Investigating uncertainty in the heating transition

A Sensitivity Analysis case study of the CEGOIA model

Florian Hesselink

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Florian Xavier Adrianus Hesselink

Student number: 4384660

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Graduation committee

First Supervisor:	Dr. ir. E.J.L. Chappin	Energy and Industry
Second Supervisor:	Dr. ir. C. van Daalen	Policy Analysis
External Supervisor:	Dr. ir. N Voulis	CE Delft

Preface

Before you is the product of six months of work and the closing chapter of my time as a student at the faculty of Technology, Policy and Management at the Delft University of Technology.

In this thesis, I got to learn about and explore the dynamics and uncertainties of a topic that matters: the energy transition in the built environment. Although the world is increasingly serious about fighting the effects of climate change, time and time again we find that transitioning into sustainable alternatives is just plain difficult. It is expensive, complicated and messy. These pains are certainly felt in the struggle of switching away from natural gas to warm our homes. In my research, I analysed the CEGOIA model, which evaluates the financial and energetic impacts of changing to sustainable heating systems. In doing so, I explained how some of these effects come to be, as well as investigate how and which developments will change them. This should make it that much easier to comprehend the effects of changing energy costs, system efficiencies and insulation programmes on the path to sustainable communities.

I will say that the process of writing this thesis during the pandemic has not always been easy. I do well when I interact with my peers regularly, having discussions about substance and receiving and giving different perspectives on day-to-day struggles. I am, therefore, especially grateful to the many people that I still got to interact with throughout despite the restrictions we face. Sometimes face-to-face, but more often on Teams, Zoom or Skype.

A first and massive *thank you* I would like to put towards the fantastic people at CE Delft. Nina, my supervisor, your unrelenting interest in me and my work, your coaching and your feedback has helped me stay sharp, structured and honest when, at times, even I couldn't follow my own fuzzy logic. Marijke and Marianne, thank you very much for helping me navigate CEGOIA. Benno, Katja, Emma, Fenneke, Joram, Jasper and Pien, thank you for your input and interest, as well as the distractions you provided to the grind of doing this research. The morning talks, lunch lectures and other events were fun and very welcome distractions. I much enjoyed working with you and know I will continue to do so in the future!

I would also like to acknowledge the great support from those at TU Delft. Emile, I've known and worked with you for a few years now and have always appreciated your constructive, enthusiastic, yet critical style. Els, I want to thank you for your insightful perspectives on the work I've been doing, which helped me approach my method from better angles. I also thank the network provided through the Energy Transition Lab, headed by Emile and Gerdien. The thesis circle with Lisette and Ruben was a great addition, and our biweekly talks at which we shared graduation struggles provided a much-appreciated sanity check.

Finally, I would like to thank my friends and family. I cannot imagine having gone through this process without the stability and support from my father, brother and friends, even if much of it was from a distance.

Florian Hesselink,
Delft, April 2021

Executive Summary

Most Dutch buildings use natural gas for heating, but sustainable alternatives are necessary to reduce emissions and curb climate change. The Dutch government plans to achieve zero emissions by 2050 and has called for local coordination of the energy transition in the built environment. This heating transition is costly as well as complicated: there is a range of systems that can be used for heating because there are many possible alternatives. Examples are heat pumps, hybrid heat pumps and district heat networks which, depending on the temperature of heat delivered, require additional insulation of buildings. Evaluation, simulation and optimization models have been developed to support policymakers in decision making. One such heating transition model is CEGOIA, developed by CE Delft. CEGOIA calculates the costs of a variety of heating systems and optimizes the allocation of scarce energy carriers such as green gas and hydrogen to find the lowest societal costs. There is a lot of uncertainty about the future of cost developments, technological improvements and governmental policy, which CEGOIA can include in its scenarios. To use these scenarios in a meaningful manner, it is crucial to know which trends dominate the system that is being modelled. As choosing a heating system also involves making an investment decision, it is also desirable that these scenarios can capture and quantify the uncertainty and risks related to making choices. To do this, it is necessary to first know how sensitive model results are to the varying developments causing uncertainty. The most sensitive trends are those that are truly consequential to the outcome of a heating transition model, and understanding them enables policymakers to identify what to focus on in making robust decisions.

Sensitivity Analysis (SA) is the study of how uncertainty propagates in models. The practice is part of a good modelling process, but a review of Dutch models and academic literature has found only a handful of cases that detail the SA process for energy transition models. What's more, is that oftentimes studies that do perform SA use methods that are inadequate to properly capture model dynamics. For this reason, this study aims to add to the body of literature on the topic with an SA case study of the CEGOIA model. The purpose of this SA was to identify a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options. Special care was taken to evaluate the steps necessary to perform SA on a heating transition model. Insights from this analysis, together with two interviews with other Dutch heating transition model owners, were used to evaluate the value of SA. All of this was done to answer the following research question:

How can uncertainty in the context of Dutch heating transition models be adequately investigated using Sensitivity Analysis?

The research approach used for answering this question involves a case study in which a Sensitivity Analysis of the CEGOIA model is performed. Interviews with model owners of two other major Dutch heating transition models, Vesta MAIS and the Energy Transition Model, are furthermore used to provide context and verify the findings of this study. Conceptualization of the CEGOIA SA involved making choices about scope, inputs, outputs and techniques. The scope chosen for this analysis is limited to the analysis of eight heating system options, including heat pumps, hybrid heat pumps, boilers and district heat nets. The total societal costs for these options were evaluated in five archetypical neighbourhoods, constructed by aggregating real-world neighbourhoods and differentiated by density and building age. Three SA techniques were used to select,

group, and evaluate sensitivities from a total of 953 CEGOIA model parameters. The first technique, making use of Fractional Factorial analysis, was used as a screening step to reduce the number of parameters to consider. The second technique, the Method of Morris, was used to identify the most sensitive parameters for each heating system option. The third and final technique involved using the Sobol' method on seven trend variables that were found to be influential for most of the evaluated heating system options. These trend variables are costs of insulation and heating systems, gas, electricity and heat network infrastructure costs and the gas price and the electricity price. This selection was restricted by the computational time needed to use the Sobol' method.

Results of the CEGOIA SA suggest that for each of the heating system options, a small but system-specific set of parameters is responsible for most of the sensitivity. Major drivers of the cost of heating alternatives are generally the prices of energy such as electricity, gas and biomass, as well as the costs of electricity and gas infrastructure. Similarly influential are the investment costs of heat production systems such as a heat pump. For district heat networks, the connection costs of the heat networks to buildings replaced the importance of those investment costs. Insulation costs were found to be very influential in neighbourhoods built before 1990, whilst heating demand was found to be of relatively low importance. These sensitivities were consistent among the different neighbourhoods and so are generalizable. When using a model like CEGOIA on a region, the objective is generally to identify which heating system option is cheapest and where. The sensitivities found using this SA imply high uncertainty margins on the model results, and as such, interpreting the model's heating system selection at face value is inadequate. Instead, those options that are close to being the cheapest should all be considered. In comparing these options, the underlying sensitivities of the options should be used to assess the confidence in their costs becoming lower or higher in the future.

The CEGOIA SA resulted in a quantitative and logical representation of a complex subject matter: the most important factors that determine the choice of one sustainable heating system over another. This choice is rarely straightforward because every neighbourhood and every building has unique properties that influence the comparison between systems. Besides this, it has demonstrated that Sensitivity Analysis can be used to explore dynamics in large and complex models such as CEGOIA, Vesta MAIS and the ETM. According to model owners, this is increasingly necessary because the questions which models need to answer – as well as the models themselves – are becoming more complicated over time. In this light, the use of SA for focussing model development is an additional useful application. Vesta MAIS and ETM model owners indicated that developing features that allow for the use of fast and flexible SA is not infeasible, and as such, can feasibly become part of their user's toolset.

Several recommendations are suggested based on the insights of this research about SA, the first of which relates to the practice of the method in modelling in general. Heating transition model developers can and should start using or more thoroughly use systematic SA methods. What's more, is that they should integrate SA as part of the development process, developing functionality with which the configuration and analysis of SA experiments are made easy. In doing so, they can improve their model with allows model users to perform more insightful analysis. In turn, society will benefit from an increased understanding of the heating transition based on this analysis.

With regards to the analysis of CEGOIA, some more specific recommendations for further SA research are suggested that would improve both practical as academic knowledge about heating transition models. One such possibility is the inclusion of energy availability factors, which were not included in this analysis. More heating system options could furthermore be analysed, including more model parameters to arrive at a complete picture of the sensitivities of heating system options. A prohibitive factor is the computation time of CEGOIA, which is quite high compared to other models such as Vesta MAIS and ETM. If this time would be reduced, further SA and the analysis of scenarios constructed using sensitive parameters could be done. In turn, these analyses can inform decision making so that a choice for a heating system can be made with more confidence than is possible now.

Contents

Tables

Figures

Appendices

Due to their size and nature, Appendices I, IV and V are attached as separate documents.

I - Scientific Article

II - Interviews

II - Neighbourhoods

IV - Experiments

V – Figures

Abbreviations

ABM	Agent-Based Modelling
DMDU	Decision Making under Deep Uncertainty
EE	Elementary Effects (Morris Method)
ESM	Energy System Model
ETM	Energy Transition Model
FF	Factor Fixing
FF	Fractional Factorial analysis
FM	Factor Mapping
FP	Factor Prioritization
GSA	Global Sensitivity Analysis
IAM	Integrated Assessment Model
IE	Interactive Effect
ME	Main Effect
MILP	Mixed-Integer Linear Programming
MM	Method of Morris
NUSAP	Numerical Unit Spread Assessment Pedigree
OAT	One factor at A Time
SA	Sensitivity Analysis
S1	First-order Sensitivity Index
ST	Total-effect Sensitivity Index
STTM	Socio Technical Transition Model

1 Introduction

1.1 Topic

A fundamental shift in the sourcing and consumption of energy is necessary to curb climate change. This shift requires large investments into systems that are capable of sustainable sourcing and delivery of power and heat. Decarbonizing modern economies requires a diverse set of often sector-specific techniques and technologies (Loftus, Cohen, Long, & Jenkins, 2015). One such sector is the heating of the built environment. Notable challenges arise in this sector due to a diverse building stock and many possible sustainable heating technologies, all of which require active participation, organisation of building owners and innovative and robust decision making. This process is hereafter referred to as the 'heating transition' in the built environment.

The Dutch government has chosen to organize this process on a neighbourhood scale, meaning that local governments focus on refurbishing buildings that are in social and physical proximity and mostly have similar physical characteristics (Ministerie van Economische Zaken en Klimaat, 2019). In this context, refurbishing refers to both the improvement of energetic performance through insulation as well as the heating system conversion to accommodate a sustainable energy source. The target is to complete the heating refurbishment of eight million buildings – seven million of which residential – from predominantly relying on natural gas to using sustainable alternatives by 2050. Several elaborate energy transition models were developed to assist local governments with this task, including Vesta MAIS, the Energy Transition Model and the main model that will be examined in this study: CEGOIA (Brouwer, 2019). These models rely on a broad range of energetic, economic and spatial information. Furthermore, they make assumptions about technological developments, resource availability and price fluctuations to project the energy system into the future, outputting information such as technology choices, emission reductions and costs. The models are mostly used in aid of vision forming by aggregating information and performing some social cost/benefit analysis on one or more subsystems of the energy system (Netbeheer Nederland, 2020).

Mathematical modelling is an increasingly common approach to informing policy decisions on complex socio-technical issues such as the energy transition (Chappin, 2011; Horschig & Thrän, 2017). There are caveats and risks related to this approach, however, since models inherently only represent a specific part of the world and do so using a limited set of data and biased logic. Researchers must understand how results are applied to answer policymakers' questions and it is equally necessary for policymakers to understand the limits of models.

Models used for the energy transition often have a large set of independent input variables as well as a set of interdependent internal variables, which leads to a better representation of complex real-world dynamics than a simpler model would (Kann & Weyant, 2000). They can therefore be characterized as describing both complex and complicated systems - which contain a lot of different components and many unknowns (van Dam, Nikolic, & Lukszo, 2013). Those properties lead to a need for more scrutiny to guarantee an acceptable level of model validity, as well as to understand the effects of uncertainty introduced.

The principal method to investigate the dynamics of the uncertainty of models is Sensitivity Analysis (SA), which is the practice of systematically attributing model outcomes to specific model inputs. SA of large techno-economic energy transition models is important, yet is often overlooked or done inadequately by modellers (Bottero, Dell'anna, & Morgese, 2021; Ferretti, Saltelli, & Tarantola, 2016; Pye, Sabio, & Strachan, 2015). There are several reasons for this. First, methods used for SA are highly model-specific, meaning there is no 'one size fits all' approach to carry out the analysis. Second, for models with many inputs and interdependent variables, attributing effects of inputs can quickly become an impractically large task as the number of simulations required to draw sensible conclusions increases exponentially with model size. Some authors conclude that a rigorous SA so thoroughly scrutinizes a model's sensitivities that the practice may reveal to be self-destructive to the model's usefulness (Iooss & Lemaître, 2015). Another explanation may be that the diverse toolkit encompassing SA and the diverse set of uses is not that well-known to modellers (Interviews with model owners, Appendix II - Interviews). Without performing SA, however, energy transition modellers cannot confidently answer policymakers' questions regarding, for example, the impact of a changing electricity price or the availability of green gas on the given recommendations. Advisors tend to know what developments introduce a lot of uncertainty and are therefore important, but they have not yet investigated and quantified this uncertainty for the heating transition (Pye et al., 2015).

1.2 Knowledge gap

Because of the significance of local circumstances, the energy transition in the built environment requires elaborate and tailored analyses. The models developed for this purpose are consequentially complicated and complex, which makes the process of validating the model difficult. This process of validation – specifically through sensitivity analysis – is important not only because it adds legitimacy to the model outcome but also because it improves understanding of the system being modelled. Alarmingly, few studies cover SA for energy transition models, even fewer specifically cover the heating transition and perform a comprehensive SA which leads to useful recommendations. The problem statement is: *There is a lack in the understanding of uncertainty in models that are used to support policymakers with organizing the energy transition in the built environment*

This statement alludes to the knowledge gap to explore: What is the potential of the practice of Sensitivity Analysis to aid the understanding of uncertainty in heating transition models? Investigating this gap requires the investigation of several topics, including a better understanding of current modelling practice, the viability of SA for these types of models and the ability of SA to provide useful insights.

1.3 Research objective and relevance

The objective of this research is to investigate the application of sensitivity analysis on energy transition models. This objective has two major aspects, the first of which is to evaluate the process itself by carrying out SA on the CEGOIA model. This analysis uncovers insights about uncertainty in the model as well as identifies specific difficulties related to carrying out SA on heating transition models. The quality of the SA results are scrutinized to evaluate the usefulness of the process to both modellers and policymakers. The second way in which this objective is fulfilled is by describing the state of SA in the field of heating transition modelling, as there is little known about it currently.

The research contributions are fourfold: First, deeper understanding is gained about the CEGOIA model. This serves as a way to guarantee the quality of its conclusions and contrasts the current use of the model with its fundamental uncertainties. This furthermore provides insights into the functioning of a heating transition model from an as of yet undocumented perspective. Second, insights about the process of SA are applied to provide lessons for future modelling, as well as nuance the use of models in real-world contexts, providing societal relevance. Third, the analysis of CEGOIA adds to the body of literature on Sensitivity Analyses for energy transition models, which as previously stated is quite sparse. Finally, by investigating the state of SA in the field and investigating its potential usefulness to modellers and policymakers, practical recommendations to improve the process of policymaking in the heating transition is done.

1.4 Research questions

This research project aims to make a contribution by investigating the identified knowledge gap by answering the following main research question:

How can uncertainty in the context of the Dutch heating transition be adequately investigated using Sensitivity Analysis?

To produce a comprehensive and structured answer to this question four sub-questions were formulated:

1. *How is uncertainty in heating transition models understood and dealt with?*
2. *How can the Sensitivity Analysis process be used for heating transition models?*
3. *What are the CEGOIA factor sensitivities and their effects*?
4. *How do CEGOIA Sensitivity Analysis results improve comprehension of heating transition models and the heating transition as a whole?*

The first question involves researching the literature as well as evaluating the CEGOIA model. By doing this, the nature of uncertainty and its various manifestations in CEGOIA are described. This description also serves as a way to focus on which uncertainties are relevant to explore in heating transition models. The second sub-question is answered to clarify the requirements for and limits to applying SA on heating transition models. Answering sub-question three then serves to combine insights about uncertainty and characteristics of heating transition models by applying them in a systematic Sensitivity Analysis. By investigating the CEGOIA sensitivities, various insights are gained about using the SA method on a heating transition model. These results are then scrutinized to conclude in what way the method has value through sub-question 4. Answering these four questions will complete the study of the applicability and usefulness of Sensitivity Analysis on the CEGOIA model. Those methodological insights will then be applied to a broader context of Dutch heating transition modelling.

1.5 Research approach & methods

The research approach used in this project is a case study of the CEGOIA model. This approach is chosen because Sensitivity Analysis requires an existing model to analyse, and creating a dummy heating transition model for this research is undesirable as well as infeasible. Since few systematic Sensitivity Analyses have been done on heating transition models, a case study approach is furthermore necessary to demonstrate the qualities and challenges of Sensitivity Analysis. This case study has a strong methodological focus, in which the experiences surrounding the process of SA are of equal importance to the analysis outcomes. CEGOIA is the only model for which the process of SA is conceptualized, applied and evaluated, but two other cases will also be compared through the means of interviews with heating transition model owners. These interviews concern the Vesta MAIS and Energy Transition Model. Insights from these cases serve to add context about uncertainty in the heating transition, validate the results of the CEGOIA SA and discuss the value of SA as an additional method. In doing so, one of the main drawbacks of case studies – few data points and a resulting low level of generalizability – is mitigated.

This research is a cooperation between CE Delft and the Delft University of Technology. CE Delft is an independent research and consulting firm which specializes in sustainability. The CEGOIA model is being developed and used by the organization's Sustainable Cities (*Duurzame Steden*) sector, which uses it to aid Dutch policymakers in developing plans to decarbonise the built environment. CEGOIA is one of several models capable of being used for this purpose, as it can be applied to any geographical area in the Netherlands and uses high-quality data (Netbeheer Nederland, 2020). Because of the cooperation, CEGOIA is used as a case study for performing sensitivity analysis.

Specific methodology related to sub-questions will now briefly be discussed and linked to the structure of this document. The first part of this research is the gathering of information about heating transition models. To this end, the following sub-question is formulated:

1. *How is uncertainty in heating transition models understood and dealt with?*

This question is answered by a combination of academic literature research, technical analysis of the CEGOIA model and other heating transition models, as well as interviews with heating transition owners. The theoretical background covering this question is reported in chapter 2, whilst the review of specific models is reported in chapter 3. The subsequent research question serves to define what SA is, what it can be used for and how it can be done:

2. *How can the Sensitivity Analysis process be used for heating transition models?*

Answering this question involves the consultation of academic literature and the conceptualization of a plan with which SA can be used on the CEGOIA model. The literature study SA is found in chapter 4, whilst the application of this knowledge, the CEOGIA SA method, is presented in chapter 5. The third sub-question focuses on the insights gained from the execution of this method:

3. *What are the CEGOIA factor sensitivities and their effects*?

The results of CEGOIA SA are generated by running the model thousands of times with variations in input values. Factor sensitivities are then estimated using statistical methods. These sensitivities are presented, and their implications are discussed in chapter 6. The final sub-question serves to connect the results of

CEGOIA SA with the insights from earlier sub-questions that culminate in a reflection on the value of the SA method:

4. *How do CEGOIA Sensitivity Analysis results improve comprehension of heating transition models and the heating transition as a whole?*

This question is answered in the discussion in chapter 7 and makes use of both SA insights and interviews with heating transition owners, which are covered in chapters 3 and 4. After having answered the four sub-questions, conclusions and recommendations are formulated in chapter 8, which serve to answer the main research question.

How can uncertainty in the context of Dutch heating transition models be adequately investigated using Sensitivity Analysis?

The main research question is then answered by combining answers about the characteristics of heating transition models, the experience with using SA methods in this case study, the results gained from the analysis as well as the discussion of their added value. Conclusions and several recommendations are presented in chapter 7. This document's structure is summarized in Figure 1.

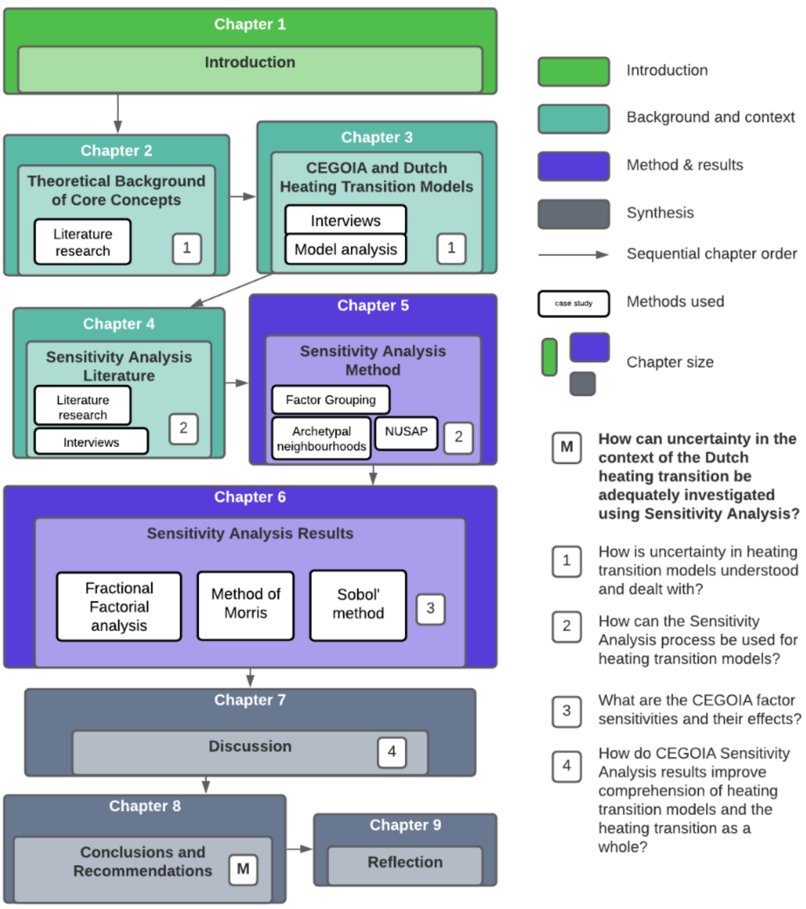


Figure 1: Document structure

2 Theoretical Background of Core Concepts

This chapter serves as an introduction to the theory behind the use of modelling for the heating transition. First, a rationale for why and how models should be used for policymaking is given in section 2.1. This explanation provides context to the CEGOIA model and serves as a basis for further interpretation of analysis results. The central concept of uncertainty – and how it relates to modelling – is developed in section 2.2. This fundament then provides the basis for answering the question '*How is uncertainty in heating transition models understood and dealt with?*' in the next chapter. Section 2.3 describes and defines what heating transition modelling is and the different approaches for it. Section 2.4 summarizes the findings of the chapter.

2.1 Models in support of policymaking

Many things can be called a model, only some of which are relevant when it comes to the purpose of policymaking. Policymaking itself is often described as a cyclical process, the so-called policy cycle. The phases in this cycle are agenda setting, policy formulation, decision making, implementation and evaluation (Veenstra & Kotterink, 2017). In recent years policy aims to address increasingly complex problems, climate change being the prime example (Marchau, Walker, Bloemen, & Popper, 2019). As a result of this trend and increased technological capabilities, data-driven and evidence-based approaches are emerging as popular ways to inform policymaking in various phases of the cycle (Veenstra & Kotterink, 2017).

The hexagon framework of policy analysis by Mayer, van Daalen, & Bots (2007) summarizes the policy analysis activities with which policymakers can be supported. A model-focused adaptation of that framework is provided in Figure 2 (Yücel & van Daalen, 2009). Six styles of models, each distinctly related to a specific objective are listed. Decision making in particular can be made easier by gathering and aggregating complicated processes in such a way that information is insightful to not only policymakers, but also other involved actors (Koussouris, Lampathaki, Kokkinakos, Askounis, & Misuraca, 2015).

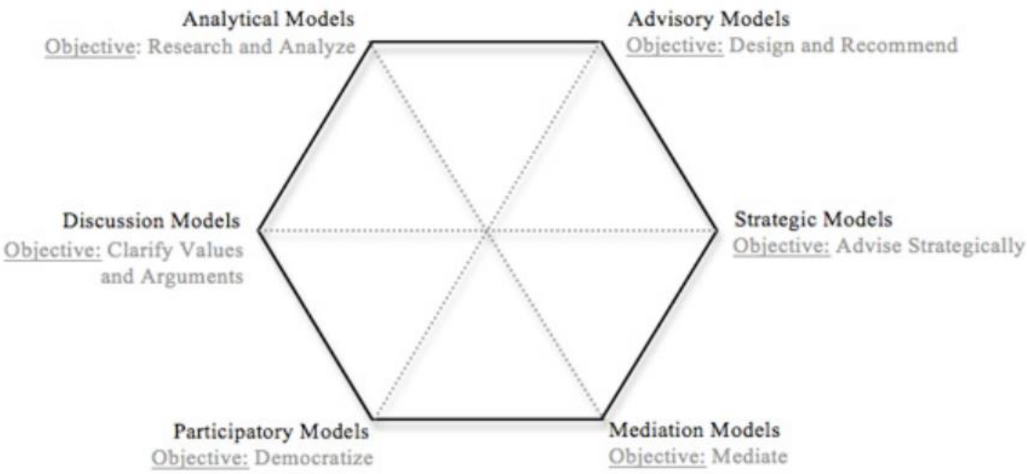


Figure 2: Hexagon model overview of types of models to support policymaking (Yücel & van Daalen, 2009)

Energy transition models for the built environment often fulfil multiple objectives of policymaking models (B A Henrich, 2020). For one, they serve to introduce a shared reality, a baseline from which actors can start discussions. Indeed, most models used in the Dutch heating transition claim to specifically fulfil this purpose. In practice, however, policymakers often use the models to fulfil the objectives of recommending solutions and advising on strategy (Brouwer, 2019). This mixed-use of model applications is problematic since the rationale behind the uses conflicts (Mayer et al., 2007). As a result, model outcomes can be interpreted in incorrect ways and even be used for (the wrong) purposes, unintended by the modeller. Clarifying values and arguments involves answering normative and ethical questions. Designing and recommending a solution requires the formulation of some shared reality on which to act, as well as a complete set of information to consider. Advising strategically can only be done if the client's position is known and needs are considered. To formulate the dilemma of the purpose of a heating transition model: policymakers wish to use them to create a strategy, which cannot be done if the set of information and assumptions is not confidently certain. This set of assumptions cannot be certain because of the uncertain nature of a future energy system, which may lead to a disagreement about a shared reality for actors involved. At the core of the mismatch is uncertainty about the energy system.

Model uncertainty can in one part be dealt with using a good modelling process. Models can be powerful tools to support decision making, but making a relevant and useful model is not easy. Good modelling practice, as described by (Nikolic et al., 2019), involves thorough applications of several principles and good practices to ensure the integrity and value of a model. Nikolic et al. focus on five general principles:

1. **All models are wrong, but some are useful**. A model is only a representation; a simplification. The amount of complexity included in the model structure is a delicate balance where too much complexity results in a very difficult to use model and too little in one that is not useful in providing answers.
2. **Modelling is making choices and assumptions**. Decisions made by a modeller are implicit to a model; the model will only ever be as good as the decision-making skills of the modeller and the assumptions on which they base it.
3. **Garbage in = garbage out**. If one makes use of inputs that are incorrectly representing the system being modelled then the outputs will also be incorrect.
4. **Re-run, repeat, reproduce, reuse and replicate**. A model needs to be set up in such a way that results can be reproduced and scrutinized.
5. **Openness is essential**. Models can have a big impact on the real world and so it is prudent to have the model and data be as transparent as possible.

With regards to model uncertainty, Nikolic et al. (2019) stress the importance of input uncertainty handling. Every parameter has a margin of error which should be described. Uncertainty is also not always symmetrical: there can be optimistic or pessimistic expectations implicit to the variable. The expected developments in the variable's value should also be described to be able to reduce the parametric uncertainty over time.

2.2 Descriptions of uncertainty

Uncertainty is an abstract concept that knows many definitions. Penrod (2001) proposes the following general definition that can be applied across disciplines: "*Uncertainty is a dynamic state in which there is a perception of being unable to assign probabilities for outcomes*". This definition implies that, until an outcome materializes, there can be no good estimation of what that outcome will be since the state of uncertainty itself changes over time. By describing uncertainty as a perception, Penrod implies uncertainty is an inherently subjective qualifier. This is, however, not necessarily the case according to the interpretation from Funtowicz & Ravetz (1990). They add that uncertainty is not just the absence of knowledge, it can also be the situation of having access to inadequate information. Information can be inexact, unreliable or border on ignorance. Access to more information can, therefore both decrease and increase uncertainty. Contrary to a lack of knowledge, a lack of information is an objective deficiency that can partially be mitigated using scenario-thinking, expert-based risk assessments and other techniques. This is the mindset that is often used in a policy context such as that of the heating transition. To add to the definition of uncertainty is that it also involves having a limited understanding of events past, current and future (Warren E. Walker, Lempert, & Kwakkel, 2013). Under this interpretation, it is especially important to acknowledge the role of subjective perceptions in the field of policymaking, seeing as a shared understanding is negotiated between actors. Lacking a shared understanding of events then results in a separate understanding of uncertainty.

The takeaway from these descriptions of uncertainty is that it is a subjective judgement rooted in one's understanding of the world. This judgement develops through access to information about events past, present and future as well as through interactions with others. As such, understanding uncertainty in the heating transition involves identifying relevant development and studying how they interact.

2.2.1 Model uncertainty

Uncertainty can be dissected and categorized in different parts when applied to modelling in support of decision making. It is this typification that is applied to the CEGOIA model in further chapters. Walker et al. provide a conceptual framework to aid in defining uncertainty ascertaining to model-based decision making (W.E. Walker et al., 2003). Any mathematical model relies on an implicit system model, which denotes the functional relationships between inputs and outputs. There are three dimensions to uncertainty in this structure: location, level and nature. Location of uncertainty points to where it manifests within a model. The level of uncertainty points to the level of knowledge available about a factor. The nature of uncertainty is a property inherent to the phenomenon being described.

The location of uncertainty in a model has five characteristics, the first of which is the context or completeness of the model: Should an element be part of a model? The second characteristic is that of structural and technical uncertainties. Should an element be modelled the way it is? The third characteristic considers both internal and external input factors. Should the factors be considered in the model? The fourth is parametric uncertainty: are parameters calibrated right, what is the quality of data used? The fifth and final characteristic of locational uncertainty is accumulated uncertainty at the point of model outcome: What assumptions in previous steps introduce uncertainty, and how has this uncertainty carried over in results? These five characteristics are relevant to the Sensitivity Analysis (SA) of CEGOIA as they can be used as a check: the SA identifies which developments are highly influential, the location of uncertainty reveals how well these developments' uncertainties are captured by the model.

