Optimising sustainable investments for CO_2 reduction in construction: a decision-making model for Hegeman Holding

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Management summary

This research was conducted at Hegeman Holding B.V. in collaboration with CAPE B.V. The project is also a part of the ECOLOGIC research project of the University of Twente. ECOLOGIC aims to make the Dutch construction logistics sector more resilient and sustainable. Hegeman is a family-owned company active in the utility and civil construction sectors in the Netherlands and Belgium.

Problem definition

Hegeman aims to achieve a sustainable certification, called the CO_2 performance ladder (CO_2PL). One of its requirements is to set an emission reduction target and show how this will be achieved. This is also one of the requirements for the Corporate Sustainability Reporting Directive (CSRD). Hegeman thus needs an investment plan to achieve its target, which is to reduce 50% of scope 1 and 2 carbon dioxide (CO_2) emissions in 2030 compared to 2024. The expected total investment cost is the leading factor in making sustainable investment decisions for Hegeman. This led to the following main research question:

"How can we determine the optimal cost-effective combination of investments to let Hegeman achieve its reduction target of 50% reduction of scope 1 and 2 CO_2 emissions in 2030 compared to 2024 to comply with the requirements for the CSDR and the CO_2PL?"

Research method

This research question is answered by formulating a generic strategic investment-decision model that optimises the set of investments and the corresponding investment year to achieve the company's CO_2 emission reduction target at minimum cost. The model not only finds the optimal set of sustainable investments but also the optimal investment year for each investment. The model is a stochastic Mixed Integer Linear Program (MILP) that combines Monte Carlo methods (MCM) and Chance Constrained Programming (CCP). MCM are used to create realistic stochastic model parameters for the reduction impact and cost of the sustainable investments. Sample Average Approximation is used to create a target constraint that uses CCP. The model uses CCP to find a more cost-efficient solution that is sufficient in 95% of all scenarios. After formulating the model, it was applied to the case study at Hegeman. The model was also implemented in a sustainable investment-decision tool that allows Hegeman to keep using the model in the future.

Results

Applying the model to the case study at Hegeman revealed that the reduction target of 50% was too ambitious and did not lead to a feasible solution. Hegeman can either include more sustainable investments as model input, or lower the target to 45%. Reducing the CO_2 emissions by 45% is possible for a minimal total cost of €55,534. Figure 1 presents the optimal investment plan for Hegeman to reach 45% CO_2 reduction as a heatmap. The fraction of all scenarios in which each investment is optimal per year is given. We presented the results to validate the model based on expert opinion. The results seemed realistic and accurate according to Hegeman (Aannemingsmaatschappij Hegeman B.V., 2025).

We tested the model's performance by comparing it to more simplistic methods, using the Marginal Abatement Cost (MAC) curve and a greedy heuristic based on the knapsack problem. The stochastic model outperforms these other methods with 65.7% and 88.9% total cost reduction, respectively. Moreover, we tested how the model performs by using either CCP or MCM. For the 45% reduction target, the MCM model was infeasible because all scenarios must meet

the target instead of only 95%. The penalty was a 4.6% deviation from the target. The CCP model also had an infeasible solution with a penalty of 10.8%. Combining CCP and MCM thus performs significantly better compared to using only one of the methods. When we compared the model's performance to its deterministic model variant, the deterministic model failed to find a feasible solution. It deviated from the 45% target with a 3.4% difference.

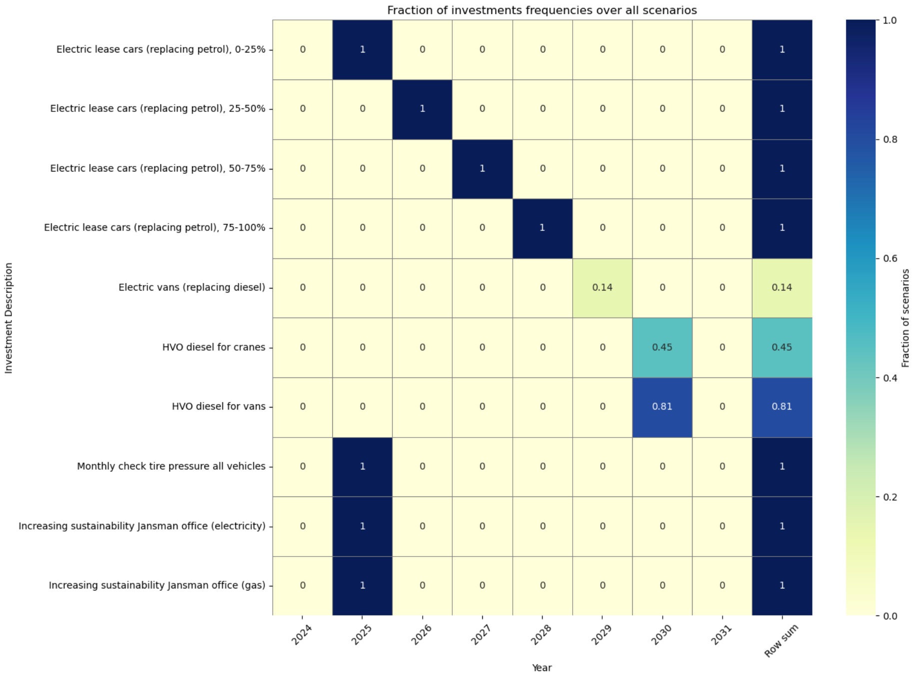

Figure 1: Heat map with the optimal investment plan for Hegeman to achieve its CO_2 emission reduction target of 45%.

Conclusions

The developed optimisation model and tool can successfully be used to answer the main research question for Hegeman, but it can also be adapted for any similar construction company. This research thus makes a practical contribution for Hegeman by finding an optimal investment plan for their current situation, and by providing an investment-decision tool that they can keep using to make strategic sustainability decisions. The practical contribution for CAPE is a generic investment-decision tool that can be adapted to fit their construction clients with similar problems.

Moreover, this research makes a scientific contribution by combining MCM and CCP with an MILP model in the context of sustainable investment planning in the construction sector. To the best of our knowledge, this is a novel concept in the literature. Using MCM to include stochastic parameters in the model also means that, generally, extremely high or low values will be picked from the tails of the distribution. By combining MCM and CCP, not all extreme scenarios need to be covered; a cost-efficient solution to the problem that satisfies the majority of all scenarios can thus be found. The model outperformed the other three more simplistic models it was compared to. The deterministic model failed to reach the emission reduction target of 45% with a 3.4% penalty. Our model outperformed the method based on the MAC curve with a 65.7% improvement, and the heuristic method with 88.9% improvement. The combination of CCP and MCM with an MILP model has thus proven to be a suitable framework for sustainable investment decision making.

Preface

Dear reader,

The study is conducted to finalise my master's degree in Industrial Engineering and Management at the University of Twente.

First, I want to thank Patricia. I learnt a lot during all our discussions, especially about the scientific side of writing a thesis. Moreover, the meetings were always very enjoyable, and I always left them with new motivation and ideas. I would also like to thank Rob for his valuable and detailed feedback, which helped me to take the quality of this research to the next level.

For the past half year, I spent most of the time working on my thesis at CAPE and Hegeman. Everyone here was always eager to help me, for which I am grateful. In particular, Tijmen, thank you for your supervision and for confiding in me to independently handle all contact with Hegeman. Lucas, thank you for helping to make my first Mendix application a success. Chiel and Bjorn, thank you for your advice and for helping me to understand the construction sector.

This thesis concludes my student time in Enschede. I would like to thank my study friends, dispuut, and housemates for making my student time a great period that I will always happily look back on. Lastly, I want to thank my parents and Bo for their support and confidence in me throughout my studies.

Hope you enjoy reading my master's thesis.

Aletta Lohschelder
Enschede, June 2025

Readers' guide

This research is divided into eight chapters, which are briefly outlined below.

Chapter 1: Introduction
The first chapter describes the context of the core problem at Hegeman and how this leads to the research question. It also explains the research design with the subquestions that will be answered per chapter.

Chapter 2: Current situation
The second chapter first discusses the relevant sustainability context to Dutch construction companies, including the emission reporting standard, the CO_2 performance ladder certification, and the CSRD regulation. The chapter then elaborates on the current sustainability context at Hegeman by presenting its carbon footprint compared to the construction sector.

Chapter 3: Literature review
This chapter aims to find a suitable model for Hegeman to select sustainable investments that let them achieve their emission reduction target. Several solution models are discussed and compared. A suitable model is then chosen for creating a sustainable investment-decision model.

Chapter 4: Mathematical model
This chapter formulates the generic investment decision model that finds the minimum-cost combination of investments that achieves a company's emission reduction target. This model is not only applicable to the use case at Hegeman but also to other similar construction companies.

Chapter 5: Applied model
In this chapter, the generic model is applied to the case study at Hegeman. All input values are explained, as well as the probability distributions for the stochastic parameters. Lastly, the programming of the model is illustrated.

Chapter 6: Results and discussion
This chapter elaborates on the results of solving the model for the case study at Hegeman. The model's performance is compared to the performance of several more simplistic methods for creating a sustainable investment plan. Moreover, a sensitivity analysis is performed to experiment with the robustness of the model.

Chapter 7: Implementation
This chapter explains how the model can be implemented at Hegeman using a tailor-made application. The chapter also explains how the application was created for Hegeman by incorporating the applied Python model.

Chapter 8: Conclusion and recommendations
This chapter summarizes the research and presents the scientific and practical contributions of the research. It then lists the recommendations, limitations, and possibilities for future research.

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Acronyms

Abbreviation	**Definition**
API	Application Programming Interface
CCP	Chance Constraint Programming
CO_2	Carbon dioxide
CO_2PL	CO_2 performance ladder
CSRD	Corporate Sustainability Reporting Directive
GHG	Greenhouse gas
HVO	Hydrotreated vegetable oil
ILP	Integer Linear Programming
LP	Linear Programming
MAC	Marginal Abatement Cost
MCDA	Multi-Criteria Decision Analysis
MCM	Monte Carlo Methods
MILP	Mixed Integer Linear Programming
MPSM	Managerial Problem Solving Method
REST	Representational State Transfer
VSS	Value of Stochastic Solution

Contents

1 Introduction

This report documents the research conducted at Hegeman B.V. in collaboration with CAPE. It is also a part of the ECOLOGIC project from the University of Twente. Section 1.1 provides an overview of the companies involved in this research, while Section 1.2 details the ECOLOGIC project to which this research contributes. Section 1.3 explains how a systematic problem-solving framework is used in this research. Section 1.4 then outlines how we identified the core problem, and Section 1.5 states the research question, scope, and research design.

1.1 Company description

This study is conducted with CAPE B.V. and Hegeman Holding B.V. Both companies are introduced in this section.

1.1.1 CAPE B.V.

CAPE B.V. (from now on referred to as CAPE) is an IT consultancy company founded in 2000 with offices in Enschede and Utrecht, in the Netherlands. They specialise in transport, logistics, supply chain, construction, and agrifood. CAPE uses user-friendly and integrated systems, mostly using low-code in Mendix (CAPE, 2024b). Mendix is a low-code development platform founded in 2005. By establishing a visual development language, Mendix eases communication and thus has the potential to bridge the gap between business and IT (Mendix, 2025).

1.1.2 Hegeman Holding B.V.

Hegeman Holding B.V. (from now on referred to as Hegeman) is an independent family enterprise working in the utility and civil construction sector in the Netherlands and Belgium. The construction companies that are a part of this are Aannemingsmaatschappij Hegeman B.V., Aarts Bouw, WVG Ontwikkeling B.V., Jansman Bouw B.V., and Bouw.Novum. Hegeman operates as a full-service main contractor, managing all construction aspects from design to execution and maintenance with their in-house specialists, a dedicated carpentry factory, and equipment service. The projects at Hegeman include nursing homes, schools, offices, churches, and factories (Aannemingsmaatschappij Hegeman B.V., 2024).

1.2 ECOLOGIC project

This research is conducted as part of the ECOLOGIC project. ECOLOGIC is a research project called Emission Control and Logistics Optimisation for Green Infrastructure Construction. The project aims to make the Dutch construction logistics sector more sustainable and resilient. The initiative is funded by the Dutch Ministry of Infrastructure & Water Management. It is also contributing to the Knowledge and Innovation Program for Emission-Free Building 2021-2023. Companies participating in this project are BauWatch, CAPE, Datacadabra, Dura Vermeer, Hegeman, Stichting Pioneering, and the University of Twente. The project involves various research groups from the University of Twente, focusing on areas such as sensor analytics, data analytics, industrial engineering, and business information systems (University of Twente, 2024). One of the project's living labs is located at a construction site in Amsterdam. This site is used as a test environment for new technologies to reduce emissions and improve construction processes (CAPE, 2024a).

The ECOLOGIC project aims to improve the sustainability of the Dutch construction logistics sector by developing data-driven insights and advanced analysis techniques. The developed theories and models are tested and evaluated in practice in the living labs (ECOLOGIC, 2023). This research aligns with the project's goal of reducing the carbon footprint of construction companies by making data-driven investment decisions to achieve the reduction targets of companies. Hegeman delivers the user case to which this research applies. Additionally, knowledge of Hegeman and CAPE is used to complete the research.

1.3 Managerial Problem Solving Method

We apply the Managerial Problem Solving Method (MPSM) by Heerkens and van Winden (2021). The MPSM is a systematic problem-solving framework using seven sequential phases listed below.

1. Defining the problem
2. Formulating the approach
3. Analysing the problem
4. Formulating (alternative) solutions
5. Choosing a solution
6. Implementing the solution
7. Evaluating the solution

Each phase of the MPSM is addressed throughout this research. Section 1.4 defines the problem in this research (phase 1). The plan of approach is outlined in Section 1.5 (phase 2). The problem is analysed in Chapter 2 (phase 3). Alternative modelling options are discussed in the literature review in Chapter 3 (phase 4), after which the most suitable model is selected in the conclusion of this chapter (phase 5). Chapter 4 formulates the generic model, and Chapter 5 applies this to the case study at Hegeman (phase 6). Chapter 6 then evaluates the results of the decision-making model (phase 7). That concludes all phases of the MPSM and thus systematically addresses the problem.

1.4 Problem identification

In this section, we will explain the problem context at Hegeman. The problems and their causality are then summarized in a problem cluster in Figure 2. Before explaining the problems, the relevant sustainability context is first introduced. This will be explained in more detail in Chapter 2.

Sustainability is becoming an increasingly important topic at Hegeman, driven especially by the stricter compliance requirements of the newly enforced Corporate Sustainability Reporting Directive (CSDR) that they need to comply with starting in 2028. The CSRD is a European regulation that supports the goal of the European Union to become climate-neutral by 2050. It provides regulation requiring companies to publish their gross emissions of scopes 1, 2, and 3 and their total greenhouse gas (GHG) emissions (European Parliament, 2022). The three scopes refer to the widely used reporting method by the Greenhouse Gas Protocol that divides the total carbon dioxide (CO_2) emissions into direct emissions (scope 1), indirect emissions from purchased electricity or energy (scope 2), and all other indirect emissions upstream and downstream in the supply chain (scope 3) (Schmitz et al., 2015). Moreover, Hegeman aims to get certified on the first level of the CO_2 performance ladder (CO_2PL) to gain a competitive advantage in obtaining new projects. The CO_2PL is a Dutch green procurement scheme used by several Dutch public authorities. Companies can get certified using the CO_2PL on levels 1, 2, or 3 based on the sustainability and energy-efficiency of their processes (SKAO, 2025). Hegeman states that a growing number of their competitors have already obtained or are in the process of obtaining CO_2PL certification (Aannemingsmaatschappij Hegeman B.V., 2025). Consequently, not complying with the CO_2PL may undermine Hegeman's competitive advantage.

The CSRD and CO_2PL overlap in some aspects. Both require Hegeman to set and achieve targets to reduce its CO_2 emissions (European Parliament, 2022; SKAO, 2025). Hegeman has set a target to reduce its CO_2 emissions by 50 percent in 2030 compared to 2024. For Hegeman to achieve this, they want to find what sustainable actions are the most cost-effective way to achieve their target. Sustainable investments are often expensive and difficult to reverse (Hegab et al., 2023). Pantović et al. (2024) state that data-driven decision-making can increase the reliability and quality of the decisions. Given the high costs and irreversibility of many sustainable measures, it is therefore crucial that Hegeman relies on data-driven decision-making to make cost-effective decisions.

The CSRD and CO_2PL also require companies to publish sustainability reports with their scope 1, 2, and 3 CO_2 emissions, as well as estimates of emissions of other GHGs. Measuring CO_2 emissions is a complex task, especially measuring scope 3 emissions (Shrimali, 2022). This is also the case for Hegeman; they thus currently only track their annual scope 1 and 2 CO_2 emissions.

Not complying with the CSRD could result in financial penalties based on the size of the violation and the company. Moreover, violating the CSRD can damage a company's reputation (Martin & Callaghan, 2024). If a company cannot attain a CO_2PL certification, it may create a financial and reputational disadvantage in attaining construction projects (SKAO, 2025).

Figure 2 outlines this set of problems and their relations. The selected core problem in this research should be possible to address in the scope of this Master's thesis, and it should be a problem that Hegeman has control over. Otherwise, it might not be possible to solve the problem.

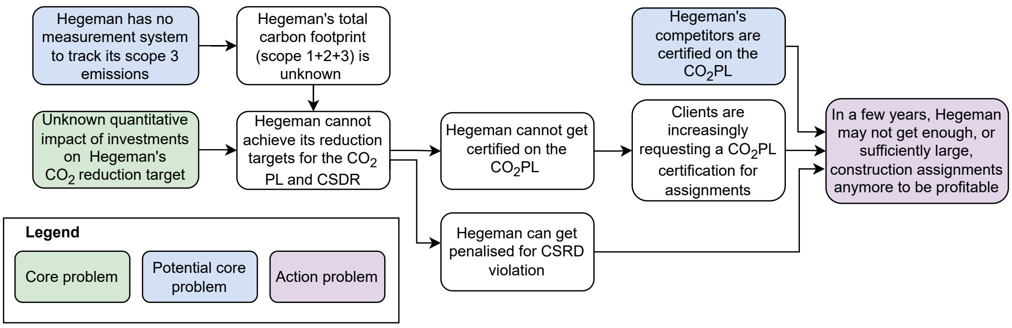


Figure 2: Problem cluster that explains how the action problem at Hegeman is caused by the core problem that we are going to provide a solution for in this research.

The main problem Hegeman foresees is the following action problem:

> *"In a few years, Hegeman may no longer be able to obtain enough, or sufficiently large and profitable, construction projects because of the absence of a CO_2PL certification and/or penalties for CSRD violations."*

The action problem is caused by several other problems. Three potential core problems emerge from the problem cluster in Figure 2. The first problem "Hegeman's competitors are certified on the CO_2PL", while Hegeman is currently not, is a problem which cannot be influenced, so this is not the chosen core problem. The other problem, "Hegeman has no measurement system to track its scope 3 emissions", was also not selected as the core problem. This is because when Hegeman needs to comply with the CSRD in 2028, the same holds for other companies in their supply chain. If these other companies upstream and downstream publish their scope 1 emissions, Hegeman can use the information to create an overview of their scope 3 emissions relatively easily. The problem will thus solve itself in a few years. That leaves the last potential core problem:

"The quantitative impact of sustainable investments on scope 1 and 2 CO_2 emissions at Hegeman is unknown, which is needed to achieve Hegeman's CO_2 reduction target to comply with the CSDR and achieve a CO_2PL certification."

This problem is within the control of Hegeman to be solved and can be addressed in the time frame of a Master's thesis. We will thus select this as our core problem.

Solving the core problem will enable Hegeman to overcome the action problem by helping Hegeman to achieve level one CO_2PL certification and comply with the CSRD. This research is not only conducted for Hegeman but also in collaboration with CAPE and within the framework of the ECOLOGIC research project. Not only Hegeman is dealing with CSRD and CO_2PL issues, but many other companies in the construction sector are as well. We will not only give specific advice to Hegeman in this study but also create a generic investment-decision model that can be used by other similar construction companies. This aligns with the goals of ECOLOGIC and is useful for other construction clients of CAPE.

The model is described as a generic model that could be used by any similar construction company. However, it is important to clarify the extent to which the model can be considered as generic. The model structure and formulation in general are generic and could probably be applied to many other construction companies. Some of the assumptions can be too restrictive or unsuitable for other construction companies since the model is based on and experimented with the case study at Hegeman. This will be addressed in more detail in Section 4.1. Applying the model to another company thus requires careful consideration regarding whether the model formulation reflects the company's problem context.

1.5 Plan of approach

In this section, we explain the research design used in this thesis. The main research question that we will focus on in this research to address our core problem is as follows:

"How can we determine the optimal cost-effective combination of investments to let Hegeman achieve its target of 50% reduction of scope 1 and 2 CO_2 emissions in 2030 compared to 2024 to comply with the requirements for the CSDR and the CO_2PL?"

