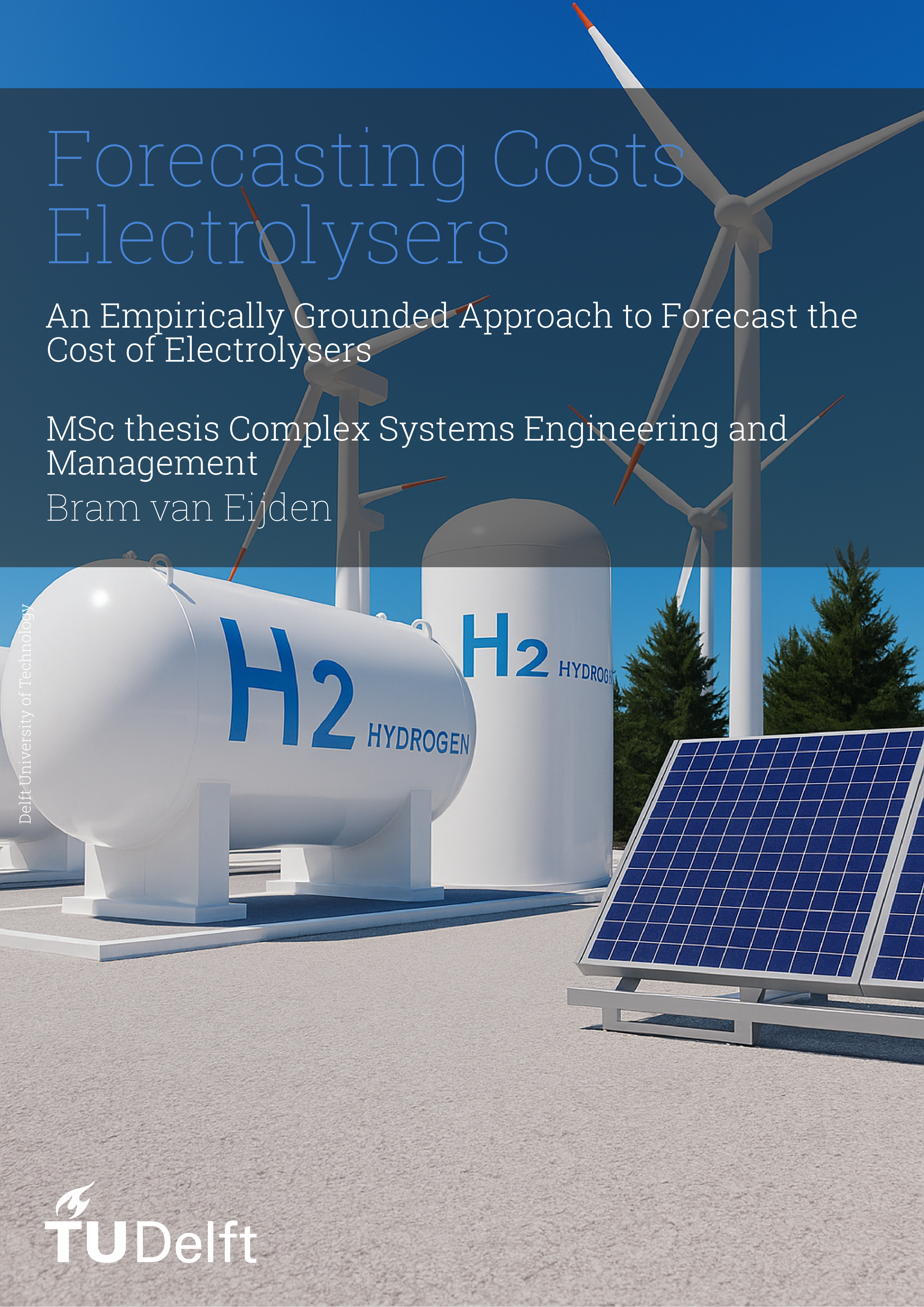
Forecasting Costs Electrolysers

An Empirically Grounded Approach to Forecast the Cost of Electrolysers

MSc thesis Complex Systems Engineering and Management

Bram van Eijden



Delft University of Technology

TU Delft

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by

Bram van Eijden

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Preface

The past months have been an intense and rewarding period during which I had the chance to dive into topics within energy modelling. Completing this thesis marks the final step of my time at TU Delft, a time in which I have grown both professionally and personally. It has been a period full of challenges, learning, and important moments of reflection.

I would like to thank Stefan Pfenninger, Francesco Lombardi, and Sepinous Azimi Rashti for their valuable feedback and guidance. Their advice helped me to improve my work and think critically. A special thank you goes to Ivan Ruiz Manuel, with whom I spent many hours. His support, patience, and clear explanations were crucial throughout the entire process.

I would also like to thank Menno and Patrick from Accenture for their inspiring input and for giving me the chance to connect my research to real-world projects. Their help made this work more practical and meaningful.

Finally, I would like to thank my family, friends, and everyone who supported me during this journey. Their support and understanding meant a lot to me.

Bram van Eijden
Delft, July 2025

Summary

Green hydrogen is increasingly recognised as an essential component for achieving global climate neutrality, offering a versatile and sustainable alternative to fossil fuels in hard-to-abate sectors such as industry, transport, and energy storage. Among the production pathways, water electrolysis using renewable electricity stands out as the most scalable and environmentally viable method. However, a major barrier to large-scale adoption is the uncertainty surrounding future electrolyser costs and deployment trajectories. Most existing cost projections rely on deterministic approaches that provide single-point estimates without explicitly addressing uncertainty, often leading to overly conservative cost decline assumptions and potentially misguided policy and investment decisions.

To address these shortcomings, this thesis develops a probabilistic, empirically grounded framework to forecast both the deployment and capital expenditure (CAPEX) of alkaline electrolysis cells (AEC) and proton exchange membrane (PEM) electrolysers. The framework integrates a logistic S-curve model to simulate technology deployment and a stochastic implementation of Wright's Law to model cost reductions as a function of cumulative capacity, explicitly incorporating uncertainty through Monte Carlo simulations. Hindcasting validation is used to assess the robustness and predictive performance of the framework, ensuring alignment with historical trends.

The results reveal that achieving the IEA Net Zero Emissions (NZE) 2050 targets would require average annual growth rates of 46% for AEC and 49% for PEM technologies, significantly higher than historical growth trends of around 39%. Even under a more conservative industrial-use scenario, focusing only on sectors such as refining, ammonia, and methanol production, substantial acceleration remains necessary, with required growth rates of 41% for AEC and 45% for PEM. These findings highlight the immense scale of the deployment challenge and the value of explicitly addressing uncertainty when evaluating policy pathways.

Cost forecasts demonstrate a clear divergence between the two technologies. AEC shows a positive experience exponent, suggesting a negative learning rate, implying potential cost increases with expanded deployment. This trend is not statistically significant ($p = 0.41$), and the model exhibits low explanatory power ($R^2 = 0.04$), indicating that historical data do not support a strong cost-deployment relationship for AEC. In contrast, PEM electrolysers display a statistically significant learning rate of 3.3% ($p < 0.01$), with an experience exponent of –0.0480 and a higher model fit ($R^2 = 0.62$). Under the reference scenario, AEC median CAPEX is projected to rise to 1,921 EUR/kW by 2030 and 2,076 EUR/kW by 2050, with a wide interquartile range reflecting large uncertainties. For PEM, median CAPEX declines to 1,800 EUR/kW by 2030 and further to 1,533 EUR/kW by 2050, with more pronounced cost reductions under high deployment scenarios.

This transparent and modular framework not only improves cost forecasting for electrolysers but is also adaptable to other emerging energy technologies facing similar learning and deployment uncertainties. By relying on openly available data and explicitly quantifying uncertainty, it provides a robust foundation for analysts, policymakers, and scenario developers. Moreover, its structure makes it suitable for integration into Integrated Assessment Models (IAMs), supporting more realistic and adaptive long-term energy transition planning. Future research should focus on expanding its application across technologies, refining empirical learning rates, and assessing policy impacts within comprehensive system-level analyses, ultimately enabling more confident and informed decisions towards a net-zero future.

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Acronyms

AEC Alkaline Electrolysis Cells.
AR6 Sixth Assessment Report.

BoP Balance of plant.

CAPEX Capital Expenditure.

FID Final Investment Decision.

IAM Integrated Assessment Models.
IEA International Energy Agency.
IPCC Intergovernmental Panel on Climate Change.
IRENA International Renewable Energy Agency.

NZE Net Zero Emissions by 2050 Scenario.

PEM Proton Exchange Membrane.

SOEC Solid Oxide Electrolysis Cells.

1 Introduction

1.1. Problem Introduction

The global energy system is undergoing a rapid transformation, driven by the need to reduce carbon emissions, improve energy security, and ensure affordable energy access [67]. Countries aim for net-zero targets, which require high investments in renewable energy technologies, with global spending on clean energy of around 1.8 trillion in 2023 [35]. Hydrogen has emerged as a promising solution to support the transition to net-zero emissions [12]. Despite this, one of the most significant challenges in planning the energy transition is the uncertainty of future technology costs [72]. Accurately predicting the costs of renewables is critical for governments, investors, and energy planners to allocate resources efficiently and design effective policies [59].

If cost estimates are inaccurate, policies may fail to support the most effective technologies or allocate subsidies inefficiently [4]. Historically, models produced by the International Energy Agency (IEA) or International Renewable Energy Agency (IRENA) have often employed deterministic forecasts, meaning they generate single-point estimates [83, 88]. A significant issue with these forecasts is that they create a false sense of precision, leading policymakers and investors to believe in highly reliable cost trajectories when, in reality, technology costs are influenced by numerous unpredictable factors [59]. Cost reductions in electrolysis depend on inherently uncertain dynamics such as technological learning, economies of scale, and policy frameworks [71]. Alternative approaches, such as probabilistic forecasting methods, account for uncertainty, yet their adoption remains limited in mainstream energy modelling [59]. This is partly because probabilistic models are often not open access and cannot be easily validated, extended, or further developed by other researchers, which restricts collective progress and broader use. By integrating uncertainty analysis more transparently, policymakers can develop more robust strategies that acknowledge the variability in technology cost trajectories and adjust policies accordingly to ensure a more adaptive and resilient energy transition.

1.2. Research objective

The primary objective of this research is to develop an empirically grounded, probabilistic, and transparent forecasting framework for estimating future capital costs of electrolyser technologies. The framework aims to address key limitations of conventional forecasting methods, including their reliance on deterministic projections, insufficient treatment of uncertainty, and lack of methodological reproducibility. To guide the research, the following main question is explored:

’How can probabilistic modelling improve the accuracy and decision-relevance of cost forecasts for electrolysers compared to traditional deterministic approaches?’

This central question is examined through three interrelated thematic areas, each addressing a distinct but complementary aspect of probabilistic forecasting in the context of electrolyser technologies. First, the thesis investigates the methodological foundations for generating probabilistic forecasts, focusing on models that jointly capture deployment and cost evolution under uncertainty. Second, it evaluates the plausibility of policy-driven deployment targets set out in IEA scenarios, by comparing them to probabilistic projections derived from empirical data. Third, the research assesses how probabilistic forecasts compare with conventional deterministic approaches, particularly those used in Integrated Assessment Models (IAM) and international energy outlooks. Together, these themes provide a comprehensive basis for understanding the strengths and limitations of probabilistic modelling in techno-economic analysis.

To structure this research, the following sub-questions are formulated:

1. Which probabilistic modelling approaches have been proposed in academic literature for forecasting technology deployment and cost trajectories in the renewable energy sector, and how effectively can these models be applied to electrolysers?
2. To what extent are the electrolyser deployment targets outlined in the IEA's Net Zero Emissions (NZE) and related scenarios technically and economically feasible?
3. How do probabilistic cost forecasts compare to deterministic projections produced by Integrated Assessment Models (IAMs) and international agencies such as the IEA?

1.3. Link with MSc program

This thesis is closely aligned with themes of the MSc Complex Systems Engineering. By developing a statistical model to project future cost trajectories of renewable energy technologies, in this case electrolysers, this research contributes to a deeper understanding of feedbacks and uncertainty in socio-technical systems. The approach reflects the systems-thinking principles of the program by understanding how technological learning, deployment rates and policy interventions evolve within complex adaptive systems. The combination of data-driven forecasting and policy-relevant insights bridges the gap between technical modelling of energy technologies and their broader economic and regulatory context. This thesis exemplifies how system-level engineering tools can inform real-world decision-making in the energy transition.

1.4. Report outline

The remainder of this report develops as follows: chapter 2 establishes the technological and policy context for hydrogen and electrolysis, outlining the operational characteristics, maturity levels, and strategic role of Alkaline Electrolysis Cells (AEC), Proton Exchange Membrane (PEM), and Solid Oxide Electrolysis Cells (SOEC) technologies in future energy systems. It also critically reviews existing forecasting approaches for cost and deployment trends in the renewable energy sector, highlighting the dominance of deterministic models and the need for transparent, uncertainty-aware alternatives. chapter 3 introduces the methodological framework of this thesis, combining a probabilistic S-curve model for deployment with a stochastic implementation of Wright's Law for cost forecasting. Special attention is given to the empirical calibration of parameters, the incorporation of uncertainty through Monte Carlo simulation, and the data-driven justification for model structure and assumptions. The results are presented in chapter 4, where probabilistic deployment and cost trajectories are generated under various scenario assumptions. This includes assessing whether growth trajectories from IEA scenarios are achievable, and how different growth rates propagate through to capital cost uncertainty. In chapter 5, these results are compared to projections from IAM and IEA. This comparative analysis focuses on methodological transparency, alignment with historical trends, and the representation of uncertainty. In chapter 6 the robustness of the probabilistic forecasting framework is evaluated through hindcasting, providing validation of the model's predictive performance. Chapter 7 discusses the broader implications of the findings. It reflects on the purpose and positioning of this work within the literature, interprets the learning rates, compares the results to deterministic models, evaluates framework reusability and generalisability, explores data sensitivity and limitations, and considers practical implications for policy and future research directions. Finally, chapter 8 serves as the conclusion of this thesis. It answers the main research question and the associated sub-questions, summarising how the findings contribute to the overall research objective.

2
Background

This chapter provides the necessary context for the deployment of electrolyser technologies. It introduces the role of hydrogen in the energy transition and outlines the key characteristics of water electrolysis technologies. It also reviews recent deployment trends, the structure of capital costs, and existing approaches to forecasting deployment and cost trajectories. Finally, it identifies the gaps in the literature.

2.1. Hydrogen as an Energy Carrier

Hydrogen is gaining prominence as a key enabler of a low-carbon energy system by offering a unique combination of versatility, scalability, and decarbonisation potential [44]. Low-carbon hydrogen is typically classified by production method: green hydrogen is produced via electrolysis powered by renewable electricity, while blue hydrogen is derived from fossil fuels with carbon capture and storage. Its function is not only confined to industrial applications, but is now increasingly recognised as a strategic energy carrier across multiple sectors in supporting climate and sustainability goals [75, 48], particularly in CO_2-intensive industries that are technically or economically challenging to decarbonise [86]. In particular, hydrogen is being positioned in the industrial sector as a clean alternative for fossil-based fuels and feedstocks, particularly in high-emission processes such as steel, ammonia, and methanol production [44]. In transport, hydrogen-powered fuel cell technologies are progressing rapidly, offering competitive solutions for heavy-duty vehicles, shipping, rail, and even aviation, where energy density and refuelling speed are critical advantages [73]. Hydrogen also plays an important role in the whole energy system, because it offers a pathway for storing excess renewable electricity through electrolysis. This enables large-scale and long-duration storage to support grid stability and flexibility [15]. Moreover, hydrogen can be transported and converted into synthetic fuels or blended into gas grids, providing crucial links between the electricity, heating and transport sectors [76, 55]. An overview of the full green hydrogen value chain, from production to end use, is illustrated in Figure 2.1.

In response to hydrogen's growing strategic importance, governments and international organisations have increasingly incorporated it into their long-term energy and climate strategies, IEA projects a sixfold increase in global hydrogen demand, from 90 Mt in 2020 to over 530 Mt by 2050, with two-thirds produced from low-carbon sources [30]. Green hydrogen is identified as the most viable long-term solution, while blue hydrogen, derived from fossil fuels with carbon capture and storage, is expected to play a transitional role. The IRENA projects that hydrogen and its derivatives, such as ammonia and synthetic fuels will supply approximately 14% of final energy consumption by 2050 in its 1.5°C pathway report [41]. Beyond decarbonisation, IRENA also highlights hydrogen's potential role in geopolitical diversification, enabling countries to export hydrogen-based fuels regardless of fossil fuel endowments [39]. The EU's hydrogen strategy mirrors these perspectives by investing in 40 GW in Europe and another 40 GW in neighbouring regions by 2030. This scale-up is considered necessary to meet climate targets, strengthen industrial competitiveness and reduce reliance on fossil fuels [10].

Despite consensus on hydrogen's strategic importance, the pathway for realising its potential is com-

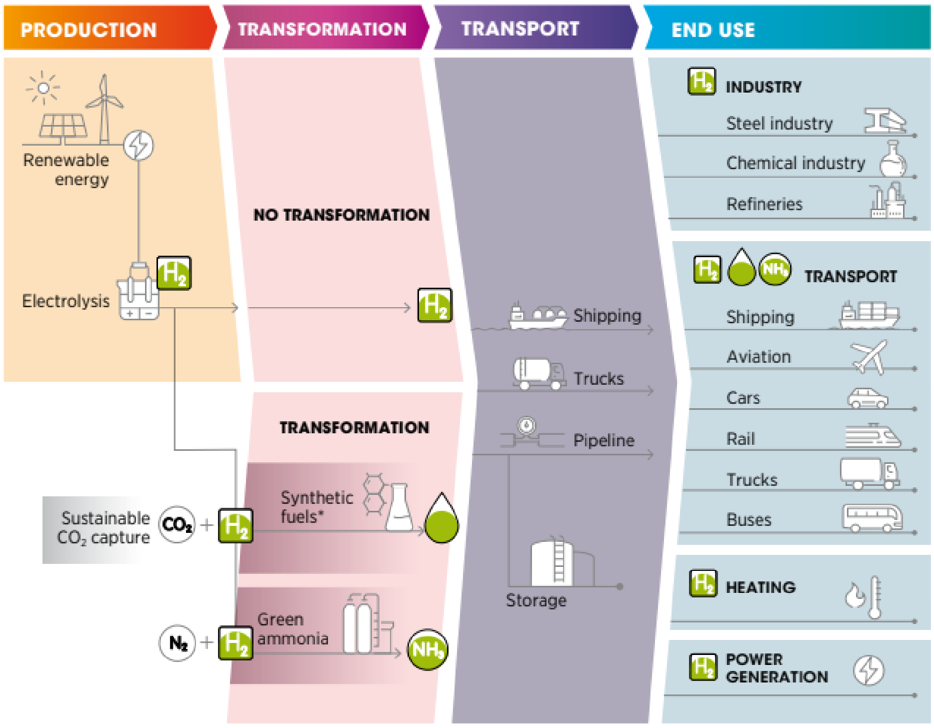

Figure 2.1: Green hydrogen value chain from renewable production to end-use applications across sectors [38]

plex. Barriers are high production costs, limited infrastructure (pipelines, storage, refuelling), regulatory uncertainty and the need for harmonised standards and certification schemes for 'clean' hydrogen [55, 77]. The contribution of hydrogen is also dependent on demand-side readiness. The integration of hydrogen technologies hinges on coordinated investments in supplying the infrastructure and a range of end-use technologies, such as fuel cells, hydrogen turbines, hydrogen-ready steel furnaces and ammonia-fuelled maritime engines [44]. However, this transition is challenged by what is called the 'chicken-and-egg' problem, meaning that hydrogen producers are hesitant to invest in large-scale, capital-intensive supply infrastructure without guaranteed demand [16]. Potential consumers are reluctant to adopt hydrogen technologies without reliable, affordable, widespread hydrogen availability. This mutual dependence between supply and demand creates a coordination failure typical of infrastructure-intensive transitions.

2.2. Water Electrolysis Technologies

Green hydrogen is typically produced through water electrolysis, where electrical energy is used to split water into hydrogen and oxygen. This is achieved via two half-cell reactions: the hydrogen evolution reaction at the cathode and the oxygen evolution reaction at the anode [8]. There are three principal water electrolysis technologies under development at this moment, which are: AEC, PEM and SOEC. Each technology has different characteristics regarding electrolyte type, operating conditions, system design and technological maturity. In Figure 2.2 the conceptual set-up of these three techniques is demonstrated.

AECs are the most established electrolysis technology, with over a century of commercial use. It uses an alkaline liquid as electrolyte and utilises nickel-based electrodes separated by a porous diaphragm that allows ion transport [49]. Some advantages of this technology are its technical maturity and operational robustness in steady-state applications, particularly in industrial environments with predictable electricity input profiles [89]. Also, it relies on abundant and relatively inexpensive materials for electrodes and other structural components [8]. This makes AECs attractive in terms of material cost and long-term durability under constant loads [49]. Conversely, these systems face limitations when operated under dynamic conditions, such as the intermittent renewable energy sources [8]. The diaphragms

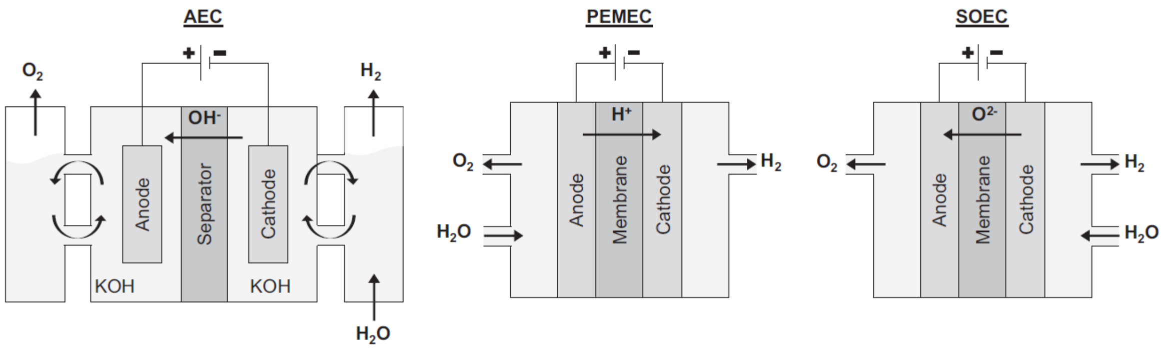

Figure 2.2: Schematic overview of the main electrolysis technologies: AEC with liquid KOH electrolyte, PEM with a solid polymer electrolyte, and SOEC operating at high temperature with a ceramic electrolyte. [49].

exhibit a degree of gas, which increases the risk of gas crossover and reduces the efficiency and safety under partial load operation [8]. Moreover, the liquid electrolyte constraints pressure flexibility and system compactness [71]. These characteristics limit the suitability of AECs for applications that require fast response or variable operation, such as grid-balancing or decentralised renewable integration [49].

PEM systems represent a more recent technological development and have seen accelerating deployment due to their compatibility with fluctuating electricity supply [8]. PEM systems use a solid polymer electrolyte membrane, which conducts protons from anode to cathode while physically separating the product gases [8]. The compact system allows for operating at higher pressures, facilitating downstream hydrogen compression and reducing the need for auxiliary mechanical compression systems [71]. It is a solid system, enhancing safety and purity, as the risk of gas crossover is minimised and the produced hydrogen is of high quality [8]. PEMs are highly responsive and can modulate production in real time, which makes them ideal for coupling with variable renewables such as wind and solar power [8]. Their ability to tolerate quick changes in load and maintain stable under transient conditions positions them well for emerging roles in grid services and decentralised hydrogen production [72]. However, PEM requires expensive and scarce materials, such as platinum and iridium [8]. The acidic environment within the membrane also places constraints on material selection, increasing the overall system costs [8]. Furthermore, progress has been made in extending system lifetimes, but durability under high current densities and prolonged cycling remains a limiting factor compared to AECs [8].