W.E. Walker et al. (2003) recognize four escalating levels of uncertainty with regards to assumptions: deterministic statistical uncertainty, scenario uncertainty, recognised ignorance and total ignorance. At the most certain level, epistemic knowledge is sufficient to be able to describe uncertainty using statistical metrics like confidence intervals. For scenario uncertainty, a range of plausible outcomes is recognized, but the validity of this range is not verifiable. Recognised ignorance is any acknowledged uncertainty that cannot be described by such a range of outcomes. These last two levels of uncertainty are very common in energy transition models (Marchau et al., 2019; Pye et al., 2018). The final dimension of Walker et al. is nature. There can either be inherent variability or an actual epistemic lack of knowledge about something which causes an uncertain nature. The former is reduceable with more research whilst the latter is not.

2.2.2 Deep uncertainty and robust decision making

Besides model uncertainty, there is a more fundamental type of uncertainty that deserves attention. The concept of deep uncertainty is said to apply in situations in which the involved actors cannot agree upon 1) the external context of the system, 2) how a system functions and is bounded and 3) the system outcomes of interest and their relative importance (Warren E. Walker et al., 2013). Deep uncertainty as defined here can be considered as a parallel to or even an attribute of 'wicked problems' (Marchau et al., 2019). Wicked problems are a class of social problems that are difficult to solve; classic examples including climate change and sustainability. Generally, wicked problems have the following properties (Conklin, 2003):

1. The problem is not understood until after the formulation of a solution.
2. Wicked problems have no stopping rule.
3. Solutions to wicked problems are not right or wrong.
4. Every wicked problem is essentially novel and unique.
5. Every solution to a wicked problem is a 'one-shot operation.'
6. Wicked problems have no given alternative solutions.

Decision making in the heating transition is a part of the energy transition that is prompted by climate change. It is a comparatively small part of a larger wicked problem, but can be described as one in and of itself following the six properties of Conklin:

1. The goal of the heating transition is clear, but the path to get there is not. How fast should heating systems be changed, what systems will be used and who will pay for them? Different stakeholders in society have different views on these issues.
2. In a way, completing the heating transition is a matter of retrofitting building heating systems, envelopes and infrastructure. Which decisions are enough to get there, however, are unclear. The goalposts may also move: what is deemed sustainable now (e.g. biomass) may not be considered as such in the future.
3. Taking houses off of natural gas, choosing for mass electrification or instead for insulation programmes are all decisions that can only in hindsight be deemed good or bad. Doing nothing and waiting for technologies to improve or economies of scale to take hold may just as well be good policymaking.

4. The efforts required for the heating transition are unprecedented, and the dynamics of affecting everybody in the country in an impactful, personal way is highly unique.
5. Deciding on a sustainable heating system for a given house or a neighbourhood requires considerations that are unique to the local circumstances. There is no 'one size fits all' decision: each intervention is unique.
6. There is no silver bullet for sustainable heating. Each alternative requires societal investments.

Since the energy transition is part of a wicked problem, it is evident that deep uncertainty is present in the field of policymaking for the energy transition in the built environment. For this reason, it is prudent to make decisions that are considered to be 'robust'. A generic definition of robustness is the ability of a system state to withstand or survive shocks, to be stable despite uncertainty (Bankes, 2010). Another definition is the ability of a system to withstand perturbations in structure without a change in function. In organization theory, robustness is defined as the capacity of an organization to retain this fundamental pattern at core characteristics under changing conditions (Capano & Woo, 2017). This quality of robustness is then characterized as being able to *"provide opportunities to develop policy processes for coping with change and shocks (and, thus, with uncertainty) either by maintaining stability or by designing more effective policies"*.

Decision making under deep uncertainty (DMDU) is a paradigm that applies when 1) systems describe a relatively high level of complexity, 2) in which there are many degrees of freedom and 3) the characterization of uncertainty is deep, rather than well-characterized (Hamarat, Kwakkel, & Pruyt, 2013; Marchau et al., 2019). These properties mean that 1) prediction of the effects of decisions are difficult, 2) there are many elements that can be changed with policy and 3) the understanding of what developments are important is unclear. To overcome deep uncertainty a modeller's strategy under this paradigm shifts away from the traditional future prediction and designing of interventions. Instead, modellers explore these systems by identifying which uncertainties make a difference. Then, plans are designed which are as insensitive to these differences or robust as realistically possible.

Lempert, Groves, Popper, & Bankes (2006) suggest a general rule-based framework with which to support DMDU, summarized in Figure 3. Essential takeaways are that this type of model-based policy support is an iterative process. Uncertainty is captured through rigorous applications of analytic methodology and used to explore a scenario space. Elaborate SA plays a big part in this methodology. Using traditional risk mitigation strategies in which probabilities are assigned to the explored scenarios is not desirable. Instead, policy alternatives are to be constructed that result in robust system behaviour under different scenario conditions. The strength of this approach is that it bypasses uncertainties at the core of a traditionally predictive manner of model use (Hamarat et al., 2013). The advantage comes at a significant investment cost in the analysis. One needs to not only analyse vulnerabilities in a model through subspace partitioning and sensitivity analysis but also apply quantitative techniques to generate scenarios. Additionally, robustness metrics need to be defined and applied to evaluate policy alternatives. DMDU is therefore a paradigm and not a method; it is best suitable for assisting longer-term policy programs.

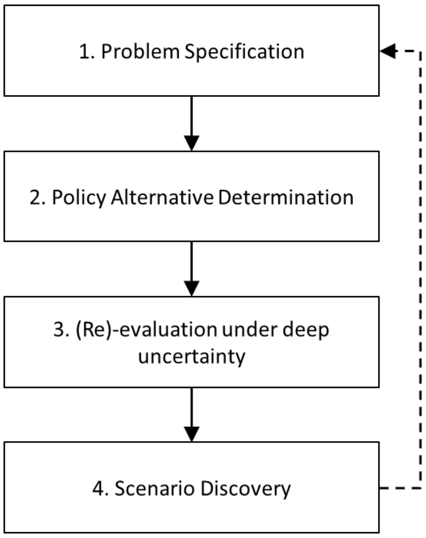


Figure 3: Decision support framework for robust decision making (Lempert et al., 2006)

Since the heating transition can be considered a wicked problem and DMDU is a paradigm that fits decision making in such circumstances, it could be useful to integrate this approach with the use of models that are currently used for heating transition modelling.

2.3 Typification of heating transition modelling

In the previous sections, the suitability of models to inform decision making in complex policy topics has been described. This section describes various modelling methodologies that are used for the energy transition in the built environment and their implications for supporting policy.

Energy transition policy evaluation is a well-studied topic that increasingly relies on a varied set of quantitative and qualitative methods, as summarized in Figure 4 (Horschig & Thrän, 2017). Quantitative models are often used to estimate the effects of a proposed policy, which then plays a big role in decision making. Hirt, Schell, Sahakian, & Trutnevyte (2020) performed an elaborate review of transition models for energy and climate solutions, and distinguished three types of modelling methodologies: Integrated Assessment Models (IAMs), Energy System Models (ESMs) and Socio-Technical Transition Models (STTMs). Integrated Assessment Models are global models that consider long term climate goals and evolutions of ecology, technology and environment; they are often used to develop long-term scenarios. In Horschig & Thrän's classification these are considered Top-Down models, whilst ESMs and STTMs are Bottom-Up style models. Energy System Models focus on the description and evolution of energy systems based on policy interactions. Finally, Socio-Technical Transition Models focus on the co-evolution of technology and society. Agent Based Models and System Dynamics models are part of this class.

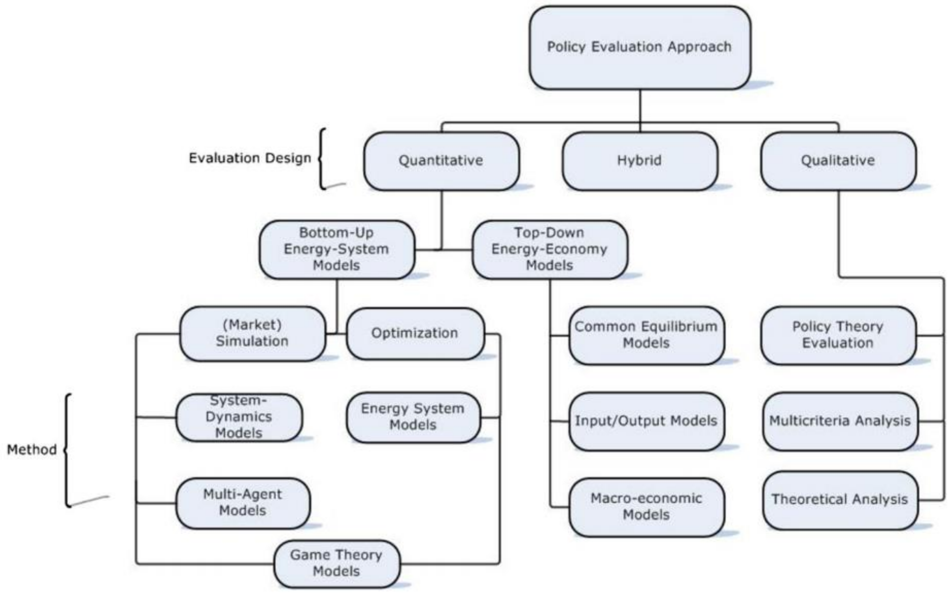


Figure 4: Classification of policy evaluation approaches - Horschig & Thrän (2017)

To understand how these modelling methodologies relate to the heating transition Henrich (2020) take an inventory of the models being used for the purpose. Henrich found a large variety of methodologies and models being used for the heating transition but could distinguish no systematic unifying principle with which to compare them. Instead, three common challenges were found. Each of the reviewed models has issues with the correctness and sensitivity of assumptions. This is to be an expected challenge for any modelling discipline. A second issue is usability for policymakers as well as the transparency of the modelling method. Models were often found to be on the side of too complicated to apply. The third issue is how economic, environmental and social factors are considered and combined. Heating transition IAMs, ESMs and STTMs all used some constellation of these three types of factors. This is not a unique property of heating transition models. Most energy transition models broadly use these dimensions for inputs.

A definition of heating transition models as considered in the scope of this research project is the following: *A heating transition model is a quantitative instrument used to support policymakers in the evaluation of policy alternatives for the energy transition in the built environment. These models describe one or more of the following factors on a specific geographic scale: energetic, economic, environmental and social.* Sub-divisions of heating transition models are further considered along the lines of Hirt et al. (2020).

2.4 Summary of insights related to uncertainty and modelling

System modelling can be used to support complex decision making in a variety of ways, but a model is not an answer. Interpretation of model results is based on a number of assumptions made about the underlying system. When discussing the energy system, these assumptions are uncertain in a variety of ways. Most critically, a lack of a shared reality between stakeholders about the state of the energy system, climate and technology cause friction in the policy cycle. Decision making for the heating transition can be described as a 'wicked problem', and the various Integrated Assessment Models (like CEGOIA), Energy System Models and Socio-Technical Transition Models that exist to support it might do well to be used under the DMDU paradigm. This chapter has provided a basis for answering the question '*How is uncertainty in heating transition models understood and dealt with?* ', further discussion of which is found in chapter 3.

3 CEGOIA and other Dutch Heating Transition Models

The state of heating transition modelling in the Dutch context is covered in this chapter. Section 3.1 provides an inventory of models that are actively used to support policymakers. It furthermore relates insights about dealing with the uncertainty described in the previous chapter from interviews with developers of Vesta MAIS and the Energy Transition Model. Section 3.2 serves as a functional description of the CEGOIA model and the subsequent section 3.3 relates how uncertainty affects the different elements to answer the question: '*How is uncertainty in heating transition models understood and dealt with?*'. Section 3.4 summarizes the findings of the chapter.

3.1 Dutch heating transition models and interviews

To provide context about Dutch heating transition models the most well-known ones were evaluated and two model owners were interviewed to provide context about how uncertainty is dealt with in their models. Table 1 provides a comparison of the main Dutch heating transition models, which were previously bundled by Brouwer (2019) and Henrich, Hoppe, Diran, & Lukszo (2021) who performed a systematic comparison of the methods and assumptions used in Dutch heating transition models.

Table 1: Classification of Dutch heating transition models

Name	**Energy Transition Model (ETM)**	**Vesta MAIS**	**CEGOIA**	**Warmte Transitieatlas (WTM)**	**Caldomus**	**Wijk-warmtemodel (WWM)**	**Integraal kostenmodel (IKM)**
Owner	Quintel	PBL	CE Delft	Over Morgen	Innoforte	DWA	DWA
Modelling methodology	Integrated Assessment Model	Energy System Model	Integrated Assessment Model	Energy System Model	Energy System Model	Energy System Model	Integrated Assessment Model
Type of model	Energy system modelling simulation	Techno-economic evaluation	Techno-economic optimization	Techno-economic evaluation	Techno-economic evaluation	Techno-economic evaluation	Economic evaluation

Out of the seven models, CEGOIA is most similar to Vesta MAIS, which is developed by the Planbureau voor de Leefomgeving (PBL), a government agency. Both model neighbourhoods (as defined by CBS) within the Netherlands and evaluate the effects of various sustainable options. WTM does this too, but Overmorgen does not provide any publicly accessible documentation for their model and so it is difficult to compare in-depth. The same lack of transparency goes for the two DWA models. Caldomus functions similarly to CEGOIA and Vesta MAIS, although the model appears to evaluate a smaller set of options than CEGOIA and Vesta MAIS. The ETM describes the entire energy system, albeit at a lower resolution than CEGOIA or the others. Due to its similarity, Vesta MAIS is selected for further discussion. The ETM is also selected because it stands out from the other models in using a different approach. Because of this, another perspective on heating transition modelling can be gained. It furthermore helps that the two selected models are transparent by providing elaborate documentation. Vesta MAIS and the ETM are both open-source models, the former being maintained by a governmental organization and the latter by a private organization, Quintel. The next section discusses the setup of the interviews with model owners at PBL and Quintel and discuss the relevant insights of these talks.

Semi-structured interviews with model owners were held, translated transcripts of which are available in Appendix II. References to, e.g. (line 62) refer to the point in the interview appendix where the sentiment was shared. The interviewees, Chael Kruip (Quintel) and Steven van Polen (PBL) each have several years of experience with the development of respectively the Energy Transition Model and Vesta MAIS. The interviews took approximately 1,5 hours each and were conducted in Dutch using videoconferencing. Several topics were discussed in the interview. The first topic to investigate was an evaluation of how heating transition modellers deal with the uncertainties within their models. SA is one method that can be used, but model owners may have very different perspectives on what is viable and important in the usage of their models. The second purpose of the interviews was to inquire about the level of familiarity the model owners have with Sensitivity Analysis. Since SA is an involved process that requires an express purpose to help structure the analysis, model owners may have no or limited interpretations of what the method involves. Finally, interviews were used to investigate the perceived value of performing Sensitivity Analysis. Not only the value for modellers themselves but also that for policymakers is discussed. The insights about the second and third point of interest are reported in chapter 4, after having provided further background about Sensitivity Analysis methods.

Vesta MAIS and dealing with uncertainty

Vesta MAIS (Multi-Actor Impact Simulation) has been in development since 2011, although development activity has snowballed in recent years. It functions similarly to the CEGOIA model (Schepers et al., 2019). Vesta MAIS is publicly available on www.github.com/RuudvandenWijngaart/VestaDV (Wijngaart, 2020). Even more so than CEGOIA, Vesta MAIS serves the purpose of aiding policymakers in creating a vision for the heating transition by evaluating the impacts of sustainable heating alternatives. It was explicitly created to evaluate national policy, but more and more, it is being used to answer questions on a regional or local level. As was conjectured in chapter 2, this mix of purposes creates tension between what the model is supposed to do and what kind of answers are desired by policymakers.

Steven van Polen shared three ways in which uncertainty is dealt with in the model. The first and most evident is that the model is purposed to rapidly evaluate multiple policies and scenarios (line 13). This way, the application of the model itself captures some uncertainty, although this uncertainty is not necessarily directly intrinsic to the model. The second way in which Vesta MAIS acknowledges and communicates uncertainty is by applying uncertainty spreads to results (line 47). Most parameters in Vesta MAIS have an optimistic and a pessimistic setting, and results are communicated to users within a spread or range of certainty, based on these settings. This way of dealing with uncertainty is more intrinsic to the model, as well as a typical example of how uncertainty is usually communicated. The third way in which uncertainty in Vesta MAIS is acknowledged and investigated is by using Sensitivity Analysis for specific trends, such as the prices of energy investment costs and learning effects (line 55). This analysis was done for one major project and specifically involved investigating the effects of changing one type of parameter to the pessimistic and optimistic settings.

In reflection on these insights about uncertainty handling in Vesta MAIS both positives and shortcomings in the approach can be highlighted. A scenario approach is a useful one and recommended under the DMDU paradigm, however the axes on which scenarios are created are important to consider too. Communicating the confidence in results based on optimistic/pessimistic value spreads for certain variables is a reasonable way to convey uncertainty, but brings other problems with it. For one, it is not possible to say anything on the distribution of outcomes within this spread. The choice of variables for which to apply this principle also matters a lot. Include too many variables and the result will consequently be a spread so large that all alternatives are within the range. Including only a few requires answering the question: which variables are important? Finally, the fact that some SA was done for Vesta MAIS is a good thing, although the method used could have been more systematic.

Energy Transition Model and embracing uncertainty

Quintel's Energy Transition Model (ETM), in development since 2010, is a holistic model that considers the entire energy system using energy balances (Quintel, 2020). Unlike CEGOIA and Vesta MAIS, the ETM does not provide a visual representation of the modelled system. Instead, it uses over 400 parameters to represents stocks and flows which summarize the development of an energy system from the current reality to a projected future year. The model is primarily an explorative model with which scenarios can be constructed and policies evaluated. Besides this general vision of how the model is being used, the model is usable as a way to quickly communicate the impacts of decisions (line 25). Increasingly, the ETM is also being used as an accounting tool as it provides a quantitative basis that can be used as input for other, more specific research (line 27). The ETM is available through an online tool at energytransitiomodel.com and documentation is available on www.github.com/quintel/etmodel.

An important difference between ETM and models like CEGOIA and Vesta is the way it is used. The ETM evaluates the effects of trends and policies on the entire energy system, but the model user has to specify all these changes and curate them to arrive at an intended outcome. This means that intrinsic model uncertainty principally relates to how the energy system is modelled, not to the numbers used for doing so. ETM model users are free to investigate the uncertainty of various model assumptions by changing sliders, since in a way the entire model is set up to be one big SA (line 35). In this way, the ETM embraces the many model and scenario uncertainties. Kruip mentions that Quintel as well as other users have performed more systematic SA in the past, usually in a focussed manner built around a certain scenario (line 36). The types of systematic Sensitivity Analysis that have been performed have generally been used to identify which individual parameters have the biggest impact. Kruip noted that the combination or interaction of sliders and how they work together would be interesting to further investigate (line 37).

In reflecting on uncertainty in the ETM it is interesting to consider how it is almost a feature of the model than something underlying working assumptions. Because of the versatility of the model it is uniquely suited to investigate the consequences of uncertain assumptions in policymaking. From a development perspective, it would be valuable and feasible to develop functionality that allows the ETM's diverse group of users to systematically perform Sensitivity Analysis.

3.2 CEGOIA Description

This research involves a case study of a heating transition model: CEGOIA. This section serves as an analysis of those CEGOIA model elements that are important for the creation of a Sensitivity Analysis plan and subsequent analysis and interpretation.

3.2.1 Describing the modelled system

The CEGOIA model calculates costs and optimizes the allocation of energy carriers for sustainable heating systems for individual neighbourhoods (Brouwer, 2019). The model can, therefore, be characterized as an economic calculation and optimization model that explores possibilities, rather than predict them through simulation. The model is implemented in Python and developed in-house at CE Delft. Results are accessible through a web-viewer as shown in Figure 5. The web-viewer provides a general overview of which systems are selected for which neighbourhoods, as well as neighbourhood specific information such as the relative costs of the considered systems and their related impacts on the usage of energy carriers such as gas and electricity. A detailed breakdown of associated costs is also available.

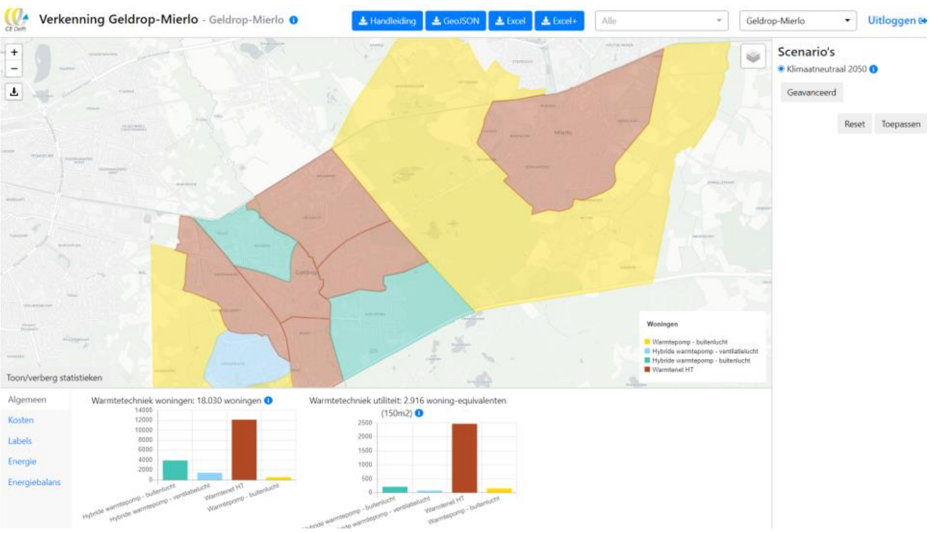


Figure 5: CEGOIA web-viewer example

CEGOIA's logic can be dissected in two principal steps. First, CEGOIA evaluates the effects of all included possible heating systems for all included neighbourhoods in the region. A configuration of a neighbourhood together with a heating system, energy carrier and insulation package is referred to as an 'option'. After having calculated the effects of all possible options for all neighbourhoods, an optimization step occurs in which energy carrier constraints are introduced. The model optimizes the allocation of energy carriers to arrive at the options for each neighbourhood that constitute the lowest costs for the entire region. An overview of the inputs for these steps is provided in Figure 6. It is important to note that most of the information provided by the model is generated in the first step, after which the second step serves as a sort of 'reality check'. This is reflected in the figure by the various inputs required for the calculation step.

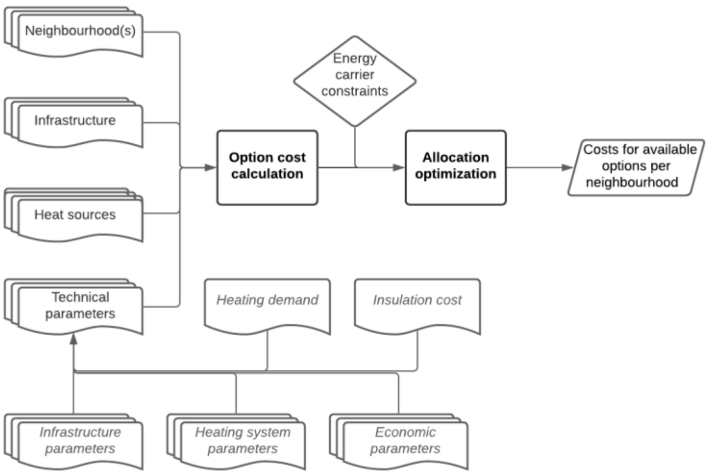


Figure 6: CEGOIA overview

3.2.2 Model inputs: spatial, scenario and modelling

The model configuration starts with the selection of a geographic region comprised of one or more neighbourhoods. The neighbourhoods in this region have spatial attributes unique to them, particularly the building stock, infrastructure and potential sources for heat. CEGOIA aggregates the neighbourhood data to a 'node' object which summarizes the energetic properties of either the residential or utility buildings in a neighbourhood. Options are calculated per node, so every residential or utility building in a neighbourhood will be assigned the same heating system.

The residential and utility nodes of neighbourhoods are evaluated by relying on a wide variety of parametric data. This data is used to model heating systems, energy demands and more. A more detailed description will follow below. By default, this parametric data is the same in different CEGOIA calculations, whereas spatial data is unique to the supplied region.

The third and final type of input to be specified in the model settings, which contain the configurations used for the calculation and subsequent optimization. Settings of relevance include the year for which the model evaluates options, the availability of energy carriers and any neighbourhood or parameter values that are overruled to better fit local circumstances.

3.2.3 Modelling parameters: heating systems and neighbourhood demand

CEGOIA makes use of a large number of variables. Besides the parameters that are used to model neighbourhood/region-specific properties or dictate the model settings, 953 parameters are pre-defined and used to perform calculations. As CEGOIA is a modular programme, the choices in model settings, not all parameters are used in every application of the model. The parameters can broadly be categorized into four groups:

- General economic parameters.
- Infrastructure-specific parameters.
- Residential & utility-specific neighbourhood parameters.
- Individual & collective-specific heating system parameters.

Economic parameters include age factors of infrastructure and installations, discount rates on investments and various tax rates. Infrastructure parameters cover the modelling of existing energy infrastructure as well as effects related to expansion and decommissioning. The parameters that describe neighbourhood characteristics are used to calculate the demand for energy and insulation values of buildings. Note that this energy demand does not only cover the demand for heating but also that of electricity for other functions. Showering, cooling, appliances and other energy sinks are part of the final demand. The set of heating system-specific parameters covers a range of different systems with their related needs for insulation levels, infrastructures and distribution systems.

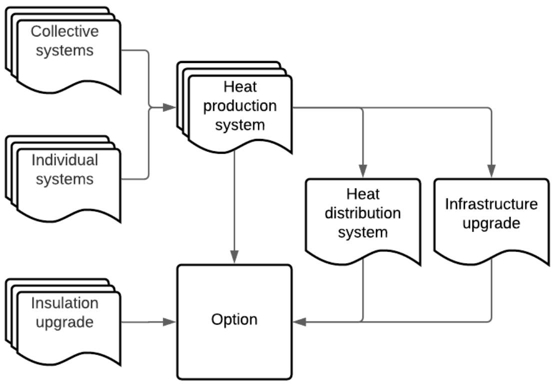


Figure 7: CEGOIA heating option attributes

As remarked earlier, an 'option' consists of the combination of several facets. Figure 7**Error! Reference source not found.** illustrates these facets as a configuration of several interventions in a neighbourhood. The principal choice for building owners is for an individual or collective heating system. The difference between these is that individual systems generate heat in the building at which it used, whilst collective systems make use of one or more central heat sources connected to a distribution heat net. These systems come with corresponding changes in the production and distribution of heat, matched with a suitable insulation upgrade of the building envelope.

Insulation packages, infrastructure upgrades and distribution systems are highly dependent on the chosen heating production system, as a choice for one production system may disqualify the use of another distribution system. For example, when considering an industrial waste heat source operating at a high temperature it is not possible to distribute the heat using the electricity grid, nor does that electricity grid need to be upgraded. For this specific example, an insulation upgrade will also not be necessary. This is to illustrate that many configurations are imaginable for an option. Depending on local circumstances and model settings the model will often evaluate over 100 option permutations per neighbourhood.

Without enumerating all configurations, Figure 8 and Figure 9 provide an overview of individual and collective heating options respectively. The figures match the heating systems and related energy carriers with an insulation/energy use requirement. Within CEGOIA, three levels of energy use intensity are used to categorize neighbourhoods' insulation needs. These levels are 70, 50 and 30 kWh/m^2, which correspond to energy labels C, B and A respectively. At an energy use of 70 kWh/m^2 or lower, a building can accept solutions that rely on Medium Temperature (MT) levels. At 50 kWh/m^2 Low Temperature (LT) solutions become feasible and at 30 kWh/m^2 or lower, Very Low Temperature (VLT) technologies can be considered.

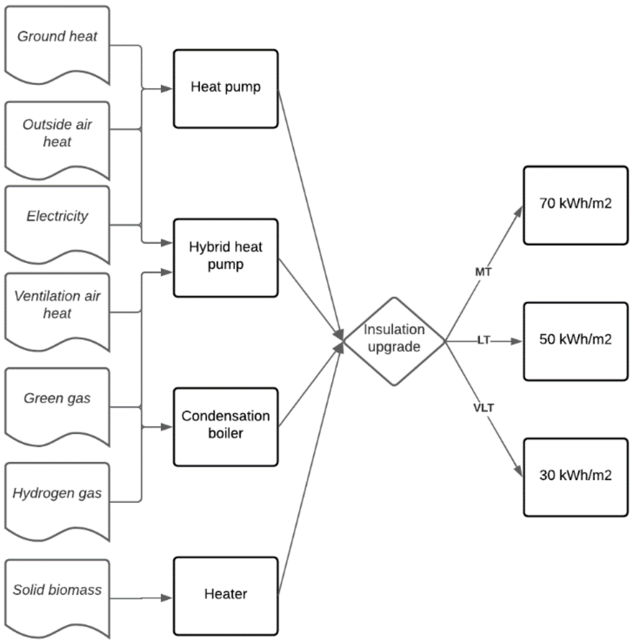


Figure 8: CEGOIA individual heating technologies

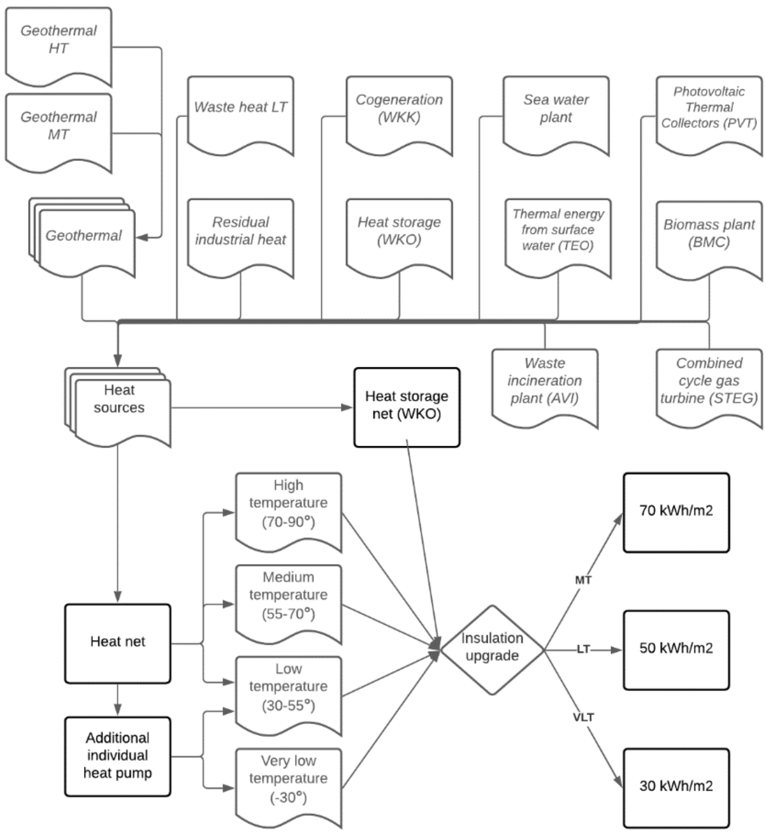


Figure 9: CEGOIA collective heating technologies

The costs calculated for each option in CEGOIA consist of five components: energy use, distribution, building insulation, installation, and collective heat source-specific costs. Not all options involve costs in all cost categories: if no insulation upgrade is required, those costs are 0 – when an individual solution is proposed no collective heat source-specific costs are made. Figure 10 breaks down these five cost items into their most significant parts.