This research aims to create an investment decision model that finds the optimal cost-effective set of investments to meet Hegeman's CO_2 emission reduction target of reducing their scope 1 and 2 CO_2 emissions by 50% in 2030 compared to 2024. The model is a strategic decision-making model. Schmidt and Wilhelm (2000) describes the difference between strategic, tactical, and operational level decisions. Strategic decisions deal with long planning horizons of multiple years and include a high degree of uncertainty. Operational decisions are made on a daily basis and contain a low degree of uncertainty. Tactical decisions are at the level between strategic and operational. These decisions have a medium degree of uncertainty and a planning horizon of several months. A strategic model is thus the most suitable in this research, because we plan for a long time horizon of several years and deal with a high level of uncertainty. Setting strategic emission reduction targets is also a requirement of the CO_2PL (SKAO, 2025). Hence, a strategic model is the most suitable for this problem.

1.5.1 Scope

Due to the limited time frame of this research and a lack of data, this research will focus solely on scope 1 and 2 CO_2 emissions, as is required for a level one CO_2PL certification. Other GHGs and scope 3 emissions are only addressed in levels 2 and 3 of the CO_2PL. Additionally, Hegeman only has carbon footprint data available about scope 1 and 2 emissions. This is currently sufficient, as the CSRD requires companies to start publishing scope 3 emissions from 2028 on. Since Hegeman aims only for a level 1 certification, this scope is appropriate.

The term sustainability is often used in this thesis in a construction context. In this research, we use the definition by Zabihi et al. (2012), who define sustainable construction as "construction activities whose negative impacts are minimised and positive impacts maximised to achieve a balance in terms of environmental, economic, and social performance".

1.5.2 Research design

We address this research question using the following research design. Each phase corresponds to one research question that is answered in one chapter.

Phase 1: Define the current situation

1. What is Hegeman's current scope 1 and 2 carbon footprint?
We answer this question using Hegeman's existing carbon footprint data. This helps us to create an image of Hegeman's current situation and where the most emissions are allocated in its supply chain.

Phase 2: Perform a literature study

2. What is a suitable investment decision model for a construction company to achieve its emission reduction target at minimum cost?
We use literature to explore existing decision-making models that could be used to find the impact of different investments on a construction company's CO_2 emissions. A combination of exploratory literature search and snowballing is used to execute this literature study. Then, we select a suitable model based on the characteristics that should be present in the model.

Phase 3: Create the solution design

3. How is the generic investment decision-making model formulated to find the set of investments that reaches the CO_2 emission target while minimising costs?
To answer this question, we formulate a generic strategic model for a construction company that wants to select the optimal set of investments to reach its emission reduction target. The model not only selects whether to select an investment, but also the optimal investment year. The model is based on existing models in the literature. This model is a generic strategic model that any similar construction company aiming to achieve their emission reduction goals for minimum costs can use.

Phase 4: Apply the model to the case study at Hegeman

4. How can the generic investment-decision model be applied to the case study at Hegeman?
In this question, we illustrate how to apply the generic model to the case study at Hegeman. We require data from Hegeman for this question to use as input data for the model. We also explain how to calculate or tune the parameters needed in the model.

Phase 5: Analyse the results

5. How does the investment-decision model perform for the case at Hegeman?
We analyse the results of running the model with Hegeman's data in this question. We first test the model's performance by comparing the results to three other, more simplistic methods.

Furthermore, we perform a sensitivity analysis to assess how changes in key parameters affect the model's performance.

Phase 6: Implement the solution at Hegeman

6. How can we implement the investment-decision model at Hegeman?
In this question, we create a tool that implements the investment-decision model for Hegeman by prioritising ease of use. This allows Hegeman to evaluate potential investments without requiring extensive technical knowledge of the model.

1.6 Deliverables

The following deliverables are the result of this research:

- A generic strategic investment-decision model that optimises the set of investments and the corresponding year of investment to achieve the company's CO_2 emission reduction target for minimum costs.
- An applied strategic investment-decision tool that optimises the set of investments and the corresponding year of investment to achieve Hegeman's CO_2 emission reduction target for minimum costs.
- A recommendation to Hegeman consisting of an optimal investment plan to achieve its CO_2 reduction target for minimum costs.

2 Context analysis

This chapter performs a sustainability context analysis for Hegeman. First, we provide background knowledge about sustainability relevant to Dutch construction companies. Section 2.1 explains the emission reporting standard. Section 2.2 then describes the CO_2PL and how companies can get certified. Section 2.3 explains how the CSRD works and how companies can ensure to meet the regulation. Section 2.4 then answers this chapter's research question:

"What is Hegeman's current scope 1 and 2 carbon footprint?"

2.1 Emission reporting

Before diving into the CO_2PL and the CSRD, it is key to understand the essentials of emission reporting. The Greenhouse Gas Protocol established a global standardized framework for measuring and managing GHG emissions according to their accounting and reporting standards. The GHG Protocol differentiates between direct and indirect emissions. Direct GHG emissions are from sources that are controlled or owned by the company, while indirect GHG emissions are a consequence of the company's activities but do not occur at their owned or controlled sources. They also introduced the concept of measuring emissions divided into three scopes. Scope 1 emissions are all direct GHG emissions. Scope 2 emissions are indirect GHG emissions because of the purchased electricity consumed by the company. Scope 3 emissions are all other indirect GHG emissions that are not in scope 2. Figure 3 visualises the GHG emissions per scope according to the GHG Protocol (Schmitz et al., 2015).

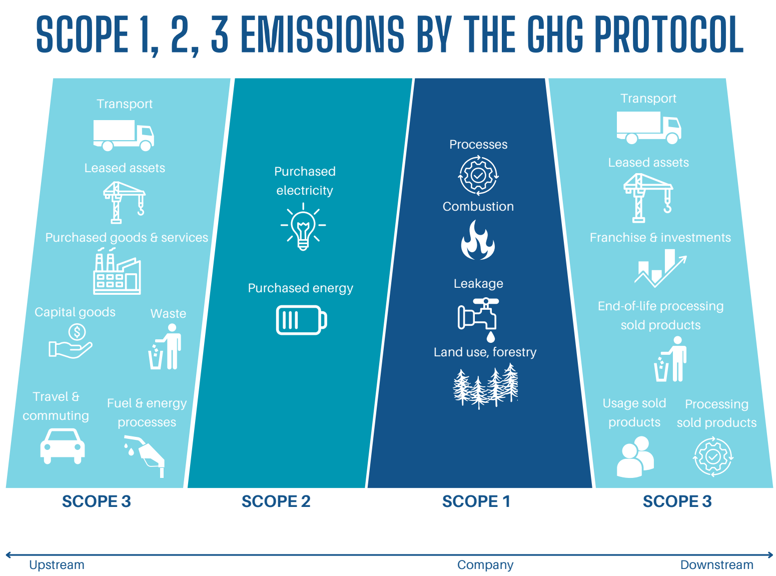


Figure 3: Visualisation of how GHG emissions are categorized into scopes 1, 2, and 3 by the GHG Protocol.

The GHG Protocol not only includes reporting about CO_2 emissions but also the other six other GHGs recognized by the Kyoto Protocol, which are methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, sulphur hexafluoride, and nitrogen trifluoride (UNFCCC, 1998). The GHG Protocol states that the GHG emissions should be measured in metric tonnes of the GHG and CO_2 equivalents (Schmitz et al., 2015).

2.2 CO_2 performance ladder

The CO_2 performance ladder (CO_2PL) is a Dutch green procurement scheme used by several Dutch public authorities. It is a carbon dioxide and energy management certification scheme, certifying companies on a level from 1 (lowest) to 3 (highest) based on their sustainability performance. The SKAO requires more from companies that are certified at higher levels. If a company meets all requirements for a certain level, it can get certified for five years, but there are intermediate audits to check on progress. ProRail developed the CO_2PL in 2009 to encourage environmentally friendly and energy-efficient performance. The Stichting Klimaatvriendelijk Aanbesteden en Ondernemen (SKAO) was founded in 2011 to take over the management of the CO_2PL (Rietbergen & Blok, 2013). This research is based on the most recent version of the CO_2PL, version 4.0 (SKAO, 2025).

Many companies seek CO_2PL certification for the fictional bidding advantage in tenders where the lowest bid would otherwise win. Higher certification levels provide a greater percentage bidding advantage. To illustrate the working of the bidding advantage, consider the following example. In a tender, company X bids 30 million euros, while the competitor bids 29 million euros. Usually, the competitor would then win the project. However, company X gets a 4% fictional bidding advantage because of its CO_2PL certification. This reduces the fictional bid to 28.8 million euros, letting company X win the bid while still receiving the full 30 million euros. This system thus rewards sustainable companies with financial benefits (Rietbergen & Blok, 2013).

To obtain CO_2PL certification, a company needs to meet a set of requirements for four overall goals: insight, reduction, communication, and collaboration. The requirements depend on the certification level the company aims to achieve. The level 1 requirements for each goal form the foundation and must also be met for levels 2 and 3. Each subsequent level adds more ambitious requirements. The four goals set by the SKAO (2025) are as follows.

- **A: Insight**: create quantitative insight into a company's emissions by calculating its carbon footprint. Scope 1 and 2 CO_2 emissions are always included. Scope 3 CO_2 emissions and other GHGs are included at higher levels (2 and 3). A formal carbon footprint report certified by an auditor is required as evidence.

- **B: Reduction**: set ambitious emission reduction goals. The reduction goal should be ambitious for the company itself and in comparison to the sector and obligations by the law. For level 3, the goal is to have zero emissions in 2050 or before. The reduction goals should be monitored, including risks and opportunities. Additionally, for each goal, a detailed action plan should be formulated, specifying the required actions, resources, responsible parties, and methods for evaluating progress. The minimum evaluation frequency per goal is at least once per year. A CO_2 management system can be a useful tool for evaluating the progress towards the targets. Annual verified reports can also be evidence of meeting the requirements.

- **C: Communication**: communicate internally and externally about the company's climate transition plan and its progress. The evidence for this goal can be provided in publicly available communication reports.

- **D: Collaboration**: collaborate with other parties to achieve the goals set in the climate transition plan. This at least includes analysing the missing information and collaborations to achieve the company's reduction goals. This goal can be measured by reporting on (required) collaborations and dialogues with experts.

Companies certified on the CO_2PL are required by the SKAO to aim for continuous sustainability improvement on all four goals. The CO_2PL uses the PDCA cycle method for this, which consists of the phases: Plan, Do, Check, and Act. For the reduction goal of the CO_2PL, for example, the procedure can be described as follows. First, a reduction goal is set (Plan), then measures for emission reduction are taken (Do), the progress is measured (Check), and the taken measures are adjusted if necessary (Act) (SKAO, 2025).

2.3 Corporate Sustainability Reporting Directive

The Corporate Sustainability Reporting Directive (CSRD) was enforced in January 2023. This regulation supports the goal of the European Union to become climate-neutral by 2050. The regulation aims to reorient capital flows towards sustainable investments and to encourage transparency and long-term planning. This requires companies to publish information about their sustainability performance and thus prevent greenwashing (European Parliament, 2022).

Similar to the CO_2PL, the CSRD also demands (by Article 19 bis 2b) a set of time-bound sustainability goals for the reduction of absolute GHG emissions for at least 2030 and 2050. The progress towards these goals should also be documented. Moreover, the CSRD uses the 3-scope model, just as the CO_2PL. Article 19 bis 2f states that the most important actual or potential negative effects connected to a company's operations or its supply chain should be reported. In addition, any actions taken by the company to prevent or reduce these effects and the results of these actions must be reported. This includes not only GHGs but also other negative effects on the environment (European Parliament, 2022).

To meet all the requirements of the CSRD, the EU adopted a framework and methodology for sustainability reporting. These are the European Sustainability Reporting Standards (ESRS) developed by the European Financial Reporting Advisory Group (EFRAG) (Dijk & Hijink, 2022). The ESRS were officially adopted by the European Commission in July 2023. In twelve standards, the ESRS covers a range of topics, including environmental, social, and governance standards (European Parliament, 2022). The European Commission and Union (2022) explains the standards. Two general standards apply to all companies. The other ten sector-specific standards are all related to one of the topics: environment, social, and governance. These ten standards only apply if the standard is relevant to the organisation. We will only explain the ESRS E1 (environment) standard, as the others are not relevant to this research. The ESRS E1 standard is called 'climate change', and it obliges organisations to calculate and publish their gross GHG emissions of scopes 1, 2, and 3, and their total GHG emissions.

2.4 Hegeman's carbon footprint

Hegeman has been working on implementing the CSRD for over two years. As a part of this, they developed a carbon footprint dashboard that continuously monitors Hegeman's scope 1 and 2 CO_2 emissions (not including other GHGs). Currently, the only year with complete carbon footprint emission data is 2024. In this section, we will present the 2024 data to provide an overview of Hegeman's annual carbon footprint.

Hegeman's total scope 1 and 2 CO_2 emissions in 2024 were 880 tonnes. When dividing according to the GHG Protocol classification, as shown in Figure 3, 81.4% of the emissions fall under scope 1, while 18.6% fall under scope 2. Hegeman's scope 1 emissions consist mainly of heating and different types of transport activities. Figure 4 displays the detailed division of Hegeman's scope 1 CO_2 emissions. The scope 2 emissions at Hegeman only contain purchased electricity for its projects and offices. With the implementation of the carbon footprint dashboard, Hegeman successfully fulfils part A ("Insight") of the first level of the CO_2PL.

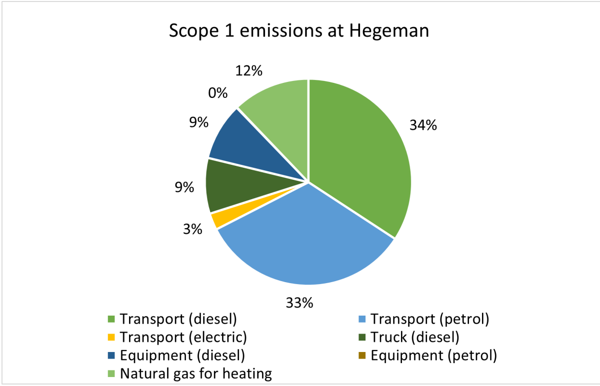
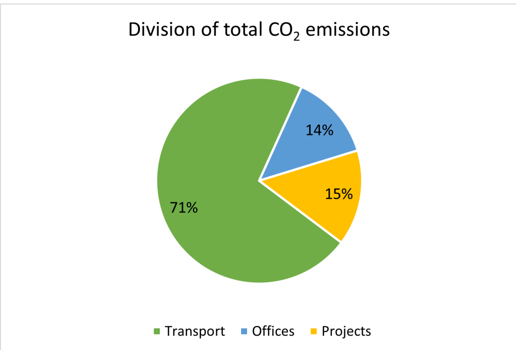
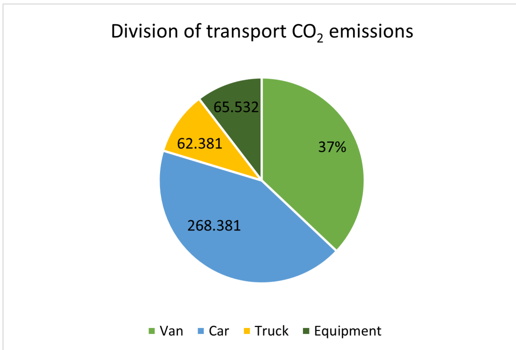


Figure 4: Division of Hegeman's scope 1 CO_2 emissions in 2024. The 'equipment (petrol)' category is so small that it is rounded to zero percent and not visible on the chart.

Figure 5a shows how Hegeman's total CO_2 emissions are divided over transport, offices, and projects, which are the three business units at Hegeman. Transport accounts for the largest share of the total emissions, followed by projects, with offices contributing the least. Figure 5b illustrates the amount of transport CO_2 emissions per type of vehicle. The fleet of vehicles at Hegeman consists of vans, cars, trucks, and equipment (e.g., forklifts, machines). Hegeman last year started a transition from petrol to electric lease cars. Within five years, all petrol cars will be replaced by electric or hybrid cars. Currently, there are 14 electric cars, 7 hybrid cars, 27 petrol vehicles, and 51 diesel vehicles.



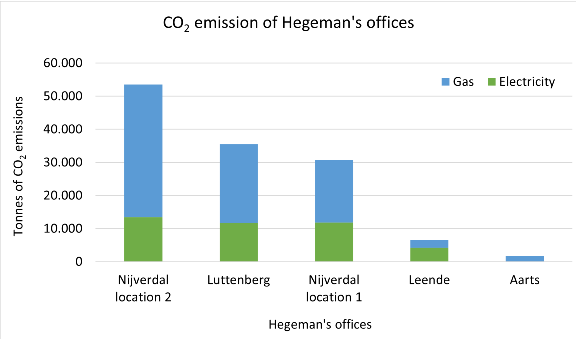
(a) Division of total CO_2 emissions over transport, offices, and projects.



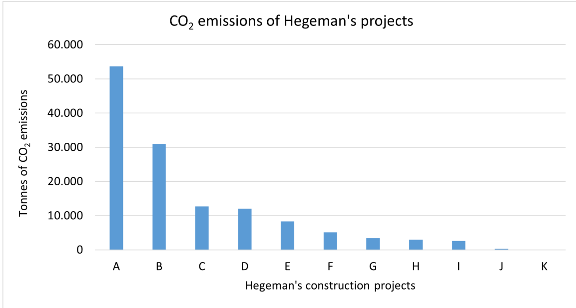
(b) Division of transport CO_2 emissions per type of vehicle.

Figure 5: Visualisation of the CO_2 emissions at Hegeman in the year 2024 in total and split in transport vehicles.

The emissions per office and project are also split up and visualised in Figures 6a and 6b, respectively. The CO_2 emissions of all offices are divided into emissions caused by using electricity (32.2%) and gas (67.8%). For some of the projects, Hegeman does not have to pay for the electricity and gas used on construction sites. These projects are not included in Figure 6b since these emissions are a part of scope 3, which is not included in the dashboard. Hegeman also owns solar panels, so this provides for a part of its energy usage in the offices. The remaining amount of energy and electricity that is needed at the offices and construction sites is purchased and shown in Figures 6a and 6b.



(a) Division of CO_2 emissions per office.



(b) Division of CO_2 emissions per project.

Figure 6: Division of CO_2 emissions per office and project at Hegeman in the year 2024.

To compare Hegeman's carbon footprint with other companies in the Dutch construction sector, we use companies' public carbon footprints published on the Envirometer (2025). It is essential to note that companies fill in the data themselves, and another party does not validate it. This may influence the comparability and reliability of the results. Due to a lack of higher-quality data, the benchmarking is based on this dataset. More than a thousand carbon footprints have been published on this platform by companies wanting to calculate their carbon footprint. Hegeman's 2024 footprint is compared to the most recent footprints of other companies since no 2024 footprints were published. Footprints with data before 2020 or with total emissions below 10 tonnes per year are excluded to select only recent carbon footprints of comparable companies. This leaves eleven companies to compare Hegeman to. This provides a benchmark for evaluating Hegeman's carbon footprint within the sector, though it may not fully represent the entire Dutch construction industry because of the small size of the sample.

Table 1 shows the carbon footprint data of the eleven Dutch construction companies as published on the Envirometer (2025), as well as Hegeman's carbon footprint. Some companies published scope 3 emission data, but that was excluded from this analysis since Hegeman did not publish their scope 3 emissions. The total yearly emissions are thus the sum of the scope 1 and 2 emissions. The average total yearly CO_2 emissions for these companies (excluding Hegeman) is 1817 tonnes of CO_2. This is more than twice as high as Hegeman's emissions, but Verboon Maasland increased the average substantially. 6 companies score higher, and 6 score lower than Hegeman on the total yearly CO_2 emissions. Hegeman's performance is thus quite average. Also noticeable in Table 1 is Hegeman's high percentage of scope 1 emissions, namely 81.4%, while the average is 60.2%. One contributing factor is that Hegeman does not distinguish between business travel (scope 1) and private travel (scope 2) in its reporting, meaning the actual scope 1 percentage is lower. However, other companies' data might also be incomplete or partly incorrect. Additionally, Hegeman's relatively low scope 2 emissions are caused by their solar panels, which reduce the need for purchased electricity. Lastly, as a Dutch company operating exclusively in the Netherlands, Hegeman avoids air travel, which would otherwise contribute to the scope 2 emissions. Including scope 3 emissions in the analysis could reveal significant differences between companies, as construction firms vary greatly in the extent to which they outsource work to subcontractors (Aannemingsmaatschappij Hegeman B.V., 2025).