SOEC operates on a complete different principle compared to AEC and PEM. SOECs rely on solid oxide ceramic material to conduct oxygen ions at elevated temperatures [49, 63]. These systems typically employ a dense electrolyte, which enables ion conduction only at high temperatures [49]. The high temperature operation of SOECs allows for substantial thermodynamic efficiency gains, as part of the energy required for electrolysis is supplied in the form of heat rather than electricity [49, 90]. This makes SOEC particularly attractive for industrial integration, where waste heat is available, or where high overall energy conversion efficiency is required. In addition to splitting water into hydrogen and oxygen, SOEC can also co-electrolyse steam and carbon dioxide to produce syngas [49]. This can be used as a precursor for synthetic fuels and chemicals. This flexibility opens pathways for carbon recycling and the production of renewable hydrocarbons. SOECs technology remains at a relatively early stage of development and commercialisation [71]. The high operating temperature introduces material challenges, regarding thermal cycling, component degradation and sealing integrity [49]. Ceramic components are prone to mechanical stress and degradation under prolonged operation, limiting the stack lifetime and reliability of the system [49]. The complete overview can be found in Table 2.1.

2.3. Current Status & Challenges

Electrolyser deployment has entered an accelerated phase, but remains far from reaching the level required to support global net-zero ambitions [83]. The following section draws on insights from the two latest reports by IEA: the Global Hydrogen Review [27] and the World Energy Outlook [32]. By the end of 2023, global installed electrolyser capacity had reached approximately 700 MW, with low-emissions hydrogen accounting for less than 1% of global hydrogen production. At present, AEC and PEM, are

Parameter	Alkaline Electrolysis (AEC)	Proton Exchange Membrane Electrolysis (PEM)	Solid Oxide Electrolysis (SOEC)
Electrolyte	Liquid KOH solution	Solid polymer (e.g. Nafion)	Solid oxide ceramic (e.g. YSZ)
Operating Temperature	Low (typically 60–80°C)	Low to moderate (typically 50–80°C)	High (typically 650–1000°C)
Operating Pressure	Low	High	Moderate
Electrode Material	Nickel-based	Platinum, Iridium	Ceramic materials
Dynamic Response	Moderate (seconds)	Very fast (milliseconds)	Moderate
System Compactness	Low (bulky systems)	High (compact design)	Moderate
Hydrogen Purity	High	Very high	High
Typical Efficiency (HHV)	Moderate	Moderate to high	Very high (can exceed 100% with heat integration)
Material Cost (Catalysts)	Low (non-noble metals)	High (noble metals)	Moderate to high (no noble metals)
Technology Maturity	Commercial/mature	Commercial/expanding	Pilot/demonstration stage
Suitable Applications	Large-scale, steady-load industrial hydrogen production	Decentralized systems, renewable-grid integration	Industrial integration, synthetic fuel and syngas production

Table 2.1: Comparison of key characteristics of the three main water electrolysis technologies: AEC, PEM and SOEC. Data sources: [8] [38]

positioned at the transition between the formative and growth phases. There are signs of take-off, as electrolyser capacity is growing rapidly in countries such as China, driven by coordinated industrial policy and capital investments. China accounted for over 40% of global Final Investment Decision (FID) in 2023 and holds nearly 60% of global manufacturing capacity, mirroring its early rise in solar PV and battery industry. Meanwhile, Europe fourfolds its FID to over 2 GW, supported by instruments like the EU Hydrogen Strategy and the Renewable Energy Directive. North American deployment is advancing through industrial hydrogen hubs and large-scale blue hydrogen projects.

Despite the growing volume of announced projects, which is nearly 520 GW globally, only a small fraction have reached FID, indicating that the project pipeline remains fragile [27]. In fact, more than 80% of additional capacity announced for near-term deployment in 2023 was not backed by FID. This gap reflects speculative announcements without firm financial closure or regulatory approval. Moreover, the pace and scale of future deployment remain uncertain due to the complex system dependencies, including the availability of renewable electricity, infrastructure and stable demand from industry or transport. These are critical risks, leading to potential project cancellations or delays. There is a clear implementation gap between announced production targets and realised investments. Industrial decarbonisation, particularly in steel, ammonia and methanol production, offers the most immediate opportunity, as green hydrogen can directly substitute grey hydrogen in these processes.

Beyond industry, transport applications such as hydrogen fuel cell trucks, aviation and shipping are beginning to attract more commercial interest. Government mandates, including ReFuelEU Aviation and California's Low Carbon Fuel Standard, are helping to create early markets [27]. Hydrogen's role in seasonal energy storage, grid flexibility, and power-to-X systems is also gaining traction, although the necessary infrastructure remains underdeveloped [27]. Despite these positive trends, the cost gap between green hydrogen and fossil-based alternatives remains a barrier. According to the IEA, even if green hydrogen production costs fall by 50% by 2030 under current policies, they are still expected to exceed fossil-based hydrogen by USD 1–3 per kilogram [27].

2.3.1. Capital Expenditure

The Capital Expenditure (CAPEX) of a water electrolysis system is typically divided into two main components: the electrolyser stack and the Balance of plant (BoP). The stack serves as the electrochemical core where hydrogen is produced, while the BoP includes all auxiliary subsystems required to support and operate the stack safely, reliably, and efficiently. The stack generally accounts for approximately 40–50% of the total system CAPEX. It comprises all components directly involved in the electrolysis process, such as electrodes, electrolytes, current collectors, membranes or diaphragms, and structural supports. Stack costs are primarily influenced by material choices, operating conditions (e.g., temperature and pressure), and manufacturing complexity. Opportunities for cost reduction lie in material substitution, standardisation of components, and advances in fabrication techniques. The BoP, making up the remaining 50–60% of system CAPEX, encompasses the supporting infrastructure needed to manage fluid circulation, power delivery, gas handling, and overall system integration. Together, these two elements define the technical and economic performance of electrolyser systems and are central to ongoing cost-reduction strategies. The cost breakdown for PEM electrolyser can be found in Figure 2.3.

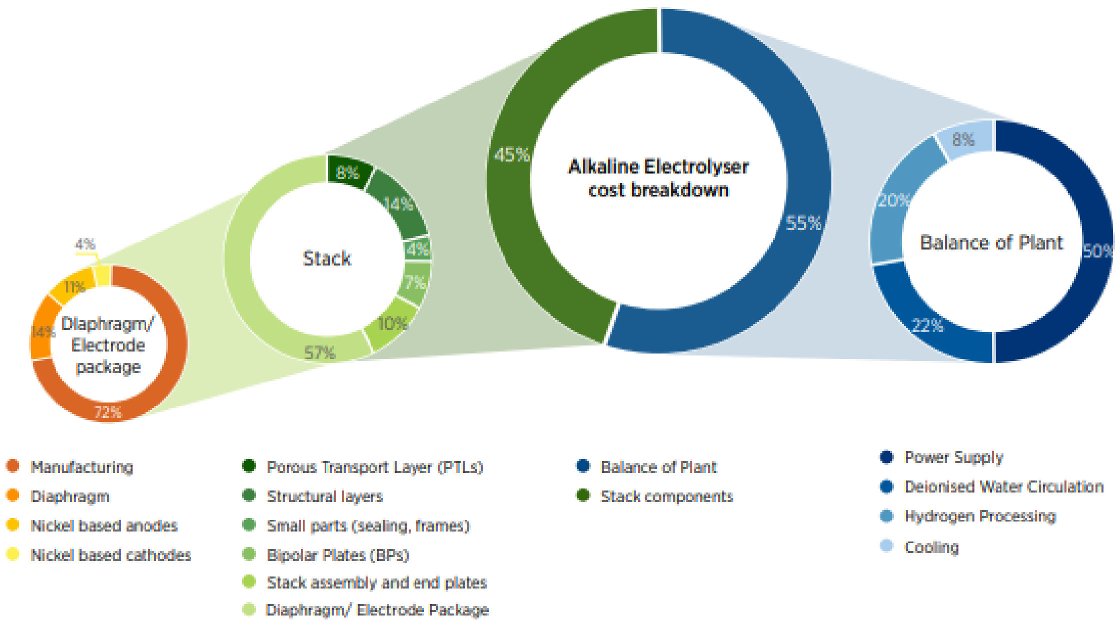

Figure 2.3: Cost breakdown PEM electrolysers divided in Stack (l) and Balance of Plant (r). Source: [38]

2.4. Forecasting models

This section outlines what models exist in the literature about the two key components of technology forecasting: the modelling of deployment through S-curve diffusion patterns and the projection of the CAPEX. Furthermore, it discusses how uncertainty is addressed in forecasting frameworks, highlighting the importance of probabilistic methods in capturing the inherent unpredictability of technological evolution.

2.4.1. Deployment

The diffusion of new technologies often follows a characteristic S-shaped curve, a pattern widely observed across sectors [83, 9]. Electrolyser deployment is expected to follow this trajectory, as it transitions from niche pilot projects to widespread adoption in decarbonisation pathways. These curves divide technological diffusion dynamics into three distinct phases [42, 53]. This is shown in Figure 2.4: a slow formative phase marked by uncertainty, experimentation and policy-supported pilots [5]. This phase ends with 'take-off' [53, 68], meaning that new technologies become capable of steady expansion [42]. This marks the beginning of the acceleration phase, where expansion is speeding up as a result of reinforcing dynamics such as improved economic return, technological learning effects and increasing policy support. These factors are collectively described as 'increasing returns' [9]. After this, the technology matures and approaches its peak penetration, where the pace of growth gradually slows. This deceleration could be driven by rising marginal costs [6, 82], challenges associated with integrating the technology into the electric grid and broader energy system [53][54]. Additionally, political pushback and social opposition can emerge [53]. Ultimately, this results in a saturation stage where the technology market share stabilises and ceases to grow further [68].

S-curve models are widely used in energy technology forecasting [9, 65, 92, 91]. These models approximate the diffusion of technologies as an S-shaped function over time. There are two commonly used S-curve types in the literature: logistic [81] and Gompertz [20] models. The logistic curve assumes a

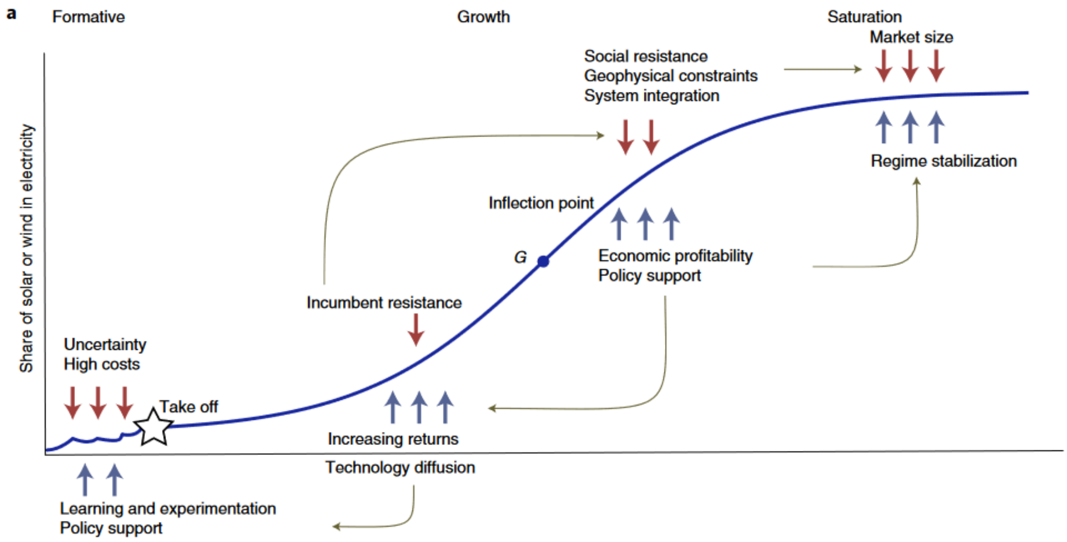

Figure 2.4: S-curve showing phases of technology diffusion. Formative, growth, and saturation, with key drivers and barriers influencing each stage. Source: [9]

symmetric growth profile. Adoption starts slowly, accelerates until a midpoint (inflexion point) and then slows down symmetrically as it did in the saturation phase. This model is appropriate when growth is limited by structural ceilings, such as maximum market size or physical capacity (this can be the case for solar panels) and when the rate of adoption is largely proportional to the remaining potential. In contrast, the Gompertz curve is asymmetric and has a more gradual deceleration after the inflexion point. It is suitable for modelling technologies whose adoption accelerates quickly but saturates more slowly. In the case of electrolysers, several indicators support the appropriateness of an S-curve approach. First, electrolyser technologies are modular, allowing for scaling through replication. Moreover, data on project announcements and policy targets suggest that electrolyser markets are moving rapidly into an acceleration phase, driven by large-scale industrial investments and increasing policy commitments.

2.4.2. Cost Projections

Cost forecasting models are analytical tools used to estimate future developments based on historical data, expert judgment, or mathematical relationships [59]. In the energy sector, these models are applied to predict the future costs, deployment or performance of technologies. Accurate forecasting supports the development of strategies for decarbonisation, infrastructure planning and market design [83]. IEA and IRENA are key institutions that provide global energy outlooks and technology cost projections [29][40]. These analyses are used for national energy strategies and international policy discussions by producing long-term energy trends. Forecasting models differ in their underlying methodologies, how they incorporate uncertainty, and the techniques used to evaluate their predictive accuracy [59]. The following sections explore these aspects in more detail by highlighting key approaches and considerations in technology cost forecasting.

Models can be categorised into expert-based and model-based approaches. Expert-based forecasting relies on the judgment and insights of industry specialists, particularly when empirical data is limited [60] or when a technology is still in its early stages of development [59]. Expert-based can be structured or unstructured, with varying degrees of methodological rigour. Unstructured expert input involves informal consultations with specialists in the field to estimate the future cost trends. This method is simple and resource-efficient, but lacks transparency and consistency, which might make it susceptible to bias [58]. A more systematic approach is expert elicitation, which employs formalised methods to structure expert input and mitigate biases [3, 60]. This technique is resource-intensive but enhances reliability by aggregating multiple expert perspectives. Another structured approach is the use of group methods, such as the Delphi technique, which employs an iterative process to refine expert opinions toward a consensus [2, 22]. Additionally, prediction markets have been explored as an alternative method, assuming that market-based mechanisms can aggregate dispersed knowledge and generate more accurate forecasts [84]. Expert-based models have several limitations: They are inherently subjective and might suffer from cognitive biases such as overconfidence and groupthink [59]. The accuracy of their projections depends on the selection of experts and the structure of the elicitation process [59].

In contrast, model-based forecasting relies on empirical data and mathematical models to project future cost developments. These models assume that past trends in technological progress will persist and serve as indicators for future cost reductions [59]. The most commonly used models in renewable energy forecasting are Wright's and Moore's Law [17, 62]. Wright's Law, also known as the learning curve model, posits that costs decline as a function of cumulative production [85]. This principle is based on learning by doing, where increased deployment leads to efficiency improvements and economies of scale. Experience curves track product costs development, including all associated cost factors such as R&D and sales. These are broader but more uncertain indicators [71]. The rate at which cost decline with cumulative production is known as the experience rate. Moore's Law, suggest that costs decline exponentially over time, independent of production levels [17, 62]. This formula was originally formulated for the semiconductor industry, but has also been observed in renewable energy technologies, where cost declines have occurred over time. Beyond these foundational models, several alternative and hybrid approaches refine the forecasting of technology costs. Goddard's Law considers the role of economies of scale in driving cost reductions [62]. The Sinclair-Klepper-Cohen model expands on this by incorporating both deployment and scale as key cost drivers [62]. Nordhaus's model blends elements of Wright's and Moore's laws, by acknowledging both time-dependent and deployment-driven cost declines [62]. The two-factor learning curve model further refines cost projections by integrating additional variables such as a Research & Development expenditures [56].

A critical concept for Wright's law underpinning model-based forecasting is the learning rate, which quantifies the relationship between cumulative production and cost reductions [69, 70]. The learning rate represents the percentage decrease in cost for each doubling of cumulative production, serving as a key metric for forecasting costs [85]. Cost reductions with increased cumulative experience can be sorted into three groups [87]: Cost reductions occur through improvements in the production process, such as technical innovations, increased worker productivity and economies of scale. They also result from changes in the product itself, including redesign, standardisation, and technological advancements. Lastly, lower input costs for materials and labour contribute to overall cost declines. In models like IAM, learning rates play an important role in determining which technologies become dominant [69]. Technologies with the highest learning rates are often favoured in energy mix projections, as many models aim to minimise system costs. Slight differences in learning rates can lead to significant variations in future energy system compositions [57]. However, the assumption that learning rates remain constant over time can be problematic, as external factors such as material constraints, policy shifts and technological breakthroughs can alter cost trajectories [69].

The selected forecasting model depends on the nature of the technology being analysed and the availability of historical data. Wright's Law is well suited for technologies with learning-by-doing effects, which is the case, for example, for photovoltaics and battery storage. Moore's Law may be appropriate when historical trends exhibit steady exponential cost reduction. Hybrid models incorporate additional variables, such as research and development (R&D). However, when models require additional parameters, overfitting can be a risk. This can lead to poor out-of-sample forecasting [83].

2.4.3. Uncertainty

Uncertainty is a critical characteristic of technological forecasting, arising from unforeseeable future changes such as technological breakthroughs, costs fluctuations, and knowledge spillovers [21]. Different forecasting approaches incorporate uncertainty in varying ways, affecting the reliability and applicability of cost projections. Models can be probabilistic or deterministic by nature. Deterministic forecasting provides a single-point estimate of future costs, while relying on learning curves such as Wright's Law and Moore's Law [83]. The learning rate is estimated using regression analysis on historical data, producing a fixed forecast trajectory. Deterministic models do not incorporate an estimate of the error of the forecast.

Probabilistic forecasting builds upon deterministic models by introducing uncertainty by considering a range of possible future outcomes. In the context of technological change, three key sources of uncertainty have been identified [59]. The first source is measurement error, which arises because the true value of technological change parameters can never be known with absolute certainty. The second source is endogenous uncertainty, which stems from the unpredictable nature of innovation itself. Since technological advancements result from complex interactions between research, market conditions, and policy decisions, future developments cannot be precisely anticipated. The third source is exogenous uncertainty, which results from unforeseen economic, political, or environmental events that may impact technology deployment and cost reduction trends. Probabilistic forecasting methods incorporate these uncertainties by allowing parameters to vary over time. One approach assumes that the technological change parameter itself is uncertain and may fluctuate [34]. In addition, stochastic noise terms might be added to models, representing shocks to the system that could arise from economic fluctuations or policy shifts [17]. Standard techniques to forecast costs are Monte Carlo simulations, which produce a distribution of potential future cost trajectories [59, 47].

Despite their advantages, probabilistic approaches remain underutilised in mainstream energy and technology cost forecasting. Several barriers explain this limited adoption. First, probabilistic models involve greater methodological and computational complexity, often requiring extensive model runs and significant computational resources that many institutions do not have [14]. Second, probabilistic approaches demand richer and higher-quality data to specify accurate probability distributions, which is often unavailable or difficult to collect for emerging technologies [36]. Moreover, institutional inertia and established practices contribute to the continued preference for simpler deterministic narratives, which are perceived as easier to communicate to policymakers and stakeholders.

2.5. Research Gap

2.5.1. Misleading sense of certainty in Energy Forecasting

There is a growing recognition that energy system models must better incorporate uncertainty. Many widely used models such as IAMs and forecasts from prominent organisations like the IEA and the IRENA, rely on deterministic projections and do not account for uncertainties [83][88][61]. A major issue with these forecasts is that they create a false sense of precision [61], leading policymakers and investors to believe in highly reliable cost trajectories, when in reality, technology costs are influenced by numerous unpredictable factors [59]. IAMs assume fixed relationships between deployment and cost reductions and neglects real-world uncertainty arising from policy shifts, economic shocks and knowledge spillovers. Deterministic approaches underestimate the variability in future cost declines and fail to capture the complexity of technological innovation [59]. Probabilistic forecasting methods have been proposed as a more robust alternative to address these shortcomings. These methods better reflect the inherent uncertainty in technological cost evolution. However, such probabilistic techniques are still underutilised in mainstream energy-economy models.

2.5.2. Underestimation of Renewable Energy Cost decline

Multiple studies have shown that energy-economy models have systematically overestimated the costs of renewable energy technologies while underestimating their deployment rates. Way et al. [83] provides empirical evidence that IAMs and IEAs reports have consistently projected higher costs for renewable technology, compared to actual cost declines. A consequence of this underestimation is that policy decisions may be based on outdated cost assumptions, which leads to suboptimal investment strategies. For example, if models predict that renewables will remain expensive for decades, governments and investors may delay crucial funding for infrastructure and market expansion. This bias has already influenced international climate policy discussions, where energy transition scenarios are often based on overly pessimistic cost projections. Moreover, not all technologies follow the same cost trajectory [83], meaning that poor forecasting can result in overinvestment in some technologies and missed opportunities in others [69]. The three electrolysis techniques follow distinct cost trajectories, efficiency levels and scalability challenges [72].

2.5.3. Lack of transparency and Repeatability

Another critical gap in the literature is the lack of transparency and repeatability in forecasting methods. Many energy system models and cost projections rely on proprietary datasets, undocumented assumptions and methodologies that are not easy to reproduce. This lack of transparency makes it difficult for researchers and policymakers to verify results, compare forecasts or assess the robustness of different models. Without standardised validation techniques, different forecasting models may produce different results. This makes it challenging to assess which models offer the most reliable predictions. Furthermore, a lack of open-access data and unclear methodological documentation further limits the ability of independent researchers to replicate findings, leading to inconsistent conclusions across studies.

2.6. Research Question

In response to the limitation identified above, this thesis investigates the following central question:

"How can probabilistic modelling improve the accuracy and decision-relevance of cost forecasts for electrolysers compared to traditional deterministic approaches?"

3
Method

This chapter presents the methodological framework developed to forecast future cost trajectories of electrolysis technologies, specifically AEC and PEM electrolysers. The approach integrates deployment forecasting via logistic S-curve modelling and cost estimation using Wright's Law with uncertainty propagation. Forecasted deployment trajectories are the key input to Wright's Law cost model, linking cumulative installed capacity to projected unit cost declines. SOEC is excluded from this analysis due to insufficient historical data on deployment and cost, preventing robust parameter estimation for forecasting. The methodological sequence is illustrated in Figure 3.1, which outlines the key data sources, forecasting techniques, and intermediate outputs.

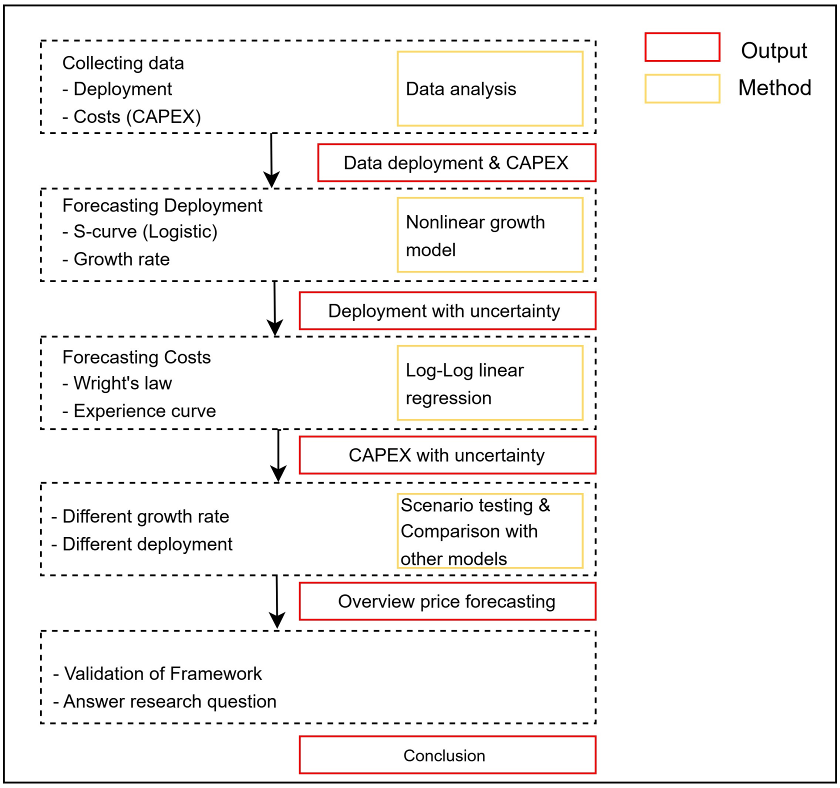

Figure 3.1: Overview of the methodological framework

3.1. Deployment AEC & PEM

Projecting the future deployment of the two electrolyser technologies is challenging due to the technology's ongoing transition from experimental to large-scale application. Conventional approaches to modelling technology diffusion (see subsection 2.4.1), such as fitting S-curve models to historical deployment data, can be misleading when a technology is in a formative or early exponential growth phase [65, 92]. This is particularly relevant for electrolysers, where early deployment was limited and fragmented. Moreover, recent years have seen a sharp policy and investment-driven acceleration.

