dynamic algorithm selection led to the barrier algorithm finding the optimised result in all instances. For the deterministic problem solved in this experiment, however, it is noted that the dual simplex method solves the model most efficiently. Therefore, the optimisation is set to utilise the latter algorithm to solve the stochastic problem as well, such that the same solving method is used for all instances. Furthermore, the model is solved 10 times for each instance, and the results are averaged over all runs to find the average VSS for each penalty variation over all runs.

5.4.2 Experiment Results

Several observations are made about the results from the deterministic and stochastic model solutions. First, it is noted that in the deterministic model, no more shortages occur during the operation of the energy hub in case a penalty of 500€/kWh or higher is set. At this penalty value, as well as any of the higher tested variations, the objective value of the model also does not change anymore, and the capacities of the installed assets remain the same.

In the evaluation of the strategic capacity decisions resulting from the deterministic model, however, shortages do occur for each of the configuration variants when the operation is optimised under uncertainty. Because the capacities do not change anymore after a certain point, and the penalty is set to even higher values, the resulting objective values also increase significantly. I.e., while in principle, the operational performance in terms of energy supply reliability is the same as equal capacities are used, the objective function increases because the penalty incurred for each shortage is higher.

In the original stochastic model, no more shortages are observed in case a shortage penalty of 1750€/kWh is set in the model. Again, at this penalty value and any penalty value larger than this, the strategic capacity decisions do not change anymore, and the resulting objective value is the same.

The results from each tested penalty variation are visualised in Figure 11. It is evident that the higher the penalty for shortages is set, the larger the VSS becomes. At the lowest penalty, the difference between the objective values of the deterministic solution under uncertainty compared to the optimal stochastic solution is minimal, hence a small VSS and an approximate 1% improvement is observed. As the penalty is increased, the VSS and the improvement percentages increase as well. A breakdown of the observed costs and computation of the VSS values for each penalty setting is included in Appendix D: VSS Results.

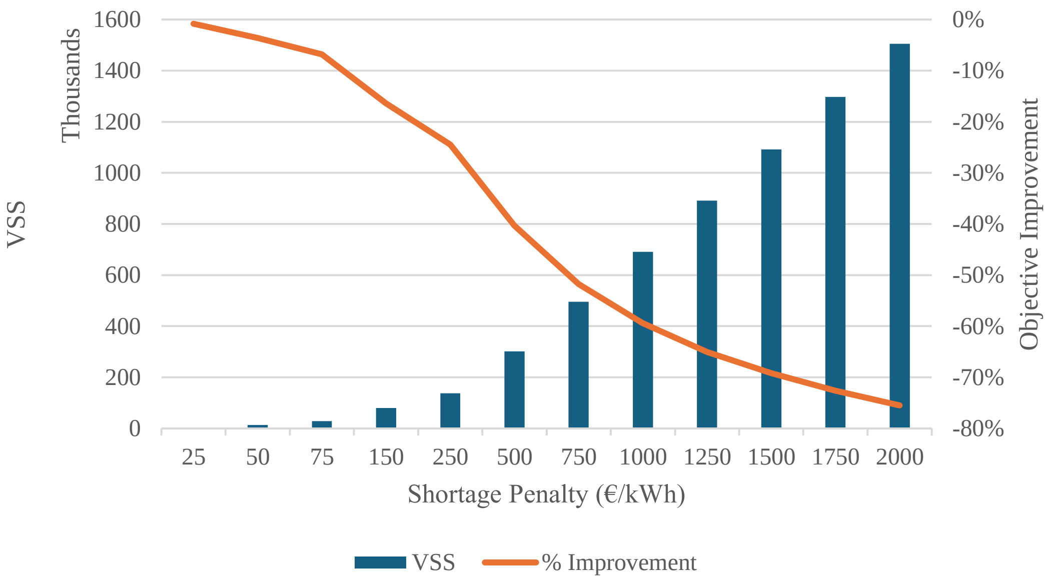


Figure 11: VSS and % improvement between deterministic and stochastic solutions

The results show that the VSS is highly dependent on the specific value of the shortage penalty. As evident from the results, the total penalty incurred in the evaluation of the deterministic results is a substantial part of the total costs. Generally, it is expected that the higher the penalty is set, the more strategic investments are made to increase the energy supply capacity in the hub to reduce energy shortages.

It is concluded that the difference between deterministic and stochastic optimisation is significant and that using a scenario-based approach leads to a more robust solution for energy hub design. Without accounting for uncertainties, the installed technology capacities are insufficient to ensure energy supply reliability once uncertainty is adequately incorporated within optimisation. However, the influence of the shortage penalty on the observed improvements in the model objective should not be ignored. This specific trade-off between investment costs and energy supply reliability is analysed in a different experiment, from which the results are presented in Section 5.5.

5.5 Energy Hub Cost/Reliability Trade-Offs

5.5.1 Experiment Setup

In this experiment, the investment cost/reliability trade-offs in energy hub design are analysed. By varying the penalty for energy shortages that is included in the objective function of the model, the effects of strategic investment decisions on improvements in energy supply reliability are analysed, and the solution space for the trade-offs is explored. The solution space is visualised by creating a Pareto-front between investment costs and the expected total penalty cost that is incurred during the energy hub's operation. Generally, the KPIs are expected to improve as fewer shortages occur, leading to lower total expected penalty costs. In addition to the exploration of the solution space for possible investments, the evolution of the consumer-level KPIs is analysed in the experiment.

The penalty is increased iteratively in each run of the model. For each penalty variation, the accompanying strategic investment costs are determined, and the improvements in the KPIs are analysed. The investment year is considered in the experiment. One week is sampled from each season, and 12 scenarios are included in the optimisation. The solver is set to utilise the barrier algorithm and to use the same instance of the model for all tested penalties, such that the results can be compared. The following set of penalties P is used in the experiment, which is incurred in €/kWh shortage:

$$\mathrm{P}(€/\mathrm{kWh}) \in \{0,25,50,75,100,150,200,250,500,750,1000,1250,1500,1750,2000,2500\}$$

5.5.2 Experiment Results

Figure 12 presents the set solutions found using the stated penalty variations. The dominated solutions and Pareto-front of the best results are indicated. It is noted that the instance in which no penalty is incurred for shortages is omitted from this plot. Logically, if there is no penalty for energy shortages, the model chooses to supply all demand through emergency generation. The Pareto-front provides insight into the specific trade-offs between making investments and the expected penalty for the analysed energy hub. In the decision-making process for the design of energy hubs, engineers can select a solution from the Pareto front based on their preference for the risks in energy supply and available budget for investments.

It is observed that the total investments increase quickly as a higher penalty is set, without improving the expected total incurred penalty significantly. As the total investment cost reaches approximately €150,000, the reduction in expected penalty becomes more significant, while the increase in total investment cost diminishes. In case the penalty is set at 1,750 €/kWh or higher, no more shortages are observed, and hence, no penalty is incurred.

For these high penalty values, although slight variations are observed between the specific capacities included in the hub, the total investment costs do not increase anymore and the overall minimised objective values in these instances are equal as well. Here, the investments should suffice to ensure energy supply under the modelled operational uncertainties. The investment strategies for the solutions in the Pareto front indicated in Figure 12 are included in Appendix E: Cost/Reliability Trade-Offs.

If the development of energy hubs prioritises minimising the expected penalty and a larger budget is available, a solution towards the higher investment end of the Pareto-front may be chosen. On the contrary, if the budget is limited, a solution with lower investment but higher acceptable risk might be selected. In principle, such decisions regarding the possible investment strategies for the energy hub vary between each project, and the Pareto-front of optimal solutions might have different characteristics as different consumers or assets are included.

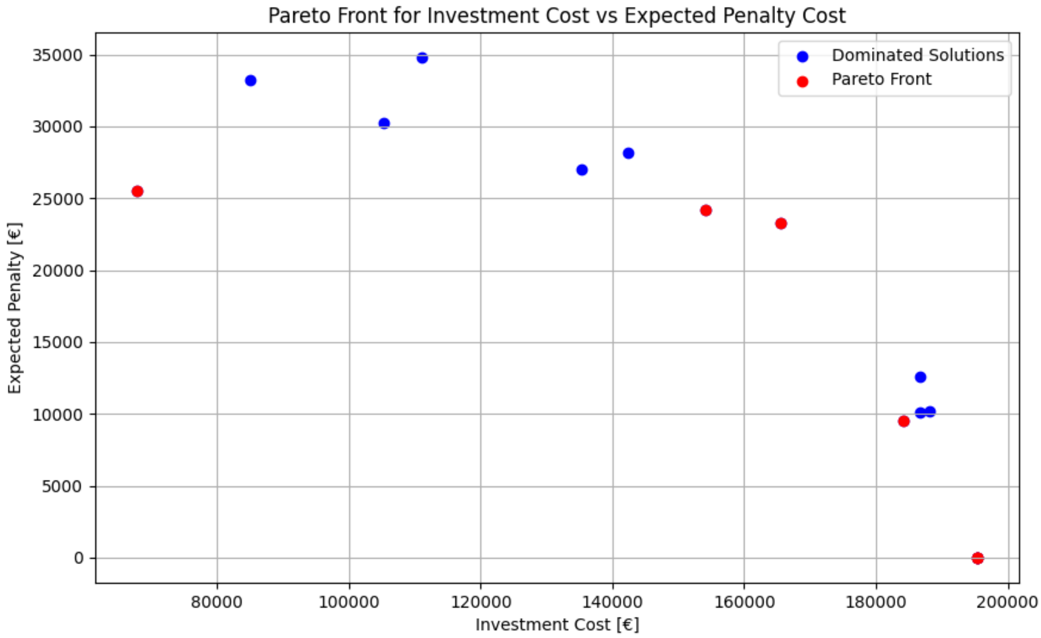


Figure 12: Energy hub cost/reliability trade-offs

In addition to the most efficient trade-offs between investment cost and energy supply reliability, the consumer-level performance indicators are analysed for each variation of the penalty. To recall, the expected unsupplied energy, the loss of load expectation, and the adequacy of supply are included in the optimisation model. It is noted that in these results, all results from the tested penalty variations are included, and not only those of the most efficient solutions indicated in the Pareto-front. Additionally, the first observations in which no penalty is incurred are omitted from the plot for clearer visualisation. Logically, if there is no penalty and all energy is supplied through emergency generation, all energy is expected to be unsupplied, the loss of load probability is 100% as each operational period has a shortage, and the adequacy of supply indicates the average energy shortage quantity is the average of the demand of each consumer.