Company	Yearly tonnes CO_2 emissions	Scope 1 (%)	Scope 2 (%)	Year
Verboon Maasland	7,416	49.6	50.4	2023
De Voogd-Grijpskerke	658	99.9	0.1	2023
Kroes	1,014	49.7	50.3	2023
Koopmans Bouwgroep	1,759	35.8	64.2	2023
Wagelaar	465	49.5	50.5	2022
Fraanje	1,302	65.7	34.3	2022
Tijssen	2,954	49.8	50.2	2022
Coen Hagedoorn Bouw	3,229	67.2	32.8	2022
De Vries Titan	465	98.8	1.2	2021
Maastveste Berben Bouw	637	49.8	50.2	2021
Bezemer Bouw	89	46.7	53.3	2021
Hegeman	*880*	*81.4*	*18.6*	*2024*

Table 1: CO_2 emission carbon footprint data for Dutch construction companies as published on the Envirometer (2025) compared to the carbon footprint of Hegeman.

2.5 Conclusion

In conclusion, the sustainability context and carbon footprint of Hegeman were explained and analysed in this chapter. By following the GHG Protocol classification of scope 1, 2, and 3 emissions, Hegeman's scope 1 and 2 CO_2 emissions for 2024 were mapped. The carbon footprint dashboard for 2024 shows that 81.4% of emissions originate from scope 1 and only 18.6% from scope 2. Transport accounts for the largest share, followed by projects and offices. Emission reduction efforts in Hegeman's transport can thus have a substantial impact. Compared to other companies in the Dutch construction sector, Hegeman's total yearly CO_2 emissions are relatively average. However, its percentage of scope 1 emissions is considered to be relatively high.

The created carbon footprint dashboard with Hegeman's scope 1 and 2 CO_2 emissions completes part A ("Insight") of the first level of the CO_2PL. However, to comply with the CSRD from 2028 onward, scope 3 emissions must also be included in the dashboard. The carbon footprint data from 2024 will be used as input data for the investment-decision model for Hegeman in Chapter 5.

3 Literature review

This chapter answers the following research question by performing a literature review.

"What is a suitable investment decision model for a construction company to achieve its emission reduction target at minimum cost?"

For the literature review, mainly a combination of exploratory research and backward snowballing was used to find relevant scientific articles. Exploratory research was mostly used to find different types of strategic decision-making models. Snowballing was especially useful for finding more studies that use the same type of modelling once we found a suitable modelling option. Often, the found articles apply the model in a different context, but it could be adapted to fit our case study.

Decision-making modelling is a broad field with many modelling options depending on the situation's characteristics. Figure 7 shows the models we explored and compared in this chapter, as well as their relations. The models are used in literature to make decisions that impact the future. The models all approach decision-making differently. We will explain why the three model categories were chosen to be included in the literature review for this research. Linear programming optimises an objective function and can be combined with stochastic models to include parameter uncertainty in the model. It can thus find optimal decisions. MCDA can be used to make decisions in complex situations with conflicting objectives, so it can be used to model complex situations. Forecasting can be used to compare the impact of different decision scenarios on predicted values and find the best scenario. To select a suitable model from these options, we need to perform a literature study on these models.

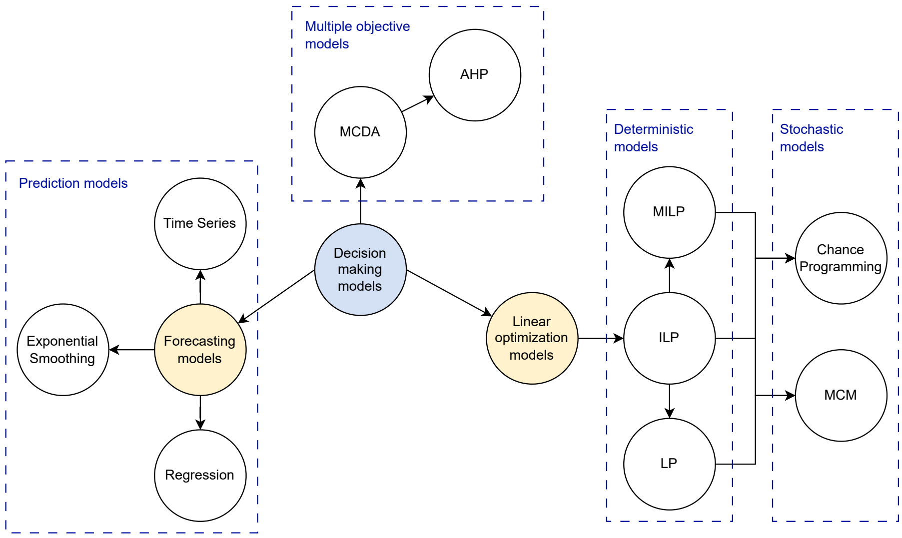


Figure 7: Overview of solution methods discussed in the literature study to find a suitable strategic decision-making model. Model categories are marked in blue and yellow. The relations between models are indicated using the blue dashed boxes.

First, we explore linear optimisation models, consisting of Linear Programming (LP), Integer Linear Programming (ILP), and Mixed Integer Linear Programming (MILP). These can be combined with Monte Carlo Methods (MCM) or Chance Constrained Programming (CCP) to include stochasticity. Then, three different types of forecasting are researched: time series, exponential smoothing, and regression. The last type of method we investigate is Multi-Criteria Decision Analysis (MCDA), of which a commonly used method is the Analytical Hierarchy

Process (AHP). For each possible solution method, we find the article that resembles the case study the closest, and consider whether the method could be applied.

To find a suitable model of all studied models in Figure 7, we define two lists of characteristics that the ideal model is required, and preferred to have. In Section 3.4, we will compare all selected models and choose a suitable model based on these characteristics.

The characteristics the model is *required* to have:

- The model should be able to make strategic decisions.
- It should be possible to include stochastic parameters in the model. Kochenderfer (2015) underlines the importance of accounting for various sources of uncertainty when creating a decision-making model. The stochasticity in sustainability decision-making models can, e.g., be due to estimation errors of parameters or missing data (Zulueta et al., 2017).
- The model should be able to minimise costs.
- The model should not rely heavily on historical data since the model decides about new investments that the company has not executed in the past. So, online data sources and estimates will mostly be used to get the input parameters, which are less accurate than historical data.
- The model should be able to not just decide about single investments but also optimise to find the best set of investments.

The characteristics the model is *preferred* to have:

- Calculating the optimal solution would be ideal, but if a method can find a good approximation, that is also accepted.
- Short running times would be beneficial. However, since we create a strategic model, it is not run often. Hence, short running times are not a strict requirement.

3.1 Linear programming

Linear programming (LP) is a type of mathematical programming for problems with only linear constraints and a linear objective function (Matoušek & Gärtner, 2007). LP can be used for modelling complex decision-making problems (Li et al., 2024). Winston (1988) explains the different types of LPs as Integer Linear Programs (ILPs) with only integer decision variables, Mixed Integer Linear Programs (MILPs) where only some decision variables are integer, and LPs where no decision variables are integer. Although ILPs and MILPs have fewer solutions than LPs, it is easier to solve LPs. This is because LPs have a continuous feasible region, so the optimal solution is always a corner point. Linderoth and Lodi (2011) explain that ILPs and MILPs are NP-hard problems, which makes them computationally intensive and time-consuming to solve. Therefore, dedicated solvers are regularly used that solve these problems based on, for example, branch-and-bound, cutting plane, and branch-and-cut algorithms, individually or in combination. Many good software packages exist for solving MILP models, such as CPLEX and Gurobi, which can both be used in combination with many different programming languages.

To incorporate stochasticity in LP (or ILP) models, techniques such as Monte Carlo Methods and Chance Constraint Programming can be used, as explained in Section 3.1.1 and Section 3.1.2, respectively.

3.1.1 Monte Carlo Methods

Earl and Deem (2008) describe Monte Carlo simulation as a type of discrete-event simulation where random configurations of a system are generated using stochastic models. During every simulation run, the random variables are allocated a value of their assigned probability distribution (Mahadevan, 1997). Monte Carlo Methods (MCM) have evolved from a 'last resort solution' to a leading methodology according to Kroese et al. (2014). The method is based on the law of large numbers and does many experiments that let random variables converge to their most often recurring values. MCM are relatively easy to understand but can also be used for complex problems. Moreover, the effectiveness of MCM is proven based on statistics and mathematics. Papadopoulos and Yeung (2001) add that the method can handle both small and large parameter uncertainties in the input quantities.

Typical uses of MCM include sampling, estimation, and optimisation. In sampling, the aim is to gather information about a random variable by doing many experiments. Estimation aims to estimate numerical quantities related to a simulation model. Lastly, optimisation strives to optimise complicated objective functions (Kroese et al., 2014).

Lerche and Mudford (2005) describe the long running time as one of the main disadvantages of using MCM. Determining the appropriate number of Monte Carlo simulation iterations to use is thus important and the subject of many articles in the literature, e.g., Driels and Shin (2004), Lerche and Mudford (2005), and Robey and Barcikowski (1992). A good balance between the accuracy of the average solution and computational time needs to be found. If we let the model run for an infinite number of iterations, the model converges to the population mean (Driels & Shin, 2004). Bukaçi et al. (2016) statistically derive the optimal number of iterations n to the formulation in equation 1. This derivation is based on a variable following a normal distribution. In this equation, z_c is the critical value of the standard normal distribution, S_x is the sample standard deviation of x, $\bar{x}$ is the mean of variable x, and E is the percentage error of the mean.

$$n = \frac{100 \cdot z_c \cdot S_x}{\bar{x} \cdot E} \tag{1}$$

Bukaçi et al. (2016) also propose another method for determining the number of iterations if you do not want to make assumptions about probability distributions. This method increases the number of iterations until the relative standard error of the mean is below one percent. This percentage (1%) can also be increased or decreased based on the length of the running time or the problem owner's wishes. IPCC (2006) also advises using this method to find the required number of iterations in formulating models for sustainability reporting.

MCM are often combined with ILP or MILP models, such as by Bhowmik and Parvez (2024), Koltsaklis and Nazos (2017), Mavrotas et al. (2010), Momen and Behbahaninia (2021), Momen et al. (2016), and Urbanucci and Testi (2018). The approach of the most relevant articles is discussed here.

Koltsaklis and Nazos (2017) include stochasticity to a regular MILP by using MCM. MCM capture the uncertainty of a set of key model parameters. In each Monte Carlo simulation run, random values are drawn from the selected probability distribution of all uncertain parameters. After the model formulation, the model is solved using the CPLEX solver. Although they apply their method to optimise the annual energy balance of a power system, the generic modelling approach seems adaptable to other situations. Bhowmik and Parvez (2024) combine a MILP with Monte Carlo simulation for supply chain network design. It deals with large investments that are difficult to reverse. They minimise costs and then verify the robustness of the model solution with respect to demand uncertainty by testing a range of demand values from a uniform distribution using Monte Carlo simulation. They also evaluate the quality of the optimisation model by comparing the baseline scenario and the optimised scenario. Momen and Behbahaninia (2021) validate the results of their numerical Monte Carlo simulation model by taking a small, simplified version of the system. Then, they compare the results of the Monte Carlo simulation to an analytical model solution based on the Markov state-space method. By increasing the number of iterations, the simulation results converge to a result only 2 percent off the exact calculation. Momen et al. (2016) validate the result of their method by comparing it to three other methods that are applied to the same problem, including a deterministic model variant. Urbanucci and Testi (2018) uses a similar approach by also comparing their model result to the result of a deterministic model.

The article of Lauinger et al. (2016) is the most similar to the case study of the reviewed MCM articles. Lauinger et al. (2016) create a linear program to determine the optimal investments and operating decisions for residential energy systems. The model was able to cut emissions by 45 to 90 percent and costs by 5 to 60 percent, depending on the model settings. The model can thus decrease costs and emissions. However, the investment decisions are seen as a first-stage decision variable, whereas we require yearly stages that allow investing each year. The model uses MCM by including scenarios for the stochastic weather variable, which is different from the case study. Moreover, the operational decisions made in the second stage are not relevant for our model. The MCM model by Lauinger et al. (2016) is thus not a suitable model for this research.

3.1.2 Chance Constrained Programming

Chance Constrained Programming (CCP) is a widely used method for modelling stochastic problems, first introduced by Charnes and Cooper (1959). CCP is also sometimes referred to as probabilistic constrained programming (Prekopa, 2015). CCP addresses stochastic uncertainty by defining a confidence level at which a stochastic constraint has to hold. The solution of a CCP model is thus a policy that generally holds with a certain confidence level (Charnes et al., 1971).

CCP problems are often intractable. The first reason for the intractability is that the feasible region of these problems is often not convex, which makes it difficult to optimise the objective function. Moreover, computing the probability that a given solution satisfies the chance constraint is difficult since it requires calculating a multivariate integral. A benefit of CCP is that some constraints do not have to be met in all situations. Covering all situations will substantially increase costs without adding much practical value compared to covering, for example, 98% of all situations (Ahmed & Shapiro, 2008).

In their article, Ahmed and Shapiro (2008) apply CCP to an NP-hard ILP problem and then approximate the problem by replacing the distribution of uncertain parameters with an empirical distribution. This method is also referred to as Sample Average Approximation (Pagnoncelli et al., 2009). This approximation method for CCP is commonly used in literature, such as by Lok-Visser et al. (2025), Luedtke and Ahmed (2008), and Zhou et al. (2021).

There are many different applications of CCP in the literature. Lv et al. (2018) use it to plan regional ecosystems under stochastic uncertainty. CCP allows them to examine the probability of violating constraints. Proietti et al. (2024) employ CCP to account for stochastic uncertainty in coefficients in the constraints and objective function of automated test assembly methods in educational measurement. Lok-Visser et al. (2025) apply CCP to set a performance level that can be deviated from, by meeting all patients' demand with the capacity of the scheduled nurses for a certain percentage of the time.

CCP has also been applied in the context of sustainable decision-making by Kim et al. (2021). They want to make cost-effective decisions with renewable energy. Also, a limited investment budget is used, so the situation is comparable to the case study. However, the CCP constraints are used to model the power output limits with uncertain renewable energy, instead of the emissions reduction target constraint that we would rather apply CCP for. The CCP model by

Kim et al. (2021) is thus not suitable for direct use in our case study.

3.2 Forecasting models

Forecasting is a widely used method for decision-making by quantifying future parameter uncertainty (Hyndman & Athanasopoulos, 2015). It uses current and historical data to make predictions. We will discuss a selection of commonly used forecasting methods based on the review by Petropoulos et al. (2022), which are time series, exponential smoothing, and regression.

Time series forecasting identifies patterns in historical data to make predictions. The resulting time series forecast includes a set of expected values and a prediction distribution. Another widely used method is exponential smoothing. Exponential smoothing bases its predictions on the weighted average of historical observations. The weight of each observation decreases as its distance from the present increases. The exponential smoothing model can be extended with a trend (Holt, 2004) or with a trend and seasonality (Winters, 1960). Regression models are based on the relationship between the dependent variable and one or more independent variables. The simplest version is a linear regression model. The parameters of the model are typically estimated by minimising the sum of squared errors. The model is usually evaluated based on cross-validation. The correlation between independent variables should be negligible to use a regression model (Petropoulos et al., 2022).

Ma et al. (2025) used forecasting in the context of sustainable decision-making. The model is used to decide whether to use, for example, electric vehicles and heat pumps based on the adoption probability. Even though the article states limited historical data is required, there is almost no historical data available in this study, so this may prevent the model from being used. Moreover, the context of aiming for adoption is not similar to the context of creating a sustainable investment plan based on minimum total costs. The forecasting model from the article by Ma et al. (2025) is thus not suitable to be applied to the problem in this research.

3.3 Multi-criteria decision analysis

Multi-criteria decision analysis (MCDA) is increasing in popularity in sustainability problems (Wang et al., 2009). MCDA is a collection of methods that are used for complex multi-criteria decision-making problems, especially if the criteria are conflicting. All MCDA methods include at least the same three steps. First, the decision problem is defined; then, the relevant criteria are defined; and lastly, the performance matrix is constructed (Thokala et al., 2016). The weighting methods in MCDA can be objective, subjective, or a combination of the two. The criteria can be both qualitative and quantitative (Baltussen et al., 2019). Saaty (1977) developed the Analytical Hierarchy Process, which uses a matrix of pairwise comparisons to find the relative importance of each criterion. The Analytical Hierarchy Process is a commonly used subjective weighting method in MCDA (Saaty & Vargas, 2012).

MCDA has previously been applied in the context of sustainable decision-making by Xue et al. (2023). They aim to decide between alternative energy sources based on multiple criteria. The considered criteria are cost, environmental impact, energy output, reliability, and scalability. The context is thus policy making on a regional or national level, instead of decisions regarding one company. Moreover, despite the importance of other criteria, cost is ultimately the deciding factor. The MCDA model by Xue et al. (2023) is thus not an appropriate method in this study.

3.4 Model selection

We investigated various solution models to find a suitable strategic decision-making model to minimise a construction company's total costs while attaining its sustainable emission reduction targets. We only consider the MILP model from the linear optimisation models since we require binary and continuous decision variables. The MILP model can be combined with either MCM to include stochasticity of parameters or with CCP to include stochasticity on the reduction target constraint. The other considered models are forecasting or MCDA. Table 2 compares the reviewed models. For each characteristic in the table, a check (✓) indicates that the model meets the criterion; otherwise, it does not. The last row shows the general characteristics the model in this research should have and could have. The checks are in brackets for the preferred characteristics since a model can still be selected if these are missing, as long as the required characteristics are met.

Model characteristics	***Required***					***Preferred***	
	Strategic decision-making model	**Include stochasticity**	**Cost minimisation**	**Possible with scarce historical data**	**Compare investment combinations**	**Optimal solution**	**Short computational time**
MILP	✓		✓	✓	✓		
MILP + MCM	✓	✓	✓	✓	✓		
MILP + CCP	✓	✓	✓	✓	✓		
Forecasting	✓	✓	✓		✓	✓	✓
MCDA	✓	✓		✓	✓		✓
This research	✓	✓	✓	✓	✓	(✓)	(✓)

Table 2: Comparison of solution models based on essential and preferred characteristics. The bottom row shows the characteristics that should be present in the model in this research.

Table 2 shows that the only models that have all the required characteristics are the MILP combined with either MCM or CCP. The other models are all missing one essential characteristic. The MILP model, on its own, is unable to incorporate stochasticity, which is why it must be paired with MCM or CCP. Forecasting requires a large amount of accurate historical data. Such data is unavailable for investments that have not been previously made. MCDA weighs multiple objectives. Given that the primary objective in this case is cost minimisation, incorporating additional objectives is unnecessary. This leaves two modelling options: combining the MILP with either MCM or CCP.

MCM and CCP do not meet any preferred characteristics, so we cannot base our decision on that. Both models are typically associated with longer running times. However, due to the characteristics of this specific problem (including a limited set of investments and an investment horizon of, at most, a few dozen years with annual decision intervals), the model size remains relatively small. Moreover, we need a strategic decision-making model so it will not be run often. The computational time is thus expected to be manageable and should not present a significant obstacle. Moreover, both model solutions are approximations of the optimal solution, not necessarily the optimal solution. However, if the model is formulated well, the approximated solution can be close to the optimal solution.

Instead of choosing one of the two, we can also consider combining both MCM and CCP with an MILP. This lets us incorporate stochasticity in the parameters and allows the target reduction constraint not to be met in all cases, leading to a more cost-effective solution. We first look into the literature for studies that combine CCP and MCM to see whether this has been used before and in what context.

Lv et al. (2018) combine a linear optimisation model with MCM to produce distribution functions of random parameters and CCP to examine the probability of violating system constraints.

Even though this model was developed to plan a regional ecosystem in China, the model characteristics show similarities to our situation. Petsagkourakis and Galvanin (2020) employ a combination of MCM and CCP for kinematic modelling, a type of mathematical modelling concerning chemical processes. A Gaussian process and MCM are applied to the stochastic process parameter. Since the process does not always allow all constraints to be met because of the stochasticity, one of the constraints is formulated as a chance constraint with a confidence level of 99 percent. Du Toit and Burdick (2011) research obstacle avoidance and collision checking in robotics. They include state uncertainties for the robot and the obstacles, and then they apply chance constraints for the probability of collision. This is then evaluated in a Monte Carlo simulation, thus combining CCP and MCM.

To the best of our knowledge, the combination of MCM and CCP has not been used with an MILP before in the literature in the context of sustainable investment planning in the construction sector. There is thus no existing model in the literature that applies to the problem in this research. This novel concept in the literature is the scientific contribution of the model we will formulate in this research.

Combining MCM and CCP with an MILP model will increase the complexity of formulating the model, compared to using one of the techniques. However, both techniques require using scenarios, making it easier to combine MCM and CCP. MCM avoid just taking an average parameter value by drawing random numbers from probability distributions. Hence, extremely high or low values could also be drawn from the tails of the distributions. Letting the model satisfy the target in those extreme scenarios is costly and often not necessary for a good average performance. CCP is therefore a valuable addition to MILP with MCM. To conclude, MCM are used to make the model more realistic by using stochastic parameters instead of deterministic ones, and CCP trades off constraint satisfaction probability against costs. The models can thus complement each other.

