Robust Policies

An Exploratory Study on the Energy Transition of the Dutch Built Environment Sector

M. Hupkens

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by

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An electronic version of this thesis is available at http://repository.tudelft.nl/.
All codes in this thesis are available on
https://github.com/markhupkens/EnergyTransitionModelling.

TU Delft

Preface

Firstly, I would like to thank the members of my graduation committee - Prof.dr. K. Blok and Dr. E. Pruyt for their support and guidance throughout the process. Without their continuous mentor ship, supportive feedback and inspirational ideas this thesis would be what it is today.

This study has been performed as a graduation internship at TNO, department of Strategy and Policy as part of the Energy Policy Lab. As such, a special thanks has to be expressed to all my colleagues at TN for enabling and supporting me to perform my research. I have greatly enjoyed working at TNO and very much appreciate the time colleagues made to share their knowledge and their insights. In particular I would like to thank Adriaan Slob for his ongoing interest, support and directions within the organization. Special thanks go Devin, Nicky and Ka-Chun for making thesislife more enjoyable on our many *off-site sessions* and refreshing walks.

Then my gratitude goes to Stefan Wigman who, next to his PHD, made time to share the technical pitfalls of using the Exploratory Modelling Workbench and explain best practices. Without your help I would have been forever stuck in Python error messages. Also, I would like to express my gratitude to the Advanced SD project groups, who at the beginning of this thesis made great progress deciphering sector-related data in an (now outdated) aim to create a cross-sectoral energy transition model. Special thanks go to Ingo Schönwandt who took a deep dive understanding Dutch spatial decomposition to jointly decipher residential data.

Last but not least, I would like to thank all my friends for their support and fun throughout my studies. Most importantly, I want to thank my family for their neverending support of my choices. Despite the fact I chose to pause my studies for almost two years to *race the sun* down-under, you have always been there to unconditionally support me in my endeavours and help me in times of need.

Finally, I want to thank Marlies for her unlimited encouragement and for cheering me up when thesis life got though.

M. Hupkens
The Hague, August 2019

Executive Summary

Today's societies face many grand challenges, such as climate change and the defeat of poverty. These challenges can be characterized as wicked problems and are hard to address as there is no single solution, many actors are involved and possible solutions are shrouded in uncertainty of possible outcomes. The energy transition required to reach carbon reduction targets set in the Paris Agreement is an example of such a challenge.

The Dutch government has undertaken an extensive multi-stakeholder process to create the climate agreement. The agreement is composed of five sectors for which policies have been formulated up to 2030. These policies should ensure the country is on track to meet carbon dioxide reduction targets set in the Paris Agreement. Energy transition policy aimed at reducing CO_2 emissions, however, is surrounded by deep uncertainties, due to climate change, technological innovations and socio-economic developments. In the face of deep uncertainty, *Conventional* decision making to find policies for a single *best guess* future is inadequate. Hence, there is a need to assess performance of policies under deep uncertainty. Policy *robustness* is a metric of policy performance that describes insensitivity to differences in future circumstances. Adaptive policies can be created that adapt to changing conditions, in contrast to more conventional *static* policies, that are constant over time.

The design of the climate agreement has proposed many promising measures, but only sparsely mentions uncertainty as an important factor for the impacts of these measures. More specifically, uncertainties are only mentioned in the chapter describing measures for the mobility sector and in the chapter judging cross-sectoral consistency in a systems approach. Hence, the effect of beneficial robust or adaptive policies for the climate agreement are unknown.

The aim of this study is to investigate how policies could be designed in such a way that they have a more robust performance, regardless of how the future develops. The study is scoped on the Dutch built environment sector and hence aims to answer the following research question:

"How could policies be designed to establish a more robust performance of the climate agreement's built environment sector?"

Methodology

In this study a modelling approach is used to answer this research question. Specifically, the Adaptive Robust Design (ARD) framework (section 2.2.3) is used to allow for experimenting with large variety of (parametric and categorical) uncertainties which are used as model inputs to assess the influence of uncertainties on policy performance. Influential uncertainties are identified using a computational model that represents the energy transition in the Dutch built environment sector. This method of exploratory modelling distinctly differs from traditional predictive modelling in the way that not a single future will be predicted. Rather, exploratory modelling aims to understand trends of multiple plausible futures.

Subsequently, the model is connected to the Exploratory Modelling & Analysis workbench in Python (see section 2.2.3 and 2.2.4). The ARD framework consists of five steps: (1) uncertainties and outcomes of interest are defined, (2) a base ensemble is created by simulating the system without any policies using these uncertainties, (3) influential uncertainties are identified from this base ensemble using advanced Scenario Discovery techniques such as PRIM and Feature Scoring (see section 5.1.1). (4) Policies are created to counter undesired effects of uncertainties. (5) Subsequent policy experiments are performed to assess the performance of these policies under uncertainty.

Energy Systems Models

A literature review has been conducted to find the state-of-the-art regarding energy systems models (see chapter 3). A wide variety of recent energy transition models exists in academic literature. More recently, a push to open source publicly funded models opened up some models to general public. Within the Dutch scope, many models are used for a variety of purposes and entertaining different scopes. The variation in both purpose and scope could explain the many models in circulation. There are few models that are fit for dynamic policy testing and are publicly available. For the Dutch built environment transition, only PBL's Vesta MAIS and Quintel's Energy Transition Model meet these criteria. They do not, however, conform to the prerequisites for connection to the EMA workbench and would subsequently require the creation of computational wrappers to interface between the model and the workbench. Given the time limit to complete this study, a pragmatic alternative is preferred and an in house model of the Dutch built environment sector has been developed.

Built Environment Energy Transition Model

In this study a *Systems Dynamics* representation of the Dutch built environment sector is used (see chapter 4). The model is scoped to residential buildings in The Netherlands divided over 10.000+ neighbourhoods (roughly 20% of the neighbourhoods are dropped due to incomplete data) and is scoped to household heat generation and does not explicitly include energy efficiency components (such as isolation), because this data is not available on a neighbourhood level. The low resolution of neighbourhoods is used to facilitate neighbourhood, or district-based policies from a bottom up perspective.

The model consists of six main components: 1) a household renovation structure that enables a renovation decision for each neighbourhood and subsequently allocates a renovated house to a heat generation alternative (2): district heating or all electric heat generation. Costs related to these renovations are scoped in this model to label jumps to the A-label energy label. 3) Energy demand is calculated for the houses in the model, based on their standard house type (apartments, row houses, corner houses, two under one roof homes and free standing homes). 4) available labour is simulated to meet renovation demand. 5) a policy structure enables policy implementation that effects household renovations. Finally, a Key Performance Indicator structure (6) captures main outcomes for policy evaluation. Next to home renovations to remove gas connections of households, carbon intensity in power generation is set be reduced by 50-80% for both electricity and district heat to *model* policies of the electricity sector within this study's scope on the built environment sector.

Subsequently, the model is used in the ARD framework. Real world open data has been gathered and prepared to create an extensive data set for the neighbourhood scale. The model is initialized from this data set to optimally represent the actual case.

Results of the Uncertainty Analysis

First, a base case analysis has been performed on the model to find key uncertainties in the energy transition of the built environment (see chapter 5). Therefor 1000 experiments have been performed with the model without any policies, but with defined and varying parametric uncertainties. A combination of Open Exploration and Scenario Discovery has been used to analyze influence of these defined uncertainties on the outcomes of the model. Three outcomes of interest have been analyzed. Contrary to expectations, the uncertainties most strongly influencing *Annual CO_2-equivalent emissions* were uncertainties related to energy supply. Namely, annual electricity demand growth and by reduction carbon intensity power generation. *Cumulative costs of renovation* were greatly influenced by a reduction in renovation costs and a standard renovation rate.

Results of the Policy Analysis

Findings from the base case analysis have been used to create policies that reduce undesirable effects of uncertainties. Subsequently, policies are evaluated on their robustness under deep uncertainty. For the three most likely policy instruments (a neighbourhood approach and subsidy in the privately owned sector, a neighbourhood approach and subsidy in the rental sector and norms to built new homes without a gas connection), three policy variations have been created, next to a no policy alternative. A static policy, a dynamic adaptive policy and a mission oriented policy have been applied to the model. A static policy subsidizes a fixed percentage over time, a dynamic adaptive policy has adjustment mechanisms to steer towards a certain goal and a mission oriented policy is deemed to have a broader approach that also targets innovation to increase the renovation rate and decrease renovation costs. For the neighbourhood approach and subsidy in both sector of privately owned homes and the rental sector, only subsidy based policies have been taken into consideration in this study. For each policy, the percentage of renovation costs to be subsidized has been used as a policy lever. In the simulation, four subsidy percentages between 20 and 80% have been simulated for each policy variant.

When discussing effectiveness of policies, policy targets should be evaluated. As targets are only known for the period up to 2030, a more general target has been maintained for 2050. This general target has been set at 95% reduction and was obtained from the Dutch climate law. Most policies simulated in this study reached 2030 targets after its deadline in 2030.

Results have been evaluated both within policy variants (withing varying subsidy levels) as between policy variants (with a constant subsidy level). The static and mission policy options showed similar trends, but maintained different absolute outcomes. Most notably, the mission policy allows for a higher renovation rate and thus cumulative renovated houses turned out highest for this policy while holding a 80% subsidy level.

The dynamic adaptive policy variant does not perform significantly better than the other two policy variants. Even though annual CO_2 emissions and cumulative renovated houses are higher, uncertainty is not reduced significantly. This shows that subsidy percentage, alone, does not ensure that policy targets for 2050 are reached. None of the policies simulated in this study have been able to reach the 2050 goal and seemed to converge around two to three million renovated homes in the 80% subsidy level. This finding was unexpected and suggests that other variables prevent more renovation to be completed. The renovation rate used in this study is likely an obstacle for ample renovations. The renovation rate used in this study is drawn from the climate agreement and seems to be too small to meet renovation demand within this study. This is demonstrated in the mission policy where an additional increase of the renovation rate by 25% resulted in higher cumulative renovated houses.

Discussion

The results of this study highlight the importance of decision making under deep uncertainty. Both with and without policies, results were strongly affected by uncertainties influencing the system. However, policies can be created to reduce influence of uncertainties governing the system. Specifically, policies that have the ability to adapt to changing circumstances, so called *adaptive policies*, have been found to be better able to cope with uncertainty compared to static policies. These findings imply that policies should be created to be adaptive and have the ability to adjust, or steer, towards a predefined goal.

Additionally, this study found that the renovation rate is a key factor in achieving renovation targets. Even when households are willing to renovate (at various subsidy percentages), renovation capacity should be adequate to meet demand. The renovation rate used in this study has been drawn from the climate agreement and seems to be insufficient to meet targets within the scope of this study. This would imply that an additional increase in renovation capacity is required to meet renovation targets, next to creating incentives for home owners to renovate. Hence, this study would suggest a combined effort that creates incentives for home owners to renovate and simultaneously incentivizes the renovation industry to increase capacity to meet demand.

In previous iterations in the Adaptive Robust Design cycle, experiments have been performed with a lower reduction target for 2050. This allowed for better adjustment by a mechanism that solely influences the subsidies awarded (see figure F.1). In that case, the dynamic adaptive policy performed significantly better than its static or mission oriented counterpart, compared to the results shown in this chapter. Subsequently switching to a higher reduction target, in line with the climate law (Klimaatwet, 2019), had unforeseen consequences in later simulations and resulted in too little adjustment room for the dynamic adaptive policy.

Conclusion

The aim of this study is to understand how policies in the Dutch built environment sector could be designed to establish a more robust policy performance. This study has identified key uncertainties influencing the built environment sector as a system and proposes policy variations to reduce the influence of these uncertainties. The experiments performed in this research confirmed that an adaptive dynamic policy can better cope with uncertainties influencing the model. Next, this study showed that subsidy-based policies alone are unlikely to reach desired targets and have to be accompanied by additional policies that accelerate renovation capacity.

The approach used in this study can be used as an example to combine current policy analysis with the concept of deep uncertainty and subsequently highlight the importance of adaptive policies. Moreover, the neighbourhood based approach embraced in this study allows for bottom up policy testing and neighbourhood specific subsidies. The approach has been particularly fruitful when it is considered that it has been based on publicly available data sources

Recommendations

Further research should be undertaken to explore impacts of the following six main recommendations. First, it is recommended to validate the model used in this study. Second, energy efficiency components should be explicitly added to the model, when data availability allows for it.

Third, future studies could investigate policies that could stimulate the renovation rate (through e.g. standardization or automation) to keep up with demand.

Fourth, further research could also analyze the impact of differentiation of collective versus individual renovations. For instance, a multi story flat will have different renovation costs than an identical number of households living in free standing houses.

Fifth, regulation on district heating will also impact renovation costs and availability across the Netherlands. Will district heat networks become open to competition and, if so, what temperatures will be defined?

Finally, uncertainties sampled in this study are by no means exhaustive. Effects of other uncertainties could also have large influence on the system, as, for instance, arrangements that stimulate solar PV by allowing owners to feed generated electricity back to the grid.

Contents

List of Figures

List of Tables

Acronyms

ARD Adaptive Robust Design. v, vii, 5, 7, 19, 33, 50, 187

EMA Exploratory Modelling and Analysis. vi, 2, 3, 7, 19, 25, 26, 34

IDR Implicit Discount Rates. 21, 22, 51

KDE Kernel Density Estimation. xiv, 26, 27, 34, 36, 37, 40–43

KDES Kernel Density Estimations. 34

KPI Key Performance Indicator. vi, 5, 26, 36

PBL Netherlands Environmental Assessment Agency. 1, 34, 187

PRIM Patien Rule Induction Method. 26

RDM Robust Decision Making. 5, 6

1

Introduction

1.1. International Grand Challenges

Today's societies face many grand challenges, ranging from climate-change and energy needs (Reid et al., 2010) to zero-hunger and the defeat of poverty (United Nations, 2018). These challenges can be characterized as *wicked problems* (Rittel and Webber, 1973) or *post normal challenges* (Funtowicz and Ravetz, 1990) and are hard to address as there is no single solution, many actors are involved, and possible solutions are shrouded in uncertainty of possible outcomes (Conklin, 2006). Governance of these wicked problems is crucial to counter their effects (Kuhlmann and Rip, 2014) for which new policy methods are needed (Mowery et al., 2010).

1.2. The Dutch Energy Transition

An example of such a wicked problem is the energy transition required to reach carbon reduction targets stated in the Paris Agreement (UNFCCC, 2015). In The Netherlands, recent efforts to reduce Dutch carbon emissions have been in the making since 2011 (see figure D.1). Despite different government coalitions, the climate agenda has been continued for almost a decade. A first attempt to create an energy agreement for sustainable growth has been made in 2013 by the Sociaal Economische Raad (2013). The newly elected government coalition of *Rutte 3* has set the ambition to reduce carbon emissions by 49% by 2030 (Rijksoverheid, 2017), two years after the Paris Agreement was made.

November 2011	Local Climate Agenda
September 2013	Presentation Energy Agreement Sustainable Growth
October 2013	Climate agenda
December 2015	International Climate agreement (Paris Agreement)
January 2016	Energy report
December 2016	Energy agenda
May 2017	Agreement Energy Intensive Industry
May 2018	Prohibition coal-fueled electricity production as of 2030
June 2018	Proposal climate law
July 2018	Proposal for key points of the climate agreement
September 2018	PBL Analysis of key points of the climate agreement
October 2018	Cabinet's appreciation the climate agreement & start second round of negotiations
December 2018	Presentation of the Design of the Climate Agreement
March 2019	Presentation of computed effects by planning bureaus

Figure 1.1: Timeline of Dutch Climate Policies (Rijksoverheid, 2019d; Hekkenberg and Koelemeijer, 2018; PBL, 2019)

To realize its ambitions, the Dutch government initiated a massive stakeholder consultation process to create a *new* climate agreement with all relevant actors. Five sector tables (Electricity, Industry, Mobility, Agriculture and Built Environment) had been created and assigned indicative reduction targets early 2018 (Lugt, 2018). Each sector was requested to draft concept measures with relevant stakeholders in their field to reach the indicative sector target.

Box 1: Dutch emission targets explained

Currently, total Dutch GHG emissions are 193 Mton CO_2-eq (2017), which is 13 % lower compared to the 221 Mton CO_2-eq baseline of 1990. Total Dutch GHG emissions should decrease to a maximum of 113 Mton CO_2-eq to reach the reduction target of 49 % GHG reduction in 2030 (compared to 1990-levels) (CBS, 2018a).
Hence, from 2017 onwards, a reduction of 80 Mtons has to be achieved. Of these 80 Mtons, the Dutch government assumes that 39 Mtons will be reduced through existing policies, the so called *"baseline policies"* (Schoots et al., 2017). The remainder of this sum has to be achieved through policy from the climate agreement, that contributes 48.7 Mtons (see Table D.1), reaching the total of 80 Mton reduction compared to 2017 emissions.

Figure 1.2: Dutch emission targets explained

The task at hand for the climate tables was to formulate additional policies to realize an additional reduction of 48.7 Mtons of CO_2-eq GHG emissions. In little less than a year, the design of the climate agreement had been made and has been published in December 2018. It proposes many different solutions for the energy transition (Klimaatakkoord, 2018; Waaijers, 2017) in order to meet the renewed reduction targets.

To put policy into practice, the climate agreement proposes *Regional Energy Strategies* (RES) to effectuate national agreements, stimulate cross-sectoral cooperation and enable societal involvement. Thirty regions have been composed in which governments, social partners, distribution system operators, business and, where possible, citizens (Klimaatakkoord, 2019, p. 224). The Netherlands has multiple levels of public governance. These RES's will form an extra dimension to facilitate, on top of the existing administrative division of national government, provincial administration and municipal administration.

1.3. Deep uncertainty

Energy transition policy, is beset by many deep uncertainties that impede *normal* decision making in this, so called, *post normal* domain (Pye et al., 2018; Li and Pye, 2018). Adaptive programming could provide a solution to cope with these uncertainties and general complexity of energy transition policies (Klimaatakkoord, 2018; Ministry of Infrastructure and the Environment, 2018), but decision making under conditions of deep uncertainty requires special attention as "analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes."(Lempert et al., 2003).

Walker et al. (2001) argue that *"[public] policies should be adaptive- devised not to be optimal for a best estimate future, but robust across a range of plausible futures."* and provide a carefully constructed adaptive policy-making framework.

Adaptive policy making emerged from the field of Exploratory Modelling and Analysis (EMA). EMA involves performing many computational experiments "... to explore the implications of varying assumptions and hypotheses." (Bankes, 1993), which has been applied in the range from combat- to policy research. Recently, Hamarat et al. (2013) and Haasnoot et al. (2013) have applied the concepts of robust decision making and adaptive policies to real-world cases (the Dutch energy transition and the Dutch Delta program respectively). Kwakkel et al. (2016a) provide a comparison of robust decision making with dynamic adaptive policy pathways. The authors conclude that "Robust Decision-Making offers insights into conditions under which problems occur, and makes trade-offs transparent. The Dynamic Adaptive Policy Pathways approach emphasizes dynamic adaptation over time, and thus offers a natural way for handling the vulnerabilities identified through Robust Decision-Making.".

1.4. Need for Informed Decision Making

It is essential for Dutch policymakers to create policies that significantly reduce carbon emissions, as "there is no right to be wrong" when battling climate change (Rittel and Webber, 1973). Making proper decisions when faced with deep uncertainty is highly complex, as man simply does not know which future will unfold.Dutch climate policies for the next decade are currently in the making. Inspired on measures proposed in the climate agreement, instruments are created to effectuate policy ambitions.

Energy transition policy aimed at reducing CO_2 emissions, is surrounded by deep uncertainties, due to climate change, technological innovations and socio-economic developments. These uncertainties prevent conventional decision making, as policy formulation for a single best guess of future circumstances is inadequate under deep uncertainty. Hence, there is a need to assess performance of policies under deep uncertainty. Policy *robustness* is a metric of policy performance that describes insensitivity to differences in future circumstances. *Adaptive* strategies can be created that are flexible to changing conditions and thus increase policy robustness, in contrast to more conventional static policies, that are constant over time.

Capano and Woo (2018) state that, although literature shows a growing interest in policy robustness, empirical cases of robust policies are limited. The authors put two reasons forward for this gap. First, operationalization and definition of robustness of policy design is difficult due to differences in understanding of uncertainty across political and social contexts. Second, the authors state that robustness tends to be mixed up with similar concepts such as resilience, which makes understanding of existing efforts in robustness of policy design hard to determine. More recently, Verroen (2018) bridged the gap between academic literature and real life policy making in a session on decision making under uncertainty.

Concepts from the fields of *Exploratory Modelling and Analysis* and *decision making under deep uncertainty* provide tools, such as *robust decision making* or *adaptive planning* to cope with these highly uncertain challenges. These tools are, however, not used in the current policy making process. This inspires the following research gap:

> **Research Gap:** The effect of robust or adaptive policies have not been reported in the current Dutch climate agreement, even though it has been presented as an adaptive agreement. This brings into question how robust energy transition policies can be formulated under deep uncertainty.

1.5. Scope: the Dutch Built Environment Sector

The formulation of the climate agreement has been a massive undertaking including over a hundred different stakeholders. Subsequently, analyses by the PBL Netherlands Environmental Assessment Agency (PBL, 2019) too has been a monumental performance in very limited time to provide a quantitative review of intended plans. Hence, this study by no means has the illusion to outdo both.

Therefor, a scope of the Built Environment Sector will be entertained. This sector has been selected for multiple reasons. First, data availability, accuracy and completeness is expected to be better than other sectors in the climate agreement such as the industrial or agricultural sector. Second, this sector holds a technical challenge (switching to sustainable energy solutions, increase household energy efficiency, etc) and a strong social challenge (how will costs be distributed, how to prevent energy inequality, etc.). Moreover, policies for the built environment will quite literately hit home for all citizens in The Netherlands and will subsequently face major scrutiny. Combined with the heterogeneity of the current Dutch housing stock and its inhabitants, these two challenges increase complexity of policymaking.

1.6. Research Goal and Main Research Question

The main goal of this research is to perform a pilot study to analyze the effects of different climate policy instruments under the influence of deep uncertainty. The aim is to create an open source work flow from data acquisition and manipulation to modelling and simulation to establish a quantitative framework for exploratory modelling and analysis of energy transition policies under deep uncertainty. Specifically, climate ambitions following from the Dutch climate agreement for the built environment sector will be addressed as a case study. The main research question to be answered in this thesis can be presented as:

"How could policies be designed to establish a more robust performance of the climate agreement's built environment sector?"

In answering this research question insights on policy performance and (in)sensitivity to changing circumstances could be obtained. Hence, creating understanding of plausible future scenarios and policies that reach desired scenarios.

1.7. Structure of the Report

This thesis consists of ten chapters. In this first chapter an introduction provides context, knowledge gaps and associated research questions. Second, the research approach is presented in chapter 2. Sub questions following from the main research question, methodology, applied frameworks and the scope of the study are discussed in more detail. Subsequently, chapter 3 begins by laying out general energy transition model taxonomies and continues to analyze the state-of-the-art regarding energy systems models. Chapter 4 elaborates on the quantitative model applied for the scope of this study. The chapter presents a general conceptual overview of the model, it's most important structures, constants and data used for model calibration. After that, a base case analysis of the system under study is performed without any implemented policies (chapter 5). Key uncertainties are highlighted and their influence on the system discussed next to presenting results and more general trends of the sector. Subsequently, chapter 6 presents a policy analysis that aims to mitigate negative effects of influential uncertainties. In this chapter, three most promising policy instruments are selected and combined in various policy implementation mechanisms, before being tested under deep uncertainty. Outcomes of these policies are presented and their implications discussed. Chapter 7 discusses interpretation and implication of results, their limitations and recommendations for future research. Thereafter, the research questions are answered in chapter 8. Finally, this thesis is concluded by offering a critical reflection on the study and its societal and academic relevance.

2

Research Approach

This chapter explains the methodology used to answer the sub questions (grouped by dominant method). Besides that, this chapter will briefly address data, tools and scope. The chapter concludes by providing an outline of research activities

The focus of this study is to explore robust Dutch energy transition policies under deep uncertainty. Building on the Robust Decision Making (RDM) framework by Lempert et al. (2006), this study proposes an Adaptive Robust Design (ARD) (Hamarat et al., 2013) approach to establish a more robust climate agreement. The goal of this Adaptive Robust Design (ARD) is to use a digital twin of the Dutch built environment sector, as discussed in the climate agreement, and test proposed policy instruments under deep uncertainty. Understanding of the performance of different strategies could help redesign, and hence improve, policy strategies to create robust policy instruments.

2.1. Sub Research Questions

The main research question presented in section 1.6 cannot be answered directly, as the energy transition is a massive systemic make-over and hence involves many uncertainties. These uncertainties strongly affect the ability for informed decision making, because dynamic relations between key factors of the system's structure are unknown. Which creates difficulties to formulate assumptions to assess long-term policy effects. Consequently, it is vital to know which key uncertainties are involved, how they affect the system and each other, and how sensitive Key Performance Indicators KPI's are to uncertainties and policy instruments. To answer this main question, the following sub questions will be adopted:

> **Sub-question 1:** What energy transition models are currently available and compose the state-of-the-art?

Before creating a quantitative model within the scope of this study, it will be beneficial to understand the current state-of-the-art in terms of energy transition modelling. Hence, an overview and taxonomy of different energy systems models should be created. Moreover, this deep-dive in existing energy systems models provides the possibility to analyze the appreciation of deep uncertainty in the energy systems modeling sector. Hence, an overview of main uncertainties provided in literature will be included in this sub-question.

> **Sub-question 2:** How can the energy transition of the Dutch built environment sector be specified in a simulation model?

A quantitative model of the Dutch energy transition in the built environment sector needs to be created to allow for quantitative policy testing. This *model* is a formalization of inputs, relations and outcomes of the conceptualization of the energy transition. Secondly, model mechanisms need to be created that enable policy instrument implementation in the digital twin of the Dutch energy transition. Each policy instrument identified in sub-question 1 needs to be formally represented in the digital twin of the energy transition.

> **Sub-question 3:** What are, according to a Deep Uncertainty approach, the key uncertainties in the energy transition of the built environment?

Understanding of the influence of uncertainties on the general outcome of the model is required, prior to policy analysis of robust policy options. Hence, this question aims to analyze outcomes of possible future of the system under deep uncertainty.

> **Sub-question 4:** Can policies be designed that accelerate the energy transition of the built environment sectorm which are robust under deep uncertainty?

Robust policies can be found through quantitative policy analysis. The three most promising policy instruments are selected and combined in various policy implementation mechanisms to be tested in the energy transition model. Large ranges of parametric uncertainty are sampled to simulate deep uncertainty. Policy variations can thereafter be analyzed on their performance to provide insights in their robustness under deep uncertainty.

2.2. Research Methods and Data collection

2.2.1. Desk Research (sub-question 1)

To answer the second sub question, a literature overview of the state of the art will be provided regarding energy systems modelling in scientific literature, complemented with models being used in public policy making or commercial advisory.

2.2.2. System Dynamics (sub-question 2)

An operationalized model of Dutch built environment sector will be created using System Dynamics to explore system behaviour under the identified uncertainties. Energy transition policies are implemented in a highly dynamic socio-technical system in which system outcomes shaped by various underlying processes and feedback loops. Because of these dynamics, system Dynamics modelling will be used to create models of the climate sectors. Moreover, the model will have to be instantiated from a very low (local) level to accommodate for different policy perspectives and to enable specific built environment policies such as a district-based approach for household renovations. Hence, the model has to include neighbourhood, district, municipality and country level.

2.2.3. Robust policy options (sub-question 3 & 4)

Robust Decision Making

The RDM framework (Lempert et al., 2006) consists of four key steps. Firstly, a conceptualization of the system under study, key uncertainties besetting the system, policy levers and outcomes of interest (Kwakkel et al., 2016b). Secondly, cases are generated using the conceptual model from the previous step (Bankes et al., 2013). During this case generation, the model behaviour is systematically explored across identified uncertainties to assess performance of candidate strategies. Step three is scenario discovery (Bryant and Lempert, 2010) which employs statistical machine learning algorithms to analyze the results of the case generation stage to reveal conditions under which candidate strategies perform poorly. These vulnerabilities are analyzed in the fourth step, trade-off analysis, to assess performance of the candidate strategies on outcome indicators (Kwakkel et al., 2016b), which can be used to redesign strategies and repeat the process.

Adaptive robust design

Building on the RDM framework, Adaptive Robust Design explicitly iterates over the RDM framework to investigate robustness of candidate policies using the System Dynamics model. The inherently iterative approach will identify vulnerabilities from troublesome scenarios and strengths from promising scenarios to create better policies (Hamarat et al., 2013).

Firstly, the problem will be conceptualized and uncertainties identified. Then, an iterative cycle begins that uses the conceptualization and uncertainties to (1) design of policies and actions, (2-3) implement candidate policies in the model, (4) case generation (exploratory modelling) of all plausible scenarios, subject to the candidate policies, (5) find troublesome and promising scenarios using scenario discovery, (6) evaluation of the performance of candidate policies using trade-off analysis and thereafter redesign policies and repeat the process (see figure 2.1).

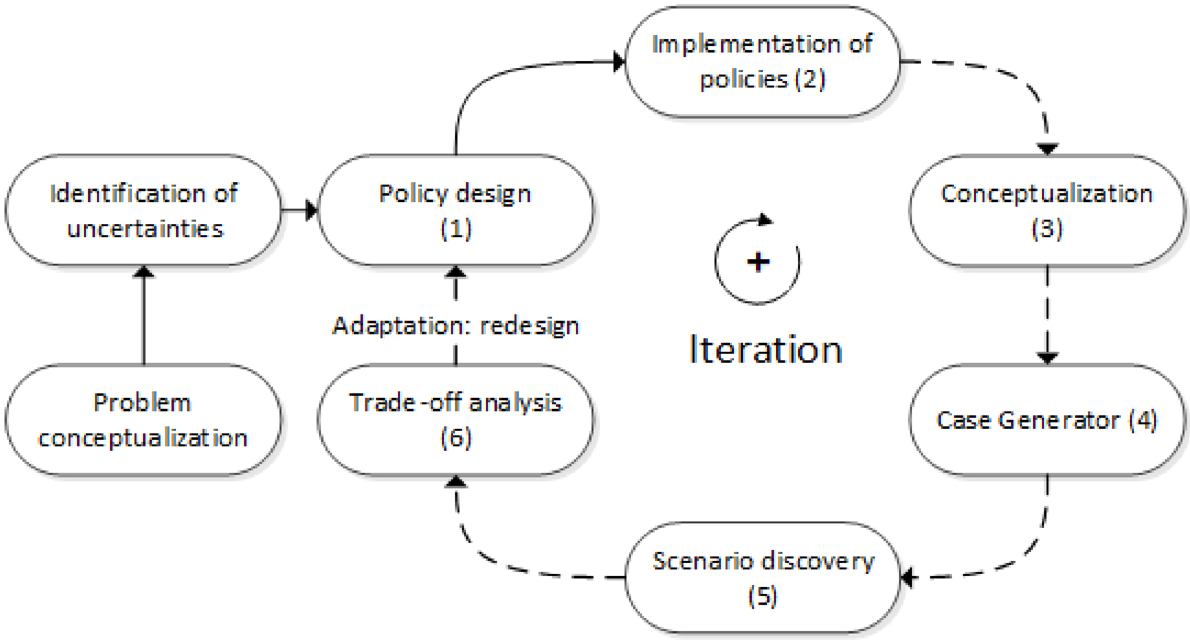


Figure 2.1: Iterative Adaptive Robust Design process according to Hamarat et al. (2013) and Lempert et al. (2006)

Exploratory Modelling and Analysis

The ARD framework requires many simulations of various experimental setups. Exploratory Modelling and Analysis (EMA) helps in this process by allowing for experimentation with various combination of input parameters (uncertainties) to analyze their effects on the system (Kwakkel and Pruyt, 2013). Specifically, EMA supports distinction of input parameters in uncertainties and policies as needed in the ARD process.

2.2.4. Data & Tools

Data will be vital to instantiate the model to have it represent the *Dutch* energy transition in the built environment sector. In order to uphold the open source character of the pilot study (see 1.6) only publicly available data sources will be consulted. As no centralized data set on energy transition information yet exists (CBS, 2019b), multiple sources will have to be acquired and merged to provide a single data file.

Vensim DSS is used to model the energy transition in the built environment sector. Vensim allows for visually structuring model relations and equations. Moreover, the DSS version of Vensim enables model compilation in C-language (a near-machine level programming language), that enables very fast simulations. Also, the Vensim DSS package avoids the necessity of specifically modelling every single model entity (neighbourhoods in this study), as it offers a sub scripting ability for a general model structure. The EMA workbench a *Python* package developed by Kwakkel (2017) provides all necessary tools to apply the ARD method to the *System Dynamics* model. The workbench connects the compiled Vensim model to Python and *injects* the policies and uncertainties, defined in its experimental setup, to the compiled model and stores outcomes of interests after simulation. This method enables simulation of several 100's if not thousands of possible scenarios with the model.

2.3. Research flow

Figure 2.2 shows the order of the research, as a result of the sub questions proposed in section 2.1. First, a literature review will be performed examining existing energy systems models. Subsequently, tooling is prepared in *Vensim* and *Python* to facilitate the ARD process later on. Thereafter, the simulation model expanded and subsequently used in the ARD process. Finally, results are discussed before concluding the study and providing critical reflections.

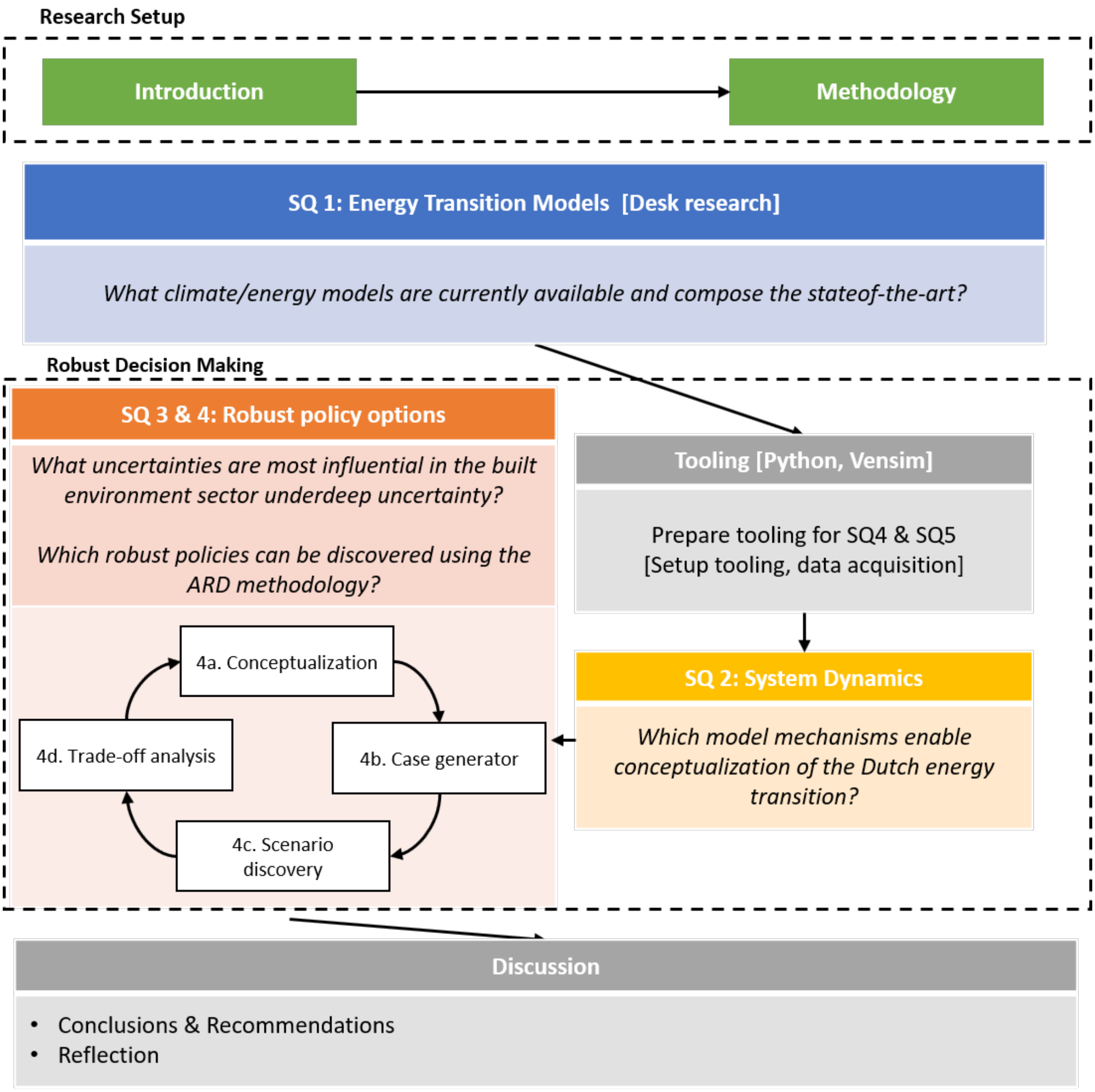


Figure 2.2: Research Flow Diagram

3

Energy Transition Models

This chapter aims to answer the second sub question by providing an overview of the current state of energy transition models. Firstly, the introduction sheds light on perspectives on energy transitions and quantitative energy systems modelling. Thereafter, an overview of energy models for policymaking is provided, grouped in academic, open source and Dutch energy models. Finally an overview of uncertainty in energy modelling is provided before concluding the chapter.

3.1. Introduction

In the face of anthropogenic climate change, it is crucial that decision makers are optimally informed for the creation of national policies to realize carbon reduction goals set in the Paris Agreement (UNFCCC, 2015). As Li and Strachan (2017) state: "The scale of the energy transition challenge is extremely daunting" and hence models and decision support tools are needed for decision makers to create effective policies.

This sections aims to explore the state-of-the-art of current energy-related models for policymaking. By providing (i) a brief introduction to energy systems modelling and (ii) an overview of current energy models for policymaking? In an effort to answer the second sub question of this thesis: *"What climate/energy models are currently available and compose the state-of-the-art?"* (see section 1.6).

3.1.1. Perspectives on Energy Transitions

Cherp et al. (2018) distinguish three main systems of interest in energy transitions. Namely (i) techno-economic (energy production, conversion and consumption), originating from energy systems analysis and economics. (ii) Socio-technical systems (energy technologies embedded in their socio-technical context), stemming from evolutionary economics and STS. (iii) Systems of political actions, which has its roots in political science and political economy. The authors go on to introduce a *multi-tier framework* for energy systems to facilitate cross-sectoral collaboration between academics and different fields, as proposed by Ostrom (2007). Regarding the shaping of energy transitions, Turnheim et al. (2015) identified five key challenges. (i) scales, geographies and temporality, (ii) complexity and uncertainty, (iii) Innovation and inertia, (iv) Normative goals of transitions and (v) Perspectives on governing transitions. In short, energy transition models should include the three specific domains as mentioned by Cherp et al. (2018) and have resolutions including the dimensions provided by Turnheim et al. (2015).

3.1.2. Quantitative Energy Systems Modelling

Quantitative analyses can support decision makers om their effort to better grasp effects of their policies. More specifically, "quantitative systems modelling studies provide a forward-looking perspective of transitions" (Turnheim et al., 2015). Cherp et al. (2018) conceptualize the energy transition as a co-evolutionary system containing two main mechanisms. Namely, (i) "those explaining the evolution of each of the subsystems" and (ii) " those connecting these subsystems".

Naturally, quantitative systems modelling has drawbacks too. Bolwig et al. (2018) argue that a quantitative systems modelling approach has limitations when considering the behaviour of the actors, the role of inertia and innovation and also explaining the spatial dimension of energy transitions."

On a similar note, Turnheim et al. (2015) mention that each quantitative approach is a lens that generates only a partial understanding of sustainability transitions. The authors provide a framework that combines quantitative systems modelling, socio-technical analysis and initiative based learning to overcome these challenges. Hence, providing a "more robust evaluation of sustainability transitions as they unfold in as complex systems transformations with emergent properties." (Turnheim et al., 2015).

As Bolwig et al. (2018) and Turnheim et al. (2015) stated, however, no single model can fully capture reality, due to many uncertainties involved. The Dutch environmental assessment agency acknowledges three main categories of uncertainties in their modelling effort: uncertainty regarding policy design, (ii) behavioral uncertainty and (iii) exogenous uncertainty (PBL, 2019).

Li et al. (2015) introduce the Socio-Technical Energy Transition (STET) model taxonomy for the characterization of integrated quantitative modelling and conceptual socio-technical transitions. Moreover, the authors provide a comprehensive overview of current (near) STET models and how they score on (i) techno-economic detail, (ii) explicit actor heterogeneity and (iii) incorporation of transition pathways.

Bolwig et al. (2018) argue that "an enriched modelling approach should not focus just on technology development and deployment, but also on feedback loops, learning processes, the importance of policy and governance and of behavioural changes, inter linkages between the energy and other economic sectors, and infrastructure development."

Similar to Bolwig et al. (2018), this study will use Li et al. (2015)'s taxonomy to create a STET model that integrates Cherp et al. (2018)'s meta theoretical framework of techno-economic, socio-technical and political perspectives on national energy transitions.

3.2. Energy Models for Policy making

This section will provide a brief overview of the state of the art regarding energy models for policy making. Three main themes will be considered: (i) a review of academic models, (ii) a review of open sourced models and (iii) a review of energy models specifically designed or calibrated for the Dutch energy sector.

3.2.1. Academic STET Models

Table3.1 provides an overview of energy transition models derived from the extensive inventory of energy transition models and assessment on STET criteria by Li et al. (2015).

Table 3.1: An overview of STET models. Source: (Li et al., 2015)

Model name	Source	Sectors	Model Class	Georesolution
BLUE-MLP	(Trutnevyte et al., 2014)	Power sector (UK)	SDM	Country
CASCADE Model Framework	(Allen and Varga, 2014)	Power sector (UK)	ABM	Country
Chappin's Power Sector-Model (ABM)	(Chappin, 2011)	Power sector (Netherlands)	ABM	Country
ElecTrans	(Yücel and van Daalen, 2012)	Power sector (Netherlands)	ABM	Country
ENGAGE DFR Module	(Gerst et al., 2013)	National energy demand and supply	ABM	Global
Computer Assisted Reasoning (CAR) Framework	(Lempert, 2002)	Global energy demand and supply	ABM	Global
Tran's Alternative Fuel Vehicle (AFV) Model	(Tran et al., 2013)	Passenger car market (UK)	MCSM	Multiple Countries
Struben's Alternative Fuel Vehicle (AFV) Model	(Struben and Sterman, 2008)	Passenger car market (California)	SDM	Region
Transition Lab Framework	(Köhler et al., 2009)	Ground vehicle transport (UK, US)	ABM + SDM	Country
Transition Lab Framework	(Bergman et al., 2008)	Residential buildings (UK)	ABM + SDM	Country

Continued on next page

Table 3.1 – continued from previous page

Model name	Source	Sectors	Model Class	Georesolution
REMG and IMAGE/-TIMER	(Daioglou et al., 2012)	Residential buildings	CGEM	Multiple Coun-tries
Charlier's Residential Sector Model	(Charlier and Risch, 2012)	Residential buildings (France)	? (IODE Bel-gium)	Country
Res-IRF and IMACLIM-R	(Giraudet et al., 2012)	Residential buildings (France)	CGEM	Country
Yücel's Housing Stock Model	(Yücel, 2013)	Residential buildings (Netherlands)	SDM	Country
Chappin's Consumer Lighting Agent-Based Model (ABM)	(Chappin and Afman, 2013)	Residential buildings (Netherlands)	ABM	Country

3.2.2. Open Model Initiative

Furthermore, the majority of energy models for policymaking or research purposes that are in use are not publicly available. The open (energy) modelling initiative aims to change that, by advocating for and actively publishing open source energy transition models.

Of the models that are openly available, many have different semantics regarding the sectors includes, KPI's determined, time resolution simulated, modelling approach applied and geospatial resolution incorporated. The open-source models presented in table 3.2 are selected on their time resolution being greater than a day and the ability to run scenarios in the model, because this study concerns long-term effects of energy transition policies and its dynamic policy implications.

Table 3.2: Opensource Energy Transition Models. Source: (Open Model Initiative, 2018)

Model	Institution	Sectors	Model class	Georesolution
EMLab-Generation	Delft University of Technology	Electricity Market, Carbon Market	ABM	Zones
Energy Transition Model	Quintel Intelligence	Households, Buildings, Agriculture, Transport, Industry, Energy	Demand driven energy model	Country
MEDEAS	University of Valladolid	Electricity, Heat, Liquid Fuels, Gas, Solid Fuels	SDM	global, continents, nations
Temoa	NC State University	all	energy system,optimization, model	single, region

3.2.3. Dutch Energy Models

The policies mentioned in Chapter D have all been evaluated on feasibility by the Dutch Environmental Agency (PBL, 2019). The agency employs several models (including both national and international scope) to calculate policy effects. The agency's assessment had been appointed for the assessment by the Dutch Ministry of Economic Affairs and climate, who had also facilitated the multi-stakeholder deliberation of the climate tables. As a result of this, PBL's analysis is most influential and hence considerably criticized (sources).

Apart from PBL's model, however, many other quantitative models are used to support policy makers in their decisions for energy transition policies. This section will present main energy models specifically used in Dutch Policy making, concentrating on the (vision) formulation phase of the policy cycle (Source policy cycle) to enable policy- and scenario evaluation.

Netbeheer Nederland (2019) have provided a large overview of computational energy models for the Dutch energy transition. These models stimulate municipalities, building corporations and energy corporations to use existing, *proven*, models. Table 3.3 shows an overview of these models, selected on the policy formulation phase and having a time horizon of a target year in the future.

Table 3.3: An overview of Dutch energy transition models, from (Netbeheer Nederland, 2019; Donker and Ouboter, 2015)

Model name(s)	Institute	Sectors	Model Class	Georesolution
Resolve-E, Competes, Tool industrie, Vesta-MAIS, Tool woningen, Phoenix, EFISCEN, CO2-Fix, NEMA, Compact, NEMA, Carbontax,Tool ZE-zones, Tool mobiliteit	PBL	Electricity, Industry, Mobility, Built Environment & Agriculture	CGEM(?)	National, International
CEGOIA	CE Delft	Built environment	Spreadsheets	Neighborhoods, national
DSSM	DNV GL	Electricity	Spreadsheets	Neighborhoods, national
DIDO	TNO	Regional decentral energy solutions	Dynamic, CGEM, ABM	Region, City
Energy Transition Model	Quintel Intelligence	Households, Buildings, Agriculture, Transport, Industry, Energy	Demand driven energy model	Country
Energie Transitie Atlas	Over Morgen	Heat	GIS	Neighborhood, region
Gebiedsmodel	Alliander	Households, companies, industries, producers and DSO's	Spreadsheets	Neighborhood, Region
Transform	Accenture	Built environment	Simulation, optimization	Neighborhood, city
Warmtevraagprofielen	ECN	Residential homes	-	Neighborhood

From the models presented in Table 3.3 only Vesta, DIDO and the Energy Transition Model allow policy implementation. This ability is crucial to allow for policy testing across various scenarios to analyze dynamic policy effects. Hence, these three models will be considered more thoroughly.

Donker and Ouboter (2015) provide an in depth analysis of many Dutch energy related models and have compared them on eight dimensions.

The authors classify the Vesta model as a static back casting model that does not include any dynamic feedback. It is a demand driven model that determines energy demand in different scenarios. Users have to manually find optimal solutions, no optimization is included. The model's time horizon spans from the present to 2050 with a yearly time resolution. The user makes many decisions top down. Energy prices are provided as an input variable for the model. Grid balancing and physical infrastructure have not been included.

DiDo is a dynamic forecasting model in terms of both pricing and forecasting. As it partly is an agent based model, information is exchanged between actors every fifteen minutes. Macro economic feedback in a dynamic pricing module that is based on the Computed General Equilibrium Model's (CGEM) yearly base price. The model is demand driven with demand curves changing yearly in the macro-economic CGEM. DiDo includes operational and investment optimization on a micro, individual level of the actors. The model's time horizon spans from ten to thirty years with a yearly resolution for macro-effects. Decisions are made via actor-specific utility functions for short- and long term choices. DiDo includes a pricing module that determines (spot)market prices based on daily forecasts and supply and demand curves. The model also simulates grid balancing on a regional level, which is extrapolated to a national level and includes physical transport infrastructure and DSOs.

The Energy Transition Model (ETM) is a static back casting model and does not include any dynamic feedback. The model is demand driven. A single performance indicator *"levelized cost"* is used to compare different technologies. Input variables have to be altered manually to reach a desired state, no optimization is included in the model. Essentially, the ETM time horizon only includes two time steps: "the present" and "the future". Similar to the Vesta model, decisions are made top down, without inclusion of any behavioural uncertainty of possible stakeholders. The ETM uses a merit order to determine pricing and also includes fuel costs as a parameter for many technologies and carriers. Inclusion of the merit order ensures grid balance and calculates necessary investments in the network. A simplified (graph) network represents the physical grid infrastructure to calculate network investment costs.

Table 3.4: Overview of Donker and Ouboter (2015)'s analysis on the DiDo, Vesta and Energy Transition Model

Dimensions	DiDo	Vesta	ETM
Dynamic/static	Dynamic	Static	Static
Supply/demand-driven	Demand	Demand	Demand
Optimization	Operational and investment	None	None
Time resolution	Yearly time steps	Yearly time steps	2 time steps
Time horizon	10-30 years	2050	2050
Level of decision making	Agents	User	User
Pricing	Supply/demand	Pricing as input variable	Merit order
Back casting/forecasting	Forecasting	Back casting	Back casting
Grid balancing	Regionally	None	Regionally
Modelling physical infrastructure	Detailed	None	Simplified

Energy models provide an important role for policy decision in The Netherlands and are characterized by their many differences. On the topic of models that include a large time horizon and allow for policy testing only three models stand out. These three models (see Table3.4) each show a different perspective on the Dutch energy transition and only two of them allow analysis of dynamic policy effects (Vesta and DiDo). The open-source model *ETM* does not include any feedback and has a time resolution of merely two time steps. Thus the ETM is less suitable for extensive policy testing.

3.3. Uncertainty in energy modelling

The search for strategic policies that accelerate the energy transition is hindered by high degrees of uncertainty on many different knowledge domains and reinforced by the high stakes for decision makers and the fear of potential path dependencies and locking to legacy assets. Pye et al. (2018) identify the future availability and costs of transition technologies, the political environment under which they may be deployed and the role of changing societal preferences and individual behaviour as key uncertainties characterizing the energy transition. Agreement on these uncertainties seems to exist, as Maier et al. (2016) and Walker et al. (2013) also note that uncertainty regarding energy transition policies is marked by complex drivers such as climate, technological innovation, socio-economic and political change and their effect on society and policymaking.

Pye et al. (2018) mark the type of challenge the energy transition entails as *"post normal science"*. A situation "where urgent near-term choices must be made in an environment where perfect information and universal agreement amongst key stakeholders is impossible to achieve" (Pye et al., 2018).

In their paper, Li and Pye (2018) have interviewed 31 UK experts from government, industry, academia, and civil society on their views on the major uncertainties surrounding the ability of the UK to meet their climate targets. Even though the authors agree that it is possible that the perspectives of the interviewees are strongly conditioned by existing frames, it does provide an empirical baseline of key uncertainties and the level of agreement amongst key stakeholders. Categorized in technological, societal, political, economical and global dimensions, Figure 3.1 shows relations between main uncertainties in the context of the UK's decarbonization goals.

The Dutch environmental assessment agency mentions the following critical uncertainties in their assessment of the climate agreement (PBL, 2019). Firstly, (i) option uncertainty regarding the design of the energy transition itself. Secondly, (ii) the policy instrumentation and its effects (state space uncertainty). Thirdly, (iii)

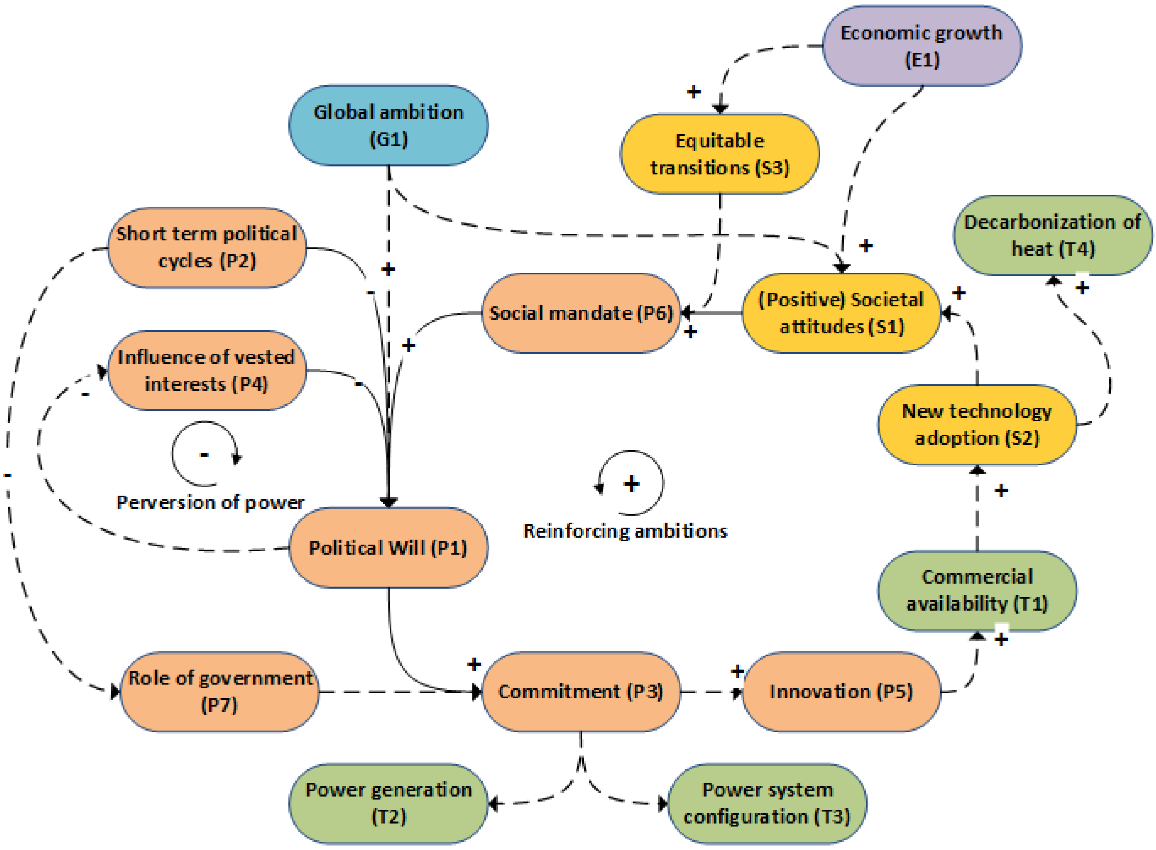


Figure 3.1: Relations between key uncertainties, from (Li and Pye, 2018)'s uncertainties in the UK's energy transition. Solid lines show relations as discussed by Li and Pye (2018), dashed lines show the author's own additions. Orange shows political factors, green technological, yellow societal, purple economic and blue global.

the response of citizens and companies to climate policies (preferential uncertainty). Fourthly, (iv) uncertainty regarding the energy prices and finally (v) uncertainty of CO_2 prices.

In line with PBL's calculations, Menkveld et al. (2017) adopt similar categories of uncertainties in their National Energy Outlook. Firstly, knowledge- or modelling uncertainties, which involves uncertainties around calculations, statistical uncertainties in sectorspecific data, or modelparameterisations and representations. Secondly, general uncertainties or externalities such as macro-economic uncertainty around GDP growth, population growth, fuel- and CO_2 prices and the pace of climatic change. Thirdly, specific policy uncertainties are entertained. These include uncertainties on the effectiveness of energy-, or carbon related policy measures.

3.4. Conclusion

The goal of this chapter is to answer the first sub question of this study:

"What energy transition models are currently available and compose the state of the art?"

In short, energy system models play a vital role in energy transition policies by providing an evidence base for policy testing (Pye et al., 2018). to answer the second sub question of this thesis, this chapter has provided a brief introduction of quantitative energy systems modelling in general, the STET taxonomy provided by Li et al. (2015) and Cherp et al. (2018)'s meta theoretical framework of techno-economic, socio-technical and political perspectives on national energy transitions. Moreover, an overview of state-of-the-art energy systems models has been provided in three groups. Namely, Academic STET models (Li et al., 2015), open source energy models (Open Model Initiative, 2018) and Dutch energy models (Netbeheer Nederland, 2019; Donker and Ouboter, 2015).

All models described in this chapter differ significantly on their dimensions, scope, modelling methodology and objectives, etc. While Li et al. (2015) and citeBolwig et al. (2018) both propose clear methodologies for modelling energy systems, standardization of models or convergence of their components still seems distant.

On another note, energy system models that allow policy testing seem to be a minority of all models classifying as energy system models. Many energy systems model focus on a specific sector and provide static forward looking perspectives of reality. Furthermore, many modellers still refrain from opening up their work to the public. Even academic and publicly funded environmental agencies keep their models to themselves. The ETM is the only open source energy model within the Dutch context. It does not, however, allow for dynamic policy testing and thus is inadequate for this study. Hence, an open source dynamic model would offer a major contribution to the existing model base for the Dutch context.

4

The Built Environment Transition Model

4.1. Introduction

The previous chapter discussed the state of the art of energy transition models and their variety. This section will discuss a fitting energy systems model in line with the intended pilot study on the Dutch built environment sector. This is done in an aim to answer the second sub question entertained in this thesis: *How can the energy transition of the Dutch built environment sector be specified in a simulation model?*

First, this chapter will highlight key data acquisition processes developed for this study, as the model has been instantiated from multi-level real-world data. Secondly, the base model that forms the backbone of this study will be discussed. Finally, modifications to the base model to prepare it for the Adaptive Robust Design method will be explained.

4.2. Data acquisition

Currently, there is no centralized, open data platform for energy transition-related data. A collaboration of public and semi-public stakeholders aims to change that through project Vivet (De Ronde, 2019; CBS, 2019b). This study, however, needs data prior to completion of the Vivet project. Hence, several *openly available* data sources have been consulted and combined by the author in order to create an extensive, publicly available and reproducible data set for the Dutch energy transition (see section B.1 for the Python code).

Moreover, the model will require the same on data on multiple scales to include these scales in later analyses. This will make data acquisition significantly more difficult given the lack of a centralized data set. Figure 4.1 shows an overview of a neighbourhood in a district of the municipality of the Hague. For the model data on every neighbourhood and district for all municipalities will have to be gathered to create a multi-scale data set for the built environment sector. All these scales had to be aligned for the simulation model to function. Hence, the output of the data merge script (section B.1) was handled by another script to remove inconsistencies (consult section B.2 for the alignment script).