This study uses the data from the IEA's Hydrogen Production and Infrastructure Projects Database [28] to construct a meaningful projection. The dataset was filtered to extract cumulative installed capacity per year, disaggregated by AEC and PEM electrolyser systems. It is further refined to include only installations powered by renewable electricity, aligning the scope with this study's focus on green hydrogen. This historical deployment is visualised in Figure 3.2, which shows the global evolution of cumulative green hydrogen production capacity. The data is categorised by the current status of ongoing projects: Operational, FID, Feasibility Study, and Concept stage. AEC electrolysers are more mature and have lower system costs, meaning they dominate the early deployment [71]. In contrast, PEM systems have shown a steeper deployment trajectory in recent years, driven by their dynamic performance and compatibility with intermittent renewable energy sources [71].

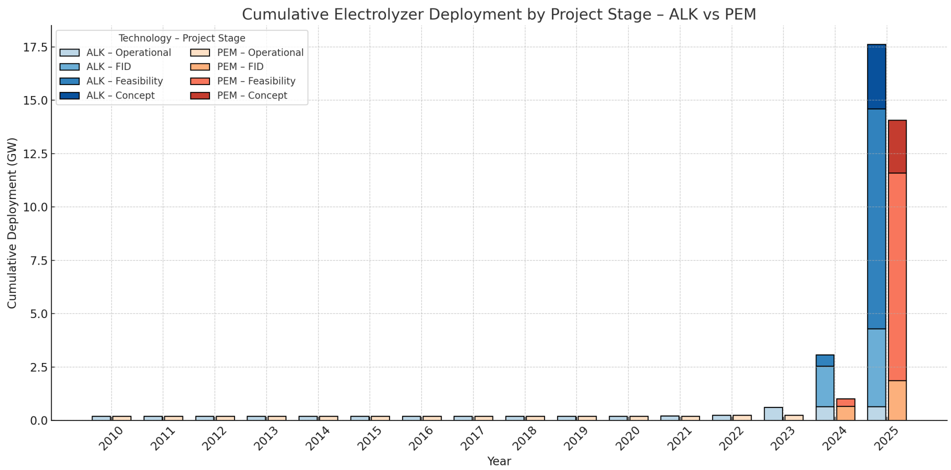

Figure 3.2: Historical deployment AEC and PEM per status. Data source: [28]

Despite the utility of this dataset, applying a standard S-curve fit over the full historical period might be inappropriate. The early observations primarily represent a pre-commercial phase characterised by demonstration projects, which do not indicate current market dynamics. Including these data points in curve-fitting exercises might bias the model in two critical ways: if no upper bound is imposed, the model may extrapolate the recent acceleration into implausibly high capacity levels by 2050, far exceeding any realistic scenario. Conversely, if a fixed asymptote is imposed to constrain the projection, the model will often converge toward that saturation value, regardless of whether the data justifies it. In either case, the result is an overly rigid projection and insufficiently grounded in empirical trends, making it poorly suited for technologies undergoing structural transition.

3.1.1. Logistic Forecasting Model

To address these limitations of historical curve fitting, this study adopts a forward-oriented, policy-driven logistic growth model formulated in discrete differential form. This aligns with the methodology of Odenweller et al. [65] and is suited to technologies in a formative expansion phase (see Figure 3.3). Moreover, this model enables probabilistic scenario generation based on uncertain but policy-relevant parameters. Instead of fitting the full historical time series, the model simulates future electrolyser capacity by drawing from three key uncertain inputs: installed capacity in 2025, the growth rate of deployment, and a time-dependent saturation curve aligned with 2030 and 2050 demand targets. These saturation levels are not fixed but evolve over time to reflect anticipated shifts in policy ambition and

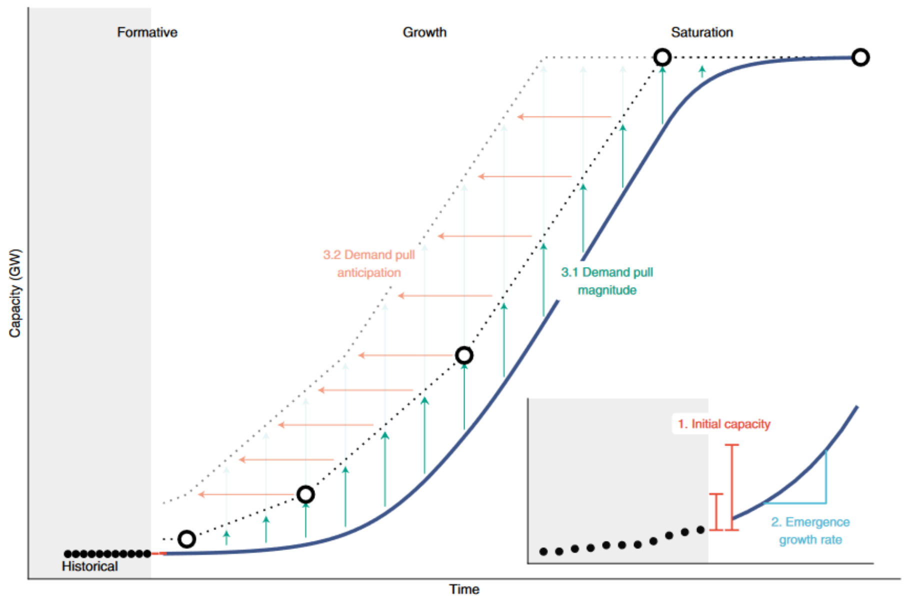

Figure 3.3: Key uncertainties in technology diffusion represented by an S-curve model, with four uncertainty dimensions: (1) the initial capacity at the start of the projection, (2) the emergence growth rate that determines how quickly deployment accelerates, (3.1) the demand-pull magnitude reflected in the saturation level for 2030 and 2050, and (3.2) the anticipation years that shift deployment earlier in time. Together, these parameters define the shape and timing of the diffusion pathway, resulting in a wide range of possible deployment outcomes. Source: [65].

market uptake. The logistic differential is defined as:

$$C_{t+1} = C_t + b \cdot C_t \left(1 - \frac{C_t}{C_{\text{max},t}}\right) \tag{3.1}$$

with the following definitions:

- C_t: cumulative installed electrolyser capacity in year t [GW]
- b: annual intrinsic growth rate [%/year]
- $C_{\text{max},t}$: time-dependent saturation level [GW], derived from demand targets
- C_0: initial capacity in the base year (2025)

This model captures the compounding nature of deployment growth while ensuring that saturation constraints are respected through a decelerating term that intensifies as cumulative capacity approaches the time-varying upper bound $C_{\text{max},t}$. Unlike deterministic curve-fitting approaches, which obscure the influence of structural uncertainty in technology evolution, this formulation tries to represent the stochastic nature of the underlying system. The model allows uncertainty into the resulting deployment trajectories by modelling the key input parameters as probability distributions rather than fixed values. The three uncertainty parameters will be further explained below:

1. Initial Capacity in 2025 (C_0)

The parameter C_0 defines the starting point of the deployment trajectory and is critical in shaping early-year dynamics of the projection. In this case, the installed capacity in 2025 involves considerable uncertainty due to long lead times, supply chain constraints and potential delays in commissioning. Rather than assigning a point estimate to this variable, the model adopts a probabilistic treatment, modelling C_0 as a truncated normal distribution whose parameters are derived from the IEA Hydrogen Production and Infrastructure Projects Database [28]. The construction of the realised and announced projects in this database reflects different project maturity levels. In this distribution, the lower bound is defined by the set of projects currently in operation. These represent confirmed capacity and thus form a conservative minimum. The mean is established by including all projects that are either operational or have reached FID, which denotes a commitment to proceed with construction and indicates short-term implementation. The upper bound extends these bounds further to include projects at the feasibility study and concept stages. Although these are more speculative, their inclusion reflects that there is a possibility that market or policy conditions could accelerate. These ranges allow the model to generate realistic uncertainty around the base-year capacity without over-representing either highly certain or purely speculative projects. The truncated normal distribution ensures that sampled values remain within physically plausible bounds and avoids long tails. The probability density function (PDF) of the truncated normal distribution used for C_0 is given by:

$$f(x \mid \mu, \sigma, a, b) = \frac{\phi\left(\frac{x-\mu}{\sigma}\right)}{\sigma\left[\Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)\right]}, \quad \text{for } x \in [a, b] \tag{3.2}$$

where:

- μ is the mean capacity estimate (operational + FID projects),
- σ is the standard deviation reflecting project uncertainty,
- a is the lower bound (operational capacity),
- b is the upper bound (operational + FID + concept + feasibility),
- $\phi(\cdot)$ is the probability density function (PDF) of the standard normal distribution, which describes the relative likelihood for a random variable to take on a given value,
- $\Phi(\cdot)$ is the cumulative distribution function (CDF) of the standard normal distribution, which gives the probability that a variable is less than or equal to a given value.

2. Emergence growth Rate

The second source of uncertainty in the model is the growth rate of cumulative electrolyser capacity. This parameter captures the underlying momentum of market expansion and how strongly deployment responds to enabling conditions such as falling costs, supportive policy frameworks and rising demand. In the logistic formulation, the growth rate determines the curve's steepness at its inflexion point, where the increase in capacity reaches its maximum. A higher growth rate leads to a more rapid scale-up and earlier inflexion, while a lower rate results in a more gradual expansion trajectory. To reflect uncertainty in how quickly the electrolysis market may grow under varying economic and policy scenarios, the model treats the growth rate as a probabilistic variable drawn from a truncated normal distribution (see Equation 3.2). For the growth rate, the parameters have the following meaning:

- x is a particular value of the growth rate,
- μ is the mean of the untruncated normal distribution,
- σ is the standard deviation,
- a and b are the lower and upper truncation bounds,
- $\phi(\cdot)$ is the standard normal probability density function,
- $\Phi(\cdot)$ is the standard normal cumulative distribution function.

3.1 Demand pull magnitude ($C_{max,t}$)

The demand pull magnitude represents the upper boundary of potential market uptake, beyond which further deployment slows as systemic, economic, or infrastructural limits are approached. In this model, the level of saturation is a dynamic function over time, reflecting the evolving scale of future hydrogen demand and policy ambition. This time-varying saturation function $C_{max,t}$ acts as a moving constraint on capacity expansion. It allows the model to imitate real-world demand signals, such as industrial targets, regulatory goals, or decarbonisation pathways and incorporates them as directional forces in the diffusion process. This formulation prevents the model from either overestimating near-term growth or underestimating long-term potential due to arbitrary curve-fitting limitations. Therefore, a linear interpolation between 2025, 2030, and 2050 defines the time-varying saturation function $C_{\text{max},t}$:

$$C_{\text{max},t} = C_i + \left(\frac{C_{i+1} - C_i}{t_{i+1} - t_i}\right)(t - t_i), \quad \text{for } t \in [t_i, t_{i+1}] \tag{3.3}$$

where:

- t_i, t_{i+1} are consecutive milestone years (e.g., 2025, 2030, 2050),
- C_i, C_{i+1} are the corresponding saturation values in GW for those years,
- $C_{\text{max},t}$ is the interpolated saturation level in year t.

3.2 Demand pull anticipation
Another parameter that influences the model's saturation level is the anticipation years. In real-world markets, investment behaviour is not purely reactive to realised demand but is strongly influenced by anticipated future conditions. To account for this, the model includes an anticipation lag of the default value of 5 years. This implies that the model responds to saturation constraints earlier than the official target year suggests. Operationally, this is implemented by advancing the saturation trajectory by five years, such that the market effectively begins tracking towards the 2030 target already in 2025 and towards the 2050 target by 2045. This captures the tendency of project developers, policymakers and investors to act based on forward-looking signals, including climate policy announcements, subsidies and strategic industrial plans.

3.1.2. Reference Case Deployment

To illustrate the model's behaviour and enable a structured comparison of alternative deployment pathways, a reference case is defined for the deployment. This represents the estimate of future electrolyser deployment, grounded in current policy ambitions and market trends. It serves as a benchmark against which variations in the model's key uncertain parameters can be explored. In Table 3.1, an overview of the baseline parameter values is presented.

Parameters	**Value**	**Unit**	**Source**
1. Initial capacity (2025)			
AEC – Mean	4.30	GW	IEA Hydrogen database [28]
AEC – Lower bound	0.66	GW	
AEC – Upper bound	17.70	GW	
PEM – Mean	2.13	GW	IEA Hydrogen database [28]
PEM – Lower bound	0.26	GW	
PEM – Upper bound	14.33	GW	
2. Growth rate (AEC and PEM)			
Mean	39	%/year	Historical growth of wind and solar capacity [7]
Lower bound	15	%/year	
Upper bound	70	%/year	
3.1 Demand pull magnitude			
AEC – 2030	398	GW	IEA NZE scenario [30]
AEC – 2050	1.137	GW	
PEM – 2030	847	GW	IEA NZE scenario [30]
PEM – 2050	2.415	GW	
3.2 Demand pull anticipation			
Default	5	Years	Assumption

Table 3.1: Overview of key model parameters for AEC and PEM Reference case

The values chosen for the initial capacity are derived from the IEA Hydrogen database, as described in Equation 3.1.1. The values for growth rate are derived from the paper of Odenweller et al. [65], who derived a representative distribution of early-stage deployment growth from historical data on Solar photovoltaic and onshore wind. In this analysis, exponential growth rates were fitted to all possible seven-year intervals between 1995 and 2010 at global level. This period was selected to capture the most dynamic expansion phases. This results in a distribution with a mean annual growth rate of 39% and a standard deviation of 11.86%. Wind and solar growth rates were selected because these technologies represent the historically fastest-growing sources of clean energy, driven by strong policy support and large-scale deployment during their early market phase. As shown by Odenweller et al. [65], their empirical expansion patterns provide a valid proxy for estimating the potential ramp-up of electrolysis, given its similarly transformative role in future energy systems and its expected dependence on comparable policy-driven dynamics.

The saturation trajectory is anchored in the optimistic targets from the IEAs Net Zero Emissions by 2050 Scenario (NZE), a pathway designed to limit global warming to 1.5°C by achieving net-zero greenhouse gas emissions globally by 2050. According to the NZE scenario, total demand for low-emission hydrogen is projected to increase from 212 Mt/year in 2030 to 527 Mt/year by 2050. Table 3.2 presents the sectoral breakdown:

Sector	**2030**	**2050**
Electricity	52	102
Refineries	25	8
Buildings and Agriculture	17	23
Transport	25	207
Industry	93	187
Total	**212**	**527**

Table 3.2: Sectoral hydrogen demand under the NZE scenario (Mt/year) [30].

In 2030, approximately 54% of total hydrogen demand is projected to be met via electrolysis, rising to 62% by 2050 [30]. This corresponds to 114 Mt/year of electrolytic hydrogen production in 2030 and 327 Mt/year in 2050. Assuming a full-load factor of 50% (i.e., 4,380 hours/year), a lower heating value (LHV) of 120 MJ/kg, and an average conversion efficiency of 70% [83], the resulting global installed electrolyser capacity required is approximately 1,245 GW by 2030 and 3,552 GW by 2050.

Based on the announced future projects (see Appendix D), this model assumes that approximately 32% of global electrolyser capacity will be based on AEC electrolysers and 68% on PEM electrolysers. This corresponds to a required installed capacity of around 398 GW for AEC and 847 GW for PEM by 2030, increasing to approximately 1,137 GW and 2,415 GW respectively by 2050.

Technology	2030 (GW)	2050 (GW)
AEC	398	1,137
PEM	847	2,415

Table 3.3: Electrolyser capacity requirements under NZE (GW), assuming 32% AEC and 68% PEM.

3.2. Forecasts costs

In this section, the methodology used to forecast the CAPEX will be described. This method uses historical cost data and the deployment projections from subsection 3.1.1 by employing Wright's Law. CAPEX data for electrolysers were compiled from two different databases: Glenk (2003-2018) [19] and from the Global Hydrogen Review (2019-2024) [27][26][25][24][31]. The dataset of Glenk & Reichelstein includes system-level costs, which cover the electrolyser stack, BoP and compression equipment and is inflation adjusted to a base year. The data coming from the IEA covers full Power-to-Gas (PtG) systems, including additional infrastructure and are approximately 15% higher compared to the costs of the other database [19]. These values were adjusted to constant euros using the GDP deflator [78]. For forecasting purposes, the CAPEX series reflects system acquisition costs in EUR2019/kW for the electrolyser stack, BoP and compression equipment. The historical CAPEX can be found in Figure 3.4. Deployment data for the corresponding years were taken from the logistic-based forecasts developed in section 3.1.1 and will be merged together with the CAPEX to the corresponding year.

3.2.1. Wright's Law Model

To model future cost developments of electrolysers, this thesis adopts Wright's Law (see subsection 2.4.2). This approach is chosen for its strong empirical performance across more than 50 technologies, particularly those undergoing rapid scale-up, such as solar PV, wind, and batteries [83].

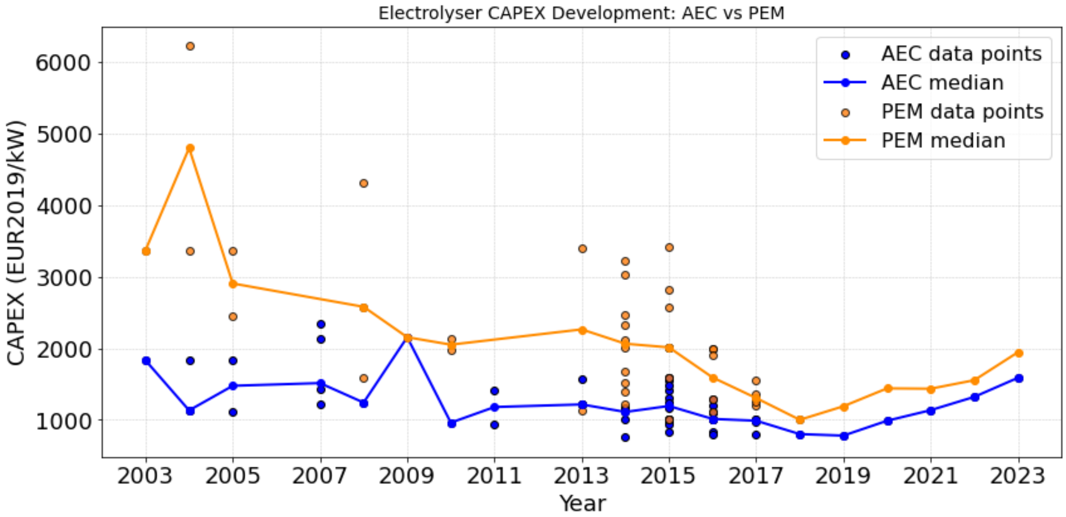

Figure 3.4: Historical CAPEX data for AEC and PEM electrolysers (2003–2023), shown with annual medians. Data are inflation-adjusted to EUR2019 and sourced from Glenk & Reichelstein [19] and the IEA. PEM shows a stronger cost decline over time, while AEC remains relatively flat with less variability.

Compared to time-based models like Moore's Law, Wright's Law better captures the role of market growth and learning-by-doing, as it links cost reductions directly to cumulative experience rather than the passage of time [62, 46]. This feature makes it especially relevant for electrolysis, where future cost trajectories are expected to be driven by deployment scale-ups supported by industrial policy and coordinated investment strategies. Furthermore, backtesting studies have shown that Wright's Law consistently outperforms alternative models in forecasting cost reductions in energy technologies, offering a statistically validated basis for long-term projections [83, 46]. The model is expressed in log-linear form as:

$$\log(C_t) = a + b \cdot \log(Q_t) \tag{3.4}$$

where:

- C_t is the cost in year t (EUR/kW),
- Q_t is the cumulative deployment in year t (MW),
- a is the intercept, representing the cost at unit deployment ($Q_t = 1$),
- b is the experience exponent.

A negative value of b implies that costs decline as cumulative deployment increases. The experience exponent b quantifies the percentage change in cost for a given percentage change in cumulative deployment.

The learning rate (LR) expresses the percentage cost reduction resulting from each doubling of cumulative deployment. It is derived from the experience exponent using the following relationship:

$$\mathrm{LR} = 1 - 2^b \tag{3.5}$$

The parameters a and b are estimated using ordinary least squares (OLS) regression of $\log(C_t)$ on $\log(Q_t)$, using all years for which concurrent cost and deployment data are available.

3.2.2. Statistical Evaluation and Hypothesis Testing

To assess whether Wright's Law is a statistically valid model for each technology, a hypothesis test is conducted. The null hypothesis (H_0) states that there is no learning effect (i.e., $b = 0$). The p-value resulting from this test indicates whether the relationship between cost and deployment is statistically significant. A low p-value (below 0.05) suggests strong evidence against the null hypothesis, confirming the presence of a learning effect.

In addition to the experience exponent b and its p-value, the regression analysis provides the standard error of b, which quantifies the uncertainty in the estimated learning rate. The noise standard deviation (σ) measures the residual variation not explained by the model, reflecting the scatter in the historical data. The coefficient of determination (R^2) indicates the proportion of variance in the cost data that can be explained by cumulative deployment, with higher values suggesting a better model fit. These parameters provide important insight into the suitability and reliability of Wright's Law for modeling future cost trajectories. Detailed results and interpretations of these statistical outputs for AEC and PEM electrolysers are presented in section 4.2.

3.2.3. Stochastic Forecasting with Shock Propagation

While Wright's Law provides a robust framework for modelling cost reduction, it is inherently deterministic and does not account for uncertainty in future cost trajectories. To overcome this limitation, this thesis adopts the stochastic extension proposed by Meng et al. [59], which introduces path-dependent uncertainty through the addition of normally distributed shocks. This formulation modulates cost evolution as a stochastic process in log-cost space. Starting from an initial known cost level in the anchor year, future costs evolve according to Wright's Law, with an added random shock at each time step. The resulting model is:

$$\log(C_{t+1}) = \log(C_t) + b \cdot \Delta \log(Q_t) + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \tag{3.6}$$

Where:

- $\Delta \log(Q_t)$ is the year-over-year change in log deployment,
- σ is the standard deviation of the residuals from the historical OLS regression.

The standard deviation of the residuals, denoted by σ, plays a central role in the stochastic shock model. It quantifies the typical deviation size between observed historical costs and the values predicted by the deterministic Wright's Law regression. Mathematically, it is computed from the residuals of the ordinary least squares (OLS) regression of $\log(C_t)$ on $\log(Q_t)$:

$$\sigma = \sqrt{\frac{1}{n-2} \sum_{t=1}^{n} \left(\log(C_t) - \log(\hat{C}_t) \right)^2} \tag{3.7}$$

$\log(\hat{C}_t)$ represents the cost predicted by the fitted Wright's Law model in year t, and n is the number of years with historical data. σ captures the historical "noise" in the relationship between cost and deployment that cannot be explained by cumulative experience alone. These deviations may arise from various factors such as policy interventions, commodity price swings, supply chain disruptions, or measurement errors. By propagating these shocks into the future, the model reflects the possibility that similar deviations could occur again, thereby widening the range of plausible cost outcomes over time. In the simulation, a new random shock is drawn from a normal distribution with standard deviation σ at each future time step.

3.3. Monte Carlo Simulation

To account for uncertainty and produce probabilistic forecasts, Monte Carlo simulations are applied to both deployment and cost models. In a Monte Carlo simulation, key uncertain input parameters are randomly sampled from defined probability distributions, and the model is run many times to generate an ensemble of possible future outcomes. This approach allows the full distribution of possible trajectories to be explored rather than providing only a single deterministic estimate.

For the deployment forecasts, Monte Carlo simulations are used to capture uncertainty in the S-curve parameters: initial installed capacity, growth rate, and saturation level. Each simulation run represents a consistent set of assumptions drawn from the defined distributions. The logistic equation is iteratively solved from 2025 to 2050, updating capacity annually. This result in a probabilistic range of cumulative electrolyser capacities. For the cost forecasts, a Monte Carlo simulation is applied by repeatedly sampling random shocks at each future time step within the stochastic Wright's Law framework. Each simulation run follows a unique cost trajectory, incorporating technological learning and possible deviations from the expected trend due to exogenous shocks.

