Modelling White Hydrogen

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Analysing EU hydrogen policy under deep uncertainty

by

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Preface

These words are the last to be written for this thesis, marking its completion. As the final deliverable for my MSc in Engineering and Policy Analysis, this thesis represents a significant milestone in my life. It is a bittersweet moment as I look fondly at my time spent at the Technical University of Delft. Beyond my academic and personal growth, I have developed a connection with the university and its people, but also with the city itself—a bond that will undoubtedly last a lifetime. Nevertheless, with these valuable experiences and a fresh MSc degree in hand, I am excited for what the future holds.

Writing this thesis would not have been possible on my own. I am fortunate to have received an irreplaceable amount of support from my loved ones, acquaintances, and everyone in between. As thanking each person individually would result in a lengthy acknowledgement, I must suffice with a simple statement: To all who have contributed to my journey in one way or another, my heartfelt gratitude is yours!

I would not have achieved this accomplishment without my graduation committee, to whom I want to express my gratitude. First, I would like to thank Dr.ir. Emile J.L. Chappin for taking the role of chair in my graduation committee. Your genuine feedback and enduring patience have enriched my work and allowed me to take pride in my thesis. Second, I would like to express my sincere gratitude to my main supervisor, Dr.ir. Willem L. Auping. Our academic collaboration preceded this thesis and has been perceived by me as pleasant, providing valuable insights into System Dynamics, the art of academics, and life in general. His proverb that an MSc thesis is not a hundred-meter sprint but a marathon rings true, although I would like to add from my experience that it is more akin to a triathlon.

My deepest thanks go to my family, whose support was unwavering. Despite being unmatched in their ability to distract me during work, the shared dinners, holidays, and “gezelligheid” kept my morale high. The same goes for my friends, roommates, and peers in Delft, Rotterdam, and The Hague, whose efforts to advise, support, and entertain are much appreciated. Thank you all for being part of this incredible journey. Your support and encouragement have made this achievement possible, and I look forward to thanking you all in person.

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Delft, June 2024

Executive summary

To prevent the worst dangers of climate change, the EU has committed to net zero by fully decarbonizing the European energy sector by 2050. While most energy sectors can be decarbonized by electrification, some "hard-to-abate" sectors need other solutions to lower their emission output. The EU has chosen green hydrogen to replace fossil fuels in such sectors. However, despite many advantages, it is expensive to produce and thus not competitive in the energy market. Therefore, the EU has created the Hydrogen Strategy as a central policy package to optimally implement green hydrogen within the energy sector. The finding of naturally occurring hydrogen, known as white hydrogen, could revolutionize the EU transition towards hydrogen as its production cost could be very low. However, as much is unknown about what effects white hydrogen could have on energy markets, it creates uncertainty for the EU and the Hydrogen Strategy. Modeling future scenarios can reduce the uncertainty for policymakers. While green hydrogen has been studied with a modeling approach, no such literature exists on white hydrogen. Thus, this study aimed to fill this knowledge gap by modeling white hydrogen to increase insights into the white hydrogen system and how it might affect the future energy system.

During this study, a Decision Making under Deep Uncertainty approach was used to analyze the effects and uncertainties of white hydrogen on the global energy system and EU hydrogen policymaking. First, a system dynamics model was made to model global energy markets, including all relevant hydrogen. This model was tested with various experiments under uncertainty. Then, multiple scenarios were developed to match the possible trajectories of a white hydrogen market. The system behavior within the model was analyzed using the Exploratory Modeling Analyses method to determine the effects of white hydrogen on the energy system. Finally, the EU hydrogen policies were analyzed in the context of the scenarios, and recommendations were made to the EU on handling the uncertainty surrounding white hydrogen.

The system analysis showed that the global energy system is heavily impacted by white hydrogen in scenarios where the white hydrogen market takes off. In specific scenarios, the price of white hydrogen may directly compete with gas prices, leading to a surge in demand. As the prices of other types of hydrogen decrease, they will also see an increase in demand, resulting in a net positive effect for all hydrogen types. However, despite rising demand, the production of white hydrogen may not keep up, leading to a lower overall usage of hydrogen. This supply-demand gap could cause significant shortages of hydrogen, which will exacerbate the existing energy shortages caused by carbon taxing and result in an overall decrease in energy usage.

The results showed that the EU can only achieve its renewable hydrogen goals by 2030 and 2050 if the white hydrogen market grows substantially. An increase in the share of white and green hydrogen will lead to greater use of renewable energy sources. This, combined with a decrease in energy demand, will achieve net zero emissions more frequently and earlier in cases where the white hydrogen market grows. While EU hydrogen policies contribute to these goals, their impact alone is not enough to achieve them. However, the white hydrogen market works well with these policies, increasing total hydrogen demand. Furthermore, results showed that the policies aimed at reducing hydrogen prices significantly impact all scenarios, with the hydrogen bank policy being particularly effective. Yet, if hydrogen becomes too expensive, the sudden increase in green hydrogen prices could harm the green hydrogen market. The results suggest that developing the white hydrogen market is crucial for achieving renewable hydrogen goals, and policies that drive down hydrogen prices are also important in reaching these objectives.

The main scientific contribution of this study lies in the modeling of white hydrogen within a dynamic system, which allows asserting the impact of white hydrogen on the energy system under multiple scenarios. The insights gained from it serve as a first indication of how the white hydrogen market may develop and how it can contribute to the adaptation of hydrogen. This study could function as a wake-up call for the EU and other governmental bodies to take white hydrogen seriously and implement timely policies to maximize its potential, enabling a more optimal transition towards renewable hydrogen and benefiting society.

Overall, this study showed that in most scenarios, white hydrogen has a significant impact on the energy system. In general, white hydrogen market growth will stimulate the hydrogen market, resulting in a higher share of renewables in the EU energy mix, increasing the chances of the EU reaching net zero. The timely adoption of white hydrogen policies could ease EU efforts to transition towards clean hydrogen. However, the EU should not bet on one horse and should continue its efforts to reduce green hydrogen costs to mitigate the risk of increasing white hydrogen costs in the future.

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List of Abbreviations

Abbreviation	Definition
BBSD	Behaviour Based Scenario Discovery
CAPEX	Capital Expenditure
DMDU	Decision Making under Deep Uncertainty
ESDMA	Exploratory System Dynamics Modelling and Analysis
EMA	Exploratory Modelling and Analysis
IEA	International Energy Agency
EU	European Union
ETS	European Trading Scheme
LHS	Latin HYpercube Sampling
LCOH	Levelised Costs Of Hydrogen
OPEX	Operational Expenditure
RES	Renewable Energy Sources
SD	System Dynamics

Chapter 1

Introduction

> *"Prometheus stole fire from the gods. We are each the heirs of that divine spark. Used wisely, the spark fuels one's journey and lights the way. Treated carelessly, the spark consumes its owner and everything in its path."*
>
> - Thomas Lloyd Qualls, Painted Oxen

The myth of Prometheus stealing fire from the gods symbolises humanity's efforts to control and utilise natural resources for its benefit. Mastering fire was the first of these efforts and marked the increasing impact of humans on their environment. But besides human ingenuity, a fire needs fuel to burn. For most of history, wood was the primary fuel for heating, cooking, and protection. However, as humanity entered the industrial age, our demand for energy increased rapidly (Wrigley 2013). Fortunately, technological progress also enabled mastery over fuels with increasingly higher energy densities previously deemed too difficult to extract or use. As a result, coal powered the Industrial Revolution. And consequentially, oil and gas fuelled the rapid economic developments of the last century (Smil 2004). However, while these fossil fuels fulfil our energy needs, they have two main drawbacks. Firstly, in contrast to human demand, their reserves are finite. Despite new findings, they will eventually become too expensive to extract or run out entirely. Secondly, their use emits CO2 emissions, causing severe environmental challenges (Höök and Tang 2013). Thus, fossil fuel usage is unsustainable. Just as Prometheus faced consequences for his actions, humanity already contends with the repercussions of fossil fuel exploitation.

Due to fossil fuel consumption and other human activities, global temperatures have risen by one degree Celsius since the pre-industrial era due to the emission of greenhouse gases (Fawzy et al. 2020). This increase is paired with changes in precipitation levels, sea-level rise, and extreme weather conditions (UNCL 2019), already yielding adverse effects on ecosystems and human activity (Abbass et al. 2022). Nonetheless, global temperatures can even increase up to four degrees by the end of this century (Nieto, Carpintero, and Miguel 2018). This poses significant concerns as a 2-degree increase is considered a critical threshold (Park et al. 2023). Beyond this point, dangerous and cascading effects within the climate will occur (NASA 2023). The International Panel for Climate Change states that to prevent a 2-degree increase in global temperatures, global emissions must be reduced to zero by 2070 (IPCC 2018). This goal is outlined in the Paris Agreement 2016, ratified by 195 countries, including the European Union. The EU has reinforced its commitment to combat climate change by incorporating this goal into the European climate law. In addition, this law includes an interim target of reducing net greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels and advances the deadline for net zero emissions to 2050 (European Commission 2021).

The EU has already implemented policy packages to reach these goals, such as the "European Green Deal" (Bäckstrand 2022). These policy packages mainly focus on the energy sector, which accounts for more than 75% of the EU's greenhouse gas (GHG) emissions, mainly using fossil fuels (ACER 2024). The path to net zero is straightforward for most industries as electrification, combined with renewable electricity production, can significantly reduce carbon emissions in a large share of the energy sector (Azadnia et al. 2023). As renewable energy technology costs have decreased over the past decade, the share of renewable electricity sources (RES) in the EU energy sector is rising rapidly (Brown 2024). However, some industries within the energy sector cannot be easily electrified. Due to a lack of technology and financial feasibility, these “hard-to-abate” industries, such as transportation and energy-intensive industries, cannot be straightforwardly decarbonised by electrification alone (European Commission 2020; Prakash, Ruiz, and Janeiro 2024). These industries require fossil fuels’ high energy density to maintain high temperatures, serve as raw materials during production processes, or efficiently propel vehicles (Åhman 2020; Wyns and Khandekar 2023).

Multiple sources have proposed biofuels and synthetic fuels as renewable options to replace fossil fuels in “hard-to-abate” industries (European Commission 2020, Franco and Giovannini 2023, Wyns and Khandekar 2023), as these fuels possess chemical properties similar to fossil fuels but are renewable (Paltsev et al. 2021). Biofuels currently represent the most significant renewable fuel in the EU, accounting for 2.1% of the EU energy mix in 2020 (Lundberg, Sánchez, and Zetterholm 2023). However, biofuels rely on arable land to produce biomass, which is limited, constraining their potential (Creutzig et al. 2014, European Court of Auditors 2023). This limitation does not impact synthetic fuels as they are produced by non-biological processes. During synthetic fuel production, primary energy carriers are converted into hydrogen (Ritchie and Roser 2023). Primary energy carriers are the first marketable element in energy supply chains (Dewulf et al. 2015). Apparent examples are fossil fuels, but RES are also a primary energy carrier by this definition. Afterwards, hydrogen is combined with CO or CO2 to create synthetic crude through the Fischer-Tropsch process (Buchenberg et al. 2023, Naik et al. 2010). This synthetic crude can then be refined into more complex fuels or methanol for chemical uses. The hydrogen produced during this process has versatile applications beyond synthetic crude fuel production. Firstly, it can serve as a feedstock for other chemical processes (Rayner et al. 2023) and potentially function as large-scale energy storage (Ajanovic and Haas 2021). Secondly, hydrogen can also be used directly as a fuel. Moreover, hydrogen can be produced entirely renewable through electrolysis. Thus, due to the scalability limitations of biofuels, the versatility of hydrogen, and the potential for a fully renewable fuel, the EU has prioritised synthetic fuels over biofuels. Specifically, the EU has chosen hydrogen as the primary option to replace fossil fuels in ”hard-to-abate” industries (European Commission 2020, P. Collins 2024).

Hydrogen is the final stage of humanity’s endeavour to harness increasingly energy-dense fuels. As the lightest molecule in nature with a highly energetic bond, hydrogen is the most energy-dense fuel available. However, due to these properties, hydrogen is highly reactive and volatile and rarely found in nature. Production and usage highly depend on human technology. Hydrogen can be classified into various types based on the production method. Literature reviews cover these different types comprehensively (Dawood, Anda, and Shafiullah 2020, Ishaq, Dincer, and Crawford 2022, Kayfeci, Keçebaş, and Bayat 2019, Lebrouhi et al. 2022, Megía et al. 2022, Nikolaidis and Poullikkas 2017). However, grey, green, and blue hydrogen are the most significant in the market and most frequently discussed in the literature. As of 2024, grey hydrogen, produced via Steam Methane Reforming (SMR) of natural gas or gasified coal, accounts for 94% of global hydrogen production (IEA 2022). SMR is not climate-friendly, releasing significant emissions (Nikolaidis and Poullikkas 2017). These emissions can be captured using Carbon Capture and Storage (CCS) technology, converting the hydrogen to blue hydrogen. Despite this, the high costs of CCS mean blue hydrogen’s market share remains minimal, though its potential is expected to grow as the technology becomes more cost-effective (Budinis et al. 2018). The EU considers green hydrogen, produced through electrolysis using RES as the only method for producing true renewable hydrogen. In 2020, green hydrogen constituted only 4% of the EU’s hydrogen production (IEA 2022). To renewably replace fossil fuels with synthetic fuels, the EU needs to increase the share of green hydrogen in the energy mix (European Commission 2023a, European Commission 2023b). Therefore, the EU has implemented the ”Hydrogen Strategy” (European Commission 2020). This strategy aims to create a renewable hydrogen market, similar to previous efforts with natural gas (Barnes 2023, Wolf and Zander 2021). Although this market has partially emerged (Vallejos-Romero et al. 2022), unlike the early natural gas market, the high production costs result in insufficient value within the supply chain for the hydrogen market to be self-financed, limiting market growth. As a secondary energy carrier, hydrogen will be significantly more expensive than the preceding primary energy source (Jovan and Dolanč 2020). And while research assesses that hydrogen production costs will decrease over the following decades (Khatiwada, Vasudevan, and Santos 2022,

O. Tang, Rehme, and Cerin 2022, Züttel, Borgschulte, and Schlapbach 2008, Yap and McLellan 2023), the trajectory of these developments is still very uncertain (Odenweller et al. 2022). In addition to production costs, several factors hinder the development of the hydrogen market. Contradictory policies (Zachmann et al. 2021), lack of standardisation (IEA 2022), and uncertainties about future hydrogen demand (Ogden et al. 2018) deter investors and national governments from committing to hydrogen, thus limiting market development (Ueckerdt et al. 2021). Consequentially, the EU is unlikely to meet its renewable hydrogen targets set for 2030 (IEA 2022, Gherasim 2022).

However, the recent discovery of natural hydrogen deposits could alter this trend. This naturally occurring hydrogen, known as white hydrogen, results from various geological processes and is extracted similarly to conventional fossil fuels from deposits (Aimikhe and Eyankware 2023). Therefore, white hydrogen has two distinct properties. Firstly, white hydrogen can be considered as the only fuel extractable that is not fossil. Secondly, white hydrogen is the only type of hydrogen where hydrogen is a primary energy carrier. White hydrogen has the best of both worlds. For these reasons white hydrogen has the potential to mitigate the hydrogen cost problems and be a game changer for the hydrogen transition (Zgonnik 2020). However, research on white hydrogen is in its infancy resulting in uncertainties about the economic feasibility and general availability of white hydrogen deposits. Previously, most knowledge on white hydrogen was generated as a byproduct of research on natural gas deposits, where hydrogen is often part of the gas mix. More recently, white hydrogen has received more attention due to findings in Albania (L. Collins 2024), Brazil (Prinzhofer, Moretti, et al. 2019), France (Carnevali 2024), and Mali (Prinzhofer, Cissé, and Diallo 2018). However, as the research only focuses on these singular findings, significant uncertainties remain about the global prospects of white hydrogen. The literature review conducted by Aimikhe and Eyankware 2023 illustrates considerable differences in research when these uncertainties are assessed. Despite these differences, more recent literature presents increasingly optimistic outlooks on the prospects of white hydrogen (L. Stalker et al. 2022), where in the best scenario, white hydrogen is as abundant and cheap as gas. This optimism is shared by the market as a wave of start-ups focusing on white hydrogen have appeared (Energy 2024).

The sudden emergence of white hydrogen as a fuel can be described as a black swan event (Taleb 2007); aside from some early signs, this emergence lay outside the realm of expectations. However, now that it has emerged, it has the potential to significantly impact the energy system. Nonetheless, the exact nature of this impact remains uncertain due to the multiple scenarios that could unfold. In addition, it is unclear how the white hydrogen system currently operates or how it will function in the future. Due to these characteristics, the uncertainty surrounding white hydrogen can be described as "deep uncertainty" (Lempert, Popper, and S. C. Bankes 2003, Walker, Lempert, and Kwakkel 2013). This deep uncertainty increases the number of possible outcomes for the energy system (Weaver et al. 2013), thus forcing EU policymakers to devise robust policies that retain their effectiveness across various future scenarios (Lempert and M. T. Collins 2007) and can be changed when new information becomes available (Walker, Lempert, and Kwakkel 2013). However, creating such policies requires a thorough understanding of the white hydrogen system and its effects on the energy system. Although research has been done on uncertainties and hydrogen policy (Farrell 2023, Koutsandreas et al. 2023, O. Tang, Rehme, Cerin, and Huisingh 2021), there is currently no research or EU policy documents addressing white hydrogen. Therefore, white hydrogen is a blind spot in the EU hydrogen strategy.

Hence, to help the EU shape effective hydrogen policy under deep uncertainty, it is essential to increase insights into the white hydrogen system and how it might affect the future energy system under multiple scenarios. Then, the EU hydrogen strategy can be tested for robustness under these scenarios. Therefore, the research question of this thesis aims to address this knowledge gap and can be formulated as follows:

- *What are the potential effects of an emerging white hydrogen market on the EU transition towards hydrogen?*

To answer this question, a Decision Making under Deep Uncertainty (DMDU) approach was deemed fit for purpose as it enables monitoring the effects of deep uncertainty and adapting policy accordingly (Marchau et al. 2019). Breaking down the main research question, the objectives of this thesis are threefold. The first goal was to determine how hydrogen relates to the energy system. Modelling is a crucial aspect of DMDU as it allows for analysis of the studied system (Kwakkel, Walker, and Haasnoot 2016). However, no existing models of the energy system incorporate hydrogen. During this thesis, a model was developed to enable such analysis. This model is based on the “Energy Mix model” (W. Auping et al. 2014, W. Auping et al. 2016), which combines the markets of major energy carriers into a single system. This thesis expands on this work by adding hydrogen to the SD model. The second goal was to examine the effects on the energy system when white hydrogen is introduced under multiple scenarios. Using the Exploratory Modelling and Analysis (EMA) method, multiple scenarios of the possible states of the white hydrogen system were created and implemented within the energy system model. The last goal was to see how the energy system under effect of these scenarios affects EU hydrogen policies and evaluate their effectiveness. The following sub-questions were formulated to achieve these goals:

- *How does hydrogen relate to the energy system, and how can hydrogen be added to the energy mix model?*
- *How does white hydrogen impact the energy system?*
- *How can white hydrogen affect EU hydrogen policies?*

The following paragraph will describe the structure of the Thesis. Chapter 2 explains the methodologies and data sources used throughout the study and details the approaches and frameworks necessary to analyse the research questions. In Chapter 3, the model and its components are elaborated, focusing on the model overview, uncertainties within the model, and the policy levers, such as the European hydrogen strategy. Chapter 4 presents the findings from the base ensemble and policy analysis sections, examining system behaviours and scenario impacts under different conditions. The discussion in Chapter 5 reflects on the limitations of the SD model, explores the research methods, and contextualises the findings within the broader field of study. Chapter 6 concludes the study by synthesising the research findings and policy recommendations; the main research question will be answered here.

Chapter 2

Methods

2.1. Decision Making under Deep Uncertainty

This study used a Decision Making under Deep Uncertainty (DMDU) approach to answer the research question. As energy transitions, such as the transition towards hydrogen, are steeped in deep uncertainty (Paredes-Vergara et al. 2024), predicting the future state of the system under transition becomes impossible, complicating policymaking. Despite the deep uncertainty, DMDU encompasses a collection of methods that still enable policy design (Stanton and Roelich 2021). These methods are based on a “monitor and adapt” paradigm (Walker, Lempert, and Kwakkel 2013). In this paradigm, deep uncertainty is managed by determining a range of possible futures, monitoring the system, and dynamically adapting policies according to the subset of scenarios that appear to be unfolding.

DMDU encompasses multiple subgroups of methods, each focusing on a different aspect of decision making under deep uncertainty. This research employs the Exploratory System Dynamics Modelling and Analysis (ESDMA) methodology. ESDMA was developed to tackle grand societal challenges (Kwakkel and E. Pruyt 2013), such as the EU hydrogen transition (Borgschulte 2016). ESDMA utilizes System Dynamics (SD) modelling to address the dynamic complexity of societal issues. In SD, uncertainty is primarily addressed by interpreting quantitative outcomes resulting from model behaviour (Meadows and Robinson 1985, Lane 2012). However, under deep uncertainty, predicting the future becomes impossible, rendering these interpretations less meaningful. Exploratory Modelling and Analysis (EMA) (Agusdinata 2008, S. C. Bankes 1993, S. C. Bankes 2002, e. a. Bankes S. C. 2013, Kwakkel 2010) addresses this limitation by running SD models under multiple scenarios and providing tools for analysis, providing insights into system behaviour under clusters of uncertainty without requiring precise outcomes.

