DISSERTATION

A HOLISTIC MULTIDISCIPLINARY DECISION-MAKING APPROACH UTILIZING MODEL-BASED SYSTEMS ENGINEERING AND SYSTEM DYNAMICS FOR NOVEL ENERGY TECHNOLOGY COMMERCIALIZATION

Submitted by

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ABSTRACT

A HOLISTIC MULTIDISCIPLINARY DECISION-MAKING APPROACH UTILIZING MODEL-BASED SYSTEMS ENGINEERING AND SYSTEM DYNAMICS FOR NOVEL ENERGY TECHNOLOGY COMMERCIALIZATION

The U.S. energy system is characterized by its complexity and the intricate interplay of various components, including electricity generation, non-electrical energy sources, energy consumption patterns, and the energy economy. As the nation transitions to more sustainable and resilient energy sources, it becomes evident that traditional decision-making approaches are insufficient to address the multifaceted challenges of modern energy systems. This research aims to develop a novel decision-making framework by integrating systems thinking and systems engineering principles to provide a comprehensive understanding of energy system behavior and facilitate the evaluation and deployment of novel energy technologies.

Chapter 1 provides an overview of the research, states the main research question and objectives, and describes an overview of the dissertation. Chapter 2 presents an overview of the intricate and multifaceted landscape of the U.S. energy system, exploring its various elements and the complex interactions among them. It provides a comprehensive overview of the current state of the U.S. energy system, including electricity generation, non-electrical energy sources, and energy consumption patterns. The chapter also highlights the critical role of the energy economy in shaping the transition to sustainable and resilient energy sources. Furthermore, the chapter examines the potential of hydrogen as a key player in the future energy system, emphasizing its ability to enhance energy security, reduce carbon emissions, and support diverse industrial applications. Finally, the chapter discusses the challenges and shortcomings of existing decision-making approaches for complex energy systems, underscoring the need for new methodologies that integrate multidisciplinary insights and address uncertainties.

Chapter 3 elaborates on the complexity of energy systems and underscores the importance of interdisciplinary approaches to address their challenges. It highlights the roles of systems thinking and systems engineering in developing a novel decision-making framework for energy systems. Systems thinking is presented as a holistic approach that considers both internal and external interactions of system elements, enabling better decision-making by providing insights into complex interactions and long-term perspectives. Systems engineering is defined as an interdisciplinary approach that ensures the successful realization of complex systems by connecting various engineering disciplines, evaluating stakeholder needs, and applying standardized methods throughout the system life cycle. The chapter also discusses specific methods and tools, such as system dynamics and model-based systems engineering, that are used in this research to develop a framework for informed decision-making in energy systems.

Chapter 4 explores the deployment dynamics of novel energy technologies, focusing on onshore wind, utility-scale solar photovoltaic, and clean hydrogen generation energy systems. The research examines various factors influencing deployment, including policy and regulation, technological advancements, economic considerations, environmental concerns, public perception, and infrastructure capabilities. Qualitative analysis identifies key dynamics such as the role of government policies and incentives, technological advancements, economic factors, environmental concerns, and public perception in accelerating technology adoption. Quantitative modeling provides insights into factors driving capacity growth and cost reductions, demonstrating the model's ability to simulate the trajectory of novel energy technology adoption. Sensitivity studies highlight the importance of resource availability, willingness to invest, and technological learning as influential factors affecting capacity growth. Scenario analyses confirm the significant impact of federal incentives and technological learning on both capacity growth, the levelized cost of energy, and the levelized cost of hydrogen.

Chapter 5 expands the exploration of energy system deployment presented in Chapter 4 into a more granular problem—the crafting of a decision support framework aimed at configuring energy systems on a smaller scale. The principal objective is to leverage systems engineering principles and tools systematically to minimize the risk of suboptimal system configurations that fail to align with stakeholder requirements or regional conditions, potentially resulting in reduced or lost profits. The need for this new approach is underscored by the inherent complexity and uncertainty in energy systems, which necessitates a structured, multidisciplinary evaluation method to facilitate high-level decision-making and ensure the selection of the most feasible and beneficial system concepts.

Finally, Chapter 6 presents conclusions, research contributions, and opportunities for future work. The findings from this research have several implications for policymakers, investors, and industry stakeholders. Policymakers are encouraged to maintain consistent and supportive government policies and incentives to reduce market volatility and encourage sustained investment in renewable energy projects. Investors can benefit from understanding the dynamics of technology adoption and the factors influencing profitable capacity, emphasizing the significance of technological learning and cost reductions. Industry stakeholders should focus on scaling up developer capacity and investing in technological improvements, collaborating with policymakers to ensure supportive regulatory environments and incentives.

In summary, the transition to novel energy technologies is a complex but essential process in addressing climate change and ensuring energy security. This research highlights the critical factors influencing this transition and provides a robust model for understanding the dynamics of energy technology adoption. By leveraging these insights, stakeholders can make informed decisions to support the accelerated deployment of renewable energy systems, contributing to a sustainable and resilient energy future.

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DEDICATION

To my best friend — my husband James Lawrence, who has supported and encouraged all my aspirations. I would not have been able to complete this journey without you being by my side. Thank you, hubby, for all your love, support, and patience.

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CCS carbon capture and sequestration *on page(s):* xi, 82, 84, 85, 92, 93, 118–121, 134, 141, 148

CLD Causal Loop Diagrams *on page(s):* x, 8, 30, 31, 39, 46, 50, 52, 58

CRF capital recovery factor *on page(s):* 63

GHG greenhouse gas *on page(s):* x, 12, 17, 24, 42, 82, 117–120, 125, 131, 148

HTSE High Temperature Steam Electrolysis *on page(s):* xi, 82, 119–122, 128, 132, 134, 141, 142

IRA Inflation Reduction Act *on page(s):* 118, 126

IRR Internal Rate of Return *on page(s):* 21, 22, 37, 116

ITC Investment Tax Credit *on page(s):* 60, 62, 70, 79

LCA Life Cycle Assessment *on page(s):* 22, 23

LCOE Levelized Cost of Energy *on page(s):* x, 3, 8, 22, 24, 49, 61–63, 74, 76, 77, 83, 92, 97, 99, 116

LCOH levelized cost of hydrogen *on page(s):* xi, 83–86, 90, 92–94, 141

LML Lifecycle Modeling Language *on page(s):* ix, 33, 106–108, 118, 123, 126, 131

LTE Low Temperature Electrolysis *on page(s):* xi, 82–86, 92, 93, 119–121, 133–136, 138, 141, 142

MAUT Multi-attribute Utility Theory *on page(s):* 104, 109, 110

MBSE Model-Based Systems Engineering *on page(s):* x, xi, 4, 15, 30, 33–35, 37, 39, 101, 104–106, 114, 115, 117, 118, 123, 125, 127, 131, 139, 140, 142–148, 150

NPP nuclear power plant *on page(s):* 19, 48, 121, 124, 128, 131, 133, 134

NPV Net Present Value *on page(s):* 21, 22, 37, 116

NREL National Renewable Energy Laboratory *on page(s):* 62

O&M operations and maintenance *on page(s):* 60, 63, 64, 79, 84, 115, 141, 143

PEM polymer electrolyte membrane *on page(s):* xi, 82, 85, 86, 119, 120, 134, 137

PPA power purchase agreement *on page(s):* 60, 67–69, 79

PTC Production Tax Credit *on page(s):* x, 59, 60, 62, 69–71, 74, 76, 77, 79, 86, 95, 97, 116, 118, 131

R&D research and development *on page(s):* 12, 14, 43, 48, 49, 51, 56, 82, 98, 116, 119, 120, 139

ROI return in investment *on page(s):* 60, 62, 63, 70, 79, 87

RPS Renewable Portfolio Standard *on page(s):* 50, 70, 71

SD System Dynamics *on page(s):* x, xi, 3, 5, 7–9, 22, 30, 32, 33, 39, 45, 46, 48, 50, 52–55, 58, 69, 78, 83, 95, 99, 147–149

SE Systems Engineering *on page(s):* 4–8, 15, 26, 28–30, 33, 39, 40, 100, 102, 104–106, 111, 112, 114, 142, 144, 145, 147

SMR Steam Methane Reforming *on page(s):* xi, 17, 19, 82, 84, 85, 92, 93, 118, 120, 121, 136, 141

SOEC solid oxide water electrolysis cell *on page(s):* xi, 82, 84, 92–94, 119, 120, 131

SSOT single source of truth *on page(s):* 35

ST Systems Thinking *on page(s):* 4–8, 26, 27, 39, 40, 102, 104, 113, 142, 144, 145, 147

SysML Systems Modeling Language *on page(s):* ix, 33, 106–108, 126

Chapter 1

Introduction

1.1 Overview

The transition to sustainable and resilient novel energy systems is a complex and multifaceted challenge that requires a comprehensive understanding of the current and future energy landscape, the potential of emerging technologies, and the development of new decision-making methodologies. This dissertation addresses these challenges by exploring the intricate landscape of the U.S. energy system, opportunities for novel energy technologies entering the existing energy system, the potential role of hydrogen in the future energy system, and the development of a novel decision support framework for energy system strategy development.

The U.S. energy system is a complex network comprising various elements and their interconnections at national, regional, and local levels. Figure 1.1 is a schematic of the overall U.S. energy system. It includes electricity generation from fossil fuels, renewables, and nuclear energy, as well as non-electrical energy sources used in industrial processes. Energy consumption patterns and the economic aspects of the energy system significantly influence the types of energy sources used to meet demand. The energy economy plays a crucial role in the transition to diverse and sustainable sources, influenced by energy production, distribution, and consumption dynamics. Energy prices, federal policies, and projected demands shape this transition.

Diversifying energy sources enhances national security and stabilizes prices, making the energy sector more resilient to disruptions. Long-term energy demand projections take into account factors such as population growth, urbanization, and economic development. Sustainable economic growth requires significant increases in energy capacity to meet rising demand while reducing reliance on fossil fuel energy sources. Hydrogen presents a unique opportunity to enhance the energy sector's resilience while making significant strides toward achieving decarbonization goals. The U.S. Department of Energy (DOE) is pursuing an ambitious Hydrogen Program Plan, enabling

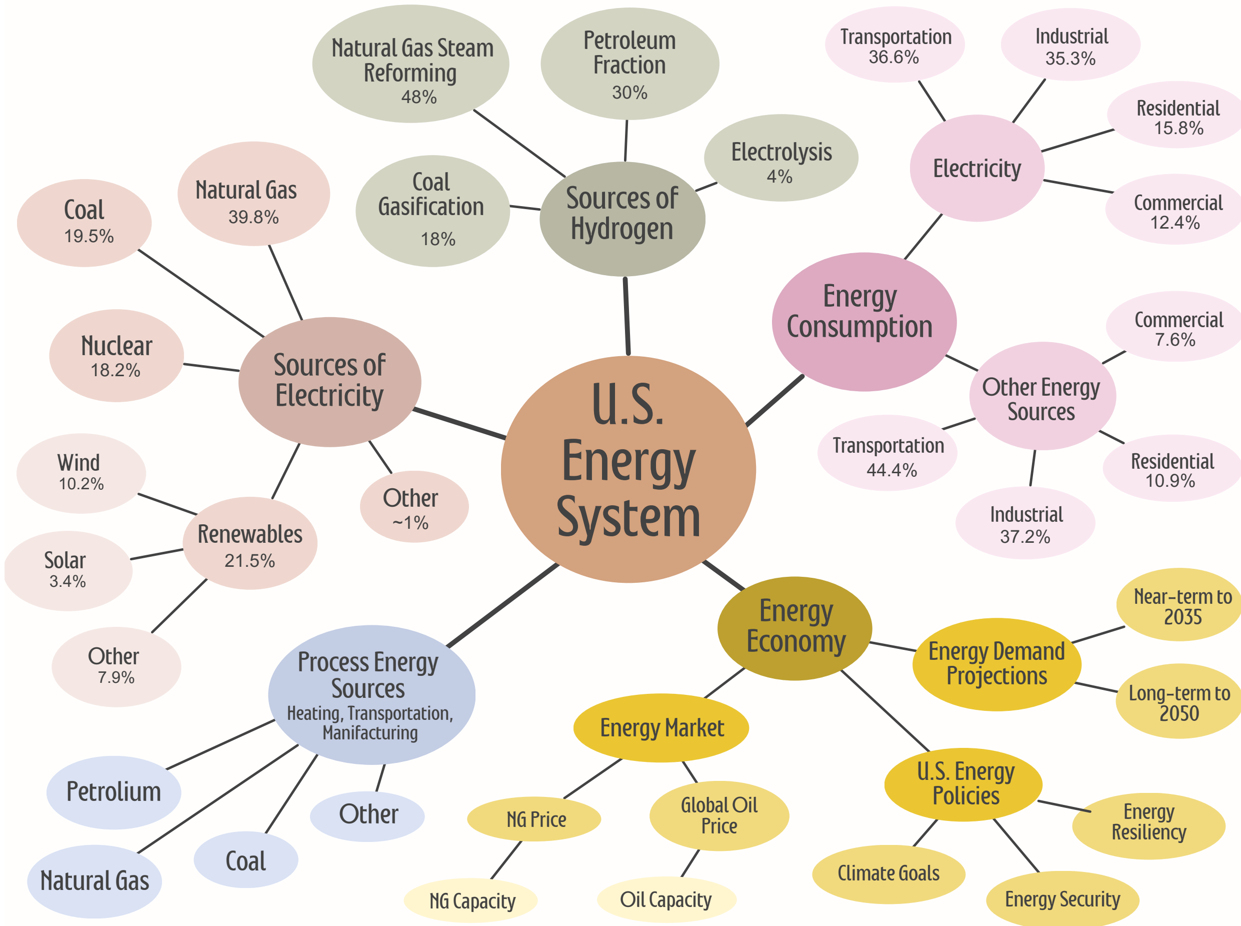

Figure 1.1: U.S. energy system schematic

energy pathways across numerous applications and sectors. Currently, hydrogen demand is primarily in petroleum refinement and ammonia production. However, demand is expected to grow significantly in industrial processes and new markets, such as hydrogen fuel cells for vehicles and the injection of hydrogen into natural gas pipelines.

The United States and many other countries are investing heavily in hydrogen production technologies and infrastructure. Significant advancements in electrolysis-based hydrogen generation technologies are making them viable for large-scale applications. Various studies have explored the feasibility of coupling nuclear plant operations with hydrogen production, and economic analyses have assessed the viability of hydrogen energy markets.

However, the large-scale commercialization of hydrogen systems has not been considered part of a macro energy system. Existing research has focused on specific aspects, such as technology maturity, cost improvements supporting economic feasibility, and overall technology capacity growth, based on multiple factors that influence the adoption of this novel energy technology. This research includes an in-depth examination of qualitative and quantitative models developed to understand the commercialization paths of novel energy technologies. The quantitative models developed in this research specifically focus on onshore wind, utility-scale solar PV, and clean hydrogen generation systems.

A System Dynamics (SD) model is developed for onshore wind energy. This model explores wind energy capacity growth in the United States, taking into account multiple influencing factors such as economic feasibility, resource availability, the growth of developer capacity to build new projects, and the maturation of the technology leading to cost reductions. The simulation results from the model will be compared with historical and projected capacity data, demonstrating the model's validity and accuracy in predicting capacity growth trends.

Following the successful validation of the wind energy model, the same modeling framework will be employed to simulate the growth of utility-scale solar PV energy in the United States. The solar model utilized solar-specific data and similarly compared simulation results to historical and projected data for utility-scale solar PV capacity growth in the United States.

The application of the same model and validation against historical data confirmed the hypothesis that the commercialization of novel energy systems follows similar patterns and is affected by the same factors. The model was subsequently used to analyze the potential futures for the commercialization of clean hydrogen generation, an energy technology at the initial stages of large-scale adoption, for which no historical data is available. The model's application to clean hydrogen generation aimed to understand potential commercialization paths by integrating factors such as technology readiness, economic feasibility, federal policies, developer readiness, and resource availability.

Sensitivity studies conducted within the quantitative modeling confirmed key factors affecting capacity growth and the Levelized Cost of Energy (LCOE). Scenario analyses further confirm the significant impact of federal incentives and technological learning on both capacity growth and cost reduction, emphasizing their importance in the successful deployment of novel energy technologies.

The research about the dynamics of novel energy technologies adoption concludes by outlining findings and making recommendations to energy sector stakeholders, including investors, utilities, and policymakers. These recommendations address the opportunities and challenges associated with deploying novel energy solutions within established energy systems, informed by insights gained from quantitative models.

Next, the research will focus on decision-making for selecting a novel energy technology to address specific stakeholder needs. Energy systems are challenging to plan and analyze due to their complexity, which stems from the heterogeneity of and dynamic interdependence among subsystem components, as well as the uncertainty related to their future state. Traditional approaches to analyzing energy strategies and decision-making tools are valuable for specific applications, such as economic assessments or detailed analyses of specific aspects of an energy system. However, they do not facilitate the initial high-level decision-making process that considers all feasible options for a new energy system.

To address these challenges, this dissertation proposes a new decision support framework that comprehensively evaluates energy systems based on the key objectives defined by system stakeholders. This framework allows for considering various perspectives, including economic, technical, and social aspects. The proposed framework employs Systems Thinking (ST) and Systems Engineering (SE) principles and tools, specifically a concept exploration approach and MBSE, combined with multicriteria decision analyses.

The proposed framework is demonstrated in a case study for selecting the conceptual solution for a novel energy system tasked with clean hydrogen production. This case study focuses on demonstrating that the proposed framework can aid in making strategic decisions, primarily for investors and utility executives. Four potential system concepts are identified, with three different hydrogen technologies and two energy sources, nuclear and solar. The concepts are evaluated based on the criteria set and ranked by decision-makers, using a multicriteria decision analysis approach.

In summary, this research offers novel and comprehensive approaches to decision-making on a large scale, such as integrating novel energy technologies with the existing energy systems, and on a small scale, such as identifying the most optimal energy system solution to address specific stakeholder needs and constraints.

1.2 Research Objectives

The purpose of this research is to develop a holistic multidisciplinary decision-making approach based on the methods and principles of ST and SE using MBSE tools.

The decision support framework aims to provide an understanding of:

- The opportunities and challenges of a large-scale deployment of novel energy technologies given economics, demands, available resources, and social aspects like federal policies
- How conceptual system designs can support the identification and selection of the optimal energy system solution for a specific need, given a set of constraints.

The high-level analysis of energy technology long-term deployment is supported by a SD model reflecting the specifics of the given technology, costs, resource availability, demands, and policies. An MBSE approach is used to model conceptual architectures of an energy system, enabling a comprehensive trade-off analysis supporting an informed selection of the optimum system architecture.

The primary research question this dissertation will address is: **Can systems thinking and systems engineering principles and tools be used to develop a framework supporting decision-making for investment strategies in nuclear-based hydrogen production?** The research objectives that will address this question are:

Research Objective 1: Conduct a comprehensive literature review on publications related to the transition of energy systems to sustainable and resilient solutions. Focus is on understanding factors that influence the deployment of new energy technologies, identifying opportunities and challenges, and examining decision-making approaches and tools that support these decisions, and as a result, identify shortcomings in the state-of-the-art methods and tools for decision-making for energy systems.

Research Objective 2: Evaluate ST and SE disciplines as foundational approaches for developing a novel decision-making framework for energy systems. Examine MBSE tools as potential bases for the decision-making framework solutions addressing the needs of comprehensive assessments of novel energy systems.

Research Objective 3: Explore the dynamics and factors influencing the commercialization and integration of new energy systems into existing infrastructures to provide insights into various aspects, such as technological advancements, policy and regulation, economic considerations, and infrastructure capabilities, that play crucial roles in the energy transition. The objective is supported by smaller tasks:

- Develop a model for a mature technology like wind energy to model dynamics between energy capacity growth and factors affecting commercialization, and validate the model using historic capacity growth and cost data.
- Use the same model with adjusted technology-specific inputs to analyze the deployment of another energy technology, specifically utility-scale solar PV, to confirm the model's technology-inclusive capabilities to analyze the dynamics of deployment of novel energy technologies.
- Adjust the model to represent the specifics of clean hydrogen technology to analyze potential futures of its deployment. Given that the technology is at the very early stage of deployment, there is no adequate historical data to calibrate the model, but the model will highlight factors with the largest impact on successful technology commercialization, providing valuable information for decision-makers such as policy makers and investors.

Research Objective 4: Develop a decision support framework for configuring energy systems on a smaller scale, leveraging SE principles and tools to minimize risks associated with suboptimal system configurations that do not align with stakeholder requirements or regional conditions. Use the hydrogen system as a case study for the decision support framework.

1.3 Dissertation Overview [1]

Chapter 2 provides a comprehensive examination of the current U.S. energy system, focusing on primary energy sources, consumption patterns, and the impact of the energy economy on transitioning to sustainable energy sources. It highlights the potential role of hydrogen in reducing carbon emissions and supporting industrial processes, as well as current hydrogen usage and projected demand growth. The chapter also discusses the challenges of clean hydrogen production and the need for robust decision-making approaches. Traditional decision-making methods' limitations are identified, underscoring the necessity for new methodologies that integrate multidisciplinary insights to support sustainable energy transitions.

Chapter 3 explores the complexity of energy systems and advocates for interdisciplinary approaches to address their challenges. It introduces ST as a holistic approach that considers internal and external system interactions, facilitating better decision-making through understanding complex interactions and long-term perspectives. The chapter also defines SE as an interdisciplinary approach that ensures the successful realization of complex systems by connecting various engineering disciplines, evaluating stakeholder needs, and applying standardized methods, all necessary aspects of a comprehensive analysis of a complex system like a novel energy system. The chapter discusses specific methods and tools, such as SD and MBSE, emphasizing their role in managing complexity and increasing project success rates. The integration of ST and SE principles is highlighted as essential for developing a comprehensive decision-making framework for energy systems.

Chapter 4 examines the deployment of novel energy technologies, focusing on commercialization and technology diffusion dynamics. The chapter identifies key factors influencing energy

[1] This dissertation contains works published in journals and presented at conferences. In these cases, the works are reproduced within this dissertation and have been reformatted to meet the dissertation style guidelines.

system transitions, such as government policies, technological advancements, social acceptance, and environmental concerns. It explores technology diffusion dynamics using Causal Loop Diagrams (CLD) and models key factors influencing adoption. The chapter presents a SD model for understanding the commercialization paths of onshore wind and utility-scale solar PV energy systems, demonstrating the model's validity through historical and projected capacity data comparisons. Sensitivity studies and scenario analyses highlight the significance of resource availability, willingness to invest, and technological learning on capacity growth and LCOE.

Building on the capabilities of the developed SD model for wind and solar energy systems, an expanded model is developed for a clean hydrogen generation energy system at the very early stages of commercialization. The general dynamics of novel energy system adoption provide validation based on the historical data for the wind and solar systems, which provide the foundation to predict the potential future for other novel energy technologies like clean hydrogen. While the main factors influencing commercialization success remain largely the same, nuances of each specific technology necessitate additional details and considerations, as was observed during the hydrogen model development.

The chapter concludes with implications for policymakers, investors, and industry stakeholders and outlines future research directions.

Chapter 5 proposes a new decision support framework that evaluates energy systems based on stakeholders' key objectives. The framework employs ST and SE principles, using a concept exploration approach and MBSE for systems analysis, combined with multicriteria decision analysis. The framework process consists of three phases: needs analysis, concept exploration, and concept definition. A trade-off analysis is conducted in the concept definition phase, allowing systematic comparison of various options. The framework's utility is demonstrated through a case study on clean hydrogen production, showing its potential to aid strategic decision-making for investors and utility executives. The framework is flexible and can be modified to address the needs of other entities, like policymakers.

Lastly, Chapter 6 summarizes this dissertation, including a summary of findings and recommendations, identifies the limitations of this research, and proposes ideas for future research.

Appendix A is a text version of the wind SD model, and Appendix B is a text version of the hydrogen SD model.

Chapter 2

Status of Energy Systems and Approaches for Decision-Making [2]

This chapter provides an overview of the intricate and multifaceted landscape of the U.S. energy system, exploring its various elements and the complex interactions among them. It provides a comprehensive overview of the current state of the U.S. energy system, including electricity generation, non-electrical energy sources, and energy consumption patterns. The chapter also highlights the critical role of the energy economy in shaping the transition to sustainable and resilient energy sources. Furthermore, it examines the potential of hydrogen as a key player in the future energy system, emphasizing its ability to enhance energy security, reduce carbon emissions, and support diverse industrial applications. Finally, the chapter discusses the challenges and shortcomings of existing decision-making approaches for complex energy systems and underscores the need for new methodologies that integrate multidisciplinary insights and address uncertainties.

2.1 Description of the U.S. Energy System

A national, regional, and even local energy system is a complex enterprise of many elements and their interconnections. Figure 1.1 is a schematic of the overall U.S. energy system. The system elements belong to the general categories described in this section.

Sources of Electricity: In the United States, as of 2023, most electricity is generated from fossil fuels, specifically natural gas and coal [2]. Fossil-fuel-based energy sources are associated with heavy carbon dioxide (CO_2) emissions, leading to a significant push for the transition to zero- or low-emission sources for electricity generation, such as renewable and nuclear energy.

[2] This chapter contains works published in [1]. The works are reproduced within this chapter and have been reformatted to meet the dissertation style guidelines.

Renewable energy sources include solar- and wind-based power generation as well as hydropower and smaller sources such as geothermal and wave energy.

Energy Sources Other Than Electricity: Large industrial processes rely on energy sources other than electricity (e.g., steam). The energy sources for the industrial processes in the United States are also mainly fossil fuels (i.e., natural gas, coal, and oil). Many industrial processes also require feedstock other than energy to produce their products (e.g., hydrogen and oxygen). For example, the steel manufacturing industry uses large amounts of hydrogen and oxygen, both generated mostly from fossil-fuel-based feedstock using processes with heavy CO_2 emissions. These areas are illustrated with process energy sources and sources of hydrogen in Fig. 1.1.

Energy Consumption: The energy consumers rely on electricity and non-electrical energy sources. Many industrial processes and the transportation sector use primarily fossil-fuel-based fuels. These hard-to-electrify industries drive the need to develop breakthrough clean energy solutions beyond electricity. Figure 2.1 shows U.S. energy consumption by source and by sectors [3].

Understandably, energy consumption directly affects demands for electricity and non-electrical energy. The types of energy sources to be used to supply the demands depend on economic aspects of the energy system, a separate yet closely-connected section of the energy system.

Energy Economy: The energy transition is significantly influenced by the energy economy, which encompasses the production, distribution, and consumption of energy. The interplay between energy markets, federal policies, and projected energy demands all shape the trajectory of this transition.

Energy prices of incumbent technologies, such as natural gas-based electricity generation, play a pivotal role. When natural gas prices are low, it can hinder the adoption of renewable energy sources as natural gas becomes a more economically attractive option [4]. Conversely, high natural gas prices can accelerate the shift toward renewables by making them more competitive in terms of cost [5]. Additionally, fluctuations in global oil prices can impact the broader energy market. High oil prices can drive investments in alternative energy sources, while low oil prices can reduce the economic incentive to invest in clean energy technologies, slowing the transition [6, 7].

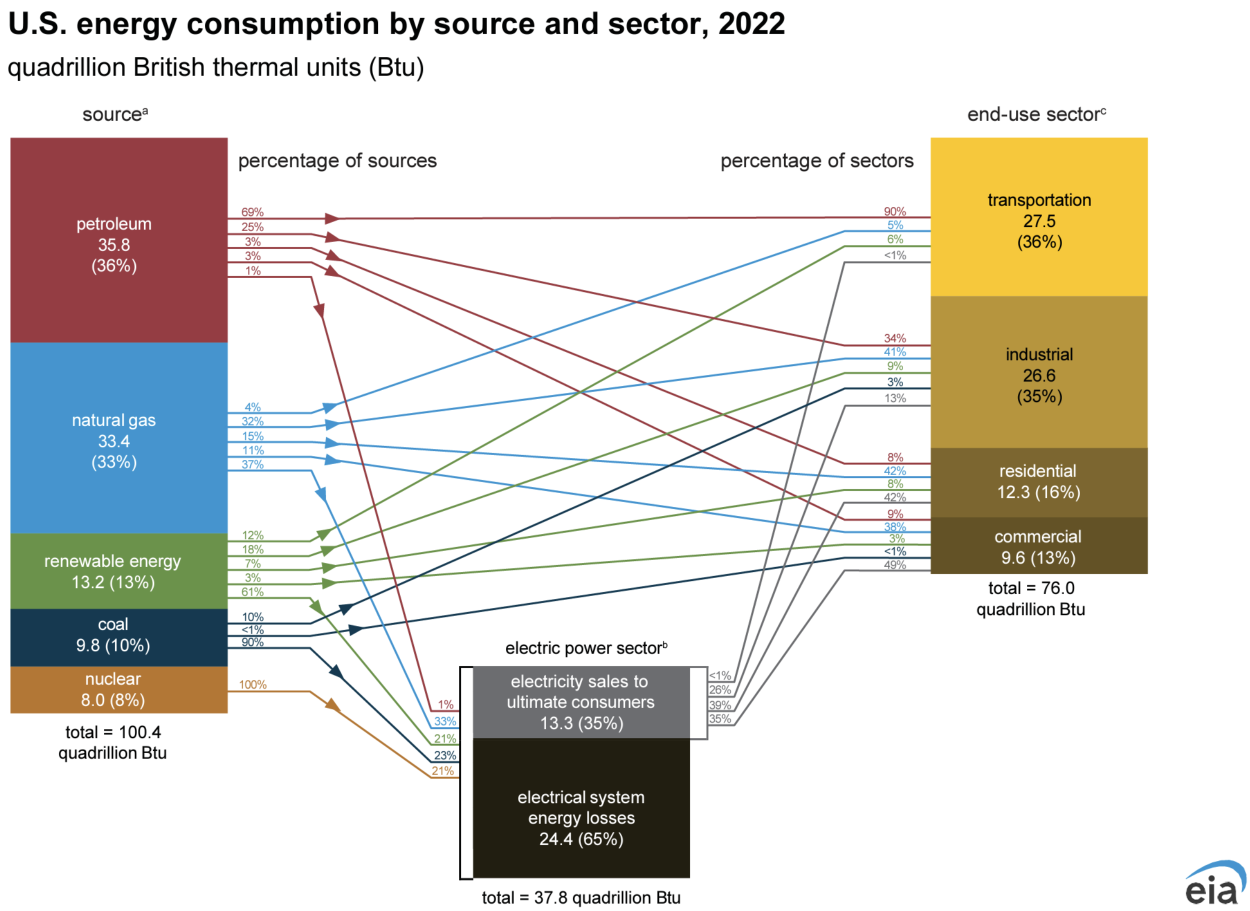

Figure 2.1: U.S. energy consumption by source and sector [3].

U.S. federal policies are also crucial in shaping the energy transition. Climate change policies aimed at reducing greenhouse gas (GHG) emissions, such as the implementation of carbon pricing or emissions trading systems, can incentivize the adoption of clean energy [8–10]. Investments in research and development (R&D) for renewable energy technologies and energy efficiency measures are critical components of climate change policy [11].

In terms of energy security, reducing dependence on imported fossil fuels by diversifying energy sources enhances national security and stabilizes energy prices. Additionally, diversifying energy sources can make the energy sector more resilient to disruptions, such as natural disasters or geopolitical conflicts [11, 12].

Projected energy demands, both short-term and long-term, also impact the energy transition. In the short term, energy demand is influenced by economic conditions, weather patterns, and techno-

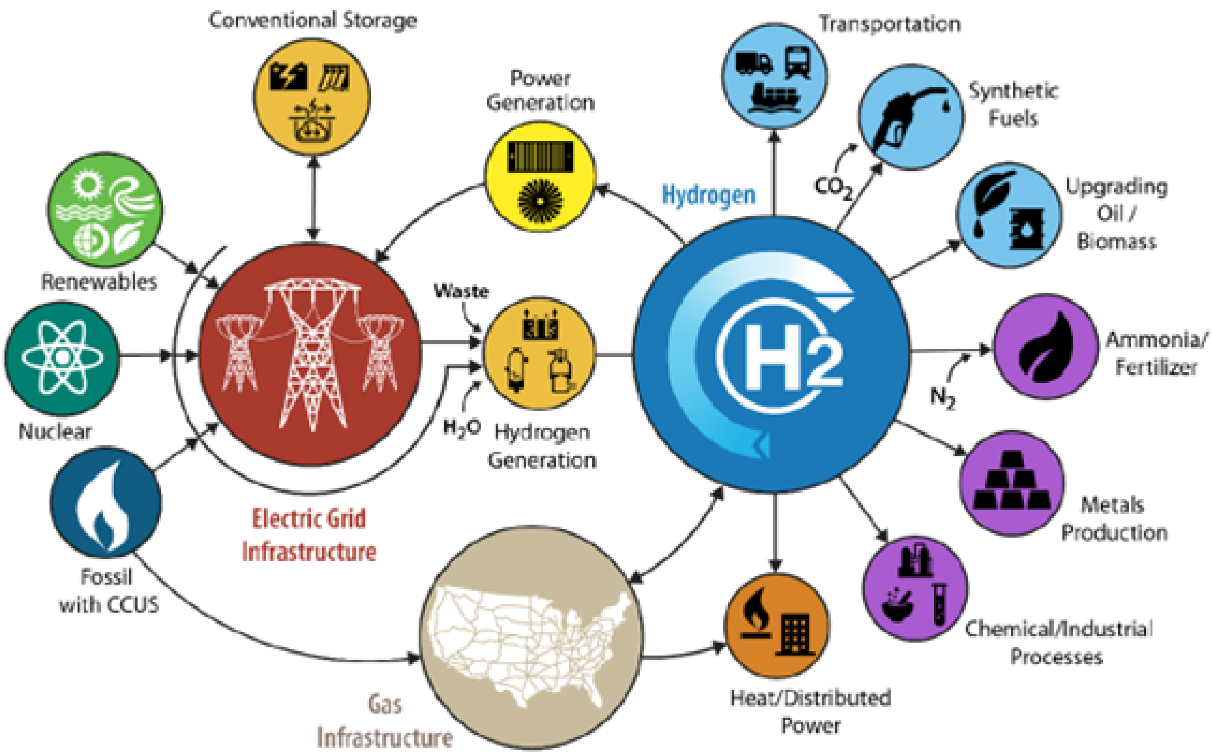

Figure 2.2: DOE's H2@Scale initiative to enable decarbonization across sectors using clean hydrogen [14]

logical advancements. Long-term energy demand projections consider factors such as population growth, urbanization, and economic development [4]. Sustainable growth requires a significant increase in clean energy capacity to meet rising demand while reducing carbon emissions [13].

In summary, the U.S. energy system is influenced by the interplay of energy market dynamics, federal policies, and projected energy demands. The evolving landscape of energy prices, driven by both incumbent and alternative technologies, along with supportive governmental policies, are key factors that will determine the pace and success of the transition to sustainable and resilient energy.

2.1.1 Hydrogen as Part of the Energy System

DOE is pursuing an ambitious Hydrogen Program Plan [14] where hydrogen enables energy pathways across numerous applications and sectors as shown in Figure 2.2.

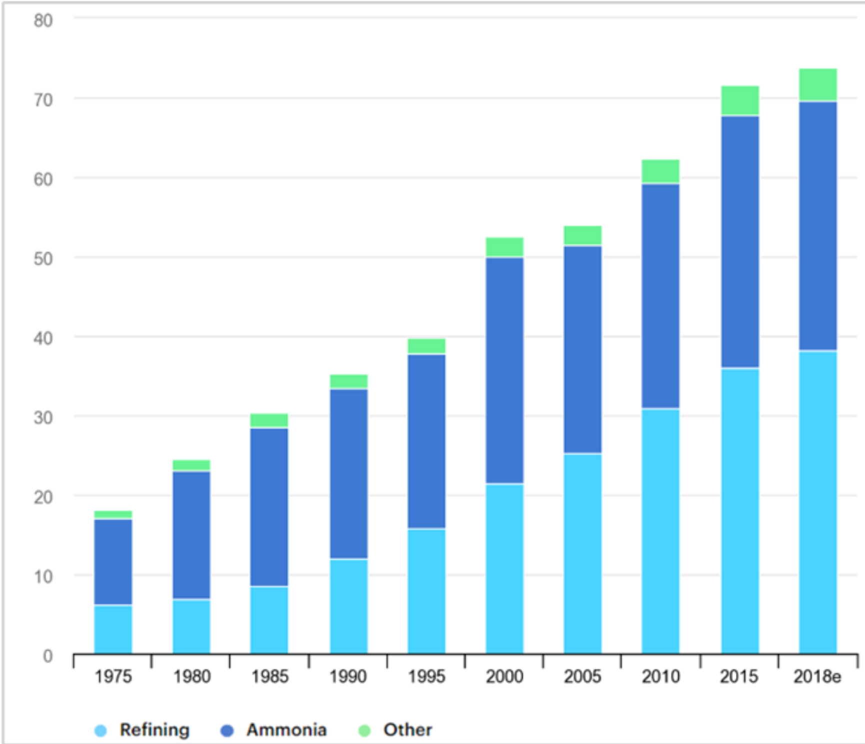

Figure 2.3: Global hydrogen demands 1975–2018 [15]

The current hydrogen demand is mainly in petroleum refinement and ammonia production. However, the demand is expected to grow significantly to support industrial processes (e.g., metal refining, synthetic fuels, chemical production) and new markets (e.g., hydrogen fuel cell powering light- and heavy-duty electrical vehicles, injection into natural gas pipelines to lower carbon emissions) [15]. The growing demand up to 2018 is shown in Figure 2.3, and the projected demand to 2030 is shown in Figure 2.4.

Understanding the significant potential of clean hydrogen, the United States, as well as many other countries, have made considerable investments into R&D, expediting the technical readiness and scalability of hydrogen production technologies and infrastructure [14, 16]. Significant efforts have been devoted to technological advancements of systems and components as discussed in [17, 18], with the electrolysis-based hydrogen generation technologies now becoming mature for large-scale industry applications [19]. The feasibility of coupling nuclear plant operations with hydrogen production has been explored and demonstrated by various studies [19–23]. Lastly, many economic analyses have investigated the viability of hydrogen energy markets [24–26].

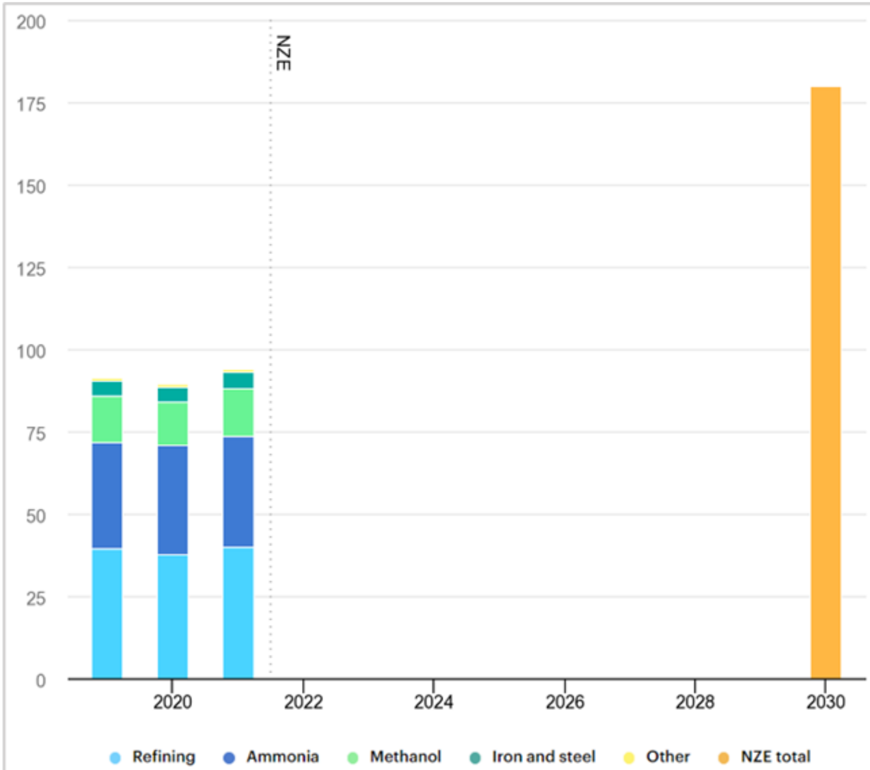

Figure 2.4: Global hydrogen demand projection to 2030 [15]

However, clean hydrogen has not been sufficiently considered as a part of a macro energy system. The existing research efforts have been focused on particular topic areas, or domains, such as technology evaluation, economic feasibility, market assessments, and regulatory concerns. These topic-focused assessments, while extremely valuable, may be missing important insights about the interconnections of the energy system elements. Another observation made for the existing studies of clean hydrogen systems is the fact that systems engineering practices, methods, and tools are not considered. This could be due to the fact that the nuclear industry has not yet fully embraced the practice of SE in general and MBSE more specifically even though other industries have used SE for decades and are now in the process of transitioning to MBSE to take advantage of numerous benefits.

Hydrogen offers a unique opportunity to increase the resiliency of the energy sector while making a dramatic impact on decarbonization goals. Per [14], "Given its potential to help address the climate crisis, enhance energy security and resilience, and create economic value, interest in producing and using clean hydrogen is intensifying both in the United States and abroad. Zero- and low-carbon hydrogen is a key part of a comprehensive portfolio of solutions to achieve a sustainable and equitable clean energy future". The same is echoed in [27]: "Hydrogen deployment is an opportunity to provide benefits to communities across America, including quality jobs, climate benefits, and decreased air pollution".

The reason why hydrogen is seen as the solution to multiple goals in the energy sector lies in its ability to act as an energy source to produce electricity as well as being the direct energy source for non-electrical energy consumers, such as the heavy transportation sector that is difficult and, in many cases, impossible to electrify. In addition, clean hydrogen can significantly reduce carbon footprints by replacing the hydrogen currently produced from fossil-fuel-based sources. As such, a reliance on hydrogen offers significant possibilities to improve the energy system by increasing its security and resilience and decreasing carbon emissions, all while supporting and strengthening the national economy. The next sections provide an overview of current hydrogen uses and the potential role of hydrogen in the improved energy system, given the successful deployment and adoption of clean hydrogen strategies and technologies.

Current Use of Hydrogen

Hydrogen's current primary use is to support multiple industrial processes as an energy source or feedstock. Hydrogen consumption in the United States as of 2021 is detailed in Figure 2.5 [14]. Currently, 99% of hydrogen in the United States is produced from fossil fuels, with 95% from nat-

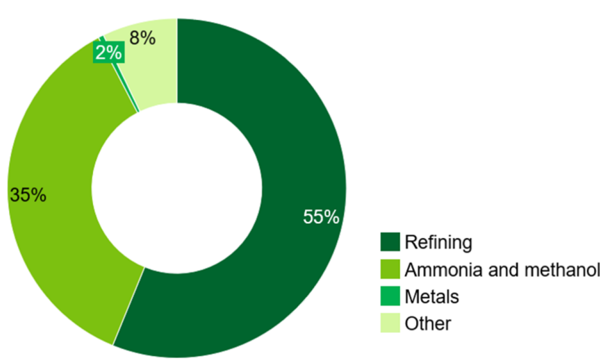

Figure 2.5: Consumption of hydrogen in the United States by end-use in 2021 [14]

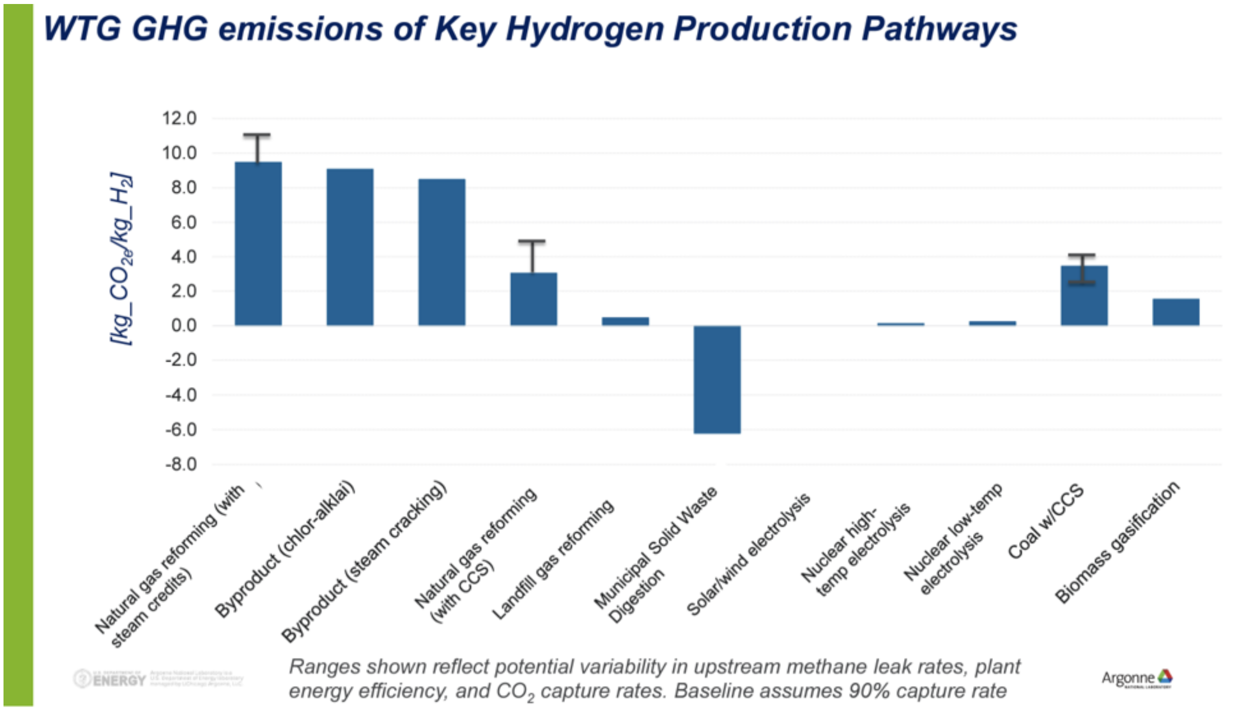

Figure 2.6: Well-to-gate GHG emissions of key hydrogen production technologies [29]

ural gas by Steam Methane Reforming (SMR) and 4% by the partial oxidation of natural gas from coal gasification [28]. Only 1% of hydrogen in the United States is produced from electrolysis, where water is split into hydrogen and oxygen using an electrochemical process. Fossil-fuel-based hydrogen production is very heavy on CO_2 emissions, as shown in Figure 2.6.

The transition of hydrogen generation from emission-heavy processes to low- or zero-carbon technologies in itself will dramatically impact national climate goals and decrease reliance on fossil fuels. However, the impact increases exponentially when reliance on hydrogen expands, as discussed in the next section.

