Assumptions in Action: Impact of Assumptions on the Relation between Electrolysis Integration and Renewable Energy

A Focus on North-Western Europe

Author: T.V.F. van Beeck
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TU Delft

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A Focus on North-Western Europe

By

T. V. F. van Beeck
Student number: 4877918

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Thesis committee:	Dr. A. F. Correljé	TU Delft
	Dr. Ir. Z. Lukszo	TU Delft
External supervisors:	Ir. W. D. van de Graaf	Gasunie
	Dr. Ir. D Kawale	Gasunie
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It took some getting used to, but the commute to Groningen eventually proved to be an interesting and valuable new experience, at the forefront of hydrogen integration. Working on this project was enjoyable and enriching, providing me with unique learning experiences and a great professional environment at Gasunie. I hope that this research contributes meaningfully to the integration of electrolysis in the Dutch energy system, which aligns with its efforts to accelerate the sustainable energy transition.

Tijn van Beeck
Amsterdam, August 2025

Executive Summary

The energy transition toward a carbon-neutral energy system presents complex challenges that require reliable system-level insights to guide investment and policy. Energy system models are essential tools in this context. They support planning by simulating interactions between technologies, markets, and policies under various future scenarios. Their strength lies in their ability to highlight structural system relationships and test the feasibility of different energy strategies.

At the foundation of these models lie assumptions and simplifications that define the internal logic of an energy system model. Importantly, a distinction must be made between assumptions (e.g., cost or efficiency parameters) and simplifications (e.g., ignoring demand fluctuations or omitting battery interaction). While simplifications make models tractable and transparent, they also risk overlooking key real-world constraints. This is why testing the impact of these assumptions and simplifications is critical: doing so ensures that model outcomes are robust and that their conclusions remain meaningful in practical applications.

Energy modelling simulates the operation and evolution of energy systems to support decision-making and policy planning. It helps simplify complex systems, forecast scenarios, and evaluate the effects of different strategies. While models are never perfectly accurate, their usefulness depends on data quality, transparent assumptions, and iterative refinement. These assumptions directly shape model credibility and must be rigorously tested to avoid the risk of unvalidated assumptions becoming accepted truths that undermine decision-making.

One such model is the Kramer and Koning Model (KKM), a stylised energy model developed to analyse the relationship between renewable electricity generation and hydrogen capacity. The KKM is appreciated for its simplicity and its capacity to clarify the fundamental relationship between renewable energy generation and electrolyser capacity - the $r : e$ relationship. However, this simplicity raises the question of how sensitive its results are to added real-world complexities and how valid its outcomes remain. This study addresses that knowledge gap by investigating: "*How Do Key Model Assumptions in the KKM Influence the Relationship Between Renewable Energy and Electrolysis Deployment?"*.

To evaluate the validity of KKM outcomes, this study introduces the Electrolyser Battery Balancing Model (EBBM) - a more detailed cost optimisation model operating under the same logic as the KKM, but with extensive additional parameters. The EBBM simulates hourly interactions between renewable supply, demand, electrolysers, and batteries. Developed in collaboration with Gasunie, a key player in the Dutch gas infrastructure and hydrogen transition, the EBBM is specifically designed to test real-world factors and find the cost-optimum interplay between renewable, electrolysis, and battery capacity. It is well-suited to validate the simplified relationships modelled by the KKM.

Firstly, a systematic identification of assumptions in the KKM was made. These were categorised as either explicit or implicit. Implicit assumptions were further divided into (1) real-world system simplifications (e.g., omitting compressors, conversion losses), and (2) wider context simplifications (e.g., sector coupling, market conditions). Based on their role in the model and feasibility for testing in the EBBM, a focused selection of assumptions was made, grouped into four categories: renewable energy, hydrogen, cost, and system simplifications. The eventual selection consisted of:

- Generation Mix;
- Electrolyser Efficiency;
- Electrolyser Limitations;
- Hydrogen Storage Cost;
- Cost Ratio between Renewables and Electrolysers;
- Neglect of Demand Fluctuations;
- Battery Interaction Exclusion;
- Demand Flexibility.

Moving on with the selected set of assumptions and simplifications, a sensitivity analysis was first conducted by incrementally reintroducing high-certainty system simplifications to the KKM base case. This included adding demand fluctuations, battery interaction, electrolyser efficiency curves, hydrogen storage cost and electrolyser limitations to create a new, more realistic base case. This updated case was then used to test the impact of four key parameters: electrolyser efficiency, demand flexibility, solar share, and the cost ratio between renewables an electrolysers. In each case, a high and low value was tested. These variations were used to assess how much each assumption shifts the $r : e$ relationship, battery sizing ($r : b$), and total system cost (c).

Firstly, the incremental addition of complexities resulted in a flatter slope and lower overall system cost compared to the original KKM. Further results showed that parameters like solar share and cost ratio significantly affect infrastructure allocation between batteries and electrolysers, while demand flexibility and efficiency assumptions moderately shift total system cost and capacity sizing. The $r : e$ relationship remained structurally linear in all cases but varied in slope and magnitude. Notably, the combination of battery interaction and electrolyser efficiency assumptions produced the largest cost savings, lowering total decarbonisation cost by several hundred euros per kW relative to the KKM.

A robustness analysis followed, designed to assess whether model outcomes remain valid under extreme input conditions (edge cases). These edge cases were selected for the same assumptions as for the sensitivity analysis. The aim was to evaluate whether the KKM's simplified relations hold up under stress. The results indicated that while the relationship itself remains observable, its quantitative implications (e.g., cost and deployment levels) vary substantially, suggesting that the relation needs to be interpreted as directional rather than predictive.

To further contextualise the findings, a comparative model analysis was conducted. This compared the $r : e$ relationship in the KKM against other existing energy system models. A longlist was developed and refined to three studies: CE Delft, E-Bridge, and a NSWPH study. Extracted data confirmed that while each model uses different frameworks, a consistent structural trend in the $r : e$ relation is present, supporting the underlying logic of the KKM, albeit under different boundary conditions.

Despite differences in geography, modelling scope, and sectoral integration, all three studies showed a similar acceleration in electrolyser deployment relative to renewable generation, particularly beyond 2040. This convergence across models suggests that the *r : e* relationship is a robust feature of future energy system dynamics, rather than an artefact of a specific model setup. It reinforces the validity of the KKM's structural assumptions, even if absolute outcomes vary. As such, the *r : e* relation emerges as a valuable comparative indicator for system modellers and energy planners aiming to align infrastructure scaling with decarbonisation timelines.

In the discussion, the findings reveal that while the KKM offers a robust conceptual tool, its practical outputs are assumption-sensitive.. Key limitations include the use of a single weather year to simulate renewable variability, a strictly unidimensional approach to parameter varying, and the degree of certainty with which a particular impact can be attributed to an assumption in another model. These issues are particularly important for policymakers or investors relying on model outputs for long-term infrastructure decisions.

The conclusion confirms that the KKM captures a fundamental structural relationship between renewables and hydrogen capacity, which reappears when evaluating other models. However, the outputs of the KKM are highly dependent on assumption quality and scope, especially regarding solar share and the cost ratio between renewables and electrolysis. The research shows that integrating high-certainty simplifications and testing uncertain variables adds valuable depth. Therefore, the KKM proves useful for identifying strategic trends in the *r : e* relation. Future research should extend this work by incorporating power-to-heat, more detailed battery interaction, and policy scenarios to increase applicability in real-world system design.

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Nomenclature

Abbreviation	Meaning
AC	Alternating Current
AEC	Alcaline Electrolysis Cells
BE	Belgium
CAPEX	Capital Expenses
CCGT	Combined-Cycle Gas Turbine
CCS	Carbon Capture and Storage
CoSEM	Complex Systems Engineering and Management
CO_2	Carbon dioxide
CR	Cost Ratio
DC	Direct Current
DE	Distributed Energy scenario in the Pathway Study 2.0
DK	Denmark
EBBM	Electrolyser Battery Balancing Model
EMMA	European Electricity Market Model
ENTSO-E	European Network of Transmission System Operators for Electricity
ENTSOG	European Network of Transmission System Operators for Gas
ETM	Energy Transition Model
GE	Germany
HVAC	High Voltage Alternating Current
HVDC	High Voltage Direct Current
H2P	Hydrogen-to-Power
IEA	International Environmental Agency
INT	International Trade scenario in the CE Delft study

Abbreviation	Meaning
IRENA	International Renewable Energy Agency
ISPT	Institute for Sustainable Process Technology
KKM	Kramer and Koning Model
LCOE	Levelized Cost of Energy
MCA	Multi-Criteria Analysis
MET	Molecular Energy Transition scenario in the E-Bridge study
NL	Netherlands
NOx	Polluting oxides of nitrogen
NSWPH	North Sea Wind Power Hub
OCGT	Open-Cycle Gas Turbine
OPEX	Operational Expenses
PEM	Proton Exchange Membrane
PV	Photovoltaic
P2H	Power-to-Hydrogen
P2H2P	Power-to-Hydrogen-to-Power
RQ	Research Question
SOEC	Solid Oxide Electrolyser Cell
SQ1	Sub-Question 1
SQ2	Sub-Question 2
SQ3	Sub-Question 3
TYNDP	Ten Year Network and Development Plan
WACC	Weighted Average Cost of Capital

Symbol	Meaning	Unit
ε	Inflection point along the e-axis	-
η_e	Electrolyser efficiency	-
ρ	Inflection point along the r-axis	-
B	Battery capacity	GWh
C_b	Battery cost	10^6 €
C_e	Electrolyser cost	10^6 €
C_r	Renewables cost	10^6 €
C_storage	Hydrogen storage cost	10^6 €
D	Demand	TWh
E	Electrolyser capacity	GW
e	Normalized electrolyser capacity	-
f	Level of decarbonisation	-
kWa	Kilowatt of average generation	kW
kWh/h	Kilowatt hour delivered per hour of generation	kWh/h
R	Renewables capacity	GW
r	Normalized average renewable generation	-

1 Introduction

1.1 Context

In response to the growing urgency of climate change, the Paris Agreement was adopted during the COP21 in 2015, committing to global decarbonizing efforts with an overarching goal of limiting global average temperature increase to below 2°C (UNFCCC, n.d.). The success of this treaty not only depends on financial assistance, but is also largely contingent on the increased roll-out of renewable capacity, mainly by means of solar-PV and wind power (Resch et al., 2008). These sources of renewable electricity generation would in time phase out carbon emissions produced by fossil-fuelled energy generation (Yuan et al., 2022), thus assisting in the achievement of climate neutrality.

Despite the benefits in enhancing energy security and lowering electricity prices (Cevik & Ninomiya, 2022), the widespread integration of renewables also brings new challenges. The variability and unpredictability of sunlight and wind results in inconsistent renewable energy production, leading to intermittency. This currently complicates the goal of complete decarbonization, since the intermittent periods will still have to be complemented by fossil fuels (Pommeret & Schubert, 2021). On the other hand, during periods where power generations exceeds power demand, curtailment of this surplus is necessary to prevent grid overload, leading to economic loss for renewable energy producers (Jacobsen & Schröder, 2012).

Effective storage of this excess energy is a promising solution, capturing excess electricity and making it available during intermittent periods using a combination of batteries and hydrogen (Suberu et al., 2014). A key advantage is its capacity for long-term energy storage (Kharel & Shabani, 2018). Unlike batteries, which are optimal for short-term storage and intraday balancing due to their efficiency and rapid response (Hannan et al., 2021), hydrogen is uniquely suited for storing excess renewable energy over weeks or months. Although hydrogen has a lower round-trip efficiency compared to batteries, its long-term storage capability makes it a valuable complement to short-term energy balancing by batteries (Yousri et al., 2023).

The method of producing hydrogen through electrolysis varies based on the source of electricity. Electrolysers can be powered by burning fossil fuels, but this process still results in CO_2 emissions. These emissions can be partially mitigated by capturing the carbon dioxide after combustion, a process known as blue hydrogen (Kheirinik et al., 2021). However, another method is generally considered more promising: green hydrogen. Green hydrogen is produced using electricity from renewable sources, such as solar PV and wind energy. When powered by these sources, the only by-product of the production process is water vapor, making green hydrogen the most sustainable option (Oliveira et al., 2021).

Recognizing this potential, the Green Deal in 2020 allocated 100 billion euros within the EU to green hydrogen development (Energy and the Green Deal, 2022) with the aim to enhance grid balancing, sector coupling and energy storage. Since this investment, many initiatives have been started throughout Europe, to ensure that electrolysis can be gradually integrated into the energy system. With a look to the future, much hope is placed in this sizeable, promising task.

1.2 Problem Statement

Hydrogen is playing a growing role in energy system planning, with major efforts underway to expand production and infrastructure, such as Gasunie's hydrogen backbone in the Netherlands (Gasunie, 2025). Integrating renewables and electrolysis into the energy system, however, proves to be quite the conundrum. Despite ongoing efforts, the interplay between renewables and electrolysis deployment remains influenced by these varying assumptions such as cost projections, renewable supply and demand profiles (Kirchem & Schill, 2023 ; Dowling et al., 2020). Gaining clearer insight into how power demand interacts with these factors is essential for timely, cost-efficient infrastructure build-out. Better modelling of these dynamics supports more informed decisions and reduces the risk of over- or underinvestment, with the aim of ultimately supporting policy-driven decision-making to guide the integration of electrolysis (Bleischwitz & Bader, 2009).

To incorporate this uncertainty effectively, energy system models are often simplified, stylized representations of reality (Fragkos et al., 2021). Policymakers rely on energy system models to inform long-term infrastructure and investment decisions under deep uncertainty. To ensure models are both informative and practical for this purpose, a balance must be struck between complexity and clarity. While extracting key trends is more valuable to policy than a complex model (Mitchell, 2009), making sure that real-world complexities are captured correctly is essential to its credibility.

An example of a highly stylized energy system models is the Kramer and Koning Model (KKM) (2024). This model was designed to assess high-level relationships and increase understanding of interplay between renewables and electrolysers, developed in collaboration with Gasunie, a key player in the Dutch gas infrastructure and hydrogen transition. Gasunie is actively involved in repurposing and expanding gas infrastructure to facilitate large-scale green hydrogen production, making models like the KKM highly relevant to their long-term planning efforts. In modelling the relation between renewable generation and electrolysis capacity, several simplifying assumptions had to be made as well. There is a pressing need to examine the validity of these assumptions in order to further substantiate model outputs and to provide more accurate and actionable insights for researchers, policymakers and industry professionals.

1.3 Literature Review

1.3.1 Energy System Modelling

Energy modelling involves simulating the operation and growth of energy systems. Models are essential for breaking down complex energy systems, allowing stakeholders to understand how specific inputs impact outputs. They assist in forecasting future energy scenarios and evaluating the potential outcomes of various policy decisions, making them essential tools for designing the road to decarbonization (Hua & Paulos, 2023). An overall distinction can be made between capacity expansion models, meant to describe how an energy system changes over time, and production cost models, meant to depict how to meet electricity demand at the lowest operational cost. While models will never be fully accurate, they are indispensable for understanding and managing these complex systems. The accuracy of a model heavily depends on the quality of data and the assumptions made. Flawed assumptions or low-quality data can lead to misleading results ('garbage in, garbage out') and interpretation errors. The key is to use models transparently and iteratively, always being open to revision and improvement (Sterman, 2002).

At the foundation of energy system models lay the input values that simplify the complex systems these models aim to portray. These assumptions and simplifications (used interchangeably) do not only consider technical aspects, but also economic, environmental and policy contexts (Pellegrino & Musy, 2017). This multifaceted coverage, while also directly influencing the reliability of model outputs, makes that these assumptions essentially shape interdisciplinary credibility and applicability of these models. This makes it necessary to rigorously evaluate and sensitivity-test this influence. The “ossification of assumptions”, as Fournet (2015) calls it, where assumptions are eventually hardened into facts without validation, often negatively impacts decision-making and increases risk, which must be prevented to retain validity.

1.3.2 Importance of Validation

The European Environment Agency (2024) specifically mentions the grave importance of critically scrutinizing assumptions that influence policy-making regarding sustainability transitions. It highlights that policies often operate under various assumptions and, if these are weak or invalid, they can lead to inadequate decisions and eventually hinder policy objectives. Assessing future risks and thereby identifying mitigation measures and safeguarding strategies is of the utmost importance when reviewing important assumptions made. Basing energy policy decisions on uncertain or untested assumptions can lead to significant risks, including misallocation of resources, ineffective policies and other unintended consequences (UKERC, 2014).

Literature outlines several methodologies for testing and validating assumptions. A key approach involves scenario analysis, where models are subjected to various hypothetical situations to assess their performance under different conditions (Paltsev, 2016). Sensitivity testing is also vital; by systematically varying input parameters, researchers can identify which assumptions significantly impact model outcomes (Nguyen & Reiter, 2015). Empirical validation, which compares model predictions against real-world data, serves as a benchmark for accuracy (Serletis, 2007), but is hard to do for hydrogen integration-based assumptions since no actual hydrogen flows are currently operational. Since energy system models are commonly used to assist decision-makers, and renewable technologies are decentralized and intermittent, effective integration requires thorough planning that accounts for non-technical constraints and flexibility options (Kachirayil et al., 2022). This highlights the importance of robustness over sensitivity, to produce reliable results under varying conditions.

1.3.3 KKM and the Role of Assumptions and Simplifications

To understand the impact of green hydrogen production on a decarbonizing power system, Kramer & Koning (2024) published “Fundamentals of Hydrogen Production and Use in a Decarbonising Power System”, a report introducing the KKM. This evaluates the deployment of electrolysers alongside renewable energy sources like wind and solar. The KKM explores how electrolysers can utilize surplus renewable energy to produce green hydrogen, which can then be stored and converted back to electricity during periods of low renewable generation. This provides useful insights into the role of hydrogen in balancing power systems increasingly dominated by renewables, especially wind. The KKM is a stylized, top-down model, using a load duration curve to represent the statistical distribution of renewable generation rather than a time-sequenced simulation. This abstraction enables broad, scenario-independent analysis of decarbonization pathways, but also limits the model's ability to capture the complexity of real-world energy systems.

King and Tunitsa (2008) use the definition of “an assertion about some characteristic of the future that underlies the current operations or plans of an organization”. A simplification on the other hand, can be seen as as “a choice among alternative ways of representing a system that focusses on reducing complexity” (Birta & Arbez, 2013). While being aware of this distinction, both terms are used jointly and interchangeably in this paper.

Explicit simplifications and assumptions in the KKM can be divided into four categories: renewables-, hydrogen-, cost- and system assumptions. Core simplifications in these categories include that demand fluctuations can be neglected, hydrogen can be stored and transported in large quantities at a modest cost and existing thermal generation can at little cost be converted from natural gas-firing to hydrogen-firing. Far from being merely boundary conditions, assumptions and simplifications are central to the model’s internal logic, shaping both its structure and outputs. These simplifications are necessary for the model to operate, but also come with several limitations, uncertainties and potential weaknesses. Their influence on model output must be made explicit to determine the reliability of the model and ensure that conclusions derived from the model remain applicable under more realistic system behaviour.

1.3.4 Contrasting Assumptions

Several models referenced in the KKM paper also explore energy system modelling regarding the interplay between renewables and electrolysis, with variating assumption. Dowling et al. (2020) for instance included batteries for short-term storage, which the KKM does not. Specifically for the Netherlands, Weimann et al (2021) assumes a cost-optimized deployment of renewables and economic incentives next to market dynamics, making economic influence on model outcomes more apparent. Also, sector- coupling isn’t taking into account as prominently by the KKM when compared to Brown et al. (2018). However, Brown’s research encapsulates the entire European power system, which accounts partly for this dissimilarity.

When looking at the study done by Weitemeyer et al. (2014), several elements stand out. Since the model focuses on Germany specifically, it contains much more detail. Fundamentally, storage assumptions and demand functions are not generalized, but programmed in detail. Also, the low-cost retrofitting is not included in the model. While this can all be attributed to the model being developed for monitoring system behaviour under varying conditions - instead of high-level, generic insights like the KKM - they however are important distinctions nonetheless. Lastly, a study by Kirchem & Schill (2023) uses flexible electrolyser use and a variable mix for renewable energy generation, constrained with cost differences. Its modelling is also much more similar to Weitemeyer’s study, focusing on Germany specifically and explicitly using both tank and cavern storage possibilities for produced hydrogen.

1.3.5 Key Takeaways

Energy system models are essential decarbonization planning tools, enabling analysis of the effects of different inputs and assumptions on the development and operation of energy systems. All models rely on simplifications, yet their value relies entirely on transparent and high-quality assumptions. Poorly founded or outdated assumptions can lead to misguided conclusions, generating ineffective perverse decisions. For credibility, it is necessary to subject these assumptions to validation methods such as sensitivity testing and scenario analysis, proving robustness.

The KKM is a simplified, high-level model for hydrogen integration in renewable power systems. The model simulates a P2H2P system with assumptions such as flat demand, low-cost hydrogen storage and transportation at large scale and low-cost gas plant refitting. While these assumptions improve the model's generalizability by decreasing model complexity, it might also limit its accuracy. Several other frameworks use more detailed representations, such as flexible application of electrolysers, alternating renewable blends, short-term storage and sector coupling. the use of contrasting assumptions exhibits the need for them to be subjected to scrutinization.

1.4 Knowledge Gap and Research Objective

The importance of assumptions made when predicting the workings of our future energy system can not be overlooked. Given the growing reliance on energy models for policymaking, it is essential to evaluate how assumptions shape model outcomes and whether they provide a solid foundation for real-world decision-making. Addressing said gaps will provide a more comprehensive understanding of assumptions and the relationship between renewable energy and electrolysis deployment.

Understanding how these assumptions are formulated, why they were selected and what their impact is on model performance are crucial. When this relation is made clear, the assumptions and the model itself can be confidently used and applied to real-world situations. Thus, this study entails an ex-ante evaluation, aiming to systematically test the KKM's assumptions and assess their impact on the relationship between renewable energy expansion and electrolysis deployment in decarbonizing power systems. This research will start off in a general manner, but will eventually narrow its focus to the North-Western part of Europe, specifically the NL/DE/DK/BE region, since this is the scope of interest for Gasunie and this is where the validity of the KKM is expected to be the highest.

1.5 Main Research Question and Sub-Questions

Considering the problem at hand, together with the identified knowledge gap and the objective of this research, this leads us to the main research question (RQ), which reads:

1) ***RQ**: "How Do Key Model Assumptions in the KKM Influence the Relationship Between Renewable Energy and Electrolysis Deployment?"*.

To answer this research question, the crucial assumptions made in the KKM regarding renewable power generation, hydrogen production, and energy storage need to be identified in sub-question 1 (SQ1). Next, in sub-question 2 (SQ2), analyses to evaluate the sensitivity and robustness of the KKM assumptions will be conducted by subjecting the assumptions and the model itself to sensitivity and robustness analysis. Lastly, in sub-question 3 (SQ3), a comparison will be drawn between the $r : e$ relation in other models and the one found in the KKM. Leading to the following overview:

2) ***SQ1: "What Are Key Assumptions in the KKM and Why Are they Made?".***
3) ***SQ2: "How Sensitive and Robust Are KKM Model Outcomes to Variations in Key Assumptions?".***
4) ***SQ3: "How Does the Renewable Generation-to-Electrolyser Build-Out Relation in the KKM Compare with Alternative Energy System Models?".***

1.5 Link to CoSEM and Societal Relevance

This research connects directly to CoSEM through courses like 'Design of Integrated Systems' and 'Sociotechnology of Future Energy Systems', which emphasize designing and managing complex socio-technical systems, especially in energy contexts (COSEM — TU Delft, n.d.). The project also aligns with key aspects of the programme, such as the integration of renewable energy technologies and their socio-economic impacts and the role of models in finding effective solutions. It's societal relevance is apparent: since our future power system will become increasingly more complex due to the growing share of renewable energy, understanding how the introduction of large-scale electrolysis influences this system is crucial to its success.

Understanding the relationship between renewable generation and electrolysis capacity is essential to ensuring that green hydrogen production can scale efficiently alongside variable renewable energy sources. This relationship directly informs how infrastructure should be sized and phased in to avoid overbuilding or underutilization, which in turn affects the affordability and reliability of the future energy system. It allows system planners to better align hydrogen production with supply variability, thereby maximizing renewable utilization. Ultimately, these insights support a more coordinated and cost-effective energy transition.

This study aims to identify relevant assumptions, demonstrate their relations, compare their values and validate them. By doing so, the reliability of energy system model foundations can be assessed. These findings will eventually help policymakers make informed decisions on hydrogen investments and achieve net-zero emissions.

1.6 Report Structure

Following the introduction, the Methodology will entail a description of how this scrutinization will take place. According to said procedure, the main research question will be answered by independently discussing each of the sub-questions in separate chapters. Firstly, the model choice for the validation of the KKM will be introduced and substantiated. After, a system description will be provided in order to create a clear overview of the system that is being discussed. The relevant assumptions and simplifications will be selected, highlighted and substantiated in the Key Assumption Identification, after which the Sensitivity and Robustness Analysis will delve into the validation of KKM outputs. The sensitivity and robustness of the model outputs to variations in assumptions and simplifications will be examined in this section. Lastly, the Comparative Analysis will contrast the KKM assumptions and simplifications, together with the relation between renewables and electrolysers, against other energy system studies

Results will be presented and discussed in each section. This will include a detailed presentation of the findings, highlighting the interconnections between assumptions and model performance. The results and other relevant topics will be critically discussed in the Discussion, identifying key insights and limitations. Finally, the Conclusion will address the primary research question and reflect on its broader implications. These deliverables will ensure the research contributes both to academic understanding and practical energy system design. Any figures, graphs or information that is being referenced to but is not directly included in the report, can be found in the Appendix.

2 Methodology

In this chapter, the logic behind the KKM will be explained, to show what it models and how it functions. Subsequently, the Electrolyser Battery Balancing Model (EBBM) will be presented, which will be used in the validation of the KKM assumptions. Lastly, the research design will be introduced. The research methods used to answer both the sub-questions and eventually the research question will be disclosed. Additionally, the data requirements and the data analysis tools and sources will be discussed.

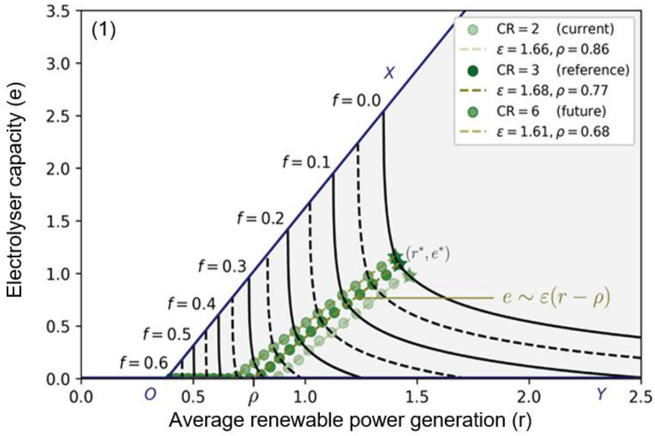
2.1 Kramer and Koning Model (KKM)

The KKM operates fundamentally on the principle of a load duration curve. This stylized mathematical model is primarily developed to provide high-level, generic insights into the relationships between variable renewable energy generation and electrolyser deployment for a decarbonizing power system. The model also analyses synergies between power system decarbonization and generation of hydrogen for export to other sectors. The KKM makes several assumptions and simplifications, as mentioned in the previous chapter. The model aims to provide a systematic exploration of the scale of renewable and electrolyser deployment necessary to achieve power system decarbonization, as determined by capital cost assumptions and the relative contribution of solar and wind capacity. It is also meant to highlight the cost synergies that can be achieved through the elimination of power-to-hydrogen and hydrogen-to-power inefficiencies by co-producing hydrogen instead of stand-alone production of hydrogen.

The authors assess the integration of green hydrogen production and electrolyser deployment within a progressively decarbonized power system, revealing that full decarbonization is cost-optimal when a significant portion of the power mix comes from wind energy (this is, in the base case for the Netherlands). They identify a critical threshold where electrolyser deployment becomes necessary, which occurs around 70% grid decarbonization for wind-dominated systems. The KKM evaluates optimal ratios for renewable and electrolyser capacities under varying degrees of grid decarbonization. The CR, reflecting relative costs between renewables and electrolysis, serves as a central sensitivity parameter in the model.

Figure 1 and 2 illustrate the core mechanics of the KKM, which determines the cost-optimal trade-off between renewable generation and electrolyser capacity to achieve varying levels of power sector decarbonisation. The left plot shows the relationship between average renewable power generation (r) and electrolyser capacity (e) for different levels of decarbonisation (f), along with the fitted curves defined by $e \sim \varepsilon\, (r - \rho)$, where ε represents the marginal electrolyser requirement and ρ the renewables threshold. This relationship is central to the model's logic and defines the cost-optimal system configuration for a given cost scenario.

The right plot presents the marginal decarbonisation cost as a function of the level of decarbonisation $(1 - f)$, showing how this cost increases sharply as full decarbonisation is approached. Together, these figures highlight the importance of system design parameters in shaping investment needs and reveal diminishing returns near the highest decarbonisation levels.



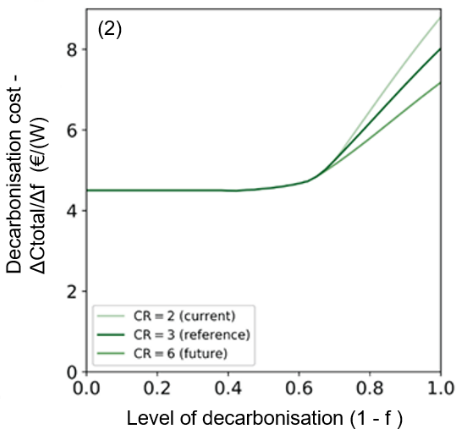
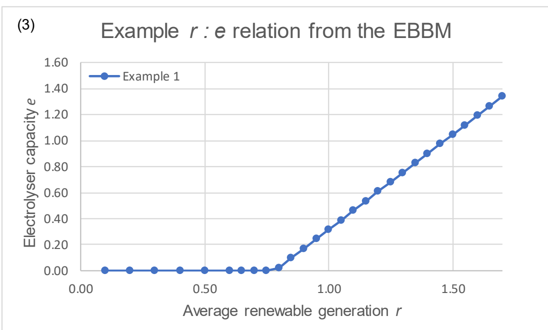


Figure 1: A cost-optimal deployment plot from the KKM report (2024), including renewables (r) and electrolysers (e) for a wind–solar mix in the Netherlands. The black lines indicating equal usable renewable energy (1 − f). Dots mark cost-optimal combinations for (r, e) in different cost scenarios, fitted by e ∼ε (r − ρ). Stars indicate the cost optima for full decarbonisation. Figure 2: Total system cost for each level of decarbonisation three different cost ratio (CR) scenarios, as mentioned in the KKM report.

2.2 Electrolyser Battery Balancing Model (EBBM)

The EBBM is a time-sequential energy system model that builds on the core structure of the KKM, but extends it with multiple additional parameters and functionalities. It is designed to simulate the integration of battery storage next to renewable electricity and electrolysis in a combined onshore and offshore Dutch energy system. By optimising these three factors while taking into account several other, the model finds individual cost-optimal solutions for different levels of decarbonisation. Separate runs can be modified with several optional refinements, like demand side flexibility, grid capacity limitations, efficiency curves, minimum loads, all of which can easily be activated or deactivated. By plotting the *r : e* relation after said optimisations, similar trends can be produced compared to the KKM. Similar cost plots can also be generated, next to the relation between renewables and battery capacity (*r : b*), which is not included in the KKM but provides additional insights. Figures 3 and 4 serve as an example of the output from the EBBM, showing the *r : e* relation and a basic cost plot respectively of an exemplary dataset (Example 1).



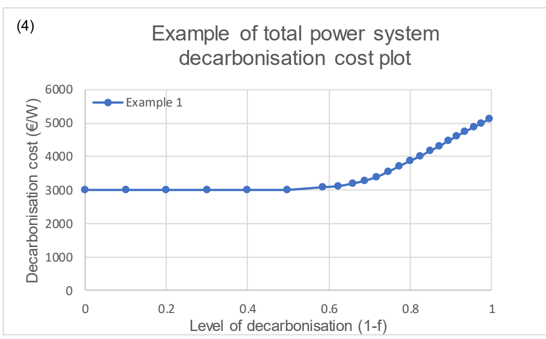


Figure 3: A representation of the r : e relation for the exemplary dataset Example 1 as produced by the EBBM, following a trend similar to the KKM Each datapoint represents an individual run where the combination of r and e is optimised. Figure 4: A representation of the total power system decarbonisation cost for different levels of decarbonisation, for exemplary dataset Example 1, as produced by the EBBM. Each datapoint represents an individual run, corresponding to Figure 3, with the cost of decarbonisation in €/W for different decarbonisation levels.

Operating at hourly resolution over a full year, the EBBM incorporates a realistic representation of how renewable energy is allocated within the system. At each time step, renewable power is first allocated to meet electricity demand. If generation exceeds demand, the surplus is used to run electrolysers and produce green hydrogen. By assigning costs of the assets, one can explore the cost effectiveness of different combinations of assets, either manually or automated.