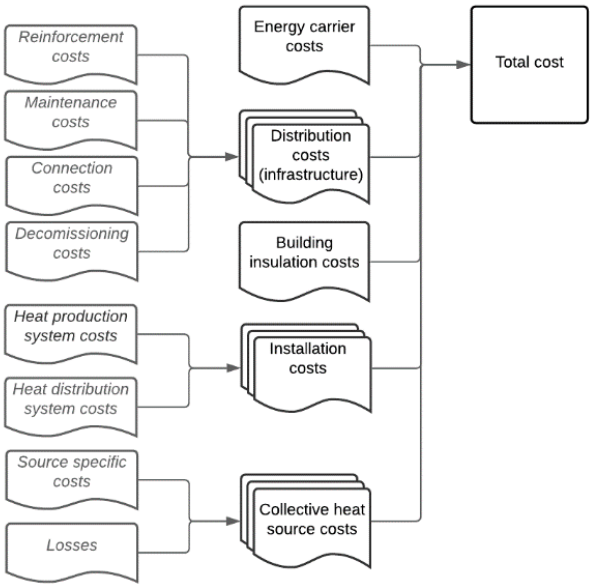


Figure 10: CEGOIA heating option costs

Energy demand for buildings in a neighbourhood is estimated by combining spatial data (like the number of buildings and their surface areas) with the use of indicator values for buildings differentiated by type and age ranges. For residential buildings these types are detached, semi-detached, end-of-terrace, mid-terrace and stacked dwellings. For utility buildings, retail, healthcare, office, meeting, education, sports, prison cell and industry functions are considered.

3.3 Purpose and uncertainty considerations

The goal of the CEGOIA model is to aid local and regional governments in the creation of a transition strategy. It does so in several ways, most apparently by identifying preferential heating alternatives for specific neighbourhoods. The model furthermore provides policymakers with information about the costs and feasibility of implementing heating alternatives. CEGOIA models neighbourhoods and calculates costs in a way that is well-suited to macro-level recommendations. However, as you zoom in to the neighbourhood level it is important to realize the range of uncertainty that results carry. Uncertainty is compounded by applying assumptions about the demand to assumptions about systems to assumptions on energy availability and so on. The purpose of the CEGOIA SA is, therefore, to *identify a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options*.

To do this decisions need to be made about how the CEGOIA assumptions – all of which have differing natures – are handled in the SA. The characterization of these various uncertainties is done following the framework of Warren E. Walker et al. (2013) by describing the location, nature and level of uncertainty. Rather than discussing each dimension separately, only relevant characteristics are discussed below.

3.3.1 Uncertainty in spatial data

Spatial refers to the model input which represents physical structures present in the modelled neighbourhood. This includes the buildings, their function, size, age and type, as well as existing infrastructure and collective heat sources. Uncertainty related to the parametric quality of these inputs is relatively low, as spatial data provided by the institutions on which CEGOIA relies could be thought of as the best attainable reflection of the current situation. In a future scenario – say in 2030 or 2050 – the physical situation of a region may well be very different. By default, CEGOIA makes no assumptions about new construction in the future as making such assumptions at the neighbourhood level would unnecessarily introduce uncertainty and complexity. Put in terms of the model uncertainty framework of Warren E. Walker et al. (2013), this is a case of epistemic lack of knowledge that cannot be reduced by performing more research.

How this data is used in the model introduces structural model uncertainty, as buildings are aggregated to the level of a neighbourhood. This choice is part of a trade-off, as decreasing the size of a neighbourhood to the level of individual buildings exponentially increases calculation costs. Those results would, in theory, be more accurate as using different heating systems in certain streets or even individual buildings would improve optimal system choices. In the current implementation in which all buildings are aggregated to one node, a false sense of homogeneity is introduced and a degree of inaccuracy stemming from these assumptions carries over to the overall model outcome.

3.3.2 Uncertainty in modelling parameters

The parameters used in calculations are by themselves model inputs, but they are not treated as such in the application of the model, i.e. they are not generally varied in simulations. The assumptions on which these parameter values are based come from a large variety of sources, and therefore introduce a varied amount of uncertainty with regards to the aforementioned four levels of uncertainty. These levels are deterministic statistical uncertainty, scenario uncertainty, recognised ignorance and total ignorance. According to the opinions of model owners most uncertainties should be labelled as ‘scenario uncertainty’ or ‘recognised ignorance’, considering values are forecasted into scenarios in the relatively far future. The cost of a heat pump, for example, may decrease by 50% from what it is now but it just as well might increase by 10%: there is no way to know.

Another type of uncertainty introduced by the model parameters is that of context. In the current version of CEGOIA, a variety of heating systems are modelled, each implementation introducing structural uncertainty. Every inclusion, as well as the omission of a possible heating system, introduces some bias in the outcome. This type of uncertainty is again the result of a rational consideration: there is a lack of epistemic knowledge about which heating systems will be relevant in the future and thus a selection needs to be made.

3.3.3 Uncertainty in model settings and constraints

Constraints that can be set in CEGOIA are largely applied to evaluate future scenarios regarding resource availability. In nature, these assumptions are based on best guesses from a variety of organizations and so at best can be labelled as 'scenario uncertainty', that is to say quite uncertain. Although this level of uncertainty falls into the same class as most of the modelling data, it is different in nature. In using the model, these settings and constraints are actively varied whilst the parameters are not. This way, constraints are recognized as contextual rather than at the core of the model.

3.4 Summary of uncertainty in Dutch heating transition models

This chapter set out to complete the answer of the question: '*How is uncertainty in heating transition models understood and dealt with?*' which was started in the previous chapter. In that chapter, it was pointed out that there exists fundamental, deep uncertainty about many of the key factors in the heating transition, not just epistemically but also between stakeholder's sense of shared realities. A handful of Dutch heating transition models exist and are used extensively by or for policymakers. Out of these, Vesta MAIS, ETM and CEGOIA are analysed in more detail. Each of these models the energy system in a slightly different way, with adds to the issues regarding a lack of shared realities. Still, more traditional manifestations of uncertainty in these models are products of the many assumptions – expressed through a high number of variables and a lot of model interactions and complexity. Some parameter values – typically those that are used to create scenarios – are uncertain to the point of recognized ignorance. In dealing with this uncertainty model owners carry out various efforts to vary and create scenarios that can reasonably capture uncertainty and be interpreted and used by policymakers. Still, many parameters in heating transition models are kept fixed so as to not complicate result comprehension, whilst the level of uncertainty of these is not insignificant.

4 Sensitivity Analysis Literature

This chapter serves to clarify what Sensitivity Analysis (SA) is and specify how it is relevant to the heating transition. A definition and explanation of the method is presented in section 4.1. The variety of use cases is then presented in section 4.2, after which well-known limitations and challenges related to the method are discussed in section 4.3. Further discussion about the state of use of SA in heating transition literature is presented in section 4.4 and reflections on it from the perspectives of Vesta MAIS and ETM model developers are finally presented in section 4.5. The last section, 4.6, again provides a summary of the chapter. The combined insights from this chapter serve as a way to partly answer the question: *'How can the Sensitivity Analysis process be used for heating transition models?'*.

4.1 Definition

A definition of sensitivity analysis, as proposed by Saltelli, Tarantola, Campolongo, & Ratto (2004), is *The study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input.* Related but different from this practice is 'uncertainty analysis', which aims to identify which parameters are uncertain, i.e. investigate *uncertainty of model output based on uncertainties in model input*. To put it another way, uncertainty analysis identifies important inputs that are to be considered uncertain, whilst sensitivity analysis quantifies the sensitivities of these inputs. Models can be characterized in many ways, but for sensitivity analysis, the following typification is relevant (Saltelli et al., 2008).

Models should be used in either a diagnostic or prognostic manner. In other words, some models can be used to evaluate what-if scenario's whilst others are supposed to be accurate representations of a system. Saltelli's second distinction in models is that they can be either 'data-driven' or 'law-driven'. A law-driven model makes use of a set of well-established laws that describe a system to predict behaviour, whereas a data-driven model infers outcomes through statistical means from a set of available data. These model properties affect the structure of a model. Saltelli et al. stress that however well-conceptualized and parameterized, no model can ever be 'proven true'. This can be attributed wholly to uncertainty, from both model selection and parameter uncertainty. It is for this reason that sensitivity analysis is crucial to the interpretation of a model, as it will inform the modeller of the character of this uncertainty.

Sensitivity analysis can be divided into two sub-fields: Local and Global sensitivity analysis (Ferretti, Saltelli, & Tarantola, 2016). Both methods consist of carrying out the following steps:

1. Determine inputs (through UA) and quantify uncertainty in terms of probability distributions and ranges.
2. Identify the output to be analysed.
3. Create and evaluate an experiment design.
4. Calculate sensitivity measures.

Differences between methods exist in steps 3 and 4. In local methods, only a 'local' change in the input space is evaluated. The most basic approach for doing this is the One factor At a Time (OAT) method. As the name suggests, the value of only one factor is varied in the experiment design. This method is relatively easy to implement and for this reason very popular in academic literature. Nevertheless, the approach has been heavily scrutinized by various authors, e.g. Ferretti et al. (2016); Saltelli & Annoni (2010); Yi & Lu (2019). Their critique involves the inadequateness of OAT to capture nonadditive effects. The method should therefore only be used if a model contains strictly linear relationships between input and output. Ex-ante this relationship is usually not well-described or known, so it could be argued that in most cases local methods should not even be considered. Indeed, several modelling disciplines used in energy transition modelling, such as Agent-Based Modelling, Optimization Modelling and System Dynamics, regularly display the nonlinearity property, because of which local SA methods are mostly unsuitable (Horschig & Thrän, 2017). For this reason, the rest of this section focuses on global techniques. Besides the principle that a sensitivity analysis method should be global, other requirements are that it should be quantitative and 'model-free' (Saltelli & Annoni, 2010). The term model-free or 'model-independent' refers to the lack of necessity to understand the functional relationships between inputs and outputs to produce accurate results.

In response to criticism on local SA, the field of Global Sensitivity Analysis (GSA) was first introduced by econometrician Edward E. Leamer (1990), who stated, "*I have proposed a form of organized sensitivity analysis that I call 'global sensitivity analysis' in which a neighborhood of alternative assumptions is selected and the corresponding interval of inferences is identified. Conclusions are judged to be sturdy only if the neighborhood of assumptions is wide enough to be credible and the corresponding interval of inferences is narrow enough to be useful."* (Saltelli & Annoni, 2010). Several GSA methods exist, some of which are discussed in the next section based on their relevance to this study (Ferretti et al., 2016).

4.2 Uses and techniques

Sensitivity analysis can provide multiple insights about model quality (Saltelli et al., 2008). The result of a sensitivity analysis, of course, is an insight into the relative importance of inputs in determining the output. Technical errors can be uncovered with this information. Models can be simplified and refocused; critical input regions identified. When applying SA to policy assessment, results can also be used to explore and corroborate the impacts of policy options given the uncertainties in the system. A summation of the various use-cases of SA is the following (Saltelli et al., 2008):

- Identify mistakes in a model.
- Investigate which parts of a model are not influential in determining its outcome, thereby identifying if and which parts can be simplified.
- Investigate which parts of a model are very influential in determining its outcome, thereby identifying if and which parts can be modelled more extensively to reduce model uncertainty.
- Increase understanding of the model by quantifying the relationships between inputs and outputs in sensitivity measures.
- Quantify uncertainty about model outcomes, making it possible to interpret the robustness of model results.

Although there are many use-cases, not every SA technique can provide all the insights listed above. In the literature, a distinction is made between three purposes for SA techniques: Factor Fixation, Factor Prioritization or Factor Mapping.

Factor Prioritization

Factor prioritization is used to identify which inputs introduce the most variance. The rationale behind this is that if one were able to accurately determine these inputs 'true' values the most variance could be reduced (Saltelli et al., 2008). This knowledge can be used to focus on model development, as well as identify fragility where model assumptions should be improved. The method used for this purpose is generally the Sobol' method – or a derivative of it, like Fourier Amplitude Sensitivity Tests (FAST) (Morio, 2011).

The Sobol' method is centred around the estimation of so-called Sobol' indices (Sobol', 2001). There are two types of Sobol' indices, n^{th}-order and total (Saltelli et al., 2010). First-order indices are "*the variance of the conditional expectation of the output given the value of an input, normalised by the total variance.*". Higher-order indices consider the confounding effect of two or more inputs on top of the First-order indices, and are defined as the sum of the first-order Sobol' index *and* all the higher-order Sobol' indices involving that parameter. These Sobol' indices, values between 0 and 1, are considered to be easy to interpret. Monte-Carlo simulations – many iterations of random sampling – are generally used to estimate Sobol' sensitivity indices. The consequence of this sampling method is that the computational cost for calculating these indices is very high, between 100(k+2) and 1000(k+2), where k is the number of factors (Ziehn & Tomlin, 2017). FAST represents variances through the Fourier series, and as the name implies, is faster than traditional Sobol' analysis. The flip side is that FAST can only indicate total Sobol' indices, not partial ones.

Factor Fixation

The fixing of factors is used chiefly to determine which inputs in a model can be ignored (Saltelli et al., 2008). Unimportant factors are 'fixed', in the sense that if one were performing Monte Carlo analysis it does not matter if a factor is varied or not, it can be fixed to one value and the outcome would not change. The Sobol' indices for these factors would therefore be 0. This method can be used to reduce dimensionality, identify redundancy and simplify models. As this explanation indicates, the Sobol/FAST method can be used for this purpose. Other methods are suitable for this purpose that are, importantly, computationally less expensive than the Sobol' method. These methods are the method of Morris (as described in the next paragraph), Derivative-based Global Sensitivity Measures (DGSM) and the Fractional Factorial method (Saltelli et al., 2008; Sobol' & Kucherenko, 2009).

The method generally referred to as the Method of Morris (MM) involves sampling input factors and analysis of results Morio (2011). Generating input factors is done through the following process. First, for every parameter x within the input space, we start by drawing a random initial value within a specified range and define it as x^0. Then, x^1 is generated by taking x^0 and adding a pseudo-random variation within the allowed range of parameter uncertainty. This is done for all parameters (k times) and the resulting set of parameter values is called a 'trajectory'. R trajectories (usually 5 to 10) are generated. From this set, a model is run R(k+1) times. The results are then used to calculate sensitivity indices: the most important of which is the Elementary Effect (EE). By taking the elementary effects over all trajectories the mean value for the elementary effect is found. A standard deviation is then calculated in addition to the effects. These sensitivity indices are subsequently used to interpret factor importance. The Morris method is considered to be a ‘screening’ method: a fast way to evaluate and screen which parameters ought to be further analysed and which should be fixed.

Morris and DGSM have a computational cost of around 10(k+1); the last method has a cost of only 2k. These techniques, rather than relying on Monte Carlo sampling from a distribution, draw Quasi-Monte Carlo samples from several ‘levels’ in a parameter range (Kucherenko & Looss, 2017). DGSM is, in essence, an alteration of the Morris method, making use of derivatives instead of variance to compute sensitivity indices (Sobol’ & Kucherenko, 2009). This is done by taking the partial derivative (delta) of the output concerning an input factor. The resulting insights are much more accurate than those from the Morris method, which is not very well-suited for GSA. The flipside is that the observed effect is not described as elaborately as when using the Sobol’ method: there is no distinction between low and high-order interactions.

The final technique, using a Fractional Factorial (FF) experiment design, is again variance-based (Saltelli et al., 2008). The method is named for its experiment sampling method. A high and a low value for every parameter is defined (represented as 1 and -1). All possible configurations with this design would result in 2^k samples. By taking a Fractional partition of this design, only ~2k experiments need to be evaluated. This is equivalent to performing an OAT analysis: each parameter is varied throughout its range exactly once. Analysis of FF design results is done simply by evaluating this main effect. As can be imagined, this method does not yield useful results when a model is highly nonlinear but can provide a computationally inexpensive evaluation of factors with linear relationships.

Factor Mapping

Factor Mapping is a process that maps portions of output spaces onto inputs (Saltelli et al., 2008). This is very useful to identify threshold effects within the model like knowing which parameters determine uniqueness, instability, runaway and robustness conditions. Another application of Factor Mapping techniques is the emulation of models that result in computationally cheaper surrogates of an underlying model. This process is also known as metamodeling, and can be done using the High-Dimensional Model Representation (HDMR) technique (Iooss & Lemaître, 2015).

A final Factor Mapping technique of note is the Delta Moment-Independent Measure (DMIM). Without going into the specifics of how it works it is important to know that it does not make use of any variance or derivatives. Because of this not everybody considers it a true Sensitivity Analysis technique. Saltelli postulated three requirements for SA: techniques are global, quantitative and model-free. Borgonova argues that moment independent should be added to the list (Borgonovo, 2007). The rationale for this inclusion is that any description of a random variable using a single moment – mean, variance, skewness, etc. – provides a loss of information about the distribution of that variable. To account for moment independence a new measure is introduced, δ. The Delta considers both the entire input and the entire output space and is calculated from correlations between them. The sample size necessary for DMIM is not related to the number of inputs, in general, 500 runs are enough to derive a sufficient confidence interval.

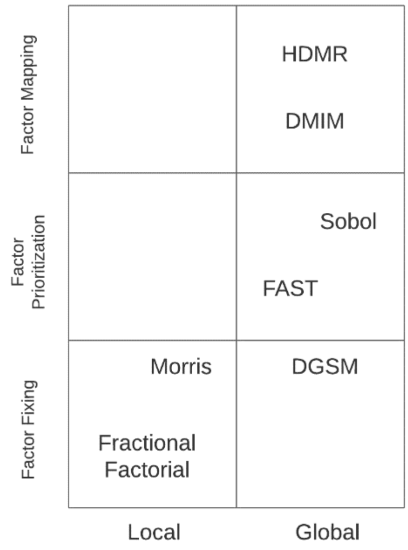


Figure 11: Classification of described SA techniques

Figure 11 sums up the techniques described in this section. The limiting factor for employing these techniques is time: Fixing requires fewer runs than Prioritization which in turn can be done faster than Mapping. The most elaborate and systematic Sensitivity Analysis includes all three activities and makes use of purely Global methods.

4.3 Pitfalls and challenges with Sensitivity Analysis

Sensitivity analysis is regularly acknowledged as a useful and indeed necessary step in model-based policy analysis (Brouwer, 2019; Nikolic et al., 2019). Nevertheless, in a systematic review Ferretti, Saltelli & Tarantola concluded that the practice is not performed as much nor as well as it should be (Ferretti et al., 2016). Although the trend has been positive in recent years, most of the reviewed studies did not use any form of SA, and the vast majority of those did use only local methods. The authors speculate as to why this is the case. For one, they suggest that modelers are very reluctant to depart from the 'baseline' of values used, owing in part to a lack of information about the distribution of the input space. OAT techniques are often used, however, and so this cannot be the only reason. It is possible that GSA is rarely used because of its brutally honest nature which may have destructive consequences on the model being used (Leamer, 2010). A final argument, perhaps a little more reasonable, is that performing GSA is often a difficult and time-intensive process (Saltelli et al., 2019).

There are several reasons why sensitivity analysis can be challenging (Ferretti et al., 2016; Horschig & Thrän, 2017; Saltelli et al., 2008). These so-called pitfalls are listed below:

- The purpose of the analysis is unclear
- Too many inputs are considered
- Low confidence in probability distributions of inputs
- Too many outputs are considered
- The model takes too long to run

Overcoming these pitfalls can generally be done using a tailored analysis process. By using not one but several of the previously described methods in conjunction with each other GSA can be made more manageable (Menberg, Heo, & Choudhary, 2016). For example, a step that can almost always be done is to apply screening methods, which reduces the size of the input space (Iooss & Lemaître, 2015). There are several methods available to define probability distributions, like a qualitative expert solicitation or by using a numerical sampling approach.

4.4 SA in energy transition modelling literature

The topic of heating transition modelling can be considered a subset of energy transition modelling. In both fields, a very limited number of studies that discuss SA in the context of energy-related policymaking were found. Two relevant systematic literature reviews were found. The first review by Saltelli et al. focuses on reviewing SA practice in nineteen different disciplines including Energy, Environmental, Engineering and Decision Science which have a relationship to the energy transition (Saltelli et al., 2019). The review found that up to 65% of studies that include SA use inadequate methods and a significant number refer to Sensitivity Analysis whilst carrying out an Uncertainty Analysis. The authors did find that fields which rely more on model use are more likely to use Global methods as opposed to Local ones. A review more closely related to the topic of this research was performed by Bottero, Dell'anna, & Morgese (2021), who focused on twelve evaluation tools used for the decision-making process in the context of the energy transition. One of these evaluation tools was SA, and so no distinction was made between Local and Global methods. The authors found an increasing trend starting in 2016 in which more energy transition SA literature was published. This trend fits into a wider one found of increased focus on the evaluation tools of energy transition policy. The 20 or so papers discussing SA surrounding the energy transition covered a variety of topics, including marine energy, electricity markets, PV systems. None of these studies focussed on building stock or sustainable heating.

Some papers covering uncertainty and sensitivity in the heating transition were found. An assessment methodology for sustainable energy transitions in neighbourhoods was developed in S. Walker, Labeodan, Boxem, Maassen, & Zeiler (2018). This study used an LCA approach which was coupled with OAT SA using Monte Carlo sampling to generate scenarios and selections of suitable clean energy initiatives. The SA in this approach served as a Multi-Criteria Analysis tool with which scenarios were evaluated, based on which policymakers would select initiatives.

Two studies performed GSA methods on simplified building energy models. Menberg et al. (2016) performed an analysis of a dummy building energy model with 11 parameters and explored the use and insights of the Morris method and Sobol' method. In comparing computational costs with extractable information, they found that both methods provide interesting insights into complex behaviour and provide a way to verify assumptions about dynamic behaviour. Sensitivity measures were further found useful to compare with other models with similar purposes. Mastrucci, Pérez-López, Benetto, Leopold, & Blanc (2017) performed a GSA study on a similar, simplified building stock energy model. Acknowledging heterogeneity in the building stock, they introduced what they call a *detailed* or archetype approach with which surrogate models were created.

These archetype surrogates were made using the variables with significant Sobol' index values and were found to produce the same results much faster than the original model.

The studies discussed in the two previous paragraphs cover policy evaluation in the heating transition and the use of GSA for the energy modelling of buildings, but no study was found that combined the two aspects. One study was found that combined GSA with policy evaluation in the energy transition as a whole. Pye, Sabio, & Strachan (2015) performed an integrated systemic analysis of uncertainty in UK energy transition pathways using the ESME model. The study identifies and highlights the impact of uncertainties of commodities and technology in the process of decarbonisation using Standard Regression Coefficients. The authors stressed that this method has a lot of value for models that support policymaking since key assumptions are identified. They pose that with this understanding, better transition strategies can be formulated. Important to note is that the analysis in their study was the first step in an iterative process. In 2018, the authors followed up with an iterated version of the study in which more and better-developed uncertainty considerations were integrated into the analysis (Pye et al., 2018).

4.5 Use and potential of SA in Vesta MAIS and ETM

PBL's Steven van Polen and Quintel's Chael Kruip were asked about how SA is used in the development and use of their model. After discussing the definition of SA, its various use-cases and the specific methods were discussed. Both model owners expressed that they had used SA for the development of their model, but the method which they had used was strictly OAT. The purposes of these analyses were to identify which parameters had a big impact and to measure how big that impact was. The other use cases for which SA can be used were also discussed.

Both model owners mentioned that although important, spotting mistakes in a model with this much development is generally done through other means such as unit tests, careful version management and (community) feedback. Steven van Polen did argue (line 71) that as the models get bigger, it is more difficult to keep an overview of how things work, and legacy issues might become problematic. Especially for new people working on the model, understanding the intricacies of the model takes a lot of playing around with it. He suggested that SA would be a comprehensive way of learning about the various levers and dynamics (line 84).

Although both PBL and Quintel indicate they have a good idea about where future model development efforts should focus, these ideas are not necessarily determined by those model features that are introducing the most uncertainty. Instead, these efforts are attuned to the questions and desires of model users and policymakers. The simplification of the model, however, is something about which both model owners expressed interest. The ETM is used by many different users for many different purposes. What's more, is that it is used at wildly varying geographic scopes, from international to the level of a village. Local decision-makers often get overwhelmed by all the options in the model, whilst many of them are not relevant in, e.g. the heating transition (line 48). Simplification of the model, in this sense, would meaning hiding those options which have little or no impact and relevance for the heating transition. Simplification can be done without performing SA, but it would be preferable to understand exactly what the impacts of variables are. In Vesta MAIS the idea of model simplification could help focus its current development (line 91). Currently, the modelling of the building envelope of houses is a major focus and a very high level of detail is going to be used in the next version of the model. Since the main vision for the model is to evaluate policy effects on a national level, one could question whether such high levels of detail adds much to its explanative power. Steven van Polen adds that other models are probably better suited at evaluating heating systems at such a local level (line 96). SA could therefore be used to structure the discussion around model development.

Quantifying the relationship between inputs and outputs is important, although the feasibility of doing this was something which both model owners were curious, yet sceptical about. For one, Chael Kruip noted the complications caused by interdependence between input variables (line 54). The number of runs required for doing SA that captures direct as well as higher-order effects was expected to be too high to be practical (line 56). After discussing the method and imagining how much time it would take to run SA on the ETM and Vesta MAIS, however, both model owners concluded it would be feasible to evaluate these effects (line 60 and 67 respectively).

For both models, the ability to indicate the robustness of results is desirable, with the important caveat that communicating uncertainty and robustness to policymakers is very difficult. Many decision-makers want to have a number about which to have discussions (Kruip, line 116), or know whether or not they will achieve their goal (van Polen, 125). Chael Kruip notes that even people that have been working on this for years find it very difficult to interpret model results and still sometimes draw the wrong conclusions from results (line 121). Steven van Polen adds that although it is difficult knowledge to communicate, the expertise of advisors and municipalities is growing (line 38). Both interviewees indicated that they would still be very interested in investigating robustness questions about their model's outcomes. Steven van Polen reflected that in a broader societal context, these types of analyses could help to get to those insights about what the impacts of policies and developments are that people are looking for (line 136). Without prescribing the future, they help with understanding the direction that things are going. It might even be valuable for PBL, as a public knowledge institute, to take a step back from further model expansion and take some time to do good SA and reflect on these sensitivities (line 146).

4.6 Summary of SA in heating transition models

This chapter served to provide insights into SA with which to partly answer the question '*How can the Sensitivity Analysis process be used for heating transition models?'*. It is concluded that there are multiple, incrementally useful applications for which SA can be employed, most notably the identification of (un)important parameters, the quantification of the influence of individual parameters and the mapping of parameters with which model dynamics can be summarized. Extracting more information comes at a cost: more model runs and/or fewer parameters can be chosen to calculate sensitivity indices of more powerful techniques. This can be an issue for heating transition models since they make use of a lot of information to model the energy system. For models with non-linear behaviour – which heating transition models might very well be due to the many interactions – typical Local SA methods are useful to only a limited extent since model interactions are ignored. Comments by model developers indicate there is value to be gained by more and better application of Sensitivity Analysis in heating transition modelling. Improvements in not only understanding the quality and limitations of a model with which to further develop it but also the understanding of complex dynamics within the heating transition are topics of considerable interest.

5 Sensitivity Analysis Method

This chapter serves to conceptualize and implement a Sensitivity Analysis method that, as outlined in chapter 3, can *identify a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options*. By doing so, an example is given that serves to answer sub-question 2 '*How can the Sensitivity Analysis process be used for heating transition models?*'. The experimental analysis plan is proposed and motivated in section 5.1. Then, in section 5.2, the necessary preparation of CEGOIA is explained. This includes the grouping of parameters, defining ranges of uncertainty to them and finding suitable neighbourhoods with which to run the model. The technical changes to the model and the mention of the statistical tools used is documented in section 5.3. Finally, section 5.4 describes the experiments that were used to generate the results as presented in chapter 6.

5.1 Analysis plan

The general procedure for Sensitivity Analysis cannot be applied directly to CEGOIA for various reasons. CEGOIA has multiple types of inputs, of which spatial data, in particular, are context-specific and hard to vary. Another issue is the large number of parameters coupled with the computational cost of running the model. Finally, the choice of SA analysis requires assumptions about the structure of interactions in the model. Analysis of a model with a lot of second-order interactions is different from an analysis of a model with mostly first-order interactions, for example. To mitigate or circumvent these issues a plan is made in which several choices are made that affect how results can be interpreted. The first choice to be made is the scope in which the model will run. Second, the variable chosen as model output is considered. Then, the selection of parameters to vary is made. Lastly, the SA techniques used for analysis are chosen based on the constellations of inputs and output.

5.1.1 CEGOIA SA scope

An important decision to make is which part of CEGOIA is analysed. As discussed in chapter 3, CEGOIA performs two steps: cost calculation and optimization. The costs of individual heating system options are first calculated for individual neighbourhoods, after which options are assigned to neighbourhoods in a region based on limited energy carrier availability. The first part assigns costs to options. The second part rules out options for neighbourhoods. Regarding these two model steps as a single model for SA is problematic. This is because the second step will introduce scenario-specific constraints to results and produce a single answer about which option is cheapest. We are however, interested in the dynamics of all options, so this would make interpreting single option variable effects impossible. Because of this, the choice is made to focus fully on the first part of CEGOIA. SA of options cost calculation will reveal the relationships between especially the modelled heating systems and costs, but entirely ignore the effect of the 'scenario constraints' such as availability of green gas or electricity. As will become evident in the following paragraphs, this choice simplifies the analysis enough so that SA can be meaningfully performed, but is an important drawback to keep in mind when interpreting results.

The model scope chosen for SA is an important choice since energy transition models such as CEGOIA are specifically created to evaluate different scenarios in different regions. The model's applicability is very diverse, and capturing this diversity with SA is important to be able to make generalized conclusions about the model. Practically, however, the choice needs to be constrained to one or a handful of scopes, since the time cost of running analysis on multiple regions under multiple scenarios is costly. For reference: 1 model run evaluating 1 neighbourhood in the SA setup used in this research takes about 3 minutes to calculate. Another major choice to make is the year to which the model is run. In use, this is often either 2030 or 2050. The decision was made to fix the end year for all SA runs to 2050, since this is the year at which the Dutch government aims to complete the heating transition and therefore provides a natural 'endpoint' to a model that calculates the cheapest endpoint.

The third and final aspect of the scope of analysis to discuss is the input region. A region consists of one or more unique neighbourhoods, in terms of building stock, density, infrastructure, and more. The costs for each neighbourhood will thus always differ, regardless of the heating system option evaluated. Comparing results between two neighbourhoods in a region is for this reason only useful if the characteristics of the neighbourhoods are sufficiently different. What constitutes neighbourhoods to be different is a discussion of its own, and is covered in the next section. The takeaway here is that the choice is made to evaluate individual neighbourhoods rather than larger regions such as municipalities since that approach does not guarantee meaningful insights. Furthermore, this is a sparing approach that ensures evaluating only neighbourhoods of interest in a controlled manner.