Role of Hydrogen in an Improved Energy System

The energy consumed in the United States as of 2022 is produced mostly from fossil-fuel-based sources, as shown in Figure 2.1. In fact, 79% of energy is generated from fossil fuels like petroleum, natural gas, and coal, as seen in Figure 2.5. Such disproportional and heavy reliance on fossil-fuel-based energy sources may challenge both the resiliency and independence of the U.S. energy system. The vulnerability of the European energy system due to heavy dependence on fossil fuel energy sources was clearly observed after the disruption in the supply chain following the Russian invasion of Ukraine in 2022. To enhance energy system resilience, the United States must diversify energy sources to increase the reliance on renewable sources and alternative energy solutions.

Hydrogen can play a major role in achieving the diversification and resiliency goals of the U.S. energy system. The reason is that hydrogen can support a wide variety of energy consumers, either by providing electricity during peak demand hours or directly serving as an energy source for industrial applications that cannot be easily electrified.

As shown in Figure 2.5, the current consumption of hydrogen is primarily in the oil refining and ammonia and methanol production industrial sectors. However, hydrogen can support multiple other industrial sectors, including heavy-duty transportation, steel and gas manufacturing, and the production of synthetic fuels for marine and aviation applications [14]. As of 2024, hydrogen's portion of the total energy consumption is very small, less than 0.01% [30]. However, this usage can change with a dedicated focus on diversification of energy sources, as hydrogen has the potential to replace liquid fuels, the currently dominant energy source, in many applications in the industrial and transportation sectors.

These industrial sectors are hard or even impossible to electrify, which makes hydrogen-based energy an attractive solution compared to renewable energy sources. Hydrogen-based energy also comes with the significant benefit of being available 24/7, rain or shine, which is a must-have condition for many industrial applications that cannot be satisfied by intermittent renewable energy, even with large batteries.

The potential demand for clean hydrogen to decarbonize industry, transportation, and electrical power co-generation can reach 10 MMT/year by 2030, 20 MMT/year by 2040, and 50 MMT/year by 2050 [14] as shown in Figure 2.7. This projected demand in clean hydrogen, shown in Figure 2.7, does not include the need to substitute the current CO_2-heavy hydrogen production with the volume of about 10 MMT/year as per the 2015 estimate [24]. The substitution of CO_2-heavy

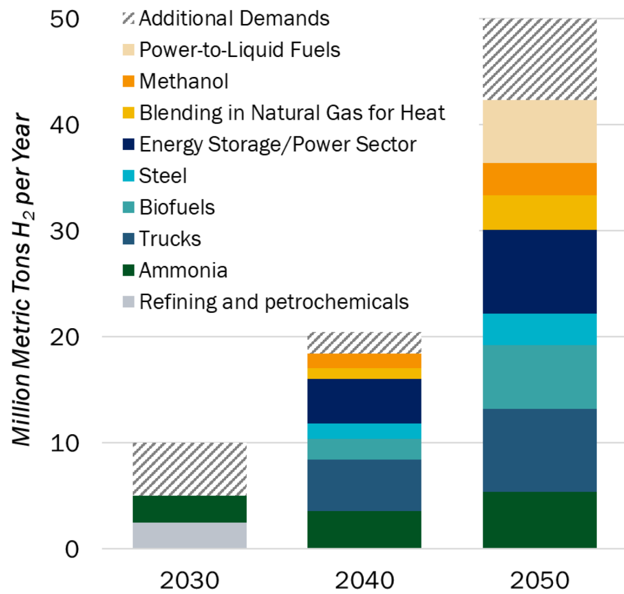

Figure 2.7: Potential demands in clean hydrogen to decarbonize industrial applications [14]

hydrogen with clean hydrogen is a near-term opportunity to dramatically reduce CO_2 emissions and demonstrate pathways for deploying clean hydrogen technologies.

While the importance of clean hydrogen to improve energy systems is absolutely clear, the success of hydrogen deployment at scale is highly uncertain. The reasons are typical for any novel system, such as technology maturity, acceptance by consumers, infrastructure readiness, supply chain, and workforce readiness, all of which contribute to large uncertainties for investors.

One of the primary challenges for clean hydrogen deployment is the cost—the unit cost of hydrogen production via electrolysis on average is around \$5.5 per kg of hydrogen as of 2025 while the cost of hydrogen production via SMR is roughly \$1.1 per kg as of 2025 [27], five times cheaper. The cost of clean hydrogen is expected to decline significantly by 2030, roughly to \$3.2 per kg [27]. As demonstrated in Section 4.5, there is a potential for clean hydrogen costs reducing to around \$1 per kg by 2050 if hydrogen deployment progresses.

Nuclear energy has a great opportunity to diversify its operational strategies by investing in an alternative revenue source, clean hydrogen. Nuclear power plants (NPPs) are uniquely well-suited to generate hydrogen compared to other clean energy sources due to the fact that nuclear energy is clean, extremely reliable, and available 365/24/7. Understandably, such a commitment would require a large investment, and nuclear utilities must carefully evaluate options and strategies for expanding their operations into hydrogen generation. The next section outlines details of nuclear-based hydrogen generation that may significantly impact the success of coupled nuclear-hydrogen generation systems.

2.2 Decision-Making for Complex Systems

This section provides an overview of the decision-making process in general and, more specifically, the methods and tools used for decisions in energy systems. Section 2.2.1 describes how we, as humans, make decisions and explains why humans struggle with decisions for complex systems. Section 2.2.2 describes approaches used to analyze energy systems along with supporting methodologies and tools. Lastly, Section 2.2.3 outlines the shortcomings of existing decision-making approaches for energy systems.

2.2.1 Humans and Decision-Making

We make decisions, small or large, important or not, using four simple steps: 1) understand the problem or need, 2) gather information and identify alternatives, 3) evaluate alternatives, and 4) select the best solution within our understanding. Most contemporary decision-making theories operate on the premise of rationality, assuming that decision makers consistently select the optimal course of action available to them, ending with the best possible solution [31]. However, these theories often overlook the challenge of determining what exactly constitutes the best action. They fail to differentiate between decision scenarios involving just two options and those involving ten, twenty, or even thousands of choices. Numerous studies have suggested that, when confronted with complex decisions, humans rely on heuristics—solutions derived through trial and error or loosely defined guidelines—to guide their choices [32–34].

A considerable body of research indicates that individuals struggle to make rational decisions when faced with an abundance of options, a phenomenon commonly referred to as information overload. Information overload refers to the discrepancy between the sheer volume of information available and humans' capacity to process it effectively. This surplus of information can impede problem-solving abilities and task execution, consequently influencing decision-making. Human brains have finite capacities for information retention, and excessive data can hinder their ability to arrive at rational decisions [35–37]. In fact, [36] suggests that the span of human memory is about seven pieces of information with some small variation.

This natural limitation of the human brain to process information necessitates measures to assist with decision-making, a *decision support system*, especially for decisions for complex problems like the ones in energy systems.

2.2.2 Existing Approaches for Analysis of Energy Strategies

Energy systems are difficult to analyze due to their complexity, which stems from the heterogeneity of and dynamic interdependence between subsystem components and the complexity of the networks that connect them, as well as the uncertainty related to their future state [38]. The complexity of evaluating energy and environmental issues is pointed out by many research studies [39–44] that point to the many sources of uncertainty, long time frames, heavy capital investments, multidisciplinary affecting factors, and a large number of stakeholders with often competing objectives. As such, an application of formal decision analysis methods is warranted and highly encouraged.

The general techniques for capital investments are discussed in [45]. The majority of the methods are economic measures (e.g., Internal Rate of Return (IRR) and Net Present Value (NPV)), with only a few capable of integrating uncertainties and non-economic measures, such as real options and sensitivity analyses. IRR and NPV are financial metrics used to assess the profitability and viability of investments. The NPV of an investment represents the present value of its associated cash inflows and outflows, discounted at the market's required rate of return. An investment is financially beneficial and adds value if it has a positive NPV, while it is considered value-diminishing and should be rejected if its NPV is negative [46]. The IRR is the break-even rate of return for an investment. If an investment's IRR exceeds the market's required return, then the investment is financially sound. In contrast, an investment is not financially viable if its IRR falls below the required rate of return that compensates for its risk [46].

Decision-making processes in the energy sector have advanced, drawing from broader investment strategies but tailoring techniques to suit the unique needs of energy systems. A study by Strantzali [40] identifies Life Cycle Assessment (LCA), cost-benefit analysis, and multicriteria decision-making as the top modeling methods for renewable energy investments. Liu's 2021 review [44] adds that, within offshore wind power investment, LCOE, Modern Portfolio Theory, and Real Option Theory are also prevalent. Reference [44] categorizes decision-making techniques into four main groups: basic, advanced, those accommodating uncertainties, and multicriteria methods. Basic methods encompass LCA and life cycle cost—which assess environmental impacts and economic performance across a system's life span, respectively—as well as discounted cash flow, a conventional tool for early-stage investment evaluation that employs NPV and IRR metrics.

Introducing novel energy technologies to the established energy system adds another layer of complexity and is associated with numerous uncertainties—is the new technology mature enough, can it be successfully integrated with the rest of the energy system elements, are the costs competitive with incumbent technologies, and many others. Understanding the energy transition to novel technologies is imperative for successful investment decision-making as well as for policymaking. Multiple approaches and models exist that evaluate the national energy system as well as potential energy transitions, as discussed below.

SD models use feedback loops and stock-flow diagrams to simulate the dynamic behavior of energy systems over time [47–54]. These models capture the interactions between different components, such as technology, policy, economics, and social factors, making them particularly useful for understanding long-term trends, feedback effects, and complex interdependencies.

Agent-based models simulate the actions and interactions of individual agents, such as households, firms, and policymakers, to understand how their behaviors contribute to the overall SD [55–58]. These models are effective for studying market dynamics, adoption behaviors, and the social diffusion of technologies, capturing the heterogeneity and individual decision-making processes.

Optimization models aim to find the optimal configuration of the energy system based on criteria like cost minimization, emissions reduction, or energy efficiency [59–64]. The optimization could be performed using other models, e.g., agent-based models, as the core part to find optimal solutions. Optimization models are well-suited for planning and designing energy systems, making investment decisions, and identifying least-cost pathways.

Integrated assessment models combine insights from multiple disciplines, including economics, environmental science, and technology, to assess the interactions between human and natural systems [65–68]. Integrated assessment models are often used to evaluate the long-term impacts of climate policies, offering a comprehensive and multidisciplinary perspective.

LCA models evaluate the environmental impacts associated with all stages of a product's life, from raw material extraction through production, use, and disposal [69–72]. LCAs provide detailed environmental impact assessments, making them useful for comparing different energy technologies in terms of their environmental impact and identifying areas for improvement.

Hybrid models combine elements from different modeling approaches to leverage their respective strengths. For instance, a hybrid model might integrate SD for long-term trends with agent-based models for individual behavior analyses. This approach offers a more comprehensive and nuanced analysis by addressing complex, multifaceted research questions.

2.2.3 Shortcomings of Existing Approaches to Decision-Making

Methods described in Section 2.2.2 have strengths and weaknesses when considering their application for the energy systems domain.

The discounted cash flow method has been successfully used for decades to evaluate investment alternatives for various domains, including energy systems. However, the finance-focused assessments tend to be biased towards short-term, less strategic investments whose benefits are easy to quantify [73]. The economics-based investment appraisal methods are also considered inadequate and incomplete for supporting evaluations of strategic investments because they do not address intangible attributes (e.g., goals for reducing GHG emissions or social acceptance). As a result, the discounted cash flow method is only considered suitable for short-term investment projects where market uncertainties are small. As noted in [44], due to limited flexibility, the discounted cash flow method is not appropriate for evaluating energy-related projects due to a volatile investment environment, and it should be used in combination with other methods rather than alone.

LCOE is the economics-based methodology commonly used for evaluating strategies and investments for energy systems. It is appropriate and applicable for a wide range of scenarios with different system strategies, investment amounts, regions, and power generation technologies [44]. However, as with the discounted cash flow method, it is not suitable to comprehensively evaluate energy-related projects because of its inability to incorporate multidisciplinary insights. Furthermore, the economics-centered approach and tools may bias decision-makers against long-term strategic investment projects, which would impede business innovations [73].

The multicriteria decision-making methods and tools are generally applicable for evaluating energy systems due to their capability to include multiple variables and assess strategies even when competing objectives exist. One should be careful with applying a multicriteria decision analysis when inputs are based on incomplete or vague data, since this method may produce unrealistic and misleading results [44]. A significant concern for evaluating strategies in the energy domain is that many inputs are indeed based on imprecise data, especially when novel energy systems are evaluated.

The approaches and models for energy system transition are well-suited for their applications. However, the models are complex, requiring experts to both develop them and interpret the results. On the other hand, decision-makers desire something that describes the problem of novel energy technology in sufficient detail and provides a clearer understanding of underlying issues and potential solutions. In order to make better-informed decisions, the stakeholders must understand system behaviors, both expected and emergent, to develop solutions with built-in mitigation strategies for unwanted dynamics.

2.3 Conclusion

This chapter presents a detailed examination of the U.S. energy system, focusing on its complexity and the interplay of various elements. It provides an overview of the current state of the energy system, describing the primary sources of electricity and non-electrical energy, as well as patterns of energy consumption. The chapter also discusses the influence of the energy economy on the transition to sustainable energy sources, highlighting the impact of energy prices, federal policies, and projected energy demands.

The potential role of hydrogen in the future energy system is explored in depth, emphasizing its ability to support various industrial processes and reduce carbon emissions. The chapter outlines current hydrogen usage, primarily in petroleum refinement and ammonia production, and projects significant growth in demand for hydrogen in new markets and industrial applications. It also covers the challenges associated with transitioning to clean hydrogen production and the need for comprehensive decision-making approaches to support this transition.

Lastly, the chapter discusses the decision-making process for complex systems, highlighting the limitations of traditional decision-making methods when applied to the energy sector. The existing approaches for analyzing energy strategies and solutions are reviewed, identifying their strengths and weaknesses. Lastly, the need for new decision-making methodologies is emphasized, where new approaches to decision-making can integrate multidisciplinary insights, address uncertainties, and balance competing objectives to support the transition to a sustainable and resilient energy system.

Chapter 3

Systems Engineering as a Foundation of a New Approach for Decision-Making [3]

3.1 Introduction

As discussed in Section 2.1, the energy system is a very complex system with multiple interconnected elements. The ST and SE are disciplines that address the challenges of complex, multidiscipline systems with evolving dynamics. This chapter describes the principles of these two disciplines that provide the foundation for the novel evaluation approaches in decision-making for energy systems. Section 3.3 provides an overview of ST and SE methods and tools used in this research to develop the novel decision-making framework.

3.2 Foundational Disciplines

3.2.1 Systems Thinking

ST focuses on the interactions of internal system elements and also the external interaction of the system with the elements of the larger system the current system is part of. ST is defined in [75] as “a way of thinking about, and a language for describing and understanding, the forces and interrelationships that shape the behavior of systems. This discipline helps us to see how to change systems more effectively, and to act more in tune with the natural processes of the natural and economic world.” ST is one of the core competencies defined in INCOSE SE Competency Framework [76], and it is based on the *systems science*, which INCOSE defines as a “transdisciplinary approach interested in understanding all aspects of systems” [77].

[3] This chapter contains works published in [74]. The works are reproduced within this chapter and have been reformatted to meet the dissertation style guidelines.

It is important to define a system to understand the concept of ST. In [78], a system is defined as "an interconnected set of elements that is coherently organized in a way that achieves something". This simple definition reveals three major elements that must be present in each system—elements, interconnections, and purpose. This leads to one of the key principles of ST—a system is more than the sum of its parts. The seven key systems principles are:

1. **Holism:** A system is more than the sum of its parts: elements, interconnects (interdependence), and purpose
2. **Purpose:** The (true) purpose of a system is the biggest determinant of its structure
3. **Three Systems:** Systems come in (at least) threes: system context, system of interest, enabling System
4. **Boundaries:** Systems boundaries depend on the perspective, purpose, and area of responsibility
5. **Evolution:** Systems have a life cycle, and they evolve
6. **Emergence:** The complexity of systems is often due to emergent (nonlinear) behavior
7. **Feedback:** Wanted or unwanted emergent (nonlinear) behavior is often determined by feedback loops (with delays) or interactions within and between the three systems.

ST relies on a holistic approach that is capable of connecting and contextualizing systems, system elements, and their environment to understand difficult-to-explain patterns of organized complexity [77]. This capability to understand and represent complex interactions is imperative for decision-making for complex systems, which is why ST is seen as the foundational methodology to build the decision support framework researched in this dissertation.

Throughout each phase of system development, systems engineers should employ ST. This task involves considering the system holistically, taking into account the entire life cycle, including stakeholders' expectations, user needs, technological advancements, and environmental, social, and policy influences. ST is a mindset that views the parts of a system in relation to each other and to other systems, rather than in isolation. The systems engineer embodies this approach, ensuring that from design to production, the system meets customer requirements, satisfies user needs, interacts smoothly with other systems, and is economically viable [79]. A systems thinker can see the big picture, recognize interconnections, consider multiple perspectives, and maintain creativity without getting bogged down in details, effectively anticipating future outcomes. This mindset is a must when considering a novel energy system that will be integrated into the large, complete energy system involving many elements and stakeholders.

When envisioning a novel energy system, one must also anticipate unexpected behaviors, given the extreme complexity of the energy sector and the integration of a new player into a well-established environment. These unintended consequences can be mitigated by proactively considering how the system will perform and making necessary adjustments from the early stages, starting from system conceptualization. It is essential to adopt a long-term perspective when addressing the need and proposing solutions, as requirements and worldviews can and will change. Technical and societal advancements present new challenges and opportunities that must be integrated into the system design. While revolutionary energy concepts are beneficial, single-purpose designs may not align with future trends. Effective leaders design robust, resilient systems and communicate clearly with stakeholders.

3.2.2 Systems Engineering

As defined in [77], "Systems engineering is an interdisciplinary approach and means to enable the realization of successful systems". The objective of SE is to direct and support the development of complex engineered systems, and the discipline of SE is different from traditional disciplines (e.g., electrical, mechanical, structural engineering), as it focuses on a system as a whole. A systems engineer connects multiple traditional disciplines and evaluates system context and stakeholder needs to achieve the optimal system solution. The reliance on SE has a significant effect on project success [80,81], which is a much-needed benefit to ensure the success of complex systems, such as novel energy systems.

While the concepts of SE have been used for centuries (e.g., through an evaluation of the needs for a new system, conceptual designs), the formal discipline of SE is relatively young compared to other engineering disciplines. The SE discipline was formed in the early to middle of the twentieth century with multiple organizations relying on SE principles to analyze, design, and develop various systems. A professional society for systems engineers was formed in 1990 in the United States called the National Council of Systems Engineering (NCOSE), renamed to INCOSE, International Council on Systems Engineering, in 1995. The issuance of the international standard ISO/IEC 15288 in 2002 formalized the discipline of SE [77].

The goal of SE is to support the delivery of the right product (or service) on time and within budget. This goal is supported by the SE objective to provide a common understanding of the system's current state and a common vision of the desired future state shared by system customers and suppliers, achieved by the application of standardized methods and tools throughout the system life cycle.

SE is particularly important for complex systems where traditional engineering and project management practices are no longer sufficient to effectively manage complexity. Multiple studies have demonstrated that the use of SE practices had a significant positive impact on project success—projects that relied on SE methods and tools were up to 80% more successful than projects that did not utilize SE [77].

Specifically, several SE focus areas [82] are used in this research, such as:

- Establishing, balancing, and integrating stakeholders' goals, purpose, and success criteria
- Establishing an appropriate life cycle model, considering the levels of complexity, uncertainty, change, and variety
- Generating and evaluating alternative solution concepts
- While considering both the problem and solution domains, taking into account necessary enabling systems and services, identifying the role that the parts and the relationships between the parts play with respect to the overall system behavior and performance, and determining how to balance all of these factors to achieve a satisfactory outcome.

3.3 Methods and Tools

This section provides an overview of SE principles and tools and their applicability to support decision-making for investments into novel energy systems.

3.3.1 System Dynamics

An SD model is an MBSE tool that leverages feedback loops and stock-flow relationships to examine the intricate interactions within an energy system. Key components of an SD model include:

- Feedback loops, or CLDs, which illustrate the interconnected relationships between different components, such as how a decrease in costs can drive an increase in technology installations, further driving down costs
- Stocks that represent accumulated quantities, such as installed capacity
- Flows, which indicate the rates of change within the system, such as the rate of incremental capacity additions.

Causal Loop Diagrams

CLDs are a valuable tool to clearly and easily represent a system feedback structure. They are excellent for quickly capturing the hypothesis about the causes of dynamics, eliciting and capturing the mental models about the SD, and communicating the important feedback relationships within the system [83].

An example of a CLD is shown in Figure 3.1, presenting the dynamics of a bank account. There are two loops—accumulation and spending. In the accumulation loop, the bank account balance increases with added money from earned interest. The increased account balance earns more money through interest, and interest earnings increase the account balance again. The cycle is continuous, and in this case, it is a reinforcing behavior since a change in one variable results in the other variable changing in the same direction. In this case, an increased account balance causes an increase in interest earned, and increased interest earnings cause an increase in account balance.

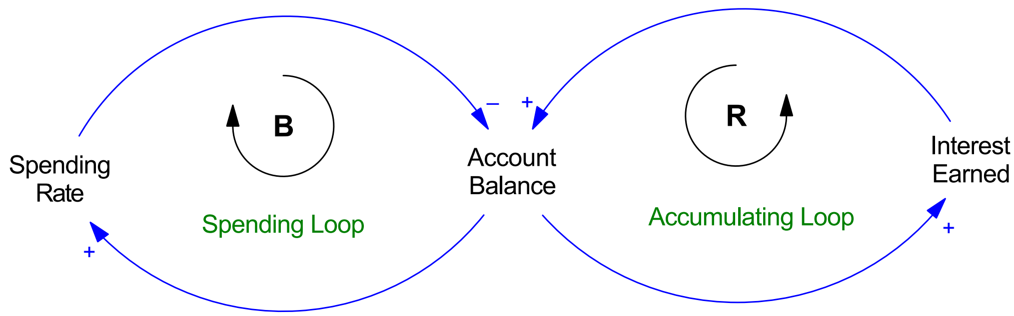

Figure 3.1: Example of a CLD

A positive relationship, depicted by a "+" sign next to the arrow, does not mean that the variable always increases. Instead, it means that a change in one variable causes the other variable to change in the same direction. In the accumulation loop in Figure 3.1, a decreased interest would cause a decreased change in the account balance (i.e., the account balance would be lower compared to what it would have been if the earned interest rate had not changed).

The spending loop in Figure 3.1, on the other hand, has different dynamics. An increase in the spending rate causes a decrease in the account balance. This is negative feedback, depicted by a "-" sign next to the arrow, since a variable changing in one direction causes the other variable to change in the opposite direction. In this case, an increased spending rate results in a decreased account balance below what it would otherwise have been if the spending rate had not decreased. The second relationship in the spending loop is a positive relationship where an increased account balance promotes an increase in the spending rate (i.e., a positive change in one variable causes a positive change in another variable).

Stocks and Flows

Stocks and flows are essential elements that facilitate the representation and analysis of complex systems over time. It is helpful to visualize a bathtub with the water faucet providing inflow and the water outlet draining water out of the bathtub. The water volume in the bathtub corresponds to the stock, while the water entering through the faucet and leaving through the drain represents the flows.

Stocks represent the accumulations or quantities of resources within the system. They function like containers that hold certain amounts of something, such as water in a tank, a population in a city, or money in a bank account. Stocks change over time based on the flows that enter or leave them, providing a snapshot of the system's state at any given moment.

Flows represent the rates at which stocks change over time. They act like pipes that either fill or drain stocks. Examples of flows include the birth and death rates for a population stock, the deposit and withdrawal rates for a bank account stock, and the water inflow and outflow for a reservoir stock.

Mathematics of an SD Model

The mathematics behind a SD model primarily revolves around differential equations, which describe how stocks and flows interact over time. Stocks are mathematically represented as integrals of the net flow rates. The value of a stock at any given point in time is determined by its initial value plus the cumulative net flows into and out of the stock over that period. This relationship can be expressed as an integral in Equation (3.1):

$$S(t) = S_0 + \int_0^t (\text{Inflow}(t) - \text{Outflow}(t))\ dt \tag{3.1}$$

where $S(t)$ is the stock at time t, S_0 is the initial value of the stock, Inflow(t) is the rate of inflow at time t, and Outflow(t) is the rate of outflow at time t.

Flows are typically functions of time and can depend on the values of stocks, external inputs, and other influencing factors. While in some simple cases, these rates may be constant, in more realistic models, they often are variable. For instance, the inflow and outflow rates may change based on the current level of the stock or other parameters in the system.

Due to the complexity of these equations, numerical methods are often employed to simulate SD models. Software tools like Vensim [84], Stella [85], and Powersim [86] are commonly used for this purpose. These SD tools discretize time and apply numerical integration methods, such as Euler's method or a Runge-Kutta method, to approximate the solutions of the differential equations.

By mathematically defining stocks, flows, and their interrelationships, SD models can simulate the behavior of complex systems over time. This approach allows for predicting potential future states and provides valuable insights into SD.

3.3.2 Model-Based Systems Engineering

The SE processes can be further improved by implementing an MBSE approach. Noguchi describes MBSE as "an emerging paradigm for improving the efficiency and effectiveness of SE through the pervasive use of integrated descriptive representations of the system to capture knowledge about the system for the benefit of all stakeholders" [87]. The system representation artifact (i.e., the *model*) is created in a consistent way by using MBSE modeling languages (e.g., Systems Modeling Language (SysML) or Lifecycle Modeling Language (LML)). The modeling language allows the system to be holistically described with interactions between its elements, system behaviors, and more via MBSE tools like Cameo Systems Modeler [88] and Innoslate [89].

The INCOSE handbook [77] discusses the benefits of MBSE compared to the traditional, document-based practice, which are improved communications between stakeholders, a better capability to manage system complexity, improved product quality, and enhanced knowledge capture and transfer. The primary benefit of MBSE is attributed to the integrated, holistic, single source of truth way to represent the system as depicted in Figure 3.2.

There is a pressing need for advanced information handling with the large volume of data that must be collected and analyzed to support truly informed decisions. The supporting information and data are multidisciplinary, including technical engineering disciplines (e.g., mechanical, electrical, computer science), economics, and social aspects. Data collection, repository, and analysis are enormous tasks, requiring a significant time investment. MBSE greatly simplifies information collection and processing and, more importantly, allows added traceability between system elements and associated documents. For example, energy systems are associated with a set of specific regulations from multiple federal and state-level governing organizations. Due to the large amount of information, it is a very complex task to develop a comprehensive set of requirements

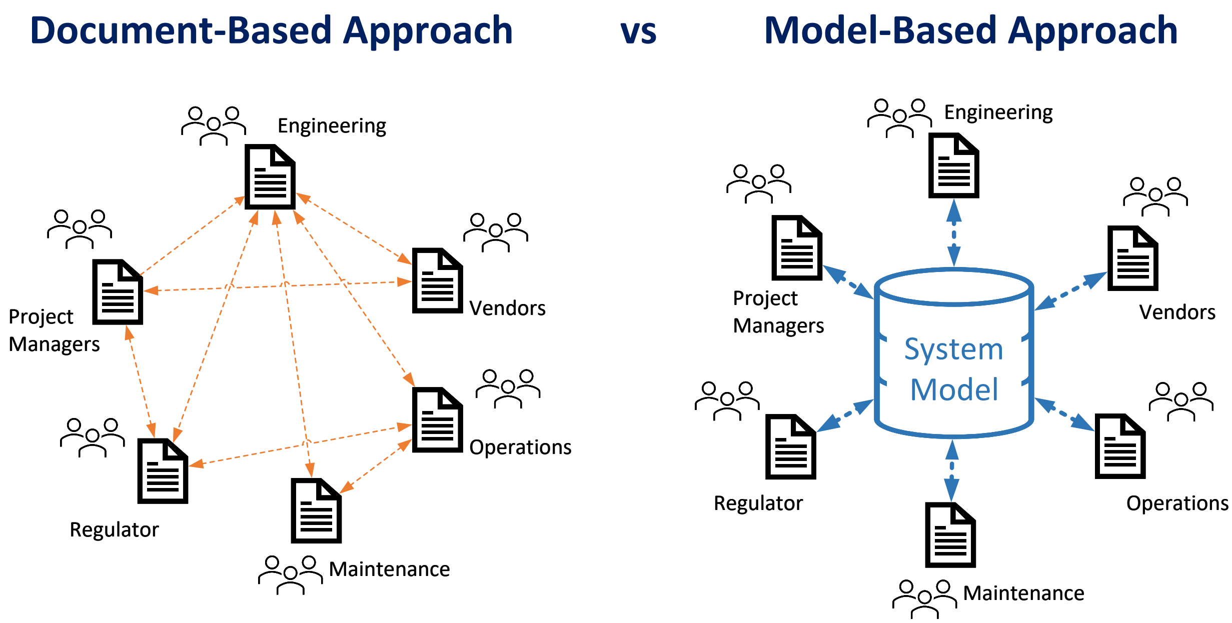

Figure 3.2: Document-based (left) versus MBSE (right)

for a given system. After the set of regulatory requirements has been developed, it is an even more complicated task to identify later on which regulatory document was the basis for the requirement assigned to a component. MBSE enables traceability between system artifacts, such that a given requirement can be assigned a relationship like "sourced from" to a document where the document is also stored as a model artifact. Such a comprehensive data repository is not possible without MBSE.

With all the information captured in a model, the system can be viewed from multiple perspectives (e.g., disciplines, tasks, stakeholders, levels of detail) to address specific interests and needs. A change in a system element is reflected in each perspective, which ensures consistency and accuracy of the information, version control, and clear communication. These capabilities enable an enhanced yet simple visualization of information. At the initial stage of a concept evaluation for a system solution, there is a significant amount of information being collected. This information is to be presented to various stakeholders and decision-makers who have different levels of technical background and various interests, thus requiring a specific set of information and level of detail to be presented to provide a clear and concise representation of the proposed system. MBSE provides

0 Stakeholder Conserns [Model::0 Prelimina	1 Stakeholder Needs [Moc	Electricity Customers	Hydrogen Customers	Plant Owner	Investors	Engineering	Technology Vendors	Manufacturing	Plant Operators	Maintenance	Regulators	Government
		2	3	16	7	8	8	3	3	3	3	10
SC-1 Affordable Electricity	3	↙		↙								↙
SC-2 Electricity Availability (24/7/365)	4	↙		↙		↙						↙
SC-3 Affordable Hydrogen	4		↙	↙			↙					↙
SC-4 Hydrogen Availability (24/7/365)	5		↙	↙		↙	↙					↙
SC-5 Hydrogen Quality	4		↙	↙		↙	↙					
SC-6 Return on Investment	2			↙	↙							
SC-7 Revenue	2			↙	↙							
SC-8 Costs	3			↙	↙		↙					
SC-9 Funding Sources	5			↙	↙		↙	↙				↙
SC-10 Technology Maturity	5			↙	↙	↙	↙					↙
SC-11 Reliability and Availability	7			↙	↙	↙	↙	↙	↙	↙		
SC-12 Safe and Easy Operation	3			↙		↙			↙			
SC-13 Spare Parts	5			↙		↙	↙	↙		↙		
SC-14 Regulatory Approvals	4			↙	↙	↙					↙	
SC-15 Regulatory Compliance	4			↙					↙	↙	↙	
SC-16 Climate Goals	3			↙							↙	↙
SC-17 Energy Independence	1											↙
SC-18 Energy Resiliency	1											↙
SC-19 Federal Energy Policies	1											↙

Figure 3.3: Traced stakeholder concerns to needs

the ability to create various viewpoints of the same system, each tailored to a specific need or specific audience. This dramatically simplifies change management compared to the document-based approach since a change in one place is reflected throughout the model, ensuring consistency and accuracy of the information, version control, and clear communication.

As an example, a representation of how system stakeholder needs are traced in the model is shown in Figure 3.3. The high-level system requirements developed from the stakeholder concerns are shown in Figure 3.4. The MBSE artifacts can be presented in a variety of forms depending on purpose and preferences. When an artifact is changed in one location, the change is reflected throughout the model. Figure 3.5 presents requirements from Figure 3.4 in the form of a diagram, and Figure 3.6 presents the same requirements in the form of a map using the SSOT.

The key benefit of MBSE is the ability to trace interconnections, which is demonstrated by connecting the stakeholder concerns to the system requirements. Figure 3.7 shows the relationship

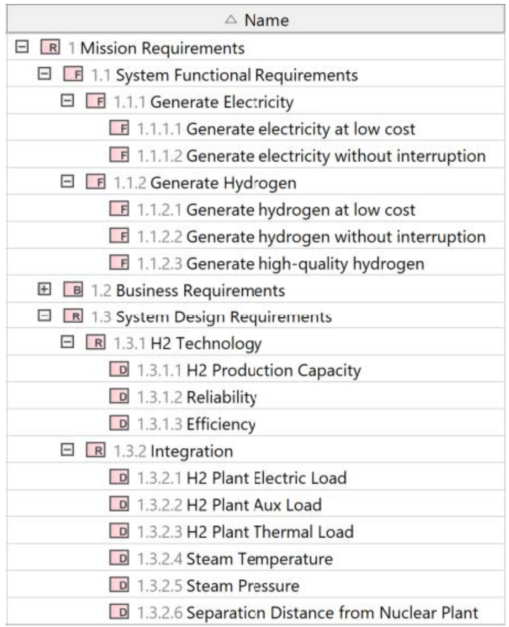

Figure 3.4: System requirements table

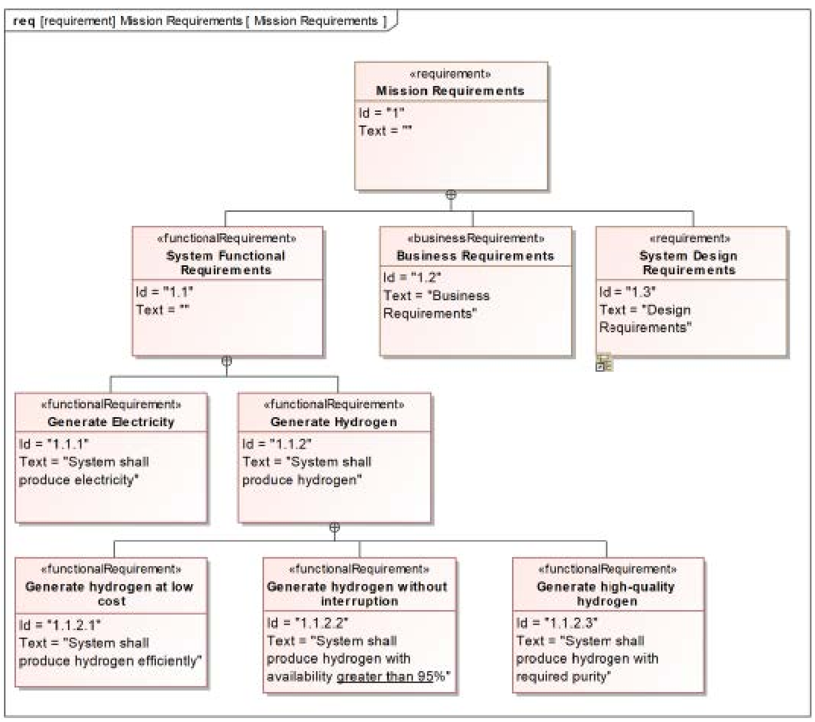

Figure 3.5: System requirements diagram

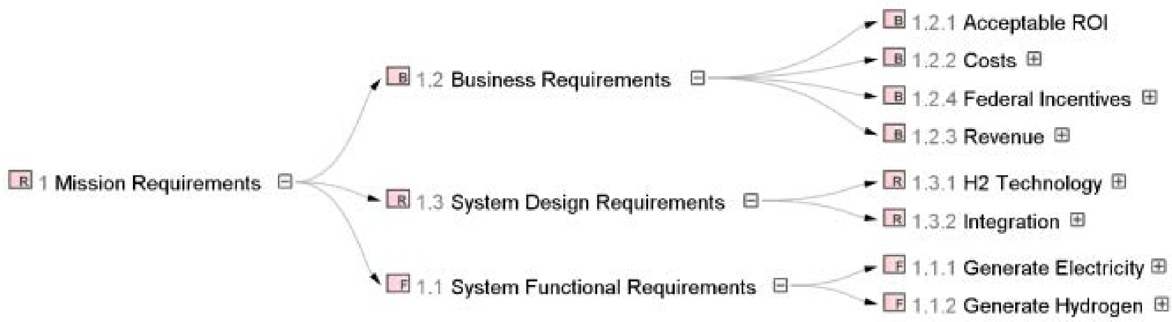

Figure 3.6: System requirements map

assignment between stakeholder concerns and system requirements, and the same relationships are maintained and traced to the stakeholders and their concerns as demonstrated in Figure 3.8.

These examples of MBSE capabilities use stakeholders and requirements artifacts, but the same concept is true for other system elements. As an example, Figure 3.9 presents a context diagram for multiple operational strategies.

Yet, some disadvantages and limitations exist. One disadvantage of using MBSE for decision support is the need for initial investment in the software tool(s) and training, where some tools can be complex and are associated with a steep learning curve. To address complexity, it's crucial to develop simple, comprehensive models using tools and languages specifically designed to handle complex systems [90]. The use of MBSE for decision support also has limitations, mainly when dealing with less complex systems where MBSE might be unnecessarily complicated and costly. Furthermore, integrating specialized evaluations into MBSE can be difficult, and using a dedicated external tool for specific analyses may be more effective. For instance, economic assessments involving NPV and IRR are typically conducted in tools like Excel. In such scenarios, carrying out the evaluations using the appropriate external tool may be preferable. Then, if an MBSE approach is utilized, one can import the results into the MBSE model to ensure a complete capture and preserve knowledge.

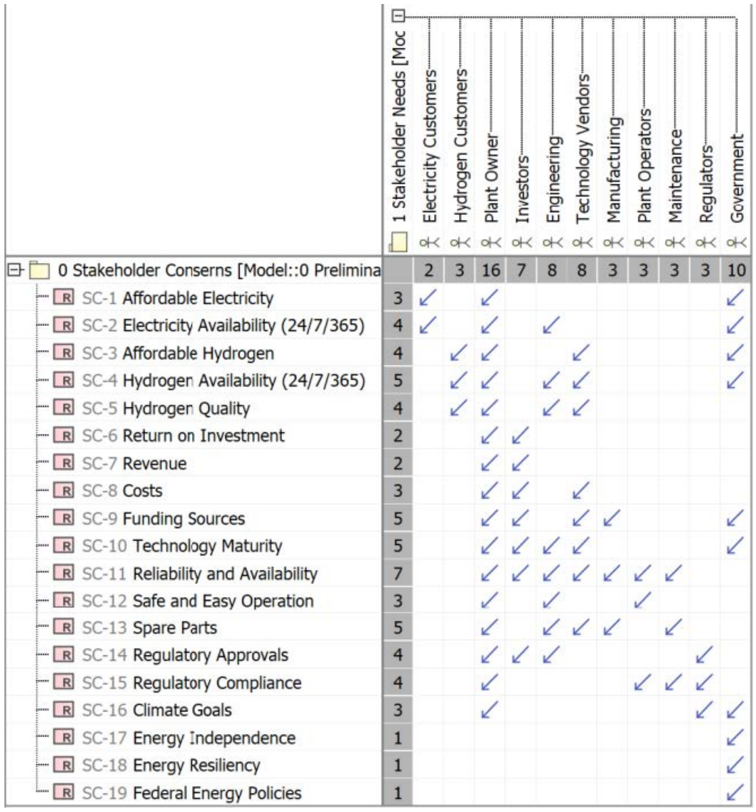

Figure 3.7: Relationship assignment between stakeholder concerns and system requirements

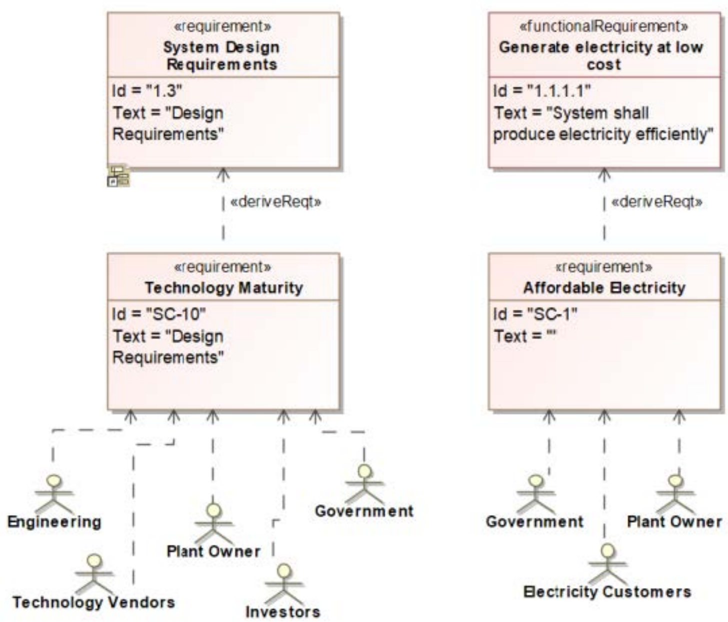

Figure 3.8: Relationship traceability

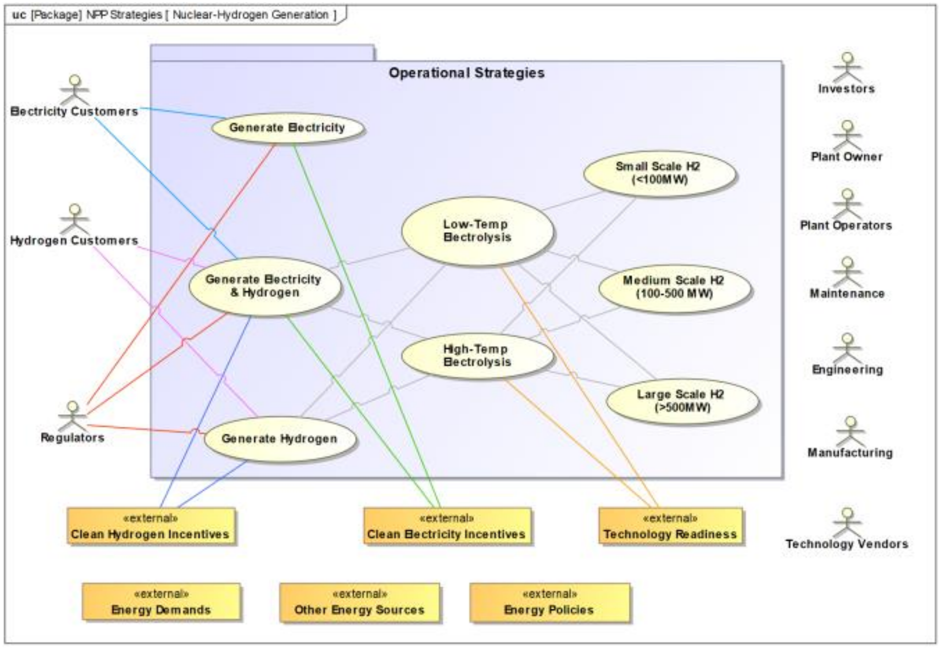

Figure 3.9: Example of a use case context diagram

3.4 Conclusion

The chapter highlights the complexity of energy systems and the need for interdisciplinary approaches to address their challenges and outlines the role of ST and SE in developing a novel decision-making framework for energy systems. ST is introduced as a holistic approach that considers both internal and external interactions of system elements. It emphasizes understanding systems as integrated wholes, enabling better decision-making by providing insights into complex interactions and long-term perspectives.

SE is defined as an interdisciplinary approach that ensures the successful realization of a complex system that connects various engineering disciplines, evaluates stakeholder needs, and applies standardized methods throughout the system life cycle. The chapter underscores the importance of SE in managing complexity and increasing project success rates.

The chapter also discusses specific methods and tools, such as SD and MBSE. The SD models use feedback loops, stocks, and flows to analyze system behavior over time, providing valuable insights through CLD and mathematical representations. MBSE offers a structured way to capture and analyze system information, improving communication, managing complexity, and supporting trade-off evaluations.

Overall, the chapter emphasizes the integration of ST and SE principles to create a comprehensive decision-making framework for energy systems, leveraging advanced tools and methodologies to address the complexities of modern energy challenges.

Chapter 4

System Dynamics Model for Evaluating Deployment of Novel Energy Technologies [4]

The deployment of novel energy technologies is a multifaceted and dynamic process influenced by various factors, including technological advancements, policy and regulation, economic considerations, social acceptance, and infrastructure capabilities. As nations and industries strive to balance economic growth with environmental sustainability, the energy transition is becoming a central focus of global efforts to combat climate change and ensure energy security for future generations. However, as noted in [91], the process of inventing and commercializing new technologies is complex and difficult to analyze. A significant challenge lies in determining how new technologies are selected for commercial investment. Historical shifts in energy technologies can be traced and evaluated, but predicting future technological trends remains challenging and highly uncertain. Most technologies that potentially will be dominant in the future likely exist today, but they are not yet widely adopted. Current methods employed for the assessment of energy transition cannot accurately analyze emerging technologies. Therefore, evaluation of multiple scenarios of technology innovation and diffusion and their alternative futures is essential for analyzing potential technological advancements.

This chapter explores dynamics of energy technology deployment, highlighting the key influencing factors, challenges, and strategies for successfully integrating new energy systems into existing infrastructures.

[4]This chapter contains works published in [1]. The works are reproduced within this chapter and have been reformatted to meet the dissertation style guidelines.

4.1 Dynamics of Novel Energy System Commercialization

The energy system transition is influenced by a complex interplay of factors, including technological advancements, government policies, economic considerations, social acceptance, geopolitical dynamics, environmental concerns, and resource availability [50, 92–96]. Changes in technology, market forces, regulations, public opinion, and international relations all play a role in driving the shift toward new energy sources and systems.

This multifaceted process involves not only the development and adoption of novel energy technologies but also the transformation of existing infrastructure, market structures, and regulatory frameworks. As nations and industries strive to balance economic growth with environmental sustainability, the energy transition is becoming a central focus of global efforts to combat climate change and ensure energy security for future generations. The key factors affecting the energy system transition are summarized below.

Policy and Regulation: Government policies, subsidies, tax incentives, and regulations play a crucial role in encouraging or hindering the energy transition, where supportive policies can significantly accelerate the adoption of novel energy technologies.

Technological Advancements: Technological innovations improve efficiency and reduce costs, making them more competitive with incumbent fossil-fuel-based energy solutions. Cost reductions due to technological advancements have been observed in wind and solar electricity generation and storage technologies [97–99].