The model charges batteries in case of excess power production. In periods of renewable shortfall, the model discharges stored electricity from the battery to meet demand. If battery storage is insufficient, the model applies a backtracking mechanism: it retroactively reduces electrolyser power consumption from earlier hours in order to restore battery charge levels and resolve the shortfall. If no resolution is possible through these internal adjustments, backup generation is triggered.

The model also allows for battery discharge to increase electrolyser throughput, provided this does not compromise future storage needs. These dynamic interactions enable the EBBM to construct detailed and internally consistent hourly profiles of power flows, hydrogen production, battery usage and curtailment for any given set of renewable generation, electrolysis and battery capacity. Scenario and sensitivity analyses are embedded within the model structure, facilitating exploration of alternative layouts and their associated impacts on performance and decarbonization pathways. For a more in-depth description of all model functionalities and profiles, see Appendix A.

2.3 Research Design

This section entails the precise research design, including all tools, data sources and requirements used to gather and structure information that answers each sub-question. The research design will utilize a mixed-methods research approach, using both qualitative and quantitative data collection and analysis to answer the research questions. A sequential design (Bryman, 2006) is used, as the answer and information related to each sub-question serves as input for the next. This method was chosen due to the combined strength of using both quantitative and qualitative methods of data analysis (Doyle et al., 2009), next to its increased generalizability and quality (Leech et al., 2009).

2.3.1 Key Assumption Identification (SQ1)

The first phase focuses on identifying, describing and evaluating key assumptions and simplifications made in the KKM, both those explicitly stated in the publication and those that are implied or not covered – inferred from omissions from the real-world system and wider context. The output of this phase will be a structured, categorized inventory of all assumptions, organized by theme (e.g., cost hydrogen related or cost related) and classified by source type (explicit or implicit). This structured overview serves not only to answer SQ1 but also to define a targeted testing scope for SQ2.

Thereafter, the logic for each of these simplifications will be argued to substantiate them and illustrate their role in the model. This will be qualitative in nature and based on a document review of the KKM itself, relevant academic literature concerning the underlying assumptions, industry and government reports on recent developments and supplementary technical documentation provided by technical and subject matter experts. For these tasks, Scopus (Zhu & Liu, 2020) and Google Scholar (Martin-Martin et al., 2016) will be utilized. This narrative will eventually support a reasoned selection of highly relevant assumptions for in-depth analysis in subsequent phases, based on impact on model outcomes, validation capabilities and interest from Gasunie.

2.3.2 Sensitivity and Robustness Analysis (SQ2)

In the second phase, the selected high-relevance simplifications from SQ1 will be tested using the Electrolyser Battery Balancing Model (EBBM), developed by Gasunie. It combines battery capacity next to electrolyser capacity and renewable for a more optimal and flexible balancing scheme. This model operates on hourly time-sequence data rather than stylized load duration curves and builds onto the KKM's logic with an extension of the parameter selection, making it well-suited to reproduce and analyse the KKM results while enabling direct quantification of simplification impacts - a more detailed description can be found in chapter 3 or Appendix A. Each analysis done will be cost optimized based on the assumption (cost, efficiencies) and enabled functionality, resulting in a mix of renewables (*r*), batteries (*b*) and electrolysers (*e*).

Analysis will be performed for five levels of decarbonisation, where *f* stands for the remaining firm fossil fuel-generated electricity in the system:

(1) 80% grid decarbonization $(1 - f = 0.8)$, without hydrogen export to other sectors;
(2) 90% grid decarbonization $(1 - f = 0.9)$, without hydrogen export to other sectors;
(3) 100% grid decarbonization $(1 - f = 1.0)$, without hydrogen export to other sectors;
(4) 100% grid decarbonization, with an additional 10% hydrogen export to other sectors;
(5) 100% grid decarbonization, with an additional 20% hydrogen export to other sectors.

These analyses for five levels of decarbonisation, allow for trending the relationship between the build-out of average renewable generation and electrolyser capacity alike the trend examined the KKM paper (Kramer & Koning, 2024). In addition, it will also allow for trending of the battery capacity and cost.

The analysis is structured in three parts: simplification assessment and assumption sensitivity. First, simplifications will be evaluated by incrementally modifying them and tracking the corresponding changes in model outputs. The simplifications tested include battery interaction, electrolyser limitations, demand fluctuations, electrolyser efficiency curves and hydrogen storage cost - all of which are explicitly defined and varied in the scenario matrix. The system simplifications omitted in the KKM are incorporated first in the EBBM to establish a new base case, as they represent well-understood, high-certainty components whose technical feasibility and empirical relevance are widely acknowledged. This will build up to reflect a more realistic and valid new base case for the subsequent parameter variations, thereby increasing the validity of the runs. A waterfall chart will be constructed to visually show the isolated and cumulative impact of each simplification on key metrics (Mahajan & Gokhale, 2019). This chart, including plots of the cost-optimal *r : e* relation, can be found in chapter 6.

Second, variations in parameter values will be tested through univariate sensitivity analysis. Univariate sensitivity analysis is well suited for this research, as it allows the isolated impact of individual assumptions on model outcomes to be assessed in a clear and systematic way, given the study's focus on evaluating how specific simplifications influence key results (Jain et al., 2011). This includes varying the generation mix, electrolyser efficiency, the cost ratio of renewables to electrolysis (CR) and demand flexibility.

Third, the robustness analysis tests whether the model's logic and conclusions hold when key assumptions are pushed to their extremes. This is done by applying best- and worst-case values (edge cases) to the same set of input variables as the sensitivity test. These variables are central to the model's structure and influence its core outcomes. By systematically varying these parameters across plausible but extreme values, the analysis evaluates the internal consistency of the model and whether its pathways remain valid when assumptions are stressed (Micskei et al., 2012). This approach helps identify which assumptions are most impactful, and whether conclusions drawn under default settings remain credible under more extreme conditions.

Each uncertain parameter will be varied across plausible low-mid-high ranges (determined by using the sources used in SQ1), after which the model will be optimized for each variation and for all five levels of decarbonisation. These variations are once again depicted in a scenario matrix. For all simulations, the outputs being tracked include total system cost per kWh/h decarbonized power (*c*), renewable installed capacity (*r*), electrolyser capacity (*e*) and battery capacity (*b*). In addition to these direct outputs, the relationship between renewable generation capacity and electrolyser deployment will be systematically tracked across all scenarios to assess how it deviates from the theoretical relationship identified in the KKM. For all runs, an optimisation gap (Voll et al., 2015) of 10% is asserted. A comprehensive overview of these cases, including plots for all runs, can be found in Appendix B.

The research will require model access and scenario-specific input data, while Excel will be used to perform statistical sensitivity analyses, generating insights into the range and reliability of model outputs under different assumptions. Excel is a powerful tool for scenario analysis, sensitivity analysis and uncertainty testing due to its built-in functionalities for modelling complex relationships, while data tables provide robust frameworks for testing parameter sensitivity in model outcomes (Guerrero, 2019). Also, since the EBBM has been designed in Excel, it will facilitate a smooth analysis of the assumptions more easily. This will provide structured insight into both the role of model simplifications and the robustness of KKM outcomes under real-world uncertainty in assumption values, answering SQ2.

2.3.3 Comparative Model Analysis (SQ3)

The third phase assesses how the *r : e* from the KKM compare to those from other models and studies in the field. This will show the impact of assumptions made in different studies and how this translates to different *r : e* relations. A selection of recent academic and industry models will be analysed for their assumptions and core relationships. This selection will largely depend on the accessibility of input data and model structure required to extract the relevant relations. Apart from the KKM paper, the research will require access to other academic papers, technical reports and industry publications to gain knowledge on the background of the KKM and considerations surrounding the assumptions made. This phase will also rely on technical and economic literature to compare findings against standards used in other sources.

In practice, this means that models already available within Gasunie, like the Pathway Study 2.0 (2024) for example, are likely to form a substantial part of the comparison. These models offer a higher likelihood of being usable for reproducing the normalized renewable-electrolyser relationships, due to the level of transparency and control over assumptions they provide to this research, and in particular because of the availability of underlying data and the possibility of support from the model authors. Nonetheless, the analysis will not be limited to these models; other academic and industry models will also be considered where sufficient documentation or data access allows for meaningful inclusion in the comparative framework.

The key relationship under examination is the link between average renewable energy generation and electrolyser build-out, as modelled in the KKM with a focus on the Netherlands. For each selected study, the nature of this relationship will be extracted and plotted using the same normalized framework applied in the KKM (the cost-optimal electrolyser capacity against average renewable power). Comparing these plots will reveal the extent to which different assumptions, simplifications, or parameter uncertainties affect this result.

Using several models to compare the *r : e* relationship ensures that the structural pattern found in the KKM is not model-specific, but reflects a broader consistency across independently developed frameworks. This cross-model agreement adds credibility to the relationship by showing that, despite differences in assumptions, similar trends emerge, thus reducing the risk of over-relying on any single model's assumptions.

2.3.4 Main Research Question

The aforementioned sub-questions will allow for a reflection on the robustness of the renewables-electrolyser relationship in the KKM: to what extent does this relationship hold across different models and under which conditions might it break down? This includes a consideration of what the presence of such a relationship does and does not imply. What are the broader implications of the renewables-electrolyser relationship, and how can it be interpreted in the context of real-world system planning. Combining these findings with earlier results, the main research question will be answered. Any deviations will be discussed, with a focus on identifying which simplifications or uncertainties are likely responsible.

3 KKM Validation Using the EBBM

The Kramer-Koning Model (KKM) and the Electrolyser Battery Balancing Model (EBBM) are both analytical frameworks aimed at optimizing renewable energy and electrolyser integration into decarbonized power systems. While sharing similar overarching objectives, each model is distinct in approach and analytical capabilities, influencing their application and validity in specific research contexts. This chapter contains a description of each model, outlining both model functionalities. Subsequently, the use of the EBBM in the KKM assumption and simplification validations will be substantiated, after which the EBBM optionality will be discussed to illustrate the model's additional complexity compared to the KKM. Lastly, the limitations associated with the use of the EBBM will be examined.

3.1 EBBM Use for KKM Validation

The choice to utilize the EBBM for validating KKM assumptions stems from the fact that the KKM, as a stylized model, deliberately applies simplifications that are not uncertainties in themselves, but fixed structural assumptions made for analytical and practical clarity. While substantiated correctly and useful for deriving generic insights from the model, these core simplifications and other assumptions cannot be validated within the KKM framework without modifying the model structure itself. In contrast, the EBBM incorporates these omitted elements by design and enables univariate testing of their effects.

The EBBM builds on the same core logic and structure as the KKM, but extends it with additional parameters and capabilities for greater detail. This means that it can reproduce the KKM's results when entering the same inputs. However, instead of relying on a load duration curve abstraction, the EBBM is built on time-series data, allowing the model to simulate actual hourly system behaviour. This shift from abstraction to temporal simulation makes it possible to quantify the impact of each individual simplification with relatively high confidence, while also exploring the interaction effects when multiple assumptions are varied simultaneously. In doing so, the EBBM preserves the conceptual integrity of the KKM but enables a more nuanced understanding of how its simplifications influence outcomes - thereby serving as a robust validation tool.

3.2 Key EBBM Input Variables

The EBBM is an elaboration on the KKM, allowing for an analysis including multiple additional aspects. This results in the EBBM having a significantly higher amount of input and output variables. The relevant input variables in relation to the validation of the KKM simplifications are discussed below. An overview of all EBBM input variables and its functionalities, including descriptions of each input variable and visualisations of both the input and output interface of the model, can additionally be found in Appendix A.

3.2.1 Capacity Parameters

The Average Renewable Energy Generation (*r*) represents the portion of renewable energy generation (*r*) relative to total system electrical energy demand (*D*) measured in (GWh/h)/(GWh/h), alternatively but indistinguishable to the commonly used TWh/y. This recurring unit emphasizes the time-sequence basis of the model. It is critical for analysing system decarbonization potential and determining the optimal relation to the electrolyser capacity (*e*), in GW of installed capacity. The Electrolyser Capacity (*e*) specifies the installed electrolyser power relative to the total system electrical energy demand (*D*), measured in (GW)/(GWh/h), and is instrumental in converting excess renewable energy into hydrogen. It is jointly assessed with r and Installed Battery Capacity (*B*, measured in GWh) to determine optimal utilisation of these assets. This is done by first optimising specified assets, after which an optimal ratio of assets is determined.

The Degree of Carbonisation (*Ug_H2-to-market-first (power+hydrogen)*), as described in chapter 2.3.2, is expressed by *Ug/D*, where *Ug* refers to the total energy delivered to consumers (in GWh) and *D* refers to the total electrical power demand (also GWh). Ug between 0 - 1 hence refers to degree of decarbonization of the power grid, where values above 1 refer to a fully decarbonized power grid with additional hydrogen. This variable is actively varied in scenario analyses to simulate different decarbonization trajectories. Lastly, the generation mix can be altered by adjusting the *Solar Share*, representing the percentage of renewable generation provided by installed solar capacity. By structuring the model in this way, the EBBM is able to evaluate system performance under a broad range of conditions. It supports sensitivity testing and scenario analysis, making it a powerful tool to validate the stylized simplifications embedded in the KKM.

3.2.2 Demand Parameters

The EBBM incorporates a wide range of input parameters that allow it to simulate a hybrid energy system under different technological, operational and economic assumptions. At its core, the model is governed by key capacity parameters that define the scale of generation and storage. The parameter Demand Curve (*Demand Curve*?) allows for choosing a specified variable demand curve or a flattened demand curve, as applied in KKM.

The parameter Demand Side Flexibility (*Demand Side Flexibility*) allows for the inclusion of flexible demand. The parameter is specified as a percentage of Demand (*D*). In case of shortage of direct supply of energy, the demand curve can be reduced by the specified percentage rather than rely on energy storage or back-up power generation. Note that the option temporarily reduces demand, it does not shift demand to other periods.

3.2.3 Efficiency Parameters

In terms of conversion efficiency, Electrolyser Efficiency (η_e) is set to 70% (at 100% load) in the base case and is consistent with KKM assumptions. It governs how effectively electrical power is converted to hydrogen. The model optionally applies a Hydrogen Efficiency Curve, a setting that either activates variable efficiency linked to operational conditions or is flattened to a constant. The electrolysis efficiency can cover all energy losses related conversion, e.g. for utilities, compression, power conversion, stack degradation as well as losses for hydrogen storage and transport. The electrolyser efficiency refers to the efficiency at maximum capacity.

3.2.4 Cost Parameters

Similar to the KKM, the EBBM also integrates key economic inputs. Note that costs refer to an annualized cost of the assets, and needs to include investment costs, operational costs, lifetime, interest rates, return and investments considerations. The Renewables Cost (*C_r*) and the Electrolyser Cost (*C_e*) together define the cost ratio (CR) that shapes investment prioritization between renewable capacity and electrolysis. In the EBBM, the cost parameters are extended with cost of batteries (*C_b*) and the cost for hydrogen storage (*C_storage*).

3.2.5 Electrolyser Limitation Parameters

Electrolysers generally don't operate well below a specified minimum load. Efficiency drops, and risk of crossover of hydrogen to oxygen increases, making it better to stop the electrolyser completely. *Minimum Load Electrolysers* allows for specifying the percentage below which individual electrolysers need to be placed on stand-by. At standby, the power consumption of electrolysers and utilities is generally small, but not zero. There can also be minor losses due to depressurization to consider. With large capacities of electrolysis installed, even a small percentage of power consumption - generally with inconvenient timing - may affect system wide considerations. The parameter *Standby Losses* accounts the percentage of power required during standby for electrolysers.

Because it's not desirable for electrolysers to stop-start with high frequency, a minimum standby period (in hours) can be defined. This feature will enforce that minimum power load is maintained during short periods below the threshold, either by interactions with batteries or if required by back-up power generation. A related parameter (which can also be switched on or off) is *Flattening, Bridging & 2nd Iteration*. This feature resolves some of the time series optimization challenges introduced by the minimum standby period feature.

3.3 Limitations of the EBBM

Like any model, also the EBBM has several limitations that must be acknowledged in the context of KKM assumption validation. First, the EBBM focuses more on operational feasibility and performance rather than full cost-optimization at a system level. While the same output can be generated, the EBBM is much more cumbersome when making these calculations. Also, the model uses hourly profiles, while variations within the hour may also be of relevance. The model considers a single reference year, whereas variations between the years will also be of relevance.

Second, the EBBM is that it does not include infrastructure costs as a separate category, nor does it account for bottlenecks in onshore electricity and hydrogen networks. As a result, the model may overestimate the feasibility of certain system configurations by ignoring the investment and spatial constraints associated with grid reinforcement or pipeline development. This limits its applicability for infrastructure planning and may lead to overly optimistic outcomes. Noteworthy also is the lack of storage capacity incorporation, which indicates the model does not include storage cost.

Third, the EBBM assumes ideal electrolyser flexibility, allowing ramping from 0–100% without explicitly modelling degradation dynamics over time. This simplification may underrepresent the operational challenges faced by real electrolyser installations, particularly in high-cycling or part-load conditions. While standby losses and minimum load thresholds are included, other nuanced behaviours such as cold starts or equipment wear are generalized into static assumptions rather than dynamic degradation modelling. By acknowledging these limitations, the EBBM remains a suitable tool for validating key assumptions of the KKM, particularly those related to energy balancing and the systemic role of storage.

4 System Description

This chapter provides a structured description of the energy system studied in this thesis. It begins with a high-level overview of the broader energy transition context and the challenges it introduces. From there, it zooms in on the emerging role of offshore electrolysis, highlighting its technical concept and relevance. A representation of this real-world system will be discussed in detail. Finally, the chapter introduces and explains the stylized system modeled in the KKM. The differences between this stylized system representation and the real-world will be highlighted and discussed.

4.1 Broader Energy System Context

The system described in the KKM is part of a larger, European energy system. In this much broader context, different factors are important to mention, to fully understand how the system is situated and what takes place outside of the KKM system boundaries.

4.1.1 The European Energy System

The European energy system is undergoing a transformation to decarbonize power generation and integrate increasing shares of renewable energy. Wind and solar power, now central to national energy strategies, bring significant variability that challenges the stability of existing power grids. This shift creates the need for new solutions for flexibility and long-term storage. Hydrogen, produced from renewable electricity and used as feedstock, is increasingly seen as a key enabler of such flexibility, particularly for seasonal balancing and possibly inter-sectoral energy transfer.

4.1.2 Offshore Wind Development in Northwest Europe

Offshore wind energy development in Northwestern Europe has become a cornerstone of the its decarbonization strategy, with the North Sea emerging as a key hub for large-scale deployment. Countries such as the Netherlands, Germany, Denmark, and Belgium have set ambitious targets for offshore wind capacity, aiming to collectively install at least 65 GW by 2030 and over 150 GW by 2050, as outlined in the 2022 Esbjerg Declaration. To accommodate this growth, the region is moving toward coordinated infrastructure planning, including the development of offshore energy hubs and interconnectors, which combine cross-border grid integration.

These hubs aim to increase system efficiency and support more flexible power distribution across borders. However, this rapid expansion of offshore wind also introduces operational challenges like grid congestion and curtailment risks (especially during periods of high wind and low demand). Without adequate transmission capacity and flexibility options, these challenges may undermine the value of these offshore assets. This highlights the need for integrated system planning and system flexibility measures.

4.1.3 Offshore Electrolysis as a System Innovation

Offshore electrolysis refers to the production of hydrogen directly at sea, typically nearby offshore wind farms. Instead of transmitting electricity to shore by HVDC cable, power generated offshore is converted to hydrogen via electrolysers mounted on platforms. This hydrogen can then be transported via subsea pipelines, avoiding onshore grid congestion and enabling scalable production aligned with North Sea wind development, while also being cheaper than power transmission over long distances. While still an emerging technology, pilot projects and feasibility studies show the growing interest in integrating offshore hydrogen into energy systems. Compared to onshore electrolysis, offshore systems typically involve higher upfront costs due to marine construction and harsher operating environments which are offset by savings on power infrastructure.

The deployment of offshore electrolysis presents several technical and logistical challenges. Platform design must account for space constraints and offshore safety standards, while maintenance is more complex and costly than on land. Compression and pipeline transport systems must also be integrated into larger storage or transmission networks. In response to these challenges, offshore backbones are being explored. These involve centralized offshore facilities that cluster generation from multiple wind farms and connect to broader regional hydrogen infrastructure. As the offshore wind build-out accelerates in the North Sea, offshore electrolysis is increasingly seen as a promising innovation.

4.1.4 Grid Integration

Grid integration encompasses how renewable electricity is dispatched and how electrolysis interacts with wider energy demand. In a real-world scenario, this includes grid congestion management, priority dispatch, frequency balancing and market participation amongst others. Offshore electrolysis is ideally built to absorb surplus renewable energy and reduce curtailment. In practice, determining “surplus” energy requires real-time grid monitoring. Transmission system operators play a central role and the electrolysis plant must interface with national or regional balancing markets. Interconnections between different countries can also play a big role in interactions with transnational grids.

Offshore wind farms close to shore are typically connected using high-voltage alternating current (HVAC) substations, while wind farms located farther offshore rely on high-voltage direct current (HVDC) transmission stations to efficiently transport electricity to land. This electrical integration is critical in linking offshore generation to electrolysis and the wider power system. Electrolysers can also support the grid by providing flexibility services such as load shifting, when equipped with smart control systems and strategically sited within the transmission network. Infrastructure limits, such as grid bottlenecks, often constrain deployment more than technology readiness.

4.1.5 Real-World Complexity to Stylized Representation

While the broader European energy context is defined by technological complexity, spatial constraints, and infrastructure interdependencies, the KKM deliberately abstracts from this complexity. Instead, it adopts a stylized and simplified representation to isolate the structural relationship between renewable generation and electrolysis capacity. By omitting several real-world factors, the KKM creates a transparent modelling environment focused on interactions between renewable generation and hydrogen production. This narrowed scope helps to identify fundamental trends in system behaviour that might otherwise be obscured in fully detailed system models.

4.2 System Scope and Boundaries

While understanding the broader context of the system, it is important to define the scope and the boundaries that exist in the KKM. This described by means of the geographic scope, chronological scope and the sectoral scope of the system.

4.2.1 Geographic Scope

The geographic scope of the KKM is centred on the Netherlands, with wider applicability to the Northwest European region. The model's base case uses input data and assumptions that reflect Dutch conditions, such as the renewable energy mix, cost parameters and performance metrics derived from national feasibility studies. For example, the assumed 80% wind and 20% solar energy mix corresponds to Dutch energy projections and offshore electrolysis parameters are based on Dutch technical studies. While spatial details like infrastructure locations, distances and national grid layouts are not specified, the model is designed to provide insights that are transferable to neighbouring countries with similar energy system dynamics, including Germany, Belgium and Denmark.

These countries, like the Netherlands, are investing heavily in offshore wind and hydrogen integration, making the KKM’s stylized framework a relevant tool for analysing system behaviour across this interconnected regional context. It can -in principle- also be applied to other countries; the base case parameters of the model will have to be adjusted for these countries, since the renewables mix will vary greatly from the target countries of this research and assumptions need to be review for the specific region.

4.2.2 Temporal Scope

The KKM uses a long-term, static modelling approach with a time horizon set around the year 2040. Rather than simulating system behaviour over time or capturing short-term operational dynamics, the model represents a scenario that reflects a decarbonized power system under future conditions. It does not provide chronological insights, such as hourly dispatch or seasonal variability, but instead treats all variables as average annual values. While this static approach provides a clearer oversight and reduces complexity, it also limits the model’s ability to capture temporal aspects such as weighted-average-cost of capital (WACC), cost & revenue phasing, OPEX, infrastructure development, changing energy landscape, nor any other aspect considering analyses over multiple years. As a result, the KKM offers high-level insights into optimal system design but does not provide guidance on the transition itself or short-term operational challenges.

4.2.3 Sectoral Scope

The KKM operates within a strictly energy-focused framework, modelling only the electricity sector and excluding interactions with other sectors such as industry, transport, or heating for instance (except for additional scenario’s of hydrogen export for the Netherlands specifically). Its primary objective is to explore the role of hydrogen as a long-term flexibility option within a decarbonizing power system, particularly under high shares of variable renewable energy. As such, the model accounts for limited sector coupling strategies, as it includes an additional scenario using hydrogen in industrial processes, but doesn’t discuss options such as using hydrogen powered vehicles or district heating. Consequently, while the KKM provides valuable insights into power sector decarbonization, its findings should primarily be interpreted within the boundaries of this sector-specific perspective.

4.3 Real-World System Components

The outlined system concerns the environment around offshore wind, onshore electrolysis and centralised offshore hydrogen production platforms. This is comprised of the entire production chain including renewable generation, hydrogen production, transportation, storage and use - including all infrastructure. For Dutch context specifically, offshore system integration is especially valuable due to the relatively large amount of offshore wind available. A system representation can be found in Figure 5, visualising all these components together in a real-world system.

4.3.1 Renewable Energy Supply

Renewable electricity is generated from a mix of onshore wind, offshore wind and solar PV. These sources are geographically and technologically distinct, each with unique generation profiles and infrastructure requirements. Offshore wind offers higher capacity factors (often around 45–55%), while onshore wind performs slightly lower (typically around 25–35%). Solar PV, although more spatially flexible, has lower capacity factors in northern regions (around 10–15%) (Lits, 2022). The relative share of each source in the system influences the intermittency and sizing of electrolysers. In a scenario with perfect incentives, only a surplus of generated electricity is available for electrolysis. However, in reality, this may change due to optimal balancing.

4.3.2 Power Transmission

Power transmission plays a critical role in integrated electrolysis systems, particularly in offshore configurations. Electricity generated by offshore wind farms is typically transported in the form of AC output via high-voltage transmission lines to a high-voltage direct current (HVDC) transmission station, or lead directly to an offshore electrolysis platform. From here it is converted into DC power and transported to shore and integrated in the grid. The inclusion of offshore HVDC substations allows for bidirectional power flow, enabling coordination between offshore and onshore assets. Power that goes to an offshore platform directly is converted on site, where the power is used directly for the electrolyser. There is no need for this construction in onshore electrolysis, since the power used onshore is already converted. Efficient and reliable transmission is essential not only to optimize electrolyser utilization but also to balance supply with demand and minimize curtailment in the renewable energy system.

4.3.3 Power Conversion and Electrolysis

Offshore electrolysis platforms enable the direct conversion of renewable electricity into hydrogen, using electricity generated by nearby offshore wind farms. Power is routed through an integrated converter and distribution system that prepares the electrical input for electrolysis. . Some systems also include voltage regulation to match the electrolyser's requirements (Singh et al., 2008), which includes voltage adaptation and basic current conditioning. Once conditioned, the electricity feeds electrolysers, where electrolysis happens by splitting water into separate hydrogen and oxygen components. Efficiency varies by technology and operational conditions such as temperature and load variability also affect performance. These factors influence system efficiency, cost and optimal deployment timelines.

4.3.4 Water Treatment, Cooling and Utilities

Electrolysis systems, whether offshore or onshore, require additional infrastructure that contributes to overall energy consumption and system design complexity. For offshore electrolysis, seawater must first undergo desalination to meet the purity standards required by electrolyser stacks, typically via reverse osmosis or multi-stage distillation processes (Delpisheh et al., 2020). In onshore systems, conventional water treatment is still necessary to remove impurities from freshwater sources, albeit at lower energy cost compared to desalination. Both system types also require continuous cooling to manage the heat produced during electrolysis, typically through water-based or air-based cooling loops, (Keshavarzzadeh et al., 2019). Lastly, essential utilities such as process control, ventilation and safety systems contribute to the baseline energy use. These operational energy demands can impact overall efficiency.

4.3.5 Hydrogen Transport and Compression

After production, hydrogen must have sufficient pressure for transportation via pipeline to shore or other destinations. When capacity is low, sufficient pressure from the electrolysis process is available to limit compression scope to onshore compression. At some point in time, this may also involve compression units, typically placed on offshore platforms when regarding offshore electrolysis, before directing hydrogen through pipelines. The required pressure level offshore depends on transport distance, capacity and destination (Makridis, 2016), and of foreseen to be anywhere between 22 and 100 bar. Subsea pipelines used for offshore hydrogen transport require robust materials and corrosion management and may span hundreds of kilometres. Costs and energy consumption associated with this step are relevant and scale with distance and capacity. Realistically, such infrastructure has substantial capital and permitting requirements, often overlooked in stylized models. Gasunie is exploring ways to transport hydrogen from offshore to onshore in the most cost effective way. This explorations includes the conversion of existing pipelines used for gas to accommodate hydrogen transport.

4.3.6 Hydrogen Storage

Once transported to shore or nearby hubs, hydrogen is stored before further use. In real-world applications, storage methods vary: pressurized tanks, liquid hydrogen tanks or geological storage (e.g. salt caverns or depleted gas fields) are expected to be used most commonly (Mehr et al., 2024). Storage plays an important role in matching variable production to flexible demand for seasonal fluctuations, and especially for shorter time fluctuations, to smoothen out production profiles. Natural occurring storage capacity is limited for a lot of countries, requiring infrastructure investment, safety precautions and regulatory approvals for these locations to be developed (Fetisov et al., 2023). It also involves energy losses during compression and reconversion, typically 2% for caverns (Hystock, n.d.). Storage technology choices significantly impact system flexibility and economic viability, since onshore storage in hydrogen tanks is much more expensive due to the construction costs associated with it.

4.3.7 Hydrogen-to-Power Conversion

Stored hydrogen can be reconverted to electricity using gas fired turbines, either built or retrofitted from existing natural gas infrastructure. In real systems, this retrofit involves burner redesign, material upgrades and safety adaptations due to hydrogen’s combustion properties (Cappelletti & Martelli, 2017). Hydrogen turbines currently under development aim to increase hydrogen shares in power generation. This reconversion pathway offers strategic grid flexibility during periods of low renewable generation, but suffers major efficiency losses of around 50–60% (Zare et al., 2022), which means that only a fraction of initially produced electricity is recovered.

Moreover, in addition to conversion infrastructure, a significant amount of new-build generation capacity (backup power in particular) is required to meet peak demand. Given the expected increase in electricity consumption, this includes not only retrofits but also entirely new hydrogen-ready capacity. This round-trip inefficiency is a key consideration in energy system design.

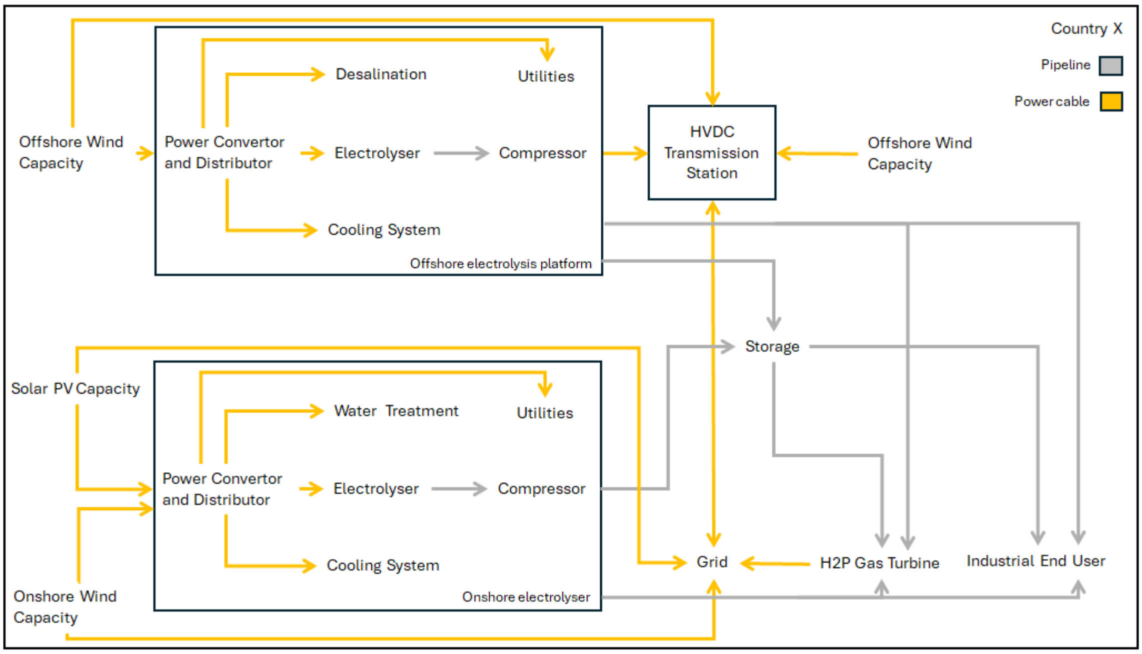


Figure 5: System representation of a real-world integrated electrolysis system.

4.4 Energy Flows and Conversion

In the system most power flow directly from the renewable source to the end user. Excess energy flows from wind and solar toward electrolysers, generating a current that first passes through an AC/DC conversion stage to ensure compatibility with the direct current required for electrolysis. Prior to this, electricity transmitted at high voltage is stepped down to lower voltage levels through HVDC converter stations to enable safe and efficient integration with local infrastructure and downstream components. This voltage transformation is a necessary step for connecting offshore generation to electrolysis and grid systems. Once converted, this electrical energy is used to split water into hydrogen, which is then compressed and transported via pipelines to a storage facility.