Figure 13 presents the observed EENS values for each of the resulting investment strategies. Each consumer is included individually, as well as the KPI values for the collective of consumers in the hub. The EENS values for the collective are, as expected, observed to improve for each increase in the investments. This is not always the case for individual consumers. Here, it is noted that although the total expected unsupplied is reduced in the hub, this does not necessarily imply that the unsupplied energy at each consumer is reduced as well. The same holds for the observed values of the loss of load probability. For the additional investments, the LOLP decreased to some degree for the collective of consumers in the energy hub (Figure 14). Again, a collective decrease does not necessarily imply a reduction in the probability of a shortage for each individual consumer. Furthermore, the adequacy of supply shows similar characteristics. While this indicator is not explicitly considered for the collective of consumers, again the performance generally improves as more investments are made (Figure 15).

In all cases, the most significant supply issues are observed for consumer 1, this being the consumer with the highest demand. While the improvements in energy supply reliability are the largest as more investments are made, it requires significant increases in the total investment before a complete energy supply is ensured for this consumer. Especially a substantial battery capacity that is included in the hub at those higher investment strategies is observed to effectively address the remaining shortages at consumer 1.

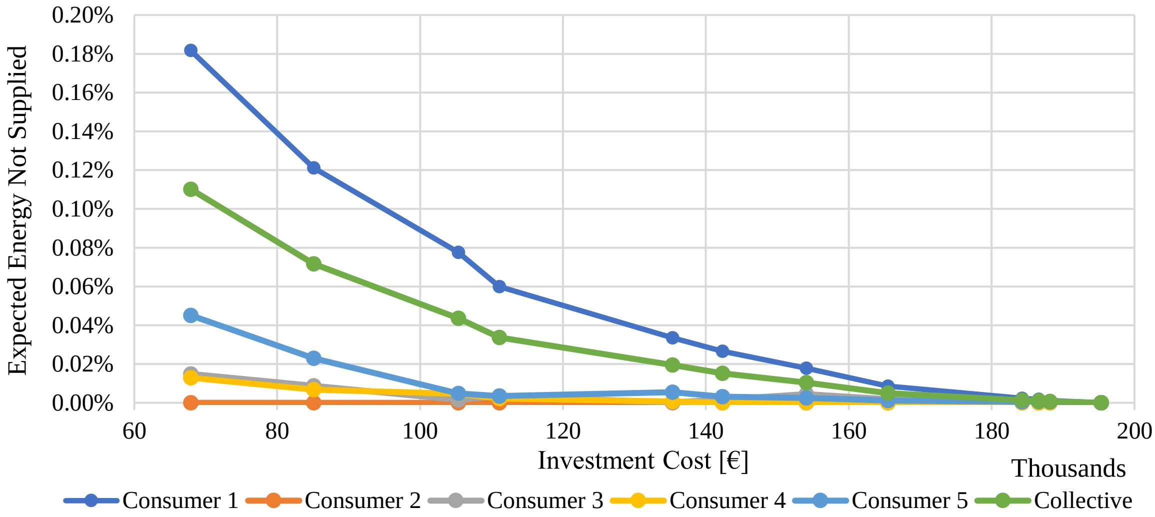


Figure 13: Observed EENS values for all cost/reliability trade-offs

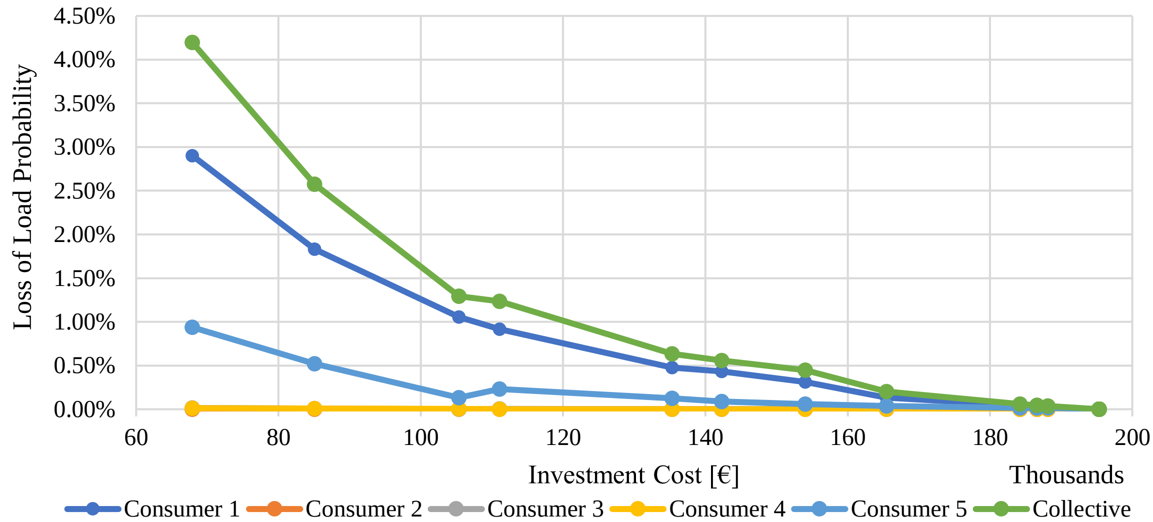


Figure 14: Observed LOLP values for all cost/reliability trade-offs

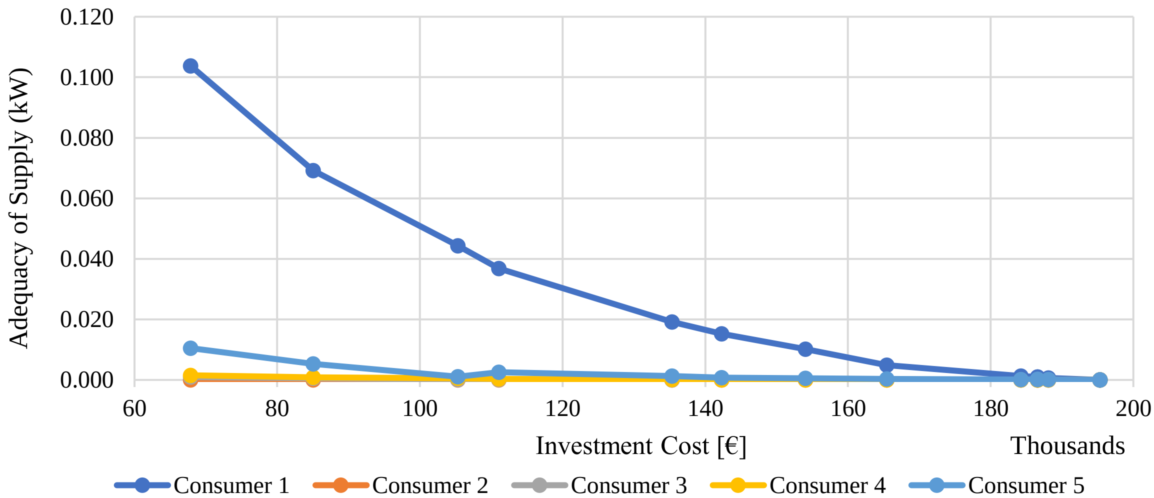


Figure 15: Observed AS values for all cost/reliability trade-offs

5.6 The Impact of Technological Degradation

5.6.1 Experiment Setup

In the previous experiments, only the investment year was considered for the optimisation of the energy hub. While these experiments did incorporate asset failures causing uncertain downtime of renewable energy generation within the optimisation of capacities and their operation, the effects of technological degradation have not yet been addressed. Generally, one would expect that the energy supply reliability decreases as the technological degradation increases. However, the extent to which the technological degradation affects the energy supply in the hub is unknown. Furthermore, as with larger penalties more investments are made in the investment year, it can be the case that the effects are not significantly severe, as a surplus in capacity is available from the start of the planning horizon.

Several configurations have been found in the Pareto-front that pose the most efficient solutions regarding investment costs and reliability (Table 10). This experiment examines how these configurations perform if technological degradation affects the available capacity to supply energy in a multi-year planning horizon. These configurations are set as fixed input in the model, such that only operation is optimised. A long-term planning horizon of 25 years is considered: Equal to the expected lifetimes of wind turbines and PV systems. The solver is set to utilise the dual simplex algorithm to optimise all model instances. The operational planning includes the sampling of five years, for which one week is sampled from each season, and 12 scenarios are generated. I.e., twenty weeks are optimised over 12 scenarios.

First, the operation is optimised for this five-year planning without incorporating degradation. The baseline performance of the configurations without degradation is hence known. Next, years 5, 10, 15, 20, and 25 are included and for each of these years, the accompanying degradation factors are applied to the generator outputs. The degradation factor restricts outputs from renewable energy generators to a certain percentage of the original output. In the investment year, 100% of the capacity is available, and this percentage decreases in each following year. Figure 16 visualises this process, showing wind turbines' higher degradation compared to that of PV systems. The plots for the expected outputs of wind- and solar energy generators are included in Appendix H: Generator Output Degradation. The operation is optimised for each configuration variant, and the supply performance is tracked under technological degradation. The KPI values from the non-degraded and degraded operational optimisation results are compared, and the decrease in energy supply reliability can be analysed for each tested configuration accordingly.

	Config. 1	**Config. 2**	**Config. 3**	**Config. 4**	**Config. 5**
Penalty [€/kWh]	25	250	500	750	1750
CAPEX [€]	67,896	154,060	165,460	184,233	195,326
Capacities					
Wind at Hub [kW]	1.46	2.05	1.73	1.73	1.30
PV at Hub [kW]	0.00	1.05	0.76	0.57	0.51
Battery at 1 [kWh]	0.09	7.39	11.53	16.64	6.78
Battery at 5 [kWh]	0.00	0.05	0.06	0.14	0.32
Battery at Hub [kWh]	0.17	0.36	2.33	1.80	17.27

Table 10: Optimal configurations set as inputs in the model

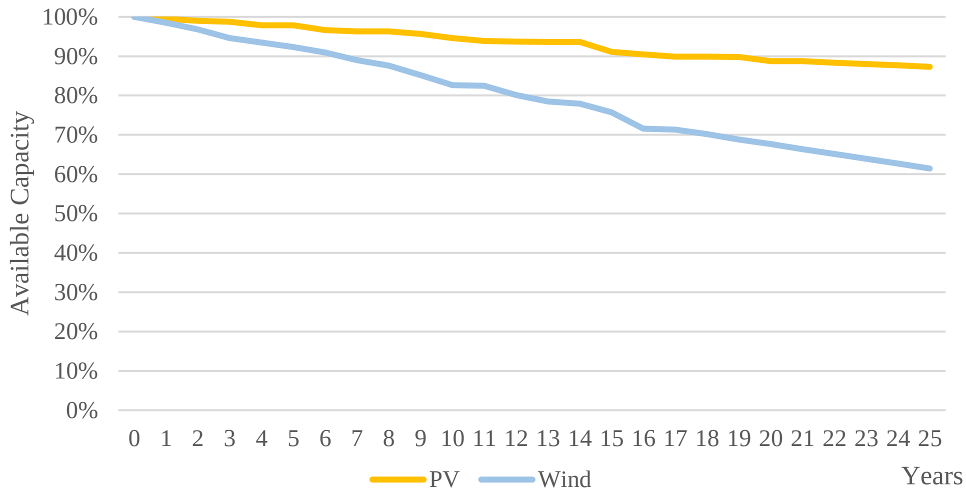


Figure 16: Technological degradation for renewable energy generators

5.6.2 Experiment Results

As expected, the energy supply reliability worsens as more technological degradation is applied to the generator outputs. While not every consumer in each configuration variant experiences a decrease in their energy supply reliability, the collective performance for all consumers worsens in each instance. Especially at consumer 1, the effects are visible (Figure 17). Although shortages already occurred during operation without applying degradation, a substantial worsening in the KPIs is observed when degradation is included.