For the following three reasons, ESDMA was chosen as the methodology for this research. Firstly, the combination of SD modelling and EMA allows ESDMA to systematically explore and analyze plausible future states of the energy system and test the effectiveness and robustness of EU hydrogen policies without neglecting deep uncertainty and dynamic complexities (Kwakkel and E. Pruyt 2015). Secondly, past research on modelling energy systems has also used an ESDMA approach, increasing the validity of this method for the purpose of this research (Hamarat and E. Pruyt 2011, Loonen, E. Pruyt, and Hamarat 2013, Erik Pruyt 2010). Additionally, as the EM model was also built using the ESDMA methodology, expanding the model using the same methodology ensures alignment with the underlying assumptions of the EM model. Thirdly, as the white hydrogen energy system is not well-defined, exploratory modelling allows for the exploration of possible configurations of this system.

2.2. Research flow

Based on DMDU research with a similar purpose (Erik Pruyt 2010), a research flow was determined (See figure 2.1). Within the research flow, five steps can be distinguished. The first step within the DMDU research flow is determining the boundaries of this research. This will determine which scope, structures, parameters, and outputs should be included within the SD model. The second step is then building the SD model with these elements. The third step combines the parameters’ uncertainty ranges

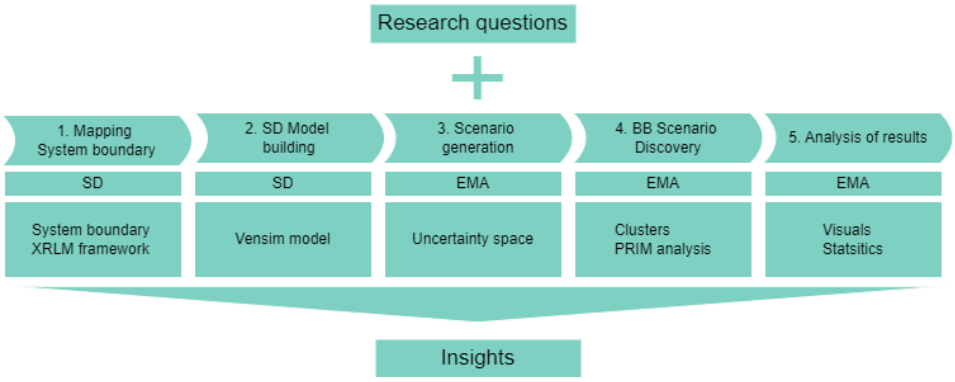

Figure 2.1: Research flow; Within the figure the first row shows the research step, the second if the step belongs to SD or EMA and the third row shows the results of each step.

with EMA to generate thousands of scenarios. The fourth step is determining dynamic patterns and clusters emerging from these scenarios. This is done using the Behaviour-Based Scenario Discovery method developed by (Steinmann, W. L. Auping, and Kwakkel 2020). The fifth step to use the results to analyse the behaviour of the energy system and the impact of the EU hydrogen policies. After these steps are conducted, conclusions and recommendations can be made, and the research approach will be reflected upon.

2.3. Problem Formulation

The starting point of the ESDMA research approach is formulating the problem. In the context of this research, formulating the problem means demarcating the problem's scope, identifying the problem's structure, and identifying all elements within this scope through literature research. However, doing this requires vast amounts of data, which need to be structured to create oversight and minimize redundancies or overlap within the data (Groves et al. 2019). For this purpose, the XLRM framework (Lempert, Popper, and S. C. Bankes 2003) was chosen to structure all information obtained by the literature research. Within the XLRM framework, all information within the problem scope is sorted into four categories corresponding to a letter within the abbreviation, see Table X.
The use of the XLRM framework has three advantages. The first advantage is that the XLRM framework ensures that all information is sorted and that there is no redundant information. As ESDMA requires much information, XLRM will reduce the workload significantly. The second advantage of using the XLRM framework is that the categories correspond to model attributes in SD modelling. Therefore, structuring the SD model building. Thirdly, the XLRM annotation is helpful as the EMA workbench can solve this equation for multiple modelling packages for f. Using this XLRM notation, a simulation model is essentially a function with a specified set of parameters, uncertainty (X), and policy levers (L) resulting in model outcome (M), where the function f is comprised of the complex relations R within the model structure (Kwakkel, Walker, and Haasnoot 2016):

$$M = f(X, L) \tag{2.1}$$

2.4. SD Modelling

The second step of this research is constructing a model using System Dynamics (SD). Vensim was chosen as the software for this research. SD, developed by Jay Forrester in 1957, is a relatively young field of modelling (Forrester 2007). System dynamics is a methodology derived from control theory that utilises feedback systems to effectively manage the non-linearity, time delays, and multi-loop structures inherent in complex and dynamic systems (Bala, Arshad, and Noh 2017). SD's feedback loop structure emulates dynamic behaviour from the interplay of positive and negative feedback loops. An important aspect of SD is its use of stocks and flows, which allows the modelling of accumulating resources such as primary energy sources, enabling the modelling of energy systems. SD is a valuable approach for dealing with the complexity characterising the global energy system (W. Auping et al. 2016; Kwakkel and E. Pruyt 2015). It offers several benefits. First, SD modelling with Vensim provides the necessary tools for scenario building and policy implementation for Decision Making under Deep Uncertainty (DMDU). This enables policy testing within the model scope and uncertainty space. Second, SD can identify essential elements and their relationships within a system by inspecting model behaviour and determining which elements are responsible (Sterman 2002). Understanding these critical factors and their interrelations provides qualitative insight into how to influence the system through policy interventions.

However, SD has its disadvantages. Due to the energy system's ever-changing state, the relevance of input data and relationships between factors can diminish over time. This poses challenges for SD, as it relies on realistic inputs to model reality accurately (Barlas 1996). Over time, SD models may generate uncertainty independently. Given that the timescale for this research spans decades, the impact of this risk increases. This research will use the Energy mix model (W. Auping et al. 2016) as a foundation for the model built within this research. This model is compatible with the current research for several reasons. First, the energy mix model aims to explore the consequences of uncertainty in the complex energy system following the exploratory modelling methodology (W. Auping et al. 2016), aligning with the methods of this research. Second, the model has been published and validated, providing a robust base for this research. Third, SD allows for the modelling and implementing hydrogen policies and their effects on the system (Kwakkel and E. Pruyt 2015), enabling comprehensive modelling of the global energy system, including hydrogen. The primary result is a qualitative insight into the system's structure, model behaviour, and leverage points (Lane 2012), which are crucial for this research methodology.

SD Modelling techniques

To actually built an SD model, the conceptual ideas of stocks, flows and feedback-loops need to be translated to reality on an interface allowing interaction. For this purpose, the Vensim software (Ventana 2024) was used. Within Vensim all model structures and relations are reduced to mathematical equations. The dynamics of the system are defined by the Stocks, mathematically defined as integrals Stocks are filled or emptied with flows, who can be affected by delays creating dynamic behaviour(Jones 2014, see equations 2.4 and 2.3. In Vensim, an auxiliary variable is used to represent intermediate calculations, constants, or functions within a model, see equation 2.4. These variables help simplify equations and improve model clarity by breaking down complex relationships into smaller, more manageable components. They do not have stocks or flows but are crucial for defining the relationships and dependencies between different parts of the model. Auxiliary variables can be used to perform arithmetic operations, logical tests, or call built-in functions, and their values are recalculated at each time step during the simulation. The following equations show the basic mathematical form of the Vensim modelling language (Vensim Documentation 2024a).

$$stocks_t = \int_0^T flows_t \, dt \quad \text{or} \quad \frac{d}{dt} stocks_t = flows_t \tag{2.2}$$

$$flows_t = g(stocks_t, aux_t, data_t, const) \tag{2.3}$$

$$aux_t = f(stocks_t, aux_t, data_t, const) \tag{2.4}$$

$$stocks_0 = h(stocks_0, aux_0, data_0, const) \tag{2.5}$$

Subscripts in Vensim

In modeling, subscripts are used to manage and simulate multiple similar entities within a single model structure (Vensim Documentation 2024b). For instance, when modeling the logistics of several stores, creating individual structures for each store can become cumbersome. Instead, a generalized structure with different inputs for each store can be used. Subscripts in Vensim allow for the computation of multiple data arrays within a single model structure, providing outputs for each subscript, thus maintaining clarity and efficiency. Although a single model structure is used, heterogeneous structures can still be implemented per subscript entities thus not limiting model building options. Here is an example of using subscripts in Vensim:

$$Stock|Location| = \int (InFlow|Location| - OutFlow|Location|) \tag{2.6}$$

$$Location = |bakery, butcher, etc.| \tag{2.7}$$

In these equations, *Location* is the subscript that can represent different stores or entities. Each variable will output results equal to the number of subscripts.

Modeling advanced structures

Advanced equations are necessary to capture the complexities of the system being modelled. Based on the basic mathematical basis of Vensim and are created from certain configurations of stocks, flows and auxiliaries. These equations help accurately represent the dynamic interactions, feedback loops, and time delays inherent in complex systems, allowing for advanced models. Within this research equations were used were implemented in other energy or economic models. The following equations were used to model advanced model relations.The equation for mix substitution (Mazzucato 1998), helps to model how changes in energy demand can influence the market share of different energy sources, which is crucial for understanding the dynamics of energy transitions. Within this research this equation was used to connect the demands of various energy carriers. The equation for mix substitution, With S as the market share, C as the energy demand, and γ as the demand substitution rate is given by equation 2.8. The scale factor equation (Morgan 2013) is essential for understanding how economies of scale can affect the costs of different energy technologies, influencing investment and policy decisions. The equation, where C represents production costs, S represents unit size, and n is the scaling factor, is given by equation 2.9.The progression rate equation (Ibenholt 2002) models the exponential growth patterns often observed in technology adoption and market expansion, providing insights into future development of energy technologies. The equation with a as the growth factor is given by equation 2.10.The learning curve equation (Ibenholt 2002) captures the effects of learning and innovation on cost reductions, which is vital for assessing the long-term viability of different energy technologies. The equation, where C is the cost factor, a is the elasticity of unit cost with respect to cumulative volume, and u is the uncertainty factor, is equation 2.11.

$$s_i = \gamma \times s_i(\overline{C} - C_i) \tag{2.8}$$

$$\left(\frac{c_1}{c_2}\right) = \left(\frac{s_1}{s_2}\right)^n \tag{2.9}$$

$$PR = 2^a \tag{2.10}$$

$$C_t = C_1 n_\tau^a e^{u\tau} \tag{2.11}$$

2.5. Scenario Generation

The fifth step of this research is scenario generation. With the EMA workbench and Python, tens of thousands of scenarios will be generated. First, a set of parameters are chosen based on their estimated effect on the system and whose value is uncertain. Then, the uncertainty space is generated; this space is bounded by the lowest and highest values of the parameters within the set. This uncertainty space represents all possible variations of inputs for the model. At last, the scenarios are generated; each scenario has its own set of values for the parameters. These values and the assignment of these values per scenario are determined by Latin Hypercube Sampling (LHS). LHS divides the uncertainty space by the number of scenarios and randomly combines these values, thus guaranteeing uniqueness and a uniform spread of values (Huntington and Lyrintzis 1998), see Figure 2.2. Additionally, as long as the input and number of scenarios stay consistent, LHS will produce the same scenario, increasing the consistency and reproducibility of the research.

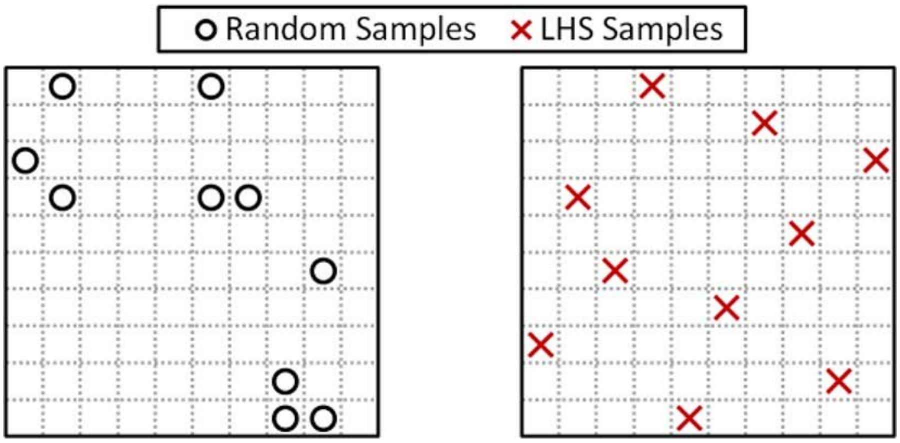

Figure 2.2: Comparison of random and Latin hypercube sampling examples in two dimensions (every row and column is sampled with LHS), made by Preece and Milanović 2015

2.6. Behaviour Based Scenario Discovery

S. C. Bankes 1993 proposed employing computational experimentation across numerous distinct realisations of inherent uncertain factors to delineate the implications of uncertainties methodically. Scenario Discovery was recommended to scrutinise the outcomes of these computational experiments and extract decision-relevant insights (Bryant and Lempert 2010,Kwakkel and Jaxa-Rozen 2016). Different temporal dynamics plausibly constitute different vulnerabilities when using Scenario Discovery for designing strategies, as is common in Robust Decision Making. An inability to separate these vulnerabilities because of a static criterion can result in an inability to briefly describe the subspace(s) from which the experiments of interest originate. In short, aggregate time series statistics may be misleading (Anscombe 1973), or such time series may be equifinal but dynamically distinct (Von Bertalanffy 1968). The model output will be time-series as the technique used to model the system in this research is SD. This aggregation of production limits the ability to design robust strategies. Thus, a Behaviour Based Scenario discovery will be performed for this research. Three steps must be followed to perform Behaviour Scenario discovery within this research (Steinmann, W. L. Auping, and Kwakkel 2020).

The first step is to simulate the system through experimentation by randomly sampling from the input parameter space. For this research, 10,000 runs will be performed. The sampled inputs will be fed into the SD model, and the resulting outputs will be systematically recorded for analysis. The second step is to apply time series clustering to the model outputs. This enables the separation of distinct model behaviours. This will result in 20-30 scenarios. The third step is to find the subspace (or region) in the input parameter space where the inputs generating the outputs of interest lie by inducing its parameter rules. The chosen parameter rule for this research is the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999), which was implemented in the Exploratory Modelling workbench (Kwakkel 2017).

2.7. System and Policy Analysis

The Policy Analysis encompasses an examination of both pre-existing policies and those newly designed, focusing on their implementation spanning the timeline from 2020 to 2050. Operating within uncertainty, the EMA workbench generates various scenarios that provide insights into these policies' potential outcomes and impacts. These scenarios will be applied to the SD model. The following steps are taken during the Policy Analyses:

The first step of the policy analysis is creating a base case scenario; within the base case, only policies already implemented are present. The base case scenario is an essential reference point, allowing for a thorough understanding of the existing policy landscape and its implications. The second step of the Policy Analysis is implementing planned policies, building upon the established base case scenario. This phase involves the implementation of policies that have been strategically devised and scheduled for execution. The purpose is to observe and assess the cumulative effects resulting from the integration of these planned policies alongside the existing ones. The last step is implementing newly designed policies. This step seeks to gauge the potential impacts of policies explicitly designed to respond to emerging challenges or enhance existing frameworks. By implementing these novel policies, the study aims to unravel their possible contributions to shaping the trajectory of developments within the designated timeframe.

This analytical framework facilitates a nuanced examination of the evolving policy landscape, considering the repercussions of already established measures and the dynamic interplay of planned and newly designed policies. This holistic approach enables a robust understanding of the potential trajectories and outcomes that may unfold in policy implementation from 2020 to 2050.

Chapter 3

Model

This chapter describes how the conceptualization of the system and literature was used to expand the Energy Mix model with a hydrogen module. Furthermore, it addresses all other components of the XLRM framework First, in section 3.1 an overview is given of how the SD model was built. Then, section 3.2 lists the uncertainties surrounding the energy system. Afterwards, section 3.3 section. The experimental set-up is presented in section 3.4. Finally, validation techniques and validation results for the model are given in section 3.5.

3.1. Model overview

This section gives an overview of the model used in this research. As the model for this Thesis was created on top of the Energy Mix model, understanding the underlying mechanism is vital to developing a coherent model. Therefore the Energy Mix model was briefly analysed. For a more elaborate analysis of the Energy Mix model, see W. Auping et al. 2014. Then the Combined model was created on top of the Energy Mix model The file for the Combined model can be found at:
https://github.com/Condor323/Modelling-White-Hydrogen.

3.1.1. Energy Mix model

Main attributes of the Energy Mix model

The Energy Mix model, developed by W. Auping, is a Vensim model designed to study fossil fuel price scenarios (W. Auping et al. 2014, W. Auping et al. 2016). This comprehensive model consists of 4000 elements, organized into six sub-models, and employs multiple subscripts to manage its complexity. It operates over a timeline from 2010 to 2045 and uses the Runge-Kutta 4-auto integration method to simulate the dynamics. An overview of the elements within the model are shown in Figure 3.1.

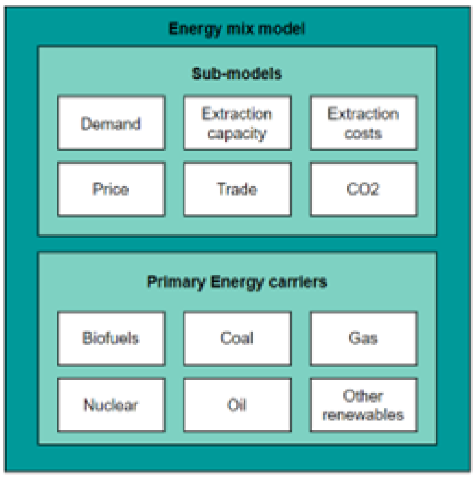

Figure 3.1: Sub-system diagram of energy mix model; showing sub-models and primary energy carriers within the model

The Energy Mix model extensively uses subscripts within its structure, enabling the modeling of energy markets for four global regions: The Americas, Greater Europe, the Far East, and the Rest of the World. Figure 3.2 illustrates how countries are divided into these groups, based on geopolitical groupings such as ASEAN and the EU and the integration of energy markets. Russia is grouped with the Rest of the World instead of Greater Europe due to its globally diversified energy exports. This division allows for the implementation of the trade sub-model and affects parameters and output interpretation when comparing old and new models. Another application of subscripts in the model is for different energy

Figure 3.2: Subscripted Regions within the Energy Mix and Combined model

carriers, including oil, gas, coal, biomass, nuclear, and renewables. While the structures for these carriers largely overlap, there are some heterogeneous structures added for specific groups of energy carriers. These variations drive different behaviors within the model and are based on assumptions. For example, fossil fuels are considered trade-able, whereas electric-based energy carriers like renewables and nuclear are not.

Sub-models of the Energy Mix model

The Energy Mix model is made up from multiple sub-models. This section will give a brief description of the function of each sub-model. A schematic overview of the model and its sub-models can be found in Appendix C.

Sub-model 1: Energy demand

The primary purpose of the energy demand sub-model is to model the energy demand of the various energy sources per region. Energy demand is modelled as a level with multiple flows determining the change in demand as a percentage. Demand increases due to economic growth, and demand changes due to price flow, which links demand and price/economic growth with a scaling factor. The third flow of demand substitution works, replacing a part of the current energy mix with the most optimal mix; this can depend on demand or supply. The height of substitution and price flows differentiate between the energy carriers, while the substitution and price flows can change the composition of the energy mix. In theory, the total sum of the substitution flow must be zero (due to computational limits, this is not the case), and the total energy demand is only changed by prices and economic growth. This sub-model also determines how much energy is used and how profitable the energy carriers are. Due to its size and connected structure, this sub-model can be considered the model's centre.

Sub-model 2: Extraction capacity

The extraction capacity sub-model determines the production capacity per energy carrier. As energy carriers are profitable, yearly change factors increase the total capacity. This increase depends on reserves for depletable energy sources, while non-depletable energy sources, such as renewables, biomass, and nuclear, are not limited to reserves. When profits fall, capacity will be put out of use temporarily; it can be turned on when profitability rises again. However, a small amount of unused capacity will deteriorate over time. This function is the decommissioning of the model's production capacity.

Sub-model 3: Extraction cost

All energy sources have a cost of production. In the extraction cost sub-model, this production cost is determined. The structure of this sub-model is more linear and smaller than the previous ones. This sub-model shows the first example of the learning curve model paradigm within the cost development learning curve structure. The unit cost of the energy sources depends on efficiency increases due to learning and the EROEI or Energy Return Over Energy Investment of energy sources. This EROEI will decrease as energy becomes less, as there is more supply or as reserves dwindle, and each unit of energy is more expensive to get out of the ground.

Sub-model 4: Resource pricing

Once the production cost of a unit of energy is known, it can be sold on the market. The resource pricing sub-model determines the market price of a unit of energy per energy carrier. This is done in multiple ways. The first price-determining mechanism is the free-floating mechanism, where the price is based on the relation between demand and supply. This mechanism balances the model as supply shortages will increase prices and thus will increase capacity. The second mechanism, “cost plus percentage,” takes the unit cost and adds a percentage as a profit fee. This mechanism reduces model dynamics as the relation from production capacity and energy demand to resource pricing is removed; this will remove feedback loops.

Sub-model 5: Trade

The trade sub-model models trade between regions and energy sources. Surpluses and shortages within regions can be traded on the market. This sub-model also contains large heterogeneous structures detailing gas trade in LNG form.

Sub-model 6: CO2 cap and trading

The CO2 cap and trading sub-model allows for calculating the number of emissions released per year per region. This structure was added between the model version of 2014 and 2016 and allows the implementation of the ETS system. This system prices CO2, giving fossil fuels a disadvantage, which enables an increase of renewables within the energy mix. More importantly, due to market mechanisms, the ETS system will decrease the total energy market size due to the extra tax. Alternatives cannot fully compensate for this decrease as the average energy price has risen; thus, demand is lost due to price elasticity (Gu, Li, and Yang 2013).