During periods of high energy demand or power shortages, the stored hydrogen is reconverted into electricity using H2P gas turbines, which burn pre-mixed hydrogen and after which the electricity is fed into the grid. Each stage of this process entails efficiency losses: for instance, with electrolysis operating at 70% efficiency and hydrogen-to-power conversion at 50% (as used in the KKM) the total round-trip efficiency amounts to roughly 35%. The efficiency of the P2H2P power generation is low, resulting is an incentive to minimize the gas-to-power route, first and foremost by system integration enabling direct use of electricity whenever possible. Also other means to store electrical energy, like batteries, play a significant role in reducing the overall contribution of the gas-to-power. A gas-to-power system with large capacity and low number of running hours is foreseen.

4.5 KKM Stylized System

The KKM system representation differs from a real-world system on several levels. A system description of the KKM and relevant omittances will be discussed in this section to highlight these differences.

4.5.1 Stylized System Description

The system presented in the KKM is a stylized representation of a real-world, hydrogen-integrated energy system, adaptable to the national context by allowing country-specific renewable capacities. It distinguishes between onshore wind, offshore wind and solar energy - though it does not specify whether solar is deployed onshore or offshore. The model assumes that surplus electricity from these sources is routed to electrolysers, where hydrogen is produced via electrolysis and transported by subsea pipelines to storage. Since the location of electrolysis is not specified, and can thus be both on- and offshore, this research doesn't explicitly focuses on either one. During periods of electricity shortfall, stored hydrogen is transported to retrofitted gas turbines for reconversion to electricity. The transport is assumed to occur via pipelines, either subsea or underground, depending on the location of the storage.

Various storage options are acknowledged, though no specific type is chosen and storage capacity is assumed to be unlimited. Likewise, pipeline transport costs are considered negligible. Exact placement of components such as wind turbines, solar panels, electrolysers, storage units and gas turbines are not specified in the model. In Figure 6, a representation of this stylized system can be found.

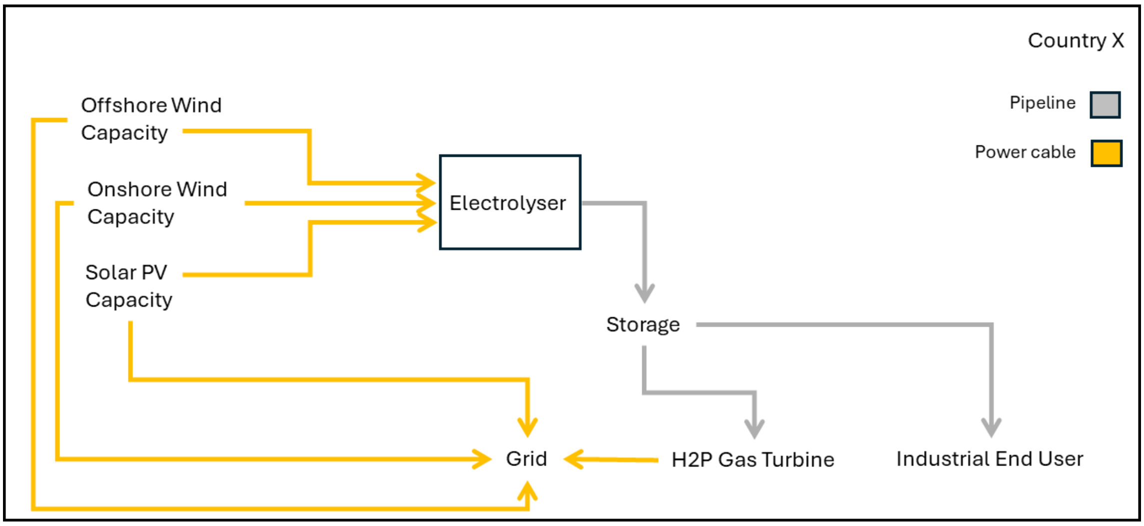


Figure 6: System representation of the stylized KKM model.

4.5.2 Omittances

While this setup serves the model's aim of prioritising cost dynamics and deployment strategies at a high level, it omits several important system components that would be essential in a real-world implementation. For example, the model does not include compressors that would be required to pressurize hydrogen before storage or transport.

Critical subsystems, such as power cables to transport current from renewables to electrolysers and AC/DC converters required to match renewable electricity formats with electrolyser input requirements, are likewise not addressed. These omissions are intentional and align with the high-level purpose of the KKM, which is to provide strategic insights into the cost dynamics and deployment timing of electrolysis technologies, rather than to offer a detailed technical model of physical infrastructure like transport and storage. Further discussion on the importance of these omittances will be provided during the Key Assumption Identification in chapter 5.

5 Key Assumption Identification

In this section, key assumptions will be derived from the KKM. This entails registering all simplifications and assumptions explicitly made in the KKM, as well as implicit assumptions inferred from model formulations and parameter choices. This will be compared to Gasunie internal documentation, highlighting factors that are deemed important to consider. A comprehensive oversight is then created by then categorizing them and assessing their relevance, answering SQ1, after which a distinction can be made between less relevant assumptions and more relevant assumptions worth pursuing. The most relevant assumptions will eventually be scrutinized in chapter 6.

5.1 Explicit Simplifications

Firstly, several simplifications and assumptions are explicitly specified in the KKM paper. This is to disclose which conscious choices have been made when developing the model. Secondly, some simplifications can be inferred from the stylized system used in the KKM. Organizing these will be done based on the four categories proposed in the Literature Review: renewables-, hydrogen-, cost- and system simplifications. For each assumption or simplification a description, its purpose and implications will briefly be discussed. An overview of all identified assumptions and simplifications can be found in Table 1.

Table 1: Identified KKM modelling assumptions, arranged by category and source type.

	Modelling Assumption	Category	Source Type
1	Cost Reduction Headroom	Cost	Explicit
2	Electrolyser Cost	Cost	Explicit
3	Electrolyser Efficiency	Renewables	Explicit
4	Exclusion of Electrolyser Limitations	Renewables	Implicit
5	Exclusion of OPEX	Cost	Implicit
6	Generation Mix	Renewables	Explicit
7	Hydrogen Source	Hydrogen	Explicit
8	Hydrogen Storage Capacity	Hydrogen	Explicit
9	Hydrogen Storage Cost	Cost	Explicit
10	Hydrogen Transport	Hydrogen	Explicit
11	Neglect of Alternative Decarbonization	Renewables	Explicit
12	Neglect of Conversion Losses	System	Implicit
13	Neglect of Demand Flexibility	System	Implicit
14	Neglect of Demand Fluctuations	System	Explicit
15	Neglect of Transmission and Transportation Losses	System	Implicit
16	Omission of Compressors	System	Implicit
17	Omission of Gas Mixing Installations	System	Implicit
18	Renewables Cost	Cost	Explicit
19	Battery Interaction Exclusion	System	Explicit
20	Turbine Retrofitting Cost	Cost	Explicit

5.1.1 Explicit Renewables-related Assumptions and Simplifications

- **Generation Mix**

The KKM assumes a fixed renewable energy mix consisting of 80% wind (12% onshore, 68% offshore) and 20% solar, chosen to reflect Dutch energy projections for 2040 as a base case. It's indicated that this data corresponds to the Global Ambition scenario of North Sea Wind Power Hub programme (Haan et al., 2023), simultaneously matching the 'Global Ambition' scenario of the Ten-Year Network Development Plan by ENTSO-E (Haan et al., 2023). The assumption of power generation mix is crucial, because electrolyser utilization is lower when producing hydrogen with solar electricity than for wind electricity (Janssen et al., 2021), which makes the cost for solar-based hydrogen production much more sensitive to electrolyser cost. However, the larger part in the energy mix base case scenario remains wind energy. This is relevant because the main focus of this research is on the Netherlands, Germany, Denmark and Belgium, which are countries with favourable (offshore) wind conditions.

That said, the assumed mix may underrepresent the increasing share of solar energy in the Dutch system. Current figures from CBS indicate a national split of around 40% solar and 60% wind (CBS, 2024), while future scenarios such as II3050 (Netbeheer Nederland, 2023) show solar reaching 35–40% of total renewable generation by 2040–2050. This raises the question of whether the base case remains realistic under evolving national planning trajectories.

It is indicated that, to test the generalizability of the model, the energy generation mix has been varied during model testing. If more solar is included in the electricity mix, the starting point of electrolyser deployment can be pushed further than for wind-dominated generation, but this comes at the expense of a higher electrolyser to renewables build-out ratio. The average renewable production, electrolyser capacity and investment cost required for full power system decarbonisation are strongly dependent on the share of solar energy generation. In wind dominated areas, electrolyser deployment starts later on, next to the build-out ratio being lower. It is found that, throughout all the cost scenarios run, the cost optimum of the amount of solar generation lies between 20% and 25% - thus making 20% suitable as a base case for the model. However, this optimum also depends on the relative cost of solar and wind generation.

- **Electrolyser Efficiency**

For both P2H and H2P, fixed efficiencies are assumed in the model, namely 70% and 50% respectively. This provides a standard baseline for energy losses in the (re)conversion of hydrogen to electricity and vice versa. When considering electrolysers, a distinction is made between three dominant types: Alkaline Electrolysis Cells (AEC), Proton Exchange Membrane (PEM) electrolysers and Solid Oxide Electrolysis Cells (SOEC) (Sebbahi et al, 2022). AEC electrolysers usually operate at an efficiency level of 65-75% (Stolten & Emonts, 2016). PEM electrolyser efficiency sits at about 80% and is expected to increase even further (Wang et al., 2022), which is significantly higher than alkaline electrolysers. SOEC electrolysers are set to outperform both alkaline and PEM electrolysers, operating at a theoretical efficiency as high as 90% (HELMETH, n.d.), when using residual heat as a thermal activation source (Tao & Virkar, 2011).

While SOEC electrolysers may seem the most fitting based on performance, this the most expensive type of electrolyser and less commercially available. PEM electrolysers are still more expensive than alkaline electrolysers, but can possibly be cheaper if hydrogen production is large enough. AEC electrolysers are the most mature and widely available type, while also being the cheapest due to use of less expensive resources (Krishnan et al, 2023). However, its also the least efficient type. These considerations substantiate the use of a fixed 70% P2H electrolyser efficiency, in the likely scenario that AEC electrolysers will be deployed. This might change to a mixed-use case, depending on the introduction of PEM or SOEC electrolysers, increasing overall efficiency.

Considering H2P, aeroderivative gas turbines will likely be used (Zhou et al., 2024), as suggested in the paper by mentioning that existing peak generation capacity could combust hydrogen instead of, or together with, natural gas. This can be attributed to fuel cells and CCGT installations being too expensive for the low operating hours that are expected (Hermans et al., 2018). OCGT installation are financially more attractive, but lack in efficiency (NSWPH, 2024). However, current efficiencies of the aeroderivative gas turbines is estimated to be around 46%, which is somewhat lower than the assumed 50% in the KKM. This also includes minor losses due to compression and storage, next to cooling, desalination, start-stop and other operational-related losses. A round-trip efficiency of 35% might thus also to result in a different value.

These simplifications make it easier to perform P2H2P calculations due to their fixed rate, instead of using efficiency curves. However, there is some leeway in these values that might be worth exploring. Also, not taking into account electrolyser limitations proves to be an element subjectable to scrutiny, since these might significantly impact investment needs in electrolyser capacity.

- **Neglect of Alternative Decarbonization**

The analysis relies on minimizing the total investment cost in electrolyser capacity and variable renewable power generation. This cost optimization assumes that no extra hydropower will be deployed, since cost of firm generation is not taken into account, thus avoiding location-specific complexity. Decarbonization by means of nuclear power and carbon capture and storage is also excluded. A distinction can be made here between pre-combustion and post-combustion CCS: the former, which produces blue hydrogen by extracting CO_2 from natural gas before combustion (Kheirinik et al., 2021), is more compatible with renewable build-out and could be integrated into a decarbonization pathways, like the ones suggested in the KKM.

Post-combustion CCS, which captures CO_2 after combustion, is considered less attractive due to its higher capital and operating costs and its generally lower carbon avoidance per unit of electricity generated (Chao et al., 2020). This decision might impact the flexibility in countries where this expansion is still possible, but is applicable to the majority of countries in the targeted area, as well as within the scope of this research paper. By making this simplification, the model fixes the amount of firm power that needs to be decarbonized, which streamlines calculations.

5.1.2 Explicit Hydrogen-related Assumptions and Simplifications

- **Hydrogen Transport Cost**

The KKM assumes that hydrogen can be transported in large quantities at modest cost, omitting transportation costs from the model. While not elaborating extensively on this parameter choice, it is inferred to be related to both economic and geographical arguments for low-cost storage. Low storage costs, combined with the widespread availability of storage locations, are used to support this simplification. Additionally, in offshore energy systems, transporting hydrogen via subsea pipelines is significantly cheaper than transmitting electricity to shore using long high-voltage direct current (HVDC) cables (Rogeau et al., 2023). This economic advantage of hydrogen transport (which are usually implicitly included in electrolyser costs) further reinforces the model's assumption that hydrogen can be transported cost-efficiently. It is worth noting that electricity grid infrastructure costs are also not included in the model, which are significantly higher than those for gas infrastructure. The underlying assumption appears to be that infrastructure costs are relatively insensitive to variation in the analysis.

Other sources also support this statement to some degree. Firstly, studies indicate that for distances up to approximately 2,500 kilometres, transporting hydrogen via pipelines is more cost-effective than alternative methods, with costs ranging between €0.09 and €0.17 per kilogram (Hydrogen Council et al., 2020). Secondly, the potential for repurposing existing natural gas pipelines for hydrogen transport presents a cost-saving opportunity, as retrofitting is generally less expensive than constructing new pipelines (EU Science Hub, 2021). Additionally, the scalability of pipeline infrastructure allows for the efficient transport of large hydrogen volumes, further reducing per-unit costs (Ma et al., 2023).

However, this refitting technology has not been widely applied yet. The Netherlands is set to be the first country to use widescale gas pipeline refitting to accommodate hydrogen transport, joining the German Kernnetz in the attempt to create a hydrogen backbone spanning the two countries (Directie Financieringen, 2024). which means that its potential success is not certain to be generalizable to other countries. Also, even though this option for hydrogen transport is significantly cheaper than others, refitting pipelines is nevertheless very costly. So while transportation costs might eventually be low and scalability increases this advantage, there is a long way to go before the infrastructure is mature enough to facilitate this cost benefit, including many financial commitments that will drive up investment costs.

Depending on electrolyser pressure levels, hydrogen compression consumes 5–10% of its energy content in electricity (Paschenko, 2024) and adds both capital and operational costs, especially when high pressures or offshore infrastructure are involved. While often omitted in stylized models like the KKM, accounting for compression improves accuracy in system cost and efficiency assessments. This raises the question of whether this simplification is fully justified.

- **Hydrogen Storage Cost**

The KKM assumes a relatively low cost for hydrogen storage, which is substantiated extensively in the paper. This is based on the premise that underground storage in salt or rock caverns is available and economically favourable. This assumption is substantiated by recent studies cited in the model, which estimate life-cycle costs of \$0.14–0.21/kg for hydrogen storage in salt caverns and \$0.25–0.35/kg for lined rock caverns, based on a 500-ton facility operating at a daily throughput of 500 tons (Mehr et al., 2024). However, in practice, not all produced hydrogen will need to be stored. Estimates suggest this may be closer to half, since not all storage capacity will undergo the same number of annual cycles, meaning that both throughput and cycling frequency should be factored into storage cost assessments.

Additional literature places the broader cost range for underground storage between €0.25 and €1.58/kg. This supports the model's position that hydrogen storage costs are considerably lower than green hydrogen production costs, making them less influential on the total system economics. The assumption allows the model to concentrate on long-duration energy storage through hydrogen, without significant economic constraints. As a result, the model can focus on optimizing generation and conversion infrastructure without having to account for the real-world complexities of flexible storage costs.

However, aboveground or alternative storage solutions often result in significantly higher cost. For instance, Andersson & Grönkvist (2019) and Papadias & Ahluwalia (2021) both highlight that aboveground storage options such as pressurized tanks or liquid hydrogen can exceed €2/kg in certain scenarios. Hydrogen storage costs also depend on how much of the storage capacity is actively used. A distinction exists between the total installed capacity and the amount of hydrogen stored over time. When storage is regularly filled and emptied, the cost per kilogram of hydrogen stored can be relatively low (as demonstrated by Mehr et al. (2024). In cases where storage is only partially used or cycled infrequently, the cost per unit of useful hydrogen increases substantially.

This relationship means that real-world storage costs can vary widely depending on utilization, while low cost assumptions are most valid under high-use conditions. As such, while the assumption may be reasonable for countries like the Netherlands or Germany where underground options are feasible and already in place for natural gas, it reduces the model's validity in regions without such geological conditions. This simplification, may undervalue the cost challenges in deploying hydrogen storage infrastructure in diverse geographic contexts.

- **Hydrogen Storage Capacity**

The KKM assumes unlimited hydrogen storage. This means that any excess hydrogen produced during periods of high renewable generation (like in summer or during windy periods) can be stored without physical constraint and then used later when renewable generation is low (like in winter). Several storage option are presented, including salt caverns (Ozarslan, 2012), aquifers, hard rock caverns and depleted oil and gas fields (Mehr et al., 2024). Salt caverns are the cheapest and most available option in Europe, with Germany and Denmark having a considerable amount of salt cavern storage possibilities, both on- and offshore (Caglayan et al., 2020). This allows the model to compensate energy supply and demand over long periods of time, especially across seasons, without having to account for the limits of actual hydrogen storage infrastructure. The model can thus function without factoring in complexities regarding sizing, siting or financing or hydrogen storage and purely focus on optimizing deployment of renewables and electrolysers.

This however inevitably underestimates system cost, especially for areas with low to no natural underground storage possibilities. This might also shift the optimal deployment towards a higher installed renewable capacity to compensate for lost hydrogen storage flexibility, which would increase the total costs. Especially in the scope of this research, the Netherlands and Belgium don't appear to share this potential as substantially, most likely having to turn to other, more costly storage methods, either below or aboveground (Papadias & Ahluwaria, 2021 ; Andersson & Grönkvist, 2019). Additionally, a lower amount of cycles contributes to higher storage costs, artificially creating an economic maximum storage capacity (Bünger, 2016).

It is indicated that the KKM enjoys less validity in regions with few storage options, thus signifying the importance of this assumption for the NL/DE/DK/BE region. However, gas storage is essential regardless of electrolyser capacity, mainly to accommodate fluctuations from renewable electricity rather than hydrogen production. Its capacity is only loosely linked to electrolysis, so excluding it has less impact than one might expect.

- **Hydrogen Source**

The paper assumes that hydrogen used in H2P is always produced from P2H, never using externally sourced hydrogen. This simplifies the overview of the source of all hydrogen, by ensuring that all use is directly tied to surplus renewable electricity. This constrains the model to internal energy flows and excludes the possibility of importing hydrogen, which might otherwise provide additional flexibility or cheaper balancing options. As a result, the model may slightly overestimate the required renewable and electrolyser capacity for full decarbonization, since it does not consider scenarios where cheaper available external hydrogen could supplement energy needs.

5.1.3 Explicit Cost-related Assumptions and Simplifications

- **Turbine Retrofitting Cost**

The KKM assumes that existing thermal generation can at little cost be converted from natural gas-firing to hydrogen-firing (or a combination of both). This is justified by the fact that retrofitting cost is a small fraction of the investment cost of new peak generation capacity. This assumption is based on technical literature and industry developments, such as the work on high-hydrogen combustors like those used in OPRA's OP16 gas turbine (Bouten et al., 2021). Although technical challenges such as flame stability, NOx emissions and material compatibility exist (Hwang et al., 2023), the model anticipates that these can be addressed at a low price through continued innovation. New thermal capacity is needed anyway in addition to these retrofitted turbines.

This simplification allows the model to treat hydrogen-to-power conversion infrastructure as economically viable, thereby emphasizing the cost of electrolysers and renewable generation as the primary cost drivers. While the assumption is optimistic, it is arguably justifiable for a stylized model like the KKM, which seeks to provide a high-level perspective of decarbonization dynamics rather than detailed engineering constraints. Although, it can be said that regardless of electrolysis build-out, additional back-up power generation is a necessary means.

- **Cost Reduction Headroom**

Headroom for cost reduction is generally assumed to be greater for electrolysers than for wind or solar. This means that electrolysers are expected to become cheaper faster than wind or solar power systems. Since the cost ratio (CR) is defined as the cost of renewable power relative to the cost of electrolysis, a bigger drop in electrolyser costs compared to renewable costs will make this ratio increase over time. So, as electrolysers become more affordable, CR rises, which influences the model's optimal deployment and suggests a future where hydrogen production becomes more economically attractive relative to building more renewables. In the model, it directly influences the values chosen for cost of electrolysis in the different scenarios, correctly covering the full range of possibilities for both now and the future, as stated in the paper. While a reference case of 3 is maintained, the realistic cost ratio nudges more towards a 2 (Hofrichter et al., 2023).

- **Electrolyser Cost**

The KKM assumes specific costs for electrolysers. For the current scenario, it adopts a cost of approximately €2250/kW, based on recent Dutch project estimates and high-end Lazard figures (ISPT, 2022; Krishnan et al., 2023; Lazard, 2023), while a reference value of €1500/kW is used for nearer-term deployment. For future scenarios, the cost is set at €750/kW, representing a 67% reduction, aligned with low-end estimates from Lazard and 2030 projections from ISPT for advanced systems (ISPT, 2022). These cost assumptions directly influence the model's CR, a metric that balances renewable generation costs against electrolyser investment, ultimately shaping deployment timing and system configuration. Additionally, the KKM assumes a uniform electrolyser cost across all countries, enabling a comparative analysis. While the reasoning behind these values is sound, the value selection can be seen as somewhat optimistic, as indicated by Kramer & Koning in the paper.

Several sources suggest both lower and higher capital cost estimates depending on technology maturity, regional supply chains and project scale. For instance, IRENA (2020) identifies a higher potential for cost reduction, with variability influenced by electrolyser type and deployment setting. Moreover, a study by Buttler & Spliethoff (2018) suggests significant regional differentiation, while Vartiainen et al. (2019) point to rapidly evolving market dynamics that can lead to divergences from static assumptions. These discrepancies point to the importance of the balance between facilitating model clarity and capturing nuanced cost dynamics.

- **Renewables Cost**

In the KKM, the cost of renewable electricity is assumed to be 70 €/MWh for the Dutch case, averaged across onshore wind, offshore wind and solar photovoltaics. This value is chosen to reflect the Netherlands' specific generation profile, which has favourable offshore wind conditions and relatively poor solar performance. The value is substantiated using information from Lazard's 2023 Levelized Cost of Energy (LCOE) report, which provides broad cost ranges for solar PV (24–96 $/MWh), onshore wind (24–75 $/MWh) and offshore wind (72–140 $/MWh) which uses an average CAPEX of ~4500 €/kWa, where kWa is a kW of average generation.

This cost input plays a central role in the KKM, as it directly influences the CR, which is a key determinant in the model's optimization of the system design. A higher assumed renewable cost leads to a lower CR, which in turn affects the extent and timing of electrolyser deployment. Additionally, the model assumes that the cost of renewable electricity does not vary between countries, which simplifies cross-country comparisons and allows the model to isolate the effects of the renewable capacity mix when assessing national decarbonization.

However, recent developments challenge these assumptions. Offshore wind auction prices in Northern Europe have shown a clear downward trend; for example, Germany's 2024 offshore wind auction concluded with significant capacity awarded at historically low price levels (Ember, 2025). Similarly, solar PV costs in Southern Europe continue to decline, showing a cost reductions of over 10% yearly for utility-scale solar projects (SolarPower Europe, 2024).

Additional benchmarking by BloombergNEF (2025) reports global average LCOEs of approximately 38 $/MWh for onshore wind, 39 $/MWh for solar PV and 81 $/MWh for offshore wind. The IEA's Global Energy Review (2025) corroborates this, placing solar and onshore wind between 38–45 $/MWh and offshore wind slightly higher. These more recent estimates suggest that the 70 €/MWh assumption used in the KKM may be conservative.

5.1.4 Explicit System Simplifications

- **Neglect of Demand Fluctuations**

A system-wide simplification utilised by the model is the neglect of demand fluctuations. It is stated that renewable generation varies much more than electricity demand, thus justifying ignoring of daily or weekly demand patterns. Since the model focuses on year-round balancing and cost-optimal deployment, a flat demand profile is a reasonable and justifiable simplification for understanding how much renewable and electrolyser capacity is needed.

However, the correlation between demand and renewable generation does exist. A positive correlation reduces the need for electrolysis, lowering system costs, while a negative correlation increases electrolyser capacity requirements and raises overall costs. Hydrogen is considered a long-term flexibility option in the model, which justifies the exclusion of short-term dynamics and the complexity of short-term load balancing from its scope. Still, peak demand remains a critical factor in determining total generation capacity, making demand fluctuations relevant.

However, this assumption can be challenged in light of recent research emphasizing the growing role of demand-side flexibility in highly renewable systems.. Research from IEA (2023) and Eurelectric (2025) highlights the integration of demand response as a key enabler of efficient renewable integration, even at medium timescales. While the KKM's abstraction is justified for modelling long-term trends, excluding demand-side flexibility may limit its ability to reflect emerging system behaviours and overestimate infrastructure needs..

- **Battery Interaction Exclusion**

In the model, short-term demand-side fluctuations and battery interactions are excluded. This simplification implicitly assigns the role of managing all types of variability, both short-term (hourly or daily) and long-term (seasonal), exclusively to hydrogen storage. Consequently, the required capacities for electrolysers and renewable energy generation are likely overestimated, as the model overlooks the contribution of potentially cheaper, short-term flexibility solutions, such as battery storage.
Batteries, for instance, offer economic advantages in managing short-term variations in demand, reducing the overall reliance on hydrogen. Therefore, this simplification may result in overstated system costs and underestimated system efficiency.

This has however been addressed in a supplementary discussion, added in the Appendix of the KKM paper. In this variation of the KKM, the model examines how adding battery storage affects system performance. Batteries are used to absorb excess renewable electricity that would otherwise go to electrolysis, allowing stored power to cover future shortages more efficiently. Two operational strategies are tested: one with abrupt reductions in electrolyser output before battery use, another with a more gradual adjustment to optimize battery charging. The model identifies an optimal battery size where additional investment becomes cost-effective, balancing trade-offs between curtailment, electrolyser use and storage. This variation shows that short-term battery storage can complement hydrogen in enhancing system flexibility and reducing overall costs. However, this variation only addresses the Netherlands, omitting other countries, which limits its applicability.

5.2 Implicit Simplifications

As mentioned in the System Description, there are some identifiable differences when looking at the differences between the real-world system and the KKM system. Not only are several simplifications and assumptions specifically mentioned in the KKM report, but some elements that have been omitted in the model are worth examining as well. This is in regard to specific real-world elements that have no part in the model, next to several factors part of the wider context the system is placed in. These inferable simplifications will be discussed in this section.

5.2.1 Real-world System Simplifications

As discussed in chapter 4, several real-world components are deliberately omitted from the KKM to reduce model complexity and maintain focus on high-level system behaviour. The exclusion of these elements introduce limitations that must be acknowledged. First, the model does not account for utility-scale transmission and transport losses, including the power required for hydrogen compression and water treatment, as well as the efficiency losses during transport via pipelines and HVDC cables. These losses, though individually insignificant, can cumulatively affect the overall efficiency, particularly in offshore systems with long transport distances (Yang et al., 2023). Additionally, OPEX are not included in the cost structure, meaning that maintenance and replacement costs not reflected in the system's economic outcomes (Hill et al., 2024).However, if this is neglected for all assets and OPEX is proportional to CAPEX, this will not impact model outcomes.

Furthermore, the model assumes ideal electrolyser performance, excluding limitations such as minimum load constraints, start-up and shutdown losses, standby energy consumption and stack degradation over time (Arsad et al., 2023). These factors can significantly impact the sizing, utilization rate, and lifetime cost of electrolysers, especially under fluctuating power input conditions. Similarly, the system omits AC/DC conversion losses, which are necessary when interfacing AC output from renewables with DC input requirements of electrolysers. Ignoring these conversion steps and their associated losses can lead to a slight overestimation of available energy for hydrogen production.

Compressors, which are essential for pressurizing hydrogen before storage or transport, are similarly omitted, along with their cost, efficiency, and operational constraints. These simplifications collectively lead to more optimistic hydrogen system performance and economics. While the omission of these real-world system components should be taken into account when interpreting the model's applicability to operational or infrastructure planning contexts, it is justifiable in the context of providing high-level insights on the build-out ratio between electrolysers and renewables.

5.2.2 Wider Context Simplifications

The KKM simplifies several broader contextual simplifications are of influence on real-world energy system planning, while outside the core techno-economic modelling framework. First, the model does not include any representation of market conditions, such as price volatility, capacity markets or balancing services. This excludes economic impulses that would typically influence the operation and profitability of electrolysers and storage systems. Likewise, subsidies, taxes or policy incentives are not accounted for. These factors often determine investment viability and deployment speed, especially in early-stage development. Similarly, complexities around supply-demand matching are ignored, instead of stemming from dynamic industrial, transport or export conditions.

The model also ignores spatial limitations and assumes a perfectly flexible and available infrastructure network. Grid constraints, such as congestion and bottlenecks, are not represented, despite being a significant real-world barrier to renewable integration. Similarly, infrastructure build-out time is not modelled, meaning that long permitting and construction timelines for pipelines, electrolysers and storage facilities are effectively ignored. Asset availability, such as downtime due to maintenance or weather-induced curtailments is likewise excluded, assuming ideal and uninterrupted operation.

Furthermore, the KKM, in its original form, adopts a power-sector-only scope, without sector coupling. In integrated energy systems, such coupling can shift optimal hydrogen use and create synergies that are not reflected in the current environment. This has however been separately added in supplementary material. In line with this, the model also omits commercial and market design considerations, such as dynamic electricity prices, using fixed cost assumptions instead. This excludes opportunities for demand response and flexible electrolyser operation in response to market signals. Demand flexibility is likewise not included in the model, while this flexibility can reduce system balancing needs and lower curtailment, making it a valuable tool in renewable energy systems. The KKM assumes a fixed demand profile instead, which simplifies the model but limits its ability to capture the full range of balancing options.

Lastly, while infrastructure costs are included in the form of capital expenses for key technologies, the model does not account for cost differentiation due to geographic or project-specific factors, nor does it include cross-border energy flows or interconnectors. By limiting its scope to a single, abstract system, the model cannot assess trade effects or transmission constraints, which are increasingly important in the European context. Acknowledging these omissions is essential for interpreting the model’s results in light of real-world deployment conditions.

5.3 Assumption Selection for further Analysis

Following the description of all assumptions and simplifications made in the KKM, a selection for further analysis is to be made. The selection is guided primarily by the research question, which investigates why key model assumptions are made and how they shape the relationship between renewable energy deployment and electrolysis integration. The characteristics of an assumption and their direct importance for the model (if applicable) also contributes to this. Secondary, the ability of the EBBM to test the sensitivity and robustness of said assumptions and simplifications is an important factor to take into account as well. Tertiary, the relevance of further scrutinization for Gasunie is taken into account.

The selection process reflects the model's simplified nature and scope, acknowledging that not all assumptions carry equal weight in shaping system behaviour. For example, some assumptions have limited impact on long-term system design, while others directly influence the model's outputs. Next to the aforementioned criteria, the selection of assumptions for scrutiny in this analysis is based on their centrality to the KKM's structure. Several assumptions, such as the generation mix, electrolyser efficiency, and the costs of renewables and electrolysers. are foundational to the KKM, directly shaping key variables like the average renewable generation and total cost. Others, like hydrogen storage costs, the neglect of demand fluctuations, battery interaction exclusion, and demand flexibility, represent broader system simplifications. Taking this process into consideration, focusing on both the goal of the model and the aim of this research, the sensitivity and robustness analysis will be conducted for the following simplifications:

- Generation Mix;
- Electrolyser Efficiency;
- Electrolyser Limitations;
- Hydrogen Storage Cost;
- Renewables Cost and Electrolyser Cost (thus effectively analysing the CR);
- Neglect of Demand Fluctuations;
- Battery Interaction Exclusion;
- Demand Flexibility.

Taken together, the selected assumptions reflect both characteristic modelling choices of the KKM and key parameters where a more detailed approach may yield significantly different insights. Scrutinizing these assumptions aligns with both the goal of the KKM and the aim and framing of the research questions, particularly SQ2, which focuses on understanding the sensitivity and robustness of model outcomes. Assumptions excluded from the analysis are either outside the scope of this research or expected to have marginal impact on key deployment dynamics.