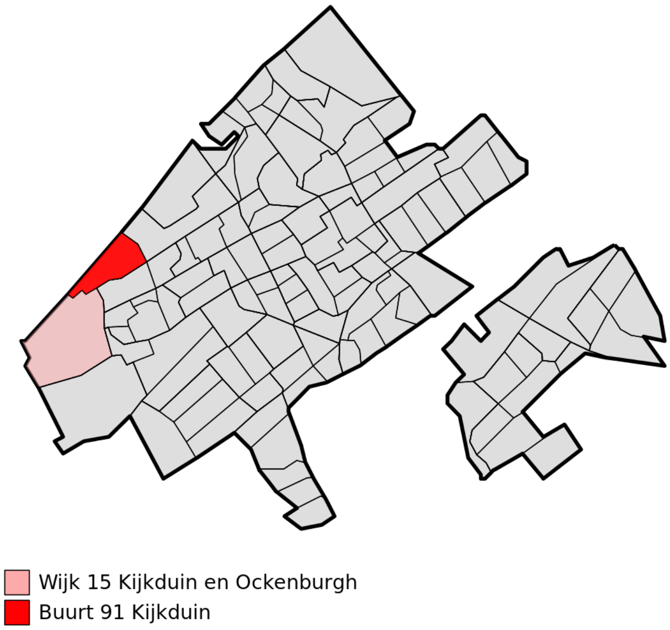


Figure 4.1: Spatial data decomposition of neighbourhood Kijkduin in district Kijkduin en Ockenburgh in the Municipality of the Hague. From (CBS, 2018b)

Table 4.1: Overview of consulted data sources

Database	Main contents [geospatial scale]	Source
Klimaatmonitor - mobility	FEV's and PHEV's, EV chargers [Zipcode 4]	(Rijkswaterstaat, 2019b)
Klimaatmonitor - energy	Energy consumption, Renewable energy sources [neighbourhood]	(Rijkswaterstaat, 2019d)
Klimaatmonitor	Green Gas and renewable heat [municipality]	(Rijkswaterstaat, 2019c)
EP-Online (BAG)	Data on building type, construction year and provisional label [zipcode + house-number]	(RVO, 2019)
CBS	Passenger vehicles [Zipcode 4]	source CBS

Table 4.1 provides an overview of consulted data sources as part of the data mining effort. Two main data sources have been used. Firstly, the "climate monitor" (Rijkswaterstaat, 2019d,b): an open data initiative from Rijkswaterstaat (Ministry of Infrastructure and Water Management) that combines several smaller data sources on their platform. For instance, the mobility subset (Rijkswaterstaat, 2019b) used in this study is based on data from Netherlands vehicle Authority (RDW). Subsequently, the energy subset (Rijkswaterstaat, 2019d) combines data from the Central Bureau for Statistics and Rijkswaterstaat. Secondly, the EP-Online provisional label data set provides detailed information per house on provisional label, building type and construction year. A CBS data set on passenger vehicles on zip code 4 level has been used to determine number of EV's and PHEV's on a neighbourhood level.

Combined, these data sets provide a detailed, open source representation of the Dutch residential housing stock and its characteristics.

4.3. The base model

This study builds on an existing built environment *System Dynamics* model made available by courtesy of dr. E. Pruyt. The model is a multi-level representation of national residential housing stock dynamics in an energy transition.

	Entities	Mapping	Houses Detached BAG2018d	Houses 2u1Roof BAG2018d	Houses Corner BAG2018d	Houses Row BAG2018	Houses SingleFloorAppartments c5 BAG2018d	Houses MultiFloorAppartments c6 BAG2018d	Construction Year	Label A BAG2018d	...	Gemiddeld elektriciteitsgebruik appartement kWh 2017
0	Annen BU16800000	Wijk 00 Annen WK168000	582	478	160	204	134	0	1973.298460	72	...	1630.0000
1	Verspreide huizen Annen BU16800009	Wijk 00 Annen WK168000	61	1	0	0	0	0	1956.096774	3	...	0.4242
2	Eext BU16800100	Wijk 01 Eext WK168001	301	146	37	40	16	0	1954.994444	11	...	2060.0000
3	Verspreide huizen Eext BU16800109	Wijk 01 Eext WK168001	47	1	0	0	1	0	1946.428571	1	...	0.4242
4	Anloo BU16800200	Wijk 02 Anloo WK168002	99	41	2	1	2	0	1954.496552	4	...	0.4242

5 rows × 33 columns

Figure 4.2: Top part of the modelsetupfile on neighbourhood level

This model in particular has been selected mainly for two reasons. First, the model provides a representative structure that allows modifications and specifications to any case within its scope. Secondly, the model has been written and packaged by *Vensim DSS*. Essential for any model in this study would be interconnectivity with the Exploratory Modelling and Analysis workbench in *Python* to perform the Adaptive Robust Design study. Vensim simulation models are well supported in this modeling workbench and thus can be connected. Moreover, Vensim DSS enables model compilation to the C programming language, which in itself might sound trivial, but results in enormous gain in computational efficiency. Thus, significantly reducing simulation time.

This paragraph will firstly provide a general structural overview of the model components. Secondly, the scope of the model is addressed and thirdly, data handling is discussed.

4.3.1. General structural overview

The model has been developed to allow policy testing on energy transition dynamics in the residential built environment sector. Figure 4.3 shows a simplistic overview of the main structures composing the model.

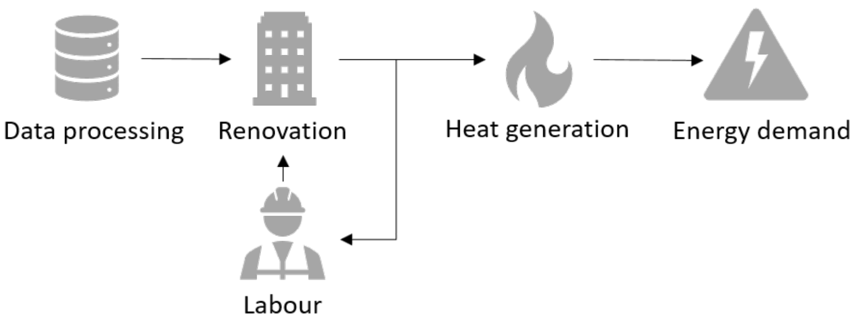


Figure 4.3: High level overview of the base model

Firstly, the data processing structure imports data for model calibration (see section 4.3.3). Moreover, the structure bridges gaps in data completeness when data is missing between one or more levels (municipalities, districts and neighbourhoods). Data on lower levels (ie. neighbourhoods) is extracted from higher levels (ie. municipalities) using distributional assumptions. Secondly, residential dwellings are divided on ownership in privately-owned, commercial rent and building corporation homes for each neighbourhood in the data. Houses can be renovated from gas-powered heating to either all all-electric or district heating. Thirdly, a demand driven labour structure simulates the required workforce for renovation. Labour shortages, due to system scarcity, are overcome by accepting foreign labour in the system. Hence, a regional labour market is assumed in the model. Subsequently, energy demand is calculated for each neighbourhood given the neighbourhood specific characteristics (see section 4.3.3 for more details).

A detailed overview of the base model structures can be found in section C.1.

4.3.2. Model scope

The model focuses on heat generation of the (Dutch) residential housing stock and does not include household energy efficiency components, because data availability on household isolation is virtually non-existent at this point in time.

Furthermore, the model differentiates between three levels of ownership. Dwellings can be either owned by building corporation, by commercial owners (for rent) or by private owners. Building corporations have societal targets next to their commercial interests and are hence deemed to become front runners in the household energy transition. Commercial- and private home owners lack such incentives and require other stimuli. Thus, policies in the model are formulated for two groups: building corporations and privately owned/commercially rented.

4.3.3. Data driven modelling approach

Albeit scattered, much building-related data is openly available in The Netherlands. This allows for accurate model calibration to represent the Dutch system using real world data. The data is used to calibrate variable values, but assumptions and theories define the relations between the variables in the model. The model provides a generic residential household renovation structure. To have the model represent the Dutch housing sector, it is calibrated to empirical data. The data driving the model has been acquired from several public sources which have been manipulated to create a single data set (see 4.2).

This data set includes many building related characteristics segmented on municipal level (N = 332), district level (N = 2533) and neighbourhood level (N = 10786). In short it includes building data (building type, building year, energy label, average value), energy data (average electricity and gas demand per building type per neighbourhood, households connected to district heating, installed PV capacity), building ownership information (private, commercial rent and corporation), population data (demographics, households).

4.4. The policy model

Building on the the base model presented in the previous section, the policy model includes several modules and structures to facilitate the pilot study and enable Adaptive Robust Design cycle, such as a policy structure, uncertainties and key performance indicators. Figure 4.4 shows a simplistic overview of the main structures composing the model, which will be discussed in more detail in this section. A detailed overview of the model structures can be found in section C.2.

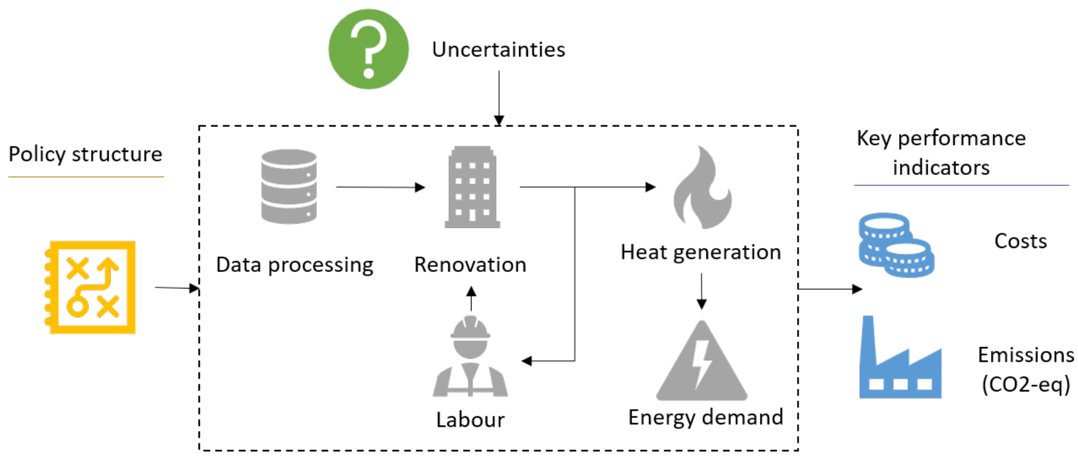


Figure 4.4: High level overview of the policy model. Inspired by the XLMR framework (Lempert et al., 2003)

4.4.1. Policy Structure

A policy structure has been implemented to mimic societal response to fiscal stimuli, such as subsidies. Decision behaviour has been modelled on a neighbourhood level, as individual household data is limited to housing characteristics rather than personal details such as income (by virtue of privacy protection). Prior to policy implementation, modules had to be added to the model to simulate renovation costs and mimic decision behaviour in neighbourhoods.

Renovation costs

To model peoples reaction to subsidy policies, renovation costs must also be included in the model. Average labels have been assigned to each neighbourhood in the data file using the BAG data mentioned in section 4.2. Assigning values ∈ (1-7) for each label ∈ (A-G) enabled numerical operations. Subsequently, label groups (1-4) have been assigned to the first, second, third and fourth quantile of the average label per neighbourhood. Basically creating for groups of neighbourhoods based on their energy label. Renovation costs have been retrieved from the Nationale EnergieAtlas (2019), which currently only offers insights in label jump costs for a single exemplary household: a row house built between 1945 and 1964. To accommodate for other building types (apartments, detached houses, etc.) and varying building years (which influences household energy efficiency) four distinct renovation costs parameters have been sampled as uncertainties in the model for each label group.

Subsidy structure

Subsidies are modelled to be awarded on a neighbourhood level, as a percentage of the renovation costs. These costs differ per neighbourhood and depend on average energy label per neighbourhood. This structure allows for creating policies that use subsidy percentage as a policy lever in a neighbourhood based approach. Various types of policies (see chapter 6) can be implemented, which will be taken into consideration in the neighbourhood decision logic given their propensity to renovate. In case of acceleration policies, the subsidy awarded can never exceed the costs of renovation.

Renovation Decision Logic and Implicit Discount Rates

The model employs subsidy cut off levels to simulate renovations in the commercial sector in the model. Specific subsidy cut-off levels sampled, depending on average building value per neighbourhood. Average building value (n=10099 neighbourhoods) has been used, rather than average income (per receiver/citizen, n=3363/4072 neighbourhoods), because of data completeness. The data set has been divided in four value groups using the first to fourth quantile of average building value per neighbourhood.

Renovation decisions by owners of private dwellings and owners of commercial rent are assumed to be alike in this study. For each time step in the simulation a neighbourhood is faced with the decision if its inhabitants want to renovate, if they haven't done so already. If a given *subsidy* is greater than or equal to a subsidy cut-off threshold for each value group, a decision to renovate is made and renovations will be performed by the current renovation rate at the time step.

Table 4.2: Sampled subsidy cut off levels

Variable	Lower bound	Upper bound	Unit	Source
Subsidy percentage cut-off level high building value	10	30	%	Assumed
Subsidy percentage cut-off level upper middle building value	30	50	%	Assumed
Subsidy percentage cut-off level lower middle building value	50	70	%	Assumed
Subsidy percentage cut-off level low building value	70	90	%	Assumed

These subsidy cut-off levels represent the minimum percentage of subsidies required for home owners to decide to renovate their homes. Implicit Discount Rates (IDR) are often used to model household investment decisions. Train (1985) provides a review of discount rates of energy related decisions. Schleich et al. (2016) revisited the Implicit Discount Rates and created a framework to better understand its underlying drivers. The authors note preferences (for example on time and risk), predictable (ir)rational behavior (bounded rationality, behavioural biases) and external barriers to energy efficiency (split incentives, lack of information, lack of capital, etc.) as most notable for the IDR. Due to these factors, the authors point out that IDR's used in models should be varied by household and technology characteristics. In line with this critical approach, Stadelmann (2017) provides a critical review of the energy efficiency gap (and its underlying discount rates) with empirical evidence.

Jaccard and Dennis (2006) discuss an estimated discount rate for energy-efficient renovation of 20.79%. Berkovec et al. (1983) present discount rates for space heating systems using household income as a proxy. The presented discount rates vary from 56 % at $1000 to 14% at $60.000. Another study showed widely varying discount rates, both between and within certain groups, ranging from 2-300% Stadelmann (2017).

Table 4.3: Required subsidies to substitute differences in implicit discount rates, assuming a payback time of 20 years. Based on equation 4.1

Discount rate [%]	Corresponding payback time [years]	Corresponding subsidy [%]
5	20	0.0
8	12.5	37.5
10	10.00	50.0
20	5.00	75.0
30	3.33	83.3
40	2.50	87.5
50	2.00	90.0
60	1.67	91.7
70	1.43	92.9
80	1.25	93.8
90	1.11	94.4
100	1.00	95.0

Table 4.2 shows the assumed subsidy cut-off thresholds for each of the value groups in the model. This subsidy cut-off threshold explicitly assumes actors predisposition on payback period (20 years) and Implicit Discount Rates.

In line with the findings of Berkovec et al. (1983) this study samples different subsidy cut-off levels (table 6.2) for different building value groups. Again, average building value is used as a proxy for household income, because data is much more complete (see section 4.4.1). Over all building value groups a subsidy cut-off level is sampled from 10 to 100 % to allow for a highly varying implicit discount rates (see table 6.2). Based on an average payback time of 20 years for a renovation, required subsidies have been calculated for each discount rate using equation 4.1.

$$subsidy_i = 1 - \frac{paybacktime}{discountrate_i} * 100 \tag{4.1}$$

Where the $paybacktime$ is set at 20 years.

Energy generation allocation

If a decisions has been made to renovate a specific neighbourhood. Then, individual households will be renovated given a dynamic renovation rate (which starts out small and increases over time). Renovation is simplified in this model as disconnection from gas infrastructure and providing heat generation by either electricity or district heating. The allocation of a dwelling disconnected from gas is performed by firstly assessing vicinity of existing district heat sources. Specific allocation fractions are sampled as uncertainties, given fractions of existing infrastructure in neighbourhoods. Thresholds for deciding which fraction to district heating to use are set at 0%, <50% and >50% of *percentage district heating fraction 2017* for no, low and high existing infrastructure (respectively). For each group of existing district heating infrastructure, different uncertainties are sampled. No existing infrastructure corresponds to uncertainty *fraction to district heat no existing infrastructure*, low existing infrastructure to *fraction to district heat low existing infrastructure* and high to *fraction to district heat high existing infrastructure*. These uncertainties are sampled for the building corporations and privately owned and commercially rented homes.

The only alternative for disconnected dwellings that cannot be included in a district heat net is to generate heat electrically, given the model's scope of gas-based, district heat, or electric heat generation. This constraint

Table 4.4: Assumed uncertainties allocation to district heating

Variable	Lower bound	Upper bound	Unit
fraction to district heat building corporation no existing infrastructure	0	30	%/year
fraction to district heat building corporation low existing infrastructure	30	70	%/year
fraction to district heat building corporation high existing infrastructure	70	100	%/year
fraction to district heat commercial sector no existing infrastructure	0	10	%/year
fraction to district heat commercial sector low existing infrastructure	10	30	%/year
fraction to district heat commercial sector high existing infrastructure	30	60	%/year

takes effect by allocating all renovated houses, that cannot be connected to district heating, to all electric heat generation.

4.4.2. Model constants

The model relies on certain constants on national level, next to the real-world multi-level data used to instantiate the model (see section 4.2). Table 4.5 shows an overview of implemented national constants and their sources. Parametric uncertainties sampled in the model are discussed in section 5.2.1.

Table 4.5: Model constants

Variable	Value	Unit	Source
Emissionfactor electricity start	0.45	kg/kWh	(Rijkswaterstaat, 2019a)
Emissionfactor natural gas start	1.791	kg/m3	(Rijkswaterstaat, 2019a)
Emissionfactor district heating start	0.035696	ton/GJ	(Rijkswaterstaat, 2019a)
Climate agreement renovation rate 2021	0.8	%/year	(Klimaatakkoord, 2019, p. 17)
Climate agreement renovation rate 2030	2.9	%/year	(Klimaatakkoord, 2019, p. 17)
Energy density district heating	0.20934	GJ/m^3	(Nuon, 2018)

4.4.3. Key Performance Indicators

The final module added to the existing *base model* is a key performance indicator (KPI) structure. To prepare the model for the Adaptive Robust Design method, outcomes need to be formulated. Therefor, specific KPI structures have been formulated for CO_2-eq emissions and costs.

Emissions

This structure creates a CO_2-eq KPI by taking the sum of local energy demand $\in$ (electricity, gas and district heat) and multiplying it an emission factor (see table 4.5). Decarbonization efforts in the energy sector have been included in the model by making the emission factors dynamic (decreasing over time) for electricity and district heating. In line with the climate agreement, carbon emissions will be reduced by 77% by 2050 (Klimaatakkoord, 2019; PBL, 2019). The amount of decarbonization reduction, however, is uncertain. Hence, the fraction of innovation on the emission factors of electricity and heat is sampled as an parametric uncertainty (see section 5.2.1). No decarbonization trajectory has been included for natural gas, as policies to accelerate the production of green gas (natural gas grade bio gas), the SDE++ subsidy, are deemed uncertain and hence not accounted to a specific sector (PBL, 2019, p. 72).

Monetary structure

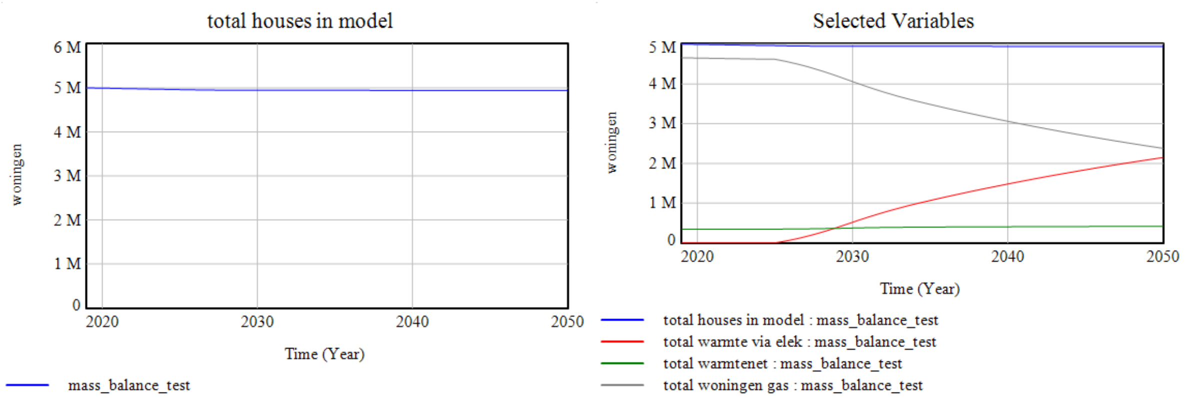
A monetary structure has been added to the base model which samples different uncertain renovation costs for each label group (see section 4.4.1 and 5.2.1) for each neighbourhood. Similar to the emission structure, renovation costs have been made dynamic by including a reduction of renovation costs over time. The amount of reduction, too, has been sampled as an uncertainty and varies from 20-50% reduction, following a subsidy grant to realize this reduction (Rijksdienst voor Ondernemend Nederland, 2019).

Total societal costs have been calculated by taking the product of the sum of renovated houses per neighbourhood and renovation costs per neighbourhood for each ownership type $\in$(building corporations, privately owned homes and commercial rent). Subsidies are calculated by either multiplying the number of renovated houses with a static subsidy amount or a dynamic annual subsidy budget.

4.5. Model Verification

To verify the equations implemented in the model, two verification tests have been conducted. First, a mass balance test has been conducted on the total number of houses in the model. Second, a mass balance test showing the total number of houses segmented by heat generation type has been performed. If the implementation has been performed correctly, the sum of houses in the model should stay constant under frozen growth rates (no new homes are constructed, no old homes are demolished).

Figure 4.5 confirms this hypothesis as the total number of houses remains constant over time (figure 4.5a. Similarly, the homes segmented by heat generation type show no clear signs of leakage in the model. Hence, it can be concluded that conceptual relations have been implemented correctly.



(a) Total houses in model (b) Total houses segmented by heat generation type

Figure 4.5: The mass balance test for the total houses in the entire model. During this mass balance test, there are no new houses built or old houses demolished, so the total number of houses does not change. The small decrease shown over time

4.6. Conclusion

The goal of this chapter is to answer the second sub question of this thesis:

"How can the energy transition of the Dutch built environment sector be specified in a simulation model?"

In this chapter a description of modifications and additions to an existing *System Dynamics* model have been discussed. Open data has been gathered and prepared for model instantiation on multiple scales and policy structures have been defined.

Main conclusions from this chapter are that the model represents a simplified perspective on household renovations in The Netherlands. Data is available, but does not uniformly represent all scales (neighbourhood - municipality). Data from even lower levels (zipcode 4 areas) has been scaled up to cope with this issue. The model's scope does not include more detail than data currently allows for. So energy efficiency efforts have been completed left out of the model. This immediately poses a major limitation to the current model, as policies will naturally also include energy efficiency measures.

In the following chapter, the model is subjected to uncertainties to gain insights in trends of possible futures without any defined policies.

5 Base case analysis

5.1. Introduction

This chapter will discuss possible outcomes of the built environment sector without any additional policies under deep uncertainty. This *base case analysis* employs of the built environment energy transition model (see chapter 4) to explore possible outcomes in order to answer the third sub question: *"What are, according to a Deep Uncertainty approach, the key uncertainties in the energy transition of the built environment?"*. Results presented in this chapter are derived from base case experimentation (see section A.1 for code) and scenario discovery (see section A.3).

5.1.1. Approach of this chapter

This sections aims to find most influential uncertainties affecting the model under deep uncertainty. Therefor experiments are generated with the model without any policies that stimulate renovations in the built environment sector.

The XLRM framework, introduced by Lempert et al. (2003) is used to summarize the experimental setup. This framework structures input, output and external factors visually. Figure 5.1 shows the XLRM framework used in this chapter.

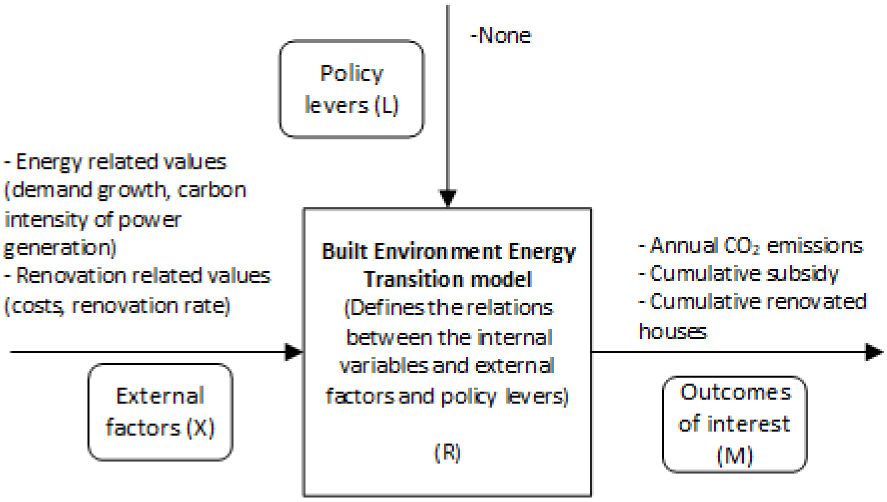


Figure 5.1: XLRM framework applied to this research

First, the experimental setup for case generation will be discussed (section 5.2 in which details are provided on parametric uncertainties and key performance indicators. These uncertainties together with selected outcomes and the defined policies are applied to the model using the EMA workbench in Python to generate experiments.

Secondly, outcomes of the simulated cases will be explored in section 5.3. Effects of these uncertainties on the outcomes of the model are explored by analyzing the trends of experiments on the outcomes of interest. This, so-called *open exploration*, is performed by plotting the lines of all performed experiments to visualize their trends over time. Additionally, Kernel Density Estimation are plotted next to the outcome plots to give insights in the distribution of cases per on the outcome's axis. Hence, providing information on the certainty that a certain value (or range of values) will be reached.

Third, scenario discovery will be performed to find most influential uncertainties and worst case scenarios in section 5.4. Most influential uncertainties in the worst case scenarios are derived for each KPI using *scenario discovery*. Scenario discovery in python uses the EMA workbench (Kwakkel, 2015), which is inspired on Bryant and Lempert (2010) who first proposed a computer assisted approach to scenario discovery using the Patien Rule Induction Method (PRIM) algorithm. PRIM finds regions in the model's input space that highly influence outcomes of interest using a lenient hill climbing optimization algorithm (Kwakkel and Jaxa-Rozen, 2016). Next, feature scoring is used to analyze and visualize the effects of uncertainties. The feature scoring method used in the EMA workbench uses univariate lineair regression tests to show influences of the models input space on the outcomes. Finally, the chapter is concluded in section 5.5.

5.2. Experimental setup

This section briefly explains the parameters set to represent the base case analysis without any policies. First, a quick overview of parametric uncertainties is provided in section 5.2.1. Thereafter, outcomes of interests are defined in section 5.2.2.

5.2.1. Uncertainties

Table 5.1 shows the uncertainty ranges sampled to generate the cases of the base analysis. Note that uncertainties have been modelled as ratios, but are displayed in the table as percentages for more intuitive interpretation. For example, an uncertainty range of 40-60% will be sampled as a ratio of 0.4-0.6 in the model. mentioned as percentages in this table have been modelled as ratios.

Table 5.1: Uncertainties in the base case ensemble

Variable	Lower bound	Upper bound	Unit	Source
Reduction carbon intensity power generation	20	50	%/year	(PBL, 2019)
Annual development of new homes	0.88	0.97	%/year	(CBS, 2019a)
Annual standard renovation rate	0.7	0.8	%/year	assumed to be lower of (Klimaatakkoord, 2019, p. 17) 50k/year
Reduction renovation costs	20	50	%	(Rijksdienst voor Ondernemend Nederland, 2019)
Renovation costs label group 1	8000	12000	Euro	(Nationale EnergieAtlas, 2019)
Renovation costs label group 2	20000	28000	Euro	(Nationale EnergieAtlas, 2019)
Renovation costs label group 3	30000	36000	Euro	(Nationale EnergieAtlas, 2019)
Renovation costs label group 4	30000	40000	Euro	(Nationale EnergieAtlas, 2019)
Annual electricity demand growth	-1	1	%/year	(Schoots et al., 2017)
Fraction houses to district heat building corporations no existing infrastructure	10	20	%	Assumed
Fraction houses to district heat building corporations low existing infrastructure	30	70	%	Assumed

Continued on next page

Table 5.1 – continued from previous page

Variable	Lower bound	Upper bound	Unit	Source
Fraction houses to district heat building corporations high existing infrastructure	70	1	%	Assumed
Fraction houses to district heat private sector no existing infrastructure	0	10	%	Assumed
Fraction houses to district heat private sector low existing infrastructure	10	30	%	Assumed
Fraction houses to district heat private sector high existing infrastructure	30	60	%	Assumed

It is yet unknown what fractions of neighbourhoods will be connected to district heating infrastructure, as this is the major challenge for the coming years. Therefor, assumptions have been made on uncertainty ranges of transitions to district heating infrastructure, depending on current capacity per neighbourhood.

5.2.2. Key performance indicators

The main goal of this study is to find policies that meet climate-agreement goals *efficiently*. Hence, main KPI's of this study relate to carbon emissions and financial costs and available labour. Therefor the following KPI's have been defined:

1. Annual CO_2-eq emissions [ton CO_2]: reflecting total annual CO_2 equivalent emissions summed over all neighbourhoods in the model.
2. Cumulative costs of renovation [€]: total costs of renovations, neighbourhood specific renovation costs summed over all neighbourhoods
3. Cumulative renovated houses [# houses]. Total number of houses that have been renovated during the simulation.

All outcomes of the KPI's are stored as a time series for each timestep in the simulation over a period of 31 years (2019 - 2050). Experiments are performed by sampling values for the parametric uncertainties using Latin Hypercube Sampling (LHS). LHS is a statistical method that generates near-random samples within the defined uncertainty ranges (see section 5.1. LHS samples from a multi-dimensional distribution which is dynamically adjusted to previously taken samples to ensure that samples are evenly distributed over the specified parameter ranges. 1000 scenarios are simulated to ensure adequate coverage of results.

5.3. Base case exploration

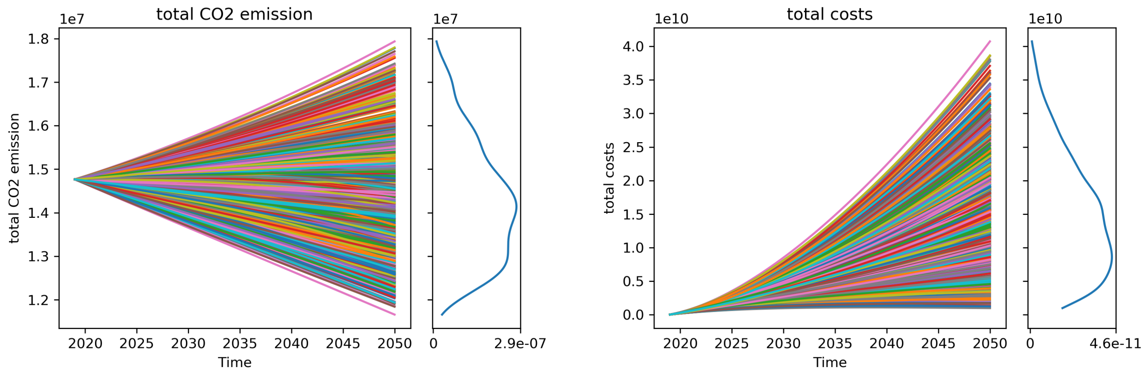
This section will discuss the results of the base case scenario of the energy transition in the built environment sector, without defined policies, but with defined uncertainties.

The set of experiments and results is first analyzed by generating line plots of all cases (i.e. the number of scenarios) for each KPI over time. Kernel Density Estimation (KDE) are shown next to these line graphs, to offer insights in the occurrence of certain outcomes, by plotting the distributions of all outcomes over the y-axis. This generates a single graph that offers insights on the potential range and robustness of the outcomes.

Figure 5.2a shows the development of total CO_2-equivalent emissions without any policies. As a result of the uncertainties (section 5.2.1) sampled on the model, outcomes vary quite largely. Starting from 15 Mton CO_2-eq in 2015, outcomes in 2050 vary from roughly 12-18 Mton CO_2-eq emissions. The KDE plot, however, shows that the majority of the cases are concentrated slightly below 14Mton (a 1 Mton decrease). The tails of the distribution shown in the KDE plot are rather short. Hence, cases are also quite strongly represented over the entire range.

Total costs of renovations are shown in figure 5.2b. Even without policies, some citizens and corporations will decide to renovate their homes. The graph shows an exceptionally large spread in outcomes, ranging from 0 to 40 billion euros. Moreover, the KDE plot shows a large spread in distribution of the cases.

Figure 5.3 shows the development of the total renovated houses over time. Given the lack of policies in the base case ensemble, it is not surprising that only a few homes changes to different methods (relatively



(a) Total CO_2-eq emissions [ton CO_2]

(b) Total costs of renovations [€]

Figure 5.2: Total CO_2-eq emissions and total renovation costs

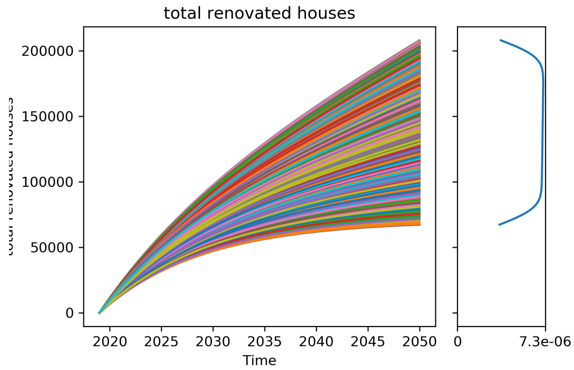


Figure 5.3: Total renovated houses [# houses]

speaking). Judging from the KDE, the cases seem very uniformly distributed over the outcome space. This could imply rather deterministic behaviour and hence high influence from uncertainties related to this KPI.

5.4. Scenario Discovery

Exploration of the base case ensemble in section 5.3 showed strongly varying KPI's over time and substantial differences in density of the outcomes. This section aims to analyze to what extent the defined uncertainties influence the model and its KPI's. The scenario discovery in this section employs the *Exploratory Modelling Workbench* (Kwakkel, 2017), which to perform scenario discovery in *Python* (**?**) and feature scoring.

PRIM (Patient Rule Induction Method) is a machine-learning algorithm used in scenario discovery. For a single KPI, cases are selected that are outside a certain threshold (say the 10% best performing or the 10% worst performing cases). Subsequently, the PRIM algorithm will try to fit the smallest box around these cases. Iteratively, the algorithm restricts dimensions in a trade-off between coverage (explain coverage) and density of results.

The scenario discovery process is carefully discussed on the primary KPI, Annual CO_2 emission. For the remaining KPI's, main results are presented and discussed.

5.4.1. Annual CO_2-eq emissions

Figure 5.5 shows the main uncertainties influencing the model KPI *Annual CO_2 emission*. These uncertainties have been used in the *PRIM* process as restricted dimensions to explain the worst performing cases (i.e. cases with highest Annual CO_2-eq emissions). The 8% worst case scenarios have been selected in this PRIM analysis to find the most dense box, which is represented as *scenario A* in figure E.2b.

Figure E.2b shows the trade offs the PRIM algorithm made in the peeling and pasting trajectory (see figure E.2a) of the restricted dimensions of the boxes. As the PRIM algorithm restricts more and more dimensions, it

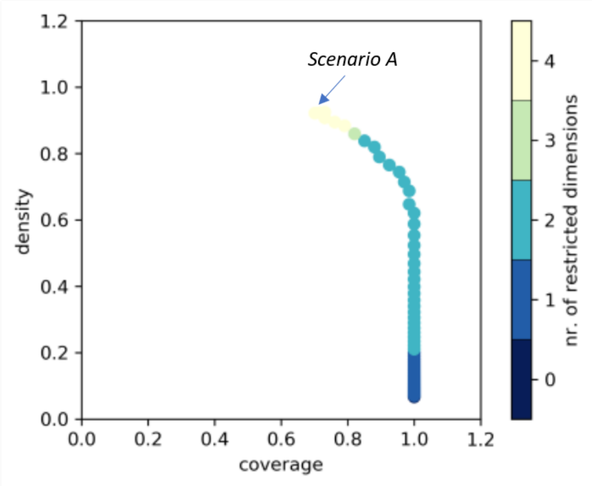


Figure 5.4: Coverage density trade-off for scenarios that describe the high Annual CO_2-eq emissions.

peels layers of parameters (uncertainties) in the subspace. Hence, we want to look at boxes at the top left of the density/coverage curve. At the highest density, the uncertainties shown in figure 5.5 are most influential.

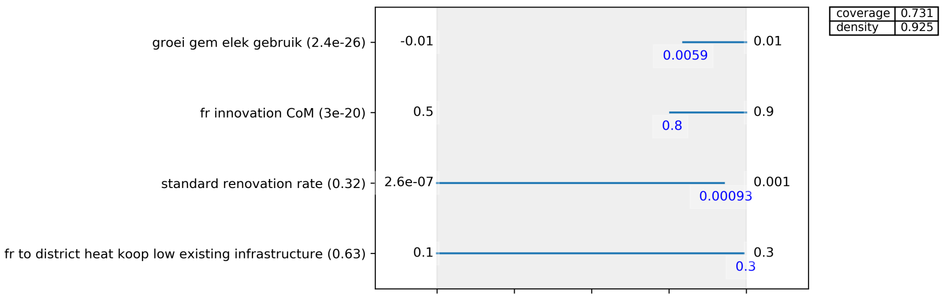


Figure 5.5: Inspection of the PRIM box KPI: Annual CO_2 emission.The figure shows parameters (uncertainties) used to define scenario A in figure E.2b. The figure also shows the density and coverage for the box drawn for scenario A: 92% of the cases that meet these conditions have high Annual CO_2-eq emissions (i.e. 92% density). Of all high CO_2 emission cases in the dataset, 73% meet these conditions (i.e. 73% coverage). Annual electricity demand growth growth and fraction innovation on emission factors are most important and statistically significant

Of the four uncertainties portrayed in graph 5.5, only the first two statistically are significant ($p<0.05$). Namely, annual electricity demand growth demand growth, p =2.4e-26 and reduction of carbon intensity in power generation, p = 3e-20.

These two significant uncertainties make sense, because the electricity growth rate directly influences total energy consumed (and thus the total CO2 emitted). Second, the innovation in carbon intensity of power generation, too, directly influences total CO2 output as it describes the innovation of carbon reduction in the power sector.

The standard renovation rate and the fraction of privately owned homes that will switch to district heating in the case of limited capacity also come up as important, but not as significant. They do, however, deserve some more attention. The standard renovation rate, as follows from the current climate agreement provides a baseline renovation rate without any additional policies. Its very interesting that this standard renovation rate does not show up as significant in the model. Rather, annual electricity demand growth growth and reduction of carbon intensity in power generation are more significant. Looking at these results from a systemic perspective, this is an interesting finding, but reductions have to be made over all sectors to reach targets.

As most houses fall in the category 'district heat no existing infrastructure', second 'district heat low existing infrastructure' and least in 'district heat high existing infrastructure' it makes sense that the low variant for privately owned homes pops up in this PRIM analysis. It is the first of these three groups (no, low, high existing infrastructure) that has an impact carbon reduction (as acquisition of new district heat sources is scoped out of this study), and more houses belong to this group rather than the group of high existing infrastructure.

5.4.2. Cumulative costs of renovation

Even without any additional policies, renovations are performed and costs will be made. A PRIM analysis has been performed on the 30% most expensive cases. This limit has been set to achieve the highest density. Figure 5.6 shows the the trade-off between coverage and density of for this scenario.

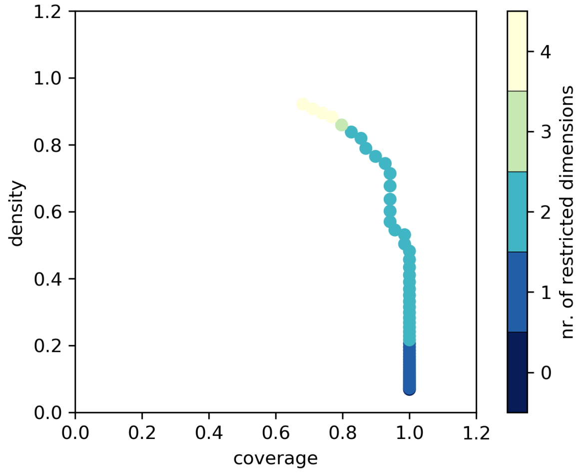


Figure 5.6: Coverage density trade-off for scenarios that describe the high cumulative costs of renovation CO_2 emissions.

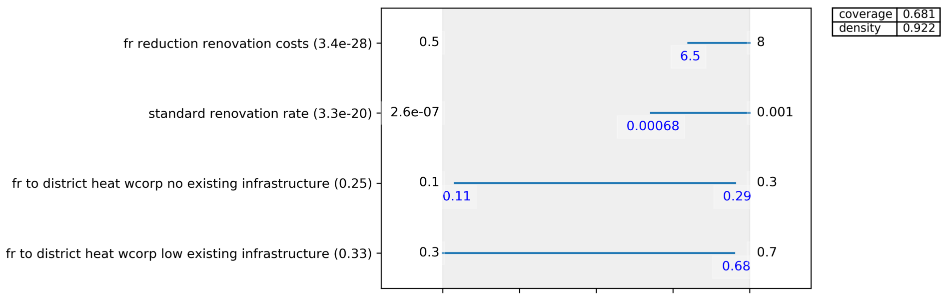


Figure 5.7: Inspection of the PRIM box KPI: cumulative costs of renovation.The figure shows parameters (uncertainties) used to define the most left scenario in figure 5.6. The figure also shows the density and coverage for the box drawn for this scenario: 92% of the cases that meet these conditions have high costs (i.e. 92% density). Of all high costs cases in the dataset, 68% meet these conditions (i.e. 68% coverage). Reduction renovation costs and the standard renovation rate are most important and statistically significant

Of the four uncertainties portrayed in graph 5.7 only the first two statistically significant ($p<0.05$) within the most dense box (coverage = 0.68, density = 0.92). Namely, Reduction renovation costs (p=3.4e-28) and standard renovation rate (p=3.3e-20).

It appears obvious that the two uncertainties mentioned above are significant in their contribution to cumulative costs of renovation. The first uncertainty directly influences individual renovation costs. The second uncertainty defines the number of houses to be renovated in case of no additional policy.

The two final two uncertainties, *fraction to district heat building corporation no existing infrastructure* and *fraction to district heat building corporation low existing infrastructure*, spike interest. Building corporations are less dependent on merely financial incentives due to their societal goals. Moreover, most corporation owned homes are in neighbourhoods with no or low existing district heating capacity. Hence, the higher the propensity of these groups is to renovate, the larger their effect on cumulative costs of renovation.

5.4.3. Uncertainty Analysis

Figure 5.8 shows a feature scoring on the main KPI's of the base case study. The figure shows influence of uncertainties (y-axis) on the model's KPI's (x-axis). Annual renovation rate (standard renovation rate), cumulative costs of renovation, annual electricity demand growth, reduction renovation costs and reduction carbon intensity power generation and annual electricity demand growth are most influential.

Figure 5.8: Feature scores of the experiments and outcomes of the base case ensemble. The figure shows influence of uncertainties (y-axis) on the model's KPI's (x-axis). Annual standard renovation rate, reduction renovation costs, annual electricity demand growth, reduction renovation costs and reduction carbon intensity power generation are most influential

.

5.5. Conclusion

This chapter set out to answer the third sub question of this study: *"What uncertainties are most influential in the built environment sector under deep uncertainty?"*.

Outcomes of the modelled built environment system under deep uncertainty without any implemented policies have been analyzed to better understand the effects of uncertainties on possible futures of the energy transition in the built environment sector. This has been done by performing an open exploration to understand trends of main KPI's and through scenario discovery to better understand influences of specific uncertainties on certain KPI's.

First, open exploration showed possible trends of main KPI's in the model. None of the main outcomes is naturally robust under the uncertainties defined in the experiments. In other words, all cases show a large spread over the KPI's.

Second, scenario discovery has been performed to understand the influence of specific uncertainties using the Patient Rule Induction Method (PRIM). In the base case ensemble, a limited number of uncertainties significantly influences the selected KPI's. Significant uncertainties influencing the selected KPI's are listed below.

- **Annual CO_2-eq emissions**: annual electricity demand growth, p =2.4e-2 and fraction innovation in carbon intensity of power generation, p = 3e-20.

- **Cumulative costs of renovation**: Reduction renovation costs (p=3.4e-28) and annual standard renovation rate (p=3.3e-20).

From to the Annual CO_2 emissions of the built environment sector, main KPI of this base case analysis, it clearly shows that additional policies are needed to secure targets set for 2030 and 2050. Hence, the next chapter will formulate policies to counter the uncertainties discovered in this chapter in an aim to create robust policies for the ambitions in the built environment sector.

6
Robust Policy Analysis

6.1. Introduction

This chapter will discuss the results of the Adaptive Robust Design methodology performed on the case of the energy transition in the Dutch built environment sector. The aim of this chapter is to answer the fourth sub question of this study: *Can policies be designed that accelerate the energy transition of the built environment sectorm which are robust under deep uncertainty?* Results presented in this chapter are derived from policy case experimentation (see section 6.3 for code) and scenario discovery (see section A.4).

To answer this question new experiments have been iteratively performed on incrementally improved models employing the ARD methodology. First, policies will be discussed which have been devised to counter uncertainty and undesirable scenarios. Second, the experimental setup is presented showing input parameters and outcomes of interest. Finally, results of the specified policies are discussed before concluding the chapter.

6.1.1. Approach of this chapter

This section aims to analyze the effects of policies to reduce negative effects of influential uncertainties as discussed in the previous chapter (chapter 5). Therefore policy instruments are selected from current policy documents. Variations how these instruments are implemented are discussed and applied to the instruments in section 6.2.

The XLRM framework, introduced by Lempert et al. (2003) is used to summarize the experimental setup. This framework structures input, output and external factors visually. Figure 6.1 shows the XLRM framework used in this chapter.

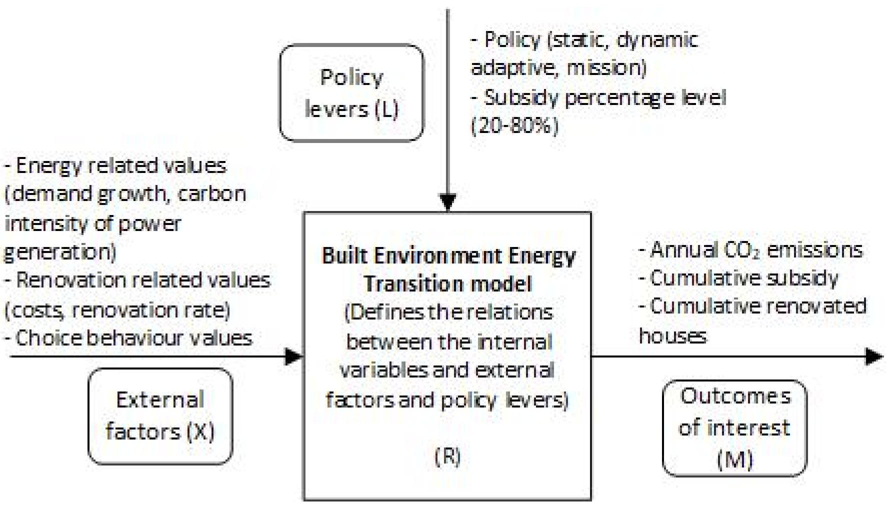


Figure 6.1: XLRM framework applied to this research

Subsequently, experiments are prepared in section 6.3 by defining additional uncertainties. These uncertainties together with selected outcomes and the defined policies are applied to the model using the EMA workbench in Python to generate experiments.

Next, policy effects are explored by analyzing the trends of experiments on the selected outcomes. This is done by plotting envelopes of outcomes grouped by policy. These envelopes show minimum and maximum value for a set of runs over time. Additionally, Kernel Density Estimations are plotted next to the outcome plots. A Kernel Density Estimation (KDE) is a way to estimate the probability density function of a variable. In these plots, the KDE offers insights in the distribution of cases per policies on the outcome's axis and hence describes the (un)certainty of the outcomes.

6.2. Policies and variations

Within the scope of the energy transition in the Dutch built environment sector, many policies have been considered in the climate agreement. These policies have been analyzed by the Netherlands Environmental Assessment Agency (PBL). This study will assess the possible effects under deep uncertainty of the three most promising instruments as discussed by PBL.

Table 6.1: Three most promising policy instruments for CO_2 emission reduction in the Dutch built environment sector according to (PBL, 2019, p. 67)

Instrument	Emission reduction in 2030 [Mton]	Investments (2019 t/m 2030)[mln euro]	National costs in 2030 [mln euro per year]
Neighbourhood approach and subsidy in the privately owned homes sector	0.2 – 1.3	1080 – 4632	24 – 28
Neighbourhood approach and subsidy in the rental sector	0.2 – 0.3	1787 – 2059	54 – 53
Norms newly built homes (gas free)	0.1 – 0.1	591 – 364	6 – -9
Total	0.5-1.7	3458-7055	84-72

Table 6.1 shows the three most promising instruments to reduce CO_2 emissions in the built environment and hence reach the climate targets for the sector. (PBL, 2019). These three instruments have been modeled in the *System Dynamics* model to simulate results with policies. The performance of these policies under deep uncertainty is strongly influenced by the delivery mechanism (policy variations). For the neighbourhood approach and subsidy in both the sector of privately owned homes and the rental sector, only subsidy based policies have been taken into consideration in this study.

6.2.1. Policy variations

A policy can be implemented in a variety of ways. The delivery mechanism selected for a specific policy naturally impacts the outcome of the policy. The list below briefly shows several possible mechanisms for policies.

- Static policy: setting a fixed policy for a preferred outcome
- Dynamic reactive policy: finding balance between two opposing KPI's over time (stop and go policy)
- Dynamic adaptive policy: create adaptive strategies that make policies robust under deep uncertainty (Walker et al., 2001)
- Capping policies (rate-based emission policy or cap-and-trade policy (Fischer, 2003)
- Mission oriented policies: aiming to accelerate R&D to realize innovations and costs reductions (Mazzucato, 2018)

For the sake of simplicity three policy delivery mechanisms have been selected on top of the no policy base case. First, a static policy is defined to reach a preferred outcome. Second, an dynamic policy is formulated that is designed to be adaptive to future developments. Third, a mission-like policy is implemented to understand effects of labour availability, scarcity and costs.

Static policy
In the static policy experiments. Subsidy percentages, static over time, are defined as policy levers in the model. Currently, rough indications of total subsidy budgets have been made public (Klimaatakkoord, 2019), but it is yet unknown how these subsidies will be distributed over different groups. Hence, subsidies percentages are varied as policy levers ranging from 0 to 80%.

Adaptive policy
Performance is dynamically evaluated for the adaptive policy experiments. Progress on the main KPI, *total CO_2 emission* is referenced to the yearly carbon budget of 2050. A multiplier kicks in if the current emissions are higher than the linear reduction path required to meet 2050 emission targets. Different multipliers are used, given the state of underachievement as shown in equation 6.1.

$$\text{subsidy multiplier}_t = \begin{cases} 2, & \text{if } \frac{\text{Annual CO}_2\text{ emission}_{t-1}}{\text{CO}_2\text{ emission 2050}} \geq 1.5 \\ 1.5 & \text{if } 1.5 > \frac{\text{Annual CO}_2\text{ emission}_{t-1}}{\text{CO}_2\text{ emission 2050}} \geq 1.25 \\ 1.25 & \text{if } 1.25 > \frac{\text{Annual CO}_2\text{ emission}_{t-1}}{\text{CO}_2\text{ emission 2050}} > 1 \\ 1, & \text{otherwise} \end{cases} \tag{6.1}$$

Mission oriented policy
For the mission oriented policy, major scaling and R&D are expected to contribute to the transition. The subsidy schematic is similar to the static policy scenario (see section 6.2.1). Major differences, however, are set in an additional *25%* higher renovation rate (of the standard renovation rate) and an additional 25 % higher decrease in renovation costs (so a higher reduction renovation costs).

6.2.2. Policy targets

Policy targets are clear on a national level. Carbon equivalent emissions should be reduced by 49% by 2030 (Klimaatakkoord, 2019) and by 95% by 2050 (Klimaatwet, 2019). The climate agreement mentions a reduction of 3.4 Mton for the built environment sector compared to the reference scenario. The reference scenario mentioned the National Energy Outlook in 2017 refers to 2015 as base year (in which the built environment sector in total accounted for 23.7 Mton of which households made up 17 Mton). A reduction of 3.4 Mton thus accounts for 15.6% reduction of the total emissions in the sector.

This study will hold PBL's targets as reference. PBL (2019, p. 25) present an emission of 24.5 Mton in 2015 and an emission ceiling of 15.3 Mton in 2030. This 38% reduction target by 2030 will be applied to the household emissions in the model alongside the general reduction targets of 49% in 2030 and 95% in 2050.

Monetary targets for subsidies are set at a cumulative subsidy of 3.5 billion euros between 2020 and 2030 for the transition of the Dutch built environment sector (PBL, 2019, p. 74).

6.3. Experimental setup

This section will present the experimental setup for the policy experiments. First, additional uncertainties will be discussed. Second, Key Performance Indicators are defined. Third, the simulation setup is discussed.

6.3.1. Uncertainties

Additional uncertainty ranges have been added on top of the uncertainty table mentioned in the previous chapter (see table 5.1. Table 6.2 shows the *additional* uncertainties sampled in the policy run. The subsidy cut-off levels are derived from implicit discount rates (see section 4.4.1).

Table 6.2: Uncertainties in the policy ensemble, additional to base case uncertainties (see table 5.1)

Variable	Lower bound	Upper bound	Unit	Source
Subsidy percentage cut-off level high building value	10	30	%	Assumed
Subsidy percentage cut-off level upper middle building value	30	50	%	Assumed
Subsidy percentage cut-off level lower middle building value	50	70	%	Assumed

Continued on next page

Table 6.2 – continued from previous page

Variable	Lower bound	Upper bound	Unit	Source
Subsidy percentage cut-off level low building value	70	90	%	Assumed
Renovation rate improvement after 2030	0	10	%/year	Assumed 10% improvement of climate agreement renovation rate (Table 4.5)

6.3.2. Key Performance Indicators

Key Performance Indicator (KPI) are defined prior to simulation to store only outcomes of interest, similar to the base case exploration. The following KPI's are selected for the policy exploration:

1. Annual CO_2-eq emission [ton CO_2]: reflecting total annual CO_2 equivalent emissions summed over all neighbourhoods in the model.
2. Cumulative subsidy [€]: total subsidized amount for all neighbourhoods accumulated over time.
3. Cumulative renovated houses [# houses]: total renovated houses for all neighbourhoods accumulated over time.

6.3.3. Simulation Setup

The policies defined in section 6.2.1, uncertainties presented in table 6.2 and outcomes from section 6.3.2 are added to the model. Each policy variation (static, dynamic adaptive and mission policy) is subsequently differentiated in a 20, 40, 60 and 80% subsidy percentage variant. Since the subsidized percentage is a clear political decision, these *policy lever* alternatives allow for assessment of effectiveness of different subsidies.

Three defined policy variants and four subsidy percentage alternatives result in 12 distinct policies to be simulated, next to a no policy variant. Again, experiments are performed by sampling values for the parametric uncertainties using Latin Hypercube Sampling (LHS). Since 13 individual policies need to be simulated, 100 scenarios per policy are simulated. Hence, a total of 1300 experiments have been performed (see chapter A).

6.4. Policy exploration

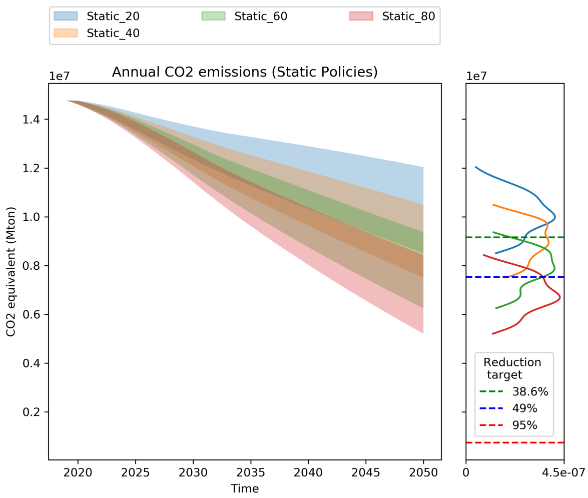
The results from the experiments discussed in the previous section will presented and interpreted in this section. In general this section consists of two parts. First, different subsidy percentage levels are compared *within* each policy variant. Second, policy variants are compared to each other with identical subsidy percentage levels. Because of the large amount of experiments, visualization of the results in this section rely on envelope plots and Kernel Density Estimation (KDE) plots. Envelop plots shows the minimum and maximum value of an outcome of interest for a set of runs over time. KDE plots show the distribution of cases on the y-axis and hence provide insights in the distribution of cases within the envelope.

6.4.1. Comparing subsidy levels within each policy

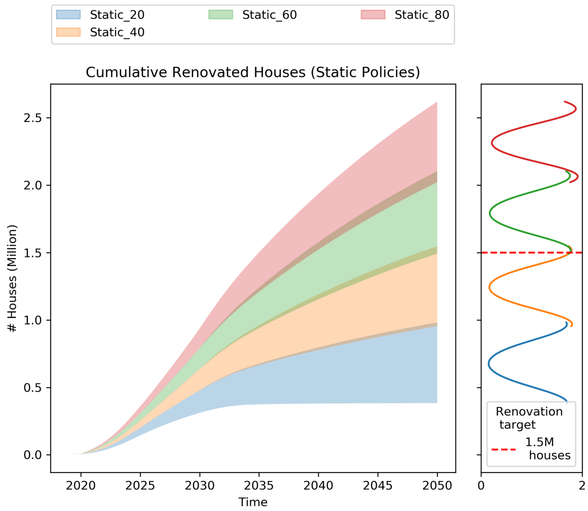
First, subsidy percentage levels are compared within each policy variant (static, dynamic adaptive policy and mission policy). All KPI's are taken into account for each policy.

Static Policy

Figure 6.2 shows the results of the experiments performed on the four subsidy percentage levels within the static policy ensemble. Differences in subsidy percentage levels effect outcomes positively. Unsurprisingly, higher subsidy percentages increase the number of renovated homes (see figure 6.2b) proportionally and hence decrease CO_2 emissions. Though different subsidy levels effect the outcomes, they do not clearly impact uncertainties around these outcomes. Distribution of outcomes does not change *significantly* between the subsidy levels. The general uncertainty distributions are similar between the groups of subsidy levels.



(a) Annual CO_2-eq emissions static policy [Mton]. The figure shows higher subsidy percentage levels resulting in lower annual CO_2 emissions. Distribution of cases does not change significantly.