Energy Mix model model behaviour

The variables within the sub-models are often interconnected, creating numerous dynamic loops and generating complex behavior. This inter-connectivity is depicted in the Casual Loop Diagram(CLD) of the model shown in Figure 3.3. General model behavior can exhibit balancing and chaotic dynamics at a high aggregate level, with multiple loops maintaining equilibrium.The model behavior reflects this dynamic: if prices drop, demand increases, depleting existing reserves and driving prices up again. The main drivers are economic growth, resource depletion, and rising energy prices. Total depletion is challenging as higher prices and improved technology enable the extraction of reserves previously considered not cost effective. However, as renewables become increasingly cheaper, they occupy a larger share of the energy mix. Introducing a CO2 price further decreases energy demand within the regions. As a result of artificially heightened energy prices, the market will decrease. This will in turn lead to decoupling of energy production capacity, increasing prices and thus further diminishing energy demand.This behavior is evident in both the 2016 and 2020 model versions. An interesting observation is that the 2016 model underestimated CO2 emissions and renewable energy use compared to the updated 2020 model.

3.1.2. Combined model

Main attributes of the Combined model

Once it was determined which assumptions and structures superseded the Energy Mix model, adding hydrogen to the model became possible. First, a CLD was created for the hydrogen market that was then linked to the CLD of the Energy Mix model, see Figure 3.3. It was concluded that both CLDs shared many similarities within their structure, which could be considered a probable representation of reality. Hydrogen is a product on the market that needs to be produced, consumed, and traded at a

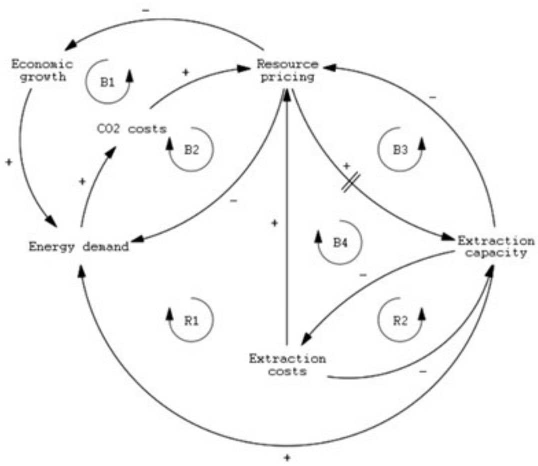

Figure 3.3: Conceptual model of the energy mix model

specific price, just like the primary energy carriers within the global Energy Mix model. However, there are also differences between the structures. Conventional hydrogen sources are secondary energy carriers produced from this model's primary energy carriers. An increase in prices for gas, coal, and renewables will thus lead to a rise in the production cost of hydrogen. This creates a balancing loop as hydrogen production will lead to more primary energy source demand, increasing prices for both, connecting both structures. A vital modelling decision arises from these observations. Hydrogen can

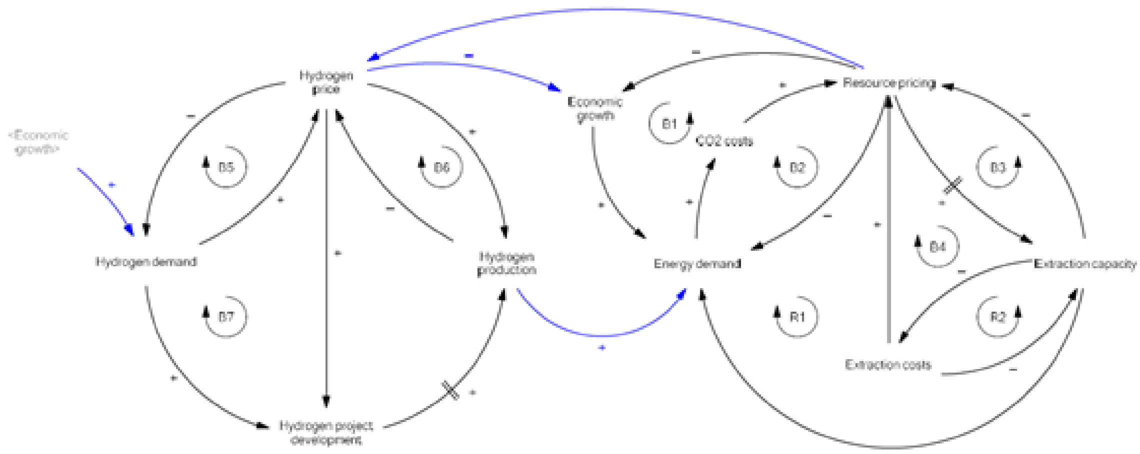

Figure 3.4: CLD of combined model; hydrogen system is connected through production usage of primary energy carriers

be modelled similarly to energy sources: does it need to be modelled as a separate structure, or can it be implemented as a subscript within the global Energy Mix model? The primary assumption in making this decision is to what extent the hydrogen market is integrated into the energy mix. An argument could be made that hydrogen is not fully integrated as the largest hydrogen demand markets use hydrogen for chemical purposes. Substitution with other energy sources is often impossible, and there are higher substitution costs as production chains must be adapted (Nuttall and Bakenne 2020). From this point of view, hydrogen demand seems independent, mainly of total energy demand. This can be supported by the notion that because hydrogen is a secondary energy carrier, the primary energy source it is derived from is always cheaper. In this sense, it can never compete in markets where energy type use is fully substitutable. In this case, hydrogen should be modelled separately from the energy sources with independent structures that determine demand, price, and supply. In this conceptualisation, only the different types of hydrogen compete against each other.

However, multiple arguments can be given regarding why hydrogen demand directly depends on energy demand. It is predicted that hydrogen will expand to markets where it will compete with other energy sources, such as transport and industry, as it is, in some markets, the only option for decarbonisation. Moreover, the IEA illustrates that demand growth in these sectors will be the most important driver of total hydrogen demand. EU policies also force demand expansion within these markets. The current decoupling of hydrogen demand can also be explained by the high cost of hydrogen compared to other energy carriers. From this perspective, hydrogen competes with other energy carriers, but it simply loses. For these reasons, it was determined that, within the boundaries of this research, hydrogen competes directly with the other energy sources for demand. As a result, the types of hydrogen were implemented as subscripts within the model. However, because of the different properties of the hydrogen system compared to the other energy carriers, heterogeneous structures were implemented for hydrogen. Sub-models were created for the largest of these structures.

Sub-models of the Combined model

Multiple additions were made to the Energy Mix model to implement hydrogen in the Energy Mix model. This section will give an overview of the changes made. A schematic overview of the model and its sub-models can be found in Appendix 6.2.

Sub-model 1: LCOH

Unit cost is modelled based only on supply- and reserve-based structures within the Energy Mix model. This is insufficient for modelling hydrogen; hydrogen cost also depends on the prices of primary energy carriers. Thus, a different sub-model was built for hydrogen unit cost to create more detailed insight into price build-up. The models can be described as implementing the general equation for LCOH as proposed by Khatiwada, Vasudevan, and Santos 2022 and O. Tang, Rehme, and Cerin 2022. The formula uses interest rates, investment per year and operational costs (energy cost of primary sources needed to produce hydrogen) to calculate the LCOH:

$$LCOH = \frac{\sum_i \left(I_i + O_i + R_i\right)/(1+r)^i}{\sum_i \left(E_i\right)/(1+r)^i} \tag{3.1}$$

where:

- I_i: investment in year i
- M_i: maintenance and service cost in the year i
- O_i: operational cost in year i
- E_i: energy (hydrogen) output in year i
- R_i: revenue income in the year i
- r: interest rate, %

Implementing this formula requires proposed input values for each year within the lifetime of the hydrogen plant. For the investment per year, this imposes no problems as the investment is made in year 0. However, it is necessary to determine the prognosed values of the operational costs and interest rates over the future. However, within Vensim, it is not possible to generate separate data points at one point in time during calculation. This could be solved by reading a vast amount of data. However, this would undermine dynamic behaviour as, in this situation, the LCOH would be calculated without any input from other sub-models. In the end, forecasts were used to determine the value at the end of the lifetime. A method was created to produce a single averaged yearly input value that could be used to calculate an LCOH for each timestep. This method takes the average of the input value at $t = 0$ and the forecasted averaged input. The next step is to calculate $(1 + r)^i$, where i represents years. This value does not need to be averaged as it can be mathematically rewritten to:

$$\frac{(1+r)^{i+1} - 1}{r/i} \tag{3.2}$$

Where i is the lifetime of the hydrogen plant in years. This formula generates an approximation between 86%-90% of a full factorial workout of the formula, which is considered good enough for this research. Now, NPVs of the hydrogen output can be determined, enabling the calculation of the capital expenditure per produced Bbtu of hydrogen. Combining this value with the energy costs per Bbtu gives the LCOH. This calculation also accounts for the conversion rates of energy carriers to hydrogen and CCS costs. Learning curves decrease CCS and capex costs and increase the conversion rate, leading to LCOH decreases independent of the other systems within the model.

Sub-model 2: Hydrogen extraction capacity

In the Energy Mix model, extraction capacity is added by multiplying the current capacity with a yearly percentage of change dependent on profitability. It was decided to improve this structure as it was suspected that more factors were relevant for production expansion. The built sub-model comprises a simple stock-flow structure. New hydrogen plants are started based on profitability and future predicted needed supply. Then, a plant can be completed or cancelled based on profitability. After some years, the plant will close. All these flows work with delays. The project completion times determine the building time of a plant. This building time will decrease due to scaling over the years. Uncertainty is a problem during the project phase of a hydrogen (**fa**. This uncertainty is modelled as constants that lower the number of new and cancelled projects built.

Sub-model 3: Forecasts

This sub-model was built to provide forecasted output for the LCOH sub-model. It functions as a hard-coded calculator within the model. It takes input and generates output. As the structure remains the same for all inputs, the structure was subscripted. This way, there is no limit to the number of inputs that can be provided. The forecast makes use of the Maclaurin-Taylor series to determine future values of the inputs:

$$f(n) = \sum_{n=0}^{\infty} \frac{x^n}{n!} \tag{3.3}$$

Where the series is modelled with two of the second power.

Additions to Existing Sub-models

Various changes were also made to the sub-models already present in the model. An overview is given in Table 3.1. As in the Demand distribution sub-model, many changes were made. They are presented below. First, a substitution flow was added as hydrogen types are substitutional for each other as they are indistinguishable after production. Therefore, they compete. To model this, a substitution flow was constructed where, each year, half of the total hydrogen demand will be redistributed via price allocation. This was chosen over a full-yearly hydrogen substitution as some hydrogen demand is fulfilled via long-term contracts or hydrogen production is integrated into the local industrial chain. Then, another substitution flow was added to model non-economical decarbonisation. Decarbonisation is caused by nudging policies or changes in consumer preferences. In this flow, 1% of yearly fossil fuel demand is substituted and redistributed over RES by allocation based on their price mix. At last, a flow was added to model growth of hydrogen due to the opening of markets due to new consumer technologies. As this can lead to exponential growth, a maximum demand growth capacity was modelled. This capacity gets smaller when demand rises, preventing exponential growth.

Sub-model	Additions to sub-model
CO2 cap and trading	Structure added to calculate ETS income.
Extraction capacity	Completed hydrogen projects and decommissioned hydrogen capacity connected to the sub-model.
Extraction costs	A change in LCOH was added as a flow into the unit cost lever.
Resource pricing	Hydrogen was added as a subscript.
Trade	Hydrogen was added as a subscript.

Table 3.1: An overview of structural additions

3.2. Uncertainty within the model

Modelling is dealing with the unknowns that arise when pursuing reality. All actions during modelling depend on the modeller's perspective and knowledge. Even parameters don't avoid this issue, as they are just the result of another modeller's work. Despite the quality of work, there will always remain a small amount of uncertainty (Sterman, 2002). To be able to deal with uncertainty, they need to become apparent. Pruyt (2014) concluded that there are four locations within a model where uncertainties can reside. They can lie within a model's parameters, structure, method, and output. This section will discuss the cause of the parametric and structural uncertainties within the model. The uncertainties within the methods and output will be discussed in Chapter 5.

3.2.1. Structural Uncertainties

Structural uncertainties within the SD methodology can be distilled to the question of how to connect dot A to dot B. In some situations, this can be easy if relations are straightforward. However, when working in complex models dealing with highly abstract topics, connecting the dots can become difficult. Within this model, two structural uncertainties were identified. These uncertainties will be implemented in the experimental setup to control for their effects.
The first structural uncertainty is the mathematical method used within the forecast sub-model. The Taylor series is a proven way of extrapolating non-linear equations. However, Vensim also provides a forecasting function with the formula:

$$\text{Forecast} = \text{input} \times (1 + \text{TRD} \times t_{\text{endtime}}) \tag{3.4}$$

$$\text{CapTRD} = \frac{\text{input} - \text{AV}}{\text{average time} \times \text{AV}} \tag{3.5}$$

$$\text{CapAV} = \int \frac{\text{input} - \text{AV}}{\text{average time}}\, dt \tag{3.6}$$

As both formulas are archaic, experimentation can tell which formula causes realistic model behavior.
The second uncertainty was how to implement a discount rate within the model. This is needed for the LCOH sub-model. Sweerts 2019 argue that the discount factor negatively correlates with higher GDP. Vassalou 2003 implies, however, that they are not correlated. As solving this dispute lies outside the scope of this research, two structures were implemented to reflect both perspectives. One structure models the discount factor as a constant. The other structure uses this constant as a base but detracts from the forecasted expected average GDP growth. This second structure is the default within the model, as forecasting enables a dynamic discount rate.

3.2.2. Parametric Uncertainties

Since 2022, a source of white hydrogen has been found in France. This resulted in some media branding white hydrogen as a game changer for hydrogen. And with estimated pricing as low as $0.5/kg, it could be. White hydrogen does not create much structural uncertainty as its extraction is modelled like gas and sold on the regular hydrogen market. The unknown lies in the number of deposits and the price to extract. Table 3.2 shows an overview of the estimated ranges of white hydrogen parameters.
Before beginning, it's uncertain whether the parameters obtained from sources are accurate. However, to gain a deeper understanding of model behavior, it's better to shift the focus from questioning the certainty of the parameters to exploring the implications of "what if" scenarios. This is done by giving a minimum and maximum value to all parameters deemed uncertain or assumed to significantly affect hydrogen within the model. An overview of these parameters is given in Table 3.3. The parametric uncertainties will be analyzed in Chapter 4.

3.2.3. Output Metrics

The EU has established several hydrogen-specific objectives to guide its policies. These objectives must also be implemented within the model to evaluate the EU's hydrogen policies using the model. Therefore, it is necessary to choose a set of output variables from the model that can serve as benchmarks for these policies, either directly or indirectly interpretable. It must be noted that throughout this thesis, the output of other variables is also presented to illustrate the effects of policies or increased

Name	Min value	Max value	Unit	Source
Average Rb over P white hydrogen	5	100	Year	Assumption
Initial extraction capacity white hydrogen	1	10,000,000	Bbtu/year	Assumption
Initial undiscovered white hydrogen	1,000,000	5.255E+09	Bbtu	Assumption
Initial unit cost	1	100,000	-	Assumption
Initial price white hydrogen	1	100,000	Dollar/Bbtu	Assumption

Table 3.2: Uncertainties for white hydrogen

Name	Min value	Max value	Unit	Source
Base uncertainty factors [Regions, Hydrogen]	0	0.7	Dimensionless	Assumption
CAPEX learning curve	0.005	0.05	1/Year	Jager-Waldau 2021
CCS learning curve	0.005	0.05	1/Year	Institute 2023
Conversion efficiency rate [Blue hydrogen]	0	0.005	1/Year	Assumption
Conversion efficiency rate [Grey hydrogen]	0	0.005	1/Year	Assumption
Conversion efficiency rate [Green hydrogen]	0	0.005	1/Year	Assumption
Hydrogen substitution rate	0.1	1	1/Year	Assumption
Initial conversion ratios [Blue hydrogen]	0.675	0.825	Dimensionless	Velazquez 2017
Initial conversion ratios [Grey hydrogen]	0.675	0.825	Dimensionless	Velazquez 2017
Initial conversion ratios [Green hydrogen]	0.63	0.77	Dimensionless	Zhang 2014
Initial EROEI green hydrogen	1	20	Dimensionless	Zhang 2014
Initial hydrogen plant CAPEX [Blue hydrogen]	48,000,000	180,000,000	Dollar	IEA 2022
Initial hydrogen plant CAPEX [Grey hydrogen]	48,000,000	180,000,000	Dollar	IEA 2022
Initial hydrogen plant CAPEX [Green hydrogen]	80,000,000	300,000,000	Dollar	IEA 2022
Initial price blue hydrogen	11,356.5	58,614.214	Dollar/Bbtu	BloombergNEF 2022
Initial price green hydrogen	23,445.69	70,337.057	Dollar/Bbtu	BloombergNEF 2022
Initial price grey hydrogen	7,803.017	23,409.052	Dollar/Bbtu	BloombergNEF 2022
Initial price renewables	9,708	29,124	Dollar/Bbtu	Assumption
Minimum construction time [Blue hydrogen]	3	5	Year	Dale 2023
Minimum construction time [Grey hydrogen]	2.5	4	Year	Dale 2023
Minimum construction time [Green hydrogen]	2	3	Year	Dale 2023
Percentage gas for secondary hydrogen	0.675	0.825	Dimensionless	Assumption
Supply elasticity Hydrogen	0.02	0.04	1/Year	Assumption
Technological hydrogen demand creation factor	0.001	0.05	1/Year	W. Auping et al. 2016

Table 3.3: Parameters within uncertainty space

insight into model behaviour.

The benchmarks used for determining the output variables were chosen by their compatibility with the purpose of the model. Consequently, benchmarks measuring matters outside of the model scope were not used. An example is benchmarking for individual hydrogen markets such as industry or refining. These were not used as the model makes no distinction between markets. Another case is benchmarks that measure behavioural factors such as people's willingness towards hydrogen, which generally fall outside the model's scope. This output will often be supported by the relative value of hydrogen within the total energy demand mix to increase analytic insight.

Vensim calculates time series as output for all elements within the model, allowing for a detailed analysis of policy impacts on the behaviour and values of these outputs. The model contains 8160 elements, so only a subset can be selected. This selection was based on logically matching variables to the benchmarks and assessing if the variable's sensitivity was high enough to be affected by the policy. This resulted in successful one-to-one mapping of all benchmarks onto model variables without additional structures to assess the benchmarks. Figure 3.5 shows the mapping of the system boundary. It should be noted that the use of British thermal units (Bbtu) for standardising measurements across different energy sources required unit conversions, influencing the absolute values of the benchmarks. These conversions are detailed in Appendix 6.2.

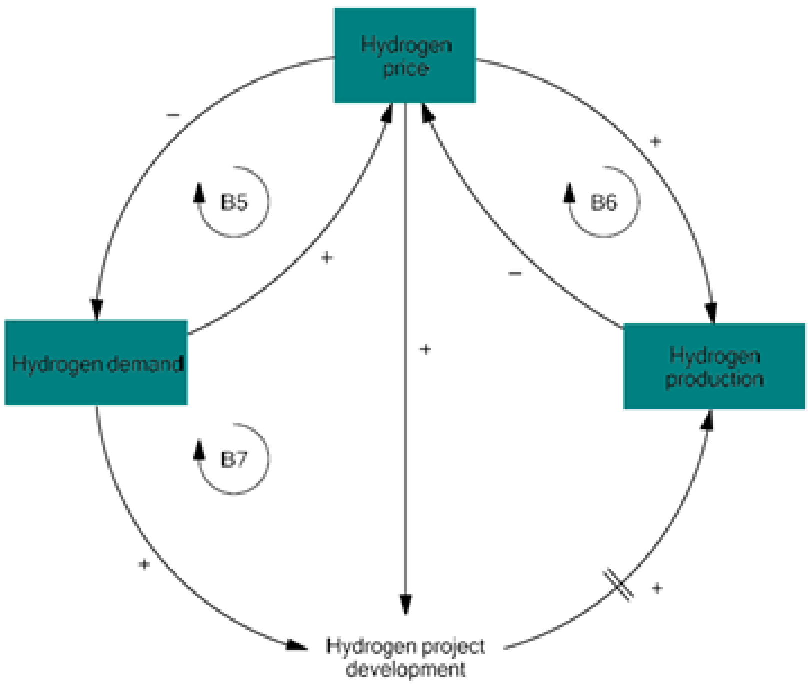

Figure 3.5: Mapping of benchmarks on the system boundary

The initial benchmark identified in the model was the European target of achieving a green hydrogen demand of 20 million tons (Mt) per year by 2030. This benchmark is critical as hydrogen is considered a vital output of the model, primarily because the uncertainty surrounding future hydrogen demand poses a significant challenge for investors. The model already establishes energy demand as a level influenced by various dynamic flows, see equation 3.7. These flows are calculated based on the existing hydrogen demand, adjusted by price changes, policy shifts, GDP fluctuations, and substitution effects. To ensure that the demand value does not turn negative, these flows are affected by balancing dynamics within the model.The second benchmark, also set for 2030, focuses on achieving an annual green hydrogen production capacity of 10 Mt. This capacity is the net result of newly completed capacity each year minus the capacity decommissioned after a 20-year lifespan, see equation 3.8. Current demand and profitability considerations influence the rate of new production capacity construction.The third benchmark within the model pertains to the cost of hydrogen, quantified through the Levelized Cost of Hydrogen (LCOH), see equation 3.9. The LCOH is modeled based on the capital expenditures (CAPEX) required to establish an electrolyser plant per unit of energy and the operational costs (OPEX), which fluctuate with renewable energy prices. The LCOH is dynamic, with CAPEX and OPEX calculated over the plant's lifetime, incorporating forecasted changes in energy prices and interest rates. Technological advancements are expected to decrease the LCOH over time.Finally, the model maps the EU's climate goals, aiming for a 55% reduction in emissions by 2030 and achieving a carbon-neutral status by 2050. This is monitored through the yearly CO2 emissions derived from the total emissions produced by all fossil fuel usage in Europe. The model quantifies these emissions based on the CO2 output per unit of fossil fuel consumed, see equation 3.10.

$$\text{Hydrogen demand}_t = \text{Hydrogen demand}_{t-1} \times (\Delta\text{Price} + \Delta\text{Policy} + \Delta\text{GDP} + \Delta\text{Substitution}) \quad (3.7)$$

$$\text{Production capacity} = \text{Production capacity finished} - \text{Production capacity decommissioned} \quad (3.8)$$

$$\text{LCOH} = \text{CAPEX} + \text{OPEX} \quad (3.9)$$

$$\text{Yearly CO2 Emissions} = \text{CO2 per fossil fuel} \times \text{Fossil fuel usage} \quad (3.10)$$

3.3. Policy Levers: The European Hydrogen Strategy

The EU has already established multiple policies and legislation that underpin its strategy for hydrogen, mainly green hydrogen, as part of its broader ambition for a climate-neutral economy by 2050. Overarching all these efforts, the EU strategy on hydrogen (European Commission 2023a) was adopted in 2020. The plan lays out a vision for achieving the set hydrogen goals. It identifies key policy areas such as developing technologies, reducing costs, supporting projects, and creating markets.
To analyze the effectiveness of EU hydrogen policies, they must be implemented within the model. This implementation is essential for evaluating their impact in this research study. The following method was used to implement the policy levers within the model: first, the policies were reviewed and organized to determine their implications. Then, it was analyzed where policies fitted on the system boundary, and policies that overlapped were combined as they would impact the system similarly. Then, the policies were implemented and quantified within the model structure. A comprehensive review identified EU policies impacting the hydrogen system. Appendix 6.2 & 6.2 provide an in-depth overview of the resulting policies and legislation. All these policies were extracted from the EU legislature and are already implemented or will be within the time frame of this research.