Economic Factors: The cost of new energy technologies versus incumbent ones, availability of financing, and the overall economic climate influence investment decisions for the energy sector.

Environmental Concerns: Growing awareness of climate change drives the demand for cleaner energy solutions. International agreements like the Paris Agreement also pressure countries to reduce GHG emissions given that the electricity sector is the primary contributor of CO_2 emissions.

Energy Security: Diversifying energy sources can enhance national energy security by reducing reliance on imported fuels and mitigating the risks associated with geopolitical tensions.

Market Dynamics: The energy market's structure, including energy prices, market competition, and the extent to which markets are open to new entrants, affects the pace and nature of the energy transition.

Availability of Resources: The availability of resources required for a novel energy technology is the key factor influencing the success of the technology's commercialization. Resource constraints, either real or perceived, add large uncertainties for the overall success of the technology commercialization, which may preclude willingness to invest in those technologies (e.g., access to fuel, land resources needed for renewable installations).

Public Perception and Social Acceptance: Public awareness and support for novel energy projects can influence their deployment. Social acceptance is crucial for the successful implementation of large-scale projects and the eventual nationwide diffusion of the technology.

Infrastructure and Grid Capability: The existing energy infrastructure's ability to integrate renewable energy sources, including grid capacity and storage solutions, affects the energy transition process.

R&D: Investment in R&D for new energy technologies and improvements in existing ones can significantly impact the speed and efficiency of the energy transition.

International Cooperation: Cross-border collaboration on technology transfer, funding, and policy alignment can facilitate a more efficient and widespread energy transition.

These factors interact in complex ways, and addressing them holistically is essential for any model that aims to describe or predict energy transitions.

4.1.1 Dynamics of Technology Diffusion

Technology diffusion is the process of adopting and spreading new technologies across markets and societies, involving various stakeholders, such as developers, manufacturers, users, policymakers, and regulators. This process unfolds in several phases [9].

In the introduction phase, the technology is brought to market and adopted by early enthusiasts. During this phase, feedback from these early users leads to refinements in design and functionality.

As improvements are made, the technology enters the growth phase, becoming more attractive to a broader audience. Adoption rates increase, production scales up, costs decrease, and significant investments in marketing and infrastructure are common. As the technology reaches peak adoption in the maturity phase, the market becomes saturated, and the rate of new adoptions slows down. The focus then shifts to incremental innovations, cost optimization, and enhancing user experience. Eventually, newer technologies may emerge, leading to a decline in the adoption of the existing technologies and prompting companies to pivot to the next wave of innovation.

Several factors influence technology diffusion. The perceived benefits of the new technology over existing alternatives, known as relative advantage, significantly impact its adoption, including improvements in cost, performance, and functionality. For energy systems, these perceived benefits are seen as a reduction of carbon emissions, an increase in electricity system resilience due to a diversification of generating sources, and increased independence from fossil fuels. Compatibility, or the extent to which the new technology aligns with existing values, past experiences, and needs of potential adopters, also plays a crucial role. For energy systems, a large part of compatibility is the availability of energy infrastructure, such as the transmission and distribution grid, to deliver electricity from the newly installed generating source to the end users.

Positive feedback loops are critical in technology diffusion. As more users adopt the technology, more data and feedback are generated, which is invaluable for further innovation and refinement, making the technology even more desirable and driving more adoption, perpetuating the cycle of improvement and diffusion, as shown in Figure 4.1.

However, diffusion is not without its challenges. Large-scale sociotechnical systems, such as energy generation, involve numerous interdependent components and subsystems. Analyzing the diffusion of such technologies requires careful consideration of the interactions between these components and the overall system behavior. Uncertainties in technological performance, market acceptance, regulatory environments, and external factors like economic conditions can hinder diffusion. For instance, the diffusion of solar energy involves not only improving photovoltaic

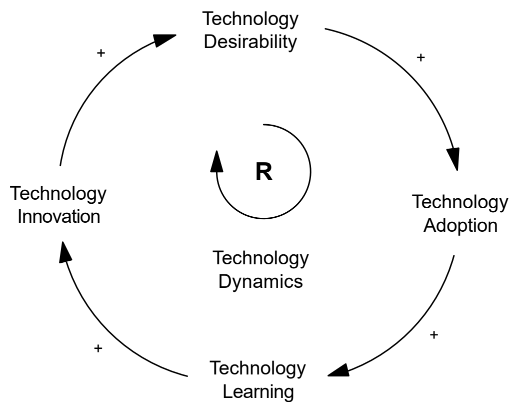

Figure 4.1: Basic dynamics of technology innovation and diffusion [100]

technology but also developing efficient manufacturing processes, establishing supportive policies, creating financial incentives, and educating consumers about the benefits of solar power.

To summarize, technology diffusion is a multifaceted process influenced by various factors and characterized by dynamic feedback loops between innovation and adoption. Understanding and leveraging these dynamics are crucial for successfully introducing and scaling new technologies, especially within complex sociotechnical systems like energy generation. The SD model developed in this research aims to address these interactive dynamics.

4.2 Qualitative Modeling of Energy Technology Deployment

This section presents a qualitative assessment of the dynamics at play for energy technology diffusion.

4.2.1 Model Formulation—Causal Loop Diagram

The key dynamics of a new technology diffusion affected by innovation are presented in Figure 4.1 [100]. The trajectory of technology commercialization can be modeled using two basic types of models—capacity growth and technology diffusion. The capacity growth models focus primarily on economic factors as the main influencing factors for the adoption of a product or technology. The technology diffusion models replicate social contagion as the main factor influencing adoption. The basic Bass model [101] of diffusion is well-known and widely used in marketing, and many SD studies are based on the Bass diffusion model [83, 102–104]. These two main types of models are often blended to include both economic and social factors influencing technology adoption. This is a well-suited approach for analyzing energy systems commercialization, and several studies have developed such integrated SD models, as described in this section.

The study described in [48] developed models to explore the transition of the European electricity generation system toward a more sustainable system characterized by lower carbon emissions. The study modeled capacity growth for major energy technologies like wind, solar, natural gas, coal, nuclear, and biomass, considering maximum potential, profitability, experience, technology improvements, and emission factors. The study presented in [100] is focused on wind energy diffusion, considering economic, technological, and resource factors. The model addresses technological improvements of wind technologies, resulting in improved capacity and ties resources to technology profitability through profitable project sites.

A few widely used models [105–107] are much broader, with the scope focused on the overall electricity market, either regional or at a national scale, with a large set of endogenous and exogenous variables. These models target scenario assessments with the focus on a specific outcome (e.g., minimize costs, minimize carbon emissions, assess the effect of policies on electricity markets).

Our research focuses on the dynamics of novel energy technology adoption and uses a capacity growth model as the basis with the addition of multiple variables affecting energy system adoption. The model formulation is discussed below.

4.2.2 Key Dynamics of Novel Energy Systems

The dynamics of energy system adoption are presented via a CLD shown in Figure 4.2. The **Capacity Growth** loop is the key behavior of the energy technology market uptake. *Expected Profits* positively affect the *Willingness to Invest*, which in turn positively affects the *Installed Capacity*. However, for resource-dependent energy systems, the availability of the limited resource could constrain growth. Wind and solar energy are dependent on the availability of land to install

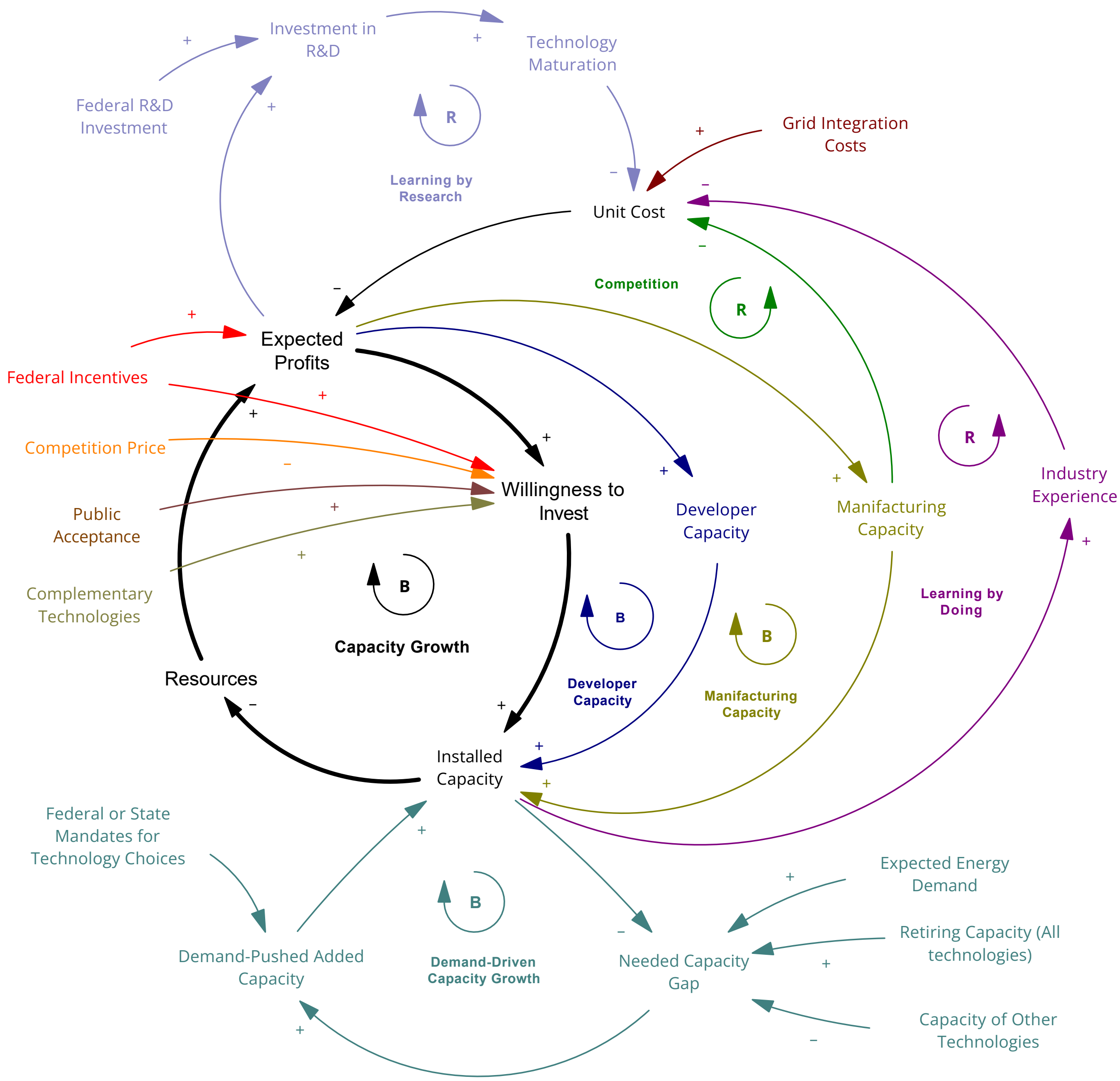

Figure 4.2: Causal loop diagram showing dynamics of deployment of novel energy systems

large-scale projects. Other energy technologies could be dependent on fuel resources, such as natural gas for combined cycle power plants or uranium for NPPs. For the resource-dependent systems, the increasing *Installed Capacity* is depleting available *Resources*. This is a negative feedback, or a constraining factor, of the Capacity Growth loop.

As discussed earlier, a positive feedback is depicted with a "+" sign and negative feedback with a "-" sign. Similar to a multiplication rule where multiplying two negatives results in a positive, an even number of negative relationships in a causal loop results in a positive, also known as reinforcing, loop (marked as R), while an odd number of negative relationships make the loop negative, also known as balancing (marked as B). Given that the Capacity Growth loop has three positive relationships and one negative, it is a balancing loop, which is identified with a "B" and a circular arrow showing the direction of the loop's dynamics.

"Learning by doing" is the most common approach to project technology cost reduction trends [108, 109]. It illustrates the relationship between the cumulative production output and unit cost reduction. This principle suggests that, as companies increase their production, they gain experience and insights, leading to more efficient manufacturing processes. Consequently, production costs decrease as a direct function of cumulative output. This phenomenon is quantitatively described by the learning rate [110–112], which measures the percentage reduction in cost for each doubling of cumulative production output. As firms continue to produce more, they discover ways to streamline processes and operations, reduce waste, and improve overall efficiency, thereby lowering the cost per unit even further. A similar concept is called "learning by research" where the technology is improving due to investments into R&D, which results in improved technology efficiency, improved reliability, and utilization of better-suited materials, which ultimately decreases the cost. Many analyses use a two-factor learning curve that considers both learning by doing and learning by research contributors to the declining costs of technologies [113, 114]. Many studies also used SD to explore learning curves within dynamics of technology development [115–118]. This research considers technological learning an essential part of energy technology adoption.

The **Learning by Doing** loop is the extension of the Capacity Growth loop where the *Expected Profits* are directly affected by the *Unit Cost*. The *Unit Cost* can be expressed as the cost of a technology unit (e.g., cost of a wind turbine or a solar panel) or can represent a unit cost of energy expressed as an LCOE measured in dollars per unit of electricity, $/MWh. The growing *Installed Capacity* increases *Industry Experience* (a positive feedback), which decreases *Unit Cost* (a negative feedback). The lower *Unit Cost* makes the *Expected Profits* larger (a negative feedback) with the *Willingness to Invest* completing the Learning by Doing loop, which is a reinforcing loop.

The **Learning by Research** loop is connected to the rest of the dynamics through the *Unit Cost* and *Expected Profits* variables—the increasing *Expected Profits* allow for larger *Investment in R&D* (a positive feedback), which in turn increases *Technology Maturation* (positive feedback), resulting in decreasing *Unit Cost* (negative feedback). The negative feedback between *Unit Cost* and *Expected Profits* completes the Learning by Research loop, which is a reinforcing loop.

Technology adoption depends heavily on industry readiness to install projects (i.e., developer capacity) and supply necessary parts (i.e., manufacturing capacity).

The **Developer Capacity** loop is a balancing loop where increasing *Expected Profits* increases *Developer Capacity*, which in turn increases *Installed Capacity*, both positive feedbacks. The loop completes through the *Resources* and *Expected Profits* variables. **Manufacturing Capacity** is very similar to the Developer Capacity loop and is also a balancing loop.

The **Competition** loop represents the industry dynamic where the spike in demand results in supply chain shortages, which allows manufacturers to increase markup on the components. The dynamic is reversed where *Manufacturing Capacity* increases to satisfy the demand and increased competition between suppliers results in lower markups and therefore decreased *Unit Cost*, which is a negative feedback. The Competition loop completes through the *Expected Profit* variable and is a reinforcing loop.

The **Demand-Driven Capacity Growth** loop represents the energy market push or resistance to producing more electricity. The needed electricity generation capacity is affected by several exogenous variables, namely *Expected Energy Demand* (dependent on national economic growth), and available electricity generation capacity represented by *Other Technologies Capacity* and *Retiring Capacity* exogenous variables. The difference between expected demand and currently available capacity is represented by the *Needed Capacity Gap* variable, which will decrease when the *Installed Capacity* is increasing (a negative feedback). The larger *Needed Capacity Gap* would increase the demand for additional electricity generation capacity, including the demand for the specific technology being modeled. This is represented by the *Demand-Pushed Added Capacity*, and its increase will increase the *Installed Capacity* (a positive feedback), closing the balancing Demand-Driven Capacity Growth loop.

While system dynamics shown in Figure 4.2 imply a dynamic, i.e., changing in time, behaviors, CLDs on their own are not time-correlated. A qualitative SD model only shows the core behaviors of the system and relationships between system elements. To see the system behaviors along the timeline, a quantitative model is required, which is covered in Section 4.3.

Other Variables in the causal loops are endogenous or internal to the system. These variables have a direct effect on system behavior, while the system also affects these variables. There are also multiple exogenous variables that affect the system, but these influencing factors are coming from "outside" of the system and are discussed below.

The *Needed Capacity Gap* is affected by the *Expected Energy Demand* (usually a function of national economic growth), *Capacity of Other Technologies* (i.e., all electricity generating technologies capable of meeting electricity demand), and *Retiring Capacity (all technologies)*. The *Federal or State Mandates for Technology Choices* represents the preference of a certain technology by the federal or local government. The Renewable Portfolio Standard (RPS) is an example of such a preference where the push is toward renewable energy technologies to reduce carbon emissions in the electricity sector. The RPS mandates will increase the demand for clean technology and decrease the demand for fossil-based technology.

The *Willingness to Invest* is affected by several economic, technical, and social factors. In a broader sense, the willingness of investors to put money into a new technology is directly influenced by the scale of uncertainty of such an investment. The uncertainties are dependent on government support represented by *Federal Incentives*—the stronger the support in terms of incentive scale and duration, the greater the willingness to invest. Another economic variable is the *Competition Price* where the attractiveness of a certain technology is measured against competitors. In addition, the cost of energy generated by the new technology is affected by accessibility to the existing infrastructure (e.g., electrical grid for wind energy). The cost of the connection to the existing grid depends on the land location and how much it would cost to connect the new site to the existing electrical grid, including new transmission lines and other infrastructure, permitting, right-of-way rights, and other costs.

Social factors can be summarized as *Public Acceptance* where a given technology could experience either public support (e.g., recent large support for clean technologies) or resistance (e.g., public resistance to nuclear energy after the Three Mile Island accident).

There are also some technical factors that could influence the attractiveness of a technology to investors. These are typically performance parameters like capacity factors or reliability, but these are considered endogenous to technological progress. However, supporting technologies, such as energy storage technologies for solar and wind generation, could either expedite or hinder the adoption of the technology of interest. This is represented by the *Complementary Technologies* variable.

Lastly, the *Federal R&D Investment* is an exogenous variable supporting the Learning by Research loop where, in addition to the endogenous progress made by the industry by allocating a portion of their profit to the R&D, the federal government provides additional external support expediting technology maturation.

It is often the case for energy systems that the same variables could be considered either endogenous or exogenous depending on the selected system boundary. For example, in the case of the national electricity generation model, *Federal Incentives* would be an endogenous element, while here, this variable is exogenous.

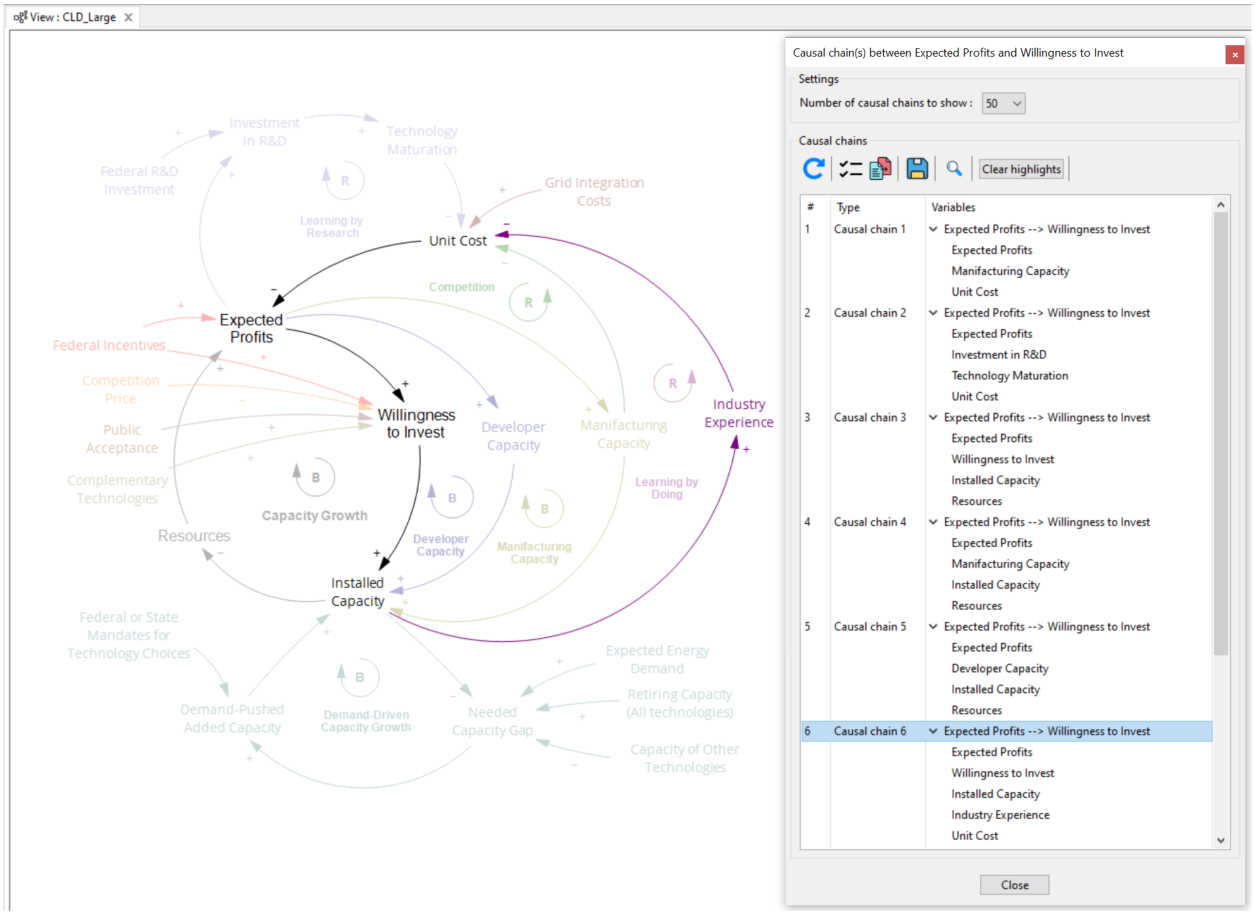

Figure 4.3: The "causal chain" function automatically highlighting the **Learning by Doing** loop from Figure 4.2 illustrating a capability of model-based SD models

4.2.3 Results of Qualitative Modeling

As discussed previously, energy systems are very complex, with highly heterogeneous elements interconnected with each other. Yet, the model-based representation via CLDs as shown in Figure 4.2 offers an intuitive, easy-to-understand way to depict complex interactions between system elements.

The elements and relationships shown in Figure 4.2 offer important insights into energy system behaviors in terms of factors enabling and limiting the system growth. The **Capacity Growth** is a balancing dynamic where the system growth expressed as *Installed Capacity* is enabled by larger *Expected Profits* and *Willingness to Invest*, yet limited by *Resources* declining as capacity increases. The **Developer Capacity** and **Manufacturing Capacity** loops are also balancing since they are dependent on the same enabling and limiting variables as the **Capacity Growth** loop. These balancing behaviors can also be described as a goal-seeking behavior where the goal is to reach a balance between the available resources and capacity growth. On the other hand, the **Learning by Doing** loop represents a reinforcing dynamic where the *Installed Capacity* growth results in *Industry Experience* growth, which causes a decrease of *Unit Cost*, which results in larger *Expected Profits*, which in turn enables increased *Installed Capacity*. This dynamic is repeated each time additional capacity is installed with no limiting factors, which makes this a reinforcing system behavior. The relationships within each loop are clear and easy to explain. However, the presence of multiple dynamics within the system is hard to visualize, and a qualitative SD model provides the ability to understand the large system perspective, dynamics within the system, and interactions with outside systems and elements.

In addition, the model-based system representation allows for additional benefits like traceability and automatic updates, which become progressively more important for larger models with dozens of feedbacks and hundreds of variables. For example, loops can be easily shown as presented in Figure 4.3 using a "causal chain" function, which helps with communicating system behaviors to the stakeholders. In this example, the Learning by Doing loop is automatically highlighted by the model.

Another traceability option is to identify all influencing parameters for the variable of interest, either through a tree diagram or an N^2 matrix. Figure 4.4 shows all variables that influence the *Installed Capacity*.

These capabilities become extremely important to support the decision-making process in a more straightforward, graphical manner, and when systems are very large with hundreds of elements, supporting scalability.

4.3 Quantitative Model of Wind Energy Deployment

This section builds on the work presented in Section 4.2 to gain quantitative insights about the dynamics of the commercialization paths of novel energy technologies. The SD model is selected

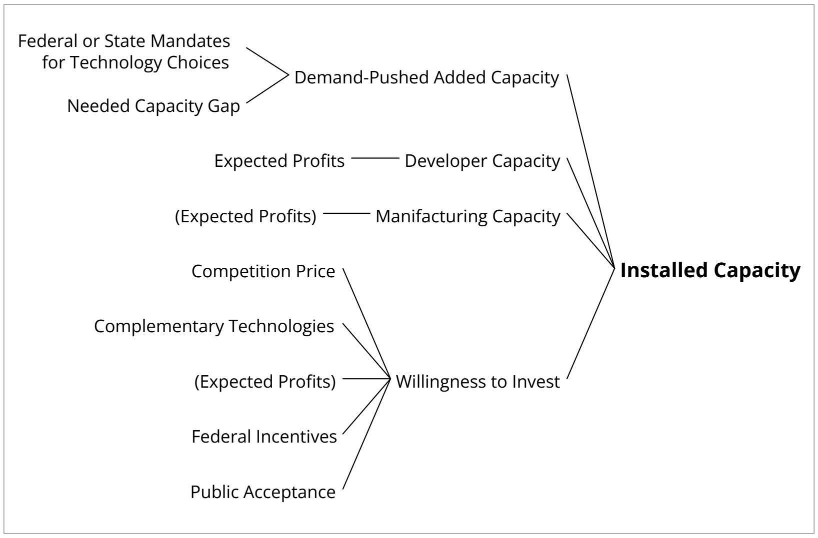

Figure 4.4: Model-based SD: identification of dependencies

to support understanding the novel energy system diffusion due to its ability to take into account multiple interdisciplinary factors, such as technology adoption, policy changes, economic impacts, and social behavior over time, enabling the simulation and evaluation of different transition pathways and policy scenarios. In addition, the specific benefit of SD models is the unique capability to demonstrate the feedback effects between model elements, which helps with understanding long-term system behaviors resulting from such dynamics.

4.3.1 Model Boundary and Key Assumptions

The most important step in modeling is the problem articulation, and a well-defined purpose is the most critical component for a successful modeling study [83]. Caution is advised against modeling an entire system rather than focusing on a specific problem. Every model represents a system, which is a collection of functionally-related elements forming a complex whole. However, for a model to be effective, it must target a specific problem and simplify rather than attempt to replicate the entire system in detail. The art of modeling involves discerning what to exclude, and the model's purpose provides a basis for determining which elements can be disregarded, ensuring that only essential features for the modeling exercise are retained. Without a clear purpose, there is no foundation for excluding certain elements that might influence the system, potentially resulting in a model too large to yield useful insights. Conversely, by modeling a specific problem, irrelevant system elements can be excluded. Thus, the recommendation is to always model a problem, not an entire system.

Purpose of the model: **Provide understanding of factors affecting the trajectory of a new energy technology commercialization to inform decision-making**

The purpose helps define the model boundary. Figure 4.2 demonstrates key dynamics of a novel energy system, but the actual model should be as simple as possible to address the purpose (i.e., provide valuable insights for the problem being examined). As such, some of the dynamics in the detailed model are removed to focus on the factors with the highest influence on the energy system market integration. The reasoning for model simplification is discussed below.

The importance of electricity demand to the success of novel energy technology integration is obvious. However, when the new technology is not expected to completely replace the incumbent technologies but rather take a somewhat smaller portion of the market, the overall electricity or energy demand is an exogenous variable affecting technology diffusion indirectly. This indirect effect is mostly related to the market uncertainties in terms of the additional energy needs and whether such needs could be satisfied by the new technology.

In the current energy system landscape, novel energy technologies still represent a smaller portion of the market, as shown in Figure 4.5 [119]. Fossil fuels account for approximately 60% of electricity generation, with nuclear providing 18% and all renewable sources combined contributing 21%. The share of renewable electricity generation has significantly increased over the past few decades, nearly doubling between 1990 and 2024. Nevertheless, individual novel technologies, such as utility-scale wind and solar, contribute only about 10% and 4%, respectively [119].

Given the substantial market demand relative to the small market share occupied by individual novel technologies, national electricity demand is not the key factor affecting technology diffusion. Consequently, the Demand-Driven Capacity Growth loop is excluded from the SD model.

Multiple researchers have argued for the need for better-defined learning curve models, specifically advocating for two-factor learning curves that account for both the effect of experience (i.e.,

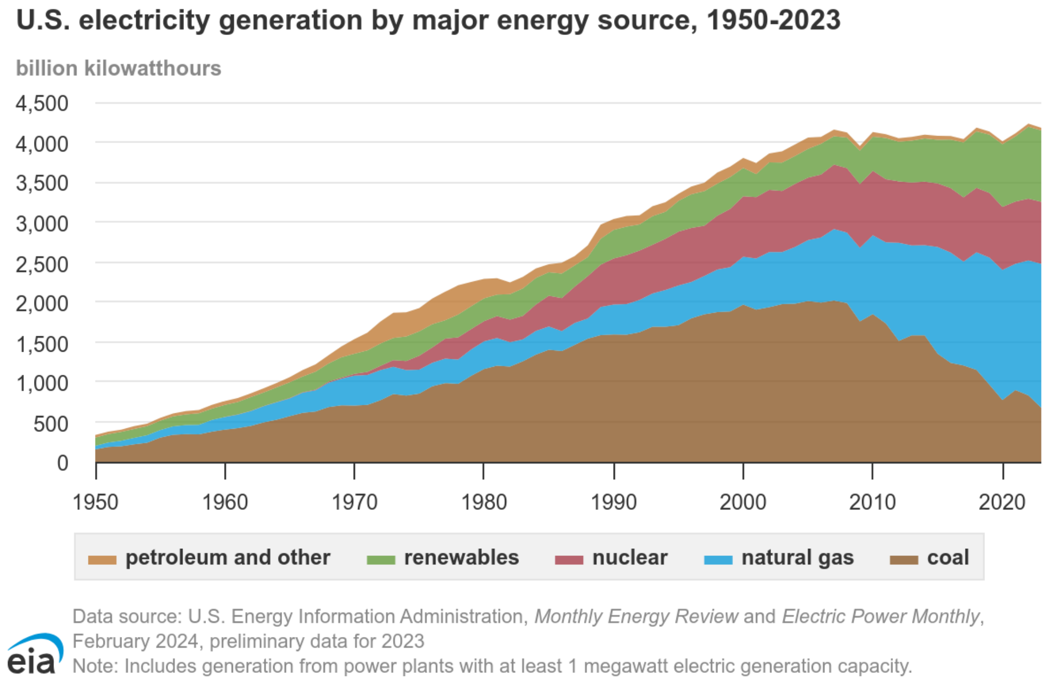

Figure 4.5: Electricity generation in the United States by major energy sources [119]

"learning by doing") and the impact of R&D (i.e., "learning by researching") [113, 114, 118, 120, 121]. Others have called for multifactor learning curves that include parameters beyond learning by doing and learning by research to enhance the understanding of technology cost reduction rates via multiple factors influencing them [122–125]. Results from studies on two-factor and multifactor learning curves indicate that installed capacity is the most influential factor in the technological cost reduction, with R&D impact being the second. These studies also highlight the challenges in precisely estimating the contributions of learning by doing versus learning by research, due to the integrated dynamics of these two processes. Furthermore, researchers have noted difficulties related to data availability for estimating the R&D contribution to overall technology cost reduction and warned that additional learning curve parameters may lead to overfitting, resulting in poor forecasts [126].

Given that the focus of this study is on technology commercialization rather than the specific factors driving cost reduction, it is reasonable to employ a simpler, single-factor learning curve where cumulative installation is the primary driver of technology unit cost reduction. As such, the

Learning by Research loop is not considered as an individual driving factor, and cost reduction via experience is used as the cumulative learning factor.

Two balancing loops, Developer Capacity and Manufacturing Capacity, are very similar—both can limit capacity growth due to restricted resources or uncertainties in the future energy market that dampen the desire to grow.

The manufacturing sector, also referred to as the supply chain, has additional dynamics where competition can significantly affect component costs, which in turn directly impact the unit cost. Dykes [100] suggests that both developer and manufacturing capacities are crucial for the market uptake of novel energy systems and incorporates both dynamics into her model. Conversely, Pruyt includes a single industry capacity factor, namely the "capacity of wind turbines construction industry," in his studies [47, 48], which aligns with the Developer Capacity in our study.

While both the developer and manufacturer capabilities are vital for the diffusion of novel energy systems, it is unclear which is more significant for the adoption of an energy system within a specific context, such as a nation's electricity system. The ability to install utility-scale power plants is certainly dependent on domestic capabilities, whereas manufacturing capacity is a global factor since many manufacturers of novel technologies supply components globally. In fact, North American manufacturers represent a relatively small portion of the total global manufacturers of wind components [127–129]. The U.S. share in solar energy component manufacturing is even smaller [130, 131].

Several research studies [100, 132] and industry assessments [133–135] indicate that component costs are influenced by supply chain availability; increased backlog in orders typically drives up component markups, increasing overall costs. However, establishing a clear correlation between individual manufacturing company order backlogs and price increases is complex due to limited access to company business information, variability in market strategies that affect pricing and markups, and multiple manufacturers in the market. Additionally, due to similar data limitations, the growth capability of manufacturing companies is difficult to predict since their growth is affected by local markets and policies and individual business plans. Therefore, the Manufacturing

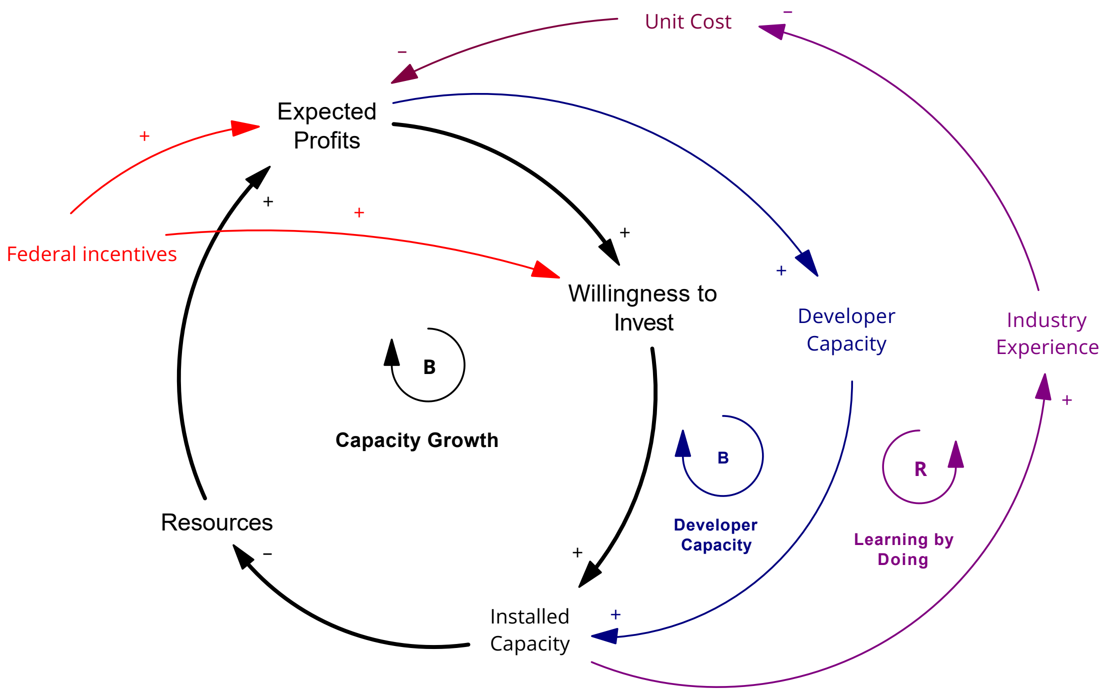

Figure 4.6: Causal loop diagram of core dynamics of novel energy system deployment

Capacity loop is excluded from the SD model for this study, and the industry capacity growth is represented via the Developer Capacity loop.

Some of the exogenous variables shown in Figure 4.2 are integrated into endogenous variables in the model. Namely, *Grid Integration Cost* and *Competition Price* are accounted for as part of the available profitable resources concept, which is explained in Section 4.3.2.

The *Public Acceptance* and *Complimentary Technologies* are not included in the model since they are considered less important to the technology diffusion, but they could be incorporated into a more detailed model later.

The revised CLD is presented in Figure 4.6, representing the boundary of the SD model built for this study as described in Section 4.3.2.

4.3.2 Model Development

The model is built for onshore wind electricity generation technology with parameters and corresponding historical data, and the core model consists of four submodels:

1. **Profitable capacity**, where resources suitable for new energy system installations are modeled based on the total available resources, their portion available for installations, and a smaller portion of the available resources is considered profitable
2. **Technological learning**, which models improvements in performance and decline in cost as a function of cumulative installation
3. **Developer capacity growth**, describing factors that affect industry capability scaling to install the growing number of projects
4. **Capacity growth**, modeling the project progress from the initial consideration to completion, including multiple factors that affect the process.

This section describes each of the submodel structures, variables, and formulas. The model is built using Vensim Professional, version 10.2.2 [84] from Ventana Systems, Inc. It allows users to create graphical models with feedback loops, stocks and flows, and causal links, facilitating the exploration of how different variables in a system interact with each other. This software is often utilized in business, environmental science, public policy, and engineering for tasks like policy analysis, strategic planning, and resource management, and has been used to model the dynamics of energy systems [100, 106, 118, 136].

Each submodel and model variables, shown in *italicized text*, are described in the following subsections. The data sources for model variables are explained in Table 4.1. Model inputs shown as <Variable> are modeled in other submodel(s).

Profitable Capacity

For wind energy, the resource is the land available for installing wind projects. The most attractive sites are the ones with better wind quality (i.e., higher wind speeds and more frequent wind days). Developers will first consider the sites with the highest wind potential and the closest to electrical grid infrastructure, as these sites are the most profitable. With the increased installations, less profitable sites will be considered next until no more profitable available land remains.

The profit of the project is calculated as the difference between the revenue from energy sales and expenses to produce energy. Incentives for energy generation in the form of a PTC are added if

Table 4.1: Variables and data sources for the wind model

Submodel	Variable	Value	Data Source
Profitable Capacity	Historical and projected electricity price data:		
	Historical (1998–2023)	Data	[137]
	Projected (2024–2050)	Data	[138]
	PTC Lookup	Data	[139, 140]
	ITC Lookup	Not used	
	Interest Rate	4%	[141]
	return in investment (ROI)	10%	
	Wind Supply Curve	Data	[142]
Technological Learning	Cumulative Global Capacity:		
	Historical (1998–2023)	Data	[143–145]
	Projected (2024–2050)	Data	[146]
	Initial Global Capacity—Total Globally Installed Capacity in 1998	10,200 MW	[143, 144]
	Initial CapEx—Total Installed Costs in 1998	2,824 $/kW	[97]
	CapEx LR—Learning Rate for Total Installed Costs	0.1312	Estimated
	Initial OpEx—operations and maintenance (O&M) Costs in 1998	98 $/kW	[98]
	OpEx LR—Learning Rate for O&M Costs	0.09	[147]
	Initial Capacity Factor—Capacity Factor in 1998	0.255	[98]
	Capacity Factor LR—Capacity Factor Learning Rate	0.0517	Estimated
Developer Capacity Growth	Initial Developer Capacity in 1998	500 MW	[98]
	Maximum Growth Rate	40%	[100]
	Developer Capacity Adjustment Time	1 year	[100]
Capacity Growth	Permit Failure Rate	75%	[100]
	Permitting and power purchase agreement (PPA) Decision Time Lookup	4–5 years	[148]
	Willingness to Invest	Data	Estimated
	Average Construction Time	1 year	[100]
	Average Project Lifetime	20–30 years	[149]
	Historical Installed Wind Capacity in the United States	Data	[98]
	Projected Wind Capacity in the United States	Data	[4]

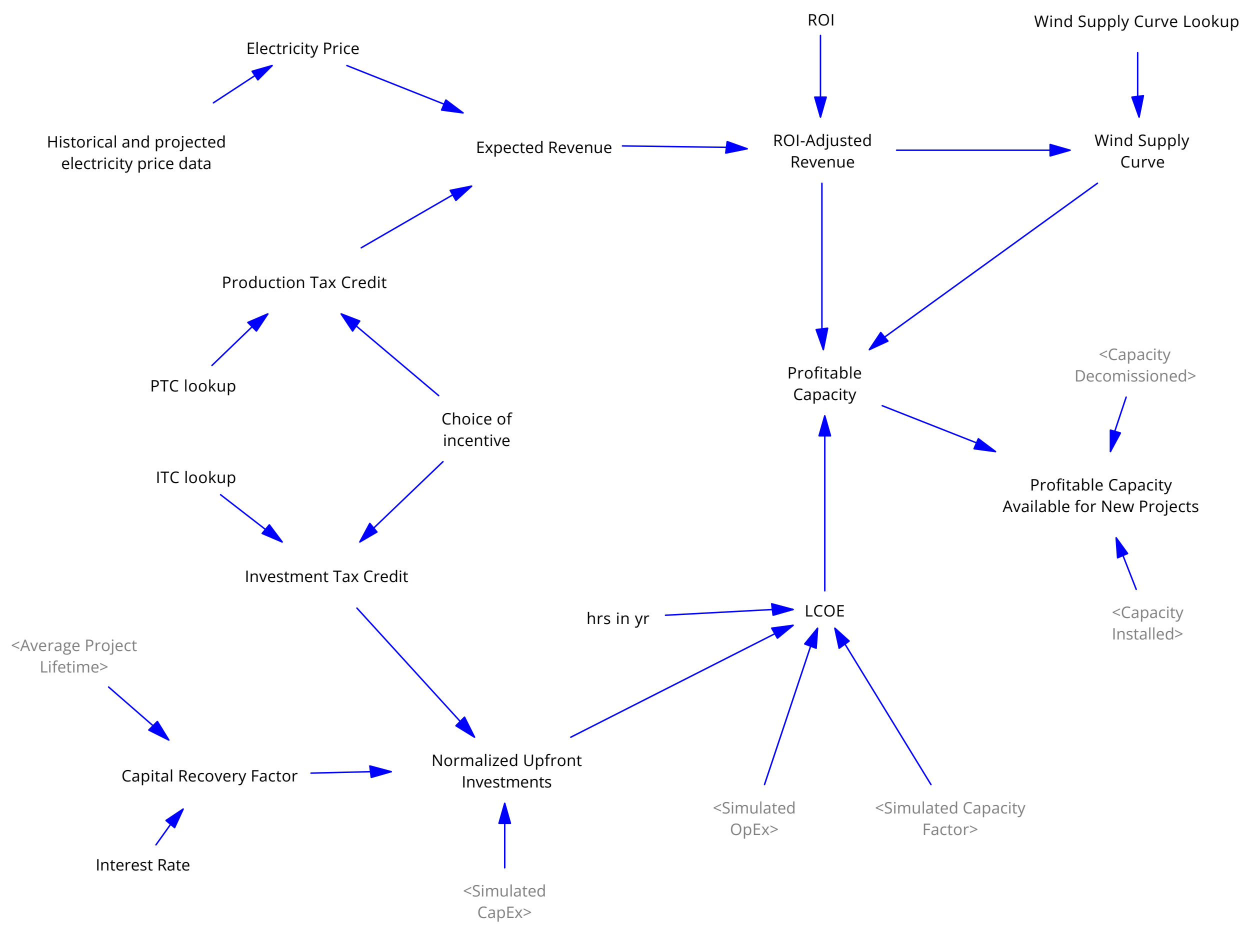

Figure 4.7: Profitable capacity model representing the relationships between *Resources*, *Expected Profits*, and *Federal Incentives* variables in the **Capacity Growth** loop in Figure 4.6

applicable. The revenue from electricity sales is represented in the model as *Electricity Price*. The historical and projected electricity prices are obtained from data in [137] and [138], respectively, which are represented by *Historical and Projected Electricity Price Data* data variable for a corresponding modeled year. The revenue is represented by the *Expected Revenue* variable, which is calculated as a sum of *Electricity Price* and *Production Tax Credit*. Expenses to produce electricity are expressed as LCOE.

The projects where expected revenue exceeds estimated costs are considered profitable, and developers will be willing to proceed with installations. The submodel is presented in Figure 4.7.

The *Choice of Incentive* allows selecting the federal incentive, which is none, Production Tax Credit (PTC), or Investment Tax Credit (ITC). For the wind energy model, the PTC incentive is used as this is the historically-used incentive for the wind projects in lieu of ITCs.

The *ROI-Adjusted Revenue* is the expected revenue considering a minimum return in investment (ROI) desired by the investors.

The *Wind Supply Curve* represents wind resource potential. Understanding the resource potential is fundamental to energy system modeling where cumulative deployment is resource-limited. The resource potential is modeled using the methodology developed by the National Renewable Energy Laboratory (NREL) [150]. The study evaluated the technical potential of onshore wind in terms of capacity, cost, performance characteristics, and grid interconnection costs. The combined metric, LCOE, represented the overall project costs, including levelized transmission and plant costs.

The dataset for the wind supply curve for various siting regimes is available from the NREL Wind Supply Curve website [142], and data for the limited access siting regime was used for our model. The NREL wind supply curve data was translated into the supply curve with available wind capacity (measured in MW) for various LCOE (measured in $/kWh) ranges. The land is considered profitable if the expected revenue is higher than the LCOE calculated for that land.

The LCOE is calculated using the same approach as used in the NREL Simple Levelized Cost of Energy Calculator [151] using Equation (4.1):

$$LCOE = \frac{\text{overnight capital cost} * \text{CRF} + \text{fixed O\&M cost}}{8760 * \text{capacity factor}} + \text{fuel cost} * \text{heat rate} + \\ + \text{variable O\&M cost} \quad (4.1)$$

where:

- overnight capital cost, also referred to as normalized upfront investment, is measured in dollars per installed kilowatt ($/kW)

- capital recovery factor (CRF) is a ratio of a constant annuity to the present value of receiving that annuity for a given length of time (dimensionless)
- fixed operations and maintenance (O&M) costs are measured in dollars per kilowatt-year ($/kW-year)
- variable O&M costs are expressed in dollars per kilowatt-hour ($/kWh)
- capacity factor is a fraction between 0 and 1 representing the actual power being generated compared to nominal installed full capacity (dimensionless)
- 8,760 is the number of hours in a year
- fuel cost is expressed in dollars per million British thermal units ($/MMBtu) and is optional since some generating technologies like solar and wind do not have fuel costs
- heat rate is measured in British thermal units per kilowatt-hour (Btu/kWh).

The fixed and variable O&M costs are usually reported as all-in O&M costs, where variable costs reported in $/kWh are converted to fixed costs based on capacity factors [147]. The fuel cost does not apply to wind energy technologies and is removed. These manipulations result in a shorter Equation (4.2), which is used in the model to calculate LCOE.

$$LCOE = \frac{\text{overnight capital cost} * \text{CRF} + \text{O\&M cost}}{8760 * \text{capacity factor}} \tag{4.2}$$

The CRF is calculated based on the interest rate i and number of years of the loan n using Equation (4.3):

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{4.3}$$

The *Profitable Capacity* variable looks up the available capacity from the wind resource data *Wind Supply Curve* when the *ROI-Adjusted Revenue* is greater than *LCOE*; otherwise, the project is considered not profitable and *Profitable Capacity* is set to zero.