(b) Cumulative renovated houses [# houses]. The wave-like pattern of the KDE graph implies that results are mostly distributed on the extremities of the envelopes. This is explained by the discrete character of the sampled subsidy cut-off levels. In the blue envelope (20% subsidy), household renovations stop after 2030, because no more household are stimulated to renovate (due to low subsidies and high renovation costs) in the minimum of the blue envelope. In the red envelope (80% subsidy), houses are continued to be renovated according to renovation rate

Figure 6.2: Envelopes of annual CO_2-eq emissions and cumulative renovated houses under static policy with four levels of subsidy coverage (20,40,60 and 80% of renovation costs). An envelope shows the minimum and maximum value for a set of runs over time.

Figure 6.3 shows envelopes of cumulative subsidies corresponding to figure 6.2. Whereas uncertainty distributions were rather similar for annual CO_2 emissions and cumulative renovated houses, they are distinctly not similar for the cumulative subsidies. The higher the subsidy percentage level, the more uncertainty on outcomes increases. In general the increase of subsidy makes sense, the higher the subsidy percentage level, the more people will apply for subsidies and hence cumulative subsidies will increase exponentially. A possible explanation for the increased uncertainty in the higher subsidy percentage regions might be that the uncertainties for the subsidy percentage cut-off levels of low building value are quite influential. To put it differently, sampled uncertainties for cut-off levels for low-value housing strongly influence the outcome of the 80% level subsidy, since this subsidy percentage level is the only variant that appeals to low building value home owners in the model. This would also explain the ceiling of renovated houses reached in the lower bound of the 20% static variant (blue envelope in figure 6.2b). Household renovations stop after 2030, because no more household are stimulated to renovate (due to low subsidies and high renovation costs) in the minimum of the blue envelope. In the red envelope (80% subsidy), houses are continued to be renovated according to renovation rate

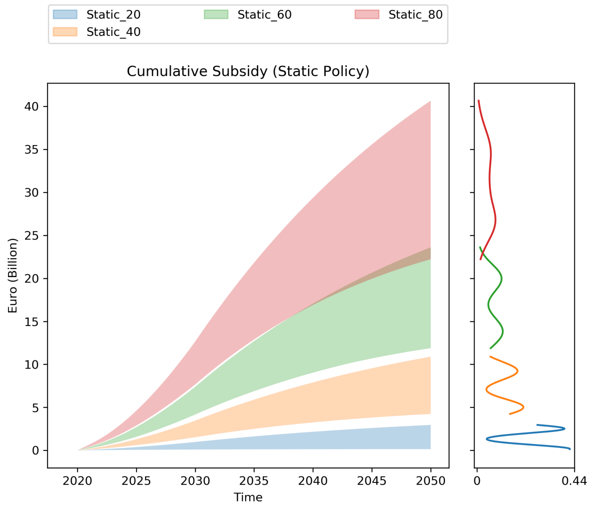
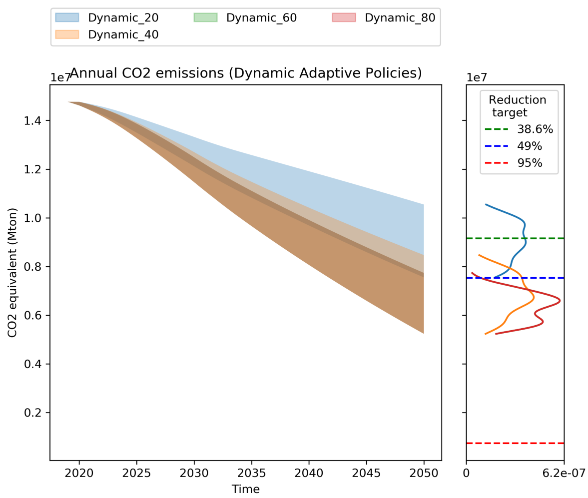


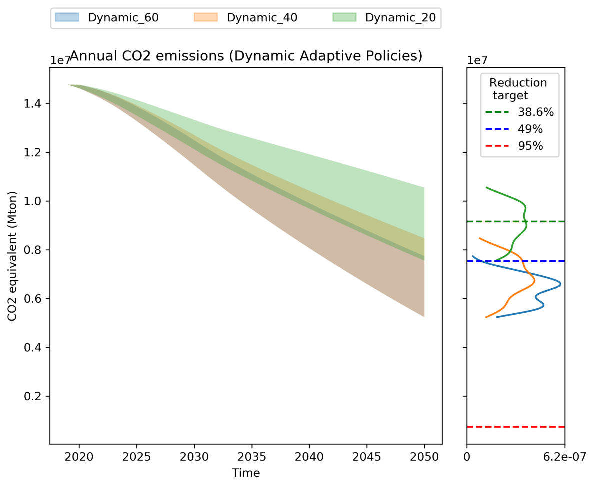
Figure 6.3: Envelopes of Cumulative subsidy static policy [euro]. The graph shows that static policies with high levels of subsidy percentages have relatively large bandwidths of uncertainty. This is explained by the increasing number of households applying for subsidies, given the sampled subsidy cut-off thresholds

Dynamic Adaptive Policy

Figure 6.4 shows the envelopes of annual CO_2 emissions under dynamic adaptive policies. Surprisingly, figure 6.4a shows only three envelopes and three KDE plots, while including all four levels of subsidy percentages. Dropping the highest level (80%) shows that the 60% subsidy level performs identical to the 80% variant (see figure 6.4b). An explanation for this might be that the 2050 target of 95% reduction is at such a high level that the multiplier is constant for the duration of the simulation and set to its highest adjustment value of 2 (see equation 6.1). Moreover, subsidies are capped at the renovation costs. This means that for both the 60% and the 80% renovation costs are fully covered, because the gap between current annual CO_2 emissions and required 2050 annual emissions is large.



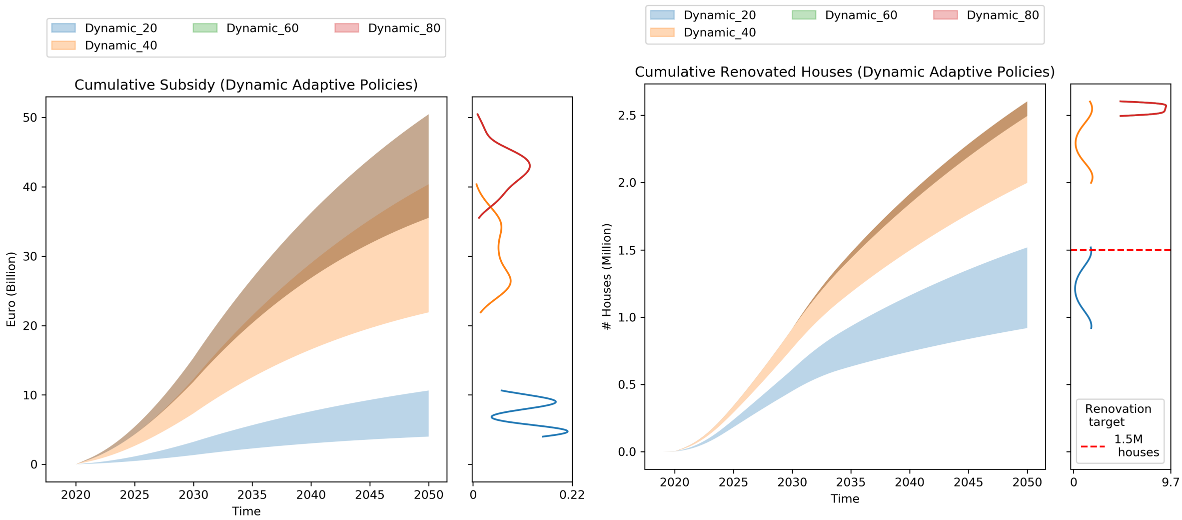
(a) Annual CO_2-eq emissions dynamic adaptive policy (20-80%) [Mton]. The figure shows lower CO_2 emissions and relatively smaller uncertainty bandwidths for higher subsidy levels



(b) Annual CO_2-eq emissions dynamic adaptive policy (20-69%) [Mton]. This figure shows that the 60 and 80% subsidy variants are identical. This is explained by the cap set on renovation costs which kicks in due to the subsidy multiplier.

Figure 6.4: Envelopes of annual CO_2-eq emissions and cumulative renovated houses under dynamic adaptive policy with four levels of subsidy coverage (20,40,60 and 80% of renovation costs). An envelope shows the minimum and maximum value for a set of runs over time.

Although cumulative subsidies are significantly larger under dynamic adaptive policy (see figure 6.5a), CO_2 emission targets for 2050 are not met. Moreover, whether 2030 targets are reached on time is also unclear based on figure 6.4. This finding was unexpected and suggests that, although people are willing to renovate, the renovation rate of houses cannot keep up with demand. The renovation rate up to 2030 is modelled according to ambitions set in the climate agreement (Klimaatakkoord, 2019, p. 15), ramping from 50.000 homes in 2021 up to 200.000 homes prior to 2030. An additional increase in renovation capacity is sampled as an uncertainty between 0 and 10% of the maximum capacity in 2030. Figure 6.4 thus shows that the renovation rate poses a boundary for reaching emission reduction goals, regardless of (additional) subsidies (see section 7.1.3).



(a) Envelopes of Cumulative subsidy dynamic adaptive policy [euro]. Again, the 60 and 80% alternative overlap. The figure shows still rather large uncertainty bounds.

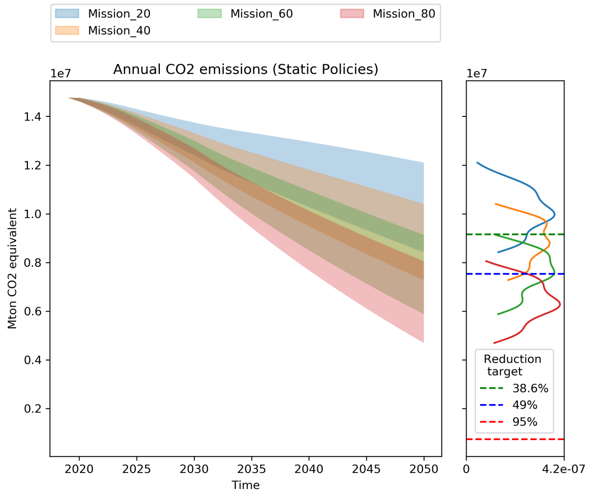
(b) Cumulative renovated houses [# houses]. The figure shows a large difference in uncertainty bandwidths. The 60 and 80% policy alternatives show a relatively small uncertainty bandwidth.

Figure 6.5: Envelopes of cumulative subsidies and cumulative renovated houses under dynamic adaptive policy with four levels of subsidy coverage (20,40,60 and 80% of renovation costs). An envelope shows the minimum and maximum value for a set of runs over time.

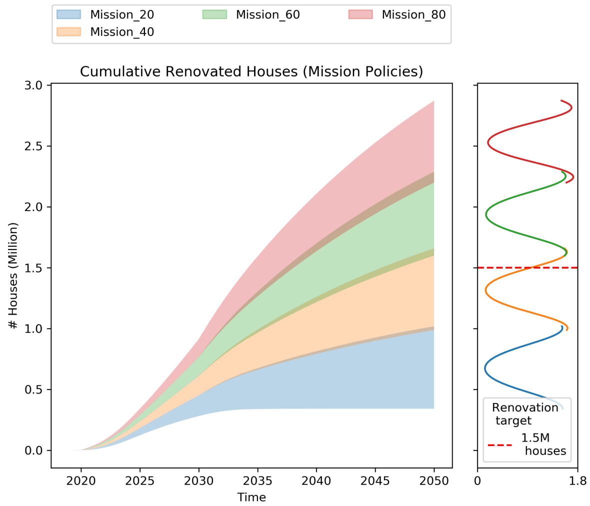
Figure 6.5a shows large cumulative subsidies. Again, having identical results for 60 and 80% subsidy levels. Figure 6.5b shows very certain outcomes for the 60 and 80% subsidy levels. To some extent, these graphs show false certainty in the high subsidy regions of 60 and 80%. The dynamic adaptive policy continuously tries to adjust the CO_2 emission trajectory for the duration of the simulation. As explained in the previous paragraph, this is likely caused by the high reduction target set in 2050, resulting in subsidies maximized at the renovation costs. This does, however, provide certainty in the cumulative subsidy in the high subsidy regions (see figure 6.5a).

Mission Oriented Policy

The effects of mission policy on CO_2 emissions are shown in figure 6.6. Although CO_2 reductions, cumulative renovated homes and cumulative subsidies are generally higher under mission policy, the trends are similar to the graphs shown in section 6.4.1. This similarity can be explained by the similarity in policy and model structure between the static and mission policy. In essence, the mission policy relies on the same policy mechanisms, but includes a *mission scale factor* that increases the renovation rate and increases the reduction of renovation costs.



(a) Annual CO_2-eq emissions mission policy [Mton]. Policies show lower CO_2 emissions with increasing subsidy levels, similar to static policy variants



(b) Cumulative renovated houses [# houses]. The wave-like pattern of the KDE graph implies that results are mostly distributed on the extremities of the envelopes. This is explained by the discrete character of the sampled subsidy cut-off levels.

Figure 6.6: Envelopes of annual CO_2-eq emissions and cumulative renovated houses under mission policy with four levels of subsidy coverage (20,40,60 and 80% of renovation costs). An envelope shows the minimum and maximum value for a set of runs over time.

While 2030 targets are within reach, similar to previous policies, the 2050 target seems too progressive to attain, even with an increased renovation rate. The upper limit of cumulative subsidies (figure 6.7) is the highest of all policy variants used in the simulations. A possible explanation for this might be that, more houses are renovated, because of the increased renovation rate under mission policy. Naturally, an increase in renovated homes leads to higher cumulative subsidies.

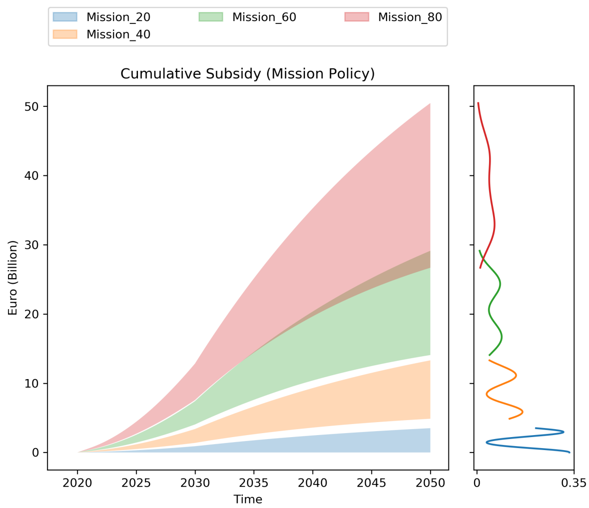


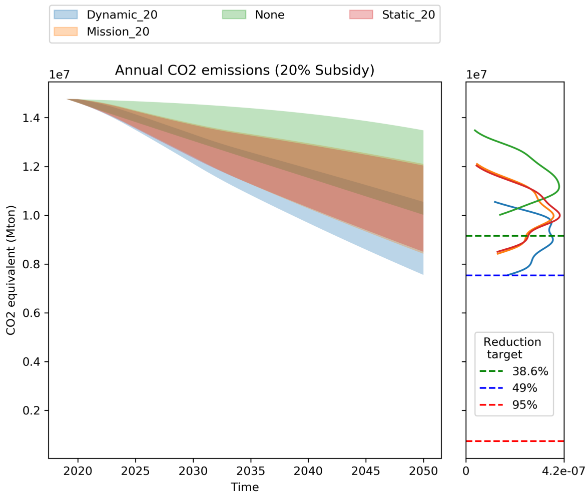
Figure 6.7: Envelopes of Cumulative subsidy dynamic adaptive policy [euro]. The graph shows that mission policies with high levels of subsidy percentages have relatively large bandwidths of uncertainty. This is explained by the increasing number of households applying for subsidies, given the sampled subsidy cut-off thresholds

6.4.2. Comparing policies with identical subsidy levels

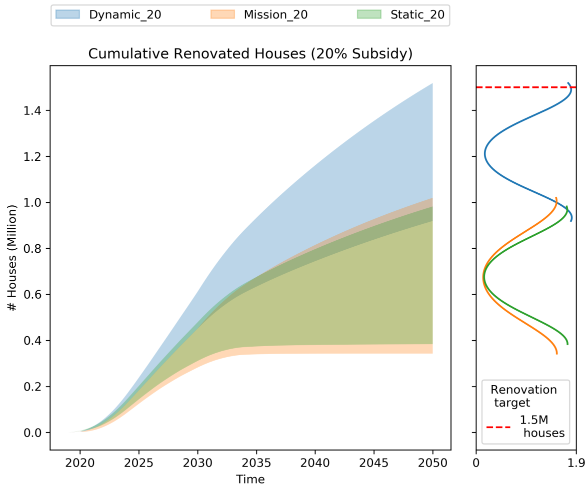
The previous section shows the effects of subsidy percentage levels within policy variants. This section analyzes the effects of policy variants within subsidy levels. Hence, this paragraph will subsequently describe policy effects of each of the four subsidy percentage levels.

20% subsidies

Results of the 20% subsidy policy lever are shown in figure 6.8. From this figure it is fair to say that the dynamic adaptive policy performs best. Still, adjustment from the multiplier (see equation 6.1) is not enough at this subsidy level to get more people to renovate. Hence, 2050 targets are out of range with this subsidy level. Moreover, as subsidies are low, uncertainties whether people will renovate are high (since, uncertainty on renovation costs will be more influential in this case).



(a) Annual CO_2-eq emissions of various policies with 20% subsidy. The graph shows similar results for static and mission policy. Overall, the dynamic policy has lowest emissions.



(b) Cumulative renovated houses of various policies with 20% subsidy

Figure 6.8: Envelopes of annual CO_2-eq emissions and cumulative renovated houses of various policies, each with 20% subsidy as policy lever. An envelope shows the minimum and maximum value for a set of runs over time.

Figure 6.9 shows cumulative subsidies at the 20% subsidy level. Unsurprisingly, uncertainty ranges of the dynamic adaptive policy are clearly highest. Total subsidies for other policies are surprisingly low. Top ranges of both static and mission policy do not exceed 4 billion euros. As a reference, PBL calculated that the climate agreement reserves 3.5 billion euros for the built environment sector up to the year 2030. There are, however, possible explanations. Most notably, the fact that people are reluctant to renovate their homes, since subsidy percentage cut-off levels simply are not reached (see table 6.2).

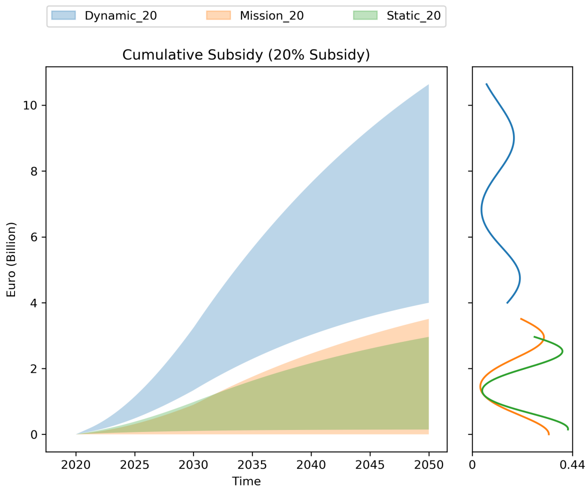
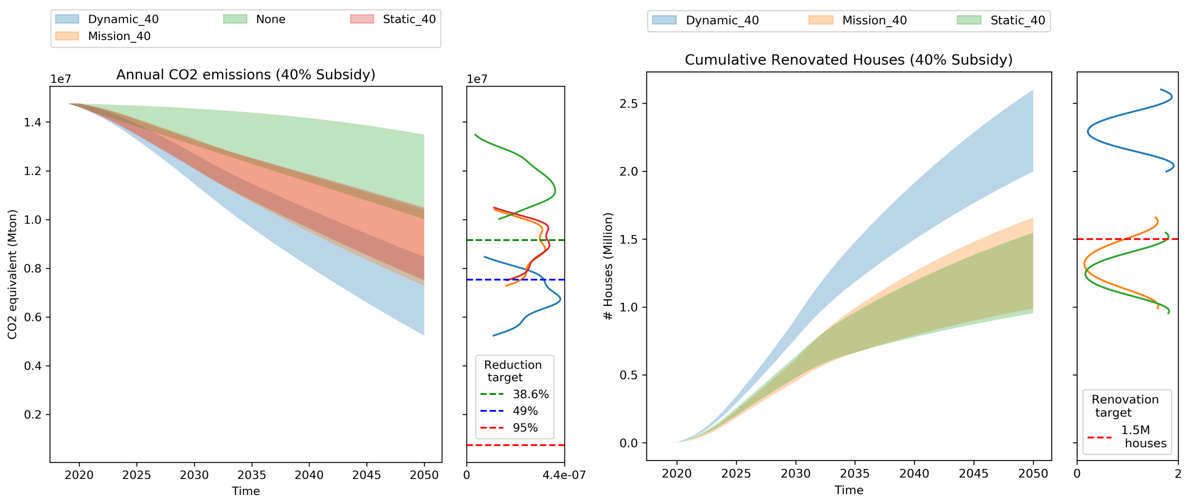


Figure 6.9: Envelopes of Cumulative subsidy of various policies with 20% subsidy as policy lever [euro]. The dynamic policy shows the largest bandwidth of uncertainty, while the mission and static policy KDE plots show results are distributed around the extremities of the envelopes. The large bandwidth of the dynamic policy can be explained by the combination of the subsidy multiplier and sampled subsidy cut-off thresholds.

40% subsidies

At the 40% subsidy level, differences between policies are significantly larger compared to the previous paragraph. In terms of both CO_2 emission reduction and cumulative renovated houses, the dynamic adaptive policy performs best. This is in line with expectations regarding the subsidy multiplier included in the dynamic adaptive policy. Results on cumulative renovated houses are still highly uncertain. The KDE plot suggests policies can most likely expect either of two extreme outcomes. This can be explained by the interplay between uncertainties sampled on subsidy cut-off levels and renovation costs. Once a cut-off level is not reached, household will not renovate. This discrete behaviour is reflected in the KDE plot.



(a) Annual CO_2-eq emissions of various policies with 40% subsidy. Differences between policies and a no policy alternative increase. Dynamic adaptive policy seems to perform best at this subsidy level, generally reaching lowest emissions

(b) Cumulative renovated houses of various policies with 40% subsidy. The wave-like pattern of the KDE graph implies that results are mostly distributed on the extremities of the envelopes. This is explained by the discrete character of the sampled subsidy cut-off levels.

Figure 6.10: Envelopes of annual CO_2-eq emissions and cumulative renovated houses of various policies, each with 40% subsidy as policy lever. An envelope shows the minimum and maximum value for a set of runs over time.

The high number of renovated homes in the dynamic adaptive policies is also reflected in figure 6.11. Due to its multiplier, the dynamic adaptive policy has much higher cumulative subsidy. The mission and static policy show similarly discrete behaviour as mentioned in the previous paragraph for cumulative renovated houses.

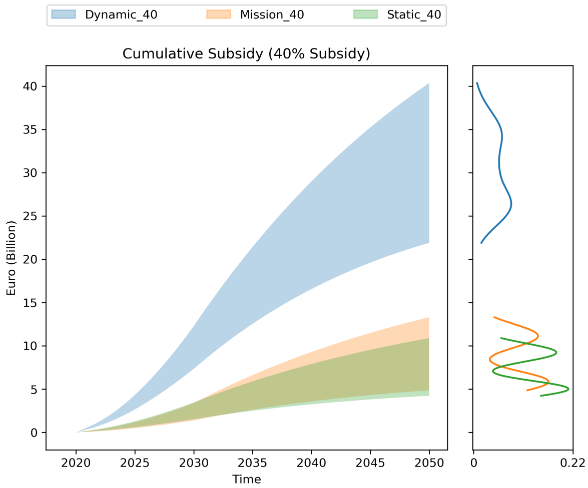
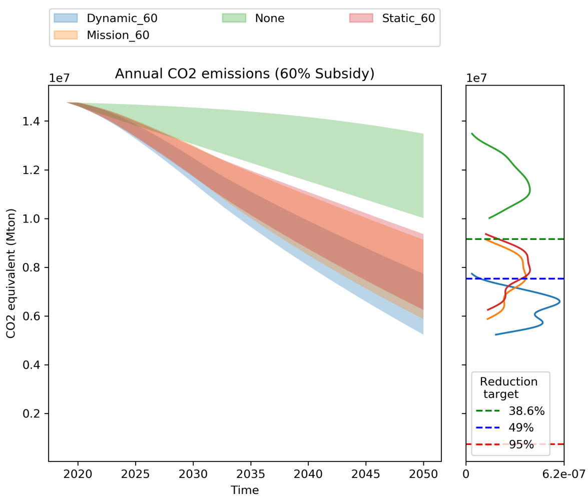


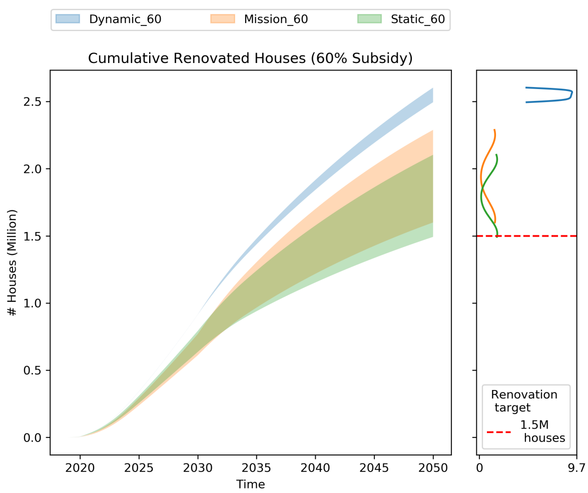
Figure 6.11: Envelopes of Cumulative subsidy of various policies with 40% subsidy as policy lever [euro]. The dynamic policy shows the largest bandwidth of uncertainty, while the mission and static policy KDE plots show results are distributed around the extremities of the envelopes. The large bandwidth of the dynamic policy can be explained by the combination of the subsidy multiplier and sampled subsidy cut-off thresholds.

60% subsidies

The 60% subsidy variant shows significant differences in certainty on outcomes of the dynamic adaptive policy (see figures 6.12b and 6.13), compared to the 20 and 40% subsidy. This surprising result is most likely related to the subsidy multiplier and its cap on renovation costs (see section 6.4.1). Other policies show increasingly improved results, substantially lower than previous subsidy levels, but still with similar uncertainty ranges on the KDE plot. From this subsidy level, 2030 goals have all been reached in 2050. A 95% reduction of emissions in the sector seems distant still.



(a) Annual CO_2-eq emissions of various policies with 60% subsidy. Dynamic adaptive policy seems to perform best at this subsidy level, generally reaching lowest emissions. Compared to lower subsidy levels, static and mission policy close in on dynamic adaptive policy.



(b) Cumulative renovated houses of various policies with 60% subsidy. Compared to lower subsidy levels, the dynamic adaptive policy as significantly reduced uncertainty at the 60% level. The mission and static policy still show most cases distributed on the extremes of the envelopes.

Figure 6.12: Envelopes of annual CO_2-eq emissions and cumulative renovated houses of various policies, each with 60% subsidy as policy lever. An envelope shows the minimum and maximum value for a set of runs over time.

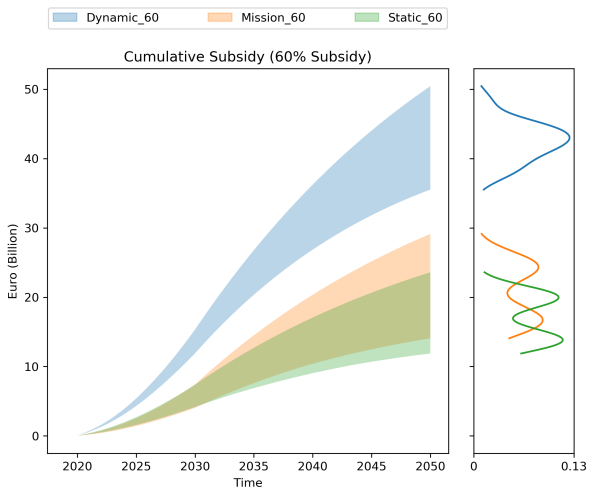
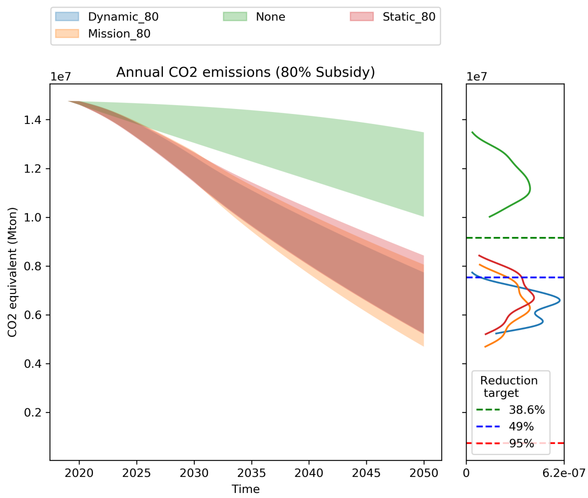


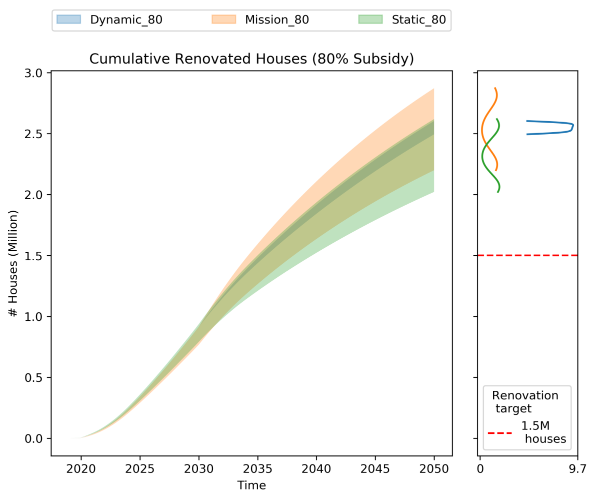
Figure 6.13: Envelopes of Cumulative subsidy of various policies with 60% subsidy as policy lever [euro]. This graph also shows increased certainty of outcomes compared to lower subsidy levels for the dynamic adaptive policy.

80% subsidies

Finally, the 80% subsidy percentage policy variants are shown in figures 6.14 and 6.15. Unsurprisingly, static and mission policy have improved and center on a similar distribution level as the dynamic adaptive policy. Surprisingly, the dynamic adaptive policy itself did not improve. This behaviour has already been explained in section 6.4.1 and is caused by subsidies capped at renovation costs. Moreover, the renovation rate does not allow for significantly more renovations, even though subsidy cut-off thresholds are met.



(a) Annual CO_2-eq emissions of various policies with 80% subsidy. At this level all policy variants have centered around roughly 7 Mton CO_2 emission.



(b) Cumulative renovated houses of various policies with 80% subsidy Similar to the 60% level, this plot shows relatively high certainty for the dynamic adaptive policy. Mission and static policy have closed in absolutely speaking, but have higher bandwidths of uncertainty.

Figure 6.14: Envelopes of annual CO_2-eq emissions and cumulative renovated houses of various policies, each with 80% subsidy as policy lever. An envelope shows the minimum and maximum value for a set of runs over time.

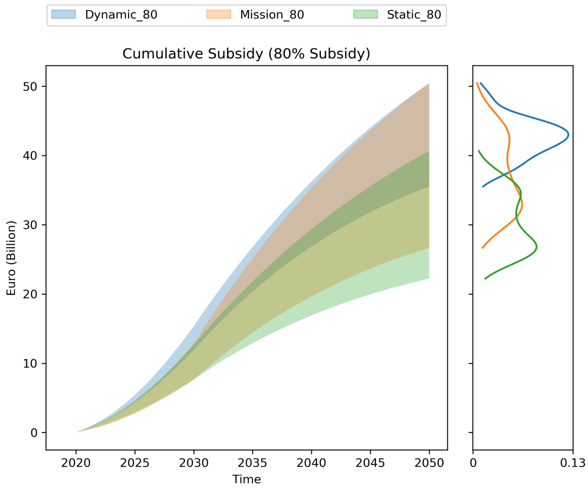


Figure 6.15: Envelopes of Cumulative subsidy of various policies with 80% subsidy as policy lever [euro]. At this level, all policies show rather large bandwidths of uncertainty.

6.5. Uncertainty Analysis

Figure 5.8 shows a feature scoring on the main KPI's of the robust policy analysis. The figure shows influence of uncertainties (y-axis) on the model's KPI's (x-axis). In contrast to the influence of uncertainties in the base case (see figure 5.8), the policy ensemble shows a strongly reduced influence of uncertainties on the policy model (see figure 6.16).

	total renovated houses	total cumulative subsidies awarded	total costs	total CO2 emission
Annual development of new homes	0.002	0.0016	0.0035	0.0039
Annual electricity demand growth	0.0013	0.00091	0.0026	0.034
Annual standard renovation rate	0.0014	0.00096	0.0028	0.0039
Fraction houses to district heat building corporations high existing infrastructure	0.0015	0.00082	0.0033	0.004
Fraction houses to district heat building corporations low existing infrastructure	0.0016	0.00082	0.0032	0.0042
Fraction houses to district heat building corporations no existing infrastructure	0.0014	0.00091	0.0024	0.004
Fraction houses to district heat private sector high existing infrastructure	0.0016	0.00078	0.0029	0.0042
Fraction houses to district heat private sector low existing infrastructure	0.0014	0.0009	0.0033	0.0036
Reduction carbon intensity power generation	0.0013	0.0012	0.0033	0.09
Reduction renovation costs	0.0014	0.0049	0.043	0.0042
Renovation rate improvement after 2030	0.0022	0.0012	0.0033	0.0038
Subsidy percentage cut-off level high building value	0.017	0.0018	0.017	0.01
Subsidy percentage cut-off level low building value	0.019	0.013	0.015	0.013
Subsidy percentage cut-off level lower middle building value	0.015	0.0063	0.013	0.014
Subsidy percentage cut-off level upper middle building value	0.021	0.0048	0.02	0.015
policy	0.9	0.95	0.84	0.77
renovation costs label group 1	0.0016	0.0011	0.0034	0.0037
renovation costs label group 2	0.0016	0.002	0.0043	0.0036
renovation costs label group 3	0.0019	0.0011	0.0038	0.0043
renovation costs label group 4	0.0014	0.002	0.0049	0.004

Figure 6.16: Feature scores of the experiments and outcomes of the policy ensemble. The figure shows influence of uncertainties (y-axis) on the model's KPI's (x-axis). Policies are most influential in the policy ensemble. Influence of uncertainties has been reduced significantly compared to the base case analysis (see figure 5.8)

.

6.6. Conclusion

This chapter set out to answer the fourth sub question of this thesis: *"Which robust policy variations can be discovered for the energy transition of the Dutch built environment sector?"*.

To answer this sub question, the model (chapter 4) and insights from the base case analysis (chapter 5) have been used to create policy variations. The most promising instruments from PBL (2019, p. 67) have been selected and implemented in three different variants compared to a no policy reference. A static policy, a dynamic adaptive policy and a mission oriented R&D policy have been implemented and complemented by four policy levers holding a subsidy percentage of 20, 40, 60 and 80%. Subsequently, the policies have been simulated under deep uncertainty.

When discussing effectiveness of policies, policy targets should be evaluated. As targets are only known for the period up to 2030, a more general target has been maintained for 2050. This general target has been set at 95% reduction and was obtained from the Dutch climate law. Most policies simulated in this study reached 2030 targets after its deadline in 2030.

Results have been evaluated both within policy variants (withing varying subsidy levels) as between policy variants (with a constant subsidy level). The static and mission policy options showed similar trends, but maintained different absolute outcomes. Most notably, the mission policy allows for a higher renovation rate and thus cumulative renovated houses turned out highest for this policy while holding a 80% subsidy level.

The dynamic adaptive policy variant does not perform significantly better than the other two policy variants. Even though annual CO_2 emissions and cumulative renovated houses are higher, uncertainty is not reduced significantly. This shows that subsidy percentage, alone, does not ensure that policy targets for 2050 are reached. None of the policies simulated in this study have been able to reach the 2050 goal and seemed to converge around two to three million renovated homes in the 80% subsidy level. This finding was unexpected and suggests that other variables prevent more renovation to be completed. The renovation rate used in this study is likely an obstacle for ample renovations. The renovation rate used in this study is drawn from the climate agreement and seems to be too small to meet renovation demand within this study. This is demonstrated in the mission policy where an additional increase of the renovation rate by 25% resulted in higher cumulative renovated houses (figure 6.14b).

Table 6.3: Overview of policy outcomes in 2050. Annual CO_2-eq emissions are shown as a reduction from CO_2 emissions in 2015.

Policy	Subsidy Percentage	Mean CO_2 reduction [Mton]	Maximum CO_2 reduction [Mton]	Maximum cumulative renovated houses [M houses]	Mean cumulative renovated houses [M houses]	Maximum cumulative subsidies awarded [Billion euros]	Mean cumulative subsidies awarded [Billion euros]
Dynamic	20	2.9	7.21	1.52	0.67	10.64	3.46
	40	3.94	9.53	2.6	1.19	40.35	15.09
	60	4.18	9.53	2.6	1.31	50.44	21.31
	80	4.18	9.53	2.6	1.31	50.44	21.31
Mission	20	2.39	6.34	1.02	0.41	3.51	0.71
	40	2.98	7.49	1.66	0.71	13.31	4.09
	60	3.57	8.89	2.29	1.0	29.13	9.83
	80	4.13	10.07	2.87	1.28	50.47	17.85
Static	20	2.41	6.26	0.98	0.43	2.96	0.71
	40	2.94	7.26	1.55	0.7	10.89	3.66
	60	3.46	8.51	2.1	0.96	23.6	8.57
	80	3.97	9.56	2.62	1.21	40.65	15.4

Table 6.3 shows mean and maximum outcomes per policy and subsidy percentage level. It summarizes policy outcomes shown in the graphs in this chapter. Compared to table 6.1, results from this study indicate higher CO_2 emission reductions and higher subsidy expenditure. It is important, however, to acknowledge the

different scope of the studies (12 years for table 6.1 vs 32 years for table 6.3) and the exploratory nature of this study compared to the predictive modelling study of (PBL, 2019).

The model underlying this study has not been validated (see section 7.3.1 for limitations and recommendations). These results therefore need to be interpreted with caution. Moreover, most figures of cumulative renovated houses show an unanticipated trend. The KDE plots of these figures are centered around the extremities of the envelopes shown in each figure. This indicated discrete behaviour in the model. Subsidy cut-off levels are sampled once for the duration of the simulation. Subsequently, once a certain cut-off level is not reached, one does not renovate. This explains the discrete behaviour of the plots.

Finally, an answer to the sub question seems clear at first. The dynamic adaptive policy has shown to be slightly more robust under deep uncertainty in this study. However, this certainty comes at a cost, quite literally. Cumulative subsidies of the dynamic adaptive policy are substantially higher than any other policy variant used in the simulations of this study. Hence, the only correct answer to this sub question depends on a trade off between robustness and policy expenditure (cumulative subsidies in this study). Due to the exploratory nature of this study limits have not been applied to either of these two criteria. Validation for such trade off should be sought in the political arena.

7
Discussion

This chapter will firstly discuss results presented in chapter 5 and chapter 6 in section 7.1. Second, a limitations are discussed in section 7.2 and future recommendations are presented in section 7.3.

7.1. Discussion of Results

This section will briefly discuss and interpret the main results of this study and try to put them into context. An important question to ask oneself when presenting results such as those in chapter 3, 5 and chapter 6 is *"what do they mean?"*.

7.1.1. Energy Transition Models

Chapter 3 presented a wide range of current Energy Transition models built or in development. Studies using energy transition models have been performed for quite some time. Recent improvements in data availability and software for computational simulations, however, enabled far more and extensive research. Subsequently, a very large variety of energy transition models has been created. This study tried to provide an overview of most of these models, mainly categorizing them on purpose of use. Academic models are well documented and much discussed about, but are mostly not available to the public. The same holds true for models created for public policy (see section 3.3). More recently, the open model initiative aimed to break open this elusiveness of public policy models. Since Python has become a main programming language, transferibiliyt of modelling was much easier. Subsequently, open source models, written in or controlled by Python, have appeared such as *MEDEAS* (see section 3.2.2).

The taxonomy presented by Li et al. (2015) provides a very interesting way to categorize this abundance of energy systems models. Naturally, the overview presented in this is most likely far for complete. It did, however, provide a snap shot of the current state of the art. Future research, however, could find many more, and perhaps better, ways to categorize these models to provide a more extensive overview. The purpose for which these energy systems models have been created varies so much and the threshold to understand and use existing models is considerable, that one could imagine the reason behind the abundance of already existing models. A great step forward, at least in the field of System Dynamics, would be to create shared and maintained open source libraries of reproducible model components. Instead of reinventing the wheel, one could look up existing model *structures* in an existing library. That said, one could argue what the benefit of this would be for individual researching trying to get their research published.

7.1.2. Base Case Analysis

Chapter 5 presented results of open exploration and scenario discovery on the model with defined uncertainties, but without any policies. First, the employed model of renovation transitions in the built environment sector is extensive and includes many outcomes on a variety of levels (neighbourhood, district, municipality and country). This allows a modeller to entertain various scopes and policy perspectives simultaneously, but also makes analysis and interpretation increasingly difficult. This resulted in a selection of key outcomes on an aggregated (country) level in a search for best and worst case scenarios.

Results showed main influence from uncertainties directly related to the built environment sector such as *standard renovation rate* and *average electricity consumption growth*. The latter mainly effecting total Co_2

emission, where the first strongly influenced all other KPI's. It must be said that the standard renovation rate complies with ambitions set in the climate agreement, so some policy had been implied in the base case ensemble (due to a lack of data of a *normal* standard renovation rate). Even so, efforts were long short of meeting carbon reduction targets.

The feature scores also showed large influence from uncertainty sampled on variable reduction carbon intensity power generation. This variable, represented emission reduction achieved in energy generation in the electricity sector. Hence, to validly represent the energy transition in the built environment sector, other sector should be included in the modelling effort, as they are interdependent.

7.1.3. Robust Policy Analysis

Chapter 6 showed results of policies aimed at mitigating effects from influential uncertainties on the base case ensemble. Three policy variations of a selection of policy instruments have been implemented and tested under deep uncertainty. Two relatively equal policy variations performed similarly (static policy and mission oriented R&D policy). The dynamic adaptive performed slightly better under deep uncertainty and maintained a direction whilst evaluating progress and steering towards its goal. The adjustment mechanism of the dynamic adaptive policy (see equation 6.1), however, was pushed to its limits with the current goal of 95 % CO_2-eq reduction by 2050 and fully adjusting for the duration of the simulation.

In previous iterations in the Adaptive Robust Design cycle, experiments have been performed with a lower reduction target for 2050. This allowed for better adjustment by a mechanism that solely influences the subsidies awarded (see figure F.1). In that case, the dynamic adaptive policy performed significantly better than its static or mission oriented counterpart, compared to the results shown in this chapter. Subsequently switching to a higher reduction target, in line with the climate law (Klimaatwet, 2019), had unforeseen consequences in later simulations and resulted in too little adjustment room for the dynamic adaptive policy.

Thus, the results showed that a policy focusing on a single tool (subsidies) has not been adequate enough to meet renovation targets within this study. Even in the dynamic adaptive policy, results showed that subsidies only affect the renovated homes to a certain point. After that, the renovation rate at which houses are renovated becomes dominant. Hence, policies should include mechanisms to scale renovation capacity next to creating incentives for renovations (subsidies in this case), to sufficiently increase renovations to meet reduction targets.

Moreover, the slightly better performance of dynamic adaptive policy has it's costs. As the dynamic adaptive policy has been designed to steer away from under performance towards meeting a distant goal, cumulative subsidies increase much earlier than in the static or mission policy cases. Remarkably, the dynamic adaptive policy was much more robust under deep uncertainty as shown in the main KPI of the analysis *total CO_2 emission*. It showed from this analysis that a robust policy needs an adaptive mechanism to make sure policies are on track and the ability to correct under achieving behaviour. The other two policy variants lacked this mechanism, making it more of a one shot wonder, which naturally results in much spread in possible outcomes under deep uncertainty.

7.2. Limitations

7.2.1. Data

Even though this study managed quite well to combine several data sets to form a single extensive data set for model initialization, current data on neighbourhood level is limited. Throughout the data set values are missing, or even values are missing for all variables of interest. If the latter occurred, the entire neighbourhood has been dropped in the data set. This resulted in approximately 2500+ neighbourhoods being lost, which account for roughly 20% of total neighbourhoods in the Netherlands. When Vivet (CBS, 2019b) has been launched, more complete data on neighbourhood level could hopefully be used, which would significantly aid completeness of future studies.

Similarly, data on household renovation costs has been derived from *label jumps* on Nationale EnergieAtlas (2019). This platform has performed an analysis to distill average label cost jumps for a single building type: a row house built between 1945 and 1964. Renovation costs for this particular segment are naturally not valid for all houses in the data set. This study has sampled wide range of uncertainty on these renovation costs to accommodate for these differences. It would be much better, however, if average label jump costs would become available for all building types and more categories of building year. Hence, renovation costs could be far better determined, which would greatly increase the validity of renovation costs in the model.

7.2.2. Model

A major limitation of the model, and selected scope in general, is the lack of other sectors in the analysis. Other sectors from the climate agreement include the electricity sector, the industrial sector, the mobility sector and the agricultural sector. All of these sectors interact with each other and exactly these interaction (or cross-sector) effects would be very interesting to observe under deep uncertainty. Moreover, this could potentially identify reinforcing or decreasing feedback effects.

Furthermore, the applied model is strongly subjected to the modeler's perspective on the functioning of the system. The model constructed entertains the understanding of system function from the modeler. This is by no means an universal truth, as other perspectives might be equally fit for purpose.Currently, however, the renovation of households can either go to all electric or district heating when disconnected from natural gas. This is a great simplification and limitation of reality and as mentioned in the model's scope (see section 4.3.2) incentives to increase energy efficiency methods cannot be simulated due the lack of data on energy efficiency metrics, such as isolation. Similar to assumptions on system behaviour, selected uncertainties and their relation to modelling structure could also be cause of bias. Many more uncertainties, such as behavioural uncertainties, could play a role in this very same study, but have not been included.

Also, the model does not include a demolition option of existing housing. It might be worth investigating if it the entire society would not be better of if certain houses will not be renovated at all. Instead, having them demolished and replaced by newly built homes. Furthermore, discovery (or creation of) new district heating capacity is scoped out of the model. This, however, greatly limits the viability of district heating in the model due to the amount of missing data on district heating capacity on neighbourhood level.

Renovation rationale of home owners is currently simplified using implicit discount rates. Aspects outside the scope of these IDR's, such as comfort, financial security or family planning could also influence one's propensity to renovate.

As data on renovation costs still is limited, this study has divided the housing stock data in four groups based on the average label per neighbourhood. Subsequently, four different uncertainties have been sampled on these groups to accommodate for differences in building type, renovation costs themselves. This greatly limits accuracy of costs in the model. A better way to include renovation costs in the model would be to assess a single houses characteristics and calculate the renovation costs by the intended label jump.

7.2.3. Robust Policy Analysis

That said, much improvement can be made to these policy variants. The mission R&D policy options is a strong simplification of a *real* mission oriented policy as described by Mazzucato (2018). Moreover, the selection of policy variants in this study excluded other, perhaps more effect, variants, such as dynamic reactive policy (stop go policy) or capping policies (rate-based emission policy or cap-and-trade policy). Section 7.3.1 elaborates on model improvements to facilitate these excluded policies in future research.

Moreover, subsidy cut-off levels are modelled to be dependent on average building value and average label group per neighbourhood. Different average building value groups have different propensities to renovate. In short, a more expensive house is deemed to be more likely to renovate even with small subsidy coverage (subsidy/renovation costs), but less expensive houses are deemed to renovate only if a large sum of expenses is covered by subsidies. Hence, if the subsidy amount is higher, an increasing number of households will apply for subsidies to renovate their homes resulting in exponential behaviour in the total subsidy amount. As the renovation rationale depends on the subsidy cut-off level, it explicitly assumes different Implicit Discount Rates for different building value groups. As average label group is also taken into account, neighbourhoods with a *good* average label (A or B) and high average building value will quickly be able to renovate their homes (as renovation costs are low an the household's requirement for subsidy coverage is also low). This directly results in energy inequality, since only "rich" households apply for subsidies. This dynamic should be corrected for in future studies to prevent unwanted energy inequality. A start would be to analyze to what extend average building value correlates to average label groups, or better: to what extent a dwellings label correlates to its value.

7.3. Recommendations

7.3.1. Model recommendations

The model applied model has limitations (as mentioned in the previous paragraph). This section aims to address these limitations by providing recommendations for improvement.

First, the current model structure focuses around the migration of households from having a gas connection to either being heated by electricity or district heating. This makes sense when energy efficiency data (energy labels or energy index) is not available, because assumptions need to made on general energy consumption per building type, rather than more accurate energy demand estimations. An improvement to the model would be to get rid of this current structure and include an entirely new flow structure of households, where they are segmented by energy label. Hence, houses are divided by label per neighbourhood and can be renovated incrementally using label steps.

This also improves the renovation logic as renovation costs could be implemented in the model more accurately. As more accurate data becomes available on renovation costs per building type and building year, better renovation costs can be selected for an intended label jump, as discussed in the previous paragraph.

The financial renovation logic in the model could also be improved after label jumps and label jump costs have been determined. If specific costs are known for the label jump and the energy savings are known for that label jump, return on investment can be calculated.

In the current model, renovation decisions are made every time step. Decision making inertia should be included in the model for a more valid representation on renovation decision making. Currently, a renovation decision is made at every time step in the simulation. Naturally, a person would not continuously decide whether or not he wants to renovate his unrenovated house, but rather would have moment throughout the year when he would be more considerate to renovate.

Average building value has been used as a predictor for ones propensity to renovate (due to limited information on income). Four groups have been created by dividing the data on building value in quantiles. These groups are used to assign different uncertainties to the propensity to renovate in a neighbourhood. If a neighbourhood is in the top quantile (ie. average housing value is among the 25% highest), the neighbourhood is assumed to be less reluctant to renovate than if it would be in the lower quantile. The model could be improved by including data on household income (as a better predictor for a households propensity to renovate) and including a much higher segmentation in groups. The current division in four groups is much too broad.

An energy taxation structure should be included in the model. The current analysis did not include any fee-bates policies, but fee-bate policies are in the making: taxes on gas are increased to lower taxes on electricity. This taxation structure could be used to also test the effect of taxation policies under deep uncertainty.

The current multi-scale model goes down to neighbourhood level. This results in a very extensively sub scripted model, which subsequently is more computationally intensive. For the lowest level decision makers in the RES (municipalities) a district-level approach would be satisfactory in current policy plans. Hence, it is recommended to up the model scale to districts instead of neighbourhoods. Prior to doing so, one should test whether housing stock in neighbourhoods is not significantly more uniform, than that of districts. If housing stock in neighbourhoods is significantly more uniform, one should reconsider to increase computational power, because the detail does provide important insights in the renovation task (it could prove to be more (cost) effective to take on homogeneous neighbourhoods first, and heterogeneous neighbourhoods later).

As mentioned in the limitations of the policy analysis (section 7.2.3), the multiplier mechanism used in the dynamic adaptive policy struggled with the high reduction target set to 95% in 2050. As the reduction was that high, the multiplier constantly tried to adjust at its maximum capacity. This showed that subsidies, alone, are not enough to realize reduction ambitions. Similarly, the static and mission oriented policy also meet this limit of the renovation rate in high-subsidy scenarios. Hence, the dynamic adaptive policy should also be able to influence the renovation rate at which homes are to be renovated. A mechanism similar to the multiplier for subsidies should be used to influence the renovation rate, next to incentivizing household through subsidies to further improve effectiveness of the policy.

Finally, to create a more valid and supported model, it should be validated by industry experts. The model and the defined policies should be subjected to validation methods such as "Evaludation" (Augusiak et al., 2014), which could improve validity, credibility and general effectiveness the model and its results.

7.3.2. EMA & ARD recommendations

Currently, variables are calculated on neighbourhood level, but results if KPI's are stored on national level. The EMA workbench stores all simulation data in the computer's RAM memory before simulation is finalized. Preferably, all KPI's are stored on neighbourhood level to allow for different interpretation by various policy makers. Local policymakers on municipal level could for instance benefit from being able to switch scope from local neighbourhoods to national targets to put their efforts into perspective. A different approach to storing data in the EMA workbench is required to achieve this in future research.

Computational performance
For better computational performance, model experiments can also be run on computer clusters (mostly running on linux). The current model setup, however, does not allow for computational experiments on a Linux machine, since the EMA and Vensim DSS connection relies on the Vensim DLL, which enables communication between the various software packages. Recently, a python package for translating Vensim models to purely Pythonic models, called PySD, released a new version which includes subscripts in model translation.

However, this method would loose the ability to run the model in compiled mode (in the C programming language), which in itself already is a great computational improvement. Hence, computational performance of the computer clusters must be significantly better to outperform the compiled simulation on a local machine (which requires a local copy of Vensim DSS).

7.3.3. Alternative Recommendations

Renovatino behaviour in this study is based on implicit discount rataes. Such financial motives are dominantly represented in other modelling studies too Wilson et al. (2015), but renovation decisions are made on many more levels as Wilson et al. (2018) have shown in their study. Future research should be conducted to better map individual renovation decisions and their indicators.

Integration of individual decision behaviour with a dynamic model would greatly increase simulation validity. Novel simulation solutions such as Ventity enable entity based system dynamics modelling and could provide tools for combining actor behaviour and system dynamics to investigate this knowledge gap in future studies.

7.4. Innovation

7.4.1. Python scraper EV chargers

EV charger data is, surprisingly, not openly available. Only aggregations to national levels have been made public. Ie. the total amount of public or private charging points in the Netherlands (Rijkswaterstaat, 2019). Much data, however, is available on interactive maps online.

Since knowledge of location (longitude and latitude), ownership (public, private, semi-public) and capacity (charging speed) could be important for dynamics in local electricity demand, a *python* webscraper has been constructed (see section B.3) that retrieves specific characteristics from an online map showing EV charging infrastructure in the Benelux from EV charging data supplier `www.eco-movement.com`. This data can subsequently be scaled to multiple levels (neighbourhood, municipality) as it includes GPS coordinates.

7.4.2. Interactive neighbourhood generation

Using a multi-level model can be a hassle from time to time. Clear decision support on higher levels (such as municipalities) can be hampered by its many sub levels (neighbourhoods in this case). Naturally, one does not know which of the 13.000+ neighbourhoods belong to which of the 350+ municipalities.

This poses quite the challenge for experimentation in scenario discovery. Specific outcomes need to be assigned prior to simulation in order to store *region-specific* KPI's, simply because the sheer numbers of entities (10.000+ in this case) prevent keeping track of all KPI's, on all levels, throughout the simulation period.

To cope with this barrier in multi-level simulation, a *python* script has been developed (see section A.6) that enables user-friendly selection of a high level entity (such as a municipality) for a simulation run. Subsequently, the script selects all neighbourhoods belonging to that specific region and automatically adds them as an outcomes to the scenario discovery simulation.

8 Conclusion

8.1. Research Summary

This research has been performed to gain insights on performance of robust policy variations to reduce carbon emissions under deep uncertainty. Robust policies can be a solution to better counter undesired uncertainties influencing the system. A case study has been performed on the Dutch built environment sector as a pilot of the Adaptive Robust Design framework. The research starts by identifying the state of the art regarding energy transition models. The study continues with the development of a case-specific system dynamics models, initialized from real-world multi-level data. Subsequently, open exploration and scenario discovery has been performed to assess the systems vulnerability to influential uncertainties. Thereafter, policy variants have been created to test policy options on their robustness under deep uncertainty.

8.2. Answers to Sub Questions

1. What energy transition models are currently available and compose the state of the art?

Chapter 3 has provided a brief introduction of quantitative energy systems modelling in general, the STET taxonomy provided by Li et al. (2015) and Cherp et al. (2018)'s meta theoretical framework of techno-economic, socio-technical and political perspectives on national energy transitions. Moreover, an overview of state-of-the-art energy systems models has been provided in three groups. Namely, Academic STET models (Li et al., 2015), open source energy models (Open Model Initiative, 2018) and Dutch energy models (Netbeheer Nederland, 2019; Donker and Ouboter, 2015).

All models described in the chapter differ significantly on their dimensions, scope, modelling methodology and objectives, etc. While Li et al. (2015) and citeBolwig et al. (2018) both propose clear methodologies for modelling energy systems, standardization of models or convergence of their components still seems distant. On another note, energy system models that allow policy testing seem to be a minority of all models classifying as energy system models. Many energy systems model focus on a specific sector and provide static forward looking perspectives of reality. Furthermore, many modellers still refrain from opening up their work to the public. Even academic and publicly funded agencies keep their models to themselves. The Dutch *Energy Transition Model* is the only open source energy model within the Dutch context. It does not, however, allow for dynamic policy testing and was thus deemed inadequate for this study.

2. How can the energy transition of the Dutch built environment sector be specified in a simulation model?

Chapter 2 provided a description of modifications and additions to an existing *System Dynamics* model have been discussed. Open data on multiple scales has been gathered and prepared to feed into the model.

Main conclusions from this chapter are that the model represents a simplified perspective on household renovations in The Netherlands. Data is available, but does not uniformly represent all scales (neighbourhood - municipality). Data from even lower levels (zipcode 4 areas) has been scaled up to cope with this issue. The model's scope does not include more detail than data currently allows for. So energy efficiency efforts have been completed left out of the model. This immediately poses a limitation to the current model, as policies will naturally also include energy efficiency measures.

3. What uncertainties are most influential in the built environment sector under deep uncertainty?

Outcomes of the modelled built environment system under deep uncertainties have been analyzed to better understand the effects of uncertainties on possible futures of the energy transition in the built environment sector in chapter 5. This has been done by performing an open exploration to understand trends of main KPI's and through scenario discovery to better understand influences of specific uncertainties on certain KPI's. First, open exploration showed possible trends of main KPI's in the model. None of the main outcomes is naturally robust under the uncertainties defined in the experiments. In other words, all cases show a large spread over the KPI's. Second, scenario discovery has been performed to understand the influence of specific uncertainties using the Patient Rule Induction Method (PRIM). In the base case ensemble, a limited number of uncertainties significantly influences the selected KPI's. Significant uncertainties influencing the selected KPI's are listed below.

- **Total CO_2 emission**: average electricity demand growth, p =2.4e-2 and fraction innovation in carbon intensity of power generation (fr innovation CoM), p = 3e-20.
- **Costs**: fr reduction renovation costs (p=3.4e-28) and standard renovation rate (p=3.3e-20).
- **Labour deficiency (renovations to all electric, renovations to district heat)**: standard renovation rate(p=1.8e-31, p=2.3e-20) and fr to district heat wcorp no existing infrastructure (p=1.8e-21, p=4.5e-17)

From to the total CO_2 emission of the built environment sector, main KPI of this base case analysis, it clearly shows that additional policies are needed to secure targets set for 2030 and 2050. Hence, the next chapter will formulate policies to counter the uncertainties discovered in this chapter in an aim to create robust policies for the ambitions in the built environment sector.