Looking at the tested configuration variants, the larger battery capacity included in the hub appears to mitigate the effects of technological degradation in those specific configurations the best. This is logical, as no degradation of the battery capacity is included in the model. So also in later years, the battery can still supply the same amount of energy, covering the decrease in production. On the contrary, the supply reliability worsens substantially in configuration variant 2, as most investments are made for wind- and solar energy capacity for the additional energy supply. Nevertheless, although the effects of technological degradation are visible in the results, the KPI values are quite small, especially for consumers with less energy demand. The foremost supply issues occur at consumer 1, where most energy is consumed. The full set of results with KPI values for all consumers is included in Appendix I: KPI Values Under Technological Degradation.

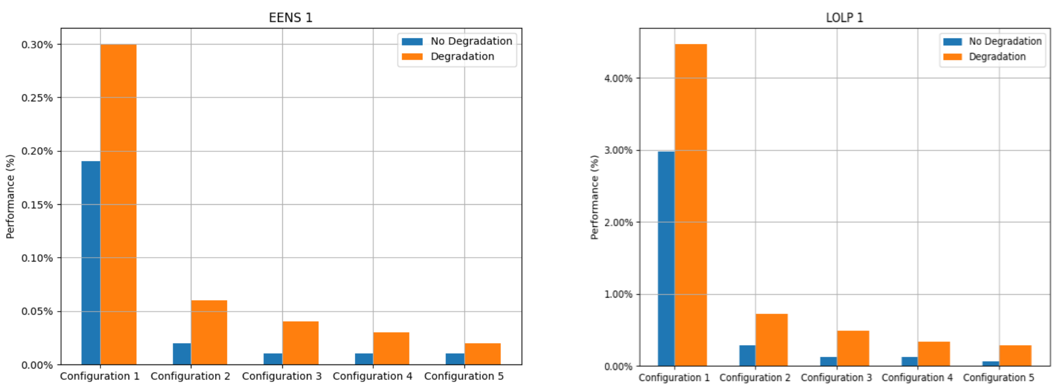


Figure 17: EENS and LOLP at Consumer 1 for each configuration variant

5.7 Conclusions

In Chapter 5, a time sampling strategy was developed and implemented in the stochastic optimisation model, the numerical inputs for the model were defined, and the modelling approaches for the uncertainties were explained. Several experiments were performed to test the model, examine the significance of stochastic optimisation compared to deterministic optimisation, analyse the investment cost/reliability trade-offs, and assess the effects of technological degradation on the energy supply reliability in a multi-year planning horizon.

A random sampling strategy was applied to create ordered and sequential operational planning horizons which were used as inputs in the optimisation model. The main goal of this approach was to limit the quantity of data to decrease computational time. Secondly, it allowed for flexibility by varying the number of operational periods that were sampled. A disadvantage of random sampling is that it is uncertain whether the sampled time series is representative of the full dataset, which affects the results of the model. It was therefore decided that in all cases, a specified number of weeks is sampled from each season to ensure seasonality is represented within model inputs. As there was limited data available for parameter tuning, several assumptions were made concerning the fixed parameters used in the model. The input data was sourced from various studies to define realistic inputs as much as possible. In this process, a hypothetical test case for the energy hub project in terms of consumers and their demands, the technical capabilities of assets, with the limitations of the power grid was defined. This test case was used for all the conducted experiments.

In the first experiment, variations of the time sampling and scenario generation inputs were used to test the limits of the optimisation model and to identify a suitable approach for further experimentation. It was observed that the solving time significantly increases as more scenarios are included. Hence, it was not feasible to incorporate very large instances of the model in the experimentation. In all cases, however, the solver managed to find an optimal solution.

In the second experiment, the value of the stochastic solution was determined. For this, the deterministic problem was solved by replacing all uncertainties with their expectation. All scenario-generated input parameters were aggregated to create a single average profile, and all other non-parametric uncertainties were excluded from the model. The resulting energy hub configurations from this instance were evaluated under uncertainty and compared to the original stochastic model solutions. The first-stage strategic capacity decisions from the deterministic model were observed to be insufficient to ensure high supply reliability under uncertainty. This led to a high penalty cost, consequently resulting in a high objective value. Because of this, the computed VSS becomes increasingly higher as the penalty cost is increased.

The third experiment explored the trade-offs between making investments and improving energy supply reliability by iteratively adjusting the penalty value. A Pareto-front was created, showing the most efficient cost/reliability trade-offs from all observations. The results indicate that initial investments still led to a significant number of energy shortages. However, as the penalty was increased, the reliability improved, and ultimately, a complete energy supply was observed. These insights help identify optimal configurations for energy hubs based on their specific reliability requirements and budget constraints. Furthermore, the performance indicators were analysed for each found solution. Most supply issues were observed for the consumer with the highest demand, and the largest capacity investments were required for this consumer to ensure energy supply.

In the last experiment, the effects of technological degradation in multi-year planning horizons were analysed. It was found that, as expected, the energy supply worsens under technological degradation. However, while the effects are most severe for consumers with large demands and the overall supply performance worsens, the effects of degradation for consumers with less demand are not as certain.

6 Conclusions, Recommendations & Future Research

6.1 Conclusions

The research presented in this thesis aims to answer the following research question: *How can Firan improve the robustness in optimal decision-making for the design of Energy Hubs, considering its energy supply reliability?* To answer this question, several steps are taken in conducting this research, through which a stochastic optimisation model is developed and tested by performing several experiments. Using the knowledge from model development and the experiment results, the main research question can be answered, and the research problem can be solved.

To recall, the research problem stated the limitations of the current optimisation process concerning lacking insight into uncertainties inherent to energy hub optimisation, and the potential benefits of taking into account the uncertainties posing a risk to energy supply reliability for the development of reliable energy hub designs. The implementation of a consumer-level analysis of the energy supply performance can provide project stakeholders with detailed knowledge and provide engineers with the opportunity to provide recommendations for potential investment strategies optimising reliability.

The findings of the research show that optimisation under uncertainty is crucial. While the capacity investments are sufficient for a completely ensured energy supply for all consumers in a deterministic model instance, it is evident that these investments are insufficient for reliable energy supply in operational optimisation under uncertainty. To improve the robustness of decision-making for the design of energy hubs, incorporating the uncertainties affecting the energy supply processes in the energy hub is crucial.

Additionally, it was observed that the energy supply reliability for the studied case does not significantly improve until a certain investment threshold is reached. After that point, larger improvements in reliability and the KPI values are observed. I.e., it was observed that a minimum budget is required before significant improvements in the energy supply reliability are observed. More importantly, however, is that by optimising the objective of the model for varying financial penalties for the occurrences of energy shortages, the costs/reliability trade-off can be explored, to identify which solutions are most optimal for a certain budget or reliability constraint. Alternatively, the minimum budget can be determined for which a complete energy supply for all consumers is guaranteed.

6.2 Recommendations

Based on the conclusions drawn from the findings of this research, several recommendations are made to improve the robustness of decision making in the design process for energy hubs. By implementing these recommendations, Firan can optimize the reliability of energy hubs accounting for operational uncertainties while effectively balancing cost considerations and stakeholder requirements.

- A stochastic approach in which the energy hubs are optimised under uncertainty accounting for different scenarios is fundamental in decision-making. This includes implementing multiple uncertainty sources, such as consumer demand profile variations and peak loads, renewable energy generator outputs, and technological uncertainties. By doing so, Firan can develop reliable energy hub designs in which the uncertainties are accounted for and mitigation strategies for the uncertainties posing a risk to the energy supply can be identified.
- The implemented model objective minimising costs and maximising energy supply reliability can be used in development projects to generate varying investment strategies along the optimal Pareto-front. In consultation with stakeholders and given their requirements, reliability can be maximised within budget constraints, or the required budget for achieving a minimum reliability threshold can be found. Firan can assess the trade-offs between investment costs and

supply improvements and communicate these insights with relevant stakeholders. This approach ensures informed decision-making by identifying optimal investment strategies that align with stakeholders' priorities and financial constraints.

- Consumer-level reliability KPIs can be leveraged to provide stakeholders with elaborate insights into the performance of the energy hub. By analysing KPIs at the consumer level, Firan can offer a detailed understanding of how collective or individual investments impact energy supply reliability. Having specific knowledge about the effects of any investment change or uncertain event on the energy hub at the consumer level enables the design of tailored solutions to ensure reliability for all stakeholders, ultimately improving overall performance.
- By analysing the effects of uncertainties such as asset unavailability and technological degradation in the operational and long-term planning horizons, supply issues and the severity of these issues are identified at the consumer level. Mitigation strategies to overcome the effects of these uncertainty can be developed accordingly.

6.3 Contributions

6.3.1 Theoretical Contributions

The theoretical contribution of this study lies in the novelty of incorporating multiple elements relevant to energy hub design, operation, and reliability analysis into a single model. The literature review discussed in Chapter 3 provided extensive insights into current developments in research on energy hubs and their optimisation. Many studies consider building-specific, or contrarily, substantially larger neighbourhood- or city-wide energy hub scales. Research into industrial-level cases with multiple large energy consumers under strict power grid withdrawal capacity bounds is limited. This research aims to address this increasingly more important aspect in the field of energy (hub) modelling.