Lastly, the *Profitable Capacity Available for New Projects* is calculated using Equation (4.4), accounting for already installed capacity and decommissioned capacity becoming available for

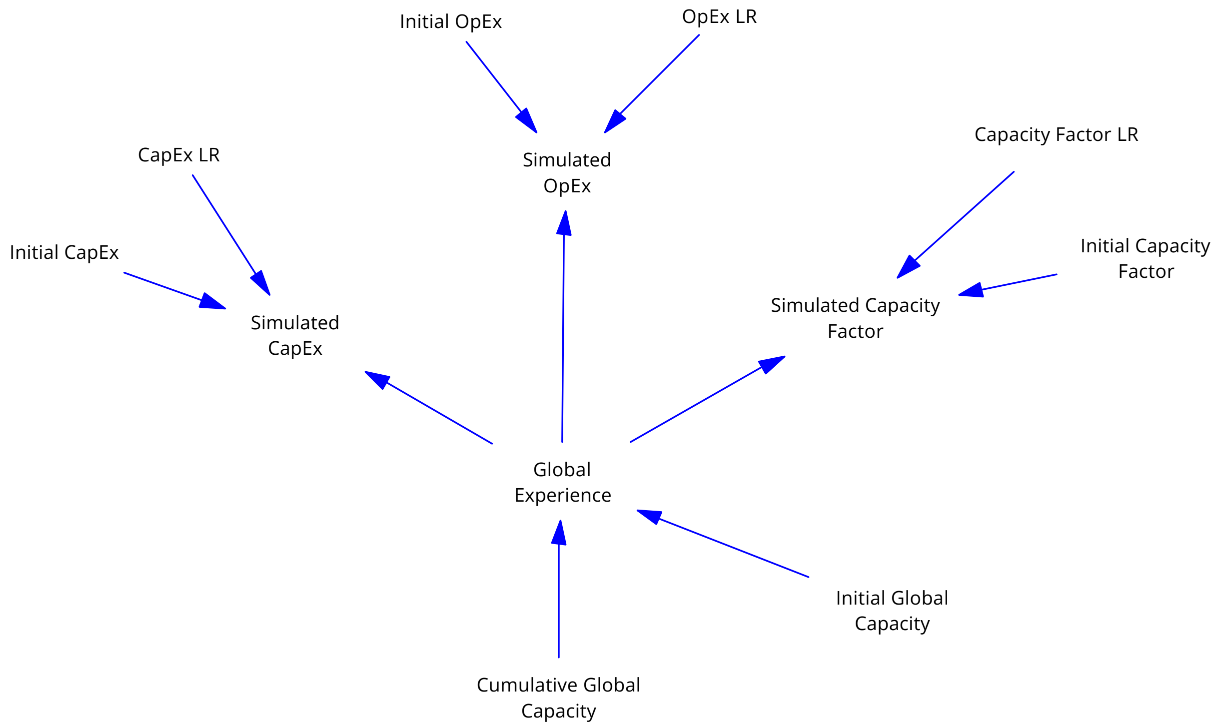

Figure 4.8: Technological learning model representing the relationships between *Industry Experience* and *Unit Cost* variables in the **Learning by Doing** loop in Figure 4.6

new installations:

$$\text{Profitable Capacity Available for New Projects} = \text{Profitable Capacity}- \\ - \text{Capacity Installed} + \text{Capacity Decommissioned} \quad (4.4)$$

Technological Learning

As discussed in Section 4.2, technology learning and innovation is a key reinforcing feedback loop affecting energy technology uptake by the market. This dynamic is modeled as a **Learning by Doing** loop shown in Figure 4.6. Gained experience results in cost reductions, including upfront investments for purchasing and installing equipment referred to as capital expenses or CapEx, as well as O&M expenses or OpEx. In addition, technological improvements and innovations lead to improved technology performance through improved reliability, improved availability, and increased energy output. For wind energy, increased turbine size, rotor diameter, and hub height resulted in a significant increase in energy outputs from a single unit. These performance improvements can cumulatively be described via a capacity factor, which is a ratio of the actual energy generated compared to installed capacity. The Technological Learning submodel is presented in Figure 4.8.

The capacity factor is a complex, aggregated parameter influenced by multiple contributing factors. The most significant contributor is the wind resource quality at the site selected for the wind project. Technological advancements, particularly increased hub height and larger rotor diameter, also have substantial impacts on the power output from wind turbines [98, 100, 152] and consequently on the capacity factor. The proliferation of wind installations, technological innovations, and learning has led to increased capacity factors. However, the quality of wind resources is gradually declining as the best sites are utilized first, leaving sites with lower wind quality for subsequent projects. This creates a dichotomy—while technological improvements drive an increase in the capacity factor, diminishing resource quality exerts a negative influence. Despite this, the overall trend in the capacity factor is upward, as reported in the Land-Based Wind Market Report [98], indicating that technological advancements are outpacing the decline in wind resource quality.

A detailed analysis of the dynamics affecting the capacity factor could involve modeling individual contributors, such as rotor diameter, hub height, and wind resource quality. However, this study opts to use an aggregate capacity factor as a variable. This approach aligns with the research focus on higher-level factors, such as the capacity factor itself, which influence technology adoption rather than on the specifics of technological improvements.

The model employs a standard learning curve formulation [111] to describe the reduction in CapEx and OpEx, as well as improvements in the capacity factor. A learning rate is the rate at which the system improves (in the case of capacity factors) or reduces costs (in the case of CapEx and OpEx) as a function of cumulative experience. Historical data is used to estimate learning rates through Excel's goal seek function to minimize the sum of least squared errors. The model uses a ratio of total global capacity installation experience over the capacity installed

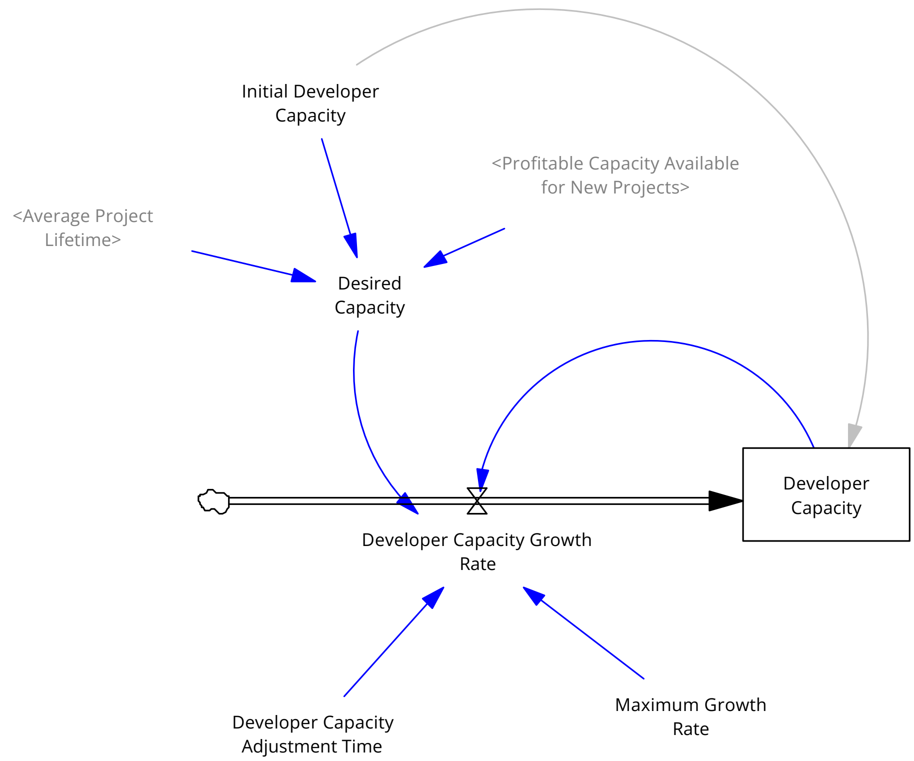

Figure 4.9: Developer capacity growth model representing the **Developer Capacity** loop in Figure 4.6

globally in 1998. Since learning is a global process, focusing solely on the U.S. experience would underestimate technology scaling and cost reductions. Therefore, global cumulative capacity is used as an exogenous input to the model.

Developer Capacity Growth

As discussed in Section 4.2, the deployment and diffusion of novel energy systems could be limited by the capabilities of developers to install energy projects. This factor is modeled as a **Developer Capacity** loop shown in Figure 4.6. The Developer Capacity Growth submodel is presented in Figure 4.9.

The *Developer Capacity* is modeled as a stock variable where capacity growth is increased with a rate equal to the *Developer Capacity Growth Rate*. It is assumed in this model that the gained developer capacity does not reduce, so there is no outflow from the stock. The *Developer Capacity*

Growth Rate is calculated using Equation (4.5):

$$\text{Developer Capacity Growth Rate} = \min[\#1, \#2] \tag{4.5}$$
$$\#1 = \frac{\text{Desired Capacity-Developer Capacity}}{\text{Developer Capacity Adjustment Time}}$$
$$\#2 = \text{Developer Capacity} * (1 + \text{Maximum Growth Rate})$$

where the *Desired Capacity* is calculated using Equation (4.6):

$$\text{Desired Capacity} = \max[\#3, \#4] \tag{4.6}$$
$$\#3 = \text{Initial Developer Capacity}$$
$$\#4 = \frac{\text{Profitable Capacity Available for New Projects}}{\text{Average Project Lifetime}}$$

Capacity Growth

As discussed in Section 4.2 and shown in Figure 4.6, capacity growth is the key dynamic of technology diffusion and adoption.

Energy project developers are the main drivers of the diffusion of energy technology since they, with the support of investors, are making the decision on how many projects are feasible to build given the market conditions and developers' resources. Energy-generating plant development follows a standard process, including site and plant development, construction, and commissioning [100]. After the plant lifetime ends, the capacity is either decommissioned or refurbished and placed back into operation (which is not modeled). The capacity growth submodel is presented in Figure 4.10.

The *Capacity Development Start Rate* is the smaller value of either *Profitable Capacity Available for New Projects* or *Developer Capacity*. The *Capacity in Development* is a stock variable representing how many projects are in development. The development stage includes project site selection, power plant design, permitting process, and securing power purchase agreement (PPA). The *Capacity in Development* is calculated as the integral between inflow rate (i.e., *Capacity De-*

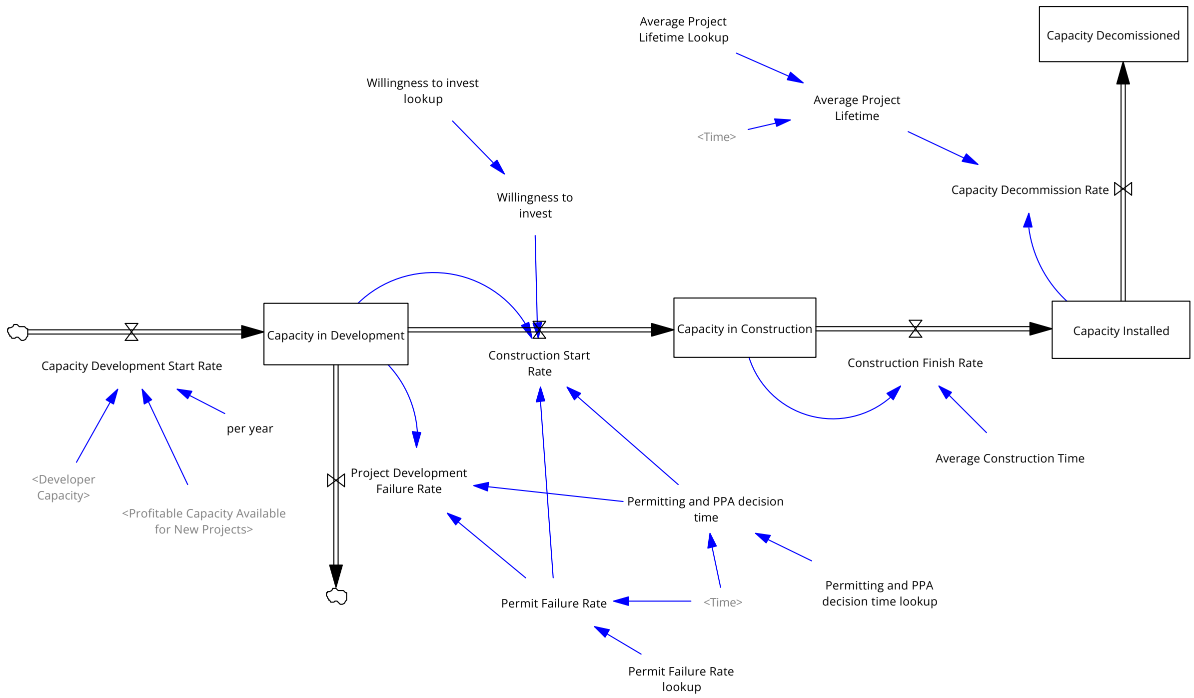

Figure 4.10: Capacity growth model representing the **Capacity Growth** loop in Figure 4.6

velopment Start Rate) and outflow rates (i.e., *Construction Start Rate* and *Project Development Failure Rate*).

The *Project Development Failure Rate* is calculated using Equation (4.7):

$$\text{Project Development Failure Rate} = \frac{\text{Capacity in Development} * \text{Permit Failure Rate}}{\text{Permitting and PPA Decision Time}} \quad (4.7)$$

The *Permit Failure Rate* is 75% for wind projects (i.e., every three out of four wind projects fail) [100]. Projects can fail because of environmental or other permit issues, public pushback from communities unwilling to have wind projects installed (i.e., a not-in-my-backyard situation), or because they fail to secure a PPA. It is assumed that failure rates for very early wind projects had a much lower failure rate due to the urgency of wind installations pushed by the oil crisis in the 1980s and an overall easier permitting process since environmental concerns and public pushback were not prominent issues at the time, but failure rates rose to 75% by 2000. It is also assumed that this rate will likely remain the same moving forward.

The *Permitting and PPA Decision Time* is estimated to be about 4.5 years today (in 2024) according to the American Clean Power fact sheet [148], an increase from 4 years in the 2000s [100]. The permitting time is assumed to gradually increase to 5 years by 2050 and is modeled accordingly.

The *Construction Start Rate* is calculated by taking the portion of not failed projects and adjusting it by the *Willingness to Invest* factor.

Factors such as willingness to invest, perceived value, satisfaction, or attractiveness are so-called soft variables, and they are the most complicated to model since they are typically an aggregate of multiple contributing factors and data is either unavailable or extremely sparse [153–155]. However, despite the difficulties, soft variables should be included in the model if they are important for the dynamics of the system. As Sterman points out, "data are not only numerical data, that 'soft' (unmeasured) variables should be included in our models if they are important to the purpose" [155].

The importance of intangible influences is pointed out in *Industrial Dynamics* [156]:

> "There seems to be a general misunderstanding to the effect that a mathematical model cannot be undertaken until every constant and functional relationship is known to high accuracy. This often leads to the omission of admittedly highly significant factors (most are "intangible" influences on decisions) because these are unmeasured or unmeasurable. To omit such variables is equivalent of saying they have zero effect - probably the only value that is known to be wrong!"

The *Willingness to Invest* is an important parameter to the novel energy system diffusion and market uptake. A similar parameter, expressed as the willingness of investors, investors' investment strategies, or relative attractiveness investment capacity, has been included in multiple studies of energy SD [48, 118, 157].

The adoption of wind energy in the United States has been significantly impacted by government support policies, namely PTC incentives. Dykes and Sterman [49] point out that inconsistent policies resulted in large volatilities, so-called boom-and-bust cycles. More recently, Frazier et al.

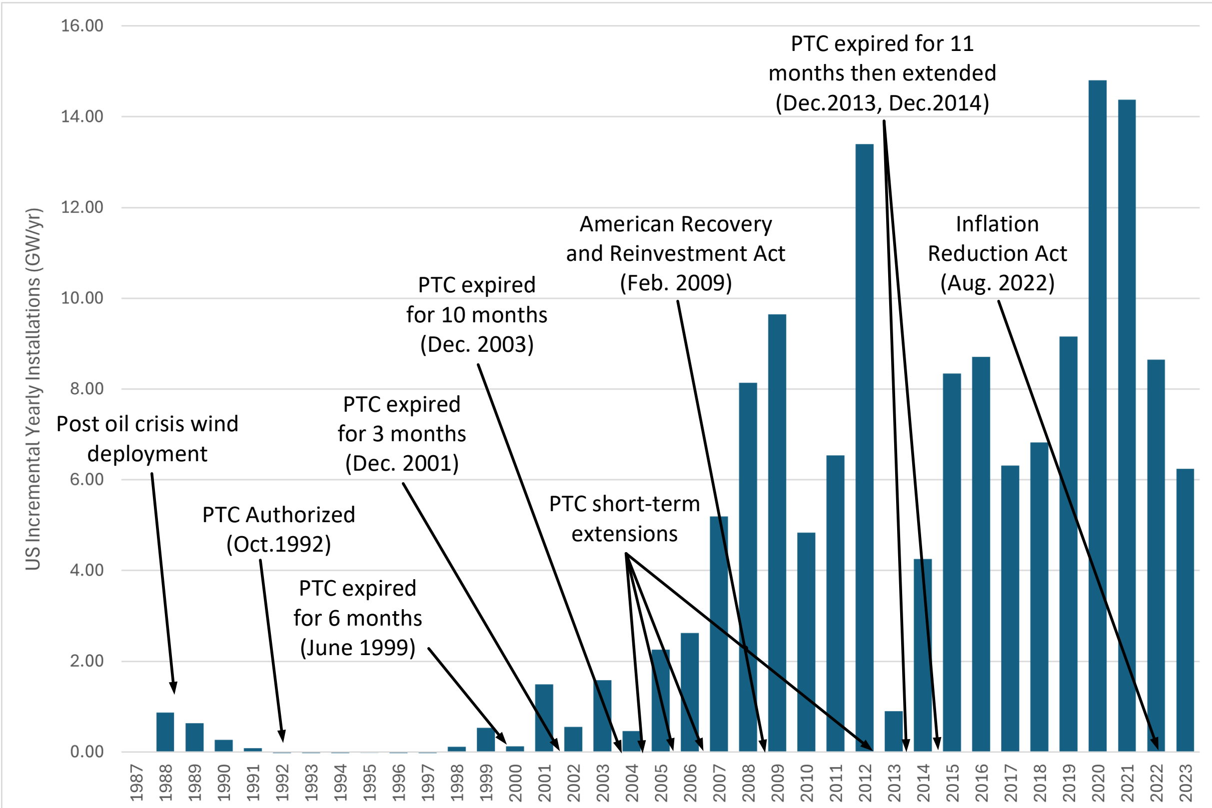

Figure 4.11: Timeline of PTCs with wind capacity additions in the United States (adopted from [8])

explored the impact of PTCs and ITCs on wind and solar deployment [8]. The study found that the policy uncertainty created a volatile market characterized by boom-and-bust cycles in wind deployment. Several independent organizations and researchers pointed out the significance of federal incentives on the success of the U.S. wind energy deployment [158–161]. Figure 4.11 shows a timeline correlation between PTCs and incremental wind capacity additions.

Every time the PTC expired, industry dramatically reduced wind project development, choosing to wait until the credit was renewed. The tax credit incentives created a unique investment opportunity for companies with large tax obligations, allowing a high ROI due to tax credits. The investors had a much lower interest in putting money into energy projects when incentives were under threat of being removed.

Besides federal incentives, several states have implemented their own initiatives to boost renewable energy production. These initiatives, known as RPS, mandate that retail electricity providers source a certain percentage or quantity of their electricity from eligible renewable sources. Although RPS programs aim to increase the proportion of renewable energy, there is still a lack of consistent empirical evidence regarding their effectiveness and whether they actually drive investments in renewable capacity [162].

Research presented in [162] revealed that states with RPSs had higher average levels of wind and solar capacity installed by 1990 compared to those without RPS, but these differences were not statistically significant. The study also indicated that, while RPS policies increased investment in wind generation capacity within these states, they had no effect on investments in solar generation. In summary, although RPS programs do influence the deployment of renewable energy sources, their impact is much smaller compared to federal incentives. As such, the model does not explicitly include RPS as a variable.

The *Willingness to Invest* is modeled as a coefficient based on the availability of PTCs, both historical and projected.

The *Capacity in Construction* represents the amount of capacity in a construction stage modeled as a stock variable and calculated as an integral between the inflow and outflow rates, the *Construction Start Rate* and *Construction Finish Rate*, respectively.

The *Construction Finish Rate* is calculated by dividing the *Capacity in Construction* by the *Average Construction Time*, which is set as 1 year based on the recent industry experience with construction on average taking between 6 and 18 months.

The *Capacity Installed* represents the amount of commissioned capacity after the plant is constructed and connected to the grid. It is modeled as a stock variable and calculated as an integral between the *Construction Finish Rate* and *Capacity Decommission Rate* with the initial installed capacity being the total installed capacity in the United States in 1998 [98].

The *Capacity Decommission Rate* is calculated by dividing the *Capacity Installed* by the *Average Project Lifetime*. The wind project lifetime has increased from 20 years in the early 2000s to 25 years in the mid-2010s and to 30 years more recently [149], which is how it is modeled in our study.

Lastly, the *Capacity Decommissioned*, which is also a stock variable, is calculated as an integral of the *Capacity Decommission Rate*.

4.3.3 Wind Energy Model Results

The outcome of the research is the model demonstrating the trajectory of the wind energy system capacity growth based on multiple factors affecting system deployment. This model also informs the user about potential scenarios of system behavior given potential variation in variables, as well as the sensitivity of a given parameter to the input variables. The goal of the model is to simulate system behaviors reasonably well so the stakeholder can use the model to inform their decisions relevant to energy system deployment prospects, such as investment strategies or policy decisions. The model development process and all the inputs are described in detail in Section 4.2 along with rationale for the values selected for each variable.

To demonstrate the validity of the model, the simulated installed capacity was compared to the historical installed wind capacity in the United States [98] and projected wind capacity [4]. Figure 4.12 shows the comparison. The model-simulated installed capacity shows a reasonable fit with both the historic data (1998–2023) and projected capacity (2024–2050). The historical capacity data is from the Land Based Wind Report [98], and the projected data is from the Energy Information Administration Annual Energy Outlook [4].

The technology growth pattern presented in Figure 4.12 clearly follows an S-curve typical for novel technology diffusion [83,91]. The S-curve represents a behavior where the technology grows slowly at the beginning, then its deployment rate rapidly increases, and subsequently slows down. The rapid increase is attributed to the technology and the benefits of incumbent technologies are being realized by a wider population, and the technological improvements through learning from mass production intensify the willingness to adopt it. The technology deployment rate is eventually slowing down due to some restricting factors (e.g., market saturation or limited resources in the case of wind energy).

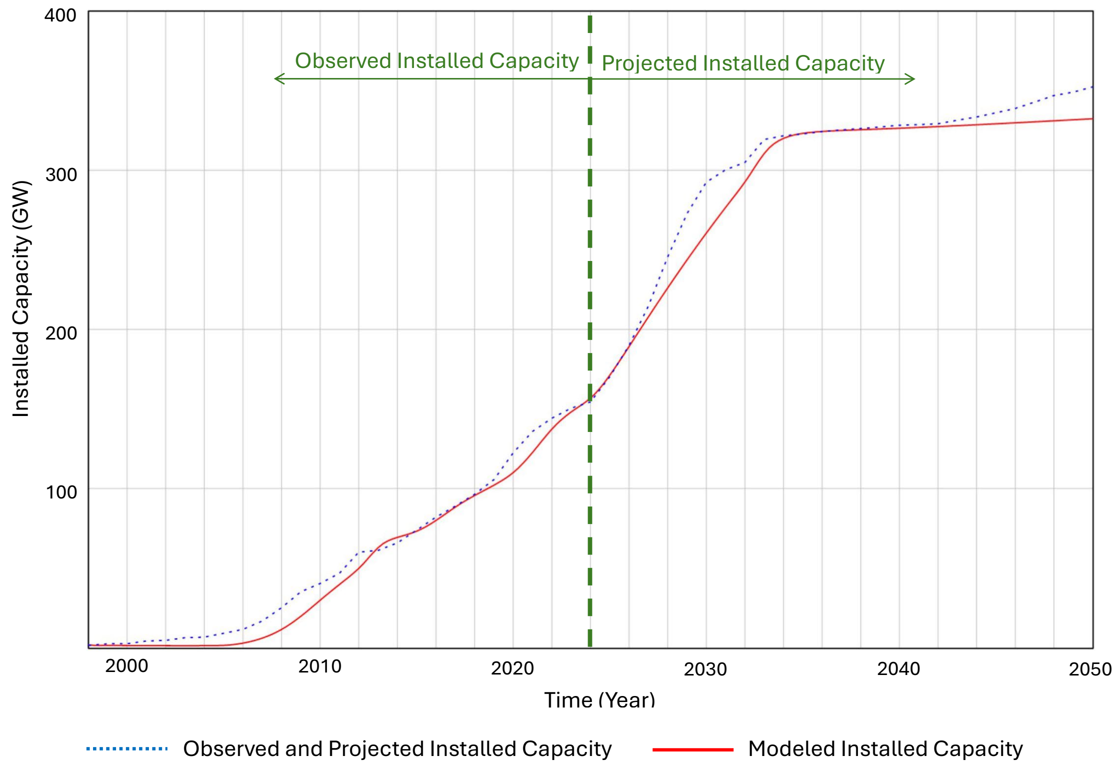

Figure 4.12: SD model-simulated installed capacity versus observed installed capacity [98] and projected installed capacity [4]

Sensitivity Studies

Additional insights about the model and the represented energy system are obtained through sensitivity studies.

Figure 4.13 presents a tornado chart showing the sensitivity of capacity growth to various elements. It shows that the capacity growth is most sensitive to the availability of resources represented as *Supply Curve*. The second most influential parameter is the *Willingness to Invest*. These insights are not surprising since the total capacity of the potential wind energy is directly affected by the available and profitable land to build wind installations. As discussed in Section 4.2.2, investors' willingness to fund wind energy projects is one of the key factors affecting the overall deployment of wind installations and total capacity growth. The next most influential factors are economic variables, namely *Initial Capacity Factor*, *Electricity Price*, *Initial CapEx*, and *Average Project Lifetime*. This is also an expected finding since the feasibility of wind installation deployment is determined using these economic parameters. The model is less sensitive to other variables representing the ability of the developers to grow their capacity and factors affecting learning rates.

The insights from sensitivity analyses provide valuable information to decision makers. From the results presented in Figure 4.13 it is easy to see that to promote faster capacity growth it is best to focus on the availability of resources (i.e., land with access to grid for wind project installations) and willingness to invest (i.e., targeted incentives for investors). The next area for potential improvements is in technology maturity, e.g., through improvements of capacity factors and lifetime. Lastly, lowering the costs through the reduction of capital expenses would also be impactful. However, other factors, while influential, are not as significant to the capacity growth (e.g., permitting decision time or developer growth rate).

Similarly, Figure 4.14 illustrates the sensitivity of the LCOE to the various model inputs. In this case, the focus is on variables affecting the cost of energy rather than capacity growth potential. The results confirm the expectation; the largest influencing factor is the *Capacity Factor* since even a small change can dramatically affect the resulting cost of energy. The rest of the economic variables have a smaller but still measurable impact on energy costs. Based on the sensitivity analysis results, it would be best to focus on technological improvements to increase the capacity factor to gain measurable cost reduction. The learning progress cannot be forced as it takes time and cumulative industry experience growth. Another opportunity to reduce costs, however, is through lower interest rates, which can be achieved with government support for technology deployment.

The outcomes from the sensitivity studies confirm the general dynamics of energy system diffusion presented in Figure 4.6 by demonstrating dependencies between variables within and between the loops.

Scenario Analysis

Next, the impacts of influential parameters, namely resource availability, the presence of PTCs, and technological learning, were analyzed. Figure 4.15 shows the capacity growth outcomes for the reduced resources (left) and availability of PTCs (right).

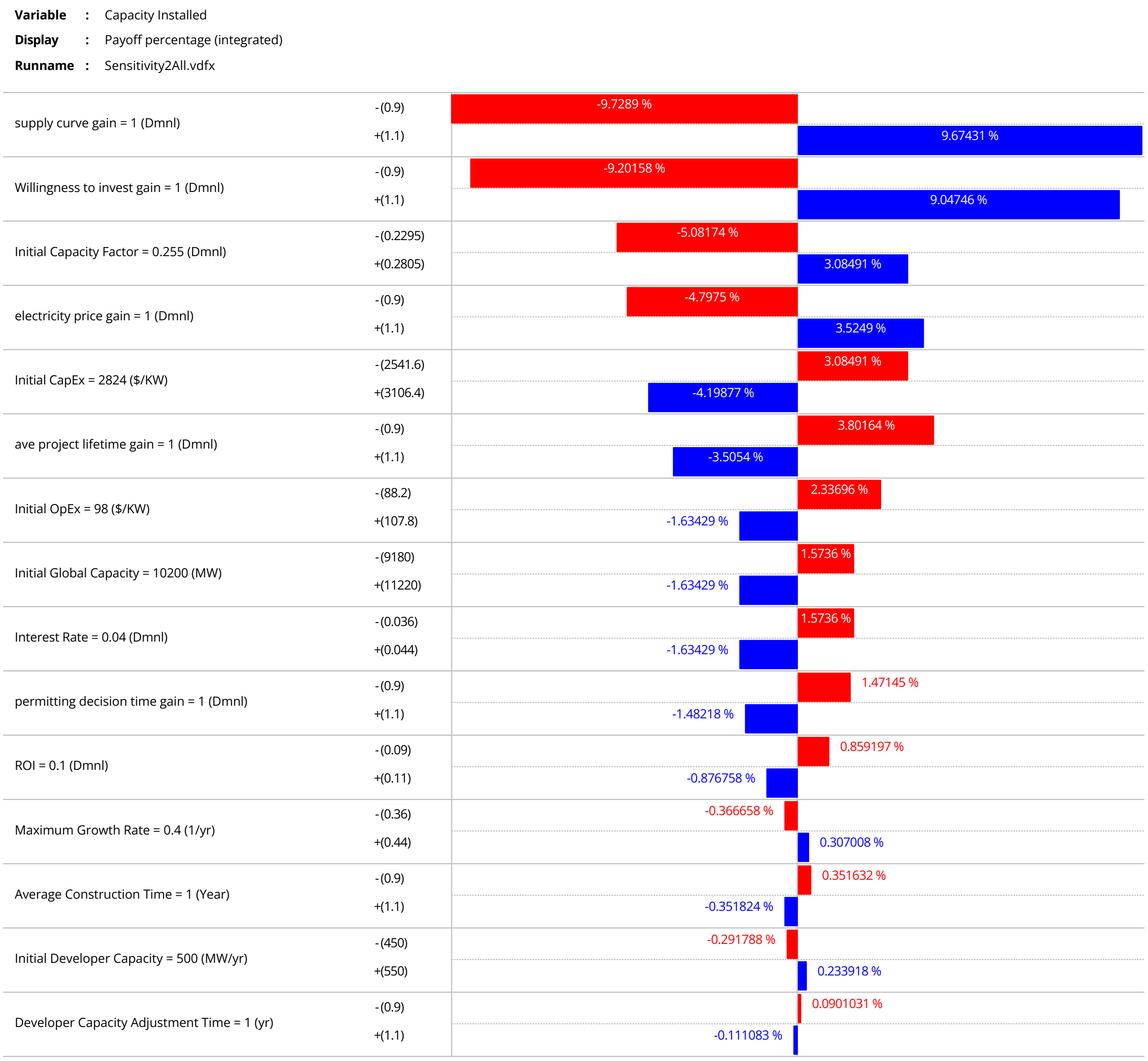

Figure 4.13: Sensitivity of capacity growth to modeled variables

The sensitivity studies showed the strong influence of the wind supply curve on capacity growth, which is confirmed by the scenario analysis. Reducing resources by 5× and 2× greatly reduced the modeled installed capacity, as shown in Figure 4.15. This is consistent with findings in [150], which points out that citing restrictions could dramatically reduce the overall wind energy growth. The wind growing capacity modeled up to 2050 has not reached the available resource potential, so increasing the available resources would have little to no impact on the modeled installed capacity.

Figure 4.14: Sensitivity of LCOE to modeled variables

The scenario simulations of the availability of PTCs confirmed the importance of the incentives; both cases where incentives are not available show a significantly smaller total installed capacity compared to the base model.

Figure 4.16 shows the impact of technological learning on the capacity growth (left) and on the LCOE (right) based on modeled scenarios with reduced and increased learning. As expected, a reduction in learning, represented by reduced learning rates, slows capacity growth, while an increase in technological learning accelerates technology adoption. Although the impact on capacity growth is not significant, the effect on the LCOE is dramatic.

This observation highlights a model limitation, where the willingness to invest is modeled as an exogenous variable primarily dependent on federal incentives. In reality, the willingness to invest is a much more complex parameter that dynamically depends on many factors beyond incentives, including LCOE, available resources, the cost and availability of competing technologies, and social factors like public acceptance.

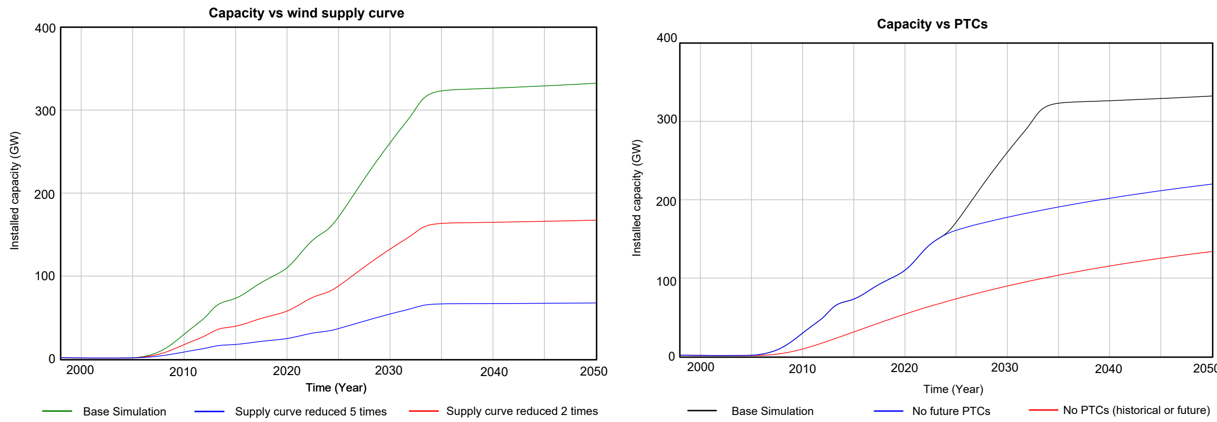

Figure 4.15: Capacity growth versus available wind supply (left); Capacity growth versus PTCs (right)

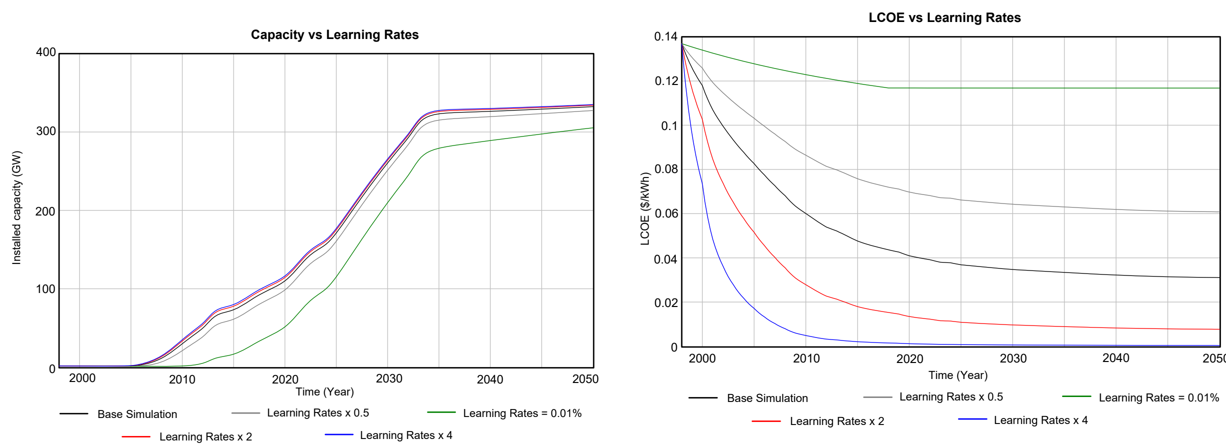

Figure 4.16: LCOE versus technological learning (left); Capacity growth versus technological learning (right)

In a comprehensive energy system model that includes all energy generation technologies, consumption, and demands, the willingness to invest would be an endogenous variable. However, this study specifically focused on the diffusion dynamics of individual energy technologies, necessitating limited model boundaries and treating the willingness to invest as an exogenous variable.

Future work could expand the study to model the willingness to invest more accurately. Although data for such a model are limited, surveys and expert solicitation techniques could be employed. More detailed modeling would require broadening the system boundaries to include additional variables, such as the costs of competing technologies and energy demands, which could remain exogenous while the willingness to invest becomes an endogenous variable. This approach would provide a better understanding of the effect that willingness to invest has on capacity growth.

4.4 Quantitative Model of Utility-Scale Solar PV Energy Deployment

4.4.1 Model Adjustments

The model described in Section 4.3 is used to model the deployment of utility-scale solar PV energy. The model itself was not changed, so Figures 4.7, 4.8, 4.9, and 4.10 are not repeated for solar energy. The data sources for model variables are explained in Table 4.2.

4.4.2 Solar Energy Model Results

To demonstrate the validity of the model, the simulated installed solar PV capacity was compared to the historical installed solar PV capacity in the United States [145] and projected solar capacity [4]. Figure 4.17 shows the comparison. The historical capacity data is from the IRENA Renewable Capacity Statistics 2024 Report [145], and projected data are from the Energy Information Administration Annual Energy Outlook [4].

The comparison in Figure 4.17 shows a very large discrepancy between the simulated and observed and projected installed capacities. The investigation of the causes revealed that profitable capacity in the model was simulated at zero up to the end of 2018, as shown in Figure 4.18.

The unavailability of profitable resources affected the installed capacity (i.e., if there is no opportunity to make a profit, there is no reason to build the system). The profitable capacity was simulated as zero correctly based on the electricity prices and the cost to make energy from the solar PV plant from 2007 to 2018.

However, the simulation does not match the historically observed installed capacity. This suggests that the developers and investors were incentivized by factors other than just profit to pursue solar PV installations. The SD model developed for this research did not explicitly account for

Table 4.2: Variables and data sources for the solar model

Submodel	Variable	Value	Data Source
Profitable Capacity	Historical and projected electricity price data:		
	Historical (2007–2023)	Data	[137]
	Projected (2024–2050)	Data	[138]
	PTC Lookup	Data	[139, 140]
	ITC Lookup	Data	[139, 140]
	Interest Rate	4%	[141]
	ROI	10%	
	Sun Supply Curve	Data	[142]
Technological Learning	Cumulative Global Capacity:		
	Historical (2007–2023)	Data	[145, 163]
	Projected (2024–2050)	Data	[146]
	Initial Global Capacity—Total Globally Installed Capacity in 2007	8,507 MW	[163]
	Initial CapEx—Total Installed Costs in 2007	18,403 $/kW	[163]
	CapEx LR—Learning Rate for Total Installed Costs	0.19	[163]
	Initial OpEx—O&M Costs in 2007	73.92 $/kW	[163]
	OpEx LR—Learning Rate for O&M Costs	0.1	[163]
	Initial Capacity Factor—Capacity Factor in 2007	0.222	[99]
	Capacity Factor LR—Capacity Factor Learning Rate	0.02	[163]
Developer Capacity Growth	Initial Developer Capacity in 2007	22 MW	[99]
	Maximum Growth Rate	600%	[99]
	Developer Capacity Adjustment Time	1 year	[100]
Capacity Growth	Permit Failure Rate	75%	[100]
	Permitting and PPA Decision Time Lookup	4–5 years	[148]
	Willingness to Invest	Data	Estimated
	Average Construction Time	1 year	[100]
	Average Project Lifetime	20-35 years	[149]
	Historical Installed Solar Capacity in the United States	Data	[145]
	Projected Solar Capacity in the United States	Data	[4]

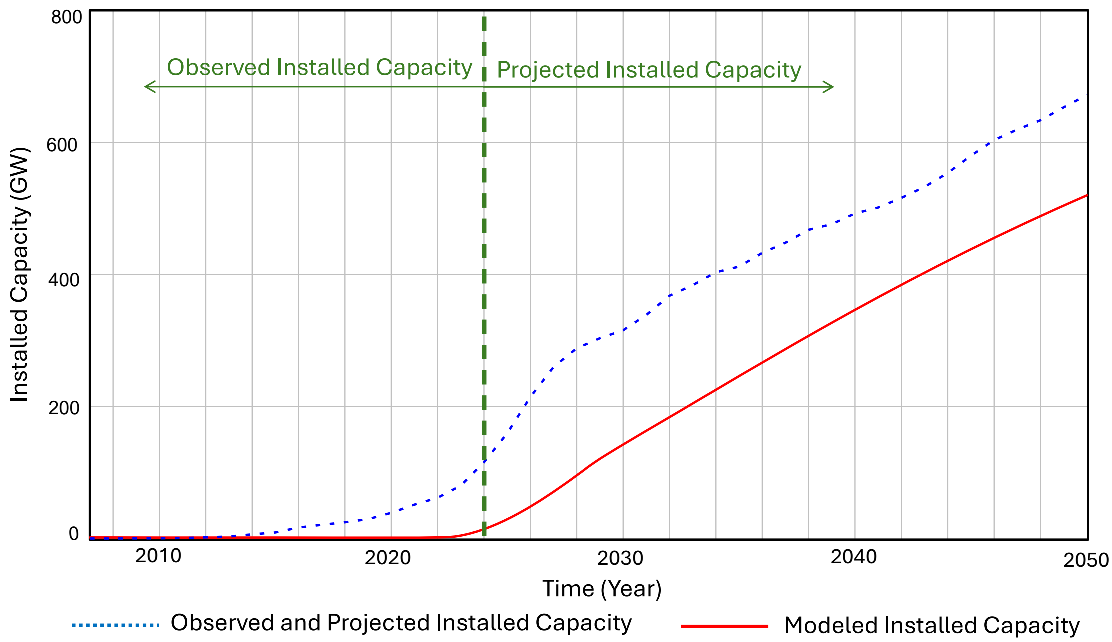

Figure 4.17: SD model-simulated solar PV installed capacity versus observed installed capacity [145] and projected installed capacity [4]

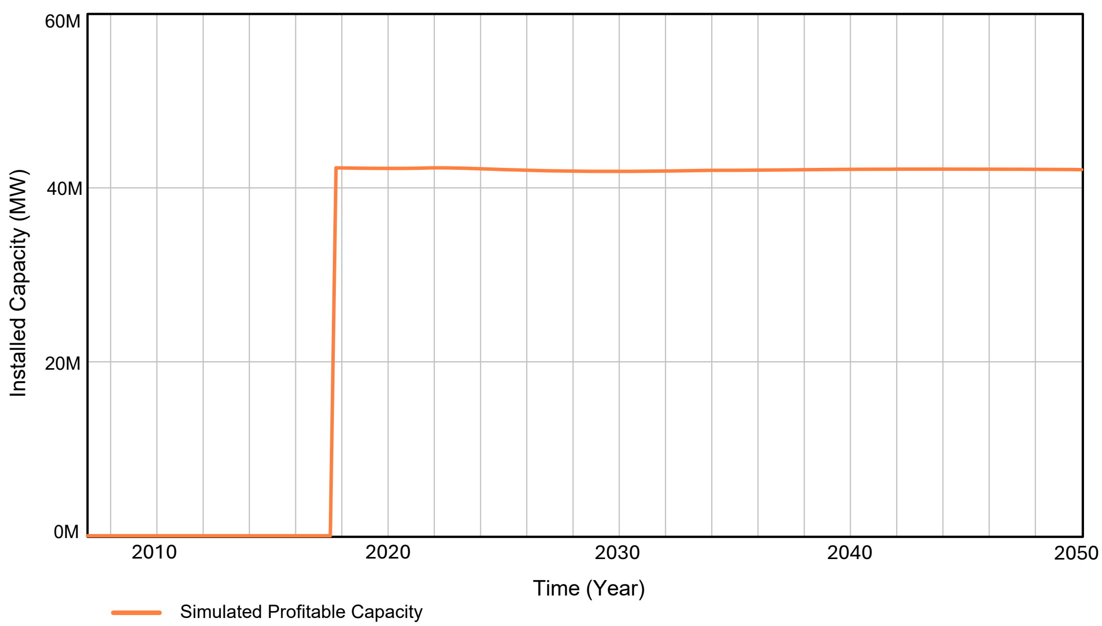

Figure 4.18: Simulated profitable capacity

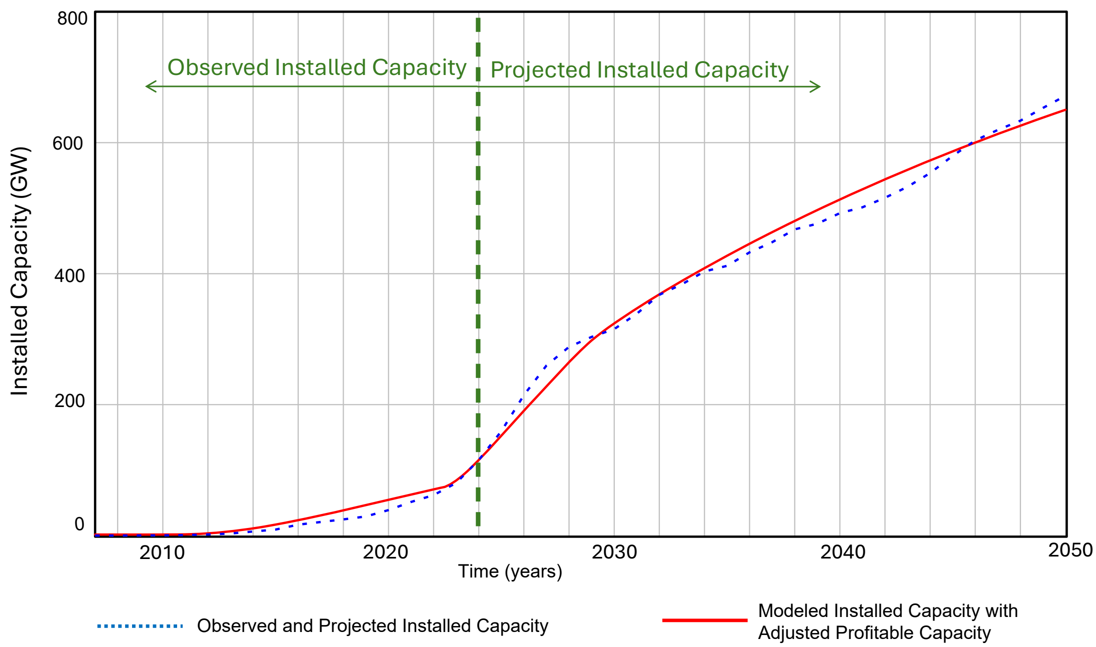

Figure 4.19: SD model-simulated solar PV installed capacity with adjusted resources versus observed installed capacity [145] and projected installed capacity [4]

policies other than tax incentives, something that future research and more detailed modeling could address.

