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Investigating the Effects of Degradation from Dynamic Power Inputs and the Role of Hydrogen Support Mechanisms

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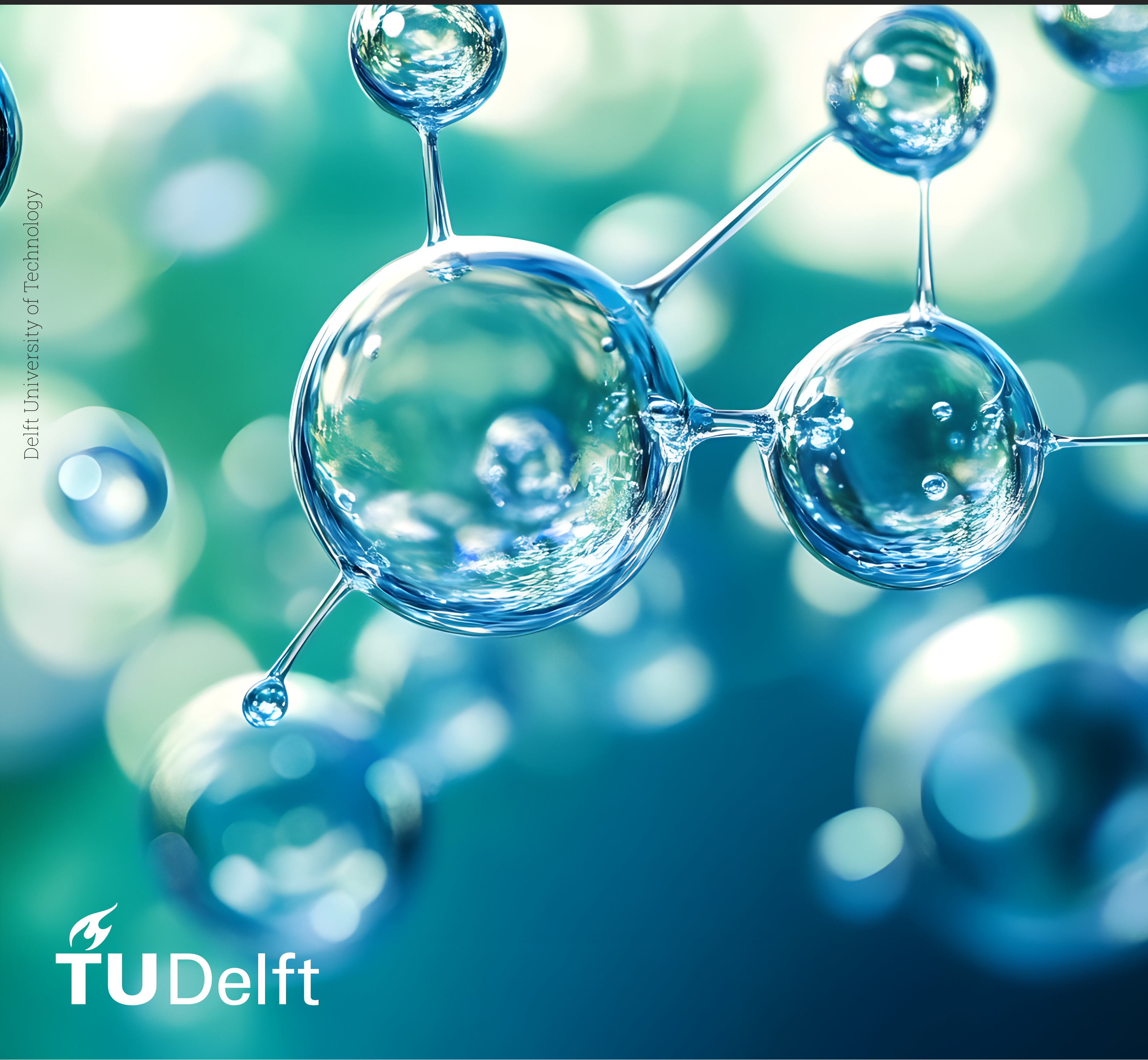

Operational Analysis of Electrolysis for Green Hydrogen Production

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by

Jerald Duffy

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Preface

This thesis marks the completion of my Masters degree in Sustainable Energy Technology at Delft University of Technology. Throughout my studies, I developed a strong interest in the technical and economic challenges of advancing renewable energy systems. This work gave me the chance to explore these challenges in greater depth, focusing on solutions that can support the ongoing energy transition.

Completing this thesis has been a valuable experience, though it required more time and effort than I initially anticipated. There were moments when progress stalled, and I had to rethink my approach to move forward. Reflecting on the process, I realize that completing this project has been as much about navigating setbacks as it has been about producing research.

I am deeply grateful to my daily supervisor, Dr. Kenneth Bruninx, for his guidance and consistent support throughout this process. I recognize that I have not always been the easiest student to guide, and that this project has taken longer than expected. Despite this, Kenneth remained patient and constructive, providing critical insights and challenging me to improve my work at every stage. His encouragement and expertise have been invaluable, and I sincerely appreciate his commitment to helping me bring this project to completion.

I would also like to thank Professor Zofia Lukszo for her guidance as chair of my thesis committee. Her feedback helped me sharpen the focus of my work and improve its clarity. Additionally, I am grateful to Professor Wiebren de Jong for his technical insights, which helped me approach some of the more challenging aspects of this project from a new perspective.

Finally, I want to acknowledge my family and friends for their support during this process. Although I may not have always shared my struggles openly, their encouragement made a real difference. Knowing I had people around me who believed in my work helped me push through the more difficult periods.

Jerald Duffy
Delft, January 2025

Abstract

Green hydrogen production through electrolysis is increasingly recognized as a critical pathway for decarbonizing the energy sector. However, the integration of electrolyzers with renewable energy systems presents several technical and economic challenges. Renewable energy sources such as wind and solar are inherently variable, leading to fluctuating power inputs that impose dynamic operating conditions on electrolyzers. These fluctuations result in degradation mechanisms, such as start-stop cycles, partial load operation, and power ramping, which reduce efficiency and impact long-term performance and economic viability. While technical challenges related to degradation have been investigated in prior research, the role of hydrogen support mechanisms, such as price premiums, in addressing these challenges remains underexplored.

This thesis extends an existing optimization framework to incorporate degradation effects into the modeling of electrolyzer performance. Degradation is represented as dynamic reductions in efficiency that evolve based on operational conditions, including cycling and variable load profiles. A rolling horizon approach is employed to simulate the cumulative impact of degradation over time, enabling the study of electrolyzer operations under realistic renewable energy inputs. The model evaluates two distinct scenarios: one in which electrolyzers operate without external policy intervention, and another where hydrogen support mechanisms are integrated into the framework. This separation allows for an examination of how these factors independently influence electrolyzer scheduling, efficiency, and the economic viability of green hydrogen production.

The findings indicate that degradation significantly influences electrolyzer performance under variable renewable energy conditions, with dynamic operating profiles leading to efficiency losses over time. The inclusion of hydrogen support mechanisms in the analysis highlights their potential to improve economic feasibility by partially mitigating the financial challenges posed by variability. However, the results are contingent on model assumptions and emphasize the importance of considering operational and market-specific factors when assessing the impact of such mechanisms.

By addressing both technical and economic aspects, this thesis contributes to the understanding of how electrolyzers perform under variable power inputs and how policy mechanisms might influence their operation. The results provide a foundation for further research into optimizing electrolyzer performance and integrating green hydrogen into renewable energy systems.

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1 Introduction

1.1. Thesis Context

Green hydrogen is emerging as a cornerstone in global efforts to decarbonize our energy system. Many countries now include hydrogen in their national strategies to meet climate targets. Historically, hydrogen has been crucial in industrial applications such as oil refining and ammonia production, as well as in processes that demand large amounts of energy, including steel manufacturing. Yet its potential extends beyond these established uses: transportation, power generation, and domestic heating, which have not typically relied on hydrogen, can benefit greatly by switching away from fossil fuels. Making this shift promises substantial reductions in emissions, underscoring the versatility of hydrogen and its importance in achieving climate goals.

Figure 1.1 illustrates the flow of hydrogen from energy sources to various end-uses. It highlights the predominant reliance on natural gas and coal, with minimal renewable or carbon capture contributions, and shows how hydrogen is distributed across multiple sectors including refining and ammonia production. As the figure suggests, current hydrogen supply chains are heavily fossil-based, underscoring the need to transition towards cleaner production pathways to reduce emissions and support a sustainable energy future.

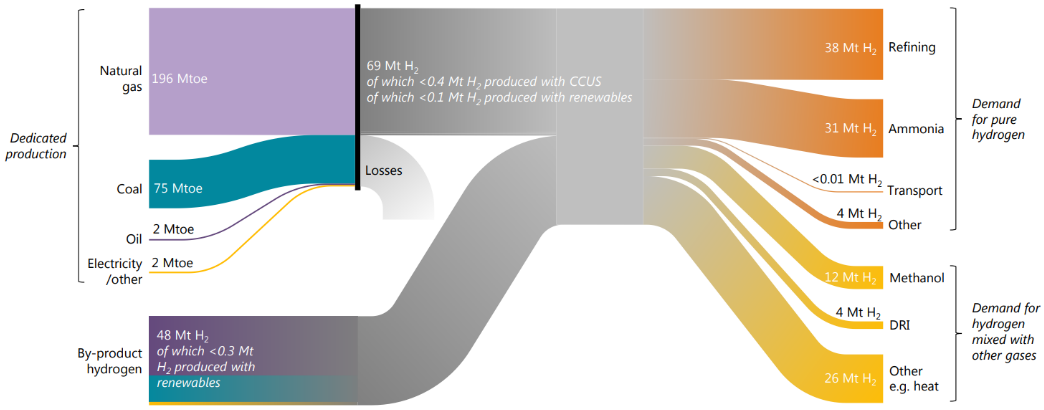

Figure 1.1: Flow of hydrogen from energy source to various end-uses[1]

Despite its well-established role, the future of green hydrogen in renewable energy systems presents new challenges requiring further exploration. Global hydrogen demand was approximately 97 Mt in 2024 and is projected to reach 614 Mt per year by 2050, accounting for about 12% of the worlds energy needs in scenarios aligned with limiting global warming to 1.5°C [2, 3]. While ammonia production and oil refining currently dominate hydrogen demand [4], broader potential, such as in heavy transport industries, synthetic fuels for aviation and shipping, industrial heating, and balancing intermittent renewable electricity, will drive significant growth by 2050. Meeting this future demand sustainably will require a shift from fossil-based hydrogen production towards renewable methods, making green hydrogen produced via electrolysis, using renewable energy a key pathway.

However, effectively integrating green hydrogen into systems that rely on intermittent renewables, fluctuating energy prices, and advanced technologies is complex. The technical constraints of these systems, combined with difficulties in accurately modeling new technologies, make it challenging to predict performance and ensure long-term sustainability. Continued research is essential to address these barriers, improve modeling techniques, and fully realize the potential of green hydrogen as a clean energy carrier.

From an economic perspective, there is widespread agreement on the importance of green hydrogen in achieving climate targets. However, progress in building a robust hydrogen market has fallen short of the pace needed to achieve critical climate goals. A major obstacle is the significant financial risk associated with investing in hydrogen technologies, especially electrolyzers. Market uncertainties, evolving policy frameworks, and fluctuating energy costs discourage large-scale investment. Furthermore, uncertainties regarding the scalability, cost-effectiveness, and efficiency of green hydrogen plants limit the pace of industrial growth. Overcoming these hurdles through research, innovation, and supportive policies is crucial for accelerating green hydrogen adoption.

In light of the aforementioned challenges, this thesis focuses on two key areas to improve our understanding of green hydrogen production within renewable energy systems. First, it examines how dynamic operations influence electrolyzer performance, with a particular focus on how degradation affects the optimal operational performance. Second, it looks at the role of hydrogen support mechanisms in shaping the economic environment for electrolytic green hydrogen production. Rather than focusing on directly optimizing green hydrogen production, this research incorporates degradation and support mechanisms into an existing model to more accurately represent the conditions under which electrolyzers operate. This approach aims to provide a clearer understanding of how these factors interact with real-world system performance and how they impact the operational behavior of an electrolyser for green hydrogen production.

With the projected expansion of hydrogen use across a range of sectors, from established industrial applications to new roles in energy storage and transportation, the urgency to develop renewable-based hydrogen production pathways becomes increasingly clear. This thesis focuses on electrolyzer degradation and hydrogen support mechanisms to enhance our understanding of the evolving role of green hydrogen production within the increasingly complex and dynamic landscape of renewable energy systems.

1.2. Problem Formulation

Green hydrogen, produced via electrolysis using renewable electricity, is often highlighted as a crucial pathway for reducing greenhouse gas emissions in sectors that are especially difficult to decarbonize. Although the production of hydrogen from electricity is not fundamentally new, the ongoing and rapid shift towards a renewable energy-based economy has introduced a range of technical and operational uncertainties that make it challenging to determine how best to integrate green hydrogen production into future energy systems. The versatility of hydrogen as an energy carrier shows great promise: it can serve as feedstock in industrial processes, act as a storage medium for renewable energy, and fuel both transport and heating. Yet, while green hydrogen can potentially replace non-renewable alternatives, there remain substantial uncertainties regarding how and when to produce it, what form of economic incentives or support should be in place, and how to accurately model and quantify key factors like degradation and the dynamic behavior of electrolysers when exposed to fluctuating power inputs.

As the energy system becomes increasingly complex and decentralized, accurately predicting the role of green hydrogen within the broader energy landscape presents significant challenges. Electricity supply from renewables is inherently variable and can create situations where an electrolyser must adapt to changing power conditions. Electricity prices can spike or drop dramatically, influencing when it is cost-effective to produce hydrogen. Furthermore, off-takers may not be willing to pay a stable or predictable price for hydrogen, and the absence of well-defined hydrogen markets adds to the difficulty of justifying large-scale investments. In summary, while green hydrogen is increasingly regarded as a critical component of global decarbonization strategies, determining the optimal parameters for its production and integration remains a complex task.

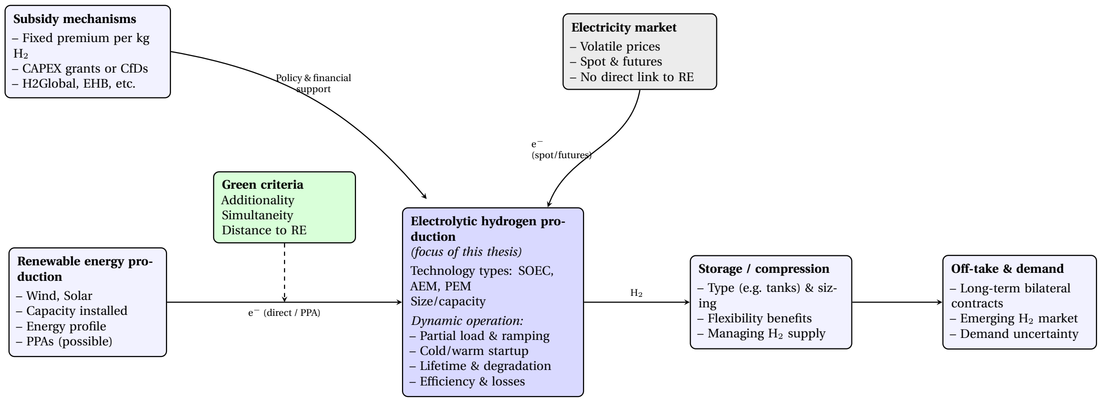

Figure 1.2: A simplified schematic of hydrogen production within a renewable energy system, illustrating the central role of the electrolyser in relation to multiple electricity sources, policy support initiatives, storage options, and enduse offtake.

Figure 1.2 provides a simplified illustration of how electrolytic hydrogen production might be placed within a broader renewable energy system. The figure is not exhaustive, but it underscores that an electrolyser rarely operates in isolation. Instead, it typically resides within a network that includes sources of renewable electricity, various procurement strategies for that electricity, possible storage and compression steps for hydrogen, and different ways to sell hydrogen to end users. Understanding this entire value chain is essential for formulating a meaningful problem statement and research direction.

On the supply side, procuring renewable electricity can happen in multiple ways: purchasing it directly from markets, relying on long-term power purchase agreements that offer more price certainty, or integrating the electrolyser with a renewable energy generator to benefit from internal flexibility. Each of these approaches affects the financial viability of the hydrogen production plant.

At the center of this system stands the electrolyser itself, a device whose performance and lifetime depend on how it is operated under dynamic conditions. Choosing the appropriate electrolyser technology is not trivial, as technologies differ in their responsiveness to changes in power input, their efficiency at various load levels, their startup characteristics, and their sensitivity to degradation over time. Accounting for the details of electrolyser performance is therefore fundamental. Additionally, storage and compression of hydrogen play an important role because they introduce flexibility that can help balance production and demand, smooth out operational challenges, and potentially improve the economics of the entire setup.

On the demand side, the market for green hydrogen remains immature and uncertain. Investors and producers face difficulties in price discovery, and there is no well-established trading system like that for electricity markets. While long-term bilateral contracts with known off-takers might reduce uncertainty and guarantee stable revenue, the current fragmentation of demand limits this approach, making it harder to ensure strong business cases that justify large-scale adoption of electrolyser technology.

To encourage investment and accelerate the emergence of a functioning green hydrogen economy, support mechanisms have been proposed and implemented. These can include premiums added to the hydrogen price to compensate producers for higher costs or subsidies to cover part of the initial capital expenses. The European Hydrogen Bank and the H2Global initiative are examples of initiatives working to reduce financial risks, though they differ in their focus on domestic production or international trade. Integrating these support mechanisms into the modeling framework poses yet another challenge, as translating policy tools and financial incentives into model parameters and constraints requires careful thought.

In summary, the development of green hydrogen production involves navigating a dense network of technical and economic uncertainties. The key problems revolve around finding ways to integrate electrolysers into renewable energy systems in a manner that accounts for the dynamic, fluctuating nature of electricity supply, the uncertain evolution of hydrogen demand and pricing, and the role of policy-driven support mechanisms. This thesis focuses on two main aspects: first, how to incorporate electrolyser degradation due to dynamic power inputs into a system model, and second, how to represent and evaluate the impact of support mechanisms on the operations of an electrolyzer for green hydrogen production.

1.3. Research objective and scope

This section introduces the main research question and sub-questions guiding this thesis. The research has two primary objectives: first, to incorporate degradation effects caused by dynamic power inputs into a detailed electrolyzer model and assess their impact on operational performance; second, to explore the role of hydrogen support mechanisms and their influence on operational strategies. By addressing these aspects, this thesis aims to provide a more realistic basis for evaluating the integration of electrolyzers into renewable energy systems, bridging technical and economic considerations.

Building on these objectives, the main research question addresses both technical and economic challenges associated with electrolyzer performance in renewable energy systems. Current models often fail to accurately capture the cumulative effects of efficiency losses and degradation under fluctuating renewable power inputs. Additionally, the influence of hydrogen support mechanisms, such as subsidies, premium contracts, or off-take guarantees, on operational strategies is frequently overlooked. Addressing these gaps is essential for developing a more comprehensive understanding of electrolyzer operations and informing strategies to optimize green hydrogen production. In this context, the main research question is:

Main Research Question:

> How does degradation due to dynamic power inputs and the implementation of hydrogen support mechanisms impact the optimal operational performance of a hybrid power plant for green hydrogen production?

The first sub-question focuses on the technical and operational characteristics of electrolyzers, addressing how factors like load range, startup times, ramping capability, and efficiency influence their performance in a variable renewable energy environment. A clear understanding of these fundamentals is essential before incorporating more complex elements like degradation or support mechanisms.

Sub-question 1:

> What are the fundamental technical and operational characteristics of electrolyzers under dynamic power inputs, and how do they shape their performance for green hydrogen production?

Unlike steady-state conditions, renewable energy systems provide a power supply that varies over time, subjecting electrolyzers to frequent changes in load and even start-stop cycles. These changing conditions can not only lower efficiency but also speed up degradation, ultimately affecting how long the electrolyzer can operate and how economically viable it remains. To accurately predict electrolyzer performance in a real-world setting, it is necessary to capture how dynamic power inputs influence degradation. The second sub-question therefore focuses on finding a way to express the impact of these variable power patterns on electrolyzer degradation and include that relationship in an operational model. By doing so, we can better understand the long-term effects of operating electrolyzers under variable conditions, leading to more reliable assessments of their efficiency, costs, and overall role within renewable-based hydrogen production systems.

Sub-question 2:

> How can degradation due to dynamic operation be quantified or approximated, and what functional form or parameters can be used to relate operational patterns to decreased efficiency?

The green hydrogen market is still in its early stages, and uncertainties about pricing and demand make it challenging for investors and operators to commit to large-scale projects. To address these issues, initiatives like the European Hydrogen Bank (EHB) and H2Global have emerged, aiming to provide financial stability and clearer market signals. These support mechanisms can help reduce investment risks and encourage more widespread implementation of electrolyzers for green hydrogen production. The third sub-question, therefore, focuses on examining how such policies and financial incentives can be evaluated. By including these support mechanisms, such as fixed premiums or investment subsidies, into a system model, we can better understand their influence on operational decisions.

Sub-question 3:

> How do hydrogen support mechanisms, such as price premiums or subsidies, influence the operational performance of electrolyzers, and what implications might they have for degradation?

Figure 1.3 illustrates the research process used in this thesis to address the research questions. The study begins with a literature review, which establishes the technical and economic context for green hydrogen production. This review focuses on understanding degradation mechanisms in electrolyzers, such as efficiency losses caused by start-stop cycles and partial load operation, as well as the potential role of hydrogen support mechanisms, including subsidies and price premiums. The insights gained from this step inform the development of an extended optimization model that incorporates degradation as dynamic efficiency losses tied to operational conditions. Simplified representations of hydrogen support mechanisms, such as price adjustments, are also integrated into the model to reflect their economic impacts.Following model development, scenarios are created to represent varying renewable energy supply conditions, operational patterns, and economic frameworks. These scenarios are analyzed to assess electrolyzer performance, with a focus on how degradation and support mechanisms influence operational efficiency and scheduling decisions. By evaluating electrolyzer behavior under realistic conditions, the research provides insights into the challenges and opportunities for integrating green hydrogen production into renewable energy systems. The findings contribute to recommendations for improving the operational and economic feasibility of electrolyzers and provide a foundation for future studies in this field.

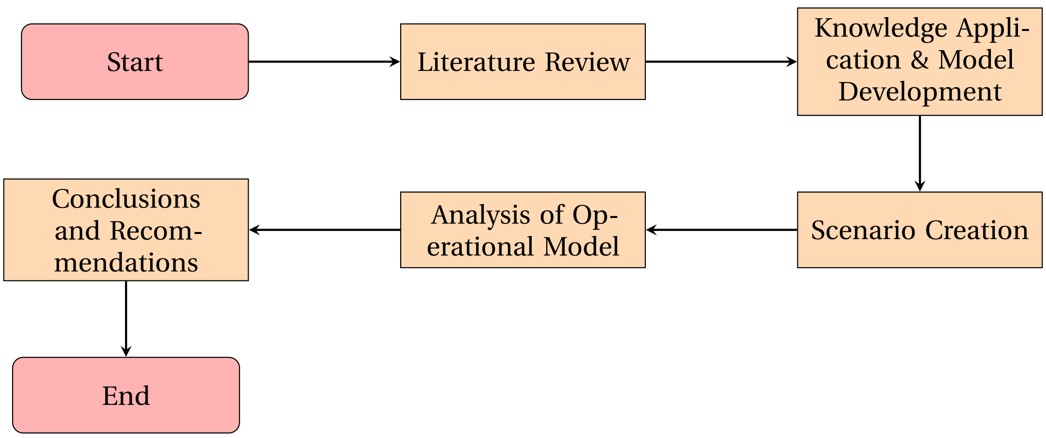

Figure 1.3: Visual representation of research approach

1.4. Report outline

This thesis begins with a detailed literature review in Chapter 2, which provides an overview of current knowledge on electrolyzer technologies and green hydrogen production. The review is divided into three sections: the first examines electrolyzer technologies and general assessments of green hydrogen's potential, the second explores techniques for modeling electrolyzer behavior, and the third focuses on the economics of green hydrogen production and the role of hydrogen support mechanisms. Chapter 3 builds on this foundation by providing background information on hydrogen production and electrolyzer technologies, highlighting key technical and operational aspects critical for integrating electrolyzers into renewable energy systems. Chapter **??** focuses on hydrogen support mechanisms, including initiatives like H2Global and the European Hydrogen Bank. It examines their structure, objectives, and potential to reduce financial risks and accelerate the adoption of green hydrogen technologies. Chapter 4 provides a comprehensive system description and a detailed explanation of the model developed in this study. It includes a thorough description of the electrolyzer model and its physical characteristics, followed by an explanation of the optimization model. The chapter then discusses how the model has been modified to incorporate the effects of degradation caused by dynamic power inputs and outlines the approach taken to include the potential impacts of hydrogen support mechanisms. This section is central to the thesis as it lays out the structure, methodology, and modifications made to address the research questions.Chapter 5 lays out and discusses the results, providing a detailed analysis of the model's performance under various conditions. It examines the operational impacts of dynamic power inputs on electrolyzer degradation and evaluates the economic effects of incorporating hydrogen support mechanisms. By connecting these findings to the broader context of green hydrogen production, the chapter offers insights into how electrolyzers can be optimized for integration into renewable energy systems, considering both technical performance and financial feasibility. Finally, Chapter 6 concludes the thesis by summarizing the key findings and demonstrating how they address the research questions established at the beginning. It highlights the contributions of this study to advancing the understanding of green hydrogen production and electrolyzer integration into renewable energy systems. The chapter also provides clear recommendations for future research to build on these insights and tackle the remaining challenges in the field.