Another limitation of using the model is that MILPs are NP-hard and can quickly become computationally extensive. Especially because generally a large number of scenarios is required for statistical accuracy, increasing the size of the solution space. Nevertheless, we create a strategic model that is used at most yearly to create sustainable investment plans. Therefore, longer runtimes are acceptable, as it does not prevent the model's practical applicability.

Moreover, the stochastic MILP model requires estimating the input distributions of the stochastic parameters. Making inaccurate assumptions decreases the quality of the model results (Chick, 2001; Cooke et al., 1993). Estimating the input distributions can be challenging, for example, due to data scarcity (Chang & Ko, 2017). If data scarcity makes it impossible to use data to select input distributions, using expert opinion can be a good solution (Leal et al., 2007).

To conclude, a MILP model combined with MCM and CCP is thus the most suitable model for the problem context in this research of the models that were compared in this chapter.

3.5 Conclusion

In this chapter, we conducted a literature review using exploratory research and backwards snowballing to find a suitable investment-decision model for a construction company aiming to achieve its CO_2 emission reduction target. We stated several required and preferred characteristics for the model. This resulted in the selection of an MILP model combined with MCM to include stochastic variables and CCP to include a probabilistic constraint for the reduction target.

The scientific contribution of this research is to combine MCM and CCP with an MILP model in the context of sustainable investment planning in the construction sector. To the best of our knowledge, this has not been done in the literature before. Applying this modelling approach to sustainable investment decision-making is thus a valuable contribution to science because of the relevance of the problem in this research to all Dutch construction companies.

By combining MCM and CCP in one investment-decision model, the two techniques can complement each other. Both techniques require using scenarios, which makes them relatively easy to combine. MCM create a realistic model by drawing random values from stochastic parameters' probability distributions, instead of using average values. This can also lead to extremely high or low values being randomly selected from the tails of the distributions. Because CCP allows the reduction target to be unmet in some scenarios, the extreme scenarios do not need to be covered in the solution. The total costs of the optimal solution can thus be much cheaper by not satisfying one or more constraints in all scenarios, which is why CCP can be a valuable addition to MCM.

4 Mathematical model

This chapter answers the research question:

How is the generic investment decision-making model formulated to find the set of investments that reaches the CO_2 emission target while minimising costs?

Section 4.1 describes the formulation of the generic mathematical model. Section 4.2 explains how SAA is used to solve the model with a chance constraint. Section 4.3 explains how a penalty can be added to find the closest attainable target in case the model is infeasible.

4.1 Conceptual model

This section formulates the mathematical investment-decision model. This formulation applies not only to Hegeman but to any similar construction company aiming to find the optimal combination of sustainable investments to achieve its emission reduction targets. If another construction company wants to apply the model, it needs to carefully examine whether the model formulation is suitable for their situation, especially regarding the list of assumptions. Especially, the indivisibility of the investments, fixed investment horizon, and additive emission reduction effects. The model has binary and continuous decision variables, only linear constraints, and a linear objective function. It is thus a Mixed Integer Linear Programming (MILP) model. Furthermore, there are stochastic parameters, so it is a stochastic model. The model also combines CCP and MCM, as explained in Chapter 3. In each Monte Carlo scenario, a different value is drawn for each stochastic parameter. Within a scenario, it is thus a deterministic parameter. The probabilistic emission target constraint makes the model a CCP model. Solving models with chance constraints is difficult, even for relatively simple linear problems. The difficulty is due to the multidimensional integration required to solve the problem exactly. CCP models are therefore often approximated using SAA (Pagnoncelli et al., 2009). Section 4.2 reformulates the chance constraint using SAA. In conclusion, we formulate a stochastic MILP decision-making model using CCP and MCM.

The model requires the company to define a list of possible sustainable investments, as well as their reduction impact, the department it impacts, and their investment and yearly costs. It might be the case that the company has already committed to several investments; in that case, these can be included in the model as fixed investments. Moreover, the company needs to enter its emission reduction target in the model. The output of the model is the optimal cost-effective set of sustainable investments that the company requires to achieve its emissions reduction target. However, the model could also have too restricted input data, in which case, there are no feasible solutions for the model. Then either the target is too ambitious, or not enough investment options are included to reduce to reach the desired target level. Section 4.3 explains how a penalty can be used in the objective function to find the closest attainable target in case the model is infeasible.

McMillan (1992) explains the difficulty of estimating costs in the construction industry. This is partly due to the uncertainty related to new technology. For long-term planning and choosing amongst alternatives, it is important to do good cost estimation (Mislick & Nussbaum, 2015). We thus approach the investment costs as a stochastic parameter. Furthermore, Vörösmarty et al. (2018) state that the impact of sustainable investments on a company's emissions is difficult to calculate because of the lack of standardised information available. While companies do face requirements on their internal processes, there is limited guidance on the marketing of their products. This lack of standardisation also leads to greenwashing. We thus also consider the emissions reduction impact of investments as a stochastic parameter.

The computational complexity of the model is primarily determined by the size of the solution space, which is determined by the number of decision variables and constraints. The number of decision variables is based on the number of investments considered (I), the length of the investment horizon (T), the number of departments (D), and the number of Monte Carlo scenarios (S). While the first three can be assumed to be relatively small, the number of scenarios is not, since it is based on when the relative standard error converges below one percent. This can significantly increase the size of the solution space. The model contains $I \cdot T \cdot S$ binary decision variables for the investment decisions ($x_{i,t,s}$) and investment statuses ($y_{i,t,s}$). Additionally, it contains $D \cdot T \cdot S$ continuous variables for the emissions per department ($c_{d,t,s}$). The model is an MILP, so it is an NP-hard problem as explained in Section 3.1. This makes the model computationally complex and time-consuming to solve, especially for large model instances (Linderoth & Lodi, 2011). In practice, the number of scenarios can be chosen to balance tractability and statistical accuracy. If there is no suitable value for the number of scenarios that balances the two, then a heuristic may be a good method of finding approximate solutions quickly. Heuristics could be explored in future research to improve scalability for larger problem instances.

To define the model, we will list the assumptions and then define the sets, parameters, decision variables, objective function, and constraints.

Assumptions

- The sustainable investments are made at the start of each year, so the impact is already visible in the year of investing. Simplifying a model by only allowing to invest at the start of each year is a common approach in modelling literature, e.g., in Kuhn et al. (2023) and de la Torre et al. (2016).
- The only changes in the company's CO_2 emissions over the years are due to the impact of the sustainable investments.
- The investments are indivisible and cannot be spread over multiple years.
- If multiple investments reduce the emissions in the same department, we assume the combined impact is the linear sum of the individual impacts, so there are no compound effects.
- The investments that are used as model inputs are all investments that the company would choose if the model results show that it is optimal.
- The investments not only require initial investment costs but can also result in increased or decreased yearly costs. We assume these yearly costs or gains (k_i) are deterministic.
- Once the model decides it is optimal to do a certain investment, it cannot be reversed in the consecutive years.
- The discount factor (δ) is the same for each investment and each year in the modelling time horizon. This approach is regularly used in similar models in the literature, such as in Hung et al. (2014), Craven and Islam (2009), Medici and Lorenzini (2014).
- The lifetime of each investment is assumed to be longer than the modelling period. So, it is not taken into account that an investment may have to be made again after its lifetime.
- The initial investment price is the same every year, only the discount factor is taken into account. Other factors, such as technological developments that may decrease the price, are not considered.

Sets

- I: possible sustainable investments, $i \in \{0, \ldots, I\}$.
- T: periods in years from now until the deadline of the reduction target, $t \in \{0, \ldots, T\}$.
- D: departments in the company's supply chain, $d \in \{0, \ldots, D\}$.
- S: Monte Carlo scenarios, $s \in \{0, \ldots, S\}$. In each scenario, a random value is drawn for the stochastic parameters. The scenarios are also used for the SAA.

Deterministic parameters

- γ: emission reduction target set by the company for year $t = T$ as compared to the initial emissions in year $t = 0$, expressed as a fraction between 0 and 1.
- δ: the yearly discount factor, expressed as a fraction between 0 and 1.
- α: confidence level representing the acceptable probability of violating the target chance constraint, expressed as a fraction between 0 and 1.
- k_i: the yearly investment costs after investment i is made, this can be positive (costs) or negative (gains).
- B: maximum investment budget per year, expressed in euros.
- m_i: this is 1 if the company has already decided to make investment i, 0 otherwise. This is used for the fixed investments the company has already committed to.
- f_i: first possible investment year after $t = 0$. Can be used if an investment is only possible after a certain year, e.g., due to technological constraints.
- l_i: last possible investment year after $t = 0$. Can be used if an investment is only possible before a certain year, e.g., due to technological constraints.
- h_d: CO_2 emissions for department d in year $t = 0$, expressed in tonnes of CO_2.

Stochastic parameters

- $e_{i,d,s}$: emission reduction impact in department d in scenario s because of investment i, expressed as a fraction between 0 and 1.
- $r_{i,s}$: initial investment costs of doing investment i in scenario s.

Decision variables

- $x_{i,t,s}$: this is 1 if the model states investment i should be done in year t in scenario s, 0 otherwise.
- $y_{i,t,s}$: this is 1 if the model states investment i has been done in year t in scenario s or before, 0 otherwise.
- $c_{d,t,s}$: the company's CO_2 emissions in department d in year t in scenario s.

Objective function

The objective function (in equation 1) minimises the total investment costs and the yearly costs or gains caused by the investments. The discount factor is used to adjust future costs to their present value. The average objective function over all Monte Carlo scenarios is minimised.

$$\text{Minimise} \quad \frac{1}{S}\sum_{s=0}^{S}\sum_{t=0}^{T}\sum_{i=0}^{I}\left(\frac{x_{i,t,s}\cdot r_{i,s}+k_i\cdot y_{i,t,s}}{(1+\delta)^t}\right) \tag{1}$$

Constraints

$$P\left[\sum_{d=0}^{D} c_{d,T,s} \leq \gamma \cdot \sum_{d=0}^{D} c_{d,0,s}\right] \geq 1-\alpha \qquad \forall s \in S \tag{2}$$

$$\sum_{i=0}^{I} x_{i,t,s}\cdot r_{i,s} + \sum_{i=0}^{I} y_{i,t,s}\cdot k_i \leq B \qquad \forall t \in T, \forall s \in S \tag{3}$$

$$\sum_{t=0}^{T} x_{i,t,s} \geq m_i \qquad \forall i \in I, \forall s \in S \tag{4}$$

$$c_{d,t,s} = c_{d,t-1,s} - \sum_{i\in I}(x_{i,t,s}\cdot e_{i,s,d}\cdot h_d) \qquad \forall d \in D,\ \forall t \in T\setminus\{0\},\ \forall s \in S \tag{5}$$

$$\sum_{i=0}^{I} e_{i,d,s}\cdot x_{i,t,s} \leq 1 \qquad \forall d \in D, \forall t \in T, \forall s \in S \tag{6}$$

$$y_{i,\tau,s} = \sum_{t=0}^{\tau} x_{i,t,s} \qquad \forall \tau \in T, \forall s \in S, \forall i \in I \tag{7}$$

$$x_{i,t,s} = 0 \qquad \forall (t < f_i \wedge t > l_i \wedge t \in T), \forall i \in I, \forall s \in S \tag{8}$$

$$c_{d,0,s} = h_d \qquad \forall d \in D, \forall s \in S \tag{9}$$

$$x_{i,t,s} \in \{0,1\} \qquad \forall i \in I, \forall t \in T, \forall s \in S \tag{10}$$

$$y_{i,t,s} \in \{0,1\} \qquad \forall i \in I, \forall t \in T, \forall s \in S \tag{11}$$

$$c_{d,t,s} \geq 0 \qquad \forall d \in D, \forall t \in T, \forall s \in S \tag{12}$$

All constraints are briefly explained. Equation 2 states that the emission reduction target should be achieved at a confidence level α. The emission reduction target is achieved if the emissions have decreased below the emission target before the target year. Equation 3 states that the yearly investment budget cannot be exceeded. Equation 4 states that the company's fixed investments should be selected in the model. Equation 5 calculates the emissions per year and per department based on the chosen investments in that year and the emissions in the year before. Equation 6 states that the sum of emission reduction fractions should be below or equal to one, since the emissions cannot be reduced further if they are zero. Equation 7 calculates the $y_{i,t,s}$variable that states whether an investment was chosen in any previous year or the current year by summing $x_{i,t,s}$ over all years, including the current year. Equation 8 states that the investment needs to happen within the allowed time range. Equation 9 assigns the initial emission value based on the model input. Equations 10, 11, and 12 are the sign constraints that set the decision variables as binary or continuous variables, respectively.

4.2 Sample Average Approximation

In this research, we apply SAA to solve our model with the chance constraint on the emission target. To do so, we have to replace the chance constraint with the SAA constraint in a deterministic form. The actual distribution in the constraint is replaced with an empirical distribution corresponding to a random sample of size N. Then, the chance constraint can be replaced with the SAA constraint in a deterministic form (Pagnoncelli et al., 2009). This requires replacing the original chance constraint in equation 2 with the SAA constraint in equation 13. We use the set of Monte Carlo scenarios S for the random sample.

$$\frac{1}{S}\sum_{s=1}^{S}\mathbf{1}\left\{\sum_{d=0}^{D} c_{d,T,s} \leq \gamma \sum_{d=0}^{D} c_{d,0,s}\right\} \geq 1-\alpha \tag{13}$$

4.3 Soft constraints to avoid infeasibility

Currently, whenever the model is infeasible, there are no solutions, and the company needs to enter different input values in order to try to create a feasible model. However, this is not practical for a company. We thus extend the model with a penalty variable, to obtain the distance between the infeasible model and the closest feasible solution. This approach is commonly used in the literature (Baeck & Khuri, 1994; Huang et al., 1994; Olsen, 1994). An additional target penalty variable is added to the model, as well as a penalty cost parameter. The cost parameter should be set to a very high number to avoid penalties being added for feasible models.

- $penalty_s$: the penalised deviation from the reduction target in scenario s, which is a continuous variable between 0 and 1.
- pc: deterministic penalty cost parameter.

Then, the target constraint in equation 13 is adjusted to equation 14 to include the penalty variable.

$$\frac{1}{S}\sum_{s=1}^{S}\mathbf{1}\left\{\sum_{d=0}^{D} c_{d,T,s} \leq penalty_s + \gamma \sum_{d=0}^{D} c_{d,0,s}\right\} \geq 1-\alpha \tag{14}$$

Lastly, the objective function from Equation 1 is adjusted to Equation 15 to include the penalty cost to avoid penalties insofar possible.

$$\text{Minimise} \quad \frac{1}{S}\sum_{s=0}^{S}\sum_{t=0}^{T}\sum_{i=0}^{I}\left(\frac{x_{i,t,s}\cdot r_{i,s} + k_i \cdot y_{i,t,s}}{(1+\delta)^t} + pc * penalty_s\right) \tag{15}$$

4.4 Conclusion

In conclusion, this chapter formulated a mathematical decision-making model to find the optimal set of sustainable investments that enables a construction company to meet its CO_2 emission reduction target while minimising costs. The model is an MILP model with deterministic and stochastic parameters. In each Monte Carlo scenario, different values are drawn for the stochastic parameters from their probability distributions. Moreover, the reduction target constraint is probabilistic and thus requires scenarios. The model is thus a stochastic MILP that uses CCP and MCM. Moreover, the model uses SAA to approximate the chance constraint. Lastly, the model can be extended with a penalty variable to calculate the deviation from the reduction target, in case the model is infeasible.

5 Applied model

This section answers the subquestion:

"How to apply the generic investment-decision model to the case study at Hegeman?"

Chapter 4 formulated the generic investment decision model that can be used for any similar construction company that aims to cost-effectively achieve its emission reduction target. In this chapter, we apply the model to the case study at Hegeman. We do this by collecting the input data and programming the model in Python. First, we will calculate and determine the input data for the case at Hegeman in Section 5.1. The model is programmed in Python in Section 5.2.

5.1 Parameter values

This section defines the parameter values for the model. It provides the input data for the deterministic parameters and probability distributions for the stochastic parameters. Also, the sustainable investments are listed, and the required number of Monte Carlo iterations is determined.

5.1.1 Deterministic parameters

Several deterministic parameters are used as model input data. Hegeman aims to reduce its CO_2 emissions with 50% by 2030 compared to their carbon footprint in 2024. The emission reduction target (γ) is thus 0.5. The modelling period is eight years. We assume that in 2024 and 2031, no investments can be made. However, 2031 is included in the model because the emission target must be achieved by the end of 2030, so the start of 2031. 2024 is used as a start year with the initial emission values. The annual discount factor (δ) used in the model is 0.0225, since Rijkswaterstaat (2021) states this value applies to any Dutch company performing calculations after 2021. The confidence level (α) for the SAA constraint is chosen by Hegeman and set at 0.05. The value 0.05 is also commonly used in the literature for chance constraints (Miller & Ulrich, 2019). Hegeman does not want to set a maximum yearly budget to spend on sustainable investments, so we set this at infinity. The penalty costs are set extremely high at $1 \cdot 10^{40}$ to only let the model use the penalty variable when the model would otherwise be infeasible.

The departments at Hegeman are transport, machines, electricity, and gas. Transport, machines, and gas contribute to scope 1 emissions, and electricity to scope 2 emissions. Transport is in scope 1 because it includes transporting employees and supplies from Hegeman to the construction sites. External deliveries to the construction sites and offices are in scope 3, and thus not included here. The initial level of CO_2 emissions in each department is given in Table 3.

Scope	**Department**	**CO_2 emissions (tonnes)**	**Percentage of total**
1	Transport	564,322	64.1%
1	Machines	65,033	7.4%
2	Electricity	164,167	18.6%
1	Gas	86,875	9.9%
1+2	*Total emissions*	*880,397*	100.0%

Table 3: Initial level of CO_2 emissions per department for Hegeman in 2024.

5.1.2 Sustainable investments

In this research, we refer to investments as Hegeman's possible actions to make its processes more sustainable to achieve the emission reduction targets. Each investment is characterized by its initial investment cost, annual expenses, the scope of its impact, the department it affects, and the percentage by which it reduces emissions within that department. Table 4 describes the sustainable investments Hegeman considers to achieve their target. The column of 'investment costs' refers to the additional costs of making the investments. For example, if the electric lease cars are not bought, Hegeman would buy petrol lease cars. The investment cost is thus the difference between electric and petrol lease cars. If the 'yearly costs' are negative, it means that there are yearly gains because of the investment.

Hegeman has already committed to some of the investments in Table 4, these fixed investments are always selected in the model solution and indicated with an asterisk (*) in the first column. This is the case for investments A and B. The other investments are all optional. Sustainable investments can either reduce energy usage or use more sustainable energy sources (Omer, 2008). Investments B, C, D, and F all reduce energy usage, while investments A and E use a more sustainable energy source.

ID	Investment	Invest. cost (€)	Yearly cost (€)	Impacted department	Impacted scope	Reduced CO_2 (%)
A*	Replace petrol cars with electric cars	€150,000	€-111,951	Transport	1	23.1%
B*	Make the Jansman office more sustainable	€0	€-178	Electricity	2	3.0%
		€0	€-507	Gas	1	3.0%
C	Use HVO diesel for cranes	€0	€3,174	Machines	1	62.2%
D	Use HVO diesel for vans	€0	€250,155	Transport	1	39.1%
E	Replace diesel vans with electric	€1,350,000	€-110,833	Transport	1	47.4%
F	Monthly check tire pressure for all vehicles	€0	€-866	Transport	1	1.5%

Table 4: Possible sustainable investments for Hegeman that are used as model input data. The fixed investments are marked with an asterisk (*) in the first column. The impacted scope is listed according to the IPCC (2006).

Investment A is replacing all petrol-powered lease cars of employees with electric cars. Hegeman has already replaced about 20% of all cars and plans to replace the remaining part equally over the next four years (2025-2028). Even though the investment is partly implemented already, its quantitative impact has not been analysed by Hegeman yet. Investment B is increasing the sustainability at the Jansman office in Luttenberg. The office undergoes a rebuild in 2025 or 2026. The reason for the rebuild is not sustainability-related, but it does have a sustainable impact (e.g., renewing the insulation). We thus set the initial investment costs at zero, and the yearly costs as the reduced costs because of less electricity and gas use. Investment C is using hydrotreated vegetable oil (HVO) diesel instead of regular diesel for operating cranes. HVO is a more sustainable type of diesel that can reduce CO_2 emissions up to 90% (Hor et al., 2023). Investment D is using the HVO diesel for vans. There are no initial investment costs for these investments. Investment E is replacing the diesel vans with electric vans. Hegeman estimates that in four years (2029), the technology will be advanced enough that the electric vans will have a sufficient range to use them on a daily basis. Investment F is doing monthly tire pressure checks for all vehicles, which also has no initial investment costs.