4. Which robust policy variations can be discovered for the energy transition of the Dutch built environment sector?

To answer this sub question, the model (chapter 4) and insights from the base case analysis (chapter 5) have been used to create policy variations. The most promising instruments from PBL (2019, p. 67) have been selected and implemented in three different variants compared to a no policy reference. A static policy, a dynamic adaptive policy and a mission oriented R&D policy have been implemented and complemented by four policy levers holding a subsidy percentage of 20, 40, 60 and 80%. Subsequently, the policies have been simulated under deep uncertainty.

When discussing effectiveness of policies, policy targets should be evaluated. As targets are only known for the period up to 2030, a more general target has been maintained for 2050. This general target has been set at 95% reduction and was obtained from the Dutch climate law. Most policies simulated in this study reached 2030 targets after its deadline in 2030.

Results have been evaluated both within policy variants (withing varying subsidy levels) as between policy variants (with a constant subsidy level). The static and mission policy options showed similar trends, but maintained different absolute outcomes. Most notably, the mission policy allows for a higher renovation rate and thus cumulative renovated houses turned out highest for this policy while holding a 80% subsidy level.

The dynamic adaptive policy variant does not perform significantly better than the other two policy variants. Even though annual CO_2 emissions and cumulative renovated houses are higher, uncertainty is not reduced significantly. This shows that subsidy percentage, alone, does not ensure that policy targets for 2050 are reached. None of the policies simulated in this study have been able to reach the 2050 goal and seemed to converge around two to three million renovated homes in the 80% subsidy level. This finding was unexpected and suggests that other variables prevent more renovation to be completed. The renovation rate used in this study is likely an obstacle for ample renovations. The renovation rate used in this study is drawn from the climate agreement and seems to be too small to meet renovation demand within this study. This is demonstrated in the mission policy where an additional increase of the renovation rate by 25% resulted in higher cumulative renovated houses (figure 6.14b).

Table 6.3 shows mean and maximum outcomes per policy and subsidy percentage level. It summarizes policy outcomes shown in the graphs in this chapter. Compared to table 6.1, results from this study indicate higher CO_2 emission reductions and higher subsidy expenditure. It is important, however, to acknowledge the different scope of the studies (12 years for table 6.1 vs 32 years for table 6.3) and the exploratory nature of this study compared to the predictive modelling study of (PBL, 2019).

The model underlying this study has not been validated (see section 7.3.1 for limitations and recommendations). These results therefore need to be interpreted with caution. Moreover, most figures of cumulative renovated houses show an unanticipated trend. The KDE plots of these figures are centered around the extremities of the envelopes shown in each figure. This indicated discrete behaviour in the model. Subsidy cut-off levels are sampled once for the duration of the simulation. Subsequently, once a certain cut-off level is not reached, one does not renovate. This explains the discrete behaviour of the plots.

Finally, an answer to the sub question seems clear at first. The dynamic adaptive policy has shown to be slightly more robust under deep uncertainty in this study. However, this certainty comes at a cost, quite literally. Cumulative subsidies of the dynamic adaptive policy are substantially higher than any other policy variant used in the simulations of this study. Hence, the only correct answer to this sub question depends on a trade off between robustness and policy expenditure (cumulative subsidies in this study). Due to the exploratory nature of this study limits have not been applied to either of these two criteria. Validation for such trade off should be sought in the political arena.

8.3. Answer to Main Question

The main research question entertained in this thesis is answered below.

"How could policies be designed to establish a more robust performance of the climate agreement's built environment sector?"

This study set out to fill the knowledge gap on the effects of robust climate policies in the Dutch energy transition. Policies can be designed in a variety of ways. This study has embraced a quantitative framework that created an energy systems model of the Dutch built environment sector. Predetermined policy instruments have been selected and various policy variants relying on different policy mechanisms have been modeled and used to simulate a thousand possible combinations in which a future could unfold. Results of this analysis have been used to asses the policy variants robustness to future uncertainties.

The way policy instruments are implemented greatly effect their future outcomes and the certainty that these outcomes will (or will not) be achieved. policies that monitor progress such as the dynamic adaptive policy greatly reduce uncertainty and hence increase the likelihood that goals are met.

Ultimately, quantitative modelling provides a means to understand system and policy dynamics under future uncertainties. No energy systems model can, however, be fully exhaustive and externalities such as actor behaviour must be considered. Hence, policies require pre-specified trigger moments to determine next policy actions, or policy mechanisms that dynamically adapt to changing externalities.

8.4. Implications for Policy Making

This project is a first exploratory study of decision making under deep uncertainty for current climate agreement policies to renovate the Dutch built environment sector. This approach provides useful tools to expand our understanding of how uncertainties influence policy performance. The findings reported here shed new light on the importance of adaptability to changing circumstances for policies related to energy transitions.

In relation to current policymaking in The Netherlands, the findings suggest that performance of policies should be monitored and room should be provided within policies to react to changing circumstances. Currently, energy transition policies in the Netherlands are divided in three stages. First, policy ambitions are set in the climate law (Klimaatwet, 2019). Second, policy measures have been proposed in the climate agreement (Klimaatakkoord, 2019). Third, the climate plan obligates the government to formulate a plan to reach ambitions set in the climate law. The first climate plan will be published in 2019, which will be primarily based on the climate agreement. Thereafter, the climate plan will be updated every five years based on new insights (Rijksoverheid, 2019e). In a way, the current organization of energy transition policies thus includes an adaptive component in which policies are evaluated based on new knowledge.

Returning to the scope of the renovation of Dutch households in the built environment sector, many parties will have to be involved to make the mission a success. This study has shown that an increase of renovation capacity is necessary next to creating incentives for households to renovate and realizing a reduction in carbon emission intensity. Innovations in, for example, household isolation and heat generation will also be vital for the national renovation to be a success. This entails the cooperation of many public and private actors. In it's current capacity, once the climate plan is formulated, the policies need to be carried out by a variety of ministries.

To benefit of the adaptive nature of the climate plan, policies should include ample adjustment mechanisms to realize their goals. A collection of responsible actors could hinder rapid decision making on these mechanisms. Perhaps the energy transition would also need innovation institutionally to create a new task force to secure progress on targets. Such an approach, similar to institutionalization of the Dutch delta program, could however be too technocratic for such a large scale *socio-technical* transition. That said, agility is needed for policies to adapt to changing circumstances. This agility is, in turn, vital from all actors involved in the sector.

> *There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns — the ones we don't know we don't know...*
>
> - Donald Rumsfeld

This quote also holds true for policy analysis under deep uncertainty. In any policy analysis, only known unknowns can be used to make quantitative models subject to future uncertainties. It is therefor vital to always to appreciate the limits of quantitative modelling efforts, regardless of their fruits.

9 Reflections

9.1. Societal Relevance

This thesis started out from personal interest and engagement in the Dutch energy transition. In the past two years, and especially over the past six months of this thesis, policies for the Dutch energy transition have become much more tangible. Moreover, (civil) engagement has strongly increased (be it positive or negative).

This thesis has set out to be a first pilot aiming to create a dynamic, multi-level and open source household renovation model to explore possible futures of the Dutch energy transition under deep uncertainty. To achieve this, data has been gathered and handled from multiple public sources to create the first open-source multi-level data set for the Dutch housing sector. Contrary to the main findings in this thesis, the model and its EMA setup can also be used for local policymakers. Moreover, the combination of the low-level model structure, high-resolution data for calibration and ability to select scopes (neighbourhood, district, municipality and country) also allows for local policy makers to put their efforts in to perspective. Naturally, the current setup still has many limitations and data can always better (ie more complete, more accurate, etc.), still this thesis has shown that it is possible to provide policy insights on several levels using the same model structure.

Naturally, others have also seen potential knowledge gaps hindering local policymakers to assess results of their policy plans. Quintel Intelligence, for instance, has recently added a new scope of *Regional Energy Strategies* (a combination of provinces and municipalities), who are burdened with the task of formulation regional strategies that enable the policy ambitions set in the climate agreement.

The resolution of this thesis is far higher than that of regions, but more importantly, the setup allows for dynamic policy testing under deep uncertainty. As this project set out to open-source all code and data, it could offer a backbone for future studies or even implementations of tooling.

At the beginning of this study policy directions were still very unclear, but over the course of the past half year and after very impressive work of many important actors, policies have been created and will most likely be implemented in the not too distant future. Studying current policy developments, as performed in this thesis, has been quite the challenge. Throughout the analysis, previous insights become outdated and obsolete, which required new direction for this course of study. While studying a contemporary challenge does provide many ways to make valuable contributions, it certainly also does have its setbacks. Personally, though, it made all the difference to make a contribution to studies on the energy transition. However, futile it might be.

9.2. Academic Relevance

Academically, this study has made a contribution by applying an existing framework to a new contemporary knowledge gap. Subsequently, The aim of this study was to create an open source work flow from data acquisition and manipulation to modelling and simulation to establish a quantitative framework for exploratory modelling and analysis of energy transition policies under deep uncertainty. A novel way has been created that utilizes existing, decentralized, data sources on multiple geospatial levels to create a single multi-level data set. All scripts and data used for this study have been made open source through github.

9.3. Concluding words

The duality of the sections in this chapters illustrates the challenge this thesis faced throughout the duration of the project. Academic relevance and societal relevance do not necessarily complement each other. On the contrary, they often have different questions that require other answers. For example, national policymakers have charged local policymakers (eg. municipalities or provinces) with the task to make the transition happen. Naturally, local officials require more detailed information than national analysts. Maintaining both perspectives within the scope of a single thesis was quite difficult. Hence, after data acquisition and modelling had been performed on a multi-level scale, the scope was upped to national KPI's for easier interpretation and comparison to other nation-wide studies.

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A

EMA Codes

This chapter provides all codes used in the Exploratory Modelling & Analysis chapters of this study (see chapter 5 and chapter 6). First, codes for base case experiments are shown in section A.1 and the policy experiments in section 6.3. Second, scenario discovery codes are shown in section A.3 for the base case and in section A.4 for the policy case. Third, feature scoring code is presented in section A.5. Finally, thesis utilities specified by the author which are used throughout the scripts mentioned in this chapter are presented in section A.6.

A.1. Experiments Base Case

Experiments Notebook Base Emsenble

@author: Mark Hupkens, 2019

Introduction

This notebook performs experiments on the basemodel without policies, but with defined uncetainties. The outcomes of these simulations are stored and later interpreted in the *Scenario Discovery notebook*.

This notebook relies on a packaged Vensim model (.vpm) to perform parallel simulations of the compiled simulation models. For dependencies of this notebook, please refer to [EMA Workbench documentation].

In [1]:
```
from ema_workbench import(Model, RealParameter,Constant,IntegerParameter,C
ategoricalParameter, TimeSeriesOutcome,
                          Policy, perform_experiments, ema_logging, save_r
esults, load_results)
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.evaluators import LHS, SOBOL
import timeit
from ema_workbench import MultiprocessingEvaluator

ema_logging.log_to_stderr(ema_logging.INFO)
import pysd
import numpy.random
import pandas as pd
numpy.random.seed(123456789)

from ema_workbench.connectors.pysd_connector import PysdModel
```

```
C:\Users\LocalAdmin\Anaconda3\lib\site-packages\ema_workbench\em_framework
\optimization.py:22: ImportWarning: platypus based optimization not availa
ble
  warnings.warn("platypus based optimization not available", ImportWarning
)
C:\Users\LocalAdmin\Anaconda3\lib\site-packages\ema_workbench\connectors\_
_init__.py:18: ImportWarning: netlogo connector not available
  warnings.warn("netlogo connector not available", ImportWarning)
C:\Users\LocalAdmin\Anaconda3\lib\importlib\_bootstrap.py:219: ImportWarni
ng: can't resolve package from __spec__ or __package__, falling back on __
name__ and __path__
  return f(*args, **kwds)
C:\Users\LocalAdmin\Anaconda3\lib\importlib\_bootstrap.py:219: ImportWarni
ng: can't resolve package from __spec__ or __package__, falling back on __
name__ and __path__
  return f(*args, **kwds)
```

Simulation

In [2]:
```
wd =r'./model/20190707 - Policymodels' # this is the directory where the m
odel is located
model = VensimModel('BuiltEnvironmentModel', wd = wd , model_file='2019071
5_Energymodel_Labour_basecase.vpm')
ema_logging.log_to_stderr(ema_logging.INFO)   # we want to see what EMA is
 doing
```

Out[2]:
```
<Logger EMA (DEBUG)>
```

Policies

As this experiments notebook aims to create the base ensemble, no policies switched on.

In [3]:
```
# Select policies

policies = [Policy('None', # turn on all policy switches
                   **{'SWITCH normering nieuwbouw':0,
                      'SWITCH elec efficiency':0,
                      'SWITCH wijkaanpak woningcorp':0,
                      'SWITCH wijkaanpak koop':0,
                     })]
```

Uncertainties

Uncertainties are defined in the cell parametric uncertaint below. Durings the simulations, uncertainties are sampled using Latin Hypercube Sampling (LHS).

In [4]:
```
# Specify uncertainties and aggregated outcomes
# No policycase, so no uncertaint

uncertainties = [RealParameter('groei gem elek gebruik', -0.01, 0.01),
                 RealParameter('groei nieuwbouw',0.0088,0.0097),
                 RealParameter('fr innovation CoM', 0.5,0.9),
                 RealParameter('standard renovation rate', 0.0,0.001),
                 RealParameter('policy time', 2020, 2025),
                 RealParameter('renovation costs label group 1', 8000, 120
00),
                 RealParameter('renovation costs label group 2', 20000, 28
000),
                 RealParameter('renovation costs label group 3', 30000, 36
000),
                 RealParameter('renovation costs label group 4', 30000, 40
000),
                 RealParameter('fr reduction renovation costs',0.5,8),
                 RealParameter('fr to district heat wcorp no existing infr
astructure',0.1, 0.3),
                 RealParameter('fr to district heat wcorp low existing inf
rastructure',0.3, 0.7),
                 RealParameter('fr to district heat wcorp high existing in
frastructure',0.7, 1.0),
                 RealParameter('fr to district heat koop low existing infr
```

```
astructure',0.1, 0.3),
                 RealParameter('fr to district heat koop high existing inf
rastructure',0.3, 0.6),
#                  RealParameter('fr to district heat koop no existing inf
rastructure',0, 0.1) # throws Vensim-EMA error (model | RUN), set uncertai
nty to 0 in model

                ]

outcomes = [TimeSeriesOutcome('total renovated houses'),
            TimeSeriesOutcome('total renovated houses wcorp'),
            TimeSeriesOutcome('total renovated houses koop'),
            TimeSeriesOutcome('total renovated houses verhuur'),
            TimeSeriesOutcome('total subsidy amount'),
            TimeSeriesOutcome('total costs'),
            TimeSeriesOutcome('total CO2 emission'),
            TimeSeriesOutcome('total warmte via elek'),
            TimeSeriesOutcome('total warmtenet'),
            TimeSeriesOutcome('total woningen gas'),
            TimeSeriesOutcome('total houses in model'),
            TimeSeriesOutcome('prijseffect schaarste manuren transitie GAS
nrELEK NL'),
            TimeSeriesOutcome('prijseffect schaarste manuren transitie GAS
nrWN NL'),
            TimeSeriesOutcome('totaal benodigde manuren transitie GebOmg G
ASnrELEK NL corp'),
            TimeSeriesOutcome('totaal benodigde manuren transitie GebOmg G
ASnrWN NL corp'),
            TimeSeriesOutcome('tekort manuren transitie GebOmg GASnrELEK N
L'),
            TimeSeriesOutcome('tekort manuren transitie GebOmg GASnrWN NL'
),
            TimeSeriesOutcome('beschikbare manuren transitie woningen GASn
rWN NL'),
            TimeSeriesOutcome('beschikbare manuren transitie woningen GASn
rELEK NL')
           ]

# Set constants: override some of the defaults of the model
constants = [Constant('baseline CoM reduction',1),
             Constant('CoM elec start', 0.45),
             Constant('CoM gas start', 1.791),
             Constant('CoM heat start', 0.0356)
            ]
```

Start Simulations

In [6]:
```
# Append specified parameters to the model
model.uncertainties = uncertainties
model.outcomes = outcomes
model.constants = constants
nr_scenarios = 1000
```

In [7]:
```
start_time = timeit.default_timer()
```

```
with MultiprocessingEvaluator(model) as evaluator:
    policy_results = evaluator.perform_experiments(scenarios=nr_scenarios,
 policies=policies)

elapsed = timeit.default_timer() - start_time
print("Total time in minutes:", elapsed/60, "-- Time per run in seconds:",
 elapsed/(nr_scenarios*len(policies)))
```

```
[MainProcess/INFO] pool started
[MainProcess/INFO] performing 1000 scenarios * 1 policies * 1 model(s) = 1
000 experiments
[MainProcess/INFO] 100 cases completed
[MainProcess/INFO] 200 cases completed
[MainProcess/INFO] 300 cases completed
[MainProcess/INFO] 400 cases completed
[MainProcess/INFO] 500 cases completed
[MainProcess/INFO] 600 cases completed
[MainProcess/INFO] 700 cases completed
[MainProcess/INFO] 800 cases completed
[MainProcess/INFO] 900 cases completed
[MainProcess/INFO] 1000 cases completed
[MainProcess/INFO] experiments finished
[MainProcess/INFO] terminating pool
[SpawnPoolWorker-4/INFO] finalizing
[SpawnPoolWorker-3/INFO] finalizing
[SpawnPoolWorker-2/INFO] finalizing
[SpawnPoolWorker-1/INFO] finalizing
```

```
Total time in minutes: 268.9098323708046 -- Time per run in seconds: 16.13
4589942248276
```

In [8]:

```
save_results(policy_results, r'C:\Users\LocalAdmin\Desktop\ETModel\results
\20190715_experiments_energymodel_labour_base_ensempble.tar.gz')
```

```
[MainProcess/INFO] results saved successfully to C:\Users\LocalAdmin\Deskt
op\ETModel\results\20190715_experiments_energymodel_labour_base_ensempble.
tar.gz
```

A.2. Experiments Policies

Experiments Notebook Policy Ensemble

@author: Mark Hupkens, 2019

This notebook performs experiments on the basemodel without policies, but with defined uncertainties. The outcomes of these simulations are stored and later interpreted in the *Scenario Discovery notebook*. In this file specific policy variants are benchmarked against the 'no policy' alternative. The policy variants all include set policies (wijkaanpak koop, woningcorp, normering nieuwbouw and efficiency) but vary in delivery mechanism: static, dynamic adaptive or mission oriented

This notebook relies on a packaged Vensim model (.vpm) to perform parallel simulations of the compiled simulation models. For dependencies of this notebook, please refer to [EMA Workbench documentation](#).

In [1]:
```
from ema_workbench import(Model, RealParameter,Constant,IntegerParameter,C
ategoricalParameter, TimeSeriesOutcome,
                          Policy, perform_experiments, ema_logging, save_r
esults, load_results)
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.evaluators import LHS, SOBOL
import timeit
from ema_workbench import MultiprocessingEvaluator

ema_logging.log_to_stderr(ema_logging.INFO)
import pysd
import numpy.random
import pandas as pd
numpy.random.seed(123456789)

from ema_workbench.connectors.pysd_connector import PysdModel
```

```
C:\Users\LocalAdmin\Anaconda3\lib\site-packages\ema_workbench\em_framework
\optimization.py:22: ImportWarning: platypus based optimization not availa
ble
  warnings.warn("platypus based optimization not available", ImportWarning
)
C:\Users\LocalAdmin\Anaconda3\lib\site-packages\ema_workbench\connectors\_
_init__.py:18: ImportWarning: netlogo connector not available
  warnings.warn("netlogo connector not available", ImportWarning)
C:\Users\LocalAdmin\Anaconda3\lib\importlib\_bootstrap.py:219: ImportWarni
ng: can't resolve package from __spec__ or __package__, falling back on __
name__ and __path__
  return f(*args, **kwds)
C:\Users\LocalAdmin\Anaconda3\lib\importlib\_bootstrap.py:219: ImportWarni
ng: can't resolve package from __spec__ or __package__, falling back on __
name__ and __path__
  return f(*args, **kwds)
```

Simulation

In [2]:
```
wd =r'./model/20190707 - Policymodels' # this is the directory where the m
odel is located
model = VensimModel('BuiltEnvironmentModel', wd = wd , model_file='2019070
5_EnergyModel_Labour_Subsidy_StaticPolicy.vpm') # model contains only 1 su
bscript
ema_logging.log_to_stderr(ema_logging.INFO)   # we want to see what EMA is
 doing
```

Out[2]: <Logger EMA (DEBUG)>

Policies

The cell below specify the policies this notebook will use in its simulations. This notebook includes a no-polcu option, identical to the base case notebook, but also includes three policy variants, which are loaded as separate models.

In [3]:
```
# Select policies

policies = [Policy('None', # turn on all policy switches
                   **{'SWITCH normering nieuwbouw':0,
                      'SWITCH elec efficiency':0,
                      'SWITCH wijkaanpak woningcorp':0,
                      'SWITCH wijkaanpak koop':0,
                     }),
            Policy('Static', model_file = '20190705_EnergyModel_Labour_Sub
sidy_StaticPolicy.vpm' ),
            Policy('Dynamic_Adaptive', model_file = '20190705_EnergyModel_
Labour_Subsidy_DynamicAdaptive.vpm'),
            Policy('Mission_R_and_D', model_file = '20190705_EnergyModel_L
abour_Subsidy_MissionRandD.vpm',
                  **{'missie schaalfactor':1.25})]
```

Uncertainties

Uncertainties are defined in the cell parametric uncertaint below. Durings the simulations, uncertainties are sampled using Latin Hypercube Sampling (LHS).

In [4]:
```
# Specify uncertainties and aggregated outcomes

uncertainties = [RealParameter('fr innovation CoM',0.2,0.5),
                 RealParameter('groei nieuwbouw', 0.0088, 0.0097),
                 RealParameter('standard renovation rate', 0.0007,0.00085)
,
                 RealParameter('policy time', 2020, 2025),
                 RealParameter('fr reduction renovation costs', 0.5, 0.8),
                 RealParameter('renovation costs label group 1', 8000, 120
00),
                 RealParameter('renovation costs label group 2', 20000, 28
000),
                 RealParameter('renovation costs label group 3', 30000, 36
```

```
000),
                 RealParameter('renovation costs label group 4', 30000, 40
000),
                 RealParameter('opschalings factor', 1, 1.1),
                 RealParameter('fraction subsidy over costs high income',0
.1,0.3),
                 RealParameter('fraction subsidy over costs upper middle i
ncome',0.3,0.5),
                 RealParameter('fraction subsidy over costs lower middle i
ncome',0.6,0.8),
                 RealParameter('fraction subsidy over costs low income',0.
8,1),
                 RealParameter('subsidy',5000,40000),
                 RealParameter('groei gem elek gebruik',-0.01,0.01)],

outcomes = [TimeSeriesOutcome('total renovated houses'),
            TimeSeriesOutcome('total renovated houses wcorp'),
            TimeSeriesOutcome('total renovated houses koop'),
            TimeSeriesOutcome('total renovated houses verhuur'),
            TimeSeriesOutcome('total subsidy amount'),
            TimeSeriesOutcome('total costs'),
            TimeSeriesOutcome('total CO2 emission'),
            TimeSeriesOutcome('total warmte via elek'),
            TimeSeriesOutcome('total warmtenet'),
            TimeSeriesOutcome('total woningen gas'),
            TimeSeriesOutcome('total houses in model'),
            TimeSeriesOutcome('prijseffect schaarste manuren transitie GAS
nrELEK NL'),
            TimeSeriesOutcome('prijseffect schaarste manuren transitie GAS
nrWN NL'),
            TimeSeriesOutcome('totaal benodigde manuren transitie GebOmg G
ASnrELEK NL corp'),
            TimeSeriesOutcome('totaal benodigde manuren transitie GebOmg G
ASnrWN NL corp'),
            TimeSeriesOutcome('tekort manuren transitie GebOmg GASnrELEK N
L'),
            TimeSeriesOutcome('tekort manuren transitie GebOmg GASnrWN NL'
),
            TimeSeriesOutcome('beschikbare manuren transitie woningen GASn
rWN NL'),
            TimeSeriesOutcome('beschikbare manuren transitie woningen GASn
rELEK NL')
           ]

# ADD:
# Set constants: override some of the defaults of the model
constants = [Constant('baseline CoM reduction',1),
             Constant('CoM elec start', 0.45),
             Constant('CoM gas start', 1.791),
             Constant('CoM heat start', 0.0356)
            ]
```

Start Simulations

In [5]:
```
model.uncertainties = uncertainties
```

```
model.outcomes = outcomes
model.constants = constants
nr_scenarios = 250
```

In [6]:
```
start_time = timeit.default_timer()

with MultiprocessingEvaluator(model) as evaluator:
    policy_results = evaluator.perform_experiments(scenarios=nr_scenarios,
 policies=policies)

elapsed = timeit.default_timer() - start_time
print("Total time in minutes:", elapsed/60, "-- Time per run in seconds:",
 elapsed/(nr_scenarios*len(policies)))
```

```
[MainProcess/INFO] pool started
[MainProcess/INFO] performing 250 scenarios * 4 policies * 1 model(s) = 10
00 experiments
[MainProcess/INFO] 100 cases completed
[MainProcess/INFO] 200 cases completed
[MainProcess/INFO] 300 cases completed
[MainProcess/INFO] 400 cases completed
[MainProcess/INFO] 500 cases completed
[MainProcess/INFO] 600 cases completed
[MainProcess/INFO] 700 cases completed
[MainProcess/INFO] 800 cases completed
[MainProcess/INFO] 900 cases completed
[MainProcess/INFO] 1000 cases completed
[MainProcess/INFO] experiments finished
[MainProcess/INFO] terminating pool
[SpawnPoolWorker-3/INFO] finalizing
[SpawnPoolWorker-1/INFO] finalizing
[SpawnPoolWorker-4/INFO] finalizing
[SpawnPoolWorker-2/INFO] finalizing
```

```
Total time in minutes: 518.397588466936 -- Time per run in seconds: 31.103
855308016158
```

In [7]:
```
save_results(policy_results, r'C:\Users\LocalAdmin\Desktop\ETModel\results
\20190708_test_experiments_policies.tar.gz')
```

```
[MainProcess/INFO] results saved successfully to C:\Users\LocalAdmin\Deskt
op\ETModel\results\20190708_test_experiments_policies.tar.gz
```

A.3. Scenario Discovery Base Case

Scenario Discovery Basecase

@author: Mark Hupkens, 2019

This notebook explores outcomes of the base case experiments using open exploration. Sensitvity of the model is analyzed in the *Feature scoring* notebook.

For dependencies of this notebook, please refer to [EMA Workbench documentation].

Importing the necessary Python modules

In [1]:
```
import thesis_utils as tu # specified own utilities package to make thesis
 life easier (thesis.utils.py)
import time

import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import scipy as sp
# import mpld3

from ema_workbench.analysis.plotting import lines
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis import prim
from ema_workbench.util import ema_logging
ema_logging.log_to_stderr(ema_logging.INFO)
from ema_workbench.util import load_results
from ema_workbench.analysis.plotting import lines, plot_lines_with_envelop
es, envelopes

# %matplotlib inline
%config InlineBackend.figure_format = 'retina'
```

```
C:\Users\LocalAdmin\Anaconda3\lib\site-packages\ema_workbench\em_framework
\optimization.py:22: ImportWarning: platypus based optimization not availa
ble
  warnings.warn("platypus based optimization not available", ImportWarning
)
```

1. Loading the data

This basecase analysis relies on experiments performd in the notebook '20190715 - Experiments Basemodel-V6 - extra uncertainty district heating.ipynb'. 1000 experiments have been simulated without any policies, but with defined uncertainties.

- See notebook '20190715 - Experiments Basemodel-V6 - extra uncertainty district heating.ipynb' for experimental design
- See Vensim model '20190715_Energymodel_Labour_basecase.mdl' for the model structure.

In [60]:
```
# Select run
fn = 'results/20190715_experiments_energymodel_labour_base_ensempble.tar.g
z'
results = load_results(fn)
experiments, outcomes = results
```

```
[MainProcess/INFO] results loaded succesfully from C:\Users\LocalAdmin\Des
ktop\ETModel\results\20190715_experiments_energymodel_labour_base_ensempbl
e.tar.gz
```

Open Exploration

First, the general trends of the experiments under uncertainty are visualized using national KPI's. Second, Kernel Densitity Estimation graphs are used to display the distrubition of cases over the KPI (the y-axis).

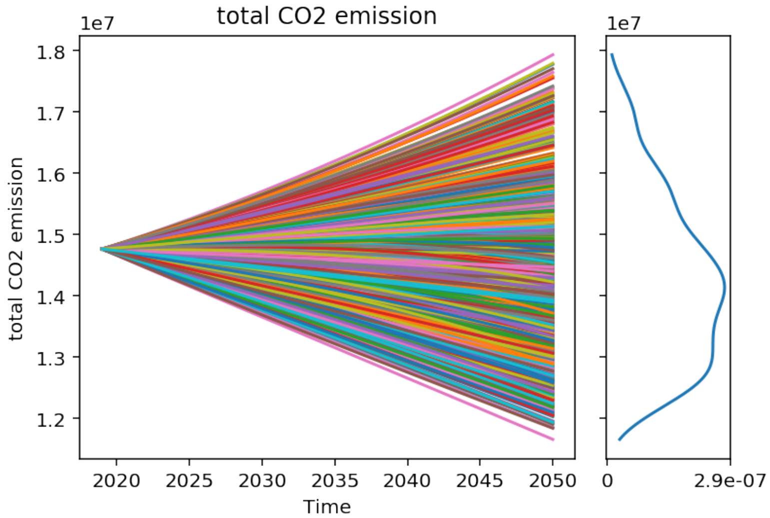
Plotting kernel density estimations graphs of aggregated results

KPI's in basecase analysis:

1. Total CO2-eq emission [Ton CO2]
2. Total costs [euro]
3. Total renovated houses [# houses]
4. Labour deficiency (all-electric, district heating) [hours]

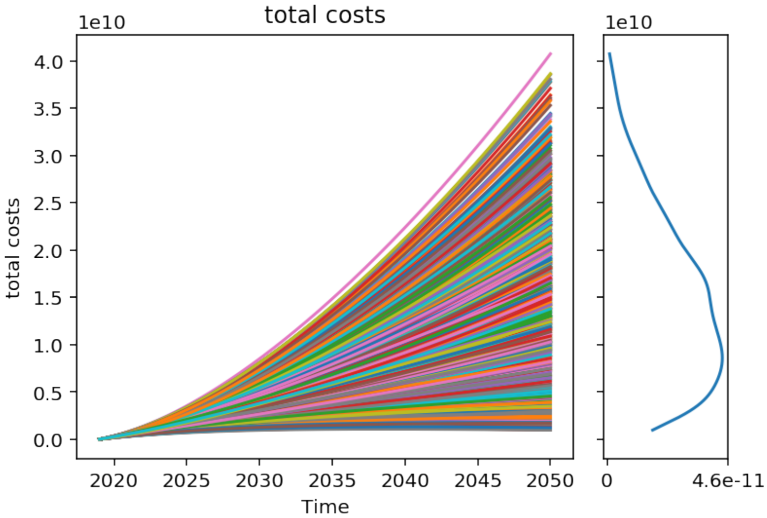
Total CO2-eq emission

In [61]:
```
fig, axes = lines(results, density=u'kde', show_envelope=False, outcomes_t
o_show='total CO2 emission')
plt.savefig('C:/Users/LocalAdmin/Desktop/ETModel/plots/scenario_basecase/'
+time.strftime('%Y%m%d')+'total_co2.png',dpi=300,)
plt.show()
```



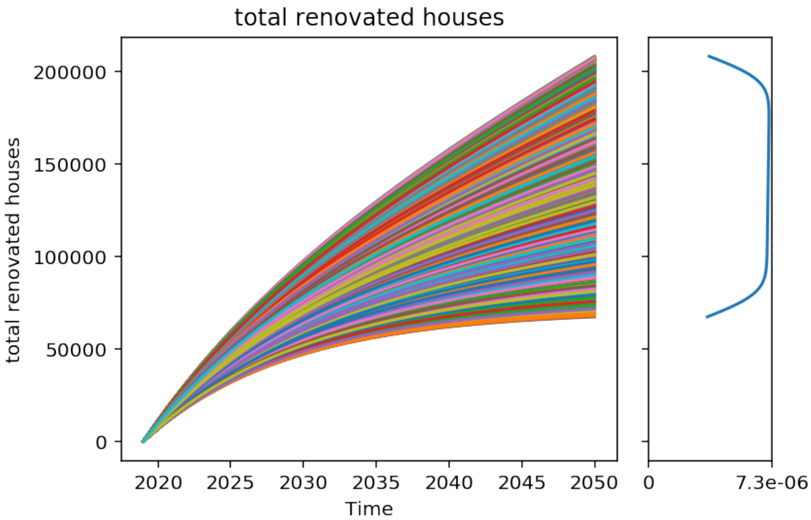
2. Total costs

In [63]:
```
fig, axes = lines(results, density=u'kde', show_envelope=False, outcomes_t
o_show='total costs')
plt.savefig('C:/Users/LocalAdmin/Desktop/ETModel/plots/scenario_basecase/'
+time.strftime('%Y%m%d')+'total_costs.png',dpi=300)
plt.show()
```



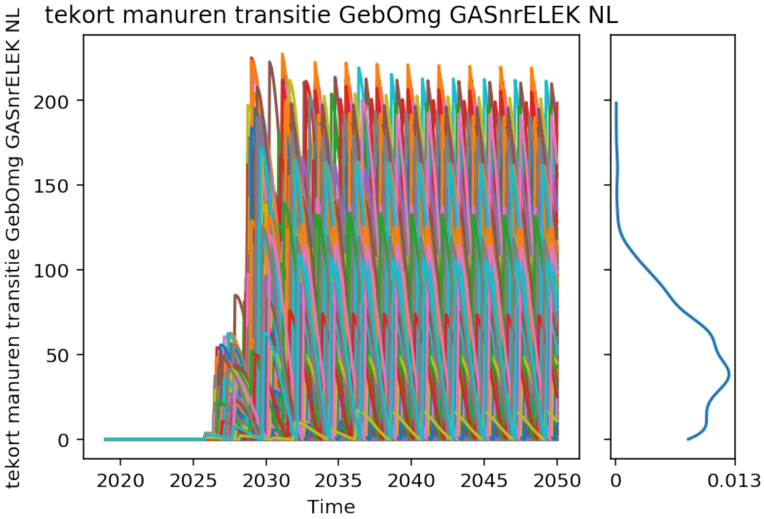
3. Total Renovated houses

In [64]:
```
fig, axes = lines(results, density=u'kde', show_envelope=False, outcomes_t
o_show='total renovated houses')
plt.savefig('C:/Users/LocalAdmin/Desktop/ETModel/plots/scenario_basecase/'
+time.strftime('%Y%m%d')+'total_renovated_houses.png',dpi=300)
plt.show()
```



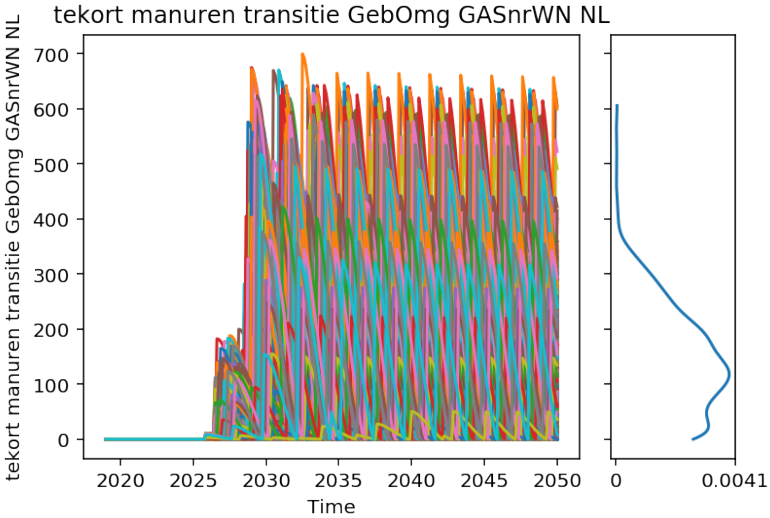
4.A Labour deficiency (all-electric) [hours]

In [65]:
```
fig, axes = lines(results, density=u'kde', show_envelope=False, outcomes_t
o_show='tekort manuren transitie GebOmg GASnrELEK NL')
plt.savefig('C:/Users/LocalAdmin/Desktop/ETModel/plots/scenario_basecase/'
+time.strftime('%Y%m%d')+'tekort_manuren_elek.png',dpi=300)
plt.show()
```



4.B Labour deficiency (district heating) [hours]

In [66]:
```
fig, axes = lines(results, density=u'kde', show_envelope=False, outcomes_t
o_show='tekort manuren transitie GebOmg GASnrWN NL')
plt.savefig('C:/Users/LocalAdmin/Desktop/ETModel/plots/scenario_basecase/'
+time.strftime('%Y%m%d')+'tekort_manuren_warmtenet.png',dpi=300)
plt.show()
```



Scenario Discovery

Scenario Discovery (Kwakkel, 2015) will be employed by performing PRIM on the main KPI's and their worst case scenarios.

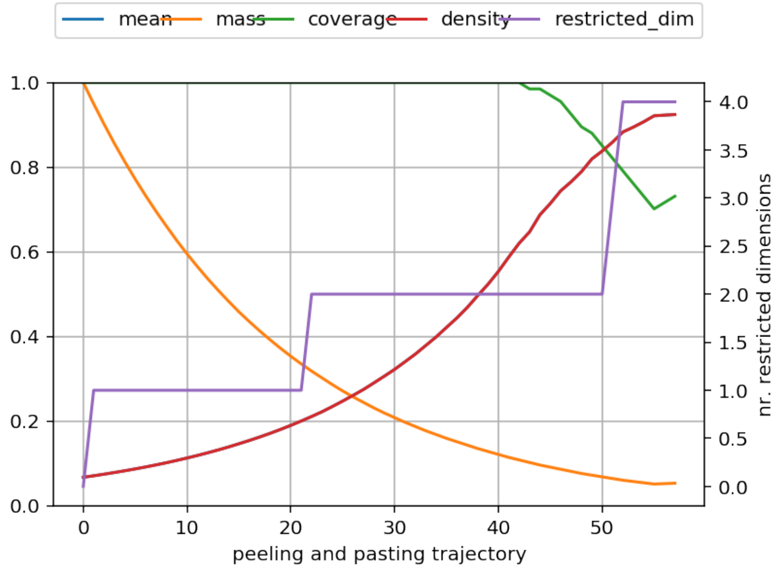
PRIM total CO2

In [67]:
```
def classify(data):
    i = 'total CO2 emission' # unit in ton
    outcome = np.max(outcomes[i], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome> (.92 * outcomes['total CO2 emission'].max())] = 1 #E^
6 Megaton
    return classes

prim_obj = prim.setup_prim(results, classify, threshold=0.8)
box_1 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 67 cases of interest
[MainProcess/INFO] mean: 0.9245283018867925, mass: 0.053, coverage: 0.7313
432835820896, density: 0.9245283018867925 restricted_dimensions: 4
```

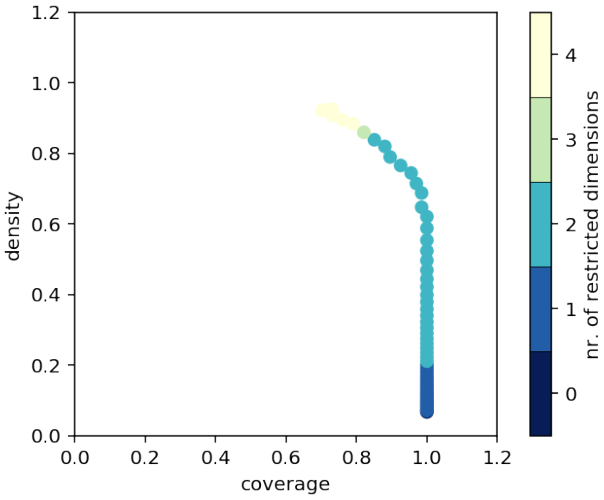
Multiple dimensions have been restricted in the peeling process. The final box contains 67 cases of interests after reaching a density of 0.92 (cases of interest in the box) and a coverage of 0.73 (cases included in the box of all cases in experiments)

In [68]:
```
# % matplotlib notebook

box_1.show_ppt()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_showp
pt_box_1.png', dpi=300,bbox_inches = "tight")
plt.show()
```



multiple dimensions have been restricted in 50 iterations shown below:

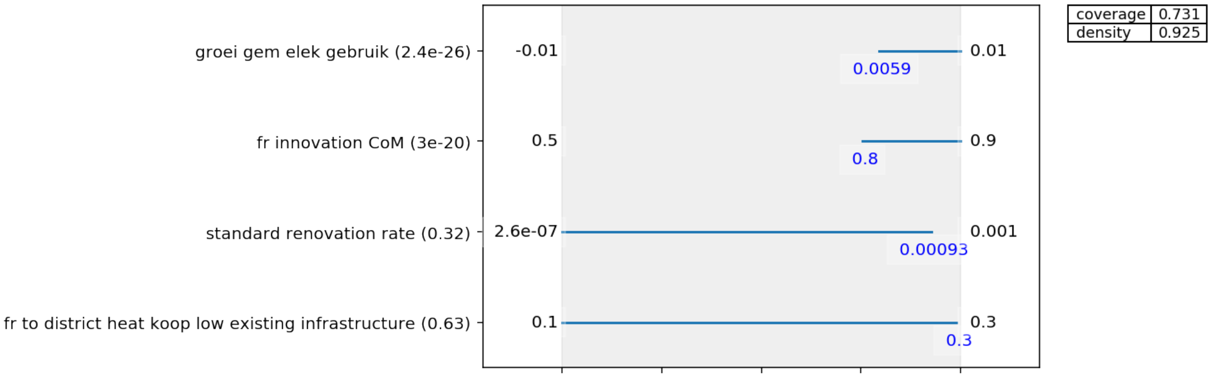
In [69]:
```
box_1.show_tradeoff()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_trade
off_box_1.png', dpi=300,bbox_inches = "tight")
plt.show()
```



As the PRIM algorithm restricts more and more dimensions, it *peels* layers of uncertainties in the subspace. Hence, we want to look at boxes at the top left of the density/coverage curve. At the highest density, the following uncertainties are most influential:

In [70]:
```
box_1.inspect()
box_1.inspect(style='graph')
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_graph
_box_1.png', dpi=300,bbox_inches = "tight")
plt.show()
```

```
coverage    0.731343
density     0.924528
mass           0.053
mean        0.924528
res dim            4
Name: 57, dtype: object

                                                        box 57
  \
                                                           min       max

groei gem elek gebruik                            5.918055e-03  0.009991

fr innovation CoM                                 8.016297e-01  0.899977

standard renovation rate                          2.620310e-07  0.000927

fr to district heat koop low existing infrastru...  1.000408e-01  0.298160



                                                     qp values
groei gem elek gebruik                            2.378311e-26
fr innovation CoM                                 3.026049e-20
standard renovation rate                          3.162436e-01
fr to district heat koop low existing infrastru...  6.289372e-01
```



Conclusion PRIM Total CO2

Of the 4 uncertainties portrayed in the graphs only the first two statistically significant (p<0.05), namely:

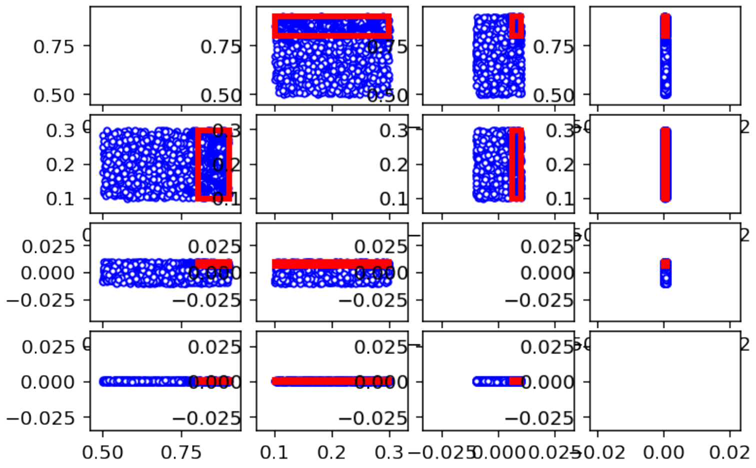
- average electricity demand growth (groei gem elek gebruik): p =2.4e-26
- fraction innovation in carbon intensity of power generation (fr innovation CoM): p = 3e-20

These two significant uncertainties make sense, because the electricity growth rate directly influences total energy consumed (and thus the total CO2 emitted). Second, the innovation in carbon intensity of power generation, too, directly influences total CO2 output as it describes the innovation of carbon reduction in the power sector.

The standard renovation rate and the fraction of privately owned homes that will switch to district heatingin the case of limited capacity also come up as important, but not as significant. They do, however, deserve some more attention. The standard renovation rate, as follows from the current climate agreement provides a baseline renovation rate without any additional policies. Its very intersting that this standard renovation rate does not show up as significant in the model. Rather, average electricity growth an innovation in carbon intensity of power generation are more significant. Looking at these results from a systemic perspective, this is an interesting finding, but reductions have to be made over all sectors to reach targets.

As most houses fall in the category 'district heat no existing infrastructure', second 'district heat low existing infrastructure' and least in 'district heat high existing infrastructure' it makes sense that the low variant for privately owned homes pops up in this PRIM analysis. It is the first of these three groups (no, low, high existing infrastructure) that has an impact carbon reduction (as acquisition of new district heat sources is scoped out of this study), and more houses belong to this group rather than the group of high existing infrastructure.

In [34]:
```
# box_1.select(21)
fig = box_1.show_pairs_scatter()
plt.show()
```



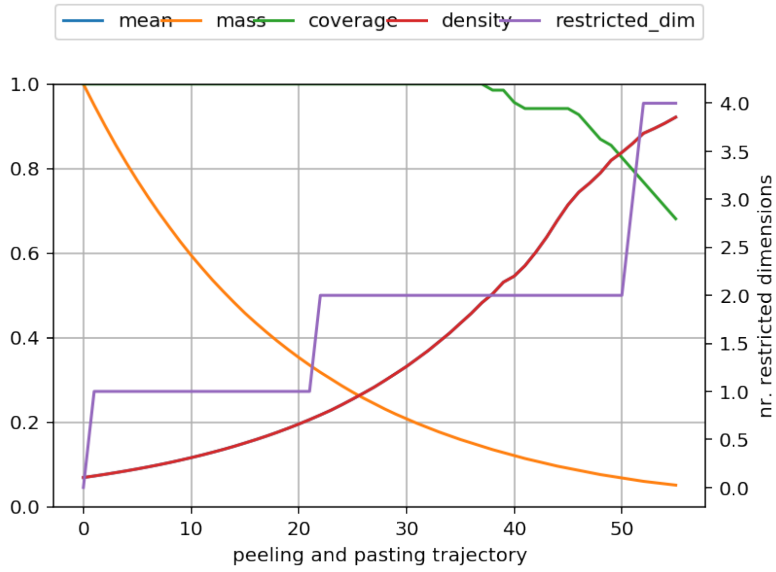
small boxes

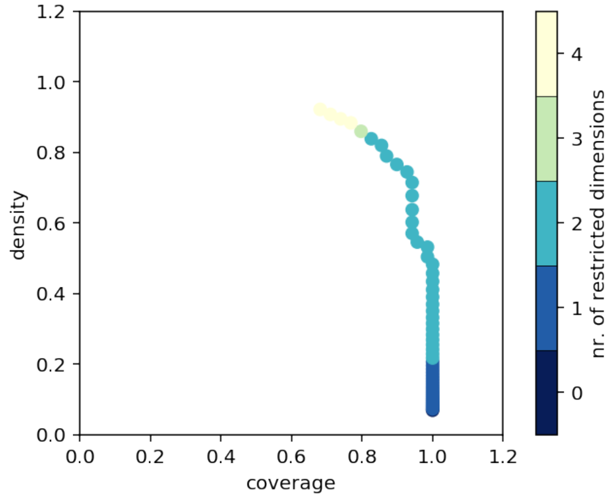
PRIM Total costs

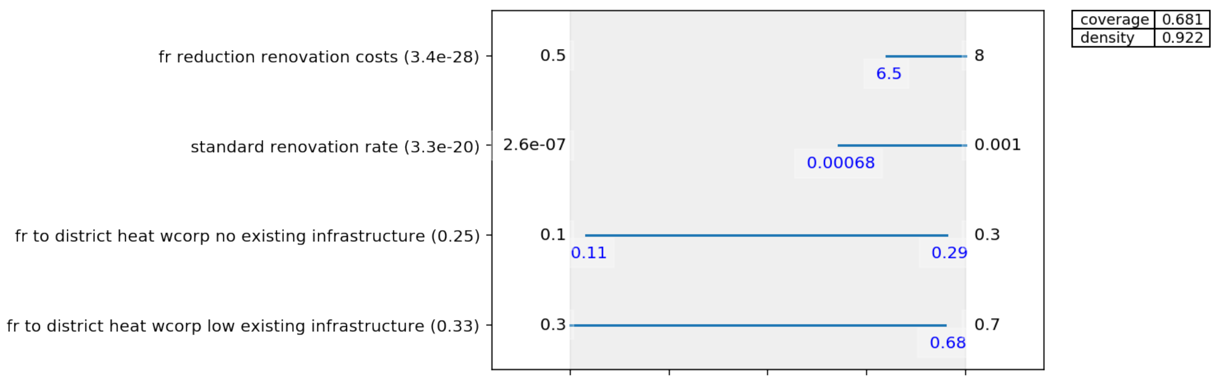
In [71]:
```
def classify(data):
    i = 'total costs'
    outcome = np.max(outcomes[i], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome> (.70 * outcomes[i].max())] = 1
    return classes

prim_obj = prim.setup_prim(results, classify, threshold=0.8)
box_2 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 69 cases of interest
[MainProcess/INFO] mean: 0.9215686274509803, mass: 0.051, coverage: 0.6811
594202898551, density: 0.9215686274509803 restricted_dimensions: 4
```

In [72]:
```
# make plots
box_2.show_ppt()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_showp
pt_box_2_costs(koop).png', dpi=300,bbox_inches = "tight")

box_2.show_tradeoff()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_trade
off_box_2_costs(koop).png', dpi=300,bbox_inches = "tight")

box_2.inspect(style='graph')
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_graph
_box_2_costs(koop).png', dpi=300,bbox_inches = "tight")

plt.show()
```







Conclusion PRIM Total costs

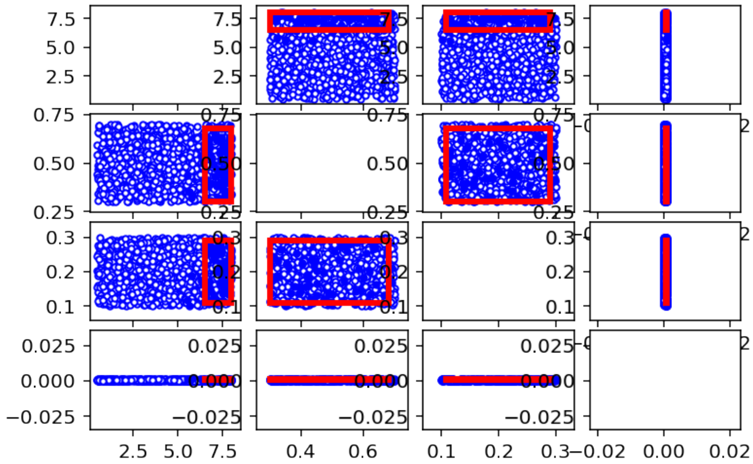
Of the 4 uncertainties portrayed in the graphs only the first two statistically significant (p<0.05) within the most dense box (coverage = 0.68, density = 0.92), namely:

- fr reduction renovation costs (p=3.4e-28)
- standard renovation rate (p=3.3e-20)

It appears obvious that the two uncertainties mentioned above are significant in their contribution to total costs. The first uncertainty directly influences individual renovation costs. The second uncertainty defines the number of houses to be renovated in case of no additional policy.

The two final two uncertainties, fr to district heat wcorp no existing infrastructure and fr to district heat wcorp low existing infrastructure, are do spike interest. Building corporations are less dependent on merely financial incentives due to their societal goals. Moreover, most corporation owned homes are in neighbourhoods with no or low existing district heating capacity. Hence, the higher the propensity of these groups is to renovate, the larger their effect on total costs.

In [45]:
```
box_2.show_pairs_scatter()
plt.show()
```



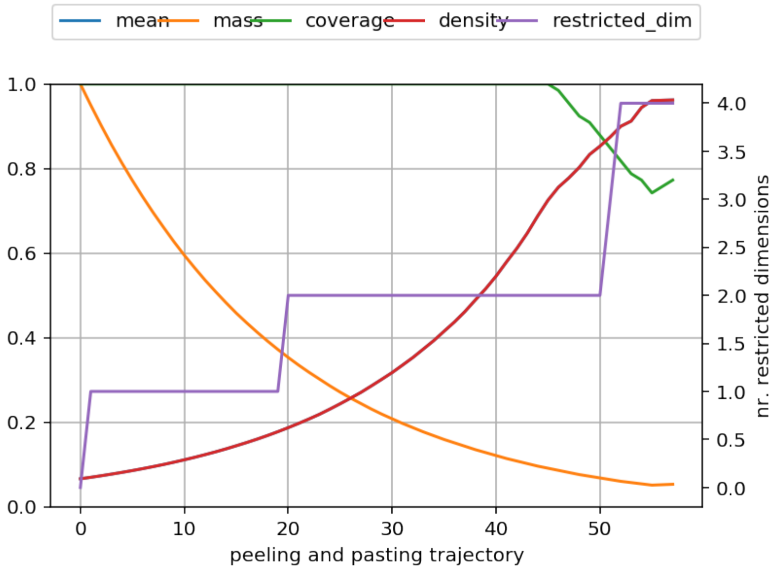
Manhours Electricity

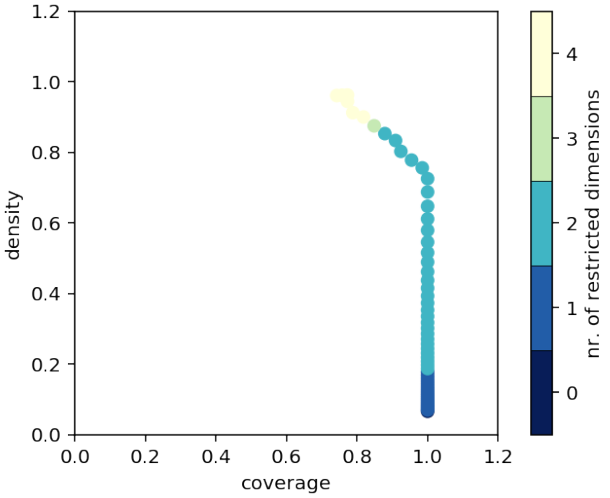
In [81]:
```
i= 'tekort manuren transitie GebOmg GASnrELEK NL'
def classify(data):
    i = 'tekort manuren transitie GebOmg GASnrELEK NL'
    outcome = np.max(outcomes[i], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome> (.75 * outcomes[i].max())] = 1
    return classes

prim_obj = prim.setup_prim(results, classify, threshold=0.8)
box_3 = prim_obj.find_box()
```

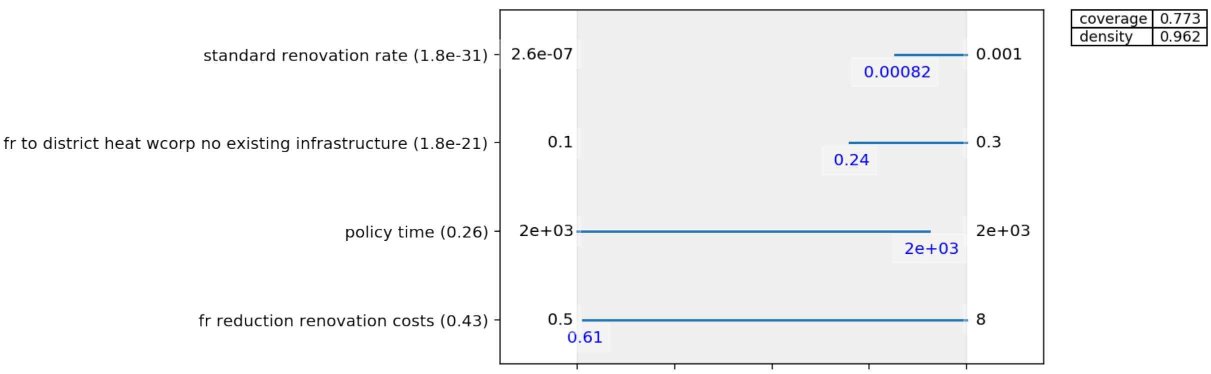
```
[MainProcess/INFO] 1000 points remaining, containing 66 cases of interest
[MainProcess/INFO] mean: 0.9622641509433962, mass: 0.053, coverage: 0.7727
272727272727, density: 0.9622641509433962 restricted_dimensions: 4
```

In [82]:
```
# make plots

box_3.show_ppt()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_showp
pt_box_3_'+i+'.png', dpi=300,bbox_inches = "tight")

box_3.show_tradeoff()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_trade
```

```
off_box_3_'+i+'.png', dpi=300,bbox_inches = "tight")

box_3.inspect(style='graph')
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_graph
_box_3_'+i+'.png', dpi=300,bbox_inches = "tight")

plt.show()
```







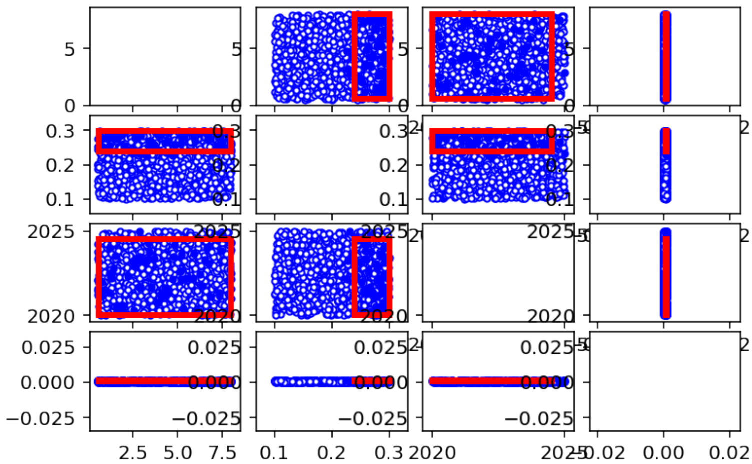
Conclusion PRIM labour deficiency electricity

The PRIM analysis shows two out of four significant uncertainties in the most dense box. Namely,

- Standard renovation rate (p=1.8e-31)
- fr to district heat wcorp no existing infrastructure (p=1.8e-21)

In the case of no policy, relatively few homes will be renovated and all of these will be explained by the standard renovation rate, which explains the first significant uncertainty. The second significant uncertainty might seem peculiar at first sight, as this PRIM analysis focuses on labour deficiency for renovations to all-electric housing. The model, however, is limited to three heating generation types (gas, district heating or all-electric). Hence, if a house is renovated it is either connected to district heating or made all-electric. In the case that current district heating capacity is too little, the house has to be made all-electric. This explains the importance of the renovation to district heating if there is no exsiting infrastructure.