3.3.1. Mapping Policies to the Model Structure

They were mapped onto the system boundary to determine where to implement the policies within the model. This was done by clustering the policies with their common goals and means. Then, an overarching policy measure was formulated per cluster and linked to the model structure. As a result, there are three main points where policies overlap with the model boundary. An overview of the clustering of policies can be found in Appendix 6.2. The mapping of the policies onto the model structure is shown in Figure 3.6.

First, policies supporting hydrogen production capacity are a recurring theme, encompassing efforts to mitigate investment risks and reduce uncertainties that might deter industry stakeholders. This category addresses the drive towards better standardization across the hydrogen sector to facilitate interoperability and safety. Demand creation policies form the second clustering, focusing on decarbonizing

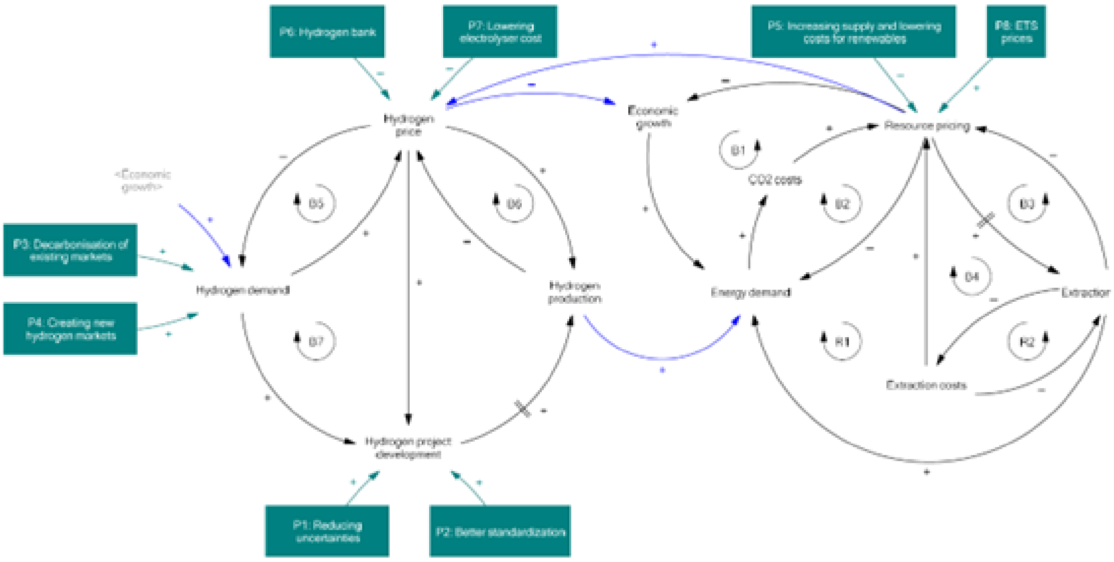

Figure 3.6: Policies mapped onto model boundary

existing markets with hydrogen replacing fossil fuels and opening markets with new hydrogen technologies. These policies map onto the energy demand sub-model. A third clustering revolves around creating competitive hydrogen prices. This involves policies that lower the costs of RES, which are critical for sustainable hydrogen production. Additionally, it might affect the establishment of a hydrogen bank to support project financing and reduce electrolyzer costs, aiming to make hydrogen production more economically viable. Furthermore, it includes increasing emissions trading system (ETS) prices, which can incentivize a higher demand for low-carbon hydrogen as fossil fuels become more expensive and thus less competitive.

3.3.2. Implementation of Policies within Model

In 2022, the European Commission established the European Hydrogen Bank. This initiative aims to foster investment security and open business avenues for renewable hydrogen production within and outside the EU. The primary goal is to stimulate private investment in the hydrogen sector by linking RES to EU demand and overcoming early investment hurdles. The bank seeks to create an initial market for renewable hydrogen, thereby generating new economic growth and employment opportunities. The EU (European Commission 2023b) outlines the detailed framework and operation of the European Hydrogen Bank. This plan includes four main pillars of action at the EU level. The domestic pillar focuses on expanding the hydrogen production market within the European Economic Area . It aims to align the supply of renewable hydrogen with market demand by providing funding as a fixed premium of 4.5 euros per kilogram of verified and certified renewable fuel of non-biological origin hydrogen. This policy is expected to heavily impact the EU hydrogen market, as 4.5 euros per kg of hydrogen will nullify price differences with grey hydrogen, blue hydrogen, and fossil fuels. For this reason, this policy measure was modeled in more detail. The hydrogen bank policy's operational mechanism is structured to support green hydrogen production financially. For each unit of green hydrogen produced, the cost is offset by a hydrogen bank premium deducted directly from the bank's funds. This premium has a maximum limit of €4.5 per kg. As the Levelized Cost of Hydrogen (LCOH) for green hydrogen is anticipated to decrease, setting a cap prevents the premium from driving the price into negative territory. This cap is determined by a specific ratio related to the cost of grey hydrogen. Additionally, to ensure the fund's sustainability, the premium adjusts downward when the hydrogen bank's reserves deplete, preventing the fund from being exhausted too rapidly. Initially funded with €800 million, the hydrogen bank will receive ongoing support from 2% of the Emissions Trading System (ETS) earnings, ensuring a steady flow of resources to support this initiative. Figure 3.7 shows a visual implementation of the policy within the model.

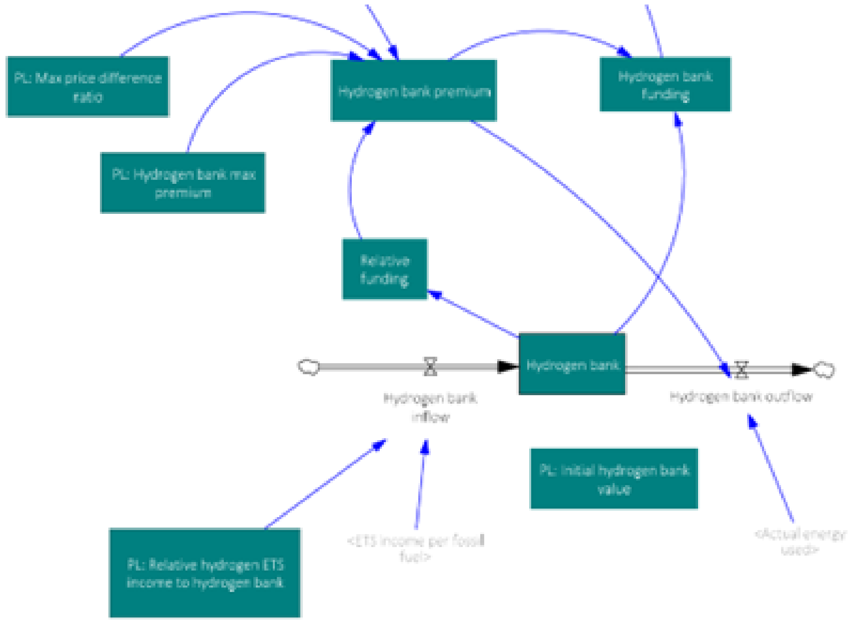

Figure 3.7: Hydrogen bank model structure

Table 5 provides a comprehensive overview and detailed descriptions of how various policies were implemented within a specific model. Each policy, labelled from P1 to P8, is thoroughly outlined to show its role and execution strategy within the model's framework.

Policy Measures	**Policy Description**	**Implementation within Model**
P1: Reducing uncertainties	Policies supporting and calming investors result in less hesitation in starting and finishing hydrogen production projects.	Decrease uncertainty by half with constant.
P2: Better standardization	Better standardization decreases the time for permits.	Decreases the building time of green hydrogen plants by a year.
P3: Decarbonization of existing markets	Public energy demand steers away from fossil fuels and toward renewables through nudging policies.	Separate substitution flow changing 1% yearly fossil demand to renewable demand.
P4: Creating new hydrogen markets	Stimulating technological innovation creates more new markets for hydrogen, which increases demand.	Increase yearly technological growth to 3%.
P5: Increasing supply and lowering costs for renewables	Prolonging the subsidies for renewables, resulting in cheaper green hydrogen **bogdanov2021**.	After the initial subsidy of 70% has ended, it will drop to 50% instead of 0.
P6: Hydrogen bank	See hydrogen bank.	See hydrogen bank.
P7: Lowering electrolyzer cost	Stimulating technological innovation decreases capex costs.	Yearly capex price reduction is increased by half.
P8: ETS prices	Increasing the base ETS price will increase fossil fuel costs, increasing renewable hydrogen's competitiveness.	Increase of ETS constant to 100 dollars per ton.

Table 3.4: Policy overview

3.4. Experimental Set-up

For the validation, experiments, and experimental setup that was designed, see Table 6. The model was run with Runge-Kutta 4 auto with a time step of 0.0078125. At the same time, the data was saved per 0.125 timestep. This was done to allow the experiments to run faster. The lower data resolution would have had no impact on the clustering and PRIM analyses as the value of this data is not affected by a higher timestep. For single experiments, 10000 was considered high enough for this research. For runs with multiple iterations, such as the policy and uncertainty analyses, 5000 per item was deemed sufficient. A higher number of runs would increase the validity of the data, but this was not possible because of the limited resources within this research.

Experiment	Number of Runs
Multivariate sensitivity analysis	10000
Extreme condition test	10000
Base Ensemble	10000
Model uncertainty	15000 (3x 5000)
Policy analyses	40000 (8x 5000)

Table 3.5: Experimental set-up

3.5. Model validation

All models must be validated to judge whether they are suitable (Barlas 1996.)This is straightforward for most models as the results can be 'fit' to rea)l-life measurements. However, the focus of System Dynamics (SD) modelling does not limit itself to the model's output. SD modelling is about the insights model behaviour provides (Forrester 1987). Model behaviour results from a scoped abstraction of reality based on the perspective and skill of the modeller. Moreover, as the abstraction is primarily empirical, the validation of SD models cannot be limited to numerical comparisons and their simple right or wrongs.

3.5.1. Validation tests

Within the literature, many validation tests are proposed, whose primary goal is to steer away from these binary answers to create instead broad substantiated confidence that the model is fit for purpose (Forrester and Senge 1980; Schwaninger and Groesser 2020; Balderstone 1999). The results of the performed tests can be found in Table 7. Based on the results of these tests the following observations were made on the validity of the model.

Test name	Results
Consistent dimension test	No dimension errors were reported
System boundary adequacy test	Done during modelling. Under assumptions okay.
Multivariate sensitivity analysis	Results in Appendix 6.2: the model is sensitive to the majority of parameters
Extreme condition test	The results are in Appendix E; the model works within the boundaries of parametric possibility. For most fractions, values between and including zero and one result in feasible mode lbehaviour, indicating a robust model structure.

Table 3.6: Validation tests and results

3.5.2. Validation of model behaviour

As a results of these validation tests, the following remarks can be made on the validity of model behaviour. First, the structural validity of the model is sufficient. In general, under all but most extreme conditions the model keep functioning, while providing logical model behaviour. However, the extraction capacity sub-model does not function properly for the purpose of this research. As white hydrogen was chosen to be modelled like fossil fuels, the extraction capacity was modelled similar. However, the extraction capacity can only increase slowly within the fossil fuel structure. This is caused by that the Energy model was built to model an energy system were the extraction capacity matches demand in the same order of magnitude. The model is thus not able to model rapid capacity expansion. The result are huge, as a shortage of supply inflates prices to absurd heights (see Figure 3.8). Furthermore, the high prices will affect demand as well thus resulting in white hydrogen under performing within the model.

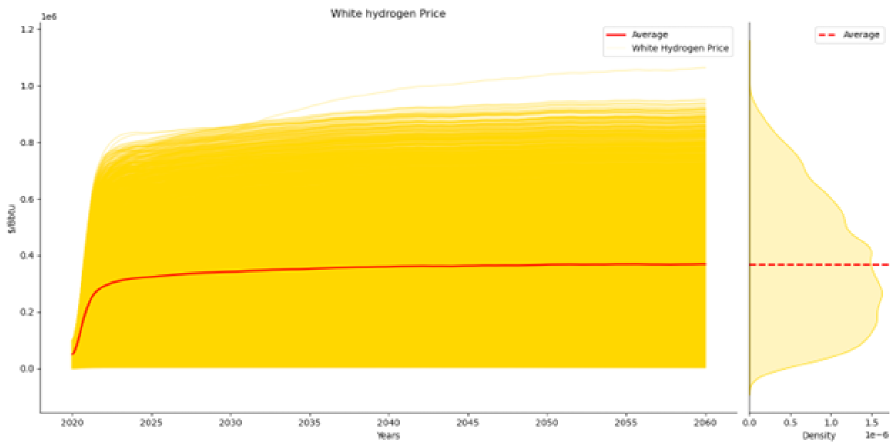

Figure 3.8: White hydrogen price; price increases dramatically due to structural flaw within model.

3.5.3. Effects structural uncertainty on validity

In section 3.2, the structural uncertainties within the model were identified and discussed in depth. To investigate the implications of these uncertainties on the validity of the mode, a focused analysis was conducted on their effects on the system, specifically targeting the LCOH. The LCOH was selected as the primary output variable for this analysis due to its direct and substantive linkage to the structural uncertainties present in the model. The results are shown in Figure 3.9. The discount factor uncertainty does not influence the LCOH; upon closer inspection, this difference can be explained by the fact that the implemented equations for the forecast have the same outcome when the Taylor series is smoothed. The discount factor influences the model behaviour; when switched off to a static one, the LCOH increases, as seen in the density plot. Although the difference is significant, it does not impact the direction of behaviour. Therefore, it can be concluded that the analysed structural uncertainties do not strongly affect model outcomes.

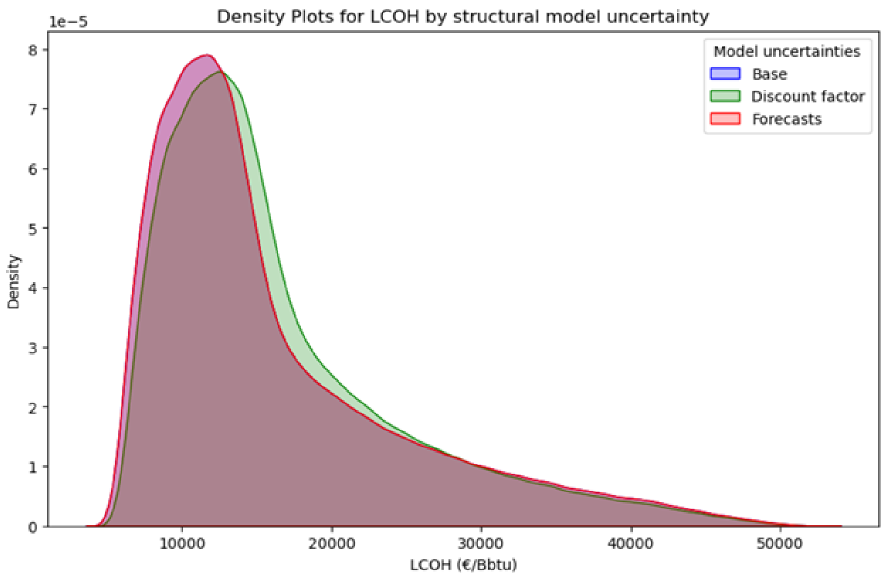

Figure 3.9: impact of model uncertainties on LCOH (structural uncertainties, n = 15000

Chapter 4

Results

This section, the system dynamics model, based on the interactions detailed in the previous section, will be utilized to evaluate potential system behaviours through an exploratory modelling analysis using the EMA Workbench. After this the two last sub question will be answered. The analyses will be conducted using statistical techniques and visual inspections on the outcome variables generated through the EMA Workbench methods. In addition to white hydrogen, green hydrogen will be a significant focus of the analyses due to its central role in EU hydrogen policies. The file with all the code that was used within this research can be found at https://github.com/Condor323/Modelling-White-Hydrogen.

First, a base ensemble will be generated using the model without any policies. In this base ensemble, the crucial barriers and drivers will be identified. Then, the boundaries within which the white hydrogen market will develop are determined. Subsequently, the impact of white hydrogen on the energy system is defined. Finally, the resilience of EU hydrogen policies under the effects of white hydrogen is analysed.

4.1. Emerging white hydrogen

4.1.1. System size

Figure 4.1 illustrates that within the uncertainty space, white hydrogen demand increases rapidly, indicating the emergence of a white hydrogen system. However, the extent of this demand increase varies significantly between runs. Therefore, the runs were divided within 5 scenarios (see Table 4.1. The size of such a The top 20% of runs, in terms of highest yearly demand, peak between 1.75 and 10 million Bbtu of yearly white hydrogen demand. In contrast, the bottom 50% of runs have demand levels under 300,000 Bbtu per year. This substantial disparity means that within Figure 4.1, the lowest 80% of runs can only be clearly inspected when the top 20% of runs are removed from the analysis.Despite this disparity, it is evident that even in the runs with the lowest demand, a significant market for white hydro-

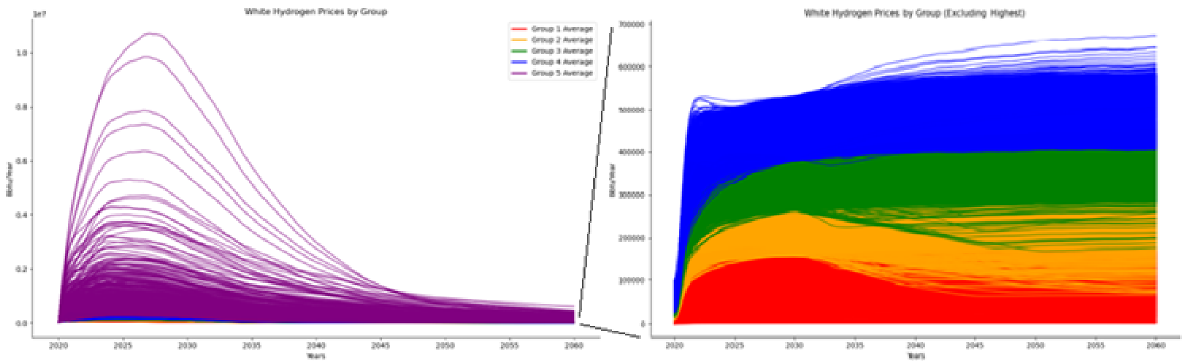

Figure 4.1: Yearly white hydrogen demand grouped per 20% percentile; Left figure shows all groups, within the right figure the top 20% of runs are excluded (Base ensemble, n = 10000).

gen still emerges). Notably, in no scenario does the market fail to develop by 2030. This consistent market emergence can be attributed to the price mechanics embedded within the system dynamics (SD) model. Due to demand substitution effects, there is always a fraction of demand for an energy carrier, regardless of its price.

Percentile	Range (Bbtu/Year)	Average (Bbtu/Year)
0-20%	1463 - 157620	95062
20-40%	157644 - 261633	212430
40-60%	261658 - 380427	320264
60-80%	380454 - 532085	450727
80-100%	532118 - 1070322	664994

Table 4.1: Range and average of White Hydrogen demand at 2030 for each percentile

4.1.2. White hydrogen behaviour

Two distinct model behaviours can be observed within the graphs, lets take a look at the 20-40% demand group were this can be clearly seen (see Figure 4.3). First, all runs increase until around 2030, the demand substitution drives this growth. Then within one group of runs the demand remain constant or grows slightly. This mode of behaviour is called limits to growth. Here, the increase in white hydrogen demand is counterbalanced by a trend in model behaviour were energy demand in general decreases. However, another group of runs shows that demand start to decrease after 2030. This means that white hydrogen becomes less competitive within the energy market.

To determine which variables have the most impact on white hydrogen PRIM analyses were used based on BBSD clustering. The results can be seen in Figure 4.4. To determine which variables have the most impact on white hydrogen, PRIM analyses were used based on BBSD clustering. Due to the presence of high outliers, the clusters created with BBSD were less meaningful than those grouped based on percentiles. However, inspecting the results of PRIM analyses over these clusters yielded insights into the variables within the model that most impact hydrogen market development.
Despite the different ranges per cluster, all results indicated that the developments were mostly dependent on the values of white hydrogen parameters within the uncertainty space. However, clusters representing the runs with the highest white hydrogen market development showed that sustained market development is only possible if green hydrogen does not become extremely competitive in the future. This underscores that white hydrogen market development is partially dependent on green hydrogen. Therefore, while white hydrogen market development is initially mainly determined by its cost and availability, it can be impacted in the long term by the competitiveness of green hydrogen.