5.1.3 Stochastic parameters

Since our model has stochastic parameters, the CO_2 reduction impact and initial investment cost, we have to estimate the type of distribution they follow. If inaccurate assumptions are made, the model quality will be low (Cooke et al., 1993). Relying on averages instead of probability distributions for stochastic parameters often gives a too positive outlook on reality (Law, 2016). A common problem in MCM is data scarcity (Chang & Ko, 2017), which is also the case in this study because Hegeman has not implemented the investments in the past, so we cannot use historical data and goodness-of-fit tests. We thus have to rely on Hegeman's expert opinion.

The CO_2 emission reduction impact ($e_{i,d,s}$) is a continuous parameter with values between 0 and 1 because it represents a fraction. We can calculate an estimate of the expected mean value, which is validated by Hegeman. These mean values are given in the 'reduced CO_2' column in Table 4. There is no reason to assume a skewed distribution according to Aannemingsmaatschappij Hegeman B.V. (2025). Normal distributions are commonly used for modelling symmetric stochastic parameters (Chang & Ko, 2017). A truncated normal distribution is thus a good option because of its bounding possibility and symmetric distribution (Burkardt, 2014). The mean of the truncated normal distribution for each investment is in the last column in Table 4. The standard deviation is based on evaluation by a financial and sustainability expert at Hegeman with knowledge about probability theory (Aannemingsmaatschappij Hegeman B.V., 2025). Most of the input data to get the reduction impact is reliable data, such as Hegeman's CO_2 footprint validated by accountants and the CO_2 emission factors set and researched by the SKAO (2025). However, for the reduction impact, there were often no scientific sources available, so some of the sources used might be biased or dated. Overall, the expert thus estimated a few percent deviation being possible, and thus a standard deviation of 0.03 is taken for all investments, except investment F, which is the tire pressure check. This is not based on data but an estimate by Hegeman, so the expert sees this as a more uncertain parameter, with a standard deviation of 0.05. For each investment option in Table 4, a figure similar to Figure 8 was presented to the expert for decision-making guidance.

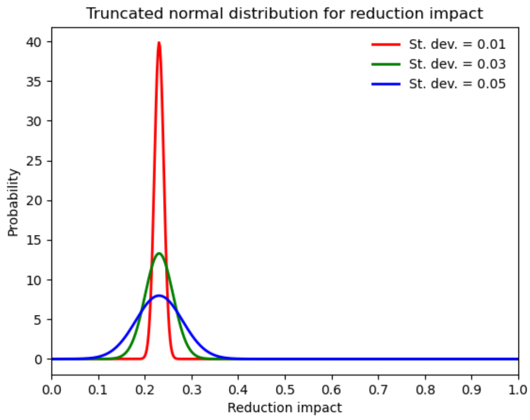
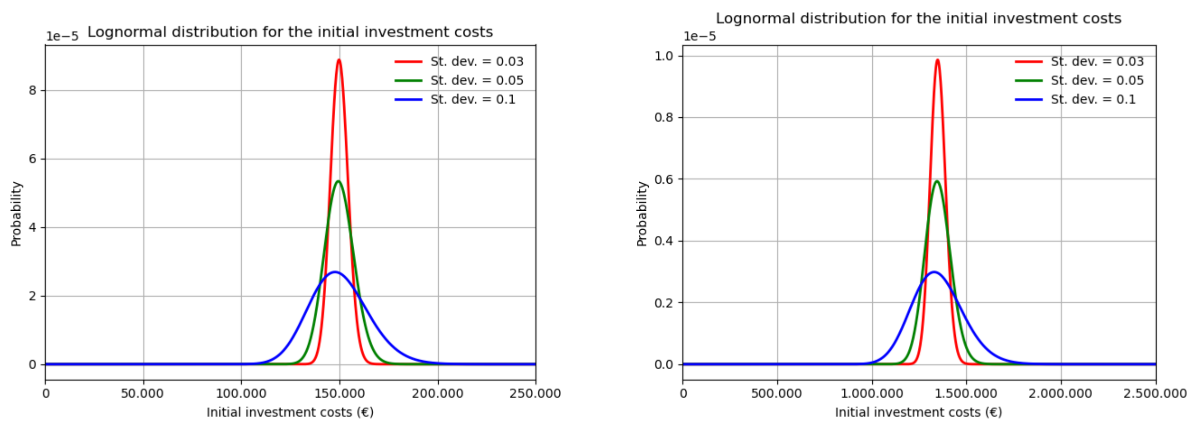


Figure 8: Standard deviation options for the reduction impact of investment A: replacing petrol cars with electric cars. A truncated normal distribution is visualised. The average reduction is 0.2309, and the standard deviation options given in the figure are 0.01 (red), 0.03 (green), and 0.05 (blue).

The initial investment cost ($r_{i,s}$) is a continuous, non-negative parameter. Applying a lognormal distribution may be suitable since this distribution is regularly used for modelling costs due to its positive skewness and restriction to non-negative values, which are also cost characteristics (Touran & Wiser, 1992). Wall (1997) confirms that this is also the case for costs in construction projects. A downside of using the lognormal distribution is the fact that it is less suitable for using expert opinion since it is generally advised only to use expert opinion on first-moment parameters and not for second-moment parameters, which is needed if the aim is to fit a lognormal distribution (Kadane & Wolfson, 1998). A commonly used distribution for modelling parameters with scarce data availability is the triangular distribution (Choudhry et al., 2014; Law, 2016). This distribution is easy to apply when relying mostly on expert opinion since it only requires the expert to set a mean, maximum, and minimum value as distribution parameters. The downside of this simplicity is that it tends to overweight extreme outcomes (Chau, 1995). For this stochastic parameter, we also use expert opinion to find the parameters per investment. Since there are only two investments in Table 4 with non-zero investment costs, we only need to find the parameters for these two investments (A and E). Since a lognormal distribution is usually more realistic than a triangular distribution and Hegeman's expert is familiar with probability theory, we opt for a lognormal distribution instead of a triangular distribution. We showed Figure 9 to the expert for a visualisation. For the costs of the lease cars, the main reason due to the varying car costs is that not everyone gets the same type of car. In some years, only a few cheaper cars get assigned. In another year, the CEO may get a very expensive car. This leads to a variance in the investment costs. The expert thus estimates that a range of at most €10,000 is a reasonable distribution range, which we translate to a standard deviation of 0.03. For the electric vans, there is more uncertainty, since Hegeman will wait for a few years until technology has advanced enough such that the vans' range is increased and thus more practical. The prices may change as well and are therefore more uncertain for this investment than for investment A. We translate this as a standard deviation of 0.05 for investment E. The mean and standard deviation cannot be immediately plugged into the distribution, but are first converted to the lognormal distribution's location (μ) and scale (σ) parameters. Since the standard deviations are relatively small, the distribution is less skewed, which makes the distribution more similar to a normal distribution (see Figure 9). For all other investments, the initial investment costs are always zero, so the standard deviation is also zero.



(a) Investment A

(b) Investment E

Figure 9: Standard deviation options for the initial investment costs of investments A and E. The average initial costs are €150,000 and €1,350,000, respectively. The standard deviation options given in the figure are 0.01, 0.03, and 0.05. Both figures display a lognormal distribution.

Table 5 summarizes the chosen standard deviation values for the impact and initial investment costs per investment based on expert opinion in this section.

Investment	**St. dev. impact**	**St. dev. costs**
A	0.03	0.03
B	0.03	0
C	0.03	0
D	0.03	0
E	0.03	0.05
F	0.05	0

Table 5: Standard deviation of the reduction impact and initial investment costs per investment.

5.1.4 Monte Carlo iterations

We need to tune the required number of Monte Carlo iterations by finding a good balance between the solution accuracy and the computational time. We find the number of required Monte Carlo iterations by using the second method proposed by Bukaçi et al. (2016), as explained in Section 3.1.1 of this thesis. This method fits because the stochastic parameters in our model do not follow regular normal distributions. So, we increase the number of iterations until the relative standard error of the mean is lower than one percent. Figure 10 shows how the average objective value converges as more Monte Carlo iterations are used. The relative standard error reaches a value of 0.9910% if 5,700 iterations are used, which is below 1%. We thus advise using 5,700 iterations. Running the model then requires less than 2 minutes of running time, which is doable for a strategic model that only needs to be used yearly.

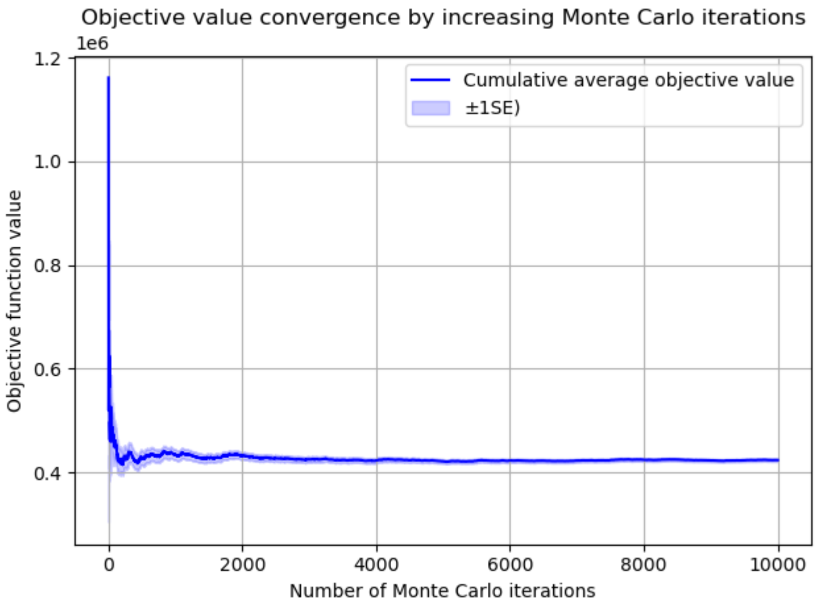


Figure 10: Convergence of the average objective value.

5.2 Programming the model

We programmed the MILP in Python and used the Gurobi solver to solve the program. Algorithm 1 illustrates the working of the program using pseudocode. The complete code can be read in Appendix A.1. A seed value is used to ensure we get the same results each model run.

Algorithm 1 Stochastic Investment Decision Model

Create optimisation model
Objective function
    Minimise total discounted costs
Constraints
    Emission reduction target SAA chance constraint
    Budget constraint
    Fixed investments constraint
    Calculate emissions reduction constraint
    Irreversible investments constraint
    Allowed investment timeline constraint
    Initial emissions constraint
Solve model

The target reduction constraint using SAA is explained in equation 13. This constraint has an indicator function, which is not supported in Gurobi. Therefore, we use an auxiliary variable z_s that states whether the reduction target is achieved for scenario s or not. This requires one additional constraint, but it does not change the model itself.

We had to add a situation-specific constraint compared to the model in Section 4.1 that states that investments B and D are mutually exclusive. We thus add the constraint in equation 16. Either HVO diesel can be used for the vans (investment B), or the vans can be replaced with electric vans (investment D), since electric vans cannot be driven using diesel.

$$x_{B,t,s} + x_{D,t,s} \leq 1 \qquad \forall t \in T, \forall s \in S \tag{16}$$

5.3 Conclusion

In this chapter, we applied the generic model from Chapter 4 to the case study at Hegeman. First, we defined the input parameters by determining probability distributions for the stochastic parameters, calculating the number of Monte Carlo iterations, and providing the sustainable investments to consider in the model. The probability distributions for the stochastic parameters were found using literature and expert opinion. This resulted in using a lognormal distribution for the investment costs and a truncated normal distribution for the reduction impact. The standard deviations per distribution were set using Hegeman's expert opinion regarding the uncertainty in the estimates of the mean. The Monte Carlo iterations were increased until the mean objective function value converged, and the standard error was below 1%. This required using 5,700 Monte Carlo iterations with a running time below 2 minutes. Then, we programmed the mathematical model in Python using the Gurobi solver. When applying the generic model to Hegeman, two additional constraints and one additional variable were needed for modelling the indicator function and two mutually exclusive investments.

6 Results and discussion

This chapter analyses the results and performance of the model and thus answers the following research question:

"How does the investment-decision model perform for the case at Hegeman?"

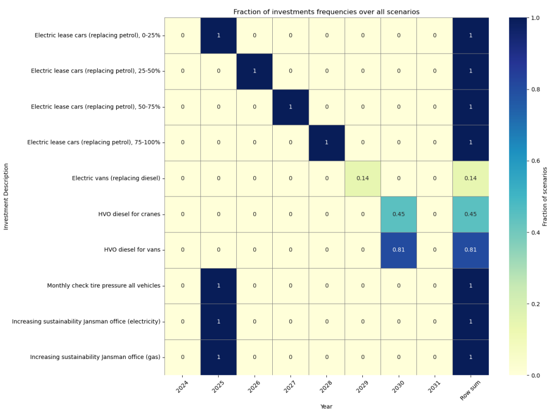
First, Section 6.1 presents the model's results and compares them to the results of the deterministic model variant. Then we measure the performance of the stochastic model against more simplistic approaches that a company would usually choose over a complex stochastic model in Section 6.2. Section 6.2.1 compares the performance to a stochastic model using either MCM or CCP. We compared the performance of our stochastic model to an approach based on the Marginal Abatement Cost Curve in Section 6.2.2 and to a simple heuristic in Section 6.2.3. Section 6.3 performs a full factorial sensitivity analysis and a seed value experiment. Lastly, Section 6.4 presents the scenario analysis consisting of a baseline scenario, best case scenario, and worst case scenario.

6.1 Model results

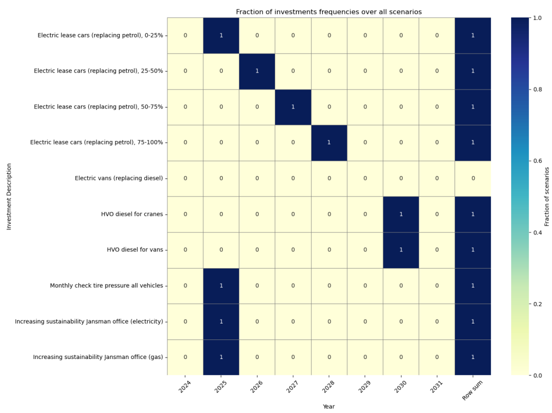
We programmed the generic mathematical model formulated in Chapter 4 in Python and used Hegeman's data to test the model. If we use the modelling settings explained in Chapter 5, we find that the CO_2 reduction target of 50% set by Hegeman is too ambitious and that there are thus no feasible solutions. That leaves Hegeman with two options: either expanding the list of sustainable investments or reducing the target. Currently, the model is not even feasible if all possible investments are chosen, so by expanding the list of investments, the model is given more options. If the target is reduced to 45%, the model can find an optimal solution. Since this is close to the original target, we advise Hegeman to reduce its target to 45%. This leads to a total cost of investment from 2025 to 2031 of €55,534, which is €0.14 per tonne of CO_2 reduced. The emissions reduced from 880,397 tonnes of CO_2 to 473,551 tonnes, which is an average reduction over all scenarios of 46.2%. This is slightly higher than the target of 45%. This is because the investments are not divisible, and can only be chosen completely or not at all.

In order to analyse the results, we compare the results from our stochastic model to its deterministic variant. This is a common approach in the literature (Momen et al., 2016; Urbanucci & Testi, 2018). The deterministic model does have a chance constraint, but MCM are not used. Comparing the deterministic and stochastic versions of a problem is often done with the Value of the Stochastic Solution (VSS). The VSS is a value of information measure. Value of information measures quantify the expected financial gain from including additional information in stochastic decision-making (Janssen & Koffijberg, 2009). If the difference between the solutions of both models is small, it might not be worthwhile to use the stochastic model since it requires more effort. The VSS is calculated by comparing the result of the stochastic model with the result of the deterministic model entered into the stochastic model (Maggioni & Wallace, 2012). The objective value of the deterministic model is €14,648, so it has significantly lower total costs than the stochastic solution. However, if we enter the optimal variable values of the deterministic solution into the stochastic model, the result is worse than the stochastic solution for this model instance. In fact, if we enter the deterministic solution in the stochastic model, we find that it is infeasible with a target penalty of 3.4%. Hence, the selected investments are insufficient to reach the reduction target if stochastic parameters are added. We can thus only calculate the VSS if we include penalties in the model. The VSS then just depends on the penalty size. Since the penalty size is set at 10^{40}, the solution of the deterministic model under uncertainty will become very large €$3.395 * 10^{38}$, which makes the VSS very large as well. The VSS would then be €$3.395 * 10^{38}$ - €55,534 = €$3.395 * 10^{38}$. This lets the performance of the stochastic model seem overly optimistic. So the VSS is not a useful validation measurement for this model. However, it does show that a deterministic model chooses overly optimistic solutions that may not be robust in practice because of its unrealistic assumption that the stochastic parameters always take their average value. The difference between stochastic and deterministic models is also often researched in the literature. Renard et al. (2013) states that stochastic models are more robust because the output is a range of solutions, whereas the deterministic model has one unique solution. Neglecting uncertainty can lead to over- or underestimating situations, as well as create bias according to Sharma et al. (2023), Wong et al. (2018), and Zarekarizi et al. (2020).

We also visualised the model results for the stochastic and deterministic models. Figure 11a shows the frequency of each investment in each year, divided over all scenarios, in a heat map. The electric car replacements are divided over the years as Hegeman planned. The construction in the Jansman office is planned for either 2025 or 2026, and according to the model, 2025 is optimal. The other investments are all optional, but tire pressure checks are always chosen from 2025 on. The other three investments are all always chosen in the same year, but are not an optimal decision in all scenarios (since the frequencies are not 1). The HVO diesel for vans and electric vans are mutually exclusive investments, which explains why their cumulative frequency is below one. The deterministic model largely shows the same results, see Figure 11b, except that it only shows frequencies of 1 or 0, and no continuous values in between. There is only one scenario in the deterministic model, so each investment is optimal (frequency of 1) or not (frequency of 0). The model solution opts to invest in HVO for cranes and vans, and not to invest in electric vans. These two investments also have higher frequencies in the stochastic model than electric vans.



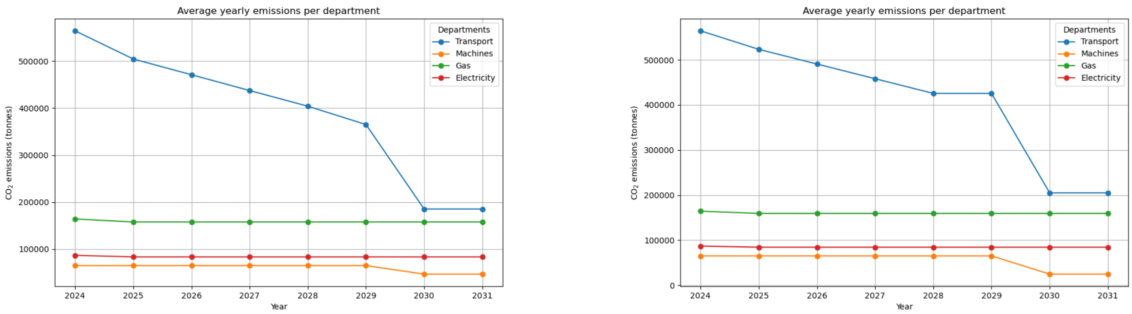
(a) Stochastic model



(b) Deterministic model

Figure 11: Frequency of choosing each investment in each year, divided over all scenarios, as well as the sum of how often each investment is chosen over the investment period.

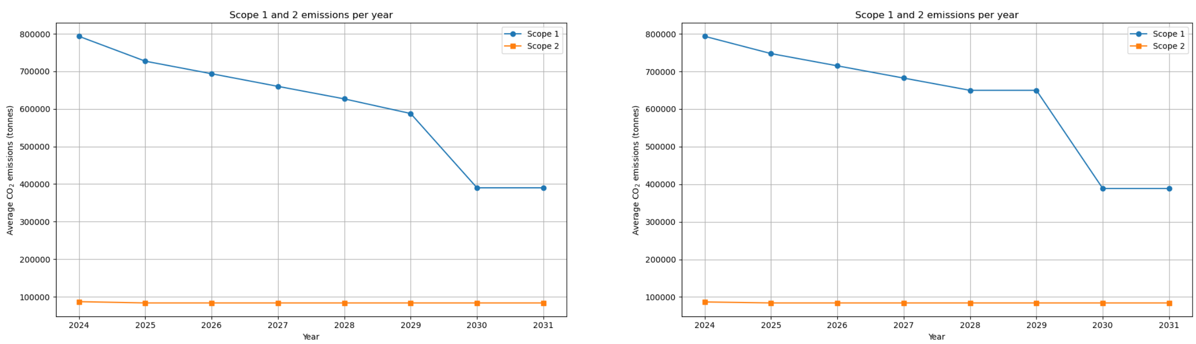
Furthermore, we are interested in the decrease of CO_2 emissions per department. Figure 12a shows this for the stochastic model, and Figure 12b for the deterministic model. The emission in the transport department shows a smoother decrease in the stochastic model than in the deterministic model, since the stochastic model averages over many scenarios instead of 1. The investments in the other three departments (machines, gas, and electricity) are always made, so the reduction patterns are the same in Figures 12a and 12b. Initially, transport contributed the largest part of the CO_2 emissions. Hence, Hegeman focuses mainly on reducing emissions in this area. Most sustainable investments thus impact this department, which is why the biggest reductions are made here. The transport department will still be the biggest contributor of emissions at the start of 2031, but with a much smaller difference compared to the other departments than in 2024. The transport department had the most reduction, namely 67.2%, followed by the machines department with 27.8%. The gas and electricity departments only reduced slightly, both by 3.9% on average. However, the expected CO_2 reduction for the gas and electricity departments that was used as input data was 3% for both departments (see table 4 in Chapter 5). We expect that the higher average reduction (3.9% instead of 3%) is due to the average (0.03) being so close to the lower bound (0) in comparison to the upper bound (1) of the truncated normal distribution for the reduction impact. Horrace (2015) confirms this by stating that truncating the normal distribution affects its moments, so also its mean. Since the difference is below one percent, we accept this difference.