6 Sensitivity and Robustness Analysis

In this chapter is used to answer SQ2, which reads: “How Sensitive and Robust Are KKM Model Outcomes to Variations in Key Assumptions?”. It is of great importance to validate these assumption by testing their sensitivity and robustness, in order to evaluate their influence on the model output. After the presentation of the experimental design, the assumptions and simplifications will be validated accordingly. First, several system simplifications will be modified together to create a new base case. From this point, the sensitivity and robustness of key assumptions will be tested by varying associated parameters during model runs. Figures presented in the results can be found enlarged in Appendix B.

6.1 Experimental Design

The experimental design serves as the structured approach through which the impact of key model simplifications and parameter uncertainties is systematically evaluated. It outlines the sequence of analyses conducted using the EBBM. By organizing the design into the incorporation of high-certainty system simplification and univariate sensitivity analysis, the design enables a transparent and replicable assessment of how structural assumptions and input variations influence system outcomes under different levels of grid decarbonisation.

6.1.1 Scenario Setup

The experiment is organized around five scenarios, each representing a different level of grid decarbonisation. These scenarios vary in the extent of renewable energy integration and hydrogen export, allowing for systematic exploration of the model’s behaviour under a broad spectrum of future energy system configurations. The levels of decarbonisation include 80%, 90%, and 100% decarbonised electricity supply, with the addition of 10% and 20% hydrogen exports to other sectors.

These scenarios, denoted by values of $1 - f$ (i.e. degrees of decarbonised fossil back-up generation, represented by ‘f’), serve as a structural backbone for both the simplification assessment and the sensitivity analyses. Each scenario is characterized by fixed assumptions regarding grid composition, demand profiles, and policy constraints, which together form the contextual framework for analysing the effect of model structure and input parameters on performance metrics such as system cost, component capacity, and deployment patterns. A brief description of these scenarios is provided in Table 2, together with what they represent in terms of system behaviour.

Table 2: Levels of decarbonisation scenario overview.

Scenario Name	Electrical Power System Decarbonisation	Excess Hydrogen Export
1 - f = 0.8	80%	None
1 - f = 0.9	90%	None
1- f = 1.0	100%	None
10 % Excess	100%	10%
20% Excess	100%	20%

6.1.2 High-Certainty System Simplifications

The experimental process begins by incorporating high-certainty system simplifications omitted from the KKM to construct a more realistic base case for further analysis. This step allows for isolating the impact of each assumption and enables a sequential build-up of system complexity. The approach ensures that both individual and cumulative effects of key components are understood before introducing additional uncertainties through parameter variation. In constructing this new base case, the simplifications tested include:

- Demand Fluctuations;
- Battery Interaction;
- Electrolyser Efficiency Curves;
- Electrolyser Limitations;
- Costs for Hydrogen Storage Capacity.

These aspects, although omitted or stylized in the original KKM, are introduced incrementally in the EBBM and chosen based on their technical certainty and empirical relevance. The changes are made one at a time, with model outputs being carefully tracked for each alteration. An overview of these changes can be found in Table 3. The key metrics assessed include system cost per unit of energy delivered, renewable capacity, electrolyser deployment and battery capacity. The system cost per unit of energy delivered will in scenarios of 80%, 90% and 100% decarbonisation regard the power used for decarbonisation, while this also entails 10% or 20% excess production and export of energy in the other two scenarios (as seen in Table 2). The result is a progressively more accurate representation of the energy system, which then serves as the definitive base case for the subsequent sensitivity analysis.

6.1.3 Sensitivity Testing

Following the definition of the new base case, the experimental design proceeds with a sensitivity analysis to assess the sensitivity of the model outcomes to changes in input assumptions. The focus here is on univariate sensitivity analysis, which evaluates the effect of altering one parameter at a time while holding all others constant (Jain et al., 2011). This approach is particularly suitable for the goals of this research, which seeks to prove the impact of individual assumptions in shaping key system outputs. The sensitivity analysis tests variations in:

- Demand flexibility;
- Electrolyser efficiency;
- Renewable generation mix;
- Cost of renewables, electrolysis (CR) and batteries.

Each parameter is varied across a plausible low-mid-high range discussed in the following sections, after which the model is re-optimized for all five levels of grid decarbonisation. For each variation, the outputs tracked are total system cost, renewable capacity, electrolyser capacity, and battery capacity. Special attention is given to how the relationship between renewable generation and electrolyser deployment deviates from the stylized trend identified in the KKM. Results are compiled into tables and visualised using comparative plots, enabling clear interpretation of trends across scenarios and assumption ranges. A full overview of results can be found in Appendix B1 and B2.

6.1.4 Robustness Analysis

In addition to the sensitivity analysis, a robustness analysis is performed to evaluate whether the model's outcomes holds under extreme assumptions. This analysis is conducted in a similar fashion to the sensitivity tests and focuses on the same set of variables: electrolyser efficiency, demand flexibility, solar share in the renewable mix, and the CR. However, the robustness analysis applies edge cases, which are values that lie outside the sensitivity bounds but remain technically or economically plausible. These edge cases are used to stress-test the model and uncover whether key relationships remain consistent. For each variation, all other parameters are held constant according to the new base case created in the testing. The results are evaluated based on the stability of the *r : e* relationship, and are presented to assess the resilience of the model's conclusions. The full set of results can be found in Appendix B3 and B4.

6.2 Transition to New Base Case

This section involves the incorporation of the high-certainty system simplification which were omitted from the KKM, but included in the EBBM. The original KKM system parameters will first be discussed briefly, after which the need for a new base case will be argumentized. The parameter sweep discusses which variables will be used to create the new base case and their role within model context. Their variation will be discussed, as well as the substantiation as to why. Lastly, the interim results after incorporating these system simplifications will be shown and interpreted.

6.2.1 KKM Parameters

The KKM is designed as a stylized model and operates on simplified assumptions to enable theoretical insights into the relationship between renewable generation and hydrogen production. As indicated in the KKM paper, the model starts from a minimal configuration as seen in Table 3: it excludes battery interaction, omits demand fluctuations and electrolyser limitations, assumes a constant electrolyser efficiency and neglects hydrogen storage cost. It also assumes an electrolyser efficiency of 70%, neglects demand-side flexibility, uses a solar capacity of 20% and a CR of 3. To reproduce the results of the KKM model with the EBBM model, these parameters are hence disabled in EBBM. While this abstraction provides oversight in exploring high-level system trends and maintains a certain degree of simplicity, it also limits the model's ability to reflect real-world dynamics.

Table 3: Input values for the KKM base case.

	Demand Fluctuations	Battery Interaction	Electrolyser Efficiency Curve	Electrolyser Limitations	Hydrogen Storage Cost	Electrolyser Efficiency	Demand Flexibility	Solar Share	CR
KKM	False	False	False	False	False	70%	0%	20%	3

To bridge this gap, a new base case is needed; one that incorporates a series of high-certainty system simplifications omitted from the KKM but supported in the more detailed EBBM. These features (demand fluctuations, battery interaction, electrolyser efficiency curves and hydrogen storage cost) are empirically grounded and technically feasible, as discussed in detail in SQ1, making their inclusion both meaningful and necessary. Integrating them allows for a more realistic representation of system behaviour and enhances the credibility of subsequent sensitivity analyses.

6.2.2 Parameter Selection

- **Demand Fluctuations**

The first variable considered is demand fluctuation. In contrast to highly variable renewable generation, electricity demand typically exhibits lower temporal variability (as discussed in the KKM report). However, neglecting even modest fluctuations can oversimplify dispatch patterns and distort capacity planning. In variation A, in addition to battery interaction, stylized flat demand is replaced with an hourly demand profile. Although the overall system impact is expected to be smaller compared to generation-side variability, this adjustment contributes to greater time scale detail and realism.

- **Battery Interaction**

The inclusion of battery interaction marks a second and significant change from the assumptions made in the KKM, where batteries are entirely excluded and hydrogen serves as the sole storage option. On the contrary, this simplification lays at the base of the EBBM, providing a highly suitable opportunity to better reflect the role of short-term storage in systems with high shares of variable renewables. The EBBM allows for automatically optimizing battery capacity based on an indicative input value, allowing for an internal determination of battery sizing. This shift introduces a more dynamic balancing mechanism into the model, and reveals how the presence, performance and cost of batteries influences the cost-optimal deployment of hydrogen and renewables. This will be done in variation B.

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- **Electrolyser Efficiency Curve**

The third refinement in variation C involves replacing fixed electrolyser efficiency with a variable efficiency curve, together with the aforementioned incorporations. Electrolyser performance is known to vary with load, typically decreasing under a certain minimal load or after an optimum load (as seen in Figure 7). Although this was not mentioned in the KKM, it is easily incorporated into the EBBM, which supports load-dependent efficiency modelling. Introducing an electrolyser efficiency curve provides a more realistic representation of how electrolysers perform under dynamic operating conditions, particularly relevant in systems with variable renewable inputs. This change enables the model to capture efficiency-related trade-offs in both cost and capacity planning. It can also be linked to the Electrolyser Efficiency (η_e), which is varied in the sensitivity analysis.

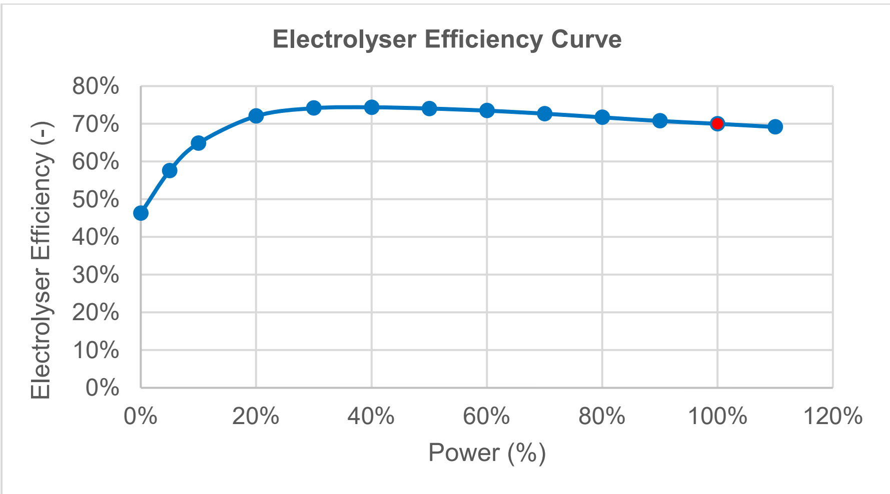


Figure 7: The electrolyser efficiency curve used in the EBBM, with η_e in red.

- **Hydrogen Storage Cost**

The model imposes hydrogen storage costs in variation D, including all other high-certainty system simplifications. The original assumption of unconstrained storage allows for ideal seasonal balancing but is not technically or economically realistic. Hydrogen storage cost is comprised of two components, reflecting an annual capacity cost of 0.79 EUR/kg (Yousefi et al., 2023) and a per-cycle cost of 0.50 EUR/kg/cycle for cavern-based storage, assuming approximately 10 full cycles per year (Bünger, 2016 ; Kruck & Crotogino, 2013). For all scenarios, including those with grid decarbonisation levels below 100% (f < 1.0), the full storage requirement is maintained.

In addition, several assumptions are applied. Short-duration storage in pipelines is excluded, which reduces the buffering potential and increases pressure on cavern storage capacity. The hydrogen demand profile is kept flat, which limits potential demand-side balancing. Furthermore, hydrogen import and export is disabled, meaning no balancing occurs via international pipelines or shipping. Lastly, long-duration storage is assumed to include both seasonal and short-term hydrogen, implying that all hydrogen ends up in cavern storage even if used for daily balancing. These constraints result in a more restrictive but realistic modelling of hydrogen storage, offering a sharper view of its economic impact and system integration challenges when capacity is limited. These parameters are central to sensitivity analyses that explore cost-driven deployment pathways.

- **Electrolyser Limitations**

Electrolyser limitations are included in variation E due to their high technical certainty and operational relevance. In real-world conditions, electrolysers perform poorly below a minimum load threshold, prompting shutdown to avoid efficiency losses and safety risks. To reflect this, a minimum load of 20% of rated capacity is applied, with standby losses set at 1%. These ensure that the model does not underestimate residual energy consumption during low-output periods. To avoid excessive cycling, a minimum standby period of 6 hours is enforced, preventing electrolysers from restarting too frequently. Additionally, the *Flattening, Bridging & 2nd Iteration* feature is activated to stabilize system behaviour in the presence of these time-series constraints. Collectively, these inputs are depicted with a True or False value. Variation E will also function as the new base case for further variations, since all high-certainty system simplifications have been incorporated conclusively.

- **Solar Share**

Finally, a 30% solar share is used in the new base case for the sensitivity analysis to align with the calibration settings of the EBBM model, which is optimized for this ratio and thus less prone to numerical instability or runtime errors. In addition to improving model robustness, this adjustment reflects updated expectations for the Dutch electricity mix. Current national projections, such as those in the II3050 (2023) scenarios, anticipate a significantly higher solar share than the 20% assumed in the KKM. Including 30% solar therefore brings the base case closer to realistic planning trajectories while ensuring technical consistency within the EBBM framework.

Notably, no separate waterfall step is included to isolate the effect of changing the solar share from 20% to 30%. This is a deliberate design choice: isolating this variable alone, while not applying the same treatment to other model-wide parameters, would introduce an unbalanced focus. Moreover, given that the adjustment is tied to the calibration of the EBBM and not a targeted system design choice, its individual effect is neither proportional nor analytically critical in the context of the analysis. The waterfall in Table 4 shows variations A-E, which include variation for each scenario.

Table 4: Waterfall chart for the construction of the new base case. Each variation is carried out for all five scenarios of (1 - f). Variation E functions as the new base case for further variations.

Variable / Variation	Inputs					
	Demand Fluctuations	**Battery Interaction**	**Electrolyser Efficiency Curve**	**Hydrogen Storage Cost**	**Electrolyser Limitations**	**Solar Share**
KKM	False	False	False	False	False	20%
A	True	False	False	False	False	30%
B	True	True	False	False	False	30%
C	True	True	True	False	False	30%
D	True	True	True	True	False	30%
E	True	True	True	True	True	30%

6.2.3 Interim Results

Before discussing the sensitivity analysis that builds on the new base case, the interim results stemming from the incorporation of all system simplifications are shortly presented. For all runs, average renewable generation (*r*), electrolyser installed capacity (*e*), battery installed capacity (*b*) and cost per kWh/h delivered (*c*) are measured and compared. The cost is comprised of renewables, battery, electrolyser and hydrogen storage cost. An overview per scenario for each variation can be found in Appendix B1.

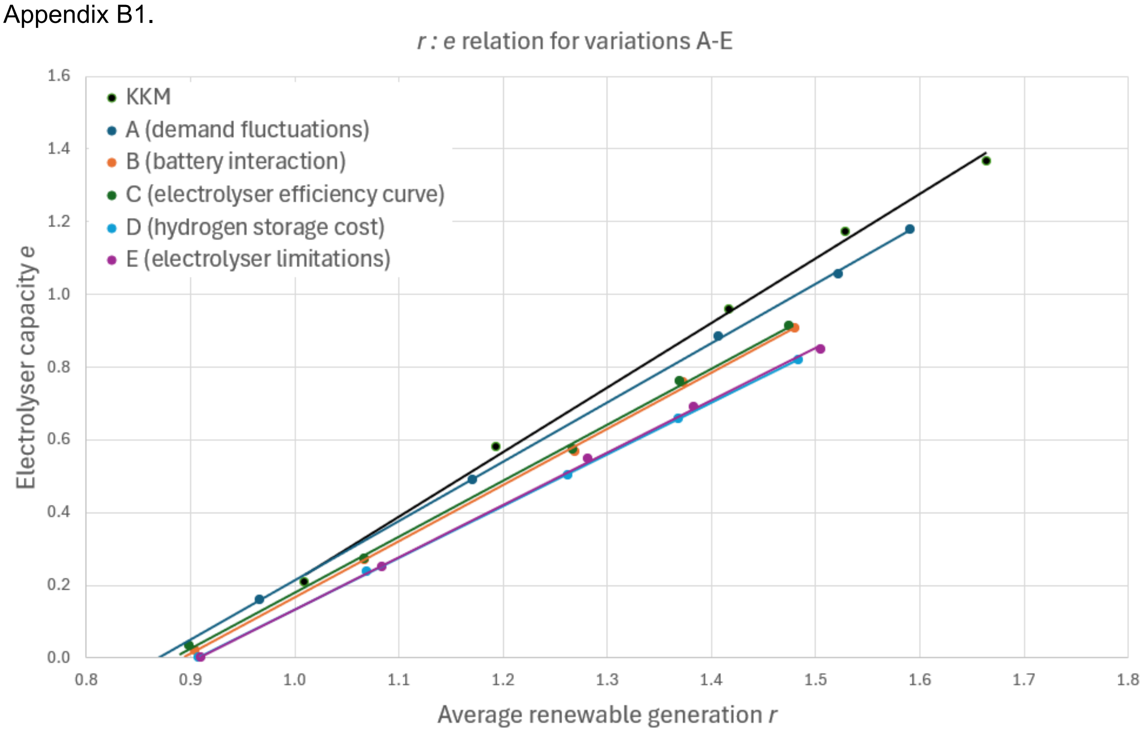


Figure 8:The r : e relation plotted for variations A-E, including the KKM as a reference. Each variation consist of five datapoints, each on a different level of decarbonisation.

- **Results of the *r : e* Relation for Variations A-E**

In Figure 8, the plots of the *r : e* relation can be seen. The black line, representing the KKM, functions as the original base case here and stands with both the highest average renewable generation and electrolyser capacity. Adding more complexity with each variation, the slope progressively flattens, meaning less renewable capacity and smaller electrolyser capacity are needed for the same decarbonization target.

The KKM and variation A (blue) are the only runs that start at higher *e* value. This can be attributed to the lack of batteries in the energy mix, which causes the need for the demand to be met by solely electrolysis and renewables. Integrating demand fluctuations in the demand profile (variation A) lowers the need for buffering with hydrogen, which causes both the *e* and *r* values to drop slightly.

The inclusion of battery interaction in variation B (orange) and the electrolyser efficiency curve in variation C (green) cause these values to drop even more drastically. Introducing batteries as a balancing option reduces the need for higher electrolyser capacity and renewable generation, explaining this value. reduction values in B and C seem stay quite consistently similar for all decarbonisation levels.

Lastly, variations D (cyan) and E (purple) introduce hydrogen storage cost and electrolyser limitations. A sudden hydrogen storage cost increases total cost, which makes it less attractive to install high amounts of electrolyser capacity, bringing down renewables with it. This goes for variation E as well, apart from the fact that the electrolyser limitations create the need for a slightly higher installed electrolyser capacity. Variation E also serves as the revised base case for subsequent model runs (F–M), as it incorporates all key simplifications from the earlier variations.

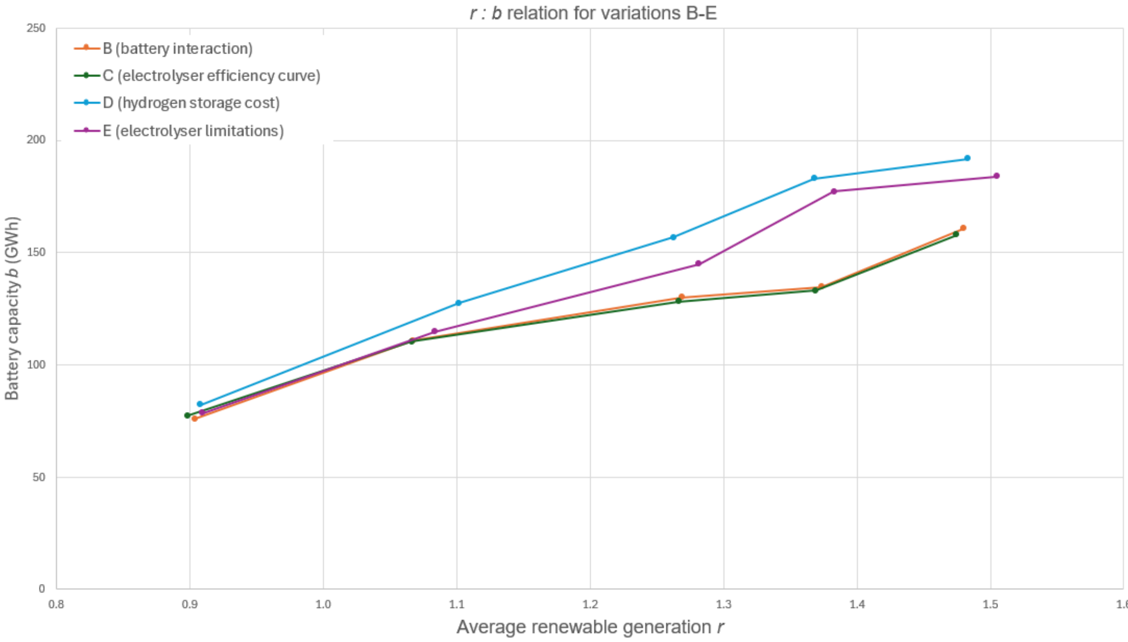


Figure 9: The r : b relation plotted for variations B-E. The KKM and variation A (demand fluctuations) are not present, as battery interaction is not included in either. Each variation consist of five datapoints, each on a different level of decarbonisation.

- **Results of the *r : b* Relation for Variations A-E**

Firstly, it can be seen that the KKM and variation A have been omitted from Figure 9. This is due to the lack of battery interaction, causing a non-existent r : b relation. In examining the other curves, a clear hierarchy emerges in how each added complexity drives battery build-out. Variation D yields the highest battery capacity across all levels of renewable generation. This corresponds with model settings that include a cost for hydrogen storage. Directly beneath it, variation E also inflates batteries, as minimum-load constraints and standby losses force more frequent hydrogen cycling that batteries must absorb.

In the middle, very close to variation B, sits variation C, for both of which a non-flat electrolyser efficiency curve modestly raises battery needs: part-load inefficiencies release extra variability onto the storage system while recycling curtailed renewable power into electrolyser operation alleviates the pressure on batteries. In sum, any variation that charges for hydrogen storage (D, E) inflates battery sizing, while those that empower batteries drive it down, showing the competing roles of long- versus short-duration storage.

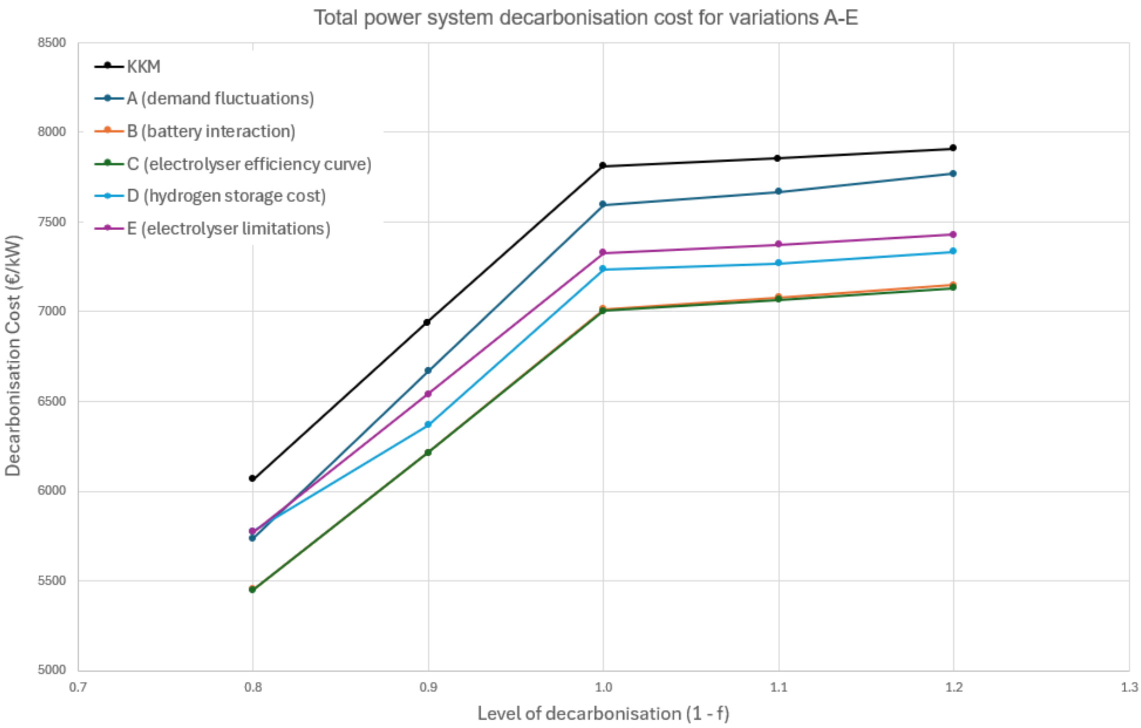


Figure 10: The total power system decarbonisation cost in €/kW for each level of decarbonisation, for variations A-E. Each variation consist of five datapoints, each on a different level of decarbonisation.

- **Results of Total Power System Decarbonisation Cost for Variations A-E**

In Figure 10, the total system decarbonisation cost curves for variations A–E reveal how each layer shifts the total investment required. System decaThe original KKM baseline incurs the highest cost at every decarbonisation level, reflecting its omission of all operational refinements. Introducing demand flexibility in variation A trims a share off that baseline by allowing renewables and electrolysers to shoulder more of the balancing burden, but it remains the second–most expensive variation.

Enabling battery interaction in variation B and incorporating a part-load electrolyser efficiency curve in variation C deliver the greatest savings, since no hydrogen storage cost has been added yet; these two variations track nearly identically because both improvements reduce reliance on oversized plant and storage. Adding hydrogen-storage cost in variation D increases cost again, as the system reverts to greater short-duration storage. Finally, incorporating electrolyser limitations (and additional costs) in variation E yields a mid-range cost that sits slightly higher than D.

Across all scenarios, costs climb steeply as decarbonisation deepens from 80 % to 100 %, then plateau slowly, highlighting that the final steps toward full decarbonisation are the most capital-intensive, but also where smart design choices can yield significant savings. Careful inclusion of operational elements can reduce total system cost by several hundred euros per kW.

6.3 Sensitivity Analysis

The sensitivity analysis examines how responsive the system is to variations in specific input parameters For each KKM assumption (renewable generation mix, electrolyser efficiency, demand flexibility and cost ratio) corresponding parameters in the EBBM are systematically and univariately varied, as can be seen in Table 5. The resulting effects are used to assess whether each simplification in the original model remains valid or introduces significant deviations.

6.3.1 Parameter Selection

- **Electrolyser Efficiency**

Electrolyser efficiency was treated as a static parameter in the KKM, with a single fixed value used across all scenarios. While this approach simplifies modelling, it neglects the fact that real-world electrolysers exhibit efficiency variation depending on not only operating conditions, but also the type of electrolyser technology. The EBBM enables the integration of a load-dependent efficiency curve, allowing for a more detailed representation of electrolyser performance. In this sweep, the electrolyser efficiency at name plate capacity (100% power) is varied as well, across a +-10% range from the reference scenario of 70% to test sensitivity: a low efficiency scenario (60%) and a high efficiency scenario (80%), substantiated by the findings in chapter 5.1.2. Implemented in variation F, this allows for assessing how efficiency assumptions affect the cost-effectiveness of electrolyser deployment.

- **Demand Flexibility**

The KKM assumes a fixed and inelastic electricity demand, reflecting a worst-case assumption in terms of system adaptability. However, real-world systems increasingly incorporate flexible demand technologies (e.g. demand response, industrial load shifting), which can reduce the need for expensive storage. A report from Publieke Zaken et al. (2025) sets this at an expected maximum of 1.9 GW out of a total demand of around 29 GW, thus representing a value of 6,5%. Costs for this flexibility however are also quite significant, standing at an estimated 3.499 €/MWh.

The EBBM allows for configurable demand flexibility, introducing a controllable margin of variation around the base demand profile. In variation G , flexibility is varied in two levels compared to the 0% in the base case and the 6.5% mentioned: low flexibility (5%) and high flexibility (10%) of the total hourly demand. This sweep examines how allowing demand to shift within defined bounds can reduce curtailment, improve resource use and lower system costs. While the EBBM automatically (and without cost) lowers the demand in situations where demand exceeds supply, it doesn't apply demand shifting, which is enabled in this sweep.

- **Solar Share**

In the KKM, renewable generation is often represented using an abstracted or balanced mix. This can mask key considerations such as the daily variability of solar or the complementarity between solar and wind output. The EBBM allows specification of the renewable mix, enabling an exploration of its influence on storage requirements, curtailment, and cost-optimal component sizing. In variation H, the percentage of *r* being generated by solar capacity is tested across a range of +-10%, compared to the 30% in the base case: 20% solar (low solar) and 40% solar (high solar). They constitute a lower value (like the one used in the KKM) next to a value that is more in line with future projections of solar capacity in Northwestern Europe, specifically the Netherlands (Netbeheer Nederland, 2023). These variations help quantify how the generation profile shapes system design.

- **Cost Ratio between Renewables and Electrolysis (CR)**

The ratio of renewables to electrolyser cost is a key driver in determining the cost-optimal energy system configuration. In the KKM, CR is assumed fixed, which limits the model's ability to reflect ongoing cost dynamics in technology development. The EBBM supports direct modification of cost assumptions, allowing for targeted analysis of this relationship. In variation I**,** the CR is varied across three plausible levels based on the KKM paper: low CR (2), baseline CR (3), and high CR (6), which constitutes an *r : e* cost (in €/kW) of 4500:2250, 4500:1500 and 4500:750 respectively. This sweep is used to evaluate how sensitive the balance between overbuilding renewables and sizing electrolysers is to relative cost assumptions.

Table 5: Variations used in the sensitivity analysis, with variation E functioning as the base case. Each variation is carried out for all five scenarios of (1 - f).

	Inputs			
	Electrolyser Efficiency	**Demand Flexibility**	**Solar Share**	**CR**
Base case (E)	70%	0.00%	30%	3
F1	60%	0.00%	30%	3
F2	80%	0.00%	30%	3
G1	70%	5.00%	30%	3
G2	70%	10.00%	30%	3
H1	70%	0.00%	20%	3
H2	70%	0.00%	40%	3
I1	70%	0.00%	30%	2
I2	70%	0.00%	30%	6

6.3.2 Sensitivity Analysis Results

For all runs, the renewable installed capacity (*r*), electrolyser installed capacity (*e*), battery installed capacity (*b*) and cost per kWh/h delivered (*c*) are measured and compared. An overview of the output of the sensitivity analysis for each variation can be found in Appendix B1.

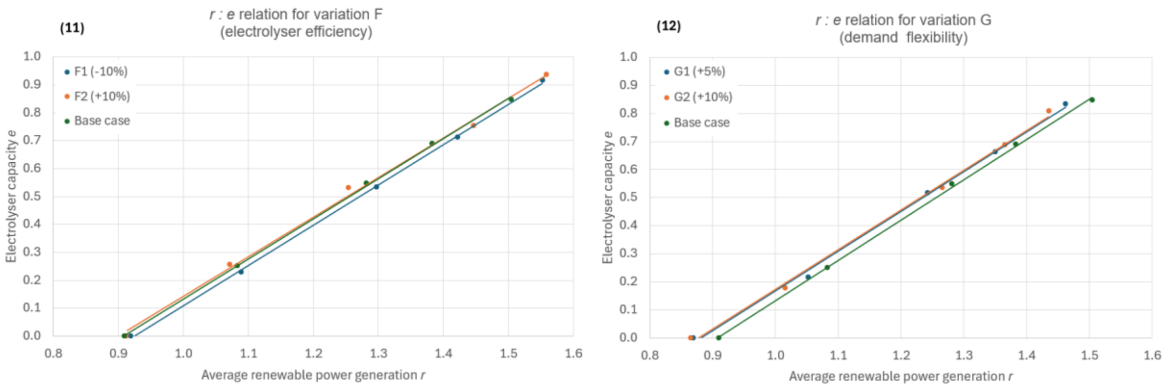


Figure 11 and 12: The r : e relation plotted for variations F (electrolyser efficiency) and G (demand flexibility). Each variation consist of five datapoints, each on a different level of decarbonisation.

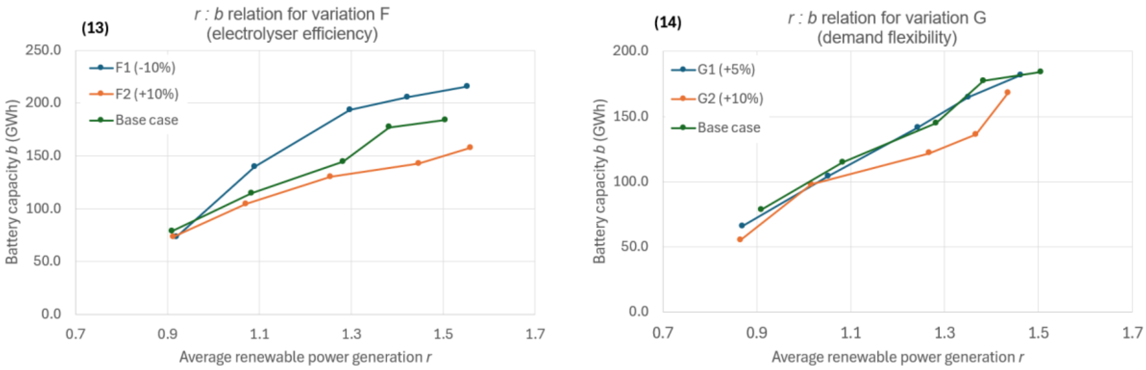


Figure 13 and 14: The r : b relation plotted for variations F (electrolyser efficiency) and G (demand flexibility). Each variation consist of five datapoints, each on a different level of decarbonisation.