This combined approach ensures that both deployment and cost uncertainties are explicitly quantified and presented as probability distributions. The probabilistic outputs are then analysed to derive median estimates, confidence intervals and percentile ranges.

3.4. Scenario Design and Setup

The reference case assumes a mean maximum growth rate of 39% in the inflexion point, reflecting historical patterns observed in wind and solar deployment. However, this assumption may be overly optimistic. Projections for hydrogen production have historically overestimated realised output, often by a factor of two to three, and continue to anticipate a faster uptake than what has been observed over the past 50 years [43]. This persistent supply constraint has important implications for long-term decarbonisation strategies. Green hydrogen may remain scarce for the next two decades, reinforcing the view that it should be reserved for applications where alternatives are limited and the mitigation impact is highest. With this analysis, two questions will be discussed. (i) What average growth rate would be required for global electrolyser capacity to meet the hydrogen demand specified in NZE scenario; and (ii) How would different deployment trajectories influence the future CAPEX of PEM and AEC electrolysers.

3.4.1. Growth Rate Scenario

To evaluate whether the historical median growth rate derived from wind and solar diffusion are sufficient to meet future electrolyser capacity targets, this thesis examines two scenario setups regarding growth rates. First, the required growth rate to meet the demand targets outlined in the IEA NZE scenario by 2050 is calculated. This scenario reflects an ambitious policy pathway in which hydrogen is widely used across multiple sectors, including transport, buildings, and electricity generation.

Second, a more constrained interpretation of hydrogen's role is considered in which the demand is limited to essential sectors only. The NZE scenario envisions a rapid and extensive expansion of hydrogen use across a broad range of energy and industrial sectors. Hydrogen is allocated substantial roles in buildings, transport, power generation, and various forms of industrial heat. However, some literature urges caution toward such an expansive deployment trajectory [43]. While not disputing hydrogen's strategic importance, these perspectives highlight that its broad application across the energy system may be neither the most efficient nor the most cost-effective path in many cases. Critics point out that converting electricity into hydrogen and using it in end-use technologies such as boilers, vehicles, or turbines entails significant energy losses [80] and high infrastructure requirements [74]. These drawbacks make hydrogen less suitable in contexts where more direct and mature decarbonisation pathways, such as battery electrification or heat pump adoption, are already available and more efficient.

Building on this more constrained interpretation of hydrogen's role, a revised scenario is proposed in which hydrogen demand is limited to applications considered technically necessary and economically justified. Based on rankings from the 'Hydrogen Ladder' [50] and 'Hydrogen Policy's Narrow Path' [33], this includes refining, hydrogenation, fertiliser, ammonia, and methanol production. Hydrogen use in buildings, agriculture, and the transport sector is excluded. As a result, global hydrogen demand is substantially lower than in the NZE scenario. By 2030, total hydrogen demand amounts to 118 Mt, rising to 195 Mt by 2050. Applying the same electrolysis-based production shares as in NZE, the corresponding green hydrogen capacity targets can be found in Table 3.4 and Table 3.5 and the calculated growth rates will be discussed in section 4.3.

Sector	NZE 2030	NZE 2050	Essential 2030	Essential 2050
Electricity	52	102	0	0
Refineries	25	8	25	8
Buildings & Agriculture	17	23	0	0
Transport	25	207	0	0
Industry	93	187	93	187
Total	**212**	**527**	**118**	**195**

Table 3.4: Sectoral hydrogen demand (Mt) under NZE and essential-use scenarios.

Technology	NZE 2030	NZE 2050	Essential 2030	Essential 2050
AEC	398	1,137	222	420
PEM	847	2,415	471	894
Total	**1,245**	**3,552**	**693**	**1,314**

Table 3.5: Electrolyser capacity requirements (GW) under NZE and essential-use scenarios, assuming 32% AEC and 68% PEM shares.

3.4.2. Costs Scenario

To evaluate the cost implications of uncertain deployment trajectories, three scenarios for global AEC and PEM capacity are defined based on a probabilistic diffusion model. These scenarios reflect increasing deviation levels from the capacity required to meet the NZE targets. The Delayed Transition (S1), represents the 5th percentile of the distribution and reflects a future in which global electrolyser deployment remains far below what is necessary. This could result from weak policy support, slow technological diffusion, and delayed market development. The Lagging Transition (S2), corresponds to the 25th percentile and captures a more moderate shortfall, where deployment advances but remains insufficient to close the demand gap by mid-century. Finally, the On-Track Transition (S3), is aligned with the median forecast and assumes that global capacity deployment progresses. This central scenario represents a future in which the electrolyser industry scales adequately to meet strategic hydrogen needs, which are presented in Table 3.2.

These three scenarios form the analytical foundation for a cost sensitivity analysis using Wright's Law. By linking each trajectory to cumulative installed capacity, the study quantifies how differences in deployment speed translate into divergent capital cost projections. Thus, the framework enables a robust comparison of cost outcomes under successful and insufficient scale-up conditions, offering insights into how market underperformance may hinder cost competitiveness through delayed learning.

3.5. Model Evaluation Methods

To ensure the robustness of the probabilistic forecasts, this thesis includes explicit model evaluation methods. These methods benchmark this model against widely used deterministic models from the IEA and Intergovernmental Panel on Climate Change (IPCC) and test the predictive accuracy.

This evaluation approach involves comparing the probabilistic forecasts generated in this study to established external scenarios from key international institutions. The results are compared to projections from the IEA and various IAMs used in IPCC reports. This comparison helps to contextualise the model outcomes within familiar policy and investment frameworks and illustrates how accounting for uncertainty might alter or refine insights drawn from traditional deterministic scenarios

The second evaluation method is based on hindcasting. This is a validation technique where a model is trained on historical data up to a certain point in the past and then used to predict known future values. This allows for direct comparison of predicted and actual outcomes. This provides evidence for the reliability and generalisability of the forecasting framework. The complete hindcasting set-up and detailed results are explained in chapter 6.

3.6. Code and Data Availability

To support transparency and reproducibility, all code and data developed for this thesis are openly available through separate persistent digital object identifiers (DOIs).

The complete modelling framework is implemented in Python and was used to simulate the probabilistic S-curve deployment forecasts, the stochastic Wright's Law cost projections, and the evaluation procedures (external scenario comparison and hindcasting). To ensure the code runs correctly, the input datasets need to be stored together with the code files in the same directory. This is required because the scripts directly reference local data files during execution.

The data and the code are available at: https://doi.org/10.4121/82988dc7-099b-45e2-81e2-3850cee1b940

In addition to the code and datasets, detailed documentation is provided to facilitate replication and enable further research or policy analysis.

4
Results

This chapter presents the outcomes of the probabilistic forecasting framework applied to both deployment and cost trajectories of electrolyser technologies. The objective is to apply the developed forecasting framework in order to quantify future deployment and cost trajectories for electrolyser technologies under uncertainty. Combining the probabilistic forecasts with experience-based cost modelling, the results aim to assess the likelihood of achieving targeted cost reductions and to explore how different growth pathways influence future CAPEX.

4.1. Deployment

For the reference case, the deployment of both AEC and PEM electrolysers is modelled using a normal distribution for initial capacity in 2025 and a shared normal distribution for annual growth rates. These input parameters can be found in Table 3.1. The distribution of the initial capacity is visualised in Figure 4.1, showing separate probability density functions for AEC on the left and PEM on the right. Both distributions are right-skewed, meaning that the tail extends more to the right side. The corresponding distribution for the annual growth rate, which applies identically to both technologies in this scenario, is shown in Figure 4.2.

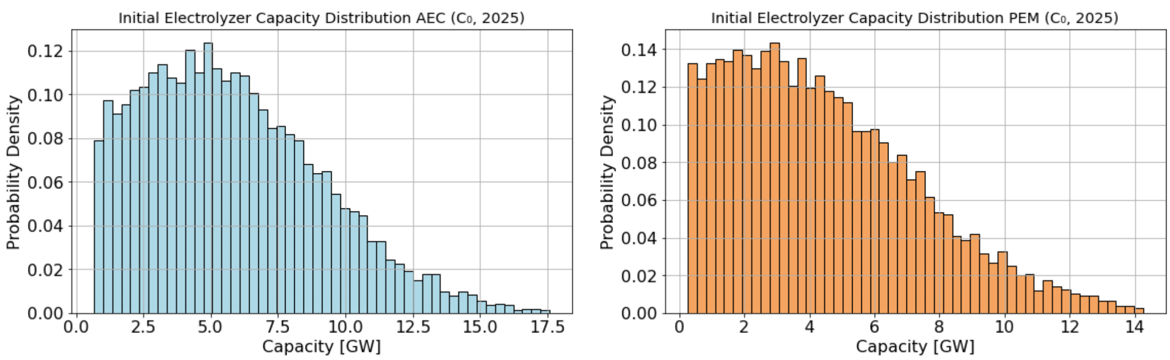

Figure 4.1: Probability distributions of initial installed capacity in 2025 for AEC (left) and PEM (right) electrolysers, used as input for the deployment forecast. The distributions reflect current market maturity and uncertainty.

To simulate the effect of policy or market guidance, the model includes predefined demand pull values for 2030 and 2050 from the NZE scenario. An anticipation time of 5 years is applied, which means the logistic growth model begins to approach these saturation levels five years before the target year, i.e. in 2025 and 2045. This simulates forward-looking investment behaviour in response to clear policy targets.

The results of the logistic forecast are shown in Figure 4.3 (a larger version is provided in Appendix A). The blue and orange lines represent the median cumulative electrolyser deployment over time, while

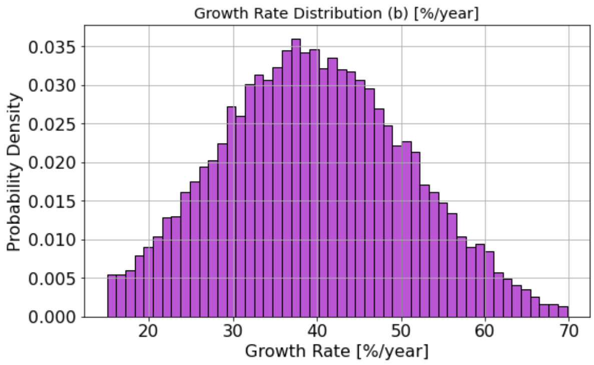

Figure 4.2: Distribution of maximum annual growth rates at the inflexion point, based on historical wind and solar deployment.

the shaded regions indicate the 50% and 95% confidence intervals. The dotted black line shows the demand pull derived from the target values and the anticipation years. The logistic model captures the expected S-curve diffusion pattern, with a slow initial uptake followed by a rapid acceleration toward 2040 before approaching saturation. By 2050, the 50% confidence interval includes the policy target for both AEC and PEM technologies. The 95% range shows a non-negligible risk of under deployment. AEC enters its saturation phase earlier, as a result of its greater technological maturity and lower final saturation potential, as evidenced by the earlier flattening of its deployment curve. In contrast, PEM, which is less mature and designed to serve higher capacity targets, continues to grow strongly beyond 2040. This indicates that AEC is approaching its practical deployment limits sooner, whereas PEM still has significant growth potential, albeit with higher uncertainty and dependency on future policy and market developments.

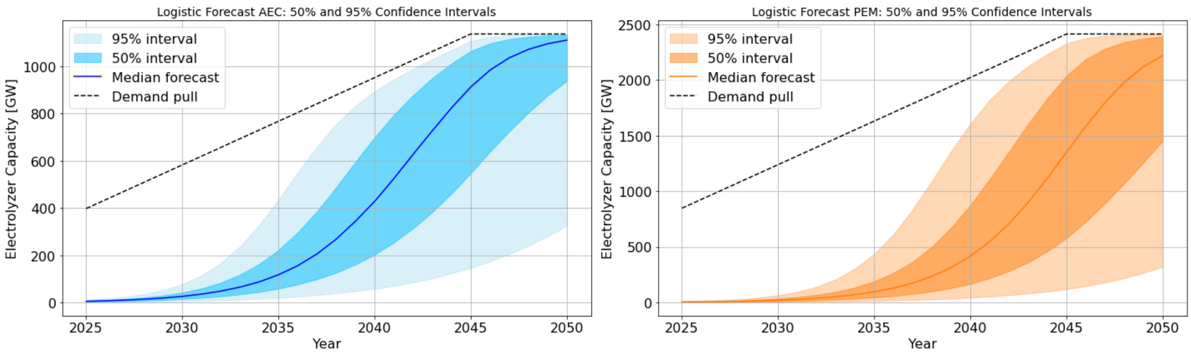

Figure 4.3: Probabilistic S-curve deployment projections for AEC (left) and PEM (right) electrolysers under the Reference Case. The solid line shows the median forecast trajectory, while shaded areas represent the 50% and 95% confidence intervals reflecting key uncertainties in model inputs. These uncertainties include: (1) initial installed capacity, visible as the starting point of each curve; (2) the growth rate, calibrated to reflect early diffusion dynamics similar to historical wind and solar adoption; and (3) the demand pull, illustrated by the dashed line, which represents net-zero emission scenario targets for 2030 and 2050 with a five-year anticipation period.

The probabilistic deployment forecasts under the reference case provide insights into both the expected growth patterns and the challenges of scaling electrolyser capacity to support net-zero targets. The median trajectories for both AEC and PEM electrolysers show significant growth beyond 2025, reflecting the current momentum and announced projects globally. However, the projections also demonstrate that, especially for PEM, fall short of the capacities needed to align with the IEAs NZE scenario.

A key insight is the role of the modelled growth rate. For the reference case, the median annual growth rate for both technologies is 39% and based on historical growth from wind and solar diffusion. While these rates already imply rapid scale-up, they are still insufficient to close the gap with policy-driven targets. This suggests that achieving net-zero compatible capacity levels would require higher growth rates than the demand pull targets. The minimum growth rates required will be further calculated and analysed in the scenario exploration in subsection 4.3.1. The wide uncertainty bands further emphasise this point, indicating substantial variability in potential outcomes. This variability signals a non-negligible risk of underdeployment, underscoring the need for targeted policy measures such as subsidies, risk guarantees, and long-term procurement contracts to secure investor confidence.

These probabilistic deployment trajectories can be directly linked to CAPEX forecasts using learning-curve approaches such as Wright's law (section 4.2). By associating each potential deployment path with corresponding cost reductions, it becomes possible to explore how different realisations of future deployment affect electrolyser CAPEX. This enables scenario analyses that illustrate how accelerating or lagging deployment influences future cost trajectories. Such integration provides policymakers and investors with valuable insights by clarifying the interplay between deployment dynamics and cost reductions, thereby supporting more informed strategic and financial planning.

4.2. Costs projections AEC and PEM

This section presents the CAPEX cost projections for AEC and PEM electrolysers. The historical CAPEX data is shown in Figure 3.4, spanning from 2003 to 2023. From 2003 to 2018, both technologies exhibit a generally slow but downward trend in CAPEX. However, the data is also highly scattered, meaning cost estimates vary significantly across sources and years. This reflects differences in system boundaries and project-specific conditions.

Moreover, in recent years (2018-2023), the long-term downward trend in CAPEX has reversed. Reported system costs for both AEC and PEM electrolysers have increased, marking a notable deviation from previous patterns. This reversal can be attributed to several interacting factors. First, global supply chain disruptions and volatility in raw material prices, particularly after the COVID-19 pandemic, have introduced substantial cost pressures across the manufacturing sector [18]. Additionally, rising energy and labour costs have further elevated the cost of equipment production and project implementation. Recent cost increases for PEM electrolysers are closely tied to the scarcity and price volatility of critical materials such as iridium and platinum [45]. Iridium is a rare material and is primarily sourced as a by-product of platinum mining in South Africa, where ongoing energy shortages have disrupted supply [13]. Moreover, demand for platinum has increased in recent years, exerting upward pressure on its market price. These factors have reversed the previous downward trend in CAPEX.

Wright's Law method is applied to estimate future cost developments by regressing the logarithm of historical CAPEX data against the logarithm of cumulative installed capacity. This approach assumes a power-law relationship between cost and deployment, where the slope of the regression line, the experience exponent b, reflects the percentage change in cost per doubling of cumulative deployment.

In Figure 4.4 the relationship between historical CAPEX versus cumulative deployment on a log scale, including trend lines for both AEC and PEM is presented. The key model output parameters and statistical indicators for both AEC and PEM electrolysers are presented in Table 4.1

Parameter	**AEC**	**PEM**
Experience exponent b	0.0460	–0.0480
Standard error of b	0.0545	0.0098
p-value	0.4099	0.0002
Noise standard deviation σ	0.2113	0.2507
R^2 (coefficient of determination)	0.0403	0.6171

Table 4.1: Wright's Law regression results for AEC and PEM electrolysers

For AEC electrolysers, the estimated experience exponent is $b = 0.0460$, which corresponds to a 4.6% increase in cost per 1% increase in cumulative installed capacity. This suggests a negative learning rate of approximately –3.3%, meaning that each doubling of cumulative deployment would result in a 3.3% increase in costs rather than a reduction, contradicting the central assumption of Wright's Law. The standard error of the estimated exponent is 0.0545, which is of the same order of magnitude as the coefficient itself. The standard error quantifies the uncertainty of the slope estimate and is determined by both the residual variance (the scatter of the data around the trend line) and the variability in cumulative deployment. The high standard error reflects the strong year-to-year cost fluctuations and

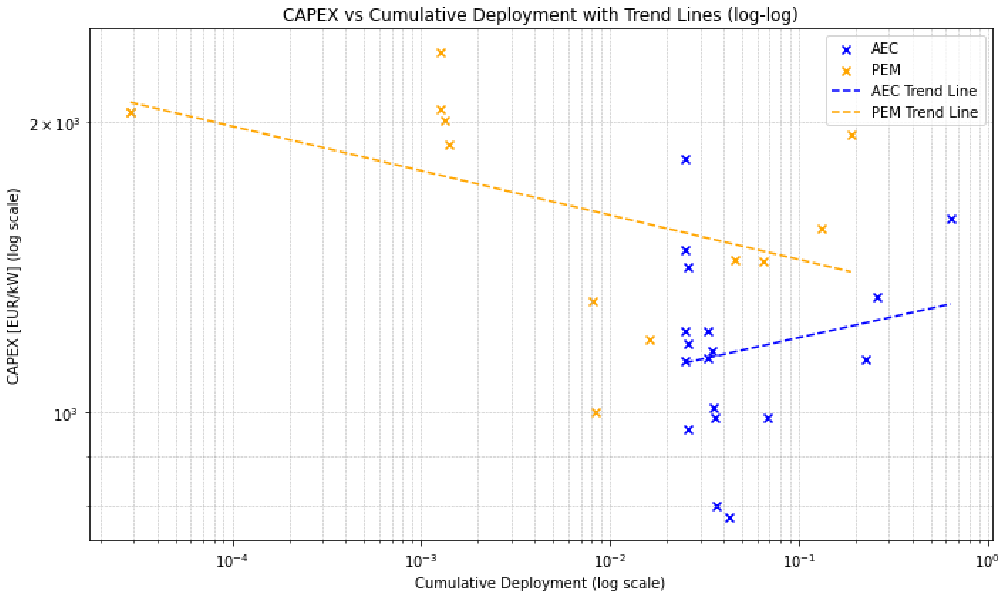

Figure 4.4: Scatter plot of historical CAPEX versus cumulative deployment for AEC and PEM electrolysers on a log-log scale, with trend lines. The upward trend for AEC confirms the absence of a learning effect and suggests potential cost increases, while the downward trend for PEM indicates a moderate cost reduction consistent with Wright's Law.

the relatively limited increase and variation in cumulative deployment over the historical period. These factors result in a low precision of the estimated learning effect. The p-value, which tests the null hypothesis that there is no relationship between cost and cumulative deployment ($b = 0$), is directly influenced by the standard error. A high standard error leads to a lower t-statistic and, consequently, a higher p-value. For AEC, the p-value is 0.4099, meaning the null hypothesis cannot be rejected, and the observed relationship is statistically indistinguishable from random variation. The poor overall model fit is further confirmed by a very low R^2 value of 0.0403 and a relatively high noise standard deviation ($\sigma = 0.2113$), highlighting the model's minimal explanatory power. These factors illustrate that the framework of Wright's Law does not work reliably for AEC with the currently available historical data, as the required assumptions of systematic cost declines and strong learning-by-doing effects are not supported.

By contrast, the model performs significantly better for PEM electrolysers. The estimated experience exponent is $b = -0.0480$, indicating that a 1% increase in cumulative installed capacity is associated with a 0.048% decrease in cost. This corresponds to a learning rate of approximately 3.3%, meaning that each doubling of cumulative deployment results in a 3.3% reduction in CAPEX, in line with the expected direction of Wright's Law. The standard error of the estimated exponent is 0.0098, which is considerably smaller than the absolute value of the coefficient. This reflects a clearer and more consistent cost decline pattern in PEM, as well as a more substantial variation in cumulative deployment over the historical period, resulting in a precise estimate of the learning effect. The p-value for PEM is 0.0002, which allows for the rejection of the null hypothesis that there is no relationship between cost and cumulative deployment, confirming the presence of a statistically significant learning effect. The overall model fit is strong, with an R^2 value of 0.6171, indicating that a substantial portion of the variance in historical costs is explained by cumulative deployment. While the noise standard deviation ($\sigma = 0.2507$) is relatively high, it is acceptable given the model's strong explanatory power and supports the robustness of the estimated learning rate.

Wright's Law provides a statistically valid and directionally appropriate model for PEM electrolyser cost development, supporting its use in future cost forecasting. In contrast, for AEC electrolysers, the relationship is statistically insignificant, directionally incorrect, and the model offers minimal explanatory power. These findings indicate that Wright's Law can be reliably applied to PEM electrolyser cost projections, whereas for AEC electrolysers, it is not applicable due to the scattered and inconsistent historical data. When historical data are too sparse or inconsistent, as is the case for AEC, these

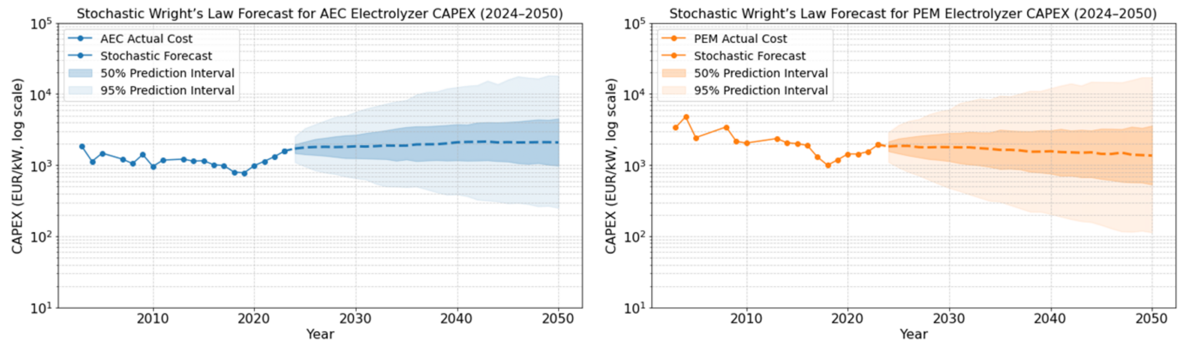

Figure 4.5: Stochastic Wright's Law forecasts for AEC (left) and PEM (right) electrolyser CAPEX with 50% and 95% confidence intervals.

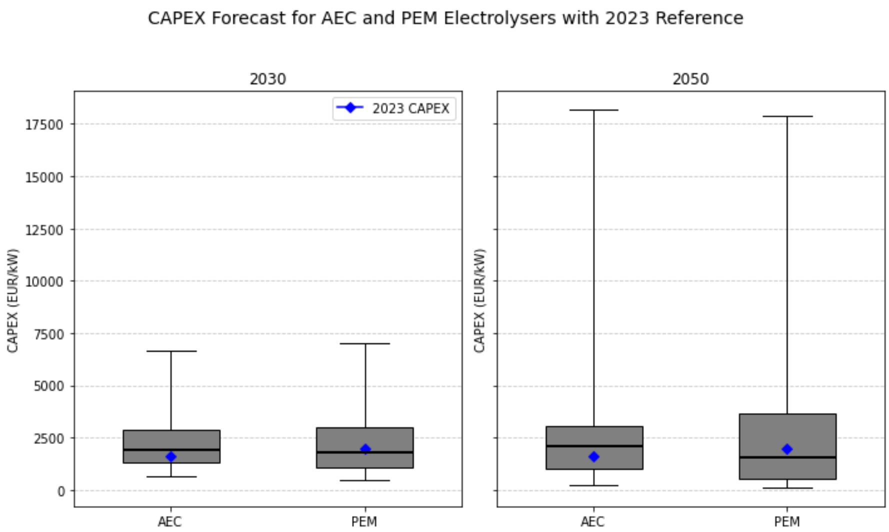

Figure 4.6: Forecasted CAPEX for AEC and PEM electrolysers in 2030 and 2050. Boxes show 50% intervals, lines mark medians, and whiskers indicate 95% intervals.

empirical learning-curve methods cannot be reliably applied. In such situations, expert elicitation aporaches may offer an alternative for generating cost projections. However, these should be used cautiously, since retrospective studies suggest that model-based time-series methods tend to provide more accurate and robust forecasting [59].