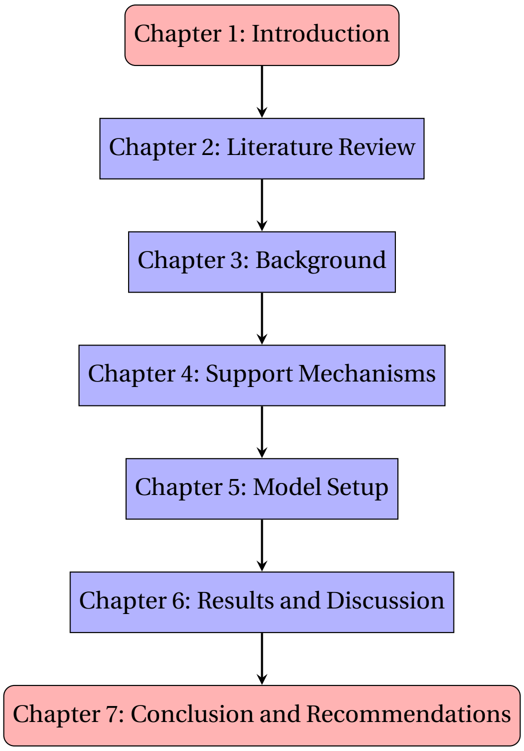

Figure 1.4: Overview of the thesis structure.

2

Literature and State of the Art

This chapter reviews the literature most relevant to this thesis, focusing on three areas: the behavior of electrolyzers under dynamic operations, how degradation can be modeled and quantified, and the potential of hydrogen support mechanisms in relation to operational performance. While green hydrogen has been studied extensively, the specific challenges of incorporating degradation effects into operational models and evaluating hydrogen support mechanisms remain less explored. Section 2.1 first looks at the relevant literature on electrolyzers in relation to green hydrogen production. This is then followed by studies that focus on modeling of electrolysers, especially under conditions of fluctuating renewable power in section 2.2. The next section 2.3 deals with degradation in electrolysers, specifically in relation to dynamic power inputs. Finally, literature pertaining to hydrogen support mechanisms is discussed in section 2.4. By combining the findings gathered in the literature study, a final research gap is identified in 2.5 which gives structure and provides the research direction for this thesis.

2.1. Hydrogen Production and Electrolyzer Technologies

Several studies have examined green hydrogen production through electrolysis and the challenges associated with integrating electrolysers into renewable energy systems. While these works span various methods and technology types, the most relevant insights for this thesis involve the technical and economic factors that influence electrolyzer performance, especially under fluctuating power inputs.

Dincer and Acar [5] highlight that renewable-powered electrolysis offers significant environmental benefits but requires cost reductions and efficiency improvements. Ji and Wang [6] confirm this, noting that although renewable-based electrolysis may start at higher costs, it can become viable with technological advances. These conclusions set the stage for understanding why detailed, accurate models are needed to capture the conditions under which efficiency and cost competitiveness are achieved.

Studies by El-Shafie et al. [7] and Yang et al. [8] emphasize the importance of electrolyzer technology selection and the operational challenges posed by dynamic renewable power. Weiss et al. [9] and Younas et al. [10] provide initial evidence that variable load conditions can accelerate degradation and efficiency losses in electrolyzers, reinforcing the need to model such effects. Brauns and Turek [11] further highlight that experimental strategies to reduce gas contamination and maintain efficiency under partial loads require additional modeling and refinement.

Overall, the studies in table 2.1 illustrate the technical and economic potential of green hydrogen while identifying persistent barriers: high initial costs, efficiency losses during dynamic operation, and the need to better understand degradation. This foundation supports the core aims of this thesis, which involve expanding electrolyzer models to capture the effects of fluctuating renewable inputs and translating these insights into more accurate, operationally useful models.

Table 2.1: Overview of key literature on green hydrogen production methods and electrolyzer technologies

Author(s)	**Year**	**Topic**
Dincer and Acar [5]	2015	Technical, financial and social comparison of different hydrogen production methods
Mengdi and Wang [6]	2021	Comparison of hydrogen production in terms of cost and life cycle assessment
El-Safei et al. [7]	2019	Overview of different hydrogen technologies
Weis et al. [9]	2019	Impact of intermittent power supply on the performance and lifetime of a PEM electrolyzer experimentally investigated
Yang et al. [8]	2023	Technical and economic comparison of ALK, AEM and PEM electrolyzer technologies
Younas et al. [10]	2022	Review of hydrogen production pathways through renewable and non-renewable sources
Brauns and Turek [11]	2022	Experimental evaluation of dynamic operating concepts for alkaline water electrolyzer
Zheng et al. [12]	2024	How dynamic operations affect electrolyzer performance and degradation in PEM, with strategies to improve efficiency and durability

2.2. Literature on Electrolyzer Modeling

A key area of research relevant to this thesis is the modeling and optimization of electrolyzers integrated with renewable energy systems. This literature examines how to represent electrolyzer performance under variable conditions, capture degradation effects, and include economic or policy constraints to guide operational decisions.

Several foundational works focused on creating baseline models for electrolyzers. Early examples include García-Valverde et al. [13], who provided a simple model for PEM electrolyzers validated experimentally, and Sánchez et al. [14], who developed a semi-empirical model for alkaline electrolyzers. Such studies established essential relationships between voltage, current density, and operating conditions. Building on these basics, Baumhof et al. [15] incorporated detailed electrolyzer physics into scheduling models for hybrid power plants, while Raheli et al. [16] tackled non-linear production curves to improve dispatch accuracy.

When integrating electrolyzers into renewable systems, dealing with fluctuating energy sources becomes crucial. Zhang and Yuan [17] addressed variable power inputs by explicitly modeling degradation and efficiency losses over time. Similarly, Matute et al. [18] and Varela et al. [19] developed optimization models that consider multiple electrolyzer operating states and changing electricity prices, offering more realistic depictions of cost-effective operation under dynamic conditions.

Beyond technical aspects, some researchers link modeling with economic and policy considerations. Nami et al. [20] and Villarreal Vives et al. [21] provide techno-economic analyses, showing how technology choices, operational strategies, and supportive policies affect long-term competitiveness. These perspectives are important for this thesis, which aims to integrate degradation modeling and support mechanisms into the analysis. By combining technical models with policy-driven incentives, these studies help form a more complete understanding of how electrolyzers can operate effectively in real-world conditions characterized by both engineering and economic challenges.

In summary, the literature on electrolyzer modeling, listed in table 2.2, supports the idea that incorporating dynamic conditions, degradation factors, and financial frameworks leads to more accurate and useful insights. This aligns with the core objectives of this thesis, which seeks to improve modeling approaches by reflecting actual constraints and incentives shaping electrolyzer performance in renewable-based hydrogen production systems.

Table 2.2: Overview of key studies on modeling and optimization of electrolyzer technologies for green hydrogen production

Author(s)	**Year**	**Topic**
Raheli et al. [16]	2023	Conic modeling approach for non-linear hydrogen production curve
Baumhof et al. [15]	2023	Modeling of electrolyzer details and physics under operational constraints
Sanchez et al. [14]	2018	Semi-empirical model for evaluating the performance of alkaline electrolyzer
Zhang and Yuan [17]	2022	Optimization and economic evaluation of PEM electrolysis considering degradation in variable power operations
Gusain et al.[22]	2020	Analyze the potential of electrolyzers to participate in ancillary services for grid support
García-Valverde et al. [13]	2012	Simple PEM water electrolyser model and experimental validation
Fragiacomo and Genovese [23]	2019	Mathematical model development for PEM and Alkaline Water electrolysis
Ulleberg[24]	2003	Modeling of advance alkaline electrolyzer: a system simulation approach
Matute et al. [18]	2021	Model for optimal dispatch of hydrogen production plant considering production, standby and idle states
Johnson et al. [25]	2023	Modeling of profits of alkaline electrolyzer participating in ancillary services
Varela et al.[19]	2021	Modeling of alkaline water electrolysis, including transitions and operational characteristics, solving MILP
Vives et al. [21]	2023	Techno-economic analysis of PEM with integrated heat recovery
Nami et al. [20]	2022	Economic potential of current and emerging electrolysis technologies for green hydrogen production
Pérez-Uresti et al. [26]	2023	Proposes a novel MINLP modeling and optimization framework for strategic investment planning related to the design and long-term capacity expansion of hydrogen supply chains

2.3. Degradation in Electrolyzers under Dynamic Conditions

While research on electrolyzer degradation is expanding, most work still focuses on steady-state conditions or PEM electrolyzers. As a result, how alkaline water electrolyzers (AELs) degrade under variable power inputs, typical in renewable-based systems, remains less understood. This gap makes it difficult to develop accurate models and guidelines for AEL operation when power supply fluctuates.

Kirsch et al. [27] studied AEL performance under varying power profiles and reported degradation rates of 1.5-7.1 $\mu V/h$ with fluctuating loads. Constant operation lowered these rates but reduced flexibility, highlighting a key trade-off between dynamic responsiveness and equipment lifespan. Meanwhile, Jung et al. [28] focused on PEM electrolyzers and found that faster voltage ramps (up to 300 mV/s) significantly increased degradation, up to 1.26 mV/h. Although this research centers on PEM systems, the importance of ramping speed for avoiding excessive degradation is a lesson that can inform AEL strategies as well.

Other studies reinforce the idea that dynamic operation intensifies wear and efficiency losses. Martinez Lopez et al. [29] observed how start-stop cycles and intermittent power reduce electrolyzer efficiency and durability, stressing the need for careful power management. Norazahar et al. [30], while examining PEM electrolyzers, linked dynamic conditions to membrane stress and hydrogen crossover issues, offering insights into general degradation mechanisms that are also relevant for AELs.

Lu et al. [31] showed that real-time optimization of load profiles can mitigate degradation in wind-hydrogen setups, a principle that could guide similar approaches for AELs. In addition, a comprehensive review by Wallnöfer-Ogris et al. [32] discussed various degradation mechanisms and their interactions, emphasizing that advanced, system-level models are needed to predict long-term effects accurately.

In short, these studies show that while we have some knowledge about how dynamic conditions influence degradation, especially in PEM systems, there is still a clear research gap regarding AELs. Without more data and improved modeling approaches that consider fluctuating power, it is challenging to develop effective operational strategies. This thesis aims to help fill this gap by incorporating degradation considerations into AEL modeling, making the resulting operational insights more realistic and useful for managing electrolyzers in renewable-based hydrogen production.

Table 2.3: Overview of key studies specifically about degradation in electrolyzers, in relation to dynamic power inputs

Author(s)	Year	Topic
Jung et al. [28]	2024	Examines the impact of different voltage ramping rates on the durability of proton exchange membrane water electrolyzers
Frensch et al. [33]	2018	Investigates degradation mechanisms in proton exchange membrane (PEM) water electrolysis cells under dynamic operation
Kirsch [27]	2024	Models and analyzes the performance and degradation of alkaline water electrolysers under varying power inputs
Lim et al. [34]	2021	Examines how voltage degradation in water electrolyzers affects their energy efficiency, economic viability, and economics
Lu et al. [31]	2023	Optimization for wind-hydrogen system PEM electrolyzer considering degradation conditions
Wallnöfer-Ogris [32]	2024	The degradation mechanisms in PEM electrolyzers, their impacts on performance and lifespan, and tools for improving technology and applications.
Martinez Lopez et al. [29]	2023	Describing physics of Alkaline, PEM and AEM technologies and implications of variable and intermittent operation
Buttler et al.[35]	2018	Comparing ALK, PEM, SOEC, in relation to efficiency, flexibility and lifetime
Norazahar et al.[30]	2024	Reliability and safety of PEM electrolyzers, focusing on degradation mechanisms
Sayed-Ahmed et al. [36]	2024	Critical review of the dynamic operation of proton exchange membrane (PEM) electrolyzers and its implications for green hydrogen production

2.4. Literature on Economics and Support Mechanisms

In addition to technical challenges, the financial environment and policy frameworks play a major role in how electrolyzers are deployed in renewable energy systems. High initial costs, uncertain hydrogen demand, and volatile electricity prices often limit early investments. To address these obstacles, recent literature examines specific support mechanisms designed to stabilize revenues and reduce risks for green hydrogen producers.

The European Commissions communication on the European Hydrogen Bank [37] offers a clear example. It proposes using competitive bidding or similar approaches to offer producers fixed premiums or contracts for difference (CfDs). This means electrolyzer operators could receive a guaranteed extra payment per kilogram of produced hydrogen, even if market prices are low. An approach like this, directly tackles the main hurdles faced by early-stage projects, covering part of the cost gap and making revenues more predictable. LCP Delta [38] outlines several policy tools, such as minimum price guarantees, CfDs, or capacity payments, and analyzes how they can shape investment decisions. These details matter because they show exactly which instruments could be integrated into an optimization model: for instance, a CfD can be represented as a stable price floor in the model, affecting when and how the electrolyzer runs.

Recently, Hoogsteyn et al. [39] find that production-based mechanisms, such as fixed premiums, can distort electricity prices and incentivize suboptimal operations, while capacity-based mechanisms are more cost-effective by avoiding these distortions. The study also highlights the ‘waterbed effect,‘ where reduced power sector emissions may lead to increased emissions in other sectors. These insights reinforce the importance of modeling support mechanisms, like fixed premiums, to evaluate their impact on electrolyzer operations.

Abolhosseini and Heshmati [40] compare established renewable support mechanisms (like feed-in tariffs or green certificates) and discuss how lessons from the renewable electricity sector can guide hydrogen policies. Similarly, Yang et al. [41] find that well-targeted subsidies can significantly boost renewable energy uptake. Applying these ideas to green hydrogen suggests that financial backing must be carefully designed to incentivize operations that align with renewable availability and system needs. For instance, a price guarantee could make the electrolyzer run more consistently, smoothing out variable supply and aiding system integration.

Economic assessments by Guerra et al. [42] and Abadie and Chamorro [43] highlight the importance of policy support in achieving competitiveness for green hydrogen. While technology improvements will lower costs over time, these studies stress that current policy initiatives, like premiums or CfDs, are essential to bridge the gap right now. This matters for the thesis because it shows that support mechanisms are not just a policy detail, but a direct factor influencing how electrolyzers are scheduled and operated in real conditions.

In summary, the reviewed literature in table 2.4 points to specific support mechanisms that could potentially affect the operations of electrolysers for green hydrogen production. Integrating these mechanisms into a operational model should provide more realistic insights.

Table 2.4: Literature related to hydrogen support mechanisms and their effectiveness

Author(s)	Year	Topic
Hoogsteyn et al. [39]	2025	Interactions and distortions of different support policies for green hydrogen
Guerra et al. [42]	2019	Evaluating cost-competitiveness of hydrogen production simulating dynamic operations across the US
Müller and Eichhammer [44]	2023	Economic complexity of hydrogen technologies and potential for hydrogen production countries
Eicke and Blasio [45]	2022	Potential for green hydrogen adoption in industrial applications such as ammonia methanol and steel production
Egli [46]	2020	An investigation into investment risk, changes over time and underlying drivers
Azadnia et al.[47]	2023	Identification and analysis of green hydrogen supply chain risk factors in different categories
Yates et al[48]	2020	Calculations for Levelized Cost Of Hydrogen (LCOH) for promising locations and sizing of off-grid PV-electrolyzer system
Yang et al. [41]	2019	Assesses the effect of government subsidies on renewable energy investments
Abolhosseini and Heshmati [40]	2014	Comparing three main support mechanisms employed by governments to finance renewable energy project feed-in-tariffs, tax incentives and tradeable green certificates
Abadie and Chamorro [43]	2023	Economic evaluation of wind-farm that feeds electrolyzer, prices estimation of when green hydrogen becomes viable
European Commission [37]	2023	Communication from the European Commission to the European Parliament on the European Hydrogen Bank
LCP Delta [38]	2023	Lists various hydrogen support mechanism types and sizes

2.5. Gaps in Existing Research

The literature surveyed in this chapter provides a solid background on green hydrogen production, electrolyzer technologies, modeling approaches, degradation under dynamic conditions, and economic and policy measures. Although many studies contribute valuable knowledge, there are two important gaps that stand out. First, while some work acknowledges that fluctuating power inputs can accelerate electrolyzer degradation, there is still a need for detailed, system-level models that incorporate these effects, especially for alkaline electrolyzers. Second, although economic incentives and policy tools designed to promote green hydrogen production have been discussed, we do not yet fully understand how these support mechanisms influence the operational decisions in future renewable energy systems

Incorporating Degradation Effects

Electrolyzers powered by renewable energy sources like wind and solar often face variable power inputs that can speed up degradation. These conditions include frequent start-stop cycles, running at partial loads, and sudden power changes. Together, these factors lead to lower efficiency and higher maintenance needs. However, many existing models either oversimplify degradation or leave it out entirely, which means they dont fully reflect how electrolyzers perform under real-world conditions. This can result in models that overestimate performance and underestimate the challenges posed by dynamic power inputs.

Degradation reduces both the efficiency and cost-effectiveness of electrolyzers over time. As operational stress builds, it causes efficiency losses, often seen as increases in cell voltage, and leads to wear on key components like electrodes and membranes. This adds to repair and replacement costs, which can quickly make operations more expensive. If degradation effects arent included in optimization models, it becomes difficult to figure out how to run electrolyzers in a way that keeps costs low while maintaining efficiency and reliability. Including these effects in models is essential to understand how electrolyzers can handle variable power inputs and remain viable as part of renewable energy systems.

Integration with Hydrogen Support Mechanisms

Support mechanisms like fixed premiums, contracts for difference, and targeted subsidies are increasingly being used to encourage green hydrogen production. These tools aim to reduce financial risks, provide more stable revenues, and help close the cost gap between green hydrogen and fossil–based alternatives. While these incentives are widely recognized in the literature, their effect on how electrolyzers are operated is often overlooked. For instance, a guaranteed minimum price for hydrogen could lead to more consistent operation, even when electricity prices are high or demand is uncertain, which might also affect degradation rates. Similarly, subsidies designed to encourage flexibility could result in load adjustments that influence both efficiency and long-term performance.

This research looks at how these support mechanisms impact operational decisions and explores their potential connection to degradation. Understanding these interactions is important for improving how electrolyzers are integrated into renewable energy systems and for designing policies that align economic goals with reliable and efficient operations.

Addressing the Gaps

This thesis addresses these gaps by extending a detailed modeling framework to include degradation effects in the operational planning of electrolyzers and by exploring how hydrogen support mechanisms influence their operational strategies. By combining these technical and economic aspects, the research aims to make simulations more realistic and provide better predictions of long-term performance. Adding support mechanisms to the model helps reveal how policies and incentives can shape operational decisions, potentially improving profitability, stability, and the integration of renewable energy.

By focusing on these two areas, this thesis goes beyond the existing literature to offer insights that can guide future research, support policy development, and encourage the adoption of green hydrogen as a key part of renewable energy systems.

3 Background Electrolysis

The following chapter discusses the underlying technical characteristics of electrolysers, with a focus on alkaline electrolysers. This is followed by an overview of electrolyzer technologies and their technical characteristics. This provides the necessary context to understand electrolytic hydrogen production, evaluate the opportunities presented by electrolyzer technologies, and analyze their key technical and operational characteristics.

For this thesis, understanding the performance of AEL systems under dynamic conditions is important. The focus is on how variable power inputs impact their efficiency and durability, as well as the potential challenges of integrating AEL with renewable energy systems. This analysis will help assess whether AEL can meet the demands of green hydrogen production in the context of an increasingly renewable energy landscape.

3.1. Fundamentals Water Electrolysis

Water electrolysis is a chemical process that splits water (H_2O) into hydrogen (H_2) and oxygen (O_2) using an electric current. This process forms the foundation of electrolytic hydrogen production and is essential for integrating hydrogen into renewable energy systems. The overall reaction is represented as:

$$2\,H_2O \longrightarrow 2\,H_2 + O_2 \tag{3.1}$$

This reaction occurs within an electrochemical cell consisting of two electrodes, an anode and a cathode, immersed in an electrolyte. The electrolyte facilitates the transport of ions between the electrodes, allowing the reactions to proceed[49]. For example, when an external voltage is applied, the following half-reactions occur at the respective electrodes for PEM electrolysis [50]:

- At the **anode** (positive electrode), water is oxidized, producing oxygen gas (O_2), protons (H^+), and electrons (e^-):

$$2\,H_2O \longrightarrow O_2 + 4\,H^+ + 4\,e^- \tag{3.2}$$

- At the **cathode** (negative electrode), protons are reduced, combining with electrons to form hydrogen gas (H_2):

$$4\,H^+ + 4\,e^- \longrightarrow 2\,H_2 \tag{3.3}$$

In alkaline systems, hydroxide ions (OH^-) replace hydrogen protons as the ions pass through the membrane, resulting in slightly different half-reactions. Regardless of the electrolyte used, the efficient transport of ions is critical to sustaining the reactions. The half-reactions that belong to alkaline electrolysis are presented below in eq.(3.4) and eq.(3.5).

$$\text{Cathode: } 2\,H_2O + 2\,e^- \longrightarrow H_2 + 2\,OH^- \tag{3.4}$$

$$\text{Anode: } 4\,OH^- \longrightarrow O_2 + 2\,H_2O + 4\,e^- \tag{3.5}$$

Alkaline Electrolyzers (AEL) are one of the oldest and most widely used electrolyzer technologies. They use a liquid alkaline electrolyte, typically a solution of potassium hydroxide (KOH) or sodium hydroxide (NaOH), to facilitate the electrolysis process. The system consists of two electrodes, an anode and a cathode, separated by a diaphragm, as shown in Figure 3.1. This diaphragm prevents the mixing of hydrogen and oxygen gases while allowing ions to move between the electrodes.

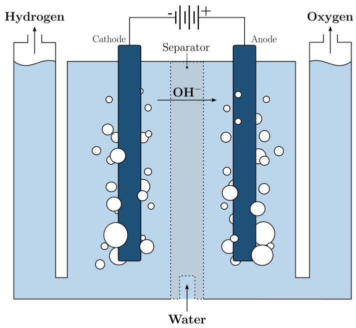

Figure 3.1: Simplified schematic of an Alkaline Electrolyzer (AEL) illustrating the basic setup and ion flow [51]

In summary, the process of water electrolysis can be broken down into three key steps:

1. **Electrochemical Reactions:** The oxidation of water at the anode and the reduction of ions at the cathode produce hydrogen and oxygen gases.
2. **Ionic Transport:** The electrolyte enables the movement of ions (H^+ or OH^-) to maintain charge neutrality and sustain the reactions.
3. **Gas Collection:** Hydrogen and oxygen gases are separated and collected at the cathode and anode, respectively, often through pressurized systems or membranes.

3.2. Comparison of Electrolyser Types

Hydrogen production through electrolysis can be achieved using three main technologies: Alkaline Electrolyzers (AEL), Proton Exchange Membrane Electrolyzers (PEMEL), and Solid Oxide Electrolyzer Cells (SOEC). Each of these technologies has distinct characteristics that make them suitable for specific applications. For instance, AEL systems are mature and cost-effective, making them well-suited for large-scale hydrogen production. PEMEL systems excel in flexibility and adaptability under variable power inputs, while SOEC systems achieve the highest efficiencies but are limited to high temperature industrial applications. This section provides a comparative overview of these technologies, emphasizing their relevance to the focus of this thesis.

As summarized in Table 3.1, AEL stands out for its affordability and scalability, which are crucial for the widespread deployment of hydrogen production systems. However, AEL systems face challenges under dynamic renewable energy inputs due to their moderate response to power fluctuations and limited flexibility in partial load operation. In comparison, PEMEL systems excel in handling variable inputs due to their rapid ramping capabilities and higher efficiency under partial loads, but their reliance on precious metals and higher capital costs make them less economically viable for large-scale applications. SOEC systems, while achieving high efficiency, are better suited for industrial processes that can leverage their thermal energy integration. A more detailed comparison of these technologies, including aspects like durability, operational range, and system complexity, is provided in Appendix D.

Table 3.1: Comparison of different electrolyser types [8], [52], [53]

Criteria	PEMEL	AEL	SOEC
Efficiency (%)	60–80	60–70	>80
Response to Power Fluctuations	Excellent	Moderate	Moderate
Capital Cost	High	Low	High
Applications	Renewable Energy Integration	Large-scale Hydrogen Production	Industrial High-temp Processes

The choice of Alkaline Electrolyzers (AEL) as the focus of this thesis is based on their maturity, cost-effectiveness, and scalability, making them a practical option for large-scale hydrogen production. While Proton Exchange Membrane Electrolyzers (PEMEL) and Solid Oxide Electrolyzer Cells (SOEC) offer advantages such as flexibility and high efficiency, AEL systems remain the most widely deployed technology due to their lower capital costs and robustness. However, despite their established role in the industry, there is limited research addressing the performance of AEL systems under dynamic renewable energy conditions. This gap is particularly important given the challenges AEL systems face when exposed to variable power inputs, such as start-stop cycles and partial load operation, which can lead to efficiency losses and accelerated degradation.