To rectify the discrepancy between the historical records and simulated output for installed capacity, the solar model was simply adjusted to have available resources (modeled as profitable capacity) at the early stage of the solar PV technology adoption. The resulting simulation is presented in Figure 4.19.

The adjustment of the available resources resulted in a reasonably close match between the simulated and actual installed capacity. This confirms that the general model of the trajectory of a novel energy system adoption performs reasonably well, not just for a single energy technology but also for two different renewable energy technologies, namely onshore wind and utility-scale solar PV.

4.5 Quantitative Model of Clean Hydrogen Deployment

Hydrogen energy systems are more complex systems compared to renewable energy systems like wind and solar energy since more interconnected elements are involved in hydrogen generation compared to electricity generation.

The available technologies for low GHG emissions hydrogen production include SMR with carbon capture and sequestration (CCS), water electrolysis, and microbial biomass conversion. There is also ongoing research related to natural hydrogen that can be harvested from under the Earth's crust, potentially in large quantities [164, 165].

SMR with CCS, also known as blue hydrogen, involves reforming methane gas to produce hydrogen and capturing emitted CO_2 to reduce GHG emissions. Water electrolysis splits water into hydrogen and oxygen, and when using low-carbon or carbon-free electrical sources, it is a zero-carbon method. There are two types of electrolysis: Low Temperature Electrolysis (LTE) and High Temperature Steam Electrolysis (HTSE). LTE technologies include alkaline water electrolysis, anion exchange membrane water electrolysis, and polymer electrolyte membrane (PEM) water electrolysis, each with varying degrees of maturity and cost. HTSE using a solid oxide water electrolysis cell (SOEC), offers high efficiency and lower costs, but is still developing. Microbial biomass conversion uses microorganisms to produce hydrogen from biomass and wastewater but is in early R&D stages. While natural hydrogen generation has gained significant attention over the last two years, there are no natural hydrogen wells that have demonstrated commercial feasibility [165].

Three main clean hydrogen technologies are considered in this research—LTE, HTSE, and SMR with CCS. A PEM electrolysis technology is selected as the LTE technology.

The clear hydrogen technologies are competing with each other as the demand for hydrogen in the United States is limited by industrial hydrogen use. However, the demand is growing and is expected to increase substantially if the cost of hydrogen falls below the price levels feasible for industrial applications. The demand growth projections based on the hydrogen price are described in detail in the research presented in [24]. The hydrogen generation process also heavily relies on energy sources like electricity, thermal energy, or natural gas, which is different from the renewable energy systems that produce energy but rely on cost-free resources like wind and sun to generate the final product.

Because of the differences, the SD model developed for renewable energy is revised to account for the differences associated with hydrogen generation. The changes made to the model are briefly outlined in Section 4.5.1. The entire model is included in Appendix B, providing a detailed description of each change.

4.5.1 Model Adjustments

The Developer Capacity Growth submodel remains unchanged, but three other submodels are modified as discussed in this section to address specifics of hydrogen generation systems. The hydrogen model differs from the wind and solar models since, instead of a single technology, it depicts hydrogen generation by three methods of clean hydrogen production. This necessitated changes to the wind model and the addition of separate submodels for each individual technology.

The Profitable Capacity model for hydrogen is presented in Figure 4.20. The main change is the separation of the levelized cost of hydrogen (LCOH) calculation into three separate submodels, one for each individual hydrogen technology. This is done because the LCOH calculation includes more variables than LCOE, and the profitable capacity model becomes too large and difficult to follow.

One notable change from the wind and solar model is in the profitable capacity definition. In the case of hydrogen, the profitable capacity is driven by the demand for hydrogen rather than resources such as wind and solar quality resources that allow efficient electricity generation. The hydrogen demand is expected to significantly increase if the price is sufficiently low for feasible industrial applications. The expected demand growth dependent on hydrogen price is discussed in detail in [24].

There are three submodels for the LCOH calculation for the three technologies considered. Figure 4.21 presents the LCOH submodel for the LTE technology, and Figure 4.22 presents LCOH

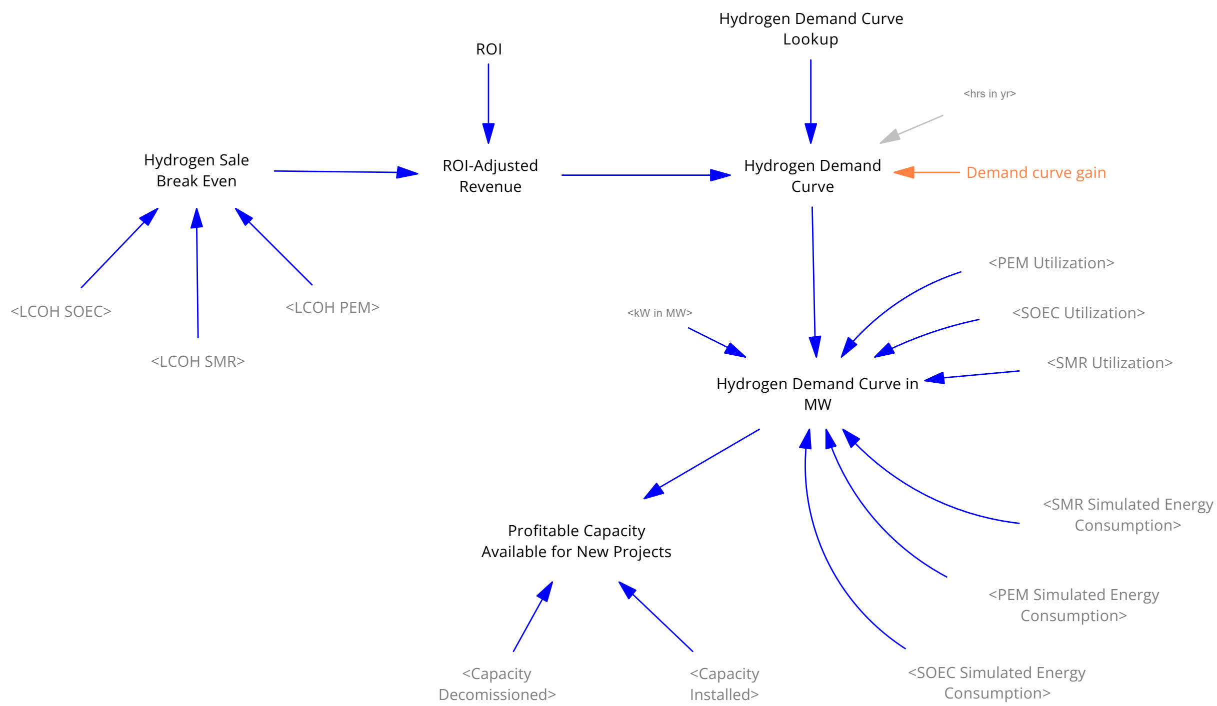

Figure 4.20: Profitable capacity model for clean hydrogen technology

submodel for the SMR with CCS technology. The LCOH submodel for the SOEC technology is identical to the LTE technology with differences only in technology-specific characteristics.

The technological learning model for hydrogen is slightly different compared to the wind and solar models because different technology characteristics are important to hydrogen technological learning. Specifically, the lifetime of electrolyzer stacks is more important than the cost of operation and maintenance (OpEx) for renewable electricity generation since stack replacement costs are a large part of the O&M costs for hydrogen plants. Similarly, instead of energy efficiency for renewable electricity generation, the energy consumption is a more appropriate variable where technology improvements (i.e., decreased energy consumption per kg of hydrogen produced) result in the reduction of LCOH incentivizing deployment. The capital expense variable (CapEx) remains an important parameter for hydrogen technology, and it is still represented in the technological learning model.

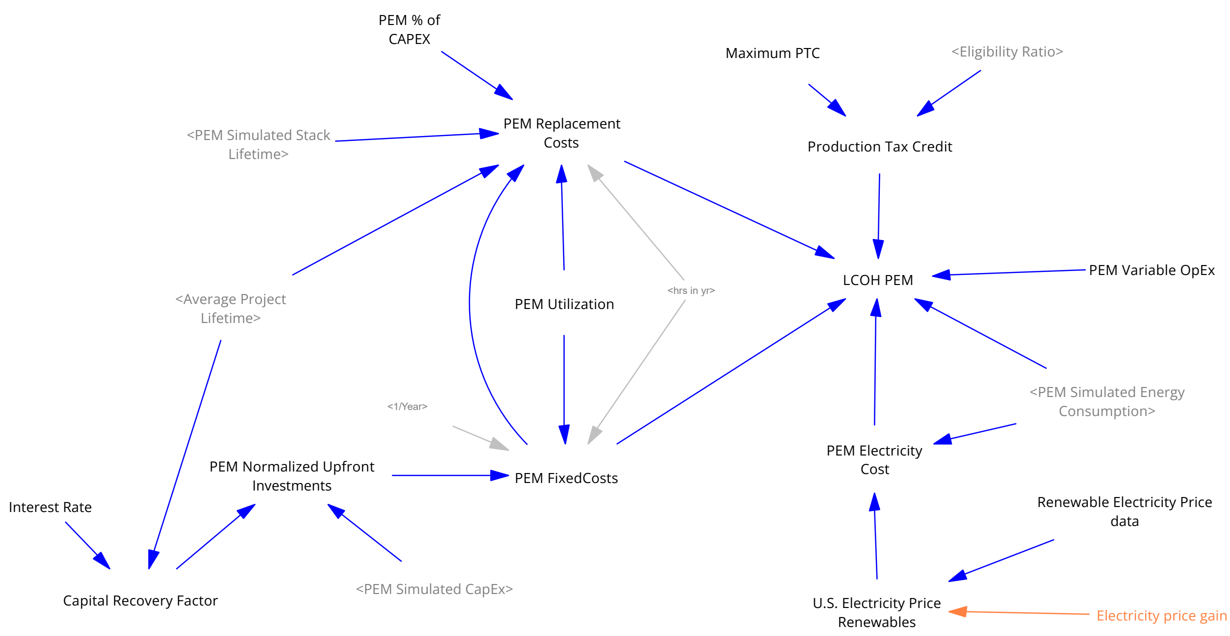

Figure 4.21: LCOH model representing calculation of the LCOH for LTE hydrogen technology represented by PEM electrolysis

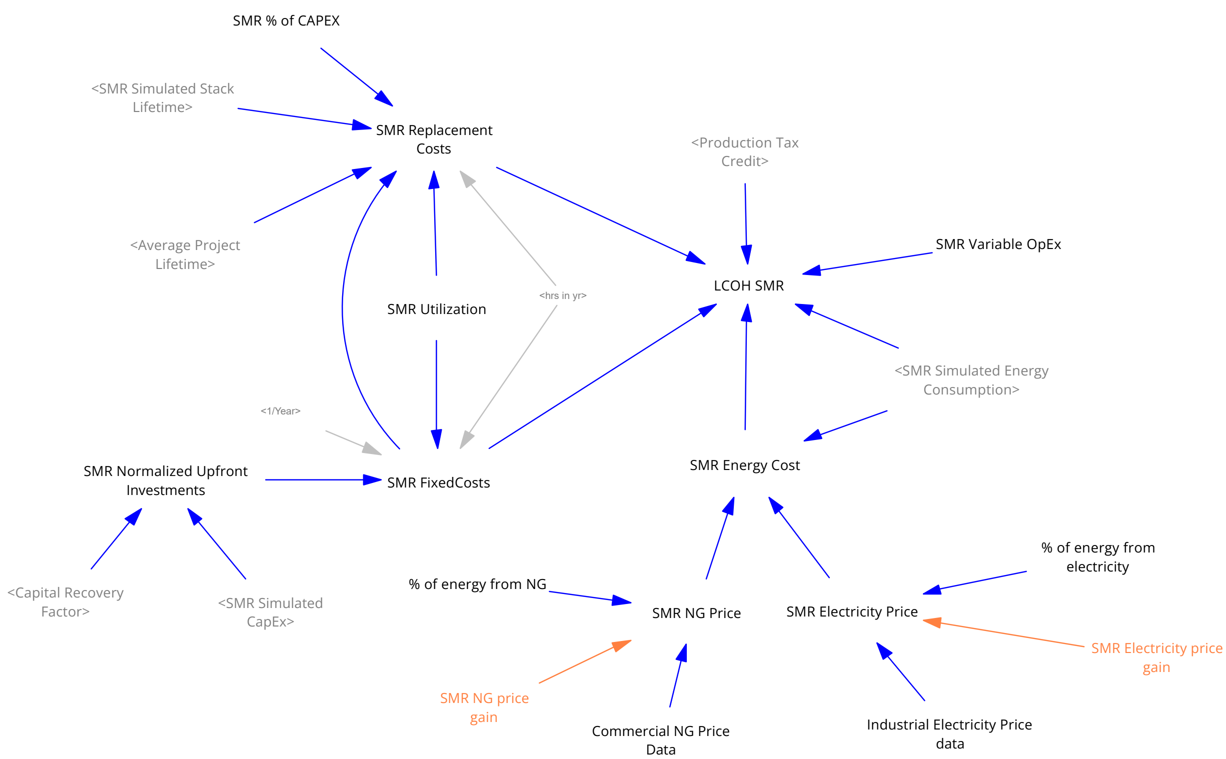

Figure 4.22: LCOH model representing calculation of the LCOH for SMR with CCS hydrogen technology

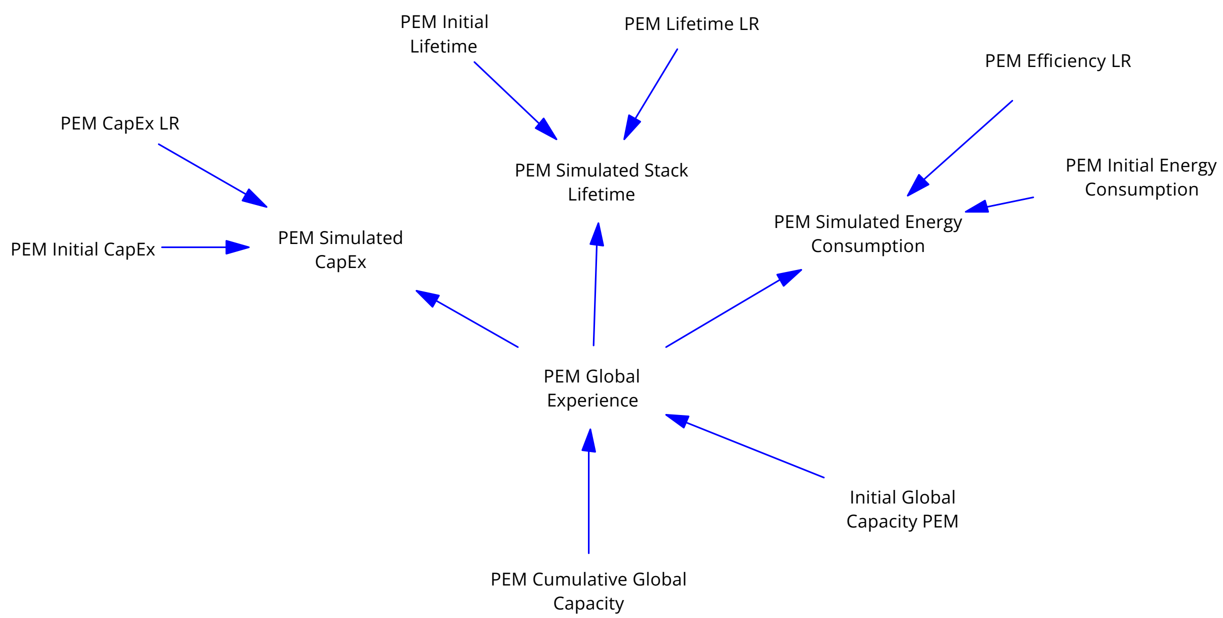

Figure 4.23: Technological learning model representing technology learning for LTE hydrogen technology represented by PEM electrolysis

The technological learning models are developed for the three considered hydrogen generation technologies. The technology learning submodel for the LTE technology represented by the PEM electrolysis is presented in Figure 4.23. The technological learning submodels for the other two technologies are identical, with differences only in technology-specific characteristics.

The last model, the capacity growth of hydrogen technology, is only slightly revised compared to the renewable electricity capacity growth.

The *Ineligible for PTC Capacity* stock variable is introduced as shown in Figure 4.24. The reason for the additional variable is the need to include the limit of incentive for hydrogen generation, which is offered for the first 10 years of operations. Since the lifetime of the facility is much longer, the first 10 years of the operation of installed capacity must be tracked. This limiting condition is included in the LCOH calculations made in the LCOH submodels as part of the *Production Tax Credit* variable.

Another change in the capacity growth submodel is the modification of project initiation failure rate calculations. In the case of renewable electricity generation, permitting and connection to the grid play a major role in project's success rate. However, permitting processes for hydrogen

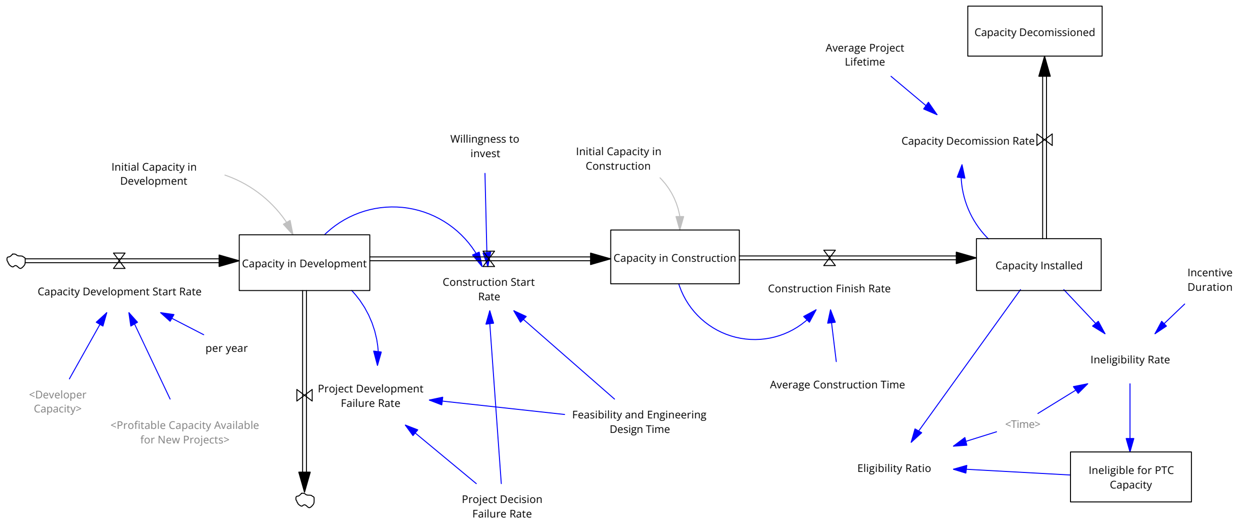

Figure 4.24: Capacity growth model representing projected hydrogen technology deployment

generation facilities are driven by engineering evaluations and not by policy aspects. Also, the three technologies considered in this research have very minimal dependence on the electrical grid, which eliminates the concerns about grid connection permits.

The data sources for model variables are explained in Table 4.3. The differences between technological characteristics of the three hydrogen technologies are summarized in Table 4.4.

Table 4.3: Variables and data sources for the hydrogen model

Submodel	**Variable**	**Value**	**Source**
Profitable Capacity	ROI	10%	Assumed
	Hydrogen Demand Curve	Data	[24]
Technological Learning	Projected Cumulative Global Capacity	Data	[166]
	Initial Global Capacity—Total Globally Installed Capacity in 2000	8,000 MW	[167]
	Initial CapEx—PEM	1,523 $/kW	[168]
	CapEx LR—PEM	0.11	[27, 169]
	Initial Lifetime—PEM	70,000 hrs	[170]
	Lifetime LR—PEM	0.1—estimated	[171]
	Initial Energy Consumption—PEM	55.5 kWh/kg	[168]
	Efficiency LR—PEM	0.025	[169]
	Initial CapEx—SOEC	1,175 $/kW	[168]

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Table 4.3 — *continued from previous page*

Submodel	Variable	Value	Source
	CapEx LR—SOEC	0.09	[169]
	Initial Lifetime—SOEC	50,000 hours	[170]
	Lifetime LR—SOEC	0.15—estimated	[171]
	Initial Energy Consumption—SOEC	45.0 kWh/kg	[168]
	Efficiency LR—SOEC	0.08	[169]
	Initial CapEx—SMR wCCS	862 $/kW	[168]
	CapEx LR—SMR wCCS	0.04	Assumed
	Initial Lifetime—SMR wCCS	43,800 hrs	[172]
	Lifetime LR—SMR wCCS	0.02	Assumed
	Initial Energy Consumption—SMR wCCS	61.8 kWh/kg	[168]
	Efficiency LR—SMR wCCS	0.01	Assumed
LCOH	Interest Rate	10%	Estimated
	Renewable Electricity Price Data	Data	Wind SD model
	PEM percent of CAPEX	0.275	[169]
	SOEC percent of CAPEX	0.15	[169]
	SMR percent of CAPEX	0.042	Estimated
	Behind Meter Industrial Electricity Price data	Data	[173]
	Industrial Electricity Price data	Data	[173]
	Commercial NG Price Data	Data	[173]
	Percent of energy from electricity	0.02	[168]
	Percent of energy from NG	0.98	[168]
Developer Capacity Growth	Initial Developer Capacity	250 MW	[167]
	Maximum Growth Rate	700%	[167]
	Developer Capacity Adjustment Time	1 year	Assumed
Capacity Growth	Project Decision Failure Rate	40%	[27]
	Willingness to Invest	0.9	[27]
	Initial Capacity in Development	5700 MW	[27]
	Initial Capacity in Construction	136 MW	[167]
	Average Construction Time	2 years	[27]
	Average Project Lifetime	30 years	[168]
	Incentive Duration	10 years	[174]

Table 4.4: Inputs for three hydrogen production scenarios evaluated in the research

Variable	**Unit**	**LTE**	**SOEC**	**SMR + CCS**
Energy source	n/a	Dedicated hybrid wind and solar electricity	Nuclear power for thermal energy and electricity	Natural gas plus grid electricity
Desired Production Rate	kg/day	500,000	500,000	500,000
Lifetime	years	30	30	30
Nameplate Capacity	kg/day	760,000	560,000	560,000
Nameplate Capacity in MW	MW	1,758	1,050	1,442
Installed CAPEX	$/kW	1,523	1,175	862
Utilization	%	66.1	90.0	90.0
Production Rate	kd/day	502,360	504,000	504,000
Totall Installed CapEx	$	2,677,038,163	1,233,228,583	1,243,197,045
Fixed OpEx w/o Replacement	$/year	138,791,595	85,274,558	32,767,164
Variable OpEx	$/kg	0.0326	0.0001	0.3385
Annualized Replacement Costs	$/year	42,274,477	62,827,662	9,033,122
Stack CAPEX	$	736,185,495	184,984,287	—
SMR Replacement Costs	$	—	—	52,214,276
Stack Lifetime	Years	70,000	50,000	—
SMR Catalyst Lifetime	Years	—	—	43,800
Annualized Replacement Costs	$/year	60,896,843	29,168,322	9,398,570
Energy Utilization	kWh/kg	55.5	45.0	61.8
Energy Utilization for SMR + CCS				
Industrial electricity	kWh/kg	n/a	n/a	1.5
Commercial Natural Gas	mmBTU/kg	n/a	n/a	0.186

4.5.2 Hydrogen Model Results

The outcome of the research is the model simulating the trajectory if the hydrogen energy system capacity growth based on multiple factors affecting system deployment. The model also informs the user about potential scenarios of system behavior given potential variation in variables as well as the sensitivity of a given parameter to the input variables. Stakeholders can use the model to inform their decisions relevant to energy system deployment prospects, such as investment strategies or policy decisions.

Sensitivity Studies

Additional insights about the model and represented energy system are obtained through sensitivity studies.

Figure 4.25 presents a tornado chart showing the sensitivity of hydrogen capacity growth to various elements. It shows that the hydrogen capacity growth is most sensitive to the availability of demand represented as the *Hydrogen Demand Curve* variable. The next most influential parameters are the *Average Project Lifetime* and *Willingness to Invest*. These insights are not surprising since the total capacity of the potential wind energy is directly affected by the hydrogen demand, influencing the decision on capacity expansion. As discussed in Section 4.2.2, an investor's willingness to fund wind energy projects is one of the key factors affecting the overall deployment of wind installations and total capacity growth.

Techno-economic variables, such as energy consumption, utilization, and efficiency for the different hydrogen technologies, are also highly influential. This is also an expected finding since the feasibility of hydrogen installation deployment is determined using these parameters. The model is less sensitive to other variables representing the ability of the developers to grow their capacity and factors affecting learning rates.

The hydrogen model includes three hydrogen generation technologies, each with its own LCOH. Figure 4.26 presents the change in LCOH for each technology for the base case (i.e., the current federal incentives are considered).

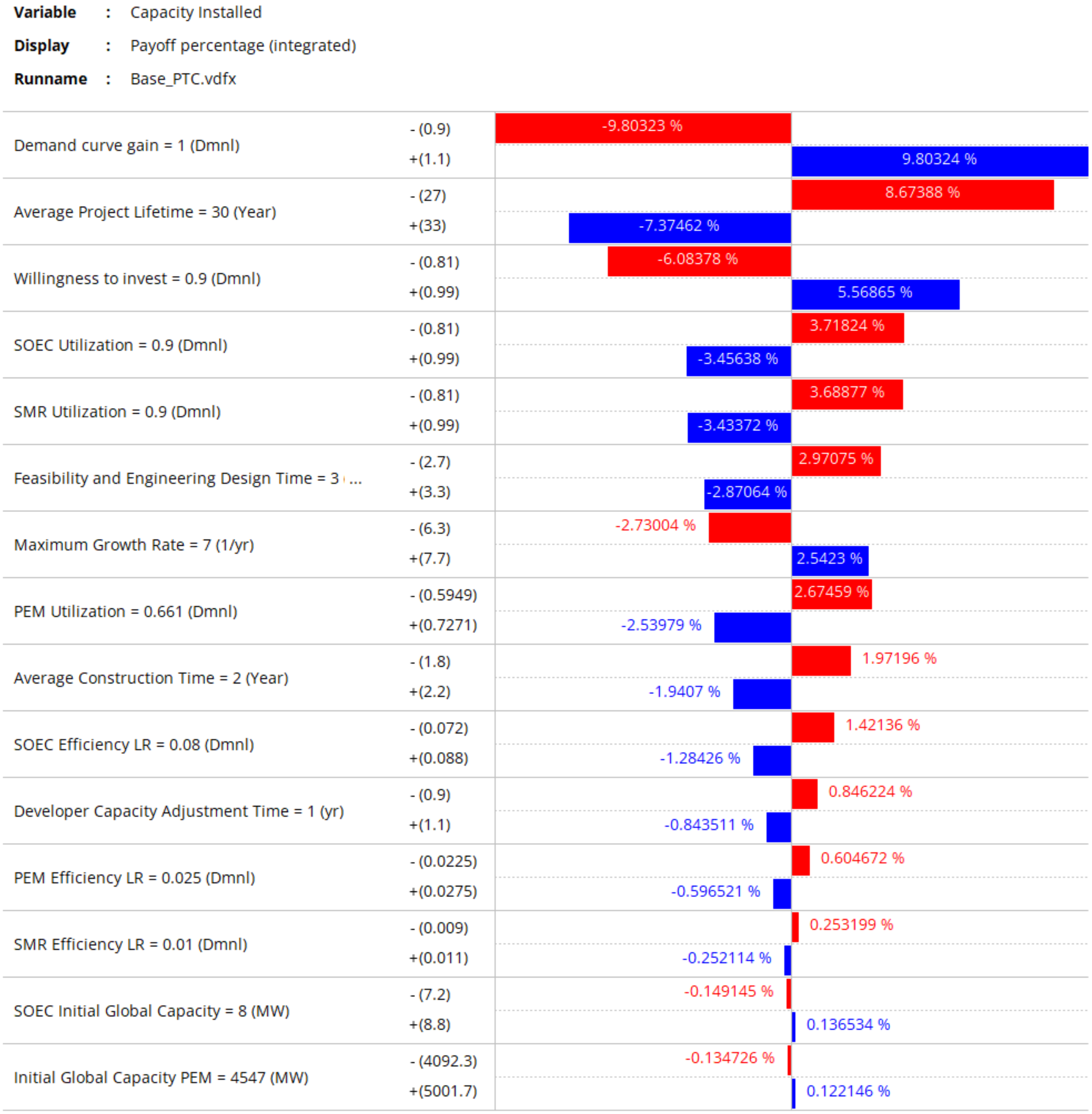

Figure 4.25: Sensitivity of hydrogen capacity growth to modeled variables

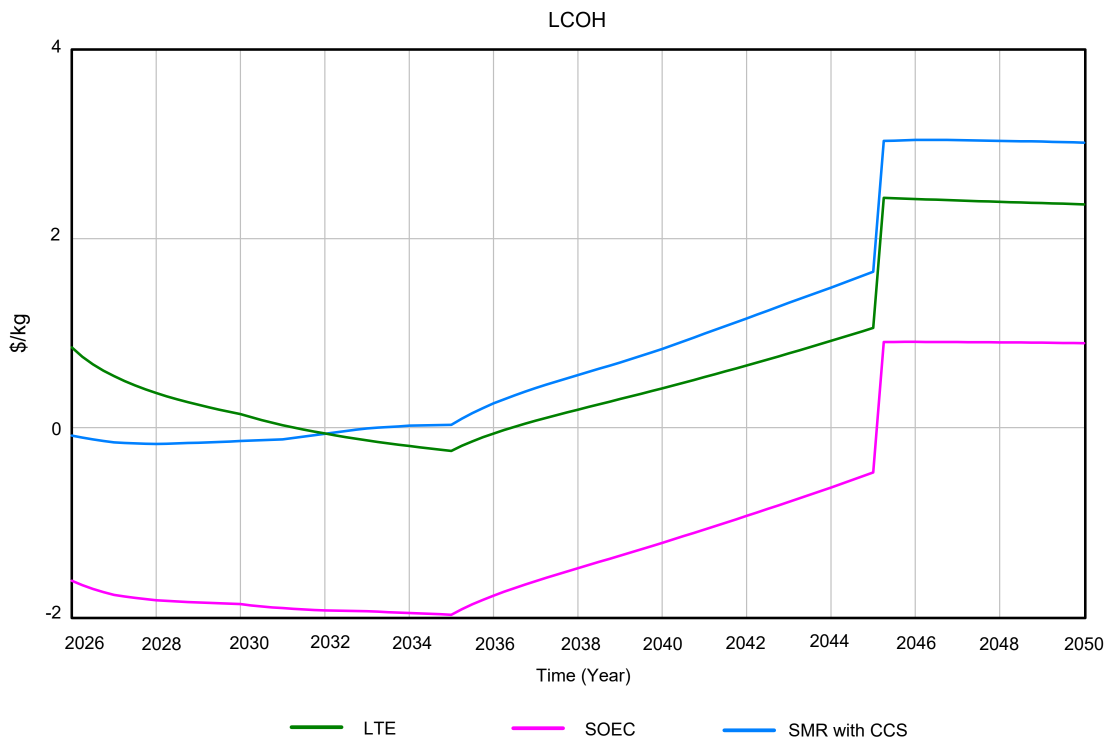

Figure 4.26: LCOH for three hydrogen generation technologies for the base case scenario

The two electrolysis technologies, LTE and SOEC, demonstrate a similar pattern of cost decline up to 2035 when the incentive is no longer available for the new installation and begin to decline as the installations age past the 10-year cutoff. On the other hand, the SMR with CCS technology costs are rising. This is explained by two main factors—the primary energy source and technology learning rates. The primary energy source of LTE is electricity from renewable energy sources. The LCOE of renewable electricity is expected to decline, which directly affects the LCOH. The SOEC electrolysis uses electricity and thermal energy from a nuclear facility with an expected decline in its LCOE and corresponding decline of the LCOH. On the other hand, the SMR with CCS technology uses natural gas as the primary energy feedstock. The cost of natural gas is expected to increase, which results in the increase of the LCOH for this technology.

Technology learning rates also play a role in LCOH decline. Electrolysis is a new technology, and both LTE and SOEC are expected to improve more than the well-established SMR technology.

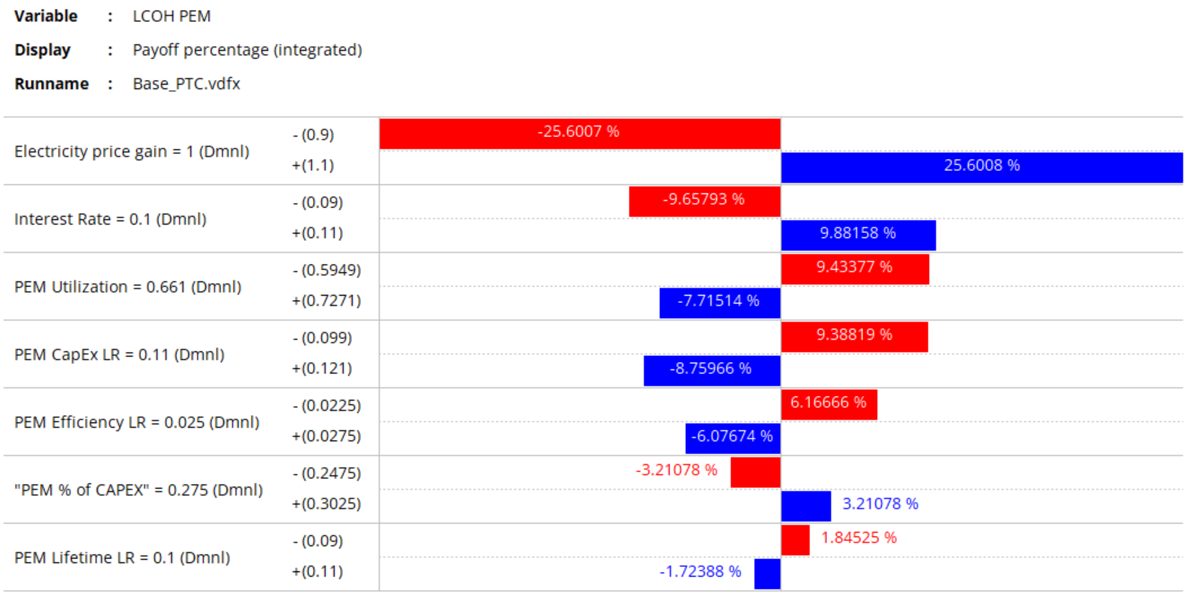

Figure 4.27: Sensitivity of LTE LCOH to modeled variables

This expectation of improvements is represented by technological learning rates, which are higher for LTE and SOEC technologies compared to SMR with CCS technology.

Figure 4.27 illustrates the sensitivity of the LTE technology LCOH to the various model inputs. Similarly, Figure 4.28 presents the sensitivity of the SOEC technology, and Figure 4.29 presents sensitivities of SMR with CCS technology.

The results confirm the expectation: the largest influencing factor is the *Capacity Factor* since even small changes dramatically affect the resulting cost of energy. The rest of the economic variables have smaller but still measurable impacts on energy costs. The outcomes from the sensitivity studies confirm the general dynamics of energy system diffusion presented in Figure 4.6 by demonstrating dependencies between variables within and between the loops.

Scenario Analysis

The goal of the hydrogen model is to explore potential futures of clean hydrogen systems deployment given multiple influencing parameters. Three scenarios are explored:

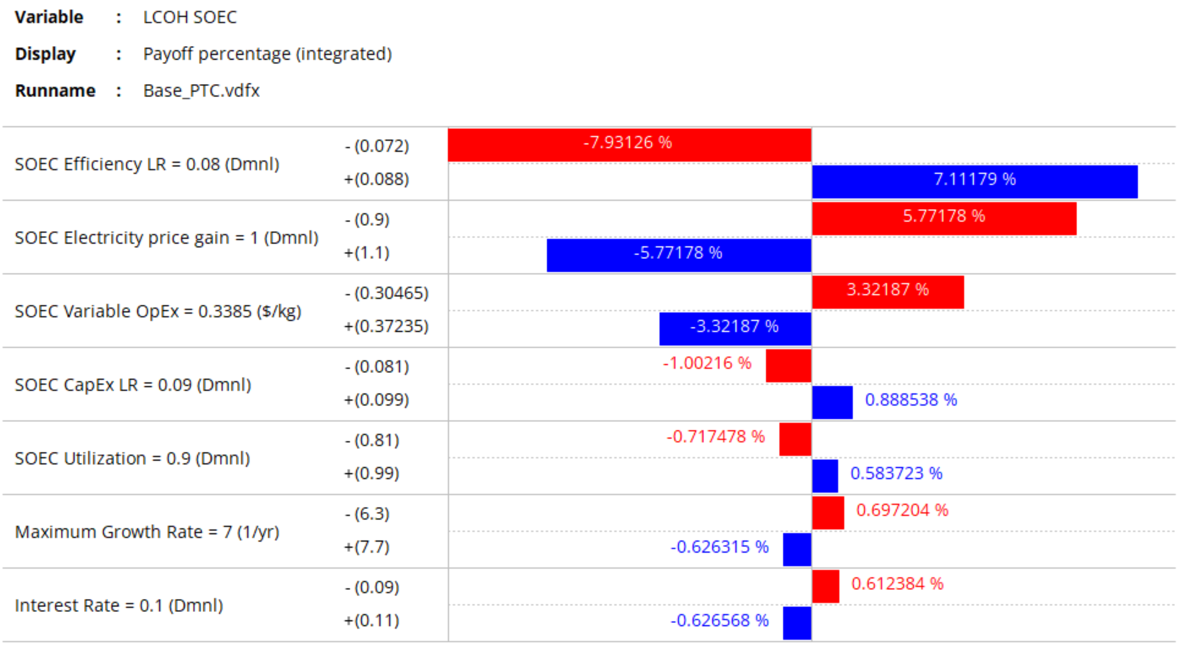

Figure 4.28: Sensitivity of SOEC LCOH to modeled variables

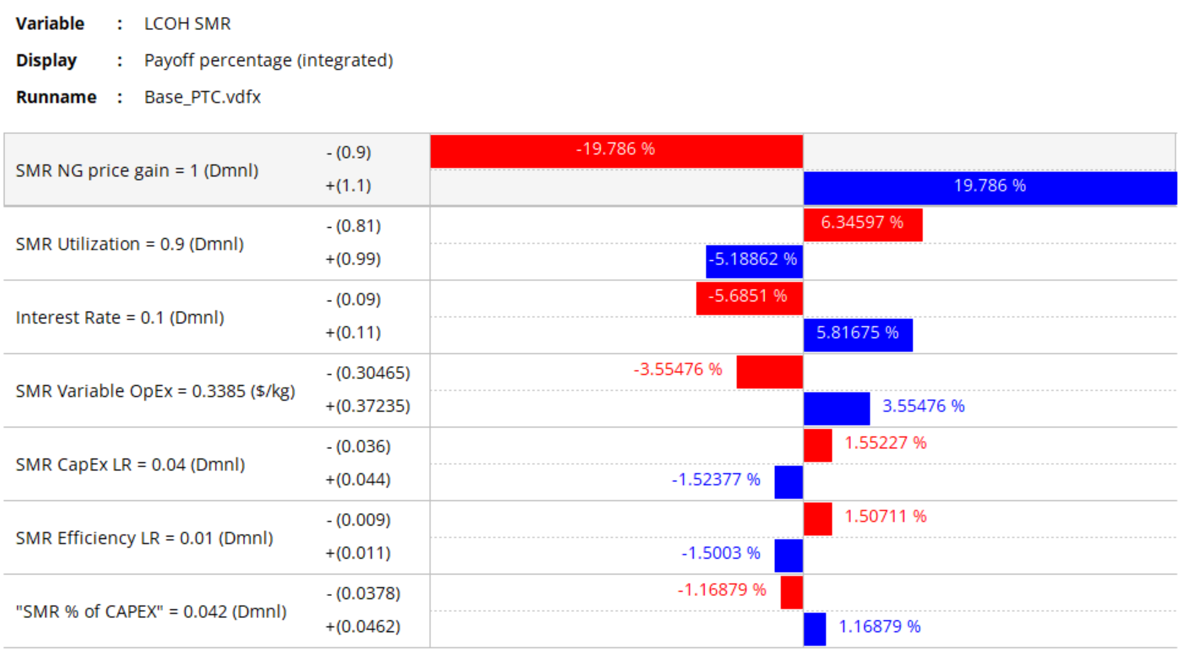

Figure 4.29: Sensitivity of SOEC LCOH to modeled variables

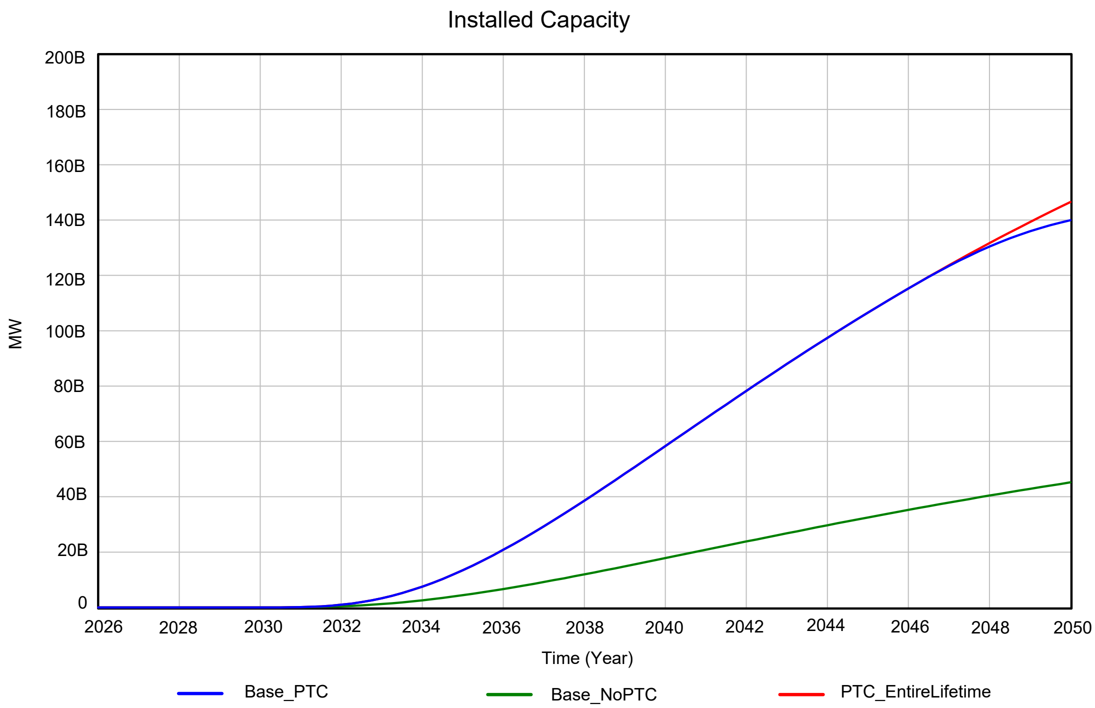

Figure 4.30: SD model simulated installed capacity for clean hydrogen generation

- Federal incentives for hydrogen are currently in place,
- No incentives
- The incentive is applicable to the entire lifetime of the hydrogen production facility instead of the first 10 years, and without the constraint on the construction date.

Figure 4.30 demonstrates the capacity growth for the three scenarios.

As expected, installed capacity by 2050 is much lower if incentives are not in place. The change in incentive duration does affect the capacity growth, but not as dramatically as a complete removal of PTCs. The impact on capacity growth is observed starting in the mid-2040s since capacity that begins construction in 2033 will be installed in about 2 years and PTC will be applicable until 2045.

The hydrogen demand curve is dependent directly on the price of hydrogen, which is dependent on the production costs. Figure 4.31 shows the hydrogen demand curve where the demand is much smaller with incentives not present or removed after eligibility time ends.

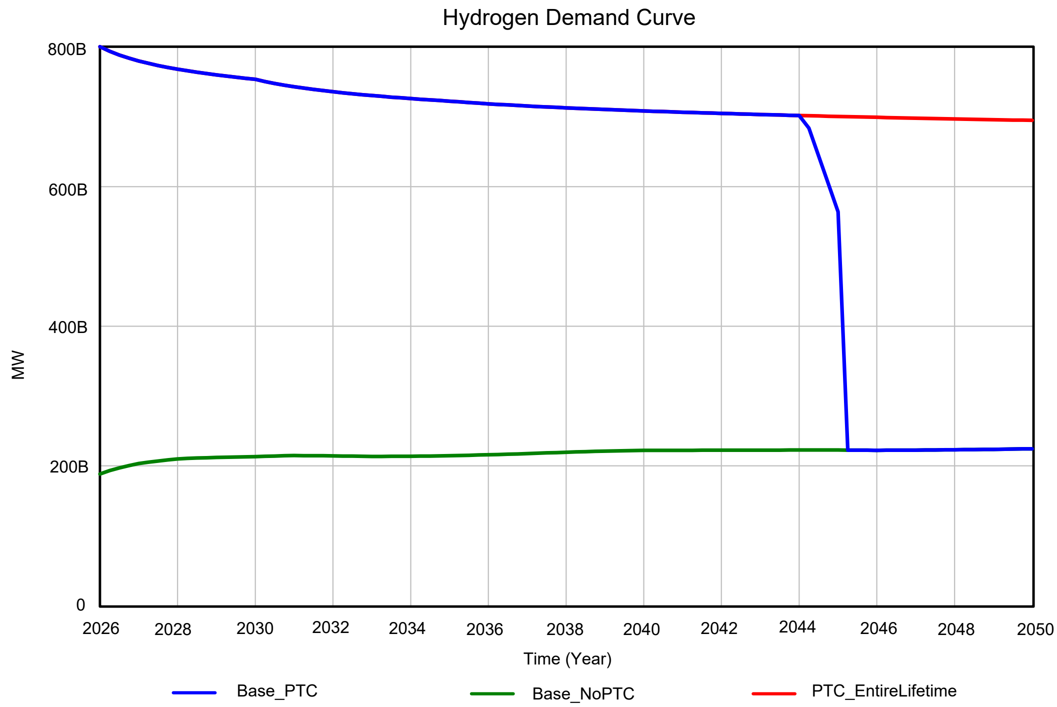

Figure 4.31: Hydrogen demand curve showing dependence between hydrogen demand on hydrogen price and the presence of incentives

While the demand for hydrogen drops immediately after the incentive is removed, the capacity growth has a time lag, which explains why installed capacity predictions diverge a few years later.