The developed model combines several elements regarding the design and operation of energy hubs, as well as their energy supply reliability. Although each aspect is inherent to energy hubs and their optimisation, they are commonly specific focus areas of the research available in the literature. This study implements both strategic- and operational decision-making under uncertainty, utilising an objective function through which cost/reliability trade-offs can be examined as a core feature of the optimisation, with the implementation of relevant consumer-level KPIs in a single modelling approach.

Furthermore, most studies combining strategic and operational optimisation for energy hubs within a single model, an hourly granularity is included for the operational decision-making process. In this research, it was aimed to achieve the most accurate results for the strategic technological capacity decisions by optimising these based on a 15-minute granularity.

6.3.2 Practical Contributions

The project's practical contributions to the company lie within the concepts developed within the modelling approach and the recommendations that can be made based on the findings of the research.

Implementing exploration of the cost/reliability trade-offs in the design process at Firan provides essential insight into the impact of strategic investments on energy supply reliability, by defining varying investment strategies along the optimal solution space. Stakeholder budget limitations or reliability requirements can be considered, and the optimal configuration according to these constraints can be determined. Furthermore, consumer-level performance indicators can be incorporated into business-client communication to provide detailed insights into the effects of investments on supply performance at each location and to develop tailored strategies to optimise energy supply performance.

6.4 Limitations & Future Research

In this section, the limitations of the research are acknowledged, and opportunities for future research are identified.

First, the limitations in the research scope are considered. Real-word energy hubs and those studied in the literature commonly consider multi-energy systems, including heat, gas, and hydrogen, with related assets such as combined heat and power systems and electrolysers. This was not included in the research. The concepts studied in this project can be further developed and tested for multi-energy systems to incorporate the uncertainties related to these additional elements and to analyse the energy supply reliability for each consumer and each energy carrier.

A second limitation of this research is the scarcity of historical data and values for parameter tuning, for which considerable assumptions were made. Although the used input profiles are equal to those used in the validation of the EHC, other parameters are based on approximations found in varying sources to create a realistic case, but one not precisely true to a real-world instance for testing. An opportunity for improvement is to test and validate the model based on real data.

Furthermore, the current model formulation considers a two-stage approach to reduce its complexity and improve the tractability of decision-making. In real-world cases, however, energy hub development projects are often considered a multi-stage strategic decision problem, with the opportunity to invest at later stages to include additional assets or capacity expansions. In most experiments, only the investment year is included in operational optimisation to mitigate the effects of capacity overinvestments. A suitable extension of the model is to include multi-stage strategic decisions to optimise long-term investment schemes for the entire planning horizon including specific technology lifetimes.

While the project has developed relevant concepts for reliability-based energy hub optimisation and analysis, the limitations are acknowledged, although several of these limitations stem from opportunities considered outside the scope of this research. Opportunities for future research are extensive, including expanding the model to encompass multi-energy systems, refining parameter values based on real-world data, and including multi-stage strategic investment decisions.

References

Abdulnasser, G., Ali, A., Shaaban, M. F., & Mohamed, E. E. M. (2022). Stochastic multi-objectives optimal scheduling of energy hubs with responsive demands in smart microgrids. *Journal of Energy Storage*, *55*. https://doi.org/10.1016/j.est.2022.105536

Anderson, F., Dawid, R., Cava, D., & McMillan, D. (2021). Operational Metrics for an Offshore Wind Farm & Their Relation to Turbine Access Restrictions and Position in the Array. *Journal of Physics: Conference Series*, *2018*, 012002. https://doi.org/10.1088/1742-6596/2018/1/012002

Anderson, F., Dawid, R., McMillan, D., & Cava, D. G. (2023). On the Sensitivity of Wind Turbine Failure Rate Estimates to Failure Definitions. *Journal of Physics: Conference Series*, *2626*(1), 012025. https://doi.org/10.1088/1742-6596/2626/1/012025

Bao, M., Ding, Y., Singh, C., & Shao, C. (2019). A Multi-State Model for Reliability Assessment of Integrated Gas and Power Systems Utilizing Universal Generating Function Techniques. *IEEE Transactions on Smart Grid*, *10*(6), 6271-6283. https://doi.org/10.1109/tsg.2019.2900796

Billinton, R., & Allan, R. N. (1990). Basic power system reliability concepts. *Reliability Engineering & System Safety*, *27*(3), 365-384. https://doi.org/https://doi.org/10.1016/0951-8320(90)90007-A

Blotenburg, S. (2023). Energieleveranciers in maag met heffing voor klanten zonnepanelen. Retrieved 24-09-2023, from https://www.rtlnieuws.nl/economie/artikel/5401775/zonnestroom-betalen-terugleveren-salderen-vandebron

Cano, E. L., Groissböck, M., Moguerza, J. M., & Stadler, M. (2014). A strategic optimization model for energy systems planning. *Energy and Buildings*, *81*, 416-423. https://doi.org/10.1016/j.enbuild.2014.06.030

Cano, E. L., Moguerza, J. M., & Alonso-Ayuso, A. (2016). A multi-stage stochastic optimization model for energy systems planning and risk management. *Energy and Buildings*, *110*, 49-56. https://doi.org/10.1016/j.enbuild.2015.10.020

Cano, E. L., Moguerza, J. M., Ermolieva, T., & Ermoliev, Y. (2013). Energy efficiency and risk management in public buildings: strategic model for robust planning. *Computational Management Science*, *11*(1-2), 25-44. https://doi.org/10.1007/s10287-013-0177-3

Cho, S., Li, C., & Grossmann, I. E. (2022). Recent advances and challenges in optimization models for expansion planning of power systems and reliability optimization. *Computers & Chemical Engineering*, *165*. https://doi.org/10.1016/j.compchemeng.2022.107924

DeCarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., McDowall, W., Pye, S., Strachan, N., Trutnevyte, E., Usher, W., Winning, M., Yeh, S., & Zeyringer, M. (2017). Formalizing best practice for energy system optimization modelling. *Applied Energy*, *194*, 184-198. https://doi.org/10.1016/j.apenergy.2017.03.001

Dekker, E., Keller, K., & Woolthuis, R. (2022). *Elektriciteits- en gasverbruik industrie, 2019-2020*. Retrieved 21-03-2024 from https://www.cbs.nl/nl-nl/maatwerk/2022/38/elektriciteits-en-gasverbruik-industrie-2019-2020

Dolatabadi, A., Mohammadi-ivatloo, B., Abapour, M., & Tohidi, S. (2017). Optimal Stochastic Design of Wind Integrated Energy Hub. *IEEE Transactions on Industrial Informatics*, *13*(5), 2379-2388. https://doi.org/10.1109/tii.2017.2664101

Ebrahimi, M., & Sheikhi, A. (2023). A local integrated electricity-heat market design among multi Smart Energy Hubs with renewable energy generation uncertainty. *Electric Power Systems Research*, *218*. https://doi.org/10.1016/j.epsr.2023.109217

Evins, R. (2015). Multi-level optimization of building design, energy system sizing and operation. *Energy*, *90*, 1775-1789. https://doi.org/10.1016/j.energy.2015.07.007

Faraji, J., Hashemi-Dezaki, H., & Ketabi, A. (2021). Stochastic operation and scheduling of energy hub considering renewable energy sources' uncertainty and N-1 contingency. *Sustainable Cities and Society*, *65*. https://doi.org/10.1016/j.scs.2020.102578

Fathima, A. H., & Palanisamy, K. (2015). Optimization in microgrids with hybrid energy systems – A review. *Renewable and Sustainable Energy Reviews*, *45*, 431-446. https://doi.org/10.1016/j.rser.2015.01.059

Gabrielli, P., Gazzani, M., Martelli, E., & Mazzotti, M. (2018). Optimal design of multi-energy systems with seasonal storage. *Applied Energy*, *219*, 408-424. https://doi.org/10.1016/j.apenergy.2017.07.142

Geidl, M., & Andersson, G. (2007). Optimal Power Flow of Multiple Energy Carriers. *IEEE Transactions on Power Systems*, *22*(1), 145-155. https://doi.org/10.1109/tpwrs.2006.888988

Geng, S., Vrakopoulou, M., & Hiskens, I. A. (2020). Optimal Capacity Design and Operation of Energy Hub Systems. *Proceedings of the IEEE*, *108*(9), 1475-1495. https://doi.org/10.1109/jproc.2020.3009323

Gestel, M. v. (2023). Naast Vandebron overweegt ook Eneco om zonnepaneelbezitters toeslag te laten betalen. Retrieved 24-09-2023, from https://www.trouw.nl/duurzaamheid-economie/naast-vandebron-overweegt-ook-eneco-om-zonnepaneelbezitters-toeslag-te-laten-betalen~b49ecf15/?referrer=

Hayes, B. P., & Prodanovic, M. (2016). State Forecasting and Operational Planning for Distribution Network Energy Management Systems. *IEEE Transactions on Smart Grid*, *7*(2), 1002-1011. https://doi.org/10.1109/tsg.2015.2489700

Herbst, A., Toro, F., Reitze, F., & Jochem, E. (2012). Introduction to energy system modelling. *Swiss Journal of Economics and Statistics*, *148*(2), 111-135. https://doi.org/10.1007/BF03399363

Hiremath, R. B., Shikha, S., & Ravindranath, N. H. (2007). Decentralized energy planning; modeling and application—a review. *Renewable and Sustainable Energy Reviews*, *11*(5), 729-752. https://doi.org/10.1016/j.rser.2005.07.005

Hirsch, A., Parag, Y., & Guerrero, J. (2018). Microgrids: A review of technologies, key drivers, and outstanding issues. *Renewable and Sustainable Energy Reviews*, *90*, 402-411. https://doi.org/10.1016/j.rser.2018.03.040

Jordan, D. C., & Kurtz, S. R. (2013). Photovoltaic Degradation Rates—an Analytical Review. *Progress in Photovoltaics: Research and Applications*, *21*(1), 12-29. https://doi.org/https://doi.org/10.1002/pip.1182

Klemm, C., & Vennemann, P. (2021). Modeling and optimization of multi-energy systems in mixed-use districts: A review of existing methods and approaches. *Renewable and Sustainable Energy Reviews*, *135*. https://doi.org/10.1016/j.rser.2020.110206

Koster, R. (2023). Netbeheerder waarschuwt voor stroomtekort in 2030. Retrieved 21-05-2024, from https://nos.nl/artikel/2459559-netbeheerder-waarschuwt-voor-stroomtekort-in-2030

Li, H., Peng, W., Huang, C.-G., & Guedes Soares, C. (2022). Failure Rate Assessment for Onshore and Floating Offshore Wind Turbines. *Journal of Marine Science and Engineering*, *10*(12). https://doi.org/10.3390/jmse10121965