This thesis focuses on AEL technology to investigate how these systems behave under fluctuating power inputs. Although AEL electrolyzers are considered well-established, there is still a noticeable gap in the literature regarding their degradation and efficiency losses when operated dynamically. By examining these operational characteristics in greater detail, this work aims to provide insights into optimizing AEL systems for renewable energy integration. The following section delves deeper into the key operating metrics pertaining to alkaline electrolysers.

3.3. Operational Characteristics and Performance of Electrolyzers

Electrolyzers play a key role in green hydrogen production, and their performance is determined by various technical and operational characteristics. Understanding these characteristics is essential for integrating electrolyzers effectively into renewable energy systems, where power supply can fluctuate significantly. This section explores the main factors that influence how electrolyzers operate, such as nominal and partial load, load range, startup times, ramping rates, and efficiency. It also looks at important performance metrics like hydrogen production rate and energy efficiency, and examines how dynamic power inputs can impact performance over time. Gaining a clear understanding of these aspects is crucial for evaluating how electrolyzers perform in real-world scenarios and lays the groundwork for modeling and optimizing their operation in systems driven by renewable energy.

3.3.1. Load Characteristics

The nominal load of an electrolyzer refers to the maximum power input at which the system achieves its highest efficiency. Partial load operation occurs when the power input is below nominal, resulting in reduced efficiency due to higher energy consumption per unit of hydrogen produced. AEL systems are particularly sensitive to partial loads, with efficiency losses and risks of instability at very low power inputs. By comparison, Proton Exchange Membrane Electrolyzers (PEMEL) are more tolerant of partial loads, maintaining stable and efficient operation across a wider range of inputs.

The load range, expressed as a percentage of nominal load, defines the span within which an electrolyzer can operate effectively. AEL systems typically function between 20 to 100% of nominal load, with reduced performance and potential instability at lower thresholds. PEMEL systems can operate efficiently across a broader range, providing greater flexibility for integration with variable power sources. These characteristics are essential for understanding how AEL systems handle fluctuating inputs from renewable energy.

3.3.2. Startup Times

Startup time is the duration required for an electrolyzer to transition from idle to full operation, influenced by system design and temperature. Cold startups for AEL systems can take several minutes due to the need to stabilize the liquid electrolyte and ensure proper ion transport. Warm startups, which occur after short idle periods, are faster but still slower than PEMEL systems, which can start almost instantaneously due to their solid-state design. For example, AEL systems typically require 15 minutes for a warm start, whereas PEMEL systems can do so in under 10 seconds [53].

Understanding startup times is essential for modeling AEL systems in this thesis, as delays impact their ability to respond to intermittent renewable energy supply. Including these operational delays in the scheduling model helps create realistic predictions for hydrogen production under dynamic conditions.

3.3.3. Ramping Rates

Startup time refers to the duration required for an electrolyzer to transition from an idle state to full operation. For AEL systems, cold startups can take several minutes as the liquid electrolyte stabilizes and ion transport is established. Warm startups are faster but still slower than those of PEMEL systems, which can transition almost instantaneously due to their solid-state design. AEL systems typically require 15 minutes for a warm start, whereas PEMEL systems can achieve the same in under 10 seconds [53]. Startup times are particularly relevant in systems relying on intermittent renewable energy, as longer delays may reduce the ability to respond to sudden increases in power availability.

3.3.4. Efficiency and Losses

Electrolyzer efficiency is evaluated using four primary metrics: theoretical efficiency, Faraday efficiency, voltage efficiency, and overall efficiency. These metrics provide insights into different aspects of system performance, energy utilization, and loss mechanisms during operation.

The theoretical efficiency represents the ideal scenario where all input energy is used to split water molecules without any losses. This efficiency is determined by the thermodynamic voltage, $V_{\text{thermodynamic}}$, which is 1.23 V under standard conditions (25 °C, 1 atm). Derived from the Gibbs free energy of the water-splitting reaction, $V_{\text{thermodynamic}}$ serves as the minimum energy requirement for electrolysis and acts as a benchmark for assessing real-world systems. In practical systems, deviations from theoretical efficiency are caused by unavoidable energy losses.

Faraday efficiency measures how effectively the applied current contributes to hydrogen production. It is expressed as:

$$\eta_{\text{Faraday}} = \frac{\text{Actual hydrogen produced}}{\text{Theoretical hydrogen production}} \times 100$$

In an ideal electrolyzer, all the applied current would be used for splitting water molecules. However, losses such as gas crossover, side reactions, or inefficiencies in the electrodes reduce Faraday efficiency, particularly under high current densities or non-optimal operating conditions. Maintaining high Faraday efficiency is critical to minimizing energy waste and ensuring reliable hydrogen production.

Voltage efficiency compares the actual cell voltage, V_{cell}, to the thermodynamic voltage. It is defined as:

$$\eta_{\text{Voltage}} = \frac{V_{\text{thermodynamic}}}{V_{\text{cell}}} \times 100$$

The cell voltage in real systems typically exceeds $V_{\text{thermodynamic}}$ due to losses caused by activation barriers, ohmic resistance, and concentration gradients. These factors collectively reduce voltage efficiency, requiring more energy input to sustain the reaction than theoretically necessary. Voltage efficiency highlights how well an electrolyzer overcomes these losses during operation.

Overall efficiency provides a comprehensive measure of how effectively an electrolyzer converts electrical energy into chemical energy stored in hydrogen. This metric incorporates both Faraday and voltage efficiencies and is expressed as:

$$\eta_{\text{overall}} = \frac{\dot{m}_{\text{H}_2} \cdot \text{LHV}_{\text{H}_2}}{V_{\text{cell}} \cdot I}$$

where $\dot{m}_{H_2}$ is the hydrogen production rate, LHV_{H_2} is the lower heating value of hydrogen (120 MJ/kg), V_{cell} is the actual cell voltage, and I is the applied current. Overall efficiency accounts for all losses in the system, making it a key indicator of electrolyzer performance under practical conditions.

3.3.5. Voltage Losses and the Polarization Curve

Efficiency losses in electrolyzers are directly related to increases in operating voltage beyond the thermodynamic minimum. These losses are illustrated through a polarization curve, which shows the relationship between cell voltage (V_{cell}) and current density (j). The total cell voltage is expressed as:

$$V_{cell} = V_{thermodynamic} + V_{activation} + V_{ohmic} + V_{concentration}$$

where $V_{activation}$, V_{ohmic}, and $V_{concentration}$ correspond to activation, ohmic, and concentration losses, respectively.

At low current densities, activation losses dominate. These arise from the energy required to overcome the reaction kinetics at the electrode surfaces. As current density increases, ohmic losses become the primary contributor. These losses, caused by resistive effects in the electrolyte, electrodes, and connections, increase linearly with current density. At high current densities, concentration losses become significant. These are caused by limitations in ion transport within the electrolyte and the diffusion of gases at the electrode surfaces, leading to a steep rise in operating voltage.

Figures 3.2 and 3.3 illustrate polarization curves for different electrolyzer types. These curves highlight how operating conditions, such as temperature and pressure, affect activation, ohmic, and concentration losses. The shape of the polarization curve provides a detailed understanding of how electrolyzers perform under varying load conditions.

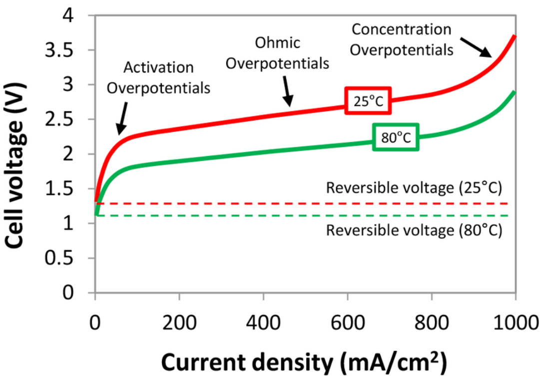

Figure 3.2: Polarization curve of an alkaline electrolyzer under varying temperatures, showing reduced losses at higher temperatures [54].

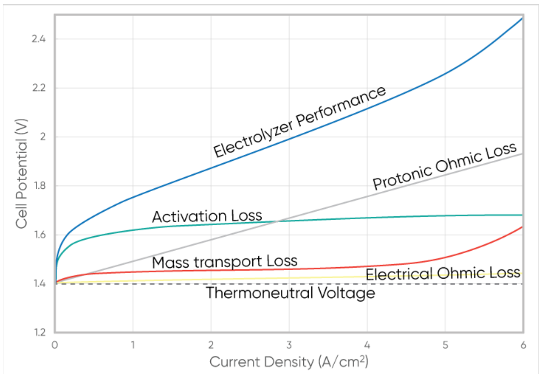

Figure 3.3: Detailed polarization curve highlighting activation, ohmic, and concentration overpotentials [55].

3.3.6. Impact of Operating Conditions

Operating conditions such as temperature and pressure significantly affect electrolyzer efficiency and performance. Higher temperatures improve reaction kinetics and ionic conductivity, reducing activation and ohmic losses. This results in better overall efficiency and lower energy consumption. However, excessive heat can accelerate material degradation, reducing the lifetime of the electrolyzer components. Similarly, elevated pressures improve gas purity by minimizing gas crossover and enhance overall efficiency. However, operating at high pressures also increases system complexity and capital costs. These trade-offs between performance, durability, and economic feasibility must be carefully managed to optimize electrolyzer operation. By adjusting temperature and pressure, it is possible to balance efficiency and durability while maintaining long-term operational stability. Understanding how these operating conditions influence performance is critical for integrating electrolyzers into renewable energy systems.

3.4. Lifetime and Degradation under Dynamic Conditions

Dynamic operation of alkaline water electrolyzers significantly impacts both their lifetime and degradation rates. While alkaline electrolyzers are known for their robustness and long operational lifetimes, their durability is challenged under fluctuating power inputs typically associated with renewable energy sources.

3.4.1. Factors Influencing Degradation

Alkaline electrolyzers experience degradation through several mechanisms, which are influenced under dynamic conditions:

- **Start-Stop Cycles**: Frequent start-stop operations increase mechanical stress on components, particularly the diaphragm and electrode coatings. This results in accelerated wear and increased potential for gas crossover [27], [56]. Kirsch reports that such cycles contribute to diaphragm damage, while Kojima et al. highlight increased catalyst stress.
- **Power Fluctuations**: Power variations cause uneven current distributions and localized overheating, leading to degradation of the catalyst layer and potential delamination of electrode coatings [56], [28]. Jung et al. (2024) observed significant voltage increases of 0.8 mV/MW during power transitions in dynamic operation.
- **Partial Load Operation**: Operating below 30% of nominal capacity leads to inefficiencies and localized overpotentials, which contribute to higher rates of catalyst and diaphragm degradation [27, 29]. Martinez-Lopez et al. emphasize that sustained partial load operation significantly accelerates material wear.

3.4.2. Observed Degradation Mechanisms

Key mechanisms contributing to performance deterioration include:

- **Electrode Surface Degradation**: Loss of active sites due to catalyst leaching and particle agglomeration under fluctuating loads [27, 56].
- **Diaphragm Wear**: Pressure fluctuations and thermal cycling increase the likelihood of diaphragm failure due to mechanical stress.
- **Gas Crossover**: Prolonged dynamic operation can lead to increased gas crossover, reducing hydrogen purity and electrolyzer efficiency.

3.4.3. Lifetime Impact

Dynamic operation reduces the effective lifetime of alkaline electrolyzers compared to steady-state conditions:

- Systems operating under steady power supply can achieve lifetimes of up to 90,000 hours, whereas dynamic conditions may shorten this to approximately 60,000–70,000 hours due to accelerated degradation [29, 27].
- The operational costs increase as degradation necessitates more frequent maintenance or replacement of components, such as diaphragms and electrodes [56, 28].

3.4.4. Strategies for Mitigation

Several approaches can mitigate the effects of dynamic operation on degradation, [27, 56, 29] :

- **Optimized Power Management**: Smoothing power inputs using batteries or hybrid systems to reduce stress during transitions. Avoiding frequent start-stop events by maintaining partial standby modes instead of full shutdowns.
- **Material Improvements**: Use of advanced catalyst coatings and robust diaphragms resistant to mechanical and thermal.
- **Operational Adjustments**: Limiting partial load operation and ensuring that operating conditions remain within optimal ranges for temperature, pressure, and current density.

3.5. Hydrogen Support Mechanisms

The successful development of green hydrogen production and infrastructure depends not only on technological advancements but also on the implementation of financial and policy frameworks to overcome existing barriers. High production costs, uncertain market demand, and the risks associated with investing in emerging technologies like electrolyzers remain significant challenges. To address these issues, governments and organizations worldwide have introduced hydrogen support mechanisms aimed at fostering market development and scaling up hydrogen adoption.

Many of these mechanisms are still in the early stages of implementation, reflecting the ongoing effort to establish a functioning hydrogen market. These support schemes often focus on de-risking investments, closing the cost gap between renewable and fossil-based hydrogen, and creating transparent market conditions to encourage broader participation. Instruments such as subsidies, tax credits, and auction-based funding platforms are central to these efforts.

A summary of some current and planned hydrogen support schemes is provided in Table 3.2, which highlights their geographical focus, funding levels, and structural approaches. While these initiatives vary widely in their design, they share the common goal of enabling the energy transition by making green hydrogen more accessible and competitive. The following subsections will examine three prominent mechanisms in greater detail: the European Hydrogen Bank (EHB), the H2Global initiative, and the Inflation Reduction Act (IRA). These examples illustrate different approaches to addressing the challenges of hydrogen adoption and provide insights into how financial and policy tools can support the development of a sustainable hydrogen economy. A more detailed overview of the structure of the EHB, H2Global and the IRA can be found in Appendix A, B and C, repectively.

Table 3.2: Various examples of hydrogen support schemes [38]

Selection of current hydrogen support schemes			
Instrument	**Country**	**Funding**	**Structure**
European Hydrogen Bank	EU	€3 billion (800m million first round)	Auction platform through "auctions-as-a-service", fixed premium per kg of hydrogen
H2Global Foundation	EU/ Germany	€4 billion (900 million)	Competitive bidding, long-term purchase agreements, and short-term sales contracts through government-backed intermediary HINTCO
Inflation Reduction Act	USA	$783 billion / uncapped	Production tax credit of up to $3/kg of H_2
Innovation Fund	EU	€3 billion for third large-scale call	Funding available for large-scale projects and covers up to 60% of relevant costs. Fund is financed by auctioning of 450 million EU ETS allowances.
Regional Hydrogen Hubs Program	Australia	AUD$526 million	Grants available for design, development, and implementation of selected hydrogen hubs.
Investment Tax Credit	Canada	CAD$17.7 billion	Tax credit for clean hydrogen production ranging from 10-40% depending on eligibility requirements such as carbon intensity and labor conditions.

4 Methodology

This chapter explains the approach used to examine the operational behavior and economic feasibility of green hydrogen production plants under varying renewable energy conditions. The main objective is to understand how the technical setup of an alkaline electrolyzer interacts with fluctuating power inputs, how these dynamic conditions lead to degradation over time, and how introducing hydrogen support mechanisms might help maintain profitability. The analysis builds on a Mixed-Integer Linear Programming (MILP) framework adapted from Baumhof et al. [15], enabling the representation and optimization of electrolyzer performance across multiple operating states.

The research questions guide the methodological choices. By focusing on key technical and operational characteristics, the electrolyzers response to variable renewable inputs can be understood. Incorporating a degradation model ensures that the system does not assume constant performance, but rather reflects the impact of start-stops, load fluctuations, and other factors that reduce efficiency and lifespan. Additionally, hydrogen support mechanisms, such as those offered by the European Hydrogen Bank or H2Global, are integrated to examine how financial incentives or price guarantees influence operational decisions and economic outcomes.

The methodology first involves selecting and refining an electrolyzer model to capture multiple operating states, changes in efficiency levels, and dynamic production profiles. Degradation aspects are then incorporated to reflect the consequences of sustained exposure to variable operating conditions. Following this, hydrogen support mechanisms are introduced in a way that can shift operational strategies and financial results. Throughout the process, realistic input data, clear system boundaries, and transparent assumptions are maintained, ensuring that the resulting insights are credible and relevant.

In the sections that follow, the mathematical formulation of the model is described, along with details on how degradation and support mechanisms are integrated. The selection of input data, system parameters, and the definition of scenarios and evaluation metrics are also presented. These components establish the foundation for assessing the research questions and ultimately interpreting the findings on the operational and economic potential of green hydrogen production.

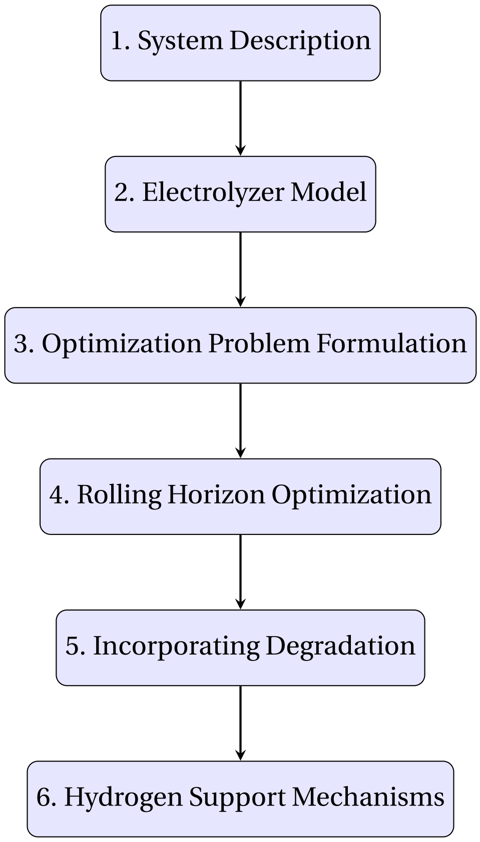

Figure 4.1: Flowchart showing the steps in the methodology, from describing the system to adding hydrogen support mechanisms.

4.1. System Description

This section introduces the model proposed by Baumhof et al., which serves as the foundation for this research. Providing a detailed and robust framework for representing the operation of an electrolyzer within a hybrid energy system, the Baumhof model incorporates multiple operational states and captures key physical and economic characteristics. Its comprehensive approach allows for the study of dynamic inputs and sets the groundwork for integrating additional factors such as degradation and hydrogen support mechanisms, which are central to this thesis.

Illustrated in Figure 4.2, the system model developed by Baumhoff et al. represents a hybrid energy setup designed to facilitate green hydrogen production. It integrates key components including a wind farm, a grid connection, an electrolyzer, a compressor, hydrogen storage, and a demand interface. Each component serves a specific function, collectively simulating the operational dynamics of renewable energy systems used for hydrogen production.

Electricity is supplied to the electrolyzer from two sources: a wind farm, introducing variability due to the intermittent nature of wind energy, and a grid connection that ensures a stable and reliable power supply when renewable generation is insufficient. The electrolyzer uses this electricity to produce hydrogen through electrolysis. The produced hydrogen is then compressed and stored in a hydrogen storage facility, which buffers the system against fluctuations in production and demand, ensuring a consistent hydrogen supply to end users.

This system design reflects the operational complexity of renewable energy-based hydrogen production and aligns closely with the objectives of this thesis. The inclusion of variable renewable inputs and a grid connection enables the analysis of how operational strategies can adapt to fluctuating energy availability. Moreover, the hydrogen storage component underscores the importance of balancing production and demand in scenarios where energy supply is unpredictable.

Building on this model, the thesis investigates two key extensions: the incorporation of electrolyzer degradation due to dynamic loading and the evaluation of hydrogen support mechanisms, such as subsidies or tax credits, on the economic viability of hydrogen production systems. By focusing on these aspects, the study aims to provide insights into optimizing system performance and ensuring long-term operational efficiency.

4.2. Detailed Explanation of the Alkaline Electrolyzer Model

This section provides a comprehensive explanation of the alkaline electrolyzer model used in this research. The model simulates the operation of an alkaline electrolyzer within a hybrid energy system, capturing the key physical and economic characteristics necessary for optimizing green hydrogen production. By understanding the detailed behavior of the electrolyzer, we can accurately model its performance and integrate it effectively into the overall system.

4.2.1. Overview of the Model

The model aims to optimize the scheduling and operation of an alkaline electrolyzer integrated with a wind farm and a grid connection. It considers various factors such as electricity prices, wind power availability, electrolyzer characteristics, hydrogen production rates, storage dynamics, and market conditions. The optimization seeks to maximize profit by determining the optimal operational strategy for the electrolyzer, accounting for operational constraints and efficiencies.

The system model is illustrated in Figure 4.2. It represents a hybrid energy system designed to facilitate green hydrogen production. The key components of the system include:

- **Wind Farm**: Provides renewable electricity, introducing variability due to wind conditions.
- **Grid Connection**: Allows for purchasing electricity from or selling excess electricity to the grid, ensuring a stable power supply when renewable generation is insufficient.
- **Electrolyzer**: An alkaline electrolyzer that converts electrical energy into hydrogen through the process of electrolysis.
- **Compressor**: Pressurizes the produced hydrogen for storage or transportation, consuming additional power.
- **Hydrogen Storage**: Stores hydrogen to buffer the system against fluctuations in production and demand, ensuring a consistent hydrogen supply to end users.
- **Hydrogen Demand Interface**: Represents the demand for hydrogen from various end users or markets.

Electricity is supplied to the electrolyzer from two sources: the wind farm and the grid connection. The electrolyzer uses this electricity to produce hydrogen, which is then compressed and stored. The stored hydrogen can be dispatched to meet demand as needed.

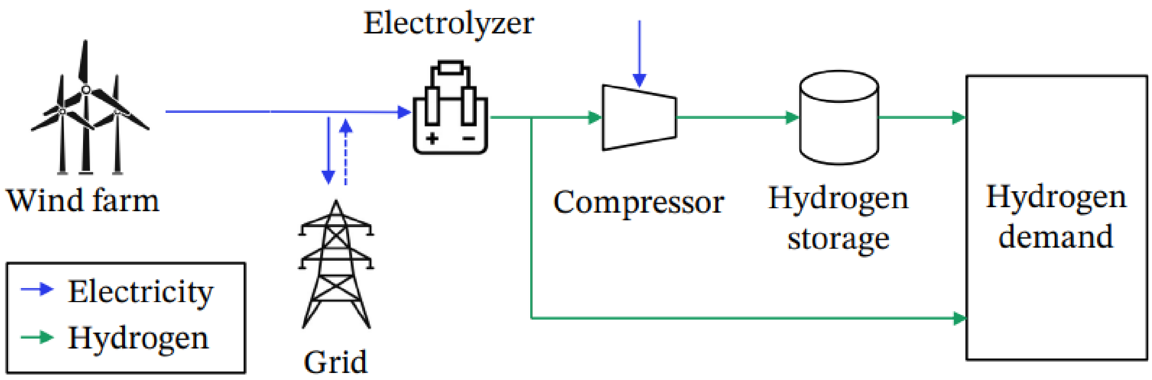

Figure 4.2: System schematic as presented in Baumhof et al. [15]

4.2.2. Components of the Model and Parameters

The model incorporates several components, each characterized by specific parameters. Table 4.1 summarizes the main components and their associated parameters used in the model.

Table 4.1: Model Components and Parameters

Component	Parameter	Value
Wind Farm	Nominal Capacity (C_W)	104.5 MW
	Capacity Factor (CF)	Scenario data
Grid Connection	Electricity Price (λ_M)	Scenario data (EUR/MWh)
	TSO Tariff (TSO_{tariff})	15.06 EUR/MWh
Electrolyzer	Nominal Capacity (C_E)	52.25 MW
	Standby Load (P_{sb})	1% of C_E
	Minimum Load (P_{min})	15% of C_E
	Cell Pressure (p_{cell})	30 bar
	Cell Temperature (T_{cell})	90°C
	Max Current Density (i_{max})	5000 A/m^2
	Cell Area (A_{cell})	0.2 m^2
	Startup Cost (λ_{start})	50 EUR/MW
	Full Load Efficiency (η_{full_load})	17.547 kg/MWh
Hydrogen Storage	Capacity (C_S)	$C_E \times \eta_{full\_load} \times 24$ kg
	Initial State of Charge (SOC_0)	0 kg
Hydrogen Market	Hydrogen Price (λ_H)	2.1 EUR/kg
	Daily Demand (C_D)	$C_E \times \eta_{full\_load} \times 4$ kg
Compressor	Mechanical Efficiency (η_C)	75%
	Inlet Pressure (p_{in})	30 bar
	Outlet Pressure (p_{out})	200 bar
	Adiabatic Exponent (γ)	1.4
	Inlet Temperature (T_{in})	40°C

Wind Farm

The wind farm has a nominal capacity of $C_W = 104.5$ MW. Its actual power output $P_{W,t}$ varies over time based on the capacity factor CF_t derived from scenario data:

$$P_{\mathrm{W},t} = \mathrm{CF}_t \times C_{\mathrm{W}}$$

This accounts for the variability in wind power generation, reflecting real-world operational conditions. The capacity factor CF_t represents the fraction of the nominal capacity that is actually generated at time t, based on wind availability the hourly time series was obtained from Renewables.ninja for Vestas V90 2000 Wind turbine located in the North Sea [57].