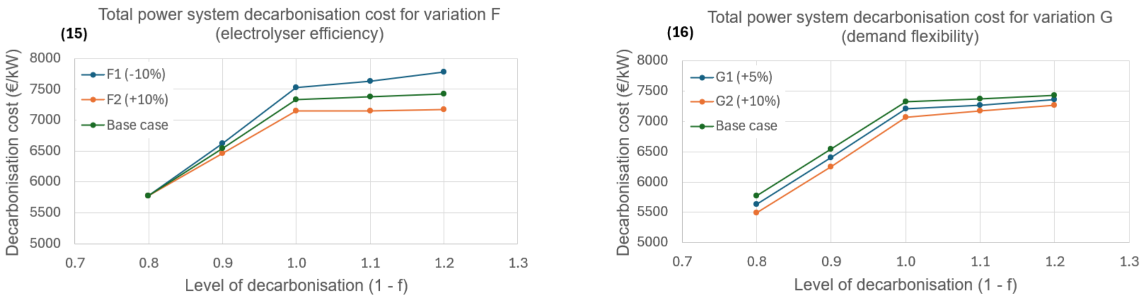


Figure 15 and 16: The total power system decarbonisation cost in €/kW for each level of decarbonisation, for variations F (electrolyser efficiency) and G (demand flexibility).

- **Results Variation F: Electrolyser Efficiency**

Variation F1 results in a slightly higher *r* compared to the base case. Initially, the required *e* is lower, but it increases beyond the base case once excess hydrogen production sets in. Accordingly, the *r : e* curve starts below the base case, then converges and eventually surpasses it. Battery deployment in F1 is substantially higher, particularly at higher levels of renewable penetration, as shown in the *r : b* curve. The total system cost is also elevated, with a notably steeper rise between 90 % and 100 % decarbonisation. In contrast, variation F2 shows both a slightly higher *r* and a slightly increased *e*, resulting from the 10 % improvement in electrolyser efficiency. Battery capacity requirements decrease in this case, with the *r : b* curve consistently falling below the base case. This reduction in battery dependency leads to lower total decarbonisation costs, particularly at full decarbonisation. The relevant trends are illustrated in Figures 11, 13, and 15.

- **Results Variation G: Demand Flexibility**

Figures 12, 14, and 15 show that variation G, which introduces increased demand-side flexibility, results in lower values for both *r* and *e* relative to the base case. In G1, a modest increase in flexibility leads to slightly reduced e across most levels of renewable availability. G2, which applies a 10 % flexibility increase, shows a more pronounced reduction in both *r* and *e*, indicating greater system efficiency. The *r : b* plot reveals that battery capacity in G1 closely follows the base case, while G2 exhibits a noticeable decline in battery requirements, especially at higher levels of *r*. In terms of total system cost, both G1 and G2 outperform the base case, with G2 achieving the lowest decarbonisation costs across the entire range. Although the shape of the cost curves for G1 and G2 remains similar to that of the base case, they consistently lie below it, highlighting the cost-saving potential of enhanced demand-side flexibility.

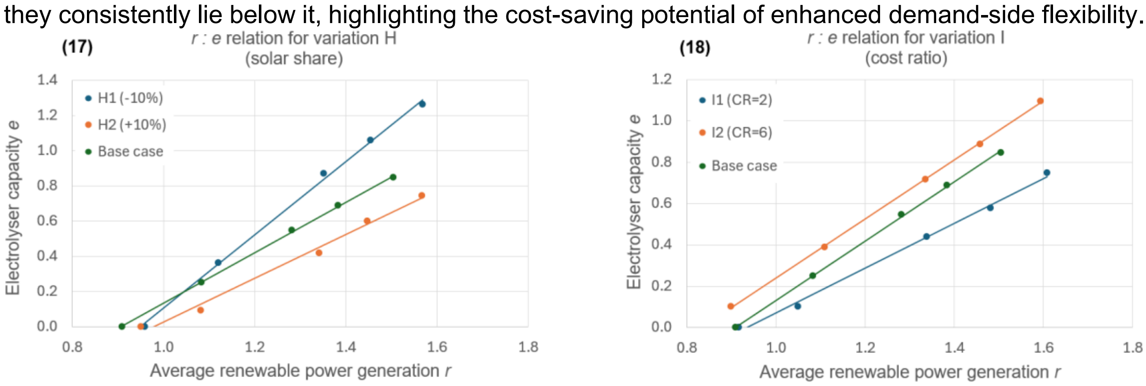


Figure 17 and 18: The *r : e* relation plotted for variations H (solar share) and I (cost ratio). Each variation consist of five datapoints, each on a different level of decarbonisation.

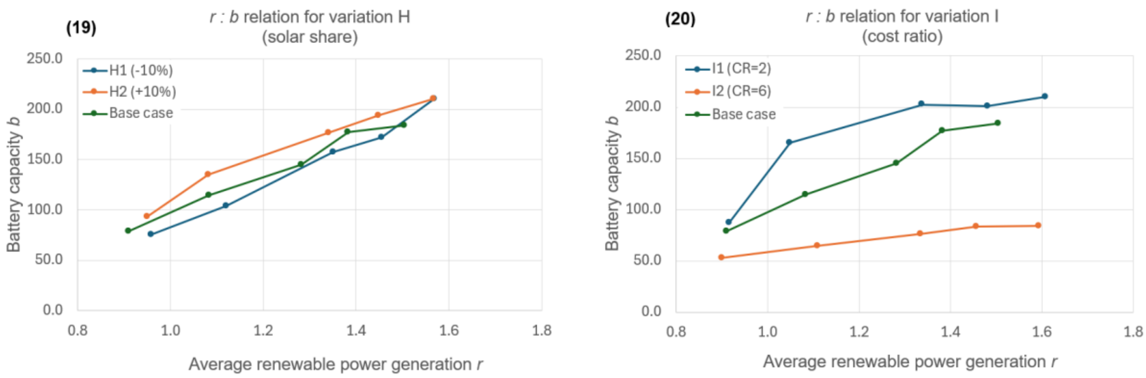


Figure 19 and 20: The *r : b* relation plotted for variations H (solar share) and I (cost ratio). Each variation consist of five datapoints, each on a different level of decarbonisation.

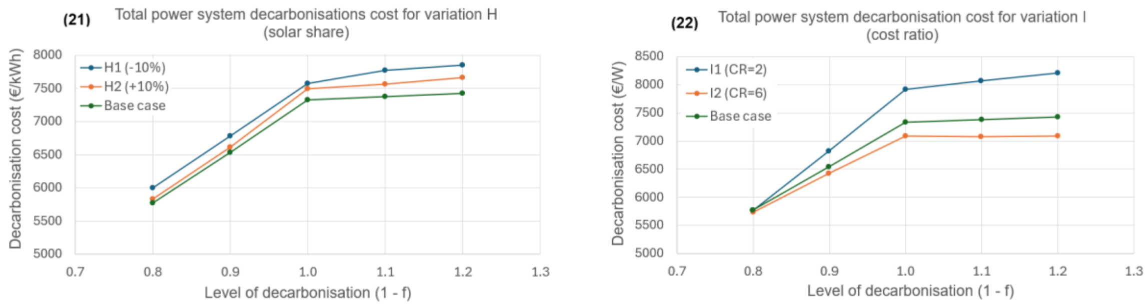


Figure 21 and 22: The total power system decarbonisation cost in €/kWh for each level of decarbonisation, for variations H (solar share) and I (cost ratio).

- **Results Variation H: Solar Share**

In variation H, a higher solar share results in a steeper *r : e* curve compared to the base case, while a lower solar share leads to a more gradual increase in electrolyser capacity. The *r : b* relation shows a stronger sensitivity to the solar share: battery capacity is higher across all r values when the solar share increases, and lower when the solar share is reduced. In the cost plot, total decarbonisation costs increase slightly in the high-solar case, particularly at higher decarbonisation levels, while the low-solar scenario remains close to the base case. The general shape of the cost curves remains consistent across all cases, with a steep increase between 0.8 and 1.0 decarbonisation followed by a plateau. These results can be observed in Figures 17, 19 and 21.

- **Results Variation I: Cost Ratio (CR)**

In variation I, reducing electrolyser costs results in a flatter *r : e* curve, with electrolysers being deployed earlier and at higher capacity. Increasing electrolyser costs causes a steeper *r : e* curve, delaying deployment to higher levels of renewable availability. The *r : b* curve shows that battery capacity decreases when electrolysers are cheaper, while higher electrolyser costs lead to increased battery deployment, especially at higher *r* values. In the cost plot, the lower-cost scenario results in slightly reduced system decarbonisation costs across all levels, while the higher-cost scenario leads to a steeper rise in cost between 0.9 and 1.0 decarbonisation. The cost curve shape remains similar across all cases. Figures 18, 20 and 22 contain the results for variation I.

6.4 Robustness Analysis

For the robustness analysis, edge cases will be used for the electrolyser efficiency, demand flexibility, solar share and the CR. These edge cases, meaning worst-case and best-case, are set by examining literature to determine plausible input values. By conducting a said stress test, the model output can be observed and whether this output holds under these extreme conditions. First, edge cases will be determined and substantiated for each parameter, after which the results will be presented. An overview of the robustness edge cases can be found in Table 6, while the numerical output is presented in Appendix B3.

6.4.1 Edge Case Selection

- **Electrolyser Efficiency**

To test the robustness of the model's conclusions under extreme performance assumptions, two edge cases for electrolyser efficiency are defined beyond the 60–80% range used in the sensitivity analysis. A worst-case efficiency of 55% reflects scenarios where electrolysers operate under degraded conditions, such as ageing stacks or technological underperformance. In contrast, a best-case efficiency of 85% simulates highly advanced PEM electrolyser technologies operating at or near optimal conditions. These extremes test whether the model's cost and capacity outcomes remain stable when hydrogen conversion becomes significantly more or less efficient than in baseline or sensitivity scenarios.

- **Demand Flexibility**

The base case assumes 0% flexibility, reflecting a fully inflexible demand profile, consistent with the KKM's original assumption. While moderate flexibility levels of 5% and 10% are explored through sensitivity analysis, the robustness analysis tests a more extreme upper bound of 20% flexibility, simulating a highly responsive system with advanced demand-side management capabilities. This edge case illustrates how strongly model outcomes depend on system adaptability and reveals whether the conclusions drawn from a rigid demand structure hold under more dynamic conditions.

- **Solar Share**

While the sensitivity analysis tested shares between 20% and 40%, the robustness analysis extends this range. A low solar share of 10% represents a wind-dominated system with more constant generation profiles and fewer daily fluctuations. In contrast, a high solar share of 50% reflects a solar-dominated future with strong diurnal variation and seasonal mismatches. These values test whether the system remains operable and cost-efficient under dramatically different generation patterns than those explored in the main analysis.

- **Cost Ratio between Renewables and Electrolysis (CR)**

The cost ratio between renewable energy and electrolysis capacity (CR) fundamentally shapes the trade-off between renewable overbuild and hydrogen infrastructure. The sensitivity analysis included values from CR = 2 to CR = 6. In the robustness analysis, this range is expanded to test CR = 1, representing high electrolysis cost, and CR = 8 representing the opposite. These edge cases allow assessment of how the model responds when cost structures are shifted.

Table 6: Variations used in the sensitivity analysis, with variation E functioning as the base case. Each variation is carried out for all five scenarios of (1 - f).

	Inputs			
	Electrolyser Efficiency	**Demand Flexibility**	**Solar Share**	**CR**
Base case (E)	70%	0.00%	30%	3
J1	55%	0.00%	30%	3
J2	85%	0.00%	30%	3
K	70%	20.00%	30%	3
L1	70%	0.00%	10%	3
L2	70%	0.00%	50%	3
M1	70%	0.00%	30%	1
M2	70%	0.00%	30%	8

6.4.2 Robustness Analysis Results

For all runs, the renewable installed capacity (*r*), electrolyser installed capacity (*e*), battery installed capacity (*b*) and cost per kWh/h delivered (*c*) are measured and compared. An overview of the output of the robustness analysis for each variation can be found in Appendix B3.

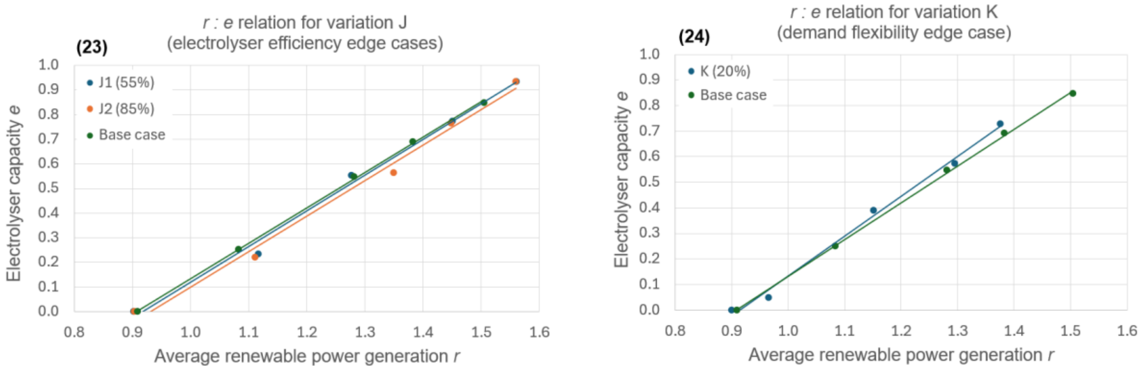


Figure 23 and 24: The r : e relation plotted for variations H (solar share) and I (cost ratio). Each variation consist of five datapoints, each on a different level of decarbonisation.

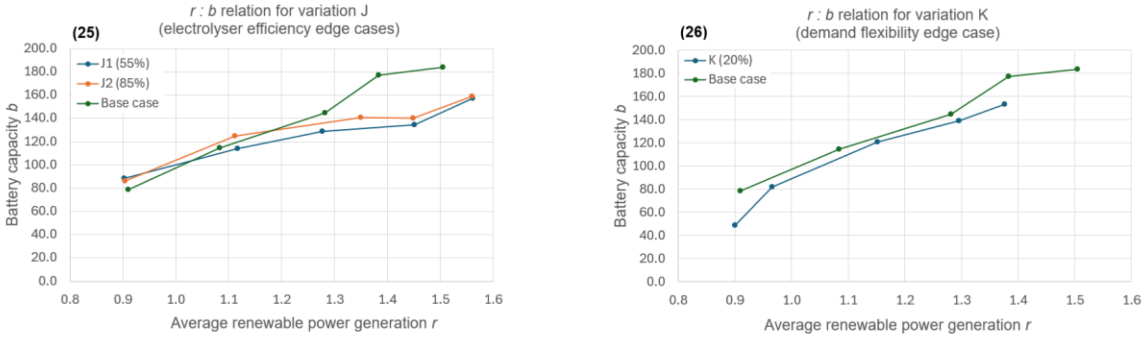


Figure 25 and 26: The r : b relation plotted for variations H (solar share) and I (cost ratio). Each variation consist of five datapoints, each on a different level of decarbonisation.

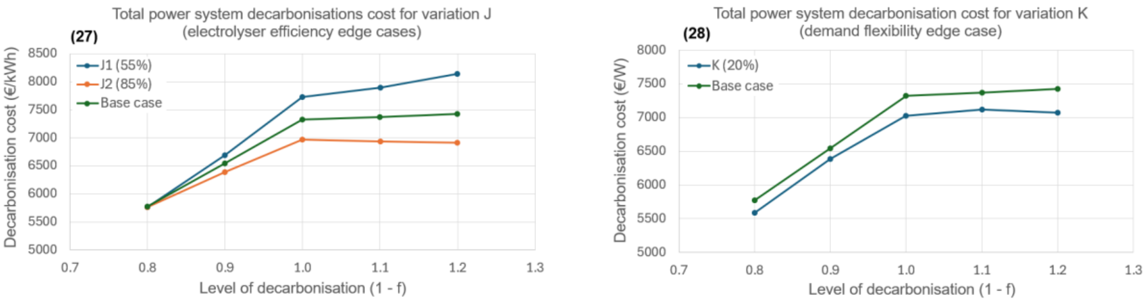


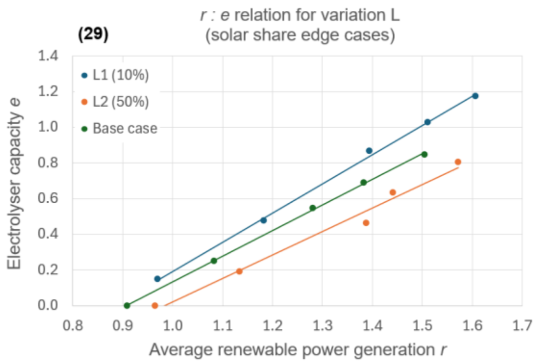
Figure 27 and 28: The total power system decarbonisation cost in €/kWh for each level of decarbonisation, for variations H (solar share) and I (cost ratio).

- **Results Variation J: Electrolyser Efficiency Edge Cases**

Figures 23, 25, and 27 present the results for variation J, which explores the impact of electrolyser efficiency ranging from 55 % (J1) to 85 % (J2). In the *r : e* plot (Figure 23), both J1 and J2 exhibit an almost linear relationship, with J1 showing the lowest electrolyser capacity and J2 slightly exceeding the base case across most values of *r*. The *r : b* relation, shown in Figure 25, reveal that J1 stays below the base case throughout the entire range of *r*, while J2 tracks just under the base case for most of the trajectory. In terms of cost (Figure 27), J1 leads to the highest decarbonisation costs, while J2 consistently achieves the lowest cost outcomes. In all three figures, the base case sits between the two variations, reflecting the expected cost and capacity effects of changing electrolyser efficiency.

- **Results Variation K: Demand Flexibility Edge Case**

Variation K is shown in Figures 24, 26, and 28, where a 20% increase in demand-side flexibility is applied. Figure 24 displays a consistent reduction in *e* compared to the base case for all levels of *r*. Battery capacity is also lower than the base case across the entire *r* range, with the difference becoming more pronounced at higher r values. In Figure 28, the total decarbonisation cost under the K variation is slightly lower than the base case for all levels of decarbonisation, with both curves maintaining a similar shape.



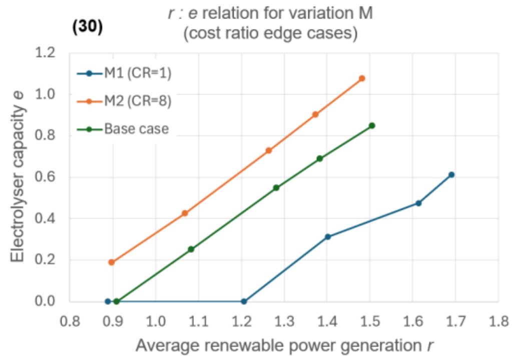
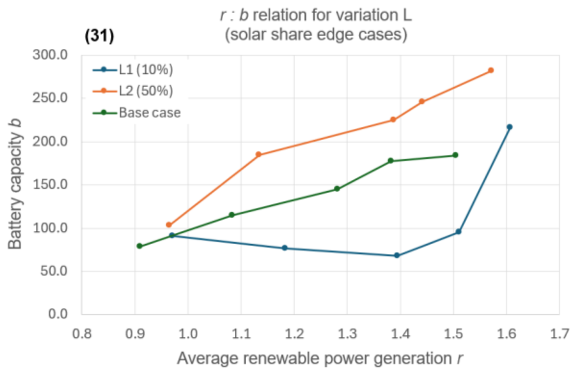


Figure 23 and 24: The r : e relation plotted for variations H (solar share) and I (cost ratio). Each variation consist of five datapoints, each on a different level of decarbonisation.



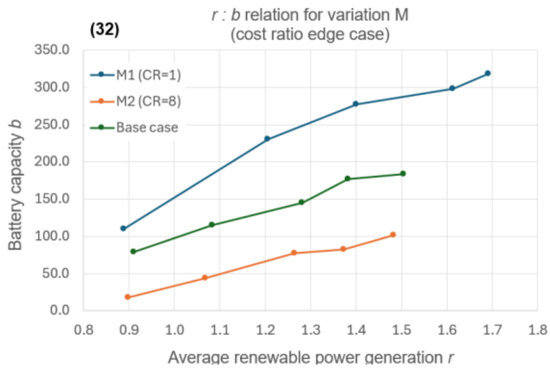
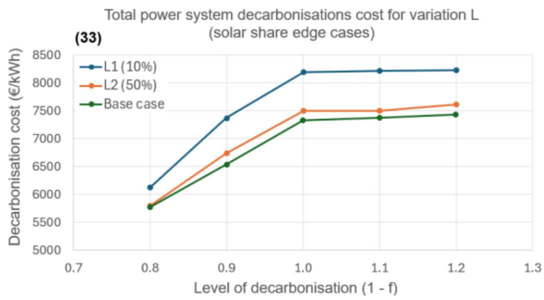


Figure 25 and 26: The r : b relation plotted for variations H (solar share) and I (cost ratio). Each variation consist of five datapoints, each on a different level of decarbonisation.



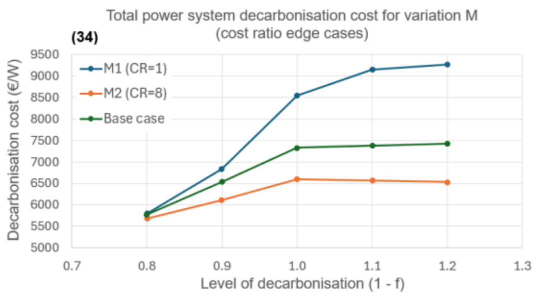


Figure 27 and 28: The total power system decarbonisation cost in €/kWh for each level of decarbonisation, for variations H (solar share) and I (cost ratio), compared to the base case (variation E).

- **Results Variation L: Solar Share Edge Cases**

Figures 29, 31, and 33 show the impact of solar share variations on system design. In the *r : e* plot (Figure 29), L1 results in higher electrolyser capacity across all *r* levels, while L2 yields lower e values than the base case. Battery capacity under L1 (Figure 31) starts below the base case but rises steeply at higher *r* levels; L2 remains consistently above the base case. Figure 33 shows that L1 has the highest system cost, the base case sits in the middle, and L2 maintains slightly lower costs throughout. These results indicate that higher solar shares can reduce electrolyser needs but increase storage requirements.

- **Results Variation M: Cost Ratio Edge Cases**

Figures 30, 32, and 34 illustrate the results for cost ratio variations between renewable and electrolyser technologies. In Figure 30, M1 (CR=1) results in lower electrolyser capacities than the base case, especially at higher *r* levels, while M2 (CR=8) shows consistently higher *e* values. The M2 curve remains above the base case across all *r* levels, while the M1 curve flattens at higher renewable availability. Figure 32 shows battery capacity rising steadily in M1 across the *r* range, remaining well above the base case. M2 exhibits the lowest battery capacity values across all renewable generation levels. In Figure 34, decarbonisation costs are highest under M1 and lowest under M2, with the base case occupying an intermediate position. Cost increases with higher levels of decarbonisation across all scenarios.

7 Comparative Model Analysis

This chapter aims to compare different modelling approaches and efforts to that of the KKM. This is done in order to answer SQ3, which reads: *"How Does the Renewable Generation-to-Electrolyser Build-Out Relation in the KKM Compare with Alternative Energy System Models?"*. To achieve this, a selection of different models and studies is made. For this selection, the relationship between the buildout of renewables and electrolysis will be extracted, next to other possible relevant overlapping aspects. These relations will then be compared to the KKM, after which notable consistencies and deviations will be highlighted, after which they will be discussed and analysed.

7.1 Alternative Model Selection

This section outlines the process through which alternative models were selected for comparative analysis against the KKM. The objective of this selection is to identify studies and models that allow for meaningful comparison of key assumptions and results, particularly the relationship between renewable energy deployment and electrolyser build-out. This forms the foundation for the comparative framework applied in the remainder of the chapter. The data from and studies executed while using these models will be used, while the models themselves will not be run due to inaccessibility.

The selection process followed a structured logic. A longlist of 28 suitable models (as found in Appendix C1) conveying key common themes was constructed, consisting of a few elements from different sources. First of all, publications similar to the KKM were gathered from a meta-study for the HyNOS (2025). These studies all formed relatable cases to the KKM, according to this meta-study. Second, the five relevant papers mentioned in the introduction of the KKM paper (and listed in the Literature Review) were added to the longlist. Lastly, two separate scenario studies were added to the longlist, due to their comprehensiveness and overlap with the KKM: the TYNDP by ENSO-E/ENTSOG (2024) and the II3050 by Netbeheer Nederland (2023). Focusing solely on studies as recent or more recent than the KKM (so 2024 or later), due to the relevance of assumptions and values, this eventually led to 9 studies being used for further inspection (found in Table 7).

7.1.1 Selection Criteria

To guide the eventual selection of the most relevant models, a set of selection criteria was applied. The first criterion was data accessibility, reflecting the need to extract or reconstruct the renewable-electrolyser relationship from the model outputs. This required not only publicly available results, but also some degree of openness regarding assumptions, input parameters and methodological detail. This included models with downloadable datasets, accessible documentation, or the possibility of author support.

The second criterion was geographic relevance. Preference was given to models that focus on or include Northwestern Europe, with particular interest in models that disaggregate national results, especially for the Netherlands. This ensures that the comparative insights remain consistent with the geographic scope and framing of the KKM.

The third criterion was model completeness in overlapping aspects. While the central relationship under analysis concerns renewable and electrolyser deployment, many of the assumptions underlying this link are only meaningful if captured within the model's scope. Models incorporating similar assumptions were therefore prioritised, provided these features were sufficiently documented.

7.1.2 Multi-Criteria Analysis

Based on these criteria, a multi-criteria analysis (MCA) was conducted to evaluate and rank models from the initial longlist. Each model was scored qualitatively across the three dimensions above. This was done on a scale of 1-3, 3 meaning well-suited, 2 meaning somewhat suitable, and 1 meaning the not suitable. This allowed for the identification of a subset of studies, of which three models were selected as most relevant to the research goals. An overview of the MCA can be found in Table 7. These three models form the analytical core of the comparative assessment that follows. Each will be introduced in further detail in the following subchapters, including an overview of its structure, assumptions and the form in which the key renewable-electrolyser relationship can be extracted.

Table 7: Multi-criteria analysis of selected models for the comparative analysis.

Nr.	Model Name	Author(s)	Criterion 1: Data Accessibility	Criterion 2: Geographic Relevance	Criterion 3: Model Overlap	Total Score
1.	More Wind at Sea for Climate Neutrality	Agora Energie-wende (2024)	1	3	2	6
2.	**System Integration Analysis for Programme VAWOZ**	**CE Delft (2024)**	**3**	**3**	**3**	**9**
3.	**Assessment for Connection Concepts for DE Far Out NS**	**E-Bridge (2024)**	**3**	**2**	**3**	**8**
4.	Infrastructure and Financing of the North Sea	Energy and Climate Policy and Innovation Council (2024)	1	3	2	6
5.	Key Insights from the North Sea Integration Model	Fluxys (2024)	2	3	2	7
6.	Offshore Power and Hydrogen Networks for Europe's North Sea	Glaum et al. (2024)	1	3	3	7
7.	Global Offshore Wind Report	Global Wind Energy Council (2024)	3	2	1	6
8.	Floating Offshore Wind Outlook	IRENA (2024)	2	2	2	6
9.	**Pathway 2.0 Study**	**NSWPH (2024)**	**3**	**3**	**3**	**9**

Resulting from Table 7, the three studies with the highest score are the following:

- System Integration Analysis for Programme VAWOZ by CE Delft (2024);
- Assessment for Connection Concepts for DE Far Out NS by E-Bridge (2024);
- Pathway Study 2.0 by NSWPH (2024).

These studies will be used in the comparative analysis, to review their overlap and differences with the output and assumptions of the KKM.

7.1.3 Model 1: System Integration Analysis for Programme VAWOZ (CE Delft)

The CE Delft (2024) study comprises a scenario study for assessing offshore wind integration into the Dutch energy system, with a primary focus on 2031–2050. It evaluates cost-optimal system configurations by balancing electric landing points and hydrogen conversion pathways for offshore wind capacity, accounting for both technical and spatial system constraints. The study uses scenario data directly from the II3050 study (2023). It investigates six total scenarios, reflecting differences in industrial activity, energy import/export dynamics, electrification and infrastructure availability. Each scenario determines the most cost- and energy-efficient balance between electric and hydrogen landing strategies, using hourly time-step simulations.

The Energy Transition Model (*Energy Transition Model*, 2025), or ETM, is used to analyse these scenarios. The ETM is an open-source simulation model developed by Quintel, widely used in the Netherlands for long-term energy planning. It provides representations of the Dutch energy system including electricity, heating, hydrogen, and industrial sectors, based on thousands of adjustable parameters and real-world data. The ETM offers a detailed insight into decarbonisation pathways and offers far more parameter than the KKM, while making it more accessible to study multiple years. However, both are suitable to study renewables-to-hydrogen dynamics.

Among the various scenarios, the comparison specifically focuses on the “International Trade” (INT) variant, a description of which can be found in Appendix C2. This scenario assumes that the Netherlands acts as a highly interconnected energy-trading hub, characterized by high levels of international energy exchange, relatively low domestic energy production costs and significant hydrogen imports. As a result, INT represents a highly suitable scenario to compare with the $r : e$ relationship from the KKM. Key insights from the INT scenario show that while electrification remains important, a significant portion of offshore wind is economically routed through hydrogen conversion. The model identifies scenario-specific trade-offs between direct electrification, electrolysis, and curtailment, depending on infrastructure constraints and hydrogen value chains.

The CE Delft and KKM study overlap in their prioritization of offshore wind, similar electrolyser efficiency assumptions, and shared goal of determining a cost-optimal $r : e$ ratio. Important assumptions include a generation mix with heavy offshore wind dominance with a lower solar input and electrolyser efficiencies around 70%. Unlike KKM, CE Delft explicitly incorporates demand variability, battery storage, spatially limited infrastructure and sector coupling, enabling realistic assessments of hourly system balancing.

7.1.4 Model 2: Assessment of Connection Concepts for DE Far Out NS (E-Bridge)

The E-Bridge (2024) study, commissioned by a consortium including various German transmission system operators, provides an analysis focused on integrating large-scale renewable energy, specifically wind in the North Sea and solar power, into the German energy system. This study aims to assess the techno-economic impacts of hydrogen production through electrolysis, highlighting its implications on infrastructure requirements and energy system stability.

Utilizing scenario-based modelling, the E-Bridge study examines multiple pathways reflecting different policy and technology assumptions. Of particular interest for comparison with the KKM is the “Molecule Energy Transition” (MET) scenario, as described in Appendix C3, which represents a vision of Germany's energy future from 2030-2045. The MET scenario for Germany is specifically based on the BMWK Langfristszenarien T-45 H2 scenario (*Langfristszenarien*, n.d.), and assumes increasing renewable deployment combined with extensive electrolyser integration to produce green hydrogen.

Although the E-Bridge study concentrates on Germany rather than the Netherlands, it remains highly relevant for comparison with the KKM due to the interconnected nature of Northwestern Europe's energy infrastructure, as well as the weather similar profiles. Both Germany and the Netherlands share similar ambitions for offshore wind exploitation, electrolyser deployment, and grid integration, making comparative insights particularly valuable.

The scenarios were modelled using the European Electricity Market Model (*The European Electricity Market Model*, n.d.), or EMMA, a tool designed for detailed techno-economic analysis of electricity markets across Europe. EMMA provides hourly resolution, simulating market dynamics including generation dispatch, grid constraints, and market prices. It integrates various generation technologies, storage solutions, and demand-side flexibility measures, offering realistic insights into system operations. EMMA's capability to assess the operational dynamics and economic viability of renewable and hydrogen infrastructure aligns closely with the aim of the KKM.

Overall, the MET scenario from the E-Bridge study offers valuable complementary perspectives to the stylized assumptions of the KKM, especially regarding the integration of electrolysis in renewable-dominated systems on a larger scale. Its emphasis on realistic technical constraints and alignment with European decarbonisation objectives makes it particularly suitable for comparative analysis within this research.

7.1.5 Model 3: Pathway Study 2.0 (NSWPH)

The third selected model is the Pathway Study 2.0, commissioned by the North Sea Wind Power Hub (NSWPH) consortium. This study is particularly well-suited for comparison to the KKM due to its relevance to the Dutch and broader Northwestern European context, its high degree of system detail, its modelling of electrolysis as part of a broader offshore integration strategy and the accessibility of both input assumptions and scenario outcomes (NSWPH, 2025).