The model can be used to simulate other scenarios where inputs related to technological improvements (e.g., energy consumption) or feedstock parameters (e.g., cost of electricity) or where financial parameters (e.g., return on investment) are altered to assess the impact on the modeled outcomes of interest (e.g., *Capacity Installed*).

4.6 Conclusion

The deployment of novel energy technologies is a multifaceted process influenced by various factors, including policy and regulation, technological advancements, economic considerations, environmental concerns, public perception, and infrastructure capabilities. The research presented in this chapter explored these dynamics through both qualitative and quantitative modeling, focusing on onshore wind and utility-scale solar PV energy systems.

4.6.1 Key Findings

Qualitative Insights

The qualitative analysis identified several key dynamics affecting the deployment of novel energy technologies. Government policies and incentives, such as PTC, play a crucial role in accelerating technology adoption. Technological advancements and learning by doing significantly reduce costs and improve performance, making new technologies more competitive. Economic factors, including electricity prices and initial capital expenditures, heavily influence investment decisions. Environmental concerns and energy security considerations drive the demand for cleaner energy solutions. Public perception and social acceptance are also critical for the successful implementation of large-scale projects.

Quantitative Insights

The quantitative modeling of onshore wind and utility-scale solar PV energy systems provided valuable insights into the factors driving capacity growth and cost reductions. The model demonstrated a reasonable fit with historical and projected capacity data, validating its ability to simulate the trajectory of novel energy technology adoption. Sensitivity studies highlighted the importance of resource availability, willingness to invest, and technological learning as the most influential factors affecting capacity growth. Scenario analyses confirmed the significant impact of federal incentives and technological learning on both capacity growth and the LCOE.

4.6.2 Implications for Stakeholders

The findings from this research have several implications for policymakers, investors, and industry stakeholders.

Policymakers: The research underscores the importance of consistent and supportive government policies and incentives in accelerating the deployment of novel energy technologies. Policymakers should consider long-term commitments to incentives like PTCs to reduce market volatility and encourage sustained investment in renewable energy projects.

Investors: Understanding the dynamics of technology adoption and the factors influencing profitable capacity can help investors make informed decisions. The model highlights the significance of technological learning and cost reductions, suggesting that investments in R&D can yield substantial returns in the long run.

Industry Stakeholders: The capacity growth and technological learning loops emphasize the need for industry stakeholders to focus on both scaling up developer capacity and investing in technological improvements. Collaboration with policymakers to ensure supportive regulatory environments and incentives can further enhance market uptake.

4.6.3 Summary

This chapter comprehensively examines the deployment of novel energy technologies, focusing on the dynamics of commercialization and technology diffusion. The energy system transition is influenced by a complex interplay of factors, including government policies, economic considerations, technological advancements, social acceptance, global dynamics, environmental concerns, and resource availability. Key factors affecting the energy system transition include policy and regulation, technological advancements, economic factors, environmental concerns, energy security, energy market dynamics, resource availability, public perception, infrastructure and grid capability, R&D, and international cooperation. Understanding and addressing these factors holistically is essential for accurately describing or predicting energy transitions.

The chapter also explores the dynamics of technology diffusion, highlighting the role of feedback loops driving adoption. Challenges in technology diffusion, particularly in large-scale sociotechnical systems like energy generation, are discussed, emphasizing the importance of considering interactions between system elements and behaviors between the elements internally within the system and with external elements and systems.

A qualitative assessment of energy technology deployment dynamics is presented using a causal loop diagram to model key factors influencing technology adoption. The chapter discusses the use of capacity growth and technology diffusion models, highlighting the importance of integrating economic and social factors.

The quantitative modeling section focuses on the SD model developed for understanding the commercialization paths of novel energy technologies, specifically onshore wind, utility-scale solar PV, and clean hydrogen generation systems.

The initial model is built for the wind energy system, exploring wind energy capacity growth in the United States given multiple influencing factors like economical feasibility, availability of resources, growth of developer capacity to build new projects, and maturation of the technology leading to cost reductions. The simulation results are compared with historical and projected capacity data, demonstrating the model's validity.

The wind model was used to simulate the utility-scale solar PV energy growth in the United States by using solar-specific data. The results from the solar model simulations are compared to the historical and projected data for the utility-scale solar PV capacity growth, which validates the solar model.

The application of the same model and validation against historical data confirmed the hypothesis that the commercialization of novel energy systems follows similar patterns and is affected by the same factors, such as technology readiness, economic feasibility, federal policies, developer readiness, and availability of resources. Therefore, the model was used next to analyze potential futures for the commercialization of clean hydrogen generation energy technology at the initial stages of large-scale adoption within the energy system, with no historical data yet available.

Sensitivity studies highlight the importance of resource availability, willingness to invest, and technological learning as key factors affecting capacity growth and LCOE. Scenario analyses confirm the significant impact of federal incentives and technological learning on both capacity growth and cost reduction.

This research concludes by outlining findings and making recommendations to the energy sector stakeholders, including investors, utilities, and policymakers, regarding opportunities and challenges associated with deploying novel energy solutions within established energy systems.

Chapter 5

Model-Based Systems Engineering for Energy System Concept Selection [5]

In the discourse of energy technology commercialization, previously explored in Chapter 4, this chapter expands into the area of a more granular problem—crafting a decision support framework aimed at configuring energy systems on a smaller scale. The principal objective is to leverage SE principles and tools systematically to minimize the risk of suboptimal system configurations that fail to align with stakeholder requirements or regional conditions, potentially leading to reduced or lost profits. The need for this new approach is underscored by the inherent complexity and uncertainty in energy systems, which necessitates a structured, multidisciplinary evaluation method to facilitate high-level decision-making and ensure the selection of the most feasible and beneficial system concepts.

5.1 Introduction

The approach to a high-level long-term strategic analysis of novel energy technology commercialization has been presented in Chapter 4. This research developed a model that enables a better understanding of factors affecting technology uptake by the energy system and pathways to successful commercialization of new technologies. Let's assume decision-makers are convinced that a new energy technology has great potential to be adopted within the energy system. The next step is to decide on a specific configuration of the energy system, or multiple systems, to be deployed. This chapter describes the research of a decision support framework that focused on a smaller-scale problem compared to the one analyzed in Chapter 4. In this chapter, the focus is on a systematic conceptual development of an energy system using SE principles and tools. This is

[5]This chapter contains works published in [74]. The works are reproduced within this chapter and have been reformatted to meet the dissertation style guidelines.

an important problem since selecting a suboptimal system concept and configuration could lead to unfavorable results, such as an incompatibility of the proposed solution with stakeholder requirements or regional conditions, as well as reduced or even lost profit. A systematic approach to concept development minimizes the risk of an improper system configuration.

5.1.1 The Need for a New Approach

Energy systems are difficult to plan and analyze due to their complexity, which stems from the heterogeneity of and dynamic interdependence between subsystem components and the complexity of the networks that connect them, as well as the uncertainty related to their future state [38]. The complexity of evaluating energy and environmental problems is pointed out by many research studies [39–44] that point to the many sources of uncertainty, multidisciplinary affecting factors, and a large number of stakeholders with often competing objectives. As such, an application of formal decision analysis methods is warranted and highly encouraged.

Regarding the use of MBSE to assist in the strategic decision-making for new systems, an extensive literature search revealed only a few targeted studies [175–177]. These investigations have provided insightful information, supporting the hypothesis of this paper that MBSE is valuable in the conceptual design stages. However, these studies fall short of combining system concepts with strategic decision-making, which is the innovative aspect of the methodology and framework presented in this research.

The traditional approaches to analyzing energy strategies as well as decision-making tools described in Section 2.2.2 are incredibly valuable for some applications, including economic assessments or conducting detailed analyses of specific aspects of an energy system. However, they do not facilitate the initial high-level decision-making process that considers all feasible options for a new energy system. Decision-makers often choose concepts that are familiar or widely advertised as the "best solution". This quick selection is followed by numerous in-depth analyses and evaluations to assess the feasibility of the chosen system configuration. These detailed evaluations often uncover conditions that render the concept unfeasible or challenging to implement, leading decision-makers back to the drawing board with wasted efforts and time spent on detailed analyses.

Instead of diving deep into the analysis of a single concept, SE principles in conceptual design strongly advocate for initially exploring as many concepts as possible to ensure the potentially best solution is not overlooked. Ensuring that selected options are highly likely to be feasible is crucial in the design of complex systems and systems-of-systems before advancing to the detailed analysis phase. This broad, unrestricted exploration, not limited to predetermined solutions, often reveals possibilities that were not originally envisioned. Using ST practices compels analysts and decision-makers to adhere to the "system as a whole" principle. In summary, the traditional economics-focused approach to evaluating energy systems is no longer sufficient, as it is too narrow and too complex to support the informed strategy selection and investment decision-making for novel energy systems.

Assessing energy systems requires a multidisciplinary approach that considers various disciplines representing the objectives and perspectives of different stakeholders. This approach allows us to evaluate whether the energy system is achieving its diverse objectives and whether these objectives are achieved in a mutually beneficial way that satisfies all the stakeholders with some interest or connection to the system. Evaluations of energy systems in the literature vary from simplistic, one-dimensional assessments focusing solely on aspects like the environmental and social sustainability of energy technologies [178, 179] to more comprehensive, multidimensional studies that incorporate multiple perspectives on energy systems [180, 181]. Reference [182] suggests that using just one metric to evaluate results can be incomplete and potentially misleading. This could result in poor decision-making and choosing less effective solutions.

The multiperspective studies and approaches allow users to gain a better understanding of system scenarios and aid in strategy formulation. Many of these multidimensional analyses aim to compare energy generation technologies, including renewable energy sources [183, 184].

In supporting decision-making processes, it is crucial not just to consider multiple dimensions for evaluation but also to be able to recognize and assess trade-offs between them [180, 185, 186].

This enables designing alternative strategies that can improve all objectives, rather than only prioritizing a single obvious aspect like economics.

Another concern is making decision analyses too complex for evaluating conceptual strategies relying on advanced modeling and simulation tools or complex formulas. For the initial selection of potential strategies, decision-makers prefer simple-to-understand approaches and would reject complex methods and tools even if they are valid and beneficial for identifying the optimal solution. For example, Idaho National Laboratory has developed a comprehensive and extremely capable Framework for Optimization of Resources and Economics tool suite to analyze the economic potential of various integrated energy systems to identify the optimal operational strategies of such systems [187]. However, the tool can be too complex for decision-makers selecting which concept of a new energy system is a better option for their organization.

A novel methodological framework is proposed to address identified gaps in the approaches currently used to assess strategies for novel energy systems. The proposed framework also addresses the difficulties associated with a typical decision-making process for any complex system. Section 5.2 describes the concept, methods, and tools used within the framework. Section 5.3 explains the process steps within the framework.

5.2 Conceptual Framework for Strategy Evaluation

Decision-makers tend to rely on their experiences and preferences rather than conducting objective evaluations among alternative solutions. Energy systems involve multiple interconnected elements, making it challenging for the human mind to manage the complexity. Without a proper methodology, concept selections carry a high risk of inconsistency and personal biases. This issue increases the risk of choosing a concept that might not be the best fit, potentially rendering the system unfeasible or unsuitable for its intended objectives. The informal evaluation of system concepts typically lacks documentation, which makes it difficult to understand the rationale behind design decisions when they are revisited (e.g., in subsequent project phases or when selecting a solution for a different region). The proposed framework addresses these challenges by facilitating comprehensive early-stage decision-making in energy systems. It offers a conceptual approach, underlying methodologies, and tools to support objective, comprehensive, systematic, and innovation-promoting evaluations of energy system solutions.

The proposed framework uses two conceptual approaches: ST using SE principles and tools, and formal decision-making using a multicriteria decision analysis. The application of ST concepts is supported by SE formal approaches and the MBSE method. The concept of formal decision-making is supported by a combination of Pugh matrix and Multi-attribute Utility Theory (MAUT) methods. The MBSE approach within the ST concept is used for guiding the steps within the framework, organizing the problem, and describing the systems in sufficient detail. The multicriteria decision analysis supports the need for an objective, comprehensive, and systematic approach to decision-making.

The disciplines of ST and SE are discussed in Chapter 3. Some of the information is repeated in this chapter for a complete picture of the proposed conceptual framework.

5.2.1 Systems Engineering

Systems engineering is "a transdisciplinary and integrative approach to enable the successful realization, use, and retirement of engineered systems, using systems principles and concepts, and scientific, technological, and management methods" [77]. The objective of SE is to direct and support the development of complex systems. A systems engineer connects multiple disciplines and evaluates system context and stakeholder needs to achieve the optimal system solution.

The goal of SE is to support the delivery of the right product (or right service) on time and within budget. This goal is supported by the objective to provide a common understanding of the system's current state and a common vision of the desired future state shared by system customers and suppliers, achieved by applying standardized methods and tools throughout the system life cycle. SE is particularly important for complex systems where traditional engineering and project management practices are no longer sufficient to manage complexity effectively.

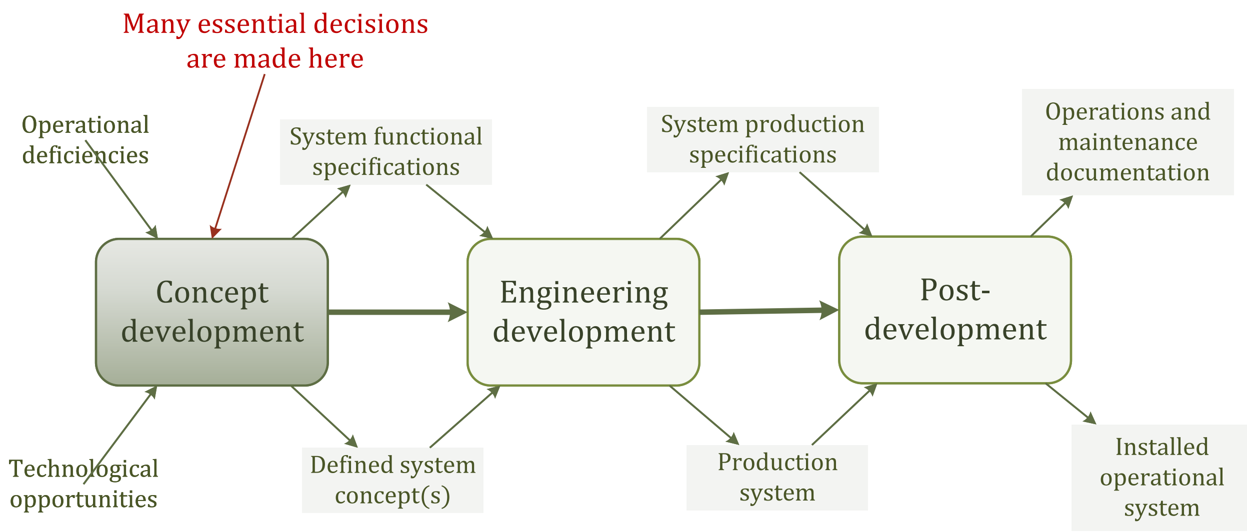

Figure 5.1: Stages in system life cycle (adopted from [79])

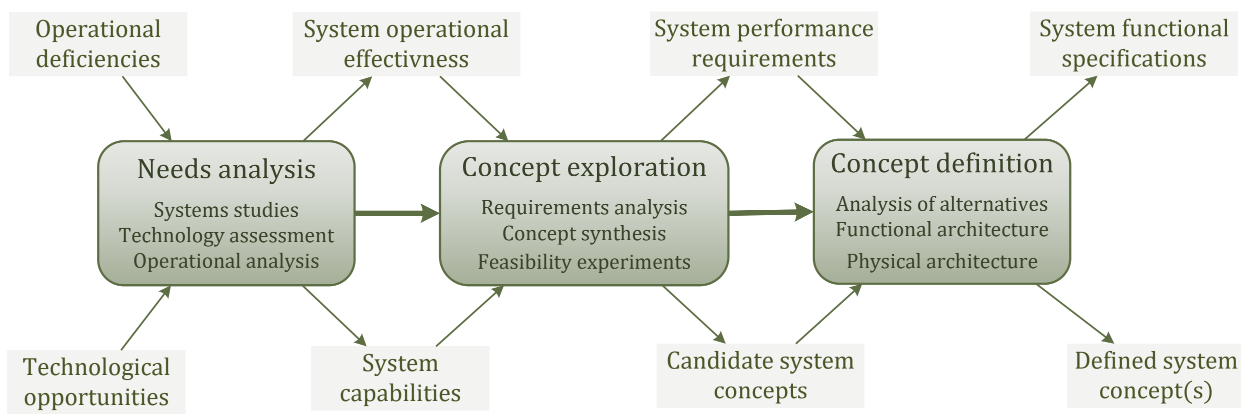

Figure 5.2: Concept development phases (adopted from [79])

Each system experiences stages in its life cycle as depicted in Figure 5.1 with SE being able to support each stage. This research is focused on the decision-making at the first stage, the concept development. The phases of the concept development guided by SE methods are presented in Figure 5.2.

5.2.2 Model-Based Systems Engineering

The SE processes can be further improved by implementing an MBSE approach. Specific benefits of MBSE compared to a document-based approach are discussed in Section 3.3.2. In relation to the decision-making framework developed in this research, MBSE is a valuable tool to aid with evaluating trade-offs guiding design decisions. MBSE allows to collect and systematically process large amount of information relative to the decisions made in the trade-off assessments. It also permits the examination of "what-if" scenarios, which helps decision-makers to try and assess different design options way before finalizing any decisions, which dramatically reduces risk and uncertainties, especially when developing complex novel energy systems.

Moreover, MBSE enables the reuse of the first-of-a-kind model for an nth-of-a-kind application. The idea is to retain the system architecture represented by the model and only modify elements that must be changed to address different conditions (e.g., a site location may necessitate changes in the system design). An MBSE model retains all the information used to select the optimal solution for an energy system given specific objectives, context, and constraints. When the context changes (e.g., due to different resources available in a different region), the optimal solution may be different. The evaluation of system conceptual solutions in a changed context would be significantly faster given the first-of-a-kind solution was developed using MBSE compared to a large set of disparate documents that would have to be analyzed to see if a changed context affects any of the requirements and the ultimate system conceptual solution.

5.2.3 Life Cycle Modeling Language with Innoslate

There are many tools and language alternatives for MBSE. Here, we use Innoslate as the MBSE tool, which is designed to support the entire system life cycle. It offers a wide array of features, including project management, requirements definition, system modeling and simulation, and verification and validation. Innoslate users can use either the LML or SysML to develop a system model and present it via diagrams. LML was developed to simplify the elements, relationships, attributes, and diagrams used in SE and project management. This project used the LML language.

LML utilizes a streamlined framework consisting of 12 primary classes and 8 subclasses, where the subclasses inherit attributes from their parent classes. This structure is designed to effectively capture critical information elements. Attributes of these classes include a "type" attribute, enhancing the definition of each class. LML also encompasses an extensive array of relationships

Table 5.1: SysML diagram mapping to LML diagrams and ontology [189]

SysML Diagram	LML Diagram	LML Entities (Ontology)
Activity	Action Diagram	Action, Input/Output
Sequence	Sequence	Action, Asset
State Machine	State Machine	Characteristic (State), Action (Event)
Use Case	Asset Diagram	Asset, Connection
Block Definition	Class Diagram, Hierarchy Chart	Input/Output (Data Class), Action (Method), Characteristic (Property)
Internal Block	Asset Diagram	Asset, Connection
Package	Asset Diagram	Asset, Connection
Parametric	Hierarchy, Spider, Radar	Characteristic
Requirement	Hierarchy, Spider	Requirement and Related entities

between classes, with the capability for almost every class to relate to itself and to other classes. These relationships also have attributes. The meta-meta model of LML mirrors components of natural language, corresponding to nouns, verbs, adjectives, and adverbs, facilitating a comprehensive language-like structure for practitioners [188].

Several types of LML diagrams are used in this study and discussed below. Spider diagrams are charts showing a hierarchical organization with an improved visualization of traceability. A spider diagram can present up to nine levels of entity decomposition. This diagram conforms to the LML Specification 1.4 [189] definition of a "Spider Diagram," which requires visualization for traceability beyond what a typical hierarchy-type diagram can offer [90]. A spider diagram can represent a hierarchical organizational chart for many classes, such as actors, actions, artifacts, requirements, resources, tasks, etc. Asset diagrams show use cases or system concepts. The asset diagram is traditionally known as a block diagram or a physical block diagram. This diagram conforms to the LML Specification 1.4 [189] definition of an "asset diagram," which requires a diagram representation of the physical components of a system model [90]. The high-level concept of operations is presented as LML action diagrams. The action diagram, traditionally known as a functional flow diagram, is a method of displaying action entities, their interactions via input/output and resource entities, and logical flow.

Innoslate offers both LML diagrams (e.g., action diagram, asset diagram) and SysML diagrams (e.g., activity diagram, block definition diagram, internal block diagram). There are also several general diagrams (e.g., diagram, N-squared diagram, tree diagram) that users can employ to improve the visualization of the system being modeled for the audience to which the system is being presented. The LML specification [189] provides a correlation between SysML diagrams, LML diagrams, and LML entities, as presented in Table 5.1.

5.2.4 Multicriteria Decision Analysis

A Pugh concept selection method, also known as a Pugh matrix, was introduced in 1991 by Stuart Pugh [190]. It was a groundbreaking work at the time, presenting a simple, yet powerful and well-structured method for the concept evaluation and selection process. This approach aids in the evaluation of alternative solutions against essential criteria to determine the concept that best fulfills these criteria.

The Pugh matrix is formatted for user-friendliness, prioritizing the clear expression of ideas and evaluation criteria instead of using strict mathematical representations. It organizes criteria vertically and alternatives horizontally, using symbols + (plus), - (minus), and S to indicate better than, worse than, and the same compared to the reference alternative, respectively. Each criterion is assessed simultaneously across all cases. Once completed, the matrix presents a summary at the bottom, highlighting how each alternative aligns with requirements and its strengths and weaknesses. This approach involves iterative reviews of the matrix until the team confirms and approves a preferred concept.

Pugh emphasized the importance of thoroughly evaluating all potential solutions, underscoring the need for a disciplined approach to concept formulation and evaluation to minimize the risk of selecting the wrong concept. The Pugh concept selection approach offers numerous benefits, such as gaining deeper insights into requirements, improving understanding of design problems and potential solutions, visualizing the interactions between proposed solutions, and fostering creativity to generate new ideas. The matrix representation is also very useful because of its simplicity and

Table 5.2: Pugh matrix

Criteria	Alternative 1	Alternative 2	Alternative 3
Criterion A	+	S	+
Criterion B	-	+	S
Criterion C	-	-	+
Total (+)	1	1	2
Total (-)	2	1	0
Total (S)	0	1	1

clear visualisation of alternatives' performances against each other. An example of a Pugh matrix is presented in Table 5.2. Based on the presented criteria scores, Alternative 3 is the best option.

However, the Pugh matrix approach has limitations. Most notably, it ignores the importance of the decision-maker's criteria, meaning all the criteria are equally important. This assumption is typically not the case in reality—decision-makers usually prioritize evaluation criteria where, for example, cost could be much more important than the incremental gain in efficiency. As such, the Pugh matrix approach is supplemented in this research by the MAUT method. MAUT uses a utility function developed based on criteria scores where decision-makers specify the importance of each criterion compared to others.

This hybrid approach was explored for the concept selection in a subsea processing domain [191]. The concept selection was conducted with team engineers and subject matter experts, and the Pugh matrix approach was used to guide the process and document the results. After completion, the study teams filled out a questionnaire to evaluate the application of the Pugh matrix. The feedback was positive and indicated that a matrix approach to concept evaluation is a good visual communication tool, facilitates an objective dialogue, and helps to improve the overall process and quality of the concept selection.

The study concluded that the suggested layout of the matrix and screening process could be implemented as a decision-making tool for the subsea processing department to enable quality assurance during concept selections [191]. A similar approach is employed in this research—an evaluation matrix is used as a tool to assist with decision-making for energy systems.

		Priority	Evaluation criteria	Weight	Alternative 1		Alternative 2		Alternative 3	
		%		%	Score	Weighted	Score	Weighted	Score	Weighted
CATEGORIES	Category A		Criterion A.1							
			Criterion A.2							
			Criterion A.3							
			Sub-category weighted score							
			Category Sum							
	Category B		Criterion B.1							
			Criterion B.2							
			Criterion B.3							
			Criterion B.4							
			Sub-category weighted score							
			Category Sum							
	Category C		Criterion C.1							
			Criterion C.2							
			Sub-category weighted score							
			Category Sum							
	Σ%		Overall weighted score							

Figure 5.3: Modified evaluation matrix

The limitations of the Pugh concept evaluation approach are overcome by adding weights based on decision-maker preferences and using quantitative scores instead of symbols. A traditional MAUT methodology is adjusted by grouping evaluation criteria into categories. This change allows the prioritization of categories in addition to weighting criteria within each category as compared to a traditional MAUT approach where all evaluation criteria are weighted at the same time. Another small tweak in the methodology is the use of percentages as weights and priority measures instead of scores, a preference from the participants in [191].

A modified evaluation matrix is presented in Figure 5.3. Equations used in the matrix are:

$$\text{Weighted Criterion} = \frac{\text{Score}}{\text{Maximum Score}} * \text{Weight} \tag{5.1}$$

$$\text{Sub-category Weighted Score} = \sum(\text{Weighted Criterion}) \tag{5.2}$$

$$\text{Category Sum} = \text{Sub-category Weighted Score} * \text{Priority} \tag{5.3}$$

The meaning of scores and their values should be established via discussion with the decision-makers based on their preferences and project specifics. The score ranges could be 1–3, 1–10, or 1–100, where the lower score represents "the worst" and the highest score represents "the best." The meaning of the scores can vary greatly between the projects and even teams performing the assessment.

For example, an evaluation of system performance could use the following scoring scheme:

1. Much worse than required
2. Somewhat worse than required
3. As required
4. Somewhat better than required
5. Much better than required

An evaluation of compliance with the requirements could use a different scoring scheme [191]:

1. Not compliant
2. Major compliance gap
3. Compliance gap
4. Minor compliance gap
5. Insignificant compliance gap
6. Fully compliant

The weight and priority scores should add up to 100% in the approach presented here.

An example of a completed modified matrix is presented in Figure 5.4 with the score scheme of 1–5, with 1 being the worst and 5 being the best.

5.3 Framework Processes

The proposition of this research is the new decision support system, a framework that uses SE principles and tools to support decision-making in energy systems. This section outlines the processes within the proposed framework as well as the tools and methods used to support them.

As discussed in Section 2.2.1, the typical decision-making process has four steps:

		Priority %	Evaluation criteria	Weight %	Alternative 1		Alternative 2		Alternative 3	
					Score	Weighted	Score	Weighted	Score	Weighted
CATEGORIES	Category A	50%	Criterion A.1	50%	3	30%	2	20%	3	30%
			Criterion A.2	30%	4	24%	2	12%	3	18%
			Criterion A.3	20%	3	12%	3	12%	5	20%
			Sub-category weighted score	100%		66%		44%		68%
			Category Sum		**33%**		**22%**		**34%**	
	Category B	40%	Criterion B.1	40%	5	40%	5	40%	5	40%
			Criterion B.2	30%	4	24%	2	12%	4	24%
			Criterion B.3	10%	4	8%	2	4%	3	6%
			Criterion B.4	10%	3	6%	3	6%	4	8%
			Sub-category weighted score	90%		78%		62%		78%
			Category Sum		**31%**		**25%**		**31%**	
	Category C	10%	Criterion C.1	60%	5	60%	4	48%	3	36%
			Criterion C.2	40%	4	32%	3	24%	2	16%
			Sub-category weighted score	100%		92%		72%		52%
			Category Sum		**9%**		**7%**		**5%**	
	Σ%	100%	Overall weighted score		73%		54%		70%	

Maximum score: **5**

Figure 5.4: Example of a completed matrix

1. Identify the problem
2. Generate solution alternatives
3. Evaluate alternatives
4. Select the best alternative

The steps in the decision-making process are well-aligned with the phases in the concept development as shown in Figure 5.5. This alignment is the basis of the proposed decision support system—instead of relying on heuristic approaches to make decisions, why not employ a structured, systematic, well-established approach offered by SE? The decision support system workflow is presented in Figure 5.6. The framework workflow is subdivided into three phases, which are discussed here.

Needs Analysis

This phase looks into the **"Why"**, that is, why the new system is needed and if there are technologies that can address the need. The main goal of the needs analysis phase is to prove that there is a real need and market for a new system. It must show that this need can be met cost-

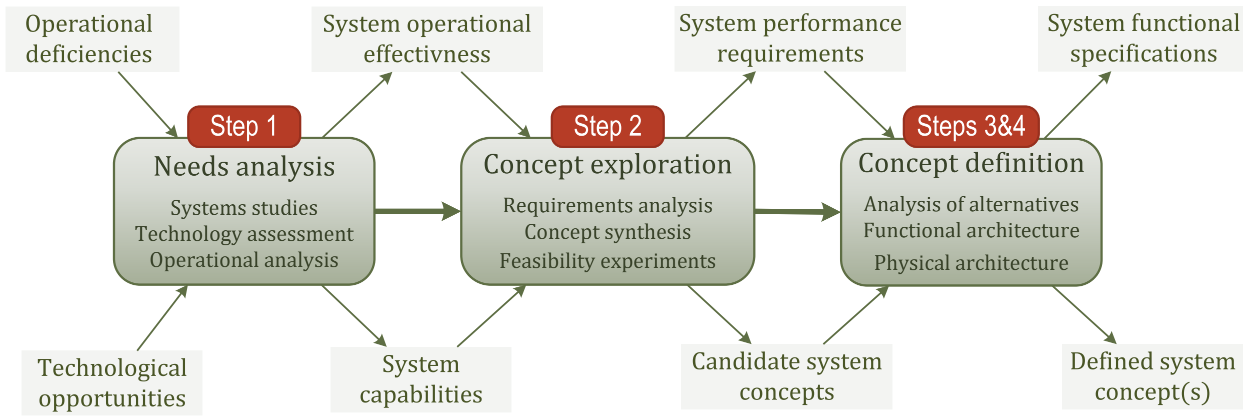

Figure 5.5: Decision-making steps alignment with the concept development process (adopted from [79])

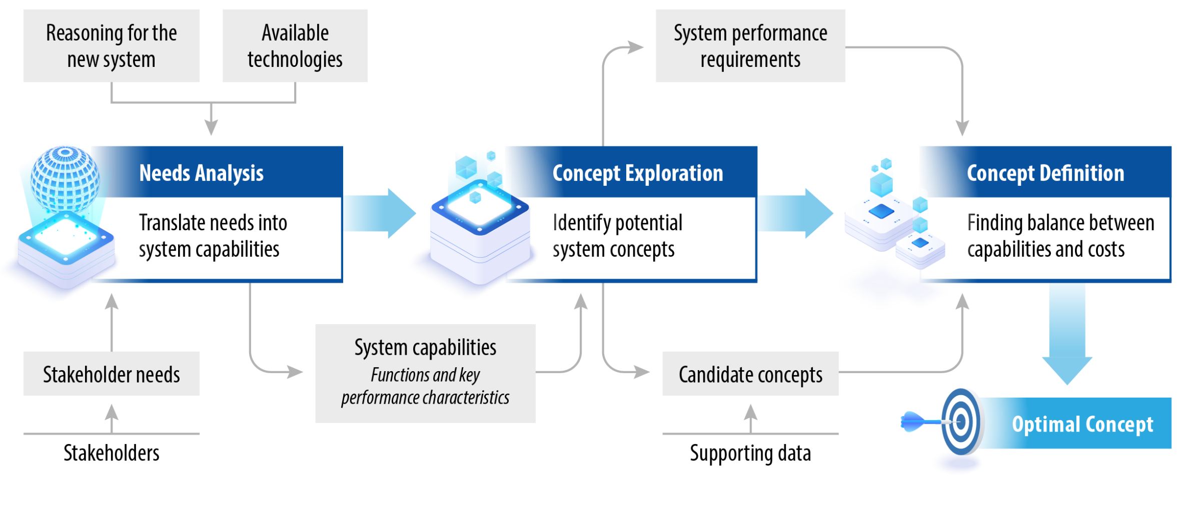

Figure 5.6: Proposed framework phases for a decision support system for energy systems

effectively and with acceptable risk by available technologies or technologies to be developed as part of this project.

When determining the need for a new energy system, engineers and decision makers must employ ST, that is, the system is evaluated holistically, taking into account the entire life cycle, including user needs, technological advancements, and environmental, social, and political aspects [79]. This mindset is a must when considering a novel energy system being integrated into the large whole energy system involving many elements and stakeholders. ST is especially important at the very early stage when strategies for new systems are being developed and explored.

The assessment of potential strategies should be wide, considering as many solutions as possible, instead of going deep into analyses of a single concept. Focusing on the details of a single solution inevitably restricts the consideration of other solutions, which often results in a suboptimal strategy selection. The importance of being able to see the big picture, recognize interconnections, consider multiple perspectives, and maintain creativity without getting hampered by details cannot be overstated when deciding strategies for novel energy systems.

The needs analysis phase has three inputs—the initial reasoning for the new system, available applicable technologies, and stakeholder needs for the new energy system. The stakeholder needs must be comprehensive, such that, ideally, the needs of all potential stakeholders are collected and analyzed. To have a comprehensive picture of all the needs for the new system, one must first have a clear understanding of all the stakeholders. Therefore, the phase includes identifying all the entities, including organizations and individuals, who may have an interest or involvement with the new energy system throughout its life cycle.

After all the stakeholders are identified and their respective needs and preferences for the system are collected, the next step is to translate the needs and desires into a clearly defined set of system capabilities. The system capabilities, which are the outcome of this phase, must include high-level system functions and key performance characteristics. The high-level functions describe what the system must do to satisfy the needs of the system. The key performance characteristics should describe, at a high level, how well the system should perform to satisfy each need. For example, the main functions for an energy system could be as simple as generate energy, convert energy to electricity, and deliver electricity to the grid. The key performance characteristics will specify, for example, required capacity, availability, and costs.

The activities in this phase are conducted using MBSE modeling tools. Stakeholders are identified, their needs are collected and analyzed, and initial requirements are developed using MBSE language artifacts like requirements, blocks, and relationships. While the SE principles could be invoked using a document-based approach, an MBSE approach offers significant improvements.

Section 3.3.2 offers additional details about the benefits of using MBSE versus a document-based approach.

Concept Exploration

In this phase, potential system concepts are identified and examined to address two key questions: "What performance is required of the new system to meet the perceived need?" and "Is there at least one feasible approach to achieving such performance at an affordable cost?" [79]. The goal of this phase is to establish a feasible goal for a new energy system before committing significant resources to its detailed exploration and development. The outputs of this phase are high-level performance requirements and a set of candidate system concepts.

It is critical to have more than one alternative to explore and understand the range of possibilities for satisfying the need. Having multiple alternatives allows decision-makers to realize the possible solutions and understand the pros and cons of each. Such an exploration-driven attitude allows and promotes the possibility of finding the optimal solution given the unique set of circumstances driven by stakeholder needs (e.g., reliable and cost-efficient green energy), regional context (e.g., favorable meteorological environment for wind power), market demands (e.g., projected energy demands given regional economics), social preferences (e.g., local community acceptance of a certain energy solution), etc.

To enable the identification of an optimal solution, various concepts of a new energy system must be considered and later evaluated given multiple technical and economical considerations (e.g., capital costs, O&M costs, technology maturity, reliability, and operability). As discussed in 5.1.1, it is important to include a third dimension in the decision-making: social considerations. These include aspects ranging from federal policies affecting the future of the energy sector to local community preferences toward a certain energy technology. All three dimensions are important to the overall system success; thus, they must be included in the concept development stage to make a truly informed solution selection.

This phase includes evaluations needed to develop supporting data to evaluate and compare identified candidate concepts. The evaluations, as mentioned earlier, fall under three large areas:

technical, economical, and social. Technical analyses include aspects like required capacity, reliability, availability, maintenance, technology readiness, necessary workforce, and supply chain. The technical characteristics are mostly quantitative (e.g., capacity, efficiency, reliability), but some can be qualitative (e.g., technology maturity).

Economical analyses are mostly traditional financial assessments of investments and profits with metrics like NPV and IRR, with metrics like LCOE included for energy systems. The economic assessments are largely quantitative, but some evaluations (e.g., investment risks) could be qualitative.

Assessments of social perspectives are generally less definitive and, therefore, could be more challenging, since they are mostly qualitative. The social considerations for an energy system involve things like climate goals, energy justice, and local community preferences. Stakeholder needs identification and evaluation becomes very important to support an evaluation of the social dimension of a proposed energy system.

It is worthwhile to mention that some considerations are cross-disciplinary. Federal policies, as an example, affect each dimension. The technology development and maturity are affected by federal funds allocated to R&D while the commercial sector's willingness to further invest into a given technology is affected by the general energy policies of the federal government. The technology maturation promotes technology adoptions and deployment, which in turn significantly affects economics where larger-scale deployments reduce the costs, phenomena known as economies at scale and the technology learning curve.

The economics of a given energy technology may be dramatically affected by federal policies like investment or PTCs and special financing schemes. There can be a reinforcing behavior where favorable economic conditions incentivize more deployments and larger-scale deployments drive the cost down. The social perspectives affect the federal policies, which affect both the technical and economic perspectives, as discussed above. On the other hand, federal policies also influence social perspectives. This impact can happen by providing information to the public about the pros and cons of various energy technologies or by incentivizing private investments and engagement in novel energy solutions (e.g., household solar panels).

This phase is supported by MBSE as well as multiple discipline- and application-specific tools and methods. Technical, physics-based models are available to develop insights into system performance, while numerous economic models and tools are available to evaluate financial performance. Some social aspects could be evaluated quantitatively using appropriate models and tools (e.g., GHG emissions for various technologies could be assessed using the GREET model [29]). Other social parameters (e.g., local community acceptance) will remain qualitative and could be documented using the requirements in MBSE and then evaluating how well each concept satisfies the requirement.

To summarize, it is important for the concept exploration phase to consider as many alternatives as possible and gather as much information as practical to derive technical, economical, and social metrics for each alternative. It is important to keep the evaluation at a high level to keep the efforts manageable and proportional to the level of detail needed to enable an informed decision about the optimal solution.

Concept Definition

This phase selects the preferred system concept. It answers the question: "What are the key characteristics of a system concept that would achieve the most beneficial balance between capability, operational life, and cost?" [79].

This is the phase where the identified candidate concepts are evaluated based on the collected and developed supporting data. A trade-off analysis is conducted using the multicriteria decision analysis approach described in Section 5.2.4. The evaluation criteria are also developed in this phase to support the decision analysis. It is critically important that the decision-makers participate in developing evaluation criteria so that the resulting trade-off analyses are realistic and truly supportive of the decision-making process.

The activities in this phase are guided by MBSE. The trade-off studies could be conducted using dedicated tools (e.g., Excel spreadsheet or Matlab) or MBSE-specialized tools if they are available within the chosen MBSE modeling software.

5.4 Case Study on Hydrogen Production

This section presents a case study demonstrating an application of the proposed framework for selecting the conceptual solution for a novel energy system tasked with clean hydrogen production with the focus on supporting investors and utility executives with their strategic decision making. As mentioned in Section 5.2.3, the MBSE approach is accomplished in Innoslate using LML.

5.4.1 Phase 1: Needs Analysis

This section defines the reasoning for the system development, identifies available technologies, and identifies stakeholders and their needs.

Problem Definition

System objective: generate clean hydrogen. The motivation for the new system is attributed to the incentives for clean hydrogen generation offered by the Inflation Reduction Act (IRA) [192] signed into the law in 2022. The IRA offers PTCs for clean hydrogen generation up to $3 per kg of hydrogen, given the lifetime emissions are less than 0.45 kg of CO_2 per kg of hydrogen. Therefore, the must-have requirement for the new system is to generate hydrogen with a system where the GHG lifetime emissions are at or below 0.45 kg CO_2 / 1 kg H_2.

Available Technologies

Given the main prerequisite of low GHG emissions, a few technical solutions are possible.

A. SMR with CCS. In an SMR method, hydrogen is produced by reforming methane gas using steam. Natural gas is the feedstock and primary energy source for the system. Nearly all hydrogen in the United States is produced using this method. The method is well-known and relatively inexpensive, using mature technologies. The main concern is the high level of GHG emissions—about 9 kg of CO_2 is released per 1 kg of generated hydrogen.

To overcome the challenge of high GHG emissions to satisfy the primary requirement for the new system, a CCS system must be included. Several CCS methodologies exist and are mature and available for large commercial applications [193].

B. Water electrolysis. In this process, water is split into hydrogen and oxygen using electrochemical processes. Electrolysis is a zero-carbon process, and lifetime carbon emissions are only attributed to supporting processes in the life cycle, such as electricity sources. Currently, the electrical grid in the United States is not qualified as low carbon since the majority of its electricity is generated using fossil-fuel-based energy sources [2]. Therefore, to satisfy the prerequisite for the system, a low-carbon or carbon-free energy source must be used for hydrogen generation via electrolysis, which includes renewable and nuclear energy sources. The two main electrolysis types are LTE with operating temperatures slightly below 100°C and HTSE with operating temperatures of 700–850°C [194]. The available LTE technologies are alkaline water electrolysis, anion exchange membrane water electrolysis, and PEM water electrolysis. The HTSE uses SOEC technology.

The *alkaline water electrolysis* is a well-established mature technology for industrial hydrogen production up to the multimegawatt range in commercial applications across the globe [194]. The benefits are a well-established technology commercialized for industrial applications, relatively low cost, stability in the long term, and non-reliance on noble metals.

Anion exchange membrane water electrolysis is a developing technology, seen to be more beneficial compared to alkaline technology due to its low cost and high performance. Despite the significant advantages, it requires further R&D toward the stability and cell efficiency essential for large-scale or commercial applications [194].

The *PEM electrolysis* is another mature technology applicable to large-scale commercial applications. It is faster and safer than alkaline water electrolysis. The major challenge associated with the PEM electrolysis is the high cost of the components [194].

The *SOEC* is an electrochemical conversion cell converting electrical energy into chemical energy. Typically, an SOEC operates with steam at high temperatures (500–850°C), which significantly reduces the power consumption and increases the energy efficiency, leading to a strong reduction in hydrogen cost due to power consumption being the main contributor to the hydrogen production cost in electrolysis [194]. The disadvantage of the SOEC technology is that it has a lower technical maturity. However, the recent technological advancement demonstrates a dramatic increase in efficiency, stability, and durability [195]. These developments have the potential to outperform conventional water electrolysis systems, paving the way for highly efficient and cost-effective hydrogen production.

C. Microbial biomass conversion. This method takes advantage of the ability of microorganisms to consume biomass and release hydrogen. Microbial electrolysis cells harness the energy and protons produced by microbes, with an added small electric current to produce hydrogen. This technology allows for the production of hydrogen from resources that otherwise cannot be used for fuel production while significantly reducing the amount of energy normally needed for wastewater treatment. While this technology is valuable and promising, it is still at the initial stages of R&D, and it will take several years before it can be commercialized and scaled for large-scale hydrogen production.

This brief overview of available technologies leads to the conclusion that, to meet the essential requirement of low GHG emissions, appropriate technologies are either an SMR with a CCS system or electrolysis with a clean energy source like renewable or nuclear energy. From this comparison of the advantages and disadvantages of electrolysis technologies [194], alkaline and PEM LTE technologies are ready for large-scale commercial deployment. The two technologies compare fairly similarly to each other [196] in terms of performance, cost, lifetime, and safety. Given the similarity between the two, the choice can be made at a later stage of the system design when the physical architecture is developed.

For the case study of a high-level concept selection, the general technology of LTE is detailed enough without specifying PEM or LTE. On the HTSE side, SOEC is rapidly maturing in terms of commercialization and large-scale deployment [195]. Therefore, three technologies are considered in the case study:

1. An SMR with a CCS system, often referred to as blue hydrogen
2. Electrolysis using LTE technology
3. Electrolysis using HTSE technology

The preference for a technology depends on the client's need and regional conditions (for example, the availability of natural gas for the SMR method or access to nuclear energy). For this case study, all three technologies are assumed feasible, there is access to the natural gas supply, and an NPP in close proximity to the envisioned site for the new hydrogen production plant.

Other large parts of the conceptual hydrogen generation system are:

- **Hydrogen production capacity**, the main input to the system initial design. The system capacity depends on specific customer needs as well as current and projected market demands. Capacity dramatically affects the unit cost of hydrogen due to the economies-at-scale factor, that is, a larger capacity results in a lower unit price. The capacity is also the main factor affecting capital costs and, therefore, the economics of the system.
- **Hydrogen storage capacity**, determined based on how much hydrogen should be stored before it is transported to the customer. The availability of hydrogen, that is, the consistent delivery of hydrogen, is important to industrial hydrogen consumers, and storage capacity could serve as the means to ensure hydrogen availability even if the facility is down for a short period of time (e.g., for maintenance).
- **Transportation of hydrogen**, options are determined based on the location of the hydrogen generation facility compared to the points of use. Possible solutions are high-pressure hydrogen tube trailers, liquefied hydrogen tankers, or pipelines. Other transportation solutions are currently being developed, but they are not ready for commercial deployment and are not considered for this case study.