Lillo, I., González-Martínez, P., Larrañeta, M., & Guasumba-Codena, J. (2018). Impact of Energy Losses Due to Failures on Photovoltaic Plant Energy Balance. *Energies*, *11*, 363. https://doi.org/10.3390/en11020363

Loulou, R., & Kanudia, A. (1999). Minimax regret strategies for greenhouse gas abatement: methodology and application. *Operations Research Letters*, *25*(5), 219-230. https://doi.org/https://doi.org/10.1016/S0167-6377(99)00049-8

Mansouri, S. A., Ahmarinejad, A., Javadi, M. S., & Catalão, J. P. S. (2020). Two-stage stochastic framework for energy hubs planning considering demand response programs. *Energy*, *206*. https://doi.org/10.1016/j.energy.2020.118124

Mavromatidis, G., Orehounig, K., & Carmeliet, J. (2018). Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach. *Applied Energy*, *222*, 932-950. https://doi.org/10.1016/j.apenergy.2018.04.019

Mavromatidis, G., & Petkov, I. (2021). MANGO: A novel optimization model for the long-term, multi-stage planning of decentralized multi-energy systems. *Applied Energy*, *288*. https://doi.org/10.1016/j.apenergy.2021.116585

Pfenninger, S., Hawkes, A., & Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, *33*, 74-86. https://doi.org/10.1016/j.rser.2014.02.003

Ren, H., Zhou, W., Nakagami, K. i., Gao, W., & Wu, Q. (2010). Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. *Applied Energy*, *87*(12), 3642-3651. https://doi.org/10.1016/j.apenergy.2010.06.013

Sanajaoba Singh, S., & Fernandez, E. (2018). Modeling, size optimization and sensitivity analysis of a remote hybrid renewable energy system. *Energy*, *143*, 719-731. https://doi.org/10.1016/j.energy.2017.11.053

Sedighizadeh, M., Esmaili, M., & Mohammadkhani, N. (2018). Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles. *Journal of Cleaner Production*, *195*, 301-317. https://doi.org/10.1016/j.jclepro.2018.05.103

Seyednouri, S. R., Safari, A., Farrokhifar, M., Ravadanegh, S. N., Quteishat, A., & Younis, M. (2023). Day-Ahead Scheduling of Multi-Energy Microgrids Based on a Stochastic Multi-Objective Optimization Model. *Energies*, *16*(4). https://doi.org/10.3390/en16041802

Shoaib, M., Siddiqui, I., Rehman, S., Khan, S., & Alhems, L. M. (2019). Assessment of wind energy potential using wind energy conversion system. *Journal of Cleaner Production*, *216*, 346-360. https://doi.org/10.1016/j.jclepro.2019.01.128

Son, Y.-G., Oh, B.-C., Acquah, M. A., Fan, R., Kim, D.-M., & Kim, S.-Y. (2021). Multi Energy System With an Associated Energy Hub: A Review. *IEEE Access*, *9*, 127753-127766. https://doi.org/10.1109/access.2021.3108142

Spertino, F., Chiodo, E., Ciocia, A., Malgaroli, G., & Ratclif, A. (2021). Maintenance Activity, Reliability, Availability, and Related Energy Losses in Ten Operating Photovoltaic Systems up to 1.8 MW. *IEEE Transactions on Industry Applications*, *57*(1), 83-93. https://doi.org/10.1109/TIA.2020.3031547

Staffell, I., & Green, R. (2014). How does wind farm performance decline with age? *Renewable Energy*, *66*, 775-786. https://doi.org/https://doi.org/10.1016/j.renene.2013.10.041

Su, H., Zio, E., Zhang, J., Li, Z., Wang, H., Zhang, F., Chi, L., Fan, L., & Wang, W. (2020). A systematic method for the analysis of energy supply reliability in complex Integrated Energy Systems considering uncertainties of renewable energies, demands and operations. *Journal of Cleaner Production*, *267*. https://doi.org/10.1016/j.jclepro.2020.122117

Trivella, A. (2018). *Decision Making under Uncertainty in Sustainable Energy Operations and Investments* Technical University of Denmark].

Vera, E. G., Cañizares, C. A., Pirnia, M., Guedes, T. P., & Trujillo, J. D. M. (2023). Two-Stage Stochastic Optimization Model for Multi-Microgrid Planning. *IEEE Transactions on Smart Grid*, *14*(3), 1723-1735. https://doi.org/10.1109/tsg.2022.3211449

Voorhoeve, P. (2022). Overbelast stroomnet raakt bedrijven en woningbouw. Retrieved 25-09-2023, from https://nos.nl/nieuwsuur/artikel/2427174-overbelast-stroomnet-raakt-bedrijven-en-woningbouw

Wu, R., Bussino, E., Bracco, S., Siri, S., Gabrielli, P., & Sansavini, G. (2021). Optimization-based reliability assessment of multi-energy systems. Proceedings of the 31st European Safety and Reliability Conference, ESREL 2021,

Yang, H. X., Lu, L., & Burnett, J. (2003). Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong. *Renewable Energy*, *28*(11), 1813-1824. https://doi.org/10.1016/s0960-1481(03)00015-6

Yang, Y., Zhang, S., & Xiao, Y. (2017). Optimal design of distributed energy resource systems based on two-stage stochastic programming. *Applied Thermal Engineering*, *110*, 1358-1370. https://doi.org/10.1016/j.applthermaleng.2016.09.049

Yue, X., Pye, S., DeCarolis, J., Li, F. G. N., Rogan, F., & Gallachóir, B. Ó. (2018). A review of approaches to uncertainty assessment in energy system optimization models. *Energy Strategy Reviews*, *21*, 204-217. https://doi.org/10.1016/j.esr.2018.06.003

Zakaria, A., Ismail, F. B., Lipu, M. S. H., & Hannan, M. A. (2020). Uncertainty models for stochastic optimization in renewable energy applications. *Renewable Energy*, *145*, 1543-1571. https://doi.org/10.1016/j.renene.2019.07.081

Zeng, Z., Ding, T., Xu, Y., Yang, Y., & Dong, Z. (2020). Reliability Evaluation for Integrated Power-Gas Systems With Power-to-Gas and Gas Storages. *IEEE Transactions on Power Systems*, *35*(1), 571-583. https://doi.org/10.1109/tpwrs.2019.2935771

A: Optimisation Model Formulation

Sets	Description	Indices
C	Set of energy consumers	$c \in C$, $hub \in C$
T	Set of technologies	$t \in T$
$T_g \subseteq T$	Subset of generators	$t_g \in T_g$
$T_b \subseteq T$	Subset of batteries	$t_b \in T_b$
Y	Set of strategic-level periods	$y \in Y$
H	Set of operational-level periods	$h \in H$
S	Set of scenarios	$s \in S$

Parameters

$D_c^{y,h,s}$	Energy demand for consumer c, at time y, h in scenario s [kWh]
$P_{t_g}^{y,h,s}$	Output profile of a generator at time y, h in scenario s [kWh]
$DF_{t_g}^{y,s}$	Technology degradation factor in each year in scenario s [%]
$FP_{t_g}^{y,h}$	Renewable energy generator failure probability [%]
$DT_{t_g}^{s}$	Downtime of failed generator assets in scenario s (in short-term periods)
PR^s	Probability of scenario s [%]
WC	Power-grid energy withdrawal cost [€/kWh]
IP	Power-grid energy injection profit [€/kWh]
IC_t	Technology investment cost [€]
MC_t	Technology maintenance cost [€/Year]
OC_t	Technology operation cost [€/Year]
WCap	Collective power grid withdrawal capacity [kW]
ICap	Collective power grid injection capacity [kW]
$MaxW_c$	Maximum withdrawal limit for consumer c [kW]
$MaxI_c$	Maximum injection limit for consumer c [kW]
$MaxT_{c_{from},c_{to}}$	Maximum energy that can be transferred between locations [kW]
SL_{t_b}	Fraction of storage lower limit [kWh]
SU_{t_b}	Fraction of storage upper limit [kWh]
SC_{t_b}	Battery charging efficiency [%]

SD_{t_b}	Battery discharging efficiency [%]
SX_{t_b}	Maximum battery charge rate [-]
SY_{t_b}	Maximum battery discharge rate [-]
P	Penalty cost for shortages in meeting energy demands [€/kWh]
DR	Discount rate
AF	Annualization factor

Variables

$GC_{t_g,c}$	Capacity of an energy generator installed at c [kW]
$BC_{t_b,c}$	Capacity of a battery installed at c [kWh]
$O_{t_g,c}^{y,h,s}$	Generator output at c, at time y, h in scenario s [kWh]
$CT_{t_g,c}^{y,h,s}$	Generator curtailment at c, at time y, h in scenario s [kWh]
$T_{c_{from},c_{to}}^{y,h,s}$	Transfer of energy at time y, h in scenario s [kWh]
$W_c^{y,h,s}$	Energy withdrawal by c, at time y, h in scenario s [kWh]
$I_c^{y,h,s}$	Energy injection by c, at time y, h in scenario s [kWh]
$E_c^{y,h,s}$	Emergency generation at c, at time y, h in scenario s [kWh]
$C_{t_b,c}^{y,h,s}$	Charging of a battery at c, at time y, h in scenario s [kWh]
$D_{t_b,c}^{y,h,s}$	Discharging of a battery at c, at time y, h in scenario s [kWh]
$SOC_{t_b,c}^{y,h,s}$	State of charge of a battery at c, at time y, h in scenario s [kWh]
$CS_{t_b,c}^{y,h,s} \in \{0,1\}$	Charge state indicator at c, at time y, h in scenario s
$DS_{t_b,c}^{y,h,s} \in \{0,1\}$	Discharge state indicator at c, at time y, h in scenario s

Objective function

$$\text{Minimize} \sum_{y}(1+\mathrm{DR})^{-y} * (\sum_{t_g}\sum_{c} \mathrm{IC}_{t_g,c} * \mathrm{GC}_{t_g,c} + \sum_{t_b}\sum_{c} \mathrm{IC}_{t_b,c} * \mathrm{BC}_{t_b,c}$$

$$+ \sum_{t_g}\sum_{c} \mathrm{MC}_{t_g} * \mathrm{GC}_{t_g,c} + \mathrm{OC}_{t_g} * \mathrm{GC}_{t_g,c} + \sum_{t_b}\sum_{c} \mathrm{OC}_{t_b,c} * \mathrm{BC}_{t_b,c} + \mathrm{E[Ann.Op.]})$$

$$\mathrm{E[Ann.Op.]} = \sum_{s} \mathrm{PR}^{s} * (\mathrm{AF} * \sum_{h}\sum_{c} \mathrm{W}_c^{y,h,s} * \mathrm{WC} - \mathrm{I}_c^{y,h,s} * \mathrm{IP} + \mathrm{E}_c^{y,h,s} * \mathrm{P})$$