5.1.2 CEGOIA SA outputs

Output has two components: costs, and heating system options. These are connected, as the structure of costs for one heating system options will be different for another. A heat net, for example, requires a larger upfront investment but perhaps has lower running costs than a heat pump. The cost variable that unifies different cost structures is 'annualized costs excluding tax (euro/year)'. Note that tax is excluded, because the costs considered are the total 'national' costs and taxes are a construct to move costs from various parties in society.

Although annualized costs excluding tax are a singular output variable, these costs will differ for various heating option systems. If the lowest cost system were to be used as selection criteria, the cheapest option would be different through simulations. In that case, very few meaningful evaluations of input could be done. For this reason, a selection of heating system options is made based on discussions with heating transition professionals at CE Delft. These are meant to reflect those options that are considered to be likely outcomes as well as a fair representation of the spectrum of different technologies. From these discussions, the following eight heating systems were selected:

1. Air-based heat pump: uses electricity, requires good insulation
2. Ground-based heat pump: uses electricity, requires good insulation
3. Condensing boiler: uses green gas, works like a conventional boiler
4. Hybrid heat pump: uses green gas and electricity, combining 1) and 3)
5. Pellet boiler: uses biomass, similar to 3)
6. HT heat net: uses available waste heat at 70-90 °C
7. MT heat net: uses available waste heat at 55-70 °C and a collective heat pump to supplement heat when demand exceeds supply

8. LT heat net: uses available waste heat at 30-55 °C and a collective heat pump to supplement heat when demand exceeds supply

5.1.3 CEGOIA SA inputs

Choices made to the model scope and outputs of interest dictate which model inputs vary and which are to be kept fixed. Chapter 3 discussed the three type of inputs which CEGOIA makes use of real-world spatial data, scenario-specific model settings and parametric data used to model the energy system and related costs. Since the choice was made for the evaluation of one individual neighbourhood at a time, such neighbourhoods must be reflective of real Dutch neighbourhoods. Rather than selecting a real-world neighbourhood with seemingly representative characteristics, an archetypal approach is used. To achieve this property, the most important physical characteristics of Dutch neighbourhoods are considered and used to construct fictional, yet (arche)typical neighbourhoods that reflect the diversity in neighbourhoods in an aggregated manner. Exactly how these neighbourhoods are constructed is discussed in section 5.2.3.

The second and third inputs: scenario-specific and model settings are not part of the scope (except the end-year of 2050) and therefore require no further conceptualization. This leaves the parametric input data used to model the energy systems of neighbourhoods. As discussed in chapter 3.1, there are 953 parameters of various types of categories used by CEGOIA. This is a comparatively large number for SA, as the inclusion of every additional parameter adds an exponential number of model runs that need to be evaluated. With the prescribed analysis method, one model run takes just shy of 3 minutes to be evaluated. As such, changing each of the 953 parameters just once and calculating the costs for the eight heating systems will take just under 48 hours. This is unworkable for more powerful SA techniques, and as such various workarounds were devised to reduce this number of parameters. This process is further explained in section 5.2.1.

5.1.4 CEGOIA SA techniques

Three schools of progressively powerful yet costly SA methods exist, as discussed in chapter 4. These are Factor Fixation, Factor Prioritization and Factor Mapping. Having defined the scope, outputs and inputs that are to be considered in the analysis, it is now possible to indicate how each of these methods can be applied and if they are feasible.

Factor Fixation (FF) is mainly used to identify which model parameters are unimportant and can thus be 'fixed'. As mentioned in the previous section, reducing the number of parameters is necessary. Sheikholeslami et al., (2019) note that in the field of environmental modelling, models having high dimensionality have more than 20 parameters. The largest model the authors found in their literature study contained 111 factors. Ignoring neighbourhood properties and energy carrier constraints, CEGOIA has 953 input parameters to consider initially. Significantly more, and therefore significantly more difficult to analyse and interpret. FF will thus be used as a filter step. The explanatory power of the techniques for this method is generally considered to be limited, and results should primarily focus on how many and which parameters are unimportant. A rule of thumb for Factor Fixation is that factor importance follows an 80/20 Pareto-distributed structure. That is to say, 80% of the observed change in outcome can be explained by 20% of the variables; conversely, 80% of variables have a negligible effect on the outcome.

Factor Prioritization can realistically only be performed with a handful of variables, as at least 100 runs per variable need to be executed. This analysis will indicate with high confidence what the sensitivities of output to inputs are. This method can only be used if Factor Fixation has taken place in which critical uncertain inputs are identified. Since there is not just one, but eight outputs to consider (since eight heating system options are evaluated), a choice will need to be made to define the sets to analyse: Will one set of parameters be able to explain variations in all outputs, or is the set of influential parameters different for every single output system? This choice has implications for the potential use of the final analysis method.

Lastly, Factor Mapping can be used to identify patterns in the settings of variables that produce certain outcomes, effectively generating 'scenarios' under which certain model behaviour can be consistently expected. An example outcome of this method for CEGOIA could be a chart that describes the relationship between the gas price and electricity price on the selection of a sustainable heating system. The prices would be on the axes and the plot would be filled with points indicating the cheapest system. The pattern of which system is selected under what circumstances would reveal much about the nature of each heating system option. Factor Mapping can also be used to create metamodels, but since a metamodel of CEGOIA would defeat its purpose of being able to take into account very specific local circumstances, this is not desirable. This type of analysis requires at least 1000 runs per variable, so it might not be feasible to apply this method to CEGOIA.

5.1.5 Summary of the analysis plan

In short, SA is performed to the year 2050, in which one neighbourhood is evaluated at a time. The output of interest is the annualized costs of eight different heating system options. This means that the allocation optimization is not part of the SA and the availability of energy carriers are not considered constraints. The modelling parameters, instead, are varied. In varying these parameter values, constant efforts are made to reduce the number of variables as this increases the possibilities for using analytical methods. Factor Fixation will in and of itself be used for this purpose. Factor Prioritization will then be used to evaluate the sensitivities of the most important parameters. Factor Mapping will likely not be used due to the computation costs of the techniques associated with the method.

5.2 Model preparation

Three activities were performed to prepare the model and operationalize the plan. These are the analysis and grouping of parametric variables, the definition of their respective uncertainties using ranges and the creation of archetypical neighbourhoods. This section describes the main considerations and steps taken in the process.

5.2.1 Parameter screening and grouping

To decrease the time required for performing analysis a parameter filtration step is performed. This filtration consists of the screening of parameters, excluding those that do not have a significant or relevant effect on the model outcome, then grouping certain parameters that represent similar effects.

Screening of input parameters was done by considering their relevance within the context of the sensitivity analysis, as not all parts of CEGOIA are of interest. To conform to specific local circumstances in the heating transition, CEGOIA was developed to be highly modular. Not all of the functionality provided by these modules can be used in the sensitivity analysis, and others are redundant. Some examples: there are multiple implementations for calculating the potential of solar panels where only the default option is necessary. Learning curves are used to model change of certain factors at 5-year intervals, the general point of interest being 2050 making the values for other years redundant. Another example is the inclusion of taxes on top of actual costs. These tax-included costs are typically used in communication to end-users rather than used as a cornerstone of the calculation process. Other parameters that are specific to certain heating system options – notably hydrogen-based systems – are not necessary to evaluate since they will not be evaluated in the SA.

Most sensitivity analysis methods assume independence between input variables. This assumption is required for the application of statistical methods that interpret and rank variable effects. In many models, however, input variables do correlate somewhat. A model which uses both oil and gas prices as inputs is an example of this, as generally speaking, the natural gas price is pegged to that of crude oil. It is therefore rather opportunistic to ignore these relationships, but in practice taking interdependence into account can prove problematic in its own right. The literature suggests factor grouping as a solution (Anderson, You, Wood, Wood-Sichra, & Wu, 2015). As the name suggests, the process involves arranging variables into a group. How the grouping happens can be done in a variety of ways. One way is to partition them based on their relative importance, for example by using a bootstrapping algorithm such as described in Sheikholeslami et al. (2019). A drawback of the algorithm is that for some models it may require an extensive implementation and a lot of time in its own right just to perform this type of grouping.

Another way to group variables is by creating a meta-model relying on qualitative assessment. To continue the example of a model using oil and gas prices, consider the formulation of a new variable called the fossil fuel price. When performing sensitivity analysis, a run considers a fossil fuel price 30% higher than the baseline. Both the oil and gas price is linked to the dummy fossil fuel price variable, and will subsequently increase by 30% from their nominal value. The obvious problem with applying this method is that it introduces the assumption of a one-to-one correlation between the grouped variables. Rarely if ever will this be a realistic reflection of the relationship between grouped variables. In considering this method the question which should be asked is whether or not a perfect correlation between a group of variables is more or less realistic than no correlation at all. The process also has a drawback in regards to reliability, as a qualitative grouping introduces the biases of the analyst into the analysis (Saltelli et al., 2008). The biases will propagate throughout the model and therefore influence the results. This needs to be taken into account when interpreting results and arriving at conclusions.

Variable groupings were created in an iterative process. At first, a draft grouping was made based on intuition which was then validated in a session with three model owners. The groupings were further modified based on their inputs and a final grouping was approved by the model owners. As mentioned, this approach could introduce the biases of those that grouped the variables, and therefore only groupings which were agreed upon unanimously were done. The logic used by the model owners in deciding which variables to group was based on a case-by-case evaluation was done in which the relationships between variables were considered. The groups and their respective uncertainty ranges can be found in Appendix IV - Experiments.

5.2.2 Parameter uncertainty ranges

After having evaluated and modified the input parameters of CEGOIA using screening groupings an uncertainty range for parameters needs to be specified. These are used in conjunction with the experimental designs generated from the techniques used for FF and FP. The process of defining parameter uncertainty ranges was done by making use of the NUSAP notational scheme (Funtowicz & Ravetz, 1990). This notational scheme is used to describe the assumptions that are made. NUSAP is an acronym of the five categories to be inventoried in applying the scheme: Numeral, Unit, Spread, Assessment and Pedigree. For CEGOIA, The 'Numeral' (parameter values) and 'Units' are given, but the 'Spread' is not and needs to be investigated. 'Assessment' refers to a qualitative judgement of assumptions. 'Pedigree' describes the strength of knowledge and use of knowledge in the analytical approach. It can be considered as a qualitative interpretation of probabilistic uncertainty.

As stated, assigning a spread or range to values was done using expert solicitation. This method was chosen primarily because of the quantity of CEGOIA parameters. Individual research to determine a spread would require very extensive desk research. CE Delft employees who developed the model have carried out this desk research in the various stages of developing CEGOIA, so having them assign spreads is a much more efficient way to do this. A rudimentary version of pedigree was used to indicate spreads, whereby experts were asked to label variable spread as certain, uncertain and very uncertain. These qualitative indications were linked to a predefined percentage difference in the parameter value. Initial associated values were proposed, but in the subsequent discussion, values were changed to better reflect participant views. Also, experts were asked to indicate the skewness moment of the probability distribution. For this symmetrical, positive and negative skews were considered. The resulting table, which summarizes the range distributions to be applied to model parameters, is displayed in Table 2. The combination of parameter groups with these pedigrees and resulting spreads can be found in Appendix IV - Experiments.

Table 2: Pedigree values used for determining parameter spreads

Certainty	symmetrical lower	symmetrical upper	positive skew lower	positive skew upper	negative skew lower	negative skew upper
certain	-15%	15%	-5%	15%	-15%	5%
uncertain	-25%	25%	-10%	25%	-25%	10%
very uncertain	-50%	50%	-15%	50%	-50%	15%

5.2.3 Archetypical neighbourhoods

CEGOIA uses various real-world data sources to calculate the sustainable heating alternative with the lowest social cost. Each Dutch neighbourhood (referred to as 'buurt' in CBS categorization) has distinct features which are considered by the model. This includes infrastructure like electricity and gas networks as well as heat nets. Also, the number of buildings, physical characteristics such as whether they are stacked units or detached, a surface area and a use-purpose such as a dwelling or retail function are part of this feature set. Since there are so many different relevant spatial and energetic features of a neighbourhood, one can conclude that each real-world neighbourhood –modelled in CEGOIA – is unique.

Archetypical neighbourhoods are proposed as a way to capture those elements of a neighbourhood that are comparable and generalizable whilst still allowing for a set of diverse neighbourhoods to be analysed. To illustrate this approach, imagine how analysis results for a neighbourhood in the middle of the historic Amsterdam city centre will be different from those of a rural neighbourhood in Drenthe. The neighbourhoods have wildly varying physical properties and we can argue it is useful and desirable to somehow take these profiles into account. Physical differences between two so-called 'Bloemkoolwijken' in Apeldoorn and Zoetermeer – neighbourhoods built from the '70s to the '90s with similar zoning codes (*bloemkool* meaning cauliflower, referring to cul-de-sac-like patterns) are much smaller. Results of sensitivity analysis for one Bloemkoolwijk are therefore somewhat applicable to what you might expect to see in another such neighbourhood.

To investigate how archetypical neighbourhoods should be defined, it is necessary to consider how physical differences between neighbourhoods influence model outcomes. Physical properties which are dominant in determining which systems are suitable for heating the building are insulation levels as well as the possibility to supply the heating demand with a supply of an energy carrier. Describing insulation values and demand for heat for an entire neighbourhood can be done by looking at surrogate metrics. The typical age of buildings is very strongly correlated with the level of insulation (Rijksdienst voor Ondernemend Nederland, 2020). Heating demand per building is correlated with the level of insulation, but also with the density of buildings within the neighbourhood. This is the case since more densely populated neighbourhoods often have more apartment buildings which are more energy-efficient than the detached dwellings one would find more often in a less densely populated neighbourhood.

Using these two dimensions distinct archetypical neighbourhoods can be defined that are representative of those in the Netherlands. To do this, data from CBS was used (Centraal Bureau voor de Statistiek, 2020). In their neighbourhood datasets, CBS has a category called *stedelijkheid* or urbanity. Urbanity is defined by the average amount of addresses within a radius of 1km. A neighbourhood is considered *non-urban* when this value is lower than 500, *suburban* when it is between 500 to 1000, *moderately urban* between 1000 and 1500, *strongly urban* from 1500 to 2500 and *very strongly urban* if the average amount of addresses within the radius is over 2500.

For each neighbourhood, CBS also reports the number of buildings built in a period. There are five periods, which are *before 1900*, from *1900 to 1945*, from *1945 to 1965*, from *1965 to 1990* and *after 1990*. From these two dimensions with five levels, 25 profiles are constructed, as shown in table Table 3.

Table 3: Neighbourhood classification matrix

	Construction year				
Urbanity	before 1900	1900-1945	1945-1965	1965-1990	1990-now
1 (high)	1	2	3	4	5
2	6	7	8	9	10
3	11	12	13	14	15
4	16	17	18	19	20
5 (low)	21	22	23	24	25

The 25 neighbourhoods classified as such do not strictly exist in the real neighbourhood data set. A neighbourhood is assigned a certain urban density, but generally, only a certain percentage of buildings are constructed within a period. For this reason, the classification of neighbourhoods is done according to the dominant construction period. For analysis, it is furthermore desirable to do this classification in a way that reduces the number of archetypical neighbourhoods from 25 to a smaller set. This step is done following an approach used internally by CE Delft. First, the density of a neighbourhood is considered. Then, the dominant function of a neighbourhood is decided: either residential or utility. Utility neighbourhoods including business parks in which industry, office space and logistics centres are clustered. Finally, the distribution of building construction periods is evaluated. Either a single dominant period or a more spread out profile is found from this step. Based on these three criteria, a list of archetypical neighbourhoods is constructed. Each real-world neighbourhood is subsequently codified by one of the constructed archetypes. The remaining archetypes are listed in Table 4. The neighbourhoods and buildings columns contain a count of real-world neighbourhoods classified as that type.

Table 4: Archetypical neighbourhoods list

Archetype no.	Construction period	Description	Neighbourhoods	Buildings
0	N/A	No dwellings/urbanity unknown	396	980
1	<1900	Old inner cities	139	159.094
2	1900-1945	1st ring, high urbanity	669	858.634
3	1945-1965	Post-war reconstruction, high urbanity	619	775.381
4	1945-1965	Post-war reconstruction, moderately urban	170	150.063
5	1945-1965	Post-war reconstruction, suburban	119	72.492
6	1965-1990	Cul-de-sac, high urbanity living	867	1.008.114
7	1965-1990	Cul-de-sac, high urbanity mixed use	327	384.140
8	1965-1990	Cul-de-sac, moderately urban	678	776.775
9	1965-1990	Cul-de-sac, suburban	634	743.186
10	N/A	Business park	895	119.959
11	>1990	Recent construction, high and moderate urbanity	1.017	1.003.789
12	>1990	Recent construction, sub and non-urban	1.035	470.688
13	<1945	Village centers	258	92.052
14	<1990	Non-urban area	3.258	780.775
15	N/A	Other	593	39.241
16	N/A	Mix of construction periods or unknown urbanity	1.245	414.532

Not all of these neighbourhoods are useful to evaluate using SA. Archetypes 0 and 16 are excluded based on having incomplete or inconsistent CBS data, and type 15 is excluded because it is too diverse and few in occurrences to be meaningful for analysis. The decision to focus on mostly residential areas was also made, disqualifying types 7 and 10. This is not simply decided for the sake of convenience. Neighbourhoods with higher levels of utility buildings are very diverse in their construction profiles, much more so than neighbourhoods that contain mostly dwellings. Arguably a further typification could be constructed for those neighbourhoods, such as industrial parks, office parks and commercial zones with varying densities. However, available data for this purpose is limited and these areas represent a comparatively small percentage of total neighbourhoods and buildings in the country. The final selection and characterization of archetypical neighbourhoods considered for Sensitivity Analysis are provided in Table 5.

Table 5: Archetypical neighbourhood matrix

<table>
<tr><th rowspan="2">Urbanity</th><th colspan="5">Construction year</th></tr>
<tr><th>before 1900</th><th>1900-1945</th><th>1945-1965</th><th>1965-1990</th><th>1990-now</th></tr>
<tr><td>1 (high)</td><td rowspan="2">1</td><td rowspan="2">2</td><td rowspan="2">3</td><td rowspan="2">6</td><td rowspan="3">11</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td><td colspan="2" rowspan="2">13</td><td>4</td><td>8</td></tr>
<tr><td>4</td><td>5</td><td>9</td><td rowspan="2">12</td></tr>
<tr><td>5 (low)</td><td colspan="4">14</td></tr>
</table>

Because every neighbourhood in the CBS dataset was linked to one of the archetypes, aggregating this data will result in the creation of a single archetypical neighbourhood. The average (relevant) values of neighbourhood characteristics were used for this purpose. The data aggregated from the CBS database was the following:

- Address density defined as the number of addresses in a single kilometre radius
- Area in hectares
- Number of residents
- Percentage of single vs multi-family dwellings
- Percentage of owner-occupied vs rented dwellings
- Percentage of dwellings owned by housing corporations
- Percentage of dwellings connected to block heating
- Average dwelling electricity consumption in kWh
- Average dwelling natural gas consumption in kWh
- Number of buildings built in a construction period

The derived values used for each archetype can be found in Appendix III - Neighbourhoods. These data points do not provide all inputs required for running CEGOIA. Other data points were gathered from the BAG (*Basisregistratie Adressen en Gebouwen*) database, which includes information about the shares of dwelling and utility types present in each neighbourhood. This also includes the share and surface area of detached, semi-detached, end-of-terrace, mid-terrace and stacked dwellings as well as the share and surface area of utility function buildings with retail, healthcare, office, meeting, education, sports, cell or industry function. The final set of inputs necessary to construct archetypical neighbourhoods was gathered from a smaller dataset of regional grid operator Enexis's data. Infrastructure information covering the number of connections, average installation year of infrastructure, the length of electricity and length of gas networks, was extracted from this dataset.

5.3 Alterations and tools

Several changes to CEGOIA were made and some specialized tools were used to carry out the sensitivity analysis. This section briefly documents the steps taken to be able to properly run and analyse CEGOIA.

5.3.1 Changes to CEGOIA

CEGOIA, developed in Python, is set up to perform all calculations for a single region in one go. A project is specified in a web environment. Here, constraints are specified in the model settings, from which various configurations are enumerated and evaluated. To run the model several tasks need to be manually executed in sequence within the web environment. Results are then written to a database, but can also be viewed in the web viewer. From this viewer, results can be downloaded in the form of an Excel sheet. This workflow is very suitable for the development and communication of tailored results for a local government. It is, however, not suitable for performing SA.

The first change that was made is how the model executes. Instead of requiring the web environment to run the model a single time, a command was created that executes all required tasks in one go and repeats the calculation a specified number of times. This workflow enables running CEGOIA in batches. A second change is the creation of a command which overwrites all parameter values in the model with those in a specific CSV row but enables the varying of parameters required for SA. This command is called by the batch command and executes before running the rest of the model. The third and final major change to CEGOIA is the inclusion of a command that writes only the required output data (the costs of various systems) to a CSV form. This command executes within the batch command as well, after which the result is deleted and a new run commences. Note that the model was run on a dedicated server, provided by CE Delft.

5.3.2 Statistical analysis tools

Implementation of the various Local and Global Sensitivity techniques described in section 4.3 can be done in a variety of ways. Luckily, implementing those specific techniques in Python or another suite was not necessary, as there exists a Python package specifically designed to aid with Sensitivity Analysis: SALib (Herman & Usher, 2018). SALib was developed principally by Jon Herman and Will Usher and contains Python implementations of many commonly used SA techniques. The techniques in the package that were used include Fractional Factorial Sensitivity Analysis, the Morris Method and Sobol' Sensitivity Analysis.

Many of these techniques were identified as potentially useful and discussed in section 4.3, and so there is some luxury in getting to pick which technique to apply without having to implement them first. The modules included within the package allow for easy sampling and analysis of datasets. SALib is, therefore, used as the main statistical analysis toolkit for this project with supplemental analysis being done using Microsoft Excel. Visualizations are carried out using Microsoft Excel and other Python libraries (notably Seaborn and Matplotlib) since SALib includes only very limited visualization options, leading to the need for manually creating scripts to generate figures and tables.

5.4 Experiment setup

Three SA techniques are applied to CEGOIA, for each of which a different experiment setup was necessary. The following section describes the output metrics observed for each of the techniques and documents the number of variables varied, model runs evaluated and estimated calculation time.

5.4.1 Fractional Factorial experiment setup

As discussed in chapter 4, Fractional Factorial (FF) analysis is an OAT technique that is used to estimate the effects of parameters on the model outcome. This technique is computationally cheap and therefore the starting point for CEGOIA analysis. The FF experiments are used to evaluate which CEGOIA parameters have a significant effect on the observed total system costs. The relevant sensitivity measures associated with Fractional Factorial design analysis are the Main and Interactive Effects (ME and IE). These indicate the direct and indirect added costs (or savings) of that variable on a heating system respectively. A high observed Main Effect of say, the price of green gas, signifies that an increase in the gas price significantly increases the overall total system costs. Conversely, a large negative ME value indicates that an increase of the parameter value results in a significantly lower total system cost. This could be the case for the efficiency of a boiler or depreciation period. FF is suitable for the evaluation of Main Effects. The method also allows for the identification of Interactive Effects for every pair combination of variables. If two parameters have high IE this indicates that they amplify each other's effect on the model outcome. This analysis setup is suitable for identifying the pairs of variables that interact and can give a rough estimate of the size of these effects. It is, however, not well-suited for the quantification and relative ranking of interactive effects and so these are not the main focus in this chapter.

The FF analysis reported on in the next chapter involves the evaluation of 265 groups of variables which represent 695 out of 953 CEGOIA parameters. For each of these (groups of) variables an upper and lower value is determined, based on the method described in section 5.2.2. The experiment setup describes, in detail, the groupings of variables and their uncertainty ranges are available in Appendix IV - Experiments. This setup was then used on some, but not all of the archetype neighbourhoods, as constructed in section 5.2.3. The smaller subset of neighbourhoods is chosen due to time constraints. The definition of the subset is based on a mix of how common and how distinct such a neighbourhood is in the Netherlands. Table 6 describes the neighbourhoods and the numbers with which they are referenced in the analysis.

Table 6: Neighbourhoods evaluated in Fractional Factorial analysis

Neighbourhood number	Description
2	High urbanity '**first ring**', predominantly built between 1900 and 1945
3	High urbanity '**post-war**', built between 1945 and 1965
6	High urbanity suburban 'Bloemkoolwijk' or '**cul-de-sac**' built between 1965 and 1990
11	High and moderate urbanity **recent** construction, built after 1990
14	Non-urban (**rural**) areas, with diverse construction periods

The number of model runs required for this method depends on the number of variables to evaluate, which in this case is 265. The number of runs required is then $2 * 2^n$. n is chosen as the lowest power of 2, which results in a value higher than 265. In this case, $2^8 = 256$ which is lower than 265. As such, 9 is chosen since $2^9 = 512$. Consequentially, $2 * 2^9 = 2 * 512 = 1024$ runs are run per neighbourhood. The calculation time for a neighbourhood was then found to be around 47 hours/2 days. Hence, evaluation of 5 neighbourhoods takes approximately 10 days.

5.4.2 Morris experiment setup

The Method of Morris (MM) evaluates Elementary Effects (EE), which capture both the Main and Interactive Effects as described by the Fractional Factorial analysis method. EE are described principally by the mean elementary effect, μ, and its standard deviation, σ. As was done in the previous analysis, the absolute of the mean EE is taken when analysing the effect to not complicate interpretation with the direction of a given effect. The absolute value is denoted using μ* (mu star). Sigma/σ can be interpreted as the Indirect (higher-order or multiplicative) Effect of a parameter. The ratio σ/μ* is used as a measure of the degree to which the effects of a parameter are direct (close to 0) or indirect (closer to 1, potentially higher). An example: the efficiency of a boiler is found to have a value of -500 for μ and a value of 400 for σ. μ* is equal to 500, and the ratio σ/μ* equals 0.8. Such values can be read to understand that an increase in efficiency leads to a decrease in total system costs, directly (by 500) and indirectly through interaction with other variables (by 400). Furthermore, a ratio of 0.8 is quite high and so the parameter displays highly interactive properties making it more difficult to draw conclusions about what effects of uncertainty about its value are. The number itself is not directly indicative and should be compared to other EE's found in the analysis. If electricity costs are found to have a much higher EE of, e.g. 20.000, it indicates that efficiency comparatively is not a very influential parameter.

The MM analysis reported on in the next chapter involves the evaluation of just 119 groups of variables which represent 491 out of 953 CEGOIA parameters. The number of groups and parameters varied is significantly smaller than in the previous analysis. This is achieved using insights from the FF analysis to reduce calculation times and increase the ability to attribute effects. The costs for insulation and demand for heat, for example, were bundled into fewer groups to get a better idea of the significance of their effect. Some parameters which were used in the previous analysis were omitted in this one, as they were found to have no effects at all. The groupings and used uncertainty range for all parameters can be found in Appendix IV - Experiments. The number of model runs required for this method is equal to $(n + 1) * T$, where n is 119 and T is equal to the number of trajectories (see section 4.2). Ten trajectories were used, resulting in 1200 model runs or 60 hours' worth of calculation time per neighbourhood.

5.4.3 Sobol' experiment setup

In the Sobol' experiment, seven 'trend' parameters are varied Globally, and their effects on the cost of eight heating system options are evaluated. These parameters are insulation costs, heating system costs, gas infrastructure costs, electricity infrastructure costs, heat net infrastructure costs, gas price and electricity price. This list of parameters was chosen based on the results of the FF and Morris analyses. The sensitivity measures resulting from Sobol' analysis are the variance-based so-called 'Sobol' indices'. First-order Sobol' indices express the percentage of variance in the result directly attributable to varying parameters. Two important features of First-order Sobol' indices are that the sum of all first-order Sobol' indices will always be 1 and that higher-order interactions are not included in the index. Total-effect Sobol' indices reflect the importance of a parameter the same way First-order indices do but include all higher-order interactions in the result. As a consequence, the sum of all Total-effect Sobol' indices will always be equal to or larger than 1. The difference between these two measures can therefore be used to evaluate the importance of higher-order effects of variables.

For each of the seven parameters, 150 samples were drawn so as to achieve an acceptable level of confidence in results (Saltelli et al., 2010). Ideally, a higher number of samples (up until 1000) is drawn, however time constraints limit the possibility of doing this. The choice was made not to separately calculate second-order Sobol' indices, as this would double the number of runs required. As a result, $150(7+2) = 1350$ runs were evaluated per neighbourhood experiment.

6 Sensitivity Analysis Results

This chapter reports and analyses the results of the CEGOIA SA that was proposed in the previous chapter. This SA was done primarily with the goal of *identifying a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options.* In section 6.1, the specific parameters for the observed significant effects are summarized and conclusions about uncertainties and their importance are drawn. Results in section 6.2 cover the effect of varying neighbourhood contexts in the model. Section 6.3 discusses non-linearity in CEGOIA. Section 6.4 covers specific sensitivities of heating system options and their implications for the (un)certainty about model outcomes, with which statements about the robustness of the model are made. Finally, a summary of the main findings and an answer to the research sub-question '*What are the CEGOIA factor sensitivities and their effects*?' is presented in section 6.5 along with a reflection on the three SA techniques used for this research.

6.1 Parameter effect screening

Screening of parameters so that 'Factor Fixing' can take place – the process of identifying parameters with low sensitivity and excluding them in more powerful analysis – is done to reduce the number of parameters to focus on. Both the Fractional Factorial (FF) technique and Method of Morris (MM) are applicable for this purpose. In doing these two analyses, several insights are to be gained about the CEGOIA model. First and foremost is the identification of the top most influential parameters within the model. Since each heating system option makes use of system-specific variables, it is expected that the lists of influential parameters will have little overlap. Because of this, screening is done separately for each of the eight heating system options. Section 6.1.1 starts with the discussion of three exemplar results, which serves as a primer and a base with which other results in the chapter can be compared. Section 6.1.2 then provides an overview of summarized screening results and section 6.1.3 contains a list of parameters with which more elaborate SA using the Sobol' method is warranted.

6.1.1 Three screening examples

A lot of results were generated using the FF and MM techniques: for each analysis eight heating system options, five neighbourhood archetypes and both residential and utility nodes are analysed, resulting in a total of 160 unique results. It is excessive to discuss each individual result, but to get an impression of what they look like a selection of three heating system options analysed using MM is presented in this section. The three options are the air heat pump, hybrid heat pump and MT heat net, which are given for the residential node of the cul-de-sac archetypical neighbourhood. This choice is made because the majority of buildings in the Netherlands are residential and the cul-de-sac is the most common neighbourhood type. These three options are specifically chosen based on an observation that they are the most common result for neighbourhoods using both Vesta MAIS and CEGOIA (PBL, 2020). Results for other options, in other neighbourhoods and in both nodes are available in Appendix V – Figures.

Figure 12 ranks those parameters with significant Elementary Effects (EE) found with MM for the three mentioned examples. The black bars over the results indicate the observed indirect effects of the parameters.