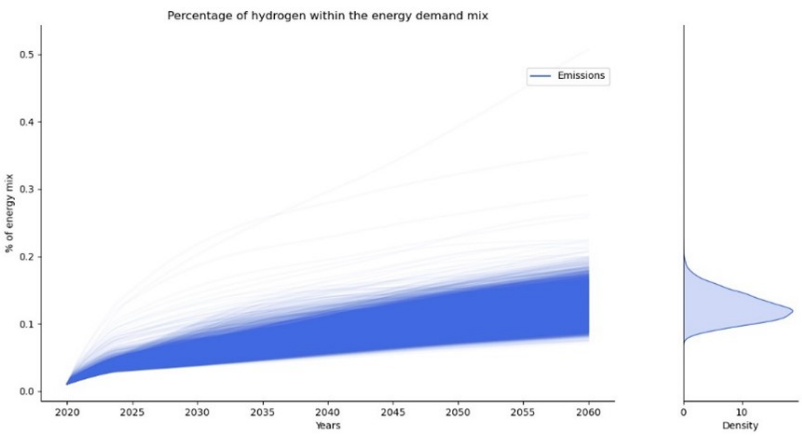

Figure 4.2: Percentage of hydrogen within the energy mix (Base ensemble, n = 10000)

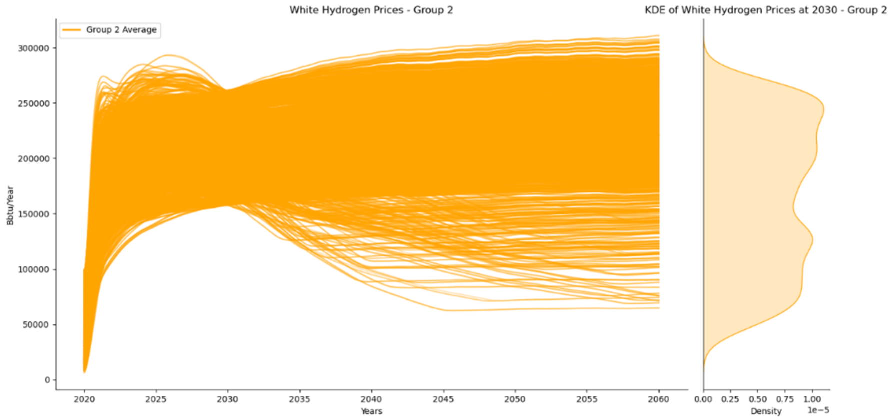

Figure 4.3: Yearly white hydrogen demand of the 20-40% percentile; two modes of behaviour can be observed, one remains constant while the other collapses (Base ensemble, n = 10000).

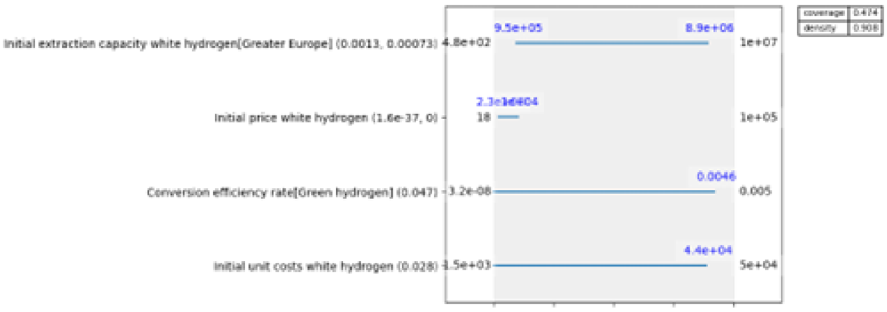

Figure 4.4: Variables having the most impact on white hydrogen market developement

4.2. Impact of white hydrogen on base ensemble

Across all simulations within the base ensemble, conventional hydrogen demand will grow significantly over the next ten years, although the growth rates vary among different runs, see Figure 4.5. This rise in demand is partially attributed to the declining prices of green hydrogen. Nonetheless, the primary catalyst for this increase appears to be demand substitution, which is especially notable given the relatively low initial share of green hydrogen.While some simulations nearly meet the ambitious demand target of 2.72 million Bbtu annually by 2030, none achieve this milestone. Post-2030, the growth in hydrogen demand generally plateaus, with most runs showing a peak in demand between 2030 and 2035. After 2040, a decline in hydrogen demand is consistently observed across all scenarios. This decrease aligns with the broader trend of diminishing general energy demand, a pattern also noted in the 2016 and 2020 versions of the energy mix model. Interestingly, despite the overall reduction in energy demand, the proportion of hydrogen within the European energy mix continues to grow, as illustrated in Figure 4.2. This suggests that hydrogen is progressively displacing fossil fuels. Interesting outliers can be observed where hydrogen demand makes up 50% of the energy mix; this can be attributed to the outliers of white hydrogen demand.

The density plots in the base ensemble show a tendency for runs to cluster into two groups. To understand this clustering, a time series clustering was conducted on the model's output, focusing on green hydrogen demand due to its importance and clear visual clustering. Iterative testing identified five optimal clusters, balancing pattern loss with the emergence of new patterns. Hard hierarchical clustering was used, allowing some overlap between scenarios to avoid arbitrary divisions and enhance interpretability. Visualisations are shown in Figure 4.6. All clusters follow a similar trend: an initial increase in energy demand, stabilisation, and then a decrease. However, energy demand differs among clusters: Cluster 0 shows high demand, Cluster 4 shows moderate demand, and Clusters 1, 2, and 3 show low demand. Table 4.2 reveals most runs are at the higher end, with few in the lower range. Cluster 3's low hydrogen demand is due to high white hydrogen demand and slower LCOH decrease, as manually analyzed.

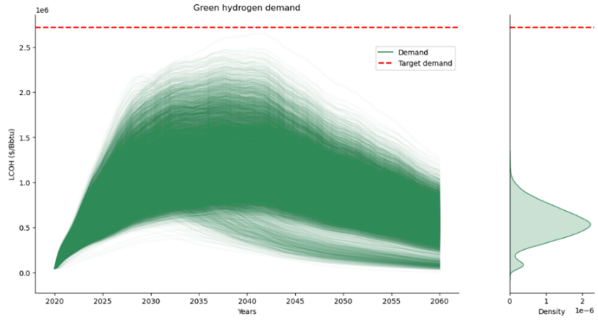

Figure 4.5: Yearly European green hydrogen demand (Base ensemble, n = 10000)

Cluster number	Number of runs
0	2807
1	420
2	54
3	4
4	6715

Table 4.2: Number of runs for each cluster

To provide more insight in what affects green hydrogen PRIM was used to determine what variables affect clustering. Therefore, PRIM analyses were conducted for all clusters. The results can be seen in Appendix 6.2. When looking at the results, it is observed that white hydrogen is a significant contributing factor to all clusters, especially cluster 1. A methodological explanation can be made by the fact that the uncertainty range of white hydrogen is very high. Thus, it generates high variances that PRIM is picking up and explains the significance. A behavioural explanation is that if white hydrogen demand takes off, it will contribute to green hydrogen demand. When the price of white hydrogen is low, it will get a fair share of the energy demand mix; when the prices of green hydrogen decrease, a substitution stream from white hydrogen towards green hydrogen will lead to significant increases in green hydrogen demand and vice versa. High demand is also determined by low uncertainty and low initial prices; although behaviour-wise, this seems obvious, it indicates that the model is working well.
The clustering of hydrogen demand could also be applied to the other output variables. The visual results of these can be seen in Appendix 6.2. The clustering of green hydrogen demand translates well to the patterns observed within hydrogen production and CO2 emissions. This could indicate a high level of connectivity between the sub-models that produce these outputs. Interestingly, the clusters seem uniformly dispersed over the runs of LCOH. This suggests that uncertainty determining LCOH outcome makes up a different part of the uncertainty space than demand. The other hydrogen types were also tested for clustering. The clustering is generally not very appliable over their behaviour. However, the distinction between relatively high and low demand could also be observed here.

4.2.1. Co2 emissions

Figure 4.7 provides a detailed visualisation of the trend in European CO2 emissions, highlighting a significant downward trajectory. However, despite this rapid decline, the pace of reduction is insufficient to meet the ambitious CO2 emissions target set for 2030. This shortfall indicates that further measures may be necessary to accelerate emission reductions to align with the stipulated goals.The graph also reveals a recurring pattern of top and bottom clusters, consistent with other outputs from the same model. This clustering effect showcases variability in performance across different simulations or regions. In the top cluster, projections indicate that it will be challenging to eliminate emissions by 2050, suggesting that current strategies in these areas might fall short of achieving a zero-emission status. Conversely, the bottom cluster demonstrates a more promising outlook, with trajectories pointing towards achieving zero emissions within the same timeframe.This divergence between clusters may reflect differences in energy policies, technological adoption rates, or the economic feasibility of implementing green technologies across various regions. The presence of these clusters underscores the need for tailored strategies that address specific regional challenges and opportunities in the transition

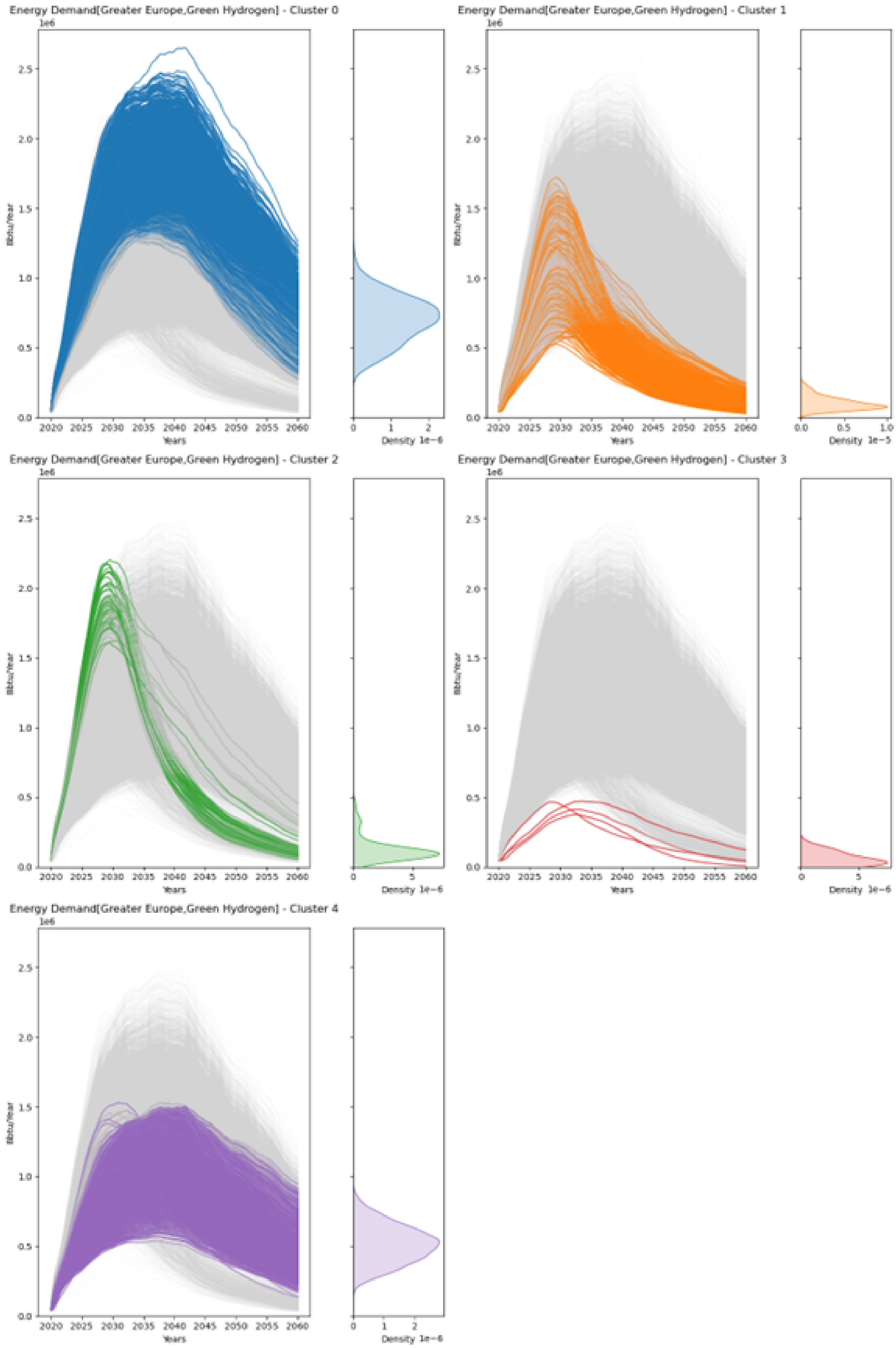

Figure 4.6: Clusters within green hydrogen demand, (Base ensemble, n = 10000)

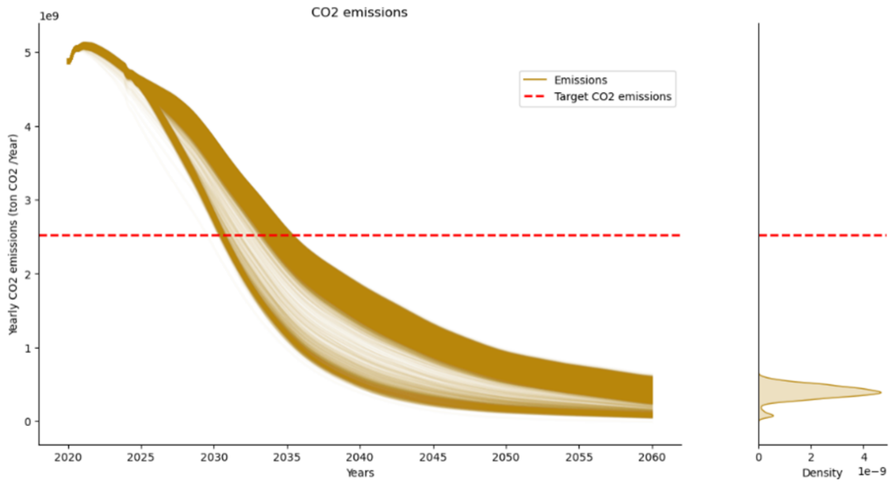

Figure 4.7: Yearly CO2 emissions; two distinct pathways

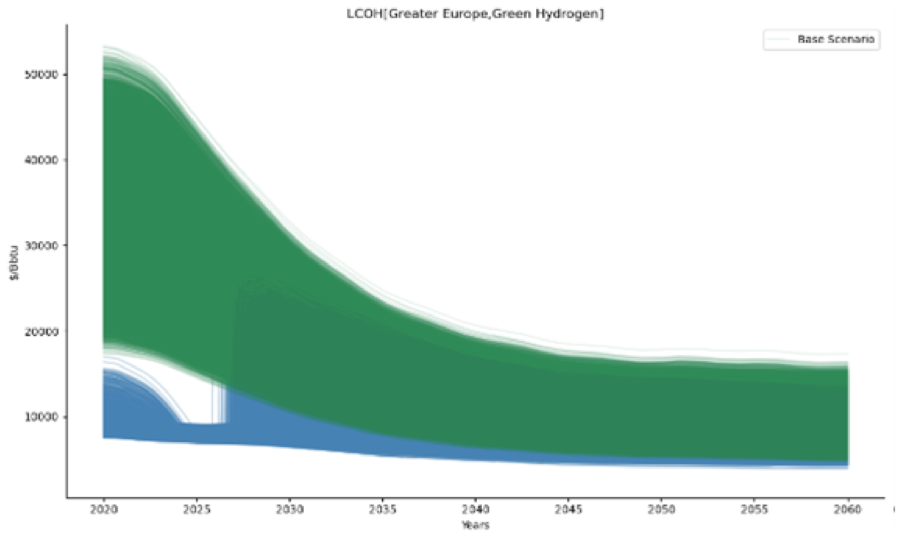

Figure 4.8: Enter Caption

to a low-carbon economy.

4.3. Impact on hydrogen policies

Visual inspections of the graphs reveal several observations about the impact of policy sets on green hydrogen demand. Firstly, all policy sets seem to enhance the expansion potential of green hydrogen demand, with some scenarios achieving the 2030 target of 20 million tonnes. However, this expansion is often accompanied by higher overshoots, which lead to a reduced average hydrogen demand by the end of the runtime in 2060. The primary cause of these overshoots is the hydrogen bank mechanism. As seen in Figure 3.7, the hydrogen bank first causes an immediate fall of the LCOH with an increase in demand. Only the bank will quickly run out of funds in 2027, skyrocketing the LCOH. As a result, demand decreases rapidly as a high initial share within the energy mix, followed by a rapid increase in price, will cause massive amounts of hydrogen to be substituted within the model. As production becomes less profitable and prices remain elevated, the demand continues to suffer. The effects of other policies could not be distinguished from the standard model behaviour. The goal of 20000 Mt of green hydrogen demand will be reached in only the best runs. However, this goal will be reached when combining white hydrogen demand with green hydrogen demand (see Figure 4.9). Thus, as the white hydrogen market emerges it will contribute to the EU reaching their hydrogen goals.

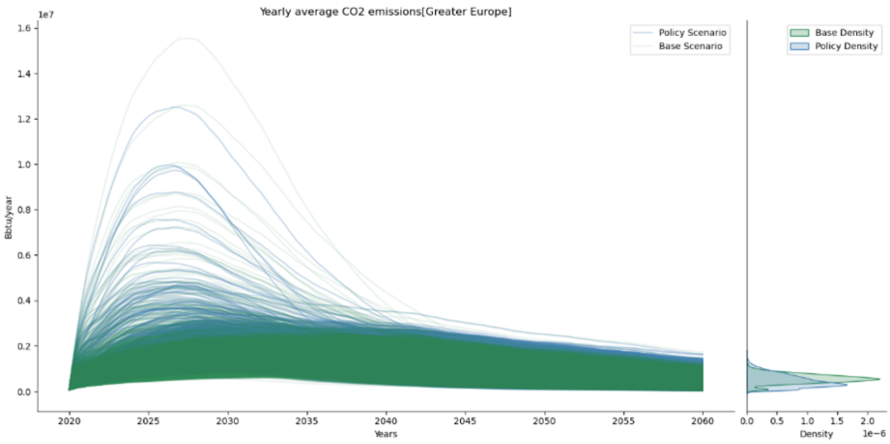

Figure 4.9: Enter Caption

Chapter 5

Discussion

This chapter will reflect on the general conduction of this research. First, Section 5.1 will contain a reflection on the research approach. Subsequently, the limitations of the SD model will be discussed in Section 5.2. Section 5.3 discusses whether the observations made during the analysis of results can be translated into meaningful insights into the real-world energy system. Then, it will be reflected on the broader hydrogen discussion and where this research occurs (See **source**). As a result of these discussions, suggestions for further research were made in Section 5.4.

5.1. Reflection on the Research Approach

5.1.1. System Dynamics

In general, system dynamics were considered a sound energy system model. The created model could capture the complexity and dynamics present within the system at a high aggregate level. However, a methodological limitation occurs when the aggregation level within the model is decreased in pursuit of realism. When aggregation levels in the model decrease, the need for labour and data increases rapidly. Thus, although the methodology allows decreasing aggregation, doing so would have surpassed the resources available during the research. However, as Wiman 2022 stated: “While realism is one guiding value in modelling, it can never be fully realised, and it competes with other values such as usefulness towards an aim, ease of understanding and communication, and resources needed for sufficient completion.”

While keeping this quote in mind, it can be reasoned that the SD model was still fit for purpose regarding realism and limited resources as it still created meaningful insights within the energy system. These insights were not only created by the model generating output but also from building the model itself. It could be argued that building the model created the most insight during this research. Dealing with structural uncertainties to translate the conceptualisation to actual model structures required research and grinding trial and error. This increased not only things inside the model scope but also things outside the boundaries of this research. As a result, validating the model for conceptual rightness became easier. An example illustrating this process was determining how hydrogen demand was connected to energy demand. Only deep within the research process was it realised that these were directly connected, and that hydrogen fully competed within the energy mix. As a result, the older model was discarded, and a new one was built from scratch. Rebuilding only took a tenth of the time for the old model. This was previously regarded as impossible without the insights gained from system dynamics model building.

5.1.2. Exploratory Modelling Analyses

Exploratory modelling was considered a suitable method as it allowed the creation of the uncertainty spaces needed to determine policy effectiveness under different scenarios. Within EMA, multiple tools were used to sort, modify, and present the data from the Vensim model. EMA also provided tools for model validation. Although multivariate sensitivity analyses were considered satisfactory, alternative methods such as SOBOL and ETPS could have provided more insights into model sensitivity. However, sensitivity was also indirectly tested during all other model runs, making this limitation acceptable.

The Python library EMA proved invaluable as much of the code needed for analyses was already present there. Behaviour-based scenario discovery was deemed suitable as a method as it successfully allowed the identification of scenarios over time series. This is considered impossible for standard scenario discovery. However, the interpretability of PRIM and time clustering are negatively related to each other, as higher levels of clustering enable PRIM to achieve better results when reducing dimensions. As can be seen, higher clustering results in clusters that cannot necessarily be intractable for real-life situations. Thus, for this model, using BBSD is primarily impactful for creating scenarios, not insights into uncertainty.

However, due to the model's complexity and the uncertainty of space's size, PRIM had difficulties finding orthogonal cuts to reduce dimension. It is unknown if using other algorithms would have yielded better results. Min-max regret to test robustness is considered sufficient. However, far more intricate methods, such as multi-objective robust decision-making, are available, which could have provided more insight into the quality of the policies.

5.2. Limitations of the SD Model

"All models are wrong, but some are more wrong than others!" This quote was originally thought to be created for this research, but upon closer inspection, it is the title of the paper written by Drake 2023. Many famous modellers have enlightened us with similar sayings. No model is perfect, as was discussed in Section 5.1. However, multiple limitations within the conceptualization, structure, and parameters of the model were encountered.