The Pathway 2.0 study evaluates long-term system configurations that support the integration of large-scale offshore wind into the European energy system, focusing in particular on cross-border grids and the optimisation of both electricity and hydrogen infrastructure. It does so through a scenario-based modelling approach built on several techno-economic input parameters, hourly time resolution and spatially explicit assumptions. This makes it one of the few publicly available studies that captures both the buildout of renewables and the deployment of electrolysis capacity across Europe.

It extracts scenario data directly from the ENTSO-E's (2024) TYNDP study, resulting in the Pathway Study 2.0 baseline scenario being based on the Distributed Energy (DE) scenario of the TYNDP (found in Appendix C4). This baseline scenario of the Pathway Study 2.0, called 'DE Free Offshore', envisions a strongly decentralised European energy system with offshore wind at its core. The result is a techno-economically optimised vision of Europe's future energy infrastructure, particularly suited for analysing large-scale hydrogen production from renewables.

A key reason for selecting this model is also practical accessibility. Given Gasunie's involvement in the NSWPH initiative, the study offers a relatively high degree of transparency into underlying assumptions and scenario design. This allows for greater control over the interpretation of results and, where necessary, correspondence with the authors to clarify modelling choices. This makes it uniquely suitable for extracting comparable indicators. The model provides sufficient data to extract renewable input levels and electrolyser capacities with their operational profiles, which are necessary to reconstruct the *r : e* relationship.

In terms of model overlap and additionality, the Pathway Study 2.0 is especially valuable for its integration of both hydrogen and electricity infrastructure, including spatial siting of electrolysers and considerations of hydrogen storage and transport. It includes reporting on the share of renewable electricity converted to hydrogen and the full-load hours of electrolyser operation, which are useful to understanding how the *r : e* relationship evolves across decarbonisation pathways. Unlike the KKM, the model includes hydrogen imports, sectoral coupling, and explicit infrastructure constraints, all of which influence the *r : e* curve. This needs to be taken into account when comparing the *r : e* relationship.

As a scenario-based planning tool, the Pathway Study 2.0 does not internally optimise the timing of hydrogen deployment, which limits direct comparison with the KKM's cost-driven tipping point logic. Nonetheless, given its transparency, geographic relevance and modelling scope, the NSWPH Pathway Study 2.0 serves as an important model in this comparative analysis. Its findings offer a comprehensive point of comparison to the stylised results of the KKM.

7.2 Model Comparison

In the following section, the relationship between renewable build-out and electrolyser deployment is examined for each selected model. For every case, the structure of this relationship is described, with attention given to any thresholds, tipping points or proportionalities. Where relevant, underlying operational assumptions are discussed to contextualize how these relationships are formed and interpreted.

7.2.1 Extraction of *r : e* Relation

For the r : e relation, the average renewable generation and electrolyser capacity is determined over the course of several datapoints (Table 8). For the CE Delft and the NSWPH study, results are found documented for years 2030, 2040 and 2050, while the E-Bridge study documented years 2035, 2040 and 2045. Firstly, the power demand in TWh is converted to GW to determine the average power demand for each year. This is then compensated for import and export numbers used in each study. Subsequently, the renewable generation by solar PV, onshore wind and offshore wind is extracted for each of these years, utilizing full load hours or a capacity factor (as mentioned in the studies) to learn the average generation in GW. Lastly, the peak total electrolyser capacity is determined.

After gathering the critical datapoints, the *r : e* relation for each of the studies was determined. By dividing average renewable generation and peak electrolyser capacity by the average demand, a datapoint in the *r : e* space could be determined and plotted for each year within each study. The result of this plot will be discussed in the next section.

Table 8: Extracted information on power demand, renewable generation and electrolysis capacity from each of the selected alternative models. Processing this data led to the values for the r : e relation in these studies.

	CE Delft			E-Bridge			NSWPH		
Scenario / Year	INT			MET			DE Free Offshore		
Parameter	2030	2040	2050	2035	2040	2045	2030	2040	2050
Power Demand (TWh)	170	190	220	758	880	1002	187	222	253
Net Export (GW avg)	1.0	1.0	2.1	-4.1	-9.4	-12.2	4.0	0.5	-1.8
Solar Generation (GW avg)	4.9	7.9	11.6	82.4	91.1	102.2	6.3	9.0	12.8
Onshore Wind Generation (GW avg)	2.8	3.3	3.7	38.1	49.1	59.9	2.6	3.9	4.3
Offshore Wind Generation (GW avg)	11.8	21.1	24.9	20.4	23.8	27.3	14.4	18.5	21.8
Electrolysis Capacity (GW avg)	6.0	15.0	18.0	21.1	30.2	39.8	6.0	16.0	26.0
Average Power Demand (GW)	20.4	22.7	27.2	23.0	37.0	50.0	25.3	25.7	27.1
Total Average Renewable Generation (GW)	19.5	32.3	40.1	141.0	164.0	189.3	23.3	31.4	38.9
Peak Electrolysis	6.0	15.0	18.0	23.0	37.0	50.0	6.0	16.0	26.0
r	0.9574	1.4213	1.4774	0.9655	1.1319	1.2424	0.9203	1.2205	1.4393
e	0.2946	0.6602	0.6624	0.2790	0.4063	0.4893	0.2371	0.6216	0.9608

7.2.2 KKM Relation Comparison

Figure 35 presents a comparison of *r* on the x-axis and *e* on the y-axis. Each line represents the progression of system build-out over time according to a specific study, with markers at key reference years or decarbonisation levels (for the KKM and variation E). This allows for a direct comparison of how much *e* is deployed for a given level of *r*. The KKM remains the benchmark, with other model outputs overlaid to explore how different system assumptions and modelling approaches influence this relationship.

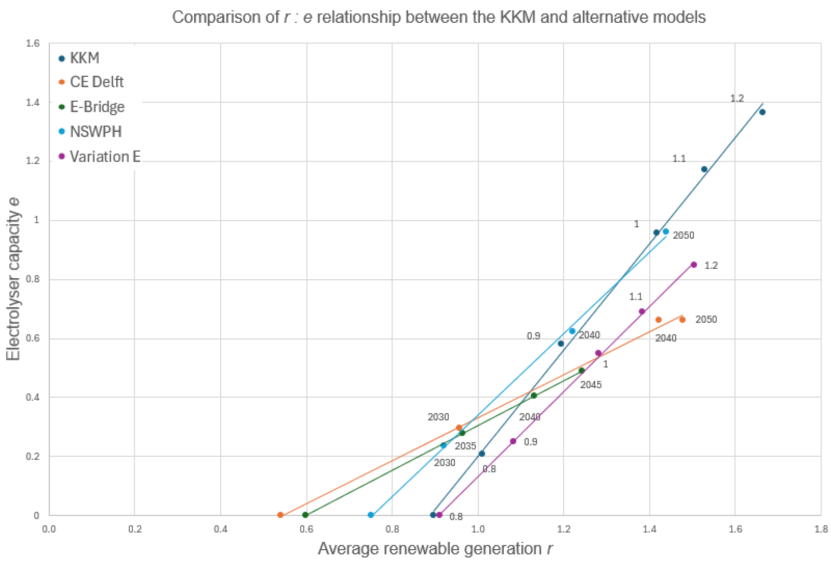


Figure 35: A plot containing the extracted r : e relations from the selected alternative models (the CE Delft, NSWPH and E-Bridge study), compared to the relation found in the KKM and variation E.

The renewable generation-to-electrolyser build-out relationship observed in the KKM aligns well with results from the three alternative models. A key finding is the consistency in the early stages of the *r : e* trajectory across all models. Around 2030 and 2035, scenarios from CE Delft, NSWPH, and E-Bridge lie within a narrow band. This suggests that in the short term, models with different structures and geographic scopes still converge on similar outcomes for the balance between renewable generation and electrolyser deployment. The onset of the slope differs slightly between models; the KKM exhibits a sharp tipping point once a renewable threshold is passed, together with the Pathway Study 2.0 and vairation E. The CE Delft and E-Bridge study show a more gradual onset, consistent with their inclusion of infrastructure constraints and sector coupling.

From 2040 onward, differences in slope become more apparent. In both CE Delft and E-Bridge, deployment accelerates significantly, mirroring the steep slope found in the KKM. This occurs despite differences in country context (Netherlands vs. Germany) and reference year (CE Delft 2050 vs. E-Bridge 2045). The limited distance between the final two datapoints in CE Delft is due to only a modest increase in power demand and electrolyser capacity between 2040 and 2050. The Pathway Study 2.0 follows a similar trajectory. Its 2050 datapoint aligns closely with the KKM's 100% decarbonisation point, and when compared to variation E, it shows a nearly parallel progression toward full decarbonisation, reinforcing the structural similarity across models.

The implication is that, regardless of the modelling approach, achieving net-zero by 2050 will likely require a similar *r : e* ratio once certain system thresholds are crossed. This strengthens confidence in using these trajectories as input for long-term infrastructure planning and policy design.

7.2.3 Broader Model Dialogue

By placing the KKM results in dialogue with other models, this comparison highlights both the strength and limitations of simplified system models. The KKM proves valuable in identifying structural relationships and tipping points in the r : e trajectory, particularly due to its cost-driven formulation and analytical transparency. However, its simplified representation of infrastructure, storage, and sector coupling makes it less equipped to capture the impact of real-world constraints. In contrast, the CE Delft, E-Bridge, and NSWPH studies offer more detailed and geographically grounded system representations, which allow for a more nuanced understanding of how system design and constraints shape the evolution of hydrogen deployment pathways.

Critically, these models do not just validate the KKM's structural insights, but they also expand the issue. For example, CE Delft's alignment with national planning scenarios (II3050), E-Bridge's integration of market dynamics and German policy, and NSWPH's pan-European scope and public accessibility each provide distinct yet complementary perspectives. Together, they help uncover trade-offs between the pacing of offshore wind and hydrogen infrastructure and the extent to which electrification and hydrogen can act as substitutes or complements.

The fact that a consistent *r : e* trajectory emerges across such diverse modelling approaches reinforces the robustness of the underlying relationship, while differences in slope or threshold highlight the role of modelled assumptions in shaping outcomes. Thus, incorporating multiple models into this analysis does not merely offer triangulation; it sharpens insight into how resilient certain system trends are. This broader comparative approach supports more robust long-term energy planning and allows both researchers and policymakers to make more informed decisions on hydrogen investment timing, infrastructure coordination, and system flexibility strategies.

8 Discussion

This chapter will discuss the key findings for each sub-question, as well as the generalizability of these findings. It will also go over the limitations that need to be taken into account when reflecting on this research paper, followed by a disclaimer on the use of AI in this thesis.

8.1 Discussion of Results

8.1.1 Sensitivity and Robustness Results Interpretation

This section entails the interpretation of results from chapter 6, will be divided in the results from the new base case creation, the sensitivity testing and the robustness analysis.

- **Implications of the New Base Case**

The progressive flattening of the *r : e* slope across variations A to E suggests that increasing model complexity reduces the need for high renewable and electrolyser capacity to reach a given decarbonisation target. The absence of battery interaction in the original KKM and variation A forces all surplus balancing into electrolysis, increasing both *r* and *e*. When demand fluctuations are introduced in variation A, this slightly lowers the need for hydrogen buffering, resulting in a modest reduction in both variables. The inclusion of battery interaction (variation B) and the introduction of an electrolyser efficiency curve (variation C) further reduce reliance on electrolysis and renewable overcapacity. These effects are consistently visible in both the *r : e* and *r : b* relationships, and are reflected in lower total system costs.

In contrast, variations that reintroduce hydrogen storage cost are hydrogen storage (D) and electrolyser operational limitations (E). In variations D and E, the surplus of storage is shifted back toward short-duration battery storage and lead to slightly higher overall costs. Variation D demonstrates a clear trade-off: when long-duration hydrogen storage becomes too costly, the system compensates by increasing battery deployment. Variation E, while incorporating performance constraints, results in only a modest rise in *e* when compared to D, due to the savings introduced in earlier steps. Altogether, this sequential analysis shows how operational constraints and flexibility options redistribute generation capacity across different components. It also reveals how the original KKM formulation, while conceptually valuable, overstates infrastructure needs when such complexities are excluded.

- **Implications of Sensitivity Testing**

In variation F, changes in electrolyser efficiency notably influence the division between battery deployment and electrolysis. Higher efficiency lowers battery demand and boosts electrolysis use, while lower efficiency does the opposite. In variation G, demand-side flexibility is introduced as a substitute for both battery and electrolyser capacity. When flexibility increases, the system absorbs more renewable energy through demand shifting, reducing the need for physical storage infrastructure. While battery capacity for G1 and G2 follows a similar or lower trend to the base case, the cost plot shows that total decarbonisation cost get lower as the amount of demand flexibility increases. However, this can be readily explained by the fact that the model does not account for the costs of demand flexibility.

Variation H indicates that a generation profile with a high solar share creates short-term surpluses that increase the system's reliance on battery storage rather than hydrogen conversion. This leads to higher battery deployment across renewable generation levels. In contrast, a lower solar share produces a more stable generation pattern, reducing short-term balancing needs and shifting more surplus into hydrogen production. This change in balancing strategy is reflected in the cost plot, where the high solar share scenario results in slightly higher system costs, particularly at higher decarbonisation levels.

Variation I demonstrates the role of the cost ratio between renewable generation and hydrogen production. When electrolyser costs are reduced, the system economically favours earlier and more extensive hydrogen deployment, reducing the need for battery storage. Conversely, when electrolysis becomes more expensive, the system shifts toward battery deployment to manage surplus electricity. This reveals that cost ratios play a major role in shaping the balance between short- and long-duration storage technologies.

- **Implications of Robustness Analysis**

The robustness analysis of variations J and K reveals that the KKM's outcomes are moderately sensitive to assumptions about electrolyser efficiency and demand flexibility. Variation J shows that changes in electrolyser efficiency affect both the magnitude of capacity deployment and total system cost, though the structural *r : e* relationship remain consistent. This suggests that while the model retains internal coherence under different efficiency assumptions, results related to cost and sizing should be interpreted with awareness of this sensitivity.

In variation K, the introduction of demand flexibility leads to systematic reductions in both storage requirements and decarbonisation costs (again, not taking into account costs that come with demand flexibility). This indicates that the exclusion of flexibility in the original model scope may underestimate the potential efficiency of future energy systems. Overall, these findings support the importance of testing input assumptions to evaluate the resilience of model outputs under plausible parameter variation.

The outcomes of variations L and M underscore how sensitive the model's infrastructure requirements are to changes in solar share and cost ratio assumptions, with direct implications for the robustness of the KKM. The divergence between L1 and L2 suggests that the balance between electrolyser and battery deployment is strongly influenced by the generation profile of renewables. This highlights the importance of properly characterising solar-wind mixes in stylised models to avoid over- or underestimating storage needs.

Similarly, the results from variation M confirm that the cost ratio between renewables and electrolysers plays a crucial role. The substantial variation in system costs and capacity outcomes across the tested edge cases demonstrates that, while the structural *r : e* relationship is preserved, its magnitude and economic implications can shift considerably. These findings support the need for careful parameter selection and scenario testing when applying simplified models like the KKM to inform planning or policy.

- **Key Takeaways**

Taken together, the sensitivity results suggest that while the *r : e* relationships are structurally robust, their slope, timing and contributions shift depending on which system parameter is varied. Across all variations, the steep rise in system cost between 80% and 100% decarbonisation and the plateau that follows, remains a consistent pattern. This reinforces the idea that the most capital-intensive shifts occur as full decarbonisation is approached. These findings are therefore best interpreted as directional rather than predictive. They remain conditioned on the stylised structure of the KKM and should be reassessed under models with higher granularity.

8.1.2 Comparative Results Interpretation

These findings suggest that the logic driving electrolyser deployment is consistent across different models, despite their varying assumptions, structures and levels of detail. Across all models, a consistent trend emerges: modest electrolyser capacity is observed in the early 2030s, followed by a seemingly linear build-out into later stages. While the KKM expresses this relationship as a function of decarbonisation level, the alternative models present it through fixed-year datapoints, allowing for temporal comparison. Across all models, a consistent trend emerges: modest electrolyser capacity is observed in the early 2030s, followed by a seemingly linear build-out into the 2040s and beyond.

The scale and timing of deployment diverge most clearly after 2040. CE Delft and E-Bridge both exhibit flatter r : e slopes when compared with the steep slope of the KKM and variation E, showing electrolyser build-out happens on a lower pace compared to other models. However, it implies a shared system behaviour: electrolysis becomes increasingly attractive as marginal renewable costs fall and curtailment pressures rise. Notably, these similarities occur despite differences in geography, modelling framework or reference year. The Pathway Study 2.0's 2050 datapoint closely aligns with the KKM's full decarbonisation point. Though based on a different modelling framework and including infrastructure constraints, imports and sector coupling, Pathway 2.0 independently identifies a trend to variation E. This convergence suggests that the KKM's stylised results can capture real-world system dynamics with surprising accuracy.

Where deviations do occur, they may largely be attributable to differences in model structure and granularity in terms of assumptions and simplifications. The KKM is an abstract optimisation model with internal thresholds, while the alternative models are more detailed and scenario-based. Altogether, the comparison confirms that while the KKM is highly stylised, it successfully captures essential system dynamics related to electrolyser deployment, while highlighting the additional detail that other models provide.

8.2 Generalisability

The findings of this thesis offer a degree of generalisability, particularly at the conceptual level. The core insight derived from the KKM, the relation $e \sim \varepsilon (r - \rho)$, is supported across a diverse set of comparator models. Despite differences in geographic focus, modelling complexity and temporal scope, these models all exhibit a steep increase in electrolyser capacity once basic electricity demand is met and renewable overcapacity begins to emerge. This convergence suggests that the *r : e* relationship observed in the KKM reflects a more fundamental dynamic rather than a by-product of simplification.

However, the practical generalisability of these results is limited by several factors. The sensitivity results reflect how the KKM behaves under change, but may not generalise to other models. They are conditioned on the base case of the KKM, while in more detailed models the same parameter shifts could lead to very different outcomes. Additionally, the KKM does not include infrastructure siting, sector coupling, or import dynamics, all of which can meaningfully influence hydrogen deployment in real systems. Therefore, while the logic of the KKM appears structurally robust, its quantitative outcomes should be interpreted with caution when applied beyond the context studied here. The underlying $r : e$ relationship shows conceptual strength, but it requires further validation under more complex and detailed modelling conditions. If it continues to hold in such contexts, the relationship could support policy making by informing decarbonisation strategies and guiding the integration of electrolysis into broader sustainability goals.

8.3 Limitations

This section outlines the limitations of the thesis, reflecting on each sub-question and how these constraints may have influenced the results.

8.3.1 Limitations of Assumption Identification

The identification of key assumptions within this thesis is subject to several limitations, particularly related to subjectivity and the reliance on inferred model behaviour. The process of selecting and classifying assumptions inevitably involved a degree of interpretation. This introduces a risk of subjectivity, as the perceived importance of an assumption was partially influenced by the researcher's framing, familiarity and the ability to explore that assumption further using the EBBM. As a result, the analysis may have been exposed to unconscious biased toward assumptions that were easier to investigate.

Moreover, many assumptions had to be inferred based on the system description and wider context, rather than being explicitly defined in the KKM's paper. This reliance on inference increases the potential for misinterpretation, creating a possibility that some inferred assumptions were incorrectly assessed in their scope or impact. Also, any process of assumption identification necessarily involves making a selection, where it is decided which assumptions to include for further analysis and which to exclude. This act of selection is itself a limitation, as it implies that certain modelling choices may have been overlooked, even if they play a less important role in the model. The final assumption set therefore reflects a selection shaped by practical considerations and scope constraints, rather than a comprehensive inventory of all model assumptions.

8.3.2 Limitations of Sensitivity and Robustness Analysis

A key limitation of the sensitivity and robustness analysis lies in the way parameter variations were implemented. Most parameters were varied individually, using discrete steps (of ±10% for instance), while all other variables were held constant. This unidimensional approach limits the ability to observe interactive effects between parameters. As a result, the analysis may miss important behaviours that only emerge when parameters shift simultaneously. Additionally, the broad step size used in the variations means that smaller inflection points in system behaviour may not have been captured.

Another important constraint stems from the underlying dataset used to represent system variability. The entire analysis is based on a single weather year, which simplifies model inputs but introduces uncertainty, particularly around short-term balancing needs. This is especially relevant for battery deployment, which is sensitive to intra-day and inter-day fluctuations in solar and wind availability. Relying on a single deterministic weather profile limits the ability to generalisable insights about the *r : b* relationship. In real-world applications, variability between years could significantly shift the required capacity or use of storage and hydrogen systems.

Finally, the results include a margin of error in the calculated ratios of electrolysis and battery capacity, stemming from the optimisation method used to derive the ideal deployment curves. In optimisation models like the KKM, results are typically approximate rather than strictly optimal. Solvers often operate within a predefined optimality margin, meaning the model output may fall within a few percentage points of the theoretical optimum. These small deviations are methodologically valid and reflect trade-offs in model solvability and computational efficiency, making it possible to determine if a certain relations are consequent instead of calculating precise values.

Nonetheless, they introduce a degree of imprecision in the ideal benchmark curves, which should be acknowledged when interpreting the robustness of these ratios. This technical uncertainty, though moderate, further limits the precision with which robustness conclusions can be drawn. Taken together, these factors suggest that while the sensitivity analysis provides valuable insights on the changing relations between renewables, electrolyser capacity, battery capacity and system decarbonisation cost, the result should be regarded as directional insights rather than exact or definitive.

8.3.3 Limitations of Model Comparison

The comparative model analysis conducted in this thesis is subject to several important limitations, primarily related to the diversity, availability, and interpretability of the models used for comparison. The selection of alternative studies was constrained both by data access and geographic relevance. Only a few studies were available with sufficient transparency to be meaningfully compared to the KKM.

One of the most fundamental constraints is the difficulty in identifying with certainty the influence of specific assumptions in the alternative models. Because each study starts from a different methodological structure, ranging from optimisation to scenario-based modelling, it is often only possible to suggest the impact of certain parameters rather than to isolate their direct effects. This structural variation undermines the ability to attribute deviations in the *r : e* relationship to a particular input or design choice with confidence.

Additionally, a second limitation concerns data availability and transparency. Most of the alternative models used in the analysis only provide basic or aggregated outputs for only a small number of datapoints, often without sufficient documentation on how these values were derived. The underlying assumptions are frequently not published in their entirety, limiting reproducibility and making it difficult to normalise and compare datapoints. The distinction between scenarios also means that the comparative framework included just a single scenario with the best context fit from each model for comparison, omitting scenario variations or internal sensitivities.

There was also a contrast in the level of detail among the selected models. While the KKM functions as a stylised optimisation model, the alternative studies are scenario-based with detailed elements like sector coupling and infrastructure planning. These methodological differences create challenges when trying to align their normalised outputs. Furthermore, the models represent single target years, while the KKM expresses results across decarbonisation levels. This discrepancy complicates direct comparisons, especially in terms of timing and scale.

Taken together, these limitations imply that the comparative analysis should be viewed as a qualitative exploration of how insights from the KKM manifest in different modelling contexts, rather than a quantitative model validation. While consistent patterns were observed, they should be interpreted with caution given the underlying differences in data resolution, assumptions and model design.

8.4 Use of AI

While preparing this work, ChatGPT was used for reviewing logical flow, spelling and grammar of the work. It was also used to rephrase passages for coherence purposes. After using this tool, the content was reviewed and edited as needed, taking full responsibility for the content of this research paper. Also, the tools Consensus and Perplexity were at times used as additional support for finding academic research regarding specific topics. The suggested papers were only consulted and referenced after careful review, taking full responsibility in the event of possible contribution to this research. Lastly, the tool Turboscribe was used to transcribe meeting recordings, which were deleted after the useful information was retrieved.

8.5 Personal Reflections

Writing my thesis was a humbling yet valuable experience. While I began the process feeling confident about my understanding of the energy transition and hydrogen systems, diving deeper into the subject made it abundantly clear how much I still had to learn. The technical details, especially those surrounding integrated electrolyser systems and system optimization, constantly challenged me to expand my knowledge and revisit what I thought I knew. Through the inevitable highs and lows of such an intensive project, sticking closely to my planning and not hesitating to ask for help proved crucial in maintaining focus and steady progress. Especially when the EBBM needed some adjusting at first, the supervision experience really helped me maintain control and focus on the relevant aspects of the research, eventually strengthening my resilience.

Regular sparring sessions with peers helped me contextualize my progress and exposed common pitfalls in the thesis process, which I could then avoid or help myself out of. A major contributor to the quality of the final product was the continuous cycle of feedback and revision. I made a deliberate effort to incorporate feedback at every stage, with a special mention to the and insightful comments from professor Koning, which sharpened the depth of my work. Overall, the thesis journey not only advanced my academic capabilities but also strengthened my resilience and understanding of both energy system modelling and the future of hydrogen.

9 Conclusion

Based on the key findings in each sub-question and the issues explored in the Discussion, a comprehensive conclusion can be drawn considering the assumptions and simplifications made in the KKM and their influence on the relation between renewable generation and electrolysis capacity. This conclusion will be presented in the following chapter, combining the insights from all chapters to subsequently answer the main research question. Lastly, possible topics for future research will be suggested, together with a comprehensive overview of the contributions made by this research paper.

9.1 Answer to Research Questions

It has been established that models are based on assumptions and simplifications. With energy system models this is no different, since the assumptions and simplifications made support the internal logic and influence model output. Validating these assumptions would thus prove essential to confirm the robustness of the model output and identify possible sensitivities. Scrutinization increases reliability and applicability, allowing the model to be used in further research or more practical applications to further experiment test relations.

This brings us to the purpose of this study, namely testing the validity of the relation found between renewable generation and the build-out of electrolysis capacity in the KKM. Given the ambitious climate goals of European nations, discovering a relation that could help plan the deployment alongside an increasing amount of renewable generation can prove to be very valuable. This way, long-term infrastructure planning can be thought out while optimising the cost for power system decarbonisation. However, since the KKM represents a highly stylized system, the aforementioned scrutinization of underlying assumptions and simplifications is essential to test the robustness of the model's outcome, determining whether or not the relation can play a role in designing future decarbonisation pathways.

9.1.1 Answer to Sub-Question 1

To begin the analysis, it was necessary to first identify the assumptions and simplifications that required closer scrutiny. This led to an examination of the explicit and implicit assumptions built into the KKM. While explicit assumptions and simplifications could be directly retrieved from the original model documentation, several implicit omissions or simplifications had to be inferred. By comparing the model's system description to that of a real-world energy system and analysing the broader system context, a comprehensive longlist of both explicit and implicit assumptions and simplifications was compiled.

Three criteria guided the selection of the final assumption set: the importance of each assumption to model behaviour, its relevance to the main research question, and the EBBM's ability to facilitate testing of that assumption. The resulting set consisted of the following elements: Generation Mix, Electrolyser Efficiency, Electrolyser Limitations, Hydrogen Storage Cost, Cost Ratio, Neglect of Demand Fluctuations, Battery Interaction Exclusion, and Demand Flexibility. This assumption set formed the basis for the sensitivity and robustness testing in SQ2 and also served as the answer to SQ1, which asked: ***"What Are Key Assumptions in the KKM and Why Are They Made?".***

9.1.2 Answer to Sub-Question 2

Scrutinising the selected set of assumptions and simplifications served as a tool to validate the model output of the KKM. First, a new base case was created by incrementally adding high-certainty simplifications enabled by the EBBM, resulting in a more realistic model formulation with added complexity relative to the original KKM. These high-certainty system simplifications consisted of electrolyser limitations, hydrogen storage cost, neglect of demand fluctuations, battery interaction exclusion, and the electrolyser efficiency curve. A key result of introducing these previously omitted simplifications is that the *r : e* curve flattened significantly, while the cost curve was reduced substantially. This demonstrates that added complexity can significantly reduce the required renewable generation and electrolyser capacity to reach certain decarbonisation levels, while also lowering the associated system cost. The omission of demand flexibility costs and limitations, however, deserves careful attention, as incorporating these constraints could significantly alter the model's outcomes.

Subsequently, the remaining assumptions in the key set were tested through multiple univariate sensitivity runs. By analysing the decarbonisation cost, the *r : e* relation, and the *r : b* relation, the effects of variations in electrolyser efficiency, demand flexibility, solar share, and cost ratio were assessed. Electrolyser efficiency and demand flexibility had a minimal impact on *the r : e* relation, slightly increasing both r and e across all decarbonisation levels.

Battery capacity, however, diverged to compensate: higher electrolyser efficiency led to reduced battery deployment, while lower efficiency increased battery demand. Demand flexibility reduced battery capacity in both tested scenarios, due to the ability to shift load. The cost plots showed a consistent decrease in system cost across all variations, except in the case of reduced electrolyser efficiency. While the direction of these outcomes was anticipated, demand flexibility in particular was shown to have a positive effect on decarbonisation cost.

Moreover, variations in solar share and CR had a more pronounced impact on the *r : e* relation. A lower solar share created a much steeper *r : e* curve, with electrolysis build-out occurring earlier and at higher levels. In contrast, a higher solar share produced a curve similar to the base case but with a delayed onset. This is due to increased generation variability, which raised battery capacity needs - opposing the trend observed with lower solar shares. Interestingly, both variations led to an increase in system cost.

Finally, the CR between electrolysis and renewable generation had a strong influence across all model outputs. Substantial divergences appeared in the *r : e, r : b*, and cost plots. A lower CR resulted in higher electrolysis capacity, lower battery capacity, and lower total system cost. A higher CR caused the system to prioritise battery storage over hydrogen production, increasing battery capacity while reducing electrolyser deployment, ultimately leading to the highest cost outcome of all variations. While CR clearly influences the ratio between electrolysis and battery deployment, its overall impact remains limited, even across a relatively wide CR range. Even when exposed to edge cases in the robustness analysis, similar trends were observed as during the sensitivity analysis, showing that even under extreme conditions the *r : e* relation holds.

Answering SQ2, which reads: ***"How Sensitive and Robust Are KKM Model Outcomes to Variations in Key Assumptions?"***: the curve found in the KKM flattens slightly when adding high-certainty system simplifications, lowering cost and introducing battery interaction as a balancing mechanism. The model outcomes seem to be most sensitive to changes in solar share and the cost ratio on all fronts, while being affected by electrolyser efficiency and demand flexibility primarily in total decarbonisation cost. Battery interaction functions as a compensating measure for the model when electrolyser capacity is deemed disadvantageous due to higher prices or unfavourable conditions for electrolysis.

Notably, while the EBBM itself is not inherently linear, the proportional relationships observed in *r : e* emerged from independently optimized solutions under varying constraint structures. Combined with the *r : e* and cost relationships holding when exposed to edge cases of each variation, this shows that the conceptual relation found in the KKM is structurally robust, even when introducing complexities or applying extreme values.

9.1.3 Answer to Sub-Question 3

The comparative model analysis conducted in this thesis demonstrates the substantial diversity and complexity found within energy system modelling. This resulted in models covering a broad range of studies, employing distinct methodologies, datasets, assumptions and geographic contexts. Data was systematically extracted, normalised, and plotted the *r : e* relationship from three selected alternative models: the Pathway Study 2.0, the CE Delft study and the E-Bridge study. These models formed the base for answering the third and final sub-question SQ3: ***"How Does the Renewable Generation-to-Electrolyser Build-Out Relation in the KKM Compare with Alternative Energy System Models?"*.**

Despite significant methodological and geographic differences all models revealed a similar fundamental relationship. Particularly, the Pathway Study 2.0 exhibited a pronounced alignment with the KKM's behaviour, validating the conceptual logic of rapid electrolyser deployment once renewable capacity surpasses certain thresholds. While the CE Delft and E-Bridge studies showed somewhat flatter slopes, which may be causes by additional constraints such as spatial siting, infrastructure limitations, and international trade dynamics, they still broadly supported the conceptual trend outlined by the KKM. Consequently, although the specific quantitative outcomes varied due to different datasets, methodological and regional differences, the comparative analysis consistently supported the robustness and general applicability of the KKM's conceptual framework across varying contexts.

9.1.4 Key Assumption Influence on the *r : e* Relation

The key model assumptions identified within the KKM significantly influence the renewable energy-to-electrolysis build-out relationship, primarily through altering the slope, timing, and cost-effectiveness of electrolyser deployment. Explicitly scrutinised assumptions such as electrolyser efficiency, demand flexibility, solar share, hydrogen storage cost, and battery interaction, each demonstrate distinct impacts on the system dynamics.

For instance, introducing battery storage substantially lowers electrolyser capacity requirements, indicating batteries serve as effective short-term balancing alternatives. Changes in electrolyser efficiency and demand flexibility primarily affect total decarbonisation cost rather than the fundamental shape of the *r : e* relationship. Conversely, variations in the solar share and cost ratios between renewables and electrolysers profoundly impact the timing and extent of electrolyser deployment and the optimal balance between short-term and long-term storage solutions.

Moreover, the sequential introduction of high-certainty system complexities demonstrated how increased model realism systematically redistributes infrastructure requirements, leading to a flattened renewable-to-electrolyser relationship relative to the original KKM.