Constraints

$$\sum_{t_g} O_{t_g,c}^{y,h,s} + D_{t_b,c}^{y,h,s} - C_{t_b,c}^{y,h,s} + W_c^{y,h,s} - I_c^{y,h,s} + T_{hub,c}^{y,h,s} + E_c^{y,h,s} = D_c^{y,h,s}\ \forall\, y \in Y,\ h \in H,\ s \in S,\ c \in C$$

$$\sum_{t_g} O_{t_g,hub}^{y,h,s} + D_{t_b,hub}^{y,h,s} - C_{t_b,hub}^{y,h,s} - I_{hub}^{y,h,s} = \sum_{c_{to} \neq hub} T_{hub,c_{to}}^{y,h,s}\ \forall\, y \in Y,\ h \in H,\ s \in S$$

$$O_{t_g,c}^{y,h,s} = \begin{cases} P_{t_g,c}^{y,h,s} * GC_{t_g,c} * DF_{t_g}^{y,s} - CT_{t_g,c}^{y,h,s} & \text{when operational} \\ 0 \text{ if failed, for duration } DT_{t_g}^{s} & \end{cases} \quad \forall\, y \in Y,\ h \in H,\ s \in S,\ t_g \in T_g,\ c \in C$$

$$SOC_{t_b,c}^{0,0,s} = SL_{t_b,c} * BC_{t_b,c}\ \ \forall\, s \in S,\ t_b \in T_b, c \in C$$

$$SOC_{t_b,c}^{y,h+1,s} = SOC_{t_b,c}^{y,h,s} + SC_{t_b} * C_{t_b,c}^{y,h,s} - SD_{t_b} * D_{t_b,c}^{y,h,s}\ \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C$$

$$SOC_{t_b,c}^{y+1,0,s} = SOC_{t_b,c}^{y,\max(H),s} + SC_{t_b} * C_{t_b,c}^{y,\max(H),s} - SD_{t_b} * D_{t_b,c}^{y,\max(H),s}\ \forall\, y \in Y,\ s \in S,\ t_b \in T_b, c \in C$$

$$SL_{t_b,c} * BC_{t_b,c} \leq SOC_{t_b,c}^{y,h,s} \leq BC_{t_b,c} * SU_{t_b,c}\ \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C$$

$$C_{t_b,c}^{y,h,s} \leq SX_{t_b} * CS_{t_b,c}^{y,h,s}\ \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C$$

$$D_{t_b,c}^{y,h,s} \leq SY_{t_b} * DS_{t_b,c}^{y,h,s}\ \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C$$

$$CS_{t_b,c}^{y,h,s} + DS_{t_b,c}^{y,h,s} = 1\ \ \forall\, y \in Y,\ h \in H,\ s \in S,\ t_b \in T_b, c \in C$$

$$\sum_{c_{to} \neq hub} T_{hub,c_{to}}^{y,h,s} \leq MaxT_{hub,c_{to}}^{y,h,s}\ \forall\, y \in Y,\ h \in H,\ s \in S$$

$$\sum_{c_{from} \neq hub} T_{c_{from},hub}^{y,h,s} = 0\ \forall\, y \in Y,\ h \in H,\ s \in S$$

$$\sum_{c \neq hub} W_c^{y,h,s} \leq WCap\ \forall\, y \in Y,\ h \in H,\ s \in S$$

$$\sum_{c} I_c^{y,h,s} \leq ICap\ \forall\, y \in Y,\ h \in H,\ s \in S$$

$$W_c^{y,h,s} \leq MaxW_c\ \forall\, y \in Y, h \in H,\ s \in S, c \in C,\ c \neq hub$$

$$I_c^{y,h,s} \leq MaxI_c\ \forall\, y \in Y,\ h \in H,\ s \in S,\ c \in C$$

$$GC_{t_g,c} \geq 0\ \forall\, t_g \in T_g, c \in C$$

$$SC_{t_b,c} \geq 0\ \forall\, t_b \in T_b, c \in C$$

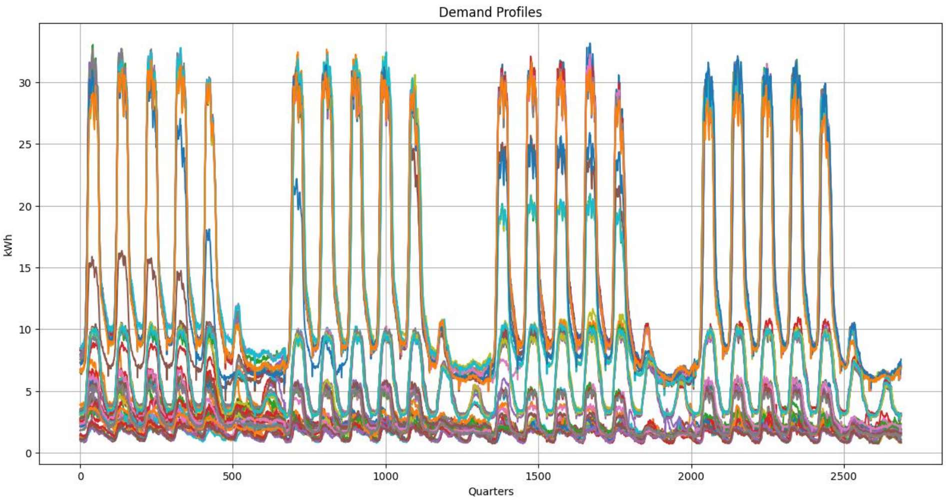
$$CS_{t_b,c}^{y,h,s},\ DS_{t_b,c}^{y,h,s} \in \{0,1\}\ \ \forall\ \ t_b \in T_b,\ y \in Y,\ h \in H,\ s \in S,\ c \in C$$