In [54]:
```
box_3.show_pairs_scatter()
plt.show()
```



small boxes

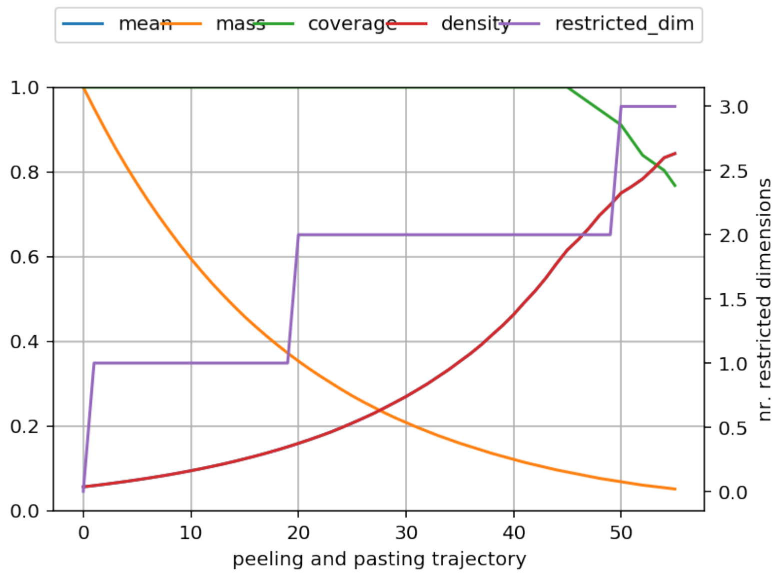
Labour deficiency District heating

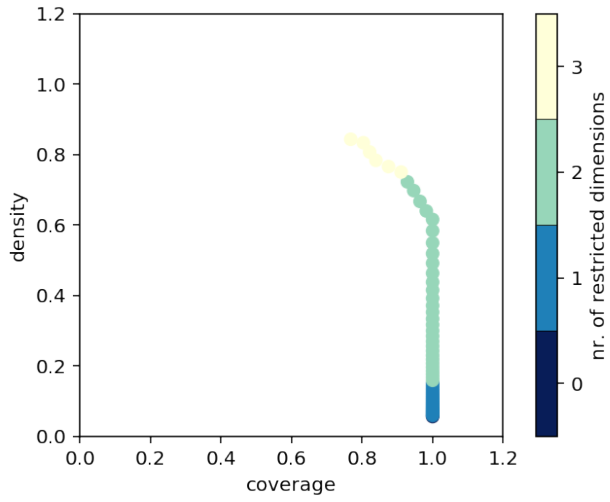
In [83]:
```
i= 'tekort manuren transitie GebOmg GASnrWN NL'
def classify(data):
    i = 'tekort manuren transitie GebOmg GASnrWN NL'
    outcome = np.max(outcomes[i], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome> (.75 * outcomes[i].max())] = 1
    return classes

prim_obj = prim.setup_prim(results, classify, threshold=0.8)
box_4 = prim_obj.find_box()
```

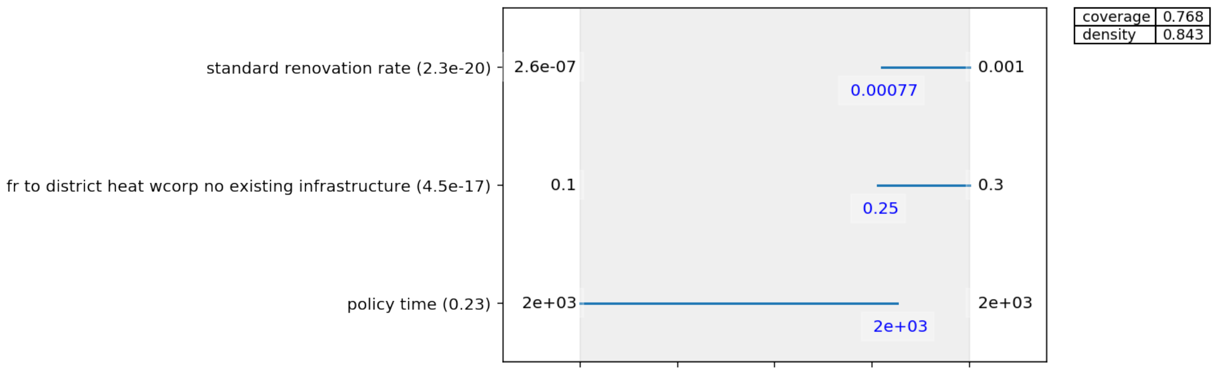
```
[MainProcess/INFO] 1000 points remaining, containing 56 cases of interest
[MainProcess/INFO] mean: 0.8431372549019608, mass: 0.051, coverage: 0.7678571428571429, density: 0.8431372549019608 restricted_dimensions: 3
```

In [85]:
```
# make plots
```

```
box_4.show_ppt()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_showppt_box_4_'+i+'.png', dpi=300,bbox_inches = "tight")

box_4.show_tradeoff()
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_tradeoff_box_4_'+i+'.png', dpi=300,bbox_inches = "tight")

box_4.inspect(style='graph')
plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_graph_box_4_'+i+'.png', dpi=300,bbox_inches = "tight")

# save figures

plt.show()
```







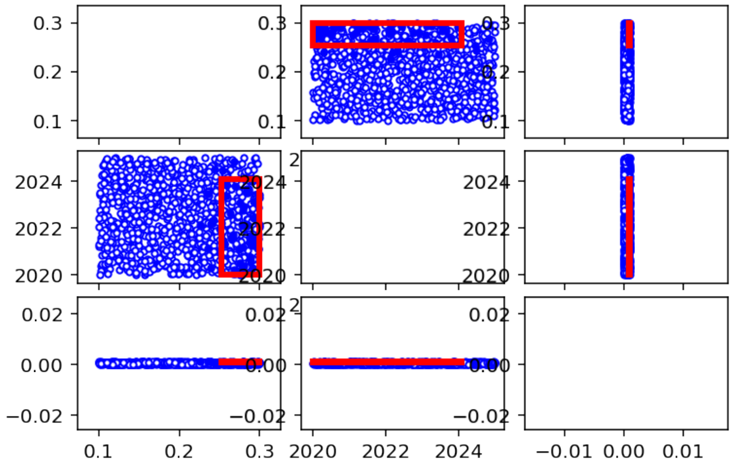
Conclusion PRIM labour deficiency district heating

The PRIM analysis shows two out of three significant uncertainties in the most dense box. Namely,

- Standard renovation rate (p=2.3e-20)
- fr to district heat wcorp no existing infrastructure (p=4.5e-17)

In the case of no policy, relatively few homes will be renovated and all of these will be explained by the standard renovation rate, which explains the first significant uncertainty. The second significant uncertainty might seem peculiar at first sight, as this PRIM analysis focuses on labour deficiency for renovations to all-electric housing. The model, however, is limited to three heating generation types (gas, district heating or all-electric). Hence, if a house is renovated it is either connected to district heating or made all-electric. In the case that current district heating capacity is too little, the house has to be made all-electric. This explains the importance of the renovation to district heating if there is no exsiting infrastructure.

In [59]:
```
box_4.show_pairs_scatter()
plt.show()
```



PRIM total renovated houses

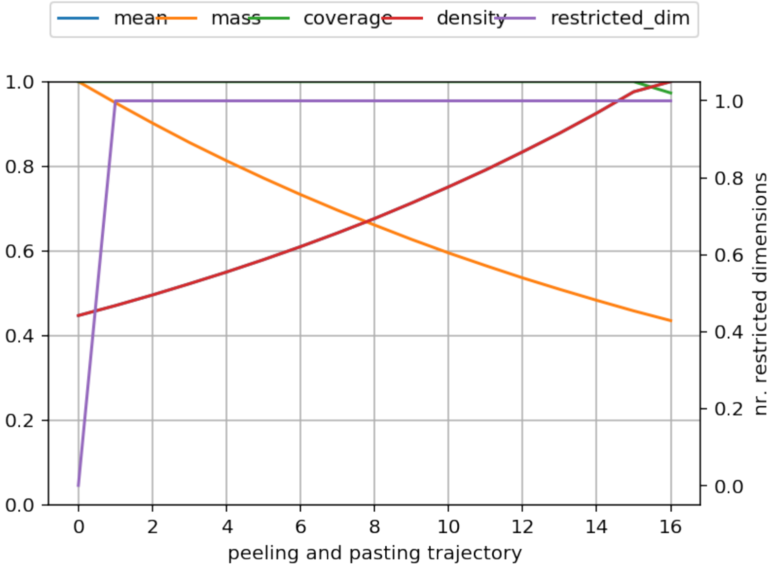
In [80]:
```
def classify(data):
    i = 'total renovated houses'
    outcome = np.max(outcomes[i], axis=1)
```

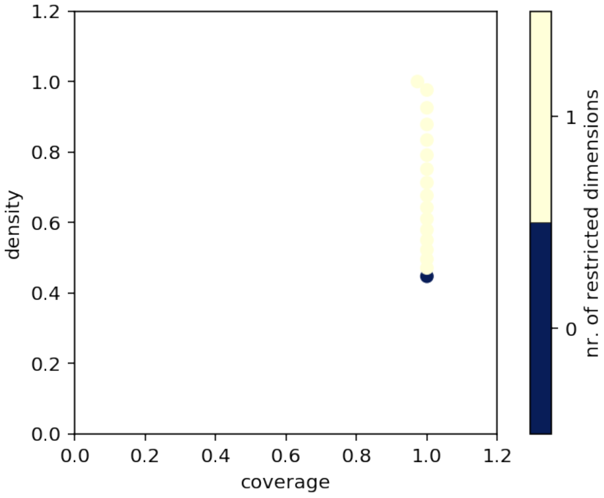
```
    classes = np.zeros(outcome.shape[0])
    classes[outcome> (.95 * outcomes[i].max())] = 1
    return classes

prim_obj = prim.setup_prim(results, classify, threshold=0.8)
box_5 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 75 cases of interest
[MainProcess/INFO] mean: 1.0, mass: 0.072, coverage: 0.96, density: 1.0 re
stricted_dimensions: 1
```

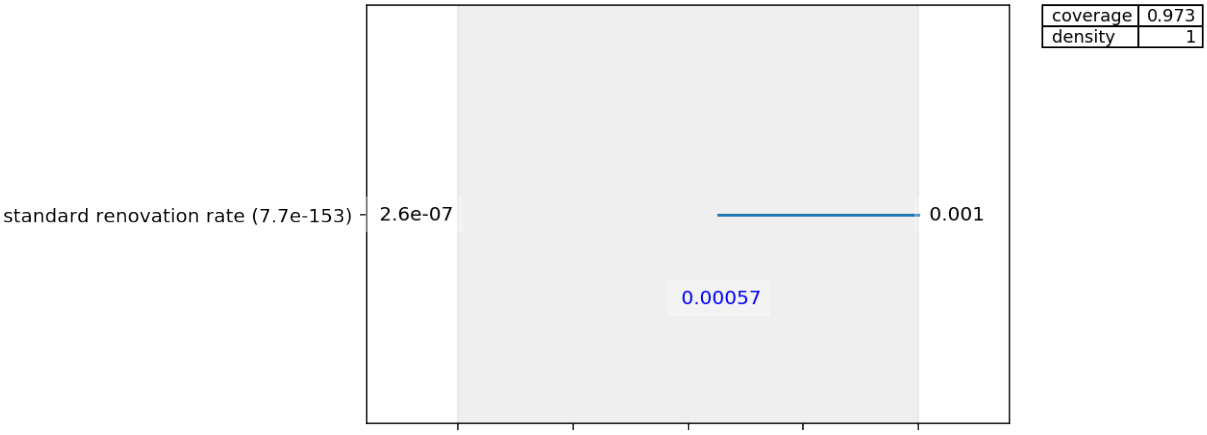
In [78]:

```
# make plots

box_5.show_ppt()
# plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_sho
wppt_box_4_'+i+'.png', dpi=300,bbox_inches = "tight")

box_5.show_tradeoff()
# plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_tra
deoff_box_4_'+i+'.png', dpi=300,bbox_inches = "tight")

box_5.inspect(style='graph')
# plt.savefig('plots/scenario_basecase/'+time.strftime('%Y%m%d')+'PRIM_gra
ph_box_4_'+i+'.png', dpi=300,bbox_inches = "tight")

# save figures

plt.show()
```





density
coverage
nr. of restricted dimensions



standard renovation rate (7.7e-153)
2.6e-07
0.001
0.00057
coverage 0.973
density 1

A.4. Scenario Discovery Policies

Scenario Discovery Policies

@author: Mark Hupkens, Date: 29 July 2019

This notebook contains results from the policy experimentation with new subsidy logic. Subsidies have been modelled to be awarded as a percentage of neighbourhood-dependent renovation costs.

Importing the necessary Python modules

In [1]:
```
import thesis_utils as tu # specified own utilities package to make thesis life easier (thesis.uti
ls.py)
import time

import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import scipy as sp
# import mpld3

from ema_workbench.analysis.plotting import lines
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis import prim
from ema_workbench.util import ema_logging
ema_logging.log_to_stderr(ema_logging.INFO)
from ema_workbench.util import load_results
from ema_workbench.analysis.plotting import lines, plot_lines_with_envelopes, envelopes

# %matplotlib inline
%config InlineBackend.figure_format = 'retina'
```

```
C:\Users\LocalAdmin\Anaconda3\lib\site-packages\ema_workbench\em_framework\optimization.py:22: Imp
ortWarning: platypus based optimization not available
  warnings.warn("platypus based optimization not available", ImportWarning)
```

Load data

In [2]:
```
# Select run

fn = 'results/20190726_experiments_policies_v2_100.tar.gz'

results = load_results(fn)
experiments, outcomes = results
```

```
[MainProcess/INFO] results loaded succesfully from C:\Users\LocalAdmin\Desktop\ETModel\results\201
90726_experiments_policies_v2_100.tar.gz
```

In [3]:
```
# divide outcomes by e6 to show outcomes in billion euros
outcomes['total cumulative subsidies awarded'] = outcomes['total cumulative subsidies awarded']  /
1e9

# divide outcomes by e6 to show outcomes in millions of renovated houses
outcomes['total renovated houses'] = outcomes['total renovated houses']  / 1e6

results = experiments, outcomes
```

In [4]:
```
# Create shorter policy names for better visualizations

for n, i in enumerate(experiments['policy']):
    if 'Dynamic' in i:
        if '20' in i:
            experiments['policy'][n] = 'Dynamic_20'
        elif '40' in i:
            experiments['policy'][n] = 'Dynamic_40'
        elif '60' in i:
            experiments['policy'][n] = 'Dynamic_60'
        elif '80' in i:
            experiments['policy'][n] = 'Dynamic_80'
    elif 'Mission' in i:
        if '20' in i:
            experiments['policy'][n] = 'Mission_20'
        elif '40' in i:
            experiments['policy'][n] = 'Mission_40'
        elif '60' in i:
            experiments['policy'][n] = 'Mission_60'
        elif '80' in i:
            experiments['policy'][n] = 'Mission_80'
```

In [5]:
```
len(np.unique(experiments['policy']))
```

Out[5]:
```
13
```

Extract policies used in experiments

In [6]:
```
policies = list(tu.return_experimented_policies(experiments=experiments))
policies
```

Out[6]:
```
['Static_40',
 'Dynamic_80',
 'Static_80',
 'None',
 'Mission_60',
 'Mission_20',
 'Dynamic_40',
 'Static_60',
 'Dynamic_60',
 'Dynamic_20',
 'Mission_80',
 'Static_20',
 'Mission_40']
```

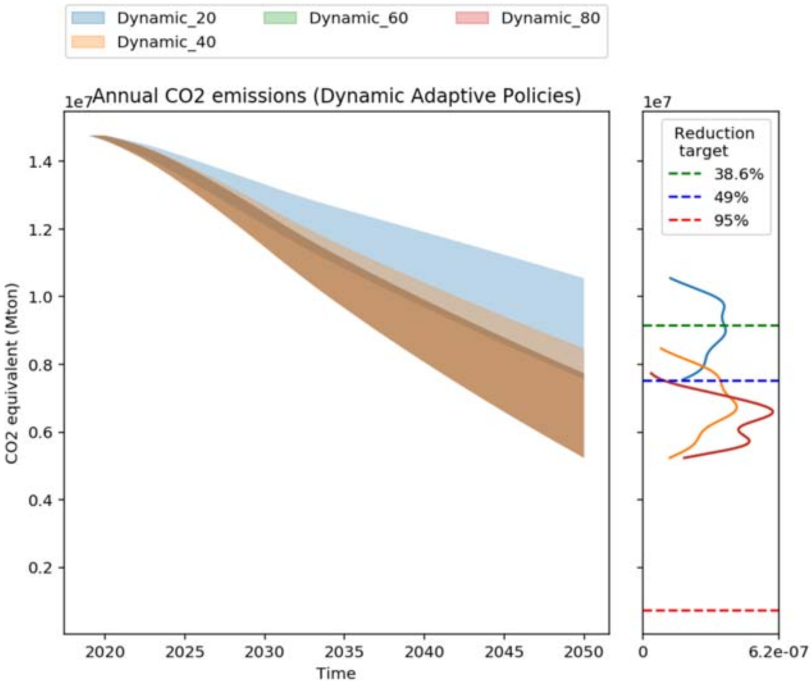
Create subsets of policy combinations

In [7]:
```
# create subsets of policy combinations

pol_20 = []
pol_40 = []
pol_60 = []
pol_80 = []
pol_dynamic = []
pol_static = []
pol_mission = []

for i in policies:
    if '20' in i:
        pol_20.append(i)
    elif '40' in i:
        pol_40.append(i)
    elif '60' in i:
        pol_60.append(i)
    elif '80' in i:
        pol_80.append(i)

for i in policies:
    if 'Dynamic' in i:
        pol_dynamic.append(i)
    elif 'Static' in i:
        pol_static.append(i)
    elif 'Mission' in i:
        pol_mission.append(i)

# sort lists for identical legends
pol_20.append('None')
pol_40.append('None')
pol_60.append('None')
pol_80.append('None')

pol_20.sort()
pol_40.sort()
pol_60.sort()
pol_80.sort()
pol_dynamic.sort()
pol_static.sort()
pol_mission.sort()
```

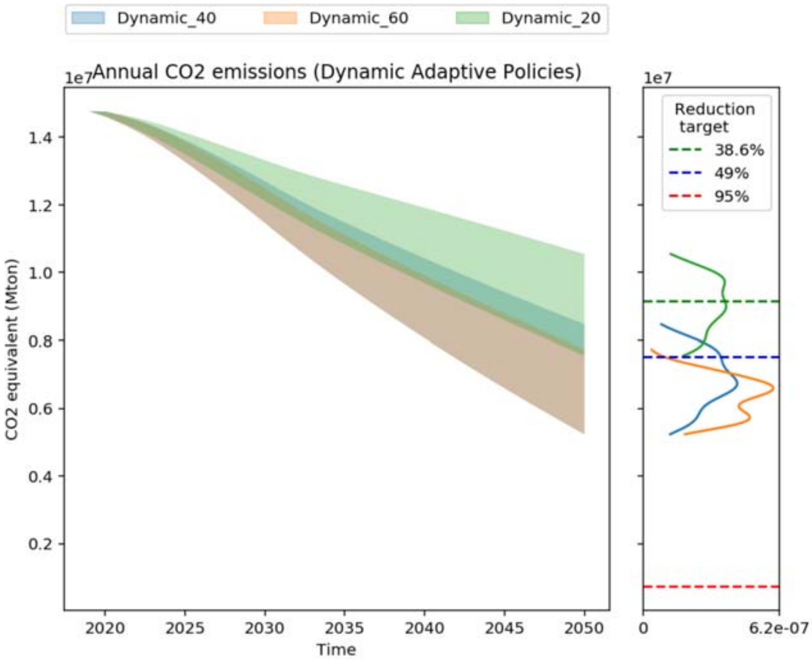
1. Dynamic policy

1.1 CO2

In [8]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total CO2 emission',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_dynamic,
                titles={'total CO2 emission':'Annual CO2 emissions (Dynamic Adaptive Policies)'},
                ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                     )

# plot targets  and legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best')
plt.legend()


# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Annual_CO2_emissions_Dynamic_Adaptive_Policies(20-80).png', d
pi=300, bbox_inches = "tight")
plt.show()
```



In [9]:
```
fig, axes = envelopes(results=results,
                      density=KDE,
                      outcomes_to_show='total CO2 emission',
                      fill=True,
                      group_by='policy',
                      grouping_specifiers= {'Dynamic_20','Dynamic_40', 'Dynamic_60'},
                      titles={'total CO2 emission':'Annual CO2 emissions (Dynamic Adaptive Policies)'},
                      ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                          )
# plot targets  and Legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best')
plt.legend()


# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Annual_CO2_emissions_Dynamic_Adaptive_Policies(20-60).png', d
pi=300, bbox_inches = "tight")
plt.show()
```



Within the subset of dynamic policies, it seems that 2 policies show identical results, though, subsidy percentages have been set differently e(0.2-0.8). Subsidies, however, are capped at the renovation costs themselves. Results in this plot are identical for dynamic 60 and 80 percent, because at a 60% subsidie level and at the behindtime CO2 reduction trajectory a doubling multiplier will be active for entire simulation period. Hence, already at the 60% subsidy policy, subsidies are already fully covering renovation costs. A higher subsidy percentage does not effect the annual co2 emissions, because renovation costs have already been fully subsidized in the lower subsidy level.

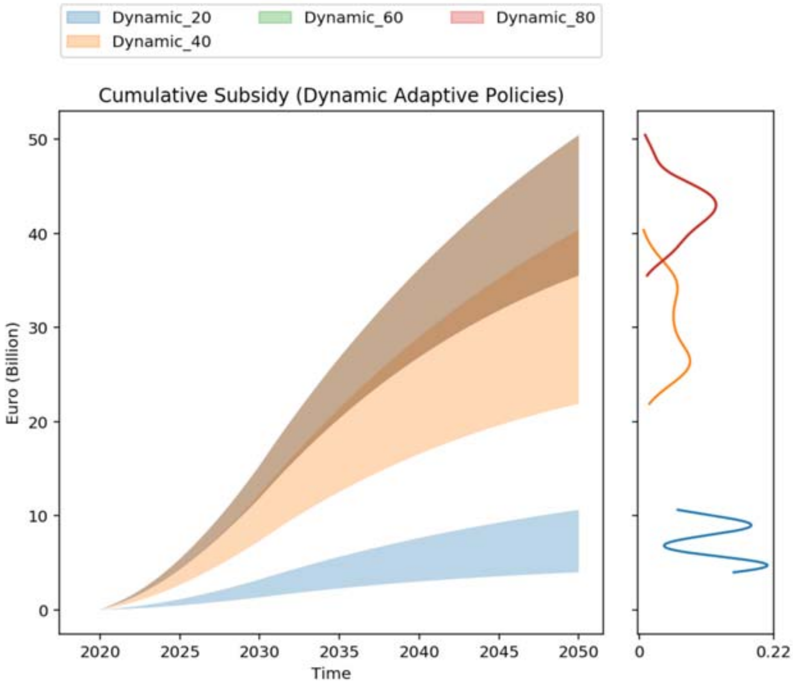
More interestingly, this implies that subsidies alone are not enough to reach targets. The rate at which houses can be renovated becomes leading right after people have been incentivized to renovate their homes. In these simulations, the renovation rates mentioned in the climate agreement (50k in 2020 to 200k homes in 2030) are adopted. From 2030 onwards an additional increase between 0 and 10% (of the 2030 renovation rate) is sampled as an uncertainty. These graphs on annual CO2 emissions show that these renovation rates are simply too little to renovate all homes by 2050, let alone renovate all of them by 2030.

In [10]:
```
time = 2030-2019
housesperyear = 200000
renovated_houses = time * housesperyear
renovated_houses
```

Out[10]: 2200000

1.2 Annual subsidies

In [11]:
```
import time
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_dynamic,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (Dynamic Adaptive 
Policies)'},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}
                     )
# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies_(Dynamic_policy).png', 
dpi=300,bbox_inches = "tight")
plt.show()
```

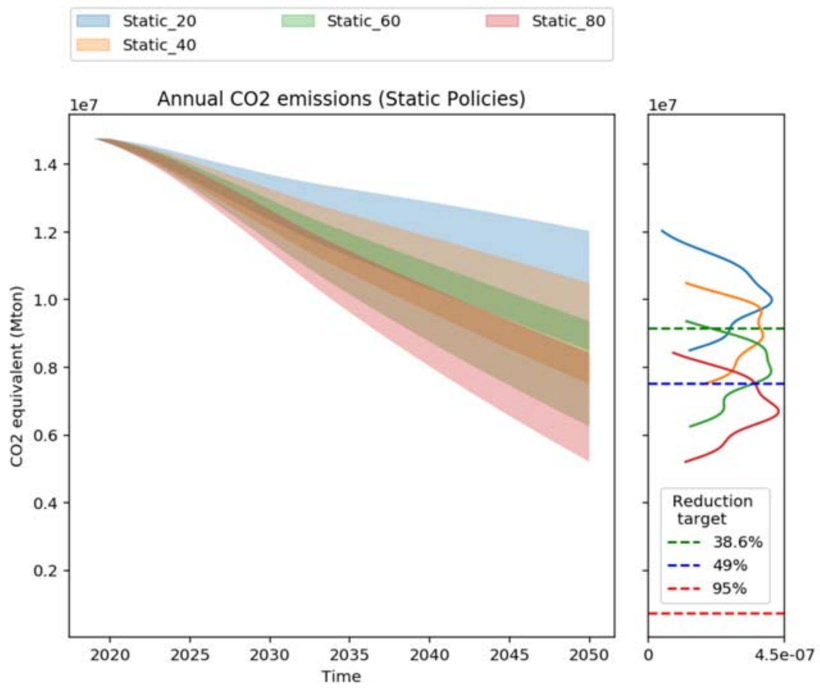


2. Static policy

2.1. CO2

100

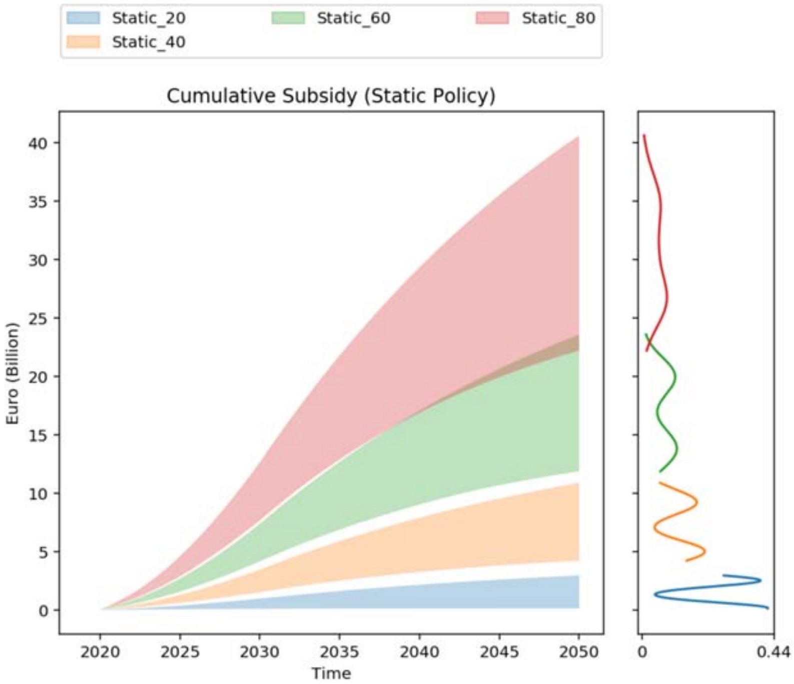
In [12]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total CO2 emission',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_static,
                titles={'total CO2 emission':'Annual CO2 emissions (Static Policies)'},
                ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                     )

# plot targets  and legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best',bb
ox_to_anchor=(0.95,.3))
plt.legend()

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Annual_CO2_emissions_Static_Policies.png', dpi=300, bbox_inch
es = "tight")
plt.show()
```



2.2. Annual subsidies

101

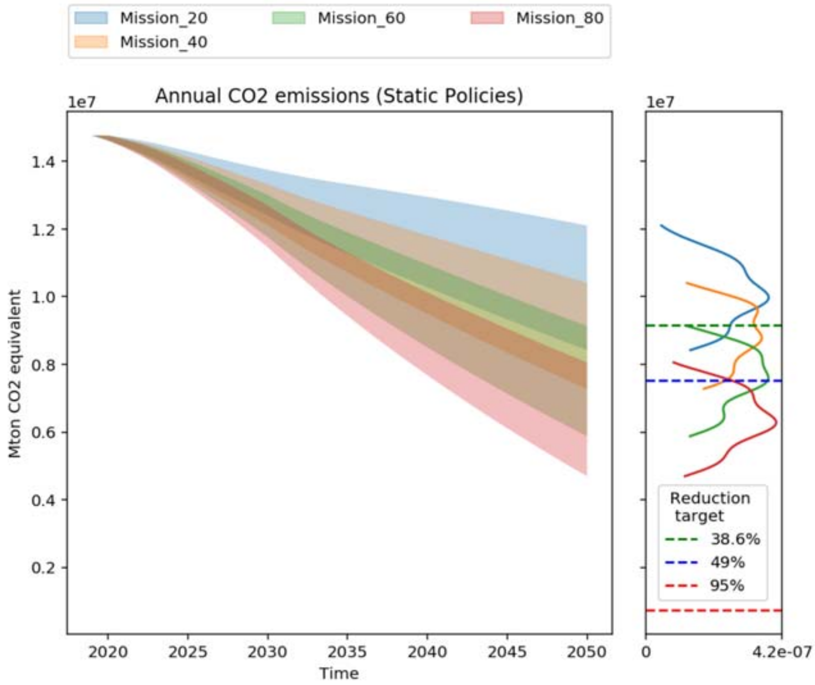
In [13]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_static,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (Static Policy)'
},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}
                     )
# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies_(Static_policy).png', d
pi=300, bbox_inches = "tight")
plt.show()
```



3. Mission policy

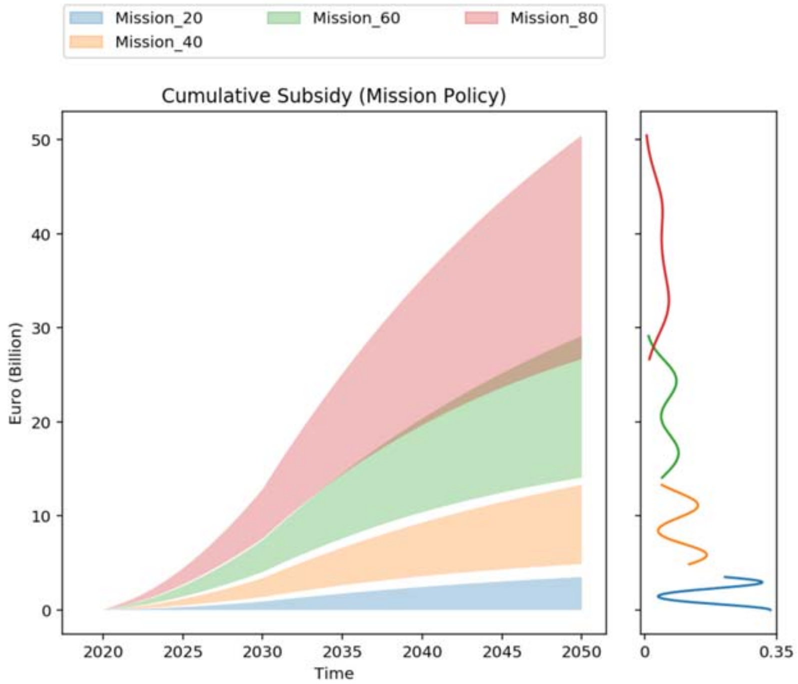
3.1. CO2

In [14]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total CO2 emission',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_mission,
                titles={'total CO2 emission':'Annual CO2 emissions (Static Policies)'},
                ylabels={'total CO2 emission':'Mton CO2 equivalent'}
                     )

# plot targets  and legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best',bb
ox_to_anchor=(0.95,.3))
plt.legend()

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Annual_CO2_emissions_Mission_Policies.png', dpi=300, bbox_inc
hes = "tight")
plt.show()
```



3.2. Annual subsidies

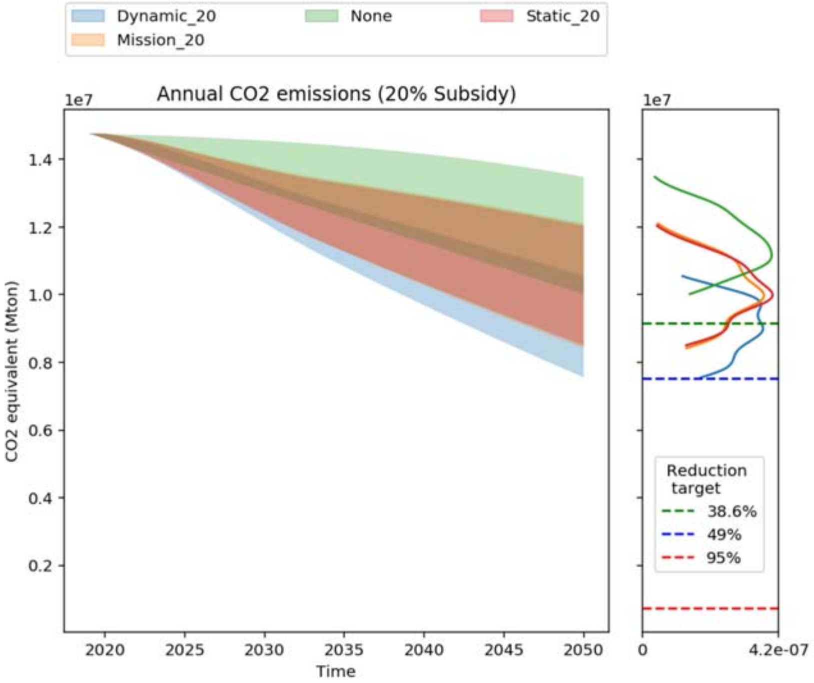
In [15]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_mission,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (Mission Policy)'
},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}
                    )
# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies_(Mission_policy).png',
dpi=300, bbox_inches = "tight")
plt.show()
```



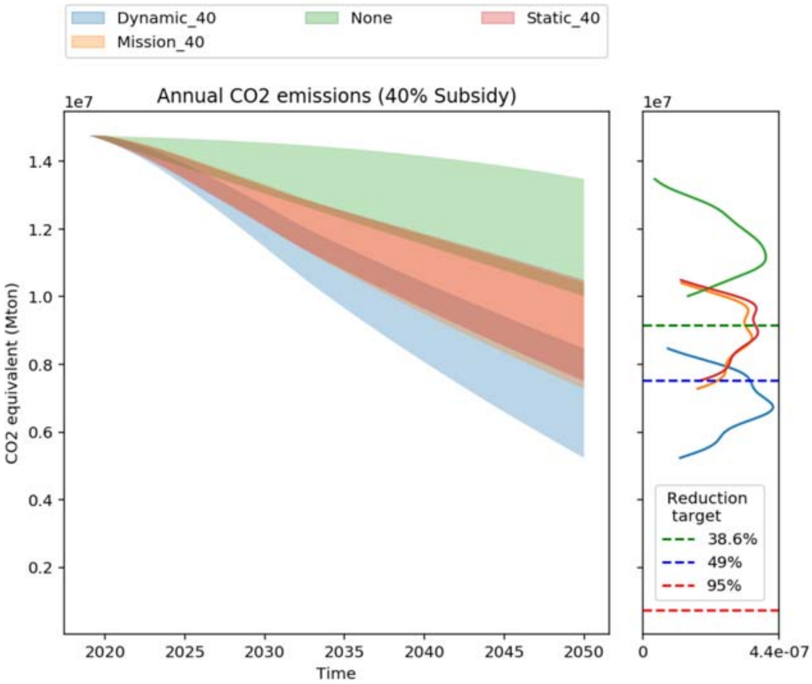
4. Grouped by subsidy plot

4.1. Co2

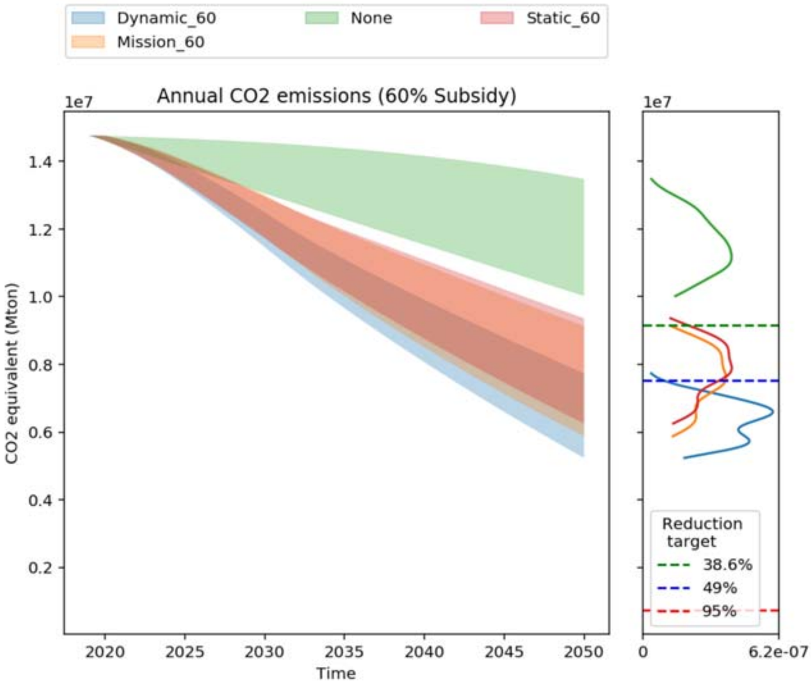
In [16]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total CO2 emission',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_20,
                titles={'total CO2 emission':'Annual CO2 emissions (20% Subsidy)'},
                ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                     )

# plot targets  and Legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best',bb
ox_to_anchor=(0.95,.35))
plt.legend()

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Annual_CO2_emissions(20_Subsidy).png', dpi=300, bbox
_inches = "tight")
plt.show()
```



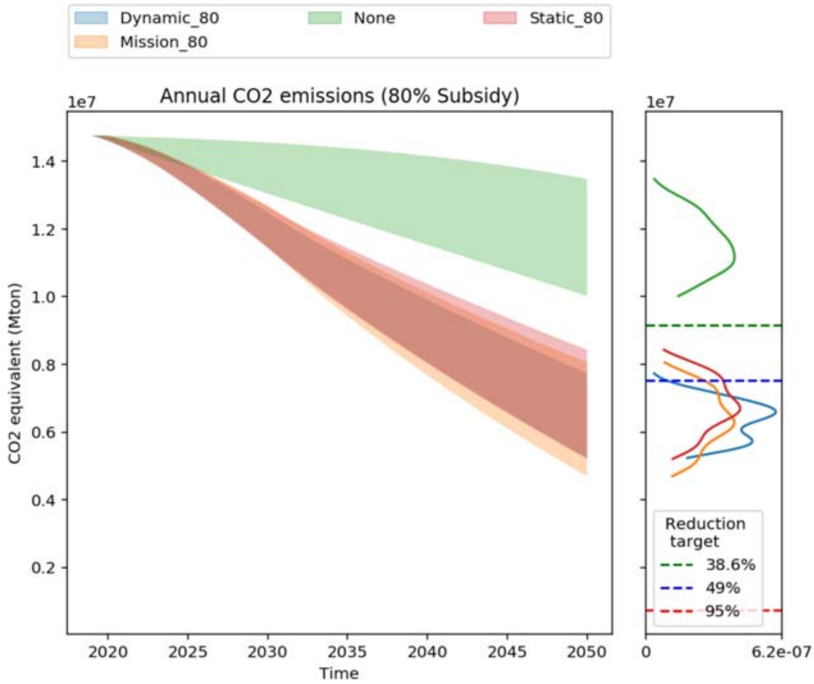
In [17]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total CO2 emission',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_40,
                titles={'total CO2 emission':'Annual CO2 emissions (40% Subsidy)'},
                ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                     )

# plot targets  and Legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best',bb
ox_to_anchor=(0.95,.3))
plt.legend()

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Annual_CO2_emissions(40_Subsidy).png', dpi=300, bbox
_inches = "tight")
plt.show()
```



In [18]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total CO2 emission',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_60,
                titles={'total CO2 emission':'Annual CO2 emissions (60% Subsidy)'},
                ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                     )

# plot targets  and legend
line1 = plt.axhline(y=(1-0.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best')
plt.legend()


# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Annual_CO2_emissions(60_Subsidy).png', dpi=300, bbox
_inches = "tight")
plt.show()
```



In [19]:
```
fig, axes = envelopes(results=results,
                 density=KDE,
                 outcomes_to_show='total CO2 emission',
                 fill=True,
                 group_by='policy',
                 grouping_specifiers= pol_80,
                 titles={'total CO2 emission':'Annual CO2 emissions (80% Subsidy)'},
                 ylabels={'total CO2 emission':'CO2 equivalent (Mton)'}
                      )

# plot targets  and legend
line1 = plt.axhline(y=(1-.38) * outcomes['total CO2 emission'].max(), color='g', linestyle='--')
line3 = plt.axhline(y=0.05 * outcomes['total CO2 emission'].max(), color='r', linestyle='--')
line2= plt.axhline(y=0.51 * outcomes['total CO2 emission'].max(), color='b', linestyle='--')
plt.legend((line1, line2, line3), ('38.6%','49%', '95%'),title='Reduction \n target',loc='best')
plt.legend()


# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Annual_CO2_emissions(80_Subsidy).png', dpi=300, bbox
_inches = "tight")
plt.show()
```

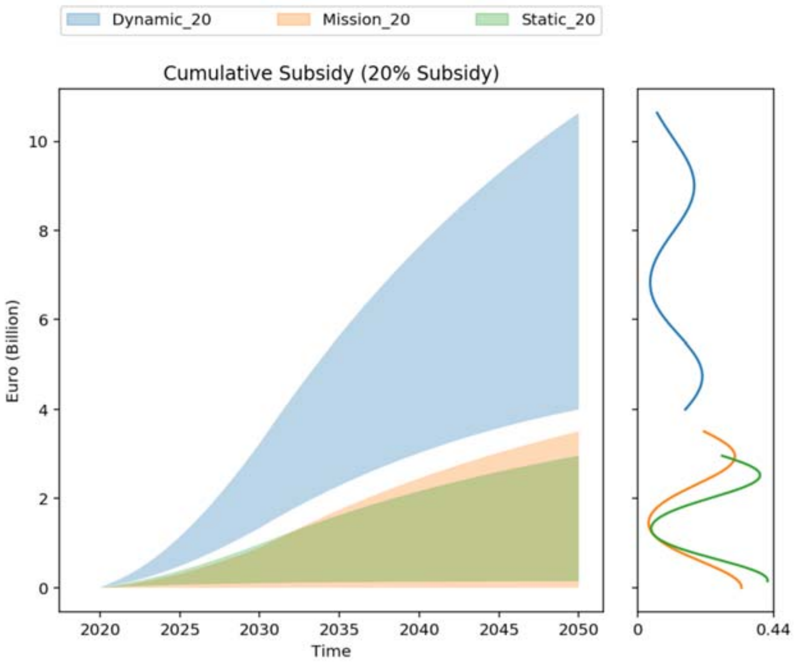


The plot shows a positive relationship between subsidy percentage (in the policies) and the amount of CO2 reduced.

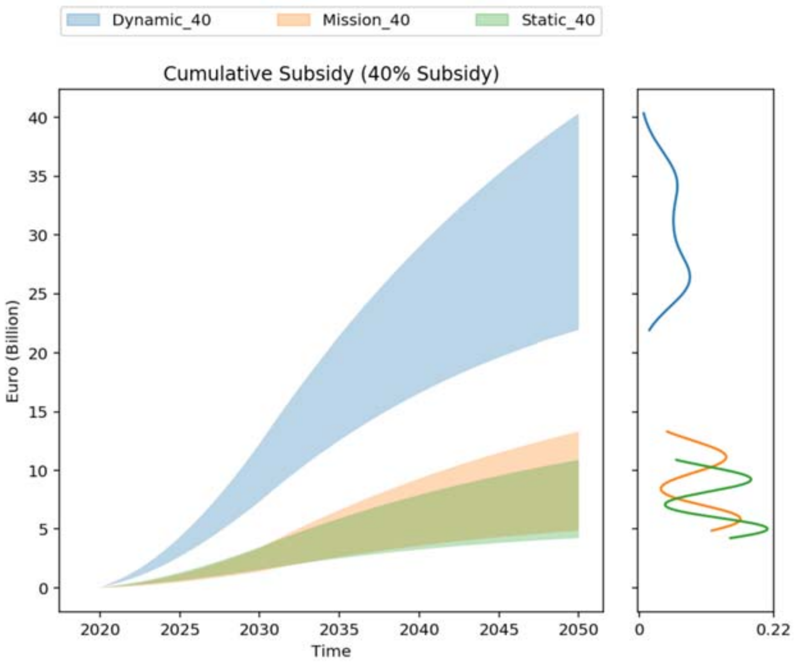
4.2. Cumulative subsidies

In [20]:
```
# Drop policy None from groups as it skews results in KDE

pol_20.remove('None')
pol_40.remove('None')
pol_60.remove('None')
pol_80.remove('None')
```

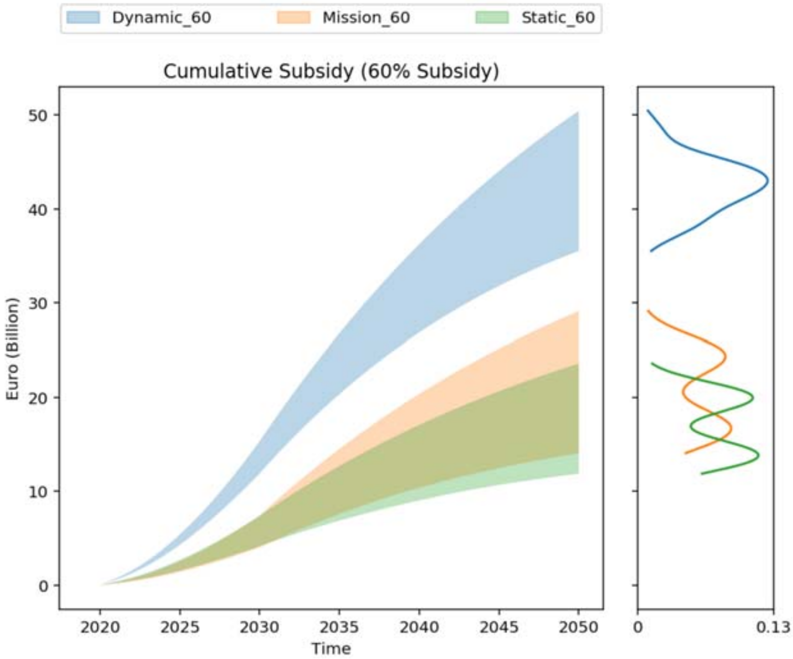
In [21]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_20,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (20% Subsidy)'},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}
                     )

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies(20_subsidies).png', dpi
=300, bbox_inches = "tight")
plt.show()
```



In [22]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_40,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (40% Subsidy)'},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}
                     )
# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies_(40_subsidies).png', dp
i=300, bbox_inches = "tight")
plt.show()
```

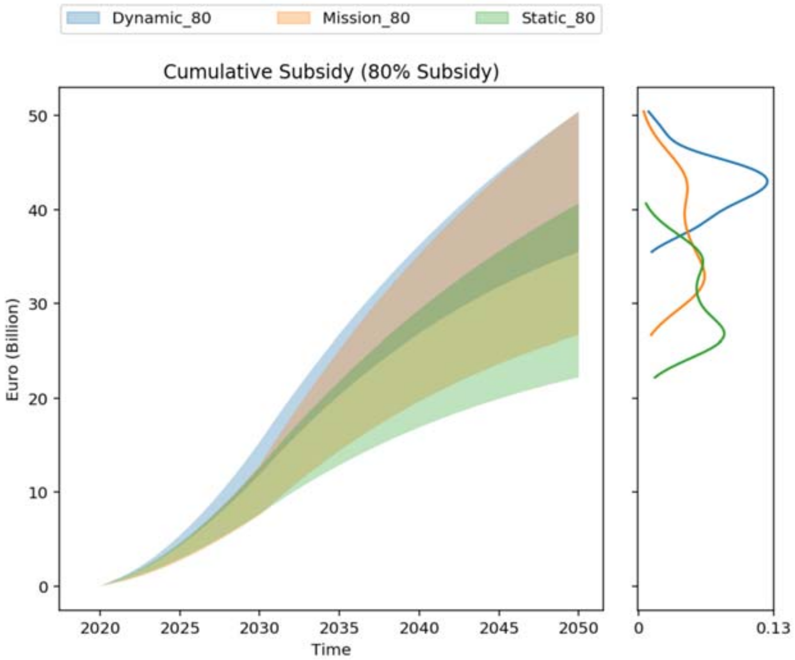


In [23]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_60,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (60% Subsidy)'},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}
                     )
# plot subsidy budget up to 2030 (3.5e9)
# x = np.arange(2020,2031,1)
# y = 3.5e8 + 3.5e8*(x-2020)
# line1 = axes['total cumulative subsidies awarded'].plot(x, y, 'r', label='subsidy')
# axes['total cumulative subsidies awarded'].legend((line1),title='Subsidy budget')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies(60_subsidies).png', dpi
=300, bbox_inches = "tight")
plt.show()
```



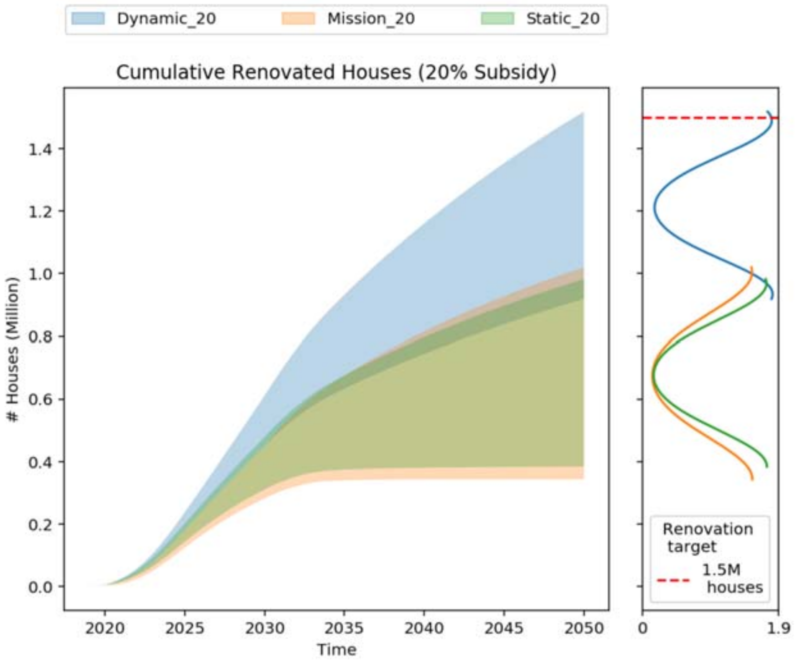
111

In [24]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_80,
                titles={'total cumulative subsidies awarded':'Cumulative Subsidy (80% Subsidy)'},
                ylabels={'total cumulative subsidies awarded':'Euro (Billion)'}

                    )
# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_Awarded_Subsidies_(80_subsidies).png', dp
i=300, bbox_inches = "tight")
plt.show()
```

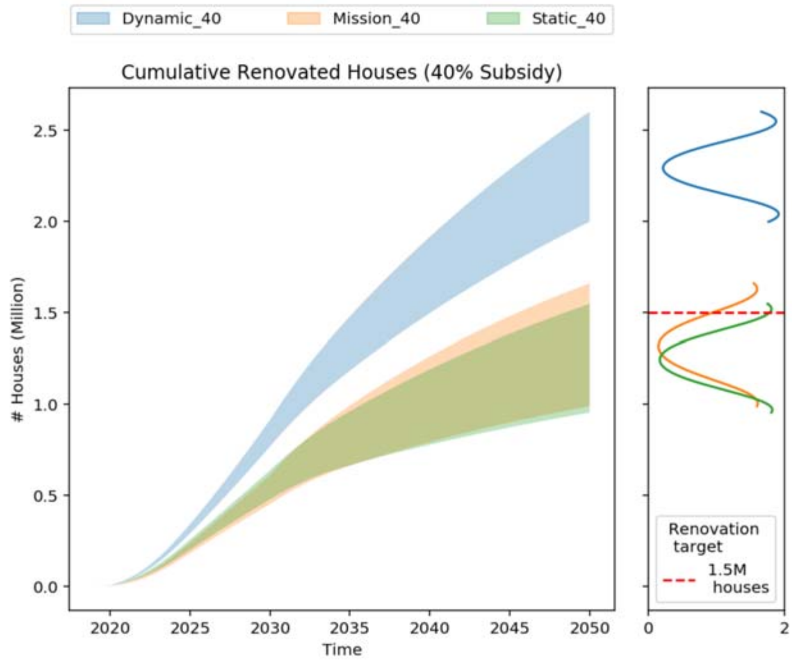


4.3 Renovated houses

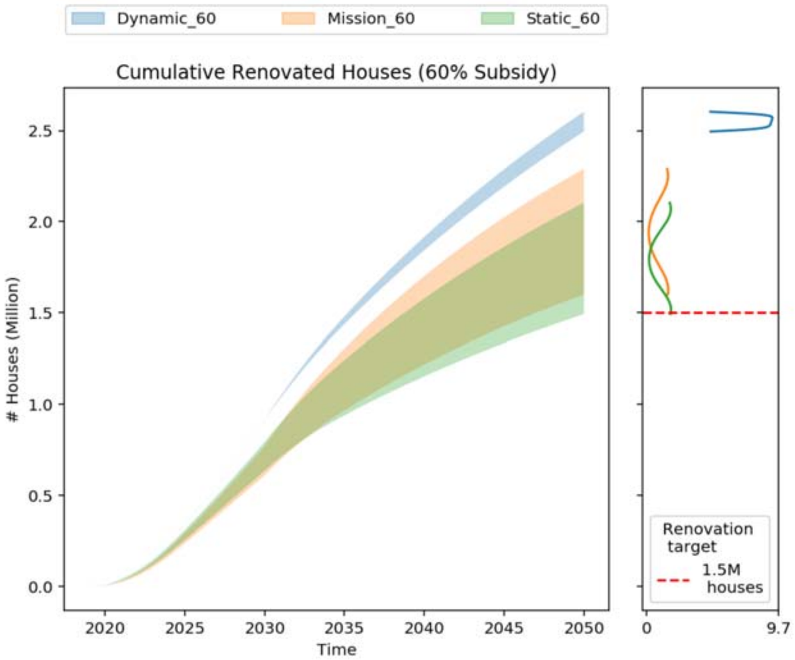
In [25]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total renovated houses',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_20,
                titles={'total renovated houses':'Cumulative Renovated Houses (20% Subsidy)'},
                ylabels={'total renovated houses':'# Houses (Million)'}
                     )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(20_subsidies).png', dpi=
300, bbox_inches = "tight")
plt.show()
```



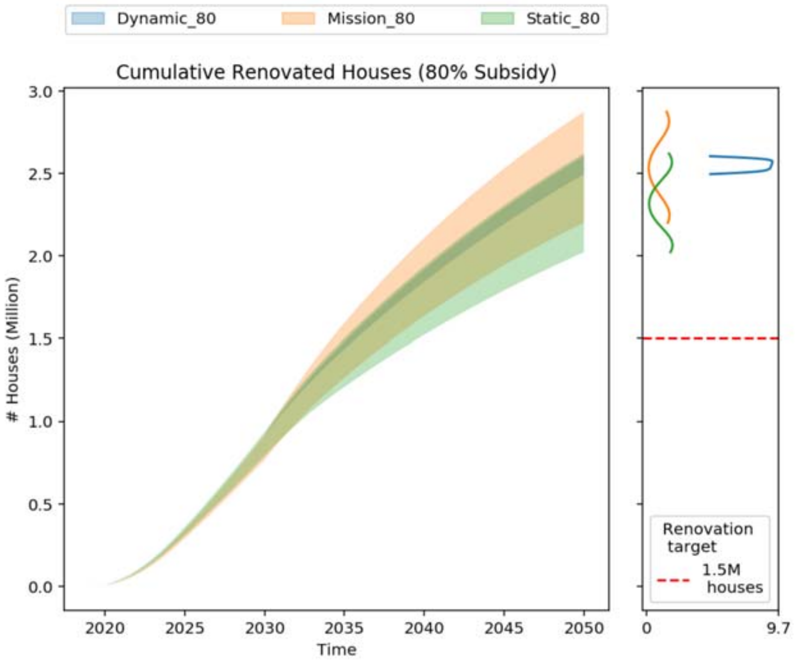
In [26]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total renovated houses',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_40,
                titles={'total renovated houses':'Cumulative Renovated Houses (40% Subsidy)'},
                ylabels={'total renovated houses':'# Houses (Million)'}
                     )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(40_subsidies).png', dpi=
300, bbox_inches = "tight")
plt.show()
```



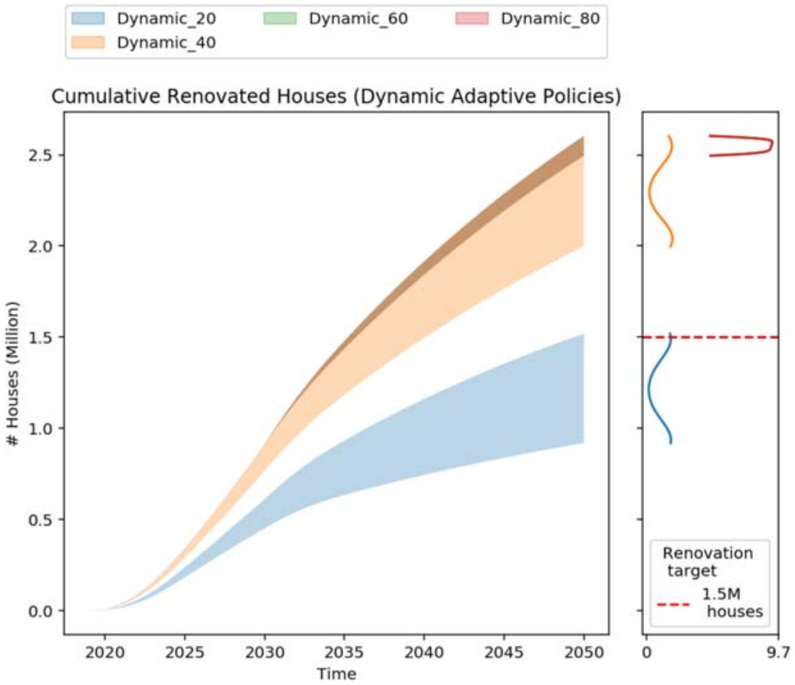
In [27]:
```
fig, axes = envelopes(results=results,
                      density=KDE,
                      outcomes_to_show='total renovated houses',
                      fill=True,
                      group_by='policy',
                      grouping_specifiers= pol_60,
                      titles={'total renovated houses':'Cumulative Renovated Houses (60% Subsidy)'},
                      ylabels={'total renovated houses':'# Houses (Million)'}
                           )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')
# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(60_subsidies).png', dpi=
300, bbox_inches = "tight")
plt.show()
```