The cost projections are based on the median trajectory of the reference deployment scenario. In Figure 4.5, the CAPEX forecasts can be found, including uncertainty ranges derived from noise standard deviation, which is explained in subsection 3.2.3. For improved visibility, an enlarged version of Figure 4.5 is provided in Appendix B.

The CAPEX projections in Figure 4.5 and Figure 4.6 reveal the differences in the expected cost trajectories of AEC and PEM electrolysers. For AEC, the stochastic forecast is slightly upward, with a median projected CAPEX of 1,921 EUR/kW by 2030, increasing to 2,076 EUR/kW by 2050. The uncertainty bounds are wide: the 50% confidence interval in 2030 spans from 1,322 to 2,845 EUR/kW, while the 95% interval ranges from 630 to 6,643 EUR/kW. By 2050, the uncertainty becomes even more pronounced, with the 50% interval extending from 998 to 3,020 EUR/kW and the 95% interval stretching from 251 to 18,200 EUR/kW. This reflects the weak statistical signal in the AEC model, where the learning effect is insignificant and the forecast is highly sensitive to historical noise and variability. In practical terms, this suggests that future cost developments for AEC remain largely indeterminate unless accompanied by substantial structural innovations or strong policy interventions.

The PEM forecast exhibits a modest but statistically significant decline. The median CAPEX is projected

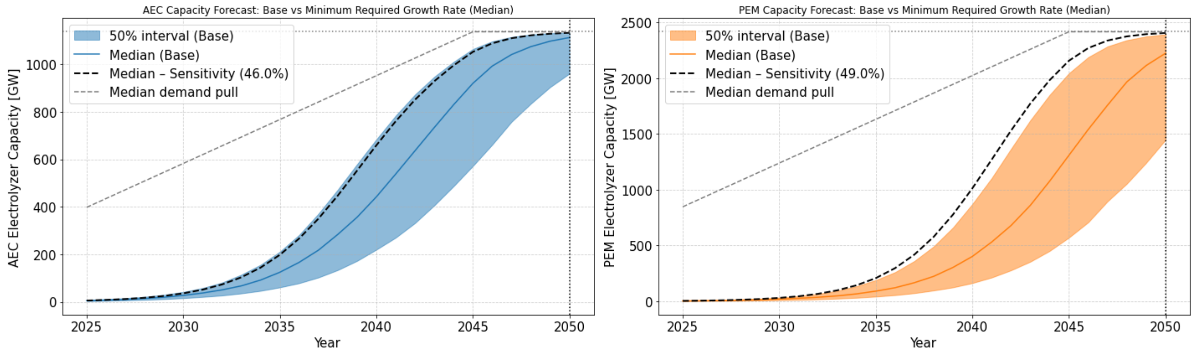

Figure 4.7: Required minimum annual growth rates for AEC (46%) and PEM (49%) to reach the 2050 NZE deployment target at the median of the forecast distribution.

to fall from 1,800 EUR/kW in 2030 to 1,533 EUR/kW by 2050. Although the decline is relatively slow, the overall trend indicates continued incremental improvement. In 2030, the 50% prediction interval spans from 1,050 to 2,988 EUR/kW, and the 95% interval from 492 to 7,010 EUR/kW. By 2050, the 50% interval ranges from 512 to 3,654 EUR/kW, and the 95% bounds extend from 118 to 17,882 EUR/kW. These intervals remain substantial, but they are narrower in relative terms compared to AEC, indicating greater confidence in the direction and magnitude of PEM cost reductions.

4.3. Scenarios

4.3.1. Growth rate

This analysis evaluates the minimum growth rate required for global electrolyser capacity to meet the NZE scenario target by 2050. The model systematically varied the growth rate to assess whether this base assumption is sufficient to achieve NZE-aligned capacity outcomes. All other model parameters were held constant relative to the base scenario. The target condition was defined as reaching the NZE deployment level in 2050 at the median (50th percentile) of the simulated capacity distribution. This condition represents a central tendency benchmark, providing a more balanced evaluation compared to upper-bound analyses.

The model estimates that a minimum fixed growth rate of 49.0% for PEM and 46.0% for AEC is required for the median forecast to meet the NZE threshold (see Figure 4.7). These rates significantly exceed the 39% baseline, implying that achieving central-aligned capacity outcomes would demand an accelerated deployment trajectory over the coming decades. These results highlight the scale of the challenge. Green hydrogen is frequently positioned as a key pillar in net-zero strategies, and the pace of deployment implied by NZE scenarios exceeds that observed in most historical energy transitions. Unlike early-stage exponential growth in solar PV or wind energy, the hydrogen value chain faces additional infrastructure, storage, permitting and end-use integration constraints. Sustaining this kind of growth rate over multiple decades would likely require targeted policy frameworks, long-term investment signals and globally coordinated industrial strategies, which are not present at this moment [32].

Building on the more constrained interpretation of hydrogen's role, a revised scenario is proposed in which hydrogen demand is limited to applications considered technically necessary and economically justified. To meet the target defined in this scenario, a growth rate for the inflexion point is 41% for AEC and 45% for PEM. While these rates are lower than the implied growth trajectory under the more expansive NZE scenario, they still exceed the historical mean growth rates observed for most renewable energy technologies. This means that even under a more conservative deployment outlook, the scale-up of electrolyser capacity, 222 GW for AEC and 471 GW for PEM by 2030, rising to 420 GW and 894 GW respectively by 2050, remains highly ambitious.

4.3.2. Costs

There are three capacity deployment trajectories, as shown in Figure 4.8. These scenarios are designed to examine how different deployment rates affect future CAPEX developments and to evaluate

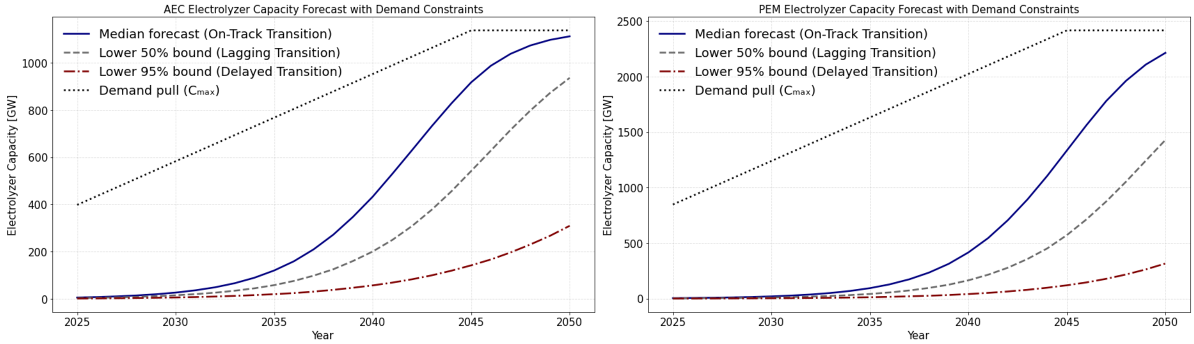

Figure 4.8: Deployment scenarios (S1: Delayed Transition, S2: Lagging Transition, S3: On-Track Transition) for global AEC (left) and PEM (right) electrolyser capacity from 2025 to 2050.

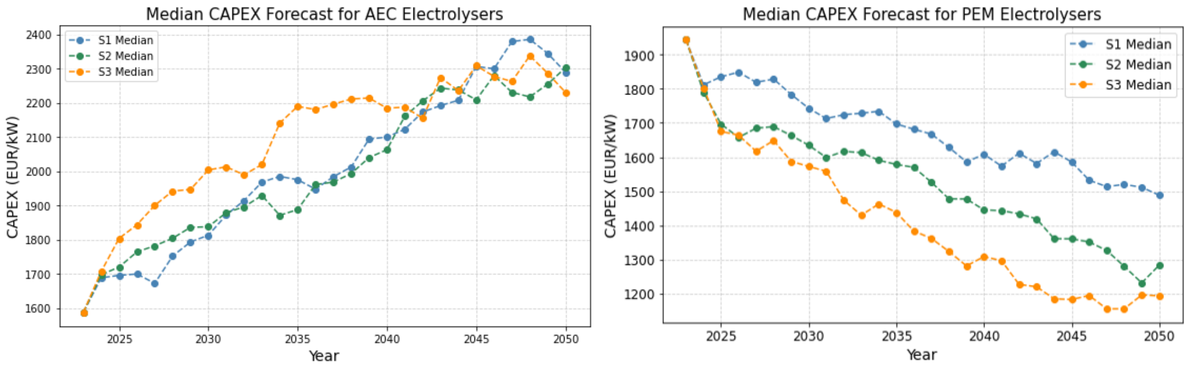

Figure 4.9: Median CAPEX trajectories for AEC (left) and PEM (right) electrolysers under three deployment scenarios: S1 (Delayed Transition), S2 (Lagging Transition), and S3 (On-Track Transition). PEM costs decline gradually across scenarios due to a positive learning effect, while AEC costs increase slightly over time and show no sensitivity to deployment, due to the absence of a statistically significant learning trend.

whether accelerated scale-up alone is sufficient to drive substantial cost reductions.

The CAPEX forecasts for electrolysers in the years 2030 and 2050 are presented across these three scenarios (see Appendix E). For PEM, the results show a gradual decrease in median costs as deployment scales up. In 2030, median CAPEX values range from 1,743 EUR/kW in the Delayed Transition (S1) to 1,573 EUR/kW in the On-Track Transition (S3). By 2050, this spread narrows further, with median values between 1,488 EUR/kW Delayed Transition (S1) and 1,193 EUR/kW On-Track Transition (S3)

These differences in scenario for PEM, though noticeable, remain modest in scale and are consistent with the logarithmic structure of Wright's Law. With a learning rate of 3.3%, even substantial differences in deployment only yield incremental changes in expected costs. This implies that even under optimistic deployment trajectories, CAPEX levels are unlikely to decline dramatically. From a policy and investment perspective, this suggests that rapid scale-up alone may not be sufficient to make electrolysers cost-competitive without additional interventions. Even in the most ambitious scenario, the model projects relatively high CAPEX levels by 2050. This could limit the strength of the investment case, as the expected returns from accelerated deployment may not justify the required capital without supplementary policy support or breakthrough innovations.

In contrast, the forecast results for AEC electrolysers appear unreliable. Due to the negative learning rate, the model projects increasing costs with higher deployment. Additionally, the projections show no variation across the three different scenarios, indicating that the results are largely insensitive to differences in deployment ambition. This combination of unexpected cost trends and weak scenario differentiation suggests that the AEC cost projections hold limited value for long-term forecasting and should be interpreted with caution. The complete median cost trajectory for both AEC and PEM of the three scenarios can be found in Figure 4.9.

5
Comparison to other models

This chapter compares the cost projections of PEM developed in this thesis to external forecasts from two major institutions: the IPCC AR6 Scenarios Database and the IEA World Energy Outlook. These institutions play a key role in shaping global hydrogen strategies, and their projections are widely used in policymaking and industry planning. AEC is excluded from this comparison due to the high uncertainty and weak learning signal in the model, which makes its cost trajectory too speculative for meaningful benchmarking. Comparing the model with projections from these sources is essential for two reasons. It shows whether this model is more conservative or optimistic than the widely used scenarios. Second, it highlights methodological differences. While the IPCC and IEA often rely on deterministic projections with fixed assumptions, this model is stochastic by nature.

5.1. Projections of IPCC (AR6)

The IPCC AR6 Scenario Database brings together more than 1.200 long-term energy climate scenarios developed by leading academic institutions [33]. These scenarios were submitted in support of the IPCC Sixth Assessment Report (AR6), which focuses on climate mitigation [37]. The scenarios are produced by IAM that simulate the evolution of global energy, land, and economic systems under different assumptions about socio-economic development, technological progress, and climate policy. Each scenario provides a consistent pathway for energy demand, emissions, technology deployment, and investment needs over the 21st century [64]. The database includes scenarios targeting different climate outcomes, limiting global warming to 1.5 °C, and those exceeding 3.0 °C by 2100. These outputs are used by the IPCC to assess the feasibility, cost, and effectiveness of different mitigation strategies across sectors, including the deployment and costs of electrolysers. The data is published and accessible and represents one of the most influential global sources for energy transition benchmarks used by policymakers, analysts and international institutions [23].

5.1.1. Cost projections of AR6

The AR6 scenarios estimate future cost developments based on assumptions, often using simplified representations of technological learning and cost evolution to enable consistency across long-term, system-wide pathways. Most IAMs apply either exogenous cost trajectories, based on predefined annual decline rates, or endogenous learning, where costs fall as a function of cumulative deployment using learning rates [11]. The cost assumptions are generally deterministic, meaning that the scenario produces a single cost path with no uncertainty range. IAMs may also impose cost floors to prevent capital costs from falling below assumed lower limits, which can artificially constrain further cost reductions even under high deployment. Technology detail is often limited and IAMs rarely differentiate between electrolyser types (AEC and PEM) or include recent market dynamics such as price volatility, material shortages, or learning stagnation.

Each scenario in the database reflects a combination of:

- Socio-economic storyline: Includes assumptions about population growth, GDP growth, and energy demand.
- Policy assumptions: Covers carbon pricing, net-zero targets, and implementation of nationally determined contributions (NDCs).
- Technology deployment trajectories: Encompasses the scale-up of technologies such as hydrogen and electrification.
- Climate outcome targets: Focuses on limiting global warming to specific thresholds, such as 1.5°C or 2°C.

This analysis compares the probabilistic cost projections for PEM electrolysers with the cost trajectories derived from four IAMs used in the IPCC AR6 Scenario Database: IMAGE, REMIND, POLES, and TIAM. Table 5.1 provides an overview of the IAMs and scenarios used. These IAMs differ in their structural design, scope and the way they handle cost evolution. IMAGE relies on exogenous cost assumptions, meaning that technology costs are pre-defined and do not adjust in response to modelled deployment outcomes. Its modelling approach emphasises the interaction between energy, land, and climate systems, but cost trends remain static over time irrespective of system behaviour [1]. In contrast, REMIND employs an optimisation framework that incorporates endogenous learning-by-doing. Here, cost reductions are linked to cumulative deployment, and the model features a high level of macroeconomic integration [52]. POLES is simulation-based and includes detailed representations of energy technologies, but cost developments are driven mainly by fixed decline trajectories, reflecting a primarily exogenous framework [66]. TIAM builds upon the TIMES framework and includes endogenous learning with relatively high technological resolution [51].

Model Name	Full Name	Institution / Developer	Key Strengths	Scenario Examples
IMAGE	Integrated Model to Assess the Global Environment	PBL Netherlands Environmental Assessment Agency	Land use, agriculture, climate–energy–land interactions	IMAGE 3.0
REMIND	Regional Model of Investments and Development	PIK (Germany)	Endogenous learning, intertemporal optimization	CEMICS
POLES	Prospective Outlook on Long-term Energy Systems	CNRS / Enerdata (France)	Technology substitution, policy scenario realism	ENGAGE
TIAM	TIMES Integrated Assessment Model	ETSAP / UCL	Bottom-up energy tech detail, optimization	Grantham 3.2 and ICM

Table 5.1: Overview of projected IAMs and example scenarios used in the AR6 Scenario Database

Figure 5.1 presents the CAPEX trajectories based on these IAMs, alongside the Wright's Law-based probabilistic forecast developed in this thesis. It is important to note that the Wright's Law model is derived from PEM electrolyser-specific data, while IAM scenarios represent electrolysers without technological differentiation. Across the IAM scenarios, cost projections vary significantly. TIAM-Grantham 3.2 and TIAM-ECN produce more optimistic cost pathways. Of the four models, TIAM-GRANTHAM 3.2 aligns most closely with the median trajectory over the entire period from 2005 to 2050. The projected costs remain well within the 50% confidence interval, indicating consistency with empirical trends. In contrast, POLES ENGAGE, IMAGE 3.0, and REMIND (CEMICS) produce more conservative projections, with cost levels generally at or above the 75th percentile of the probabilistic distribution. Static cost assumptions or restrictive cost floors that do not allow continued learning effects might be the reason for this divergence.

This comparison underscores the benefit of using probabilistic, empirically grounded forecasts in technology assessment. The model not only presented historical learning behaviour but also provides a transprent range of uncertainty. This stands in contrast to deterministic IAM outputs, which may understate the potential for cost reductions or fail to reflect the full range of plausible outcomes.

5.2. Projections IEA

In addition to comparing model-based cost trajectories with peer-reviewed literature and historical benchmarks, it is relevant to contrast these findings with projections from major institutional scenarios. One prominent reference is the IEA, which published scenario-based cost expectations in World

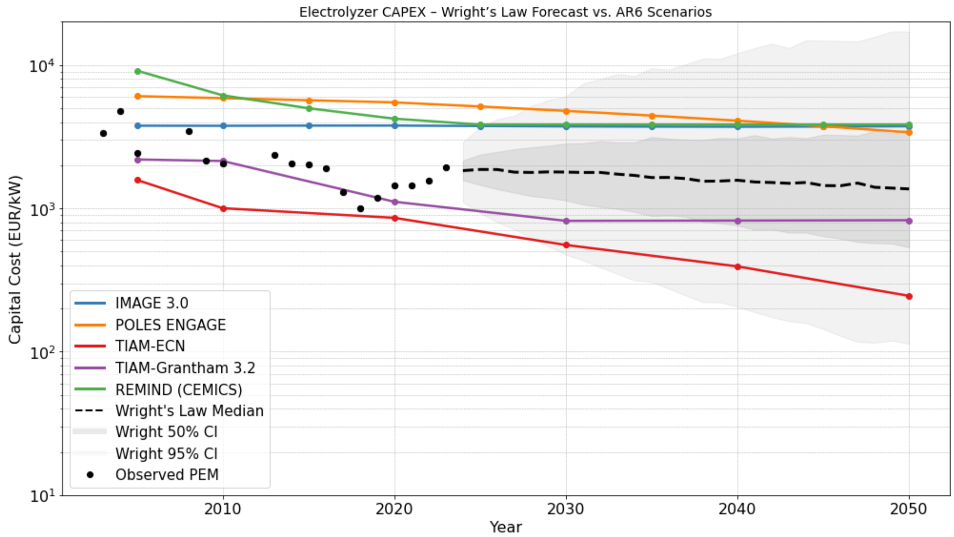

Figure 5.1: Comparison of PEM electrolyser cost projections from selected IPCC AR6 scenarios (IMAGE 3.0, POLES ENGAGE, TIAM, and REMIND) with the Wright's Law-based probabilistic forecast developed in this study. TIAM-Grantham aligns most closely with the median Wright's Law trajectory, while IMAGE, REMIND, and POLES show more conservative paths that lie near or above the 75th percentile. This illustrates key methodological differences between deterministic IAM outputs and stochastic, data-driven forecasts

Energy Outlook (WEO) [32]. The WEO outlines three key scenarios that differ in ambition and policy implementation: the Stated Policies Scenario (STEPS), which reflects existing policy frameworks; the Announced Pledges Scenario (APS), which incorporates all formal national targets; and the NZE scenario, which is discussed earlier.

IEA electrolyser cost projections are not technology-specific but instead reflect a global weighted average across various electrolysis technologies. These estimates encompass regional differentiation, with the lower bound representing cost developments in China, where manufacturing scale and supply chains drive more aggressive cost reductions, and the upper bound, which represents the rest of the world. This regional framing introduces asymmetries in global average projections that are important to contextualise when comparing with technology-specific probabilistic forecasts, such as those developed in this thesis. The different scenarios are presented in Table 5.2.

	Stated Policies			**Announced Pledges**			**NZE scenario**		
Year	2030	2035	2050	2030	2035	2050	2030	2035	2050
Lower range	850	810	710	750	620	550	640	560	520
Upper range	1320	1180	1010	1050	940	820	960	860	780

Table 5.2: IEA electrolyser CAPEX projections (EUR/kW) under three scenario frameworks: Stated Policies, Announced Pledges, and Net Zero Emissions (NZE).

This section compares the model-based electrolyser capital cost forecasts with the IEA's NZE by 2050 scenario to ensure methodological consistency between cost and deployment projections. This comparison is chosen because the NZE scenario was also used as the basis for the deployment trajectory that underpins the cost projections in this study. Since Wright's Law relates cost reductions to cumulative deployment, aligning both components with the same scenario ensures that the assumptions on learning-by-doing are coherent with the underlying policy and market context. This consistency strengthens the validity of the comparison and avoids mixing trajectories derived from fundamentally different world-views or policy ambition levels. As such, the NZE scenario serves as a benchmark that is both ambitious and directly aligned with the assumptions embedded in the model. The comparison between the model and the projections of IEA can be found in Figure 5.2.

While the deployment trajectory in the model is aligned with the NZE scenario, the IEA's CAPEX are consistently lower than those generated by the model used in this thesis. This difference is most pro-

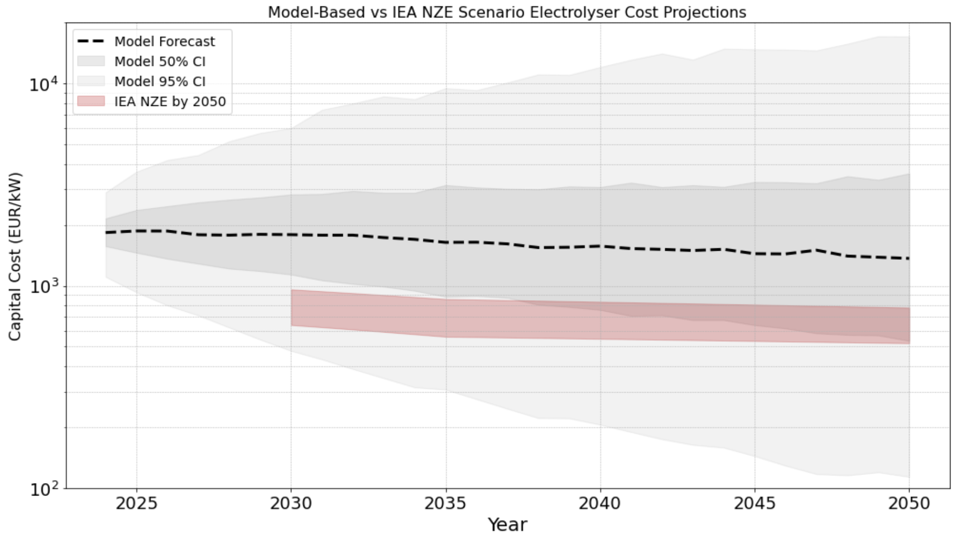

Figure 5.2: Comparison of probabilistic PEM CAPEX forecasts with IEA NZE scenario projections. The model-based forecast aligns with the NZE deployment trajectory but results in higher median costs. This reflects more conservative, data-driven learning assumptions, while the IEA's estimates may rely on optimistic expectations for future breakthroughs or policy acceleration.

nounced in the near to medium term. Several factors could explain this divergence. The IEA projections may incorporate more optimistic assumptions about future technological breakthroughs, supply chain improvements, or policy interventions that accelerate cost reductions. In contrast, the model used in this study is calibrated on historical cost and deployment data, and applies empirically derived learning rates in a probabilistic framework. As a result, it tends to produce more conservative cost trajectories, particularly under conditions of high uncertainty.

6
Validation

Hindcasting is a validation technique to test the predictive accuracy of models by simulating forecasts made at earlier points in time and comparing them to actual observed outcomes [46]. This approach reflects the forecasting process by preventing the model from fitting to future data that would not have been available at the time of prediction, ensuring a fair test of its predictive capabilities. Hindcasting is particularly valuable in technology forecasting because technological progress often exhibits complex and uncertain dynamics [17]. Technologies such as solar photovoltaic, batteries, and electrolysers undergo rapid changes in deployment, making historical patterns challenging to project forward reliably. Hindcasting provides a practical method for assessing whether historical cost models, such as Wright's Law, would have yielded reliable forecasts if they had been applied in the past.