Options for a hydrogen generation system are depicted in Figure 5.7. There are five major choices for the system: production capacity, technology, energy source, storage capacity, and

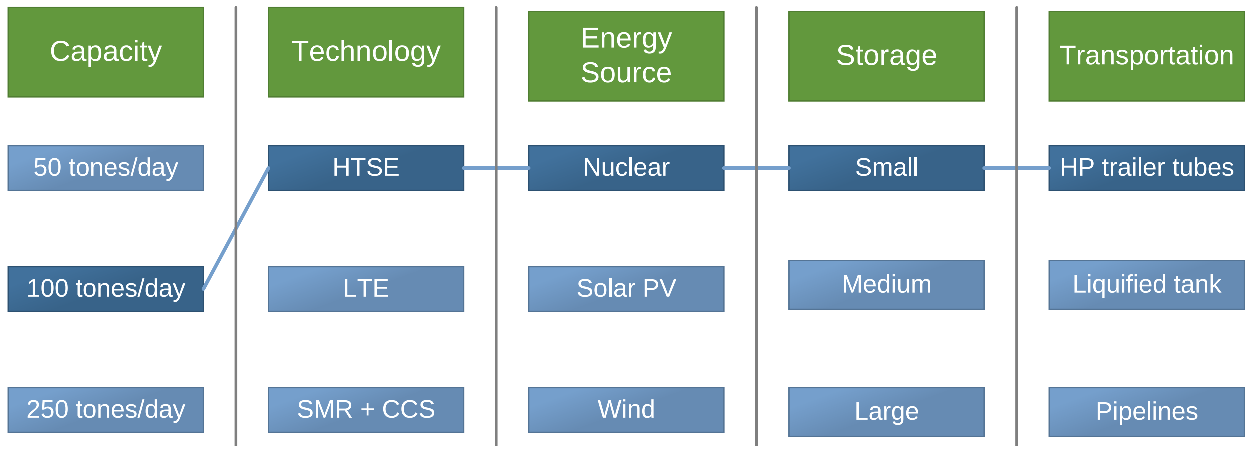

Figure 5.7: Possible solutions for a hydrogen production system (one feasible solution is highlighted)

transportation option. One feasible solution is highlighted in Figure 5.7, i.e., a capacity of 100 tons of hydrogen per day, HTSE technology, nuclear energy source, small capacity for hydrogen storage system, and transportation of high-pressure hydrogen via tube trailers. However, many other solutions are feasible. With only three alternatives considered for each main choice, there are $3^5 = 243$ possible options for a system configuration, or system architecture patterns [175]. Understandably, making an informed decision between these many options using heuristics is not a reasonable approach, which only strengthens the argument for the need for a better decision support system.

Stakeholders

The system's success is improved dramatically when all stakeholders are identified, and their needs are carefully examined. In many cases, stakeholders are overlooked at the initial system development stage, which results in large modifications to the initially envisioned approach when stakeholders and their needs are discovered later. For example, the local community is usually affected by a new energy system, yet community needs and preferences traditionally have not been considered in the process for the initial system design decisions. Consider a scenario where a hydrogen production system is envisioned with solar power as an energy source. With all the economic and technical analyses in place, developers move with a site selection only to discover that the local community opposes the installation of solar farms to preserve the aesthetics of the

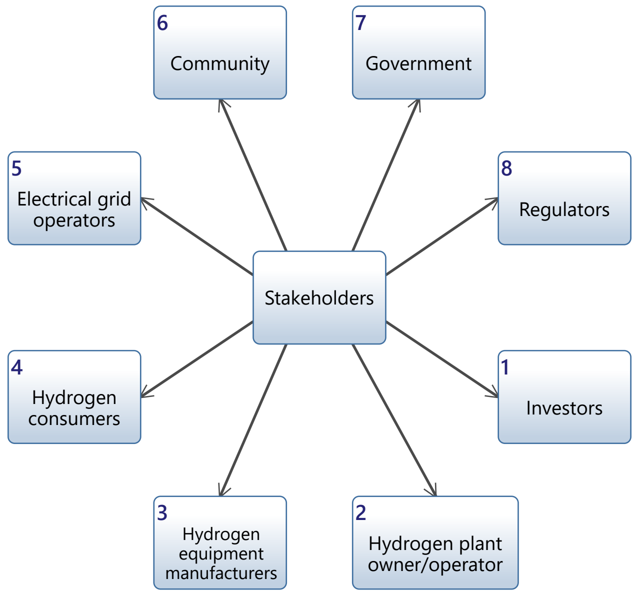

Figure 5.8: Stakeholders of a hydrogen generation system

natural surroundings. This important information needs to be considered at the beginning of the project to either select another energy source or a different location for the hydrogen facility.

MBSE provides the opportunity to integrate different views of multiple disciplines at a very early stage of system development. Stakeholders of a hydrogen generation system are shown in Figure 5.8, where system stakeholders are represented via a spider diagram in Innoslate [89]. In this case, spider diagram elements representing stakeholder types (e.g., Investors) are "statements" class artifacts sourced from an external "Stakeholders" Word document that was used to collect information about the system stakeholders. The arrows in the spider diagram are the "source of" type of LML relationships, showing the traceability between the artifact in the model and the source of information. Alternatively, stakeholder types could be represented as Artifact class with parent-child relationships between "Stakeholders" and stakeholder groups (e.g., "Investors") represented as the "decomposed by" type of LML relationship.

This case study considers the following stakeholders:

- **Investors:** a single investment company or a set of investors.

- **Hydrogen plant owner or operator:** a company that owns a single facility or a utility that owns and operates multiple energy systems, potentially including generation, transmission, and in some cases, distribution energy systems in their portfolio.
- **Hydrogen equipment manufacturers:** companies manufacturing main hydrogen production systems and components (e.g., electrolyzers) and supporting systems (e.g., hydrogen storage systems and components).
- **Hydrogen customers:** existing and potential large-scale commercial hydrogen users. A hydrogen consumer could be a large industrial facility that already uses hydrogen as the feedstock for their processes (e.g., ammonia production), industrial enterprises with an interest in novel hydrogen applications (e.g., synthetic fuel producers), or large-scale hydrogen suppliers, like hydrogen hubs supporting smaller hydrogen consumers.
- **Electrical grid operators:** companies that operate regional and national electrical grids. The relevance of the electrical grid is twofold. First is the concern about electricity otherwise available to the grid being diverted to generate hydrogen, which is the case with existing NPPs. Second is the benefit of using hydrogen as an energy storage to supplement grid demands during emergent electricity shortages (e.g., weather-related unavailability of renewable electricity generators).
- **Local community:** cities, towns, indigenous tribes, etc.
- **Government:** federal, state, and local governments.
- **Regulators:** federal, state, and local entities whose objectives and obligations are to ensure public and environmental safety of the new energy system throughout its entire life cycle.

Additional stakeholders may include legal entities, certification organizations, workforce development organizations, etc. However, these secondary stakeholders become important during the later stages of system development and do not need to be considered at the conceptual system selection stage.

Stakeholder Needs

Either one or multiple stakeholders have a need for the new system, which is the reason for the system design and construction. Other stakeholders may not have a need for the system itself, but they have requirements for the system's performance. The stakeholder needs and concerns for a hydrogen generation system are discussed below. MBSE assists greatly with the needs analysis, where it serves as a data collection and analysis tool. MBSE enables traceability between stakeholders and their needs, and model artifacts provide a clear representation of the information, see Figure 5.9 for MBSE examples.

- **Investors:** The need for the new energy system is to generate profit.
- **Hydrogen plant owner or operator:** The main objective is the safe and profitable operation of the facility. An objective that recently became the top priority for many utilities is reducing GHG emissions. Driven by the net-zero goals set at the enterprise level, many electrical utilities are developing long-term strategies for an integrated energy system where preferences are being shifted from fossil-fuel-based to clean energy sources. The decarbonization goals become even more important given the plans of shutting down coal-driven power plants, where the lost energy sources must be efficiently and urgently replaced with clean energy sources.
- **Hydrogen equipment manufacturers:** The main objective is to generate profit from manufacturing hydrogen-related systems and components with supporting objectives of growing capacity, improving technical characteristics, and ensuring the safe and reliable operation of their equipment. Climate-related goals are also often an important objective.
- **Hydrogen customers:** The main objective is to have consistent access to a large volume of high-quality hydrogen at a reasonable price. The secondary objective, becoming progressively more important for many enterprises, is reducing GHG emissions from their processes.
- **Electrical grid operators:** The objectives of the grid operators are to have reliable grid operations and an adequate system capacity to provide electricity without interruptions to all their customers. This objective is supported by the goal of having a diverse set of generators

to ensure grid resiliency in cases of an expected increase in electricity demands (e.g., peak hours) or during emergent conditions when some sources become unavailable.

- **Local community:** The main objectives of a local community are uninterrupted access to electricity and other energy sources, climate-related goals, safe operations of the industrial facilities, and economic goals, such as employment opportunities and tax revenue from the businesses. An equally important objective is the preservation of natural resources—the amount of resources needed to support a new energy system, the environmental quality of natural resources, and the protection of the visual appeal of the local area and its surroundings.
- **Government:** The main objectives of the government for energy systems are to ensure equitable, realizable, and affordable access to energy sources for the people, ensuring environmental quality and the protection and preservation of natural resources, all while supporting the nation's economic goals. Driven by the urgency to combat climate change and the need to enhance energy sector security, resilience, and independence, the government has a large focus on the technological advancement of novel energy solutions and technologies. The government's support of the energy sector is provided through various incentives (e.g., the production and investment tax credits offered in the IRA). The incentives are often offered at both federal and state levels, promoting the commercial advancement of certain energy solutions.
- **Regulators:** These agencies include the Nuclear Regulatory Commission, Federal Energy Regulatory Commission, Environmental Protection Agency, Occupational Safety and Health Administration, etc.

System Capabilities

The system capabilities are described as functional and performance characteristics of the system presented as "requirements." Requirement is a subclass of the "statement" class in LML. Requirements are handled in Innoslate via requirement documents or via SysML requirement diagrams. The requirement document artifact is used for the case study due to its simplicity and

	24/7/365 supply of hydrogen	Generate profit	High-quality hydrogen	Large-volume supply of hy...	Low-cost hydrogen	Preserve and protect natura...	Reduce GHG emissions	Reliable and resilient electri...	Reliable operation of hydro...	Resilient energy sector	Safe operation of hydrogen ...
1 Investors		×							×		×
2 Hydrogen plant owner/operator		×	×						×		×
3 Hydrogen equipment manufactur...	×	×	×	×	×				×		×
4 Hydrogen consumers	×		×	×	×		×		×		
5 Electrical grid operators								×			
6 Community						×	×	×			×
7 Government						×	×	×		×	
8 Regulators						×					×

Entity	Rationale
Generate profit	Generate profit by producing hydrogen with positive NPV and IRR>5%
Safe operation of hydrogen plant	Hydrogen facility must be safe to operate in compliance with all applicable regulations
24/7/365 supply of hydrogen	Provide uninterrupted supply of hydrogen
Large-volume supply of hydrogen	Provide hydrogen at required large capacity
Low-cost hydrogen	Cost of hydrogen should be comparative to the hydrogen market price in the region
High-quality hydrogen	Hydrogen should be high-purity to support industrial processes
Reduce GHG emissions	Hydrogen generation process should have well-to-gate lifecycle greenhouse gas emissions not more than 4.0 kg of CO2 per kg of hydrogen
Reliable and resilient electrical grid	Electrical grid should provide reliable operations at all times and be resilient against sudden changes in supply and demand
Preserve and protect natural resources	Minimize use of natural resources, such as air, water, land, rare minerals, fossil resources, etc. and ensure the resources are protected from potential harm caused by industrial processes
Resilient energy sector	Energy sector should have adequate capacity to support national needs and be resilient against emergent changes on domestic and international markets

Figure 5.9: Stakeholder needs analysis in MBSE: (left) traceability between stakeholders and needs and (right) concise list of stakeholder needs

intuitive document-like format familiar to the decision-makers. Traceability between stakeholders, their needs, and requirements is enabled by MBSE. Another benefit of MBSE is the ability to develop high-quality requirements satisfying established characteristics of well-written requirements: necessary, appropriate, unambiguous, complete, singular, feasible, verifiable, correct, and conforming [77]. The high-quality requirements will not only support the concept development stage as part of the decision support framework, but they will be the foundation of the next phase of the system life cycle: engineering development.

An example of the relationships between the "Safety" performance requirement and associated stakeholder needs and stakeholders is shown in Figure 5.10 where the "PR-5, Safety" requirement is one of the "performance requirements" derived from the stakeholder need "Safe operation of hydrogen plant" expressed by five stakeholder groups (i.e., investors, hydrogen plant owner/operator, hydrogen equipment manufacturers, community, and regulators).

The output of this phase, system capabilities, is presented as system functional and performance requirements, shown in Figure 5.11 and Figure 5.12, respectively.

5.4.2 Phase 2—Concept Exploration

In this phase, system concepts for a hydrogen generation facility are explored to identify feasible solutions for the system with the required capabilities and performance characteristics specified

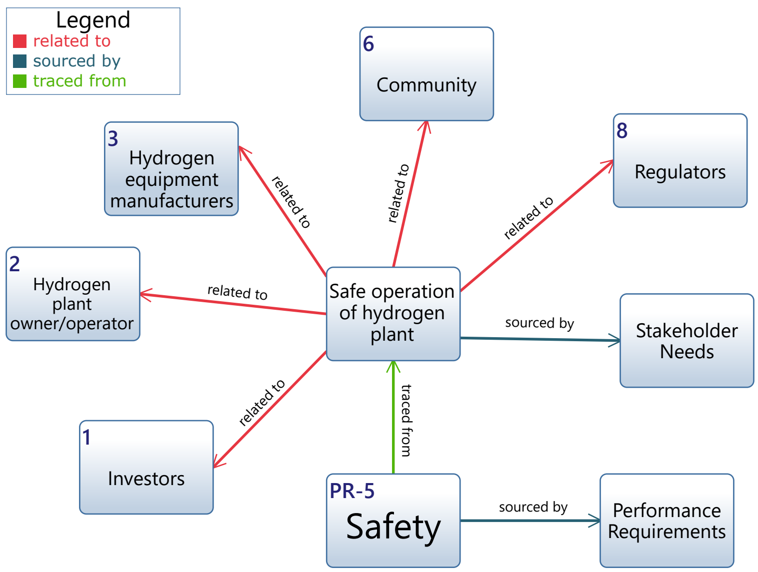

Figure 5.10: Example of traceability of requirements in Innoslate

in the needs analysis presented in Section 5.4.1. Four potential system concepts are identified, with three different hydrogen technologies and two energy sources, nuclear and solar.

Solution 1—HTSE and Nuclear Energy Source

The main system characteristics are:

- An NPP provides thermal energy and electricity to the hydrogen generation facility.
- The hydrogen generation facility is located next to the NPP.
- Modifications for the NPP are needed to support thermal energy (i.e., steam) extraction to support HTSE.
- The NPP continues to supply the remaining electricity to the grid.
- Produced hydrogen is already high purity, but remaining moisture and oxygen must be removed to meet the required ultra-high purity level.
- The storage capacity is driven by the requirement of an uninterrupted supply of hydrogen to the customer. Given the constant hydrogen production, storage must be sized for the unavailability of hydrogen generation caused by either planned or unplanned downtime of the hydrogen facility. Maintenance of the hydrogen facility is planned to be performed online, supported by the built-in redundancies in the configuration of the hydrogen generation sys-

Entity	Rationale	Labels
FR-1 Generate Hydrogen The system shall generate hydrogen at required production rate	The system production rate and availability of hydrogen supply is specified by the hydrogen customer(s)	Functional Requirement
FR-1.1 Provide infrastructure for … The system shall provide infrastructure to enable and support hydrogen generation	The infrastructure includes production system(s) and supporting system(s) that enable generation of hydrogen and is dependent on selected hydrogen production technology and required technical characteristics (e.g., production rate)	Functional Requirement
FR-1.2 Provide resources for H2 … The system shall supply resources necessary for hydrogen generation	The resources needed for hydrogen generation depend on selected technology and may include: energy, water, land, feedstock, etc.	Functional Requirement
FR-2 Purify Hydrogen The system shall purify hydrogen to meet the required level of hydrogen quality	The required level if hydrogen quality is specified by the hydrogen customer(s)	Functional Requirement
FR-2.1 Provide infrastructure for … The system shall provide infrastructure to enable and support hydrogen purification	The infrastructure for H2 purification is dependent on required quality of hydrogen and selected technology of hydrogen generation; infrastructure includes main and supporting system(s)	Functional Requirement
FR-2.2 Provide resources for H2 … The system shall supply resources necessary for hydrogen purification	The resources for hydrogen purification are dependent on the required quality of hydrogen and technology of hydrogen production	Functional Requirement
FR-3 Store Hydrogen The system shall store generated hydrogen	The hydrogen storage capacity is determined based on the requirement to have uninterrupted supply to the hydrogen customer(s)	Functional Requirement
FR-3.1 Provide infrastructure for … The system shall provide infrastructure to enable and support hydrogen storage	The storage infrastructure is dependent on available hydrogen storage technologies and required characteristics	Functional Requirement
FR-3.2 Provide resources for H2 … The system shall supply resources necessary for hydrogen storage	The resources for hydrogen storage are dependent on hydrogen storage technologies	Functional Requirement
FR-4 Deliver Hydrogen The system shall deliver hydrogen to customer(s)	The hydrogen delivery options are dependent on availability of existing infrastructure and potential of new hydrogen transportation solutions	Functional Requirement
FR-4.1 Provide infrastructure for … The system shall provide infrastructure for hydrogen delivery to the customer(s)	The hydrogen transportation infrastructure depends on available technologies, existing infrastructure, distance to the customer(s), and required technical characteristics (e.g., volume)	Functional Requirement

Figure 5.11: Hydrogen generation system key functions

Entity	Rationale	Labels
PR-1 Hydrogen production rate The hydrogen production facility shall supply hydrogen at a minimum rate of 50,000 kg of hydrogen per day	The minimum production rate is specified by the hydrogen customer	Performance Requirement
PR-1.1 Storage capacity The storage system shall provide capacity adequate to support minimum required supply rate from the hydrogen production facility	The capacity of the storage system is determined based on minimum required hydrogen supply rate and availability	Performance Requirement
PR-2 Hydrogen purity The hydrogen generation facility shall supply hydrogen with the purity rate of at least 99.99%	The minimum purity level is specified by the hydrogen customer	Performance Requirement
PR-3 Availability The hydrogen generation facility shall supply hydrogen at least 363 days per year	The maximum unavailability is 2 days per year (minimum availability is 99.5%)	Performance Requirement
PR-4 Reliability Reliability of hydrogen generation facility shall be at least 99.6%	The reliability of hydrogen generation facility is determined based on the required availability of the hydrogen generation facility	Performance Requirement Reliability Requirement
PR-4.1 Reliability of H2 generating system The hydrogen generation system shall have reliability of at least 99.9%	The reliability of hydrogen generation system is determined based on required reliability of the hydrogen generation facility	Performance Requirement Reliability Requirement
PR-4.2 Reliability of H2 storage system The hydrogen storage system shall have reliability of at least 99.9%	The reliability of hydrogen storage system is determined based on required reliability of the hydrogen generation facility	Performance Requirement Reliability Requirement
PR-4.3 Reliability of H2 purification system The hydrogen purification system shall have reliability of at least 99.9%	The reliability of hydrogen purification system is determined based on required reliability of the hydrogen generation facility	Performance Requirement Reliability Requirement
PR-4.4 Reliability of H2 transportation system The hydrogen transportation system shall have reliability of at least 99.9%	The reliability of hydrogen transportation system is determined based on required reliability of the hydrogen generation facility	Performance Requirement Reliability Requirement
PR-5 Safety The hydrogen production facility shall provide measures for ensuring safe operations	Safety parameters are prescribed in applicable codes and standards and monitored by regulatory agencies	Performance Requirement Safety Requirement

Figure 5.12: Hydrogen generation system key performance characteristics

tem. However, the energy supply by the NPP is interrupted when the plant is offline for refueling outages, which typically last 15–40 days every 2 years. During the planned NPP outages, the hydrogen generation facility will be powered by the electrical grid, which will cause reduced profitability due to the inability to claim clean hydrogen PTCs because grid electricity does not satisfy the low GHG emissions requirement. This period also causes stresses for grid operation since the normal electricity supply from the NPP is unavailable, and additional electricity from the grid is being used to produce hydrogen.

- Transportation infrastructure is required since the hydrogen customer is located approximately 20 miles from the hydrogen generation facility adjacent to the NPP (an assumed condition). The regional circumstances pose significant constraints on building a dedicated pipeline; therefore, a traditional mode of transporting hydrogen in high-pressure tube trailers is the selected transportation solution after a quick comparison of costs with the hydrogen transportation approach.
- Stored hydrogen could be used to produce electricity if needed to support emergent grid operations by reversing SOEC to act as solid oxide fuel cells to generate electricity instead of hydrogen.

The system concept is presented in Figure 5.13 as an LML asset diagram. The high-level concept of operation is presented in Figure 5.14 as an LML action diagram.

As discussed previously, MBSE supports system development by providing a clear understanding of the relationships between system elements, which is enabled by the traceability between modeled elements. The relationships between actions and assets are explicitly included as modeled artifacts, a specific benefit of MBSE compared to a document-based approach to system development. An example of traceability between *asset, action, input/output, resources* system artifacts is presented in Figure 5.15. In this case, *HTSE.3 Generate hydrogen via HTSE* action *generates* output *Hydrogen*; it is *performed by* asset *1.2.1 Solid Oxide Electrolizers*, it *consumes* resources *DC Power* and *High-Temp Steam*, provided by actions *HTSE 1, 1.2, 2, 2.4*.

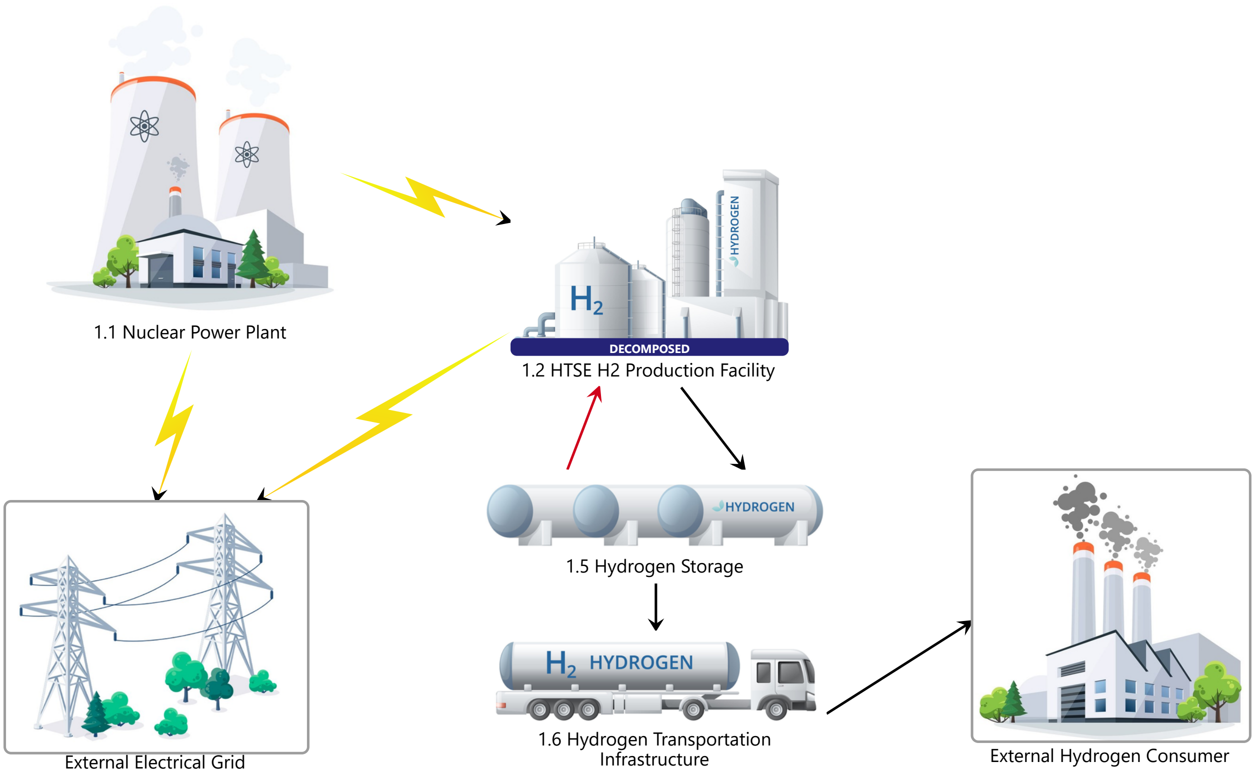

Figure 5.13: Solution 1—hydrogen generation via HTSE with a nuclear energy source

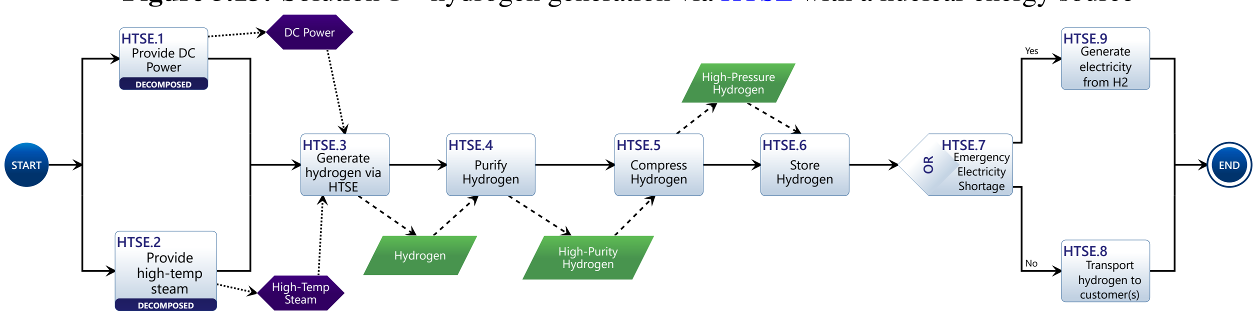

Figure 5.14: Solution 1—concept of operations

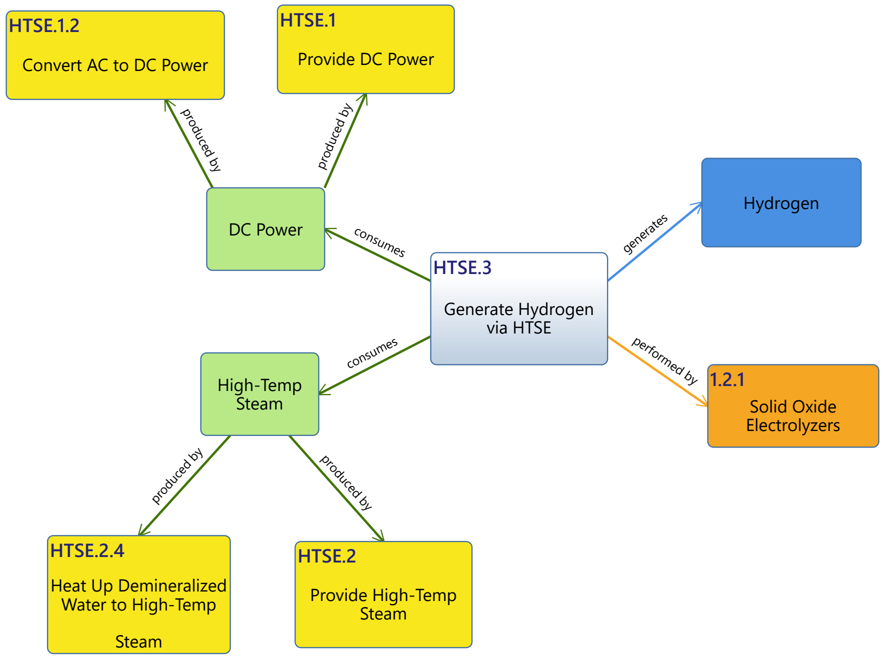

Figure 5.15: Traceability of asset and action model artifacts

While not shown here for brevity, traceability to system functional and performance requirements and inherently to stakeholders and their needs is also maintained for asset and action artifacts. Such detailed yet simple integration of all system elements, top to bottom, enables quick and intuitive system exploration by users such as system designers and engineers, project managers, decision-makers, and other stakeholders. The all-inclusive system representation also supports enhanced knowledge collection, retention, and transfer. Lastly, the model being the single source of truth enables quick changes of a conceptual solution or the development of additional conceptual solutions as required, given the system context, stakeholder-specific objectives, or site-specific constraints.

Solution 2—LTE and Nuclear Energy Source

The main system characteristics are:

- An NPP provides electricity as the only energy source to the hydrogen generation facility.
- The hydrogen generation facility is located next to the NPP.
- The NPP continues to supply the remaining electricity to the grid.

- Storage and transportation aspects are the same as in Solution 1.

Key differences from Solution 1:

- Instead of HTSE, LTE PEM is the electrolysis technology.
- No modifications are required for the NPP since thermal energy is not extracted.
- A purification system is not required as the hydrogen generated from PEM electrolysis is already at the required level of purity.
- There is no reverse operation option of electricity generation from stored hydrogen, but there is still an option to curtail hydrogen production to supply electricity generated by the NPP to the grid instead of producing hydrogen.

The system concept is presented in Figure 5.16 as an asset diagram. The high-level concept of operation is presented in Figure 5.17 as an action diagram.

Solution 3—SMR with a CCS System

The main system characteristics are:

- Currently used technology for hydrogen generation.
- The new hydrogen generation facility will include a CCS system to qualify as a low-carbon hydrogen technology.
- Electrical grid supplies electricity to supporting systems (i.e., hydrogen purification, compression, and storage).
- The hydrogen generation facility, in this case, will be located in close proximity to the industrial consumer, and a dedicated, newly built pipeline infrastructure will be used as the transportation system.
- Captured CO_2 is transported via specialized truck trailers and stored offsite in an underground CO_2 sequestration repository.

Key differences from Solutions 1 and 2:

- Feedstock is natural gas instead of water.
- Significant CO_2 emissions necessitate a CCS system, processes, and infrastructure.

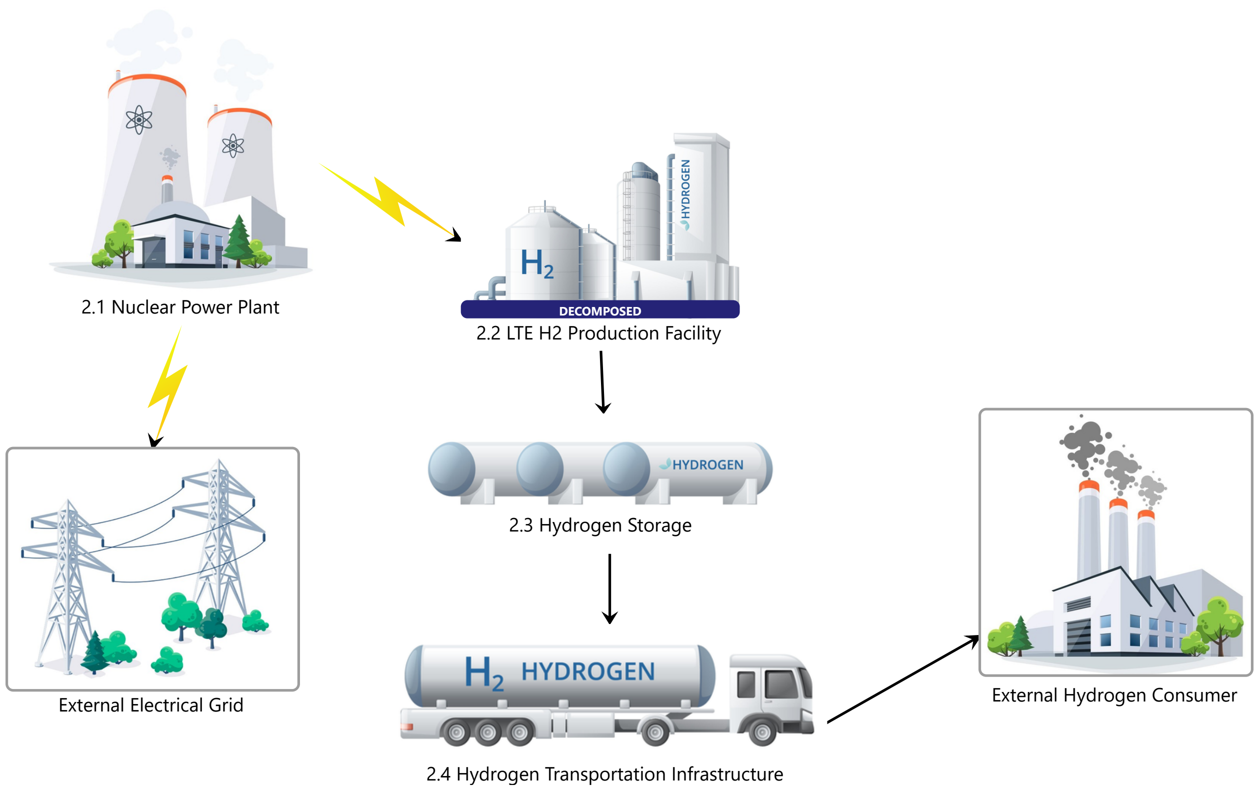

Figure 5.16: Solution 2—hydrogen generation via LTE with a nuclear energy source

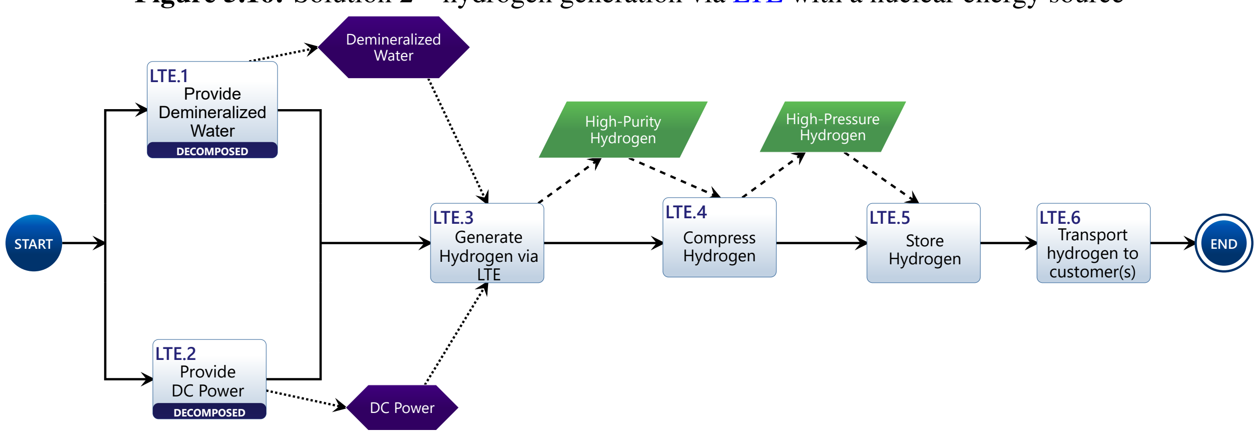

Figure 5.17: Solution 2—concept of operations

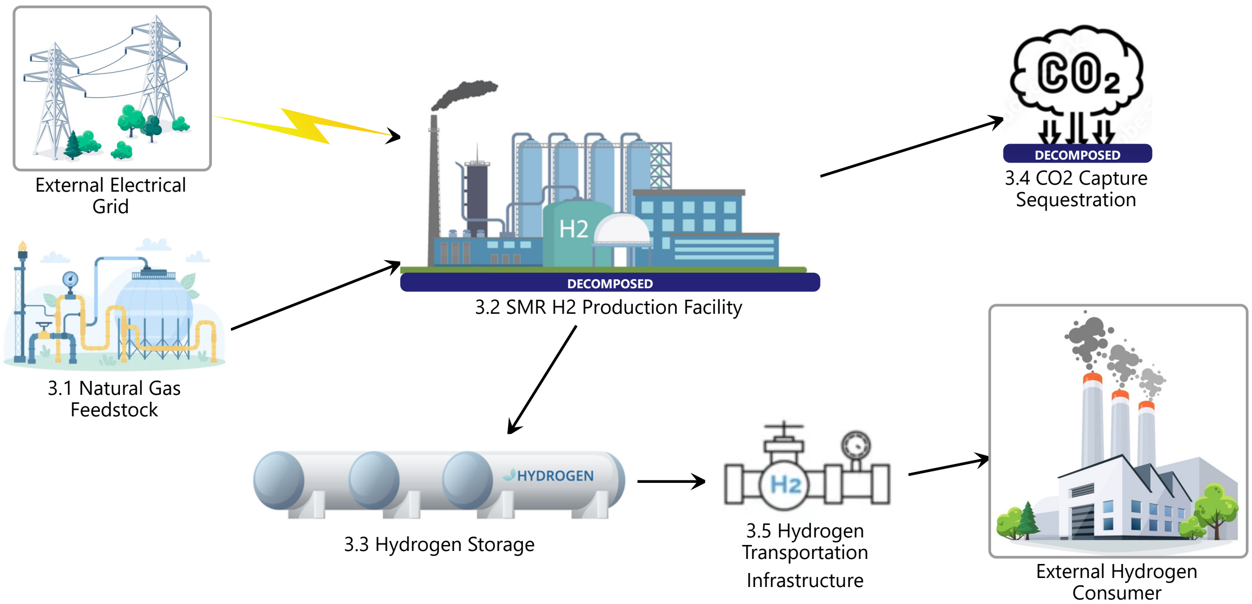

Figure 5.18: Solution 3—hydrogen generation via an SMR

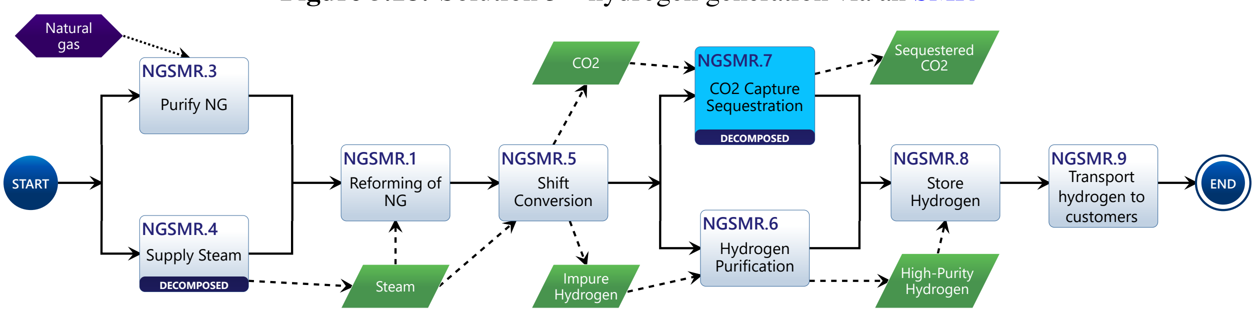

Figure 5.19: Solution 3—concept of operations

- The purification process is much more extensive as produced hydrogen is a low-level purity with many byproducts that must be removed.
- There is no flexible operation option to support the grid other than curtailing hydrogen generation, which only conserves a limited amount of electricity.

The system concept is presented in Figure 5.18 as an asset diagram. The high-level concept of operation is presented in Figure 5.19 as an action diagram.

Solution 4—LTE and Solar Energy Source

The main system characteristics are:

- A solar power plant located next to the hydrogen generation facility provides electricity to the hydrogen generation facility. The hydrogen generation is performed when a solar power plant supplies electricity, where the daylight duration and meteorological conditions affect the availability and efficiency of solar power generation. To ensure the critical requirement of a consistent hydrogen supply to the customer, the solar power plant is sized accordingly to produce a large amount of hydrogen during the day, store generated hydrogen, and not produce hydrogen when solar power is unavailable. Battery energy storage is another possible solution to overcome the challenge of the intermittent availability of solar energy, but this option is less cost-efficient than overproducing and storing hydrogen.

- A purification system is not required as the hydrogen generated from PEM electrolysis is already at the required level of purity.
- Storage capacity is driven by the requirement of an uninterrupted supply of hydrogen to the customer. The hydrogen production rate during the day is much larger than the rate of hydrogen discharge to the customer, requiring a large-capacity storage unit.
- Transportation infrastructure is required since the hydrogen customer is located approximately 10 miles from the hydrogen generation facility (an assumed condition). The shorter distance and regional circumstances allow for the construction of a dedicated pipeline infrastructure, which will be used as the transportation system.

Key differences from Solution 2:

- A new energy source, a solar power plant, needs to be built to support hydrogen generation.
- A much larger storage capacity is needed to account for the consistent hydrogen supply to the customer.
- Hydrogen transportation infrastructure is simpler as the new hydrogen generation facility supported by a solar power plant is located closer to the hydrogen consumer.
- The hydrogen facility combined with a solar power plant requires a large parcel of land to support the large energy demands.

The system concept is presented in Figure 5.20 as an asset diagram. The high-level concept of operation is presented in Figure 5.21 as an action diagram.

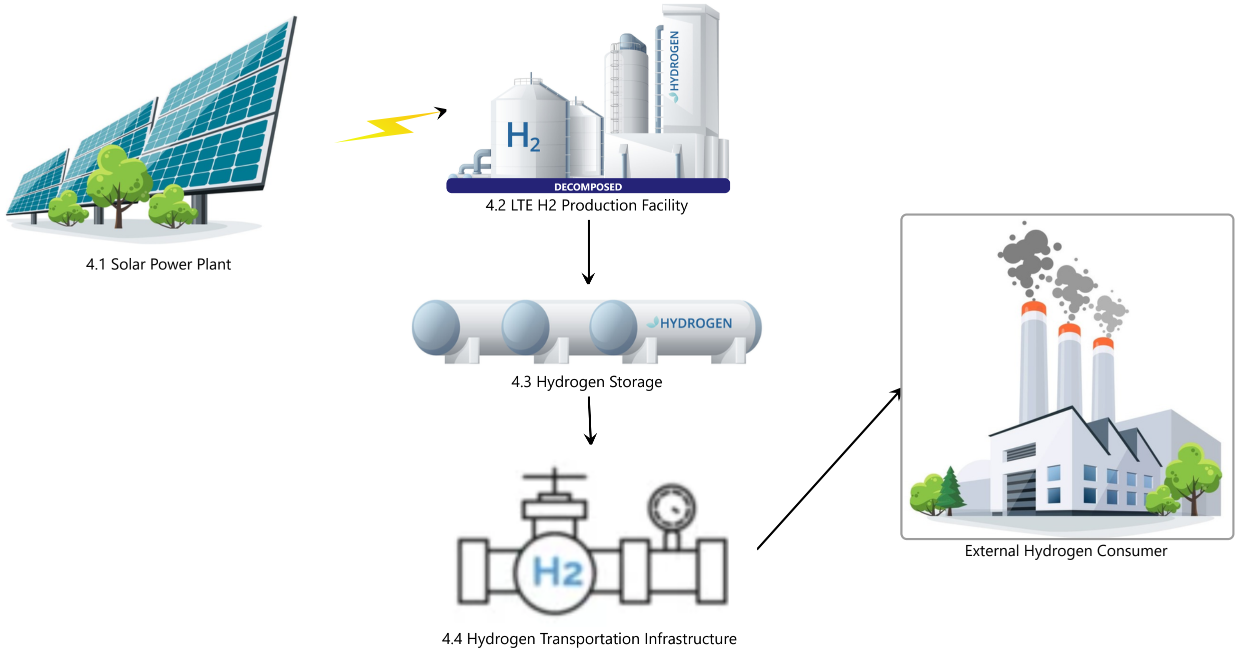

Figure 5.20: Solution 4—hydrogen generation via LTE with a solar energy source

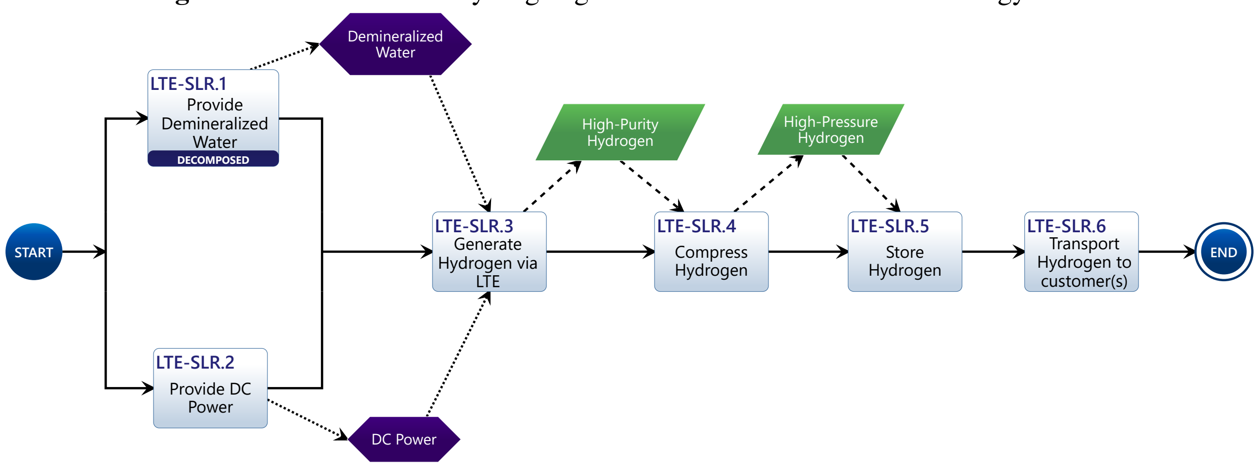

Figure 5.21: Solution 4—concept of operations

Supporting Data

Information pertinent to the conceptual system design in all three dimensions (i.e., technical, economical, and social) is developed using discipline-specific tools. Additional R&D is needed to support integrating external tools with MBSE, which is outside the scope of this research focused on the concept of a new decision support system rather than technical solutions for integrating multiple software tools in MBSE. This paper does not present details of supporting data development, for example, cost estimates, since they are outside of the main focus (i.e., the decision support framework). Instead, high-level results are used for the trade-off analysis performed in the Concept Definition phase outlined in Section 5.4.3. The hydrogen generation cost data was developed using the NREL H2FAST Excel-based tool [197].

Supporting data for the concepts should be collected in the MBSE model to enable data collection, retention, and sharing. An example of supporting data collection is presented in Figure 5.22. In this example, the cost information for the action HTSE.3 Generate hydrogen via HTSE is recorded.

5.4.3 Phase 3—Concept Definition

This is the phase where the four concepts for the hydrogen generation system are evaluated and compared against the requirements developed from stakeholder needs. A trade-off analysis is conducted using the multicriteria decision analysis approach described in Section 5.2.4.

The evaluation criteria were established across four categories: "Economics of H2 Generation," "Economics of Support Systems," "Other Technical Considerations," and "Social." These categories and evaluation criteria were informed by the stakeholder needs translated into system requirements and performance characteristics as part of the Needs Analysis phase described in Section 5.4.1. Industry experts provided their inputs for category priorities and evaluation criteria weights, indicating their importance.