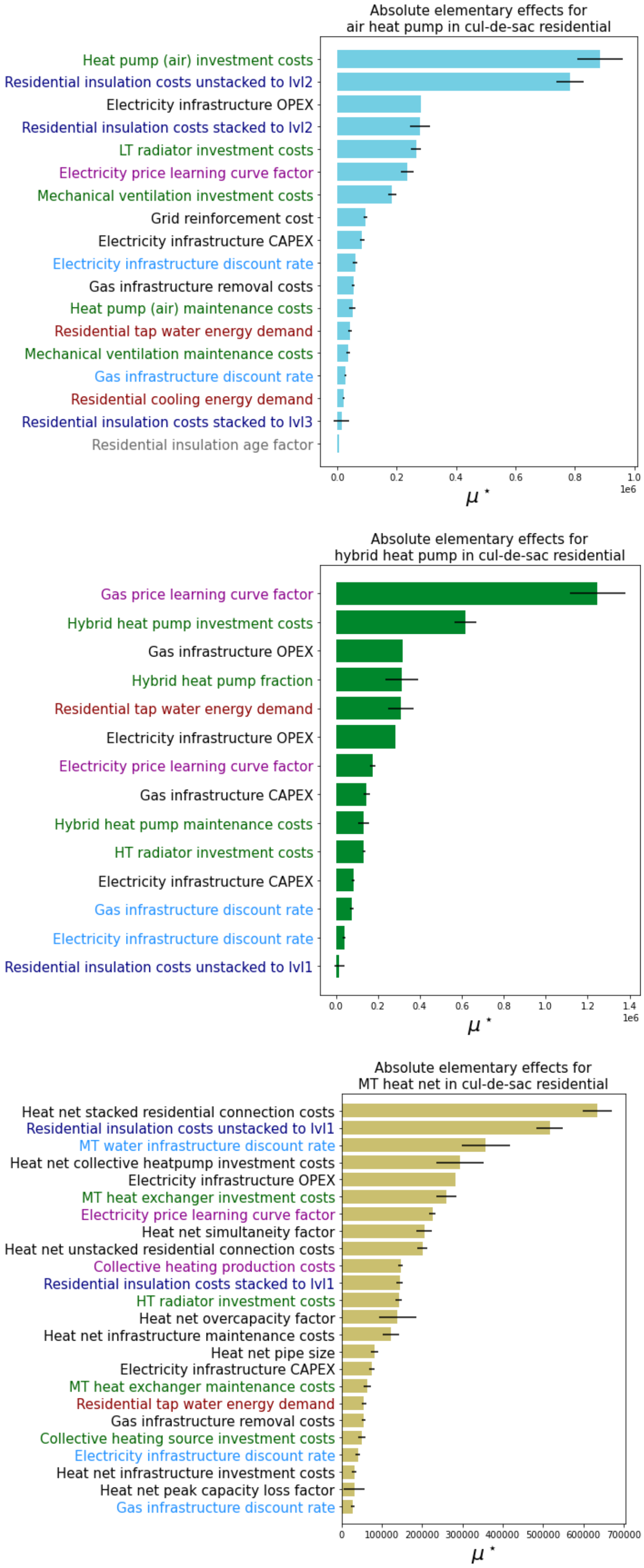


Figure 12: CEGOIA Elementary Effects for three heating options in a cul-de-sac neighbourhood. Air heat pumps (blue), hybrid heat pumps (green) and MT heat net (yellow). Parameters on y-axis are coloured by similarity: black indicates infrastructure parameters, dark blue insulation, light blue discount rates, green heating systems, red energy demand and pink energy prices.

The first chart in Figure 12 reports that for a typical Dutch house in a typical Dutch neighbourhood the costs of insulation and the costs for the heat pump itself are the main sources of sensitivity; changes in these values influence how cheap or expensive the total system will be the most. Other parameters of note are the electricity price, radiator and ventilation costs. Although often a topic when discussing electrification, grid reinforcement costs have a relatively small effect. Because the cul-de-sac neighbourhood uses averaged data from real neighbourhoods, this implies that reinforcement costs are not often going to be a deciding factor in choosing an alternative. The OPEX costs for electricity infrastructure is a parameter that is very influential in each of the heating system options. Yet, in the big picture, they may not be very important to decision making in the heating transition. This is because these costs are about the same for any of the heating system options evaluated by CEGOIA. After all, all buildings are required to be connected to – and pay for – the electricity grid.

The second chart concerns hybrid heat pumps. Their costs are mostly influenced by the price of gas and the investment costs for the pump itself. The fraction of electricity/gas is also important. If hybrid heat pump installers can realize low investment costs as well as a high fraction of electricity use without spending much money on insulation this option will often be the cheapest in comparisons.

The third and final chart shows the effects of MT heat net parameters. The connection costs of heat nets, insulation costs, collective heat pump investment costs and the discount rate used for MT heat net infrastructure are the most influential parameters. Developments that decrease the connection costs will have the biggest effect on the choice of MT heat nets. The discount rate – which is set to 6% in CEGOIA – is of particular interest. These rates are set by heat net investors to reflect the profitability of an investment. Lower discount rates result in a cheaper total system, and could be realized by collectivizing heat net investment by public institutions. Other parameters that are also of notable consequence are the electricity price, costs of the collective heat source and further heat net specific parameters such as the simultaneity factor, overcapacity factor and pipe sizing. Somewhat surprisingly the costs of the heat from a collective heat source is not as influential as the collective heat pump – which is required to meet peak demand.

A number of general observations can be made about the charts in Figure 12. The first and foremost remarks concern the composition of each of the three lists. As remarked in section 5.4, almost 200 parameters were included in this specific analysis, yet only about 15-25 parameters have any measurable effect on the annualized societal costs of these systems. What's more, is that in each case 1-3 parameters account for the majority of the EE. The conclusion to draw is that for each heating system option, only a handful of model parameters – which represent real-world trends in technology and economics – are relevant to understand. To illustrate: there is a situation in which an air heat pump system is slightly more expensive than a hybrid heat pump for a given set of buildings. If the efficiency of a heat pump increases marginally by 5%, then the air heat pump system will barely become any cheaper; it is unlikely to make up the difference. But if the costs of gas decrease by 5%, then the hybrid heat pump system will likely become cheaper than the air heat pump system. If the costs of the heat pump become cheaper by 5%, however, the air heat pump will remain the cheapest option. Heat pump manufacturers should therefore focus on realizing lower costs rather than increasing efficiency if they want to sell more heat pumps. Another remark about the structure of the results in Figure 12 relates to the number of variables in each option. The MT heat net has 24, the air heat pump 18, and the hybrid heat pump has 14. The heat net has more and also more variables with larger EE than either heat pumps. The higher number is a reflection of the fact that heat nets are more complicated systems

- the dimensioning of the heat net comes on top of the energy costs, installations & modifications in buildings that are required for the heat pumps. The higher average EE indicates that heat nets are more sensitive in general: there are multiple factors that can make it so that heat nets become more or less expensive than other systems, whilst hybrid heat pumps will only become very unattractive if gas prices and investment costs increase dramatically. In a way, this makes a choice for an MT heat net riskier than hybrid heat pumps since there are more factors that can 'go the wrong way', although just as many can 'go the right way'.

6.1.2 Overall screening results

The goal of screening is to identify the financially most influential CEGOIA parameters which denote the most important developments in the heating transition. These developments are heating option specific, as was noted in the previous section. Figure 13 contains a heat map that summarizes simultaneous results for the eight heating system options, again in the typical residential cul-de-sac neighbourhood. In this figure, lighter colours indicate higher Main Effects (gained via Fractional Factorial analysis), whereas darker ones indicate lower effects. The absolute value of ME is displayed logarithmically so that a cell's colour better reflects the importance of a variable for a system. On the x-axis, the eight heating options are found; on the y-axis a selection of parameters. Variables on the y-axis are coloured as a visual aide. Variables with a similar typification (e.g. economic factors, prices, demand, infrastructure factors) will generally have the same colour. The eight parameters with the highest observed effects for an option are included on the y-axis.

There are a number of parameters that have high ME amongst multiple or all of the heating system options in Figure 13. Shared amongst all is the depreciation period for building installations and modifications, electricity infrastructure OPEX, electricity price, and residential tap water demand. These five parameters are important, yet at the same time, are not necessarily crucial for the heating transition as a whole. The reason for this is the following. The question models like CEGOIA try to answer is w*hat sustainable heating system is cheapest in which building, given local characteristics*. To answer this question, the cost of the entire building energy system is calculated, but some parts of that equation are the same regardless of what alternative is chosen. This is especially true for electricity OPEX costs. To a lesser extent it also holds for the electricity price and tap water demand, as higher values for these do increase the costs for electricity and gas-based more respectively.

Other parameters that are relevant for more than one option relate to gas and heat net infrastructure, insulation costs and (HT or LT) radiator investment costs. Heating system investment costs and efficiencies and in the case of a pellet boiler biomass costs conclude the list of parameters of notable and consistent influence.

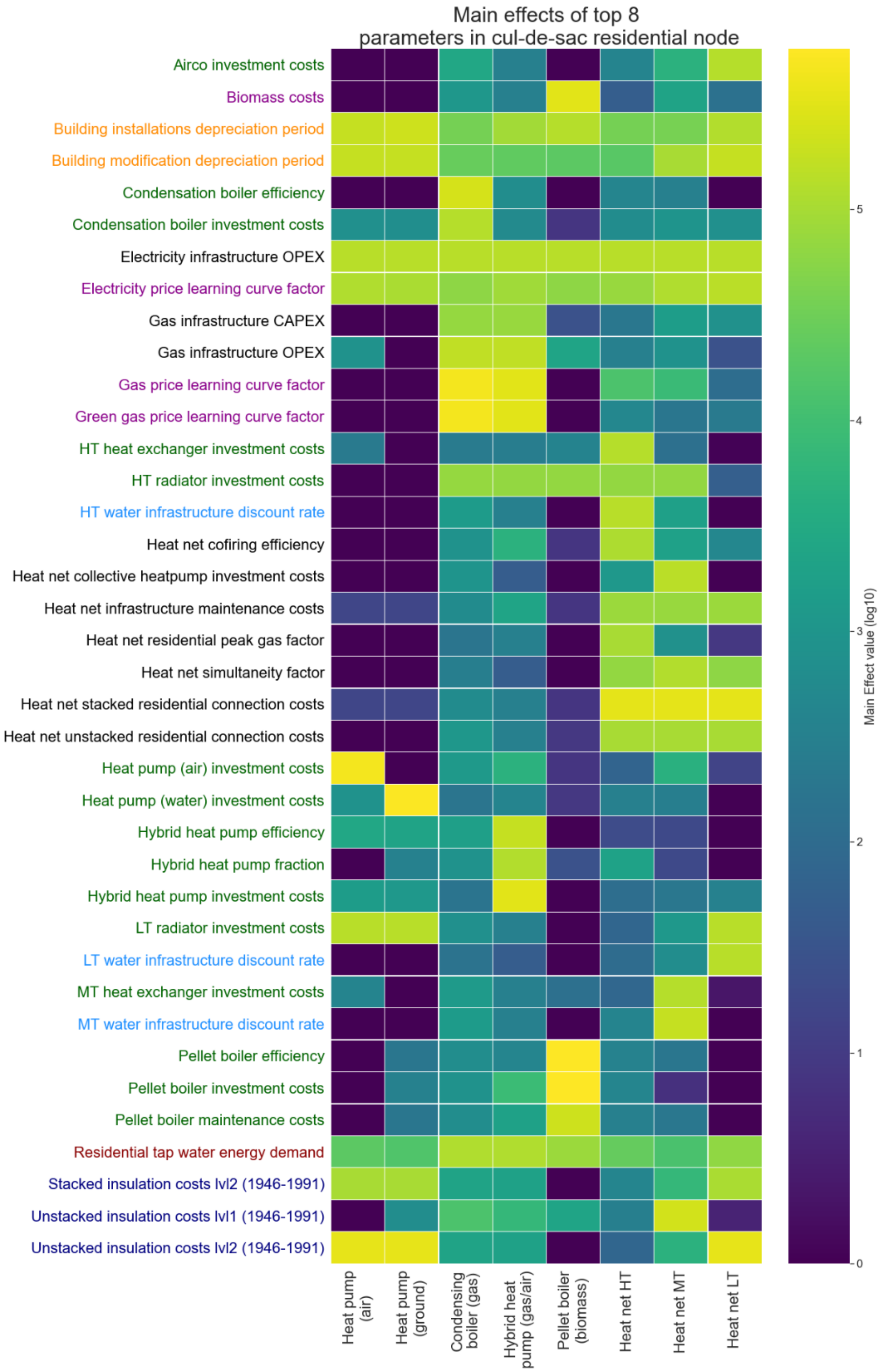


Figure 13: Heat map of absolute Main Effect values on the residential node of the cul-de-sac neighbourhood, top 8 variables for each option included. Lighter colours indicate higher values. Effects plotted logarithmically.

It was mentioned in section 6.1.1 that some options were found to have more influential parameters than others. This indicates a lower system complexity which simplifies the understanding of relevant uncertainties. To illustrate: to know how competitive a hybrid heat pump is going to be, one needs primarily consider the uncertainty about the costs of green gas and the heat pump. For a heat net, the costs of connecting to the heat net as well as its dimensioning, collective heat pump costs, the discount rate on top of insulation costs need to be considered. Although not directly necessary for screening purposes, a comparison of complexity is useful as it improves comprehension of the available heating system options. A count of parameters with significant effects on system costs are available in Table 7 (for residential buildings) and Table 8 (for utility buildings). Counts are presented of parameter Main Effects with respect to the highest observed Main Effect for that heating system option. Brighter colours are attributed to the highest value in a row, so that it becomes apparent that, e.g. Low Temperature heat nets have many influential parameters in the residential option, whilst pellet boilers have very few. A ranking of complexity, from least complicated to most complicated, is the following:

- Pellet boiler
- Condensing boiler, air heat pump, ground heat pump
- Hybrid heat pump, HT heat net, MT heat net
- LT heat net

Table 7: Distribution of variable contributions to option costs for a residential node, calibrated to the highest Main Effect value for that option, averaged over five neighbourhoods

Average number of variables with effects	Heat pump (air)	Heat pump (ground)	Condensing boiler (gas)	Hybrid heat pump (gas/air)	Pellet boiler (biomass)	Heat net HT	Heat net MT	Heat net LT
more than 30%	5	5	6	8	5	4	7	9
10%-30%	8	6	7	9	4	12	11	12
5%-10%	8	8	5	2	4	8	8	9
1%-5%	15	17	9	14	5	17	20	22
less than 1%	229	230	239	231	247	224	220	212

Table 8: Distribution of variable contributions to option costs for a utility node, calibrated to the highest Main Effect value for that option, averaged over five neighbourhoods

Average number of variables with effects	Heat pump (air)	Heat pump (ground)	Condensing boiler (gas)	Hybrid heat pump (gas/air)	Pellet boiler (biomass)	Heat net HT	Heat net MT	Heat net LT
more than 30%	8	7	9	10	6	5	8	8
10%-30%	6	6	12	12	8	16	12	11
5%-10%	8	7	10	10	7	11	14	13
1%-5%	12	14	31	36	29	48	21	20
less than 1%	230	231	202	198	215	184	210	213

6.1.3 Variable selection for Sobol' analysis

In further analysis (Factor Prioritization) the Sobol' method is used on a handful of variables that are varied through Monte Carlo sampling. Since the number of sampling draws required for high confidence in FP methods is between 100 and 1000 per parameter, the total number of model runs quickly rises as more variables are included. It is thus sensible to realize the limited ‘budget’ of variables available. Table 9 provides the CEGOIA time cost for running this analysis on a single neighbourhood with 4 to 8 variables.

Table 9: Estimated calculation times for Sobol’ analysis of 4, 6 and 8 CEGOIA parameters

Variables [D]	**Samples [N]**	**Runs first-order effect [N * (D + 2)]**	**Calculation time [minutes]**	**Calculation time [days]**	**Runs second-order effect [N * (2D + 2)]**	**Calculation time [minutes]**	**Calculation time [days]**
4	100	600	1.800	1,3	1.000	3.000	2,1
	250	1.500	4.500	3,1	2.500	7.500	5,2
	500	3.000	9.000	6,3	5.000	15.000	10,4
6	100	800	2.400	1,7	1.400	4.200	2,9
	250	2.000	6.000	4,2	3.500	10.500	7,3
	500	4.000	12.000	8,3	7.000	21.000	14,6
8	100	1.000	3.000	2,1	1.800	5.400	3,8
	250	2.500	75.00	5,2	4.500	13.500	9,4
	500	5.000	15.000	10,4	9.000	27.000	18,8

Since there is a limited budget of computational time for Sobol’ calculations, a selection of a handful of parameters must be made based on the screening results. For this reason, the choice is made to create seven macro grouped variables – groups of previously created groups – that are influential consistently for all heating options, in different nodes and different neighbourhoods. They were selected based on the variables included in the various heat maps and bar charts, and in such a way that they represent somewhat independent trends. In the end, seven so-dubbed *trend variables* are sampled 150 times each. They are:

- **Insulation costs**: Includes all costs associated with insulation upgrades: every energetic performance level, building type and building period for both residential and utility applications. This includes stacked and unstacked building types and all insulation levels.
- **Heating system costs**: Covers investment costs and maintenance costs of production (like heat pumps and pellet boilers), and distribution systems (radiators). Ideally, these costs would be split between individual and collective systems, as well as production and distribution systems. This would, however, necessitate the inclusion of too many variables to be feasible. The choice is made not to include system efficiencies as these vary wildly between different systems and would make interpretation of the trend variable convoluted. Ideally, heating system efficiencies would be one of the next variables to include in the trend list.
- **Gas infrastructure costs**: Covers the CAPEX, OPEX as well as removal costs for gas infrastructure, and represents the trend of adding or removing new gas infrastructure.
- **Electricity infrastructure costs**: Covers the CAPEX, OPEX as well as reinforcement costs for electricity infrastructure. OPEX was previously discussed not to matter too much for deciding between different systems. However, CAPEX and reinforcement costs are influential parameters of themselves, and as such, electricity infrastructure is included.
- **Heat net infrastructure costs**: Encapsulates a wide range of costs, specially selected based on their appearance on the heat maps. Includes connection costs, peak factors and provisions.
- **Gas price**: The cost of (green) gas in 2050 based on the learning curve factor.
- **Electricity price**: The cost of electricity in 2050 based on the learning curve factor.

Some likely candidates for trend variables are notably absent in the list. One of these is biomass costs, which are only relevant for pellet boilers. Another trend that instinctively should be part of what matters for sustainable heating system costs is energy demand. With the exception of tap water demand, model results did not show a significant effect of increased or decreased energy demand on the overall option cost. It might be true that energy demand represents a significant chunk of energy system costs, but changing this demand does not appear to produce a significant change in costs. All things considered, the generalization to seven trend variables does not do full justice to the complexity of each heating system option. The computational costs of the Sobol' method for the CEGOIA model are limiting in this regard.

6.2 Effects of different neighbourhood contexts

Section 6.1 provided an answer to what the most important parameters are in CEGOIA, by extension informing about the most important factors in the heating transition. Before performing further analysis using the seven trend variables, this section focuses on the effects of local contexts. A neighbourhood that is full of new rowhouses will have different energy demand needs than a city centre, and as such, section 6.2.1 focuses on the differences in results between different archetypical neighbourhoods. Since CEGOIA calculates separate results for residential buildings in a neighbourhood and utility buildings (the two 'nodes'), it makes sense that this results in a different set of sensitivities as well. Section 6.2.2 discusses these differences.

6.2.1 Differences between neighbourhoods

The five archetypical neighbourhoods (first ring, post-war, cul-de-sac, recent and rural) differ primarily on two dimensions, building age and density. Correlations between different neighbourhoods from FF analysis are shown in Table 10. On average, correlations are very high with the lowest being 83% and the highest being 98%. The conclusion that can be drawn from this outcome is that local circumstances do matter in determining what uncertainties have an impact on system costs, but only account for a small part (max of 17%) of the total sensitivity. The remainder of the sensitivity is attributable to non-location specific characteristics.

Table 10: Averaged correlations of option sensitivities between residential nodes of five neighbourhoods: higher values indicate sensitivities of neighbourhoods are more alike.

Residential node correlations between neighbourhoods averaged over all options	First ring	Post-war	Cul-de-sac	Recent	Rural
First ring	1,00	0,95	0,91	0,90	0,83
Post-war	0,95	1,00	0,98	0,94	0,89
Cul-de-sac	0,91	0,98	1,00	0,88	0,85
Recent	0,90	0,94	0,88	1,00	0,93
Rural	0,83	0,89	0,85	0,93	1,00

The difference in correlations between neighbourhoods is due to density and building age. Parameters that especially matter for these two factors are insulation and infrastructure costs respectively. More insulation measures are required for older buildings, and so their related parameters will have higher effects in, e.g. a first ring neighbourhood than a recent one. Following from Table 10, neighbourhoods constructed between 1945 and 1990 (post-war and cul-de-sac neighbourhoods) correlate very highly, suggesting that sensitivity to insulation costs between these periods are very similar. The rural neighbourhood is the only one with a significantly lower density than the others, and has a mixed-age building stock of on average larger and more free-standing houses. As observable in Figure 14, these characteristics result in more infrastructure meters per building (higher electricity OPEX effect), as well as a need for more insulation costs (higher insulation cost effect). Despite the high effect of insulation costs, the rural neighbourhood correlates most highly with the recent neighbourhood which has a relatively high sensitivity to infrastructure costs. Because this correlation is higher, the conclusion is drawn that the sensitivity to infrastructure costs as a whole is larger than insulation costs. This suggests the existence of a tipping point where sustainable heating systems which make use of little to no energy infrastructure (i.e. off-grid) might be the cheapest solution for rural applications, even if they require a lot of insulation modifications.

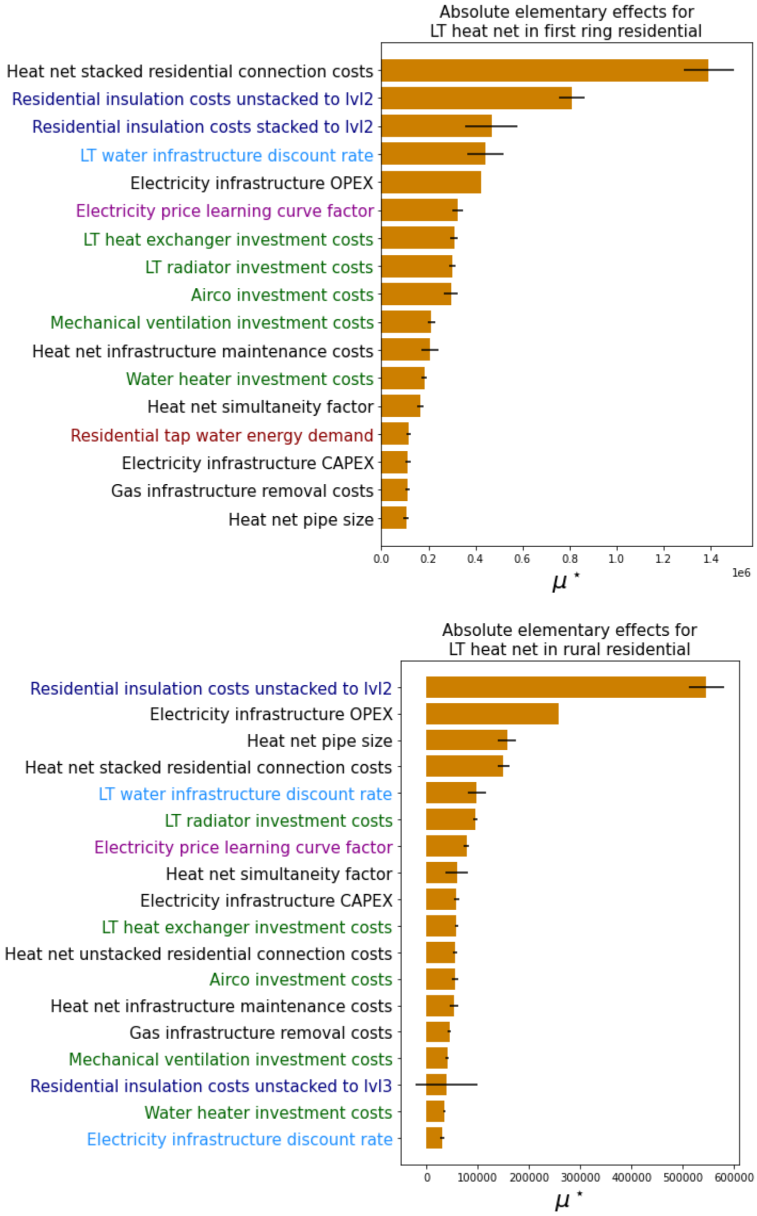


Figure 14: MM results for LT heat net in old urban neighbourhood (top) and mixed-age rural neighbourhood (bottom)

As a whole, the difference in results based on neighbourhoods is not entirely unsurprising. Still, the analysis has demonstrated there are only two factors necessary to explain differences between neighbourhood outcomes of CEGOIA and other heating transition models. Since most neighbourhoods in the Netherlands are (sub)urban, insulation costs, in particular, dictate the decision for a heating alternative.

6.2.3 Differences between residential and utility nodes

Residential and utility nodes represent two sets of fundamentally different energy needs, something which is reflected in CEGOIA. Although utility energy demand profiles can vary quite a lot, e.g. retail, office or education usage, generally speaking, their energy demands are higher.

Table 11 contains comparisons between residential and utility nodes for different options in each of the five neighbourhoods. Correlations from 0,22 to 0,84, and in general, the sensitivities of pellet boilers are most alike in the two whilst those of heat nets are least alike. So what causes these differences? Some of it can be explained by modelling choices. The parameters used to model insulation upgrades and costs are different for residential and utility nodes. Due to the nature of the correlation calculation, those insulation parameters will not correlate at all. This still does not explain all of the difference. In fact, certain parameters are structurally more sensitive for the costs of utility buildings than for residential buildings. Figure 15 contains a comparison of residential and utility effects for an air heat pump in the same neighbourhood. The higher energy demand of a utility node leads to a higher sensitivity to not just demand itself but also the price of energy. It also leads to a higher sensitivity to insulation costs. Conversely, the sensitivity of utility buildings to infrastructure OPEX costs is much lower.

The differences between residential and utility sensitivities lead to other interpretations of what uncertainties are important in deciding on what sustainable heating alternative to choose from. Choices for residential buildings are more sensitive to the costs of the heating system, whilst choices for utilities are more sensitive to the consumption and costs of energy. For residential buildings, this means that the choice for a sustainable alternative should include an assessment of effects on heating system costs and necessary infrastructure, whilst the choice for utility buildings should have more focus on assessing risks with regards to energy costs.

Table 11: Correlations between residential and utility nodes in five neighbourhoods: higher values indicate lower variance in neighbourhood and node characteristics.

Correlations of option sensitivities within residential and utility node	First-ring	Post-war	Cul-de-sac	Recent	Rural
Heat pump (air)	0,59	0,59	0,61	0,57	0,40
Heat pump (ground)	0,63	0,63	0,65	0,61	0,42
Condensing boiler (gas)	0,50	0,53	0,64	0,52	0,51
Hybrid heat pump (gas/air)	0,45	0,48	0,59	0,47	0,42
Pellet boiler (biomass)	0,77	0,79	0,84	0,75	0,66
Heat net HT	0,22	0,26	0,31	0,28	0,32
Heat net MT	0,32	0,34	0,36	0,33	0,33
Heat net LT	0,31	0,36	0,39	0,39	0,35

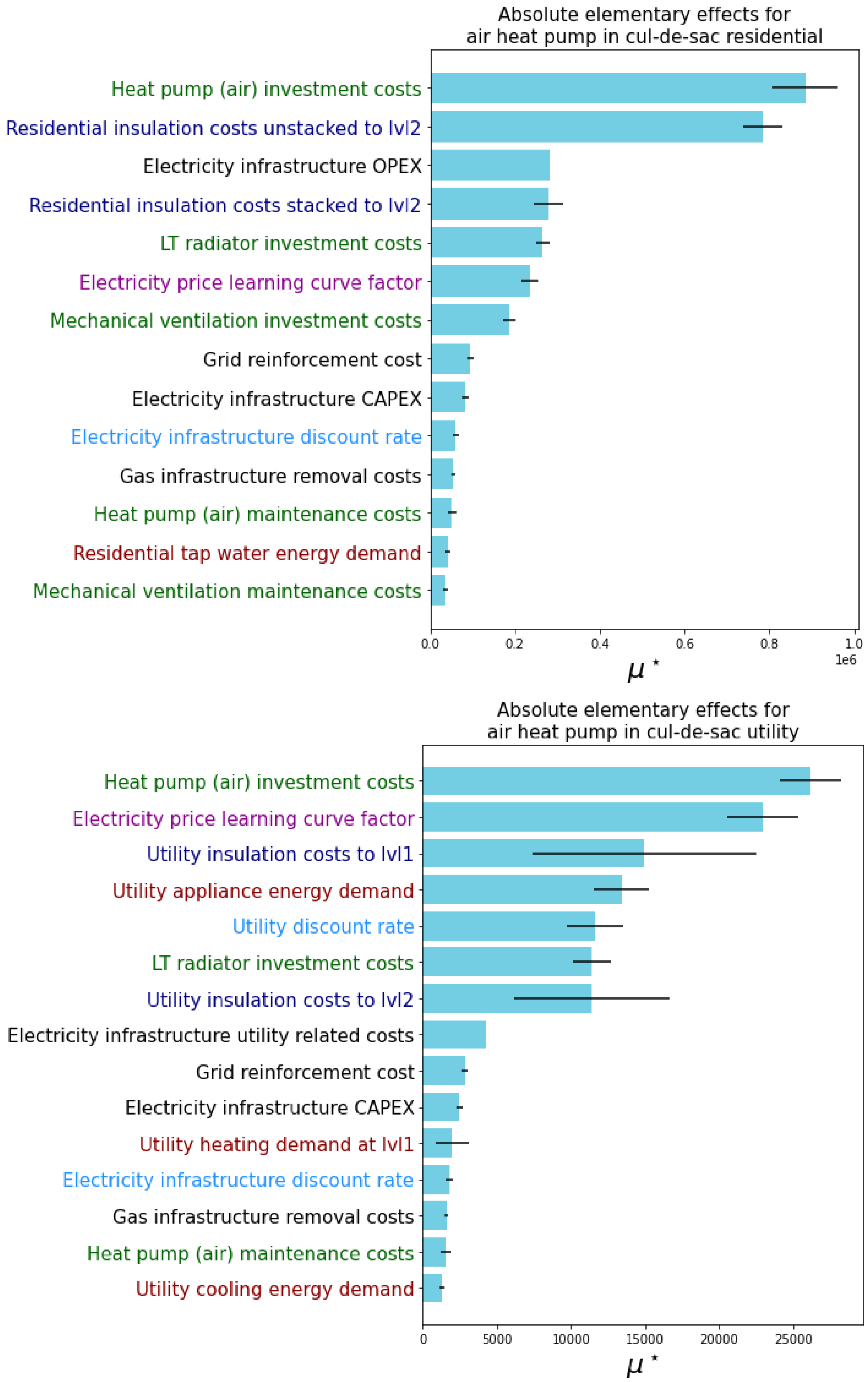


Figure 15: MM comparison of air heat pump parameters in cul-de-sac residential (top) and utility (bottom) node

6.3 Higher-order effects in CEGOIA

The interpretation of parameter effects is made easier or more difficult, depending on the degree to which higher-order effects take place inside a model. If, say, increased space heating demand causes a cost increase of X and a boiler efficiency decrease causes a cost increase of Y, the total system costs increase by X and Y in each separate scenario. If both changes happen at the same time, a less efficient boiler will have to work even harder to meet a higher space heating demand. In this example, an interaction (Z) takes place which causes the total system costs to increase by Z * (X + Y). The presence and size of higher-order effects in CEGOIA was evaluated using the Morris and Sobol' methods: the result is that there are some interactions, but these are not responsible for a high amount of model sensitivity.