(a) Stochastic model (b) Deterministic model

Figure 12: Decline of CO_2 emissions over time in each department because of sustainable investments.

We are also interested in the emission reduction per scope 1 and 2. Figure 13 shows the decrease in scope 1 and 2 emissions at Hegeman as a result of making sustainable investments. The departments in scope 1 (transport, machines, gas) reduce significantly more than the scope 2 department (electricity). This was expected, given that seven out of the eight possible investments from Table 4 target scope 1 emissions, and only one investment targets scope 2. The initial scope 1 emissions made up the vast majority of the total (scope 1 and 2) CO_2 emissions in 2024. Therefore, Hegeman focused mostly on reducing scope 1 emissions while selecting possible sustainable investments. Moreover, the fact that scope 1 emissions are directly a result of a company's actions, whereas scope 2 is indirect. This may make it easier for Hegeman to reduce scope 1 CO_2 emissions compared to scope 2.



(a) Stochastic model (b) Deterministic model

Figure 13: Decline of CO_2 emissions over time in per scope because of sustainable investments.

The model is elaborately discussed with Hegeman, who validated that the outcomes seemed realistic and the proposed investment plan looked practical (Aannemingsmaatschappij Hegeman B.V., 2025). Hegeman's approval based on expert opinion serves as additional model validation.

6.2 Comparison with more simplistic models

In this section, we will compare the model's performance to the performance of several simplistic methods that a company would usually prefer over a complex stochastic model.

6.2.1 Comparison with only MCM or CCP

We explained in Chapter 3 how the combination of MCM and CCP with an investment decision-making model has, to the best of our knowledge, not been researched in the literature before. In this section, we compare how the model with either MCM or CCP on its own would perform. We compare this to our complete stochastic model with MCM and CCP by entering the MCM and CCP solutions into the complete stochastic model.

All models are run with the same parameters as in Section 6.1, so using a target of 45%. First, we run the model with only MCM. This model is infeasible, as all scenarios need to meet the reduction target and not 95% of all scenarios. The target penalty for the MCM model is 5.6%. If we enter the solution of the MCM model in the stochastic model (with MCM + CCP), the solution is still infeasible with a target penalty of 4.6%. The penalty became smaller by entering the MCM solution in the stochastic model, because the CCP allows the target constraint not to be met for some scenarios. This is still an insufficient relaxation to make the model feasible.

Then, we computed the results of the CCP model, which resulted in an objective function of €-7275.49. This presents a huge improvement, because there are now only deterministic parameters, and the target only needs to be met in 95% of all scenarios because of the chance constraint for the reduction target. This allows the model to find a good solution. If we then plug this solution into the stochastic model, we get an infeasible model with a target penalty of 10.8%. Including or excluding MCM from the CCP model thus makes a significant difference.

We can conclude from these experiments that including CCP in the model allows us to find a cheaper solution for not meeting the target in 5% of the time. Moreover, we found that excluding MCM allowed us to find a good model solution. However, if it was then entered into the stochastic model, the target was far from being met. Combining MCM and CCP in one stochastic model thus lets us find realistic, robust, and cost-efficient results.

The penalty for the model using only CCP was larger than for using only MCM. For this case study, including only MCM in the MILP results in a more accurate solution than including only CCP. However, this could be different for different alpha values.

6.2.2 Comparison with Marginal Abatement Cost Curve

A commonly used policy tool in assessing the impact of sustainable actions is the marginal abatement cost (MAC) curve (Kesicki & Strachan, 2011). The MAC curve can represent the complex case of finding a balance between emission reduction and investment costs in a simplistic graph. This is especially useful since cost is the leading factor for most companies in sustainability decision-making (Department of Energy & Climate change, 2009). The MAC curve sorts investments from cheapest to most expensive price per tonne of CO_2 reduction (on the y-axis). Also, the percentage of the total CO_2 emissions of the company that can be reduced with the curve is given (on the x-axis). The cumulative percentage reduction of all investments is not equal to the total possible emission reduction if there are mutually exclusive investments. For Hegeman's case, it is not possible to both invest in electric vans and let the vans drive on HVO diesel. Although the x-axis shows a cumulative reduction of almost 80%, this is in practice thus not possible. The costs per investment are calculated using the Net Present Value formula and the discount factor. The same discount factor is used as in our MILP model; this factor is given in Section 5.1.1.

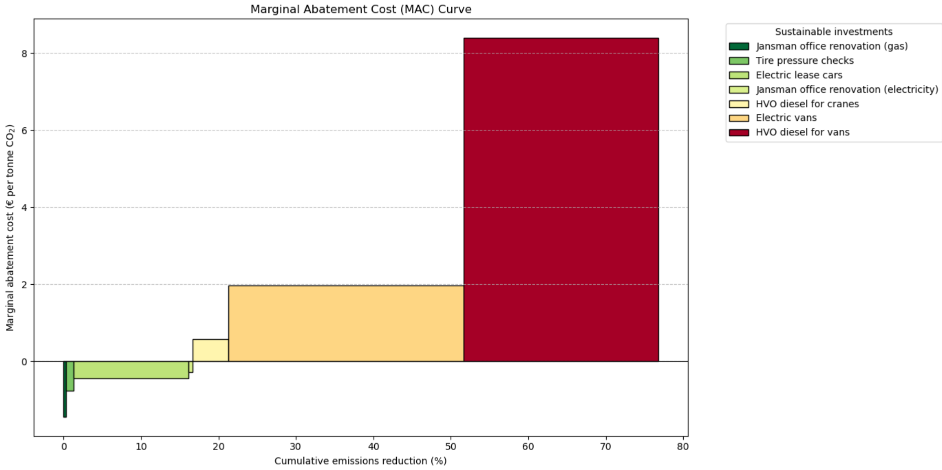


Figure 14: Marginal Abatement Cost Curve that sorts the investments from cheapest to most expensive per reduced tonne of CO_2 emissions.

We used the modelling input data to create a MAC curve for the case at Hegeman in Figure 14. Instead of the total CO_2 emissions, we only consider the scope 1 and 2 emissions again. All possible sustainable investments determined by Hegeman are sorted from cheapest to most expensive per tonne of CO_2 reduction. This graph can thus also be used to make an investment plan. The advantage of using our stochastic model is that it cannot only select an optimal investment mix, but also optimise the investment year. We assumed all investments would occur in the current year to make the MAC curve, which would result in a very high investment in 2025 for Hegeman. If we let all investments except the fixed investments occur in the first modelled year (2025), we get an objective value of €162,088 for a 45% reduction. Using the stochastic model thus results in a 65.7% cost decrease compared to placing all investments in the first year based on the investment combination given by the MAC curve in Figure 14. Figure 15 shows the heat map corresponding to this situation. We can thus conclude that the MAC curve is a useful tool for visualisation and decision-making support, but that it should not be used on its own. This is a supported claim in the literature. Kesicki and Ekins (2012) confirm that excluding intertemporal dynamics is a restriction of MAC. They also describe other limitations of MAC curves, such as omitting additional benefits of GHG reduction, limited inclusion of uncertainty, and missing transparency about assumptions.

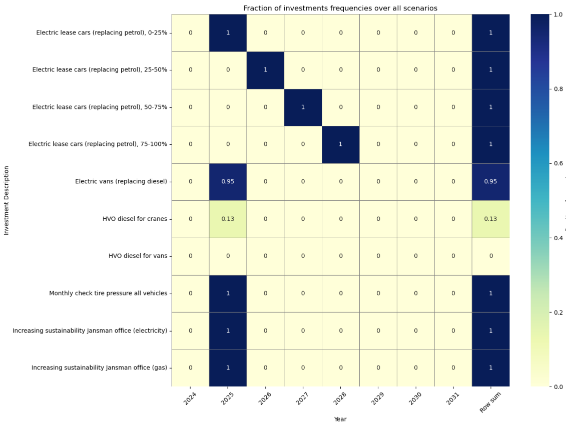


Figure 15: Heat map of using the MAC curve solution as input for the stochastic model.

6.2.3 Comparison with a simple heuristic

Usually, companies do not approach these types of problems using complex stochastic modelling. Therefore, we want to test its added value in this section by comparing its performance to the performance of a simple heuristic approach. We use a greedy heuristic based on the greedy heuristic used for the 0-1 Knapsack Problem (Csirik et al., 1991). In the first heuristic iteration, we add the fixed investments and check if the reduction target is already met. If not, we continue. In each iteration of the heuristic, we add the investment that is cheapest per tonne of CO_2 reduced. We keep adding investments until we reach the CO_2 reduction target. Each investment is done in the first feasible year if its yearly costs are negative (gains) and in the last feasible year if the yearly costs are positive (costs).

Table 6 presents the used data, as well as the solution generated using the heuristic. The initial investment costs are also included in the yearly costs by dividing by their expected lifespan. The lifespan is determined using Hegeman's experience (Aannemingsmaatschappij Hegeman B.V., 2025). To calculate the total yearly costs, we thus divide the initial investment costs by five and add the yearly costs or gains. This is more straightforward than the cost calculation for the MAC, but also less accurate.

ID	Investment	Yearly cost sum (€)	CO_2 reduction (tonnes)	Cost/ impact (€/tonne)	Selected?	Invest. year
A	Replace petrol cars with electric cars	€-81,951	130.3	€-629	Fixed	2025 - 2028
B	Make the Jansman office more sustainable	€-685	7.5	€-91	Fixed	2025
C	Use HVO diesel for cranes	€3,174	40.4	€78	Iter. 2	2030
D	Use HVO diesel for vans	€250,155	220.6	€1,134	No	-
E	Replace petrol vans with electric	€159,167	267.4	€595	Iter. 3	2030
F	Monthly check tire pressure for all vehicles	€-866	8.5	€-102	Iter. 1	2025

Table 6: Implementation of the heuristic.

First, fixed investments A and B are selected, which cumulatively sum up to a 15.7% CO_2 reduction. The target has not been reached yet, so the algorithm continues. Then the cheapest investment is added, so investment F in 2025. The cumulative reduction is then 16.6%. Then investment C in added in 2030, which sums up to 21.2% cumulative reduction. Then, investment E is selected in 2030, which sums up to 51.6% cumulative reduction, which means the algorithm can stop since the reduction target of 45% is reached. If we enter this heuristic solution (as presented in Table 6) in the stochastic model, we get an objective value of €498,319 and an achieved CO_2 reduction of 54.2%. The added value of using a stochastic model is thus €498,319 - €55,534 = €442,785. The stochastic model improves the solution by 88.9%. It makes sense that the costs of the simple heuristic are substantially higher, since more reduction is achieved than was needed for the target. Although the stochastic model is more complex and time-consuming, there is a significant cost benefit for companies to implement it.

6.3 Sensitivity analysis

We perform a sensitivity analysis to evaluate the robustness of the model. The distributions of the stochastic parameters were chosen using expert opinion in Section 5.1.3, which is a less reliable source than historical data (Utkin, 2006). It is thus good to test the impact of varying the distributions using a sensitivity analysis. Moreover, the alpha value of the chance constraint is now chosen based on a feeling by Hegeman and because 0.05 is a common value in the literature (Miller & Ulrich, 2019). However, we do not know what the effects of changing the alpha value are. Hegeman might want to change it in case it is very robust or flexible. For example, Hegeman may decide to decrease the alpha value by a few percent if it is not very costly, to increase the number of scenarios that meet the target. Frey and Patil (2002) state that a sensitivity analysis is a useful method for verifying and validating a model. It can help to prioritise additional data collection or research and identify critical control points. Sensitivity analysis methods can be mathematical, statistical, or graphical. Graphical methods visually represent the effects of input on output and are regularly used as a screening method before further analysis or to show complex dependencies. Mathematical methods assess sensitivity by calculating the output for a range of possible input values (Salehi et al., 2000). Statistical methods assign a probability distribution to input values to assess the effect of variance on their outputs. One or more inputs can be varied simultaneously (Andersson et al., 2000). We will apply a mathematical sensitivity analysis in this section because it allows us to precisely quantify the impact of changing individual outputs.

6.3.1 Full factorial sampling

Reed et al. (2022) describe several methods of experimenting with parameter values in a sensitivity analysis, such as one-at-a-time (ceteris paribus), full factorial sampling, and fractional factorial sampling. Only the main effects are studied in one-at-a-time sampling, while full factorial studies all effects, but it is more computationally extensive. It is therefore common in the literature to apply full factorial sampling at two (extreme) levels per factor (Montgomery, 2017). We will also use this approach. We apply a full-factorial analysis for three parameters and two levels; there are thus eight experiments. Table 7 shows the tested parameter values as well as the resulting objective value for a 45% reduction target. The standard deviations are used for all investments with a non-zero parameter value. For all three parameters, we experiment with a higher and a lower value. The alpha value is now set at 0.05, so we experiment with 0.025 and 0.075. The standard deviations are set at 0.03, so we experiment with 0.01 and 0.05 for both impact and cost.

Experiment	**Alpha**	**Impact st. dev.**	**Cost st. dev**	**Objective value**
1	0.025	0.01	0.01	€83,901
2	0.025	0.01	0.05	€82,073
3	0.025	0.05	0.01	€60,851
4	0.025	0.05	0.05	€60,367
5	0.075	0.01	0.01	€37,676
6	0.075	0.01	0.05	€34,357
7	0.075	0.05	0.01	€14,575
8	0.075	0.05	0.05	€12,304

Table 7: Experimental parameter values for the full factorial sensitivity analysis.

In all experiments, we found an optimal solution. Experiment 8 performs the best with an objective value of €12,304. The worst objective value of €83,901 was found in experiment 1. Increasing the alpha value loosens the SAA target constraint by allowing more scenarios not to meet the target. Therefore, it improves the objective function value. Higher standard deviations of the impact and costs also improve the objective value, as is shown in Table 7.

The average objective is €48,263. We then calculated the individual effects by computing the average objective value for each parameter-level combination. We then calculated the average percentage deviation from the mean objective. The parameter with the most impact was the alpha value, with a deviation percentage of 48.8%. This was followed by the standard deviation of the impact, with 23.3%, and the standard deviation of the cost, with only 2.0%. Setting the alpha parameter accurately is thus much more important than estimating the standard deviation of the cost. It makes sense that the standard deviation of the impact has more impact than the standard deviation of the costs, since the standard deviation of the cost is zero for all experiments except two. We thus advise Hegeman to choose the alpha value and standard deviation of the impact carefully, and spend less time determining the standard deviation of the cost.

We found the lowest total cost for the highest values for all three parameters. Previously, we experimented with slightly different but still realistic values. Now, we want to find whether the same effects also occur for more extreme values. Since we found that the individual impact of the standard deviation of the cost is only small, we keep this value at 0.05 and do not further experiment with it. Table 8 shows the experimental parameter values and their results. The extreme full factorial analysis yields the same conclusion as the previous full factorial analysis. Namely, that the highest values for all parameters lead to the lowest total cost. We also recalculated the individual effects. We found the deviation percentage of the mean for the alpha parameter to be 27.8%, while the standard deviation of the impact had a deviation of 76.3%. Interestingly, in our initial experiment in Table 7, the alpha parameter had a larger deviation, and now in the more extreme experiment, the standard deviation of the impact does. This may be because of relatively larger differences between the two levels of the full factorial analysis compared between the original and the extreme experiments.

Experiment	**Alpha**	**Impact st. dev.**	**Cost st. dev**	**Objective value**
9	0.15	0.05	0.05	€-55,057
10	0.15	0.10	0.05	€-175,390
11	0.075	0.10	0.05	€-142,464

Table 8: Experimental parameter values for the full factorial sensitivity analysis with more extreme parameters for the alpha value and standard deviation of the impact.

6.3.2 Experimenting with seed values

Moreover, we experiment with different seed values to test the robustness of the model in case different random numbers are used. We do this by testing eight different seed values and comparing the objective function values. Figure 16 visualises the results of this analysis. The mean objective value of these objectives is €57,761, the standard deviation is €2,346, and the coefficient variation of the mean is 0.041 (4.1%). This is generally considered a low coefficient of variation, which indicates that the model performance is consistent over the used seed values (Zady, 1999).

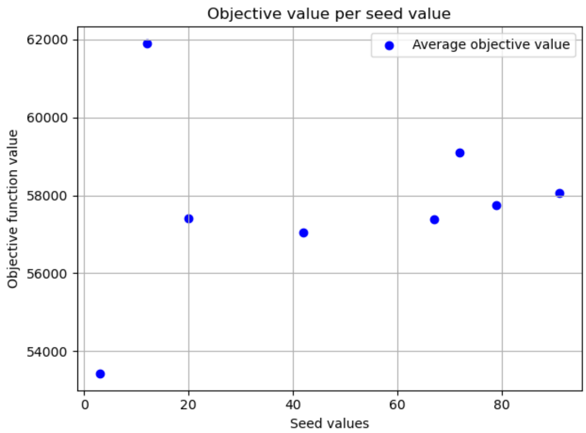


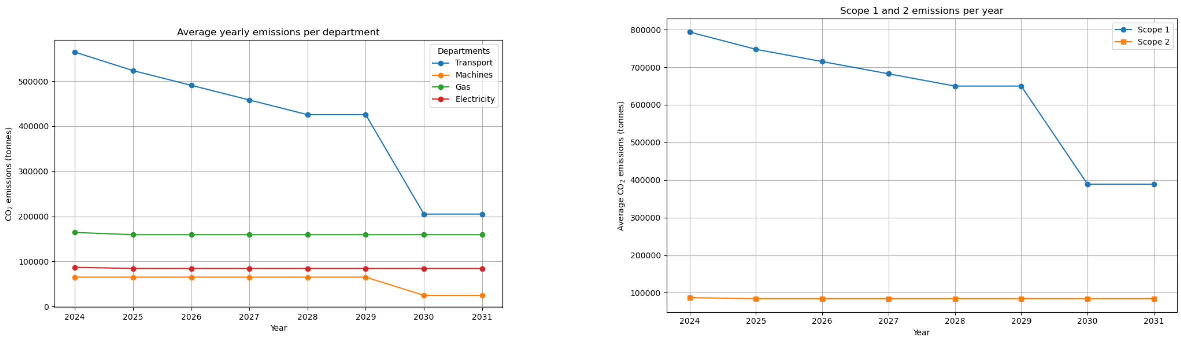
Figure 16: Objective values for experimenting with different seed values.

6.4 Scenario Analysis

This section evaluates different scenarios at Hegeman to assess how the model performs under varying conditions. First, a baseline scenario is tested to see how much emissions can be reduced while only executing the fixed investments. Then we consider an optimistic scenario to find the impact of subsidies. Finally, we consider a pessimistic scenario that includes an annual budget constraint, simulating the case where Hegeman faces tighter economic conditions.

6.4.1 Baseline scenario

An interesting result for Hegeman is to see how much emissions the baseline scenario with only the fixed investments would reduce. This includes only the replacement of cars by electric cars and the reconstruction of the Jansman office. The total emissions would reduce by 16.3% for €-412,506 costs because of these investments. The costs are negative (gains) since the electric cars pay themselves back and the Jansman investment has no initial costs. The CO_2 reduction as a result of the fixed investments is shown per department in Figure 17a and per scope in Figure 17b, respectively.



(a) Emissions per department (b) Emissions per scope

Figure 17: Decline of CO_2 emissions over time per scope and per department. Results of the baseline scenario with only the fixed investments.

6.4.2 Best case scenario

One of the possible best case scenarios for Hegeman is receiving subsidies for its sustainable efforts. Various sustainability-related subsidies for companies exist in the Netherlands (KVK, 2025). These subsidies can significantly reduce the initial investment costs of sustainable investments. In this scenario, we will assume that the initial investment costs for all investments decrease by 10% because of granted subsidies. The resulting objective function value (total costs) for a 45% reduction target is €25,172. This is an improvement of 54.7%, which is much more than the cost reduction resulting from the subsidy. This significant improvement is becaue the initial costs are a substantial part of the total costs, and because the average cost reduction is used in a lognormal distribution, which can create a bigger than linear effect. Even with the received subsidies, it is not possible to achieve Hegeman's initial reduction goal of 50%, since costs were not the restricting factor in failing to achieve the reduction goal.