To illustrate the variability of wind power generation, Figure 4.3 presents the wind profile expressed as a capacity factor over the optimization horizon.

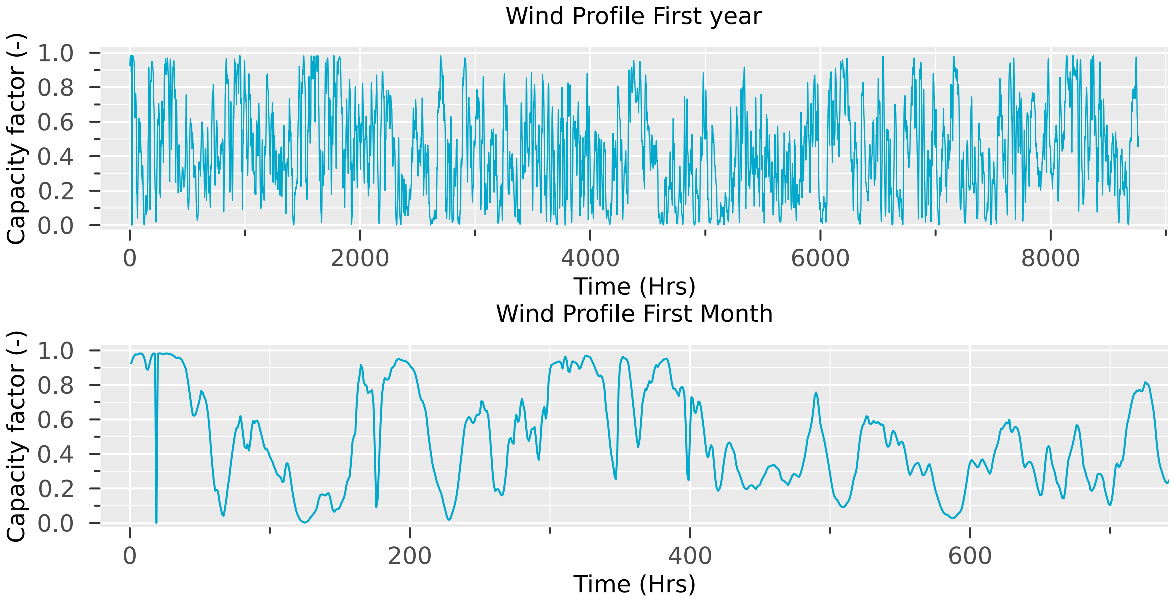

Figure 4.3: Wind profile expressed in capacity factor

Grid Connection

The grid connection allows the system to buy electricity when renewable generation is insufficient and sell excess electricity when available. The electricity purchase price $\lambda^{\mathrm{in}}_{\mathrm{M},t}$ includes the market price and additional tariffs:

$$\lambda^{\mathrm{in}}_{\mathrm{M},t} = \lambda_{\mathrm{M},t} + \mathrm{TSO}_{\mathrm{tariff}}$$

where $\lambda_{\mathrm{M},t}$ is the market electricity price at time t, and $\mathrm{TSO}_{\mathrm{tariff}}$ is the tariff charged by the transmission system operator (TSO). The TSO tariff accounts for the costs associated with the use of the transmission network.

Similarly, when selling electricity back to the grid, the electricity selling price $\lambda^{\mathrm{out}}_{\mathrm{M},t}$ is:

$$\lambda^{\mathrm{out}}_{\mathrm{M},t} = \lambda_{\mathrm{M},t} - \mathrm{TSO}_{\mathrm{tariff}}$$

The variability of electricity prices significantly impacts the operational strategy of the electrolyzer. High electricity prices may discourage purchasing from the grid, while low prices provide opportunities to supplement wind generation. Figures 4.4 and 4.5 illustrate the electricity price data used in the model over different time periods. The data for the day-ahead electricity prices in the Netherlands was obtained from the ENTSO-e Transparency platform [58].

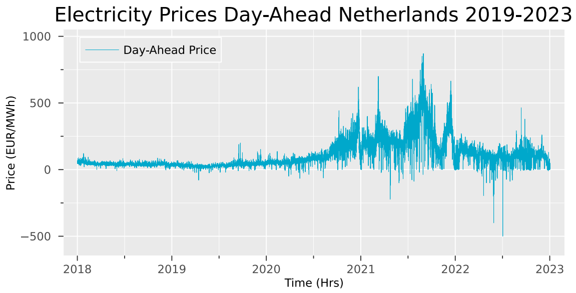

Figure 4.4: Electricity prices from 2019 to 2023

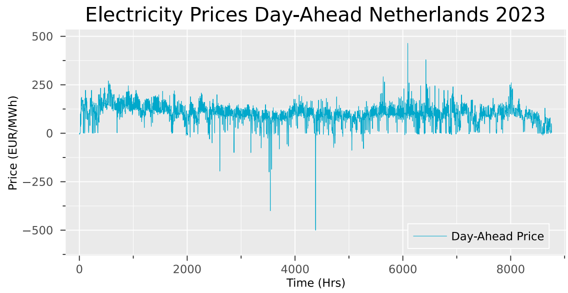

Figure 4.5: Electricity prices for 2023

Figure 4.6: Illustration of electricity price data used in the model

These figures show the fluctuations in electricity prices, which are crucial inputs for the optimization model to determine the most cost-effective operation of the electrolyzer.

Electrolyzer

An alkaline electrolyzer with a nominal capacity of $C_\mathrm{E} = 52.25$ MW (half of the wind farm capacity) is used. Key operational parameters include:

- **Standby Load**: $P_\mathrm{sb} = 1\% \times C_\mathrm{E}$, representing the power consumption when the electrolyzer is in standby mode.
- **Minimum Load**: $P_\mathrm{min} = 15\% \times C_\mathrm{E}$, indicating the minimum operational power level to prevent damage or inefficiency.
- **Cell Pressure and Temperature**: $p_\mathrm{cell} = 30$ bar, $T_\mathrm{cell} = 90°$C, the operating conditions within the electrolyzer cells.
- **Startup Cost**: $\lambda_\mathrm{start} = 50$ EUR/MW, representing the cost associated with starting up the electrolyzer from an off state.
- **Full Load Efficiency**: $\eta_\mathrm{full\_load} = 17.547$ kg/MWh, the hydrogen production efficiency at full load operation.

The electrolyzer's performance is modeled using detailed electrochemical equations, capturing the relationship between power input and hydrogen output, which are crucial for optimization.

Hydrogen Storage

The storage system has a capacity of:

$$C_\mathrm{S} = C_\mathrm{E} \times \eta_\mathrm{full\_load} \times 24\ \mathrm{kg}$$

This allows for 24 hours of hydrogen production at full electrolyzer capacity, providing flexibility in meeting hydrogen demand and smoothing out production fluctuations due to variable renewable generation.

Hydrogen Market and Demand

The hydrogen produced is sold at a market price $\lambda_\mathrm{H} = 2.1$ EUR/kg. The system aims to meet a daily hydrogen demand:

$$C_\mathrm{D} = C_\mathrm{E} \times \eta_\mathrm{full\_load} \times 4\ \mathrm{kg}$$

This represents the commitment to supply a certain amount of hydrogen to end users each day, influencing the operational strategy of the electrolyzer and storage.

Compressor

The compressor pressurizes the hydrogen for storage or transportation. Its specific energy consumption e_C (in MWh/kg) is calculated based on thermodynamic relationships:

$$e_C = \frac{RT_{in}}{M_{H_2}} \frac{\gamma}{\gamma - 1} \frac{1}{\eta_C} \left(\left(\frac{p_{out}}{p_{in}} \right)^{\frac{\gamma-1}{\gamma}} - 1 \right) \times \frac{1}{3,600,000}$$

where:

- $R = 8.314$ J/(mol$\cdot K$) is the universal gas constant.
- $T_{in} = 40 + 273.15$ K is the inlet temperature of the compressor.
- $M_{H_2} = 2.0159 \times 10^{-3}$ kg/mol is the molar mass of hydrogen.
- $\gamma = 1.4$ is the adiabatic exponent for diatomic gases.
- $\eta_C = 75\%$ is the mechanical efficiency of the compressor.
- $p_{in} = 30$ bar and $p_{out} = 200$ bar are the inlet and outlet pressures, respectively.

This equation calculates the energy required to compress one kilogram of hydrogen from p_{in} to p_{out}.

4.2.3. Description of Electrolyzer Characteristics

An alkaline electrolyzer uses an alkaline electrolyte (typically potassium hydroxide, KOH) to facilitate the electrolysis of water, producing hydrogen (H_2) and oxygen (O_2) gases. The key performance characteristics of an electrolyzer cell include:

- **Voltage-Current Relationship**: Defines how cell voltage varies with current density, influencing the energy consumption.
- **Faraday Efficiency**: Accounts for the efficiency of converting electrical energy into chemical energy, considering side reactions and losses.
- **Hydrogen Production Rate**: Determines the amount of hydrogen produced based on operating conditions such as current density and temperature.

Understanding these characteristics is essential for accurately modeling the electrolyzer's performance and optimizing its operation within the energy system. The electrolyzer model is based on empirical equations that describe the electrochemical reactions and operational behavior of alkaline electrolyzers. Ulleberg [24] provides an empirical model for electrolyzer behavior considering the relationship between voltage and current density. The final formulation has been given by Sánchez et al. [14], which also takes into account operating temperature and pressure. These equations are crucial for accurately representing the electrolyzer's performance and are used to determine optimal operating strategies.

Cell Voltage Calculation

The total cell voltage U_{cell} is calculated as the sum of the reversible cell voltage U_{rev} and the overpotentials due to ohmic losses ΔU_{ohmic} and activation $\Delta U_{activation}$:

$$U_{cell} = U_{rev} + \Delta U_{ohmic} + \Delta U_{activation} \tag{4.1}$$

This equation represents the actual voltage required across the electrolyzer cell to drive the electrochemical reactions, taking into account various losses.

Reversible Cell Voltage U_{rev}: The reversible cell voltage is the theoretical minimum voltage required for electrolysis to occur without any losses. It depends on the cell temperature T (in Kelvin):

$$U_{rev}(T) = a_1 - a_2 T + a_3 T \ln(T) + a_4 T^2 \tag{4.2}$$

where:

- $T = T_{\text{cell}} + 273.15\,\text{K}$ is the absolute temperature.
- $a_1 = 1.5184\,\text{V}$, $a_2 = 1.5421 \times 10^{-3}\,\text{V/K}$, $a_3 = 9.523 \times 10^{-5}\,\text{V/K}$, $a_4 = 9.84 \times 10^{-8}\,\text{V/K}^2$ are empirical constants.

This equation models the thermodynamic potential of the electrolyzer cell, which decreases slightly with increasing temperature.

Ohmic Losses ΔU_{ohmic}: Ohmic losses arise due to the resistance of the electrolyte and electrodes to the flow of electric current. They are calculated as:

$$\Delta U_{\text{ohmic}} = R_{\text{cell}} \times i \tag{4.3}$$

with the cell resistance R_{cell} given by:

$$R_{\text{cell}} = (r_1 + d_1) + r_2 T + d_2 p \tag{4.4}$$

where:

- i is the current density (A/m^2), representing the electric current per unit area of the electrode.
- $p = p_{\text{cell}}$ is the cell pressure (bar).
- $r_1 = 4.45153 \times 10^{-5}\,\Omega \cdot \text{m}^2$, $r_2 = 6.88874 \times 10^{-9}\,\Omega \cdot \text{m}^2/\text{K}$, $d_1 = -3.12996 \times 10^{-6}\,\Omega \cdot \text{m}^2$, $d_2 = 4.47137 \times 10^{-7}\,\Omega \cdot \text{m}^2/\text{bar}$.

This term accounts for voltage losses proportional to the current density, which increase with higher currents due to greater resistance.

Activation Overpotential $\Delta U_{\text{activation}}$: Activation overpotential is associated with the energy barrier for initiating the electrochemical reactions at the electrodes. It is given by:

$$\Delta U_{\text{activation}} = s \ln\left(\left(t_1 + \frac{t_2}{T} + \frac{t_3}{T^2}\right) i + 1\right) \tag{4.5}$$

where:

- $s = 0.33824\,\text{V}$ is an empirical constant related to the Tafel slope.
- $t_1 = -0.01539$, $t_2 = 2.00181\,\text{K}$, $t_3 = 15.24178\,\text{K}^2$ are empirical constants.

This term captures the non-linear increase in voltage required to overcome activation energy barriers at the electrodes, especially significant at low current densities.

Total Cell Voltage Equation:

Combining the above components, the total cell voltage is expressed as:

$$U_{\text{cell}}(T, p, i) = U_{\text{rev}}(T) + R_{\text{cell}}(T, p) \times i + s \ln\left(\left(t_1 + \frac{t_2}{T} + \frac{t_3}{T^2}\right) i + 1\right) \tag{4.6}$$

This comprehensive equation models the actual voltage required across the electrolyzer cell, incorporating thermodynamic, ohmic, and activation considerations, and is essential for determining the power consumption at different operating points.

Faraday Efficiency η_{F}: Faraday efficiency accounts for losses due to side reactions, gas crossover, and other inefficiencies, affecting the actual hydrogen production rate compared to the theoretical maximum. It is calculated as:

$$\eta_F(T,i) = \left(\frac{i^2}{f_{11} + f_{12}T + i^2}\right)(f_{21} + f_{22}T) \tag{4.7}$$

where:

- $f_{11} = 478645.74\,\mathrm{A^2/m^4}$, $f_{12} = -2953.15\,\mathrm{A^2/m^4/K}$, $f_{21} = 1.0396$, $f_{22} = -0.00104/\mathrm{K}$ are empirical constants.

This equation models the efficiency with which the electric current contributes to hydrogen production, considering the effects of temperature and current density. Faraday efficiency typically increases with current density up to a point, then levels off or decreases due to increased losses.

Hydrogen Production Rate: The hydrogen production rate per cell is calculated using Faraday's law, adjusted for Faraday efficiency:

$$\dot{M}_{H_2}(T,i) = \frac{\eta_F(T,i) \cdot M_{H_2} \cdot i \cdot A_{\text{cell}}}{2F} \tag{4.8}$$

where:

- $\dot{M}_{H_2}$ is the mass flow rate of hydrogen (kg/s).
- $M_{H_2} = 2.0159 \times 10^{-3}$ kg/mol is the molar mass of hydrogen.
- $A_{\text{cell}} = 0.2\ \mathrm{m}^2$ is the cell area.
- $F = 96,485.3321$ C/mol is Faraday's constant.

This equation quantifies the hydrogen output based on the operating conditions of the electrolyzer, considering both the current supplied and the efficiency of conversion.

For the entire electrolyzer system with n_c cells:

$$\dot{M}_{H_2,\text{sys}}(T,i) = n_c \cdot \dot{M}_{H_2}(T,i) \tag{4.9}$$

Power Consumption of the Electrolyzer: The power consumption per cell is

$$P_{\text{cell}}(T,p,i) = U_{\text{cell}}(T,p,i) \cdot i \cdot A_{\text{cell}} \tag{4.10}$$

The total power consumption for the electrolyzer system is:

$$P_{\text{total}}(T,p,i) = n_c \cdot P_{\text{cell}}(T,p,i) \tag{4.11}$$

This represents the electrical power required to operate the electrolyzer at a given current density, accounting for all cells in the system.

Cell Efficiency η_{cell}: The cell efficiency represents the ratio of the energy content of produced hydrogen to the electrical energy consumed, indicating how effectively the electrolyzer converts electrical energy into chemical energy:

$$\eta_{\text{cell}}(T,p,i) = \frac{\dot{M}_{H_2}(T,i) \cdot \text{HHV}}{P_{\text{cell}}(T,p,i)} \tag{4.12}$$

where $\text{HHV} = 39.41$ kWh/kg is the higher heating value of hydrogen, representing the energy content per kilogram.

This efficiency metric is essential for evaluating the performance of the electrolyzer under different operating conditions and is used in calculating the overall system efficiency.

Number of Cells in the Electrolyzer: To determine the number of cells n_c required for the electrolyzer stack to meet the nominal capacity C_{E}:

$$n_c = \frac{C_{\text{E}} \times 10^6}{P_{\text{max, cell}}} \tag{4.13}$$

where:

- $P_{\text{max, cell}}$ is the maximum power consumption per cell (W), calculated at the maximum current density i_{max}:

$$P_{\text{max, cell}} = U_{\text{cell}}(T, p, i_{\text{max}}) \cdot i_{\text{max}} \cdot A_{\text{cell}} \tag{4.14}$$

This calculation ensures that the electrolyzer design meets the desired capacity by determining how many cells are needed to achieve the total power input.

Modeling the Hydrogen Production Curve

The relationship between the electrolyzer's power input and hydrogen output is non-linear due to the complexities of electrochemical reactions and efficiency variations with operating conditions. To incorporate this relationship into the optimization model while keeping computational complexity manageable, the production curve is approximated by constructing it with linear segments.

Segmentation of the Production Curve The production curve is divided into S segments, each represented by a linear equation relating hydrogen production rate $\dot{M}_{\text{H}_2}$ to the electrolyzer power input P_{E}:

$$\dot{M}_{\text{H}_2} = a_s \cdot P_{\text{E}} + b_s \quad \text{for segment } s = 1, 2, \ldots, S \tag{4.15}$$

where:

- a_s is the slope of segment s, representing the incremental hydrogen production per unit of power input.
- b_s is the intercept of segment s, accounting for baseline production at zero power input (which may be zero).
- P_{E} is within the power range defined for segment s.

Figures 4.7 and 4.8 illustrate the non-linear hydrogen production curve and its linear approximation through segmentation.

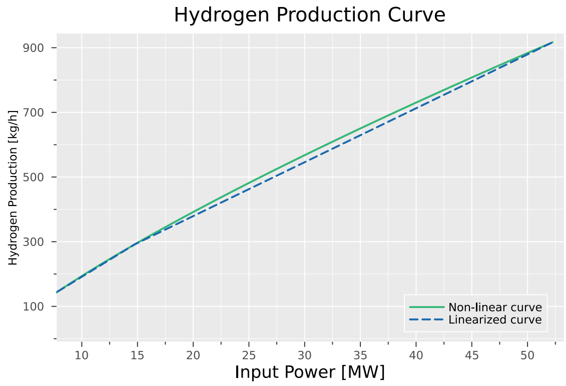

Figure 4.7: Non-linear hydrogen production curve with linearized production curve

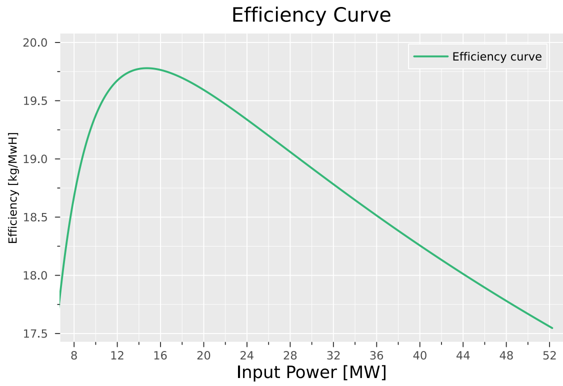

Figure 4.8: Non-linear efficiency curve

The coefficients a_s and b_s are determined by fitting linear equations to the production curve over the specified power ranges. This involves:

1. Calculating the hydrogen production rate $\dot{M}_{\mathrm{H}_2}$ and power consumption P_{E} at various current densities i using the detailed equations previously described.
2. Plotting $\dot{M}_{\mathrm{H}_2}$ versus P_{E} to obtain the non-linear production curve.
3. Dividing the curve into segments where linear approximation is acceptable.
4. Using linear regression or piecewise linear approximation to determine a_s and b_s for each segment.

Incorporation into the Optimization Model By expressing the hydrogen production rate as a piecewise linear function of power input, the optimization model can use a Mixed Integer Linear programming, to determine the optimal operating points. The use of linear segments simplifies the computational complexity while providing a reasonable approximation of the electrolyzer's performance.

Constraints are added to the optimization model to ensure that the power input P_{E} and hydrogen production $\dot{M}_{\mathrm{H}_2}$ stay within the defined ranges for each segment and that only one segment is active at a time. Binary variables may be used to model the activation of segments.

4.2.4. Summary

This detailed mathematical description of the alkaline electrolyzer model provides the foundation for optimizing its operation within the hybrid energy system. By understanding and accurately modeling the electrolyzer's behavior, the study can effectively explore strategies to maximize efficiency and profitability.

4.3. Optimization Problem Formulation

Building upon the detailed modeling of the alkaline electrolyzer and the system components described in the previous sections, we now formulate an optimization problem to determine the optimal operational strategy of the hybrid energy system. The objective is to maximize the profit from hydrogen production and electricity trading while satisfying all technical and operational constraints. This optimization accounts for the dynamic nature of renewable energy generation and market conditions, enabling efficient and economically viable operation of the system.

4.3.1. Optimization Model Overview

The optimization model aims to schedule and control the operation of the electrolyzer, hydrogen storage, and electricity transactions over a discrete time horizon T, typically divided into hourly intervals. The model considers the variability in wind power generation, electricity market prices, and hydrogen demand, seeking to maximize the total profit.

To effectively capture the operational decisions, the model is formulated as a **Mixed-Integer Linear Programming** (MILP) problem. MILP is a mathematical optimization approach that involves linear relationships in the objective function and constraints, with the inclusion of both continuous and integer (specifically, binary) variables. The integer variables allow the model to represent discrete decisions, such as the on/off states of equipment or activation of specific operational modes.

MILP problems are solved using specialized algorithms, such as branch-and-bound or branch-and-cut, which systematically explore feasible solutions by dividing the problem into smaller subproblems. The linearity of the relationships ensures that efficient solution methods can be applied, making MILP a suitable choice for large-scale optimization in energy systems.

4.3.2. Decision Variables

The decision variables in the optimization model represent the quantities that can be controlled or adjusted to achieve the objective. They include both continuous variables, representing quantities like power flows and hydrogen production rates, and binary variables, representing discrete operational states.

- $m_t \geq 0$: Electricity sold to the grid at time t (MWh).
- $m_t^{\text{in}} \geq 0$: Electricity purchased from the grid at time t (MWh).
- $e_{t,s} \geq 0$: Electrolyzer electricity consumption in segment s at time t (MWh).
- $e_t^{\text{tot}} \geq 0$: Total electrolyzer electricity consumption at time t (MWh).
- $h_t \geq 0$: Hydrogen produced at time t (kg).
- $h_t^{\text{d}} \geq 0$: Hydrogen supplied directly to meet demand at time t (kg).
- $d_t \geq 0$: Hydrogen sold to the market at time t (kg).
- $c_t \geq 0$: Compressor electricity consumption at time t (MWh).
- $s_t^{\text{in}} \geq 0$: Hydrogen stored (input to storage) at time t (kg).
- $s_t^{\text{out}} \geq 0$: Hydrogen withdrawn from storage at time t (kg).
- $\text{SOC}_t \geq 0$: State of charge of hydrogen storage at time t (kg).
- $z_t^{\text{on}} \in \{0, 1\}$: Binary variable indicating if the electrolyzer is *on* at time t.
- $z_t^{\text{off}} \in \{0, 1\}$: Binary variable indicating if the electrolyzer is *off* at time t.
- $z_t^{\text{sb}} \in \{0, 1\}$: Binary variable indicating if the electrolyzer is in *standby* mode at time t.
- $z_t^{\text{start}} \in \{0, 1\}$: Binary variable indicating if the electrolyzer *starts up* at time t.
- $z_{t,s}^{h} \in \{0, 1\}$: Binary variable indicating if hydrogen production occurs in segment s at time t.

4.3.3. Objective Function

The objective of the optimization is to maximize the total profit over the time horizon T. The profit is calculated as the revenue from selling hydrogen and electricity minus the costs associated with purchasing electricity and starting up the electrolyzer. The objective function is formulated as:

$$\max \sum_{t \in T} \left[m_t \lambda_{M,t} + d_t \lambda_{\text{H}} - m_t^{\text{in}} \lambda_{M,t}^{\text{in}} - z_t^{\text{start}} \lambda_{\text{start}} \right] \tag{4.16}$$

Where:

- $\lambda_{M,t}$: Market electricity price at time t (EUR/MWh).
- $\lambda_{M,t}^{\text{in}} = \lambda_{M,t} + \text{TSO}_{\text{tariff}}$: Electricity purchase price including transmission tariffs (EUR/MWh).
- λ_{H}: Hydrogen selling price (EUR/kg).
- λ_{start}: Cost associated with starting up the electrolyzer (EUR).
- z_t^{start}: Binary variable indicating startup events, which incur costs.

This objective function captures the economic trade-offs involved in operating the hybrid energy system. Selling electricity to the grid and hydrogen to the market generates revenue, while purchasing electricity from the grid and starting up the electrolyzer incur costs. The optimization seeks to find the balance that maximizes profit while adhering to operational constraints.

4.3.4. System Constraints

The optimization problem is subject to a series of constraints that represent the physical limitations of the system components and operational requirements. These constraints ensure that the solutions provided by the optimization model are feasible and practically implementable.