Importantly, comparative analysis with other models, notably the Pathway Study 2.0, affirmed that despite differences in methodologies and assumptions, the essential conceptual relationship proposed by the KKM remains robust and broadly applicable. Hence, explicitly addressing the main research question ***"How Do Key Model Assumptions in the KKM Influence the Relationship Between Renewable Energy and Electrolysis Deployment?***", it can be concluded that key assumptions in the KKM significantly impact this relationship through changes in both the level of deployment and the system's characteristics. The fundamental proportional relationship between renewable energy generation and electrolyser deployment remains structurally sound and consistently observable across varied scenarios and contexts.

9.1.5 General Implications

The structural consistency of the $r : e$ relationship across all compared models provides a robust basis for long-term hydrogen infrastructure planning. This indicates that, regardless of modelling approach, renewable generation and electrolyser capacity will need to scale in tandem beyond a critical system threshold. However, differences in the pace and steepness of this build-out highlight the importance of modelling operational constraints, flexibility measures, and spatial realities. While simplified models like the KKM are valuable for identifying system-level tipping points and high-level trends, they should be complemented by more detailed models when informing investment phasing, infrastructure coordination, or sector integration.

The analysis also shows that decarbonising the final shares of electricity is costly, but that additional hydrogen production beyond this point adds relatively little marginal cost, supporting a phased strategy where hydrogen is layered onto an already decarbonised grid. This aligns with the broader hydrogen system perspective described by Kramer & Koning (2024), who stress that the feasibility and value of hydrogen production depend not only on electrolysis technology but also on the system context in which it is embedded. Their work underscores the importance of aligning infrastructure deployment with system-wide dynamics, a point that is operationalised in this thesis through the $r : e$ framework.

Finally, operational refinements such as battery interaction, demand flexibility, and electrolyser behaviour significantly reduce system cost, suggesting they should be prioritised both in future model development and in real-world design decisions.

9.2 Future Research

Building on the findings of this thesis, several directions for further research are recommended to deepen and broaden understanding of the $r : e$ relationship. First, the KKM could be extended from its current static framework into a time-resolved version. This would allow for the simulation of year-by-year developments in renewable capacity, hydrogen demand, and infrastructure roll-out, enabling a more realistic assessment of investment phasing and the timing of tipping points.

Second, further work is needed to incorporate infrastructure constraints explicitly into the modelling framework. While the KKM abstracts from siting, grid limitations and network expansion, these factors are critical in determining where and how electrolysers can be deployed at scale. This would allow for more realistic interpretation of the slope and timing of hydrogen build-out. Similarly, sector coupling (especially through power-to-heat technologies) could be added to capture the competition and synergy between hydrogen, electrification and heat demand in the decarbonisation process.

In addition to these structural extensions, the role of energy storage by batteries deserves further detailed investigation. The KKM currently excludes batteries, yet they play a critical role in balancing short-term variability in renewable supply. Future research could explore the *r : b* relationship and how this interacts with hydrogen deployment. The inclusion of batteries could alter the *r : e* curve by reducing curtailment and shifting the timing of when surplus electricity is diverted to electrolysis. Testing the impact of a varying battery price would also be a very insightful addition. This effect would be especially important to test under multiple weather year simulations, both as isolated simulations and as sequential time series, to evaluate system robustness and battery interaction across different conditions. Such research would support a more nuanced understanding of the trade-offs between electricity storage and hydrogen conversion.

Finally, policy scenario analysis could enhance the practical relevance of the *r : e* relationship. Future studies could test how policy instruments such as curtailment pricing or infrastructure subsidies influence the cost-optimal timing and scale of electrolysis deployment. These policy interventions may shift model behaviour, and their inclusion would allow for a more realistic exploration of how strategic incentives influence system development. Together, these research directions would significantly advance the conceptual foundation laid in this thesis, helping to bridge the gap between stylised relations and the operational, spatial and political realities of the real-world energy transition.

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Appendix

A. Electrolyser Battery Balancing Model

A1. Model Functionality Description

The section below gives a description of the EBBM's functionalities, as found in Peping (2025).

The EBBM model simulates the interaction between renewable energy generation, electricity demand, electrolysers, and batteries on an hourly basis over a full year. Renewable power generation is used to meet hourly electricity demand directly. Any surplus renewable energy, after satisfying direct demand, is allocated to the operation of electrolysers for hydrogen production. If the electrolyser capacity is fully utilized and excess energy remains, this surplus is directed to battery charging.

When direct power supply cannot meet electricity demand, the model draws on battery storage. If the battery's state of charge (SOC) is insufficient, the system pre-emptively reduces the electrolyser load in prior hours to prioritize battery charging ahead of an expected shortage. This strategy allows the system to anticipate and respond to future shortfalls. If both the battery and reduced electrolyser operation are unable to meet demand, backup power from a gas-fired plant is used.

Conversely, when electricity demand is fully met by renewable generation, and the electrolysers are not operating at full capacity, the battery may discharge to increase electrolyser power input—provided this does not compromise battery availability for future demand shortages. Whether this reverse discharge strategy is applied depends on expected curtailment and the battery's ability to recharge later. This approach prioritizes maximizing hydrogen production when feasible.

To further optimize energy system performance, the model identifies the optimal timing and intensity of battery use in relation to electrolyser operation. Specifically, it compares the battery SOC curve with the electrolyser input curve to determine key inflection points. The model seeks to maximize electrolyser operation during hours when battery discharge can most effectively supplement insufficient renewable input. This is achieved by aligning peaks in battery availability with dips in renewable supply to the electrolysers, ensuring that hydrogen production continues even when direct renewable input temporarily drops. In this way, the battery discharge is not applied uniformly, but strategically, to maintain electrolyser throughput while preserving battery charge for critical demand moments.

The model also includes operational profiles for batteries and electrolysers. Battery operations are tracked through state-of-charge curves and charging/discharging rates. Electrolyser performance is recorded via production profiles and energy input curves. These outputs enable a detailed understanding of system behaviour and energy flow dynamics, including power generation, direct consumption, battery storage use, and hydrogen production.

Shortages are tracked across all hours. When they occur, the model follows a hierarchy: direct supply first, then battery discharge, followed by electrolyser load reduction, and finally backup power usage. In moments of surplus, the model follows the reverse order—first meeting demand, then charging the battery, and lastly increasing electrolyser output.

The final output includes cumulative energy data: direct power supplied, curtailed energy, battery charging and discharging, electrolyser load, and hydrogen production. Additionally, a normalized demand and supply profile is generated, allowing evaluation of energy balance throughout the year and identifying critical bottlenecks, surpluses, and backup energy needs. This forms the basis for assessing system decarbonization performance and identifying strategic roles for batteries and electrolysers in balancing intermittent renewable supply.

A2. Overview and Description of EBBM Input Variables

Input Variable	Denomination	Unit
Average Renewable Power Generation	*r*	(GWh/h)/(GWh/h)
Electrolyser Capacity	*e*	GW/(GWh/h)
Average Demand	*D*	GWh/h
Demand Curve	*Demand Curve?*	0=flat, 1=demand profile
Battery Capacity	*Bess_storage*	GWh
Battery Cost	*c_bess*	€/kWh
Renewables Cost	*c_r*	€/(kWh/h)
Electrolyser Cost	*c_e*	€/kW
Firm Generation Cost	*c_f*	€/kW
Battery Efficiency	*η_bess*	-
Electrolyser Efficiency	*η_e*	-
Hydrogen-to-Power Efficiency	*η_p*	-
Minimum Load Electrolysers	*Minimum Load Electrolysers*	%
Standy Losses	*Standy Losses*	%
Cold Standby Losses*	*Cold Standby Losses*	%
Minimum Standby Period	*Minimum Standby Period*	h
Flattening, Bridging & 2nd Iteration	*Flattening, Bridging & 2nd Iteration*	0=off, 1=on
Hydrogen Efficiency Curve	*Hydrogen Efficiency Curve*	0=flat, 1=curve
Power Transport Limit of Energy in Offshore Hub(s)	*Power Transport Limit of Energy in Offshore Hub(s)*	%
Ratio of Solar Generation to Wind	*Solar Ratio*	%
Demand Flexibility	*Demand Flexibility*	%
Ideal Electrolyser Utilisation	*e/e_ideal*	%
Power Successfully Allocated to Demand	*Ug/Ug_target*	-
Ideal Battery Utilisation	*b/b_ideal*	%
Offshore Hubs	*Hubs*	0=no hub, 1=hub1, 2=hub1 + hub2
Power Transmission Converted to Power-to-Gas	*HVDC -> PtG Capacity*	GWe AC transmission/GW PtG installed
Degree of Decarbonisation	*Ug_H2-to-market-first (power+hydrogen)*	-

Appendix A2: Overview of input variables for the EBBM.

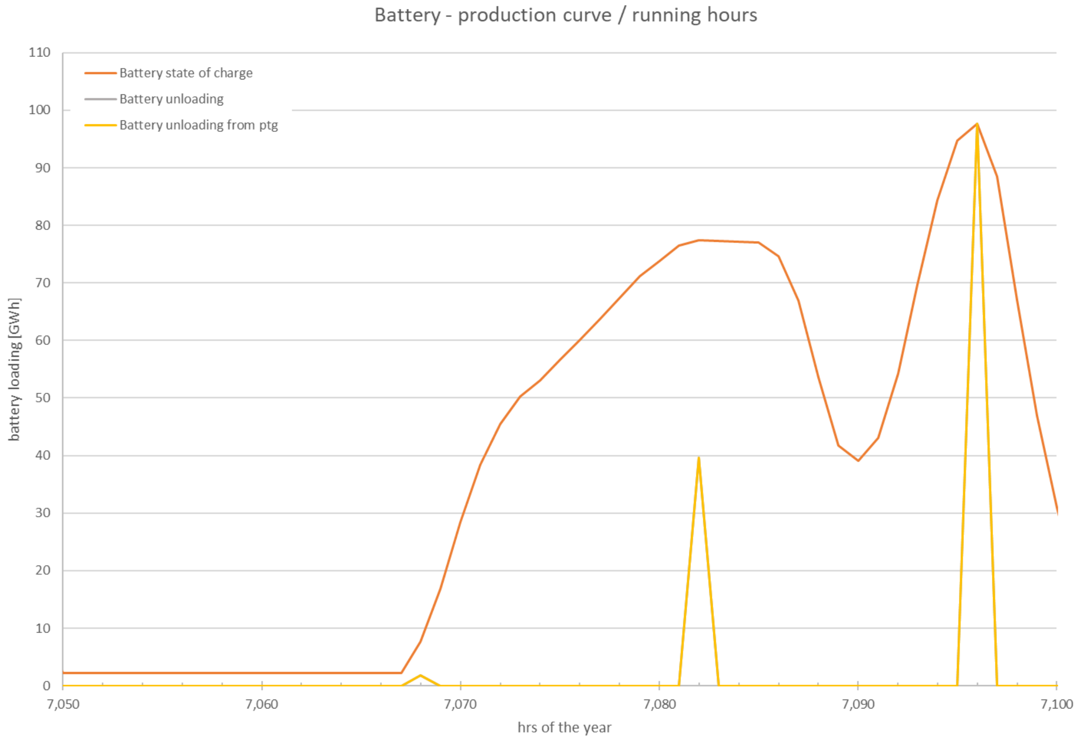
r	VALUE	(GWh/h) / (GWh/h)
e	VALUE	GW / (GWh/h)
D	28.9	GWh/h
Demand curve?	1	0=flat, 1=demand profile
bess_storage	VALUE	GWh
c_bess	100	EUR/kWh
c_r	4500	EUR/(kWh/h)
C_e	2250	EUR/kW
C_f	3000	EUR/kW
η_bess	90%	
η_e	70%	
η_p	50%	
Minimum load electrolysers	20%	% of capacity rating
standby losses	1%	% of capacity rating
cold standby losses	not used	% of capacity rating
minimum standby period	6	hrs
Flattening, bridging & 2nd iteration	1	0=off, 1=on
Hydro[illegible] Grafiekgebied [illegible]rve	1	1=curve, 0=flat
power transport limit of Energy in offshore hub(s)	100%	for offshore wind
solar ratio	30%	
Demand flexibility	0%	GW/GW
e/e_ideal	100%	GW/GW
Ug/Ug target	100.00%	(-/-)
b/b_ideal	100%	(GWh/GWh)
Hubs	1	0=no hub, 1=hub1, 2=hub1+hub2
HVDC->PtG capacity	100%	GWe AC transmission / GW PtG installed
Ug_H2-to-market-first (power + hydrogen)	0.8	target value

Appendix A2: Dashboard with input values and constants used in the EBBM.

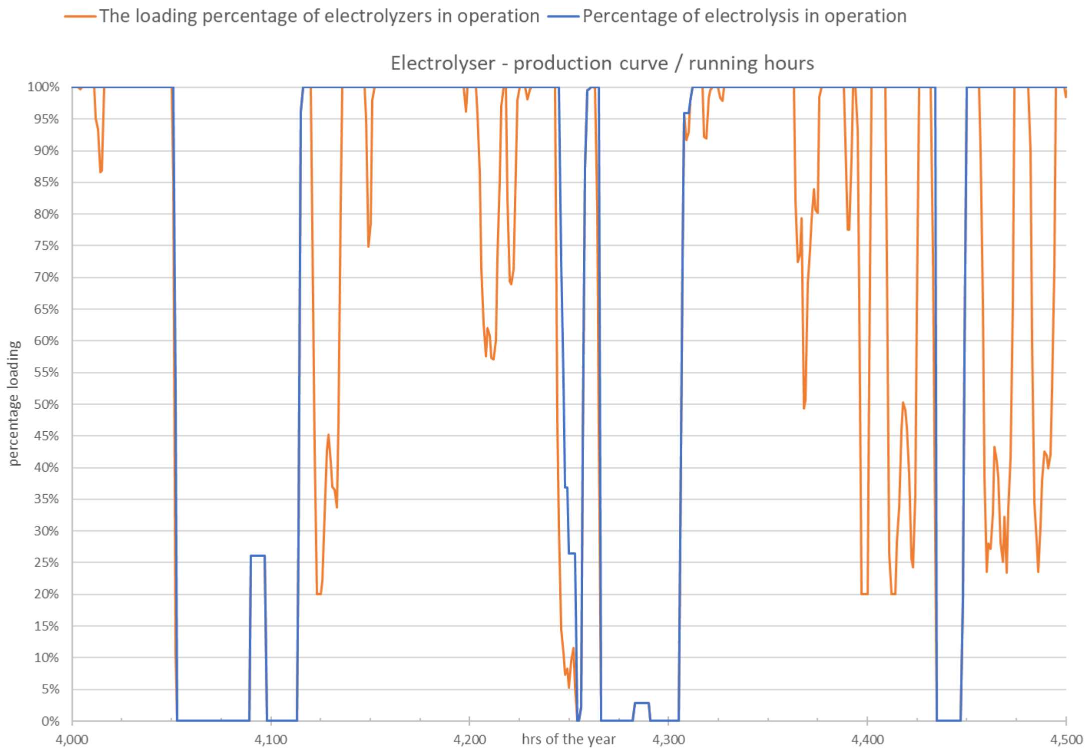
Input Variable	Description
Average Renewable Energy Generation (r)	Represents the portion of renewable energy generation relative to total system energy demand, measured in GWh/h.
Electrolyser Capacity (e)	Defines the proportion of installed electrolyser capacity, measured in GW.
Average Demand (D)	Average total system energy consumption
Demand Curve (Demand curve?)	Determines if demand is flat or follows typical patterns
Installed Battery Capacity (B)	Available battery storage capacity in the system, measured in GWh
Battery Cost (c_b)	Investment cost per unit of battery storage capacity.
Renewables Cost (c_r)	Investment cost per unit of renewable capacity.
Electrolyzer Cost (c_e)	Investment cost per unit of electrolyser capacity.
Cost of Firm Energy (c_f)	Investment cost per unit of non-renewable capacity.
Battery Efficiency (η_b)	Round-trip efficiency of battery storage
Electrolyzer Efficiency (η_e)	Efficiency of converting electricity to hydrogen.
Hydrogen to Power Efficiency (η_p)	Efficiency of converting hydrogen to electricity.
Minimum Load Electrolysers	Specifies the lowest safe operational capacity for electrolyzers.
Standby Losses	Energy needed to maintain electrolyzers in readiness during standby.
Cold Standby Losses	Energy losses during cold standby conditions.
Minimum Standby Period	Minimum idle duration to avoid degradation from frequent cycling.
Flattening, Bridging & 2nd Iteration	Model-specific operational adjustment process.
Hydrogen Efficiency Curve	Indicates if hydrogen conversion efficiency is constant or variable.
Power Transport Limit of Energy in Offshore Hub(s)	Applies transmission limits for offshore-to-shore power; offshore electrolysis capacity fills gap.
Energy in Offshore Hub(s)	Energy directly used offshore, bypassing shore-based demand.
Demand Flexibility	Ability of system demand to dynamically adjust, reducing storage needs.
Ideal Electrolyser Utilisation (e/e_ideal)	Target operational utilization rate for electrolyzers.
Power Successfully Allocated to Demand (Ug/Ug target)	Effectiveness of renewable power matched to demand.
Ideal Battery Utilisation (b/b_ideal)	Benchmark for optimal battery use.
Offshore Hubs (Hubs)	Number of offshore renewable generation hubs included.
Power Transmission Converted to Power-to-Gas Capacity (HVDC -> PtG capacity)	Limits on transmission converted into hydrogen production capacity.
Degree of Carbonisation (Ug_H2-to-market-first (power + hydrogen))	Prioritization of hydrogen and electricity delivery to market.

Appendix A2: Description of EBBM input variables.

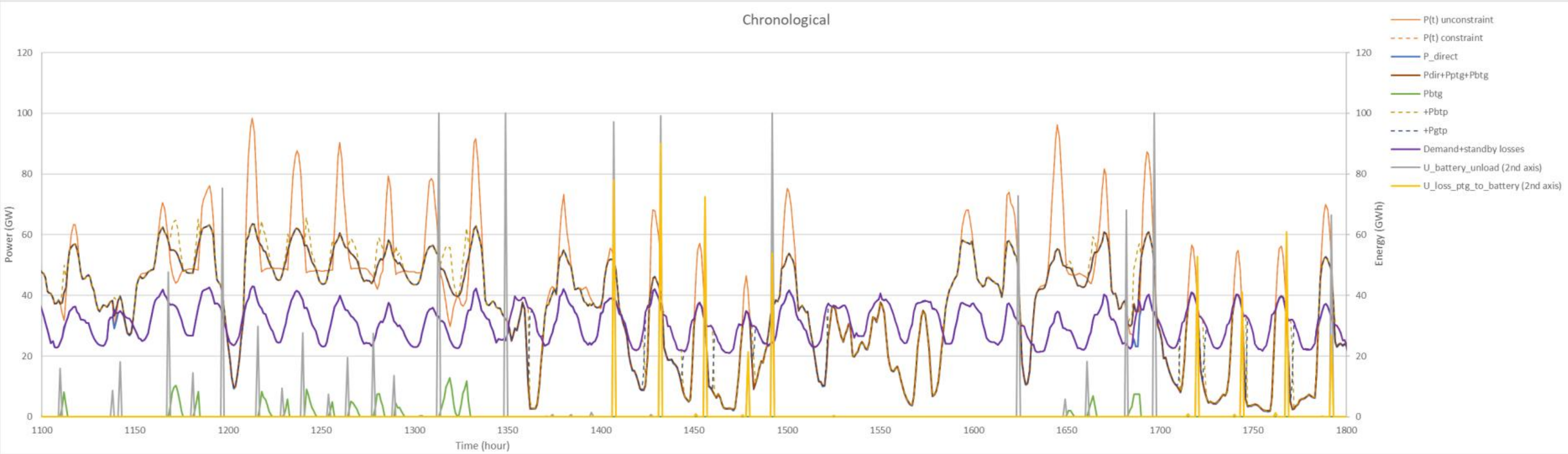
A3. Example Profiles



Appendix A3: Example of battery production profile, as produced by the EBBM.



Appendix A3: Example of electrolyser production profile, as produced by the EBBM.



Appendix A3: A chronological time-series plot, as produced by the EBBM.

B. Sensitivity and Robustness Analysis

B1. Overview of Runs and Output of the Sensitivity Analysis

		Inputs					Outputs			
		Demand Fluctuations	Battery Interaction	Electrolyser Efficiency Curve	Hydrogen Storage Cost	Electrolyser Limitations	Renewable Capacity (R)	Electrolyser Capacity (E)	Battery Capacity (B)	Cost per kWh/h Decarbonisation (C)
KKM	0.8	False	False	False	False	False	1.0097	0.2075	0.0	6068
	0.9	False	False	False	False	False	1.1937	0.5799	0.0	6939
	1	False	False	False	False	False	1.4166	0.9572	0.0	7812
	10% Excess	False	False	False	False	False	1.5288	1.1707	0.0	7853
	20% Excess	False	False	False	False	False	1.6638	1.3653	0.0	7910
A	0.8	True	False	False	False	False	0.9667	0.1591	0.0	5736
	0.9	True	False	False	False	False	1.1706	0.4882	0.0	6667
	1	True	False	False	False	False	1.4069	0.8420	0.0	7594
	10% Excess	True	False	False	False	False	1.5220	1.0568	0.0	7667
	20% Excess	True	False	False	False	False	1.5907	1.2096	0.0	7767
B	0.8	True	True	False	False	False	0.9042	0.0212	75.9	5454
	0.9	True	True	False	False	False	1.0676	0.2711	110.7	6215
	1	True	True	False	False	False	1.2690	0.5688	130.1	7014
	10% Excess	True	True	False	False	False	1.3736	0.7584	134.7	7079
	20% Excess	True	True	False	False	False	1.4798	0.9064	160.8	7148
C	0.8	True	True	True	False	False	0.8988	0.0329	77.4	5452
	0.9	True	True	True	False	False	1.0667	0.2733	110.3	6213
	1	True	True	True	False	False	1.2665	0.5753	128.3	7006
	10% Excess	True	True	True	False	False	1.3691	0.7662	133.1	7065
	20% Excess	True	True	True	False	False	1.4750	0.9139	158.0	7131
D	0.8	True	True	True	True	False	0.9083	0.0001	82.2	5777
	0.9	True	True	True	True	False	1.1021	0.2216	127.5	6367
	1	True	True	True	True	False	1.2626	0.5213	156.9	7235
	10% Excess	True	True	True	True	False	1.3680	0.6590	183.0	7271
	20% Excess	True	True	True	True	False	1.4834	0.8187	191.8	7333
E	0.8	True	True	True	True	True	0.9099	0.0001	78.6	5773
	0.9	True	True	True	True	True	1.0836	0.2508	114.8	6541
	1	True	True	True	True	True	1.2818	0.5480	144.9	7328
	10% Excess	True	True	True	True	True	1.3831	0.6903	177.2	7375
	20% Excess	True	True	True	True	True	1.5048	0.8474	184.0	7430

Appendix B1: Overview of runs and output for variations A-E from the waterfall chart.

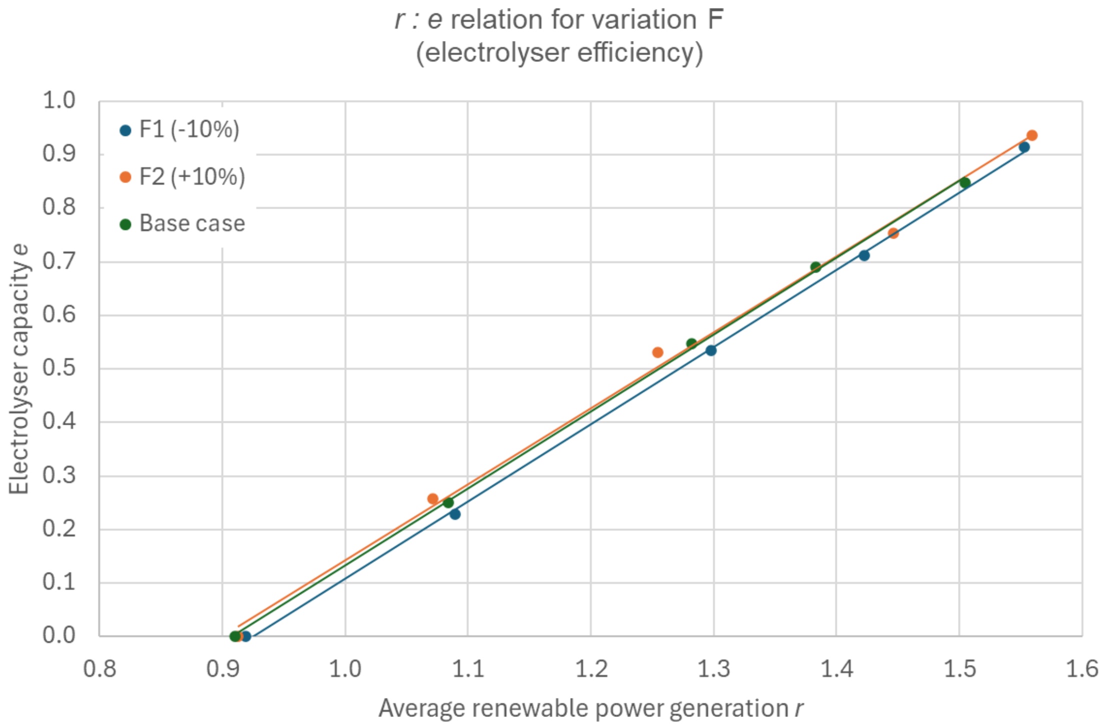
		Inputs									Outputs			
		Demand Fluctuations	Battery Interaction	Electrolyser Efficiency Curve	Hydrogen Storage Cost	Electrolyser Limitations	Electrolyser Efficiency	Demand Flexibility	Solar Share	CR	Renewable Capacity (R)	Electrolyser Capacity (E)	Battery Capacity (B)	Cost per kWh/h Decarbonisation (C)
Base case (E)	0.8	True	True	True	True	True	70%	0%	30%	3	0.9099	0.0001	78.6	5773
	0.9	True	True	True	True	True	70%	0%	30%	3	1.0836	0.2508	114.8	6541
	1	True	True	True	True	True	70%	0%	30%	3	1.2818	0.5480	144.9	7328
	10% Excess	True	True	True	True	True	70%	0%	30%	3	1.3831	0.6903	177.2	7375
	20% Excess	True	True	True	True	True	70%	0%	30%	3	1.5048	0.8474	184.0	7430
F1	0.8	True	True	True	True	True	60%	0%	30%	3	0.9192	0.0001	73.5	5770
	0.9	True	True	True	True	True	60%	0%	30%	3	1.0897	0.2286	139.7	6617
	1	True	True	True	True	True	60%	0%	30%	3	1.2977	0.5342	193.5	7525
	10% Excess	True	True	True	True	True	60%	0%	30%	3	1.4226	0.7120	205.6	7631
	20% Excess	True	True	True	True	True	60%	0%	30%	3	1.5527	0.9149	216.1	7777
F2	0.8	True	True	True	True	True	80%	0%	30%	3	0.9128	0.0001	73.7	5770
	0.9	True	True	True	True	True	80%	0%	30%	3	1.0714	0.2569	104.5	6466
	1	True	True	True	True	True	80%	0%	30%	3	1.2547	0.5312	130.5	7148
	10% Excess	True	True	True	True	True	80%	0%	30%	3	1.4466	0.7545	142.9	7152
	20% Excess	True	True	True	True	True	80%	0%	30%	3	1.5593	0.9364	157.7	7169
G1	0.8	True	True	True	True	True	70%	5%	30%	3	0.8695	0.0001	65.7	5634
	0.9	True	True	True	True	True	70%	5%	30%	3	1.0521	0.2167	104.0	6401
	1	True	True	True	True	True	70%	5%	30%	3	1.2432	0.5163	141.4	7207
	10% Excess	True	True	True	True	True	70%	5%	30%	3	1.3507	0.6618	165.0	7269
	20% Excess	True	True	True	True	True	70%	5%	30%	3	1.4626	0.8332	182.0	7357
G2	0.8	True	True	True	True	True	70%	10%	30%	3	0.8655	0.0001	55.4	5494
	0.9	True	True	True	True	True	70%	10%	30%	3	1.0158	0.1768	98	6246
	1	True	True	True	True	True	70%	10%	30%	3	1.2666	0.5341	121.9	7067
	10% Excess	True	True	True	True	True	70%	10%	30%	3	1.3661	0.6882	136.4	7175
	20% Excess	True	True	True	True	True	70%	10%	30%	3	1.4358	0.8087	168.3	7269

Appendix B1: Overview of runs and output for variations F and G of the sensitivity analysis..

		Inputs									Outputs			
		Demand Fluctuations	Battery Interaction	Electrolyser Efficiency Curve	Hydrogen Storage Cost	Electrolyser Limitations	Electrolyser Efficiency	Demand Flexibility	Solar Share	CR	Renewable Capacity (R)	Electrolyser Capacity (E)	Battery Capacity (B)	Cost per kWh/h Decarbonisation (C)
Base case (E)	0.8	True	True	True	True	True	70%	0%	30%	3	0.9588	0.0001	75.3	5997
	0.9	True	True	True	True	True	70%	0%	30%	3	1.1208	0.3643	103.9	6784
	1	True	True	True	True	True	70%	0%	30%	3	1.3514	0.8713	157.5	7575
	10% Excess	True	True	True	True	True	70%	0%	30%	3	1.4550	1.0581	171.9	7769
	20% Excess	True	True	True	True	True	70%	0%	30%	3	1.5692	1.2641	210.0	7846
H1	0.8	True	True	True	True	True	70%	0%	20%	3	0.9503	0.0001	93.4	5829
	0.9	True	True	True	True	True	70%	0%	20%	3	1.0822	0.0941	135.2	6617
	1	True	True	True	True	True	70%	0%	20%	3	1.3414	0.4173	176.8	7499
	10% Excess	True	True	True	True	True	70%	0%	20%	3	1.4480	0.5994	194.0	7568
	20% Excess	True	True	True	True	True	70%	0%	20%	3	1.5669	0.7454	210.4	7666
H2	0.8	True	True	True	True	True	70%	0%	40%	3	0.9161	0.0001	87.1	5774
	0.9	True	True	True	True	True	70%	0%	40%	3	1.0489	0.1023	165.4	6821
	1	True	True	True	True	True	70%	0%	40%	3	1.3382	0.4394	202.6	7917
	10% Excess	True	True	True	True	True	70%	0%	40%	3	1.4819	0.5790	201.1	8066
	20% Excess	True	True	True	True	True	70%	0%	40%	3	1.6083	0.7483	210.1	8208
I1	0.8	True	True	True	True	True	70%	0%	30%	2	0.8997	0.1023	53.2	5740
	0.9	True	True	True	True	True	70%	0%	30%	2	1.1092	0.3892	64.5	6420
	1	True	True	True	True	True	70%	0%	30%	2	1.3352	0.7183	76.6	7084
	10% Excess	True	True	True	True	True	70%	0%	30%	2	1.4573	0.8893	83.5	7077
	20% Excess	True	True	True	True	True	70%	0%	30%	2	1.5935	1.0964	84.3	7087
I2	0.8	True	True	True	True	True	70%	0%	30%	6	0.8997	0.1023	53.2	5740
	0.9	True	True	True	True	True	70%	0%	30%	6	1.1092	0.3892	64.5	6420
	1	True	True	True	True	True	70%	0%	30%	6	1.3352	0.7183	76.6	7084
	10% Excess	True	True	True	True	True	70%	0%	30%	6	1.4573	0.8893	83.5	7077
	20% Excess	True	True	True	True	True	70%	0%	30%	6	1.5935	1.0964	84.3	7087

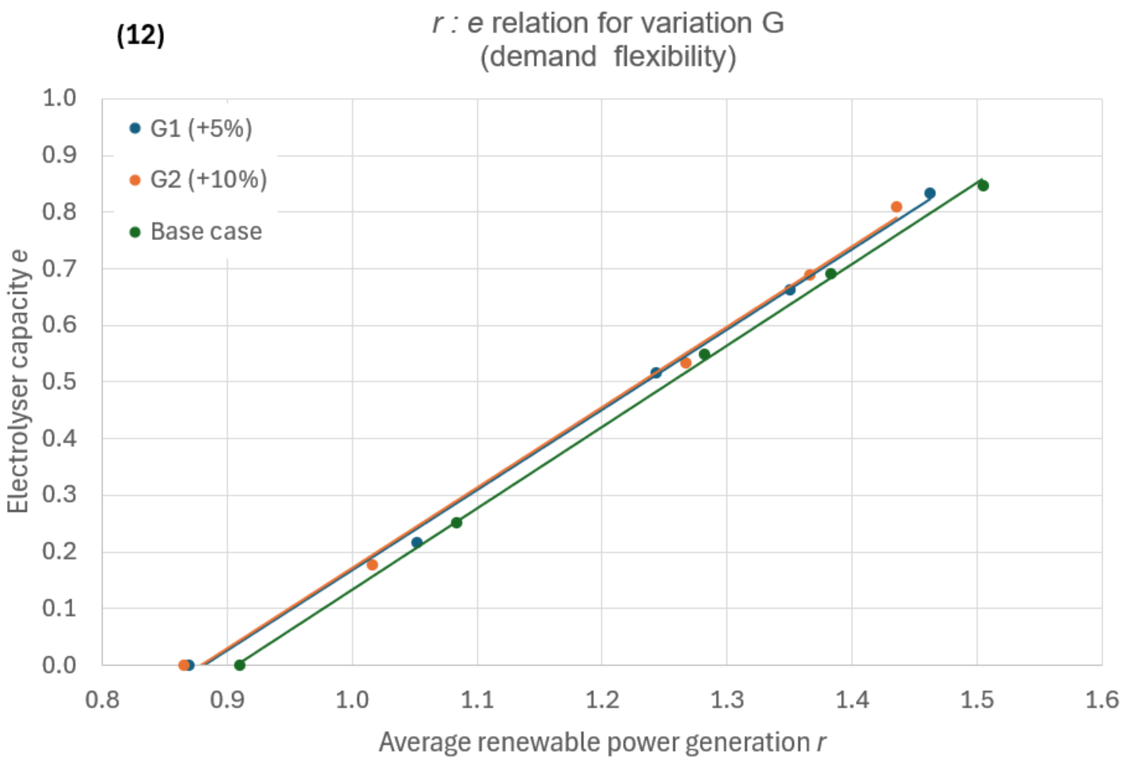
Appendix B1: Overview of runs and output for variations H and I of the sensitivity analysis.