6.4.3 Worst case scenario

A possible worst case scenario is that Hegeman experiences a period of financial setbacks. This means that their priority will probably be less focused on sustainability. Hegeman could then decide to set a maximum annual investment budget for sustainability. If the yearly budget is set at €100,000 and the reduction target at 45%, the model can still find an optimal solution of €57,060. If we compare this to the optimal value without the budget constraint of €55,534, this is a 2.7% deterioration. Installing a maximum yearly sustainability budget, while maintaining the same reduction target, might decrease the maximum yearly costs, but the overall costs will not decrease and may even increase. Even in a situation with financial setbacks, we thus do not advise using a maximum sustainable investment budget, since this can only lead to higher total costs eventually. The budget constraint could be more useful if we allowed splitting investments (e.g., replacing the diesel vans not at once, but spread over multiple years).

6.5 Conclusion

This chapter presented and analysed the results of the model. Hegeman's initial target of 50% was found to be too optimistic and did not lead to feasible solutions. However, a target of 45% can be achieved at a total cost of €55,534. If Hegeman does want to achieve a 50% reduction, more sustainable investments should be added as model input.

We experimented with a stochastic model using only MCM or CCP. For both the solution of the MCM and the CCP model, entering the solution in the stochastic model resulted in infeasibility. The penalties were 4.6% and 10.8% for the MCM and CCP models, respectively. We can conclude that using only the CCP model made the model less realistic, and using only MCM made the model too restrictive and thus costly. Both are suboptimal solutions compared to the stochastic model with both CCP and MCM.

Then we constructed a MAC curve and compared the solution extracted from the MAC curve in the stochastic model to our optimal solution. We found a 65.7% improvement of the stochastic model over the solution using the MAC curve. We can thus conclude that the MAC curve can be a useful aid for decision-making, but does not lead to good solutions on its own.

Then, we compare the performance of the stochastic model with a simple greedy heuristic based on the knapsack problem. The stochastic model improves the solution of the heuristic by 88.9%. Despite the extra computational effort and complexity, the added value is thus substantially higher for a stochastic model.

Additionally, we performed a three-level full-factorial sensitivity analysis on the chance-constraint alpha parameter, standard deviation of the impact, and initial investment cost. We calculated the average percentage deviation from the mean objective value for each parameter-level combination. We then found a deviation of 48.8% for the alpha parameter, 23.3% for the standard deviation of the cost, and 2.0% for the standard deviation of the impact. We advise Hegeman to spend the most time on tuning the parameters that have the highest effects. Then, we experimented with the seed values. A coefficient of variation of 0.041 (4.1%), which indicates consistent performance of the stochastic model over the eight seed values used.

Finally, we conducted a scenario analysis, in which we evaluated the baseline scenario, a best case scenario, and a worst case scenario. The baseline scenario reduces emissions by 16.3% by only executing the two fixed investments. In the best case scenario, Hegeman is granted a subsidy that reduces the initial investment costs by 10%. This improves the objective by 54.7%. In the worst case scenario, Hegeman is not doing well financially and decides to set a maximum annual sustainable investment budget of €100,000. This increases the objective value by 2.7%. So we advise Hegeman against setting a maximum annual budget constraint, as it may seem convenient to have well-spread yearly costs, but eventually it can ultimately only be more costly.

7 Implementation

This chapter describes how Hegeman can implement this research using an investment-decision tool and thus answers the following research question:

"How can we implement the investment-decision model at Hegeman?"

We do not want to use our decision-making model just once to provide Hegeman with the optimal investment plan for their current situation, but we want them to keep using the model for making optimal and sustainable investment decisions. Hegeman's management has no technical modelling experience. Providing Hegeman with just the Python model is thus not a good solution. We thus created a custom-made investment-decision tool for Hegeman that implements the Python optimisation model.

We use the Mendix program to develop the tool for Hegeman. Mendix is one of the most used and well-known tools for low-code development (Bucaioni et al., 2022). Low-coding development allows the user to build software with a limited amount of coding (Sahay et al., 2020). This allowed us to create a simple but functional application relatively quickly.

First, Section 7.1 of this chapter describes the functionality of the application. The used domain model is explained in Section 7.2. Then, Section 7.3 outlines how the connection between the Python model and the Mendix application is made. Lastly, the application validation by Hegeman is described in Section 7.4, including a list of possible future improvements.

7.1 Application functionality

The application should allow the user at Hegeman to enter all input data, consisting of their emission reduction target and sustainable investments. Then the user selects the target and investments to use as input data for the optimisation model. Afterwards, the user hits the optimisation button, which calls the Python investment-decision model. When the calculations are finished, a dashboard is shown to the user with the output of the model. This process is summarized in the process flow in Figure 18.

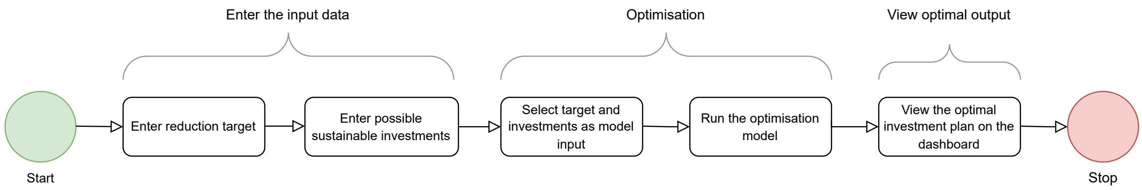


Figure 18: Process flow for the users of the investment-decision tool for Hegeman.

The application dashboard with the model's optimisation output is presented in Figure 19. All other pages of the application are included in the Appendix in Section A.2.

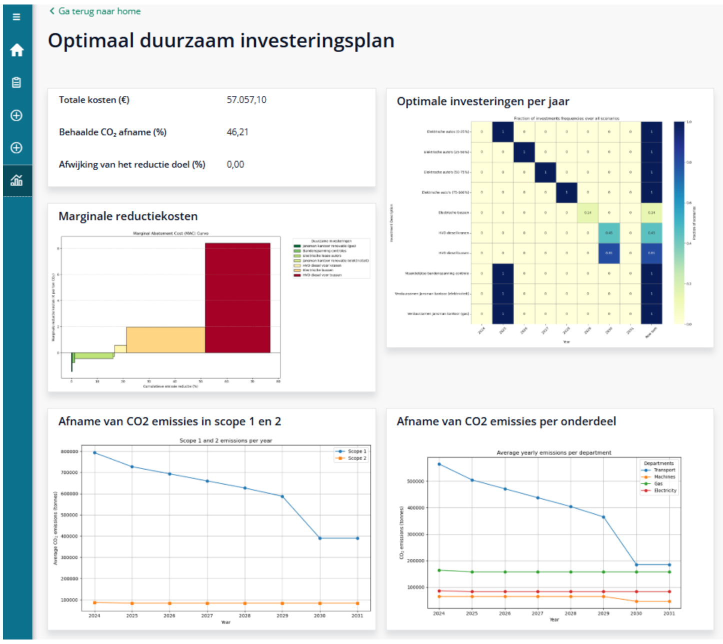


Figure 19: Dashboard with the output data figures in the application for Hegeman.

7.2 Domain model

A Mendix application requires a domain model. This includes the entities and attributes of the model, as well as relations between entities. Figure 20 shows the domain model for our Mendix application.

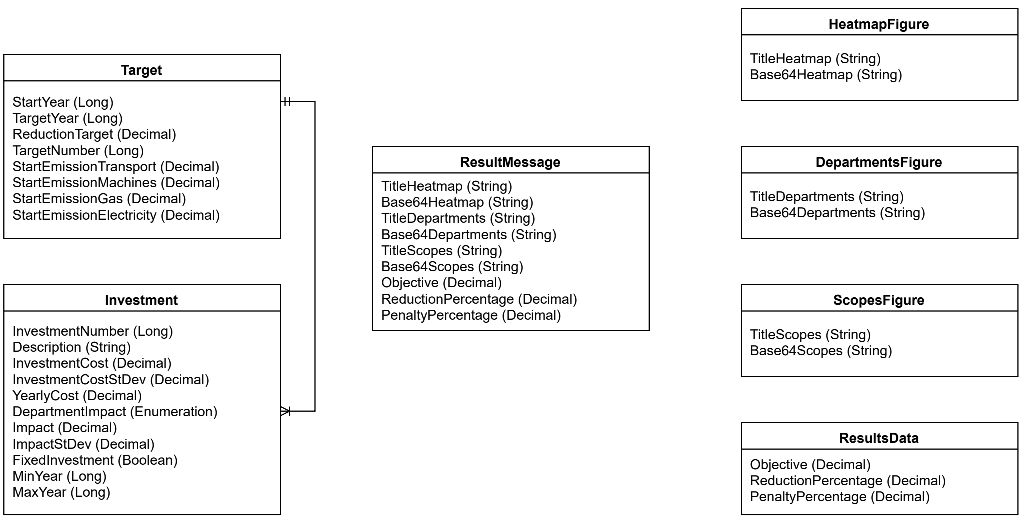


Figure 20: Domain model for the Mendix application consisting of all entities, attributes, and relations. The attribute types are given in brackets. The line from the 'Target' to the 'Investment' entity represents a one-to-many relationship.

The user enters the reduction target ('Target') they want to achieve. This can be done using a set of possible sustainable investments ('Investment') that the user considers. There is thus a one-to-many relationship between the target and investment entities. The model output consists of a single message sent from the Python environment to the Mendix application. This is the 'ResultMessage' entity, which is later split into four output entities. These four entities include three entities used for the figures: 'HeatmapFigure', 'DepartmentsFigure', and 'ScopesFigure'. The last entity, 'ResultsData', includes the numerical data: the objective function, achieved reduction, and target penalty. All information in the 'ResultMessage' entity is used in the output dashboard in Figure 19.

7.3 Creating the connection between Mendix and Python

The mathematical model is programmed in Python, and the application is made in Mendix. For the Python model to receive the input data entered by the user and to send the model result back to Mendix, we need to establish a connection between Mendix and Python. The button used to run the optimisation model calls the REST API function from Mendix. An API is an Application Programming Interface that is used to connect systems. REST is a common architecture for APIs and stands for Representational State Transfer. Mendix's 'Call REST (POST)' method allows us to both send and receive data. For both systems to know what type of message to expect, we use JSON structures. JSON lets the user enter keys (attributes) and the type of value per key (Coocksey, 2014). The JSON format can be handled in both Mendix and Python. We then use import and export mappings in Mendix to connect the keys from the JSON structure to the attributes of the entity in the domain structure in Mendix. The process flow in Figure 21 shows the process of integrating Mendix and Python.

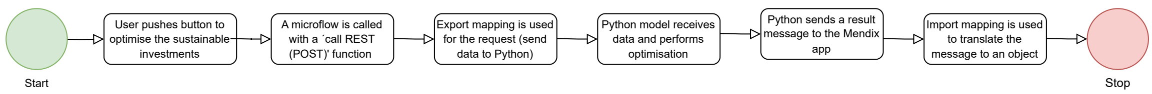


Figure 21: Process chart of integrating the Mendix application and the Python model.

During the development phase, the application is tested in a local environment. However, to make the tool accessible for practical use by Hegeman, the application needs to be deployed to a server environment. Deploying the application is beyond the scope of this research and was thus not executed.

7.4 Application validation

After developing the Mendix application, we conducted a demonstration and validation session with Hegeman. During the session, we explained how the application was set up and allowed Hegeman to test it in a local environment. After the demonstration, we asked Hegeman for feedback about the application. This end-user feedback is useful in deciding how to further improve the application and what aspects are good already.

The inquiry regarded three aspects: usability, appearance, and feasibility of implementation. Overall, Hegeman was positive about the application. Hegeman appreciated the neat appearance of the application. Furthermore, they liked the simplistic interface, which made the application user-friendly and self-explanatory in use. The main aspect Hegeman was enthusiastic about is the output dashboard. They feel this will allow them to base their decisions on actual quantitative results. The graphs are easy to understand, according to them, and can help them to justify their sustainable decisions to the management team. When Hegeman decided to replace all petrol cars with electric cars, they did not know exactly how much emissions this would reduce. This application can help them avoid such situations in the future. Moreover, it helps them in achieving CO_2 certification. The runtime of a few minutes was not a problem for Hegeman, as it supports strategic decision-making, so it is not intended for frequent use (Aannemingsmaatschappij Hegeman B.V., 2025). Further testing is required before deploying the application, since Hegeman only tested with an already entered dataset. Additionally, testing with other datasets on a production environment would be useful to improve the model.

7.4.1 Possible improvements

This list of possible improvements for the investment-decision application was created primarily based on feedback from Hegeman. The list is sorted from the highest to the lowest priority based on Hegeman's feedback. The possibilities for improvement are currently not incorporated in the application, as they are not within the scope of this thesis. However, if Hegeman decides to implement the application, incorporating these improvements could significantly enhance its quality.

- Deploy the application and let it run on a server instead of on a local environment.
- The MAC curve is now added manually to the dashboard, not generated automatically by running the model like the other figures on the dashboard.
- Add a progress bar while the optimisation model runs, as this is more user-friendly (Li et al., 2021).
- A functionality where the user can download a report with all information on the dashboard could be added. These reports could also be saved in the application itself.
- Improve styling of the application to make it more professional and more similar to Hegeman's other applications. This will allow Hegeman to adapt to it more quickly.

7.5 Conclusion

To conclude, we created an application for Hegeman that implements the stochastic investment decision Python model in a Mendix application. This allows Hegeman to use the application without having to understand the technical details of the model.

This chapter explained the general functionality and the connection between Mendix and Python visually using process flows. Moreover, the domain model with the entities and relations that form the basis of the application is described. Lastly, we conducted a demonstration and evaluation session with Hegeman to gather feedback on the application. The application was evaluated based on usability, appearance, and feasibility of implementation. Hegeman stated that the application scored well on all three criteria. Possibilities for further application improvements based on Hegeman's feedback are also listed in this chapter. The most important one for Hegeman is letting the application run on a server instead of a local environment, such that Hegeman can actually use the application.

8 Conclusion and recommendations

This chapter concludes the research and discusses the recommendations. First, Section 8.1 summarizes the research. Then, the practical and scientific contributions of the research are listed in Section 8.2. Section 8.3 explains the recommendations and Section 8.4 discusses the limitations and possibilities for further research.

8.1 Summary

In this research, we aimed to answer the main research question:

"How can we determine the optimal cost-effective combination of investments to let Hegeman achieve its target of 50% reduction of scope 1 and 2 CO_2 emissions in 2030 compared to 2024 to comply with the requirements for the CSDR and the CO_2PL?"

We solved the research question by creating a generic strategic investment-decision model that optimises the combination of sustainable investments that can achieve a company's emission reduction target at minimum cost. The model also finds the optimal year to do each investment. The investment-decision model is a stochastic MILP that combines CCP and MCM. MCM are used to make the model more realistic by including stochastic parameters for the cost and reduction impact. CCP is implemented using SAA to find a more cost-efficient solution by allowing the reduction target not to be met in a small percentage of all scenarios.

The generic investment-decision model was then applied to the case study at Hegeman. We found that the target of a 50% reduction was too ambitious for Hegeman and thus did not yield feasible results. Hegeman can either decrease the target to 45%, which is feasible, or add more sustainable investments as input in the model to find a feasible solution. The target of 45% can be achieved for a total cost of €55,534. The optimal investment plan is presented for Hegeman as a heatmap. Using a stochastic model may result in a different optimal investment plan for each scenario, except for the fixed investments. These investments are chosen in each scenario. This is summarised with a fraction of the scenarios in which it is optimal to invest, divided by all scenarios. We presented the results to validate the model based on expert opinion. The results seemed realistic and accurate according to Hegeman (Aannemingsmaatschappij Hegeman B.V., 2025).

The model performance was tested by comparing it to more simplistic methods, based on the MAC curve and using a simple greedy heuristic. The stochastic model outperforms these simple methods with 65.7% and 88.9% total cost reduction, respectively. We also evaluated our model's performance in comparison with a model using either MCM or CCP, instead of combining the methods. For the 45% target, the model using only MCM was infeasible because it would have to meet all scenarios instead of 95%. The penalty was a 4.6% deviation from the target. For the CCP model, we also found an infeasible solution with an even higher penalty than the MCM model, of 10.8%. Combining CCP and MCM thus performs significantly better compared to using only one of the methods. Furthermore, a two-level full factorial sensitivity analysis was performed to find the effects of changing the target level and the standard deviation of the cost and impact. It was found that the alpha parameter had the highest individual impact (48.8%), then the standard deviation of the cost (23.3%), and lastly, the standard deviation of the impact (2.0%). We thus advise Hegeman to spend the most time tuning the parameters that impact the solution the most.

8.2 Practical and scientific contribution

The contributions of this research are both practical and scientific. The practical contribution for Hegeman is the optimal sustainable investment plan that can help them reach their reduction target by making sustainable investments at minimum total costs. Moreover, we implemented the applied Python model in a Mendix application that is easy to use for Hegeman and that they can keep using to create sustainable investment plans.

The practical contribution for CAPE is a generic model implemented in Mendix that they can adapt and use for similar construction companies dealing with the same problem. Many construction companies are dealing with the same problems, hence the application can be a successful product for CAPE and help many of their clients. Despite the fact that the model is described as a generic model, careful consideration is required before applying the model to another construction company. Especially regarding the suitability of the list of assumptions, e.g., the indivisibility of the investments, fixed investment horizon, and additive emission reduction effects.

The scientific contribution of this research is the novelty of the generic strategic investment-decision model. This is a stochastic MILP model incorporating MCM and CCP using SAA. The combination of MCM and CCP with an MILP in the context of sustainable investment planning in the construction sector has, to the best of our knowledge, not been used in the literature before. There was thus no existing suitable model in the literature that could be applied to Hegeman's case study. Combining MCM and CCP with a stochastic MILP model is a useful combination. Using MCM for stochastic parameters with many scenarios means that typically, a few extremely high or low values will be picked from the tails of the distributions. It is unnecessary and expensive to find a solution that also covers these extreme scenarios. CCP prevents the model from finding solutions that cover the extreme scenarios and thus complements the features of the model with MCM. CCP thus trades off constraint satisfaction probability against cost. The model can be applied to any similar construction company wanting to optimise their investment strategy based on cost-effectiveness to achieve their emission reduction targets.

8.3 Recommendations

Hereby, we list our recommendations for Hegeman if they want to implement our application in practice.

- The application is tested in a local environment during the development phase. The application needs to be deployed to a server environment to make it accessible for practical use by Hegeman.
- We suggest aiming for high-quality input data because the model's performance is highly dependent on the quality of the data entered into it. Especially, calculating the probability distributions based on data instead of relying on expert opinion can improve the quality of the model output.
- If Hegeman is not interested in purchasing the license for the Gurobi solver, the model can easily be adjusted to use a free solver. This may increase the model's runtime, so we advise considering this when deciding which solver to use.

8.4 Limitations and further research

This research has the following limitations because of the bounded scope. The following limitations can be further researched upon to improve and extend the possibilities with our model.

- After 2028, all companies are required by the CSRD to publish their emission data of scopes 1, 2, and 3. From then on, it will be easier to extend the model to include scope 3 emissions. Once Hegeman has scope 3 CO_2 emissions data available, the model can be extended to include that data. This requires only minor model adjustments, but estimating the impact of an investment might be more difficult if scope 3 is included. Further research is required for this.

- Further research is advised to include not only CO_2 emissions in the model but also the other GHGs recognized by the Kyoto Protocol (UNFCCC, 1998). Finding the impact of investments on all GHGs is challenging and probably requires additional research, as most research focuses only on CO_2 emissions (Bows-Larkin et al., 2014).
- Currently, the model optimises the output based solely on cost minimisation. For the case study at Hegeman, this was the most fitting model. However, many other objectives could be considered in sustainability decision-making, which may be suitable for different case studies. Cayir Ervural et al. (2018) consider costs, generated energy, social acceptance, and energy potential as objectives in an MCDA analysis for sustainable energy investment planning. Todorov and Marinova (2011) include costs, benefits to society, and scope 1, 2, and 3 emissions as objectives in their sustainability goal programming model. Zander and Kächele (1999) also consider the soil erosion and nitrogen leaching as objectives.
- The model currently requires each investment to be indivisible and thus made in one year. Allowing (some) investments to be divided over multiple years can make it more financially appealing to companies to follow their optimal investment plan. Ideally, users would be able to select in the application whether each investment is divisible over multiple years.
- In this research, we only tested the model on one case study. Testing the model on other case studies of different construction companies can further validate the model's performance. Most of the model formulation and solution methods are formulated generically, and this part of the model can be directly applied to other similar construction companies. Moreover, the company needs to find all required input data and calculate the number of Monte Carlo iterations. However, not all assumptions may apply to all construction companies. In particular, the indivisibility of the investments, fixed investment horizon, and additive emission reduction effects. If a company wants to use the model but deviates from the list of assumptions, model adaptations are required before the model can be applied to the company.
- The model is generically formulated in Chapter 4.1, without any aspects that are only applicable to construction companies. Therefore, we suggest not only applying the model to other construction companies for further validation, but also to explore the possibility of using it for companies operating in different sectors. Decreasing emissions is also relevant in other Dutch sectors, such as logistics and agriculture (Borgstein et al., n.d.; Moeke & Kin, 2023).
- In this thesis, we used expert opinion to select the standard deviations of the probability distributions for the cost and impact parameters. Further research could focus on data-driven parameter estimation techniques using, for example, machine learning techniques or regression analysis. These methods do require historical data or data from online datasets (Mohammed et al., 2025; Petropoulos et al., 2022).
- The model relies on the assumption that all investments have a longer lifetime than the modelling period, so it does not consider that an investment might need to be redone after its lifetime. Other companies may want to model over a longer horizon and thus want to include this aspect.
- The model could also be used for investing on a shorter term by making monthly decisions. The model can be turned into a tactical model with only small adjustments. This can be especially useful for companies that consider a shorter total modelling horizon.