5.2.1. Conceptual Limitations

The high aggregate level of modelling chosen during the conceptualisation captured trends in system behaviour, such as the predicted decrease in energy demand and CO2 emissions and the rise of renewables within Europe over the coming decades. However, the high aggregate level of modelling does not allow the modelling of most policies proposed or implemented by the EU, as these are designed specifically for different economic sectors. These various economic sectors were not considered because of the high aggregate level of modelling.

A conceptual dilemma was how to connect the hydrogen and energy system. The systems can be modelled coupled to each other, or completely decoupled. It can be argued that large parts of the hydrogen market are decoupled from the energy system, and thus demand cannot flow freely. While a coupled system allowed better modelling of the interactions between the energy system and hydrogen. Also, it is expected that the hydrogen market will decouple in the future. For these reasons, the systems were connected. Nevertheless, the truth lies in between. From this perspective, it should be noted that the systems for all energy carriers are semi-coupled. Modelling this semi-coupled energy system would have resulted in more realistic market behaviour, and would be an interesting angle for new research.

Within the model, the only meaningful distinction within the market is simply the price. However, the sole importance of price is questionable as factors such as availability and usability also play a role. Usability or infrastructure is not taken into account in this research. This is meaningful as underdeveloped hydrogen infrastructure can hinder the ability to allocate demand and supply. Furthermore, the internalised cost of infrastructural development would be higher for hydrogen than for mature energy markets, driving up hydrogen costs. Thus, it can be argued that the lack of infrastructure within the model leads to an overestimation of hydrogen.

A similar conceptual shortcoming of the model is the absence of electricity markets within the model. This is problematic for multiple reasons. Firstly, dynamics between the electricity and energy markets determine system behaviour for energy consumption Bencivenga 2010. Secondly, as the share of renewables and green hydrogen demand increases as predicted, major dynamics within the model will be missing as all those elements are heavily dependent on power prices. Lastly, as electricity generation is a significant part of energy demand, fossil fuel demand will be overestimated without conversion rates from fossil fuel to electricity.

5.2.2. Structural Limitations

Although modelling on top of the EMM provided a sound starting point for further modelling, it also created some discussion points. A significant shortfall of the final model is that there was no reflection on the “fit for purpose” of separate structures within the EMM during the modelling process. This is because the model was assumed to be fit for purpose in general. Therefore, no structures were removed, leading to the possibility of existing redundant structures within the model. As these will often account for a lower aggregation level of modelling, this will not affect the quality of the results. However, due to redundant structures, understanding of model behaviour can be reduced.

Full independence is assumed as all hydrogen types were modelled as separate energy carriers within the model. However, they are still the same product, as a kilogram of green hydrogen is chemically identical to a kilogram of white hydrogen. Thus, there will also be extra internal price competition. Within the model, this was modelled by adding an extra substitution flow. However, during trade, hydrogen is modelled as heterogeneous, while it can be homogeneous in trade. This means the demand shortage of green hydrogen in Europe cannot be filled with European white hydrogen; it must be imported from another region. The internal hydrogen market can thus not regulate itself as it would. However, introducing certifications for hydrogen would support heterogeneous modelling of the hydrogen sources as this would enable differentiating hydrogen in the marketplace.

Multiple problems arose while implementing policies related to the EU’s hydrogen economy. One of the main issues was that some policies exceeded the conceptual boundaries of the model. Policies aimed at increasing the societal acceptance of hydrogen or those with broad environmental goals did not always align with the model’s sub-model boundaries. Even minor differences between the policies and model could hinder quantification. Some policies were challenging to quantify accurately within the model’s parameters due to their nuanced objectives or indirect impact on the hydrogen sector, as their measured unit was absent within the model. To solve this issue, these policies were often modelled as dimensionless constants acting as multipliers.

Another challenge was the variability in how legislation was interpreted and implemented by different member states and how funds were allocated and spent within national contexts. The EU allows member states significant discretion in prioritising projects and directing funds, leading to divergent outcomes and impacts. This makes it difficult to quantify the effects of policies across the entire EU uniformly. The interpretation of legislative directives and the allocation of financial resources can differ widely, reflecting diverse national strategies and priorities, further complicating efforts to model policy impacts accurately within the EU’s hydrogen economy.

Lastly, the cross-cutting nature of some policies introduces further complexity. Many EU policies are designed to impact multiple sectors simultaneously, making it difficult to assess their precise influence on each sub-model. Thus, determining the relative weight of a policy across different aspects of the model was often tricky or even impossible.

5.2.3. Parametric Limitations

The main limitation of the used parameters is that, due to time constraints, the same parameters were used per region. This prevents independent system behaviour per region. Although this is not a big problem for this research due to the focus on Europe, future research must first fill this data gap if it wants to study global price dynamics.

5.3. Discussion of the Results

Within this research, there is no base case where white hydrogen does not emerge. This caused by that white hydrogen is implemented as a subscript within the model. It is not possible to completely remove white hydrogen from the model as this will break the model. As a result, there is no true base case where white hydrogen demand is completely zero. This degrades the quality of all results and analyses assessing the effects of white hydrogen.

From the results, it could be seen that the demand for hydrogen exhibits a marked increase at the onset of model runs, driving a rapid expansion of these sectors. While partly the result of the model having to start up, it could also be seen that hydrogen is too competitive in the energy mix. The sudden rise hints at hidden costs not calculated in this model's hydrogen price. Examples of this are the cost of buying consumer goods that can use hydrogen or the costs of developing a hydrogen infrastructure. For these reasons, hydrogen could be overestimated in the result. However, for white hydrogen, the flaws in the extraction capacity sub-model led to undercapacity of production, driving up prices and thus hampering expansion of the market within the model. For white hydrogen it is thus uncertain if the results are estimated too low or too high.

The results of the BBSD are questionable; However, the time clustering reveals existing clusters, and the PRIM analyses show severe dependency on white hydrogen in forming clusters within the uncertainty space. This is caused by the extreme values modelled for white hydrogen within the uncertainty space. Although probable, the high variance generated by the range of uncertainty will offset PRIM, resulting in PRIM revealing white hydrogen uncertainty as leading for cluster make-up. More elaborate techniques are required for dimension reduction, or white hydrogen needs to be excluded from the uncertainty space.

Significant differences in impact can be observed for the policies themselves. The hydrogen bank has a significantly higher impact than the other policy levers. This can be attributed to most policies increasing learning curves or shortening delays. However, these have an effect; they increase flow relatively and are counterbalanced by the balance mechanisms within the model. As the hydrogen bank implemented an absolute price, the model dynamics do not affect it.

5.4. The Broader Context: The Prospect of a White Hydrogen Boom

The starting intention of this research was to enable EU policymakers to adapt their hydrogen policies to deep uncertainty by improving insights into the possible developmental pathways and effects of the white hydrogen system. If policymakers have at least some rationale, more available information will lead to policies that are more likely to benefit society. A better understanding of risks and having policy pathways ready for multiple scenarios will smoothen the EU's transition towards hydrogen, benefitting society.

This research could serve as a wake-up call for EU policymakers worldwide to realise that white hydrogen could be a game changer in the transition towards renewable hydrogen. Additionally, markets could feel emboldened by the increasing hydrogen demand reported in this research. As a result, more attention and funds are drawn to the white hydrogen market, resulting in this research being a self-fulfilling prophecy. Because of this impact, an assessment of the societal effect of an emerging white hydrogen system needs to be made.

The results of this research imply that the white hydrogen market can grow dramatically in most scenarios in the coming decades, significantly impacting the energy system. The current situation has similarities with the start of the gold rush or oil boom Boschee 2023; J. Stalker 2022; there are the prospects of high profitability, limited extraction locations and high demand leading to rapid development of production capacity Nash 1998. Additionally, white hydrogen findings on European ground could fulfil the long-term policy goal of increasing Europe's energy independence. Consequently, these developments would require a total overhaul of the EU hydrogen strategy. Ironically, this research has only increased the uncertainty surrounding EU hydrogen policies by creating insight into white hydrogen.

The transition towards hydrogen is a critical societal issue and a central topic in discussions about the energy transition. This research on white hydrogen will contribute significantly to this dialogue. Furthermore, it will provide insights into a currently underexplored area for EU policymakers, assisting them in making more informed decisions. Therefore, this thesis fulfils the requirements of a typical thesis for the MSc in Engineering and Policy Analysis.

5.5. Further Research

This research has attempted to fill the knowledge gap of connecting hydrogen to the energy market. Although some success was made in filling the knowledge gap, further research is needed to finish the job. Building on the advancements made in this study, future research could take several directions to improve on the limitations discussed within this research:

- Developing the research methodology to support robust decision-making, incorporating a more comprehensive array of data and scenario analyses to test the resilience of energy strategies under various conditions.
- More research is needed to determine a price of hydrogen that also internalises costs for hydrogen infrastructure or means to consume it, as it is suspected that the lack of these factors inflates hydrogen's ability to compete within the model.
- Future research must provide accurate parameters for white hydrogen as the uncertainty range decreases the validity of PRIM results.
- Reducing the level of aggregation in the model allows for a more nuanced representation of individual market demands and regional disparities. This would enable more precise modelling outcomes, resulting in modelling more specific EU policies, leading to insights that better reflect the complexities of real-world energy systems.
- Enhanced parametrisation for different regions would account for local variations in energy supply, demand, infrastructure, and policy environments, leading to tailored strategies for energy transition.
- A dedicated focus on the supply dynamics of energy commodities, rather than just price mechanisms, could provide a deeper understanding of potential bottlenecks, investment needs, and the scalability of various energy sources in the transition towards a sustainable energy future.

Chapter 6

Conclusion & Recommendations

6.1. Conclusion

This research used an exploratory system dynamic modelling approach to build a model that could analyse the effects of an emerging white hydrogen market on the global energy system. During this research, hydrogen was successfully added to the EM model, allowing exploration of the global energy system under different uncertainties and policies. Adding hydrogen to the model required conceptualising the hydrogen market as fully integrated within the primary energy carrier market. This created a situation where hydrogen competes in the same market with the same energy sources from which it is created, seemingly creating a disadvantage for hydrogen. White hydrogen is unique as it is the only hydrogen primary energy carrier and is depletable. Due to this fact, this research has determined that white hydrogen economics will more resemble natural gas than the secondary hydrogen market.

The global energy system is heavily impacted by white hydrogen in scenarios where the white hydrogen market takes off. In these scenarios, white hydrogen prices compete directly with gas, resulting in explosive growth in demand. Other hydrogen types take a share of this demand as they decrease in price, resulting in net positive effects on the other hydrogen types. White hydrogen production will lag far behind demand despite rising demand, resulting in lower net usage. The gap between supply and demand will cause significant shortages of hydrogen, reinforcing already existing energy shortages caused by carbon taxing. These energy shortages will lead to a total decrease in energy usage.

This research shows that the EU can only reach some renewable hydrogen goals in 2030 and 2050 if the white hydrogen market develops substantially. The rising share of white and green hydrogen increases renewables within the energy mix. Combined with decreasing energy demand, this will result in net zero being reached more often and earlier in scenarios where the white hydrogen market will develop. The EU hydrogen policies also contribute to reaching these goals but do not impact the system enough. Although the white hydrogen market does not structurally affect the policies, it does synergise well with them, increasing total hydrogen demand. Still, the net effects of the policies are insignificant compared to those of an emerging white hydrogen market, raising questions about their cost-effectiveness. As an exception, policies that drive down hydrogen prices have significant effects in all scenarios, with the hydrogen bank policy being especially effective. However, if hydrogen runs out of money, the sudden spike in green hydrogen prices harms the green hydrogen market.

The main scientific contribution of this research was modelling white hydrogen within the context of a dynamic system. For the first time, the uncertainty around white hydrogen was converted into possible impacts on the energy system. Although the model relies on many assumptions, insights from the model can function as a first indication of how the white hydrogen market will develop under specific scenarios and how it can contribute to the adaptation of hydrogen. Furthermore, this research could be a wake-up call for the EU and other governmental bodies to take white hydrogen seriously. Timely policies will maximise the potential of white hydrogen, enabling a more optimal transition towards renewable hydrogen, thus benefiting society.

Future research can expand the SD model to lower aggregation levels for more detailed results and inter-regional dynamics. Likewise, the model can be expanded to design and test white hydrogen policies. Finally, different modelling techniques should be used to model white hydrogen, as this will add needed perspective to the results of this research.

6.2. Recommendations

Based on the conclusions above and observations made throughout this research, multiple recommendations can be made to the EU concerning its hydrogen policies:

- White hydrogen is a potential game-changer for the EU hydrogen strategy. However, it is a blind spot as EU hydrogen policy documents do not mention white hydrogen. Thus, it is recommended that the EU recognise white hydrogen as a potential factor in its transition towards renewable hydrogen and consequently implement white hydrogen within the hydrogen strategy. This will enable monitoring developments of the white hydrogen market and adapt accordingly.
- The second recommendation is to reduce uncertainty ranges by increasing surveying efforts for white hydrogen while starting structural searching efforts for white hydrogen in existing data. This policy could be very cost effective as prospecting cost are low, while the benefits could be high.
- By reducing the uncertainty ranges, the EU can better shape its policies. Furthermore, finding white hydrogen on European ground could increase EU energy in-dependency.
- To kickstart the development of the white hydrogen market, it is recommended that the EU mark white hydrogen as renewable within the hydrogen certification system. Thus, the EU presents white hydrogen as an alternative way for member states to reach their hydrogen goals, which will, in turn, increase activity within the white hydrogen market.
- Finally, although funds must be directed to develop the white hydrogen market, the EU should focus on lowering green hydrogen production prices. This is because extraction costs will increase when white hydrogen reserves are depleted. Low green hydrogen prices are needed to prevent a rapid increase in hydrogen prices and the full collapse of the renewable hydrogen market. However, this collapse can also be caused by letting the hydrogen bank run dry. Thus, the EU needs to be decisive in their commitment to the hydrogen bank.

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Appendix A: Hydrogen Legislature EU This table was based on the work of Gherasim 2022.

Categories	**Legislative File/Communication**	**Provisions**
Definitions	Amendment to the Renewable Energy Directive (REDIII)	Art. 2 (36): renewable fuels of non-biological origin means liquid and gaseous fuels the energy content of which is derived from renewable sources other than biomass (compared to REDII, the definition in REDIII is extended to RFNBOs in all end-use sectors, not only transport)
		Art. 29a (new): RFNBOs can account towards RES targets in RED only if their GHG savings equal at least 70% => the Commission is empowered to adopt a DA to specify the methodology
	Delegated Act on a Union methodology and rules for RFNBOs production	Rules on additionality, as well as temporal and geographical correlation between the production of the renewable electricity used in electrolyser and the production of the renewable hydrogen
	Delegated Act on methodology for assessing GHG emissions savings from RFNBO/RCF	Methodology based on accounting life-cycle emissions of producing RFNBOs. Fossil fuel comparator for RFNBOs set at 94 gCO2eq/MJ
	Directive on common rules for the internal markets in renewable and natural gases and H2	Art. 2 (2) ‘renewable gas’ means biogas as defined in Article 2, point (28) of Directive 2018/2001, including biomethane, and renewable gaseous fuels part of fuels of non-biological origins (‘RFNBOs’) as defined in Article 2, point (36) of that Directive’ => certification in accordance with art. 29 and 30 of the REDII. (Art. 8.1)

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Continuation of Table		
Categories	**Legislative File/Communication**	**Provisions**
		Art. 2 (10): 'low-carbon hydrogen' means hydrogen the energy content of which is derived from non-renewable sources, which meets a greenhouse gas emission reduction threshold of 70% => certification methodology to be published by end 2024.
Demand / supply targets	Amendment to the Renewable Energy Directive (REDIII)	Demand-side mandatory targets: • Industry: 50% of RFNBOs out of the total H2 consumption by 2030 (vs. 35% Council vs. European Parliament introducing a 70% target for 2035 vs. European Commission proposing a 78% target in the REPowerEU Communication) • Transport: 2.6% of RFNBOs in transport (vs. European Parliament: 2.6% by 2028 and 5.7% by 2030 (with 1.2% dedicated to maritime sector); Council: 5.2% + making it indicative; vs. European Commission proposing a 5.7% target in REPowerEU)
	Energy Taxation Directive	The lowest minimum rate of €0.15/GJ applies to RFNBOs. Low-carbon hydrogen and related fuels will also benefit from that same rate for a transitional period of 10 years.
	CO2 Standard for new cars and vans	100% emissions-free cars and vans put on the market from 2035, including fuel-cell and other hydrogen-powered vehicles.
Infrastructure	Alternative Fuels Infrastructure Regulation	1 H2 refueling station / every 150 km along the TEN-T core network and in every urban node (vs. EU Council: 1 H2 refueling station / every 200 km)
	TransEuropean Network for Transport (TEN-T) Regulation	Requirements for the deployment, across the TEN-T network of the charging and refueling infrastructure needed for alternative transport fuels in line with AFIR.
	TransEuropean Network for Energy (TEN-E) Regulation	H2 transport infrastructure and certain types of electrolyzers have been included in the scope of the revised TEN-E Regulation. H2 infrastructure projects must comply with specific criteria such as: significantly contributing to sustainability, including by reducing GHG emissions, by enhancing the deployment of renewable or low carbon H2 (with emphasis on H2 from renewable sources in particular hard-to-abate sectors).
	Regulation on the internal market for renewable and natural gases and H2	Proposal to create a European Network of Network Operators for Hydrogen (ENNOH)) to define a non-binding Union-wide ten-year network development plan for H2, targeted at the needs of developing H2 markets. Max. 5% blending of H2 in natural gas networks.
		Continued on next page

Continuation of Table		
Categories	**Legislative File/Communication**	**Provisions**
Funding for research, Innovation, Scaling Up	EU Emissions Trading Scheme Directive	• Current EU-ETS benchmark for H2 products refers to steam reforming of hydrocarbon feedstock. The production of hydrogen through electrolysis is not described. In its revision, the EC proposed to review this before the period 2026-2030. • The Innovation Fund (money raised from the auctioning of 450 million ETS allowances over 2020-2030) is open to projects for breakthrough technologies for all energy-intensive industry sectors covered by Annex I to the EU ETS, e.g. electrolyser manufacturing, H2 production/use. • The Modernisation Fund (revenues based on the auctioning of 2% of the total allowances for 202130) can support H2 activities concerning namely the production and use of renewable H2, green H2 fuelled trains/trucks/cars etc.
	REPower EU	In the REPowerEU Communication, the Commission committed to mobilizing EU funding for the deployment of renewable hydrogen (10mt by 2030) under CEF, Cohesion Policy and RRF. A specific REPowerEU window under the InvestEU Advisory Hub will support: • innovative electrification and hydrogen applications in industry • innovative clean tech manufacturing (such as electrolyzers and fuel cells)

Appendix B: EU hydrogen funding instruments

EU Instrument	**Type of H2 Project**	**Budget**
Connecting Europe Facility Energy	Cross-border H2 transmission & distribution projects, storage, electrolysers => 100MW; 70% GHG saving requirement	CEF-E total budget (2021-2027) = 5.84bn€ (min. 60% needs to be allocated to climate objectives)
Connecting Europe Facility Transport	H2 refuelling infrastructure on the TEN-T road and railway networks, dedicated to public transport in urban nodes and to the deployment of H2 alternative fuels for TEN-T maritime and inland ports, inland waterways.	CEF-T total budget (2021-2027) = €25.8 bn€, out of which, the Alternative Fuels Infrastructure Facility (AFIF) for 2021-2023 = 1.575bn€

Cohesion Policy funds (ERDF, CF, REACT-EU)	Hydrogen is not explicitly mentioned, but projects' eligibility to the funding depends on the priorities identified in the national and regional programs	Total ERDF budget = 191bn€, Total CF budget = 43bn€, 30% ERDF and 37% CF targets to support innovation and entrepreneurship in the transition to a climate-neutral economy.
Horizon Europe	Pillar II of Horizon Europe covers the research and innovation partnerships between the Commission, EU countries, and industry, among which the most emblematic ones are: The Clean Hydrogen Partnership (1bn€), with a key 2030 target of producing clean hydrogen at €1.5-3/kg and developing hydrogen valleys; The European Partnership for Clean Aviation (735m€); Clean steel – low-carbon steelmaking	Horizon Europe total budget: 95.5 bn€ (2021-2027)
Innovation Fund	Breakthrough technologies for all energy-intensive industry sectors covered by Annex I to the EU Emission Trading System Directive, including electrolyser manufacturing and H2 end-use applications. Projects need to demonstrate financial and business maturity.	Estimated total budget of 20bn€ (based mainly on the auctioning of 450 m EU-ETS allowances)
Invest EU	InvestEU could provide repayable support for projects including clean H2 production, supply (at commercial scale), on-site storage, deployment of refuelling infrastructure for transport, and critical infrastructure supporting H2 deployment.	The InvestEU Fund could mobilize 372 bn€ of public and private money through an EU budget guarantee of 26.2 bn€
Just Transition Fund	The main purpose of the fund is to alleviate the impact of the energy transition. It supports a wide range of activities, from reskilling to smart and sustainable local mobility, decarbonizing industry, etc. Allocation of funds depends on the Just Transition Plans drafted by MSs and approved by the Commission.	JTF total budget = 19.2bn€
LIFE Program – Clean Energy Transition stream	Directed namely at technical assistance, demonstration, 'close-to-market' projects featuring innovative, demonstrative solutions that offer clear environmental and/or climate benefits.	Total budget for 2021-2027 for the Clean Energy Transition stream: 997 m€
Modernisation Fund	Targeted at supporting the 10 lowest income EU countries in their transition to climate neutrality. The Modernisation Fund can support H2 activities concerning namely the production and use of green hydrogen from renewable electricity; assets like green H2 fuelled trains/trucks/cars; high-efficiency hydrogen CHP.	Revenues from the auctioning of 2% of the total allowances for 2021-30 under the EU-ETS

The Recovery and Resilience Facility	Activities and projects funded through the RRF depend on every country's Recovery and Resilience Plan. Two flagship areas identified by the Commission are important for H2 projects: PowerUp and Recharge and Refuel, targeting sustainable transport and charging, including hydrogen refuelling stations	The RRF will provide up to €337.97 billion in grants and €385.85 billion in loans. 37% of the overall amount needs to be directed to the green transition.