Electricity Balance Constraint

At each time step t, the net electricity balance must be maintained:

$$m_t = P_{\text{W},t} + m_t^{\text{in}} - e_t^{\text{tot}} - c_t \tag{4.17}$$

This constraint ensures that the electricity sold to or bought from the grid accounts for:

- $P_{\text{W},t}$: Electricity generated by the wind farm at time t (MWh).
- m_t^{in}: Electricity purchased from the grid at time t (MWh).
- e_t^{tot}: Total electricity consumed by the electrolyzer at time t (MWh).
- c_t: Electricity consumed by the compressor at time t (MWh).

Positive values of m_t indicate net electricity sold to the grid, while negative values represent net electricity purchased.

Electrolyzer Operational States Constraints

The electrolyzer operates in one of three states: *on*, *off*, or *standby*. This is modeled using binary variables:

$$z_t^{\text{on}} + z_t^{\text{off}} + z_t^{\text{sb}} = 1 \quad \forall t \in T \tag{4.18}$$

This constraint ensures that at any given time t, the electrolyzer is in exactly one state.

Electrolyzer Power Consumption Constraints

When the electrolyzer is *on*, its power consumption must be within the minimum and maximum operating limits:

$$P_{\text{min}} z_t^{\text{on}} \leq e_t^{\text{tot}} - P_{\text{sb}} z_t^{\text{sb}} \leq C_{\text{E}} z_t^{\text{on}} \quad \forall t \in T \tag{4.19}$$

Where:

- P_{min}: Minimum operating power of the electrolyzer (MW).
- C_{E}: Nominal capacity of the electrolyzer (MW).

- P_{sb}: Standby power consumption (MW).

When the electrolyzer is in *standby* mode, its power consumption is limited to the standby power:

$$e_t^{\text{tot}} = P_{\text{sb}} z_t^{\text{sb}} \quad \forall t \in T \tag{4.20}$$

Electrolyzer Startup Constraint

Starting up the electrolyzer from an *off* state incurs a cost and is represented by:

$$z_t^{\text{start}} \geq z_t^{\text{on}} - z_{t-1}^{\text{on}} - z_{t-1}^{\text{sb}} \quad \forall t > 1 \tag{4.21}$$

For the first time step:

$$z_1^{\text{start}} \geq z_1^{\text{on}} \tag{4.22}$$

This constraint ensures that z_t^{start} is set to 1 when the electrolyzer transitions from *off* or *standby* to *on*, capturing the startup events and associated costs.

Hydrogen Production Constraints

The hydrogen production at time t is calculated based on the segmented production curve derived from the electrolyzer model:

$$h_t = \sum_{s \in S} \left(a_s e_{t,s} + b_s z_{t,s}^h \right) \tag{4.23}$$

Where:

- a_s and b_s: Slope and intercept of segment s in the hydrogen production curve.
- $e_{t,s}$: Electricity consumption in segment s at time t.
- $z_{t,s}^h$: Binary variable indicating activation of segment s at time t.

Only one segment can be active when the electrolyzer is *on*:

$$\sum_{s \in S} z_{t,s}^h = z_t^{\text{on}} \quad \forall t \in T \tag{4.24}$$

The power consumption in each segment is bounded by:

$$P_s^{\text{min}} z_{t,s}^h \leq e_{t,s} \leq P_s^{\text{max}} z_{t,s}^h \quad \forall t \in T, \forall s \in S \tag{4.25}$$

Where P_s^{min} and P_s^{max} are the minimum and maximum power levels for segment s.

Hydrogen Balance Constraints

The hydrogen produced is either supplied directly to meet demand or stored for later use:

$$h_t = h_t^{\text{d}} + s_t^{\text{in}} \quad \forall t \in T \tag{4.26}$$

The hydrogen sold to the market is met through direct supply and withdrawal from storage:

$$d_t = h_t^{\text{d}} + s_t^{\text{out}} \quad \forall t \in T \tag{4.27}$$

Hydrogen Storage Dynamics
The state of charge (SOC) of the hydrogen storage is updated over time:

$$\text{SOC}_t = \text{SOC}_{t-1} + s_t^{\text{in}} - s_t^{\text{out}} \quad \forall t > 1 \tag{4.28}$$

With the initial state:

$$\text{SOC}_1 = \text{SOC}_0 \tag{4.29}$$

The storage capacity is limited by:

$$0 \leq \text{SOC}_t \leq C_{\text{S}} \quad \forall t \in T \tag{4.30}$$

Where C_{S} is the maximum storage capacity (kg).

Hydrogen Demand Constraint
The system must meet the daily hydrogen demand C_{D}:

$$\sum_{t \in T_{\text{day}}} d_t \geq C_{\text{D}} \quad \forall \text{days} \tag{4.31}$$

This constraint ensures that over each day, the total hydrogen sold meets or exceeds the required demand.

Compressor Consumption Constraint
The compressor electricity consumption is proportional to the amount of hydrogen being stored:

$$c_t = s_t^{\text{in}} e_{\text{C}} \quad \forall t \in T \tag{4.32}$$

Where e_{C} is the specific energy consumption of the compressor (MWh/kg).

Market Transactions Constraint
Electricity purchased from the grid is only used for standby operation:

$$m_t^{\text{in}} \leq P_{\text{sb}} z_t^{\text{sb}} \quad \forall t \in T \tag{4.33}$$

This constraint ensures that the system does not purchase electricity from the grid for hydrogen production, aligning with the objective of producing green hydrogen using renewable energy.

4.3.5. Three-State Operation of the Electrolyzer
The electrolyzer operates in three distinct states, each representing different operational modes and associated with specific constraints and costs:

1. **On State** ($z_t^{\textbf{on}} = 1$): The electrolyzer actively produces hydrogen, consuming electricity within its operational limits (P_{min} to C_{E}). The hydrogen production rate is determined by the segmented production curve.
2. **Standby State** ($z_t^{\textbf{sb}} = 1$): The electrolyzer is ready to start hydrogen production but is not actively producing hydrogen. It consumes a small amount of electricity (P_{sb}) to maintain operational readiness, allowing for faster startup compared to the off state.
3. **Off State** ($z_t^{\textbf{off}} = 1$): The electrolyzer is completely shut down, consuming no electricity. Transitioning from off to on incurs a startup cost and may involve a delay, reflecting the practical considerations of equipment operation.

Modeling these states enables the optimization model to capture the operational flexibility and costs associated with starting up and shutting down the electrolyzer. The inclusion of startup costs discourages frequent transitions between states, promoting stable and economically efficient operation when market conditions are favorable.

4.3.6. Contextualizing the Constraints

The constraints in the optimization model are designed to reflect the practical considerations and physical realities of operating a hybrid energy system. The electricity balance constraint ensures that all sources and sinks of electricity are accounted for, maintaining the feasibility of the power system. The operational state constraints represent the physical limitations and capabilities of the electrolyzer, including its ability to start up, shut down, and operate within certain power ranges.

The hydrogen production constraints integrate the detailed electrolyzer model by utilizing the segmented production curve. This allows the optimization to accurately represent the non-linear relationship between power input and hydrogen output, while maintaining computational tractability through linear approximations.

Hydrogen balance and storage dynamics are critical for ensuring that hydrogen production aligns with demand and storage capacities. The model accounts for the time-varying nature of hydrogen demand and the strategic use of storage to buffer production and consumption.

Market transaction constraints reflect regulatory and strategic considerations, such as limiting the purchase of electricity from the grid to standby operation. This aligns with the objective of producing green hydrogen by primarily using renewable energy sources.

Overall, these constraints ensure that the optimization not only seeks economic efficiency but also produces solutions that are technically feasible and align with operational objectives.

4.3.7. Integration with the Electrolyzer Model

The optimization model integrates seamlessly with the detailed electrolyzer model presented earlier. By incorporating the segmented hydrogen production curve, the model captures the nuanced performance characteristics of the electrolyzer. The variables $e_{t,s}$ and $z^h_{t,s}$ correspond to the linear segments of the production curve, allowing the optimization to select the most efficient operating point within each segment.

This integration ensures that the optimization accounts for the varying efficiencies and production rates at different operating points, reflecting the real-world behavior of the electrolyzer. It enables the model to make informed decisions about when and how much hydrogen to produce, considering both economic and technical factors.

4.3.8. Implementation and Solution Approach

The optimization problem is implemented using the JuMP package in Julia, which provides a high-level, user-friendly interface for mathematical optimization modeling. The Gurobi optimizer is employed to solve the MILP problem efficiently, leveraging advanced algorithms designed for mixed-integer linear problems.

The implementation process involves defining the decision variables, parameters, objective function, and constraints as per the mathematical formulation. Input data such as wind power generation profiles, electricity prices, and hydrogen demand are integrated into the model. The solver then processes the MILP formulation to find the optimal values of the decision variables that maximize the objective function while satisfying all constraints.

By using MILP and a powerful solver like Gurobi, the model can handle the complexity arising from binary variables and piecewise linear relationships, providing high-quality solutions within reasonable computational times.

4.3.9. Insights from the Optimization Model

Solving the optimization problem yields valuable insights into the optimal operation of the hybrid energy system. The model determines the optimal scheduling of the electrolyzer, including when to produce hydrogen, when to remain in standby, and when to shut down. It identifies the best times to utilize wind power for hydrogen production versus selling electricity to the grid, based on market prices and demand.

The model also provides strategies for managing hydrogen storage, indicating when to store excess production and when to draw from storage to meet demand. It quantifies the impact of startup costs and operational constraints on profitability, highlighting the importance of operational flexibility and efficient equipment utilization.

These insights inform decision-making for system operators, enabling them to optimize economic returns while maintaining reliable and sustainable operations. The model serves as a valuable tool for planning and operational optimization in the context of renewable energy integration and green hydrogen production.

4.4. Implementation of Rolling Horizon Optimization

Building upon the original optimization model, which considered the entire simulation period in a single run, we recognized the need for a more dynamic approach that could adapt to changing conditions over time. To address this, we modified the model to employ a rolling horizon optimization framework. This section details the changes made to the original model, explains how the rolling horizon approach functions, and highlights the importance of these modifications.

4.4.1. Motivation for the Rolling Horizon Approach

In the original model, the optimization was performed over the entire period (e.g., one year), assuming perfect foresight of all future events. While this provided a comprehensive solution, it lacked flexibility in adapting to real-time changes in system states and external variables such as electricity prices, wind power generation, and hydrogen demand. Moreover, sudden fluctuations or unforeseen events could not be accounted for, potentially leading to suboptimal or impractical operational strategies.

To enhance the model's adaptability and more accurately reflect real-world operations, we introduced a rolling horizon approach. This method allows the model to update incurred degradation in between optimization runs.

4.4.2. Modifications to the Optimization Model

To implement the rolling horizon framework, several key changes were made to the original optimization model:

Division of the Simulation Period

The total simulation period is divided into multiple smaller horizons. Each horizon consists of:

- **Look-Back Period**: A specified number of past hours (e.g., 20 days) to inform the initial state of the current horizon.
- **Optimization Horizon**: The current period over which the optimization is performed (e.g., one day).
- **Look-Ahead Period**: A future period (e.g., 20 days) included in the optimization to anticipate upcoming events and make proactive decisions.

This structure allows the model to consider past states and future expectations when optimizing current decisions.

Iterative Optimization Process

The optimization is executed iteratively for each horizon:

1. **Initialization**: State variables such as the state of charge (SOC) and the electrolyzer's operational status are set based on the final states from the previous horizon.
2. **Data Slicing**: Relevant data arrays (e.g., electricity prices, wind power generation) are extracted for the current horizon.
3. **Optimization**: The model optimizes over the current horizon, considering the initial state and horizon-specific constraints.
4. **State Update**: After optimization, state variables are updated to reflect the end states of the current horizon, serving as initial conditions for the next horizon.
5. **Result Aggregation**: Results from each horizon are collected to form the complete solution over the entire simulation period.

Adjustment of Constraints and Variables

Constraints and variables were adjusted to align with the rolling horizon framework:

- **Time Indexing**: All time-dependent variables and constraints are indexed over the current horizon rather than the entire simulation period.
- **State Variable Continuity**: Variables representing the electrolyzer's operational states and the SOC are updated between horizons to ensure continuity.

- **Demand Fulfillment**: Demand constraints are enforced over appropriate time intervals within each horizon, accounting for partial periods if necessary.
- **Initial Conditions**: The model incorporates initial conditions for variables at the start of each horizon based on updated state variables.

4.5. Incorporation of Degradation into the Optimization Model

Building upon the rolling horizon optimization framework, we further enhance the model by incorporating degradation effects on the electrolyzer's performance. This integration simulates the gradual decline in efficiency and capacity over time due to operational stressors. In this section, we explain how degradation is incorporated into the model, why the rolling horizon approach is necessary, and outline the key modifications made to the optimization process.

4.5.1. Motivation for Incorporating Degradation

In real-world operations, electrolyzers experience performance degradation due to factors such as start-stop cycles, cumulative operating hours, and power fluctuations. Ignoring these effects can lead to overly optimistic performance estimates and suboptimal operational strategies. By modeling degradation, we aim to:

- **Reflect Realistic Performance**: Accurately represent the declining efficiency and capacity over time.
- **Optimize Operational Decisions**: Adjust strategies to account for degradation, potentially extending system lifespan and improving economic returns.
- **Plan Maintenance Activities**: Identify optimal times for maintenance or component replacement based on the degradation state.

4.5.2. Modifications to the Optimization Model

To incorporate degradation, we introduce a degradation factor that adjusts the electrolyzer's hydrogen production curve. This factor represents the cumulative effect of degradation on performance and is updated iteratively within the rolling horizon framework.

Introduction of the Degradation Factor

The degradation factor, denoted as deg_factor, starts at an initial value of 1.0 (no degradation) and decreases over time as degradation accumulates. It simulates efficiency loss due to operational stress, resulting in reduced hydrogen production for a given power input. The hydrogen production M is adjusted as:

$$M = \text{deg\_factor} \times M_{\text{H}_2,\,\text{original}}$$

where $M_{\text{H}_2,\,\text{original}}$ is the hydrogen production without degradation.

Updating the Hydrogen Production Curve

At the beginning of each optimization horizon, the hydrogen production curve is recalculated using the current degradation factor. This effectively shifts the production curve downward, simulating reduced hydrogen output due to degradation caused by dynamic power inputs. Figure 4.11 illustrates the original and shifted hydrogen production curves.

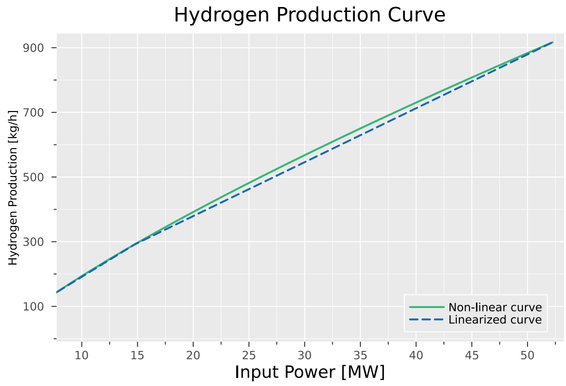

Figure 4.9: Non-linear hydrogen production curve without degradation

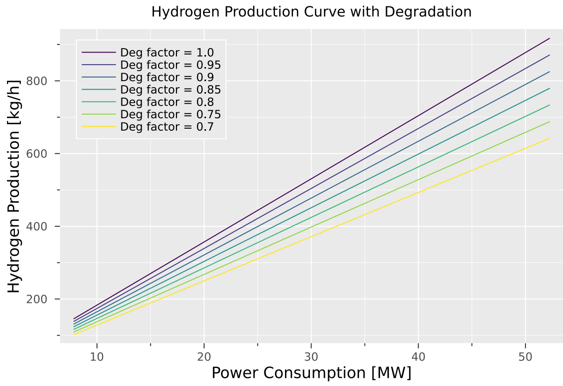

Figure 4.10: Shifted hydrogen production curve with degradation

Figure 4.11: Effect of degradation on the hydrogen production curve

By updating the production curve, the model ensures that operational decisions are based on the current performance level of the electrolyzer, accounting for efficiency losses over time.

Calculation of Degradation Metrics

Within each optimization horizon, we calculate incremental degradation based on three primary factors:

1. Start-Stop Cycles The number of start-stop cycles (N_{ss}) contributes to degradation. The incremental degradation from start-stop cycles is:

$$\Delta D_{\text{ss}} = N_{\text{ss}} \times d_{\text{ss}}$$

where d_{ss} is the degradation increment per start-stop cycle.

2. Cumulative Operating Hours Operating hours (H_{op}) also contribute to degradation. The incremental degradation from operating hours is:

$$\Delta D_{\text{oh}} = H_{\text{op}} \times d_{\text{oh}}$$

where d_{oh} is the degradation increment per operating hour.

3. Power Fluctuations Frequent power changes can accelerate degradation. The total power fluctuation (ΔP) is the sum of absolute differences in power input between consecutive time steps:

$$\Delta P = \sum_{t=2}^{T} |P_{\text{el}}(t) - P_{\text{el}}(t-1)|$$

The incremental degradation from power fluctuations is:

$$\Delta D_{\text{pf}} = \Delta P \times d_{\text{pf}}$$

where d_{pf} is the degradation increment per unit of power change.

Updating the Cumulative Degradation and Degradation Factor

The total incremental degradation for the horizon is:

$$\Delta D_{\text{total}} = \Delta D_{\text{ss}} + \Delta D_{\text{oh}} + \Delta D_{\text{pf}}$$

The cumulative degradation is updated:

$$D_{\text{cumulative}} = D_{\text{cumulative}} + \Delta D_{\text{total}}$$

To ensure the degradation factor does not fall below a minimum allowable performance level ($\text{deg\_factor}_{\text{min}}$), we cap the cumulative degradation:

$$D_{\text{cumulative}} = \min(D_{\text{cumulative}}, 1.0 - \text{deg\_factor}_{\text{min}})$$

The degradation factor is then:

$$\text{deg\_factor} = 1.0 - D_{\text{cumulative}}$$

Integration into the Rolling Horizon Framework

The rolling horizon approach is essential for incorporating degradation because it allows iterative updates of the degradation state and adjusts operational decisions accordingly. At the beginning of each horizon, we:

1. **Recalculate the Production Curve**: Adjust the hydrogen production curve using the current deg_factor, reflecting efficiency loss.
2. **Optimize with Updated Parameters**: Solve the optimization problem using the degradation-adjusted production curve.
3. **Update Degradation Metrics**: Post-optimization, calculate the incremental degradation and update $D_{\text{cumulative}}$ and deg_factor for the next horizon.

4.5.3. Necessity of the Rolling Horizon Approach

Incorporating degradation requires the model to consider the impact of past operations on current performance and future decisions. The rolling horizon approach is necessary because:

- **Temporal Dependency**: Degradation accumulates over time, affecting future performance. The model must update the degradation state iteratively.
- **Dynamic Adaptation**: Operational strategies need to adjust based on the current degradation state to optimize performance and longevity.
- **Computational Feasibility**: Optimizing the entire simulation period with degradation is computationally intensive. Rolling horizons break the problem into manageable segments.

Without the rolling horizon framework, accurately modeling the time-dependent nature of degradation and its impact on system performance would be challenging.

4.5.4. Summary of the Degradation Incorporation Process

The process of incorporating degradation involves:

1. **Initialization**: Set $\text{deg\_factor} = 1.0$ and $D_{\text{cumulative}} = 0.0$.
2. **Adjustment of Production Curve**: At each horizon's start, update the hydrogen production curve with the current deg_factor.
3. **Optimization**: Solve the optimization problem with the degradation-adjusted parameters.
4. **Degradation Calculation**: Post-optimization, compute incremental degradation based on operational factors.

5. **State Update**: Update $D_{\text{cumulative}}$ and deg_factor for the next horizon.

By integrating degradation into the rolling horizon optimization model, we enhance its realism and ability to generate operational strategies that account for the electrolyzer's performance decline over time.

4.6. Incorporating Degradation Through Voltage Increase

Previously, we approximated degradation by directly scaling down the hydrogen production curve. Although this was conceptually simple, it did not fully capture the underlying electrochemical effects of degradation on the electrolyzer. In reality, degradation manifests as an increase in cell voltage (overpotential) for a given current density, rather than merely reducing hydrogen output at the same power input.

This section explains how we refined our approach by modeling degradation as an increase in cell voltage within the rolling horizon optimization framework. By linking degradation to physical electrochemical parametersspecifically the cell overpotentialwe achieve a more accurate representation of how efficiency and hydrogen production are affected over time.

4.6.1. Voltage-Based Degradation Modeling

Degradation in an electrolyzer typically leads to higher overpotentials. In other words, the cell requires a greater voltage to drive the same current density as it degrades. This increased cell voltage means more electrical energy is consumed to produce the same amount of hydrogen, effectively lowering the systems efficiency. By incorporating an additive degradation term into the cell voltage calculation, we directly capture the reduction in efficiency due to physical wear and tear, catalyst deterioration, membrane thinning, and dynamic operational stresses.

This voltage-based method stands in contrast to simply shifting the hydrogen production curve downward. The latter approach can underestimate efficiency losses and misrepresent operational decisions because it does not reflect the increased electrical effort needed at the cell level. By adjusting the cell voltage, the model naturally shows how degradation demands more power for the same hydrogen output, offering a more authentic picture of how performance degrades over time.

4.6.2. Implementation in the Rolling Horizon Model

In the rolling horizon approach, the model is solved iteratively over smaller time windows. At the start of each horizon, we:

1. **Update the Degradation State:** Using historical indicatorssuch as cumulative operating hours, number of start-stop cycles, and frequency of rapid power changesthe model computes how much the degradation voltage term should increase. These indicators are based on literature-supported relationships that link dynamic stressors to increased overpotential.
2. **Recalculate Cell Voltage:** The cell voltage U_{cell} is adjusted to:

$$\boxed{U_{\text{cell}}(i, T, p) = U_{\text{rev}}(T) + \eta_{\text{over}}(i, T, p) + V_{\text{deg}}}$$

   where V_{deg} is the degradation-related voltage increment. This increment grows as the electrolyzer endures more dynamic operations and accumulative stress.
3. **Re-derive the Production Curve:** With the updated cell voltage, we re-solve for the current densities corresponding to different power levels. This step ensures that the production curve reflects not just a uniform scaling but a fundamental change in the electrochemical efficiency. We use a numerical root-finding process (via a Python function called from Julia) to determine the current density for each power input, considering the higher overpotential.

Once the updated production curve and cell efficiency are known, the optimization problem is solved again for the next horizon. Over successive horizons, the model continuously adapts to the evolving degradation state, accurately capturing how operating decisions (e.g., avoiding frequent start-stops or large power ramps) can mitigate future efficiency losses.

4.6.3. Chosen Indicators and Their Influence on Voltage

We do not rely on a single degradation factor. Instead, we accumulate V_{deg} based on specific operating conditions known to cause degradation:

1. **Operating Hours:** Longer operating hours at high current densities can gradually weaken catalyst layers and membranes. We increase V_{deg} proportionally to total operating hours.

2. **Start-Stop Cycles:** Frequent turning on and off creates thermal and mechanical stresses. Each start-stop cycle adds a fixed voltage increment:

$$V_{\text{deg}} \leftarrow V_{\text{deg}} + \beta_{\text{ss}} \cdot n_{\text{cycles}},$$

where β_{ss} is the voltage increment per cycle and n_{cycles} is the number of new start-stop events in the period.

3. **Partial Load Operation:** Running at low loads can cause uneven current distribution and bubbles on electrodes, accelerating wear. For each hour of partial load operation, we add a small voltage increment:

$$V_{\text{deg}} \leftarrow V_{\text{deg}} + \beta_{\text{pl}} \cdot t_{\text{partial}},$$

where t_{partial} is the total partial-load hours during the horizon.

4. **Power Fluctuations (Ramping):** Rapid changes in input power (ramps) increase stress on the system. If we detect large ramping events, we increment V_{deg}:

$$V_{\text{deg}} \leftarrow V_{\text{deg}} + \beta_{\text{pf}} \cdot n_{\text{events}},$$

where n_{events} is the count of power changes above a certain threshold.

Each of these indicators is based on findings in the literature that link dynamic conditions to increased overpotential. By adding up their contributions, we ensure V_{deg} reflects the electrolyzer's actual operating history.

4.6.4. Integration into the Rolling Horizon Approach

The rolling horizon approach allows us to update V_{deg} at the start of each horizon:

1. **Compute New V_{deg}:** Based on the previous horizon's datahours operated, number of start-stops, partial load durations, and power rampswe add the corresponding increments to V_{deg}.
2. **Recalculate the Production Curve:** With the new V_{deg}, the cell voltage increases. We then solve for current densities and hydrogen production again:

$$P_{\text{cell}} = i \times A_{\text{cell}} \times U_{\text{cell}}(i, T, p),$$

where U_{cell} now includes V_{deg}.

3. **Re-Optimize:** Using this updated curve, the model determines the optimal strategy for the next horizon, considering the now less efficient electrolyzer.