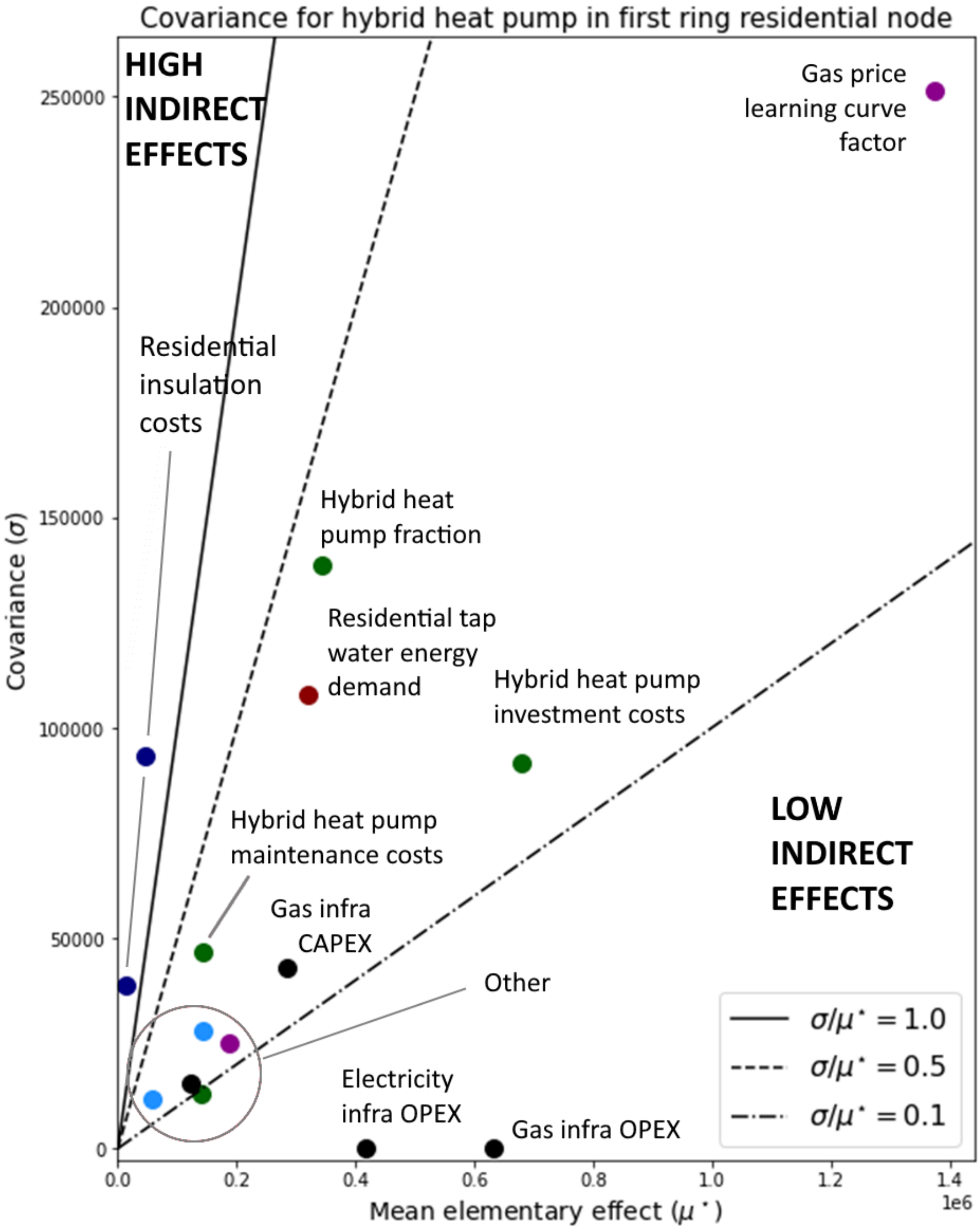


Figure 16: Higher-order effects in first ring neighbourhood hybrid heat pump option. Variables to the left of the black lines have highly interactive properties.

As discussed in section 4.4, MM analysis produces Elementary Effects (EE, μ) and covariance (σ) statistics about parameters. μ represents direct effects, whilst covariance describes higher-order effects. The parameters with significant EE for a hybrid heat pump in a first ring neighbourhood are plotted in Figure 16 with μ on the x-axis and σ on the y-axis. A number of things in this figure deserve attention. For one, the gas price factor (top right) has both a very large direct and indirect effect. Relatively speaking. However, it is not the parameter with the most higher-order effects. The standardized covariance (σ/μ*) ratio, of which 1, 0.5 and 0.1 lines are plotted, indicates how much higher-order effects are related to a variable.

The residential insulation costs have a ratio of over 1, which means that a lot of other variables interact with it to arrive at the total costs of insulation. Meanwhile, electricity and gas infrastructure OPEX costs have no covariance, and thus interact with no other variables in the model: their costs are directly added to the total system costs. A parameter with a higher standardized covariance ratio contributes to a more difficult to calculate cost, and it is therefore harder to estimate what changing the value of the parameter will do to the costs of the total system. Although this can be a problem, in the case of Figure 16 the higher-order effect parameters (with covariance ratios over 0.5) are mostly present in lower impact variables.

The standardized covariance ratio of parameters differs little if anything when looking at different neighbourhoods, and both residential and utility nodes display consistent ratios as well. Generally speaking, a number of parameters consistently have high interaction effects (insulation costs and heating demand) whilst OPEX costs have none at all. Most other parameters have standardized covariance ratios between 0.1 and 0.5, which makes anticipating the effect of changing their values relatively predictable because changes in parameter values are expressed in results in a straightforward manner.

The result of finding relatively few higher-order interactions in CEGOIA has consequences for the techniques used in this Sensitivity Analysis. As mentioned in section 4.2, there exist ‘Local’ and ‘Global’ SA techniques, wherein the former class of techniques is computationally cheaper but incapable of capturing higher-order effects. Conversely, Global techniques can capture these effects but come at very high computational cost. By concluding that CEGOIA contains relatively few higher-order effects, the case could be made that Global techniques – in the case of this research the application of the Sobol’ method - are of limited extra explanative value and that Morris results can be used as a reliable measure for sensitivities.

There is another question that can be asked about higher-order interactions in CEGOIA: Which are the variables that parameters with high second-order effects interact with? This question cannot be answered with the more powerful Method of Morris, but could be done crudely using FF since this method estimates Interactive Effects (IE). IE are reported in a list of all possible combinations of variables and a number indicative of Indirect Effects. These numbers themselves are not useful, however, because every 265 variable pairs (the number of variables in FF analysis) have the same attributed IE value. The next set of 265 pairs has different, lower values, which does indicate that these pairs have strictly lower IE than the set before it. Because of this, it is not the value but the order in which pairings appear which is of interest using the FF technique. Using FF to identify pairings and MM to identify which variables IE are attributed to in conjunction would allow for the identification of paired, interacting variables. The added value of this exercise is an increased understanding of the model, but may not produce very major improvements in comprehension: an estimated guess about relationships can in practice often be made by evaluating the formulas used in implementing the model. What’s more is that the two FF and MM experiments performed for this analysis make use of slightly different sets of variables, because of which this comparison cannot be made.

6.4 Heating option sensitivities

Sensitive CEGOIA parameters are those parameters that represent the uncertainty that determines which heating system option is selected for a neighbourhood. So far, the CEGOIA model dynamics have been analysed, and identification of influential parameters has been made through parameter screening. In this subsection, the effects of those screened parameters are further analysed. Section 6.4.1 focuses on the results of the Sobol' analysis, which is used to determine a final prioritization of which parameters are most important for each heating system option. Then, section 6.4.2 discusses what the effects of the sensitivities are for choosing which heating system option is cheapest in CEGOIA.

6.4.1 Prioritization of parameters

Questions such as '*What are the most important aspects of a heat pump and a heat net that determine whether the one or the other is cheaper?'* are answerable with a rank-ordering of all the different aspects and their relative importance. Such an ordering is attained using the Sobol' method, which produces Sobol' indices that signify how much of the total observed variance is attributable to one parameter. This analysis was done using the seven trend variables proposed in 5.1.2. Three examples of results from Sobol' analysis for air heat pumps, hybrid heat pumps and MT heat nets are presented in Figure 17. The blue bar denotes first-order effects, S1 (conceptually very similar to the previously discussed Main Effects and Standardized Mean Elementary Effect), whilst the orange bar indicates the total-order effects, ST. The S1 values in a chart always add up to 1 (and so can be read as a percentage of sensitivity), whilst the ST values can add up to more than 1. Since higher-order effects are limited, S1 and ST values are generally very similar. The black bars denote the 95% confidence bound.

The charts in Figure 17 tell a clear story about the sensitivities of the three heating system options. For air heat pumps, insulation costs and heating system costs (heat pump, radiators, ventilation) are of about equal importance whilst the costs of electricity are not at all that important. Uncertainty surrounding the costs of a hybrid heat pump system are mainly determined by the price of gas, but the costs of the heat pump and the fraction gas/electricity do also play a role. For the heat net, the costs of the net itself are by far the most important factor. These figures present a way to quickly communicate to policymakers or regular citizens what the most important developments are that affect the choice of a heating system, without going into too much detail.

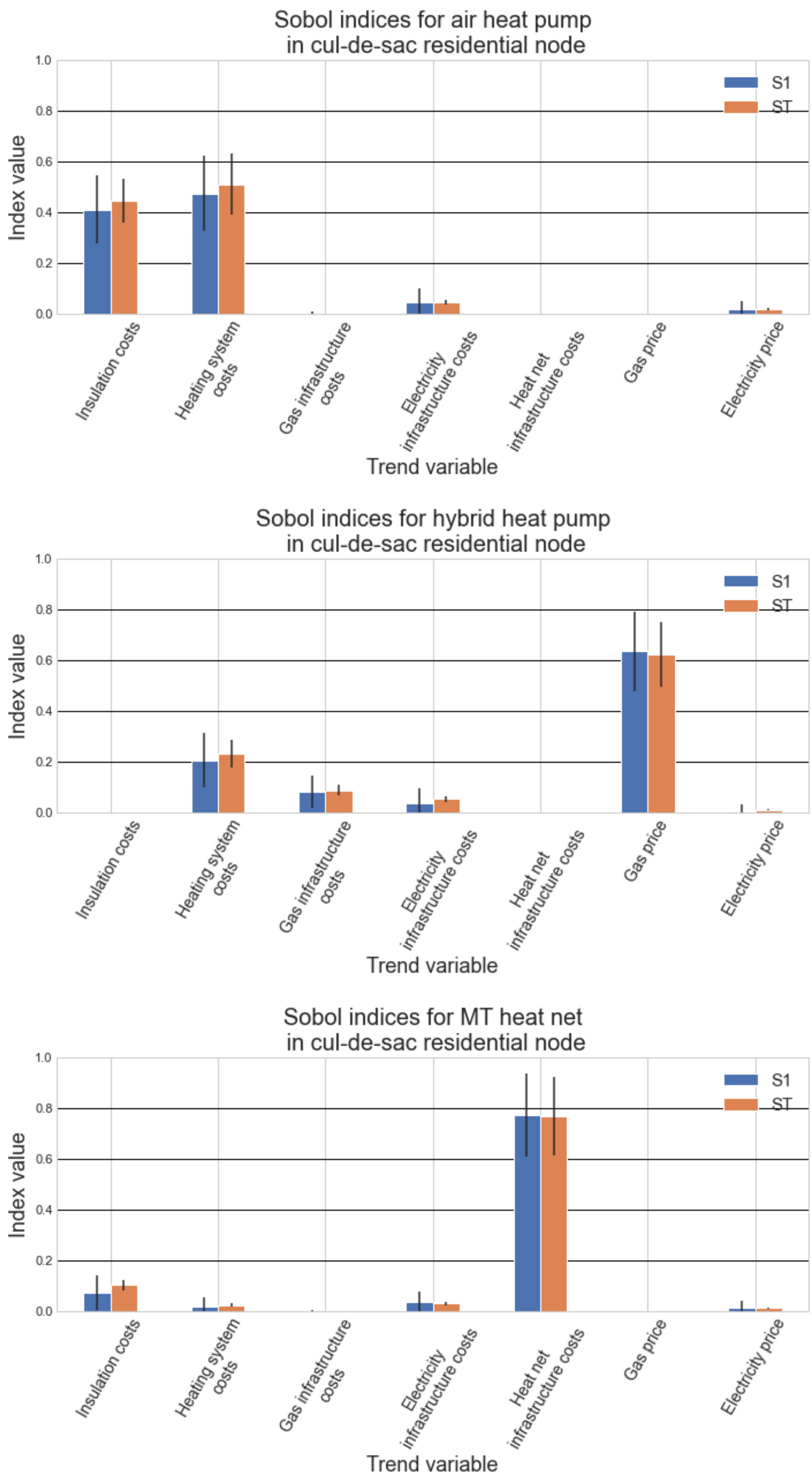


Figure 17: Sobol' indices found for three heating options in a cul-de-sac neighbourhood. Air heat pumps (top), hybrid heat pumps (middle) and MT heat net (bottom). Seven trend variables (x-axis) are included in this analysis

If, say, a modeller or a stakeholder that has to make an investment decision looks at Figure 17 they may well desire a more detailed picture. Because only seven variables are included in this analysis, which are applied to each of the eight heating system options the possibility for a more thorough understanding is limited. In further research, the Sobol' method could be used for individual heating system options with a more specific set of parameters. The results from parameter screening can be used to construct these sets. Since the Sobol' method is so computationally expensive and higher-order effects in CEGOIA are limited, results from MM could be used instead.

The Sobol' indices evaluated for all results are reported in Table 12 and Table 13. The values for the residential and utility node are averaged over the five archetypical neighbourhoods, and lighter colours in each column indicate the most influential variable. Results between the different neighbourhoods were generally found to be similar, although insulation importance is again higher in older neighbourhoods.

Table 12: Averaged total-effect Sobol' indices in residential neighbourhoods

Residential Sobol' sensitivities	**Air heat pump**	**Ground heat pump**	**Condensing boiler**	**Hybrid heat pump**	**Pellet boiler**	**HT heat net**	**MT heat net**	**LT heat net**
Insulation costs	40%	36%	0%	0%	0%	0%	6%	26%
Heating system costs	41%	46%	2%	15%	79%	2%	1%	23%
Gas infrastructure costs	0%	0%	16%	23%	0%	0%	0%	0%
Electricity infrastructure costs	12%	11%	7%	11%	16%	14%	9%	9%
Heat net infrastructure costs	0%	0%	0%	0%	0%	76%	75%	30%
Gas price	0%	0%	72%	47%	0%	0%	0%	0%
Electricity price	2%	1%	0%	0%	0%	1%	1%	2%

Some options have results that are very alike and well within the margin of error: the air and ground-based heat pump are exposed to functionally the same uncertainties – heating system costs, insulation costs and to a much lesser extent, electricity price and infrastructure. Condensing boilers and hybrid heat pumps are similar, as are HT and MT heat nets. These groupings imply that if a heating system choice is to be made between one of them, the alternative estimated to be cheapest can confidently be selected since the uncertainties that are going to change the financial picture of an air-based heat pump are fundamentally the same as that of a ground-based heat pump.

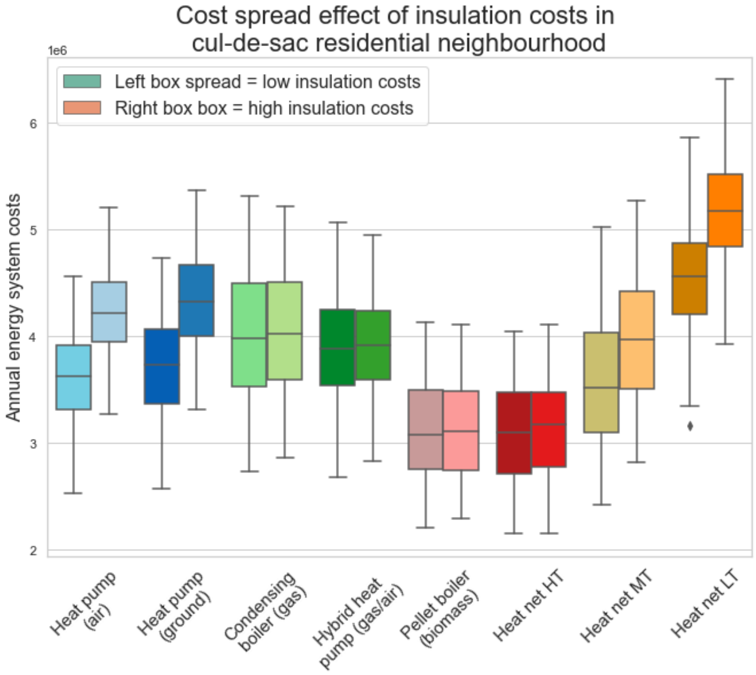
Table 13: Averaged total-effect Sobol' indices in utility neighbourhoods

Utility Sobol' sensitivities	Air heat pump	Ground heat pump	Condensing boiler	Hybrid heat pump	Pellet boiler	HT heat net	MT heat net	LT heat net
Insulation costs	29%	25%	16%	10%	1%	0%	19%	29%
Heating system costs	38%	47%	10%	34%	83%	25%	11%	29%
Gas infrastructure costs	0%	0%	2%	2%	0%	0%	0%	0%
Electricity infrastructure costs	3%	2%	1%	1%	1%	3%	2%	3%
Heat net infrastructure costs	0%	0%	0%	0%	0%	34%	42%	9%
Gas price	0%	0%	56%	28%	0%	0%	0%	0%
Electricity price	28%	23%	11%	17%	12%	34%	20%	26%

6.4.2 Effects of sensitivity in CEGOIA

Now that the sensitivities for each heating system option have been identified and described, conclusions are drawn about their implications. First, the effect of sensitivities on the costs of heating system options is evaluated, from which the confidence and robustness of CEGOIA results are judged. Second, their effects on the usefulness of heating transition modelling are considered. Finally, the implications of CEGOIA sensitivities for policy and decision-making are discussed.

Sobol' index results from the previous section describe sensitivity, but do not relate the size of these effects in terms of euros. What do changes in the trend parameters mean in absolute terms? How much can they change which system is the cheapest? In many cases, these trends have a significant effect on the costs of the system. The two charts in Figure 18 are created by selecting one trend parameter at a time. Results are divided into two box spreads: the first box spread contains results in which the lower half of values for the selected parameter were taken. The second box spread contains the remaining higher half. The reason to do this is to isolate the effects, in euros, of an 'optimistic' and a 'pessimistic' scenario on the costs of an option. To illustrate how this works, consider a case where variable costs were varied between 50% and 150% of the implemented CEGOIA parameter. The lower half box spread will contain costs found when the selected variable was between 50% and 100% of its normal value. The change in the average system costs can in this way be attributed to the spliced variable. The variable spliced in the chart to the left is insulation costs whilst the variable spliced in the righthand chart is heating system costs. Since a lot of variance in box spreads is explained by the other parameters varied in the Sobol' analysis it is best to consider the average values of the box spread (middle line of the box) when comparing the two.



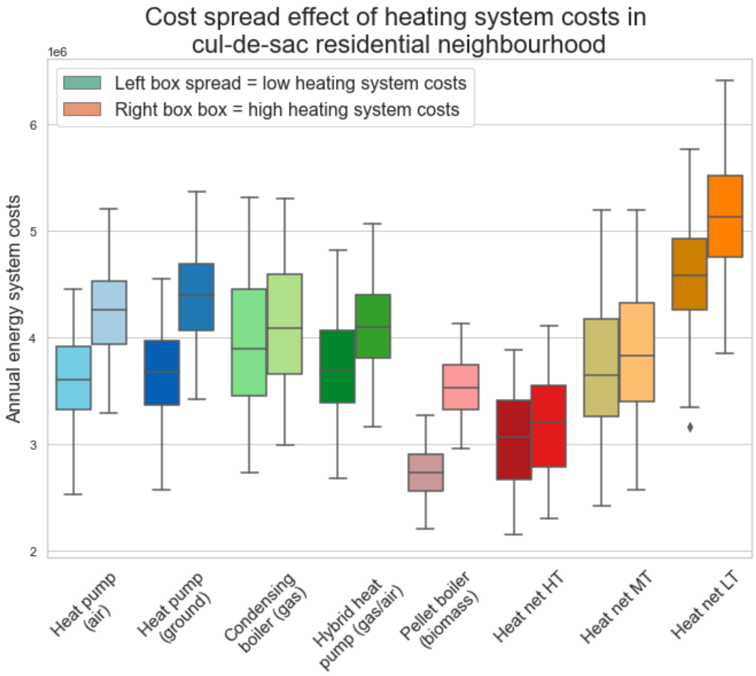


Figure 18: Cost spreads of heating system options from 1350 Sobol' runs. Effects of changing insulation costs (top) and effects of changing heating system costs (bottom). For each heating system option on the x-axis, two box spreads are plotted. The leftmost spread contains results found using the lower value for the varied variable, whilst the rightmost spread contains the results found using the higher value.

The difference between the two box spreads listed for each option in Figure 18 indicates how much of an effect uncertainty in the trend variable has on the costs of a heating system option, expressed in euros. The two main takeaways from these graphs are that even a swing in the costs of one trend variable can change what the cheapest option is, and that the total uncertainty range (expressed by the full lengths of the box spreads) is large. In this experiment, the HT heat net and pellet boiler are seemingly found to be the cheapest options, but if these options are not available then the choice for the next best option is well within the range of ‘it could go either way’. In other words, the confidence in CEGOIA results, based purely on costs, is not high enough to identify the absolute preferent alternative.

Low confidence in choosing the absolute cheapest option does not mean the model cannot be used for that purpose. From Figure 18 one can conclude that the LT heat net is probably never going to be the cheapest option for this particular neighbourhood, but that many of the other options could be. An ‘option prioritization’ is produced by the model, from which a lot of useful information can be derived. For this particular case, the viability of an HT heat net and pellet boilers should be further investigated, and if both are viable, then a further discussion can be made about the different sensitivities. A pellet boiler system is much less complicated than a heat net and its sensitivities relate mostly to the costs of the boiler itself and the fuel it uses. If biomass is readily available, then perhaps this should be the choice. Suppose there is the possibility to construct a heat net against low discount rates with low connection costs, then perhaps this should have the preference. In the end, local circumstances will always dictate what the best economical choice is, and even then, building owner preferences should always play a role in the final decision making.

One way in which CEGOIA can – and to some extent is – used is by evaluating multiple future scenarios. These scenarios currently focus on varying the availability of energy carriers and collective heat sources. Although availability is not part of the SA experiments, a number of additional dimensions to scenarios can be suggested. Varying the energy costs (electricity, green gas, biomass, hydrogen and collective heat sources), as well as the costs of heating systems, will encapsulate a lot of the sensitivity present in the model. The value in doing this in everyday model use is that the identified option prioritization is tailored to local circumstances rather than general model sensitivity insights, such as described in the previous paragraphs. This approach leads to more robust recommendations and leaves room for well-informed local final decision making. A necessity to being able to handle this is further calculation optimization of the CEGOIA model so that it becomes fast enough to evaluate multiple scenarios.

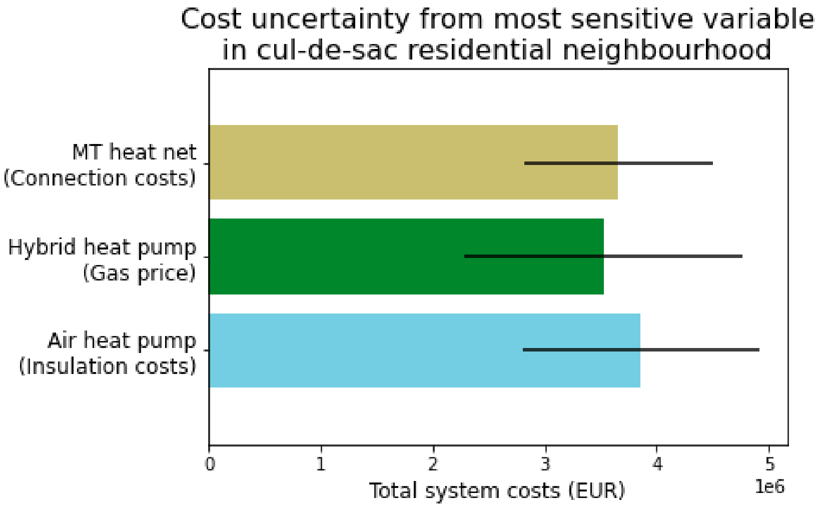


Figure 19: Uncertainty bounds for three heating system option costs based on most sensitive factor

An example of what an uncertainty margin may look like is presented in Figure 19. For each of these three options the effect of the most sensitive parameter on the total costs is added from the most optimistic to the most pessimistic estimation. Although the hybrid heat pump is the cheapest out of the principal results, a ‘worst regret’ motivated choice could be made for the MT heat net which has less exposure to uncertainty.

6.5 Summary of results

The purpose of the CEGOIA Sensitivity Analysis was to *identify a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options*. To this purpose, a small set of parameters that cause the most sensitivity in calculating the cheapest sustainable alternative heating system has been identified. Sensitivity to a parameter indicates that changes in the value of the parameter will cause a lot of change in the total energy system costs. These parameters are specific to each heating system:

- Heat pumps are principally sensitive to the investment cost of the pump. The price of the electricity, costs of grid reinforcement and efficiency of the pump are much less influential.
- Hybrid heat pumps and condensing boilers are most sensitive to the price of green gas and the costs of the pump/boiler itself. Gas infrastructure-related costs are also influential. The electricity component of a hybrid heat pump is much less sensitive than the gas component.
- Pellet boilers are sensitive to the costs of the boiler and to a lesser extent the price of biomass.
- Heat nets are sensitive to a lot of parameters, most significantly the connection costs of the net to a building. Other influential parameters relate to dimensioning of the heat net; these include the discount factor, heat exchanger and maintenance costs.
- Additionally, low temperature heat-producing systems (heat pumps and LT heat nets) are very sensitive to the costs of insulation and the demand for warm tap water.

The general list of option sensitivities is further affected by neighbourhood characteristics. Neighbourhood density, building age and energy demand profile (differentiated through varying residential and utility energy usage profiles) have the following effects on sensitivities.

- Neighbourhoods built predominantly before 1990 have a higher sensitivity to the costs of insulation, whilst recently built neighbourhoods have almost none.
- Less dense neighbourhoods have a higher sensitivity to the costs of infrastructure. This includes CAPEX, OPEX of both gas and electricity infrastructure, as well as gas removal and grid reinforcement costs.
- Utility buildings have a higher sensitivity to the price of energy and demand for warm tap water than residential buildings. Consequently, they have a higher sensitivity to insulation costs as well.

With these sensitivities, the question '*What are the CEGOIA factor sensitivities and their effects*?' can be answered. The SA results have several implications concerning the level of uncertainty of heating costs, confidence in CEGOIA results and heating transition process.

Uncertainty margins over the costs of heating transition options are difficult to attribute in a useful manner since the uncertainty in CEGOIA results – and by extension, the heating transition – is very large. For each sustainable heating system there are multiple factors that, depending on how they develop in future decades, can sway the total system cost significantly. Collective systems generally have more variables to which they are sensitive than individual ones, because of which the risk assessment is more convoluted. Conversely, individual systems are more sensitive to individual parameters such as heat pump investment costs or green gas prices, which makes assessment more straightforward. Still, the uncertainty underlying each parameter's sensitivity – and by extension, each heating system option – is fundamentally different.

This knowledge can be used to evaluate the effects of developments and policy at an international level on which sustainable system is likely to become preferent. If, for example, the Netherlands committed to a pathway in which it heavily incentivizes innovation in green gas production then hybrid heat pumps and condensing boilers will very likely come to dominate the outcomes of any analysis. Alternatively, if the organizational and financial challenges related to the construction of heat nets are overcome and organizations emerge with the right know-how to reduce critical costs, then these may become the dominant solution. This is to say that to some extent, the answer of which option(s) will sustainably heat our homes in 2050 still very much engineerable through policymaking. No policy direction will likely result in a longer period of high uncertainty about investments into sustainable heating systems.

The effect of the sensitivities found using this SA imply that CEGOIA cannot be confused to identify the absolutely cheapest system with much confidence. Instead, it ought to be used to identify one or more options that are likely not to be the most expensive options. This selection should then be used in local settings in which unique neighbourhood circumstances are considered to estimate system cost with more confidence, as well as using building owner preferences to decide on which system to adopt.

7 Discussion

This research has been a methodological study to evaluate the usefulness of Sensitivity Analysis for heating transition models. There is certainly societal attention for uncertainty about the energy transition. Several energy models are used to aid policymaking in the Dutch energy transition in the built environment, but the literature suggests that the use of SA in the field is limited, especially with regards to more systematic approaches. Having performed SA on the CEGOIA model, several key insights were found about the model, the method and its purpose. Section 7.1 presents the primary relevance of these insights. Further discussion about CEGOIA insights is covered in section 7.2. A discussion on the Sensitivity Analysis method used for CEGOIA is found in section 7.3. Finally, section 7.4 covers implications for the heating transition as a whole.

7.1 Scientific and societal relevance

The knowledge gap this study aimed to fill in is the deficiency in the understanding of uncertainty effects in models that are used to support policymakers in the heating transition. The case study of Sensitivity Analysis on the CEGOIA heating transition model contributes to academic discourse by providing an example of how SA can be used to increase the knowledge about energy transition models. The method used to prepare CEGOIA for SA further used a novel approach to handle the complexity of large models as well as generalize results for different contexts. Although every SA is bespoke, elements of this approach can be applied for the analysis of other heating transition models.

The result of this case study and the SA method as a whole have societal relevance with regards to its value for model-based policymaking. Local policymakers in the heating transition are increasingly using heating transition models such as CEGOIA but have difficulty in dealing with complex model dynamics and deep uncertainty. Insights from SA of heating transition models can help modellers, policymakers, and everyday people understand the origin and effects of the uncertainties that we as a society face in the heating transition. What's more, is that several Dutch heating transition modellers were found not to use systematic SA in the development of their models. Through this body of work, model developers are prompted to investigate the uses which SA can have for their models. In doing so, models can be improved so that more knowledge and understanding is generated about the heating transition – and perhaps the energy transition as a whole.