Appendix C: Model overview

Name	**Value 2010**	**Value 2020**	**Unit**	**Comment & Source**
Base economic growth r1	3.48E-03	1.26E-02	1/year	Greater Europe, See region definition
Base economic growth r1	3.00E-02	4.53E-02	1/year	Far East - Change order of constants and decouple RoW as data is available, See region definition
Base economic growth r3	7.46E-02	1.60E-02	1/year	Americas, See region definition
Base economic growth Row	7.46E-02	3.61E-02	1/year	RoW, See region definition
Balancing price CO2 per ton	7.00E+00	2.50E+01	Dollar/t	**parry2022**
CO2 emissions of coal	8.90E+01	9.46E+01	t/bbtu	Average of sectors coal mix, **epa2020**, p22-23
CO2 emissions of natural gas	5.31E+01	5.31E+01	t/bbtu	Apparently no uncertainty, **epa2020**, p23
CO2 emissions of oil	8.09E+01	7.12E+01	t/bbtu	Between 59.58 and 102.41 t/bbtu, average, **epa2020**, p23
Decoupling of energy and GDP factor FE	0.00E+00	1.27E-01	1/year	**wang2021**

Decoupling of energy and GDP factor GE	0.00E+00		1/year	**wang2021**
Decoupling of energy and GDP factor NA	0.00E+00		1/year	**wang2021**
Decoupling of energy and GDP factor RoW	0.00E+00		1/year	**wang2021**
Delay time LNG facilities	4.04E+00	4.29E+00	s	See 2020 calculations; correction for different areas? **global2022**
Delay time new capacity Am	8.29E+00	8.29E+00	year	no clear data
Delay time new capacity FE	7.87E+00	7.87E+00	year	no clear data
Delay time new capacity GE	1.56E+01	1.56E+01	year	no clear data
Effect of supply shortage on GDP growth	-1.00E-01	-4.90E-01	1/year	See 2020 calculations; implement with index as relation is with 1% of shortage **shahbaz2015**
End year subsidy level renewables	2.03E+03	2.06E+03	year	end of run/ scenarios subsidies
Experience curve parameter extraction	-5.13E-01	-2.81E-01	Dmnl	See calculations, See calculations
Final Time	2.05E+03	2.06E+03	Year	new final time +10 years
Initial active capacity	9.39E-01	9.39E-01	Dmnl	data unfindable
Initial capacity gas RoW	2.38E+07	4.58E+07	bbtu/Year	rename, EIA 2021
Initial coal price	3.77E+03	2.45E+03	Dollar/bbtu	huge assumption -> one price?, **statista2021**
Initial energy demand Am	1.10E+08	1.27E+08	bbtu/Year	See calculations, See calculations / EIA data EIA 2021

Initial energy demand FE	1.50E+08	1.96E+08	bbtu/Year	See calculations, See calculations / EIA data EIA 2021
Initial energy demand GE	1.64E+08	1.08E+08	bbtu/Year	See calculations, See calculations / EIA data EIA 2021
Initial energy demand RoW	8.29E+07	9.67E+07	bbtu/Year	See calculations, See calculations / EIA data EIA 2021
Initial energy demand shares Am	0.3664, 0.2488, 0.199, 0.097, 0.0163, 0.0725	0.372063539, 0.315832650, 0.084942949, 0.063986874, 0.090163323, 0.073010664	Dmnl	See calculations, See calculations / EIA data EIA 2021
Initial energy demand shares FE	0.2563, 0.0805, 0.5615, 0.0337, 0.0007, 0.0672	0.259506531, 0.117271408, 0.481906144, 0.025834543, 0.065602322, 0.049879052	Dmnl	See calculations, See calculations / EIA data EIA 2021
Initial energy demand shares GE	0.3585, 0.3678, 0.1275, 0.069, 0.0041, 0.0732	0.299816225, 0.34007176, 0.127505032, 0.082086287, 0.071584843, 0.078935854	Dmnl	See calculations, See calculations / EIA data EIA 2021
Initial energy demand shares RoW	0.456, 0.2123, 0.1781, 0.001, 0.0122, 0.1309		Dmnl	See calculations, See calculations / EIA data EIA 2021
Initial EROEI biofuels	2.00E+00	3.50E+00	Dmnl	Energy return on investment (EROI) of biomass conversion systems in China: Meta-analysis focused on system boundary unification

Initial EROEI other renewables	5.00E+00	1.00E+01	Dmnl	Highly dependent on mix wind and solar => solar EROEI increased over 10 years EIA 2021
Initial extraction capacity coal America	2.57E+07	1.64E+07	bbtu/Year	EIA 2021
Initial extraction capacity coal Far East	7.57E+07	1.25E+08	bbtu/Year	EIA 2021
Initial extraction capacity coal Greater Europe	1.90E+07	3.84E+07	bbtu/Year	EIA 2021
Initial extraction capacity gas America	2.82E+07	5.76E+07	bbtu/Year	EIA 2021
Initial extraction capacity gas Far East	3.40E+06	1.46E+07	bbtu/Year	EIA 2021
Initial extraction capacity gas Greater Europe	6.38E+07	4.06E+07	bbtu/Year	EIA 2021
Initial extraction capacity oil America	2.13E+07	5.71E+07	bbtu/Year	EIA 2021
Initial extraction capacity oil Far East	8.16E+07	3.55E+07	bbtu/Year	EIA 2021
Initial extraction capacity oil Greater Europe	9.75E+07	1.99E+07	bbtu/Year	EIA 2021
Initial extraction capacity oil RoW	4.06E+07	6.70E+07	bbtu/Year	EIA 2021
Initial gas prices	8895,4330,11000, 11000	2000, 3200, 4200, 3133	Dollar/bbtu	IEA 2020
Initial GDP	2.06942e+13, 1.59964e+13, 1.24408e+13, 1.39174e+13	2.75E+13, 2.14E+13, 2.65E+13, 8.98E+12	Dollars	Suspected difference in region definition, Bank 2020
Initial LNG export capacity Am	6.85E+04	4.75E+06	bbtu/Year	Suspected difference in region definition, IGU 2021
Initial LNG export capacity FE	6.92E+01	3.06E+06	bbtu/Year	IGU 2021
Initial LNG export capacity GE	8.05E+06	3.85E+06	bbtu/Year	IGU 2021
Initial LNG export capacity RoW	1.37E+07	1.26E+07	bbtu/Year	IGU 2021
Initial LNG import capacity Am	6.47E+06	5.33E+06	bbtu/Year	See 2020 calculations, al. 2022

Initial LNG import capacity FE	1.37E+07	2.58E+07	bbtu/Year	See 2020 calculations, al. 2022
Initial LNG import capacity GE	7.14E+06	9.70E+06	bbtu/Year	See 2020 calculations, al. 2022
Initial LNG import capacity RoW	6.80E+01	4.15E+06	bbtu/Year	See 2020 calculations, increase partly due to country definition, al. 2022
Initial long term average energy price	1.09E+04	1.20E+04	Dollar/bbtu	Index with 2010 value as base, JGEA 2020
Initial oil price	1.41E+04	7.47E+03	Dollar	See calculations; bought on low market, can adjust to (rolling) average, See calculation
Initial price renewables	2.20E+04	1.94E+04	Dollar/bbtu	See calculations, IRENA 2021
Initial shortage effect on decoupling	0.00E+00		1/year	Determined after run iterations
INITIAL TIME	2.01E+03	2.02E+03	Year	+10 years
Initial unit costs biofuels	3.19E+04	2.23E+04	Dollar/bbtu	IRENA 2021
Initial unit costs coal	1.62E+03	3.23E+03	Dollar/bbtu	AFR 2021
Initial unit costs nuclear	1.33E+04	1.47E+04	Dollar/bbtu	50$ MWh, Association 2021
Initial unit costs oil	5.00E+03	5.50E+03	Dollar/bbtu	
Initial unit costs other renewables	5.15E+03	2.73E+03	Dollar/bbtu	Used relative decrease of cost, IRENA 2021
Maximum relative mothballing	0.3	2.937198068	1/year	The amount of times the long term elasticity is bigger than the short term elasticity, Xavier Labandeira 2017

Number of years since beginning of extraction capacity	150, 100, 500, 70, 15, 40	160, 110, 510, 80, 25, 50	Year	Adding 10 years
Reduction in initial CO2 cap	0.00E+00	0.00E+00	t/(Year*Year)	Only present in EU
Relative part emissions under CO2 cap FE	4.50E-01	2.50E-01	Dmnl	45% covered by China, India, and Japan will follow soon; can be predicted that in next years will rise to 45% for full region, ICAP 2021
Relative part emissions under CO2 cap GE	4.50E-01	3.00E-01	Dmnl	38% by EU, some member states have National ETS complementing the EU system, some nations in GE have none => 40% is accurate, ICAP 2021
Relative part emissions under CO2 cap NA	4.50E-01	4.00E-01	Dmnl	Some liberal US states + Canada + Mexico have implemented ETS. Cover varies from 75% in NA and 40% in Mexico - will be implemented, ICAP 2021
Relative part emissions under CO2 cap RoW	0.00E+00	5.00E-02	Dmnl	Australia and NZ have one, Nigeria will implement one, ICAP 2021
Relative subsidy level on renewables FE	0.00E+00	2.00E-01	Dmnl	Multiple sources, intuitive

Relative subsidy level on renewables GE	7.50E-01	7.00E-01	Dmnl	Multiple sources, intuitive
Relative subsidy level on renewables NA	5.00E-01	6.00E-01	Dmnl	Multiple sources, intuitive
Relative subsidy level on renewables RoW	0.00E+00	5.00E-02	Dmnl	Multiple sources, intuitive
Short term demand elasticity	3.94E-03	2.07E-01	Dmnl	Much higher?, Xavier Labandeira 2017