4.6.5. Comparison to Direct Production Curve Shifts

Figure 4.12 and Figure 4.13 illustrate the new approach. Instead of just lowering the hydrogen output at a given power, the required power for a certain hydrogen production level increases as degradation sets in. The result is a less steep apparent downward shift in production per power input, but a more realistic representation of increased power consumption for the same hydrogen output.

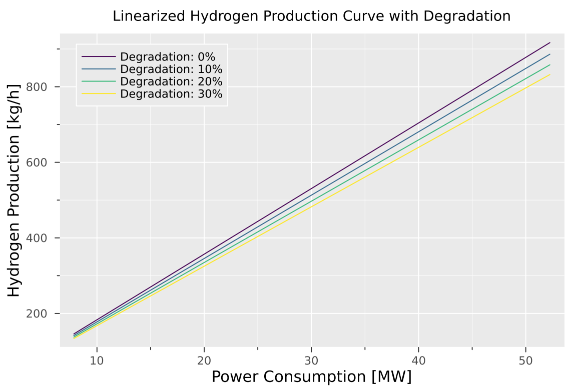

Figure 4.12: Effect of degradation on the hydrogen production curve

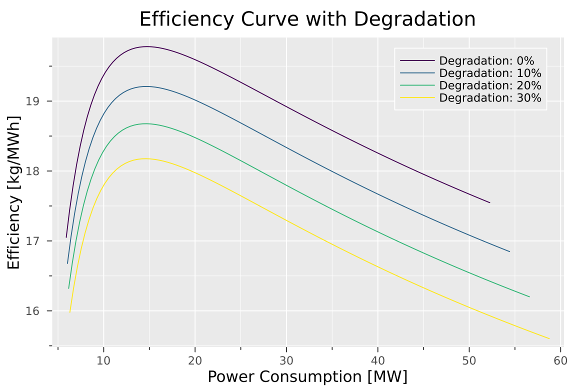

Figure 4.13: Effect of degradation on the efficiency curve

In essence, the voltage-based approach aligns more closely with physical principles: as degradation accumulates, the electrolyzer does not simply produce less hydrogen at the same powerit must consume more power to maintain the same hydrogen production, or equivalently, it achieves less hydrogen per unit of power, reflecting lower efficiency.

4.6.6. Supporting Literature and Dynamic Indicators

This voltage-increase method is grounded in studies linking operational stressors to overpotential growth. Literature indicates that frequent cycling, partial-load operation, and rapid load changes accelerate degradation mechanisms such as catalyst loss and membrane wear. By translating these dynamic indicators into incremental voltage terms, we ensure the models degradation representation aligns with empirically observed phenomena.

4.6.7. Summary

By incorporating degradation through a voltage increase, we achieve a physically grounded and dynamic model of electrolyzer performance over time. The rolling horizon framework allows us to continuously adjust for the evolving degradation state, ensuring that operational strategies reflect both immediate economic opportunities and the long-term goal of maintaining efficiency. Compared to the direct curve-shift method, this approach provides a more realistic depiction of how dynamic operational inputs drive actual electrochemical degradation and efficiency losses.

4.7. Incorporation of Hydrogen Support Mechanisms

Building upon the enhanced model that accounts for degradation, we further extend the optimization framework to incorporate the effects of hydrogen support mechanisms, such as subsidies or premiums provided by entities like the European Hydrogen Bank. These mechanisms are designed to promote the production and adoption of hydrogen by providing financial incentives to producers. In this section, we explain how to model the impact of such support mechanisms, specifically focusing on how a price premium on hydrogen can be integrated into the existing optimization model.

4.7.1. Modeling Hydrogen Price Premiums

The European Hydrogen Bank aims to stimulate the hydrogen market by offering a premium on the price received for hydrogen produced using renewable energy sources. This premium effectively increases the revenue per unit of hydrogen sold, thereby improving the economic viability of hydrogen production projects. To model this effect, we adjust the hydrogen price parameter in the optimization model to reflect the additional income from the premium.

Let us denote the original hydrogen price as λ_{H} and the premium provided by the support mechanism as λ_{premium}. The effective hydrogen price received by the producer becomes:

$$\lambda_{\text{H, effective}} = \lambda_{\text{H}} + \lambda_{\text{premium}}$$

This adjusted hydrogen price directly influences the revenue term in the objective function of the optimization model.

4.7.2. Integration into the Optimization Model

The objective function of the optimization model aims to maximize the total profit over the optimization horizon. It includes revenue from hydrogen sales, revenue from electricity sales, costs of electricity purchases, startup costs, and other operational expenses. By incorporating the hydrogen price premium, the revenue from hydrogen sales is increased accordingly.

The updated objective function becomes:

$$\max \sum_{t \in T} \left(m_t \lambda_{\text{M},t} + d_t \lambda_{\text{H, effective}} - m_{\text{in},t} \lambda_{\text{M, in},t} - z_{\text{start},t} \lambda_{\text{start}} \right)$$

where m_t is the electricity sold to the market at time t, $\lambda_{\text{M},t}$ is the electricity market price at time t, d_t is the hydrogen sold at time t, $\lambda_{\text{H, effective}}$ is the adjusted hydrogen price including the premium, $m_{\text{in},t}$ is the electricity purchased from the grid at time t, $\lambda_{\text{M, in},t}$ is the electricity purchase price at time t, $z_{\text{start},t}$ is the startup indicator variable at time t, and λ_{start} is the startup cost.

By increasing $\lambda_{\text{H, effective}}$, the model is incentivized to produce and sell more hydrogen when it is economically favorable, considering the additional revenue from the premium.

4.7.3. Impact on Operational Decisions

The inclusion of the hydrogen price premium affects the operational decisions made by the optimization model. It may lead to increased hydrogen production during periods when the premium makes hydrogen sales more profitable than electricity sales. The scheduling of the electrolyzer operation may be adjusted to maximize hydrogen output when electricity prices are low and the premium enhances profitability. Additionally, the utilization of storage facilities may change to balance hydrogen production and sales in response to market conditions and the premium. These adjustments aim to capitalize on the financial incentives provided by the support mechanism, thereby improving the overall economic performance of the system.

4.7.4. Considerations for Implementation

When integrating the hydrogen price premium into the model, it is important to consider several aspects. The premium offered by the support mechanism may vary over time or be subject to certain conditions. If the premium is time-dependent or contingent on meeting specific criteria, the model must be adjusted to reflect these factors, possibly defining $\lambda_{\text{premium},t}$ as a time-dependent parameter. Support mechanisms often come with regulatory requirements or constraints that need to be modeled. These may include caps on the total premium received, reporting obligations, or penalties for non-compliance. Incorporating these constraints ensures that the optimization results are compliant with the relevant policies. Moreover, the introduction of a hydrogen price premium can influence market dynamics, potentially affecting electricity prices, demand patterns, and competition. While modeling these broader market effects may be beyond the scope of the current model, it is important to acknowledge their potential impact on the system's operation.

4.7.5. Simulation Results

By applying the adjusted model with the hydrogen price premium, we can assess the impact of the support mechanism on the system's performance. The simulation results may show an increase in total hydrogen production and sales revenue, improved profitability due to the additional income from the premium, and changes in the operational schedule of the electrolyzer and storage utilization. These outcomes provide valuable insights into the effectiveness of the support mechanism and its influence on the operational strategies of hydrogen producers.

4.7.6. Conclusion

Incorporating hydrogen support mechanisms, such as the price premium from the European Hydrogen Bank, into the optimization model enhances its ability to simulate real-world economic conditions and policy incentives. By adjusting the hydrogen price parameter, the model captures the financial benefits provided by the support mechanism, allowing for more informed decision-making and strategic planning. This integration is crucial for evaluating the viability of hydrogen production projects under different policy scenarios and contributes to a better understanding of how support mechanisms can drive the adoption of renewable hydrogen technologies.

5 Results and Discussion

In this chapter, we present the results of our optimization models under various scenarios to address the research questions outlined earlier. We begin by validating the original optimization model using the rolling horizon approach to ensure its reliability over extended periods. This validation is crucial to establish confidence in the model's ability to simulate real-world operations effectively.

Subsequently, we examine the scheduling decisions of the model without considering degradation and compare them with the outcomes when degradation is incorporated. This comparison sheds light on the impact of degradation on the operational strategies and overall system performance, highlighting the importance of accounting for degradation in long-term planning.

We then explore the effects of hydrogen support mechanisms by introducing a price premium into the model. This scenario simulates the influence of financial incentives, such as those provided by the European Hydrogen Bank, on hydrogen production profitability and scheduling decisions. Understanding this impact is essential for evaluating the effectiveness of policy instruments designed to promote green hydrogen production.

Finally, we combine the degradation modeling with the hydrogen price premium to assess how these factors interact and influence the system's performance. This comprehensive analysis provides insights into the optimal operational strategies under varying economic and technical conditions.

The findings from these scenarios are analyzed to provide a deeper understanding of the electrolyzer's operational behavior and the economic viability of hydrogen production under different circumstances.

5.1. Results of Case Study (Base-scenario)

To evaluate the performance of the optimization model and gain insights into the operational strategies of the hybrid energy system, simulations were conducted over a one-year period. The hydrogen production curve was linearized using two segments to balance accuracy and computational efficiency. These adjustments ensure a realistic representation of system behavior while maintaining manageable computational complexity. The results are summarized in Figure 5.1, which presents six key operational variables over time. The plots include the state of charge (SOC) of the hydrogen storage system, hydrogen production rates, electricity transactions (both bought and sold), electricity market prices, and hydrogen sales. This comprehensive visualization provides a detailed understanding of the system's operational dynamics throughout the year.

5.2. Case study of original operational model

Figure 5.1: Operational results from the one-year simulation. The plots show (from top left to bottom right) the state of charge of hydrogen storage, hydrogen production, electricity bought in SB-mode, electricity sold, electricity price, and hydrogen sold.

The state of charge plot reveals the dynamic usage of the hydrogen storage system, with periods of high SOC indicating effective storage of excess hydrogen for later use. Hydrogen production closely follows periods of abundant renewable electricity, while electricity buying and selling reflect the system's responsiveness to market prices.

In addition to operational insights, Table 5.1 provides key numerical results from the optimization model. These include the objective value, revenue contributions, electricity costs, startup costs, and the maximum SOC achieved by the hydrogen storage system.

Metric	Value
Objective Value	€38,166,958.01
Electricity Revenue	€35,325,258.96
Hydrogen Revenue	€2,923,489.68
Electricity Cost	€803.10
Startup Cost	€80,987.50
Max SOC	22,003.94

Table 5.1: Key numerical results from the one-year optimization, 2 segments, hydrogen price 2.1

The objective value of €38.17 million represents the total profit achieved over the simulation period. This profit is derived from two primary revenue streams: electricity sales and hydrogen sales. Electricity sales contributed the majority, generating €35.33 million, which accounts for approximately 92.6% of total revenue. Hydrogen sales generated an additional €2.92 million, accounting for 7.4% of total revenue.

The substantial electricity revenue demonstrates the system's ability to capitalize on high electricity prices by selling surplus renewable electricity. Conversely, hydrogen production is prioritized during periods of low electricity prices, optimizing cost-effective operations. This balance ensures maximum economic returns while leveraging renewable energy sources effectively.

The electricity cost of €803.10 and startup cost of €80,987.50 indicate minimal operating expenses relative to the revenue streams, further highlighting the efficiency of the model. The hydrogen storage system's maximum SOC of 22,003.94 kg showcases its capacity to buffer production and demand effectively. This enables consistent hydrogen supply even during periods of reduced production, reflecting the robustness and flexibility of the system.

In summary, these results highlight the optimization model's success in maximizing economic performance. By dynamically responding to market conditions and efficiently utilizing storage and production capabilities, the system demonstrates the potential for sustainable and profitable operation of hybrid energy systems. This study underscores the feasibility and economic viability of integrating renewable energy sources and green hydrogen production in modern energy systems.

5.3. Scenario structure

- **Validation of the Original Optimization Model**: We validate the model using the rolling horizon approach, comparing its outputs with expected results to ensure accuracy.
- **Impact of Degradation on Scheduling Decisions**: We analyze the differences in scheduling and performance metrics when degradation is considered versus when it is ignored.
- **Effects of Hydrogen Support Mechanisms**: We assess how the introduction of a hydrogen price premium affects operational decisions and profitability.
- **Combined Effects of Degradation and Support Mechanisms**: We examine the interplay between degradation and the price premium, evaluating their combined impact on system performance.
- **Discussion**: We discuss the implications of the results in relation to the research questions, providing interpretations and insights derived from the analysis.

Each section delves into the specific scenario, presenting the results and providing analysis to understand the underlying factors influencing the outcomes.

5.4. Validation of the Original Optimization Model

To validate that the rolling horizon optimization framework can replicate the performance of the original model, we conducted a verification experiment over a one-week simulation period. In this assessment, the original optimization modelrun over the entire week in a single stepwas compared against several rolling horizon scenarios with varying look-ahead (LA) periods. No look-back period was considered in this validation. By examining multiple look-ahead durations, we gain insight into how much foresight the rolling horizon model requires to approximate the globally optimized baseline.

The following scenarios were examined:

1. **Original Optimization**: The baseline scenario, optimizing the entire one-week horizon at once.
2. **Rolling Horizon (LA = 1 day)**: The model is re-optimized daily with a 1-day look-ahead, offering limited foresight.
3. **Rolling Horizon (LA = 3 days)**: The model now plans three days ahead, providing more insight into future conditions than the 1-day scenario.

4. **Rolling Horizon (LA = 7 days)**: Extending the look-ahead to a full week should closely approximate the conditions considered by the original optimization.
5. **Rolling Horizon (LA = 11 days) and (LA = 14 days)**: These scenarios assume even greater foresight than the original single-run model, potentially enabling the rolling horizon approach to match or exceed the original performance.

Table 5.2 presents the objective values and key revenue and cost components for each scenario, with values formatted neatly. The objective value represents total profit, computed as the sum of electricity (El.) and hydrogen (H_2) revenues minus electricity procurement and startup costs.

Scenario	Total Obj (EUR)	El. Revenue (EUR)	H_2 Revenue (EUR)	El. Cost (EUR)	Startup Cost (EUR)
Original	795,432.5	744,194.0	53,090.6	58.86	2,612.5
RH la=1d	775,448.0	717,748.0	62,925.1	0.00	5,225.0
RH la=3d	790,179.5	738,255.0	57,149.1	0.00	5,225.0
RH la=7d	795,397.5	744,159.0	53,090.6	58.86	2,612.5
RH la=11d	795,397.5	744,159.0	53,090.6	58.86	2,612.5
RH la=14d	795,397.5	744,159.0	53,090.6	58.86	2,612.5

Table 5.2: Scenario comparison with values neatly formatted.

From Table 5.2, it is evident that shorter look-ahead horizons limit the models ability to plan effectively. When the look-ahead is only one day, the rolling horizon approach yields a lower total objective value and incurs higher startup costs compared to the original optimization. With a 3-day look-ahead, performance improves, but the model still does not fully match the original scenario.

Notably, once the look-ahead period reaches about a week (7 days) or longer, the rolling horizon models outcomes become nearly indistinguishable from the original optimization's results. In these scenarios (7, 11, and 14 days), both the total objective value and the cost-revenue balance align closely with the baseline. This indicates that providing the rolling horizon method with sufficient foresight allows it to approach the globally optimized solution.

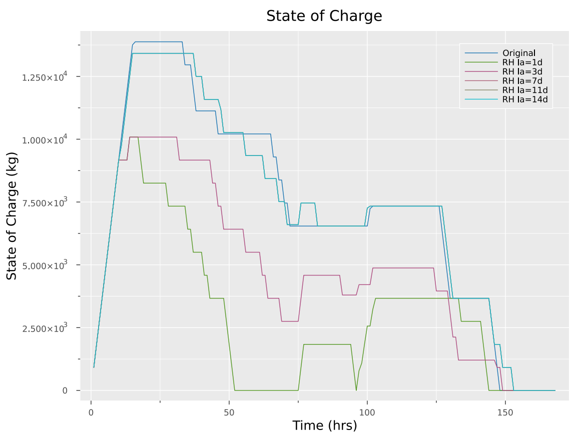

Figure 5.2: State of Charge (SOC) comparison between original and rolling horizon scenarios.

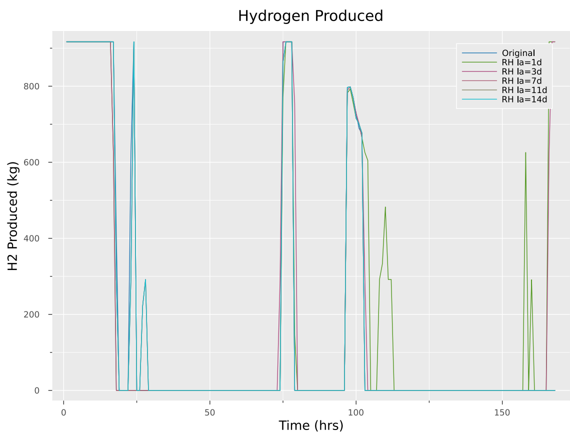

Figure 5.3: Hydrogen Production during the first week for original and rolling horizon scenarios.

Figures 5.2 and 5.3 further illustrate this behavior. With very short look-ahead horizons (e.g., 1 day), both the SOC and hydrogen production patterns deviate significantly from the original solution. As the look-ahead increases (3 days, and eventually 7 days or more), these discrepancies diminish. By the time the look-ahead period equals or exceeds the full optimization horizon (7 days), the rolling horizon models operation closely mirrors the original outcome, demonstrating that adequate foresight is crucial.

In summary, this validation shows that the rolling horizon optimization can effectively replicate the original models decisions and profitability if provided with a sufficiently long look-ahead horizon.

Short look-ahead periods result in suboptimal adjustments and reduced profits, but as the horizon extends, performance converges to the global optimum. This finding lays a solid foundation for applying the rolling horizon approach in more complex scenarios, such as when integrating dynamic power input-driven degradation effects into the optimization model.

5.5. Impact of Degradation on Scheduling Decisions

In this section, we present the results of scheduling decisions obtained from the rolling horizon optimization framework when coupled with two degradation modeling approaches. These approaches are used to evaluate the system's ability to incorporate degradation into operational planning effectively. The aim is twofold: to verify the correctness of the implementation and to assess the implications of degradation on operational efficiency and hydrogen production scheduling.

Degradation Model 1: Simplified Hydrogen Production Shift

To explore how degradation can be included in the rolling horizon model, we adopted a simple approach that directly adjusts the hydrogen production curve. This method mainly checks whether the model can handle gradually declining performance rather than providing exact physical accuracy.

The concept is to use a "degradation factor" that scales down the hydrogen production potential over time. Instead of detailed electrochemical modeling, we simply apply a uniform reduction to the coefficients (a and b) that define the piecewise linear production curve. We start with a factor of one, meaning no loss in efficiency. As the model runs from day to day, it monitors key operational features like how often the electrolyzer starts and stops, how long it runs at partial load, and how much the power input changes. Each of these factors adds up to some measure of degradation.

The degradation factor is then updated by adding small, arbitrarily chosen increments tied to these operational indicators. Since we do not yet have a precise, literature-based formula connecting dynamic power inputs to efficiency drops, these increments are meant as a simple stand-in. This way, the model simulates a general decline in hydrogen output without needing complex data.

Over a full year, this degradation factor slowly moves below one, meaning the electrolyzer produces less hydrogen than before. Tracking the number of start-stop cycles provides a direct count of how operational patterns might speed up this artificial degradation.

In summary, this direct scaling approach is a practical test. It shows that the rolling horizon optimization can adapt to a gradually decreasing hydrogen production capability and still run smoothly. While refining the actual degradation relationships remains a future task, this framework is flexible enough to incorporate efficiency losses once more realistic data become available.

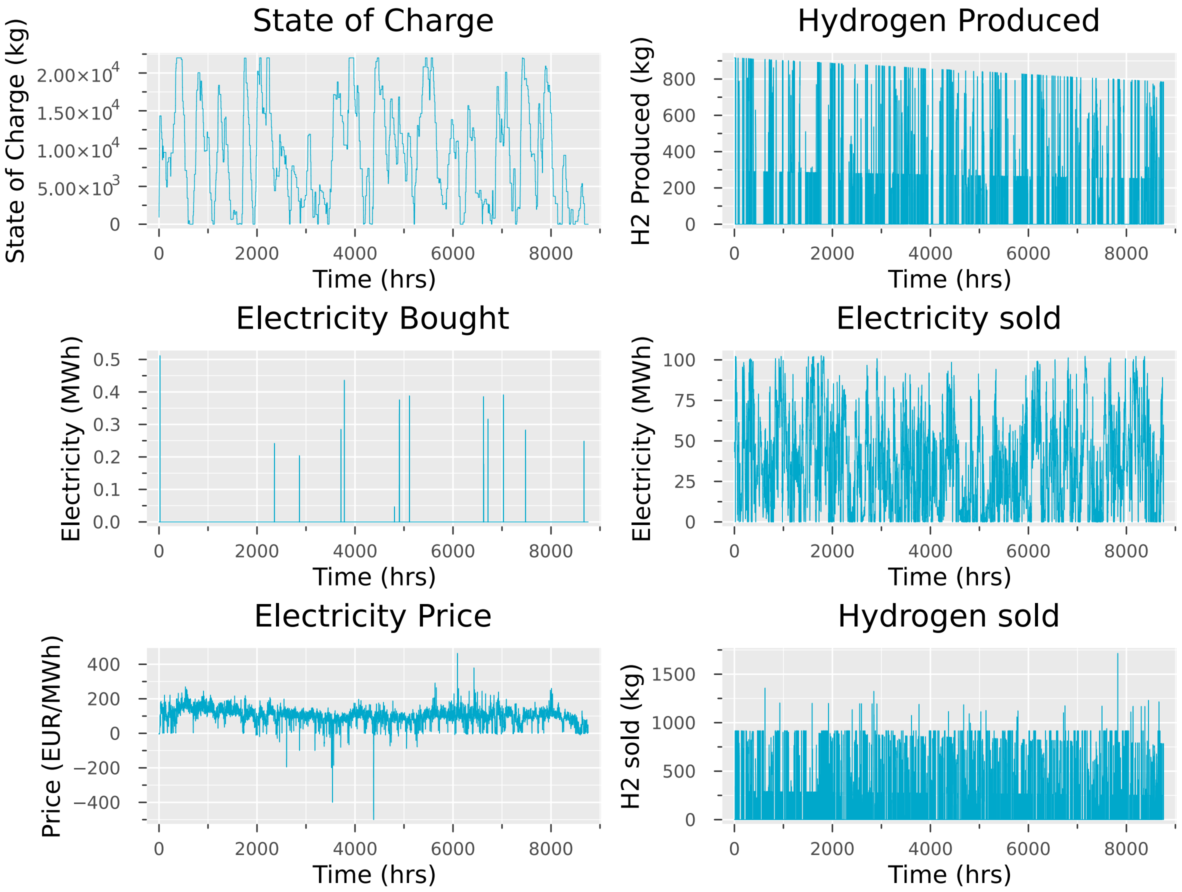

Figure 5.4: Time-series evolution of key system metrics over the one-year rolling horizon simulation with a direct degradation factor applied. From left to right, top to bottom: State of Charge of hydrogen storage, hourly hydrogen production rates, electricity purchases from the grid, electricity sales, the fluctuating electricity price, and hydrogen sales. These plots illustrate how operational decisions and market conditions evolve as the system experiences incremental performance reductions in hydrogen output due to the imposed degradation factor. Look-ahead of 14 days

Metric	**Value**
Objective Value	€ 37,731,503.05
Electricity Revenue	€ 34,938,758.87
Hydrogen Revenue	€ 2,874,534.79
Electricity Cost	€ 803.10
Startup Cost	€ 80,987.50
Max SOC (kg)	22,003.94
Cumulative Degradation (%)	14.59
Final Degradation Factor	0.8541
Total Start-Stop Cycles	31.0

Table 5.3: Summary of key outcomes from the rolling horizon optimization with a simplified degradation model, including economic performance, storage utilization, and degradation-related metrics

Degradation Model 2: Cell Voltage Adjustment

In this section, the results from a year-long rolling horizon simulation are presented, where electrolyzer degradation is modeled as incremental increases in cell voltage. Instead of using traditional methods that reduce efficiency or impose fixed penalties, this approach ties degradation directly to physical changes in the electrolyzer, such as growing internal resistance. This gives a more realistic view of how performance declines over time.

The electrolyzer faces several stressors during operation, including long hours of use, frequent start-stop cycles, and fluctuating power inputs from renewable sources. These stressors lead to specific effects like catalyst degradation, membrane thinning, overheating, and uneven current distribution caused by bubble dynamics. Instead of treating these as abstract efficiency losses, they are represented as gradual increases in voltage, reflecting findings from studies on how PEM electrolyzers age.

Within the rolling horizon optimization, the model updates the cell voltage step by step based on recent operating conditions. Key factors include total operating hours, the number of start-stop events, time spent at partial load, and power fluctuations above a certain threshold. These factors are incorporated into the model using degradation rates based on experimental data. As the simulation progresses, rising voltage affects the system's production costs, prompting the model to adjust its hydrogen production schedules to balance profitability with the long-term health of the electrolyzer.