The conceptual solutions were identified in the Concept Exploration phase described in Section 5.4.2. Supporting information collected and assembled within the MBSE model for each

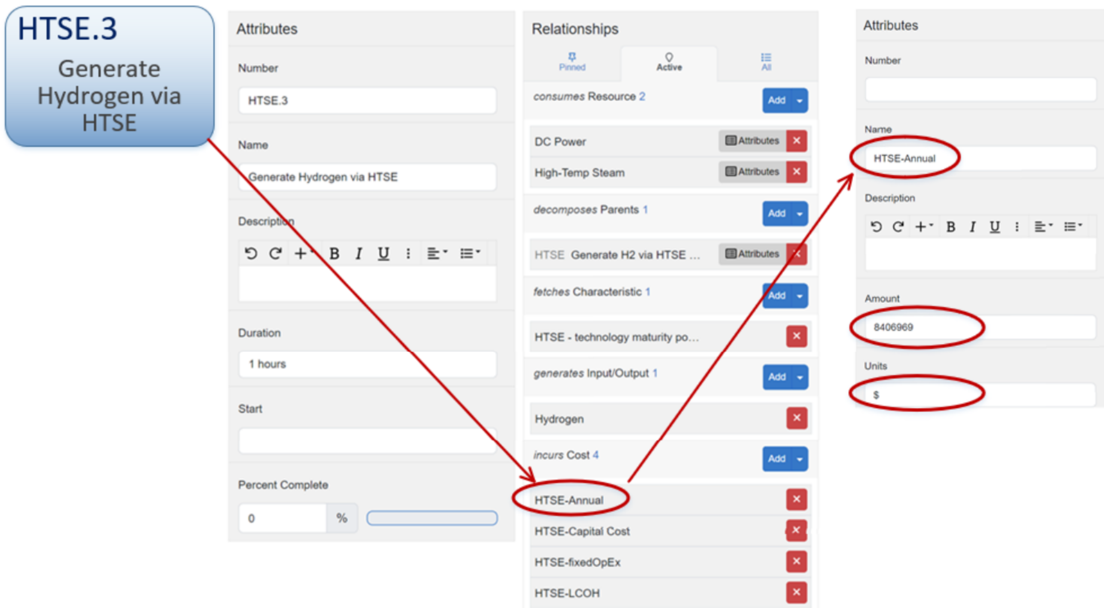

Figure 5.22: Supporting data in MBSE

solution was used to evaluate the solutions against each criterion. A scoring system ranging from 1 to 5, where 1 is the lowest and 5 is the highest score, was used to rate the solutions. Finally, the overall weighted score for each solution was determined using the methodology described in Section 5.2.4.

The activities in this phase are supported by MBSE, which enables traceability between the requirements and system elements, which are either system functions shown via action diagrams or system assets performing the functions shown via asset diagrams.

The trade-off studies could be conducted using dedicated external tools (e.g., Excel spreadsheet) or directly in MBSE via specialized integrated solutions. In this case study, an Excel spreadsheet is used to demonstrate the application of a trade-off analysis as part of the decision support system. The decision analysis matrix for the four solutions for hydrogen generation is presented in Figure 5.23. Supporting data stored in the MBSE model is consolidated in the decision analysis matrix. The weights and priority scores are hypothetically developed based on the author's experience and familiarity with the stakeholder preferences. In a real-life system development case, the scores would be developed by the system developers based on the preferences of decision-makers.

	Priority	Evaluation criteria	Weight	Solution 1 - HTSE + Nuclear Energy			Solution 2 - LTE + Nuclear Energy			Solution 3 - SMR + CCS			Solution 4 - LTE + Solar		
	%		%	Estimates	Score	Weighted	Estimates	Score	Weighted	Estimates	Score	Weighted	Estimates	Score	Weighted
Economics of H2 Generation	40%	Capital Costs	30%	$108,203,341	4	24%	$76,145,446	5	30%	$302,568,403	2	12%	$279,225,351	3	18%
		Fixed OpEx	10%	$5,032,017	4	8%	$3,700,361	5	10%	$8,680,996	3	6%	$13,569,224	2	4%
		Annualized replacement	30%	$8,406,969	2	12%	$1,281,387	5	30%	$1,503,525	5	30%	$4,698,846	3	18%
		LCOH	30%	$3.46	4	24%	$2.55	5	30%	$5.13	1	6%	$3.96	4	24%
		Sub-category weighted score	100%			68%			100%			54%			64%
		Category Sum			**27%**			**40%**			**22%**			**26%**	
Economics support systems	30%	Purification	30%	simple	3	18%	not needed	5	30%	complex	1	6%	not needed	5	30%
		Storage	30%	small	5	30%	small	5	30%	small	5	30%	very large	1	6%
		Transportation	30%	tube trailers, 20 mi	1	6%	tube trailers, 20 mi	1	6%	pipe, 2 mi	5	30%	pipe, 2 mi	5	30%
		CO2 transport + storage	10%	0	5	10%	0	5	10%	$4,106,250	1	2%	0	5	10%
		Sub-category weighted score	100%			64%			76%			68%			76%
		Category Sum			**19%**			**23%**			**20%**			**23%**	
Other technical considerations	20%	H2 generation techn. maturation	40%	High potential to increase efficiency / decrease costs	5	40%	Medium potential to increase efficiency / decrease costs	4	32%	Mature technology, some potencial for CCS	1	8%	Medium potential to increase efficiency / decrease costs	4	32%
		Support of electrical grid operation	50%	Spinning capacity, flexibility to re-direct production, electricity generation form stored H2	5	50%	Spinning capacity, flexibility to re-direct production	4	40%	None	1	10%	None	1	10%
		Regulatory acceptance / licensing	10%	Modifications to NPP for thermal dispatch and electricity intake, H2 safety risks	2	4%	Modifications to NPP for electricity intake, H2 safety risks	4	8%	H2 safety, EPA rules for NG as feedstock	5	10%	H2 safety, EPA rules for large land use for solar farm	4	8%
		Sub-category weighted score	100%			94%			80%			28%			50%
		Category Sum			**19%**			**16%**			**6%**			**10%**	
Social	10%	Use of resources	60%	water + energy	5	60%	water + energy	5	60%	NG + electr	3	36%	Large land + water	1	12%
		Climate goals contribution	40%	clean / nuclear waste	4	32%	clean / nuclear waste	4	32%	CO2 emmiting + CCS	1	8%	clean / PV recycle	5	40%
		Sub-category weighted score	100%			92%			92%			44%			52%
		Category Sum			**9%**			**9%**			**4%**			**5%**	
Σ%	100%	Overall weighted score		65%			79%			48%			58%		

Maximum score: **5**

Figure 5.23: Multicriteria decision analysis for hydrogen generation solutions (red circled cost from the Amount attribute in Figure 5.22)

The results of the multicriteria decision analysis shown in Figure 5.23 demonstrate that each of the four proposed solutions has pros and cons.

- **Solution 1—HTSE and Nuclear Energy Source** has low capital and O&M costs, favorable LCOH, and dual-use for grid resilience. It offers a simple purification process and efficient hydrogen storage. However, it faces high replacement costs, inefficient hydrogen transport, and potential regulatory delays.
- **Solution 2—LTE and Nuclear Energy Source** excels in low costs and simple infrastructure but shares HTSE's transport inefficiencies and lacks the capability to generate electricity from hydrogen.
- **Solution 3—SMR with a CCS System** offers a better transportation option and low O&M costs but has high capital costs and LCOH due to CCS, complex purification, and relies on fossil fuels, impacting climate goals negatively.
- **Solution 4—LTE and Solar Energy Source** has lower LCOH than Solution 3, yet higher capital costs and significant storage demands due to solar intermittency. It benefits from easy transport and climate advantages, but requires substantial land for solar infrastructure.

Based on the evaluation results, the best option for a hydrogen generation plant is Solution 2, where LTE technology is used to produce hydrogen supported by nuclear electricity. Solution 1 is the second-best option, and it is currently suboptimal compared to Solution 2 due to the higher cost of hydrogen generation. However, HTSE technology has made dramatic improvements in efficiency, reliability, and costs. This indicates that Solution 1 may soon become the best option, surpassing Solution 2.

5.5 Conclusion

This chapter advocates for a new decision support framework that comprehensively evaluates energy systems based on the key objectives defined by system stakeholders. This framework allows for considering various perspectives, including economic, technical, and social aspects. The chapter also reviews existing decision-making approaches in energy systems, highlighting their gaps and shortcomings.

The proposed framework employs ST and SE principles and tools, specifically using a concept exploration approach and MBSE for systems analysis, combined with multicriteria decision analysis. The framework process consists of three phases: needs analysis, concept exploration, and concept definition. The needs analysis phase explores why the new system is needed and if there are technologies that can address the need. The concept exploration phase establishes feasible goals for the new energy system before committing significant resources to its detailed exploration and development. The concept definition phase evaluates identified candidate concepts based on using supporting data, either developed or collected, as part of this phase's work. In this phase, a trade-off analysis is conducted using multicriteria decision analysis, which allows for an objective, systematic, and transparent comparison of various options and subsequent selection of the solution most suitable to accomplish the key objectives of the new system. The developed framework can support decisions during the planning and design stages of new energy systems and investment strategies in novel energy solutions. The decision support framework presented in this paper is demonstrated in a case study for selecting the conceptual solution for a novel energy system tasked with clean hydrogen production.

The case study focused on demonstrating that the proposed framework can aid in making strategic decisions, primarily for investors and utility executives. While many studies have evaluated energy systems from the standpoint of sustainability to inform policymakers, this research is distinct as it targets investors and utility executives. The approach calls for a multidisciplinary, integrated evaluation of energy solutions, with sustainability as an optional criterion. The framework presented is flexible and can be modified to address the needs of other interested entities, like policymakers, with sustainability being the more prominent criterion.

While the case study focused on system deployment (e.g., system capital costs), acceptance by stakeholders, the approach is well-capable of including considerations of the entire lifecycle. Specifically, a more detailed analysis of the O&M expenses could be performed and included in the decision-making. Similarly, system disposal options at the very end of the lifecycle could be considered. Lastly, the MBSE model setup for the concept selection is very useful for guiding system development through design, construction, operation, and disposal phases.

The proposed decision-making framework aims primarily at investors and utility executives in the energy sector, particularly those focused on the commercialization of novel energy technologies, such as clean hydrogen production. However, the framework can be very useful for policymakers as well to analyze how existing or envisioned policies may affect choices in technologies.

Applications for industry decision-makers (e.g., Manufacturers of Hydrogen):

- Investment Decisions: The framework helps manufacturers assess the feasibility of transitioning from “dirty” (high carbon footprint) hydrogen production methods to “clean” (low or zero carbon emissions) technologies. By evaluating different system configurations and their associated costs and benefits, manufacturers can make informed investment decisions.
- Risk Minimization: The tool provides a structured approach to identify and mitigate risks associated with suboptimal system configurations that may not align with stakeholder re-

quirements or regional conditions. This is crucial for manufacturers to avoid costly mistakes during the investment phase.

- Stakeholder Engagement: The tool facilitates a multidisciplinary evaluation that takes into account the needs and objectives of various stakeholders, including investors, manufacturers, and local communities. This helps policymakers develop strategies that are more likely to gain broader support and address multiple interests.

and the applications for policymakers:

- Policy Development: Policymakers can use the tool to evaluate the implications of various energy technologies and configurations on achieving sustainability goals. By understanding how different systems perform against established criteria, they can craft policies that promote cleaner technologies.
- Resource Allocation: Policymakers can utilize the insights generated from the tool to allocate resources effectively, ensuring that investments in energy technologies are directed towards the most feasible and beneficial options for future energy systems.

In summary, the decision-making framework supports both industry stakeholders and policymakers by providing a comprehensive framework for evaluating energy system configurations, thereby aiding in the transition to cleaner energy solutions and the effective formulation of related policies. Benefits of a similar approach, i.e., concept selection using multicriteria decision analysis, were explored in [191]. The feedback from industry experts who participated in the case study for selecting the system concept for an offshore energy technology was positive, indicating that the matrix approach enhances the process and quality of concept selection.

The research contribution is attributed to combining the ST and SE disciplines supported by MBSE methods and tools, with multicriteria decision-making methodology in an integrated framework targeting a more comprehensive, multidisciplinary, objective, and systematic approach to strategic decision making for novel energy systems. To clearly demonstrate the research contribution, it is essential to emphasize the synergistic benefits that arise from the integration of ST and SE disciplines, as facilitated by MBSE methods and tools, with multicriteria decision-making methodology. By adopting ST, the research inherently addresses complex problems in a holistic manner, acknowledging the interdependencies and interactions within the energy systems. SE provides a disciplined approach to the development and lifecycle management of such systems, ensuring they meet the myriad of requirements and constraints. The utilization of MBSE methods and tools can be a game-changer, as it allows for the creation of a shared, unambiguous model of the system that can be used for the initial strategic decision-making and later utilized throughout the entire project life cycle. Moreover, when integrated with multicriteria decision-making methodology, the framework becomes exceptionally powerful. This framework enables the incorporation of diverse criteria that reflect economic, environmental, social, and technical perspectives, which are often at odds in the strategic planning of energy systems. The robustness of the decisions can be vastly improved by considering these multiple criteria systematically and objectively.

Unlike previous studies focused on evaluation of energy systems, such as those described in [37, 177–181, 184, 185], this research introduces a decision support tool that simplifies the comparison of energy concepts and aids in selecting the best option based on criteria set and ranked by decision-makers. Multiple literature sources [180–184] point out that understanding energy systems necessitates considering a range of disciplines and dimensions to reflect the diverse goals of energy systems and incorporation of perspectives of different stakeholders. Furthermore, relying on a single metric for evaluation can lead to incomplete and sometimes misleading conclusions [182], potentially resulting in suboptimal decisions and inferior solutions.

Therefore, the framework developed in this research goes beyond the single-discipline evaluations found in works like [187, 197, 198] by offering a comprehensive approach that evaluates energy solutions from technical, economic, and social perspectives, including stakeholder values regarding climate objectives and conservation of natural resources. Moreover, this framework differs from those centered solely on multicriteria decision-making [183, 186, 191] by enhancing the multicriteria evaluation matrix with a systematically compiled MBSE model that aggregates detailed information on each energy concept.

There are some challenges that should be considered before immediately utilizing the proposed framework. As discussed in Section 3.3.2, a limitation of the framework can be the extra effort required to gather and organize information within the MBSE model as well as the potential learning period adopting an MBSE software tool. The framework also includes a multicriteria decision matrix that offers a straightforward comparison of various options, but can become cumbersome and information-heavy if too many options are assessed simultaneously.

Chapter 6

Conclusions and Future Work

This research developed an integrated approach to decision-making for novel energy systems. More specifically, the research explored integrating novel energy solutions into the existing overall energy system. This work started by exploring the complexities of the energy systems and the inherent difficulty of decision-making, especially for new energy systems. Understanding the dynamics of energy transitions is critically important to support policy development and investment decision-making.

The SD model developed in this research explored factors affecting novel energy deployment, highlighting the importance of costs, policies, and technological learning to system commercialization. This part of the research is focused on understanding the high-level dynamics of novel energy system deployment, which are useful for understanding the long-term dynamics of novel energy technology adoption by the overall energy system.

The second part of the research developed a more granular decision support framework focused on identifying the optimal conceptual solution for an energy system. The optimal solution requires considering multiple objectives and constraints, the perspectives of many stakeholders, and an unbiased evaluation of possible options. An SE approach and MBSE tools, as well as a multicriteria decision analysis method, were used to develop a framework for system concept development and selection.

6.1 Contributions

This research makes significant contributions to the field of energy system decision-making by developing a novel decision support framework that integrates ST, SE principles, and multi-criteria decision analysis. The framework uniquely combines the holistic perspective of ST with the structured approach of SE, supported by the use of MBSE methods and tools. This integration ensures a comprehensive consideration of technical, economic, and social dimensions in the decision-making process.

The research addresses the urgent need for transitioning to sustainable and resilient energy sources by providing a method for evaluating and implementing novel energy technologies. The case study on hydrogen production demonstrates the framework's applicability to clean energy solutions, contributing to the broader goal of reducing GHG emissions and enhancing energy security. The flexibility and adaptability of the framework allow it to be tailored to different energy systems and stakeholder needs, making it a versatile tool for various decision-making scenarios. Future research can further expand and refine the framework, integrating additional criteria and enhancing its applicability to a wider range of energy solutions and contexts.

The use of MBSE enhances knowledge collection, retention, and transfer and allows for the creation of a shared, unambiguous system model that can be used throughout the entire project life cycle. This approach facilitates quick changes and evaluations of various conceptual solutions, ensuring that all feasible options are considered before making a final decision.

6.2 Future Work

This research has developed two decision-supporting tools—an SD model to analyze potential trajectories of the novel energy system deployment and the framework supporting a conceptual design of a specific energy solution. The SD model can be used either as-is or with minor modifications to explore behaviors and deployment trajectories for several other energy technologies, such as:

- Batteries
- Thermal energy storage systems
- Offshore wind energy
- CCS technologies
- Hydrogen storage technologies
- Hydrogen transportation technologies

- Natural hydrogen generation
- Nuclear energy
- Biomass energy

The framework for energy system concept development and selection can be used for any system, not just an energy system, where multiple objectives must be considered along with specific constraints. The framework can be especially helpful when stakeholders are evaluating energy solutions that are dependent on regional factors. Both solar and wind energy systems are highly dependent on regional wind or solar sources, proximity to the grid, capacity of the local grid, and availability of energy storage solutions. Fossil fuel-based energy technologies are dependent on feedstock resources like natural gas or coal, as well as accessibility to the grid if the energy production facility is not located near the consumer. Nuclear energy is not dependent on rationality or access to fuel, but like other electricity-generating technologies, it is dependent on availability to the grid. Nuclear energy also has the benefit of being able to provide thermal energy, but the consumer must be located in close proximity for this option to be economically viable.

While the developed SD model and framework for system concept selection are valuable tools to support decision-making for energy systems, several improvements could be made as discussed below.

System Dynamics Model Improvements

Comprehensive Modeling: Expanding the model to include additional variables, such as the costs of competing technologies and energy demands, can provide a more detailed understanding of the willingness to invest as an endogenous variable.

Policy Analysis: Further analysis of the impact of state-level policies can offer a more comprehensive view of the policy landscape affecting deployment opportunities for novel energy systems.

Social Factors: Incorporating public perception and social acceptance more explicitly in the model can improve the accuracy of projections, particularly for technologies facing significant public resistance or support.

Global Perspective: Extending the model to include global market dynamics and international cooperation can provide insights into cross-border technology transfer and the global diffusion of novel energy systems.

Concept Selection Framework Improvements

Future research may expand the framework to integrate discipline-specific evaluations within MBSE. Additional work, fully or partially automating the generation and evaluation of various conceptual designs using identified subsystem options [175] would expand the potential solution set, thereby considering a broader set of possible concepts that may have been overlooked previously. This feature could also help address concerns regarding too many options to evaluate in the multicriteria decision matrix. Direct incorporation of other criteria, such as sustainability, could be explored to address the needs of other interested stakeholders, like policymakers.

The model and results from the case study can be presented to and used by key stakeholders, with feedback systematically collected to provide specific evidence of the benefits of this framework and to identify areas for potential improvements. These improvements can make the decision-making framework more automated and interconnected, improving the framework's effectiveness in various systems and contexts.

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Appendix A

System Dynamics Model for Wind Energy

This appendix presents the wind energy system dynamics model in XMILE format. The system dynamics wind model developed in this research is available in the open-source GitHub repository: https://github.com/lawrencesv/SD-Model-Wind-Energy accessed on May 14, 2025.

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    <vendor>Ventana Systems, Inc.</vendor>
    <created>
    </created>
    <modified>
    </modified>
    <name>
    </name>
    <caption>
    </caption>
  </header>
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    <stop>2050</stop>
    <dt>0.25</dt>
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  <model>
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          Capacity Decommission Rate
          </inflow>
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          </eqn>
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          Construction Start Rate
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          Construction Finish Rate
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          Capacity Development Start Rate
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```

```
        <outflow>
        Construction Start Rate
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        Project Development Failure Rate
        </outflow>
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        </eqn>
        <inflow>
        Construction Finish Rate
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        <outflow>
        Capacity Decommission Rate
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      <units>MW/yr</units>
      <doc>Developer capacity, Installed Capacity (MW) per year</doc>
        <eqn>
        Initial_Developer_Capacity
        </eqn>
        <inflow>
        Developer Capacity Growth Rate
        </inflow>
    </stock>
    <aux name="Average_Project_Lifetime">
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      <doc></doc>
        <eqn>
Average_Project_Lifetime_Lookup(Time)*ave_project_lifetime_gain         </eqn>
    </aux>
    <aux name="Capacity_Decommission_Rate">
      <units>MW/yr</units>
      <doc>Total installed capacity delayed by the average lifetime of a wind project</doc>
        <eqn>
Capacity_Installed/Average_Project_Lifetime         </eqn>
    </aux>
    <aux name="Capacity_Development_Start_Rate">
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        <eqn>
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    </aux>
    <aux name="Construction_Finish_Rate">
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Capacity_in_Construction/Average_Construction_Time          </eqn>
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    <aux name="Construction_Start_Rate">
      <units>MW/yr</units>
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```

```
(1-Permit_Failure_Rate)*Capacity_in_Development*Willingness_to_invest/Permitting_and_PPA_decision_time          </eqn>
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    <aux name="Developer_Capacity_Growth_Rate">
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MIN((Desired_Capacity-Developer_Capacity)/Developer_Capacity_Adjustment_Time, Developer_Capacity*(1+Maximum_Growth_Rate))         </eqn>
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Electricity_Price+Production_Tax_Credit         </eqn>
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Cumulative_Global_Capacity/Initial_Global_Capacity          </eqn>
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```
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        <eqn>
IF_THEN_ELSE( "ROI-Adjusted_Revenue"<LCOE , 0 , Wind_Supply_Curve )          </eqn>
    </aux>
    <aux name="Profitable_Capacity_Available_for_New_Projects">
      <units>MW</units>
      <doc>Determination of how much capacity is still available given the total profitable capacity and already installed capacity</doc>
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    <aux name="ROI-Adjusted_Revenue">
      <units>$/(KW*hr)</units>
      <doc>Used to determine the total available profitable capacity given the expected revenuew adjusted (reduced) to incorporate minimum ROI</doc>
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      <doc>Simulated capacity factor</doc>
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    <aux name="Simulated_CapEx">
      <units>$/KW</units>
      <doc>Simulated total installed costs (Capital Expenses) for 1kW of wind capacity</doc>
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```

```
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     due to failure to secure a power purchase agreement (PPA). It is assumed that failure
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    market urgency, lack of NIMBYism and generally easier environment for permitting.</doc>
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Assumed to increase to 5 years at 2050.
From (Dykes, 2016): Project development time (including permitting and contracting) is
    typically 5 years including 1 year for prospecting (4 years in exclusion of prospecting
    time). It is assumed that early projects in the 80's were much easier to permit for a
    number of reasons including market urgency, lack of NIMBYism, and generally less complex
    permitting requirements during the time period.</doc>
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    doc>
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        <doc>Capacity Factor Learning Rate - estimated based on historical observations for the
     US installations</doc>
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 0.0517          </eqn>
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        <doc>Global Learning Rate for Total Installed Costs (CapEx) - estimated in excel
    spreadsheet based on historical data.</doc>
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        <doc>Adjustement time for developer capacity growth is 1 year (assumed)</doc>
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```
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    </aux>
    <aux name="Initial_Capacity_Factor">
      <units>Dmnl</units>
      <doc>Initial capacity factor in 1998</doc>
        <eqn>
0.255         </eqn>
    </aux>
    <aux name="Initial_CapEx">
      <units>$/KW</units>
      <doc>Global total installed cost in 1998 (in 2023 $)</doc>
        <eqn>
2824          </eqn>
    </aux>
    <aux name="Initial_Developer_Capacity">
      <units>MW/yr</units>
      <doc>Initial developer capacity in 1998, an estimate based on incremental capacity additions in 2001-2002 (3-4 years later)</doc>
        <eqn>
500         </eqn>
    </aux>
    <aux name="Initial_Global_Capacity">
      <units>MW</units>
      <doc>Initial globally-installed capacity in 1998</doc>
        <eqn>
10200         </eqn>
    </aux>
    <aux name="Initial_OpEx">
      <units>$/KW</units>
      <doc>US O&M Cost (2023 $/kW-yr) in 1998</doc>
        <eqn>
98          </eqn>
    </aux>
    <aux name="Interest_Rate">
      <units>Dmnl</units>
      <doc>Interest rate = 4% for energy projects (Feldman, 2020)</doc>
        <eqn>
0.04          </eqn>
    </aux>
    <aux name="Maximum_Growth_Rate">
      <units>1/yr</units>
      <doc>Maximum capacity growth rate per year</doc>
        <eqn>
0.4         </eqn>
    </aux>
    <aux name="OpEx_LR">
      <units>Dmnl</units>
      <doc>9% LR is used based on industry estimates (Wiser, Bolinger, Lantz, 2019)</doc>
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0.09          </eqn>
    </aux>
    <aux name="per_year">
      <units>1/yr</units>
      <doc></doc>
        <eqn>
1         </eqn>
    </aux>
    <aux name="permitting_decision_time_gain">
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      <doc></doc>
        <eqn>
1         </eqn>
    </aux>
    <aux name="ROI">
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      <doc>ROI = 10% is used as the min required for investment decision making</doc>
        <eqn>
```

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        &lt;doc&gt;&lt;/doc&gt;
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&lt;/xmile&gt;
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Appendix B

System Dynamics Model for Hydrogen Energy

This appendix presents the hydrogen system dynamics model in XMILE format. The system dynamics hydrogen model developed in this research is available in the open-source GitHub repository: https://github.com/lawrencesv/SD-Model_Hydrogen accessed on May 14, 2025.

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    <vendor>Ventana Systems, Inc.</vendor>
    <created>
    </created>
    <modified>
    </modified>
    <name>
    </name>
    <caption>
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  </header>
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    <start>2026</start>
    <stop>2050</stop>
    <dt>0.25</dt>
  </sim_specs>
  <model>
    <variables>
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        <doc></doc>
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          0
          </eqn>
          <inflow>
          Capacity Decomission Rate
          </inflow>
      </stock>
      <stock name="Capacity_in_Construction">
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        <doc>0.5 MW is assumed as initial capacity in construction in 1984</doc>
          <eqn>
          Initial_Capacity_in_Construction
          </eqn>
          <inflow>
          Construction Start Rate
          </inflow>
          <outflow>
          Construction Finish Rate
          </outflow>
      </stock>
      <stock name="Capacity_in_Development">
        <units>MW</units>
        <doc></doc>
          <eqn>
          Initial_Capacity_in_Development
          </eqn>
          <inflow>
          Capacity Development Start Rate
          </inflow>
```

```
          <outflow>
          Construction Start Rate
          </outflow>
          <outflow>
          Project Development Failure Rate
          </outflow>
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      <stock name="Capacity_Installed">
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        <doc>Initial installed capacity = 1720 MW in 1998 (EIA_InternationalElectr_Capacity)</doc>
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          1512
          </eqn>
          <inflow>
          Construction Finish Rate
          </inflow>
          <outflow>
          Capacity Decomission Rate
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      <stock name="Developer_Capacity">
        <units>MW/yr</units>
        <doc>Developer capacity, Installed Capacity (MW) per year</doc>
          <eqn>
          Initial_Developer_Capacity
          </eqn>
          <inflow>
          Developer Capacity Growth Rate
          </inflow>
      </stock>
      <stock name="Ineligible_for_PTC_Capacity">
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        <doc></doc>
          <eqn>
          0
          </eqn>
          <inflow>
          Ineligibility Rate
          </inflow>
      </stock>
      <aux name="Capacity_Decomission_Rate">
        <units>MW/yr</units>
        <doc></doc>
          <eqn>Capacity_Installed/Average_Project_Lifetime          </eqn>
      </aux>
      <aux name="Capacity_Development_Start_Rate">
        <units>MW/yr</units>
        <doc></doc>
          <eqn>
MAX(0, MIN(Developer_Capacity, Profitable_Capacity_Available_for_New_Projects * per_year))            </eqn>
      </aux>
      <aux name="Capital_Recovery_Factor">
        <units>Dmnl</units>
        <doc>Capital Recovery Factor (NREL Simplified LCOE Calculator Documentation)</doc>
          <eqn>(Interest_Rate*(1+Interest_Rate)^Average_Project_Lifetime)/(((1+Interest_Rate)^Average_Project_Lifetime)-1)          </eqn>
      </aux>
      <aux name="Construction_Finish_Rate">
        <units>MW/yr</units>
        <doc></doc>
          <eqn>
Capacity_in_Construction/Average_Construction_Time          </eqn>
      </aux>
      <aux name="Construction_Start_Rate">
        <units>MW/yr</units>
        <doc></doc>
```

```
        <eqn>
(1-Project_Decision_Failure_Rate)*Capacity_in_Development*Willingness_to_invest/Feasibility_and_Engineering_Design_Time         </eqn>
      </aux>
      <aux name="Desired_Capacity">
        <units>MW/yr</units>
        <doc></doc>
          <eqn>
MAX(Initial_Developer_Capacity, Profitable_Capacity_Available_for_New_Projects/Average_Project_Lifetime)           </eqn>
      </aux>
      <aux name="Developer_Capacity_Growth_Rate">
        <units>MW/(yr*yr)</units>
        <doc></doc>
          <eqn>
MIN((Desired_Capacity-Developer_Capacity)/Developer_Capacity_Adjustment_Time, Developer_Capacity*(1+Maximum_Growth_Rate))         </eqn>
      </aux>
      <aux name="Eligibility_Ratio">
        <units>Dmnl</units>
        <doc></doc>
          <eqn>IF_THEN_ELSE ( Time>2045 , 0 , (Capacity_Installed-Ineligible_for_PTC_Capacity)/Capacity_Installed )         </eqn>
      </aux>
      <aux name="Hydrogen_Demand_Curve">
        <units>kg/hr</units>
        <doc></doc>
          <eqn>Hydrogen_Demand_Curve_Lookup("ROI-Adjusted_Revenue")*Demand_curve_gain/hrs_in_yr        </eqn>
      </aux>
      <aux name="Hydrogen_Demand_Curve_in_MW">
        <units>MW</units>
        <doc></doc>
          <eqn>kW_in_MW*Hydrogen_Demand_Curve * ((PEM_Simulated_Energy_Consumption+SOEC_Simulated_Energy_Consumption
+SMR_Simulated_Energy_Consumption)/3) / ((PEM_Utilization+SOEC_Utilization+SMR_Utilization)/3)          </eqn>
      </aux>
      <aux name="Hydrogen_Sale_Break_Even">
        <units>$/kg</units>
        <doc></doc>
          <eqn>(LCOH_PEM+LCOH_SOEC+LCOH_SMR)/3          </eqn>
      </aux>
      <aux name="Ineligibility_Rate">
        <units>MW/Year</units>
        <doc></doc>
          <eqn>IF_THEN_ELSE ( Time<2035 , 0 , Capacity_Installed/Incentive_Duration )         </eqn>
      </aux>
      <aux name="LCOH_PEM">
        <units>$/kg</units>
        <doc>Levelized Cost of Energy - the minimum price at which energy must be sold for the energy project to break even.</doc>
          <eqn>(PEM_FixedCosts+PEM_Replacement_Costs)*PEM_Simulated_Energy_Consumption+PEM_Electricity_Cost+PEM_Variable_OpEx-
Production_Tax_Credit         </eqn>
      </aux>
      <aux name="LCOH_SMR">
        <units>$/kg</units>
        <doc>Levelized Cost of Energy - the minimum price at which energy must be sold for the energy project to break even.</doc>
          <eqn>(SMR_FixedCosts+SMR_Replacement_Costs)*SMR_Simulated_Energy_Consumption+SMR_Energy_Cost+SMR_Variable_OpEx
-Production_Tax_Credit          </eqn>
      </aux>
      <aux name="LCOH_SOEC">
        <units>$/kg</units>
```

```
      <doc>Levelized Cost of Energy - the minimum price at which energy must be sold for the energy project to break even.</doc>
        <eqn>(SOEC_FixedCosts+SOEC_Replacement_Costs)*SOEC_Simulated_Energy_Consumption+SOEC_PEM_Electricity_Cost+SOEC_Variable_OpEx
-Production_Tax_Credit          </eqn>
    </aux>
    <aux name="PEM_Electricity_Cost">
      <units>$/kg</units>
      <doc></doc>
        <eqn>PEM_Simulated_Energy_Consumption*"U.S._Electricity_Price_Renewables"         </eqn>
    </aux>
    <aux name="PEM_FixedCosts">
      <units>$/(KW*hr)</units>
      <doc></doc>
        <eqn>PEM_Normalized_Upfront_Investments*"1/Year"/
(PEM_Utilization*hrs_in_yr)         </eqn>
    </aux>
    <aux name="PEM_Global_Experience">
      <units>Dmnl</units>
      <doc>Global experience - ratio of cumulative globally-installed capacity to the initial capacity in 1984</doc>
        <eqn>
PEM_Cumulative_Global_Capacity/Initial_Global_Capacity_PEM          </eqn>
    </aux>
    <aux name="PEM_Normalized_Upfront_Investments">
      <units>$/KW</units>
      <doc></doc>
        <eqn>(PEM_Simulated_CapEx)*Capital_Recovery_Factor          </eqn>
    </aux>
    <aux name="PEM_Replacement_Costs">
      <units>$/(KW*hr)</units>
      <doc></doc>
        <eqn>"PEM__of_CAPEX"*PEM_FixedCosts*(Average_Project_Lifetime*PEM_Utilization*hrs_in_yr
/PEM_Simulated_Stack_Lifetime)          </eqn>
    </aux>
    <aux name="PEM_Simulated_CapEx">
      <units>$/KW</units>
      <doc>Simulated total installed costs (Capital Expenses) for 1kW of wind capacity</doc>
        <eqn>PEM_Initial_CapEx*PEM_Global_Experience^((ln(1-PEM_CapEx_LR)/ln(2)))         </eqn>
    </aux>
    <aux name="PEM_Simulated_Energy_Consumption">
      <units>KW*hr/kg</units>
      <doc>Simulated capacity factor</doc>
        <eqn>PEM_Initial_Energy_Consumption*PEM_Global_Experience^((ln(1-PEM_Efficiency_LR)/ln(2)))         </eqn>
    </aux>
    <aux name="PEM_Simulated_Stack_Lifetime">
      <units>hrs</units>
      <doc></doc>
        <eqn>PEM_Initial_Lifetime*PEM_Global_Experience^((ln(1+PEM_Lifetime_LR)/ln(2)))
      </eqn>
    </aux>
    <aux name="Production_Tax_Credit">
      <units>$/kg</units>
      <doc>IRA hyrogen production tax cfredit 45V = 3$/kg for plants beginning construction in 2033 or sooner.</doc>
        <eqn>Maximum_PTC*Eligibility_Ratio          </eqn>
    </aux>
    <aux name="Profitable_Capacity_Available_for_New_Projects">
      <units>MW</units>
      <doc>Determination of how much capacity is still available given the total profitable capacity and already installed capacity</doc>
        <eqn>Hydrogen_Demand_Curve_in_MW-Capacity_Installed+Capacity_Decomissioned          </eqn>
    </aux>
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```
    <aux name="Project_Development_Failure_Rate">
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        <eqn>
MAX(0, Capacity_in_Development*Project_Decision_Failure_Rate/ Feasibility_and_Engineering_Design_Time)         </eqn>
    </aux>
    <aux name="ROI-Adjusted_Revenue">
      <units>$/kg</units>
      <doc>Used to determine the total available profitable capacity given the expected revenuew adjusted (reduced) to incorporate minimum ROI</doc>
        <eqn>Hydrogen_Sale_Break_Even*(1-ROI)         </eqn>
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    <aux name="SMR_FixedCosts">
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(SMR_Utilization*hrs_in_yr)         </eqn>
    </aux>
    <aux name="SMR_Global_Experience">
      <units>Dmnl</units>
      <doc>Global experience - ratio of cumulative globally-installed capacity to the initial capacity in 1984</doc>
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    </aux>
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    <aux name="SMR_Normalized_Upfront_Investments">
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      <doc></doc>
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    <aux name="SMR_Replacement_Costs">
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      <doc></doc>
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/SMR_Simulated_Stack_Lifetime)          </eqn>
    </aux>
    <aux name="SMR_Simulated_CapEx">
      <units>$/KW</units>
      <doc>Simulated total installed costs (Capital Expenses) for 1kW of wind capacity</doc>
        <eqn>SMR_Initial_CapEx*SMR_Global_Experience^((ln(1-SMR_CapEx_LR)/ln(2)))         </eqn>
    </aux>
    <aux name="SMR_Simulated_Energy_Consumption">
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      <doc>Simulated capacity factor</doc>
        <eqn>SMR_Initial_Energy_Consumption*SMR_Global_Experience^((ln(1-SMR_Efficiency_LR)/ln(2)))         </eqn>
    </aux>
    <aux name="SMR_Simulated_Stack_Lifetime">
```

```
      <units>hrs</units>
      <doc></doc>
        <eqn>SMR_Initial_Lifetime*SMR_Global_Experience^((ln(1+SMR_Lifetime_LR)/ln(2)))
      </eqn>
    </aux>
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    <aux name="SOEC_FixedCosts">
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      <doc></doc>
        <eqn>SOEC_Normalized_Upfront_Investments*"1/Year"/
(SOEC_Utilization*hrs_in_yr)          </eqn>
    </aux>
    <aux name="SOEC_Global_Experience">
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      <doc>Global experience - ratio of cumulative globally-installed capacity to the initial
   capacity in 1984</doc>
        <eqn>SOEC_Cumulative_Global_Capacity/SOEC_Initial_Global_Capacity         </eqn>
    </aux>
    <aux name="SOEC_Normalized_Upfront_Investments">
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      <doc></doc>
        <eqn>(SOEC_Simulated_CapEx)*Capital_Recovery_Factor         </eqn>
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    <aux name="SOEC_Replacement_Costs">
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  hrs_in_yr
/SOEC_Simulated_Stack_Lifetime)          </eqn>
    </aux>
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    </eqn>
    </aux>
    <aux name="SOEC_Simulated_Energy_Consumption">
      <units>KW*hr/kg</units>
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  )/ln(2)))          </eqn>
    </aux>
    <aux name="SOEC_Simulated_Stack_Lifetime">
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      <doc></doc>
        <eqn>SOEC_Initial_Lifetime*SOEC_Global_Experience^((ln(1+SOEC_Lifetime_LR)/ln(2)))
          </eqn>
    </aux>
    <aux name="U.S._Electricity_Price_Renewables">
      <units>$/(KW*hr)</units>
      <doc></doc>
        <eqn>Electricity_price_gain*Renewable_Electricity_Price_data          </eqn>
    </aux>
    <aux name="Hydrogen_Demand_Curve_Lookup">
      <units>kg/Year</units>
      <doc>Sun supply curve in terms of calculated LCOE for total capacity available for the
  installation in the U.S. Based on (NREL Solar Supply Curve https://www.nrel.gov/gis/solar-
  supply-curves), Limited Access Scenario (most restrictive) is used</doc>
```

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FID to COD is 2 years</doc>
          <eqn>2          </eqn>
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      </aux>
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        <doc></doc>
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      </aux>
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        <doc>Adjustement time for developer capacity growth is 1 year (assumed)</doc>
          <eqn>
  1         </eqn>
      </aux>
      <aux name="Electricity_price_gain">
        <units>Dmnl</units>
        <doc></doc>
          <eqn>1          </eqn>
      </aux>
      <aux name="Feasibility_and_Engineering_Design_Time">
        <units>Years</units>
        <doc>DOE Hydrogen Liftoff 2024, pg.27:
feasibility study - 1 yr
front-end engineering design (FEED) - 2 yrs</doc>
          <eqn>3          </eqn>
      </aux>
      <aux name="Initial_Capacity_in_Construction">
        <units>MW</units>
        <doc>Per IEA Hydrogen Projects, US capacity in development in 2025 is  136 MW which is assumed as initial capacity</doc>
          <eqn>136          </eqn>
      </aux>
      <aux name="Initial_Capacity_in_Development">
        <units>MW</units>
        <doc>Hydrogen liftoff report 2024 (pg.3) - 6 MMTA capacity is announced for electolysis production.
PEM exact % is not known, but it is at least 17%
50% of announced project are expected to fail to proceed to the development stage
Estimated PEM Initial Capacity in Development:
6MMTA * 30% of electolysis announced capacity * 50% success rate = 0.9MMTA = 5702MWe</doc>
          <eqn>5700         </eqn>
      </aux>
      <aux name="Interest_Rate">
        <units>Dmnl</units>
        <doc>10% is selected to match H2Lite estimated LCOH for PEM and SOEC reasnably well
From NREL H2Lite:
Return on Eqyuity - 10.2%
Interest rate - 4.4%</doc>
          <eqn>0.1          </eqn>
      </aux>
      <aux name="Maximum_Growth_Rate">
        <units>1/yr</units>
```

```
        <doc>Maximum capacity growth rate per year. Per IEA Hydrogen Project, capacity growth between 2024 and 2025 is 716% globally. The US is still behin the global hydrogen production industry, but hydrogen hubs are expected to expedite hydrogen capacity development. Therefore, 700% is assumed</doc>
          <eqn>7          </eqn>
      </aux>
      <aux name="PEM__of_CAPEX">
        <units>Dmnl</units>
        <doc>Approximated stack costs in % of installed CAPEX
Installation - 50% of total Installed CAPEX - IEA Global Hydrogen Review 2024, Figure 3.9
Stack % of uninstlled CAPEX for PEM = 60%, for AEC=50% (Bohm_2019, Table 4)
% of Installed CAPEX = 0.55*0.5=0.275 (27.5%)  - average for LTE</doc>
          <eqn>0.275          </eqn>
      </aux>
      <aux name="PEM_CapEx_LR">
        <units>Dmnl</units>
        <doc>LR
11% for PEM stack cost decline - Bohm_2019
11% for Stack for electrolizer facility & Installation - Pathways to Commercial Liftoff: Clean Hydrogen (2024 update) - pg.31
11% is confirmed to be reasonable as it matches estimated 40% LCOH decline  by Pathways to Commercial Liftoff: Clean Hydrogen (2024 update) - pg.11</doc>
          <eqn>0.11         </eqn>
      </aux>
      <aux name="PEM_Efficiency_LR">
        <units>Dmnl</units>
        <doc>Bohm_2019 - learning rates for power density for 3 different technologies
PEM: -2.5%
AEC: -5.5%
SOEC: -8.0%</doc>
          <eqn>0.025          </eqn>
      </aux>
      <aux name="PEM_Lifetime_LR">
        <units>Dmnl</units>
        <doc>Assumed.
Increase in projected lifetime is expected as shown in Gerloff_2023 Table 3.</doc>
          <eqn>0.1          </eqn>
      </aux>
      <aux name="PEM_Utilization">
        <units>Dmnl</units>
        <doc>66.1% for hybrid solar and wind (NREL H2Lite)</doc>
          <eqn>0.661          </eqn>
      </aux>
      <aux name="PEM_Variable_OpEx">
        <units>$/kg</units>
        <doc></doc>
          <eqn>0.0326         </eqn>
      </aux>
      <aux name="per_year">
        <units>1/yr</units>
        <doc></doc>
          <eqn>
  1          </eqn>
      </aux>
      <aux name="ROI">
        <units>Dmnl</units>
        <doc>ROI = 10% is used as the min required for investment decision making</doc>
          <eqn>
  0.1         </eqn>
      </aux>
      <aux name="SMR__of_CAPEX">
        <units>Dmnl</units>
        <doc>Estimated to roughly match the annualized replacement cost reported in NREL H2Lite </doc>
          <eqn>0.042          </eqn>
      </aux>
      <aux name="SMR_CapEx_LR">
        <units>Dmnl</units>
```

```
        <doc>LR   = 4% assumed for SMR w CCS
SMR technology is mature, only CCS portion will experience benefots from learning.</doc>
          <eqn>0.04         </eqn>
      </aux>
      <aux name="SMR_Efficiency_LR">
        <units>Dmnl</units>
        <doc>Assumed - low for well-established technology</doc>
          <eqn>0.01         </eqn>
      </aux>
      <aux name="SMR_Electricity_price_gain">
        <units>Dmnl</units>
        <doc></doc>
          <eqn>1          </eqn>
      </aux>
      <aux name="SMR_Lifetime_LR">
        <units>Dmnl</units>
        <doc>Assumed. Established technology, learning is very limited</doc>
          <eqn>0.02         </eqn>
      </aux>
      <aux name="SMR_NG_price_gain">
        <units>Dmnl</units>
        <doc></doc>
          <eqn>1          </eqn>
      </aux>
      <aux name="SMR_Utilization">
        <units>Dmnl</units>
        <doc>90% for SMR w/CCS facility powered by NG & grid electiricty (default from NREL H2Lite)</doc>
          <eqn>0.9          </eqn>
      </aux>
      <aux name="SMR_Variable_OpEx">
        <units>$/kg</units>
        <doc>NREL N2Lite - SMR w/CCS</doc>
          <eqn>0.3385         </eqn>
      </aux>
      <aux name="SOEC__of_CAPEX">
        <units>Dmnl</units>
        <doc>Approximated stack costs in % of installed CAPEX
Installation - 50% of total Installed CAPEX - IEA Global Hydrogen Review 2024, Figure 3.9
Stack % of uninstlled CAPEX = 30% for SOEC (Bohm_2019, Table 4)
% of Installed CAPEX = 0.3*0.5=0.15 (15%)</doc>
          <eqn>0.15         </eqn>
      </aux>
      <aux name="SOEC_CapEx_LR">
        <units>Dmnl</units>
        <doc>LR
9% for SOEC stack cost decline - Bohm_2019 - used as SOEC LR
11% for Stack for electrolizer facility & Installation - Pathways to Commercial Liftoff: Clean Hydrogen (2024 update) - pg.31</doc>
          <eqn>0.09         </eqn>
      </aux>
      <aux name="SOEC_Efficiency_LR">
        <units>Dmnl</units>
        <doc>Bohm_2019 - learning rates for power density for 3 different technologies
PEM: -2.5%
AEC: -5.5%
SOEC: -8.0%</doc>
          <eqn>0.08         </eqn>
      </aux>
      <aux name="SOEC_Electricity_price_gain">
        <units>Dmnl</units>
        <doc></doc>
          <eqn>1          </eqn>
      </aux>
      <aux name="SOEC_Lifetime_LR">
        <units>Dmnl</units>
        <doc>Assumed.
Increase in projected lifetime is expected as shown in Gerloff_2023 Table 3.</doc>
```

```
          <eqn>0.15         </eqn>
      </aux>
      <aux name="SOEC_Utilization">
        <units>Dmnl</units>
        <doc>90% for HTSE facility power by nuclear energy (default from NREL H2Lite)</doc>
          <eqn>0.9          </eqn>
      </aux>
      <aux name="SOEC_Variable_OpEx">
        <units>$/kg</units>
        <doc>NREL N2Lite - SOEC with Nuclear</doc>
          <eqn>0.3385         </eqn>
      </aux>
      <aux name="Willingness_to_invest">
        <units>Dmnl</units>
        <doc>DOE Hydrogen Liftoff 2024, pg.27:
Project success factors between FEED and Final Investment Decision (FID) = 90%</doc>
          <eqn>0.9          </eqn>
      </aux>
    </variables>
  </model>
</xmile>
```