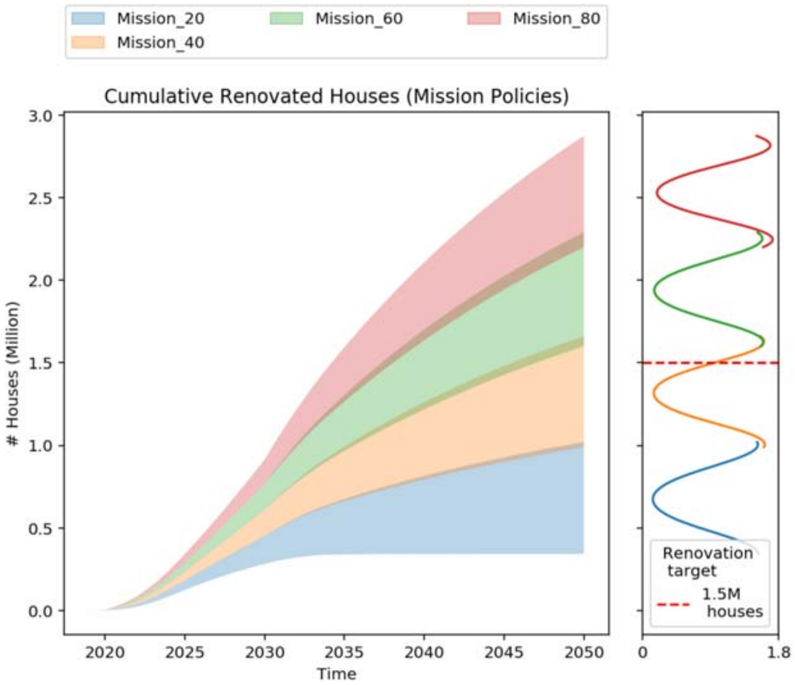
In [28]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total renovated houses',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_80,
                titles={'total renovated houses':'Cumulative Renovated Houses (80% Subsidy)'},
                ylabels={'total renovated houses':'# Houses (Million)'}
                     )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(80_subsidies).png', dpi=
300, bbox_inches = "tight")
plt.show()
```



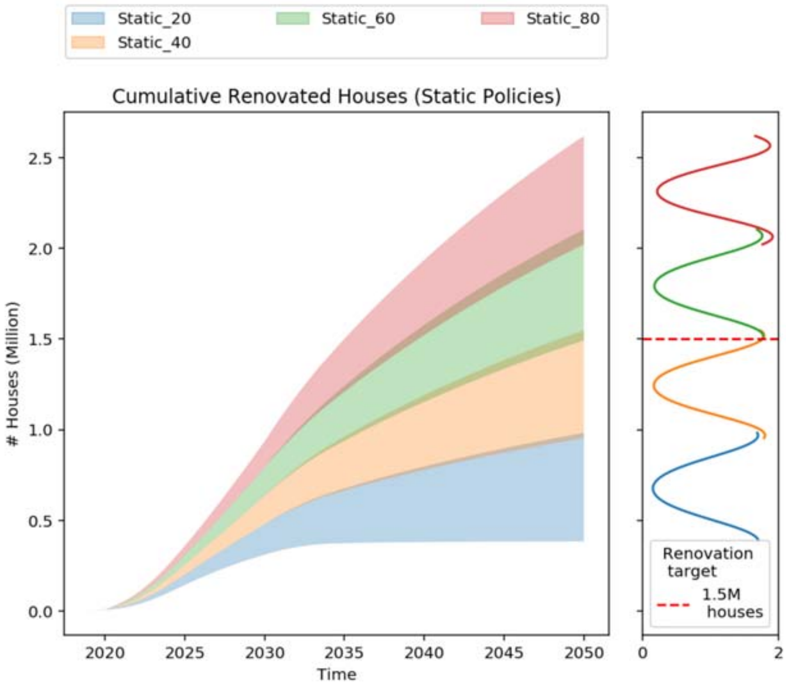
In [29]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total renovated houses',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_dynamic,
                titles={'total renovated houses':'Cumulative Renovated Houses (Dynamic Adaptive Po
licies)'},
                ylabels={'total renovated houses':'# Houses (Million)'}
                     )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(Dynamic).png', dpi=300,
bbox_inches = "tight")
plt.show()
```



In [30]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total renovated houses',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_mission,
                titles={'total renovated houses':'Cumulative Renovated Houses (Mission Policies)'
},
                ylabels={'total renovated houses':'# Houses (Million)'}
                     )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(Mission).png', dpi=300,
bbox_inches = "tight")
plt.show()
```



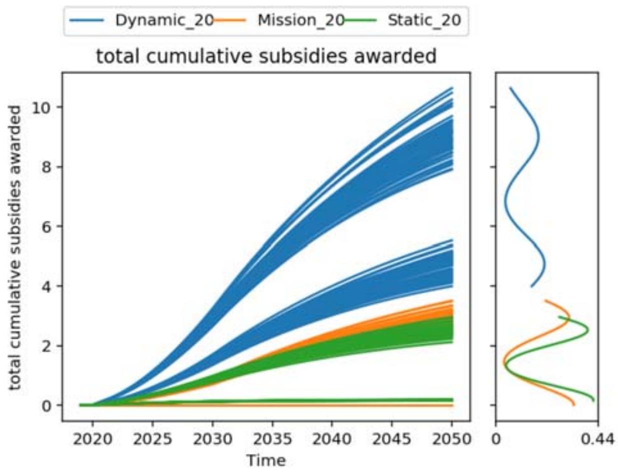
In [31]:
```
fig, axes = envelopes(results=results,
                density=KDE,
                outcomes_to_show='total renovated houses',
                fill=True,
                group_by='policy',
                grouping_specifiers= pol_static,
                titles={'total renovated houses':'Cumulative Renovated Houses (Static Policies)'},
                ylabels={'total renovated houses':'# Houses (Million)'}
                     )
line1 = plt.axhline(y=1.5, color='red', linestyle='--', label='1.5M \n houses')
plt.legend(title='Renovation \n target')

# Save
fig.set_size_inches(8,6)
plt.savefig('plots/scenario_policies/Envelope_Cumulative_renovated_houses(Static).png', dpi=300, b
box_inches = "tight")
plt.show()
```



119

In [32]:
```
fig, axes = lines(results=results,
                density=KDE,
                outcomes_to_show='total cumulative subsidies awarded',
                group_by='policy',
                grouping_specifiers= pol_20,
                titles={'total CO2 emission':'Cumulative Renovated Houses (Static Policies)'},
                ylabels={'total CO2 emission':'# Houses'}
                     )
plt.show()
```

```
[MainProcess/WARNING] key error in do_ylabels, no ylabel provided for `total cumulative subsidies awarded`
[MainProcess/WARNING] key error in do_titles, no title provided for `total cumulative subsidies aw
arded`
```



Create table of outcomes

In [63]:
```
outcomes_for_table = ['total CO2 emission',
                      'total cumulative subsidies awarded',
                      'total renovated houses']
```

In [137]:
```
outcomes['total CO2 emission'].max()
```

Out[137]: 14765408.0

In [130]:
```
d = []
for policy in policies:
    selected_results = tu.slice_results(experiments=experiments, outcomes=outcomes, policy=policy)
    d.append({'Policy': policy,
              'Annual CO2 emission min': selected_results[1]['total CO2 emission'].min(),
              'Annual CO2 emission max': selected_results[1]['total CO2 emission'].max(),
              'Annual CO2 emission mean': selected_results[1]['total CO2 emission'].mean(),
              'Cumulative subsidies awarded min': selected_results[1]['total cumulative subsidies
 awarded'].min(),
              'Cumulative subsidies awarded max': selected_results[1]['total cumulative subsidies
 awarded'].max(),
              'Cumulative subsidies awarded mean': selected_results[1]['total cumulative subsidies
awarded'].mean(),
              'Cumulative renovated houses min': selected_results[1]['total renovated houses'].min
(),
              'Cumulative renovatead houses max': selected_results[1]['total renovated houses'].ma
x(),
              'Cumulative renovatead houses mean': selected_results[1]['total renovated houses'].m
ean()
             })
```

In [192]:
```
import pandas as pd
df_table = pd.DataFrame(d)

# add seperate columns for policy and percentage
df_table['Percentage']= df_table['Policy'].str.split("_",1).str[1]
df_table['Policy']= df_table['Policy'].str.split("_",1).str[0]
# Calculate reduction
df_table['Mean CO2 reduction'] = df_table['Annual CO2 emission max'] - df_table['Annual CO2 emissi
on mean']
df_table['Maximum CO2 reduction'] = df_table['Annual CO2 emission max'] - df_table['Annual CO2 emi
ssion min']
```

In [193]:
```
# Beautify the table


df_table['Mean CO2 reduction'] = df_table['Mean CO2 reduction']/1e6
df_table['Maximum CO2 reduction'] = df_table['Maximum CO2 reduction']/1e6

df_table = df_table.rename(columns={'Mean CO2 reduction':'Mean CO2 reduction [Mton]',
                          'Maximum CO2 reduction': 'Maximum CO2 reduction [Mton]',
                          'Cumulative renovatead houses max':'Cumulative renovated houses max [M ho
uses]',
                          'Cumulative renovatead houses mean':'Cumulative renovated houses mean [M
 houses]',
                          'Cumulative subsidies awarded max':'Cumulative subsidies awarded max [Bil
lion euros]',
                          'Cumulative subsidies awarded mean':'Cumulative subsidies awarded mean [B
illion euros]'
                         })
df_table.drop(['Annual CO2 emission max',
               'Annual CO2 emission mean',
               'Annual CO2 emission min',
               'Cumulative renovated houses min',
               'Cumulative subsidies awarded min'],
              inplace=True, axis=1)
```

In [196]:
```
# rearrange
cols = df_table.columns.tolist()
cols = cols[-2:] + cols[:-2]
df_table = df_table[cols]
df_table
```

Out[196]:

	Policy	Percentage	Mean CO2 reduction [Mton]	Maximum CO2 reduction [Mton]	Cumulative renovated houses max [M houses]	Cumulative renovated houses mean [M houses]	Cumulative subsidies awarded max [Billion euros]	Cumulative subsidies awarded mean [Billion euros]
0	Static	40	2.939828	7.258255	1.547244	0.696646	10.894588	3.655211
1	Dynamic	80	4.181880	9.530335	2.603651	1.306148	50.443469	21.314507
2	Static	80	3.969878	9.559074	2.619571	1.205295	40.653967	15.395988
3	None	NaN	1.486250	4.747432	0.161051	0.084759	2.511862	1.223181
4	Mission	60	3.567050	8.888918	2.288859	1.004981	29.132988	9.830192
5	Mission	20	2.388709	6.344406	1.019654	0.413463	3.507677	0.708797
6	Dynamic	40	3.936263	9.530335	2.602112	1.185199	40.354693	15.090002
7	Static	60	3.464768	8.512401	2.103567	0.957108	23.597537	8.570260
8	Dynamic	60	4.181880	9.530335	2.603651	1.306148	50.443469	21.314507
9	Dynamic	20	2.897626	7.210981	1.518462	0.671174	10.638348	3.456620
10	Mission	80	4.129544	10.071556	2.873070	1.281970	50.470846	17.854594
11	Static	20	2.406756	6.262664	0.982143	0.427123	2.960721	0.710109
12	Mission	40	2.982424	7.486335	1.659452	0.714255	13.305162	4.091620

In [197]:
```
df_final = df_table.groupby(['Policy', 'Percentage']).mean().round(2)
df_final
```

Out[197]:

		Mean CO2 reduction [Mton]	Maximum CO2 reduction [Mton]	Cumulative renovated houses max [M houses]	Cumulative renovated houses mean [M houses]	Cumulative subsidies awarded max [Billion euros]	Cumulative subsidies awarded mean [Billion euros]
Policy	**Percentage**						
Dynamic	**20**	2.90	7.21	1.52	0.67	10.64	3.46
	40	3.94	9.53	2.60	1.19	40.35	15.09
	60	4.18	9.53	2.60	1.31	50.44	21.31
	80	4.18	9.53	2.60	1.31	50.44	21.31
Mission	**20**	2.39	6.34	1.02	0.41	3.51	0.71
	40	2.98	7.49	1.66	0.71	13.31	4.09
	60	3.57	8.89	2.29	1.00	29.13	9.83
	80	4.13	10.07	2.87	1.28	50.47	17.85
Static	**20**	2.41	6.26	0.98	0.43	2.96	0.71
	40	2.94	7.26	1.55	0.70	10.89	3.66
	60	3.46	8.51	2.10	0.96	23.60	8.57
	80	3.97	9.56	2.62	1.21	40.65	15.40

In [198]:
```
df_final.to_clipboard()
```

A.5. Feature Scoring

Feature scoring

Featurescoring (poor man's alternative for sensitivity analysis) on the basecase ensemble (without any policies) and policycase

- Date: 11 July 2019
- M. Hupkens

In [1]:
```
from ema_workbench import load_results
from ema_workbench.analysis import feature_scoring
```

```
C:\Users\markhupkens\Anaconda3\lib\importlib\_bootstrap.py:219: ImportWarning: can't resolve packa
ge from __spec__ or __package__, falling back on __name__ and __path__
  return f(*args, **kwds)
```

1. Basecase

In [2]:
```
experiments, outcomes = load_results('C:/Users/markhupkens/EnergyTransitionModelling/Final noteboo
ks/Results/20190715_experiments_energymodel_labour_base_ensempble.tar.gz')
```

In [3]:
```
outcomes.keys()
```

Out[3]:
```
dict_keys(['TIME', 'total renovated houses', 'total renovated houses wcorp', 'total renovated hous
es koop', 'total renovated houses verhuur', 'total subsidy amount', 'total costs', 'total CO2 emis
sion', 'total warmte via elek', 'total warmtenet', 'total woningen gas', 'total houses in model',
'prijseffect schaarste manuren transitie GASnrELEK NL', 'prijseffect schaarste manuren transitie G
ASnrWN NL', 'totaal benodigde manuren transitie GebOmg GASnrELEK NL corp', 'totaal benodigde manur
en transitie GebOmg GASnrWN NL corp', 'tekort manuren transitie GebOmg GASnrELEK NL', 'tekort manu
ren transitie GebOmg GASnrWN NL', 'beschikbare manuren transitie woningen GASnrWN NL', 'beschikbar
e manuren transitie woningen GASnrELEK NL'])
```

In [4]:
```
keys_to_keep = ['total renovated houses',
                'total costs',
                'total CO2 emission']

new_outcomes = {key: outcomes[key] for key in keys_to_keep}
```

In [5]:
```
# Rename keys to match
new_outcomes['Cumulative renovated houses'] = new_outcomes.pop('total renovated houses')
new_outcomes['Annual CO2 emission']  = new_outcomes.pop('total CO2 emission')
new_outcomes['Cumulative costs of renovation']  = new_outcomes.pop('total costs')
```

In [6]:
```
# Rename uncertainties
experiments.dtype.names=['Reduction carbon intensity power generation',
                         'Reduction renovation costs',
                         'Fraction houses to district heat private sector high existing infrastruc
ture',
                         'Fraction houses to district heat private sector low existing infrastruct
ure',
                         'Fraction houses to district heat building corporations high existing inf
rastructure',
                         'Fraction houses to district heat building corporations low existing infr
astructure',
                         'Fraction houses to district heat building corporations no existing infra
structure',
                         'Annual electricity demand growth',
                         'Annual development of new homes',
                         'policy time',
                         'renovation costs label group 1',
                         'renovation costs label group 2',
                         'renovation costs label group 3',
                         'renovation costs label group 4',
                         'Annual standard renovation rate',
                         'scenario_id',
                         'policy',
                         'model'

                        ]
```

In [7]:
```
def remove_field_name(array, name):
    '''removes a dtype column from the uncertainties in the experiments'''
    names = list(array.dtype.names)
    if name in names:
        names.remove(name)
    b = array[names]
    return b
```

In [8]:
```
experiments = remove_field_name(experiments, 'policy')
experiments = remove_field_name(experiments, 'policy time')
experiments = remove_field_name(experiments, 'model')
```

In [9]:
```
x1 = experiments
y1 = new_outcomes

fs1 = feature_scoring.get_feature_scores_all(x1,y1)
```

```
C:\Users\markhupkens\Anaconda3\lib\site-packages\pandas\core\frame.py:6692: FutureWarning: Sorting
because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
C:\Users\markhupkens\Anaconda3\lib\site-packages\pandas\core\frame.py:6692: FutureWarning: Sorting
because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
```

In [25]:
```
import seaborn as sns
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(12,8))

base = sns.heatmap(fs1, cmap='viridis', annot=True)
base.set_xticklabels(base.get_xticklabels(),rotation=90)
plt.tight_layout()
plt.savefig('C:/Users/markhupkens/Dropbox/Thesis/EMA/PLOTS/Feature_Scoring_Basecase.png', dpi=300,
bbox_inches='tight')

plt.show()
```

2. Policy

In [11]:
```
experiments2, outcomes2 = load_results('C:/Users/markhupkens/Dropbox/Thesis/FINAL/Final results/20
190726_experiments_policies_v2_100.tar.gz')
```

In [12]:
```
outcomes2.keys()
```

Out[12]:
```
dict_keys(['TIME', 'total cumulative subsidies awarded', 'total subsidy awarded annually', 'total
renovated houses', 'total renovated houses wcorp', 'total renovated houses koop', 'total renovated
houses verhuur', 'total costs', 'total CO2 emission', 'total warmte via elek', 'total warmtenet',
'total woningen gas', 'total houses in model', 'prijseffect schaarste manuren transitie GASnrELEK
NL', 'prijseffect schaarste manuren transitie GASnrWN NL', 'totaal benodigde manuren transitie Geb
Omg GASnrELEK NL corp', 'totaal benodigde manuren transitie GebOmg GASnrWN NL corp', 'tekort manur
en transitie GebOmg GASnrELEK NL', 'tekort manuren transitie GebOmg GASnrWN NL', 'beschikbare manu
ren transitie woningen GASnrWN NL', 'beschikbare manuren transitie woningen GASnrELEK NL'])
```

In [13]:
```
keys_to_keep = ['total renovated houses',
                'total cumulative subsidies awarded',
                'total costs',
                'total CO2 emission']

new_outcomes2 = {key: outcomes2[key] for key in keys_to_keep}
```

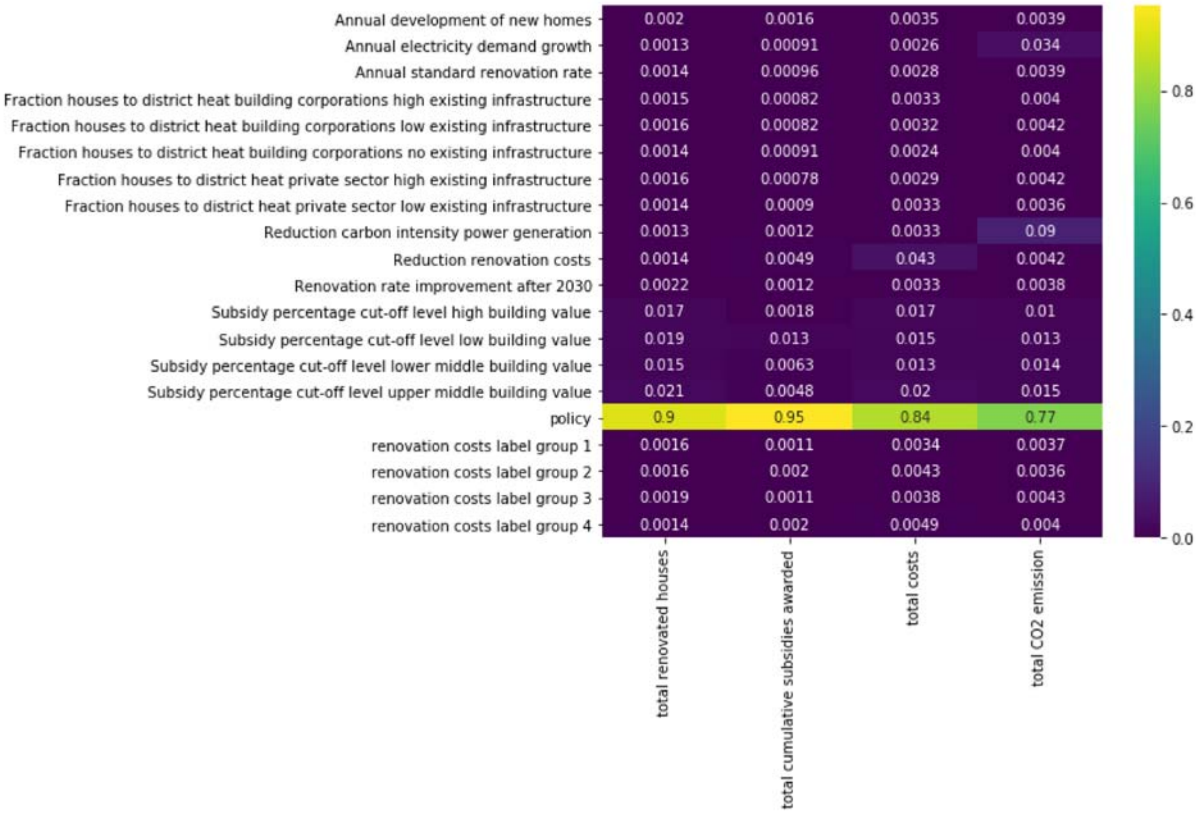
In [14]:
```
# Rename uncertainties
experiments2.dtype.names=['Reduction carbon intensity power generation',
                         'Reduction renovation costs',
                         'Fraction houses to district heat private sector high existing infrastruc
ture',
                         'Fraction houses to district heat private sector low existing infrastruct
ure',
                         'Fraction houses to district heat building corporations high existing inf
rastructure',
                         'Fraction houses to district heat building corporations low existing infr
astructure',
                         'Fraction houses to district heat building corporations no existing infra
structure',
                         'Subsidy percentage cut-off level high building value',
                         'Subsidy percentage cut-off level low building value',
                         'Subsidy percentage cut-off level lower middle building value',
                         'Subsidy percentage cut-off level upper middle building value',
                         'Annual electricity demand growth',
                         'Annual development of new homes',
                         'Renovation rate improvement after 2030',
                         'renovation costs label group 1',
                         'renovation costs label group 2',
                         'renovation costs label group 3',
                         'renovation costs label group 4',
                         'Annual standard renovation rate',
                         'scenario_id',
                         'policy',
                         'model'
                        ]
```

In [15]:
```
experiments2 = remove_field_name(experiments2, 'model')
```

In [16]:
```
x2 = experiments2
y2 = new_outcomes2

fs = feature_scoring.get_feature_scores_all(x2,y2)
```

```
C:\Users\markhupkens\Anaconda3\lib\site-packages\pandas\core\frame.py:6692: FutureWarning: Sorting
because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
C:\Users\markhupkens\Anaconda3\lib\site-packages\pandas\core\frame.py:6692: FutureWarning: Sorting
because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
C:\Users\markhupkens\Anaconda3\lib\site-packages\pandas\core\frame.py:6692: FutureWarning: Sorting
because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
```

In [26]:
```
import seaborn as sns
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(12,8))

sns.heatmap(fs, cmap='viridis', annot=True)
plt.tight_layout()
plt.savefig('C:/Users/markhupkens/Dropbox/Thesis/EMA/Feature_Scoring_Policies.png', dpi=300, bbox_
inches='tight')

plt.show()
```



A.6. Thesis Utilities

Thesis Utilities

Utilities file for scenario discovery backup and make coding life easier. @author: Mark Hupkens, 2019

In [ ]:
```
# coding: utf-8
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time

from ema_workbench.analysis.plotting import lines
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis import prim
from ema_workbench.util import ema_logging
ema_logging.log_to_stderr(ema_logging.INFO)
from ema_workbench.util import load_results
from ema_workbench.analysis.plotting import lines, plot_lines_with_envelop
es, envelopes


# ### Plotting lines and saving results

def plot_all_lines(results, outcomes, grouped, save, title):
    if grouped == True:
        for kpi in list(outcomes.keys())[1:]: # drop first entry (TIME)
                fig, axes = lines(results, density=u'kde', show_envelope=F
alse,outcomes_to_show=kpi, group_by='policy')

                if save==True:
                    plt.savefig('plots/scenario_policies/'+time.strftime('
%Y%m%d')+ title +'_lines_grouped_' + kpi + '.png',dpi=1200)
                else:
                    print(kpi + ' was not saved')
    else:
        for kpi in list(outcomes.keys())[1:]: # drop first entry (TIME)
            fig, axes = lines(results, density=u'kde', show_envelope=False
,outcomes_to_show=kpi)

            if save==True:
                plt.savefig('plots/scenario_policies/'+time.strftime('%Y%m
%d')+ title + '_lines_' + kpi + '.png',dpi=1200)
            else:
                print(kpi + ' was not saved')

def plot_all_envelopes(results, outcomes, grouped, save, title):
    if grouped == True:
        for kpi in list(outcomes.keys())[1:]: # drop first entry (TIME)
                fig, axes = envelopes(results, density=u'kde',outcomes_to_
show=kpi, group_by='policy', fill=True)
```

```
                if save==True:
                    plt.savefig('plots/scenario_basecase/'+time.strftime('
%Y%m%d') + title + '_lines_grouped_' + kpi + '.png',dpi=1200)
                else:
                    print(kpi + ' was not saved')
    else:
        for kpi in list(outcomes.keys())[1:]: # drop first entry (TIME)
            fig, axes = envelopes(results, density=u'kde',outcomes_to_show
=kpi, fill=True)

            if save==True:
                plt.savefig('plots/scenario_policies/'+time.strftime('%Y%m
%d') + title + '_lines_' + kpi + '.png',dpi=1200)
            else:
                print(kpi + ' was not saved')


def slice_results(experiments, outcomes, policy):
    '''Selects policy from experiments and keeps only outcomes of selected
 policy'''

    import numpy as np
    global sliced_results
    new_experiments=experiments.copy()
    new_outcomes=outcomes.copy()

    ids_removed = []    # list for removed ids
    ids_not_removed = [] # ids for remaining runs

    counter=0      # As we delete lines, the index of the new ndarray chang
es. This counter accounts for that.

    for i in range(len(experiments)):
        if experiments['policy'][i] != policy:
            counter+=1
            ids_removed.append(i)
            for key in outcomes.keys():
                new_outcomes[key]=np.delete(new_outcomes[key], i-(counter-
1), 0)
            new_experiments=np.delete(new_experiments, i-(counter-1), 0)
        else:
            ids_not_removed.append(i)
    sliced_results=(new_experiments, new_outcomes)
    return sliced_results

def plot_individual_policies_lines(experiments, outcomes, policy,outcomes_
to_show):
    '''Plot individual policy experiment sets'''
    sliced_result = slice_results(experiments, outcomes, policy)

    fig = lines(sliced_result, outcomes_to_show=outcomes_to_show, density=
KDE)
    print('Plot of policy: ', policy)

def plot_individual_policies_envelopes(experiments, outcomes, policy,outco
mes_to_show):
    '''Plot individual policy experiment sets'''
```

```
    sliced_result = slice_results(experiments, outcomes, policy)

    ig,axes = envelopes(sliced_result, outcomes_to_show=outcomes_to_show,
fill=True , group_by=False, density=KDE)
    print('Plot of policy: ', policy)

#### Buurt selector

# Import data and Define functions to clean data and select buurten from m
unicipalities
import ipywidgets as widgets


# Functions for case selection

def merge_and_clean_mapping():
    '''Merge mappings and entities of modelsetup files to get neighbourhoo
ds'''
    # Import data
    df_buurt = pd.read_excel('C:/Users/LocalAdmin/Desktop/ETModel/model/ba
ckup/MSETMnlEPdataMHv02.xlsx',sheetname='buurt')
    df_wijk = pd.read_excel('C:/Users/LocalAdmin/Desktop/ETModel/model/bac
kup/MSETMnlEPdataMHv02.xlsx',sheetname='wijk')
    df_gem = pd.read_excel('C:/Users/LocalAdmin/Desktop/ETModel/model/back
up/MSETMnlEPdataMHv02.xlsx',sheetname='gemeente')

    df_mapping = df_buurt.iloc[:, 0:2].merge(df_wijk.iloc[:, 0:2],left_on=
'Mapping', right_on='Entities',how='inner')
    df_mapping.drop('Entities_y',axis=1,inplace=True)
    df_mapping.rename(columns={'Entities_x':'Buurt','Mapping_x':'Wijk','Ma
pping_y':'Gemeente'},inplace=True)
    df_mapping['Gemeente_name'] = df_mapping['Gemeente'].str.split(' G').s
tr[0]
    return df_mapping

def get_buurten(gemeente):
    '''Return and save list of buurten and selected municipality'''
    global neighbourhood_list
    global selected_gemeente

    df = merge_and_clean_mapping()
    df_y = df.loc[df.Gemeente_name==gemeente]
    neighbourhood_list = list(df_y.Buurt)
    selected_gemeente = gemeente
    print('Number of neighbourhoods in',' ',selected_gemeente,' :',len(nei
ghbourhood_list))
    return neighbourhood_list

def create_dropdown_values():
    global gemeente_list
    df_wijk = pd.read_excel('C:/Users/LocalAdmin/Desktop/ETModel/model/bac
kup/MSETMnlEPdataMHv02.xlsx',sheetname='wijk')
    gemeente_list = df_wijk.Mapping.str.split(' G').str[0].unique()
    return gemeente_list

def select_buurten():
    '''Create interactive dropdown to select buurten from municipalities''
```

```
'
    gemeente = create_dropdown_values()
    widgets.interact_manual(get_buurten, gemeente=gemeente)

def return_experimented_policies(experiments):
    l=[]
    for i in range(len(experiments)):
        l.append(experiments[i][-2])
    policies = set(l)
    return policies
```

B

Data Codes

This chapter provides all codes used in the data acquisition and data merge process to prepare the real-world data for the multi-level modelling effort. First, scripts cleaning and merging several data sets are shown in section B.1. Section B.2 presents scripts to allign the several levels, so that all entities appear in their mapping and vice versa. Finally, section B.3 presents code used to scrape EV charging data from online sources

B.1. Data Merge Model Setup

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
# from data_prep.py import
```

Modelsetup (datamerge)

This notebook uses the following datasets to merge ep-online(BAG) data with klimaatmonitordata:

1. BAG data per house, including buildingtypes, retrieved from: [eponline]
2. Energy data per buurt, retrieved from: [klimaatmonitor]
3. [Solar PV data per neighbourhood (CBS)]
4. on chargingpoints (private)
5. [FEV and PHEV data on low scale]
6. [CBS data on vehicles per zipcode]
7. [Green gas and renewable heat per municipality]

@author: Mark Hupkens last edit: 13-05-2019

All code available on [github repo]

> **To do (21-05):**
>
> 1. fix column naming issue on import in vensim: add sheet name to column variables.
> 2. Check length of variables and their mapping --> buurten have more wijken as mapping than wijken have entities (see modelfix file)

Step 1: importing data

In [2]:
```
'''Import Data'''

# BAG data
df = pd.read_csv('C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/mast
erdf.csv', error_bad_lines=False, sep =';') # handled data from https://ww
w.rvo.nl/sites/default/files/2019/01/Voorlopige_labels_okt2018.zip

# Energy Data
df_energy_buurt = pd.read_excel("C:/Users/markhupkens/Dropbox/EnTransition
NL/0. Data/Klimaatmonitor (energieverbruik , stadsverwarming, pv - Buurten
,wijken en gemeenten 2017).xls",sheet_name='Buurt')
df_energy_gemeente = pd.read_excel("C:/Users/markhupkens/Dropbox/EnTransit
ionNL/0. Data/Klimaatmonitor (energieverbruik , stadsverwarming, pv - Buur
ten,wijken en gemeenten 2017).xls",sheet_name='Gemeente')
df_energy_wijk = pd.read_excel("C:/Users/markhupkens/Dropbox/EnTransitionN
```

```
L/0. Data/Klimaatmonitor (energieverbruik , stadsverwarming, pv - Buurten, wijken en gemeenten 2017).xls",sheet_name='Wijk')
df_inkomen_buurt = pd.read_csv("C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/CBS_2017_Inkomen_Buurt.csv",sep=';')

# Replace string values with nan value 0.424
df_energy_buurt.replace(to_replace='?',value=0.4242,inplace=True)
df_energy_buurt.replace(to_replace='-',value=0.4242,inplace=True)

df_energy_gemeente.replace(to_replace='?',value=0.4242,inplace=True)
df_energy_gemeente.replace(to_replace='-',value=0.4242,inplace=True)

df_energy_wijk.replace(to_replace='?',value=0.4242,inplace=True)
df_energy_wijk.replace(to_replace='-',value=0.4242,inplace=True)

# green gas and renewable heat
df_heat = pd.read_excel("C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/Klimaatmonitor. Green gas and heat- Gemeenten.xls",sheet_name='Gemeenten')
```

1. Solar PV data

In [3]:
```
'''1. Solar PV per neighborhood'''

# Solar PV data, url: https://www.cbs.nl/nl-nl/nieuws/2019/17/vermogen-zonnepanelen-meer-dan-de-helft-toegenomen
df_solar = pd.read_csv("C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/Zonnestroom__wijken_en_buurten__2017_16052019_130403.csv", sep=';', error_bad_lines=False)

# clean data
df_solar['Regioaanduiding/Soort regio (omschrijving)'] = df_solar['Regioaanduiding/Soort regio (omschrijving)'].str.split(" ").str[0]

# Select levels
df_solar_buurt = df_solar.loc[df_solar['Regioaanduiding/Soort regio (omschrijving)']=='Buurt']
df_solar_wijk = df_solar.loc[df_solar['Regioaanduiding/Soort regio (omschrijving)']=='Wijk']
df_solar_gem = df_solar.loc[df_solar['Regioaanduiding/Soort regio (omschrijving)']=='Gemeente']
```

In [4]:
```
# To Do
```

2. FEV and PHEV

In [5]:
```
''' FEV and PHEV Data'''

df_fev = pd.read_excel('C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/Klimaatmonitor - Aantal geregistreerde  EV- PHEV2019 - Postcodes.xls',sheet_name='Auto s voertuigen 2019 Postcode')
df_voertuig = pd.read_csv('C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/Motorvoertuigen_cbs_postcode.csv',error_bad_lines=False, sep=';')
```

```
df_pc = pd.read_csv('C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/2
017-cbs-pc6huisnr20170801_buurt/pc6hnr20170801_gwb.csv',sep=';')
df_pc_buurt = pd.read_csv('C:/Users/markhupkens/Dropbox/EnTransitionNL/0.
Data/2017-cbs-pc6huisnr20170801_buurt/buurtnaam2017.csv',sep=';',encoding
= 'unicode_escape')
df_pc_wijk = pd.read_csv('C:/Users/markhupkens/Dropbox/EnTransitionNL/0. D
ata/2017-cbs-pc6huisnr20170801_buurt/wijknaam2017.csv',sep=';',encoding =
'unicode_escape')
df_pc_gemeente = pd.read_csv('C:/Users/markhupkens/Dropbox/EnTransitionNL/
0. Data/2017-cbs-pc6huisnr20170801_buurt/gemeentenaam2017.csv',sep=';',enc
oding = 'unicode_escape')
```

a. Zipcode coupling dataframe (CBS)

In [6]:
```
df_pc = df_pc.merge(df_pc_buurt,
                    left_on='Buurt2017',
                    right_on='BUURT2017').merge(df_pc_wijk,
                                                left_on='Wijk2017',
                                                right_on='WIJK2017').merge
(df_pc_gemeente,

 left_on='Gem2017',

 right_on='GEM2017')

df_pc['PC4'] = df_pc['PC6'].str[:4]
df_pc.drop_duplicates(subset='PC4', keep='first', inplace=True)
```

b. Vehicles dataframe (CBS + Klimaatmonitor (RDW)

In [7]:
```
# Create merge columns
df_fev['Postcode'] = df_fev["Auto's/voertuigen 2019 - Postcodes"].str.spli
t(" ").str[0]
df_voertuig['Postcode'] = df_voertuig['RegioS'].str.split(" ").str[0]
df_fev = df_fev.merge(df_voertuig,left_on='Postcode', right_on='Postcode',
 how='inner')

# Add buurt,wijk and gemeente names based on pc4
df_veh = df_fev.merge(df_pc, left_on='Postcode', right_on='PC4', how='inne
r')
```

c. group data

In [8]:
```
'''Group data in wijken en gemeenten (pc4)'''

# Gemeenten
df_veh_gem = df_veh.groupby('GEMNAAM').agg({"Aantal geregistreerde elektri
sche personenauto's (FEV)":'sum',

    "Aantal geregistreerde plug-in hybride personenauto's (PHEV)":'sum',

    "Aantal geregistreerde personenauto's op aardgas (CNG)":'sum',

    "Aantal geregistreerde hybride personenauto's":'sum',
```

```
    "Personenauto's op waterstof (H2)":'sum',

   'Personenauto_2':'sum'})
df_veh_gem['Benzine_Diesel']=df_veh_gem['Personenauto_2']-(df_veh_gem["Aan
tal geregistreerde elektrische personenauto's (FEV)"] +
                                                           df_veh_gem["Aan
tal geregistreerde plug-in hybride personenauto's (PHEV)"] +
                                                           df_veh_gem["Aan
tal geregistreerde personenauto's op aardgas (CNG)"] +
                                                           df_veh_gem["Aan
tal geregistreerde hybride personenauto's"] +
                                                           df_veh_gem["Per
sonenauto's op waterstof (H2)"])
# Wijken
df_veh_wijk = df_veh.groupby('WIJKNAAM').agg({"Aantal geregistreerde elekt
rische personenauto's (FEV)":'sum',

    "Aantal geregistreerde plug-in hybride personenauto's (PHEV)":'sum',

    "Aantal geregistreerde personenauto's op aardgas (CNG)":'sum',

    "Aantal geregistreerde hybride personenauto's":'sum',

    "Personenauto's op waterstof (H2)":'sum',

   'Personenauto_2':'sum'})
df_veh_wijk['Benzine_Diesel']=df_veh_wijk['Personenauto_2']-(df_veh_wijk["
Aantal geregistreerde elektrische personenauto's (FEV)"] +
                                                           df_veh_wijk["Aa
ntal geregistreerde plug-in hybride personenauto's (PHEV)"] +
                                                           df_veh_wijk["Aa
ntal geregistreerde personenauto's op aardgas (CNG)"] +
                                                           df_veh_wijk["Aa
ntal geregistreerde hybride personenauto's"] +
                                                           df_veh_wijk["Pe
rsonenauto's op waterstof (H2)"])
```

In [9]:
```
df_veh_wijk.drop('Personenauto_2', axis=1, inplace=True)
df_veh_gem.drop('Personenauto_2', axis=1, inplace=True)
```

In [10]:
```
df_veh_wijk.head()
```

Out[10]:

WIJKNAAM	Aantal geregistreerde elektrische personenauto's (FEV)	Aantal geregistreerde plug-in hybride personenauto's (PHEV)	Aantal geregistreerde personenauto's op aardgas (CNG)	Aantal geregistreerde hybride personenauto's	Personenauto's op waterstof (H2)	B
's Gravenmoer	4.0	8.0	1.0	25.0	0.0	
's-Gravenpolder	3.0	10.0	1.0	38.0	0.0	
's-Heer Abtskerke	8.0	17.0	0.0	52.0	0.0	

Aalsmeerderbrug/ Oude Meer/ Rozenburg / Schiphol Rijk	89.0	36.0	46.0	20.0	0.0
Aarlanderveen	3.0	4.0	0.0	26.0	0.0

Building stock data on buurt-level

Firstly, binary columns have to be created to allow for counting in a groupby dataframe. 13 new columns are added to show housing type (c1-c6) and label (A-G).

In [11]:
```
''' Create housing matrix'''

# Add housing matrix to enable building type count at the end of the scrip
t
df.loc[df['Housing Type']=='C1', 'Houses Detached BAG2018d'] = 1
df.loc[df['Housing Type']=='C2', 'Houses 2u1Roof BAG2018d'] = 1
df.loc[df['Housing Type']=='C3', 'Houses Corner BAG2018d'] = 1
df.loc[df['Housing Type']=='C4', 'Houses Row BAG2018'] = 1
df.loc[df['Housing Type']=='C5', 'Houses SingleFloorAppartments c5 BAG2018
d'] = 1
df.loc[df['Housing Type']=='C6', 'Houses MultiFloorAppartments c6 BAG2018d
'] = 1

# Add preliminary evaluation
df.loc[df['Preliminary Evaluation']=='A', 'Label A BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='B', 'Label B BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='C', 'Label C BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='D', 'Label D BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='E', 'Label E BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='F', 'Label F BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='G', 'Label G BAG2018d'] = 1

# Add Numerical labels (A=1, G=7)
df.loc[df['Preliminary Evaluation']=='A', 'Average Label BAG2018d'] = 1
df.loc[df['Preliminary Evaluation']=='B', 'Average Label BAG2018d'] = 2
df.loc[df['Preliminary Evaluation']=='C', 'Average Label BAG2018d'] = 3
df.loc[df['Preliminary Evaluation']=='D', 'Average Label BAG2018d'] = 4
df.loc[df['Preliminary Evaluation']=='E', 'Average Label BAG2018d'] = 5
df.loc[df['Preliminary Evaluation']=='F', 'Average Label BAG2018d'] = 6
df.loc[df['Preliminary Evaluation']=='G', 'Average Label BAG2018d'] = 7


# convert to string
df['Neighbourhood Code'] = df['Neighbourhood Code'].astype(str).str.split(
".").str[0] #.map(str).str.split(".").str[0]
df['District Code'] = df['District Code'].astype(str).str.split(".").str[0
] # or .map(str).str.split(".").str[0]
```

1. Group Data

In [12]:
```
'''Group adressdata in neighborhoods within municipalities'''

# group data
df_bag = df.groupby(['Municipality Name',
                     'Neighbourhood Name',
                     'Neighbourhood Code']).agg({'House No':'count',
                                                  'Houses Detached BAG2018d':'
count',
                                                   'Houses 2u1Roof BAG2018d':'
count',
                                                  'Houses Corner BAG2018d':'co
unt',
                                                  'Houses Row BAG2018':'count'
,
                                                  'Houses SingleFloorAppartmen
ts c5 BAG2018d':'count',
                                                  'Houses MultiFloorAppartment
s c6 BAG2018d':'count',
                                                  'Construction Year':'mean',
                                                   'Label A BAG2018d':'count',
                                                   'Label B BAG2018d':'count',
                                                    'Label C BAG2018d':'count'
,
                                                    'Label D BAG2018d':'count'
,
                                                    'Label E BAG2018d':'count'
,
                                                    'Label F BAG2018d':'count'
,
                                                    'Label G BAG2018d':'count'
,
                                                    'Average Label BAG2018d':'
mean'})

# Rename column and duplicate index for merge later on
df_bag.rename(columns={'House No':'Houses All BAG2018d'})
df_bag['Neighbourhood Name_2'] = df_bag.index.get_level_values('Neighbourh
ood Name')
df_bag['Municipality Name_2'] = df_bag.index.get_level_values('Municipalit
y Name')
df_bag['Neighbourhood Code_2'] = df_bag.index.get_level_values('Neighbourh
ood Code') # string values for easy merge
```

In [13]:
```
df_bag['Average Label BAG2018d'].describe()
```

Out[13]:
```
count    12987.000000
mean         4.093182
std          1.309312
min          1.000000
25%          3.149821
50%          4.166434
75%          5.048930
max          7.000000
Name: Average Label BAG2018d, dtype: float64
```

In [14]:
```
'''Group adressdata in districts within municipalities'''
```

```
# group data
df_bag_wijk = df.groupby(['Municipality Name',
                          'District Name',
                          'District Code']).agg({'House No':'count',
                                                 'Houses Detached BAG2018d':'
count',
                                                  'Houses 2u1Roof BAG2018d':'
count',
                                                 'Houses Corner BAG2018d':'co
unt',
                                                 'Houses Row BAG2018':'count'
,
                                                 'Houses SingleFloorAppartmen
ts c5 BAG2018d':'count',
                                                 'Houses MultiFloorAppartment
s c6 BAG2018d':'count',
                                                 'Construction Year':'mean',
                                                  'Label A BAG2018d':'count',
                                                  'Label B BAG2018d':'count',
                                                   'Label C BAG2018d':'count'
,
                                                   'Label D BAG2018d':'count'
,
                                                   'Label E BAG2018d':'count'
,
                                                   'Label F BAG2018d':'count'
,
                                                   'Label G BAG2018d':'count'
})

# Rename column and duplicate index for merge later on
df_bag_wijk.rename(columns={'House No':'Houses All BAG2018d'})
df_bag_wijk['District Name_2'] = df_bag_wijk.index.get_level_values('Distr
ict Name')
df_bag_wijk['Municipality Name_2'] = df_bag_wijk.index.get_level_values('M
unicipality Name')
df_bag_wijk['District Code_2'] = df_bag_wijk.index.get_level_values('Distr
ict Code') # string values for easy merge
```

In [15]:

```
'''Group adressdata in districts within municipalities'''

# group data
df_bag_gem = df.groupby(['Municipality Name']).agg({'House No':'count',
                                                 'Houses Detached BAG2018d':'
count',
                                                  'Houses 2u1Roof BAG2018d':'
count',
                                                 'Houses Corner BAG2018d':'co
unt',
                                                 'Houses Row BAG2018':'count'
,
                                                 'Houses SingleFloorAppartmen
ts c5 BAG2018d':'count',
                                                 'Houses MultiFloorAppartment
s c6 BAG2018d':'count',
                                                 'Construction Year':'mean',
```

```
                                                    'Label A BAG2018d':'count',
                                                    'Label B BAG2018d':'count',
                                                     'Label C BAG2018d':'count'
,
                                                     'Label D BAG2018d':'count'
,
                                                     'Label E BAG2018d':'count'
,
                                                     'Label F BAG2018d':'count'
,
                                                     'Label G BAG2018d':'count'
})

# Rename column and duplicate index for merge later on
df_bag_gem.rename(columns={'House No':'Houses All BAG2018d'})
df_bag_gem['Municipality Name_2'] = df_bag_gem.index.get_level_values('Mun
icipality Name')
```

Step 2 Merge All Data

- **df_bag[buurt, wijk, gemeente]**: data for each building on housingtype, provisional label and building year
- **df_energy [buurt, wijk, gemeente]**: average energy consumption
- **df_solar[buurt, wijk, gemeente]**: # installations and KW
- **df_veh[wijk, gemeente]**: EV's, PHEV's and Diesel/petrol

Buurten

In [16]:
```
df_inkomen_buurt.head()
```

Out[16]:

	ID	WijkenEnBuurten	Gemeentenaam_1	Codering_3	GemiddeldInkomenPerInkomensontvanger_65
0	0	NL00	Nederland	NL00	32.0
1	1	GM1680	Aa en Hunze	GM1680	31.6
2	2	WK168000	Aa en Hunze	WK168000	34.0
3	3	BU16800000	Aa en Hunze	BU16800000	33.3
4	4	BU16800009	Aa en Hunze	BU16800009	.

In [17]:
```
'''Buurt: merge grouped bag data with klimaatmonitordata on buurt'''

df_merged_buurt = df_bag.merge(df_energy_buurt,
                               left_on='Neighbourhood Name_2',
                               right_on='Buurt',how='left').merge(df_solar
_buurt,
                                                                   left_on
='Neighbourhood Name_2',
                                                                   right_o
```

```
n=df_solar_buurt['Wijken en buurten'],
                                                                  how='lef
t')

df_merged_buurt = df_merged_buurt.groupby(['Municipality Name_2',
                                           'Neighbourhood Name_2',
                                           'Neighbourhood Code_2']).mean()
 # group by original index
```

Wijken

In [18]:
```
df_veh_wijk.index
```

Out[18]:
```
Index([''s Gravenmoer', ''s-Gravenpolder', ''s-Heer Abtskerke',
       'Aalsmeerderbrug/ Oude Meer/ Rozenburg / Schiphol Rijk',
       'Aarlanderveen', 'Abbenes / Buitenkaag', 'Abcoude', 'Achthuizen',
       'Aetsveldsepolder', 'Afferden',
       ...
       'Zuid', 'Zuidas', 'Zuidland', 'Zuidoost', 'Zuidwest', 'Zuigerplaspa
rk',
       'Zwaanshoek', 'Zwammerdam', 'Zwanenburg', 'de Hoef'],
      dtype='object', name='WIJKNAAM', length=1903)
```

In [19]:
```
'''Wijk merge grouped bag data with klimaatmonitordata on wijk'''

df_merged_wijk = df_bag_wijk.merge(df_energy_wijk,
                                   left_on='District Name',
                                   right_on='Wijk',
                                   how='left').merge(df_veh_wijk,
                                                     left_on='District Name
_2',
                                                     right_index=True,
                                                     how='left').merge(df_s
olar_wijk,
                                                                       lef
t_on='District Name_2',
                                                                       rig
ht_on='Wijken en buurten',
                                                                       how
='left')

df_merged_wijk = df_merged_wijk.groupby(['Municipality Name_2',
                                         'District Name_2',
                                         'District Code_2']).mean() # grou
p by original index
```

Gemeenten

In [20]:
```
'''Gemeente merge grouped bag data with klimaatmonitordata on Gemeente'''

df_merged_gemeente = df_bag_gem.merge(df_energy_gemeente,
                                      left_on='Municipality Name',
                                      right_on='Gemeente',
```

```
                                    how='left').merge(df_veh_gem,
                                                      left_on='Municipality 
Name_2',
                                                      right_index=True,
                                                      how='left').merge(df_h
eat,
                                                                        left
_on='Municipality Name_2',
                                                                        righ
t_on="Thema's  - Gemeenten",
                                                                       how='
left')

df_merged_gemeente = df_merged_gemeente.merge(df_solar_gem,
                                              left_on='Municipality Name_2
', # .astype(str),
                                              right_on='Wijken en buurten'
, #.str[2:].str.strip(" ").str.lstrip("0"),
                                              how='left')

df_merged_gemeente = df_merged_gemeente.groupby(['Municipality Name_2']).m
ean() # group by original index
```

Clean merged dataset

In [21]:
```
# Drop index columns (used for merging)
l_drop= ['Huisnummer', 'Buurt2017', 'Wijk2017', 'Gem2017', 'BUURT2017',
       'WIJK2017', 'GEM2017']

# df_merged_buurt.drop(l_drop,axis=1,inplace=True)
# df_merged_gemeente.drop(l_drop,axis=1,inplace=True)
# df_merged_wijk.drop(l_drop,axis=1,inplace=True)
```

In [22]:
```
# Remove special characters from column names
df_merged_gemeente.columns = df_merged_gemeente.columns.str.replace("[",""
).str.replace("]","")
df_merged_buurt.columns = df_merged_buurt.columns.str.replace("[","").str.
replace("]","")
df_merged_wijk.columns = df_merged_wijk.columns.str.replace("[","").str.re
place("]","")
```

Step 3. Create new Model-setup

Import modelsetup file and merge new data on geospatial index (buurt, wijk, gemeente)

In [23]:
```
# Import model setup files

df_mod_gemeente = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransition
NL/0. Data/ModelSetUpEnergieNL02 (1).xlsx",sheet_name='gemeente')
df_mod_buurt = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL/
0. Data/ModelSetUpEnergieNL02 (1).xlsx",sheet_name='buurt')
df_mod_wijk = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL/0
. Data/ModelSetUpEnergieNL02 (1).xlsx",sheet_name='wijk') # wijkdata horri
```

```
ble from klimaatmonitor
df_mod_mod = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL/0.
 Data/ModelSetUpEnergieNL02 (1).xlsx",sheet_name='ModelSpecification')
```

In [24]:
```
# split entity string to match building data on municipality name
df_mod_gemeente['Municipality Name'] = df_mod_gemeente["Entities"].str.spl
it(" G").str[0]
df_mod_wijk['Wijk Code'] = df_mod_wijk["Entities"].str.split(" W").str[-1]
.str.strip("K").str.strip(" ").str.lstrip("0") # Wijk on wijkcode, ditchin
g leading 0's
df_mod_buurt['Buurt Code'] = df_mod_buurt["Entities"].str.split(" B").str[
-1].str.strip("U").str.strip(" ").str.lstrip("0") # Buurt on buurt code, d
itching leading 0's
```

In [25]:
```
# fillna with 0.4242

df_merged_gemeente.fillna(0.4242,inplace=True)
df_merged_wijk.fillna(0.4242,inplace=True)
df_merged_buurt.fillna(0.4242,inplace=True)
```

In [26]:
```
'''Merge prepared data with modelsetup data'''

# Gemeenten
df_mod_gemeente = df_mod_gemeente.merge(df_merged_gemeente, left_on='Munic
ipality Name', right_on= df_merged_gemeente.index,how='inner')
df_mod_gemeente = df_mod_gemeente.drop(['Municipality Name'], axis=1)

# Buurten
df_mod_buurt = df_mod_buurt.merge(df_merged_buurt,
                                  left_on='Buurt Code',
                                  right_on= df_merged_buurt.index.get_leve
l_values('Neighbourhood Code_2'),
                                  how='inner')
                                                      # df_mod_buurt = df_m
od_buurt.drop(['Buurt Name'], axis=1)

# Wijken
df_mod_wijk = df_mod_wijk.merge(df_merged_wijk, left_on='Wijk Code', right
_on=df_merged_wijk.index.get_level_values('District Code_2'),how='inner')
# df_mod_wijk = df_mod_wijk.drop(['District Name_2'], axis=1)
```

Add classes to neighbourhoods

- based on building value, assign value classes. divide in quantiles and assign integer
- based on % district heat, assign quantitles of district heat availability

In [27]:
```
'''Add quantile groups of average labels''' # LOW QUANTILE = GOOD LABEL (A
=1)

df_mod_buurt.loc[df_mod_buurt['Average Label BAG2018d']<=df_mod_buurt['Ave
rage Label BAG2018d'].quantile(q=0.25), 'label group'] = 1

df_mod_buurt.loc[(df_mod_buurt['Average Label BAG2018d']>=df_mod_buurt['Av
```

```
erage Label BAG2018d'].quantile(q=0.25)) &
                  (df_mod_buurt['Average Label BAG2018d']<=df_mod_buurt['Av
erage Label BAG2018d'].quantile(q=0.50)), 'label group'] = 2

df_mod_buurt.loc[(df_mod_buurt['Average Label BAG2018d']>=df_mod_buurt['Av
erage Label BAG2018d'].quantile(q=0.50)) &
                  (df_mod_buurt['Average Label BAG2018d']<=df_mod_buurt['Av
erage Label BAG2018d'].quantile(q=0.75)), 'label group'] = 3

df_mod_buurt.loc[(df_mod_buurt['Average Label BAG2018d']>=df_mod_buurt['Av
erage Label BAG2018d'].quantile(q=0.75)) &
                  (df_mod_buurt['Average Label BAG2018d']<=df_mod_buurt['Av
erage Label BAG2018d'].quantile(q=1.00)), 'label group'] = 4
```

In [28]:

```
df_mod_buurt['label group'].value_counts()
```

Out[28]:

```
1.0    3247
4.0    3247
3.0    3247
2.0    3247
Name: label group, dtype: int64
```

In [29]:

```
'''Add value classes'''
# distribute neighbourhoods in 4 classes based on building value from 1 (l
owest quantile) to 4 (highest quantile)

df_mod_buurt.loc[df_mod_buurt['woningwaarde keuro buurt']<=df_mod_buurt['w
oningwaarde keuro buurt'].quantile(q=0.25), 'value group'] = 1

df_mod_buurt.loc[(df_mod_buurt['woningwaarde keuro buurt']>=df_mod_buurt['
woningwaarde keuro buurt'].quantile(q=0.25)) &
                  (df_mod_buurt['woningwaarde keuro buurt']<=df_mod_buurt['
woningwaarde keuro buurt'].quantile(q=0.50)), 'value group'] = 2

df_mod_buurt.loc[(df_mod_buurt['woningwaarde keuro buurt']>=df_mod_buurt['
woningwaarde keuro buurt'].quantile(q=0.50)) &
                  (df_mod_buurt['woningwaarde keuro buurt']<=df_mod_buurt['
woningwaarde keuro buurt'].quantile(q=0.75)), 'value group'] = 3

df_mod_buurt.loc[(df_mod_buurt['woningwaarde keuro buurt']>=df_mod_buurt['
woningwaarde keuro buurt'].quantile(q=0.75)) &
                  (df_mod_buurt['woningwaarde keuro buurt']<=df_mod_buurt['
woningwaarde keuro buurt'].quantile(q=1.00)), 'value group'] = 4
```

In [30]:

```
df_mod_buurt['value group'].value_counts()
```

Out[30]:

```
4.0    3264
3.0    3258
1.0    3236
2.0    3230
Name: value group, dtype: int64
```

In [31]:

```
df_show = df_mod_buurt.drop(columns=['Bevolking buurt', 'Mannen buurt',
       'Vrouwen buurt', 'Bevolking 0 tot 15 jaar buurt',
       'Bevolking 15 tot 25 jaar buurt', 'Bevolking 25 tot 45 jaar buurt',
       'Bevolking 45 tot 65 jaar buurt', 'Bevolking 65 jaar of ouder buurt
```

```
',
       'Bevolking Geboorte en sterfte Geboorte totaal aantal buurt',
       'Bevolking Geboorte en sterfte Geboorte relatief per 1 000 inwoners
 buurt',
       'Bevolking Geboorte en sterfte Sterfte totaal aantal buurt',
       'Bevolking Geboorte en sterfte Sterfte relatief per 1 000 inwoners
buurt',
       'Huishoudens totaal buurt', 'Eenpersoonshuishoudens buurt',
       'Huishoudens zonder kinderen buurt', 'Huishoudens met kinderen buur
t',
       'huishoudensgrootte ', 'Bevolkingsdichtheid per sqkm buurt',
       'Woningvoorraad buurt', 'woningwaarde keuro buurt',
       'eengezinswoning pc buurt', 'meergezinswoning pc buurt',
       'onbewoond pc buurt', 'Koopwoningen pc buurt',
       'Huurwoningen totaal pc buurt',
       'Huurwoningen woningcorporatie pc buurt',
       'Huurwoningen overige verhuurders pc buurt',
       'Eigendom onbekend pc buurt', 'Bouwjaar voor 2000 pc buurt',
       'Oppervlakte ', 'Oppervlakte land ha buurt',
       'Oppervlakte water ha buurt', 'Buurt Code', 'House No'])

df_show.head()
```

Out[31]:

	Entities	Mapping	Houses Detached BAG2018d	Houses 2u1Roof BAG2018d	Houses Corner BAG2018d	Houses Row BAG2018	Houses SingleFloorAppartments c5 BAG2018d	Mu
0	Annen BU16800000	Wijk 00 Annen WK168000	582	478	160	204	134	
1	Verspreide huizen Annen BU16800009	Wijk 00 Annen WK168000	61	1	0	0	0	
2	Eext BU16800100	Wijk 01 Eext WK168001	301	146	37	40	16	
3	Verspreide huizen Eext BU16800109	Wijk 01 Eext WK168001	47	1	0	0	1	
4	Anloo BU16800200	Wijk 02 Anloo WK168002	99	41	2	1	2	

5 rows × 35 columns

Check data on income per neighbourhood

In [32]:
```
df_inkomen_buurt = pd.read_csv("C:/Users/markhupkens/Dropbox/EnTransitionNL/0. Data/CBS_2017_Inkomen_Buurt.csv", sep=';')

df_inkomen_buurt['GemiddeldInkomenPerInkomensontvanger_65'] = pd.to_numeric(df_inkomen_buurt['GemiddeldInkomenPerInkomensontvanger_65'].str.lstrip(' ').replace('.', np.nan)) * 1000
df_inkomen_buurt['GemiddeldInkomenPerInwoner_66'] = pd.to_numeric(df_inkomen_buurt['GemiddeldInkomenPerInwoner_66'].str.lstrip(' ').replace('.', np.nan)) * 1000

len(df_inkomen_buurt.loc[df_inkomen_buurt['GemiddeldInkomenPerInwoner_66'] >0])
```

Out[32]: 4072

In [33]:
```
len(df_mod_buurt.loc[df_mod_buurt['woningwaarde keuro buurt']>0]) - len(df_mod_buurt.loc[df_mod_buurt['woningwaarde keuro buurt']==0.4242])
```

Out[33]: 10099

Data completeness of building value is far higher than data completeness of income per capita or average income per person.