The results show how the system responds to rising production costs due to increasing voltage. Instead of pushing for high production that would worsen degradation, the model adapts by moderating output, reducing start-stop events, and smoothing power usage to limit harsh fluctuations. Over the year, this results in a more balanced and sustainable operational strategy that meets hydrogen demand while managing degradation effectively.

This method goes beyond simple models by integrating a physics-based degradation framework into the rolling horizon optimization. It reflects the real trade-offs that operators must navigate, showing how operational strategies can prolong the electrolyzers lifespan, slow voltage increases, and maintain economic value. The results emphasize the importance of adaptive decision-making in managing assets under variable market conditions and fluctuating renewable energy availability.

Rolling horizon with degradation model, realistic degradation values

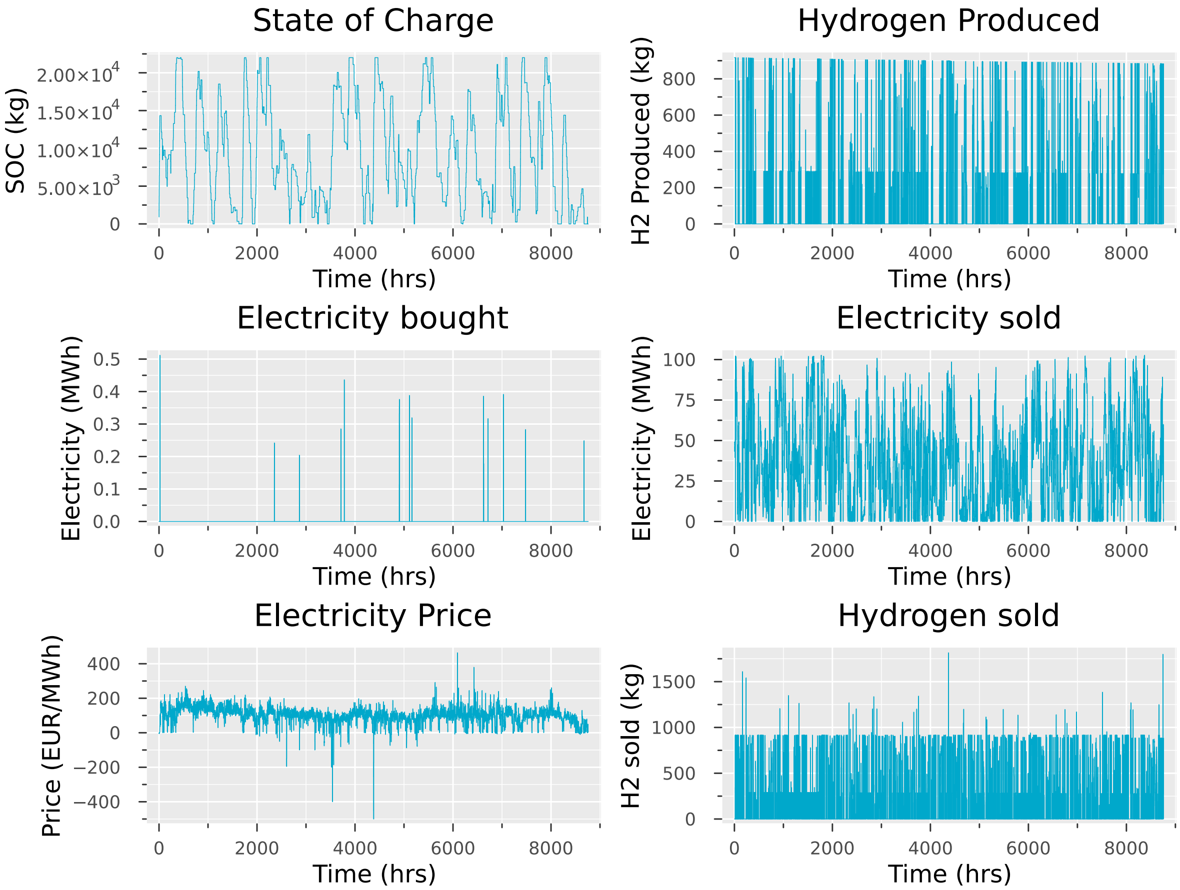

Figure 5.5: Time-series plots showing the operational dynamics of the hydrogen production system over a one-year rolling horizon simulation. The graphs illustrate key metrics, including the state of charge (SOC) of the hydrogen storage, hydrogen production rates, electricity transactions (bought and sold), electricity market prices, and hydrogen sales. These results reflect the system's behavior under dynamic loading conditions, incorporating degradation effects modeled as incremental increases in cell voltage, with a 14-day look-ahead optimization horizon.

Table 5.4: Time-series evolution of key system metrics over the one-year rolling horizon simulation with a degradation reflected as an increase in cell voltage leading indirectly to a downward shift of the hydrogen production curve. 14 day look ahead.

Metric	**Value**
Objective Value (€)	38,036,395.02
Electricity Revenue (€)	35,212,206.35
Hydrogen Revenue (€)	2,908,632.18
Electricity Cost (€)	843.50
Startup Cost (€)	83,600.00
Max SOC (kg)	22,003.94
Total Start-Stop Cycles	32.00
Total Partial Load Hours (hrs)	1,384.0
Total Normal Load Hours (hrs)	1,380.0
Total Power Events	71.0
Final Degradation Voltage (mV)	93.4

In this scenario, the rolling horizon optimization model runs for a full year (8,760 hours) with a 14-day look-ahead at each step. The electrolyzers cell voltage slowly increases over time due to different types of wear. Operating at normal load (above 30% capacity) adds about 8 V/h, while running at partial load (below 30%) adds about 15 V/h. Every start-stop cycle adds around 0.15 mV, and each large power jump above 40 MW adds 0.8 mV.

These numbers come from studies in the literature, giving a more realistic picture of how real electrolyzers degrade. As the cell voltage rises, making hydrogen costs more energy, so the model must adjust its plans. Instead of simply reducing hydrogen production as time goes on, this approach changes the cell voltage itself. By doing so, the model balances short-term gains against long-term health and efficiency of the electrolyzer.

Rolling horizon with degradation model and more severe degradation

In this additional scenario, the same rolling horizon optimization simulation was conducted for one year (8,760 hours) with a 14-day look-ahead at each step. However, the degradation rates for operating hours, start-stop cycles, and power fluctuations were doubled compared to the previous scenario to examine the effects of accelerated wear on system performance.

Doubling the degradation values results in a faster increase in the electrolyzers cell voltage over time, significantly impacting the cost and efficiency of hydrogen production. The model dynamically adjusts its operational strategies in response, re-optimizing hydrogen production schedules to balance short-term profitability with the need to mitigate the accelerated performance decline. This scenario highlights the sensitivity of operational planning to degradation rates and underscores the importance of proactive management to maintain system sustainability under harsher conditions.

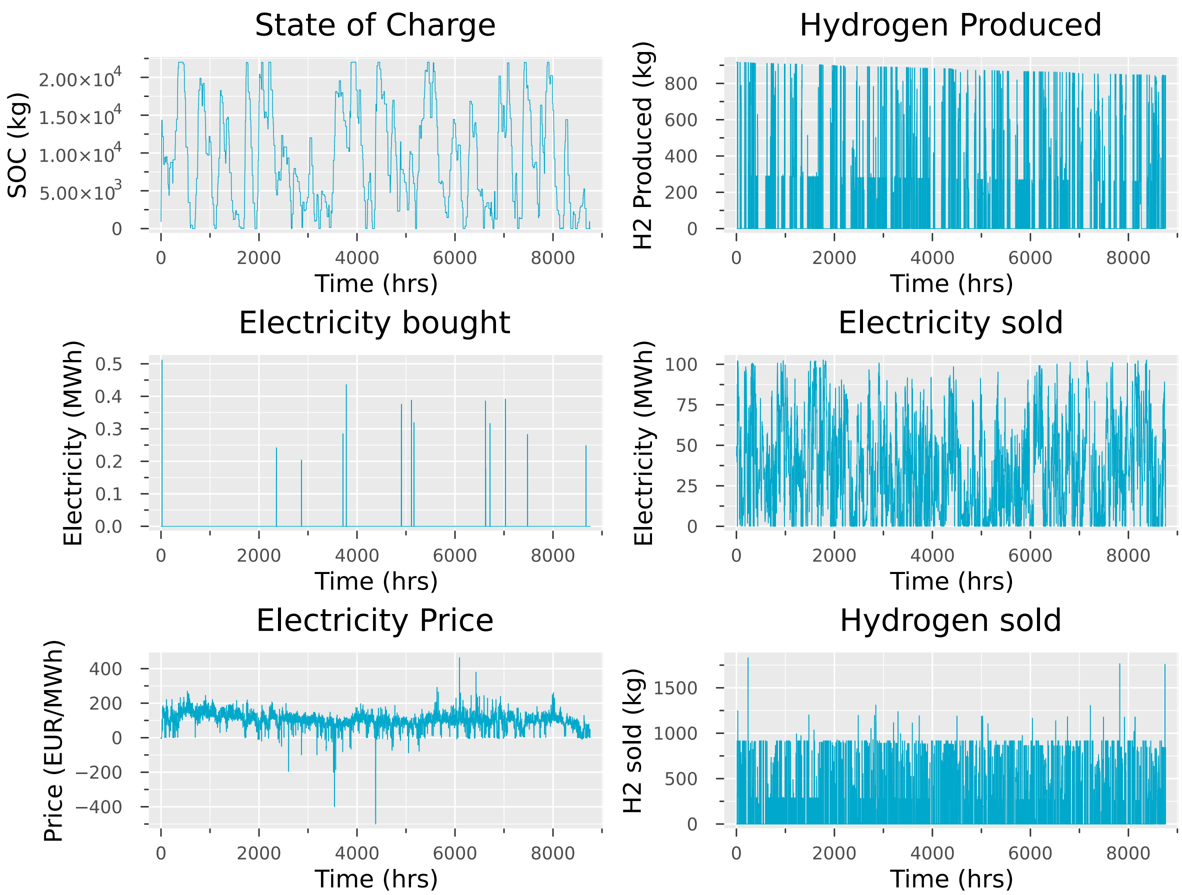

Figure 5.6: Time-series plots showing the operational dynamics of the hydrogen production system over a one-year rolling horizon simulation with double the degradation values

Table 5.5: Time-series evolution of key system metrics over the one-year rolling horizon simulation with a degradation reflected as an increase in cell voltage leading indirectly to a downward shift of the hydrogen production curve. 14 day look ahead

Metric	Value
Objective Value (€)	37,887,050.94
Electricity Revenue (€)	35,079,937.40
Hydrogen Revenue (€)	2,894,169.54
Electricity Cost (€)	843.50
Startup Cost (€)	86,212.50
Max SOC (kg)	22,003.94
Total Start-Stop Cycles	33.00
Total Partial Load Hours (hrs)	1,321.0
Total Normal Load Hours (hrs)	1,446.0
Total Power Events	84.0
Final Degradation Voltage (mV)	207.066

5.6. Effects of Hydrogen Support Mechanisms

In this section, we introduce a hydrogen support mechanism inspired by initiatives such as the European Hydrogen Bank (EHB). Instead of relying solely on market-based hydrogen prices, we supplement the electrolyzers hydrogen revenue with a fixed premium to reflect the added financial support that an EHB-like instrument could provide. For demonstration, we select a premium of 2 EUR/kg of hydrogen. This is a hypothetical value chosen to illustrate the potential impact of such a subsidy on the operations and profitability of a renewable-based hydrogen production system.

By incorporating this premium, the optimization model now perceives each kilogram of produced hydrogen as having additional guaranteed value on top of the baseline hydrogen price. The aim is to see how the electrolyzers dispatch strategy, hydrogen production rates, and overall economic performance evolve in response to this financial incentive. Since the electrolyzer can now earn more for each kilogram of hydrogen it sells, we might anticipate shifts toward higher utilization rates, especially during periods when previously marginal production might not have been economically attractive.

In the following results, we present the outcomes of running the rolling horizon optimization model with this 2 EUR/kg EHB premium. The model retains the same operational constraints and input data as before, except that the hydrogen revenue stream now includes the added premium. We will examine how the electrolyzers state-of-charge trajectory, hydrogen production profile, electricity trading patterns, and overall economic indicators are affected. This analysis helps highlight how policy interventions or support mechanisms can enhance the competitiveness and stability of green hydrogen production within integrated renewable energy systems.

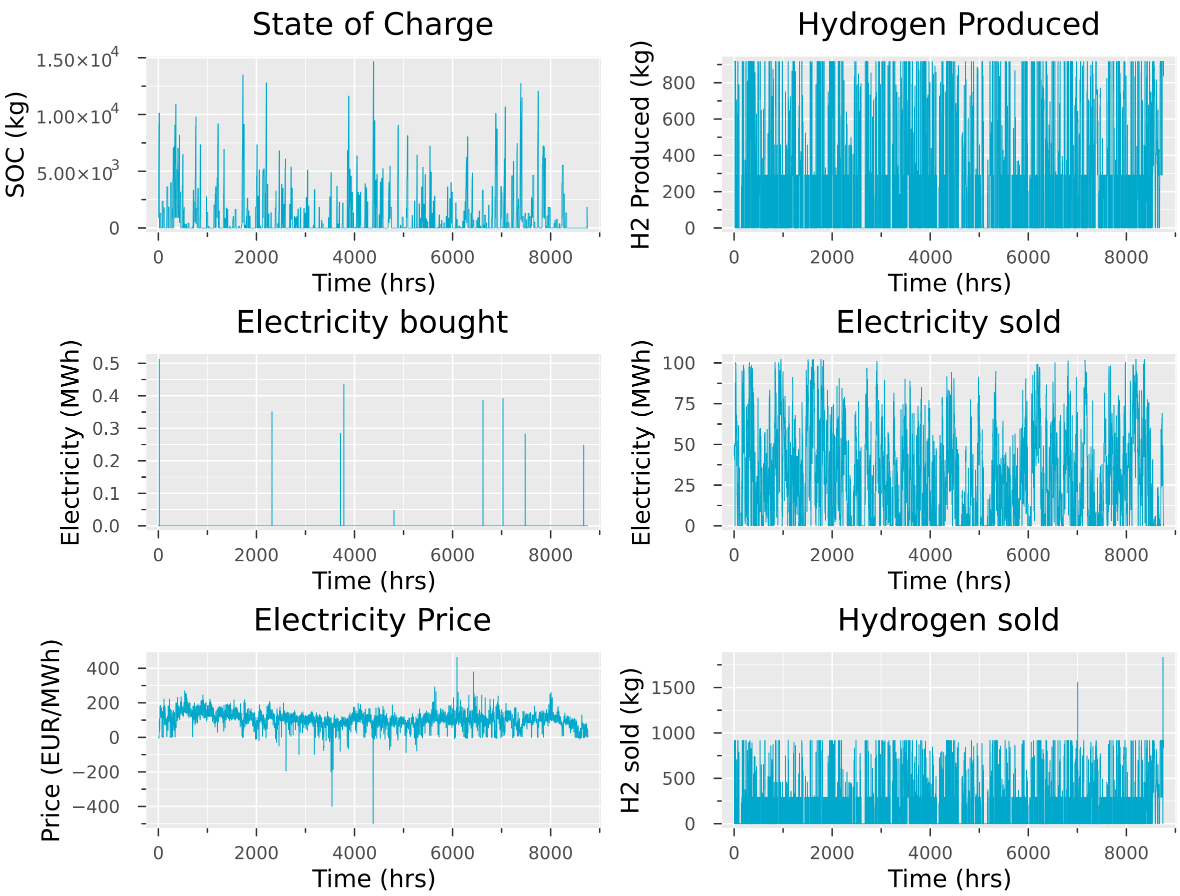

Figure 5.7: Simulation results of the rolling horizon approach with a premium implemented and nodegradtion implemented. EHB hydrogen premium of €2/kg H2

Table 5.6: Key metrics from the rolling horizon simulation results, reflecting one year of operation. The degradation model is reflected by a cell voltage increase, although here the final degradation voltage increment is zero. EHB hydrogen premium of €2/kg H2

Metric	Value
Objective Value (€)	36,227,933.42
Electricity Revenue (€)	30,753,682.95
Hydrogen Revenue (€)	6,227,113.75
Electricity Cost (€)	463.28
Startup Cost (€)	752,400.00
Max SOC (kg)	14,669.27
Total Start-Stop Cycles	288.0
Total Partial Load Hours (hrs)	2,446.0
Total Normal Load Hours (hrs)	2,105.0
Total Power Events	58.0
Final Degradation Voltage (mV)	0.0

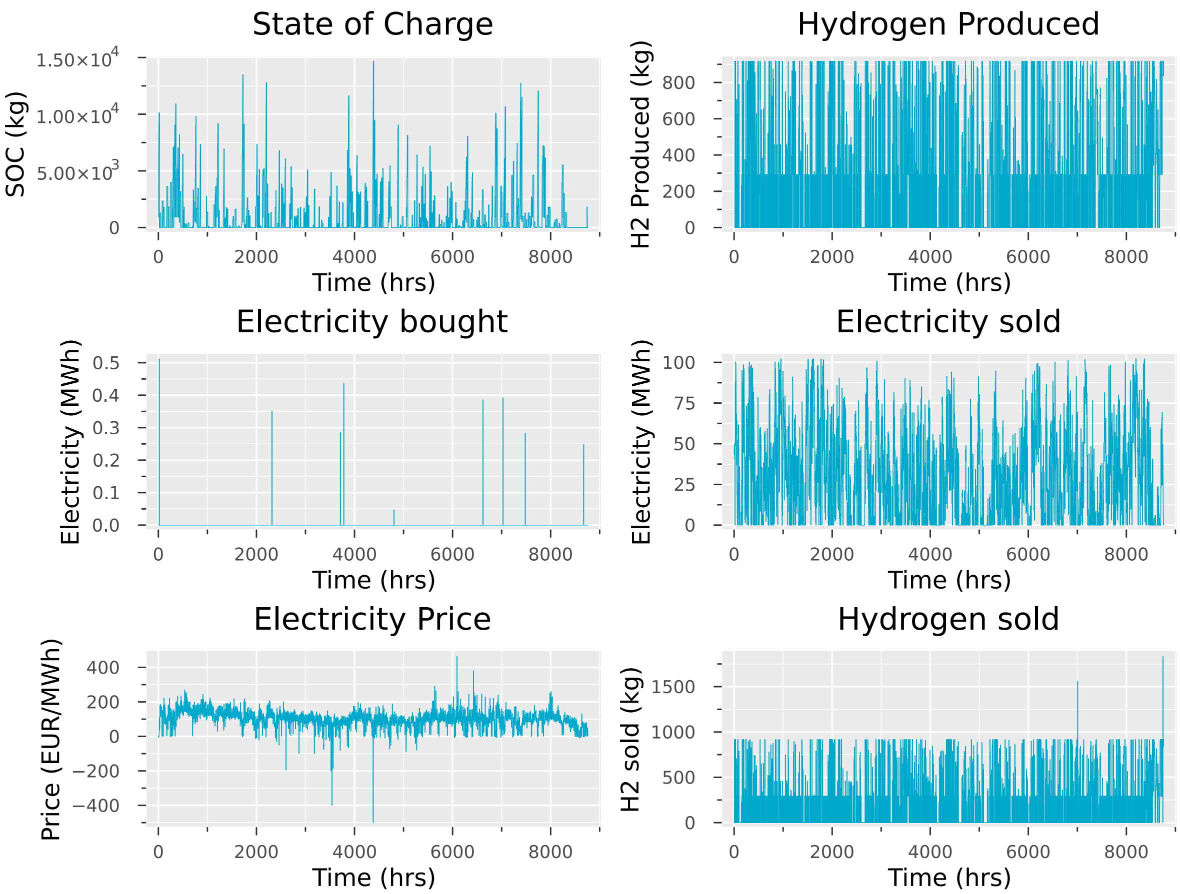

Figure 5.8: Rolling horizon approach and hydrogen premium of €4/kg of hydrogen

Table 5.7: Key metrics from the rolling horizon simulation results, reflecting one year of operation. The degradation model results in no final voltage increment (0.0 mV). An EHB hydrogen premium of €4/kg H_2 has been applied.

Metric	Value
Objective Value (€)	43,084,951.65
Electricity Revenue (€)	23,292,204.57
Hydrogen Revenue (€)	20,156,473.31
Electricity Cost (€)	588.73
Startup Cost (€)	363,137.50
Max SOC (kg)	14,669.27
Total Start-Stop Cycles	139.0
Total Partial Load Hours (hrs)	2,237.0
Total Normal Load Hours (hrs)	3,982.0
Total Power Events	46.0
Final Degradation Voltage (mV)	0.0

Table 5.8: Key system performance metrics under two different hydrogen price premiums.

Metric	Premium = 2.0 €/kg H_2	Premium = 4.0 €/kg H_2
Objective Value (€)	36,227,900.00	43,085,000.00
Electricity Revenue (€)	30,753,700.00	23,292,200.00
Hydrogen Revenue (€)	6,227,100.00	20,156,500.00
Electricity Cost (€)	463.29	588.73
Startup Cost (€)	752,400.00	363,137.50
Total Cycles	288.0	139.0
Partial Load Hours (hrs)	2,446.0	2,237.0
Normal Load Hours (hrs)	2,105.0	3,982.0
Power Events	61.0	47.0

Increasing the hydrogen premium from 2.0 to 4.0 €/kg H_2 leads to a substantial rise in the objective value, reflecting higher overall profitability. This increase in profitability arises primarily from the significant boost in hydrogen revenue, which becomes the dominant income source as the electrolyzer focuses on hydrogen production rather than electricity sales. Consequently, electricity revenue declines since selling electricity to the grid becomes less attractive when hydrogen production is more profitable.

From an operational standpoint, the system exhibits fewer start-stop cycles and more stable, full-load operation under the higher premium scenario. Normal load hours increase dramatically, indicating that the plant tends to run at optimal conditions for hydrogen production. In contrast, partial load hours and power events decline, suggesting a smoother and less fluctuating operational pattern. Overall, higher hydrogen premiums incentivize more continuous electrolyzer operation at stable conditions, increasing hydrogen output and reducing operational stress.

6 Conclusion and Recommendations

This thesis explored the impacts of degradation due to dynamic power inputs and the implementation of hydrogen support mechanisms on the optimal operational performance of a hybrid power plant for green hydrogen production. Section 6.1 revisits the research questions proposed, after which section 6.2 discusses the main limitations of this study. Finally, this is used to provide recommendations for further research in section 6.3.

6.1. Revisiting Research Questions

This section revisits the main research question and sub-questions formulated at the start of this thesis to evaluate how the findings address them. The goal is to synthesize the key insights gained from the research and highlight the contributions made to understanding the optimization of green hydrogen production in hybrid power plants.

Main Research Question

How does degradation due to dynamic power inputs and the implementation of hydrogen support mechanisms impact the optimal operational performance of a hybrid power plant for green hydrogen production?

The findings of this thesis show that both degradation and hydrogen support mechanisms play a critical role in shaping the operational and economic performance of hybrid power plants. Degradation, modeled as incremental increases in cell voltage, highlighted how dynamic power inputs reduce the efficiency of electrolyzers over time. This impact on efficiency necessitates strategic adjustments in operational scheduling to balance short-term hydrogen production with long-term performance sustainability.

On the other hand, hydrogen support mechanisms such as price premiums significantly enhanced the economic feasibility of green hydrogen production. These mechanisms incentivized consistent production patterns and reduced reliance on volatile electricity market revenues. Together, these two factors demonstrate the necessity of considering both technical and policy-related elements when optimizing hybrid power plants for green hydrogen production.

Sub-question 1

What are the fundamental technical and operational characteristics of electrolyzers under dynamic power inputs, and how do they shape their performance in green hydrogen production?

This research identified several key characteristics that influence electrolyzer performance under dynamic conditions, including startup times, ramping capabilities, nominal and partial load ranges, and efficiency profiles. For example, startup delays and limited ramping speeds in alkaline electrolyzers affect how quickly they can respond to fluctuations in renewable energy inputs. Moreover, operating outside nominal load ranges led to reduced efficiency and increased wear, emphasizing the importance of maintaining optimal load conditions wherever possible. These insights were integral to developing an optimization model that reflects real-world operational challenges.

Sub-question 2

How can degradation due to dynamic operation be quantified or approximated, and what functional form or parameters can be used to relate operational patterns to decreased efficiency?

Degradation was quantified in this thesis by modeling incremental increases in cell voltage. This approach directly linked operational patterns, such as the number of start-stop cycles, the time spent at partial loads, and power fluctuations, to efficiency losses. Each of these factors contributed to cumulative degradation, which was dynamically updated within the rolling horizon optimization framework. This method allowed for a realistic representation of how operational intensity affects long-term performance. The results emphasized the trade-offs between operational decisions, such as frequent cycling to maximize short-term profits, and the long-term impacts on electrolyzer lifespan and efficiency.

Sub-question 3

How do hydrogen support mechanisms, such as price premiums or subsidies, influence the operational performance of electrolyzers, and what implications might they have for degradation?

Hydrogen support mechanisms were modeled by integrating price premiums into the objective function of the optimization model. These premiums increased the effective hydrogen price, making hydrogen production more profitable during periods of low electricity prices. This led to operational strategies that prioritized hydrogen production over electricity sales when premiums were active. The results demonstrated how such mechanisms could stabilize revenues and encourage the consistent operation of electrolyzers, even in uncertain market conditions. By reducing dependency on electricity market fluctuations, these mechanisms offer a practical way to support the growth of green hydrogen production.