- We recommend that any construction company (using this model) to research which subsidies it might be entitled to. This is not yet included in the costs of the model, but it can save Dutch construction companies a considerable amount of money, according to Subsidiebureau Nederland (2024). The company can then adjust the input data based on the received subsidies and reoptimise the investment plan.
- We recommend including the future price prediction in the model, instead of using the current price and only considering the discount factor. For example, expected technological developments that may decrease the price can be taken into account as well.
- The model currently bases the investment decisions primarily on cost-efficiency. In practice, additional factors may influence whether and when investments are implemented. For example, new initiatives in organisations often fail because of ineffective change management (Oakland & Tanner, 2007). This may lead to investments being made later than the optimal investment year based on the model output or even not at all. Moreover, new laws and regulations could prevent investments from being made. Future research could incorporate such relevant additional factors.
- In the case of Hegeman, we modelled the total achieved emission reduction as the additive sum of the reduction impact of individual investments. This assumption is suitable for Hegeman because of the independence of the considered investments. So we recommend further research using case studies of other construction companies to examine whether additive modelling is applicable or if interaction effects between investments occur. For example, if a company simultaneously installs solar panels and starts using electric vehicles, the vehicles can be charged with the energy generated by the solar panels. The achieved emission reduction may then be larger than the sum of the individual investments' impacts. If there are significant interaction effects between investments, additive modelling is not a suitable method.
- Future research can be dedicated to modelling risk in a broader sense. Currently, the risk of not achieving the reduction target is operationalised using a cost penalty. The penalty is used to get the distance between the infeasible solution and feasibility, which is commonly used in the literature (Baeck & Khuri, 1994; Huang et al., 1994; Olsen, 1994). However, risk can also be modelled more broadly, for example, as the variance of emission reductions across scenarios, or as systematic failure in extreme scenarios. This can contribute to more robust decision-making under uncertainty.
- We recommend studying the model's behaviour with larger solution spaces. If this results in intractable runtimes, exploring heuristic methods could be a solution.

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A Appendix

A.1 Python code

This section of the Appendix includes the complete Python code that was programmed in Section 5.2. This is the Python model, which also shows how Mendix connects to the Python model.

```
import pandas as pd
import gurobipy as gp
from gurobipy import GRB
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import truncnorm
from scipy.stats import lognorm

#import the function to write an image to base 64
from figure_to_base64 import encode_image_to_base64

# Connect the Mendix and Python models
from flask import Flask, request, jsonify
app = Flask(__name__)
@app.route('/process_data', methods=['POST'])

def process_data():
    S = range(5700)  # Number of Monte Carlo iterations

    # For reproducibility
    np.random.seed(42)

    # Retrieve the JSON data from the request
    data = request.get_json()
    df_investeringen = pd.DataFrame(data['investeringen'])

    # Extract target data
    target_start_year = int(data['StartJaar'])
    target_end_year = int(data['DoelJaar'])
    target = float(data['ReductieDoel'])
    target = target / 100 #convert to fraction instead of percentage
    start_emissions=[]
    start_emissions.append(float(data['StartEmissieWagenpark']))
    start_emissions.append(float(data['StartEmissieMachines']))
    start_emissions.append(float(data['StartEmissieGas']))
    start_emissions.append(float(data['StartEmissieElektriciteit']))

    #convert to integer or float
    df_investeringen['EenmaligeKosten'] =
        df_investeringen['EenmaligeKosten'].astype(float)
    df_investeringen['EenmaligeKostStDev'] =
        df_investeringen['EenmaligeKostStDev'].astype(float)
```

```
df_investeringen['JaarlijkseKosten'] =
    df_investeringen['JaarlijkseKosten'].astype(float)
df_investeringen['Impact'] = df_investeringen['Impact'].astype(float)
df_investeringen['ImpactStDev'] =
    df_investeringen['ImpactStDev'].astype(float)
df_investeringen['MinJaar'] = df_investeringen['MinJaar'].astype(int)
df_investeringen['MaxJaar'] = df_investeringen['MaxJaar'].astype(int)
# df_investeringen['Beschrijving'] = df_investeringen['Beschrijving']

# Extract investment data
initial_costs = df_investeringen['EenmaligeKosten'].to_numpy()
st_dev_costs = df_investeringen['EenmaligeKostStDev'].to_numpy()
yearly_costs = df_investeringen['JaarlijkseKosten'].to_numpy()
reduction_impact = df_investeringen['Impact'].to_numpy()
st_dev_impact = df_investeringen['ImpactStDev'].to_numpy()
department_impact = df_investeringen['ImpactOpOnderdeel'].to_numpy()
mandatory = df_investeringen['AlGekozen'].to_numpy()
start_year = df_investeringen['MinJaar'].to_numpy()
end_year = df_investeringen['MaxJaar'].to_numpy()
description = df_investeringen['Beschrijving'].to_numpy()

#transform data in right shape
for i in range(0,len(df_investeringen)):
    # convert impact to fraction instead of percentage
    reduction_impact[i] = reduction_impact[i]/100
    # startyear
    if start_year[i] == 0: # if not filled in, it's the first year
        start_year[i] = 0 #translate from e.g. 2024 to 0
    else:
        start_year[i] = start_year[i] - target_start_year
    # endyear
    if end_year[i] == 0: # if not filled in, it's the first year
        end_year[i] = target_end_year- target_start_year
    else:
        end_year[i] = end_year[i] - target_start_year

    if mandatory[i] == "Ja":
        mandatory[i] = 1
    elif mandatory[i] == "Nee":
        mandatory[i] = 0
    else:
        print("wrong data entered for Mandatory, for i:",i)
# transform also the target year data
target_end_year = target_end_year - target_start_year
target_start_year = 0

# Change departments input format for easier use later
for i in range(0,len(department_impact)):
    if department_impact[i] == "Wagenpark":
        department_impact[i] = 0
    elif department_impact[i] == "Machines":
```

```
            department_impact[i] = 1
        elif department_impact[i] == "Gas":
            department_impact[i] = 2
        elif department_impact[i] == "Elektriciteit":
            department_impact[i] = 3
        else:
            # this loop should not be entered because of checks in Mendix
            print("The input data was not entered correctly")


# Define sets
D = [0,1,2,3]  # Departments: transport,machines,gas,electricity
T = range(target_end_year-target_start_year+1)  # Time periods
I = range(len(df_investeringen))  # Investments

# Deterministic parameters
delta = 0.0225  # Discount factor
M = 1000000000
alpha = 0.05 #confidence level for the chance constraint
penalty_cost = 1e40 #very high to prevent penalties

# Stochastic parameters
costs = np.zeros((len(S), len(I)))
emission_reduction_factors = np.zeros((len(S), len(I), len(D)))

for s in S:
    for i in I:
        # Truncated normal reduction per department per investment
        for d in D:
            a = (0 - reduction_impact[i]) / st_dev_impact[i]
            b = (1 - reduction_impact[i]) / st_dev_impact[i]
            if d == department_impact[i]:
                emission_reduction_factors[s, i, d] = truncnorm.rvs(a, b,
                loc=reduction_impact[i], scale=st_dev_impact[i])
            else:
                emission_reduction_factors[s, i, d] = 0
        # Sample lognormal initial investment cost per investment
        if initial_costs[i] != 0 :
            mu = np.log(initial_costs[i]) - (st_dev_costs[i]**2)/2
            scale = np.exp(mu)
            costs[s, i] = lognorm(s=st_dev_costs[i], scale=scale).rvs()
        else:
            costs[s,i] = 0

# Create Gurobi Model
model = gp.Model("Stochastic Investment Decision Model")

# Decision variables
x = model.addVars(I, T, S, vtype=GRB.BINARY, name="x")
y = model.addVars(I, T, S, vtype=GRB.BINARY, name="y")
c = model.addVars(D, T, S, vtype=GRB.CONTINUOUS, name="c")
```

```
z = model.addVars(S, vtype=GRB.BINARY, name="z")
target_penalty = model.addVar(vtype=GRB.CONTINUOUS, name="target_penalty")

# Objective function: Minimise total costs (avg over all MC simulations)
total_costs = 1/len(S)* gp.quicksum(
    (x[i, t, s] * costs[s, i] + yearly_costs[i] * y[i, t, s]) / (1 + delta)
    for i in I for t in T for s in S)
total_costs = total_costs + penalty_cost*target_penalty
model.setObjective(total_costs, GRB.MINIMIZE)

# Set the constraints

# 1. Chance Constraint on emissions based on SAA
model.addConstr(
    ((1 / len(S)) * gp.quicksum(z[s] for s in S)) >= 1 - alpha,
        name="ChanceConstraint")

# 2. Assign value to z_s based on whether the reduction target is met
for s in S:
    model.addConstr(gp.quicksum(c[d, T[-1], s] for d in D)
        <= (1-target+target_penalty) * gp.quicksum(c[d, 0, s] for d in D)
        + M * (1 - z[s]), name=f"TargetAchieved_{s}")

# Stay below investment budget
# Not used for Hegeman, but can be commented in for the complete model.
# for t in T:
#     for s in S:
#         model.addConstr(gp.quicksum(x[i, t, s] * costs[s, i] for i in I)
    <= budget, name=f"Budget_{s}_{t}")

# 3. Do all mandatory investments
for i in I:
    for s in S:
        model.addConstr(
            gp.quicksum(x[i, t, s] for t in T) >= mandatory[i],
                name="MandatoryInvestments")

# 4. Calculate emissions based on reduction impact
for d in D:
    for t in T:
        for s in S:
            if t >0:
                model.addConstr(
                    c[d, t, s] == c[d,t-1,s] -
                    (gp.quicksum(start_emissions[d]*x[i,t,s]*
                    emission_reduction_factors[s, i, d] for i in I)),
                    name=f"EmissionReduction_{d}_{t}_{s}")

# 5. Determine y based on x (investment dependency)
for tau in T:
    for s in S:
```

```
        for i in I:
            model.addConstr(
                (y[i, tau, s] == gp.quicksum(x[i, t, s]
                for t in range(tau + 1))),
                name=f"InvestmentDependency_{t}_{s}")

# 6. Can only invest within allowed range
#6a. startyear
for i in I:
    for t in T:
        for s in S:
            if t < start_year[i]:
                model.addConstr(x[i, t, s] == 0,
                name=f"TimeRestrict_{i}_{t}_{s}")
#6b. endyear
for i in I:
    for t in T:
        for s in S:
            if t > end_year[i]:
                model.addConstr(x[i, t, s] == 0,
                name=f"TimeRestrict_{i}_{t}_{s}")

# 7. set the emissions in the first year (t=0)
for d in D:
    for s in S:
        model.addConstr(c[d, 0, s] == start_emissions[d],
        name="StartEmissions")

# 8. investments 4 and 6 can never both occur
for s in S:
    model.addConstr(gp.quicksum(x[4,t,s]+x[6,t,s] for t in T)<=1,
    name="either_A_or_B") #either electric vans or use HVO diesel

# Solve model
model.optimize()

# Display results and plot
if model.status == GRB.INFEASIBLE:
    print("Model is infeasible.")
elif model.status == GRB.OPTIMAL:
     # Track total costs
    total_investment_costs = 0
    total_yearly_costs = 0

    # Track investments, emissions and penalty by year
    investment_per_year = {t: [] for t in T}
    emissions_by_department = {d: [] for d in D}

    for i in I:
        for t in T:
            for s in S:
```

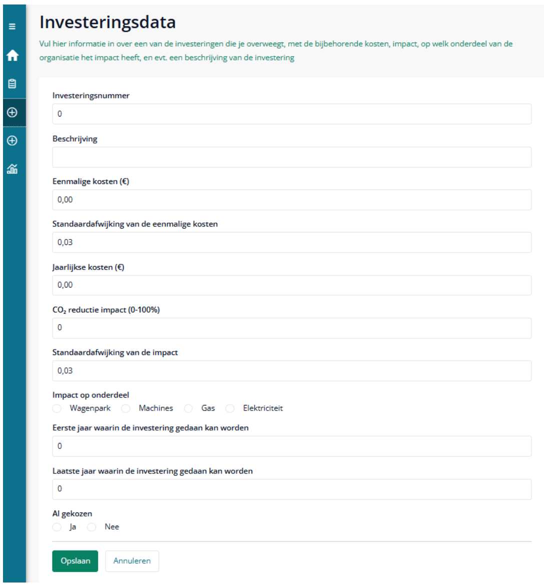
```
                if x[i, t, s].X > 0.5: #binary x so 0 or 1
                    investment_per_year[t].append(i)
                    total_investment_costs += (x[i, t, s].X * costs[s, i])
                    / (1 + delta) ** t
                    total_yearly_costs += (yearly_costs[i] * y[i, t, s].X)
                    / (1 + delta) ** t

# Calculate emissions by department over all years and iterations
for d in D:
    for t in T:
        emission_sum = 0
        for s in S:
            emission_sum += c[d, t, s].X
        emissions_by_department[d].append(emission_sum / len(S))

# PLOT: EMISSION REDUCTION OVER TIME PER DEPARTMENT
plt.figure(figsize=(10, 6))
D_Labels = ["Transport", "Machines", "Gas", "Electricity"]
for d in D:
    plt.plot(T, emissions_by_department[d], marker='o',
    label=D_Labels[d])
plt.title("Average yearly emissions per department")
plt.xlabel("Year")
plt.ylabel("CO$_2$ emissions (tonnes)")
plt.legend(title="Departments")
plt.xticks(ticks=list(T), labels=[f"20{t + 24}" for t in T])
plt.grid(True)
plt.savefig("MENDIX_departments.png")

# PLOT: SCOPE 1 AND 2 EMISSIONS
scope1_emissions = [emissions_by_department[0][t] +
emissions_by_department[1][t]
        + emissions_by_department[2][t] for t in T]
scope2_emissions = emissions_by_department[3]

plt.figure(figsize=(10, 6))
plt.plot(T, scope1_emissions, marker='o', label='Scope 1')
plt.plot(T, scope2_emissions, marker='s', label='Scope 2')

plt.title("Scope 1 and 2 emissions per year")
plt.xlabel("Year")
plt.ylabel("Average CO$_2$ emissions (tonnes)")
plt.xticks(ticks=list(T), labels=[f"20{t+24}" for t in T])
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.savefig("MENDIX_scopes.png")

# PLOT HEATMAP: matrix frequencies per investment per year
investment_matrix = np.zeros((len(I), len(T)))
```

```
# Populate the matrix
for i in I:
    for t in T:
        chosen_count = sum(x[i, t, s].X > 0.5 for s in S)
        investment_matrix[i, t] = chosen_count / len(S)  # Normalize

# Calculate the sum of each row and add it as the last column
row_sums = investment_matrix.sum(axis=1).reshape(-1, 1)  # row sum
investment_matrix_with_sums = np.hstack([investment_matrix, row_sums])
# Add the sums as the last column

# Create the plot
plt.figure(figsize=(14, 10))
sns.heatmap(
    investment_matrix_with_sums,
    annot=True,
    cmap="YlGnBu",
    cbar_kws={'label': 'Fraction of scenarios'},
    vmin=0, vmax=1,
    linewidths=0.5,
    linecolor='gray',
    xticklabels=[*range(1, len(T) + 1), 'Sum'],
)

plt.title("Fraction of investments frequencies over all scenarios")
plt.xlabel("Year")
plt.ylabel("Investment Description")
plt.xticks(ticks=np.arange(len(T) + 1) + 0.5, labels=[f"20{t+24}"
    for t in T] + ['Row sum'], rotation=45)
plt.yticks(ticks=np.arange(len(I)) + 0.5, labels=description,
    rotation=0)
plt.tight_layout()
plt.savefig("MENDIX_heatmap.png")

final_emissions_per_dept = [emissions_by_department[d][T[-1]]
    for d in D]
total_final_emissions = sum(final_emissions_per_dept)
total_initial_emissions = sum(start_emissions)

# CO2 reduction percentage
reduction_percentage = (total_final_emissions - total_initial_emissions)
    /total_initial_emissions * 100
reduction_percentage = - reduction_percentage

#calculate obj. value without penalties
obj_excl_penalties = 0
for i in I:
    for s in S:
        for t in T:
            obj_excl_penalties += (x[i, t, s].X * costs[s, i]
                + yearly_costs[i] * y[i, t, s].X) / (1 + delta) ** t
```

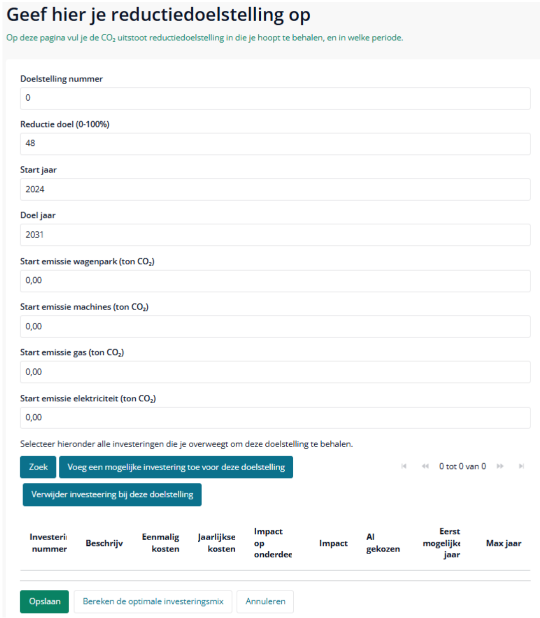
```
        obj_excl_penalties = obj_excl_penalties/len(S)


    # make base64 strings of the images using the function in other python file
    base64_heatmap = encode_image_to_base64("MENDIX_heatmap.png")
    base64_scopes = encode_image_to_base64("MENDIX_scopes.png")
    base64_departments = encode_image_to_base64("MENDIX_departments.png")

    result = {
        'Base64Departments': base64_departments,
        'Base64Heatmap': base64_heatmap,
        'Base64Scopes': base64_scopes,
        'Objective': round(obj_excl_penalties, 2),
        'ReductionPercentage': round(reduction_percentage, 2),
        'PenaltyPercentage': round(100 * target_penalty.X, 2)
    }

    # Return the result as JSON to Mendix
    return jsonify(result)


# This program runs on port 8000
if __name__ == '__main__':
    app.run(debug=True, port=8000)
```

A.2 Mendix application

In this section, the pages of the Mendix application are presented in the figures below. The output dashboard was already shown in Figure 19 in Chapter 7. Entering the input data can be done in Figure 22a for the investments, and in Figure 22b for the reduction target. Figure 23a shows the home page. Lastly, Figure 23b shows the overview page with all the data the user entered.



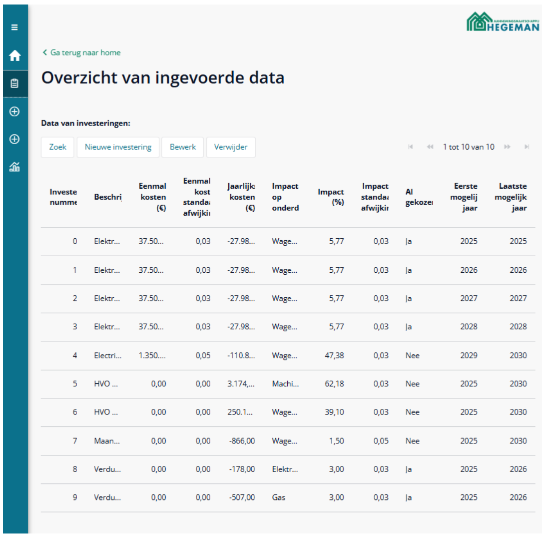
(a) Enter sustainable investment page.



(b) Enter emission reduction target page.

Figure 22: Application pages for entering input data.

(a) Home page of the application.



(b) Overview page of all input data.

Figure 23: Application home and overview page.