6.1. Hindcasting setup

Hindcasting is used to evaluate the predictive accuracy of Wright's Law in explaining historical cost developments of PEM electrolysers. The procedure is designed to simulate how forecasts would have performed using only the information available up to each point in time. In this setup, a sequence of cumulative training windows is defined, each starting in 2003 and extending up to a terminal year t_0. Specifically, each training window uses data from 2003 through t_0, where t_0 ranges from 2007 (the minimum length of five years) to 2022. This cumulative window approach allows the model to continually incorporate all available historical data up to the forecast origin.

At each forecast origin year t_0, the parameters of Wright's Law are re-estimated using an ordinary least squares regression on the log-transformed cost and log-transformed cumulative deployment data. The regression provides new estimates of the experience exponent $\hat{b}$ and the intercept parameter $\hat{a}$. Forecasts are generated for each year following t_0, up to a maximum of five years ahead. This restriction is imposed to ensure that each forecast horizon has a sufficient number of origin years contributing to the error statistics, which enhances the statistical robustness of the hindcasting evaluation. Beyond a five-year horizon, the number of available forecasts is limited, which reduces the reliability of the mean squared forecast error (MSFE) estimates.

It is important to note that not all future years are available as valid forecast targets for each origin. For example, in some early forecast origins (such as $t_0 = 2010$ or $t_0 = 2011$), certain immediate years after t_0 are excluded due to missing cost data. As a result, the first forecast horizon for $t_0 = 2010$ starts at $\tau = 3$, and for $t_0 = 2011$ at $\tau = 2$. This ensures that only years with actual observed cost data are used in the error evaluation, maintaining consistency and avoiding artificially low or undefined error metrics. An overview of the hindcasting structure is provided in Appendix C.

The forecast for the cost in year $t_0 + \tau$ is then computed using the estimated Wright's Law model:

$$\hat{y}_{t_0+\tau} = \hat{a} + \hat{b}\,\log(x_{t_0+\tau}), \tag{6.1}$$

where $\hat{y}_{t_0+\tau}$ is the predicted log-cost and $x_{t_0+\tau}$ is the cumulative deployment in the forecast year. The intercept $\hat{a}$ is calibrated to match the last available year in the training window to ensure continuity at the forecast origin.

The accuracy of the forecast is assessed using the forecast error

$$\mathcal{E}_{t_0,\tau} = y_{t_0+\tau} - \hat{y}_{t_0+\tau}, \tag{6.2}$$

where $y_{t_0+\tau}$ is the observed log-cost in year $t_0 + \tau$. The squared forecast errors are then averaged across all available origin years to compute the mean squared forecast error (MSFE) for each horizon τ:

$$\text{MSFE}_\tau = \frac{1}{N_\tau} \sum_{t_0} \mathcal{E}^2_{t_0,\tau}, \tag{6.3}$$

where N_τ is the number of valid forecasts at horizon τ.

The hindcasting procedure is carried out for all origin years t_0 from 2007 to 2022, and for forecast horizons τ ranging from 1 to the maximum year for which data are available (up to 2023). For each t_0, forecasts are generated for every feasible future year $t_0 + \tau$, subject to data availability.

The overall procedure at each forecast origin comprises the following steps:

1. Define the cumulative training window from 2003 to t_0.
2. Estimate the slope $\hat{b}$ and intercept $\hat{a}$ using linear regression on log-cost and log-deployment data.
3. Generate forecasts for each horizon τ using actual future deployment values.
4. Calculate forecast errors by comparing predictions to observed log-costs.

Forecast horizons naturally decrease as t_0 approaches the end of the dataset, resulting in fewer available long-horizon forecasts. Consequently, the number of contributing forecasts per horizon diminishes for longer horizons, which should be considered when interpreting the MSFE values.

6.2. Hindcasting Results

Table 6.1 summarises the hindcasting performance of Wright's Law across different forecast horizons. The mean squared forecast error (MSFE) and corresponding root mean squared error (RMSE) are reported for horizons up to five years ahead, along with the number of forecasts (count) contributing to each estimate. The results show a clear trend of increasing forecast error with longer horizons. For a one-year-ahead forecast ($\tau = 1$), the RMSE is approximately €280 per kW, indicating relatively accurate short-term predictions. As the horizon increases, the RMSE steadily rises, reaching €458 at two years and €591 at three years. This trend continues, with the error growing to €683 over four years and peaking at €722 over five years ahead.

Horizon (τ)	MSFE	RMSE	Count
1	78,621	280	10
2	209,532	458	9
3	349,702	591	9
4	466,889	683	8
5	521,873	722	7

Table 6.1: Mean squared forecast error (MSFE), root mean squared error (RMSE), and number of forecasts for each horizon. Errors are expressed in €/kW.

The gradual increase in RMSE reflects the accumulating uncertainty when predicting costs further into the future. The performance deterioration at longer horizons is expected, as small errors in deployment projections and parameter estimates compound over time. Nevertheless, the overall magnitude of the errors remains moderate, supporting the validity of Wright's Law as a useful framework for medium-term cost forecasting. It is important to note that the number of contributing forecasts (count) decreases with longer horizons, from ten forecasts at horizon one to only seven at horizon five. This decline is a result of limiting the forecast horizon to five years and the finite length of the historical data. Consequently, the statistical robustness of the MSFE estimates decreases slightly for longer horizons, and this should be considered when interpreting the results.

7 Discussion

7.1. Purpose and Positioning of this work

The central aim of this thesis is not to deliver a precise forecast of electrolyser costs but rather to investigate and characterise the deep uncertainty surrounding such forecasts. While studies in the hydrogen domain might focus on producing optimistic trajectories or deterministic scenarios, this thesis takes a different approach. This model emphasises the range of plausible futures over any single-point estimate. This methodological choice reflects a growing recognition within the academic literature that deterministic projections, such as those published by the IEA or the IPCC, can obscure the real extent of uncertainty. These institutional models often provide cost projections for electrolysis technologies that are presented as authoritative reference points, yet they are typically devoid of confidence intervals. Moreover, it is unclear how these cost projections are produced. The methodologies behind them are rarely documented in sufficient detail to allow scrutiny of replication, making it difficult to assess their reliability or underlying assumptions. This is particularly problematic given that such forecasts are frequently used as inputs for energy strategies, investment roadmaps, and funding allocations [79]. When cost trajectories are presented without uncertainty, they can foster overconfidence in policy and investment decisions, especially when cost evolution is highly uncertain. In contrast, instead of presenting specific future costs for electrolysers, this thesis provides a structured assessment of how such outcomes depend on technology learning dynamics and deployment scale. By embedding uncertainty into the modelling process, this work contributes to a more transparent and risk-aware approach to decision-making in hydrogen policy.

7.2. Interpretation learning rates

IAMs and many scenario studies typically treat electrolysis as a single homogeneous technology, assuming uniform cost-reduction pathways across all electrolyser types. This simplification overlooks important differences in technological maturity, cost structures, and learning dynamics, which may lead to misleading conclusions about future cost trajectories. Addressing this gap, the results reveal a clear divergence between AEC and PEM technologies.

In this analysis, AEC does not exhibit a statistically significant learning trend. This unexpected outcome challenges the widespread assumption that clean energy technologies inherently follow cost-reduction pathways driven by cumulative deployment. The absence of a learning trend might indicate that the empirical model used, which is grounded in historical cost and deployment data, is not fully suitable to capture the cost evolution of AEC, particularly when data is sparse or reflects structural shifts not captured in past trends. Without major targeted innovations or policy interventions, AEC costs may remain stable or even increase in the future, rather than decline as often assumed. This observation suggests that AEC costs might not decline naturally with scale, which could indicate underlying structural or market limitations that deserve further investigation.

In contrast, PEM electrolysers show a clear trend of cost reduction associated with increased deployment, consistent with learning dynamics observed in other modular clean technologies. This indicates that PEM is more likely to experience reinforcing cost declines as deployment scales, which reduces long-term economic risks and increases investor and policy confidence. The combination of higher potential deployment growth and a demonstrated capacity for cost reduction positions PEM as a more favourable candidate for markets and applications where achieving future cost competitiveness is critical. From a strategic perspective, this suggests that PEM could be prioritised in policy frameworks.

7.3. Comparison with deterministic models

This section discusses the strengths and weaknesses of deterministic and probabilistic modelling approaches, highlighting their complementary roles in energy system planning. By contrasting these methods, the analysis clarifies why a probabilistic framework was chosen in this thesis and how it addresses important limitations inherent in deterministic scenarios. A summary of the main differences and key insights is provided in Appendix F.

Deterministic modelling has historically been the default in energy system planning, technology cost forecasting, and IAMs. By assuming fixed input parameters and relationships, deterministic models generate a single-point outcome or a set of discrete scenarios. This simplicity makes them computationally efficient, transparent, and easy to communicate. These features are highly valued in policy documents and regulatory contexts. Moreover, IAM often provides a small set of narrative scenarios (e.g., 'Current Policies,' 'Sustainable Development') with single cost and deployment pathways, enabling policymakers to explore broad storylines without explicitly quantifying uncertainty.

However, deterministic approaches become problematic when applied to long-term forecasts involving emerging technologies and high uncertainty, as is the case for electrolyser costs and hydrogen economy planning. Deterministic models implicitly assume that deviations from a chosen scenario are either negligible or can be addressed by rerunning new scenarios. This leads to an overconfident, single-narrative view of the future, ignoring the range of possible outcomes and their likelihood.

Probabilistic models explicitly address this limitation by incorporating uncertainty distributions. They produce a range of possible futures with associated probabilities, enabling nuanced assessment of risks and opportunities. In the context of technology cost forecasting, probabilistic approaches provide decision-makers with critical information, such as 'there is a 75% probability that PEM electrolyser costs will fall below a given threshold by 2035.' This enables policymakers to design flexible support instruments (e.g., dynamic subsidies or adaptive policy triggers) and helps investors assess potential downside risks, thereby hedging their portfolios accordingly.

Despite these advantages, probabilistic models face several barriers to adoption. First, the data must be available and appropriately structured for use within the model, which was not the case for AEC. Second, they involve higher computational demands, as Monte Carlo simulations or stochastic optimisations can require thousands of model runs, especially when exploring complex system interactions. Furthermore, probabilistic outputs such as distributions and confidence intervals are more challenging to communicate to non-technical stakeholders and policymakers, who often prefer concise point estimates. Finally, strong institutional inertia persists, as IAM and many policy frameworks remain deeply rooted in deterministic scenario approaches.

Moreover, probabilistic models also have intrinsic limitations. When input data is highly variable, as is the case for both electrolyser technologies, the resulting uncertainty bands can become very broad. While such wide bands transparently convey a lack of precise knowledge and help reveal risk exposure, they may complicate policy and investment decisions by offering less precise guidance. This highlights a trade-off: probabilistic models avoid false certainty but can sacrifice sharpness when data is weak. The broad cost intervals for electrolysers in this thesis illustrate both the strengths and limitations of probabilistic modelling. They underscore the importance of ongoing data collection and transparent reporting. As more real-world cost data becomes available, probabilistic models will produce narrower and more actionable forecasts, thereby increasing their value for strategic decision-making.

While probabilistic models face these limitations, this thesis explicitly addresses several of them. First, the framework is designed as an open-access tool, supporting broader data availability and transparency over time. As more deployment and cost data become accessible through shared contributions, the forecasts produced by this approach will become more precise and decision-relevant. Second, the use of Wright's Law as a cost forecasting model keeps computational demands low. Unlike complex stochastic optimisation, Wright's Law is a conceptually straightforward, empirically validated method tested across dozens of technologies, shown to produce robust cost forecasts while avoiding overfitting due to its simple structure and limited parameter requirements. This makes the model practical and replicable even with limited computing resources. Finally, the thesis explicitly addresses communication challenges by presenting clear 50% and 95% confidence intervals and providing interpretative context, helping policymakers and stakeholders understand that wide uncertainty bands highlight areas where flexibility and adaptive strategies are most critical, rather than signalling indecision. Through these design choices, the approach demonstrated here lowers the barriers that have historically hindered wider adoption of probabilistic modelling in energy system planning.

Importantly, deterministic and probabilistic models should not be viewed as mutually exclusive. Instead, they can complement each other within hybrid planning frameworks. Deterministic models remain useful for creating baseline scenarios and communicating clear policy narratives, while probabilistic overlays can assess the robustness of these pathways and inform adaptive mechanisms. For instance, a deterministic capacity expansion plan can be stress-tested with probabilistic sensitivity analyses on demand growth, technology costs, or fuel price trajectories to evaluate the likelihood of achieving system adequacy or cost targets.

7.4. Framework reusability and generalisability

While this thesis focuses on electrolysers, the underlying probabilistic framework is designed to be broadly applicable to other energy technologies. For cost forecasting, the framework employs Wright's Law to model cost reductions as a function of cumulative deployment. This relationship is well established for modular, mass-manufactured technologies where learning-by-doing and economies of scale play a significant role. Examples include solar PV modules, battery systems, wind turbines, and electric vehicles. In contrast, non-modular or highly site-specific technologies, as well as commodity-dependent sectors like fossil fuels, often do not exhibit cost trends that can be effectively captured by Wright's Law. In these cases, costs are driven more by raw material markets, geopolitical factors, and unique project characteristics rather than cumulative production experience.

Applying Wright's Law effectively requires not only robust empirical data, including historical cost records and deployment data, but also evidence of a statistically significant relationship between cost reductions and cumulative deployment. If sufficient data are available and a statistical test confirms that costs decline with experience, this approach can be confidently extended to other existing or emerging renewable energy technologies. Without such empirical support and validation, forecasts risk becoming speculative and less reliable for decision-making.

7.5. Data Fragility and the Sensitivity of Learning Rates

A central challenge in estimating future electrolyser costs is the limited availability and quality of historical CAPEX data. Compared to more mature emerging energy technologies, such as solar PV or wind, the cost history for water electrolysis is short, sparse, and fragmented. Existing datasets often mix system boundaries (stack only vs. full system), technologies (AEC vs. PEM), and project types (pilot vs. commercial scale), making them difficult to interpret and standardise. In addition, reporting practices vary across sources, with few data points providing detailed breakdowns. This data fragility has direct consequences for learning curve analysis. Wright's Law, which relates cost reductions to cumulative deployment, is sensitive to both the length and stability of the underlying time series. When only a small number of data points are available, or when those points are affected by short-term shocks, estimated learning rates become unstable and strongly dependent on the selected time window. The increase in CAPEX after 2020 represents a structural break that the model is ill-equipped to capture.. The model assumes continuity in market dynamics and policy conditions, but these assumptions no longer hold. The result is a growing disconnect between modelled expectations and empirical reality. These observations undersc/ore the fragility of learning rates and the importance of contextual awareness when applying them. Learning is not a law of nature, but a contingent outcome shaped by economic, political, and material constraints.

The assumption that technology costs decline smoothly over time is embedded in many energy system models. This view is often operationalised through deterministic learning curves, implying that costs will decrease at a steady, predictable rate as deployment increases. They are not always reliable for emerging technologies like electrolyser, whose cost dynamics remain unstable and heavily exposed to exogenous shocks. Recent years have highlighted the extent to which CAPEX is shaped by factors beyond cumulative deployment. Global supply chain disruptions, particularly in critical materials like iridium and platinum metals, have contributed to price spikes and procurement bottlenecks. Inflationary pressures in the broader economy, driven by pandemic recovery, commodity market instability, and geopolitical tensions, have further complicated the cost environment. In parallel, policy volatility, such as changing eligibility criteria in subsidy schemes or delayed implementation of hydrogen strategies, has introduced uncertainty in demand signals and investor confidence. These factors introduce discontinuities and reversals that make cost evolution more erratic. The result is a system in which cost does not simply decline with deployment, but fluctuates in response to macroeconomic and political shocks. Recent data suggest that the technology is not yet on a stable learning trajectory. Rather than exhibiting mature cost dynamics, electrolysers are highly sensitive to external disruptions, suggesting it is still in a formative phase where scale, supply security, and policy alignment are not yet sufficiently established to support sustained cost reductions. This means that the behaviour of the costs of electrolysers underscores that electrolysers cannot be treated as mature, high-confidence learning technologies. Any forecasting framework that assumes smooth, uninterrupted progress risks understating both the present volatility and the future uncertainty.

7.6. Practical implications of probabilistic IAMs

IAMs are simulation tools that combine energy systems, economic development, land use, and climate dynamics into a single framework. These models are widely used by the IPCC, IEA, national governments, and research institutes to explore possible pathways toward long-term climate targets, such as limiting global warming to 1.5 °C or achieving net-zero emissions by 2050 (see section 5.1. IAMs help to answer questions such as, what mix of technologies do we need? What are the expected emissions trajectories? How high might carbon prices need to be?

In their current form, IAM typically relies on deterministic cost projections for key technologies. For example, they often assume a single expected cost decline trajectory. The model then identifies the 'optimal' or 'least-cost' energy system pathway based on these fixed assumptions. As a result, outputs from these models, such as future technology shares, system costs, and emissions, are presented as single-point values. However, the results section reveals that many low-carbon technologies are highly uncertain and depend on various factors, including learning rates, policy support, and market dynamics. By integrating probabilistic cost forecasts, these fixed cost assumptions can be replaced with distributions that reflect this uncertainty. This approach can be applied to all technologies with uncertain future costs.

When probabilistic cost distributions are integrated into IAMs, the models move beyond using a single fixed cost trajectory for each technology. Instead, they can specify a range of possible future cost pathways, each with an associated probability. In this approach, all other input parameters are held constant, as the analysis focuses exclusively on uncertainty in technology costs.

For example, suppose there is a 5% probability that a particular technology cost declines to a very low level. In that case, the model can show how this specific cost outcome affects system-level results, such as technology adoption shares, total system costs, or emissions trajectories. Instead of presenting a single optimal pathway, the IAM can then communicate that under this low-cost scenario, the technology becomes widely adopted and overall system costs are significantly reduced. In contrast, under higher-cost scenarios, its deployment remains limited. This probabilistic framing clarifies the implications of cost uncertainties, providing policymakers and planners with a more nuanced, risk-aware perspective on future energy system pathways.

7.7. Limitations

Several limitations should be acknowledged to place the results in their proper context. These limitations relate to data quality, model assumptions, and the scope of the analysis.

Inconsistent Cost Definitions Across Sources
The CAPEX data used in this study are sourced from different data sources. These datasets differ in how they define system boundaries, ranging from stack-only costs to full systems of Power-to-Gas configurations. Even when harmonised through post-processing, such heterogeneity introduces uncertainty that is difficult to quantify. This variability can lead to noisy or biased input data, ultimately affecting the reliability of the model outputs. However, this approach was necessary due to limited data transparency and inconsistent reporting practices across industry and institutional sources.

Focus on Capital Costs Only
The modelling framework developed in this thesis focuses exclusively on CAPEX per unit of installed capacity. While this metric is important, it does not capture the full economic picture. A comprehensive assessment of electrolyser competitiveness would ideally include levelised cost of hydrogen (LCOH), operational expenditures, energy efficiency, and system integration costs. In particular, electricity price volatility, utilisation rates, and maintenance requirements can substantially affect the economics of hydrogen production. Moreover, the model does not account for plant-level economies of scale, meaning larger electrolyser installations typically benefit from lower unit costs due to more efficient engineering design, shared infrastructure, and bulk procurement.

Uniform Global Learning
This study applies Wright's law under the assumption of a single, global learning rate for each electrolyser technology. This overlooks the fact that cost reductions driven by learning-by-doing are often geographically uneven. In practice, learning effects can vary significantly across regions. The model implicitly averages across these diverse regional contexts by assuming a globally homogeneous learning curve. This can lead to two potential sources of bias: first, the learning rate may overstate cost reductions in slower-developing markets where local constraints impede deployment efficiency or technological absorption. Second, it may understate learning potential in more advanced regions where favourable policy environments, innovation ecosystems, or economies of scale accelerate progress.

7.8. Future Research

Building on the methodological foundation developed in this thesis, several avenues for future research emerge that extend beyond addressing current limitations. These directions aim to enhance the model's applicability, relevance, and integration within a broader decision-making context.

While the present model is calibrated using global deployment data, future research could investigate the feasibility and value of regionalised forecasting. Differences in policy incentives, electricity costs, infrastructure readiness, and industrial demand suggest that electrolyser learning trajectories may diverge significantly across geographies. Applying the model at the national level, particularly for China, could uncover spatial heterogeneity in cost dynamics and better inform localised policy interventions. However, the practical implementation depends critically on the availability of the country-specific historical data on both deployment and cost. If such dataset can be reliably assembled, this line of research would enhance the granularity and policy relevance of the forecasting framework.

Another promising direction is the integration of this cost forecasting approach into broader energy systems and IAMs. Coupling the deployment-cost dynamics with full-system models would allow researchers to endogenise technology learning within scenarios that account for electricity generation, sectoral energy use, infrastructure bottlenecks, and climate constraints. This integration could quantify how electrolyser cost reductions influence least-cost hydrogen supply pathways, or how different policy portfolios shape deployment trajectories in feedback with learning effects. Such coupling would also enable more nuanced assessments of electrolyser system value under varying demand-side profiles, renewable energy penetrations, and carbon pricing. This represents an important step to empirically grounded cost dynamics into long-term planning models that policymakers and international institutions use.

Lastly, future research could focus on translating the forecasting framework into a practical, data-driven decision-support tool for policymakers, planners, and industry stakeholders. Such a tool would allow users to input updated or region-specific data and generate tailored, probabilistic cost outlooks aligned with their specific timelines and targets. By enabling scenario-specific analysis with quantified uncertainty, this model-based tool could support procurement strategies, subsidy allocation, and infrastructure investment decisions. Ideally, the tool would be an interactive dashboard or software platform with user-defined assumptions, real-time data integration, and intuitive visualisations. This would bridge the gap between empirical academic forecasting and operational planning needs, offering a transparent, adaptable interface for navigating the evolving economics of hydrogen technologies.

8 Conclusion

This chapter combines the insights developed throughout the thesis to assess the effectiveness and relevance of probabilistic modelling for forecasting electrolyser costs. The objective is to evaluate whether the proposed approach offers a meaningful improvement in supporting strategic decision-making under uncertainty. By synthesising the outcomes of deployment modelling, cost projections, and scenario analysis, this chapter reflects on the implications for energy planning, investment, and policy design in the context of green hydrogen development.

8.1. Answers to sub-questions

Which probabilistic modelling approaches have been proposed in academic literature for forecasting technology deployment and cost trajectories in the renewable energy sector, and to what extent can these models be applied to electrolysers?

Probabilistic modelling approaches for forecasting technology deployment and cost trajectories have gained increasing prominence in the academic literature on the energy transition. With respect to deployment, S-curve models, especially the logistic and Gompertz functions, are commonly used to capture the non-linear diffusion dynamics of technology over time (see subsection 2.4.1). These models divide the adoption process into three phases: formative, growth, and saturation. The logistic model assumes symmetric growth around an inflexion point, while the Gompertz model allows for asymmetric diffusion, gradually decelerating as it approaches saturation.

In this thesis, traditional curve-fitting of logistic or Gompertz models based on historical electrolyser deployment data was assessed and found to be problematic. As outlined in section 3.1, much of the early deployment data reflects a pre-commercial demonstration phase. Including these data points in curve-fitting exercises may bias the model in two key ways: unconstrained fits can lead to implausibly high capacity projections by 2050, while fixed saturation assumptions can cause the model to converge toward arbitrary asymptotes not supported by the data. The deployment forecasting approach proposed by Odenweller et al. [65] was adopted to overcome these limitations. This method generates probabilistic S-curve trajectories by using policy targets, such as those from the NZE Scenario, as a constraint for future saturation levels. By sampling over uncertain input distributions for initial deployment, growth rate, and saturation level, the method yields deployment pathways consistent with scenario targets while accounting for uncertainty. However, this approach is not entirely empirical, as it relies partly on externally defined policy goals, rather than purely historical data.