Table 4: Model parameter

Model views

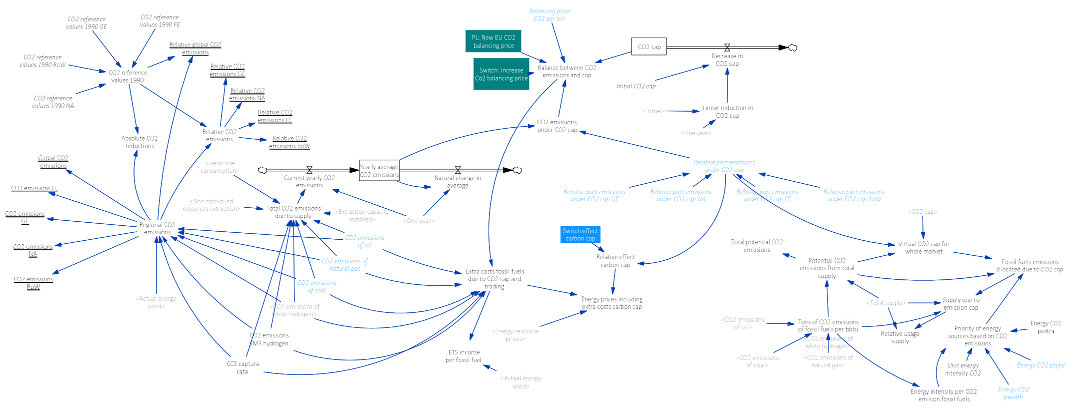

Figure 1: Co2 sub-model

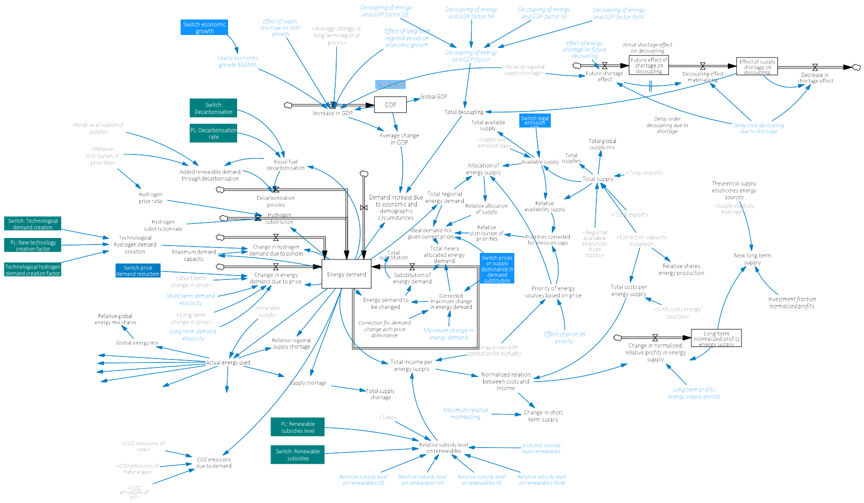

Figure 2: demand sub-model

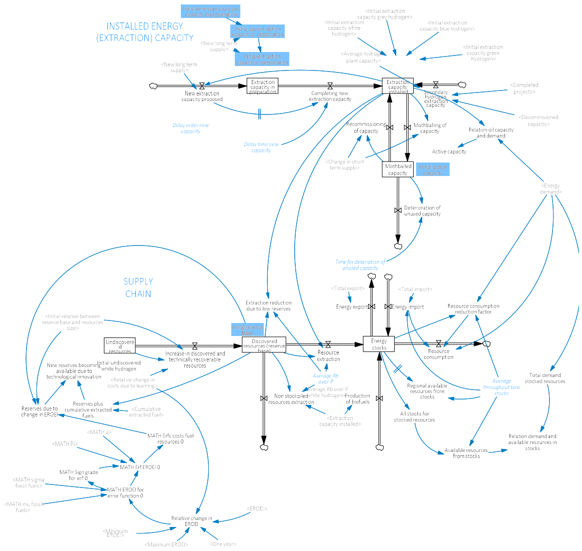

Figure 3: Extraction capacity sub-model

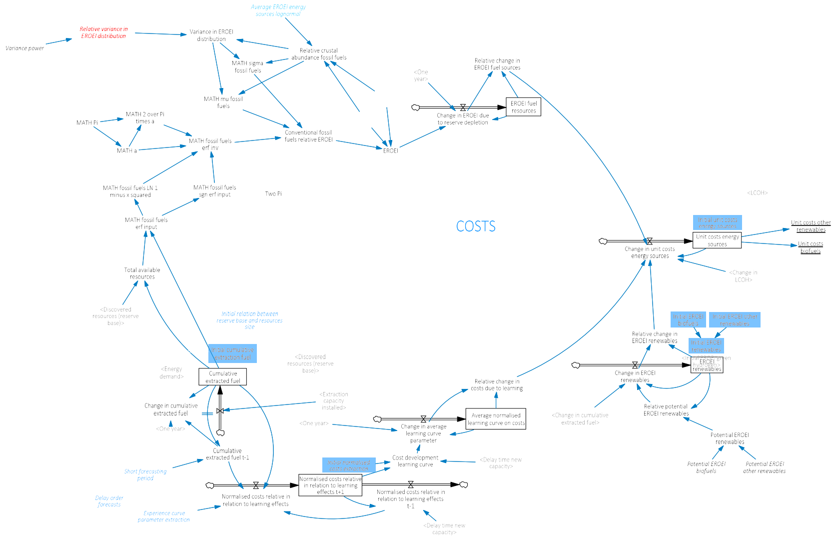

Figure 4: Extraction cost sub-mode

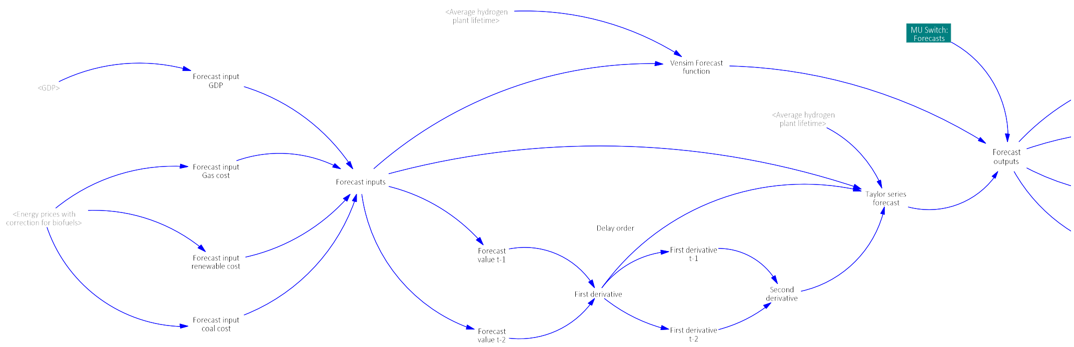

Figure 5: Forecast sub-mode

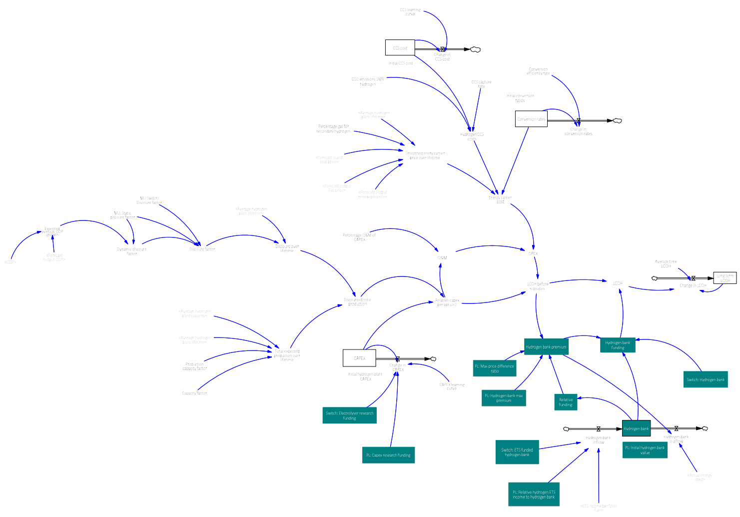

Figure 6: LCOH sub-model

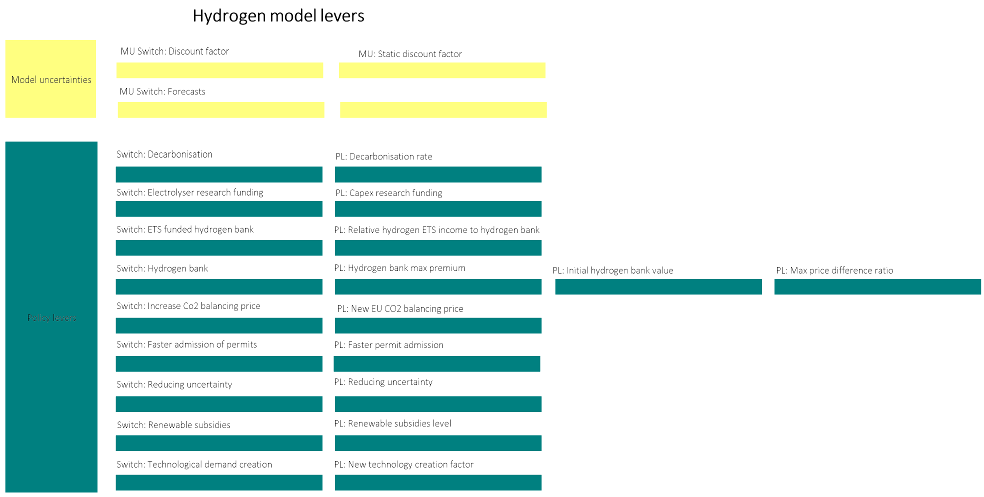

Figure 7: Model lever sub-model

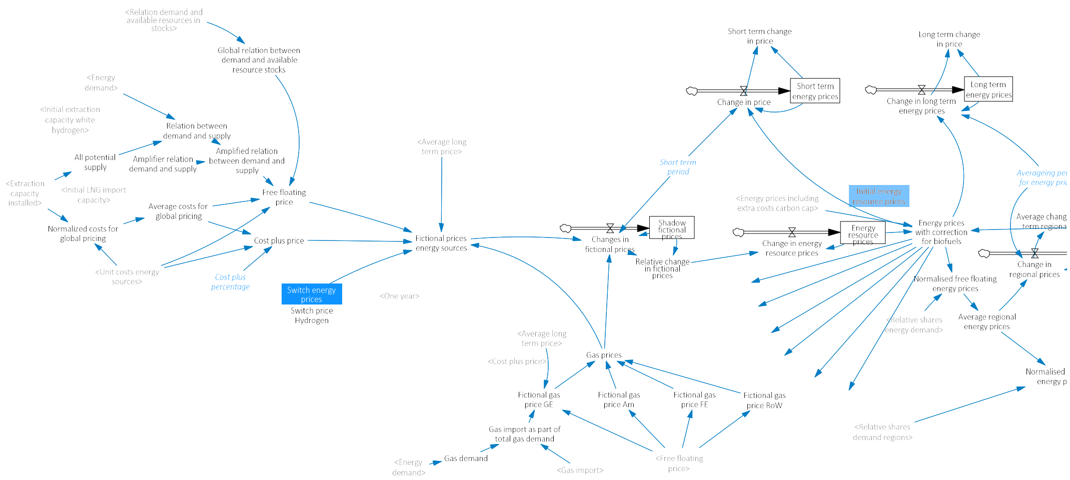

Figure 8: Resource pricing sub-model

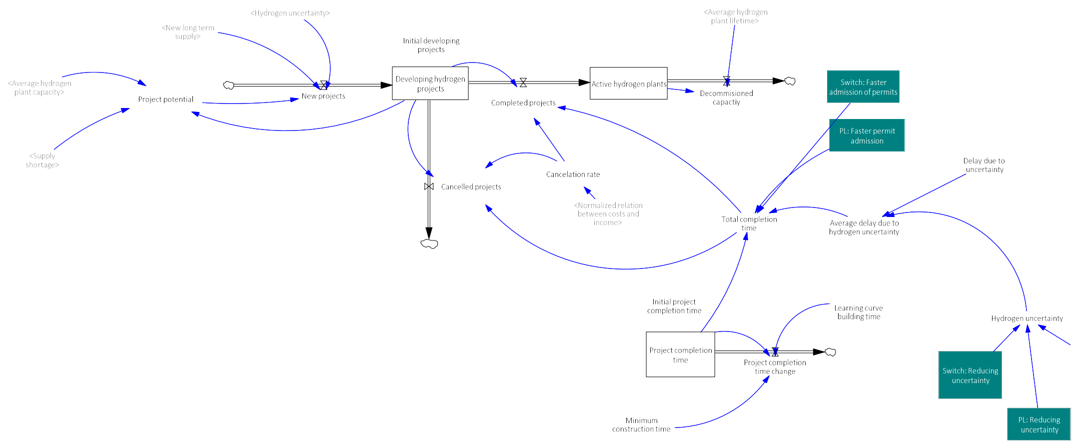

Figure 9: Secondary hydrogen capacity sub-model

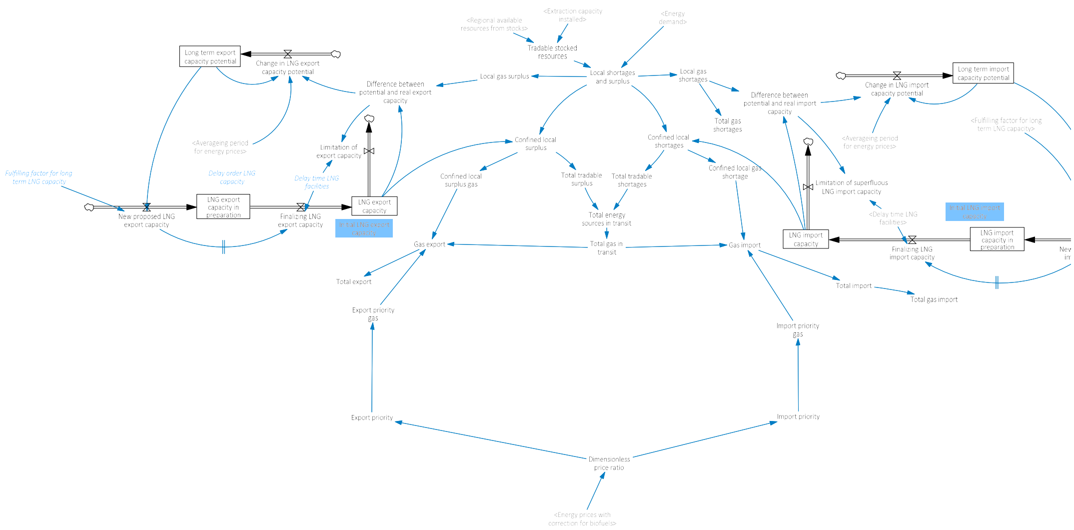

Figure 10: trade sub-model

Appendix D: Conversions in research

Table 5: Conversion from Real Life Targets to Model Units

KPI	Benchmark Value	Benchmark Units	Model Output Value	Model Units
Green hydrogen demand	20	Mt H2/year	2.72E+06	Bbtu/year
Green hydrogen production capacity	10	Mt H2/year	1.36E+06	Bbtu/year
Cost of Green hydrogen	1.5	Euro/kg H2	14653	Dollar/Bbtu H2
Yearly CO2 Emissions	2.519E+09	Ton/year	2.519E+09	Ton/year
Renewable demand	42.5%	Dimensionless	42.5%	Dimensionless

Appendix E: Policy Analyses Set-up

The policies described in Table 6 were actively implemented within the model, allowing for a detailed analysis of the resultant outputs. These policies were mainly assessed in the context of the specific sub-model where they were applied. The implementation of these policies was controlled by switches, with a value of 0 indicating that a policy was deactivated and a value of 1 indicating activation. These switches were sampled using a Latin Hypercube sampling method to ensure a comprehensive exploration of potential policy impacts. This method was chosen for its efficiency in covering the range of possible settings evenly and comprehensively. After sampling, the policies were integrated into the model using a full factorial design (See Table 7). This design approach facilitated a systematic analysis of all possible combinations of policy states, thereby allowing for a thorough investigation of the interaction effects between different policies and their cumulative impact on the model's output. This rigorous methodology enabled a robust evaluation of how individual and combined policy implementations could influence the system dynamics captured by the sub-model.

Output	Policy measures
Extraction capacity	P1: Reducing uncertainties P2: Better standardisation
Green hydrogen demand	P3: Decarbonisation of existing markets P4: Creating new hydrogen markets
LCOH	P5: Increasing supply and lowering costs for renewables P6: Hydrogen bank P7: Lowering electrolyser cost P8: ETS prices

Table 6: Policies and benchmark output

Policy sets	P1	P2	P3	P4	P5	P6	P7	P8
S1	0	0	1	1	1	0	0	1
S2	1	0	0	1	0	1	1	1
S3	0	0	1	1	1	1	1	0
S4	1	1	1	0	1	1	0	0
S5	0	1	0	1	0	0	1	0
S6	1	1	0	0	0	0	0	1
S7	1	1	0	0	0	1	1	0
S8	0	0	1	0	1	0	0	1

Table 7: Factorial design

Appendix F: Results **Green hydrogen clusters projections**

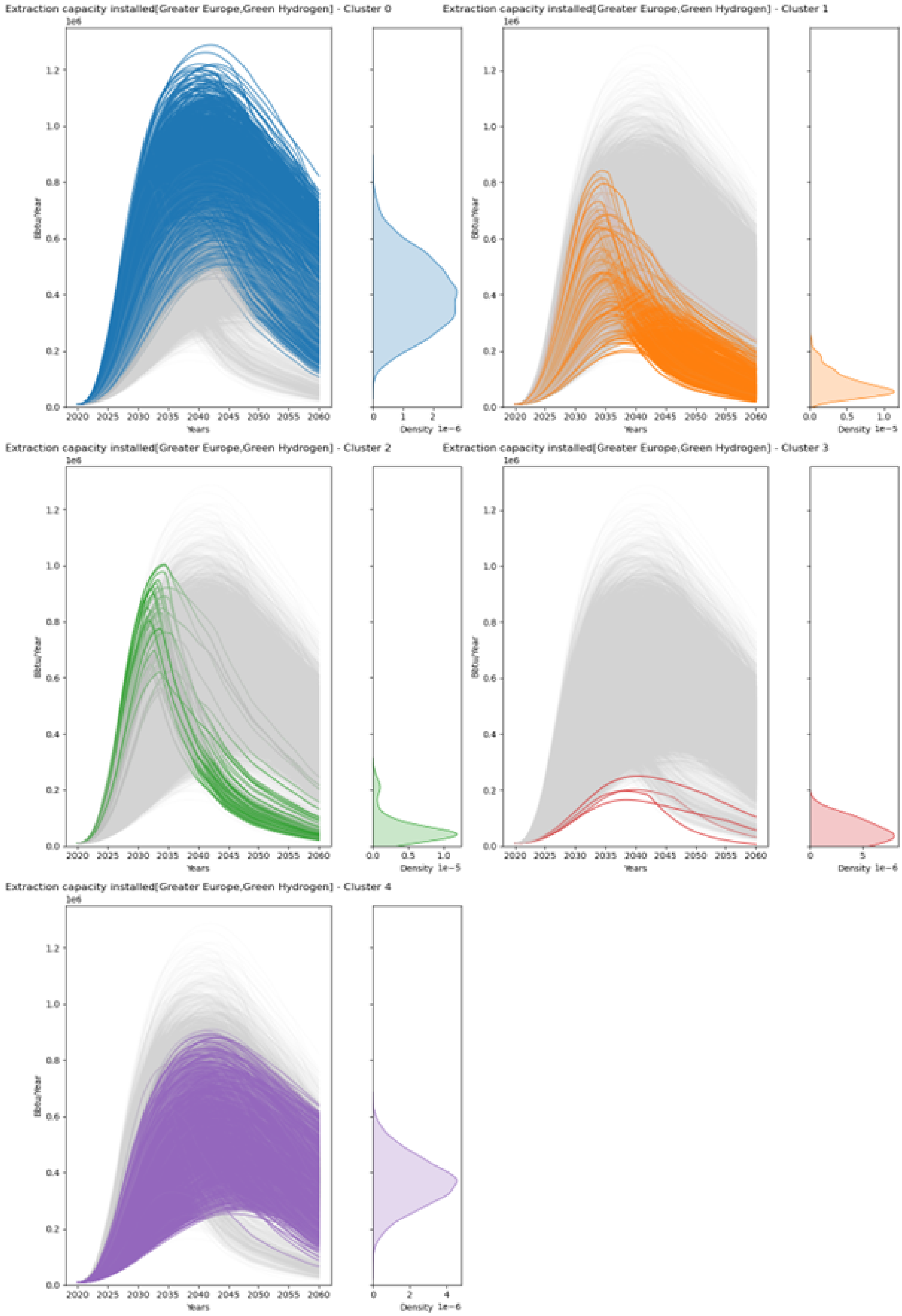

Figure 11: Green hydrogen clusters projected on extraction capacity

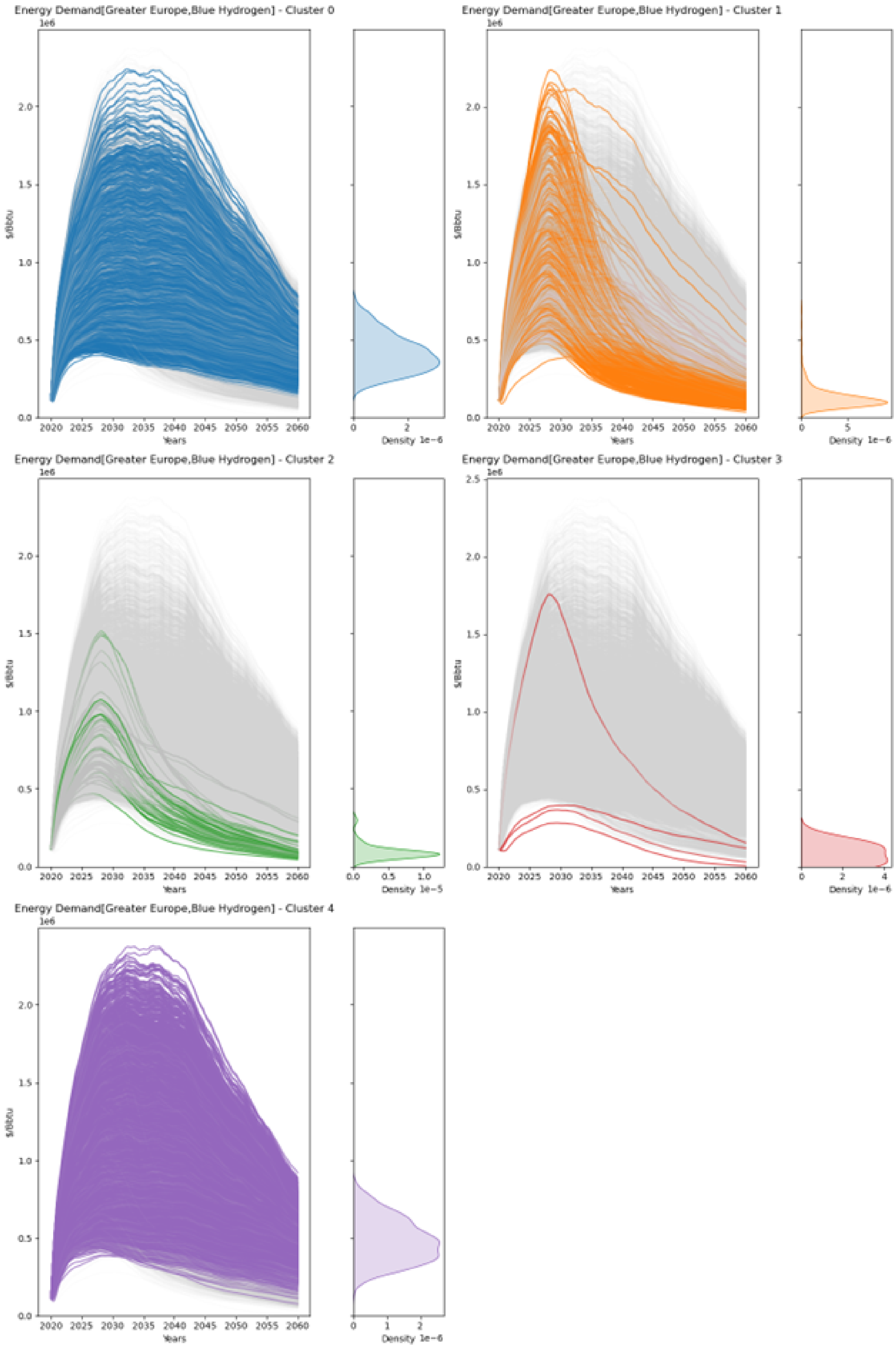

Figure 12: Green hydrogen clusters projected on grey hydrogen demand

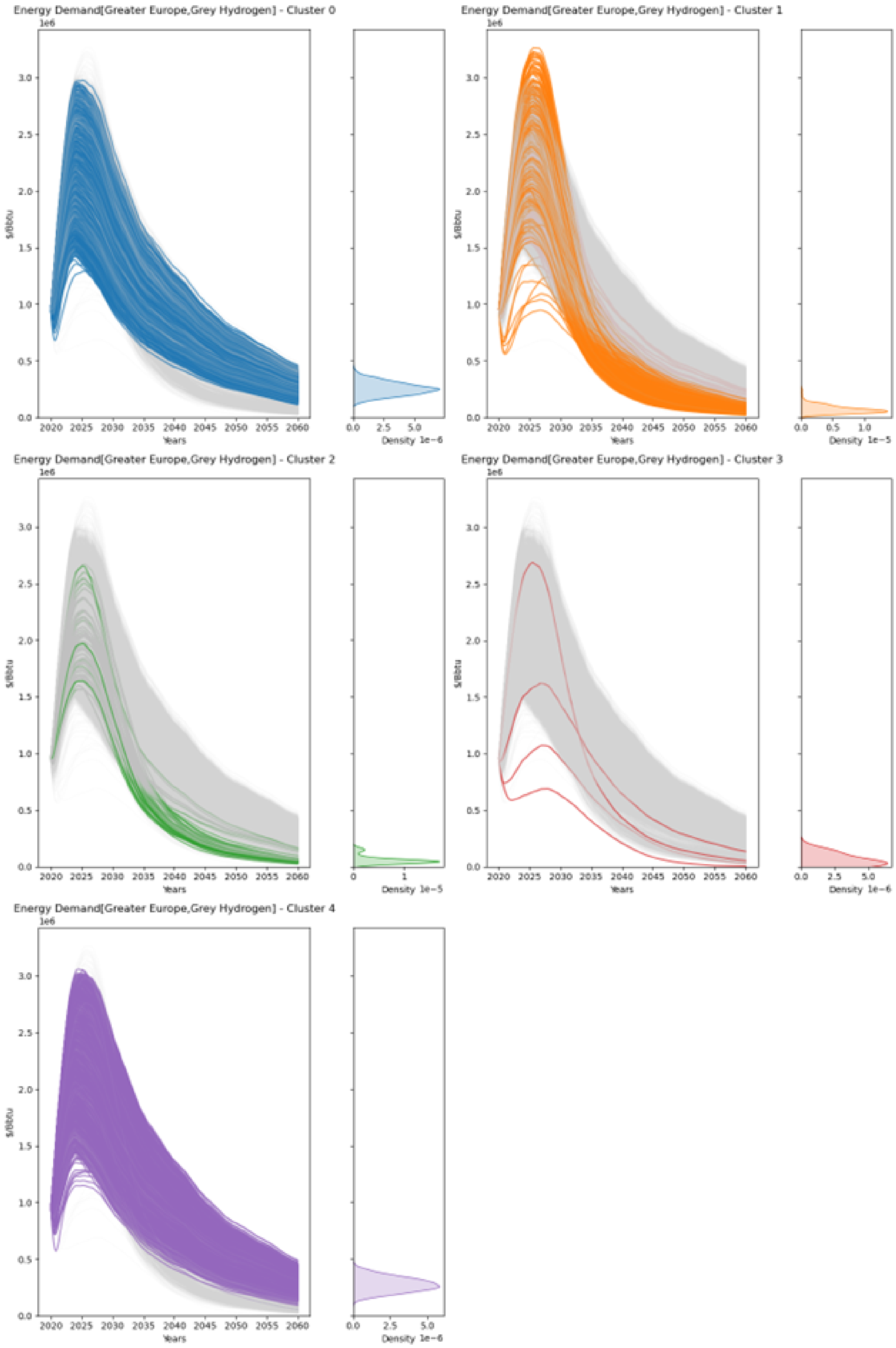

Figure 13: Green hydrogen clusters projected on extraction capacity

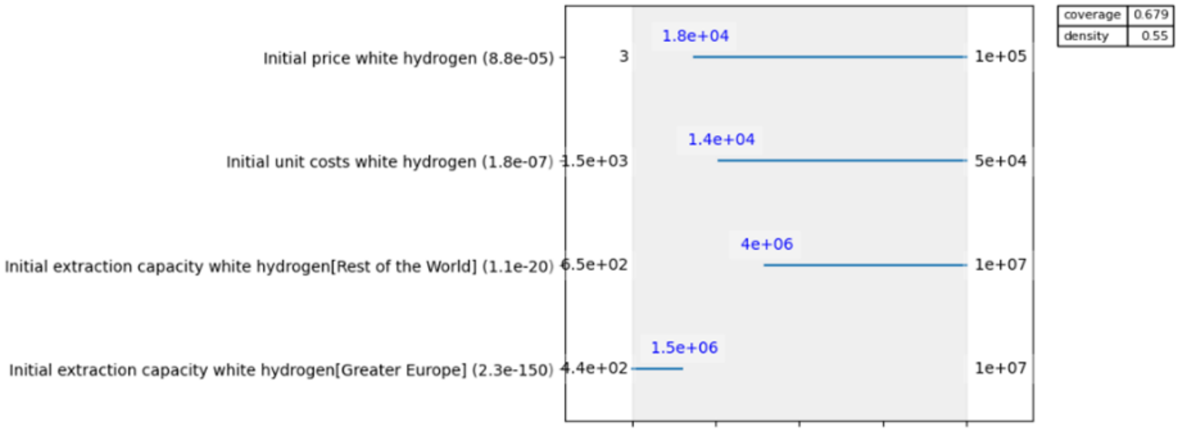

Figure 14: prim green hydrogen clustering - low demand cluster

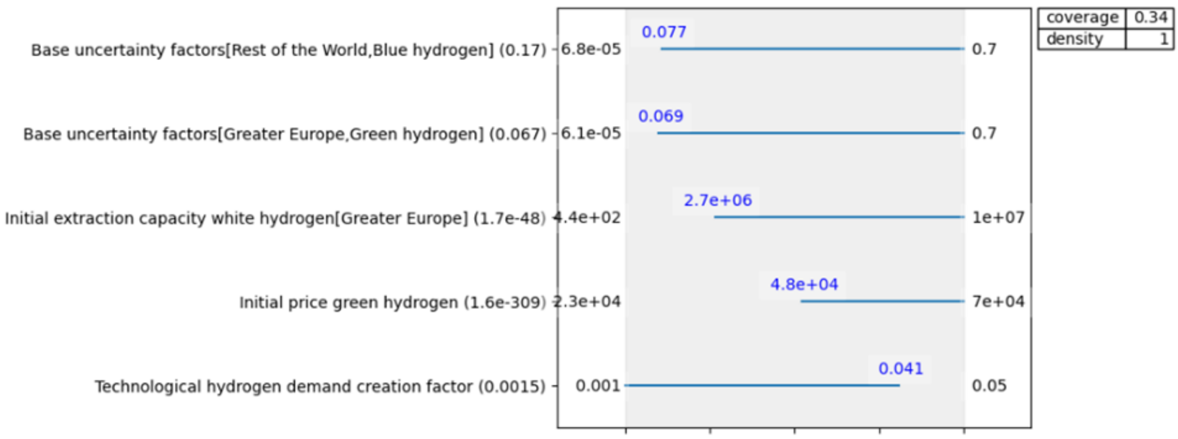

Figure 15: prim green hydrogen clustering - average demand cluster

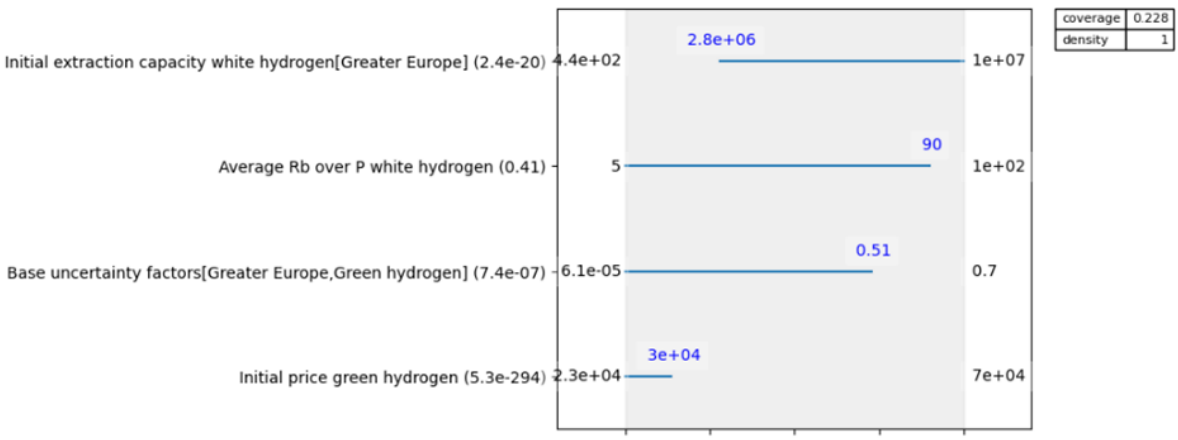

Figure 16: prim green hydrogen clustering - high demand cluster