7.2 Discussion about CEGOIA SA results

The CEGOIA SA has identified a clear set of parameters that primarily control how much the costs of a heating system option fluctuates given uncertainty about their values. Although this set is unique to each heating system, a clear few factors are drivers of uncertainty. This list includes, for example, the costs of insulation, the investment costs of the heating systems themselves and the costs of energy. The results furthermore indicate that the effects of these factors are large, resulting in a high margin of uncertainty about the model output. Since the purpose of CEGOIA is to identify which option is feasible and cheapest for a neighbourhood, model results need to be contrasted with these uncertain factors. This is a subtly different use of CEGOIA, changing from a tool for evaluation and recommendation to a tool for evaluation and prioritization. An option prioritization, including, say, the three cheapest options for a neighbourhood, should then be used as input for further analysis. In further analysis, scenarios can use the most influential factors as dimensions. A more quantitative indication of how robust the choice for a certain heating system is can be gained from this approach, which helps the heating transition process at a local level.

The number of sensitive parameters and their relative effect varies significantly for each heating system option. This is a reflection of the complexity of the heating system option. As a general rule, individual heating system options are sensitive to fewer parameters than collective systems. The difference in effect between the top-most influential parameter and the second-most (and third-most, fourth-most etc.) influential parameter is furthermore a reflection of complexity. Finding there are few sensitive parameters does not necessarily mean that an option is less uncertain, but it does indicate that the uncertainty is easier to comprehend and attribute. If the top-most influential parameter is much more influential than those coming after it, then this means that this value is most important in determining whether or not the option is going to be cheapest. To illustrate how this can be of use, consider how heat pumps have fewer and generally less influential parameter uncertainties than heat nets have. If in a neighbourhood, both options are viable and the costs of the two are found to be roughly equal, then a preference could be given for the heat pump since its risk is easier to control for.

One of the reasons why models like CEGOIA are useful is because they take into account the local context. The amount, age and type of buildings and infrastructure determine the choice for a sustainable heating system. Sensitivities indicate that only the uncertainty about insulation and infrastructure costs are fundamentally different between local contexts. In other words, local circumstances matter in determining the model outcomes, but the uncertainty to which that outcome is subject has a mostly similar nature and effect. Only in the oldest of neighbourhoods and the most rural of areas are the effects of these sensitivities so important that they dictate the uncertainty of a system's cost as a whole. The effect of this is that the sensitivities as found for the archetypical neighbourhoods can be translated to real-world neighbourhoods with high confidence.

Another observation from the CEGOIA SA is that the amount and influence of higher-order effects caused by parameter interactions are limited. This is a helpful insight because it helps with comprehension of cause and effect in a complicated model. In a situation with no higher-order effects, e.g. an electricity price increase coupled with an increase of electricity use of both 20%, will cause the total costs to increase by 20%. In reality, higher use coupled with higher prices will make for a cost increase of more than 20%. The effects of these relationships in CEGOIA is limited, meaning that the total cost in this example may increase by 23%, but not 40%. Because of this, the effects of parameter uncertainty can mostly be interpreted as standalone, and the interaction with other developments can mostly be ignored. The only notable exception to this is insulation costs. If insulation becomes significantly more expensive and so does, for example, energy use, then the option as a whole will become much more expensive very quickly. Another result from this result is that Morris Method results can be used as a reasonably good proxy for what the actual sensitivities and factor prioritizations in CEGOIA are.

There are some limitations to discuss concerning this SA, which mostly have to do with the experimental setup as decided on in chapter 5. As a whole, the results of this CEGOIA SA serve as a quantification of what factors are most important in determining what is the cheapest heating system given that the future is uncertain. Even so, it is neither a perfect quantification nor does it answer all questions about uncertainty in the heating transition. Some parameters are missing, most notably the lack of the availability of energy which is a crucial and highly uncertain factor. A further deficiency in this analysis is that only eight heating system options are included, whilst others exist. Some of these, like hydrogen-based systems, are modelled by CEGOIA but not included in the scope. Other systems exist that are not modelled by CEGOIA, although the argument could be made that these are not likely to become very widespread.

The type of questions about the heating transition that can be answered using this SA is also a point of discussion. In this analysis, SA was used to generate an overview of sensitive uncertainties about the societal costs of several heating system options. As such, insights only apply to this specific aspect of the heating transition. Other aspects such as end-user costs, the availability of energy or even the preference and acceptance of end-users are matters that deserve to be investigated but could not be done in this research or even with this model.

7.3 Discussion about SA method used for CEGOIA

CEGOIA served as a case study to investigate what insights could be gained about a heating transition model using Sensitivity Analysis. To be able to do any sort of systematic SA, several key decisions had to be made to overcome typical pitfalls, as described by (Ferretti et al., 2016; Horschig & Thrän, 2017; Saltelli et al., 2008). The first pitfall of SA is using it in a manner in which the purpose of the analysis is unclear. The purpose of the CEGOIA analysis was to *identify a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options*. This is a broad question, which, if answered successfully, can be used to take CEGOIA insights and apply them to a broader, societal context. The possibility to do so is limited primarily by the extent to which model results are generalizable to the real world. A side note is that this specific experimental setup can only answer a specific set of questions. This CEGOIA SA only focuses on the total annualized societal costs of heating systems, which cover distinctly different uncertainties than those related to, say, end-user costs.

The second pitfall of SA is the consideration of too many input variables. CEGOIA, with 953 parameters and even more geographic and energy availability related settings certainly has many inputs, especially when considering that other studies found SA being applied to a maximum of 110 parameters (Sheikholeslami et al., 2019). Several steps were taken to overcome this issue and filter the parameters. Availability of energy carriers was excluded to perform logically consistent analysis, with the caveat that results have no bearing on these uncertainties. Reduction of the number of parameters was initially achieved by limiting the analysis scope to a set of eight heating options, by which parameters specific to technologies that were not included could be eliminated. Further reduction was achieved by the grouping of parameters so that variations in their value moves jointly. Whilst the first filtration only limits the number of heating systems about which conclusions can be drawn, the second filtration introduces assumptions about the interdependence between the variables in a group. This step does not necessarily limit the understanding that can be gained about sensitivities, but it does obscure information about relationships within the model. Further filtration was done using SA techniques in the form of Factor Fixing: both Fractional Factorial (FF) analysis and the Method of Morris (MM) were used to identify further parameters which could be removed or grouped. The confidence in the screening with this method is much higher and so preferable to manual grouping. The Sobol' method involved the selection of eight (grouped) variables with which the principal uncertainties for all heating options in CEGOIA were attributable. Although eight is a comfortable number of variables to understand and get a general impression of sensitivities, the number is on the lower end of what would be suitable for the complexity of the model. Since eight heating systems were considered that use different technologies, the aggregation of variables resulted in the loss of explanative power for anyone wanting more detail about sensitivity. To conclude on this point, the method used for the reduction of parameters is useful and effective. Still, care must be taken in grouping parameters so that the complexity of the model is not oversimplified to a point where insights become too generic. If this were to happen it would be better to refocus the analysis on questions about specific parts of the model, such as a single heating system.

The third SA pitfall is low confidence in probability distributions of inputs. The method used for the CEGOIA analysis, expert elicitation following the NUSAP scheme, is useful especially for a situation in which there are many input variables. It is necessary to acknowledge that there is a quantity vs quality trade-off in using this method. That does not, however, mean that the uncertainties used for the analysis were unsuitable for its purpose. This purpose was to identify and quantify a general set of sensitivities. Any general conclusions about the uncertainties in complex models such as CEGOIA will have probability distributions that are difficult to express in numbers. This means that however well researched, any uncertainty distribution and its effects on the calculated sensitivities needs to be interpreted as an indicative measure rather than as absolute truth.

The fourth SA pitfall is the consideration of too many outputs. In the traditional sense, this would be the cost of the heating system options for the CEGOIA analysis. In a broader interpretation, this also includes a variety of options (eight), neighbourhoods (five) and nodes (two) that were evaluated. Effectively, this means that not one but eighty outputs were considered for three different analysis techniques. Context, in this regard, significantly complicates the SA process for energy transition models. It is a necessary evil; however, that is particularly important for these types of models to investigate. Much of their value comes from being able to apply the same energy system evaluations to different regions. The archetypical neighbourhoods approach was found to be a useful way of identifying and operationalizing crucial contextual differences. Edge cases, in which neighbourhoods have unique characteristics that completely change system costs are however not well described by using this approach.

The fifth and final SA pitfall is that a model takes too long to run. This has been a complicating factor for CEGOIA, more so than perhaps other models like ETM and Vesta MAIS would experience. CEGOIA is not optimized for the evaluation of single neighbourhoods, and the initialization of the model takes up a lot of processing power. As such, most individual runs took just under 3 minutes to complete. This was workable for experiments with 1.000-1.500 runs but hindered running experiments that evaluate more parameters and calculate more powerful sensitivity measures or achieve higher confidence intervals. To enable such insights the order of runs that could be calculated in the same time frame would have to be 5.000 to 10.000.

Three techniques were ultimately used to analyse CEGOIA sensitivities: Fractional Factorial (FF) analysis, the Method of Morris (MM) and the Sobol' method. FF and MM are Local techniques, which Ferretti et al. (2016), Saltelli & Annoni (2010) and Yi & Lu (2019) all describe as being inadequate for models in which higher-order interactions take place. Results between the three techniques were however found to be surprisingly similar. As such, FF, MM and other systematic OAT techniques may not be entirely unsuitable for the analysis of sensitivities of heating transition models after all. Although MM indicated which parameters had higher-order effects, it did not yield a meaningful representation of the sets of variables that interact with each other, something which would have been valuable. The Sobol' method and its indices provide the most intuitive way of interpreting sensitivities with a high degree of confidence than previous methods. The applicability of this method was found to be very limited, because of the high number of runs required to evaluate the sensitivities of parameters.

It is also important to reflect on the transferability of the SA process used for CEGOIA: this specific combination of methods is not necessarily useful for every other heating transition model. The definition of the analysis scope, inputs and outputs involve making choices that meaningfully affect how results can be interpreted. Certain elements of this analysis are transferable. A unifying element for heating transition models is the diversity in contexts in which the model is run, and as such the archetypical approach is useful for other models too. The grouping of variables can also be used on other heating transition models, as all of them seem to have a large number of input parameters.

7.4 Discussion about potential of SA for the heating transition

The CEGOIA model, as well as Vesta MAIS and the ETM, are models that are used to create visions about the energy system. To achieve this purpose, they share some specific characteristics: they make use of a large and diverse set of economic, geographic and energetic parameters to model current and future energy systems in detail. To do this, a lot of assumptions about the developments in technology, economics and society need to be made that are fundamentally uncertain. Interviews with model owners and literature research have suggested that uncertainty about these assumptions is often dealt with in terms of scenario uncertainty, by varying several key assumptions in what interviewees referred to as SA. Although such an approach can provide model users with insights in specific scenarios, such knowledge cannot be generalized with much confidence since no statistical direct or indirect effects are systemically estimated. This implies that the fundamental issue has to do with a lack of knowledge about SA methods and uses. Important to note is that the discussion about these insights is based on experiences with CEGOIA and two interviews, which is a very limited set of results from which to generalize.

The idea that SA can assist heating transition model development by identifying key areas to focus on – and key areas to give lower importance to – is something that was found to be of interest by model owners. Currently, development decisions are often made to meet the evolving requirements of model users. Introspection about the sensitivities of the model appears not to be high on the agenda, although this knowledge can be used as an argument in the discussion of which parts to further develop. This goes for new development, but also model simplification. As the heating transition models get larger and more complicated with new functionalities, development and model use gets more difficult. Simplification, based on insights from SA, could help lower the barrier for model users and policymakers to understand as well as get involved with the models. It is important to admit that SA is not the only way in which model focus can be improved. Model owners are aware of the difficulty in communicating results and especially nuance about uncertainties and are actively engaged in improving their models to overcome these issues. SA could therefore be considered as an addition to the toolset.

The importance of robustness of model results has reportedly become an increasingly important topic for model developers and advisors in recent years. A scenario approach is often applied in using heating transition models to capture the effects of uncertainty. Although model experts will generally have a feel for which parameters have high sensitivities, a general quantification of these uncertainties in the model would provide a better starting point for such analyses. This is something where SA can add a lot of value since an overview of the most important sensitivities (as was done on CEGOIA with Sobol' indices) for a certain model application makes it much easier for model users to create good scenarios and for policymakers to understand what matters. Still, local policymakers' are not necessarily receptive to these nuances as they complicate the decision-making process. Policymaking under the DMDU paradigm – in which continuous uncertainty evaluation using SA methods takes place to arrive at robust policy in highly uncertain long-term processes – can therefore be a valuable way of dealing with the heating transition.

8 Conclusions & Recommendations

This chapter contains the main takeaways about Sensitivity Analysis for heating transition models that were derived from this research project. This is done first by addressing the main research questions and answering the related sub-questions in section 8.1. Several recommendations about CEGOIA and the practice of SA for the heating transition are presented in section 8.2.

8.1 Conclusions

This thesis set out to answer the following research question:

How can uncertainty in the context of Dutch heating transition models be adequately investigated using Sensitivity Analysis?

The research approach used to answer this question was a case study in which Sensitivity Analysis was done on the CEGOIA model. The purpose of this SA was to identify a set of key uncertainties and quantify their sensitivities that are generalizable to different contexts and heating system options. Special care was taken to evaluate the steps necessary to perform SA on a heating transition model. Insights from this analysis, together with two interviews with other Dutch heating transition model owners, were used to evaluate the value of the SA.

Explicitly answering the main research question involves discussing three elements. First, the steps that are necessary to perform SA. Second, the way in which Dutch heating transition models cause specific issues for this analysis. And third, the manner in which model uncertainty can be clarified by doing SA.

Addressing the steps for SA, the following can be concluded. SA has a variety of methods and use-cases that range from basic identification of influential parameters, the prioritization of the most important parameters and finally, the evaluation of how these parameters and their uncertainty ranges interact with the outcome of a model under. The more elaborate the question, the more elaborate the experiment design. If a model is set up so that it can easily evaluate many model runs, then more elaborate experiment designs are quite easy to implement using open-source tools. The challenge lies in the conceptualization of the experiments and the interpretation of results.

In the context of complications specific to heating transition models, the most relevant property that complicates analysis is that of local context. Models like CEGOIA produce results that are highly specific to the region being analysed and creating a useful SA experiment design with which results can be generated that hold in multiple contexts is challenging. For CEGOIA, this was done by limiting the scope to the analysis of one output metric by varying eight heating system options in five individual, archetypical neighbourhoods.

The results of the CEGOIA analysis clarify model uncertainty by the identification of those parameters that are both inherently uncertain and highly influential in determining the costs of varying heating system options. CEGOIA attempts to identify the option that has the lowest total costs, but the margins of uncertainty for the costs it finds are large. As such, for many buildings, multiple systems can realistically become the cheapest option in the future. The sensitivities of specific options further reveal what developments are dominant in deciding the costs of systems. This points to the limitations of using heating transition models to determine what heating system is the best choice. In real-world neighbourhoods, the choice between alternatives is not only reliant on technical analysis of societal costs but also social needs such as the preference of users and the way in which they can finance a retrofit. These are separate criteria in the decision-making process, and integrating them into heating transition models is probably not feasible. Because of this, current heating transition models are better suited to analyse the effects of policy interventions at an international, national or regional level instead of the local one.

In addition to this conclusion, it is significant to mention that systematic SA is currently underused as a method to analyse the heating transition. The case study has demonstrated and identified ways in which SA can improve the modelling as well as the use of heating transition models in multiple ways. This is chiefly done through the identification and quantification of elements that are both influential and uncertain – and those that are not. With this knowledge, model developers can improve their models and better communicate uncertainty in results, which leads to more robust recommendations. SA techniques can furthermore be applied to quantitatively answer complex questions about the effects of various developments on the costs and feasibility of the heating transition.

In support of this conclusion about the main research question, this research is structured around four sub-questions. The answers to these questions are presented in the following paragraphs.

How is uncertainty in heating transition models understood and dealt with?

As a general observation, uncertainty is a lack of knowledge about what will come, but also a lack of a shared reality between stakeholders. Heating transition modelling helps to formalize which knowledge is crucial and play a role in negotiating such a shared reality. Heating transition models are a diverse set of bottom-up and top-down models that are calibrated to a specific geographic scale and consider a selection of energetic, economic, technological, environmental and/or social factors. They apply a consistent set of functions in a scenario configuration over different contexts.

There are different modes of uncertainty to be distinguished in this arrangement. For one, how elements of a heating system are modelled and the level of model detail in which this is done introduces structural model uncertainty. Three categories of model parameters that are origins of uncertainty are recognized: spatial, modelling and scenario parameters. The first group of parameters describes the physical characteristics of the region, such as the buildings and infrastructure. Uncertainty in this category pertains to the accuracy of information about the current and future physical system. These parameters introduce a lot of variety when the model is used in different contexts. Fundamentally, however, this variance is not crucial for the purposes in which heating transition models are used. A similar conclusion can be made about modelling parameters, which are used to translate the inputs of a model to the desired outputs. The values of model parameters, if not following from natural law, typically represents the best-estimate average of a certain probability distribution.

Scenario parameters describe various trends, such as the prices and availability of energy, as well as the costs and efficiencies of technology. These parameters are inherently uncertain and therefore have a major effect on the interpretation of model outcomes. Usually, modellers and model users use scenario building along the lines of one or more of these trends. In practice, however, the way in which this is done can still be much improved by using a more systematic approach.

How can the Sensitivity Analysis process be used for heating transition models?

Sensitivity Analysis is conceptually straightforward but doing it in a meaningful manner is difficult. The first question to ask when considering SA on a heating transition model is what the purpose of the analysis will be. CEGOIA and other models can be used in many different ways to answer a variety of questions. SA can be used to find generalized descriptions of model sensitivity but can also be used on more specific (sub)elements of a model. The definition of an analysis purpose results in a scope with which inputs and outputs are selected.

Heating transition models often have a lot of input variables that could be considered for evaluation with SA. Spatial data should be systematically varied to be able to interpret the effect of the context in which the model is used. A way to do this is by creating typical contexts, such as the archetypical neighbourhoods that were constructed for CEGOIA. Model parameters and scenario/setting variables can be varied in separate analyses as well as taken together. If varied together, the influence of scenario variables will likely be larger than the model parameters. SA techniques are practical so long as the number of parameters and the time to calculate the model results is limited. Several ways to reduce the number of parameters exist and apply to heating transition models. These include the grouping of factors that are natural to move together and the screening of parameters with basic SA techniques.

The calculation time for CEGOIA was found to be a limiting factor to SA, but other models such as the ETM and Vesta MAIS have much lower calculation times and as such have more potential for SA. More details about – and a higher level of confidence in sensitivity results, are attainable with more model runs. The number of runs required to evaluate which parameters are influential for the model outcome is about 2 to 10 times the number of parameters. To estimate direct and indirect sensitivities of parameters with confidence runs totalling about 100 to 1000 times the number of parameters are necessary. These numbers vary based on the required confidence interval and the degree to which there exist interactions between variables in the model. For CEGOIA it was found these interactions were significant but not dominant in determining the model outcome. This is important because typically the SA used by model developers is not systematic and varying one factor at a time. Such an approach is unsuitable for heating transition models as it will result in misinterpretation of what the important model parameters are.

What are the CEGOIA factor sensitivities and their effects?

Sensitivities found for CEGOIA were evaluated for eight different heating system options and five neighbourhoods with diverse physical characteristics. For each option, a set of ten to twenty parameters were found to have any significant influence on the total costs of the sustainable heating system. Generally speaking, the costs are very sensitive to a set of only one to five parameters. These parameters are often the price of the energy carrier(s) used by the system, the investment costs and efficiency of the heat production system and the costs for infrastructure. For heat nets, in particular, several parameters affecting heat net dimensioning were found to be of influence. The most important of these is the connection costs of buildings to the net.

Other parameters that contribute significantly to the model outcome are the maintenance of the heat production system and investment costs into the heat distribution system. The costs of insulation become more significant as the age of buildings in the neighbourhood gets older. The (heat) energy demand of buildings was found to not have much direct influence on the system costs. Indirectly, however, both insulation and energy demand were found to contribute significantly to the costs of the overall system.

With these results statements can be made about the confidence in CEGOIA predictions. A general observation is that as a whole, the margin of uncertainty in results is quite high. As a consequence, the decision of whether a certain option is going to be cheaper than another is often very uncertain. For this reason it is important to further investigate whether an option is more or less uncertain than another, and which developments are the primary drivers of the uncertainty. To reduce uncertainty in the heating transition policymaking should furthermore be based on controlling these developments.

Another use for the CEGOIA SA results has to do with focusing model development. The results have highlighted those parameters which are very influential, and as such deserve to be considered for further research. Better estimations or modelling structure can be considered, for example by re-evaluating the parameters that are used to model insulation costs or those that dictate how technological learning is modelled.

How do CEGOIA Sensitivity Analysis results improve comprehension of heating transition models and the heating transition as a whole?

SA was found to have the potential to improve heating transition modelling in multiple ways. Insight into which CEGOIA parameters are influential and which are not is useful to the model developers. All model variable values are uncertain to some degree, but quantifying which of them are important allows developers to focus on better modelling of those parameters that matter. Conversely, elements of CEGOIA which are not influential to the model's outcome can be recognized as such and given lower priority. A further use found for SA is that it is a good way of evaluating and understanding model dynamics. CEGOIA, the ETM and Vesta MAIS each have many different components and modules, more of which are added as every year goes by. This (increasing) complexity makes it difficult for outsiders to understand how the models work. It also makes it difficult to evaluate the effects of changes to the model. SA can be used as a tool to understand and monitor these ever-changing dynamics.

The results of SA can also be used by advisors when using the model to advise policymakers. It was noted that local heating transition policymakers often are not particularly interested in the uncertainty of the recommendations generated with the help of models. This is because being difficult to understand makes decision making and the communication of those decisions to citizens more difficult. Vesta MAIS and ETM interviewees stressed the importance of improving policymakers' comprehension of model limitations because of uncertainty. The results of SA can help increase this understanding by providing a quantified overview of – or even an interactive tool illustrating – the most important sensitivities of heating system options. This can then help policymakers and advisors in constructing scenarios that capture relevant uncertainty, leading to better decision making.

8.2 Recommendations

Based on this research into Sensitivity Analysis for heating transition analysis, several recommendations for further research and SA use are formulated.

- Performing further SA of the CEGOIA model using the Sobol' method in which a heating option specific list of parameters is used produces a more detailed summary of the sensitivities in the model. This is the logical next step in continuing the work presented in this model and serves primarily to further improve the quality of results. By combining detailed Sobol' results for the different heating system options, a definitive ranking of which parameters are most important can be achieved.
- Investigating ways in which the calculation time of CEGOIA – and by extension, CEGOIA SA – can be reduced unlocks the evaluation of more parameters using more powerful SA techniques. It additionally allows for the switch to a more scenario-based approach in the use of CEGOIA for advising policymakers. As a result of doing so, the model can be used to evaluate heating system dynamics such as uniqueness, instability, runaway and robustness conditions. With this knowledge, a more reliable assessment of the effects of policy choices can be made. This, in turn, leads to a better grasp on uncertainty and opens the way for robust decision making about which heating system options should be implemented where.
- One factor that is often talked about in the heating transition but was not included in the CEGOIA SA is the availability of energy carriers. On a small neighbourhood scale, availability works more like a Boolean than a number, and as such, analysis of the effects of this availability necessitates the evaluation of a larger region. Therefore, Sensitivity Analysis which includes availability, requires a different experimental setup. The resulting better understanding of the interactions between energy availability and system choice can help provide policymakers, especially at the national level, with making better choices
- Heating transition model developers should make systematic SA an integral part of their toolkit. What's more, is that they can and should integrate SA as part of the development process, developing functionality with which the configuration and analysis of SA experiments are made easy. In doing so, they improve their development process as well as the understanding of their models based on quantitative insights. It furthermore enables them to create more intricate scenarios and experiments with which to answer specific questions about the effects of policy in local contexts.
- Modellers should use SA to investigate uncertainty in the heating transition, and publish their findings. The state of the literature on this topic using a systematic and quantitative method in energy transition models was found to be lacking. By using SA and publishing their they can contribute significantly to the understanding of the heating transition. Although this CEGOIA study provides an insightful perspective about this transition, the results of the study are heavily influenced by the way CEGOIA models and approaches the transition. A different experimental setup using CEGOIA can also yield different or more specific results. As such, reviewing combined insights from different SA studies done on different models would be valuable.

9 Reflection

With this final reflection chapter, I impart my personal thoughts about the work presented in this document. This includes a reflection on the Sensitivity Analysis method, as well as comments about the experience of using it for the CEGOIA model. It furthermore includes my thoughts about energy system modelling and the heating transition process as a whole. With these comments, I aim to offer any reader insights into the problems and dilemmas I faced so that if need be, they can learn from it and do better.

9.1 Reflection on the CEGOIA Sensitivity Analysis

Going into this study, I was acquainted but not quite familiar with Sensitivity Analysis. Not entirely unlike the model owner interviewees I spoke with, I knew it was considered good modelling practice but not quite aware of in what way it can be beneficial. Looking back at the results I found for CEGOIA I will say that although they are certainly interesting, to someone familiar with heating systems, they are also not world-shocking. In reflecting on the results with CEGOIA developers, they stated how the results mostly confirmed what they had known about the model and the heating transition as a whole. It took me a while to realize that the value of the SA that I was able to do is, for a large part, the identification of and quantitative underpinning of how important certain ‘parameters’ are. As a tool for communication to people less familiar with the alternative heating systems, this can be of great benefit to increase comprehension of a topic as complex as the heating transition. Since the heating transition will – at one point or another – directly affect everyone in society, I think such a tool is of vital importance.

There is still a lot of potential left for using SA techniques than I was able to demonstrate for the CEGOIA model. I spent a lot of time investigating Global Sensitivity Analysis techniques and Factor Mapping applications but could not apply them in the timeframe of this thesis. Looking back, I believe that the question I set out to answer was too broad to make use of these methods anyway. To give an idea of possible applications: SA can be used to quantify how robust an investment decision for the construction of a heat net is going to be. Alternatively, it could be used to quantify the effects of national policy with regards to electrification, gas imports, hydrogen strategies and more on the heating transition. I expect that as time goes on, more and more of these complicated questions will have a need for answering and that SA techniques are a useful, yet often overlooked, way of investigating uncertainties.

9.2 Reflection on the heating transition

Having worked on investigating the sensitivities of the CEGOIA model and followed the discussions at CE Delft about working with policymakers, I believe there are several critical ways of looking at the heating transition. Energy system models like CEGOIA and the ETM can come a long way in clarifying the technical and financial challenges. CEGOIA can help locals by presenting those options that are likely to be among the cheapest alternative. Even so, at the most detailed level – that of an individual building – insights from, e.g. Vesta MAIS should not be the basis on which to make a decision.

As demonstrated by the results of this SA, there are many factors that determine whether or not one option might become cheaper than another, few of which can be considered certain. It is my impression that, as of now, too much value is attributed to the direct outcome of heating transition models, and too little is given to the trends that make them so. This is because municipalities have been given charge of the process. Realistically, however, they cannot be expected to influence those factors in a meaningful way, and so they can do little to mitigate uncertainty and make for a clearer picture. The Dutch government, however, could. For that reason, I think this is the most pressing barrier in the heating transition is a lack of leadership and direction at the national level.

To end this reflection on an optimistic note, I will add that the Dutch energy transition policy has been taking a much more defined shape in recent years. Something is being done. As both interviewees of Quintel and PBL noted, the community and quality of heating transition modellers have been growing, as has the understanding of policymakers. If these trends continue in the future, then we may well succeed in retrofit our heating systems to sustainable alternatives before it is too late.

9.3 Reflection on the research process

When I started out with this research, I aimed to discover how far I could get with using Sensitivity Analysis on the CEGOIA model. In the earliest stages, this meant that a lot of time was spent learning about the various SA methods and techniques, and I had, as it turned out, overly ambitious ideas about what was feasible. Still, the exploratory nature of this approach allowed me to be flexible in deciding when and where to spend my time. This was a good thing since, as it turned out, working with CEGOIA and adapting it so that it could be used for Sensitivity Analysis was a bigger task than initially anticipated. There were a few reasons for this. The model is quite elaborate, and getting to know it even superficially took some time in and of itself. Specifically, the interface between the code, the server and the web viewer made it difficult to make changes. Further effort was required to keep control of the size of experiments, each involving the varying of hundreds of grouped variables. The way in which experiment files that are interpretable by CEGOIA are generated furthermore turned out to be very error-prone. Because the evaluation time of individual experiments is several days and the analysis and interpretation of results take a lot of time, finding and correcting errors in experiment setups was arduous.

If I could go back and change the way in which I carried out the Sensitivity Analysis, I would do much the same except for the final step of Sobol' analysis. Instead of running Sobol' experiments in which eight heating systems are evaluated in five neighbourhoods using the same set of seven parameters, I would focus on three heating systems (heat pump, hybrid heat pump and MT heat net) in three neighbourhoods (old, new and rural) and then evaluate a set of parameters that is more specific to each heating system option. If there was more time, I would also have used a Factor Mapping technique on a single example and used it to illustrate how robust decisions can be made from such insights. Imagine, for example, a chart in which electricity and gas prices are on the axes. Dots represent the cheapest model outcomes or alternatively the distance between the cheapest and second cheapest option.

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Appendix II – Interviews

Structure and purpose

Two semi-structured interviews were conducted. The interviewees, Chael Kruip (Quintel) and Steven van Polen (PBL) each have several years of experience with the development of respectively the Energy Transition Model and Vesta MAIS. The interviews took approximately 1,5 hours each and were conducted in Dutch using videoconferencing. There are multiple purposes for conducting these interviews, hence the semi-structured nature of the set-up. The first reason for conducting this interview is to evaluate how heating transition modellers handle the uncertainties within their models. SA is one method, but model owners may have very different perspectives on what is viable and important in the usage of their models. This way, important context is provided for this thesis. A second purpose is to inquire about the level of familiarity the model owners have with Sensitivity Analysis. Since SA is an involved process which requires an express purpose to help structure the analysis, model owners may have no or limited interpretations of what the method involves. The third purpose is to investigate the perceived value of performing Sensitivity Analysis. Not only the value for modellers themselves but also that for policymakers is discussed.

Interviews were structured into three sections, discussing the following topics. In the first section, informal introductions were made and formalities with regards to the purpose and usage of the interview were handled. Then, the interviewee was asked several questions to clarify their relationship with and purpose of the energy transition model. Finally, inquiries as to the model owners experience with sensitivity analysis were then made.
A short presentation explaining the method and purpose of Sensitivity Analysis was then held. The following discussion focused on the different type of purposes, and the interviewee was asked to comment on the relevance to and experience with their model. After concluding this section, a selection of CEGOIA results was shared to help the interviewee visualize and understand how SA can provide insights. The interviewee was asked to interpret the results and their consequences, and describe what results for their model could look like. After this section, the interviewee was asked to look at the results and the method from several different perspectives: that of a modeller, that of an advisor, that of a policymaker and that of a regular person. From these viewpoints, they were asked to comment on what value they could see in the insights and what limitations they saw in them. To conclude, the interviewee was asked to motivate whether or not they would be interested in using SA on their models.

Transcripts

Transcripts of each interview are provided below. Since the interview was conducted in Dutch, the transcripts are translated and meant to be interpreted as indicative of the sentiments of the interviewee and conversation, but no direct quotes can be used.