Regarding cost forecasting, subsection 2.4.2 outlines the distinction between expert-based and model-based approaches. Among the latter, Wright's law has demonstrated strong empirical performance, particularly when it includes stochastic elements to capture path-dependent uncertainty. These stochastic Wright's Law models account for the accumulation of random shocks (subsection 3.2.3) and are calibrated to observed data using hindcasting (chapter 6). Applied to electrolysers technologies, Wright's Law yielded significantly different outcomes (Table 4.1). The model calculated for PEM electrolyser a statistical learning rate of 3.3%, with an R^2 value of 0.617, indicating a correlation between cumulative capacity and cost reductions. In contrast, the model for AEC produced an experience exponent that was not statistically significant, and the direction of the estimated effect contradicted expectations. This suggests that AEC costs are not well explained by deployment trends alone.

These findings highlight the potential and limitations of probabilistic modelling approaches. While such methods offer transparent and data-driven pathways to incorporate uncertainty into technology forecasting, their application depends critically on the maturity of the technology and the availability of reliable data (section 7.5). For PEM, probabilistic deployment and cost forecasts are both statistically valid and policy-relevant. For AEC, however, probabilistic cost modelling remains inconclusive due to insufficient empirical support.

To what extent are the electrolyser deployment and costs targets outlined in the IEA's Net Zero Emissions (NZE) and related scenarios technically and economically feasible?

The NZE scenario published by the IEA outlines ambitious deployment targets for electrolysers technologies, requiring rapid scale-up to meet global decarbonisation goals. However, a critical assessment of these targets indicates that their technical and economic feasibility remains highly uncertain. As shown in subsection 4.3.1, achieving the electrolyser capacity levels implied by the NZE scenario necessitates a growth rate of approximately 46% for AEC and 49% for PEM between 2023 and 2050. This exceeds historical growth rates observed for even the fastest-growing renewable technologies. For comparison, the growth rate of Solar PV and wind, based on the deployment of wind and solar PV technologies as reported in Odenweller et al. [65], stands at 39% (see subsection 3.1.2). Exceeding this benchmark suggests that the NZE pathway would require an unprecedented acceleration of industrial deployment, manufacturing capacity and supply chain scaling.

To test the feasibility under more moderate assumptions, the deployment of electrolyser was limited to essential applications in refining and industry (see subsection 4.3.1). Even in this more conservative case, the required growth rates remain at 41% for AEC and 44% for PEM, which is still well above the observed value. These findings suggest that the IEA projected deployment targets may not be technically achievable within the time frame unless extraordinary policy, financial and logistical interventions are implemented.

Economic feasibility was assessed by translating the three deployment scenarios (delayed, lagging and on-track scenarios) into associated cost trajectories using a stochastic Wright's Law framework (see subsection 4.3.2). The median forecasts across all scenarios show a decline in CAPEX for PEM over time, as expected for a positive learning rate of 3.3%. Between 2030 and 2050, the median CAPEX values for PEM electrolysers decrease by approximately 15-24%, depending on the scenario. In contrast, AEC has a negative learning rate, meaning that the costs will increase over time (see Appendix E).

More critically, the large uncertainty bands around these projections can lead to a lower investment appeal of electrolyser technologies. Although unit costs are expected to decline, the reduction is too slow and uncertain to offer investors the clear economic signals needed to justify large-scale capital commitments.

These findings question the technical and economic feasibility of the NZE electrolyser deployment targets. The required growth rates significantly exceed historical precedents, and although capital costs are expected to decline for PEM, the reductions are slow and highly uncertain. Without major interventions to mitigate both technical bottlenecks and economic risks, the realisation of these deployment pathways appears unlikely within the current policy and industrial landscape.

In addition, the capital cost projections produced in this thesis are higher than those presented in the IEA's NZE scenario (see Figure 5.2). According to the IEA, electrolyser CAPEX is expected to fall gradually from a range of 640 EUR/kW - 960 EUR/kW in 2030 to 520-780 EUR/kW by 2050. In contrast, the model-based forecasts presented here suggest that costs will likely remain well above these levels for both AEC and PEM technologies, even under optimistic deployment and growth rate assumptions. This indicates that the IEA may be underestimating the financial and technological challenges involved in achieving low electrolyser costs.

How do probabilistic cost forecasts compare to deterministic projections produced by Integrated Assessment Models (IAMs)?

The deterministic cost projections from IAMs are primarily based on predefined scenarios that combine economic, technological, policy, and environmental assumptions to illustrate potential energy and emissions pathways. IAM scenarios rely on exogenously defined technological learning rates, deployment trajectories, policy contexts, and often incorporate assumptions like minimum achievable cost thresholds ('floor costs'). While these scenarios offer clear trajectories to inform policy and economic decisions, they assume a single, certain future outcome without explicitly quantifying uncertainty or variability in technological developments.

When comparing the IAM with the model from this thesis, the IAM scenarios differ notably in their relative plausibility compared to the stochastic form of Wright's Law. Specifically, the TIAM-Grantham scenario is closely aligned with historical experience, falling clearly within the 50% confidence interval derived from the probabilistic approach, making it a highly plausible and reliable scenario. Other IAM scenarios such as IMAGE 3.0, POLES ENGAGE, and REMIND (CEMICS) lie at the boundary of this 50% interval, implying that these projections are relatively conservative. Their cost forecast reflects more cautious assumptions regarding technological learning, resulting in slower projected cost reductions. The TIAM-ECN scenario, situated outside the 50% interval, embodies notably optimistic assumptions about electrolyser cost reductions and technological learning rates. Its underlying conditions significantly diverge from historically observed trends, making this scenario comparatively less reliable and indicating that realisation would require extraordinary technological breakthroughs or unprecedented policy actions.

The comparison between the IAM scenarios and the forecasts of this thesis offers insights into the robustness and realism of scenario-based projections. This enables policymakers and investors to assess the likelihood of various energy transition pathways critically. This improves decision-making by highlighting which deterministic scenario can confidently inform policymakers to critically evaluate the possibility of different energy transition pathways. This enhances decision-making by highlighting which deterministic scenarios can confidently inform policy and investment decisions, and which scenarios should be approached with greater caution and contingency planning due to their lower likelihood and higher associated risks.

Furthermore, the probabilistic approach developed in this thesis can be integrated IAM to enhance their robustness and realism. As discussed in section 7.6, embedding probabilistic cost trajectories within IAM allows these models to move beyond single deterministic pathways and better reflect the inherent uncertainty in technological development. This integration supports the creation of adaptive policy strategies that remain effective across a wider range of future outcomes. Moreover, the framework's modular and generalisable design enables its application to other emerging clean energy technologies beyond electrolysers (see section 7.4). IAMs rely on a wide range of input parameters beyond just costs (e.g., policy measures, carbon budgets), but by integrating probabilistic cost distributions into these models, the resulting output spectrum can effectively serve as sensitivity analysis that shows how different cost trajectories (ranging from highly optimistic to more conservative outcomes), could influence technology adaption rates, energy mix shifts, and emissions reductions.

8.2. Main conclusion

The study was guided by the following research question:

How can probabilistic modelling improve the accuracy and decision-relevance of cost forecasts for electrolysers compared to traditional deterministic approaches?

This study demonstrates that probabilistic modelling offers a significant improvement over traditional deterministic approaches by combining deployment trajectories with cost forecasting, taking into account uncertainty. The model captures the distribution of initial capacity, growth rates, and learning effects through Monte Carlo simulations. The approach quantifies the probability of meeting key cost benchmarks under different deployment conditions, which enhances its value for strategic planning. For policymakers and stakeholders, this translates into a clearer understanding of the risks associated with underperformance and the opportunity space for cost competitiveness if deployment is accelerated. Probabilistic modelling improves accuracy not by predicting a 'more correct' number, but by providing a structured, transparent view of uncertainty. This makes the forecast more relevant and actionable for guiding investment and policy decisions in a rapidly evolving hydrogen landscape.

References

[1] PBL Netherlands Environmental Assessment Agency. *Integrated Assessment of Global Environmental Change with IMAGE 3.0 - Model description and policy applications |*. July 7, 2014. URL: https://www.pbl.nl/en/publications/integrated-assessment-of-global-environmental-change-with-image-30-model-description-and-policy-applications (visited on 06/14/2025).

[2] Thomas Allen et al. "A Delphi Approach to Develop Sustainable Food System Metrics". In: *Social Indicators Research* 141.3 (Feb. 2019), pp. 1307–1339. ISSN: 1573-0921. DOI: 10.1007/s11205-018-1865-8. URL: https://doi.org/10.1007/s11205-018-1865-8 (visited on 03/17/2025).

[3] Laura Anadon. *Expert Judgments about RD&D and the Future of Nuclear Energy \textbar Environmental Science & Technology*. URL: https://pubs.acs.org/doi/10.1021/es300612c (visited on 03/18/2025).

[4] Abiodun Awosina, Ruben Ndihokubwayo, and Julius Fapohunda. "Effects of inaccurate cost estimate on construction project stakeholders". In: *Journal of Construction Project Management and Innovation* 8.2 (Oct. 2018). Publisher: University of Johannesburg, pp. 1886–1904. DOI: 10.10520/EJC-134351660d. URL: https://journals.co.za/doi/10.10520/EJC-134351660d (visited on 02/24/2025).

[5] Nuno Bento, Charlie Wilson, and Laura Diaz Anadon. "Time to get ready: Conceptualizing the temporal and spatial dynamics of formative phases for energy technologies". In: *Energy Policy* 119 (Aug. 1, 2018), pp. 282–293. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2018.04.015. URL: https://www.sciencedirect.com/science/article/pii/S0301421518302313 (visited on 04/18/2025).

[6] Jorge Blazquez et al. "The renewable energy policy Paradox". In: *Renewable and Sustainable Energy Reviews* 82 (Feb. 1, 2018), pp. 1–5. ISSN: 1364-0321. DOI: 10.1016/j.rser.2017.09.002. URL: https://www.sciencedirect.com/science/article/pii/S1364032117312546 (visited on 04/18/2025).

[7] BP. *Energy Outlook | Energy economics | Home*. bp global. Oct. 7, 2024. URL: https://www.bp.com/en/global/corporate/energy-economics/energy-outlook.html (visited on 05/08/2025).

[8] Marcelo Carmo et al. "A comprehensive review on PEM water electrolysis". In: *International Journal of Hydrogen Energy* 38.12 (Apr. 22, 2013), pp. 4901–4934. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2013.01.151. URL: https://www.sciencedirect.com/science/article/pii/S0360319913002607 (visited on 04/17/2025).

[9] Aleh Cherp et al. "National growth dynamics of wind and solar power compared to the growth required for global climate targets". In: *Nature Energy* 6.7 (July 2021). Publisher: Nature Publishing Group, pp. 742–754. ISSN: 2058-7546. DOI: 10.1038/s41560-021-00863-0. URL: https://www.nature.com/articles/s41560-021-00863-0 (visited on 04/18/2025).

[10] European Commission. *A hydrogen strategy for a climate-neutral Europe*. Aug. 7, 2020. URL: https://energy.ec.europa.eu/system/files/2020-07/hydrogen_strategy_0.pdf.

[11] Léo Coppens, Simon Dietz, and Frank Venmans. "Optimal climate policy under exogenous and endogenous technical change: making sense of the different approaches". In: (). URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4797273.

[12] Hydrogen Council. *Hydrogen for Net Zero*. Hydrogen Council. Nov. 3, 2021. URL: https://hydrogencouncil.com/en/hydrogen-for-net-zero/ (visited on 06/07/2025).

[13] David Davis. *Global Mine Supply of Platinum Will Fall by 500koz-1,000koz as Power Shortages in South Africa Bite Into Production from 2023 to 2027*. Auctus Metals: Expert Precious Metal Portfolio Management Services. Dec. 27, 2022. URL: https://auctusmetals.com/global-mine-supply-of-platinum-will-fall-by-500koz-1000koz-as-power-shortages-in-south-africa-bite-into-production-from-2023-to-2027-by-dr-david-davis/ (visited on 06/03/2025).

[14] Joseph DeCarolis et al. "Formalizing best practice for energy system optimization modelling". In: *Applied Energy* 194 (May 15, 2017), pp. 184–198. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2017.03.001. URL: https://www.sciencedirect.com/science/article/pii/S0306261917302192 (visited on 06/29/2025).

[15] ESIG. *Green hydrogen in power system models*. Apr. 2024. URL: https://www.esig.energy/green-hydrogen-in-power-system-models/ (visited on 04/16/2025).

[16] Hydrogen Europe. *Hydrogen Infrastructure: The Recipe for a Hydrogen Grid*. Oct. 2024. URL: https://hydrogeneurope.eu/wp-content/uploads/2024/10/2024.10_HE_Hydrogen-Infrastructure-Report.pdf.

[17] J. Doyne Farmer and François Lafond. "How predictable is technological progress?" In: *Research Policy* 45.3 (Apr. 2016), pp. 647–665. ISSN: 0048-7333. DOI: 10.1016/j.respol.2015.11.001. URL: https://www.sciencedirect.com/science/article/pii/S0048733315001699 (visited on 03/19/2025).

[18] World Economic Forum. *This is how COVID-19 has disrupted global supply chains*. World Economic Forum. Oct. 18, 2021. URL: https://www.weforum.org/stories/2021/10/this-is-the-state-of-supply-chain-disruptions/ (visited on 05/14/2025).

[19] Gunther Glenk and Stefan Reichelstein. "Economics of converting renewable power to hydrogen". In: *Nature Energy* 4.3 (Mar. 2019). Publisher: Nature Publishing Group, pp. 216–222. ISSN: 2058-7546. DOI: 10.1038/s41560-019-0326-1. URL: https://www.nature.com/articles/s41560-019-0326-1 (visited on 05/09/2025).

[20] Benjamin Gompertz. "On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. In a letter to Francis Baily, Esq. F. R. S. &c. By Benjamin Gompertz, Esq. F. R. S". In: *Abstracts of the Papers Printed in the Philosophical Transactions of the Royal Society of London* 2 (Jan. 1997). Publisher: Royal Society, pp. 252–253. DOI: 10.1098/rspl.1815.0271. URL: https://royalsocietypublishing.org/doi/10.1098/rspl.1815.0271 (visited on 06/01/2025).

[21] Rob Gross et al. "An assessment of future costs estimation methodologies in the electricity generation sector". In: ().

[22] Caroline Hussler, Paul Muller, and Patrick Rondé. "Is diversity in Delphi panelist groups useful? Evidence from a French forecasting exercise on the future of nuclear energy". In: *Technological Forecasting and Social Change*. The Delphi technique: Past, present, and future prospects 78.9 (Nov. 2011), pp. 1642–1653. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2011.07.008. URL: https://www.sciencedirect.com/science/article/pii/S0040162511001442 (visited on 03/17/2025).

[23] IAMC. *AR6 Scenario Explorer and Database*. URL: https://data.ece.iiasa.ac.at/ar6/#/workspaces (visited on 06/14/2025).

[24] IEA. *Global Hydrogen Review 2021 – Analysis*. IEA. Oct. 4, 2021. URL: https://www.iea.org/reports/global-hydrogen-review-2021 (visited on 05/23/2025).

[25] IEA. *Global Hydrogen Review 2022 – Analysis*. IEA. Sept. 22, 2022. URL: https://www.iea.org/reports/global-hydrogen-review-2022 (visited on 05/23/2025).

[26] IEA. *Global Hydrogen Review 2023 – Analysis*. IEA. Sept. 22, 2023. URL: https://www.iea.org/reports/global-hydrogen-review-2023 (visited on 05/23/2025).

[27] IEA. *Global Hydrogen Review 2024 – Analysis*. Oct. 2, 2024. URL: https://www.iea.org/reports/global-hydrogen-review-2024 (visited on 04/21/2025).

[28] IEA. *Hydrogen Production and Infrastructure Projects Database*. Oct. 2024. URL: https://www.iea.org/data-and-statistics/data-product/hydrogen-production-and-infrastructure-projects-database.

[29] IEA. *IEA – International Energy Agency*. IEA. URL: https://www.iea.org (visited on 03/25/2025).

[30] IEA. *Net Zero by 2050 – Analysis*. Apr. 2021. URL: https://www.iea.org/reports/net-zero-by-2050 (visited on 04/16/2025).

[31] IEA. *The Future of Hydrogen – Analysis*. IEA. June 14, 2019. URL: https://www.iea.org/reports/the-future-of-hydrogen (visited on 05/23/2025).

[32] IEA. *World Energy Outlook 2024 – Analysis*. Oct. 16, 2024. URL: https://www.iea.org/reports/world-energy-outlook-2024 (visited on 04/21/2025).

[33] "Mitigation Pathways Compatible with Long-term Goals". In: *Climate Change 2022 - Mitigation of Climate Change*. Ed. by Intergovernmental Panel On Climate Change (Ipcc). 1st ed. Cambridge University Press, Aug. 17, 2023, pp. 295–408. ISBN: 978-1-00-915792-6. DOI: 10.1017/9781009157926.005. URL: https://www.cambridge.org/core/product/identifier/9781009157926%23c3/type/book_part (visited on 06/04/2025).

[34] International Energy Agency. *Experience Curves for Energy Technology Policy*. OECD, July 7, 2000. ISBN: 978-92-64-17650-8 978-92-64-18216-5. DOI: 10.1787/9789264182165-en. URL: https://www.oecd.org/en/publications/experience-curves-for-energy-technology-policy_9789264182165-en.html (visited on 03/21/2025).

[35] International Energy Agency. *Global energy investment in clean energy and in fossil fuels, 2015-2023*. IEA. 2024. URL: https://www.iea.org/spotlights/global-investment-in-clean-energy-is-on-course-to-reach-usd-1-8-trillion-in-2023 (visited on 03/24/2025).

[36] IPCC. *Annex III: Scenarios and Modelling Methods*. 2022. URL: https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_Annex-III.pdf#:~:text=Furthermore%2C%20although%20attempts%20have%20been,The.

[37] IPCC. *Sixth Assessment Report*. URL: https://www.ipcc.ch/assessment-report/ar6/ (visited on 06/14/2025).

[38] IRENA. *Green Hydrogen Cost Reduction*. 2020. URL: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/%202020/Dec/IRENA_Green_hydrogen_cost_2020.pdf.

[39] IRENA. *Green hydrogen strategy: A guide to design*. July 30, 2024. URL: https://www.irena.org/Publications/2024/Jul/Green-hydrogen-strategy-A-guide-to-design (visited on 04/16/2025).

[40] IRENA. *IRENA – International Renewable Energy Agency*. URL: https://www.irena.org/ (visited on 03/25/2025).

[41] IRENA. *World Energy Transitions Outlook 2023: 1.5°C Pathway*. June 22, 2023. URL: https://www.irena.org/Publications/2023/Jun/World-Energy-Transitions-Outlook-2023 (visited on 04/16/2025).

[42] Staffan Jacobsson and Anna Johnson. "The diffusion of renewable energy technology: an analytical framework and key issues for research". In: *Energy Policy* 28.9 (July 31, 2000), pp. 625–640. ISSN: 0301-4215. DOI: 10.1016/S0301-4215(00)00041-0. URL: https://www.sciencedirect.com/science/article/pii/S0301421500000410 (visited on 04/18/2025).

[43] Nathan Johnson et al. "Realistic roles for hydrogen in the future energy transition". In: *Nature Reviews Clean Technology* 1.5 (May 2025). Publisher: Nature Publishing Group, pp. 351–371. ISSN: 3005-0685. DOI: 10.1038/s44359-025-00050-4. URL: https://www.nature.com/articles/s44359-025-00050-4 (visited on 05/19/2025).

[44] Fanourios Kourougianni et al. "A comprehensive review of green hydrogen energy systems". In: *Renewable Energy* 231 (Sept. 1, 2024), p. 120911. ISSN: 0960-1481. DOI: 10.1016/j.renene.2024.120911. URL: https://www.sciencedirect.com/science/article/pii/S0960148124009790 (visited on 04/16/2025).

[45] Subramani Krishnan et al. “Present and future cost of alkaline and PEM electrolyser stacks”. In: *International Journal of Hydrogen Energy* 48.83 (Oct. 1, 2023), pp. 32313–32330. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2023.05.031. URL: https://www.sciencedirect.com/science/article/pii/S0360319923022590 (visited on 06/03/2025).

[46] François Lafond et al. “How well do experience curves predict technological progress? A method for making distributional forecasts”. In: *Technological Forecasting and Social Change* 128 (Mar. 2018), pp. 104–117. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2017.11.001. URL: https://www.sciencedirect.com/science/article/pii/S0040162517303736 (visited on 03/18/2025).

[47] Blake Lane et al. “Forecasting renewable hydrogen production technology shares under cost uncertainty”. In: *International Journal of Hydrogen Energy* 46.54 (Aug. 5, 2021), pp. 27293–27306. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2021.06.012. URL: https://www.sciencedirect.com/science/article/pii/S0360319921021558 (visited on 03/21/2025).

[48] Thanh Tuan Le et al. “Fueling the future: A comprehensive review of hydrogen energy systems and their challenges”. In: *International Journal of Hydrogen Energy* 54 (Feb. 7, 2024), pp. 791–816. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2023.08.044. URL: https://www.sciencedirect.com/science/article/pii/S0360319923039988 (visited on 04/16/2025).

[49] Markus Lehner et al. *Power-to-Gas: Technology and Business Models*. SpringerBriefs in Energy. Cham: Springer International Publishing, 2014. ISBN: 978-3-319-03994-7 978-3-319-03995-4. DOI: 10.1007/978-3-319-03995-4. URL: https://link.springer.com/10.1007/978-3-319-03995-4 (visited on 03/25/2025).

[50] Michael Liebreich. *Hydrogen Ladder Version 5.0*. May 30, 2024. URL: https://web.archive.org/web/20240530145512/https:/mliebreich.substack.com/p/hydrogen-ladder-version-50 (visited on 06/14/2025).

[51] Richard Loulou and Maryse Labriet. “ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure”. In: *Computational Management Science* 5.1 (Feb. 1, 2008), pp. 7–40. ISSN: 1619-6988. DOI: 10.1007/s10287-007-0046-z. URL: https://doi.org/10.1007/s10287-007-0046-z (visited on 06/14/2025).

[52] Gunnar Luderer et al. “Description of the REMIND model (Version 1.6)”. In: (). URL: https://www.pik-potsdam.de/en/institute/labs/energy-transition/remind16_description_2015_11_30_final.

[53] Jochen Markard. “The next phase of the energy transition and its implications for research and policy”. In: *Nature Energy* 3.8 (Aug. 2018). Publisher: Nature Publishing Group, pp. 628–633. ISSN: 2058-7546. DOI: 10.1038/s41560-018-0171-7. URL: https://www.nature.com/articles/s41560-018-0171-7 (visited on 04/18/2025).

[54] Eric Martinot. “Grid Integration of Renewable Energy: Flexibility, Innovation, and Experience”. In: *Annual Review of Environment and Resources* 41 (Volume 41, 2016 Oct. 17, 2016). Publisher: Annual Reviews, pp. 223–251. ISSN: 1543-5938, 1545-2050. DOI: 10.1146/annurev-environ-110615-085725. URL: https://www.annualreviews.org/content/journals/10.1146/annurev-environ-110615-085725 (visited on 04/18/2025).

[55] Flavio Pinheiro Martins et al. “Hydrogen and the sustainable development goals: Synergies and trade-offs”. In: *Renewable and Sustainable Energy Reviews* 204 (Oct. 1, 2024), p. 114796. ISSN: 1364-0321. DOI: 10.1016/j.rser.2024.114796. URL: https://www.sciencedirect.com/science/article/pii/S1364032124005227 (visited on 04/16/2025).

[56] Thomas Mayer et al. “Feasibility study of 2020 target costs for PEM fuel cells and lithium-ion batteries: A two-factor experience curve approach”. In: *International Journal of Hydrogen Energy*. HYFUSEN 37.19 (Oct. 2012), pp. 14463–14474. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2012.07.022. URL: https://www.sciencedirect.com/science/article/pii/S0360319912015972 (visited on 03/17/2025).

[57] Alan McDonald and Leo Schrattenholzer. “Learning rates for energy technologies”. In: *Energy Policy* 29.4 (Mar. 1, 2001), pp. 255–261. ISSN: 0301-4215. DOI: 10.1016/S0301-4215(00)00122-1. URL: https://www.sciencedirect.com/science/article/pii/S0301421500001221 (visited on 04/03/2025).

[58] Jing Meng et al. "Appendix - Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition". In: *Proceedings of the National Academy of Sciences* 118.27 (July 6, 2021). Publisher: Proceedings of the National Academy of Sciences, e1917165118. DOI: 10.1073/pnas.1917165118. URL: https://www.pnas.org/doi/10.1073/pnas.1917165118 (visited on 03/21/2025).