6.2. Limitations of the Study

While this thesis provides valuable insights into the optimization of green hydrogen production in hybrid power plants, several limitations should be acknowledged. Addressing these limitations in future research could enhance the robustness and applicability of the findings.

1. Assumptions in Degradation Modeling

The degradation model used in this thesis, based on incremental increases in cell voltage, captures the broad effects of operational parameters such as start-stop cycles, partial-load operation, and power fluctuations. However, the model relies on generalizations from existing literature rather than detailed experimental data specific to the electrolyzer system under consideration. This introduces potential inaccuracies in quantifying degradation, particularly when applied to specific operational scenarios or electrolyzer technologies. Future work should incorporate experimental validation to refine the relationships between operational patterns and efficiency losses.

2. Simplifications in the Optimization Framework

The optimization model was developed using a rolling horizon framework to simulate dynamic conditions. While this approach improves adaptability and computational efficiency, it assumes perfect knowledge of market conditions, renewable energy supply, and system states within the look-ahead horizon. In practice, these inputs are subject to forecasting errors and uncertainties. Incorporating stochastic or robust optimization methods could better account for uncertainties and provide more resilient operational strategies.

3. Limited Scope of Hydrogen Support Mechanisms

The inclusion of hydrogen support mechanisms was limited to price premiums. Although this is a relevant and widely discussed policy tool, other mechanisms such as capacity payments, contracts for difference, and subsidies for capital costs were not explicitly modeled. Additionally, the model assumes static premiums, which do not reflect potential variations due to policy changes, market dynamics, or compliance requirements. Expanding the model to include a broader range of support mechanisms and time-dependent incentives would provide a more comprehensive analysis of policy impacts.

4. Narrow Focus on Alkaline Electrolyzers

This thesis focused exclusively on alkaline electrolyzers, which, while cost-effective and mature, have specific limitations under dynamic renewable energy conditions. Other technologies, such as Proton Exchange Membrane (PEM) and Solid Oxide Electrolyzers (SOE), were not evaluated but may offer superior performance in certain applications. A comparative analysis of different electrolyzer technologies would provide more generalizable insights and help identify the most suitable systems for various renewable energy contexts.

5. Simplified Representation of Renewable Energy Systems

The renewable energy input to the optimization model was represented using wind power data and a simplified grid interaction. This narrow focus does not capture the complexities of hybrid systems that combine multiple renewable sources, such as solar and wind, or the integration of energy storage solutions like batteries. Future research should expand the scope to include more complex renewable energy systems and their interactions with electrolyzer operations.

6. Economic and Environmental Factors

The economic analysis in this thesis primarily focused on profitability from hydrogen production and electricity trading. However, other critical factors, such as lifecycle costs, capital expenditures, and maintenance expenses, were not included in the model. Similarly, environmental considerations, such as carbon emissions, water usage, and recycling of electrolyzer components, were not addressed. Integrating these factors into the optimization framework would provide a more holistic assessment of green hydrogen production's feasibility and sustainability.

7. Computational and Model Limitations

The rolling horizon framework divides the optimization into smaller time segments, improving computational feasibility. However, this approach may still face limitations in scalability when applied to larger systems or extended time horizons. Additionally, the piecewise linearization of the hydrogen production curve simplifies the problem but may introduce inaccuracies in capturing non-linear behavior. Developing more efficient algorithms and exploring advanced linearization techniques could improve model accuracy and scalability.

8. Policy and Market Dynamics

The model assumes relatively stable market conditions and policy frameworks. In reality, green hydrogen markets are still in their infancy, and significant uncertainties exist regarding demand, pricing, and regulatory environments. These factors can have a profound impact on the economic performance of hydrogen production systems. Future studies should incorporate scenario analysis to account for these uncertainties and evaluate the resilience of the optimization strategies under varying policy and market conditions.

9. Data Availability and Generalization

The input data used in this thesis, including wind profiles, electricity prices, and operational parameters, were based on specific case studies and assumptions. This limits the generalizability of the findings to other regions, renewable energy mixes, or market conditions. Expanding the dataset and validating the model across multiple case studies would improve its applicability and relevance.

10. Real-Time Implementation Challenges

While the optimization framework demonstrates theoretical feasibility, real-time implementation may face challenges due to computational delays, data acquisition issues, and system integration complexities. Testing the framework in real-world pilot projects would help identify and address these practical barriers, bridging the gap between theory and application.

Summary of Limitations

In summary, this thesis provides a robust foundation for optimizing green hydrogen production under dynamic conditions, but several areas warrant further exploration. Addressing the outlined limitations will enhance the model's accuracy, scalability, and applicability, providing a more comprehensive understanding of green hydrogen production in renewable energy systems.

6.3. Recommendations

Building on the findings and limitations of this study, several recommendations can be made to guide future research. These recommendations aim to address the key gaps identified and ensure that the work contributes to the broader adoption of sustainable hydrogen technologies in renewable energy systems.

First, a critical area for future research is the refinement of degradation modeling. While this thesis successfully demonstrated the inclusion of degradation effects through incremental voltage increases, the relationships between operational stressors and efficiency losses were based on generalized parameters from the literature. To enhance accuracy, future studies should prioritize experimental validation of these relationships for specific electrolyzer technologies and operational conditions. By developing more precise degradation parameters, such as the impacts of start-stop cycles, load cycling intensity, and partial-load operations, optimization models can provide more reliable predictions of electrolyzer performance over time. Additionally, integrating material-level degradation mechanisms, such as catalyst wear and membrane thinning, would improve the physical realism of the model and its applicability to different electrolyzer technologies.

Another important recommendation is to expand the optimization framework to include hybrid renewable energy systems. This thesis focused on wind energy inputs, but real-world systems often combine multiple renewable sources, such as wind, solar, and hydroelectric power. Incorporating hybrid systems into the model would provide a more comprehensive understanding of how varying energy inputs interact with electrolyzer operations. Moreover, including energy storage solutions, such as batteries or thermal storage, would allow the model to explore strategies for buffering energy supply fluctuations and optimizing overall system efficiency. These additions would make the optimization framework more relevant to the complexities of modern renewable energy grids.

From a methodological perspective, enhancing the handling of uncertainties is another key recommendation. The rolling horizon approach used in this study assumed perfect foresight within the look-ahead horizon, which is rarely achievable in real-world operations. Future research should incorporate stochastic optimization or robust decision-making techniques to account for uncertainties in renewable energy supply, electricity prices, and hydrogen demand. Such methods would enable operators to develop resilient strategies that maintain economic and operational performance under variable conditions. Scenario-based analyses could also be employed to evaluate the sensitivity of the optimization outcomes to changes in market dynamics or policy environments, providing greater insights into the robustness of the proposed solutions.

In terms of economic and environmental assessments, this study primarily focused on operational profitability and scheduling. However, future work should incorporate a broader range of economic factors, including lifecycle costs, capital expenditures, and maintenance requirements. Additionally, integrating environmental impact assessments, such as carbon footprint calculations, water usage, and material recycling, would provide a more holistic evaluation of green hydrogen production systems. These assessments would help identify trade-offs between economic and environmental performance, enabling more informed decision-making for stakeholders.

Policy design is another critical area where recommendations can be made. The inclusion of hydrogen price premiums in this study demonstrated the potential of support mechanisms to enhance economic viability and incentivize consistent operations. However, a more diverse range of policy instruments should be considered in future research, including capacity payments, contracts for difference, and investment subsidies. These mechanisms could be modeled as additional constraints or objectives to capture their impacts on operational decisions and system profitability more comprehensively. Furthermore, the dynamic nature of policy environments should be reflected in the model by introducing time-varying incentives or compliance requirements. Policymakers should also prioritize the development of long-term hydrogen purchase agreements to stabilize markets and reduce investor uncertainty, thereby accelerating the adoption of green hydrogen technologies.

In summary, the recommendations outlined here emphasize the need for continued refinement and expansion of optimization models, deeper integration of economic and environmental factors, and proactive policy design to support green hydrogen production. By addressing these areas, future research and development efforts can build on the foundations established in this thesis, driving the transition to sustainable and resilient energy systems.

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A

European Hydrogen Bank

The European Hydrogen Bank (EHB) was established as a critical initiative to overcome key economic and market barriers that currently impede the large-scale adoption of green hydrogen. These challenges include the significant cost disparity between renewable hydrogen and its fossil-based alternatives, limited financial incentives for producers, and the lack of a fully developed hydrogen market. By allocating 3 billion through the EU Innovation Fund, the EHB serves as a cornerstone of the EUs hydrogen strategy, aiming to create a competitive and transparent market environment that encourages investment, facilitates supply and demand connections, and accelerates the deployment of green hydrogen technologies.

The establishment of the EHB aligns with the broader goals outlined in the REPowerEU Plan and the Green Deal Industrial Plan, both of which are integral to the EUs climate and energy strategy. These plans set ambitious targets to produce 20 million tonnes of renewable hydrogen annually by 2030, with half of this target sourced domestically and the other half imported from international producers. Achieving these targets requires a multifaceted approach that addresses both economic and logistical challenges, and the EHB plays a central role in coordinating these efforts.

Objectives and Structure

The EHB is structured around four main pillars, each designed to address specific barriers to market creation and hydrogen adoption:

1. **Domestic market creation:** Encouraging the production of renewable hydrogen within the EU by providing financial support to producers through competitive auctions.
2. **Hydrogen imports:** Promoting international trade in renewable hydrogen by offering green premiums to offset cost gaps with fossil-based alternatives.
3. **Transparency and coordination:** Enhancing market clarity and investment confidence by providing data on hydrogen flows, demand, infrastructure needs, and pricing.
4. **Integration with financial instruments:** Leveraging existing funding mechanisms such as Horizon Europe and the EU Emissions Trading System (ETS) to ensure efficient allocation of resources.

These pillars work in tandem to establish a well-functioning hydrogen market, aligning supply with demand while addressing economic and logistical challenges. Figure A.1 visually represents the activities of the EHB.

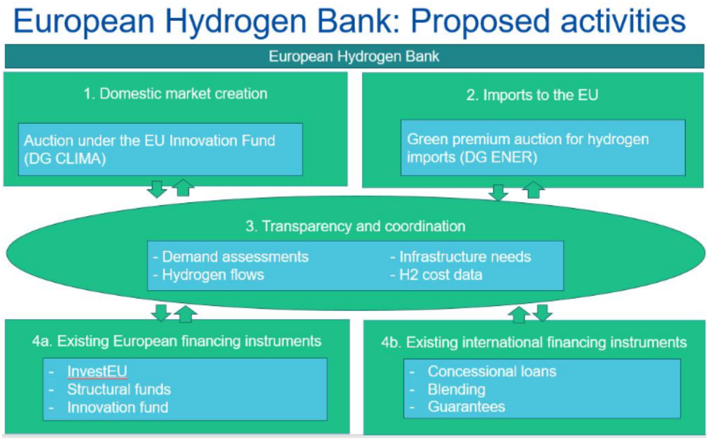

Figure A.1: Proposed activities of the European Hydrogen Bank [59]

Implementation via Auctions

A central component of the EHBs strategy is its auction-based funding mechanism, designed to connect renewable hydrogen producers with off-takers while ensuring cost efficiency and maximizing the impact of public funds. These auctions operate under the "Auctions as a Service" model, which centralizes the auction process across EU member states to streamline operations and improve transparency.

The auction system works as follows:

- Producers submit bids specifying the amount of financial support they require per kilogram of hydrogen produced. These bids are ranked by cost-effectiveness, with the lowest-cost bids being awarded fixed premiums.
- The fixed premium provides a price floor for renewable hydrogen, helping to bridge the cost gap with fossil-based hydrogen and offering producers a stable revenue stream.
- Funding is allocated in two stages: first through the EU Innovation Fund, which clears bids based purely on cost competitiveness, and then through additional member state contributions for projects within their jurisdiction. This ensures that funding is directed 1
- Promotes cost competitiveness by aligning production costs with the price consumers are willing to pay.
- Establishes a foundation for global collaboration on renewable hydrogen production and trade.

Figure A.2 illustrates how green premiums are used to address cost gaps and secure long-term agreements for international hydrogen production.

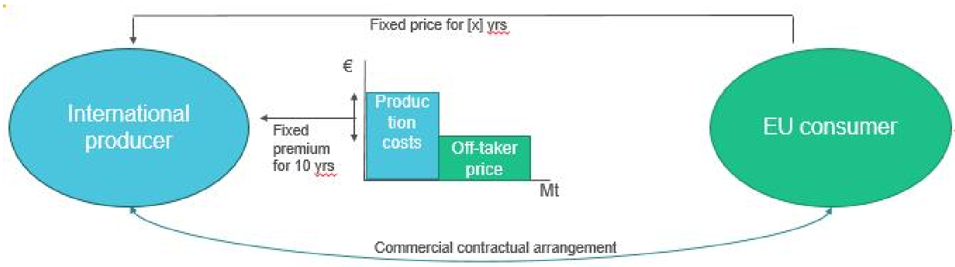

Figure A.2: Framework for international hydrogen production [59]

However, challenges such as geopolitical risks, varying regulatory frameworks, and the introduction of the Carbon Border Adjustment Mechanism (CBAM) add complexity to this process. Addressing these challenges will be crucial to establishing secure and efficient international hydrogen supply chains.

Coordination and Integration

To maximize its impact, the EHB integrates its activities with existing financial instruments, ensuring efficient resource allocation and alignment with broader EU climate goals. Key funding mechanisms include:

- **Horizon Europe:** Providing grants for research and innovation in renewable hydrogen technologies.
- **InvestEU:** Offering financial guarantees to reduce investment risks for hydrogen projects.
- **EU Emissions Trading System (ETS):** Generating revenues to fund the Innovation Fund, which finances EHB activities.

These synergies enhance the EHBs ability to address the complex financial and logistical challenges of scaling up hydrogen production and infrastructure. By leveraging multiple funding sources, the EHB ensures that its activities remain cost-effective and impactful.

B

H2Global

The H2Global mechanism is an innovative initiative designed to address key challenges in establishing a global hydrogen market. It aims to mitigate price, market, and regulatory risks by fostering business models and investment opportunities across the entire hydrogen value chain. The primary focus is on importing renewable hydrogen and its derivatives via long-term contracts and selling them through short-term off-take agreements, while compensating for price differences. This structure supports the production and adoption of green hydrogen and Power-to-X (PtX) products, contributing to decarbonization efforts in sectors such as industry, energy, and transport.

H2 Global has received substantial financial backing from the German government, including an initial 900 million and a further 3.6 billion pledged for future operations up to 2036. This funding underscores the initiative's critical role in facilitating the adoption of renewable hydrogen. The mechanisms international focus enables imports from regions outside the EU, while its structure also allows for potential application within the EU, fostering intra-European hydrogen collaboration.

Functioning of the Mechanism

Central to H2Global is its intermediary, the Hydrogen Intermediary Network Company (HINTCO), which oversees the procurement and sale of hydrogen. HINTCO operates on a principle similar to Contracts for Difference (CfD), where any price discrepancies between supply and demand are compensated through public funding. This approach ensures fair pricing and mitigates the higher production costs associated with green hydrogen and PtX products compared to fossil-based alternatives.

Figure B.1 illustrates the operational framework of H2Global. The intermediary procures hydrogen through competition-based procurement processes and subsequently sells it via short-term agreements, with grant authorities covering any price differences.

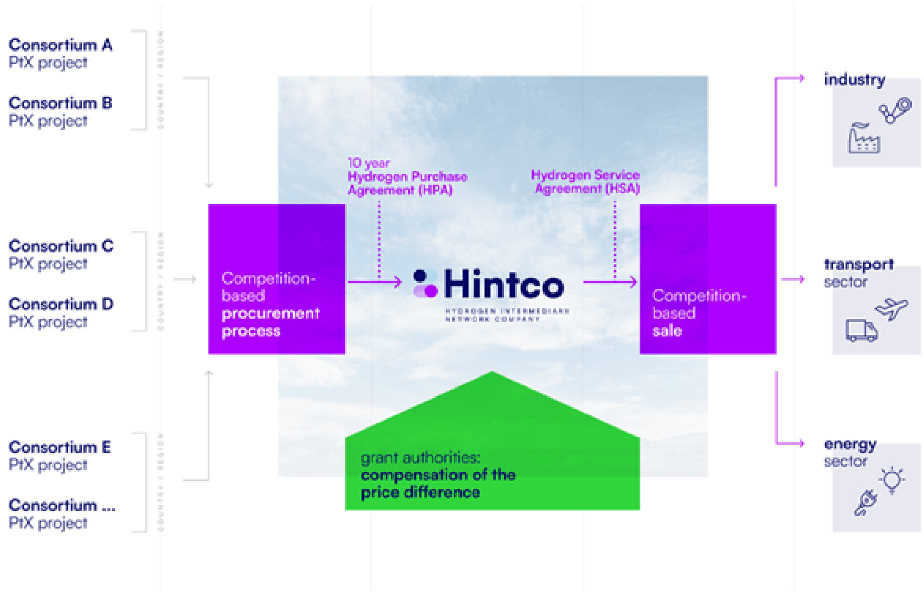

Figure B.1: HINTCO operational scheme [60]

A key feature of H2Global is its ability to establish a global market price for green hydrogen through competitive bidding. This system ensures efficient allocation of resources, stimulates market transparency, and drives the adoption of renewable hydrogen at scale. Figure B.2 demonstrates how market regulation and willingness to pay could narrow the gap between supply prices and demand prices over time.

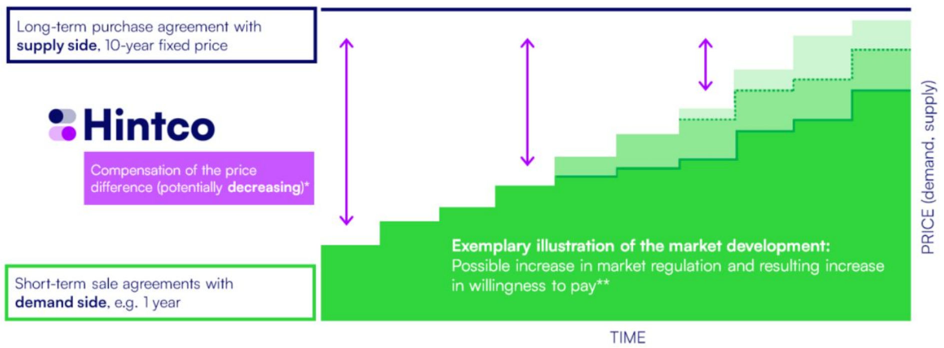

Figure B.2: Market development under H2Global [60]

Flexibility Through Funding Windows

To enhance its adaptability, H2Global employs customized funding windows tailored to specific geographies, products, and criteria. This flexibility allows the initiative to address diverse market needs and accelerate the deployment of specific hydrogen technologies. Figure B.3 highlights the structure of these funding windows, which align with the priorities of the funding bodies involved.

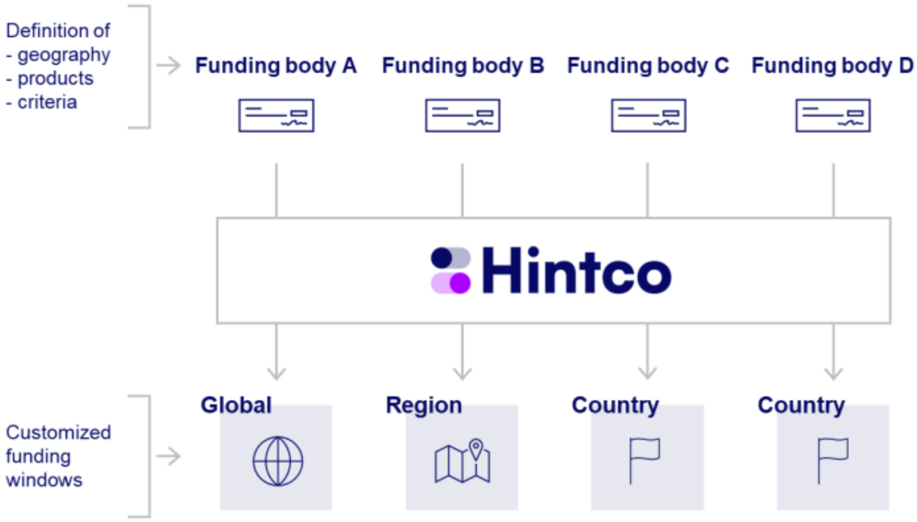

Figure B.3: Customized funding windows in H2Global [60]

Significance and Outlook

H2Global represents a crucial step toward a sustainable and competitive hydrogen economy. By bridging the cost gap and fostering a reliable supply chain, the initiative supports the integration of green hydrogen into global markets. Its emphasis on regulatory alignment, fair competition, and environmental objectives ensures long-term viability and scalability.

As the initiative expands, further collaboration with European and global stakeholders will be essential to address challenges such as geopolitical risks, varying regulatory frameworks, and technological readiness. By establishing a robust framework for international hydrogen trade, H2Global contributes significantly to achieving climate goals and driving the global energy transition.

C
Inflation Reduction Act

The Inflation Reduction Act (IRA) is the United States most ambitious step to accelerate the development of renewable hydrogen and expand its domestic market. Unlike Europes competitive bidding mechanisms, the IRA offers direct financial incentives through tax credits of up to \$3/kg for renewable hydrogen production. The total funding for Energy Security and Climate Change programs under the IRA amounts to \$370 billion over the next decade, making it one of the largest climate-focused financial frameworks in the world.

The tax credits are available to hydrogen projects that begin construction before 2023 and are provided in two forms: a production tax credit (PTC) or a 30% investment tax credit (ITC). The amount of the credit depends on the carbon intensity of the hydrogen produced, with higher credits awarded for lower-emission processes. This approach encourages producers to adopt cleaner production methods and significantly lowers the cost gap between renewable hydrogen and its fossil-based alternatives. Table C.1 shows the credit values for different emission levels.

Table C.1: CO_2 Emissions and Credit Values under the IRA [61]

kg of CO_2/kg of H_2	Credit Value (\$)
4 - 2.5 kg CO_2	\$0.60/kg of H_2
2.5 - 1.5 kg CO_2	\$0.75/kg of H_2
1.5 - 0.45 kg CO_2	\$1.00/kg of H_2
0.45 - 0 kg CO_2	\$3.00/kg of H_2

On top of hydrogen-specific credits, the IRA also provides additional production tax credits until 2032 to support domestic manufacturing of renewable energy technologies and components. This creates a competitive advantage for U.S. suppliers, making the United States an increasingly attractive hub for renewable hydrogen production and related industries.

However, despite the IRA's financial incentives, one of the key challenges in the U.S. market remains insufficient demand for renewable hydrogen. This has delayed investment decisions as producers struggle to secure long-term off-take contracts with buyers. While the IRA addresses supply-side issues by reducing production costs, developing stable demand will be critical for further scaling the market.

The financial framework introduced by the IRA is already influencing the global hydrogen market. Its generous incentives have put pressure on other countries, particularly in Europe, to speed up their own support mechanisms to remain competitive. Without timely action, there is a real risk that European investors and developers may shift their focus to the U.S., where financial conditions for renewable hydrogen are more favorable. This highlights the importance of implementing robust hydrogen support mechanisms to ensure Europe retains its position in the emerging global hydrogen economy.

The IRA demonstrates how straightforward financial incentives can make renewable hydrogen more competitive, lower barriers to adoption, and promote innovation. By linking credits to carbon intensity, it aligns financial benefits with environmental goals, making it highly relevant to discussions on policy frameworks that can support green hydrogen production at scale.

D

Comparison Electrolyzer Technologies

There are three primary types of electrolyzers used for hydrogen production: Alkaline Electrolyzers (AEL), Proton Exchange Membrane Electrolyzers (PEMEL), and Solid Oxide Electrolyzer Cells (SOEC). Each of these technologies has unique operating principles, technical characteristics, advantages, and limitations, making them suitable for different applications. Table D.1 gives a more descriptive and more complete comparison of the three aforementioned electrolyzer types.

Table D.1: Comparison of Electrolyzer Technologies based on key operational characteristics, costs, and applications. [8], [52], [53]

Criteria	**PEMEL**	**AEL**	**SOEC**
Electrolyte	Solid Polymer Membrane	Liquid Alkaline Solution (KOH/NaOH)	Solid Oxide Ceramic
Operating Temperature	50–80°C	60–90°C	700–1,000°C
Efficiency	60–80%	60–70%	>80%
Hydrogen Purity	Very High	High	High
Response to Power Fluctuations	Excellent	Moderate	Moderate
Catalyst Material	Precious Metals (Pt/Ir)	Non-precious Metals (Ni)	Non-precious Metals
Durability/Lifespan	Moderate	High	Moderate
System Complexity	Moderate	Low	High
Capital Cost	High	Low	High
Suitable for Dynamic Operation	Yes	Yes	Limited
Thermal Energy Integration	No	No	Yes
Commercial Maturity	Developing	Mature	Emerging
Typical Applications	Renewable Energy Integration, Industrial Applications	Large-scale Industrial Production	Industrial Applications with Waste Heat Utilization