4. Export new modelspecification file

In [34]:
```
# export as xlsx to genereate new modelspecification file
from pandas import ExcelWriter

# with pd.ExcelWriter('D:/markhupkens/Dropbox/EnTransitionNL/0. Data/ModelSetUpEnergyNL01_MH.xlsx') as writer:  # doctest: +SKIP
with pd.ExcelWriter('C:/Users/markhupkens/Dropbox/EnTransitionNL/ModelSetUpEnergyNL01_MH_avglabelgroup.xlsx') as writer:  # doctest: +SKIP
    df_mod_buurt.to_excel(writer, sheet_name='buurt')
    df_mod_wijk.to_excel(writer, sheet_name='wijk')
    df_mod_gemeente.to_excel(writer, sheet_name='gemeente')
    df_mod_mod.to_excel(writer, sheet_name='ModelSpecification')
```

OR ADD SPECIFIC COLUMN TO EXISTING FILE

In [35]:
```
# Select columsn to merge
df_new = df_mod_buurt[['Entities', 'label group','Average Label BAG2018d']]
```

In [36]:
```
# Import exsiting file
df_import_gemeente = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL/MSETMnlEPdataMHv02.xlsx",sheet_name='gemeente')
df_import_buurt = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL/MSETMnlEPdataMHv02.xlsx",sheet_name='buurt')
df_import_wijk = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL/MSETMnlEPdataMHv02.xlsx",sheet_name='wijk') # wijkdata horrible from klimaatmonitor
```

```
df_import_mod = pd.read_excel("C:/users/markhupkens/Dropbox/EnTransitionNL
/MSETMnlEPdataMHv02.xlsx",sheet_name='ModelSpecification')
```

In [37]:
```
df_final_buurt = df_import_buurt.merge(df_new,left_on='Entities', right_on
='Entities',how='inner')

# export as xlsx to genereate new modelspecification file
from pandas import ExcelWriter

# with pd.ExcelWriter('D:/markhupkens/Dropbox/EnTransitionNL/0. Data/Model
SetUpEnergyNL01_MH.xlsx') as writer:  # doctest: +SKIP
with pd.ExcelWriter('C:/Users/markhupkens/Dropbox/EnTransitionNL/ModelSetU
pEnergyNL02_MH_avglabelgroup.xlsx') as writer:  # doctest: +SKIP
    df_final_buurt.to_excel(writer, sheet_name='buurt')
    df_import_wijk.to_excel(writer, sheet_name='wijk')
    df_import_gemeente.to_excel(writer, sheet_name='gemeente')
    df_import_mod.to_excel(writer, sheet_name='ModelSpecification')
```

B.2. Multi Scale Allignment

In [1]:
```python
import pandas as pd
```

Multi-scale-alignment

- Alignement of spatial resolution in modelsetup data
- Part of the energytransitionmodelling effort

@author: Mark Hupkens @date: 16-05-2019

In [2]:
```python
'''Import files'''
df_gem = pd.read_excel("D:/markhupkens/Dropbox/EnTransitionNL/0. Data/ModelSetUpEnergyNL01_MH.xlsx", sheet_name='gemeente')
df_buurt = pd.read_excel("D:/markhupkens/Dropbox/EnTransitionNL/0. Data/ModelSetUpEnergyNL01_MH.xlsx", sheet_name='buurt')
df_wijk = pd.read_excel("D:/markhupkens/Dropbox/EnTransitionNL/0. Data/ModelSetUpEnergyNL01_MH.xlsx", sheet_name='wijk')
df_mod = pd.read_excel("D:/markhupkens/Dropbox/EnTransitionNL/0. Data/ModelSetUpEnergyNL01_MH.xlsx", sheet_name='ModelSpecification')
```

Q: how do model scales line up in the data?

In [3]:
```python
print(df_wijk.Entities.nunique())
```

```
3067
```

In [4]:
```python
print(df_buurt.Mapping.nunique())
```

```
3067
```

A: There are more wijken included as a mapping on buurt-level, than as there are entities on wijk-level A2: same applies for municipalities

Allign data resolutions

In [5]:
```python
'''Check and keep only rows if entities and mappings line up'''

# Keep only gemeenten that are mappings in wijk
df_gem_new = df_gem.loc[df_gem.Entities.isin(df_wijk.Mapping)==True]

# Keep only wijk rows whose mapping is an entity in gemeente
df_wijk_new = df_wijk.loc[df_wijk.Mapping.isin(df_gem_new.Entities)==True]

# Keep only wijk rows whose entity is a mapping in df_buurt
df_wijk_new = df_wijk_new.loc[df_wijk_new.Entities.isin(df_buurt.Mapping)==True]

# Keep only buurten whose mapping is an entity in df_wijk
```

```
df_buurt_new = df_buurt.loc[df_buurt.Mapping.isin(df_wijk_new.Entities)==T
rue]
```

In [6]:
```
print('df_buurt_new has length',len(df_buurt_new))
print('df_wijk_new has length', len(df_wijk_new))
print('df_gem has length',len(df_gem_new))
```

```
df_buurt_new has length 11649
df_wijk_new has length 2729
df_gem has length 342
```

Check new data resolutions

In [7]:
```
# buurt to wijk
(df_buurt_new.Mapping.isin(df_wijk_new.Entities)==True).value_counts()
```

Out[7]:
```
True    11649
Name: Mapping, dtype: int64
```

In [8]:
```
# Wijk to gem
(df_wijk_new.Mapping.isin(df_gem_new.Entities)==True).value_counts()
```

Out[8]:
```
True    2729
Name: Mapping, dtype: int64
```

In [9]:
```
# Gem to wijk
(df_gem_new.Entities.isin(df_wijk_new.Mapping)==True).value_counts()
```

Out[9]:
```
True    342
Name: Entities, dtype: int64
```

All resolutions now line up, as all mappings in a low-resolution dataframe are included as entities in a high-resolution dataframe

Data completeness

How much data has been lost in the alignment process

In [10]:
```
print(len(df_gem)-len(df_gem_new),'Gemeenten have been lost', (len(df_gem)
-len(df_gem_new))/len(df_gem)*100 )
print(len(df_wijk)-len(df_wijk_new),'Wijken have been lost', (len(df_wijk)
-len(df_wijk_new))/len(df_wijk)*100)
print(len(df_buurt)-len(df_buurt_new),'Buurten have been lost', (len(df_bu
urt)-len(df_buurt_new))/len(df_buurt)*100)
```

```
0 Gemeenten have been lost 0.0
338 Wijken have been lost 11.020541245516792
1339 Buurten have been lost 10.309516476747767
```

Export data to new stup file

In [11]:
```
# export as xlsx to genereate new modelspecification file
from pandas import ExcelWriter

with pd.ExcelWriter('D:/markhupkens/Dropbox/EnTransitionNL/0. Data/ModelSe
tUpEnergyNL02EPMH3Aligned.xlsx') as writer:  # doctest: +SKIP
    df_buurt_new.to_excel(writer, sheet_name='buurt')
    df_wijk_new.to_excel(writer, sheet_name='wijk')
    df_gem_new.to_excel(writer, sheet_name='gemeente')
    df_mod.to_excel(writer, sheet_name='ModelSpecification')
```

In [12]:
```
print(len(df_buurt_new))
print(len(df_wijk_new))
print(len(df_gem_new))
```

```
11649
2729
342
```

B.3. EV Charger Scraper

EV charger scraper

- Notebook to scrape available data on public and private ev chargers in The Netherlands
- Data from oplaadpalen.nl
- Quick visualization
- part of MSc thesis at Delft University of Technology

@author: Mark Hupkens

In [1]:
```
import pandas as pd
import requests
# import urllib2
from bs4 import BeautifulSoup
import urllib.request
import numpy as np
```

API Parameters

- access_type element of (public, company, private)
- availability (available, in use)
- charging & power (Normal, fast)

Loop over a range of gps coordinates

In [2]:
```
# Loop over range to create box
zoom ='15'
accesstype = 'public,company,private' # gather types of chargers
d = {}
boxes = [ (lon, lat) for lon in np.arange(50.5,54,.1) for lat in np.arange
 (3.4,7.5,.4)]

for count, box in enumerate(boxes):
    if count==0:
        box = (str(boxes[count])+","+str(box))
        box = box.replace(")","").replace("(","").replace(" ","")
    else:
        box = (str(boxes[count-1])+","+str(box))
        box = box.replace(")","").replace("(","").replace(" ","")

    url = 'https://oplaadpalen.nl/api/maplist/clusterset?box='+box+'&zoom=
'+str(zoom)+'&accessType='+accesstype+'&available=available,charging&power
=fast,normal'
    response = requests.get(url)
    data = response.json()
    df = pd.DataFrame.from_dict(data['data'])
    if len(df) != 0: # only save data if len>0
        d[box] = df
```

```
        print(box,len(df))
```

```
50.5,7.399999999999999,50.6,3.4 58
50.6,7.399999999999999,50.7,3.4 114
50.7,7.399999999999999,50.800000000000004,3.4 297
50.800000000000004,7.399999999999999,50.900000000000006,3.4 603
50.900000000000006,7.399999999999999,51.00000000000001,3.4 537
51.00000000000001,7.399999999999999,51.10000000000001,3.4 479
51.10000000000001,7.399999999999999,51.20000000000001,3.4 491
51.20000000000001,7.399999999999999,51.30000000000001,3.4 487
51.30000000000001,7.399999999999999,51.40000000000001,3.4 362
51.40000000000001,7.399999999999999,51.500000000000014,3.4 843
51.500000000000014,7.399999999999999,51.600000000000016,3.4 932
51.600000000000016,7.399999999999999,51.70000000000002,3.4 664
51.70000000000002,7.399999999999999,51.80000000000002,3.4 548
51.80000000000002,7.399999999999999,51.90000000000002,3.4 1448
51.90000000000002,7.399999999999999,52.00000000000002,3.4 1790
52.00000000000002,7.399999999999999,52.10000000000002,3.4 2616
52.10000000000002,7.399999999999999,52.200000000000024,3.4 1577
52.200000000000024,7.399999999999999,52.300000000000026,3.4 1386
52.300000000000026,7.399999999999999,52.40000000000003,3.4 2156
52.40000000000003,7.399999999999999,52.50000000000003,3.4 666
52.50000000000003,7.399999999999999,52.60000000000003,3.4 468
52.60000000000003,7.399999999999999,52.70000000000003,3.4 482
52.70000000000003,7.399999999999999,52.80000000000003,3.4 225
52.80000000000003,7.399999999999999,52.900000000000034,3.4 77
52.900000000000034,7.399999999999999,53.000000000000036,3.4 165
53.000000000000036,7.399999999999999,53.10000000000004,3.4 150
53.10000000000004,7.399999999999999,53.20000000000004,3.4 270
53.20000000000004,7.399999999999999,53.30000000000004,3.4 280
53.30000000000004,7.399999999999999,53.40000000000004,3.4 63
53.40000000000004,7.399999999999999,53.50000000000004,3.4 20
53.50000000000004,7.399999999999999,53.600000000000044,3.4 12
53.600000000000044,7.399999999999999,53.700000000000045,3.4 3
53.700000000000045,7.399999999999999,53.80000000000005,3.4 2
```

In [3]:

```
# Show length of all stored dataframes
l=[]
for key in d:
    l.append(len(d[key]))
sum(l)
```

Out[3]: 20271

In [4]:

```
# Save unique heading combinations
l2=[]
for key in d:
    if d[key].columns.values.tolist() not in l2:
        l2.append(d[key].columns.values.tolist())

l2
```

Out[4]:

```
[['id', 'point', 'power', 'publicaccess', 'status'],
 ['cluster', 'id', 'point', 'power', 'publicaccess', 'status'],
 ['staticCluster']]
```

In [5]:

```
# Append keys of correct columnumber to list
```

```
l_5col = []
l_6col = []
l_1col = []

for key in d:
    if d[key].columns.values.tolist() == l2[0]:
        l_5col.append(key)
    elif d[key].columns.values.tolist() == l2[1]:
        l_6col.append(key)
    elif d[key].columns.values.tolist() == l2[2]:
        l_1col.append(key)
```

In [32]:
```
# Used lists of keys to create dataframes

df_5_col = pd.DataFrame(columns = l2[0])
df_6_col = pd.DataFrame(columns = l2[1])
df_1_col = pd.DataFrame(columns = l2[2])

for key in l_5col:
    df_5_col = df_5_col.append(d[key],ignore_index=True)
for key in l_6col:
    df_6_col = df_6_col.append(d[key],ignore_index=True)
for key in l_1col:
    df_1_col = df_1_col.append(d[key],ignore_index=True)
```

In [7]:
```
# Drop useless column
df_6_col.drop('cluster', axis=1, inplace=True)
```

Function to parse data

In [8]:
```
def parse_df(df):
    if df.columns.isin(['id', 'point', 'power', 'publicaccess', 'status'])
.all() or df.columns.isin(['cluster', 'id', 'point', 'power', 'publicacces
s', 'status']).all():

        # Extract Dict data
        df = df.merge(df['point'].apply(pd.Series), left_index=True, right
_index=True) #lng lat
        df = df.merge(df.status.apply(pd.Series), left_index=True, right_i
ndex=True) #availability charging

        #drop columns
        df = df[['power','publicaccess','lat','lng','available','charging'
]]
        return df
    else:
        print('Scraped data not in correct format')
```

In [9]:
```
# Parse data and merge
df_charge = parse_df(df_5_col)
df_charge = df_charge.append(parse_df(df_6_col))
```

In [10]:
```
df_charge.head()
```

Out[10]:

	power	publicaccess	lat	lng	available	charging
0	22080	Public	50.50073376	5.24111517	1	0
1	22000	Public	50.50283086	5.11911117	0	0
2	22000	Public	50.50300603	5.87175581	0	0
3	22080	Private	50.50388791	4.46993699	2	0
4	22000	Public	50.50503506	5.88437543	0	0

In [33]:

```
df_1_col = df_1_col.staticCluster.apply(pd.Series)
df_1_col['publicaccess'] = 'unknown'
df_1_col.head()
```

Out[33]:

	lat	lng	count	publicaccess
0	52.01225628	6.13546952	1	unknown
1	52.01644447	6.13132338	1	unknown
2	52.04621124	5.67533739	1	unknown
3	52.04557260	5.66836542	1	unknown
4	52.01906509	5.66270176	1	unknown

In [12]:

```
df_charge = df_charge.append(df_1_col)
len(df_charge)
```

```
C:\Users\markhupkens\Anaconda3\lib\site-packages\pandas\core\frame.py:6692
: FutureWarning: Sorting because non-concatenation axis is not aligned. A
future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
```

Out[12]: 20271

In [13]:

```
# Data overview
df_charge.publicaccess.value_counts()
```

Out[13]:

```
Public     9123
Company    3467
unknown    2616
Private    2545
Name: publicaccess, dtype: int64
```

In [14]:

```
# store data
df_charge.to_csv('data/ev_chargers_scraped.csv')
```

Plot with geopandas

In [15]:
```
df_charge = pd.read_csv('data/ev_chargers_scraped.csv')
```

In [16]:
```
import geopandas as gpd
from shapely.geometry import Point, Polygon
import descartes
import matplotlib.pyplot as plt
%matplotlib inline
```

In [17]:
```
df_charge.lng = pd.to_numeric(df_charge.lng)
df_charge.lat = pd.to_numeric(df_charge.lat)
```

In [18]:
```
geometry = [Point(xy) for xy in zip (df_charge.lng, df_charge.lat)]
geometry[:3]
```

Out[18]:
```
[<shapely.geometry.point.Point at 0x1931eac7da0>,
 <shapely.geometry.point.Point at 0x1931eac7e10>,
 <shapely.geometry.point.Point at 0x1931eac7f98>]
```

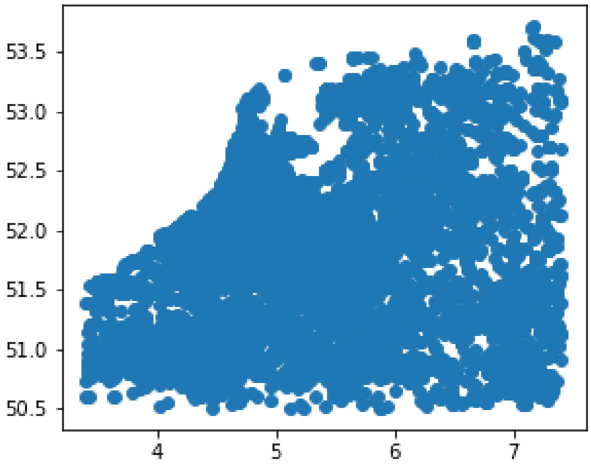
In [19]:
```
gdf = gpd.GeoDataFrame(df_charge, geometry=geometry)
gdf.head()
```

Out[19]:

	Unnamed: 0	available	charging	count	lat	lng	power	publicaccess	geometry
0	0	1.0	0.0	NaN	50.500734	5.241115	22080.0	Public	POINT (5.24111517 50.50073376)
1	1	0.0	0.0	NaN	50.502831	5.119111	22000.0	Public	POINT (5.11911117 50.50283086)
2	2	0.0	0.0	NaN	50.503006	5.871756	22000.0	Public	POINT (5.87175581 50.50300603)
3	3	2.0	0.0	NaN	50.503888	4.469937	22080.0	Private	POINT (4.46993699 50.50388791)
4	4	0.0	0.0	NaN	50.505035	5.884375	22000.0	Public	POINT (5.88437543 50.50503506)

In [30]:
```
gdf.crs = {'init' :'epsg:4326'}
gdf.plot()
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x19322133b38>
```


53.5
53.0
52.5
52.0
51.5
51.0
50.5
4
5
6
7

C

Model Overview

This chapter provides an overview of the most important model structures used in the Vensim model.

C.1. Base Model

This section shows the main structural components of the basemodel used in the analyses in this study.

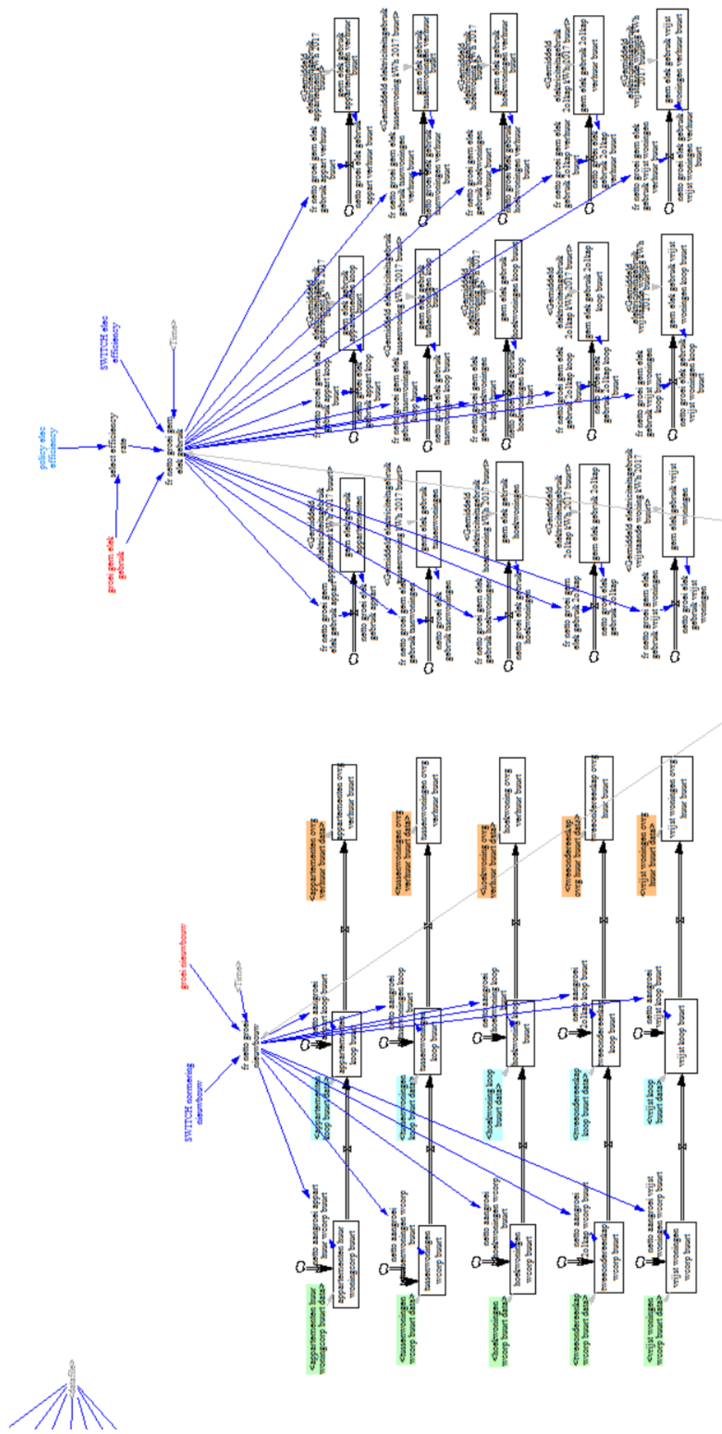


Figure C.1: Base model: general housing structure and electricity demand accumulation

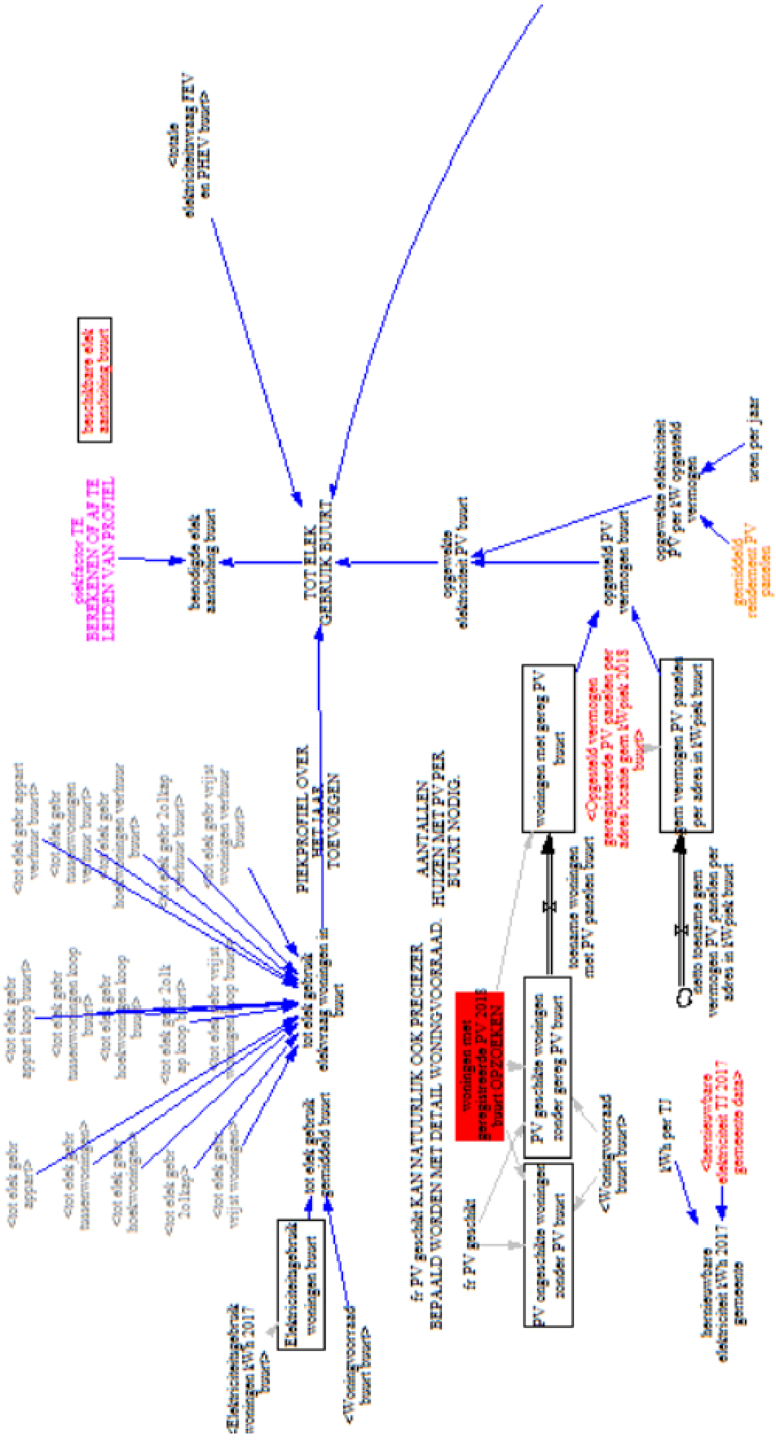


Figure C.2: Base model: electricity demand

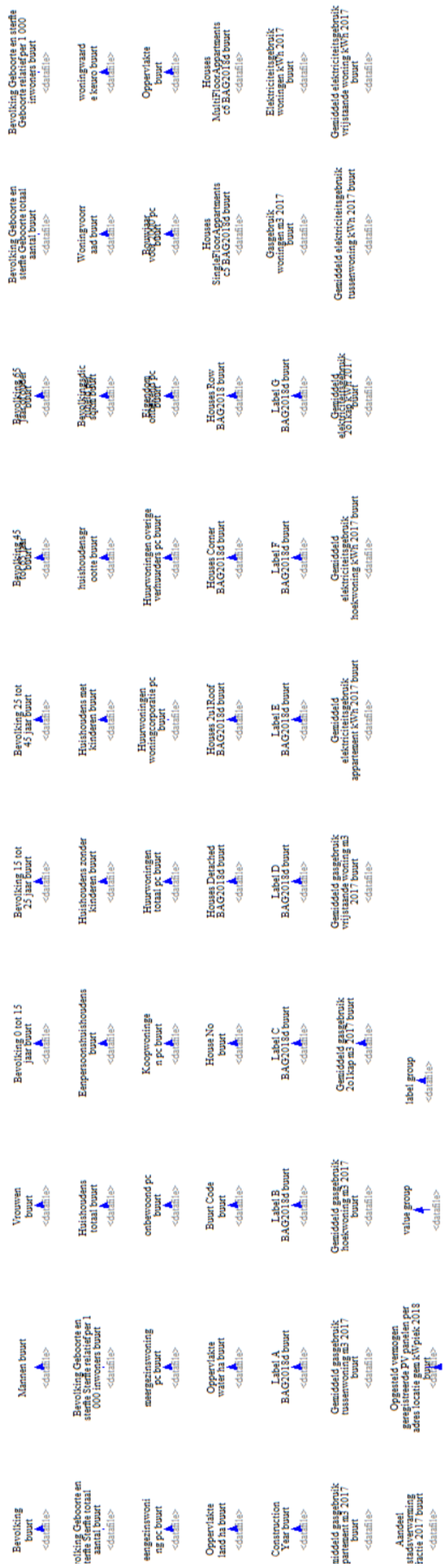


Figure C.3: Base Model: data import. Data described in section 4.2 and section B.1

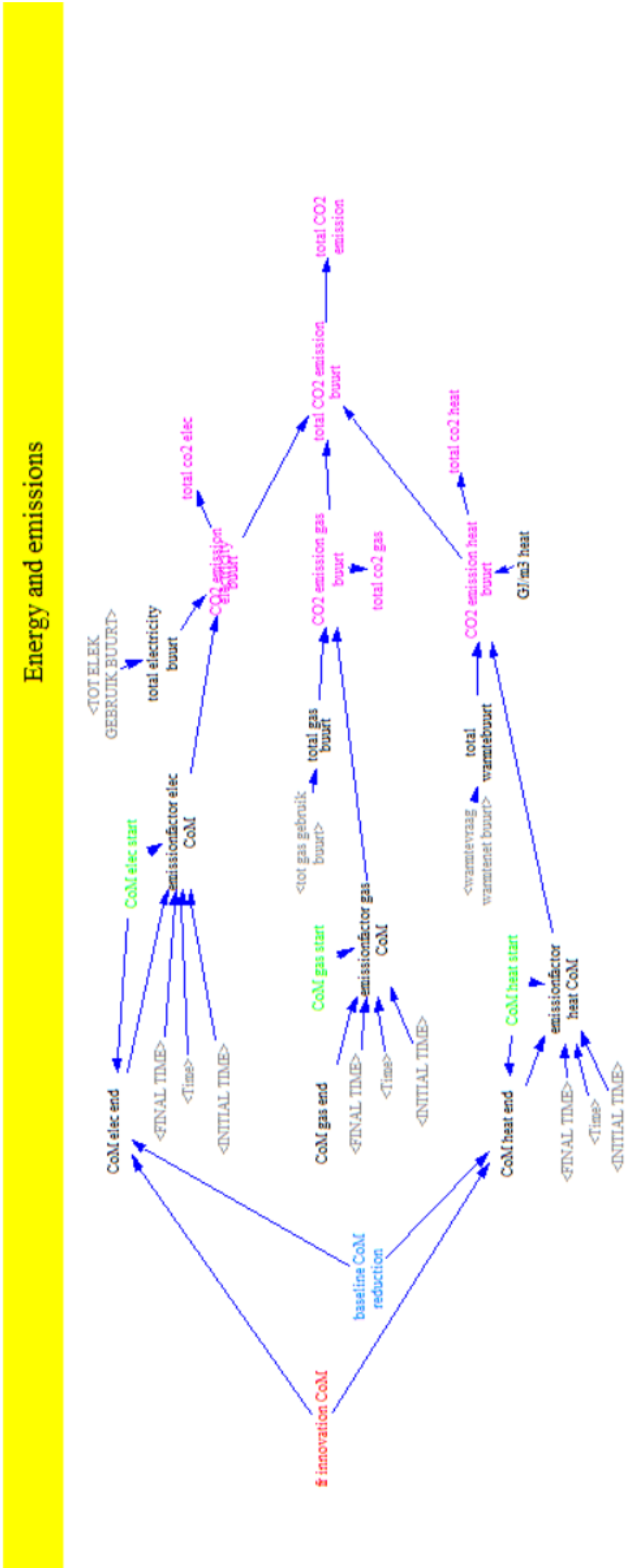


Figure C.4: Base Model: KPI structure CO_2-eq emissions. Emissions are calculated by summing total emissions per neighbourhood and multiplying them with a (dynamic) emission factor.

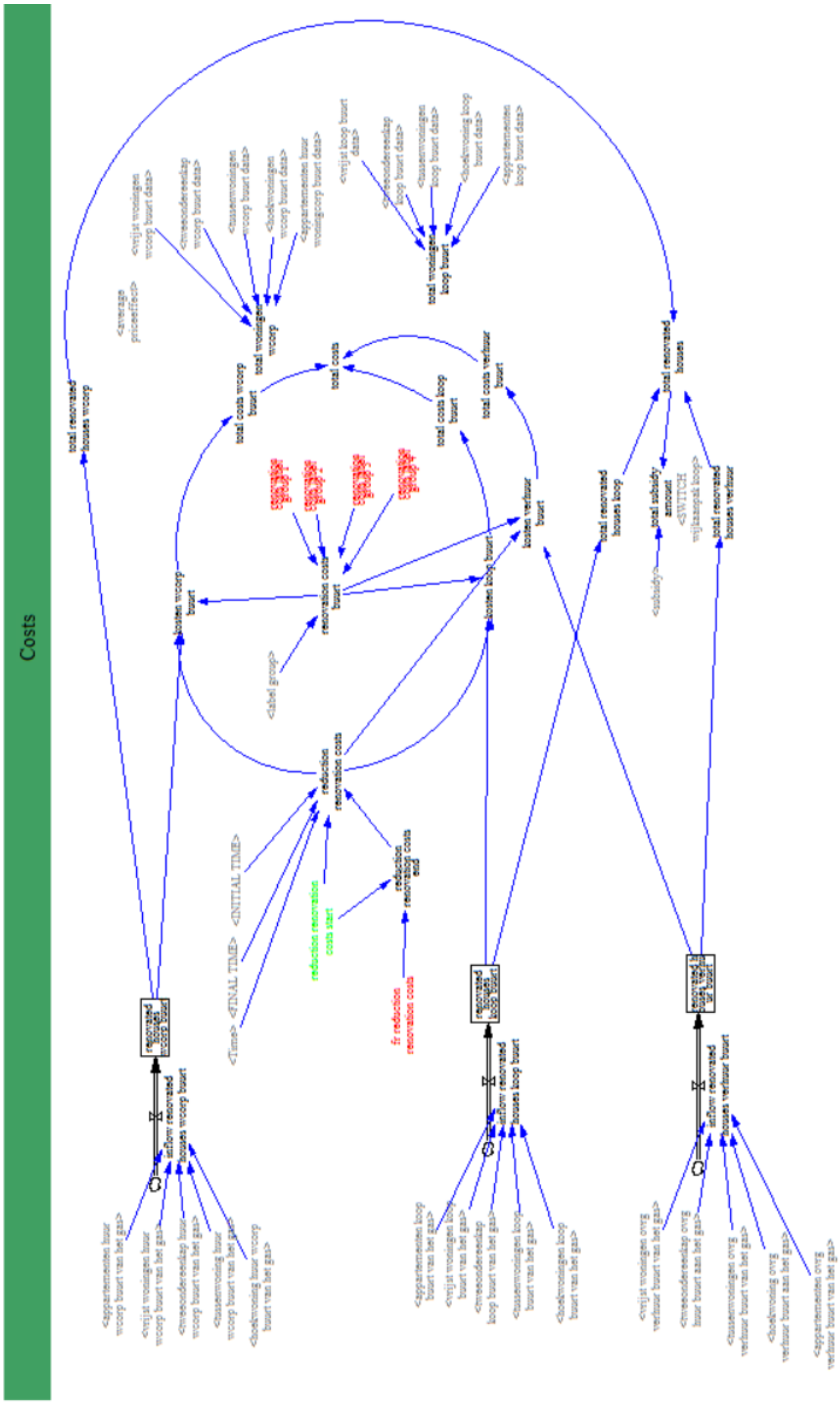


Figure C.5: Base Model: KPI structure costs. Summing total renovations per neighbourhood with total costs of renovated homes (sampled as uncertainty)

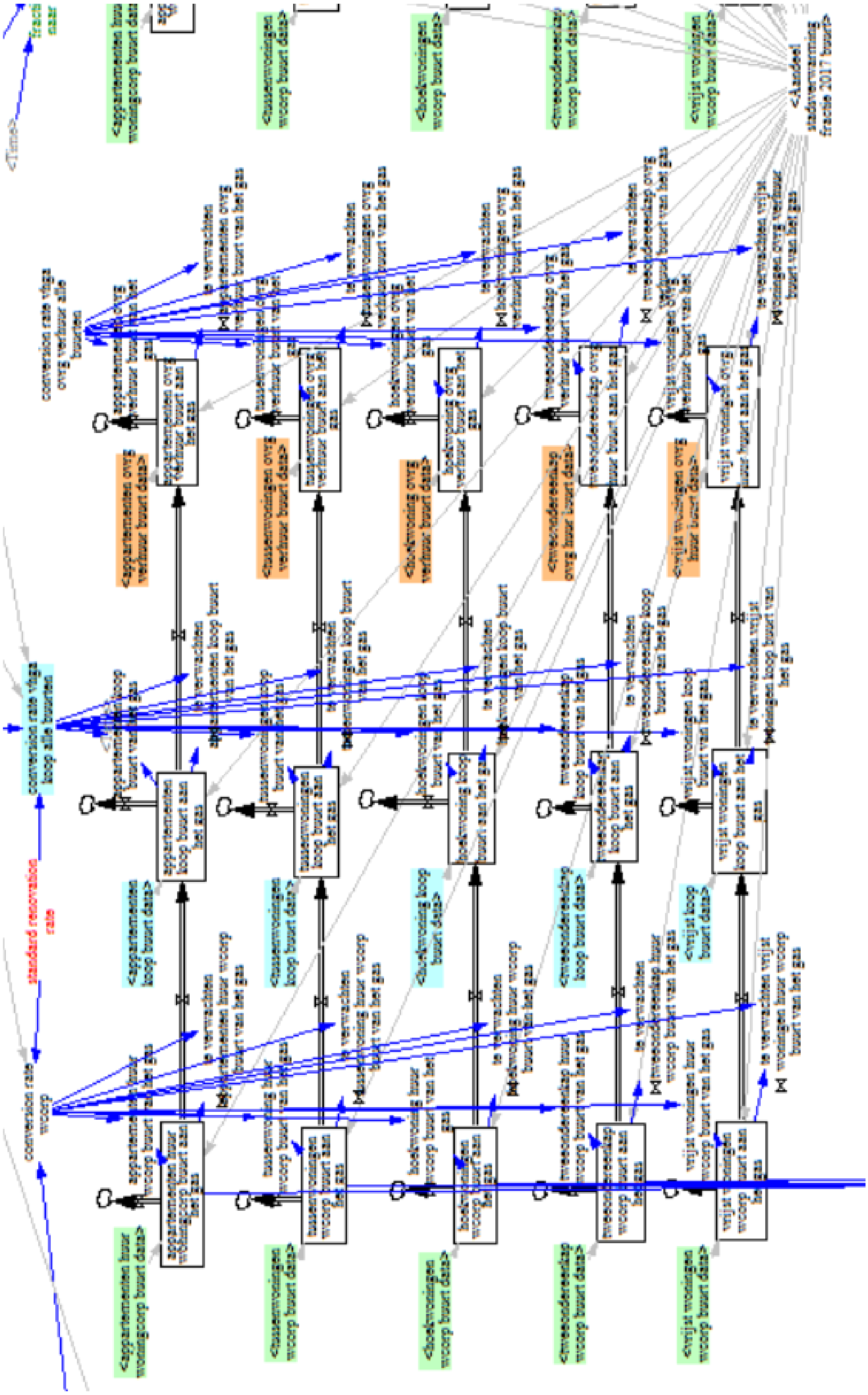


Figure C.6: Base Model: Renovation stock flow structure. Structure that allows renovations if, decisions to renovate have been made on a neighbourhood level.

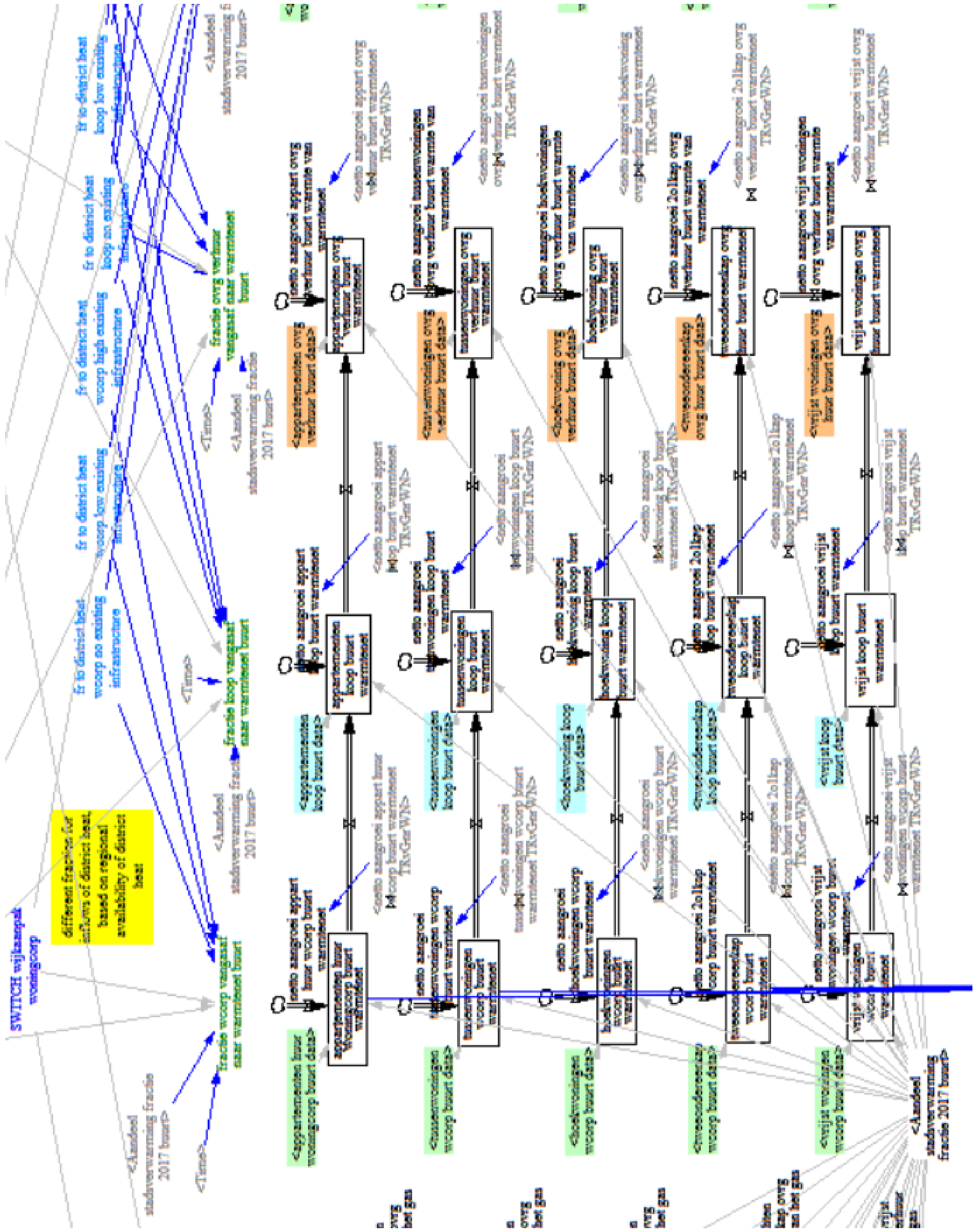


Figure C.7: Base Model: Renovation to district heating

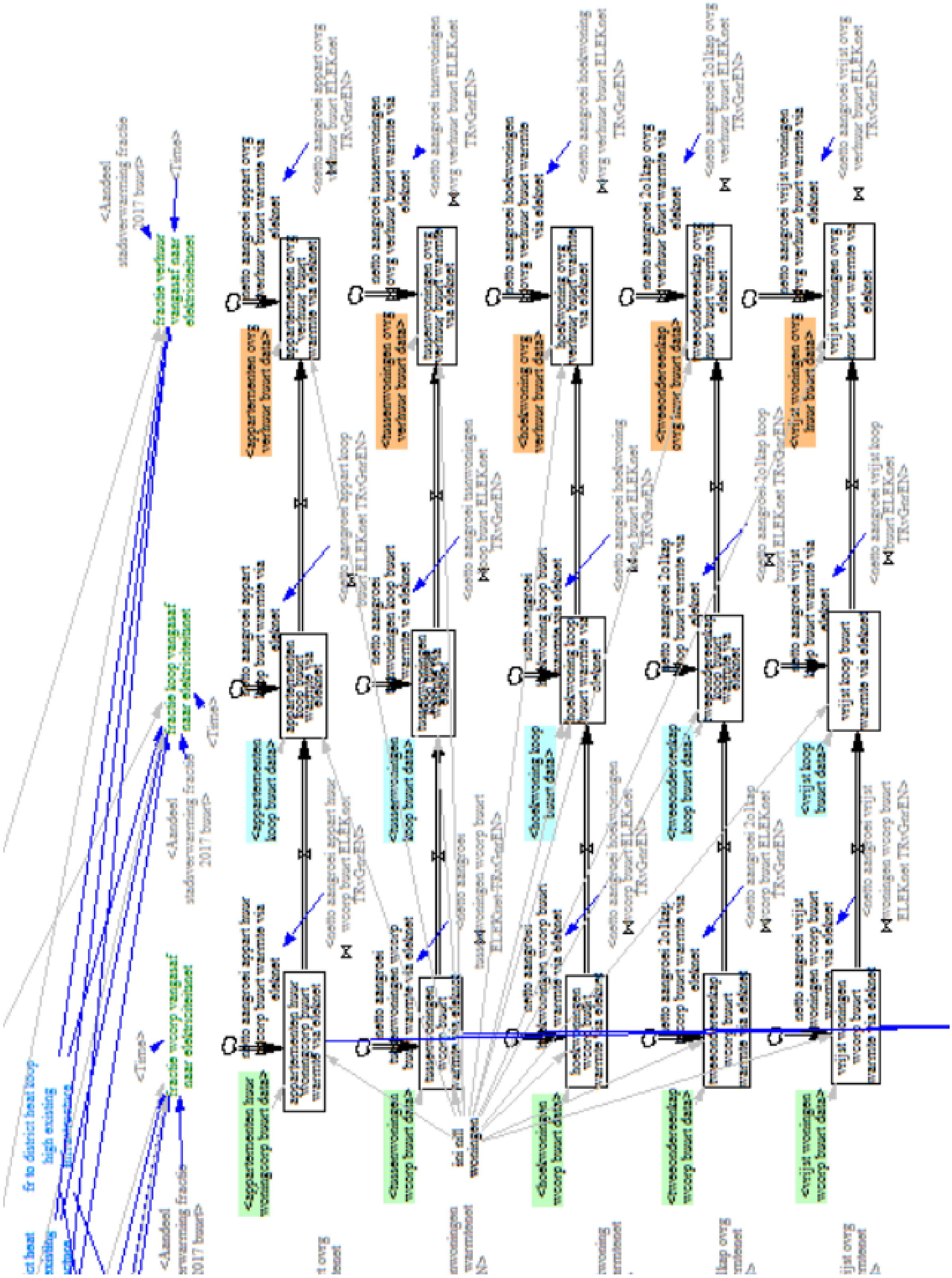


Figure C.8: Base Model: Renovation to all electric

C.2. Policy Model

This section presents main structures used in the policy models employed in this study.

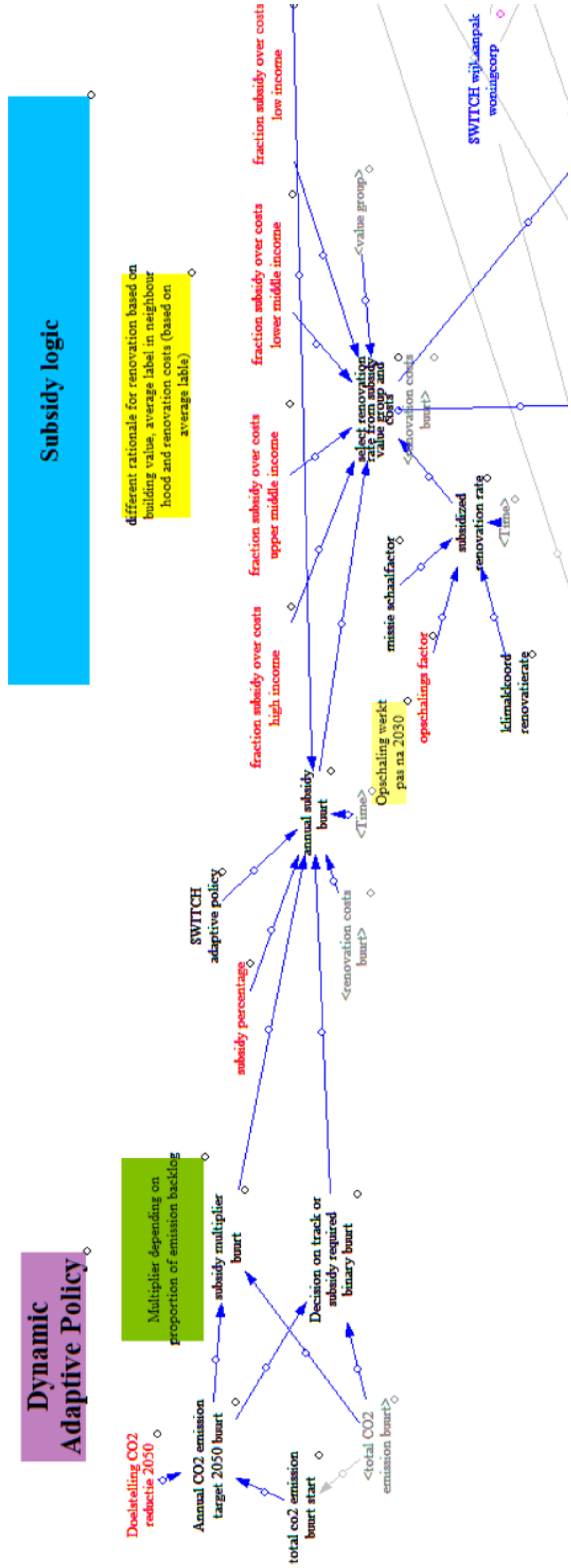


Figure C.9: All policies (Switched): propensity to renovate structure

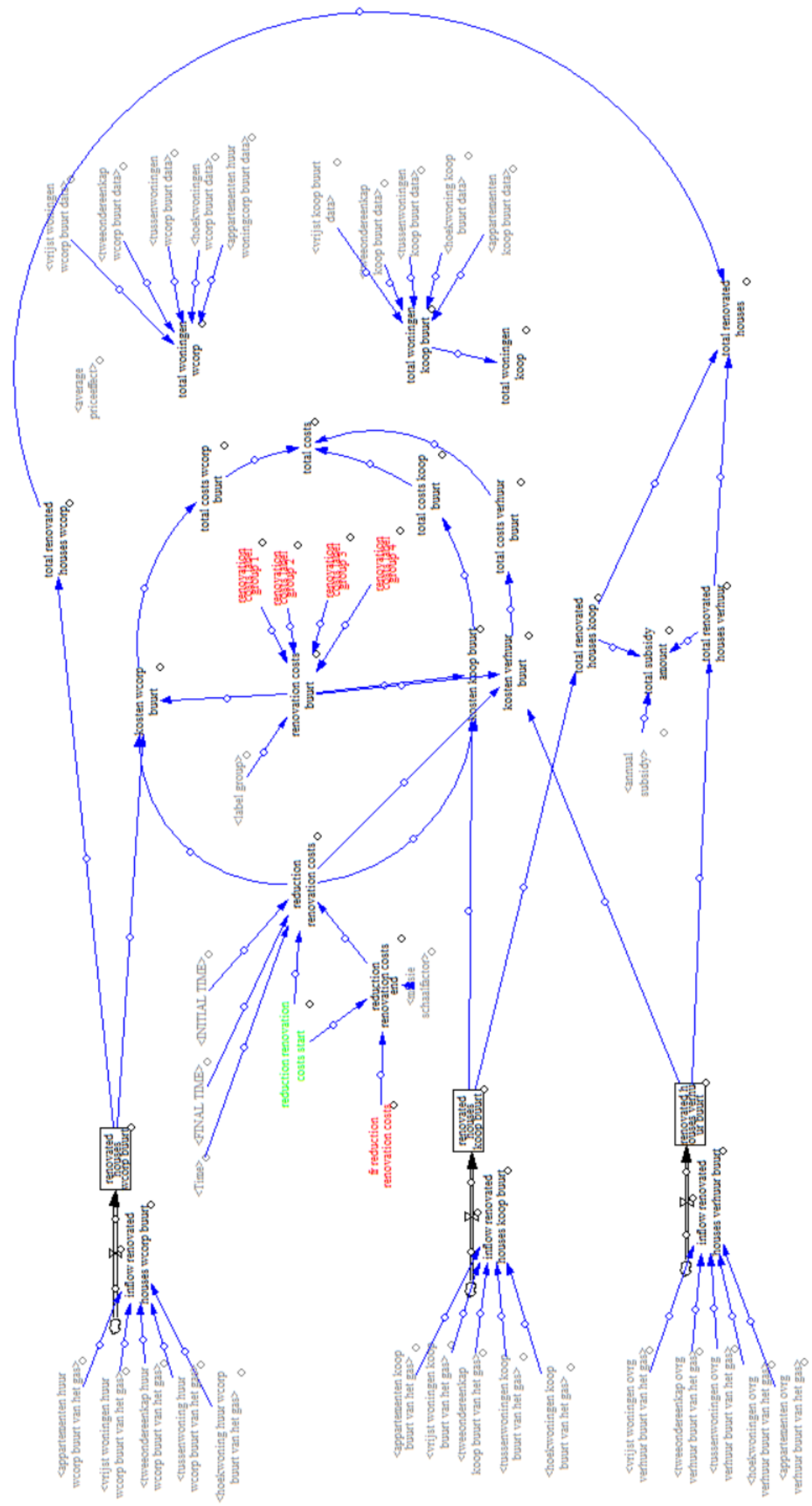


Figure C.10: Mission: propensity to renovate structure

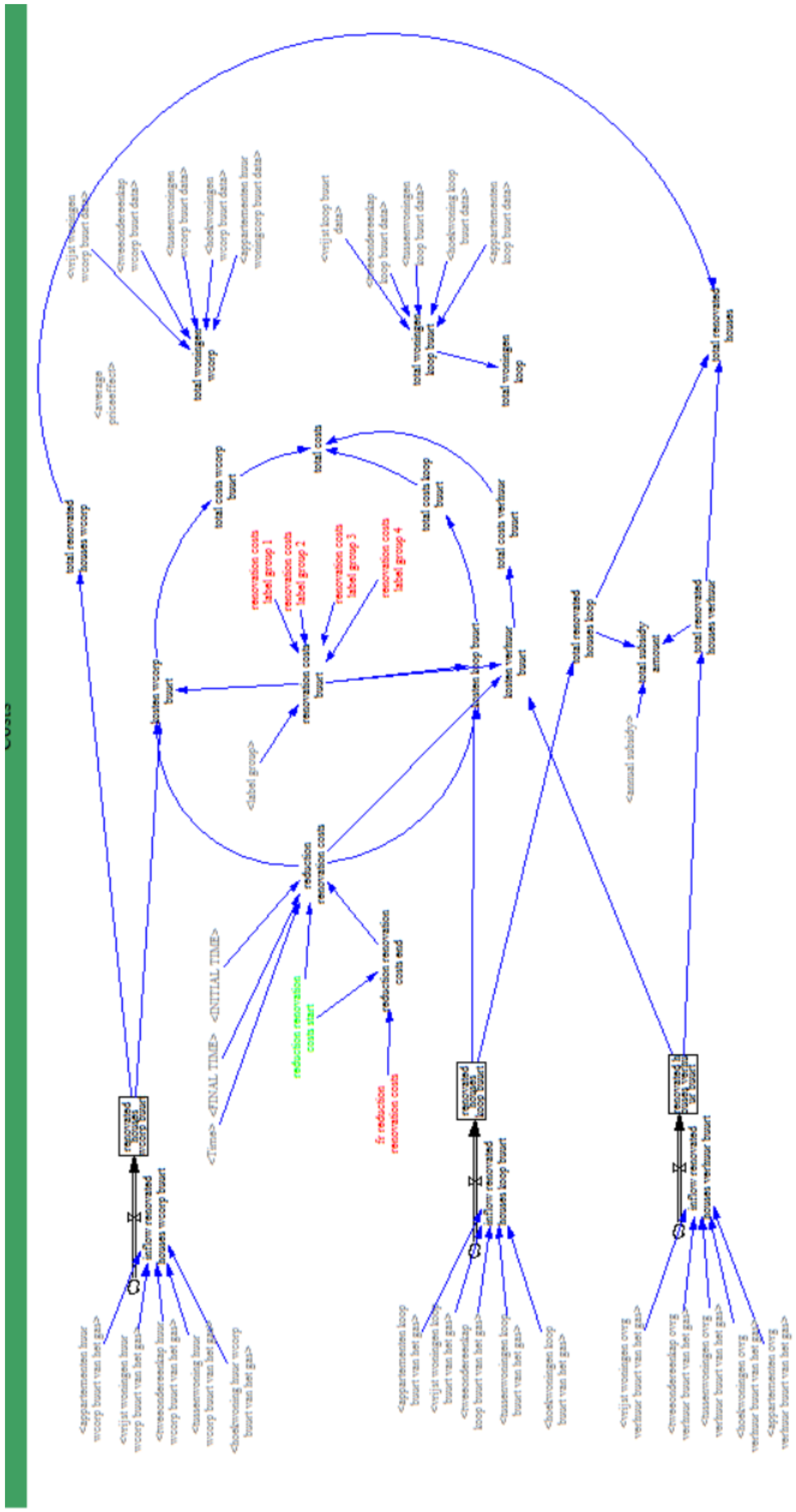


Figure C.11: Dynamic and static: renovation costs

D

The Dutch Energy Transition

This chapter aims to answer the first sub question by identifying baseline- and additional policies in the Dutch climate agreement. Firstly, a quick chronological introduction to dutch energy policy is given. Thereafter, baseline policies, additional policies and instruments are discussed in separate paragraphs. Finally the chapter is concluded by answering the sub question.

D.1. Introduction

Dutch climate policies to mitigate effects of climatic change have been in the making since 2011 (see figure D.1). Despite different government coalitions, the climate agenda has been continued for almost a decade. A first attempt to create an energy agreement for sustainable growth has been made in 2013 by the Sociaal Economische Raad (2013). The newly elected government coalition of *Rutte 3* has set the ambition to reduce carbon emissions by 49% by 2030 (Rijksoverheid, 2017), two years after the Paris Agreement was made.