[59] Jing Meng et al. "Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition". In: *Proceedings of the National Academy of Sciences* 118.27 (July 2021), e1917165118. DOI: 10.1073/pnas.1917165118. URL: https://www.pnas.org/doi/full/10.1073/pnas.1917165118 (visited on 03/17/2025).

[60] M. Granger Morgan. "Use (and abuse) of expert elicitation in support of decision making for public policy". In: *Proceedings of the National Academy of Sciences* 111.20 (May 2014), pp. 7176–7184. DOI: 10.1073/pnas.1319946111. URL: https://www.pnas.org/doi/full/10.1073/pnas.1319946111 (visited on 03/17/2025).

[61] M. Granger Morgan and David W. Keith. "Improving the way we think about projecting future energy use and emissions of carbon dioxide". In: *Climatic Change* 90.3 (Oct. 1, 2008), pp. 189–215. ISSN: 1573-1480. DOI: 10.1007/s10584-008-9458-1. URL: https://doi.org/10.1007/s10584-008-9458-1 (visited on 03/25/2025).

[62] Béla Nagy et al. "Statistical Basis for Predicting Technological Progress". In: *PLoS ONE* 8.2 (Feb. 28, 2013), e52669. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0052669. URL: https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0052669 (visited on 03/21/2025).

[63] Somtochukwu Godfrey Nnabuife et al. "Integration of renewable energy sources in tandem with electrolysis: A technology review for green hydrogen production". In: *International Journal of Hydrogen Energy* 107 (Mar. 10, 2025), pp. 218–240. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2024.06.342. URL: https://www.sciencedirect.com/science/article/pii/S0360319924025825 (visited on 04/17/2025).

[64] Brian C. O'Neill et al. "The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century". In: *Global Environmental Change* 42 (Jan. 1, 2017), pp. 169–180. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2015.01.004. URL: https://www.sciencedirect.com/science/article/pii/S0959378015000060 (visited on 06/14/2025).

[65] Adrian Odenweller et al. "Probabilistic feasibility space of scaling up green hydrogen supply". In: *Nature Energy* 7.9 (Sept. 2022). Publisher: Nature Publishing Group, pp. 854–865. ISSN: 2058-7546. DOI: 10.1038/s41560-022-01097-4. URL: https://www.nature.com/articles/s41560-022-01097-4 (visited on 04/11/2025).

[66] I2AM Paris. *The POLES model*. URL: https://www.i2am-paris.eu/detailed_model_doc/poles.

[67] Mohammad Fazle Rabbi et al. "Energy Security and Energy Transition to Achieve Carbon Neutrality". In: *Energies* 15.21 (Jan. 2022). Number: 21 Publisher: Multidisciplinary Digital Publishing Institute, p. 8126. ISSN: 1996-1073. DOI: 10.3390/en15218126. URL: https://www.mdpi.com/1996-1073/15/21/8126 (visited on 02/24/2025).

[68] Jan Rotmans, René Kemp, and Marjolein van Asselt. "More evolution than revolution: transition management in public policy". In: *Foresight* 3.1 (Jan. 1, 2001). Publisher: MCB UP Ltd, pp. 15–31. ISSN: 1463-6689. DOI: 10.1108/14636680110803003. URL: https://doi.org/10.1108/14636680110803003 (visited on 04/18/2025).

[69] Edward S. Rubin et al. "A review of learning rates for electricity supply technologies". In: *Energy Policy* 86 (Nov. 2015), pp. 198–218. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2015.06.011. URL: https://www.sciencedirect.com/science/article/pii/S0301421515002293 (visited on 03/18/2025).

[70] Sascha Samadi. "The experience curve theory and its application in the field of electricity generation technologies – A literature review". In: *Renewable and Sustainable Energy Reviews* 82 (Feb. 2018), pp. 2346–2364. ISSN: 1364-0321. DOI: 10.1016/j.rser.2017.08.077. URL: https://www.sciencedirect.com/science/article/pii/S1364032117312224 (visited on 03/17/2025).

[71] Schmidt. “The future cost of electrical energy storage based on experience rates \textbar Nature Energy”. In: *Nature Energy* 2.17110 (Oct. 7, 2017). DOI: 10.1038/nenergy.2017.110. URL: https://www.nature.com/articles/nenergy2017110 (visited on 03/18/2025).

[72] O. Schmidt et al. “The future cost of electrical energy storage based on experience rates”. In: *Nature Energy* 2.8 (July 10, 2017). Publisher: Nature Publishing Group, pp. 1–8. ISSN: 2058-7546. DOI: 10.1038/nenergy.2017.110. URL: https://www.nature.com/articles/nenergy2017110 (visited on 03/10/2025).

[73] Sage Sebastian, Samantha Wijewardane, and Sesha Srinivasan. “Recent advances in hydrogen production, storage, and fuel cell Technologies with an emphasis on inventions, innovations, and commercialization”. In: *Solar Compass* 8 (Dec. 1, 2023), p. 100065. ISSN: 2772-9400. DOI: 10.1016/j.solcom.2023.100065. URL: https://www.sciencedirect.com/science/article/pii/S2772940023000334 (visited on 04/16/2025).

[74] Roxana T. Shafiee and Daniel P. Schrag. “Carbon abatement costs of green hydrogen across end-use sectors”. In: *Joule* 8.12 (Dec. 18, 2024), pp. 3281–3289. ISSN: 2542-4351. DOI: 10.1016/j.joule.2024.09.003. URL: https://www.sciencedirect.com/science/article/pii/S2542435124004215 (visited on 06/14/2025).

[75] M. Shahabuddin, Geoffrey Brooks, and Muhammad Akbar Rhamdhani. “Decarbonisation and hydrogen integration of steel industries: Recent development, challenges and technoeconomic analysis”. In: *Journal of Cleaner Production* 395 (Apr. 1, 2023), p. 136391. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2023.136391. URL: https://www.sciencedirect.com/science/article/pii/S0959652623005498 (visited on 04/16/2025).

[76] Deepak Sharma et al. “Deep learning applications for disease diagnosis”. In: Jan. 1, 2022, pp. 31–51. ISBN: 978-0-12-824145-5. DOI: 10.1016/B978-0-12-824145-5.00005-8.

[77] Gagan Deep Sharma et al. “Socio-economic aspects of hydrogen energy: An integrative review”. In: *Technological Forecasting and Social Change* 192 (July 1, 2023), p. 122574. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2023.122574. URL: https://www.sciencedirect.com/science/article/pii/S0040162523002597 (visited on 04/16/2025).

[78] Statista. *Global inflation rate from 2000 to 2024, with forecasts until 2030*. Statista. May 28, 2025. URL: https://www.statista.com/statistics/256598/global-inflation-rate-compared-to-previous-year/ (visited on 06/02/2025).

[79] David S.-K. Ting and Ahmad Vasel-Be-Hagh, eds. *Mitigating Climate Change: Proceedings of the Mitigating Climate Change 2021 Symposium and Industry Summit (MCC2021)*. Springer Proceedings in Energy. Cham: Springer International Publishing, 2022. ISBN: 978-3-030-92147-7. DOI: 10.1007/978-3-030-92148-4. URL: https://link.springer.com/10.1007/978-3-030-92148-4 (visited on 06/10/2025).

[80] Falko Ueckerdt et al. “Potential and risks of hydrogen-based e-fuels in climate change mitigation”. In: *Nature Climate Change* 11.5 (May 2021). Publisher: Nature Publishing Group, pp. 384–393. ISSN: 1758-6798. DOI: 10.1038/s41558-021-01032-7. URL: https://www.nature.com/articles/s41558-021-01032-7 (visited on 06/14/2025).

[81] P.F Verhulst. “Notice on the law that a population follows in its growth”. In: (1838). URL: https://www.neo-classical-physics.info/uploads/3/4/3/6/34363841/verhulst_-_law_of_population.pdf.

[82] B Wanner. *Is exponential growth of solar PV the obvious conclusion? – Analysis*. IEA. Feb. 6, 2019. URL: https://www.iea.org/commentaries/is-exponential-growth-of-solar-pv-the-obvious-conclusion (visited on 04/18/2025).

[83] Rupert Way et al. “Empirically grounded technology forecasts and the energy transition”. In: *Joule* 6.9 (Sept. 21, 2022). Publisher: Elsevier, pp. 2057–2082. ISSN: 2542-4785, 2542-4351. DOI: 10.1016/j.joule.2022.08.009. URL: https://www.cell.com/joule/abstract/S2542-4351(22)00410-X (visited on 04/07/2025).

[84] Justin Wolfers and Eric Zitzewitz. “Prediction Markets”. In: *Journal of Economic Perspectives* 18.2 (June 2004), pp. 107–126. ISSN: 0895-3309. DOI: 10.1257/0895330041371321. URL: https://www.aeaweb.org/articles?id=10.1257/0895330041371321 (visited on 03/21/2025).

[85] T. P. Wright. “Factors Affecting the Cost of Airplanes”. In: *Journal of the Aeronautical Sciences* 3.4 (Feb. 1936), pp. 122–128. DOI: 10.2514/8.155. URL: https://arc.aiaa.org/doi/10.2514/8.155 (visited on 03/17/2025).

[86] Xi Yang et al. “Breaking the hard-to-abate bottleneck in China’s path to carbon neutrality with clean hydrogen”. In: *Nature Energy* 7.10 (Oct. 2022). Publisher: Nature Publishing Group, pp. 955–965. ISSN: 2058-7546. DOI: 10.1038/s41560-022-01114-6. URL: https://www.nature.com/articles/s41560-022-01114-6 (visited on 04/17/2025).

[87] Sonia Yeh and Edward S. Rubin. “A review of uncertainties in technology experience curves”. In: *Energy Economics* 34.3 (May 1, 2012), pp. 762–771. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2011.11.006. URL: https://www.sciencedirect.com/science/article/pii/S0140988311002805 (visited on 03/21/2025).

[88] Xiufeng Yue et al. “A review of approaches to uncertainty assessment in energy system optimization models”. In: *Energy Strategy Reviews* 21 (Aug. 1, 2018), pp. 204–217. ISSN: 2211-467X. DOI: 10.1016/j.esr.2018.06.003. URL: https://www.sciencedirect.com/science/article/pii/S2211467X18300543 (visited on 03/21/2025).

[89] Kai Zeng and Dongke Zhang. “Recent progress in alkaline water electrolysis for hydrogen production and applications”. In: *Progress in Energy and Combustion Science* 36.3 (June 1, 2010), pp. 307–326. ISSN: 0360-1285. DOI: 10.1016/j.pecs.2009.11.002. URL: https://www.sciencedirect.com/science/article/pii/S0360128509000598 (visited on 04/17/2025).

[90] Xiongwen Zhang et al. “Towards a smart energy network: The roles of fuel/electrolysis cells and technological perspectives”. In: *International Journal of Hydrogen Energy* 40.21 (June 8, 2015), pp. 6866–6919. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2015.03.133. URL: https://www.sciencedirect.com/science/article/pii/S036031991500779X (visited on 03/25/2025).

[91] Nik Zielonka and Evelina Trutnevyte. “Probabilities of reaching required diffusion of granular energy technologies in European countries”. In: *iScience* 28.2 (Feb. 21, 2025), p. 111825. ISSN: 2589-0042. DOI: 10.1016/j.isci.2025.111825. URL: https://www.sciencedirect.com/science/article/pii/S2589004225000859 (visited on 03/24/2025).

[92] Nik Zielonka, Xin Wen, and Evelina Trutnevyte. “Probabilistic projections of granular energy technology diffusion at subnational level”. In: *PNAS Nexus* 2.10 (Oct. 1, 2023), pgad321. ISSN: 2752-6542. DOI: 10.1093/pnasnexus/pgad321. URL: https://doi.org/10.1093/pnasnexus/pgad321 (visited on 03/24/2025).

A

Deployment

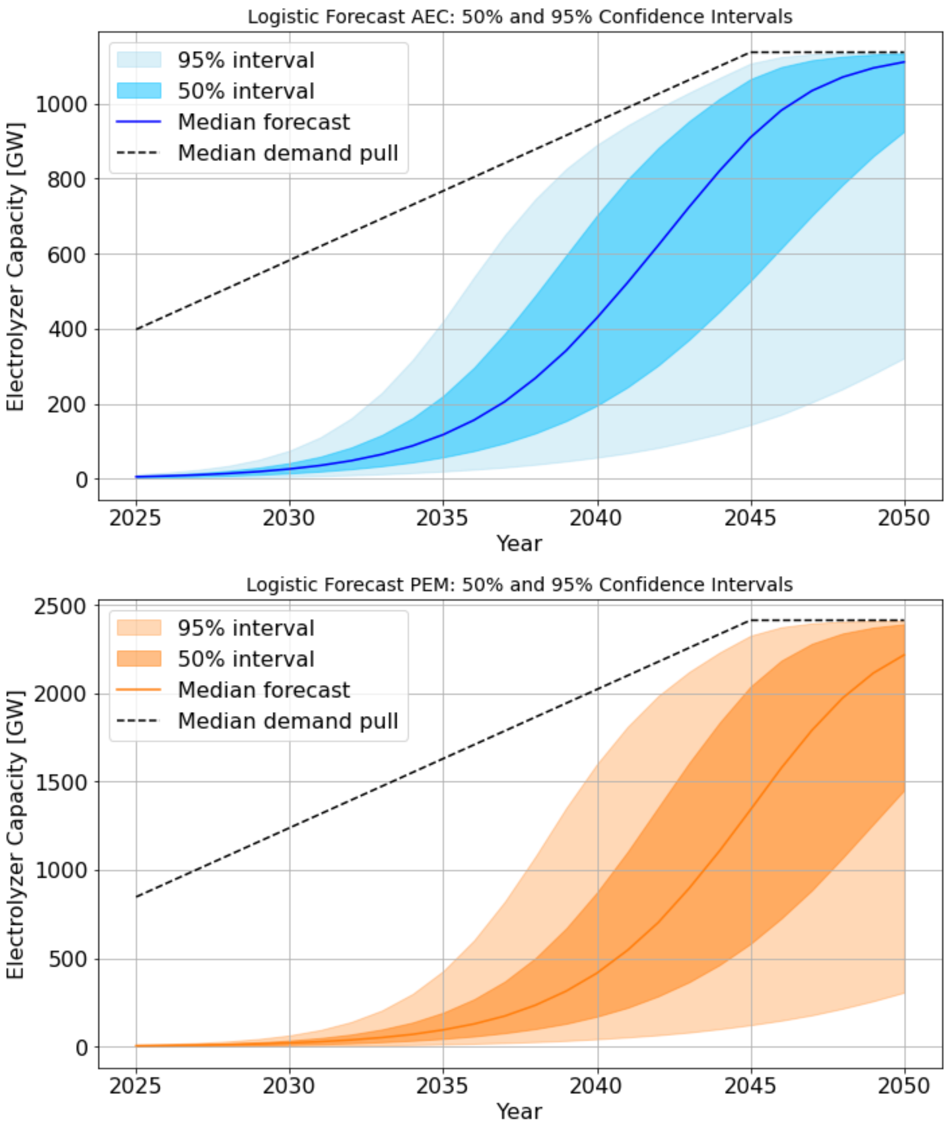

Figure A.1: Electrolyser deployment projections for AEC (top) and PEM (bottom).

B

Stochastic Wright's Law

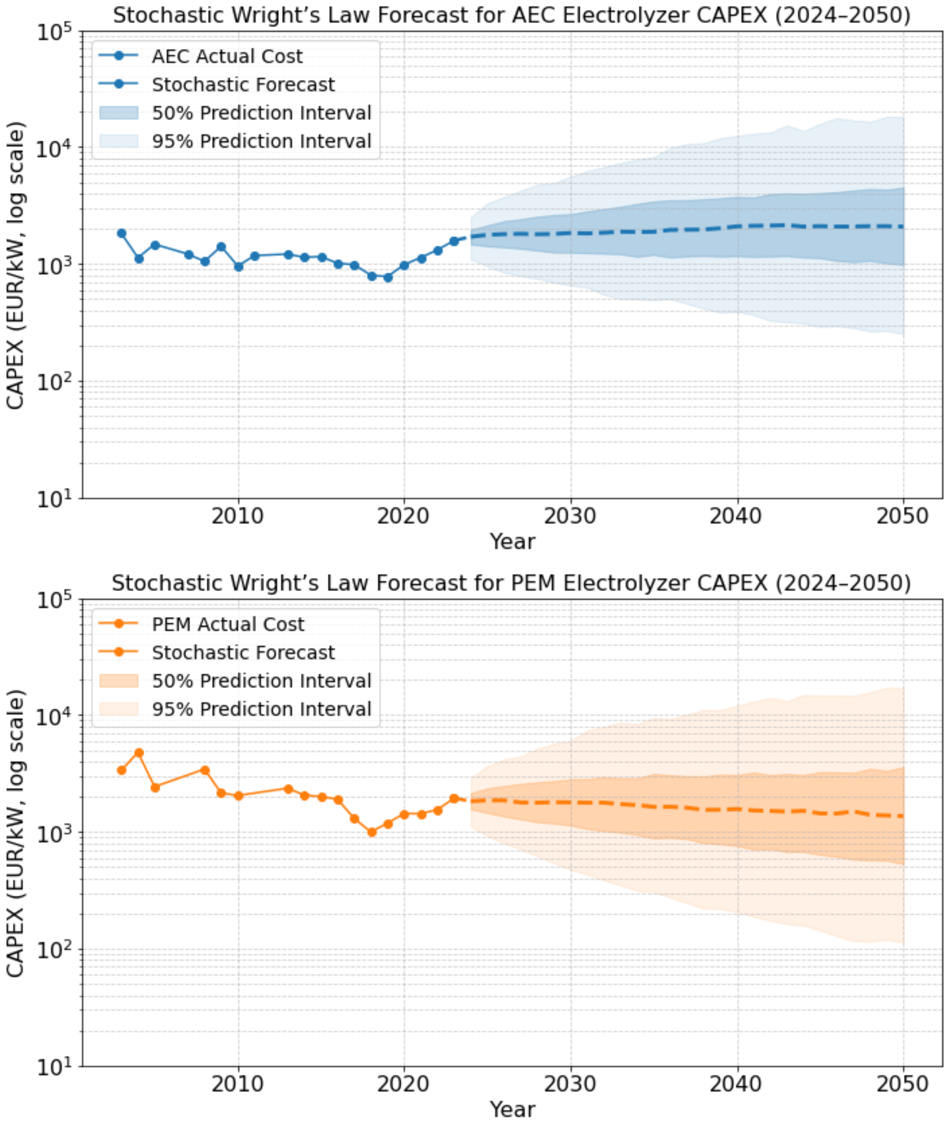

Figure B.1: Stochastic Wright’s Law forecasts for AEC (top) and PEM (bottom) electrolyser CAPEX from 2024 to 2050, including 50% and 95% prediction intervals

C

Setup for Hindcasting

Forecast Origin (t_0)	Training Window	Forecast Years (τ)
2007	2003–2007	2008 ($\tau = 1$), …, 2012 ($\tau = 5$)
2008	2003–2008	2009 ($\tau = 1$), …, 2013 ($\tau = 5$)
2009	2003–2009	2010 ($\tau = 1$), …, 2014 ($\tau = 5$)
2010	2003–2010	2013 ($\tau = 3$), 2014 ($\tau = 4$), 2015 ($\tau = 5$)
2011	2003–2011	2013 ($\tau = 2$), …, 2016 ($\tau = 5$)
2012	2003–2012	2013 ($\tau = 1$), …, 2017 ($\tau = 5$)
2013	2003–2013	2014 ($\tau = 1$), …, 2018 ($\tau = 5$)
2014	2003–2014	2015 ($\tau = 1$), …, 2019 ($\tau = 5$)
2015	2003–2015	2016 ($\tau = 1$), …, 2020 ($\tau = 5$)
2016	2003–2016	2017 ($\tau = 1$), …, 2021 ($\tau = 5$)
2017	2003–2017	2018 ($\tau = 1$), …, 2022 ($\tau = 5$)
2018	2003–2018	2019 ($\tau = 1$), …, 2023 ($\tau = 5$)
2019	2003–2019	2020 ($\tau = 1$), …, 2023 ($\tau = 4$)
2020	2003–2020	2021 ($\tau = 1$), …, 2023 ($\tau = 3$)
2021	2003–2021	2022 ($\tau = 1$), 2023 ($\tau = 2$)
2022	2003–2022	2023 ($\tau = 1$)

Table C.1: Hindcasting setup showing cumulative training windows and forecast years with horizons. Forecasts are limited to a maximum horizon of five years to ensure sufficient data availability.

D

Announced Future Projects

Year	ALK Concept	ALK Feasibility	ALK Construction	ALK Operational	ALK Total	PEM Concept	PEM Feasibility	PEM Construction	PEM Operational	PEM Total	Total
2024		128.95	1263.78	31.25	1423.99		28.50	155.13	43.90	227.53	1651.52
2025		453.90	1187.34		1641.24		1737.69	750.75		2488.44	4129.68
2026	70.00	1989.49	2773.52		4833.01	52.00	5678.92	166.17		5897.09	10730.10
2027		1922.50	100.00		2022.50		3297.19	328.70	100.00	3725.89	5748.39
2028	830.00	1552.82			2382.82	570.00		3640.00	50.00	4260.00	6642.82
2029		1094.97			1094.97						1094.97
2030		890.00	50.00		940.00				10365.87	10365.87	11305.87
2032									1400.00	1400.00	1400.00
2033									500.00	500.00	500.00
Total (MW)	900.00	8032.63	5374.64	31.25	14338.53	11732.56	15866.31	1222.05	43.90	28864.82	43203.35
Share (%)					32%					68%	100%

Table D.1: Planned electrolyser capacity by technology and development status (MWel).

E

CAPEX under different deployment scenarios

Scenario	Tech.	Year	Median (EUR/kW)	50% Interval	95% Interval
S1	AEC	2030	1,812	1,244–2,668	605–5,024
		2050	2,289	1,079–4,776	299–17,020
	PEM	2030	1,743	1,143–2,671	470–6,295
		2050	1,488	576–3,780	119–21,595
S2	AEC	2030	1,837	1,267–2,788	646–6,146
		2050	2,302	1,083–4,865	269–18,677
	PEM	2030	1,635	1,044–2,518	428–5,818
		2050	1,283	542–3,056	99–17,113
S3	AEC	2030	2,003	1,324–2,830	664–5,703
		2050	2,230	1,111–4,791	253–17,995
	PEM	2030	1,573	995–2,434	423–5,961
		2050	1,193	528–2,874	108–16,003

Table E.1: Stochastic Wright's Law forecast for AEC and PEM electrolyser CAPEX in 2030 and 2050 under scenarios S1, S2, and S3

F

Comparison of deterministic and probabilistic models in technology cost forecasting

Aspect	Deterministic models	Probabilistic models
Approach	Fixed input parameters; single-point outcomes or discrete scenarios.	Incorporate uncertainty distributions; produce ranges and probabilities of outcomes.
Advantages	Computationally efficient; transparent and easy to communicate; suitable for policy narratives and baseline scenarios.	Explicitly capture uncertainty; provide risk and probability information; enable flexible and adaptive policy design.
Disadvantages	Overconfident single view of future; ignore likelihood of deviations; may mislead on risk exposure.	Higher data and computational demands; more difficult to communicate; wide uncertainty bands can complicate decisions.
When preferable	Mature technologies with stable trends; quick scenario explorations; policy documents needing simple storylines.	Emerging technologies (e.g., electrolysers); high uncertainty contexts; risk-informed planning and investment analysis.
Output type	Single outcome or small set of scenarios.	Full distribution (e.g., 50% and 95% confidence intervals), probability statements.
Policy and investment use	Provides clear headline pathways; easy to set targets.	Supports hedging strategies; adaptive subsidies; dynamic policies (e.g., triggers).
Communication	Simple, concise, easier for non-technical stakeholders.	More challenging; requires careful explanation to avoid misinterpretation.
Limitations	False sense of precision; lack of flexibility in policy response.	May have wide intervals; less “sharp” guidance when data is weak.
Complementarity	Useful for base scenarios and narratives.	Useful as overlay to stress-test deterministic plans, adding robustness assessments.

Table F.1: Comparison of deterministic and probabilistic models in technology cost forecasting