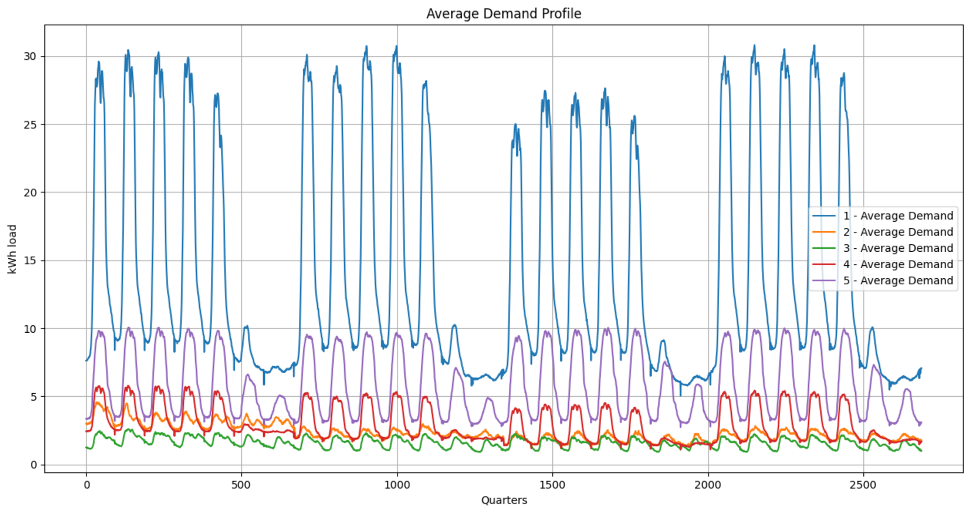
All other variables ≥ 0

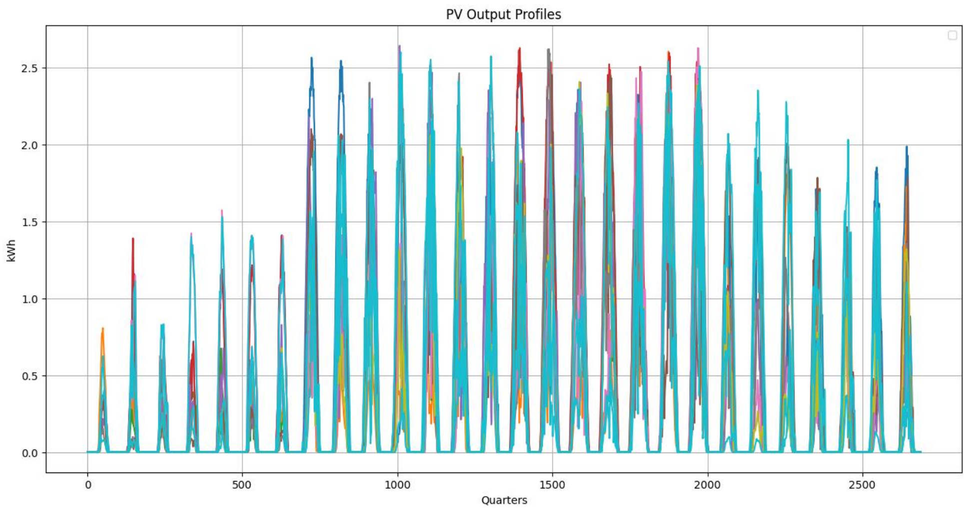
B: Observed Model Solving Times

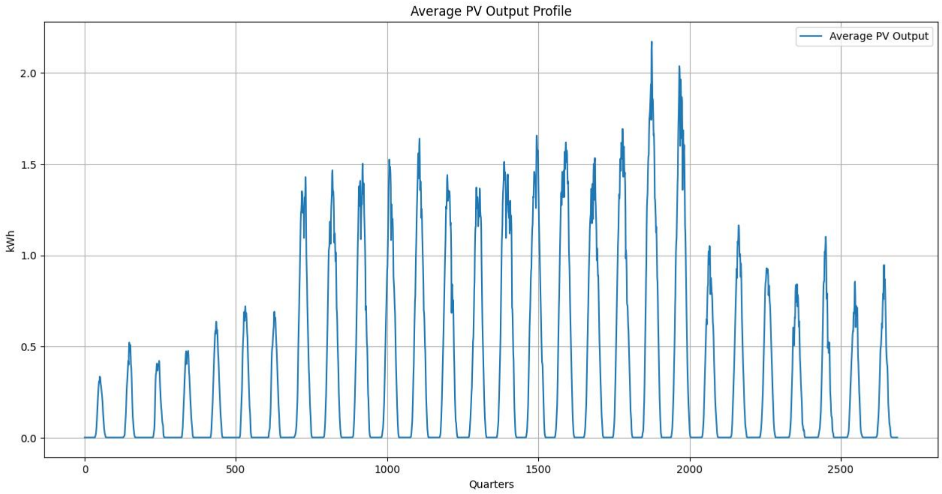
	Years, Total Weeks, No. of Scenarios											
	1,4,1	**1,4,5**	**1,4,8**	**1,4,10**	**1,4,12**	**1,4,15**	**1,4,20**	**1,8,1**	**1,8,5**	**1,8,10**	**1,8,15**	**1,8,20**
Objective Values	€513,552	€495,205	€475,896	€506,876	€475,841	€485,295	€477,338	€430,776	€505,592	€483,759	€516,142	€487,997
Solving Times:												
Seconds	5.46	78.43	166.39	197.58	322.85	510.60	1138.88	17.85	291.02	1161.95	2699.39	4709.24
Minutes	0.091	1.31	2.77	3.29	5.38	8.51	18.98	0.29	4.85	19.37	44.99	78.49
CAPEX	€230,572	€201,307	€194,431	€198,785	€182,280	€177,587	€172,807	€177,041	€216,434	€183,396	€204,500	€181,348
OPEX	€282,980	€293,898	€281,465	€308,091	€293,561	€307,708	€304,531	€253,735	€289,158	€300,363	€311,642	€306,649
Investments												
Wind at Hub [kW]	0.47	0.61	0.94	1.07	1.67	1.51	1.50	1.35	0.58	1.17	0.91	1.41
PV at 1 [kW]	0	0	0	0	0.27	0	0	0.0077	1.21	0.20	0	0.98
PV at 2 [kW]	0	0	0	0	0	0	0	0	0	0	0	0
PV at 3 [kW]	0	0	0	0	0	0	0	0	0	0	0	0
PV at 4 [kW]	0	0	0	0	0	0	0	0	0	0	0	0
PV at 5 [kW]	0	0	0	0	0	0	0	0	0	0	0	0
PV at Hub [kW]	0	0.015	0.41	0.49	0.42	0.61	0.63	1.00	0	0.41	0.72	0
Battery at 1 [kWh]	24.88	13.76	20.43	26.76	5.92	17.36	16.72	6.77	24.00	9.20	21.74	16.65
Battery at 2 [kWh]	0	0	0	0	0	0	0	0	0	0	0	0
Battery at 3 [kWh]	0	0	0	0	0	0	0	0	0	0	0	0
Battery at 4 [kWh]	0	0	0	0	0	0	0	0	0	0	0	0
Battery at 5 [kWh]	0	0	0.053	0.17	0	0.011	0.016	0.010	0	0.085	0.051	0.0035
Battery at Hub [kWh]	15.33	19.41	6.82	0	12.17	1.42	1.70	11.03	6.48	13.20	6.29	1.75

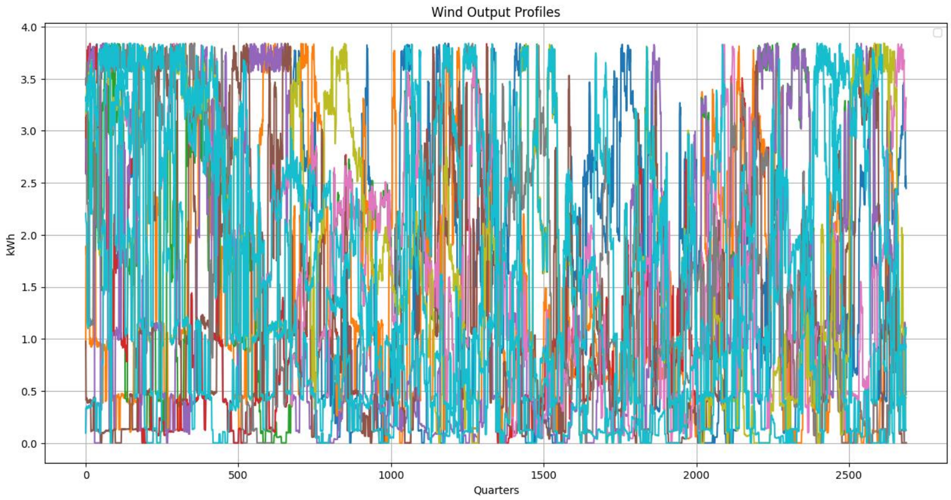
C: Scenarios and Average Input Profiles

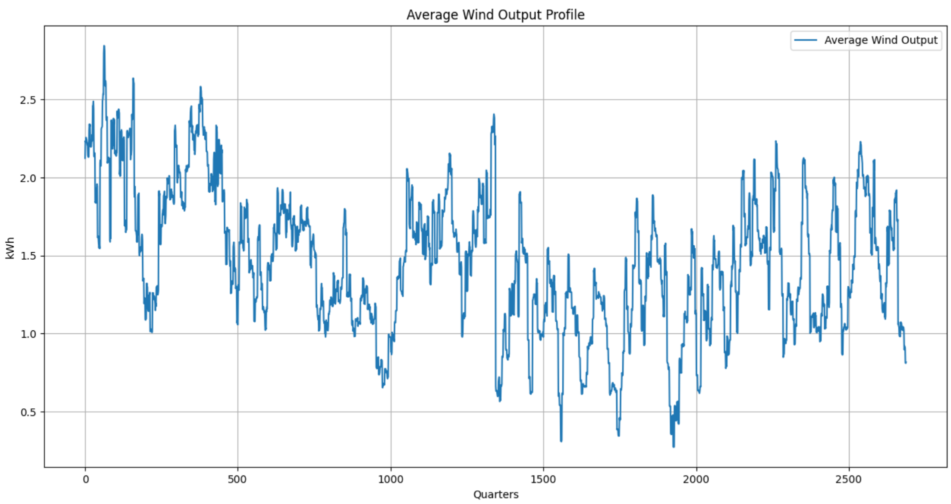







Average PV Output Profile
Average PV Output
kWh
Quarters
0.0
0.5
1.0
1.5
2.0
0
500
1000
1500
2000
2500


Wind Output Profiles
kWh
Quarters
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
500
1000
1500
2000
2500


Average Wind Output Profile
Average Wind Output
kWh
Quarters
0.5
1.0
1.5
2.0
2.5
0
500
1000
1500
2000
2500

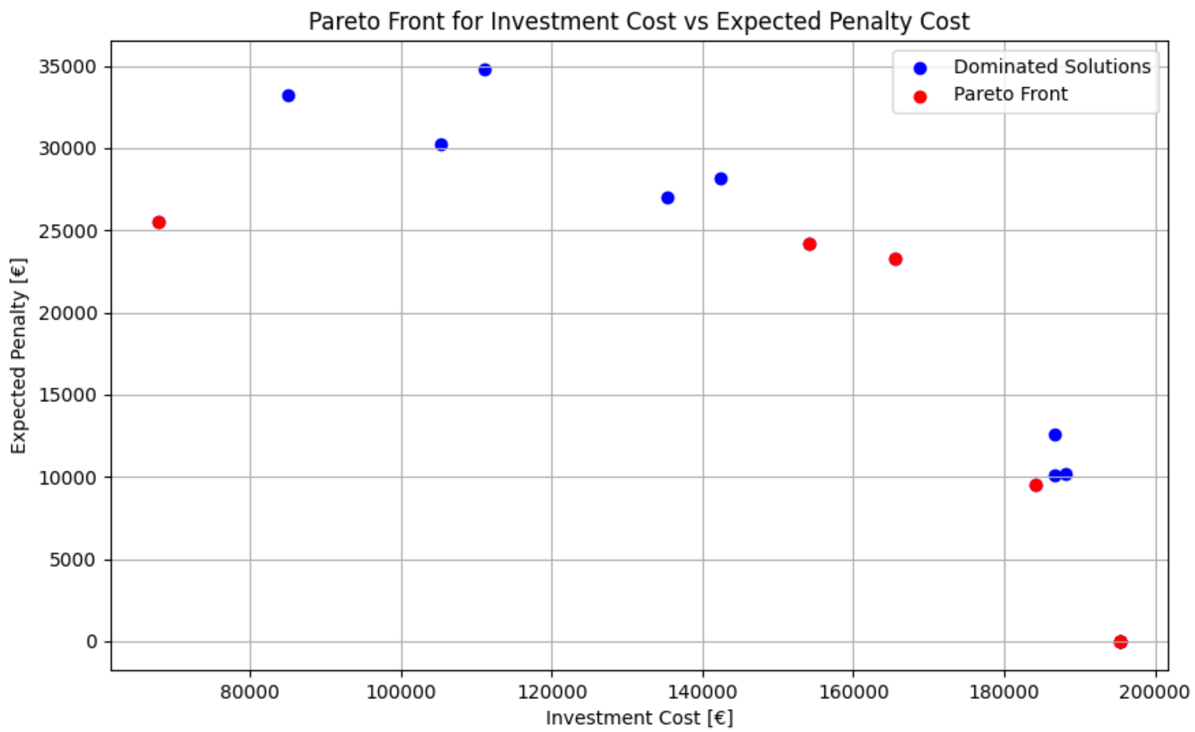
D: VSS Results

The tables below show a breakdown of the cost components and computed VSS values found in each of the tested penalty settings in the experiment explained in Section 5.4.