Interview Chael Kruip (Quintel)

Background ETM

I started working at Quintel nine years ago as a modeller. Back then, ETM just moved online from an Excel implementation and we worked on making it ready for further development. Nowadays I am the lead on technical model development, mostly strategic and vision but also contents wise, developing and prototyping new features. Development into ETM has been ongoing for about 11 years, with an average of 13 people working on it. We have a large backlog of new ideas to implement, currently 21. We prioritise ourselves, but the development agenda is shared with partners. Ideas for which there is enthusiasm amongst partners are further developed in consortia with different parties.

Using ETM

The way we use ETM is focussed on having it be open access, which means we do not know exactly how the model is used. We do see that the model is being used by various parties, in the Netherlands but also at universities in the UK and Germany to name a few. There is also a lot of users that know us, who call us and give us direct feedback. They contribute to the development of the model in that way. We see a lot of parties use our model in a lot of different ways, from which we learn how the model can be improved to better connect to the desires of users. The use of the model leads to new ideas for development in this way, and when we implement those ideas there are more ways in which the model can be used to solve problems and support the energy transition.

Purpose/vision ETM

Our vision is that is useful to think about the energy system as a whole. A systemic, holistic view of the energy transition. All of it is in there, all sectors and energy carriers. All relevant geographic scopes and time scales – insofar that is possible. So that you do not solve a problem in one area and move it to another area. This way you make sure that plans are as integral as possible, charting all relevant aspects allowing us to get all relevant stakeholders into the picture and at the table. That is our general vision. In practice we see the ways in which it is used is diverse. To communicate, to create shared scenarios with broad support. We also see the model increasingly being used as an accounting tool. In this way the entire future energy system is quantified and used as input for tools that have a more specific geographic or infrastructure scope. The DSO's have been using the model as part of underwriting their infrastructure investment plans. It is versatile, interactive and transparent. Important to note that it is a simulation model, not an optimalization. We want users to do their own research and play with the model to find their own answers.

SA in ETM

I know of SA, it's not the first time I've heard of it but I would not say I am super familiar with it, and I would like to learn a bit more about it. The ETM works with sliders and within seconds gives you an answer, and so it is easy to do an analysis by looking at what changes lead to. In a way, the entire model is one big SA. We have also done it systematically in the past, usually assuming a future scenario and selecting a number of sliders to vary and find which have the biggest impact. Berenschot for example has used this to find the most important costs within the model. What I find very interesting about this is that everything works together. It is more relevant to look at a combination of sliders than at individual sliders.

~Explaining SA~

Uses of SA

Maybe a boring answer but all of the five uses you presented I find useful. We are currently working with the model on all types of levels, such as national and regional. On a municipal level, we typically notice that the decision makers there have a different worldview than for example DSO's who look at a national, and integral way. They need a supportive decision making tool and the ETM is at its place there but often local decisionmakers are overwhelmed by the amount of options in the model. Many of these options are relevant for a national level but not on a municipal level, they do not need to have vision about this. So we are interested in changing the interface of the ETM to match the needs of different types of users. That's why I am especially interested in SA use 3 (simplification). Not by deleting parts of the model, but by hiding them. I have an instinctive idea about how you could do this but I am interested to know if you can quantify this using such exercises.

Robustness too I find interesting, but I keep finding having a worry about the method. In the methods you described you make assumptions about the independence of input variables. In the real world this is not the case. *Explanation of how interactive effects are part of the method*. I do still have some scepsis about the method. There are 400 sliders in the ETM, if you only do min and max values of these you already have 2^{400} options. That is a lot… How much can you reduce the amount of combinations? I would like to know more about it because I think that is the crux of whether or not this would work. *Explanation about the amount of runs necessary*. 1000*400 sliders could work for the ETM as it would take roughly a week.

Other ways of using SA

To find mistakes we have a suite of automated tests that we run every day to find mistakes in the development process. Besides that we test regularly with colleagues that are not directly involved with development. Another way we do this is from a feedback form in the model. A lot of users know how to find us by phone, mail or the form. They regularly reach out to suggest improvements.

We focus on what is important by focussing on what happens in practice. This we do by listening to others, advisors or end-users. We use the model ourselves throughout the year for a number of projects. Always with the focus of whether the model still connects to what is desired and what it can do.
As stated, simplifying the model is especially a thing for the local energy transition. This mainly concerns the user interface and the calculation method of the model.

The relationship between input and output is an interesting one, what we notice is that as you work with the ETM for a couple of years you get a feeling for the levers in the system: this slider is important in combination with that slider, this one is always relevant, this one rarely, except when… This is tacit knowledge that is there with experts and heavy users but which is difficult to quantify. We would like to start a project in which we quantify these relationships and have those lessons be suggested by the model. Besides the graphs and values in the dashboard, the model will say 'Dear user, we notice you have selected a high uptake for EV's but have not changed the refinery sector to reflect this. This might be interesting to look at'. In this way we can coach the model users. This requires an extensive list of all of these types of relationships and that forces us to concretely define our understanding of these relationships. Instead of providing model users with extensive lists, figures or tables we would like to provide them with insights that are specific for their scenario. Those insights could be suggestions for improvement of the scenario or relevant points of attention.

The final one, robustness, is interesting. I believe we mostly do this by changing the sliders. We are aware of this. Recently we put the Klimaat & Energieverkenning (KEV) into the model. There was some discussion about how expensive the measures would be. The assumptions about energy prices that were put into the KEV were different from that in the start year. With the ETM it is then really easy to change those initial values. This ended up showing that the future scenario really wasn’t that much more expensive, which showed that a lot of uncertainty is attributable to those price values. We don’t do it in a systemic way, more in a very focused and question-specific way.

An interesting project that has the goal of assessing robustness is the Gridmaster project, in which TU Delft is involved with Igor Nikolic and Jan Kwakkel. But also Siemens, TenneT, Stedin, the harbour of Rotterdam and more are involved in this project. First we are going to embrace uncertainty by feeding the ETM with an enormous amount of future scenarios. This, together with the asset model of TNO will serve as a market model of the port of Rotterdam. They will then be fed with a lot of future scenarios, almost a parametric study. For each of these futures, every hour for a number of years to 2050 and later will be evaluated and impacts on infrastructure assessed. With this you can configure an infrastructure plan and compare it to all of those futures, and see in what percentage of future scenarios those plans are robust. This aligns with the EMA workbench method, related to deep uncertainty.

CEGOIA results

Comment on the result of electricity infrastructure CAPEX effects: I understand it being there, but it is only relevant if reinforcement of the electricity grid is required in the neighbourhood. This changes from neighbourhood to neighbourhood and is very context specific. Since the context is so determinant for the result my concern is if you can derive generalized conclusions without also enormously varying the context. This would inflate your solution space a lot.

I am interested in a picture in which you show the different types of costs in which you have uncertainty plotted over these different costs. For an outsider, the context is also important. I would like to see the effect of uncertainty expressed in euros.

SA as method for policymakers

This may sound cynical but the majority of policymakers are not ready for this type of work. In politics there is a need for a number, which serves as a point of departure for further discussion. Not just an analysis of uncertainty and statements about robustness, but even a simple uncertainty band is too problematic for policymakers. I do really believe there is a need for awareness of uncertainty in models, policymakers will eventually need to be educated about the relative explanative power of a model. How we are going to get there a very beautiful unsolved problem. Even people like me who have been doing this for years and are very familiar with this find it challenging at times, asking the wrong questions or making the wrong conclusions. I can only imagine what your reaction is like if you do not have the background knowledge. In the Gridmaster project we are working with strategists of professional organizations. We do try to translate things in easy to digest language but the most customers are very substance-focused, as opposed to policymakers.

SA for ETM?

I do think such an analysis would be very useful and interesting for the ETM and I believe our API and model setup is very suitable for it. I would like to support a graduate intern in doing this.

Interview Steven van Polen (PBL)

History Vesta MAIS

I started at PBL 7,5 years ago with industry. I switched between PBL and ECN (now TNO) a number of times. The second time I came back to PBL (2016) my assignment was to help with Vesta, changing it to Vesta MAIS. The switch between Vesta to Vesta MAIS was to add policy instruments and make Vesta open source so more people could start using it. Vesta development started in 2010, initiated by Ruud van der Wijngaart. Back then, we started getting questions about spatial issues like geothermal and heat nets. The topic of energy savings also frequently came up. There is some balance between these two, and Ruud sought a way to combine these within PBL in a single model: Vesta. CE Delft has helped along this development, principally by providing input data. The first big step was launching Vesta MAIS when it became publicly available. Since then, a snowball effect has happened, making the model and its use bigger and bigger. 2016 was also the year in which the government decided the energy transition would become more of a local responsibility. Because of this choice, we evaluated a number of cases, like Utrecht and Drechtsteden to see if Vesta MAIS could be of any help. The Startanalyse became the principle way in which this was later done. Vesta is very good at evaluating technologies under different scenarios and policies, this works really well with the questions of the Startanalyse. The model has grown a lot, we have a pool of about 20 active users – mostly consultants but also some municipalities. There are different gradations of how involved users are with the model but slowly we are seeing a larger Vesta community. Besides development of Vesta MAIS, I am also the one at PBL that calculates the energy bill.

Purpose of Vesta MAIS

The primary purpose of Vesta was and is to provide insights about the effect of national policy on the heating transition in the Netherlands. As PBL, our mandate is to support the national government and advice about policy. Although it's purpose is to be used at a national level, more and more we see the model being used to answer regional questions. As you do analysis on a more local level, say at street level, I do think you should probably use some other model like CHESS. Those are much more specialized at modelling e.g. heat demand. Vesta is much more broad in the way this is modelled.

I do see some tensions between using it for regional questions instead of national. I think Vesta can be used well if you consider thoroughly what you use as inputs and that the regional level is suitable because it considers spatial characteristics. Still, the things you put in need to be very well thought-out. For example, a municipality may find a certain neighbourhood is not connected to a heat net whilst they did expect it to be. Under further investigation it became apparent that the heat source was just outside the borders of the municipality, and so was not considered in the calculation. Scope is important. It is important to help not only those people at the municipality, but also model users to understand the effects of the choices we make and what they mean for the analysis. If what you put in does not result in that which you expect, the consequence is not necessarily that the model is bad. You need to be aware of what is happening in the model. This makes the spatial, regional application of Vesta sometimes problematic.

This is very difficult knowledge to communicate. We see the expertise of advisors growing, and being in active and useful discussions with municipalities. When this happens the model is doing its purpose: as a tool to let people ask questions. Still, it remains a complex issue. The results of the Startanalyse are another example, as you overwhelm people with numbers and pictures. The entire story behind the information is more important, however, and it is difficult to make that story stick.

Prior knowledge of sensitivity analysis

I think there is often some confusion about the terminology and idea about sensitivity analysis. The 'spread' of results is often what people interpret as uncertainty or even sensitivity but I know that is something else. In Vesta this spread is generated using pessimistic and optimistic estimations, the average of which is often that which is presented. That spread is what we can say about the values of parameters now, but uncertainty is that which manifests in the future. How will a technology develop? I can make an estimate, but that is uncertain. The next step in making those estimates is sensitivity analysis so as to find out which uncertainties have the most effects on result.

SA in Vesta

We try to do sensitivity analyses as often as possible, we have done those for the Startanalyse as well. It is not always an easy story to tell. In Startanalyse 2019 we did 5 SA: energy prices, learning effects, changes in investment costs, one specific for label A and the last I can't remember. In the Startanalyse of 2020 we didn't do as many, we focussed on learning effects and energy prices, as these were the biggest factors resulting from the 2019 analysis. There is also green gas and hydrogen, which is different in nature. We haven't analysed these as they are very difficult to estimate. Internally we did evaluate multiple scenarios, e.g. without green gas to see if and what the effects of it was. We used pessimistic and optimistic settings to do the SA, keeping all settings on either setting. We applied the results of this analysis on regular Vesta results through the use of bar diagrams.

Explaining SA

The way you describe systemic variations is very interesting, the way we do it now is not as neat. It would be very interesting to see that interaction. Vesta is also very fast in calculating, it takes only a second or so to calculate results for a neighbourhood. We have changed to an Azure environment recently, in which you can add capacity as needed. We can evaluate the model for the entire country in about 15 minutes. It would be feasible and certainly useful to get a better understanding of dependencies in the model this way.

Uses of SA

Spotting mistakes: It doesn't happen very often that there are mistakes. It does sometimes happen that the model becomes so big that at a point you look back in the code and realize the way things were modelled two years ago made sense but perhaps it could be done in a better way now. You might find a weird outcome due to something that was modelled back then but that you notice should now be different. That is something you can see from SA. We do this now by testing results of new code with older results, although this way we can't necessarily find issues that were already there. The bigger the model becomes, the more this becomes an issue. We try to add more and more to the model so that it better describes the real world. At times, I look at parts and think what is happening here? It takes two days to find how and why it works and realize that we may have given the wrong input or something. When you develop a new part of the model you check it thoroughly and let it do its thing. But eventually, you get to a point where it is so big that you need to rely on all the different parts working well. And if you then want to add a new part you have to go back and figure out all the relationships all over again. We are not a point where we can't trust what we did in the past, but it is an issue. In the last two years development of the model went very fast and there are now many complex levels of it. For new people starting in our team it is very difficult to understand how different modules relate to each other. It would be a good idea to have new people starting out perform a number of sensitivity analyses to get a feel of the model, all the different relations. I notice it is becoming more and more difficult to understand those.

Focus of modelling: We are not good at simplification, we always keep everything in. It would be good to sometimes accept the way things are and keep it simple. We are really good at model expansion. There is always something to add to the model. Currently we are modelling buildings to a very detailed level, which is in a way very pretty but it also asks a lot of us and the model. It could be asked whether or not it is useful to include it. We are trying to say something about 8 million dwellings, should we be looking this specifically at the different types of walls and their effects on the building envelope? Vesta suggests 'packets' of interventions to bring the energetic performance from one level to another, and uses an average cost for it. But we don't know which specific interventions for each individual building are necessary, and you could question whether this information would improve the model. There are other models, like one that TNO uses that are much more focused on policy effects like changing energy performance norms. For such questions you do have to go to this level of detail, but in doing so you keep adding stuff under the hood that works through. Our programmer does make separate modules which you can turn off and on, which is a great way of keeping this separate, but in general we keep adding more and more stuff, some of which we may rarely end up using.

Relationships in models and robustness: Robustness is becoming more and more important in the story we tell. It is difficult to do well, but makes your position to advisors and policymakers much better. Big changes in results are not strange for us as we have a feel for how uncertain outcomes are. Communicating that uncertainty, even as a number, can therefore be valuable but it needs to be in a story. People are looking for some magnitude of order to attribute the importance of a certain effect to, as a way to have some certainty.

Results CEGOIA

The small effect of electricity price for (hybrid) heat pumps is very surprising, since the majority – say 70% - of energy used by the system is electricity – even if other energy demands are met through gas. Warm tap water might make up for it and explain it. Also interesting to see how the confidence margin is smaller in the total effect sensitivity indices.

The pictures in which you see the difference in costs are very nice. When we compare multiple options we always notice that they are often very close in costs, except for some cases with heat nets, and so this image is recognizable to me.

Usefulness SA

As a modeller I think SA could be a method that is manageable and I would be very interested to do it in a more structured manner like you showed. If you can make these plots it can quickly give me a sense of how much impact a certain change has. Comparing multiple methods, trends and neighbourhoods also gives me more sense of what I am looking at and what is happening.

As an advisor I see the value, but it is very difficult to tell policymakers, politicians, municipalities and ministries about this. They do not want a margin of error, they want a number. They want to know whether or not they will achieve their goal, and if you tell them that it depends on circumstance they will tell you that is not of use to them. As an advisor I think this would be nice to know yourself, but I do not know if your customer would be so happy. They often ask for other things.

As a policymaker, like I said, they do not want this. What we (modellers) find interesting is not the answer they need. It just makes it vague.

As a citizen I think this this would be quite pleasant knowledge. Knowledge institutes need to have this type of knowledge available. I sometimes compare the energy transition to the Apollo launch. That process was very rocky, there was a lot of mistakes and failed launches. Like Apollo, we should accept that things can go wrong in the heating transition and say: we saw it went wrong, we are going to compensate you (citizen) and learn from this. These analyses can help getting to the types insights about what the impacts of policies and developments are, which is what people are looking for. How much can I do with this? We do not know 'the' answer, but we do know the direction that things can go. This analysis give a basis for defining that direction. We, as a knowledge institute, should perhaps press ourselves to communicate more of such a message. People are looking for numbers, and we know energy prices are highly uncertain and highly impactful. With all of our projections there should be a note that says: we assume something about very uncertain prices. We should always show what the effects of higher or lower prices are. The systemic approach you've used makes it so there is more confidence in the message that can convince others. Between modellers this is also important to compare. You've shown that the electricity price is not as influential in CEGOIA as we perhaps have found it to be, that is an interesting point of discussion with which we model owners can compare our models with and explain differences. To sum up, as a means of providing information I think SA can help, and it might be a good thing to take a moment to stop development and do this. It may give us more insights than yet another expansion of the model.

Appendix III – Neighbourhoods

Archetypical neighbourhoods data

Classification of archetypes, based on datasets from (Centraal Bureau voor de Statistiek, 2020) and (PDOK, 2020).

<table>
<tr><th rowspan="2">Urbanity</th><th colspan="5">Construction year</th></tr>
<tr><th>before 1900</th><th>1900-1945</th><th>1945-1965</th><th>1965-1990</th><th>1990-now</th></tr>
<tr><td>1 (high)</td><td rowspan="2">1</td><td rowspan="2">2</td><td rowspan="2">3</td><td rowspan="2">6</td><td rowspan="3">11</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td><td colspan="2" rowspan="2">13</td><td>4</td><td>8</td></tr>
<tr><td>4</td><td>5</td><td>9</td><td rowspan="2">12</td></tr>
<tr><td>5 (low)</td><td colspan="4">14</td></tr>
</table>

Urbanity is divided into 5 categories. A neighbourhood is considered *non-urban* when this value is lower than 500, *suburban* when it is between 500 to 1000, *moderately urban* between 1000 and 1500, *strongly urban* from 1500 to 2500 and *very strongly urban* if the average amount of addresses within the radius is over 2500.

For each neighbourhood, CBS also reports the number of buildings built in a period. There are 5 periods, which are *before 1900*, from *1900 to 1945*, from *1945 to 1965*, from *1965 to 1990* and *after 1990*. From these two dimensions with 5 levels, 14 types are specified, some covering more than 1 level of urbanity and or construction years. This is done because in the real dataset there are few if any neighbourhoods that can be categorized as such.

Every neighbourhood in the CBS dataset was classified as one of these profiled. The number of neighbourhoods and amount of buildings for each archetype is listed below.

Archetype no.	Construction period	Description	Neighbourhoods	Buildings
0	N/A	No dwellings/urbanity unknown	396	980
1	<1900	Old inner cities	139	159.094
2	1900-1945	1st ring, high urbanity	669	858.634
3	1945-1965	Post-war reconstruction, high urbanity	619	775.381
4	1945-1965	Post-war reconstruction, moderately urban	170	150.063
5	1945-1965	Post-war reconstruction, suburban	119	72.492
6	1965-1990	Cul-de-sac, high urbanity living	867	1.008.114
7	1965-1990	Cul-de-sac, high urbanity mixed use	327	384.140
8	1965-1990	Cul-de-sac, moderately urban	678	776.775
9	1965-1990	Cul-de-sac, suburban	634	743.186
10	N/A	Business park	895	119.959
11	>1990	Recent construction, high and moderate urbanity	1.017	1.003.789
12	>1990	Recent construction, sub and non-urban	1.035	470.688
13	<1945	Village centers	258	92.052
14	<1990	Non-urban area	3.258	780.775
15	N/A	Other	593	39.241
16	N/A	Mix of construction periods or unknown urbanity	1.245	414.532

Neighbourhood numbers 6 (merged with 7), represents the most buildings. Recent construction (11) is the second largest group. After this, first ring (2) describes the highest number of buildings. Post war high urbanity (3), rural (14), moderate and suburban cul-de-sac (8 and 9) all represent between 700.000 and 800.000 buildings. Together, these 8 neighbourhoods typify a majority of real Dutch neighbourhoods (6 out of 8 million). It is these neighbourhoods the SA will focus on to provide conclusions and gain insights which are relevant for the majority of situations.

To model the archetypical neighbourhoods, an average was taken of real neighbourhoods based on their classification to the previously explained scheme. The variables in the following table were all taken from the CBS dataset.

CBS variable value	1	2	3	4	5	6	8	9	11	12	13	14
'STED',	1	1	2	3	4	2	3	4	2	4	4	5
'OAD',	6.340	3.751	2.479	1.246	771	2.299	1.253	750	2.012	458	919	145
'OPP_LAND',	18	34	48	65	87	44	82	145	54	336	108	467
'AANT_INW',	1.946	2.609	2.500	1.855	1.284	2.525	2.584	2.664	2.203	1.062	775	561
'P_MGEZW',	77	46	49	25	16	37	19	13	37	12	12	6
'P_KOOPWON',	36	53	43	53	60	52	62	66	62	73	67	73
'P_HUURCORP',	22	25	45	38	23	38	28	24	24	10	9	7
'P_STADVERW',	3	1	2	0	1	6	3	0	13	2	0	0
'G_GAS_TOT',	1.155	1.420	1.230	1.503	1.749	1.199	1.421	1.580	1.035	1.591	1.846	2.009
'G_ELEK_TOT'	2.298	2.651	2.488	2.873	3.184	2.824	3.061	3.184	3.088	3.639	3.348	3.661

Different construction periods are used between CBS data, BAG data and CEGOIA inputs. Because these periods are different, the number of buildings that fit in a certain CBS period need to be mutated to a spread that is usable by CEGOIA. Data was transformed from construction periods before 1900, 1900-1945, 1945-1965, 1965-1990 and after 1990 to the periods of before 1920, 1920-1974, 1975-1989, 1990-1994 and after 1994. This was done assuming a uniform distribution of buildings within a period. This assumption is not ideal but no higher resolution information about construction periods could be attained.

Construction period	1	2	3	4	5	6	8	9	11	12	13	14
before 1920	56%	4%	0%	1%	2%	1%	1%	1%	1%	2%	10%	6%
1920-1974	17%	64%	9%	10%	12%	3%	4%	6%	6%	6%	45%	17%
1975-1989	18%	20%	75%	72%	70%	85%	80%	70%	19%	24%	30%	56%
1990-1994	2%	2%	3%	3%	3%	2%	3%	4%	12%	11%	2%	3%
after 1994	8%	10%	13%	14%	13%	9%	13%	18%	62%	57%	12%	17%

Residential buildings are divided by type. CEGOIA takes four input typses: detached, semi-detached, mid and end-terrace and stacked. These correspond to the types registered in the BAG dataset. CBS data only provides information about the number of stacked and unstacked buildings, however. The share of detached, semi-detached, mid and end-terrace houses was therefore estimated. This estimation was done so as to reflect the national totals of each housing type, based on estimates by RVO (https://www.rvo.nl/onderwerpen/duurzaam-

Residential type	1	2	3	4	5	6	8	9	11	12	13	14
Detached	0%	0%	0%	5%	20%	3%	5%	20%	2%	70%	50%	70%
Semi-detached	3%	3%	3%	20%	45%	5%	25%	45%	5%	15%	30%	15%
Mid and end-terrace	20%	52%	48%	50%	19%	56%	51%	22%	56%	3%	8%	9%
Stacked	77%	46%	49%	25%	16%	37%	19%	13%	37%	12%	12%	6%

ondernemen/gebouwen/wetten-en-regels/nieuwbouw/energieprestatie-epc/referentiewoningen-epc). Mid and end-terrace houses are combined in this classification because CEGOIA uses the same values to describe the energetic properties of these buildings. The following table with distributions for each type in each neighbourhood was used.

The same distinction in use-types exists for utility buildings. The CBS dataset however already contained the share of each utility type for each neighbourhood, and so no transformations had to be performed. The following table contains the distribution of types in each neighbourhood.

Utility function	1	2	3	4	5	6	8	9	11	12	13	14
Retail	22%	16%	14%	13%	13%	13%	14%	15%	17%	9%	13%	7%
Lodging	4%	2%	1%	1%	2%	1%	1%	2%	1%	5%	1%	6%
Healthcare	3%	8%	7%	8%	10%	10%	8%	7%	8%	6%	5%	3%
Offices	25%	20%	16%	15%	10%	11%	15%	11%	20%	10%	14%	6%
Meeting	20%	12%	12%	10%	10%	12%	9%	10%	10%	8%	10%	9%
Education	7%	15%	18%	13%	7%	19%	12%	7%	10%	5%	6%	4%
Industry	8%	16%	16%	29%	28%	13%	28%	39%	18%	45%	38%	55%
Sports	1%	2%	5%	3%	4%	5%	5%	4%	3%	3%	3%	3%
Other	10%	9%	11%	8%	15%	15%	8%	6%	12%	7%	8%	6%

Other data required to create CEGOIA archetype neighbourhoods include the average surface area of building types and information about the length and age of electricity and gas infrastructure. Surface areas for each type of building in each Dutch neighbourhood were retrieved from the BAG dataset. The used data is summarized in the following table.

Average surface area (m2)	1	2	3	4	5	6	8	9	11	12	13	14
Dwellings total	**104.424**	**123.925**	**117.240**	**101.840**	**74.354**	**120.422**	**138.216**	**152.419**	**113.733**	**66.445**	**51.403**	**37.784**
Utility total	**13.432**	**5.835**	**5.003**	**4.428**	**3.360**	**2.021**	**4.097**	**6.029**	**6.107**	**2.105**	**3.022**	**1.066**
Retail	2.434	845	308	375	557	99	349	679	538	1.225	296	963
Lodging	1.556	2.850	2.734	2.952	2.479	1.500	2.369	2.676	2.809	1.429	1.250	456
Healthcare	14.955	7.412	5.963	5.391	2.649	1.674	4.427	4.519	7.381	2.465	3.255	925
Offices	11.709	4.589	4.383	3.460	2.631	1.899	2.766	3.999	3.574	1.998	2.383	1.401
Meeting	4.188	5.476	6.624	4.395	1.701	2.934	3.707	2.975	3.734	1.256	1.381	561
Education	4.841	6.170	6.028	10.120	7.245	2.016	8.237	15.738	6.340	10.713	8.791	8.256
Industry	488	719	1.688	1.175	1.135	777	1.393	1.708	1.085	677	625	395
Sports	91	104	14	47	31	1	1	6	67	109	108	20
Other	6.215	3.455	4.244	2.653	3.735	2.291	2.539	2.369	4.518	1.617	1.846	846

The following table summarizes the dimensioning of the archetypical neighbourhoods.

Parameter	1	2	3	4	5	6	8	9	11	12	13	14
dwellings_amount_total	**1157**	**1277**	**1244**	**877**	**604**	**1175**	**1157**	**1179**	**987**	**441**	**354**	**237**
dwellings_amount_before_1900	640	52	4	9	10	11	6	15	11	7	36	14
dwellings_amount_1900_1945	194	817	107	92	71	36	47	75	56	27	161	41
dwellings_amount_1946_1991	208	252	931	633	425	999	929	828	188	110	106	132
dwellings_amount_1992_2005	58	78	101	72	48	65	88	131	367	148	25	25
dwellings_amount_after_2005	58	79	101	72	49	65	88	131	365	149	26	25
dwellings_surface_area_total	**104.424**	**123.925**	**117.240**	**101.840**	**74.354**	**120.422**	**138.216**	**152.419**	**113.733**	**66.445**	**51.403**	**37.784**
dwellings_surface_area_before_1900	57.973	5.046	449	1.103	1.223	1.119	812	2.012	1.259	1.143	5.108	2.197
dwellings_surface_area_1900_1945	17.528	79.268	10.065	10.616	8.851	3.690	5.657	9.685	6.408	4.084	23.384	6.571
dwellings_surface_area_1946_1991	18.426	24.470	87.801	73.457	52.266	102.360	110.783	107.042	21.734	16.093	15.500	21.181
dwellings_surface_area_1992_2005	5.249	7.571	9.463	8.332	6.007	6.626	10.482	16.840	42.166	22.563	3.705	3.918
dwellings_surface_area_after_2005	5.249	7.571	9.463	8.332	6.007	6.626	10.482	16.840	42.166	22.563	3.705	3.918
utility amount_total	**174**	**101**	**152**	**114**	**103**	**159**	**109**	**125**	**97**	**73**	**71**	**66**
utility_amount_before_1920	106	0	0	0	0	0	0	0	0	0	0	0
utility_amount_1920_1974	18	65	115	76	64	0	0	62	15	9	40	30
utility_amount_1975_1989	33	9	14	15	16	105	60	23	5	4	12	16
utility_amount_1990_1994	2	3	5	2	1	0	1	1	10	8	1	1
utility_amount_after_1994	15	24	18	21	22	54	48	39	67	52	18	19
utility_surface_area_total	**51.559**	**30.326**	**28.310**	**28.169**	**18.142**	**10.643**	**23.583**	**33.938**	**27.673**	**19.762**	**19.128**	**13.173**
utility_surface_area_before_1920	32.470	9.856	1.189	1.610	1.258	244	567	1.406	999	880	5.768	1.784
utility_surface_area_1920_1974	9.209	14.927	20.032	18.411	11.574	4.170	9.319	13.513	4.026	3.426	8.908	5.606
utility_surface_area_1975_1989	4.696	1.838	2.519	3.538	2.378	5.059	10.120	11.519	2.129	2.035	1.694	3.051
utility_surface_area_1990_1994	864	618	762	768	489	195	596	1.250	3.420	2.237	460	455
utility_surface_area_after_1994	4.319	3.088	3.808	3.841	2.443	976	2.981	6.250	17.099	11.184	2.298	2.276

The amount of surface area for dwelling buildings of different types in different construction periods was calculated using the distribution percentages found in previous tables. The same method was used for calculating the average surface area of various utility types by construction era.

The average length of infrastructure per building was found from an Enexis dataset, available internally through CE Delft but not publicly available. The values used for gas and electricity infrastructure are in meters per object in a neighbourhood.

Average infra length per object (m)	1	2	3	4	5	6	8	9	11	12	13	14
Gas infrastructure length	13	23	21	27	35	18	34	61	40	50	49	66
Electricity infrastructure length	22	23	28	58	45	23	40	72	46	72	76	91

The collective heat sources available for neighbourhoods to use are geothermal and industrial waste heat. The choice for these sources is not arbitrary, as the costs of heat nets using them vary significantly based on the cost of heat production. Yet, the variance in available collective heat sources is large and CEGOIA only makes use of the cheapest option. The cheapest option will very if there are many possible sources to pick from, which makes the formulation of generalized conclusions impractical. Evaluating multiple sources is therefore considered unfeasible within the scope of this sensitivity analysis.

As the analysis was performed, time constraints became apparent and the number of evaluated neighbourhoods was limited to 5. These five represent the majority of buildings in the country and capture diverse building periods and densities. They are:

2: first ring neighbourhoods, 1900-1945

11: recent construction, 1990-now

3: post-war reconstruction, 1945-1965

14: rural neighbourhood (any period)

6: cul-de-sac, 1965-1990