November 2011	Local Climate Agenda
September 2013	Presentation Energy Agreement Sustainable Growth
October 2013	Climateagenda
December 2015	International Climateagreement (Paris Agreement)
January 2016	Energyreport
December 2016	Energy agenda
May 2017	Agreement Energy Intensive Industry
May 2018	Prohibition coal-fueled electricity production as of 2030
June 2018	Proposal climatelaw
July 2018	Proposal for key points of the climate agreement
September 2018	PBL Analysis of key points of the climate agreement
October 2018	Cabinet's appreciation the climate agreement & start second round of negotiations
December 2018	Presentation of the Design of the Climate Agreement
March 2019	Presentation of computed effects by planning bureaus

Figure D.1: Timeline of Dutch Climate Policies (Rijksoverheid, 2019d; Hekkenberg and Koelemeijer, 2018; PBL, 2019)

Currently, Dutch greenhousegas emissions amount to roughly 0.5% of worldwide CO_2 emissions (The World Bank, 2019), which some argue is rather insignificant and hence provides little incentive for decarbonization policies (Luttikhuis, 2017; Mommers, 2018). However, if corrected for population, Dutch CO_2 emissions per capita are considerable compared to other countries (see figure D.2). Table **??** shows current Dutch emissions per sector and the proposed ceilings to arrive at 49% CO_2 emission reduction by 2030.

This chapter aims to provide an overview of all current and potential climate policies in The Netherlands in an attempt to answer the sub question stated in **??**: *"Which base- and additional policies can be identified in the design of the Dutch climate agreement?"*

Firstly, an overview of baseline decarbonization policies from current government coalition *Rutte 3* is provided in section D.2. Subsequently, an inventorization of additional policies drafted in the climate agreement

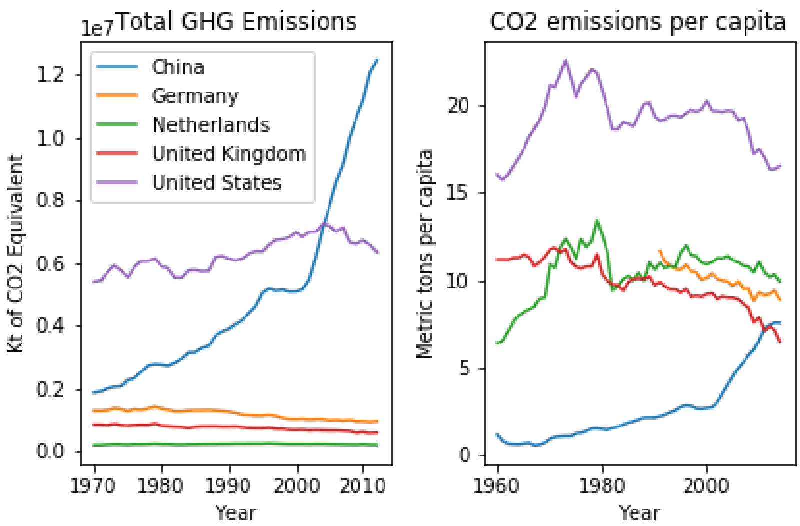


Figure D.2: Different perspectives on CO_2 emissions (World Bank, 2019a,b)

is provided in section D.3. Section 3.3 elaborates on main uncertainties in current climate policies and section D.5 concludes this chapter.

D.2. Baseline Policies: Government Coalition Agreement

The *Rutte 3* coalition presented sector specific decarbonization targets in their government agreement (NOS, 2017). The newly installed government set a target of 49% CO_2-eq reduction of by 2030, exceeding reduction targets mention in the Paris Agreement(UNFCCC, 2015). To kickoff their progressive climate ambitions the coalition set sector specific reduction targets that amounted to a total of 56 Mton CO_2-eq reduction.

Table **??** provides an overview of reduction targets as mentioned in the government agreement (Rijksoverheid, 2017) assigned to different sectors. However, no policies had yet been created, hence these targets would mostly show ambition in the coming policy formulation process.

More recently, PBL (2019) published all calculated measures in their analysis of the effects of the climate agreement. The authors also included climate related policies which would be implemented regardless of additional climate policies, so called *"baseline policies"*. Most instruments in the baseline policies are attributed to the electricity sector, such as inclusion of grid-on-sea costs in grid rates, a ban on coal or a minimum CO_2 price for electricity production. Next are baseline policies for the built environment sectors focusing on an intensification of the SDE+ subsidy scheme (focusing on renewable heat and green gas), increasing the ISDE (investment subsidy renewable energy) and increase enforcement on regulations for the utility sector. Included baselines policies for the mobility sector include an implementation of truck tax and implementation of EU standards for passenger cars and trucks or delivery vans. The agricultural sector would already face policies to facilitate the remediation of pig farming. Addressing societal upheaval around odor nuisance would go hand in hand with reducing carbon emissions of the agricultural sector, simply by reducing the number of pig farmers. Finally, baseline policies for the industrial sector only include development of the Emissions Trading Scheme (ETS) in an international context. Table **??** provides an overview of all instruments included in the baseline policy path.

D.3. Additional Policies: Focal Points Climate Agreement

To realize its ambitions, the Dutch government *Rutte 3* initiated a stakeholder consultation process to create a *new* climate agreement with relevant actors to realize their ambition set in the coalition agreement. Five sector tables (Electricity, Industry, Mobility, Agriculture and Built Environment) had been created and assigned indicative reduction targets early 2018 (Lugt, 2018). Each sector was requested to draft concept measures with relevant stakeholders in their field to reach the indicative sector target.

In short, the task at hand for the climate tables was to formulate additional policies (on top of the existing baseline policies) that would attain a reduction of 48.7 Mtons of CO_2-eq GHG emissions. In little less than a

Box 1: Dutch emission targets explained

Currently, total Dutch GHG emissions are 193 Mton CO_2-eq (2017), which is 13 % lower compared to the 221 Mton CO_2-eq baseline of 1990. Total Dutch GHG emissions should decrease to a maximum of 113 Mton CO_2-eq to reach the reduction target of 49 % GHG reduction in 2030 (compared to 1990-levels) (CBS, 2018a).
Hence, from 2017 onwards, a reduction of 80 Mtons has to be achieved. Of these 80 Mtons, the government assumes that 39 Mtons will be reduced through existing policies, the so called *"baseline policies"* (Schoots et al., 2017). The remainder of this sum has to be achieved through policy from the climate agreement, that contributes 48.7 Mtons (see Table D.1), reaching the total of 80 Mton reduction compared to 2017 emissions.

Figure D.3: Dutch emission targets explained

year, the climate agreement had been made and has been published in December 2018. It proposes many different solutions for the energy transition (Klimaatakkoord, 2018; Waaijers, 2017) in order to meet the renewed reduction targets (shown in Figure **??**). For the sake of feasibility not all measures will be included in this study. Hence, this section will focus on a selection of the focal points per climate table as mentioned by Rijksoverheid (2019a,b,c,f,g) (see Chapter **??**), selected on the concreteness of the proposed measure.

Table D.1: Main Reduction Targets Climate Sectors (Klimaatakkoord, 2018)

Sector	Reduction Target (Mton CO_2-eq)
Electricity	20.2
Industry	14.3
Mobility	7.3
Agriculture	3.5
Built Environment	3.4
Total	*48.7*

D.3.1. Electricity

The electricity sector had been attributed the highest reduction target (table **??**). In addition to its own target, most cross-sectoral effects between the climate tables would amount to some increase in electricity use, which requires facilitation by the electricity sector and hence increases their challenge. Many different stakeholders joined the main table, chaired by Kees Vendrik, to create new measures for the sector *and* to defend their company's interests.

Most concrete solutions proposed by the electricity sector included measures around (i)a CO_2 minimum price, (ii) increasing the offshore wind capacity, (iii) increasing the onshore renewable energy generation and (iv) energy storage (see section **??**):

1. A minimum CO_2 price will be introduced for electricity generated with fossil fuels.
2. Largest [renewables] growth comes from offshore wind farms. These will grow to 49 Billion KWh by 2030.
3. Renewable energy on land (wind and solar) also grows significantly. This [renewable energy generation] will increase to 35 Billion KWh annually.
4. Electricity production will be more subject to changing weather. This requires a flexible system that matches supply and demand. This could be achieved with storage, back-up generation plans, converting electricity in (hydrogen)gas or heat and links with neighbouring countries.

The enumeration above is merely a selection of proposed measures listed in section **??** and are derived from focal points aggregated by Rijksoverheid (2019a).

Note that although the electricity sector specifically mentions a minimum CO_2 price for electricity generated from fossil fuels, this policy measure had already been included in current policies (see section D.2).

D.3.2. Industry

The Netherlands are home to a large carbon intensive industrial sector that has been assigned the second largest reduction target. Monetizing carbon emissions would directly affect the competitive position of Dutch industry and hence provided a considerable challenge to reach consensus for the table Ronde (2018a). Environmental organizations and NGO's, however, lost faith in an effective climate agreement and dropped their endorsement (Ronde, 2018b).

Most concrete solutions recommended by the industry table included (i) ambitions to increase energy efficiency, (ii) capture CO_2 emissions and store it underground (CCS) or (iii) put it to use as a feedstock (CCU). (iv) Utilize residual heat for district heating and (v) create a bonus-malus system that rewards progressive decarbonization plans and penalizes conservative plans (see section **??**).

1. Industrial plants will be able produce even more efficiently, through a variety of technologies. [The sector] has high expectations of different heat-use, utilization of heat pumps and recycling of materials.
2. CO_2 can be stored in empty gas fields in the North sea. Carbon Capture and Storage (CCS) can realize a reduction of carbon emissions on the road to full decarbonization [of industry].
3. CO_2 can be captures and used as a feedstock in other fields such as greenhouses and synthetic fuels.
4. Residual heat from industrial processess will be put to use to provide heat to offices, residential areas and greenhouse farms, which will decrease natural gas demand in other sectors.
5. The design of the climate agreement proposes measures that oblige companies to reduce their carbon emissions. Progressive plans are rewarded subsidies. Conservative, or none, plans will be penalized. Hence, rewarding pioneers and correcting conservative companies.

The enumeration above is merely a selection of proposed measures listed in section **??** and are derived from focal points aggregated by Rijksoverheid (2019c).

D.3.3. Mobility

The government coalition already included an ambitious target of EV-only sales by 2030 (Rijksoverheid, 2017). The sectortable mobility aimed to create measures to enable this policy target.

Main ambition of the sector is to electrify personal transport by (i) making EV's financially more attractive through subsidies pro EV and levies on fossil vehicles, (ii) increasing the coverage of the EV charging grid and (iii) electrifying all public transport. Moreover, (iV) biofuels would enable an additional emission reduction of the existing fossil fleet. Finally, (v) the table suggests mobility in itself should be changed and focus on mobility as a service, more bikes and public transport and less carkilometers (Duijnmayer, 2018).

1. Cars without [carbon] emissions will become common before 2030.
2. 1.8M charging points will become available by 2030.
3. All (5000) public transport buses will be 100% free of emissions by 2030. The same holds true for construction vehicles and mobile appliances.
4. The scarce sustainable biofuels will preferably be used for heavy transport segments
5. Work-related personal mobility can be decarbonized by implementing new parking policy, transfer to a full electric fleet, free public transport, stimulating bicycle use, introduce a bonus-malus in mobility budgets, distribute mobility cards for lease-users

The enumeration above is merely a selection of proposed measures listed in section **??** and are derived from focal points aggregated by Rijksoverheid (2019g).

D.3.4. Agriculture

Rijksoverheid (2019f) categorized the policy recommendations of the climate table of agriculture and landuse in four distinct groups. Namely, life stock farming, horticulture, land use and consumers.

Most concrete solutions recommended by the agriculture and landuse table included (i)differently process manure to reduce GHG emissions, (ii) replace fossil heat demand with geothermal or residual heat sources in the horticulture industry and substitute the absent CO_2 with captured CO_2 from the industrial sector. (iii) Peatlands should be kept wet to reduce GHG emissions, (iv) foodwaste and animal protein should be reduced. Finally, (v) biomass can be produced by the sector, but should be wisely used.

1. Plans to differently process manure of cattle will be made in 2019, as manure emits the powerful greenhouse gas methane. This starts in the life stock pen where manure is processed differently. Other life stock diets can result in a methane reduction.

2. Horticulture will be disconnected from the gas infrastructure.Geothermal installations or residual heat of industry will satisfy the heat demand instead. Captured CO_2 from industrial process will be used for the growth of plants - as a form of Carbon Capture and Utilization (CCU).
3. Peat lands should be kept wet to reduce green house gas emissions.
4. Companies and organization will stimulate people to waste less food. Less meat consumption in favor of vegetable protein will help too.
5. Agriculture can produce biomass. Firstly as a soil fertilizer. Secondly as animal feed or other food. Thirdly as a building block for the [petro]chemical industry. Finally as a fuel for heat or electricity.

The enumeration above is merely a selection of proposed measures listed in section **??** and are derived from focal points aggregated by Rijksoverheid (2019f).

D.3.5. Built Environment

While having the lowest reduction target (absolutely speaking), the built environment sector plays a tremendous role in the energy transition as a whole. Socioeconomic support is vital, because all citizens are affected by policies for the built environment.

The table's main recommendations focus on (i) an early kickstart of residential renovation through building corporations, (ii) proof of concept neighborhoods to increase standardization and reduce unit costs. (iii) new financial schemes need to unburden homeowners in their effort to make their homes more sustainable and (iv) new energy taxes should tweaked so investments will be returned through energy savings.

1. Building corporations will kick start the [residential] transition by making their 2.4M housing stock more sustainable. They promised not to increase housing costs as a result.
2. Proof of concepts will be launched for natural-gas free neighborhoods and kick start projects. Together they are a first step in standardization of building types and [rebuilding] approaches. This results in lower costs.
3. There will be building-related funding [for sustainable rebuilding]. The loan will be transferred to the new owner when the house is sold.
4. Energy tax on gas will increase, tax on electricity will decrease.

The enumeration above is merely a selection of proposed measures listed in section **??** and are derived from focal points aggregated by Rijksoverheid (2019b).

D.3.6. Cross-sectoral effects

Cross sectoral consistency is emphasized in the appendix of the climate agreement and expresses the need for system integration, vision on energy carrier and infrastructure and choices in organization and regulation. The document clearly states ambitions on this topic, but lacks concrete measures to ensure cross-sectoral consistency. It does, however, show a roadmap of government visions, market organizations and stakeholder programs to ensure a more consistent climate agreement,

Table D.2: Timeline cross-sectoral consistency (Klimaatakkoord, 2018)

Period	Policy Plans
2019	Regional Energy Strategies
Early 2019	Infrastructure Outlook 2050 Gasunie / Tennet
Mid 2019	Government Vision CCS market organization and financing of CO2 infrastructure. The statutory framework must be adjusted no later than 2021.
Mid 2019	Government Vision on the market organization for collective heating networks. The legal frameworks must be adjusted by 2021 at the latest
2019	Gasunie and TenneT start an integral infrastructure exploration 2030-2050 in collaboration with regional DSO's. Deadline 2021.
2019	Government starts a program on spatial planning and spatial reservations for main energy systems on a national scale.
2019-2020	CO2 reduction plans industry sector

Continued on next page

Table D.2 – continued from previous page

Period	Policy Plans
2020	Detailed government vision on market organization & energy transition. Including a policy agenda towards 2030, that addresses organization from a systems perspective on regulation, costs of new infrastructure (mainly heat, hydrogen and CO2. Taking into account the implications for gas- and electricity networks for scenario's 2030-2050.
(from) 2020	Detailed monitor security of supply
End 2021	Transition visions heat

D.4. Additional Instruments

Policy measures mentioned in section D.3 mainly show ambitions rather than concrete instruments to be implemented by government ministries. As these measure had to be analyzed, however, the ministry of economic affairs & climate distilled concrete instruments from the climate agreement and provided them to the Dutch Environmental Assessment Agency (PBL). In their assessment of the climate agreement, PBL (2019) provide an overview of instruments the authors included in their analysis of the climate agreement. Table **??** (see appendix **??**) shows all concrete instruments implemented in their analysis of the impacts of the climate agreement.

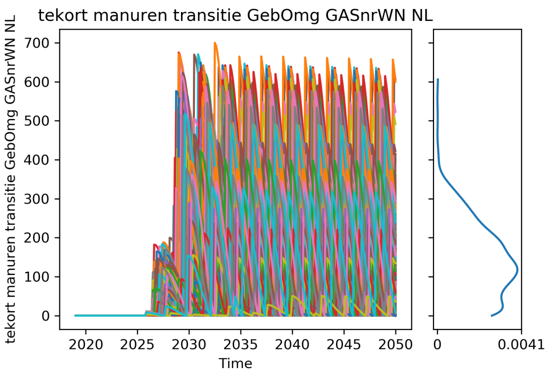
D.5. Conclusion

The aim of this chapter was to answer the first sub question "Which base- and additional policies can be identified in the design of the Dutch climate agreement?". Baseline policies and instruments have been identified in the coalition agreement of Dutch government and from an overview of existing policies from the Dutch Environmental Assessment Agency (see section D.2 and Table **??** for full list). Additional policies have been derived from the climate agreement (see section D.3) based on their level of concreteness and are complemented by more concrete instruments from the Dutch Environmental Assessment Agency (see section D.2 and Table **??** for full list). These baseline and additional policies will form a starting point for policy modelling in later stages of the study.

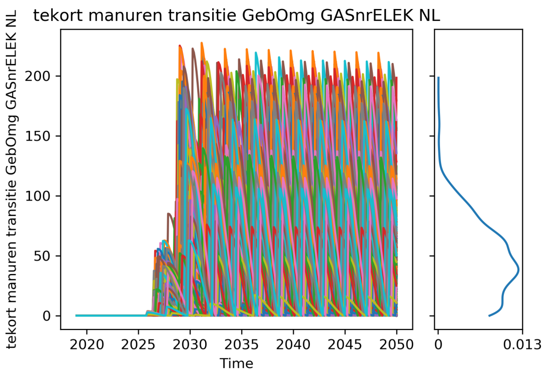
E

Basecase analysis

E.1. Open exploration



(a) Deficiency man hours for renovation to district heat [hours]



(b) Deficiency man hours for renovation to all-electric [hours]

Figure E.1: Labour deficiency for renovations

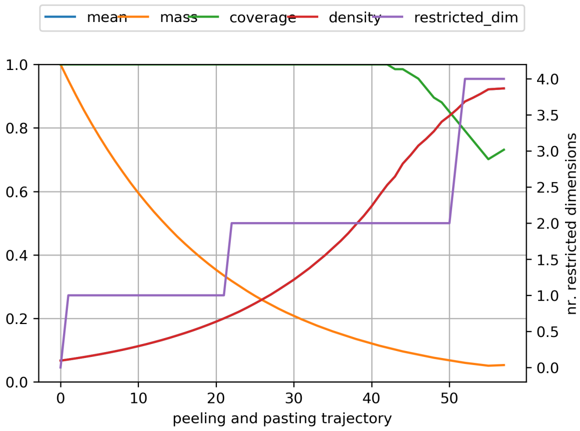
Both figure E.1a and E.1b show similar patterns, even though they differ in absolute terms. Generally speaking, labour deficiency in the policy scenario is very limited. A relatively higher ratio of district heating could be explained by a lack of incentive for households to change the way they heat their homes.

E.2. Scenario discovery

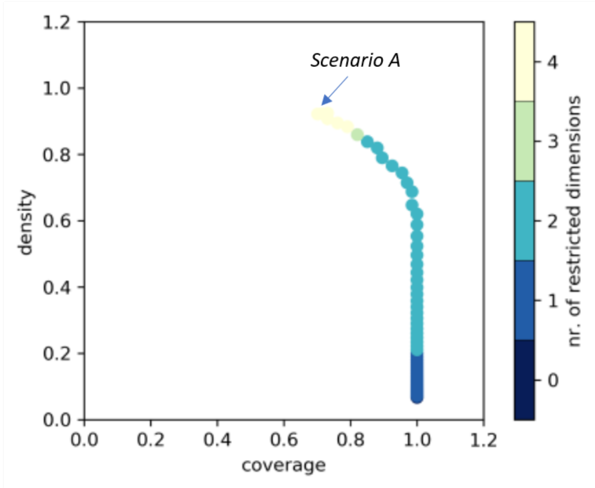
E.2.1. Labour deficiency

Policy timing and renovation demand could influence labour deficiency strongly. This section briefly discusses a PRIM analysis performed on labour deficiency for renovation to district heating and renovation to all-electric households. For both KPI's, the 25 % worst performing cases (i.e. cases with highest labour shortages) have been selected to perform the PRIM analysis.

Figure 5.6 shows the peeling and pasting trajectory and the trade-off between coverage and density.

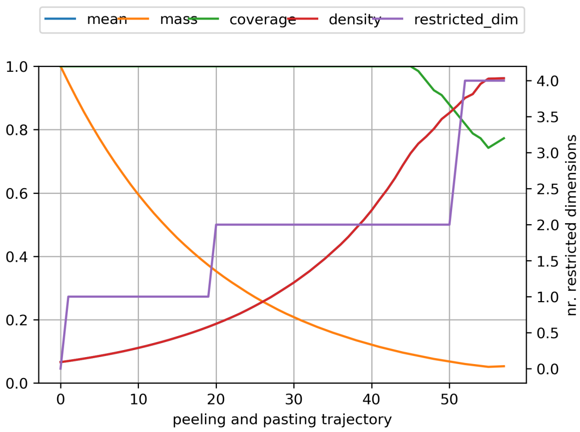


(a) Peeling and pasting trajectory

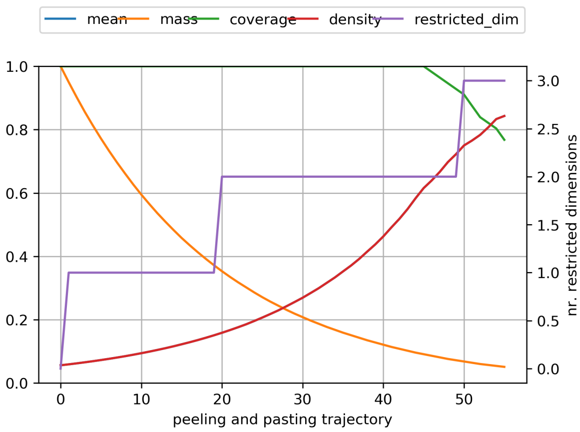


(b) trade off between coverage and density

Figure E.2: Coverage density trade-off for scenarios that describe the high Annual CO_2 emissions.

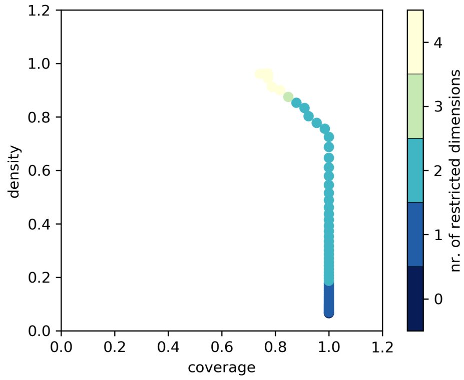


(a) Gas to all-electric

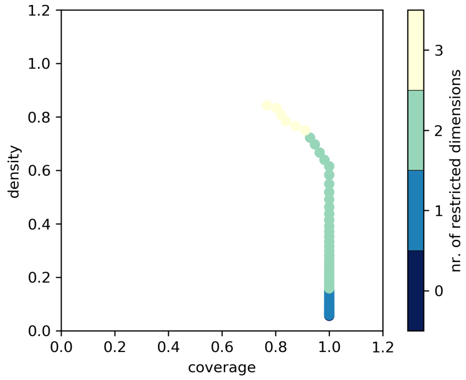


(b) Gas to district heat

Figure E.3: Peeling and pasting trajectories of PRIM analysis



(a) Gas to all-electric



(b) Gas to district heat

Figure E.4: PRIM trade-offs between coverage and density

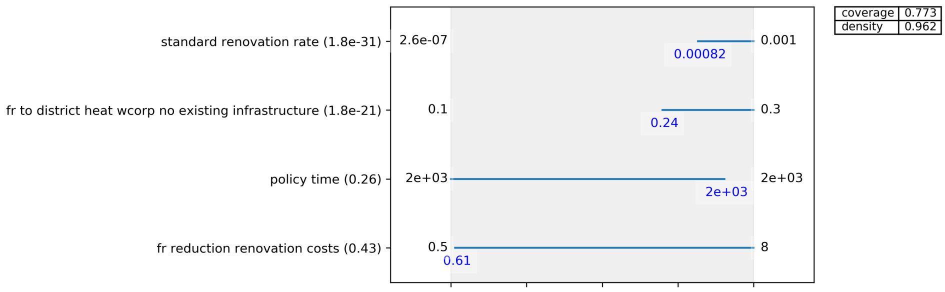


Figure E.5: PRIM inspection of boxes gas to all-electric

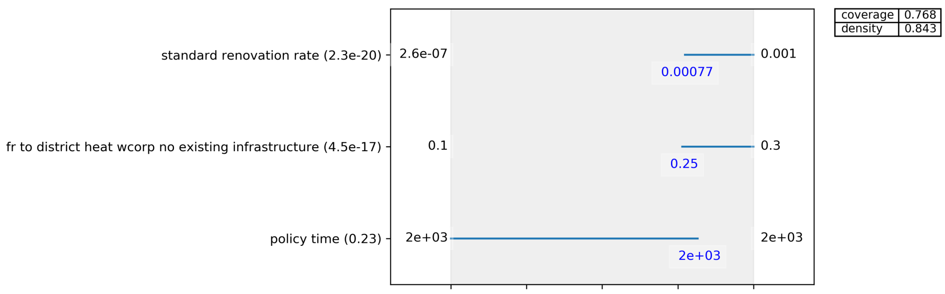


Figure E.6: PRIM inspection of boxes gas to district heat

F

Robust Policy Analysis (Previous iteratation)

This chapter shows a first iteration of robust policy formulation using the ARD methodology. Main differences compared to the chapter in the main body if this report are the goals set for the dynamic adaptive policy. In this chapter, a target of 49% reduction of CO_2 emissions by 2050 is maintained, whilst the newer analysis (found in section 2.2.3) sets the target to 95% reduction by 2050 in accordance with the Dutch climatelaw (Klimaatwet, 2019).

F.1. Introduction

This chapter will discuss the results of the Adaptive Robust Design methodology performed on the case of the energy transition in the Dutch built environment sector. The aim of this chapter is to answer the fourth sub question of this study: *What policies to accelerate the energy transition of the built environment are robust?* Results presented in this chapter are derived from policy case experimentation (see section 6.3 for code) and scenario discovery (see section A.4).

To answer this question new experiments have been iteratively performed on incrementally improved models employing the ARD methodology. First, policies will be discussed which have been devised to counter uncertainty and unwanted scenarios. Second, the experimental setup is presented showing input parameters and outcomes of interest. Finally, results of the specified policies are discussed before concluding the chapter.

F.2. Policies and variations

Within the scope of the energy transition in the Dutch built environment sector, many policies have been considered in the climate agreement. These policies have been analyzed by the Netherlands Environmental Assessment Agency (PBL). This study will investigate the possible effects under deep uncertainty of the three most promising instruments as discussed by PBL.

Table F.1: Three most promising policy instruments for CO_2 emission reduction in the Dutch built environment sector according to (PBL, 2019, p. 67)

Instrumentation	Emission reduction in 2030 [Mton]	Investments (2019 t/m 2030)[mln euro]	National costs in 2030 [mln euro per year]
Neighbourhood approach and subsidy in the commercial sector	0,2 – 1,3	1080 – 4632	24 – 28
Neighbourhood approach and subsidy in the rental sector	0,2 – 0,3	1787 – 2059	54 – 53
Norms newly built homes (gas free)	0,1 – 0,1	591 – 364	6 – -9
Total	0.5-1.7	3458-7055	84-72

Table 6.1 shows the three most promising instruments to reduce CO_2 emissions in the built environment and hence reach the climate targets for the sector. PBL (2019). These three instruments have been modeled in the *System Dynamics* model to simulate results with policies. The performance of these policies under deep uncertainty is strongly influenced by the delivery mechanism (policy variations) of said policy.

F.2.1. Policy variations

A policy can be implemented in a variety of ways. The delivery mechanism selected for a specific policy naturally effects the outcome of the policy. The list below briefly shows several possible mechanisms for policies.

- Static policy: setting a fixed policy for a preferred outcome
- Dynamic reactive policy: finding balance between two opposing KPI's (stop and go policy)
- Dynamic adaptive policy: create adaptive policies robust under deep uncertainty (Walker et al., 2001)
- Capping policies (rate-based emission policy or cap-and-trade policy (Fischer, 2003)
- Mission oriented policies: aiming to accelerate R&D to realize innovations and costs reductions (Mazzucato, 2018)

For the sake of simplicity three policy delivery mechanisms have been selected on top of the no policy base case. First, a static policy will be defined to reach a preferred outcome. Second, an dynamic policy is formulated that is designed to be adaptive to future developments. Third, a mission-like policy is implemented to understand effects of labour availability, scarcity and costs.

Static policy

In the static policy experiments. Subsidy amounts, static over time, are sampled as uncertainties in the model. Currently, rough indications of total subsidy budgets have been made public (Klimaatakkoord, 2019), but it is yet unknown how these subsidies will be distributed over different groups. Hence, subsidies are varied over a wide range of 5000 to 40000 euros, which account for limited subsidy coverage ,regardless of label group, to full coverage, for all label groups (see table 6.2. A static policy is implemented with a varying subsidy amount and policy timing (as uncertainties).

Adaptive policy

Performance is dynamically evaluated for the adaptive policy experiments. Progress on the main KPI, *total CO_2 emission* is referenced to the yearly carbon budget of 2050. A multiplier kicks in if current emissions are higher than the 2050 goal. Different multipliers are instantiated, given the state of underachievement as shown in equation 6.1.

$$\text{subsidy multiplier} = \begin{cases} 2, & \text{if } \frac{\text{total CO}_2\text{ emission}}{\text{CO}_2\text{ budget 2050}} \geq 1.5 \\ 1.5 & \text{if } 1.5 > \frac{\text{total CO}_2\text{ emission}}{\text{CO}_2\text{ budget 2050}} \geq 1.25 \\ 1.25 & \text{if } 1.25 > \frac{\text{total CO}_2\text{ emission}}{\text{CO}_2\text{ budget 2050}} > 1 \\ 1, & \text{otherwise} \end{cases} \tag{F.1}$$

Mission oriented policy

For the mission oriented policy, major scaling and R&D are expected to contribute to the transition. The subsidy schematic is similar to the static policy scenario (see section 6.2.1). Major differences, however, are set in an additional *25%* higher renovation rate (of the standard renovation rate) and an additional 25 % higher decrease in renovation costs (so a higher reduction renovation costs).

F.2.2. Policy targets

Policies are created to meet targets within realistic boundaries. Currently, the CO_2 emission target for 2050 is set at a 3.4 Mton reduction (20% compared to 2015 levels) (Klimaatakkoord, 2019). The 2050 target is set at a more generic 49% reduction in line with the Paris agreement (2030 goal), as the horizon of this study expands past the scope of the climate agreement.

Monetary targets for subsidies are set at a yearly maximum of 3.5 billion euros for the transition of the Dutch built environment sector (PBL, 2019, p. 74). The subsidies naturally does not cover all costs required for the transformation. There is, however, no clear boundary for such *societal costs* and hence needs to be answered in the political arena.

F.3. Experimental setup

F.3.1. Uncertainties

Additional uncertainty ranges have been added on top of the uncertainty table mentioned in the previous chapter (see table 5.1.

Table F.2: Uncertainties in the policy ensemble

Variable	Lower bound	Upper bound	Unit	Source
Fr innovation emissionreduction	20	50	%/year	(PBL, 2019)
Annual development of new homes	0.88	0.97	%/year	(CBS, 2019a)
Annual standard renovation rate	0.07	0.08	%/year	(Klimaatakkoord, 2019, p. 17) 50k/year
fr reduction renovation costs	50	80	%	(Rijksdienst voor Ondernemend Nederland, 2019)
renovation costs label group 1	8000	12000	Euro	(Nationale EnergieAtlas, 2019)
renovation costs label group 2	20000	28000	Euro	(Nationale EnergieAtlas, 2019)
renovation costs label group 3	30000	36000	Euro	(Nationale EnergieAtlas, 2019)
renovation costs label group 4	30000	40000	Euro	(Nationale EnergieAtlas, 2019)
Renovation speed improvement after 2030	100	110	%/year	Assumed 10% improvement of climate agreement renovation rate (Table 4.5)
fraction subsidy over costs high income	10	30	%	Assumed
fraction subsidy over costs upper middle income	30	50	%	Assumed
fraction subsidy over costs lower middle income	60	80	%	Assumed
fraction subsidy over costs low income	80	1	%	Assumed
subsidy	5000	40000	euro	25-100% subsidies
Annual electricity growth	-1	1	%/year	(Schoots et al., 2017)
fr to district heat wcorp low existing infrastructure	.3	70	%	Assumed
fr to district heat wcorp high existing infrastructure	70	1	%	Assumed
fr to district heat koop no existing infrastructure	0	10	%	Assumed
fr to district heat koop low existing infrastructure	10	30	%	Assumed
fr to district heat koop high existing infrastructure	30	60	%	Assumed

F.3.2. Key performance indicators

Key performance indicators are also similar to the ones used in the previous chapter, but an extra outcome of interest is added: *total subsidy amount*. This KPI sums awarded subsidies over all policies.

1. Total CO_2-eq emission [ton CO_2]: reflecting total CO_2 equivalent emissions summed over all neighbourhoods in the model.

2. Total subsidy amount [€]: total awarded subsidies.
3. Total renovated houses [# houses]. Total number of houses that have been renovated during the simulation.
4. Labour deficiency [hours]: difference between available and required hours for household renovations

F.4. Policy exploration

This section will discuss the exploration of the policy ensemble. Each KPI is considered and examined to what extent policies have effect on its future outcomes.

F.4.1. CO_2 emissions

Main criterion for effective policy is the expected CO_2-eq emissions over time. Figure **??** shows implications of the various policies over time.

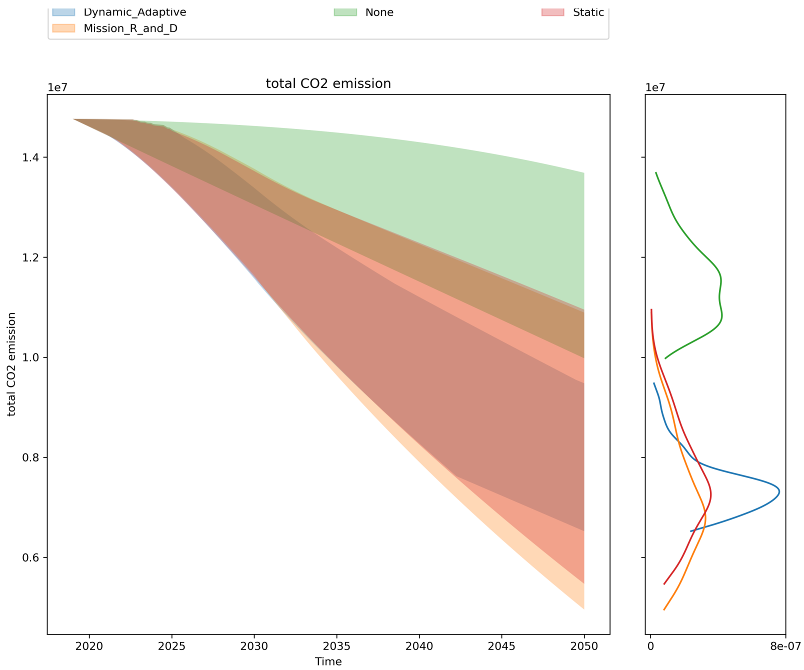


Figure F.1: Total CO_2-eq emissions [ton] of policies under defined uncertainties and with defined policies

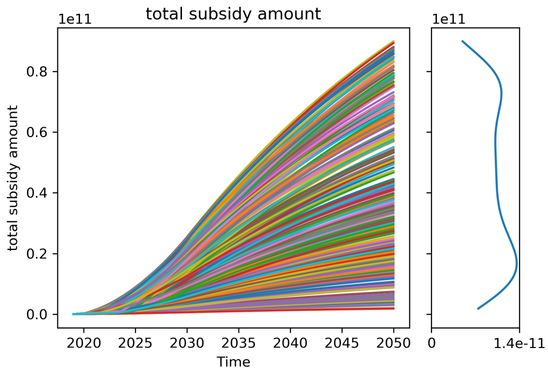
The figure clearly shows the wide spread of possible outcomes. Ranging from approximately 5-14 Mton CO_2-eq. What is interesting in this figure, is the difference in the KDE plot. All policy variants naturally outperform the reference scenario without any policies.

The dynamic adaptive policy (in blue) clearly stands out from the other two policy variants. It's KDE is strongly centered around the 2050 CO_2 target of 7.6 Mton (51% of the 2015 level), fanning out to approximately 10Mton.

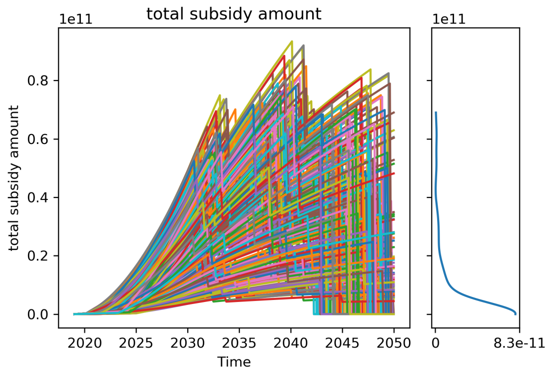
In sharp contrast to the focused KDE of the dynamic adaptive policy are the other two policy variants. Both the static and mission policies show relatively most cases around the desired goal. Their outcomes are, however, much more uncertain as the KDE show a much wider distribution of cases over the KPI.

F.4.2. Subsidies

The previous paragraph showed effective results. However, the first *if* raised by public and parliament will be on the affordability of suggested measures. Figure **??** shows development of subsidies over time for each of the defined policies.

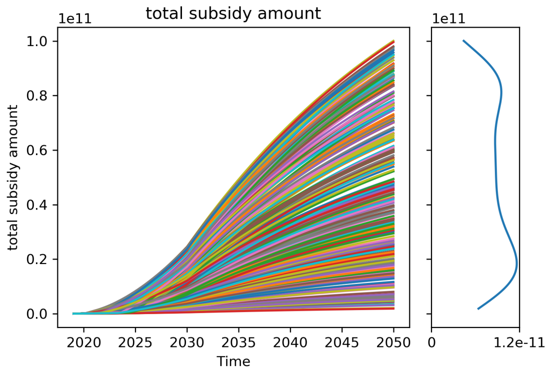


(a) Static policy

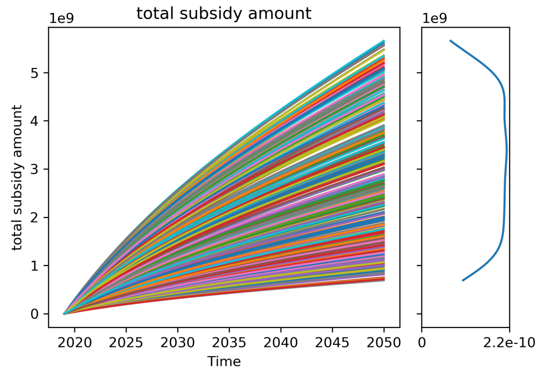


(b) Dynamic adaptive policy

Figure F.2: Total CO_2-eq emissions under static and dynamic adaptive policy



(a) Mission R&D



(b) No policy

Figure F.3: Total CO_2-eq emissions under mission R&D and no policy

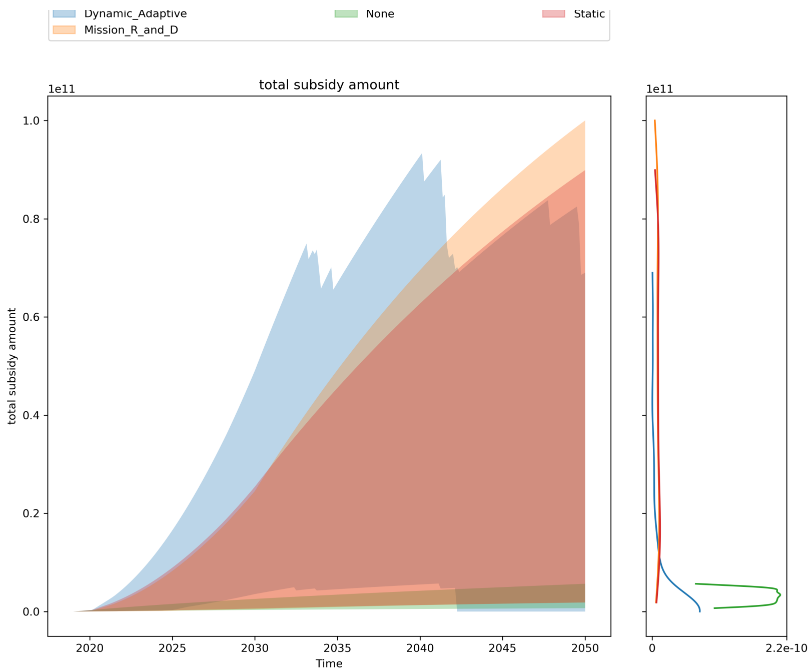
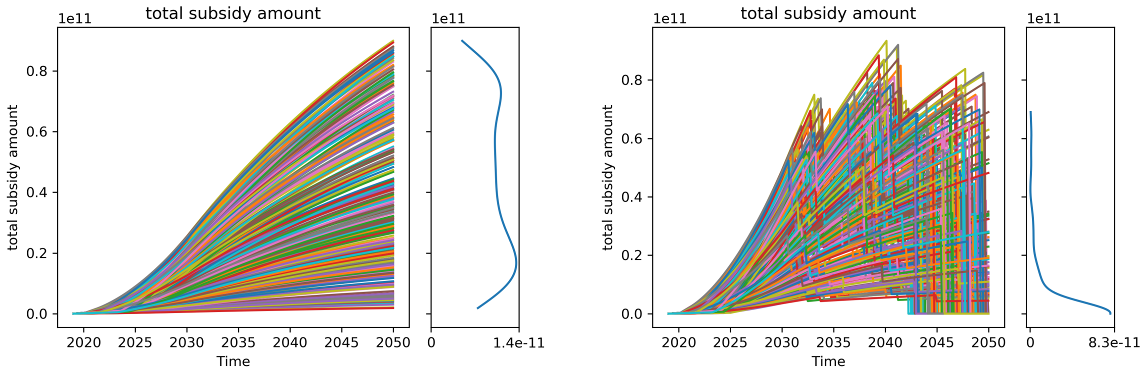


Figure F.4: Total subsidized amount [euro] of policies under defined uncertainties and with defined policies

What is striking in this figure is the extremely uncertain outcome of all policy variants. Glancing back on the uncertainties sampled in these experiments, this is quickly explained by the parametric range the subsidy amount is sampled over (see F.2). Because of the fact that subsidies are sampled from 5000 euros (roughly half of the cheapest, sampled renovation costs) to 40000 euros (100% of the most expensive renovation), the total subsidy amount itself ranges from 0 to a staggering 100 billion euros (annually). The graph does, however, provide insights in the timing of policy expenditure. The dynamic adaptive policy clearly kicks in early. The subsidy multiplier is initiated quickly, as evaluated progress is deemed insufficient.



(a) Static policy

(b) Dynamic adaptive policy

Figure F.5: Subsidy amount for Static and Dynamic adaptive policy

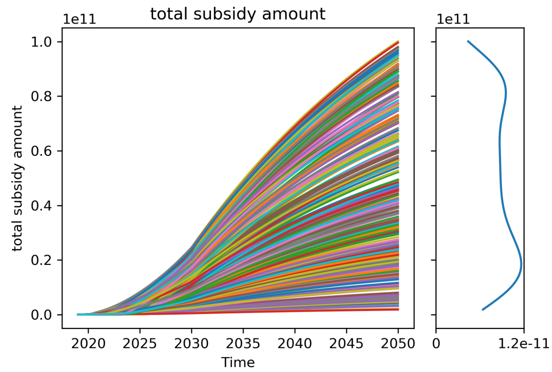


Figure F.6: Mission R&D

Figure F.5 and F.6 show line plots of the total subsidy amount for each policy. The static policy and mission R&D policy show similar patterns. Virtually identical KDE plots indicate the similarity of the two policies. In essence, the mission R&D policy relies on the same structure as the static policy, but includes a higher renovation rate and a higher decrease in renovation costs. Both policies are unable to reduce uncertainties as the KDE plots show in figure F.5a and F.6.

The dynamic adaptive policy (figure F.5b) shows a very different trend and KDE. What stands out in the graph is the noncontinuous trajectory of the various cases. This can be explained by the discrete character of this policy as defined by equation F.1. As soon as a threshold is met, a new multiplier is instantiated. This results in decreasing annual subsidy amounts.

Surprisingly, cases seem most frequently distributed around 0. At a closer look, however, cases are distributed between 0 and approximately 10 billion euros. The multiplier mechanism is a pretty blunt instrument that simply multiplies the static subsidy amount. In extreme cases, where the subsidy coverage is too little due to high renovation costs (upper range of uncertainty of renovation costs) even though subsidies are relatively high (upper range of uncertainty of subsidies), the multiplier still kicks in resulting in exceptionally high annual subsidy levels. This in turn results in high total subsidy amounts. These mechanics could explain the surprisingly low KDE plot of this policy.

F.4.3. Renovated houses

Another KPI to show effectiveness of policies is the number of renovated houses. Current ambitions have set their sights on a renovation ambition of 1.5M homes by 2030 (Klimaatakkoord, 2019, p. 17). Figure F.7 shows effects of various policies on the number of renovated homes over time.

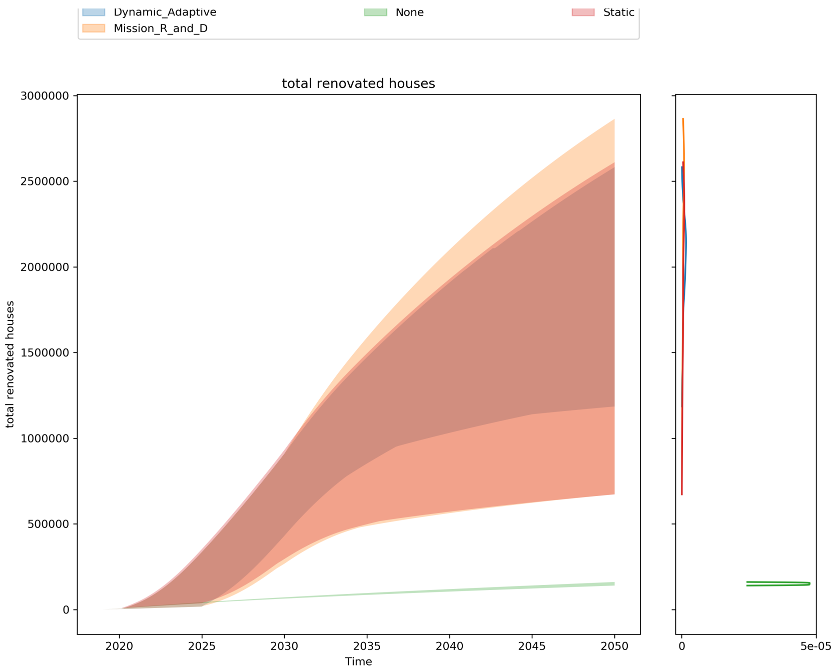
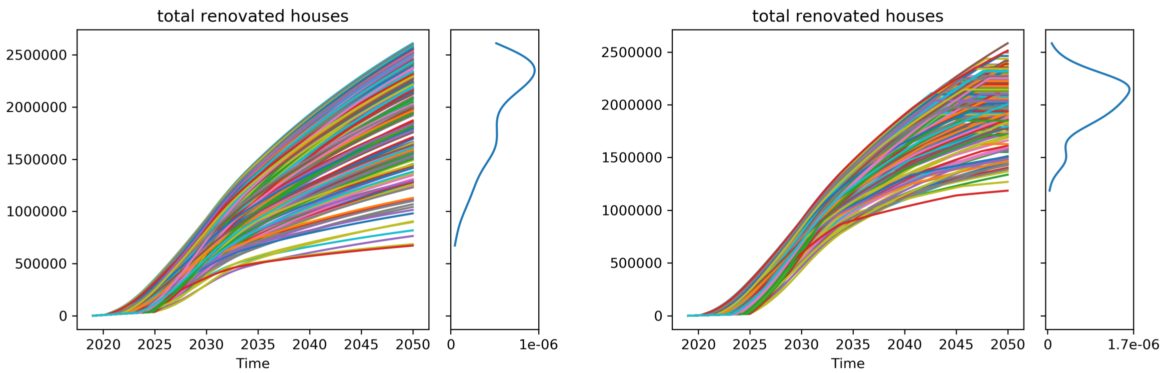


Figure F.7: Renovated houses [# of houses] grouped by policy

It is apparent that there is a very large difference between (any) policy and the no policy reference scenario. The number of renovated houses in the no policy scenario is so certain, that it completely skews the KDE plot. Hence, KDE plots of the policy variations are incomparable, because of their higher distribution on the KDE PLOT.

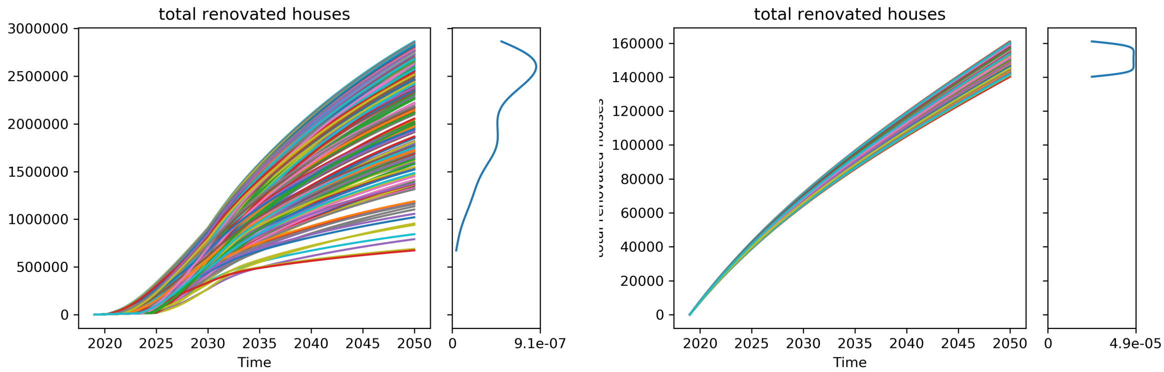


(a) Static policy

(b) Dynamic adaptive policy

Figure F.8: Renovated houses for static and dynamic adaptive policy

Figures F.8 and F.9 provide a more comprehensive comparison of the effect of different policies on the number of renovated houses. The static and mission R&D policy variations (see figures F.8a and F.9a) show similar KDE plots. Their absolute numbers vary mostly on the upper limit of the KPI total renovated houses.



(a) Mission R&D

(b) No policy

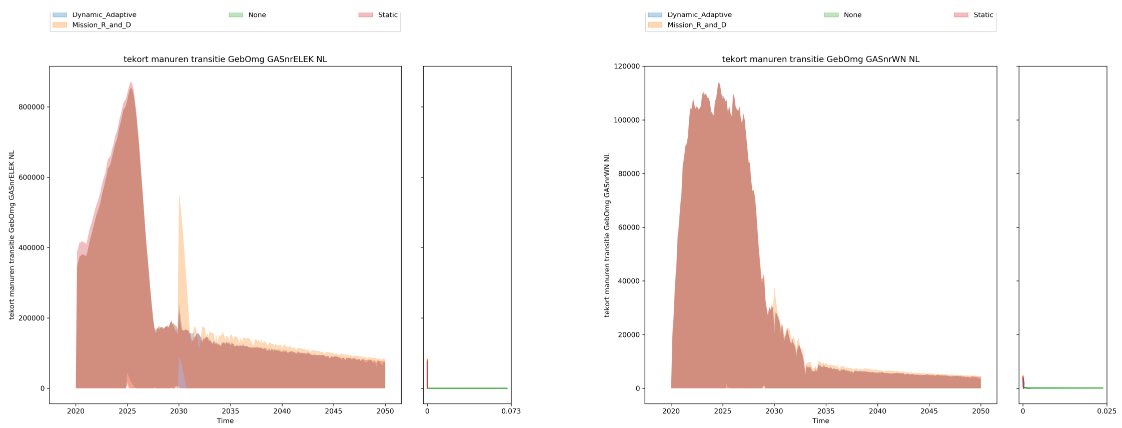
Figure F.9: Renovated houses for mission R&D policy and the no policy reference

The mission policies upper limit almost reaches three million renovated homes. Whereas the static policy enables renovation of a maximum of two-and-a-half million homes in the most positive scenario. Despite the high absolute numbers, the cases are quite strongly distributed over the y-axis.

The dynamic adaptive policy option (figure F.8b), on the other hand, shows a much smaller spread in possible outcomes. The distribution of cases over the y-axis of this policy is much more contained, as shown in the graphs KDE. Nevertheless, outcomes still vary from approximately 1.25M - 2.5M renovated homes, but the spread under dynamic adaptive policy is much smaller than in any other policy (apart from the no policy reference).

F.4.4. Labour deficiency

Labour demand will strongly increase if the renovation of the built environment sector sets off. Figure F.10 shows grouped policy plots for both labour deficiency for renovation to all-electric and renovations to district heat.



(a) Labour deficiency renovations to all-electric

(b) Labour deficiency renovations to district heat

Figure F.10: Labour deficiency for renovations to all-electric and district heating grouped by policy

For all policies (apart from the no policy reference), shortages peak shortly after policies are implemented and take several years to be smoothed. Moreover, an additional renovation rate increase in the mission R&D policy causes an extra spike in 2030. For all policies, demand for labour is too high to supply ample capacity for the transition for the duration of the simulations. The labour market is modelled such, that it is entirely demand driven and is not directly influenced by policies. This explains the backlog and the inability for policies to counter shortages.

Individually (see section **??**), the graphs show no additional insights. All policy plots show similar trends and similar (low) KDE's, but high shortages shortly after policy implementation.

F.5. Uncertainty analysis

Similar to the section on sensitivity analysis in the previous chapter (see **??**) a sensitivity analysis has been performed using *feature scoring* on the policy results. Figure F.11 shows the feature scores of the policy ensemble.

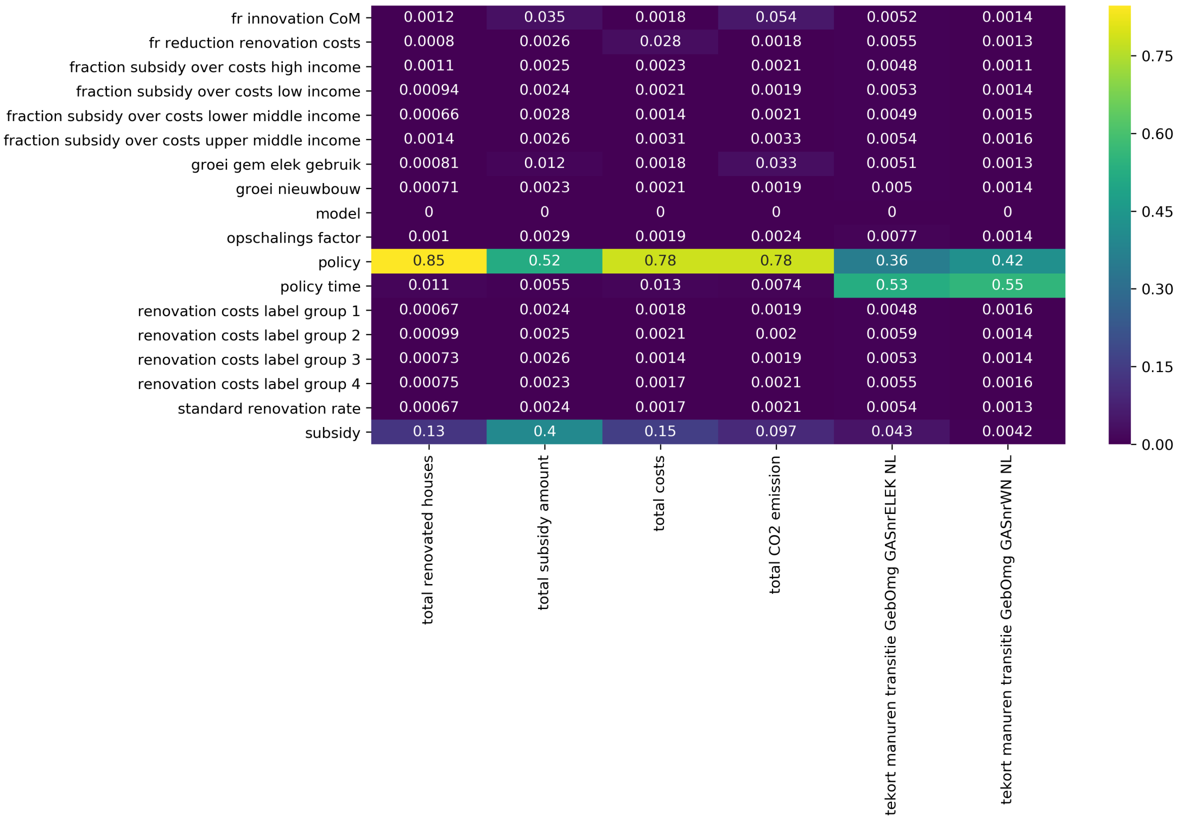


Figure F.11: Feature scores of the experiments and outcomes of the policy ensemble. The figure shows influence of uncertainties (y-axis) on the model's KPI's (x-axis).

Whereas the base case ensemble was strongly influenced by uncertainties, the policy ensemble seems to be less affected by uncertainties. The only uncertainties that do play a large role are policy time and subsidy. Both variables that *can* be influenced by policy makers, but are sampled as uncertainty to analyze impacts of variations (in timing or subsidy amount). Overall, the policy ensemble seems mostly influenced by the policy variation implemented. Regardless of the spread in outcomes discussed in section F.4, figure F.11 shows ability to mitigate influence from dominant uncertainties through policies.

F.6. Conclusion

This chapter set out to answer the fourth sub question of this thesis: *"Which robust policy variations can be discovered for the energy transition of the Dutch built environment sector?"*.

To answer this sub questions the model (chapter 4) and insights from the base case analyses from chapter 5 have been used to create policy variations. The most promising instruments from PBL (2019, p. 67) have been selected and implemented in three different variants compared to a no policy reference. A static policy, a dynamic adaptive policy and a mission oriented R&D policy have been implemented and simulated under deep uncertainty. Main KPI's have been evaluated and the goal-seeking dynamic adaptive policy shows its cases to be distributed more closely around desired targets. This holds true for both the KPI *total CO_2 emission*, *total subsidy amount* and *total renovated houses*. Regarding labour shortages, however, there appear to be little differences in the general trend of labour deficiency. In all policy cases, labour shortages peak after policy implementation.

The dynamic adaptive policy variation of the selected policy instruments turned out to be most robust under deep uncertainty. Other policy variations too reduced uncertainty of possible futures, but the spread of cases (KDE plots) remained relatively higher compered to the adaptive policy.