Penalty [€/kWh]	25	50	75	150	250	500
Deterministic evaluation under uncertainty						
Objective Value	353,239	385,509	413,348	490,674	561,262	747,866
Grid Costs [€]	266,390	262,817	260,634	257,758	255,596	255,626
Total Penalty [€]	42,352	69,631	94,457	167,838	232,778	415,492
OPEX [€]	308,742	332,448	355,092	425,596	488,374	671,118
CAPEX [€]	44,497	53,061	58,256	65,078	72,888	76,748
Stochastic model solution						
Objective Value	350,309	371,530	385,101	410,171	423,841	446,459
Grid Costs [€]	260,825	255,976	253,029	246,920	245,169	246,011
Total Penalty [€]	28,515	33,212	34,920	36,305	27,697	38,975
OPEX [€]	289,340	289,188	287,948	283,225	272,866	284,986
CAPEX [€]	60,969	82,342	97,153	126,946	150,975	161,473
VSS [€]	2,930	13,979	28,247	80,503	137,421	301,407
% Improvement	-0.83%	-3.63%	-6.83%	-16.41%	-24.48%	-40.30%

Penalty [€/kWh]	750	1000	1250	1500	1750	2000
Deterministic evaluation under uncertainty						
Objective Value	957,656	1,162,820	1,370,430	1,578,040	1,785,650	1,993,260
Grid Costs [€]	255,625	255,626	255,626	255,626	255,626	255,626
Total Penalty [€]	625,283	830,442	1,038,059	1,245,663	1,453,274	1,660,885
OPEX [€]	880,908	1,086,068	1,293,685	1,501,290	1,708,900	1,916,511
CAPEX [€]	76,748	76,752	76,745	76,750	76,750	76,749
Stochastic model solution						
Objective Value	461,757	472,024	479,290	486,177	488,514	488,514
Grid Costs [€]	253,599	242,758	237,760	236,609	217,351	217,350
Total Penalty [€]	34,145	29,453	34,656	41,047	0	0
OPEX [€]	287,744	272,211	272,416	277,656	217,351	217,350
CAPEX [€]	174,013	199,813	206,874	208,521	271,163	271,164
VSS [€]	495,899	690,796	891,140	1,091,863	1,297,136	1,504,746
% Improvement	-51.78%	-59.41%	-65.03%	-69.19%	-72.64%	-75.49%

E: Cost/Reliability Trade-Offs



Pareto Front Solutions

Penalty [€/kWh]	25	250	500	750	1750	2000	2500
Obj. Val. [€]	353,452	425,422	442,069	447,710	456,499	456,499	456,499
CAPEX [€]	67,896	154,060	165,460	184,233	195,326	195,326	195,326
OPEX [€]	285,556	271,362	276,609	263,477	261,173	261,173	261,173
Total Penalty [€]	25,555	24,165	23,257	9,525	0	0	0
Investments:							
Wind at Hub [kW]	1.46	2.05	1.73	1.73	1.30	1.30	1.30
PV at 1 [kW]	0.00	0.00	0.00	0.00	0.00	0.00	0.19
PV at Hub [kW]	0.00	1.05	0.76	0.57	0.51	0.51	0.31
Battery at 1 [kWh]	0.09	7.39	11.53	16.64	6.78	8.08	8.18
Battery at 2 [kWh]	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 3 [kWh]	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 4 [kWh]	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 5 [kWh]	0.00	0.05	0.06	0.14	0.32	0.32	0.32
Battery at Hub [kWh]	0.17	0.36	2.33	1.80	17.27	15.98	15.87

F: Cost/Reliability Trade-Offs; Investment Decisions

Penalty setting	**0**	**25**	**50**	**75**	**100**	**150**	**200**	**250**	**500**
Investments									
Wind at Hub	0.00	1.46	1.73	1.95	1.99	2.05	2.05	2.05	1.73
PV at 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at Hub	0.00	0.00	0.10	0.26	0.36	0.59	0.61	1.05	0.76
Battery at 1	0.00	0.09	0.97	2.59	2.91	5.25	6.73	7.39	11.53
Battery at 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 5	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.05	0.06
Battery at Hub	0.00	0.17	0.15	0.15	0.21	1.07	0.90	0.36	2.33
CAPEX [€]	0.00	67,896	85,080	105,356	111,084	135,345	142,318	154,060	165,460
OPEX [€]	n/a	285,556	288,507	281,510	285,175	275,620	276,708	271,362	276,609

Penalty setting	**750**	**1000**	**1250**	**1500**	**1750**	**2000**	**2500**
Investments							
Wind at Hub	1.73	1.73	1.73	1.54	1.30	1.30	1.30
PV at 1	0.00	0.00	0.00	0.00	0.00	0.00	0.19
PV at 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 3	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 4	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV at Hub	0.57	0.56	0.56	0.55	0.51	0.51	0.31
Battery at 1	16.64	15.65	15.99	16.29	6.78	8.08	8.18
Battery at 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 3	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 4	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Battery at 5	0.14	0.32	0.32	0.32	0.32	0.32	0.32
Battery at Hub	1.80	3.18	2.84	4.34	17.27	15.98	15.87
CAPEX [€]	184,233	186,601	186,602	188,132	195,326	195,326	195,326
OPEX [€]	263,477	264,076	266,593	267,402	261,173	261,173	261,173

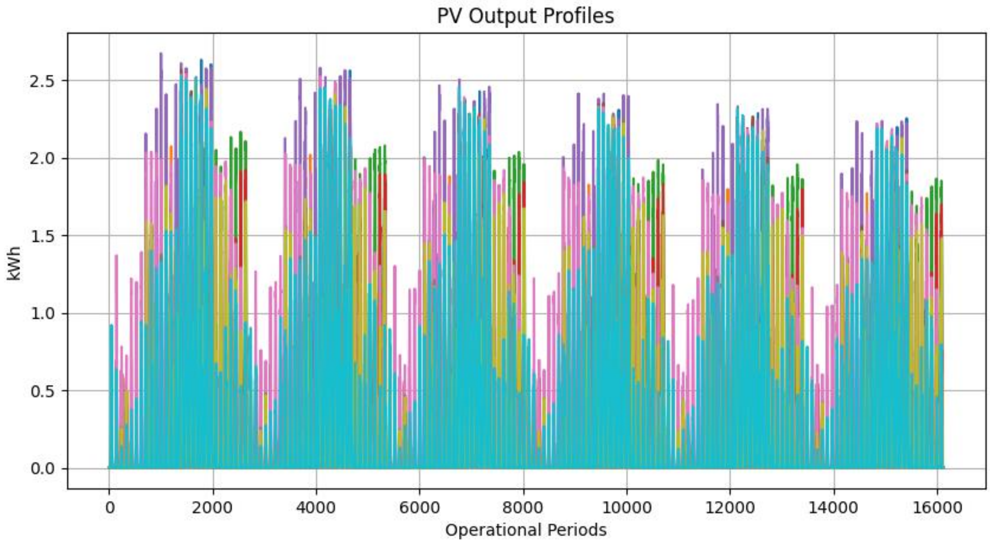
G: Cost/Reliability Trade-Offs; KPI Values

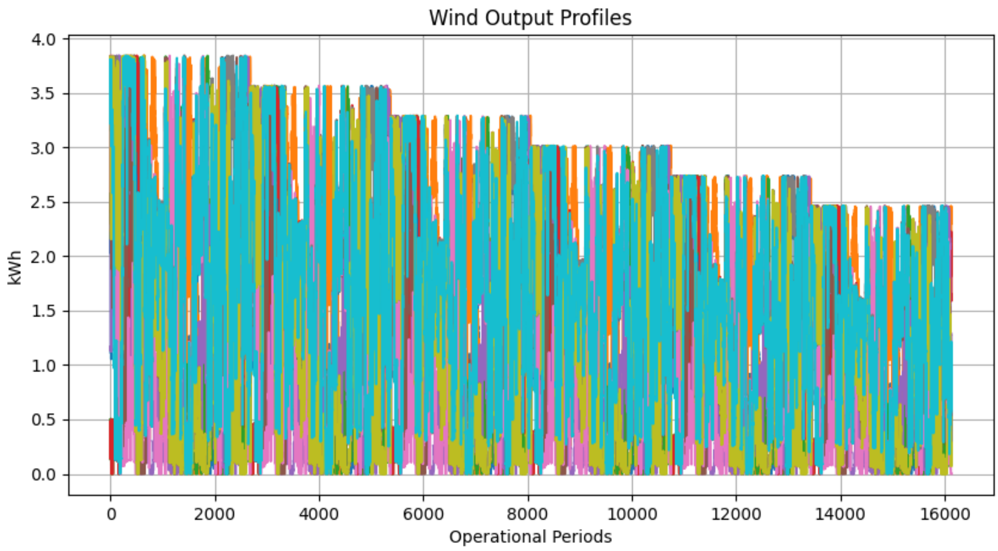
Penalty **KPI**	**0**	**25**	**50**	**75**	**100**	**150**	**200**	**250**	**500**
$EENS_1$	114.02%	0.18%	0.12%	0.08%	0.06%	0.03%	0.03%	0.02%	0.01%
$EENS_2$	184.06%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$EENS_3$	225.40%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$EENS_4$	167.41%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$EENS_5$	134.45%	0.05%	0.02%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%
$LOLP_1$	100.00%	2.90%	1.83%	1.06%	0.92%	0.48%	0.43%	0.31%	0.13%
$LOLP_2$	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$LOLP_3$	100.00%	0.11%	0.10%	0.03%	0.04%	0.02%	0.04%	0.07%	0.03%
$LOLP_4$	100.00%	0.25%	0.13%	0.07%	0.04%	0.01%	0.00%	0.00%	0.00%
$LOLP_5$	100.00%	0.94%	0.52%	0.13%	0.23%	0.13%	0.09%	0.06%	0.04%
AS_1 [kW]	65.0844	0.1037	0.0692	0.0443	0.0368	0.0192	0.0152	0.0102	0.0049
AS_2 [kW]	17.5216	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AS_3 [kW]	14.3838	0.0010	0.0006	0.0001	0.0002	0.0000	0.0001	0.0003	0.0001
AS_4 [kW]	19.8727	0.0015	0.0008	0.0006	0.0003	0.0001	0.0000	0.0000	0.0000
AS_5 [kW]	31.2328	0.0105	0.0053	0.0011	0.0025	0.0013	0.0007	0.0006	0.0003

Penalty **KPI**	**750**	**1000**	**1250**	**1500**	**1750**	**2000**	**2500**
$EENS_1$	< 0.00%	< 0.00%	< 0.00%	< 0.00%	0.00%	0.00%	0.00%
$EENS_2$	< 0.00%	< 0.00%	< 0.00%	< 0.00%	0.00%	0.00%	0.00%
$EENS_3$	< 0.00%	< 0.00%	< 0.00%	< 0.00%	0.00%	0.00%	0.00%
$EENS_4$	< 0.00%	< 0.00%	< 0.00%	< 0.00%	0.00%	0.00%	0.00%
$EENS_5$	< 0.00%	< 0.00%	< 0.00%	< 0.00%	0.00%	0.00%	0.00%
$LOLP_1$	0.04%	0.03%	0.03%	0.02%	0.00%	0.00%	0.00%
$LOLP_2$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$LOLP_3$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$LOLP_4$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
$LOLP_5$	0.01%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%
AS_1 [kW]	0.0013	0.0010	0.0010	0.0007	0.0000	0.0000	0.0000
AS_2 [kW]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AS_3 [kW]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AS_4 [kW]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AS_5 [kW]	0.0001	0.0002	0.0001	0.0001	0.0000	0.0000	0.0000

H: Generator Output Degradation

The plots below show the expected renewable energy generation outputs per installed unit capacity for years 0, 5, 10, 15, 20, and 15 when technological degradation under uncertainty is applied.





I: KPI Values Under Technological Degradation