B2. Plots of Sensitivity Analysis Runs

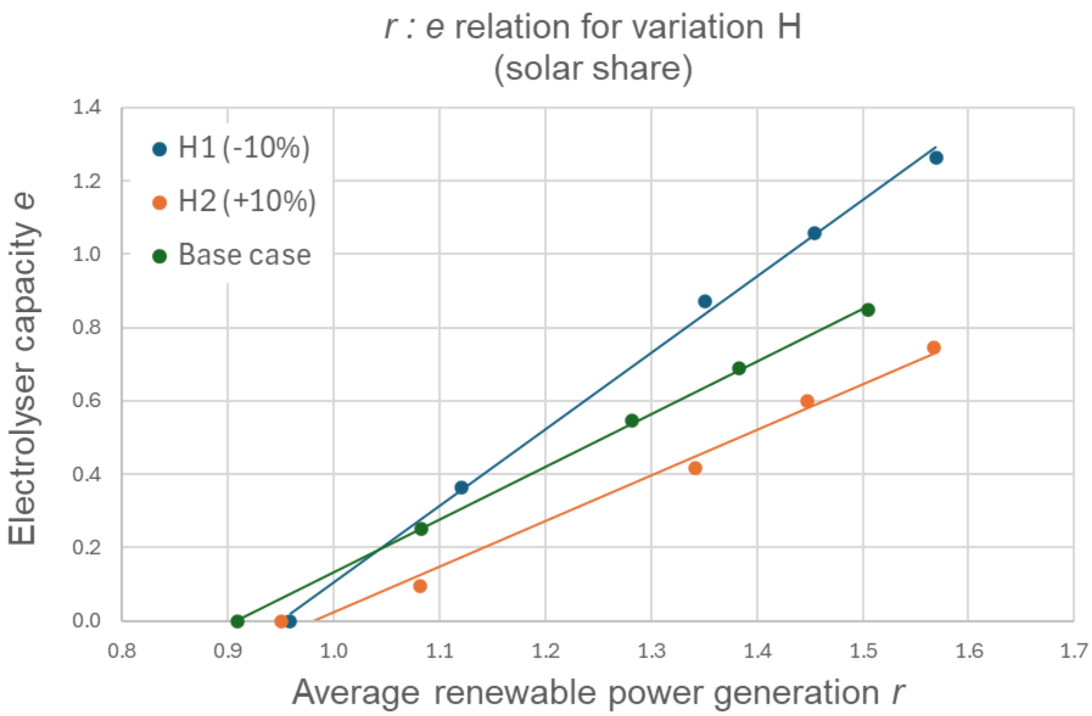


Appendix B2: r : e plot for variation F (electrolyser efficiency).

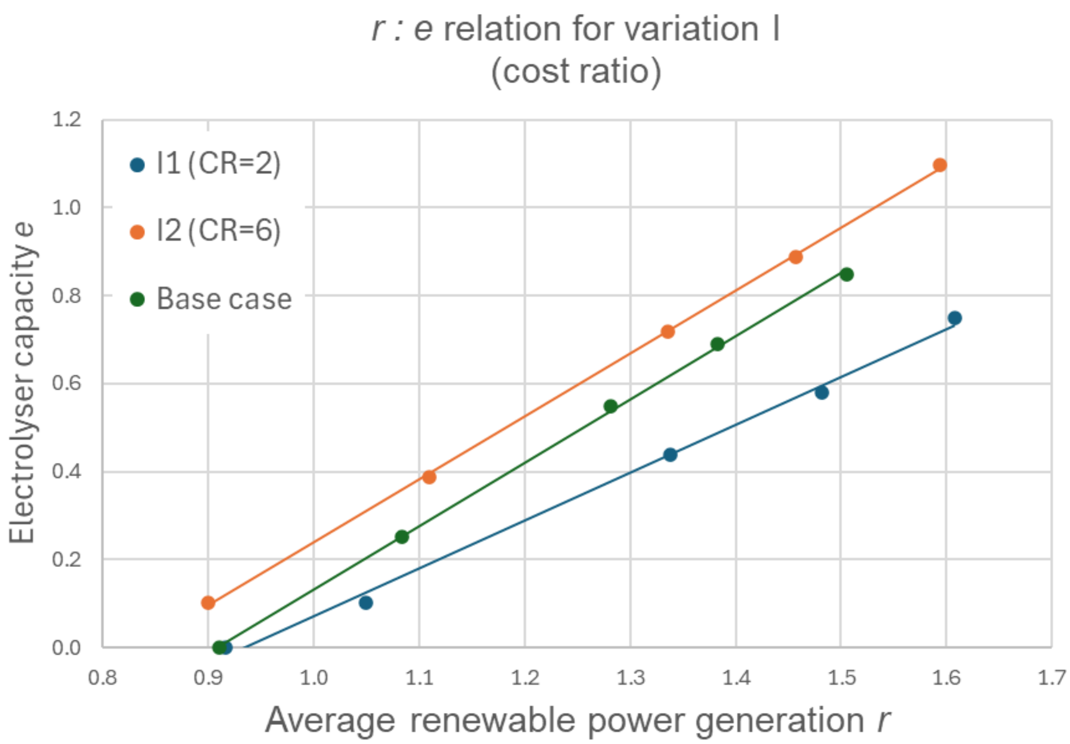
(12)



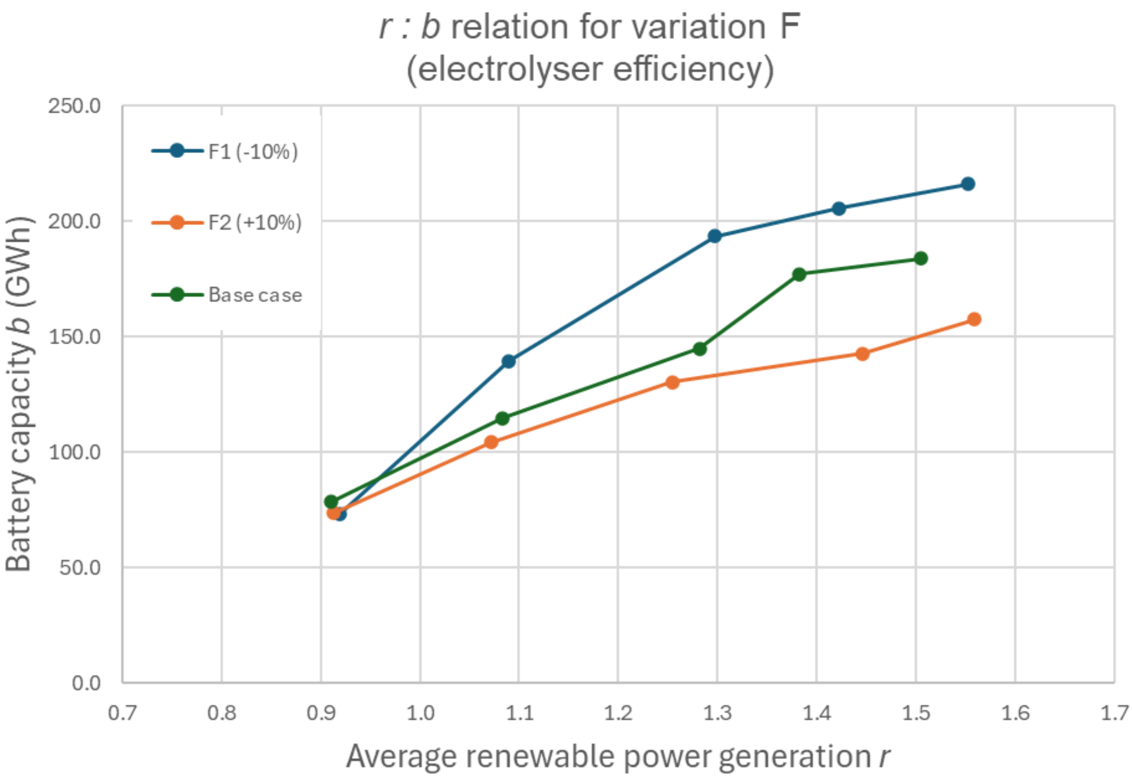
Appendix B2: r : e plot for variation G (demand flexibility).



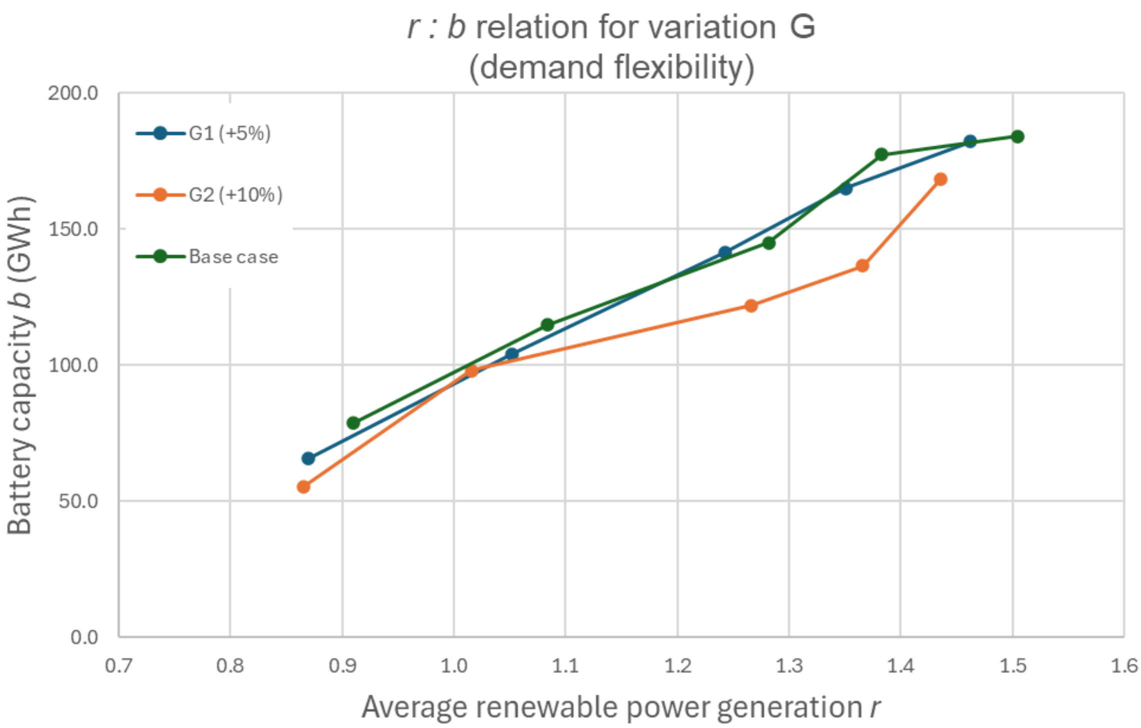
Appendix B2: r : e plot for variation H (solar share).



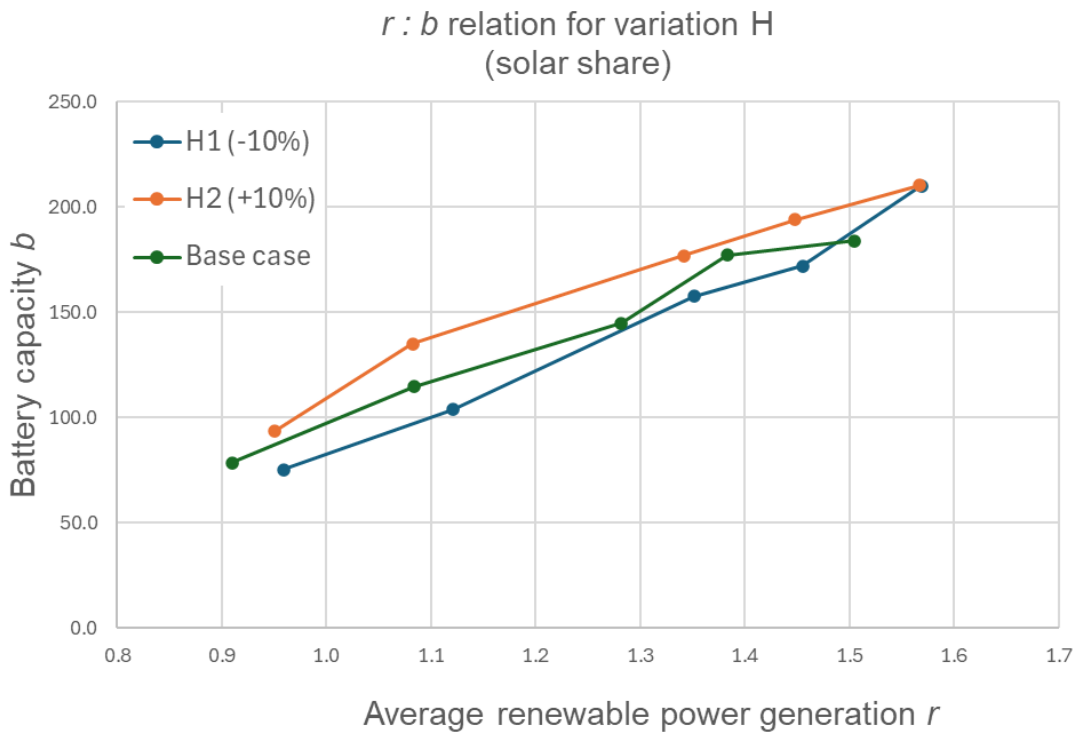
Appendix B2: r : e plot for variation I (cost ratio).



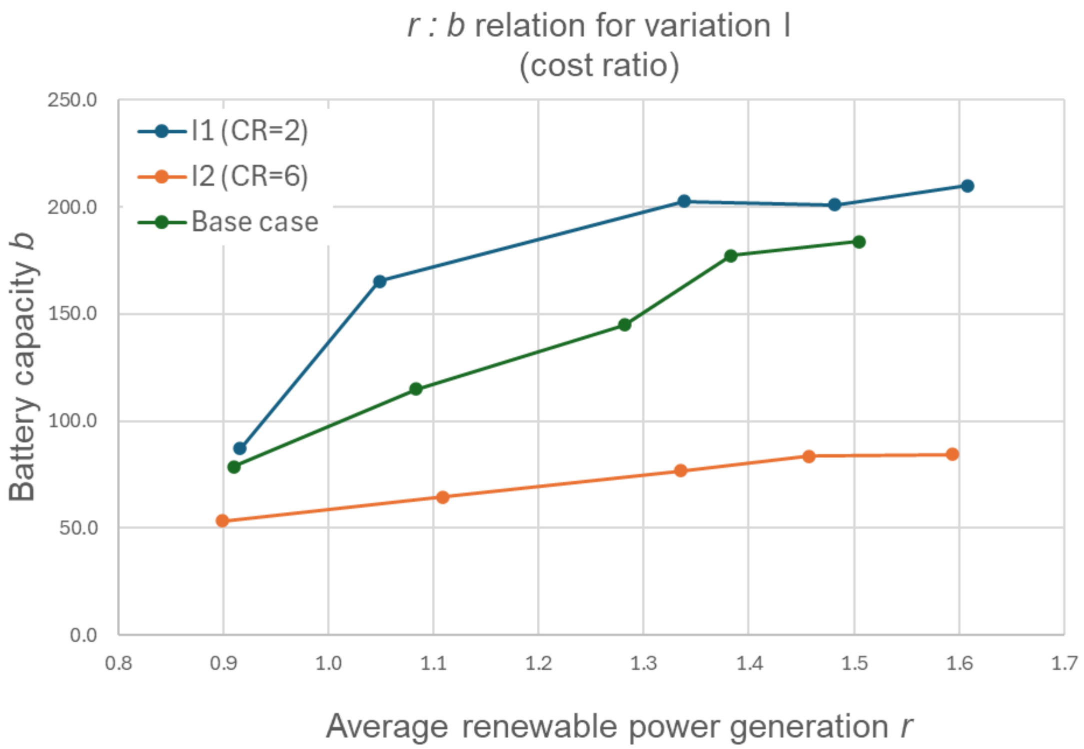
Appendix B2: r : b plot for variation F (electrolyser efficiency).



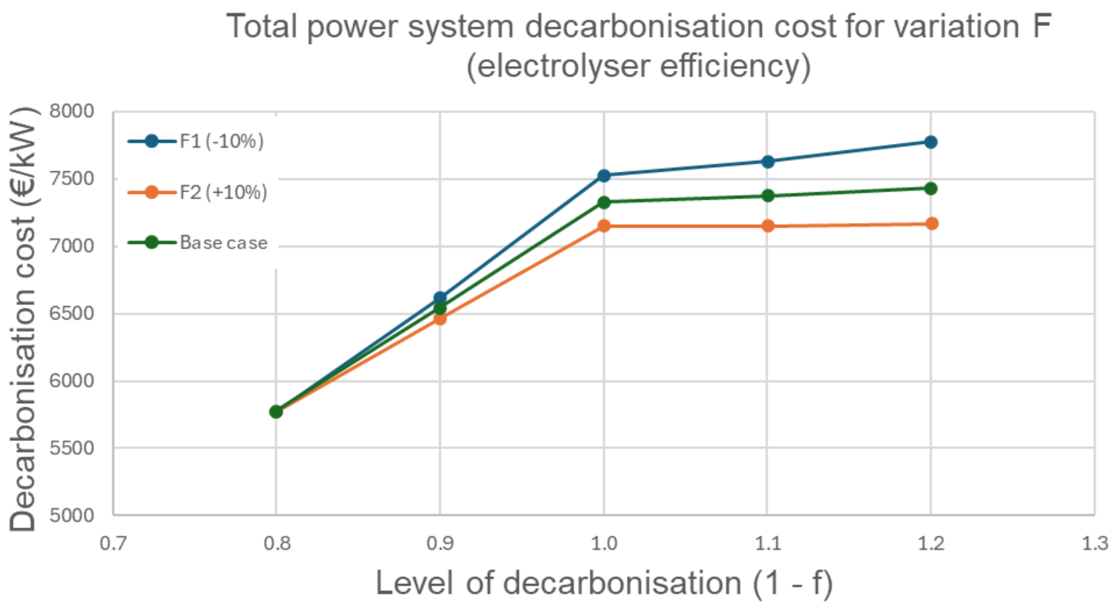
Appendix B2: r : b plot for variation G (demand flexibility).



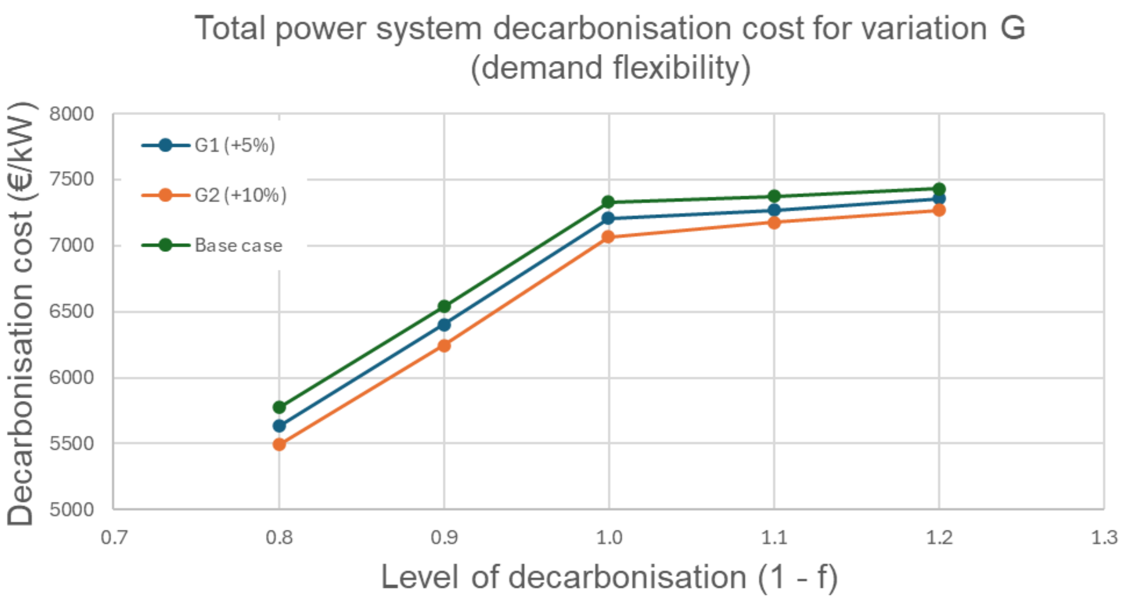
Appendix B2: r : b plot for variation H (solar share).



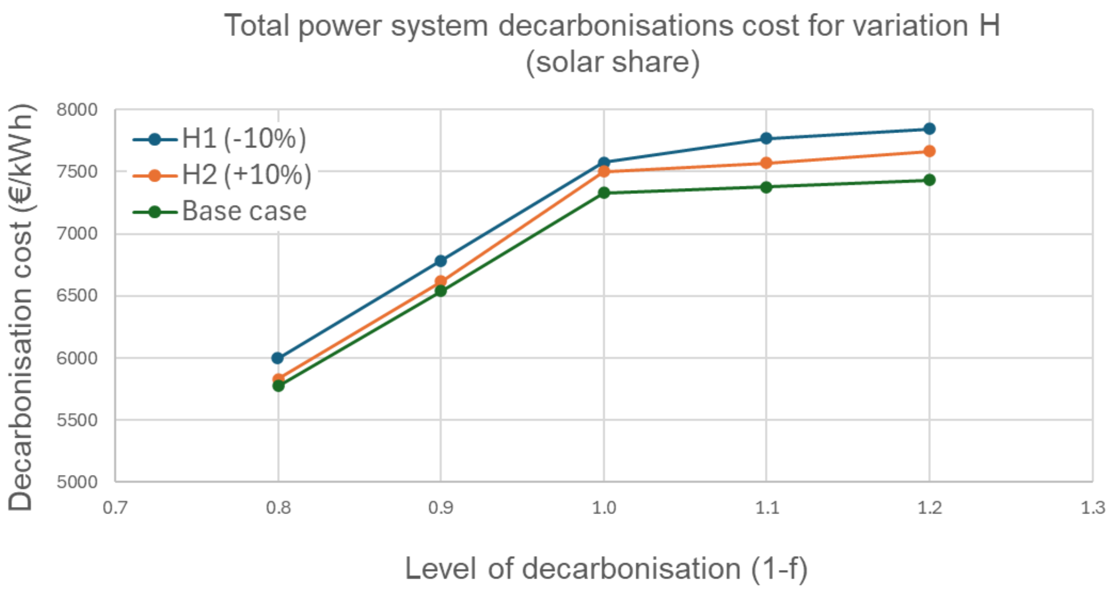
Appendix B2: r : b plot for variation I (cost ratio).



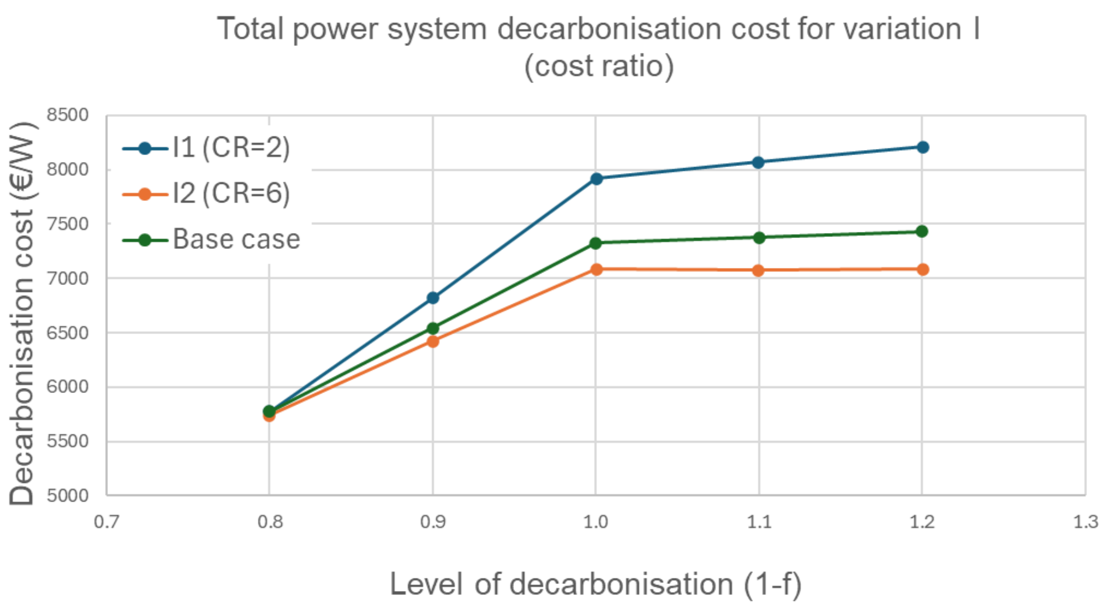
Appendix B2: Total power system decarbonisation cost for variation F (electrolyser efficiency).



Appendix B2: Total power system decarbonisation cost for variation G (demand flexibility).



Appendix B2: Total power system decarbonisation cost for variation H (solar share).

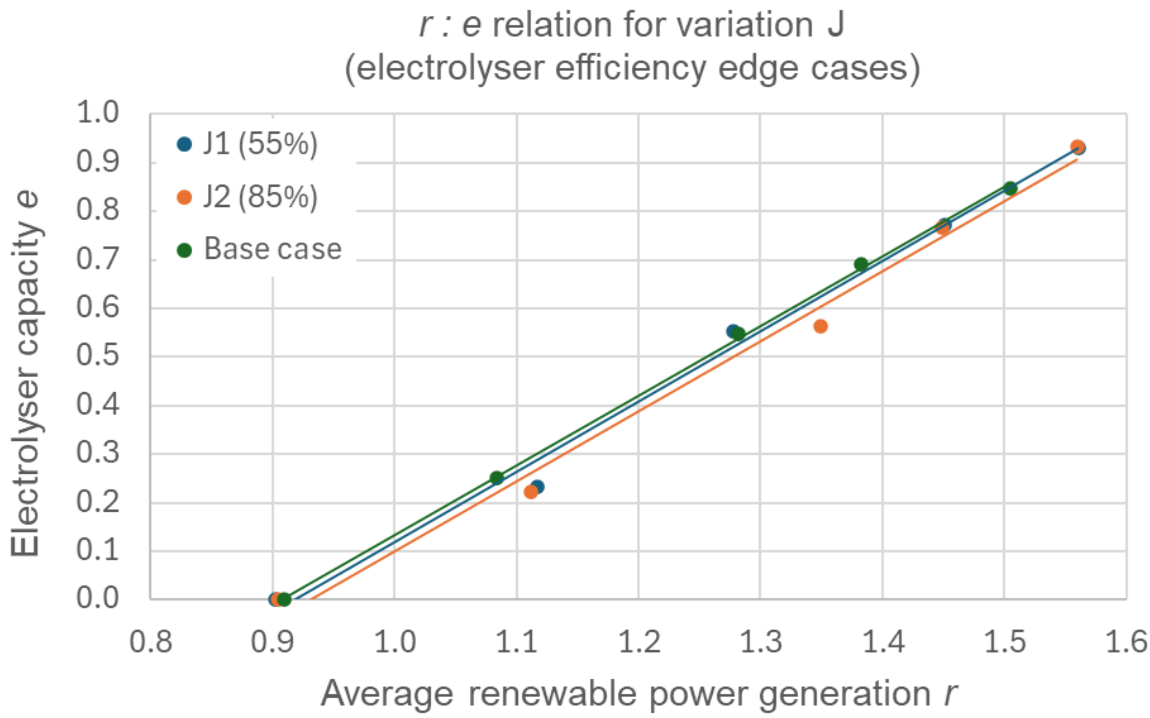


Appendix B2: Total power system decarbonisation cost for variation I (cost ratio).

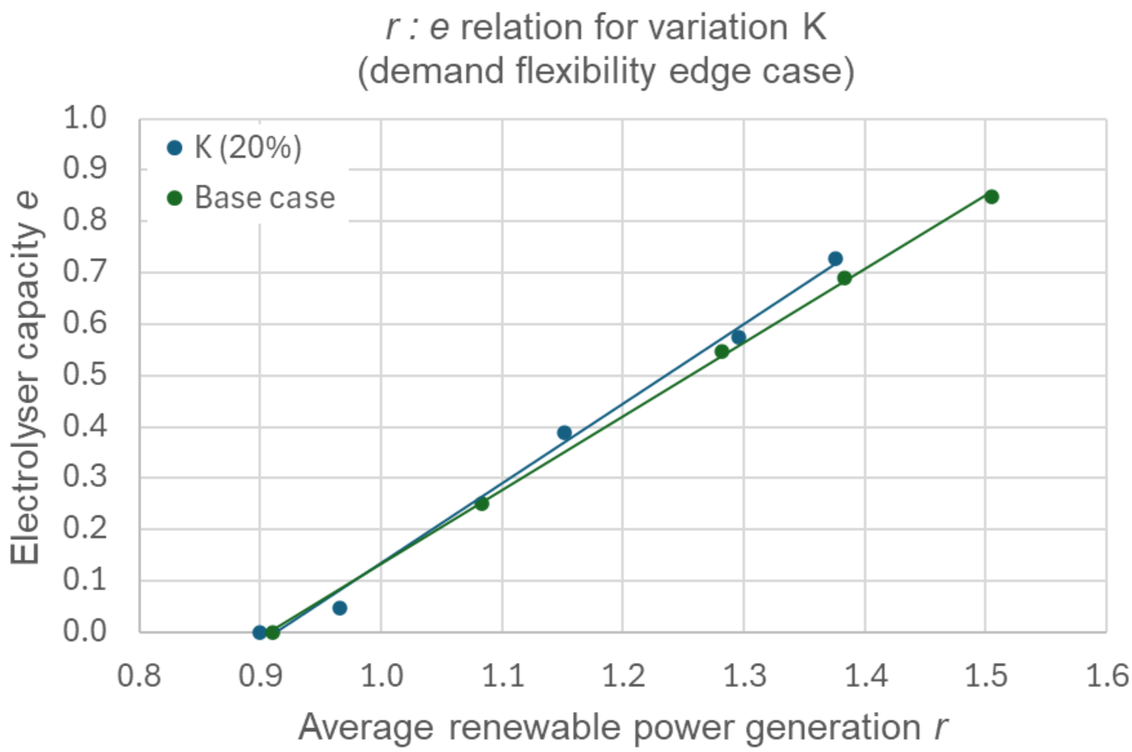
B3. Overview of Runs and Output of the Robustness Analysis

		Inputs					Outputs			
		Demand Fluctuations	Battery Interaction	Electrolyser Efficiency Curve	Hydrogen Storage Cost	Electrolyser Limitations	Renewable Capacity (R)	Electrolyser Capacity (E)	Battery Capacity (B)	Cost per kWh/h Decarbonisation (C)
J1	0.8	True	True	True	True	True	0.9025	0.0001	88.3	5767
	0.9	True	True	True	True	True	1.1170	0.2337	114.0	6694
	1	True	True	True	True	True	1.2777	0.5519	129.0	7728
	10% Excess	True	True	True	True	True	1.4510	0.7713	134.7	7896
	20% Excess	True	True	True	True	True	1.5609	0.9319	157.5	8139
J2	0.8	True	True	True	True	True	0.9040	0.0001	86.3	5767
	0.9	True	True	True	True	True	1.1119	0.2212	124.7	6393
	1	True	True	True	True	True	1.3496	0.5632	140.7	6974
	10% Excess	True	True	True	True	True	1.4486	0.7654	139.9	6936
	20% Excess	True	True	True	True	True	1.5601	0.9326	158.8	6916
K	0.8	True	True	True	True	True	0.9766	0.0001	48.7	5586
	0.9	True	True	True	True	True	0.9654	0.0483	81.9	6386
	1	True	True	True	True	True	1.1517	0.3881	121.1	7024
	10% Excess	True	True	True	True	True	1.2956	0.5739	139.0	7117
	20% Excess	True	True	True	True	True	1.3761	0.7284	153.4	7077

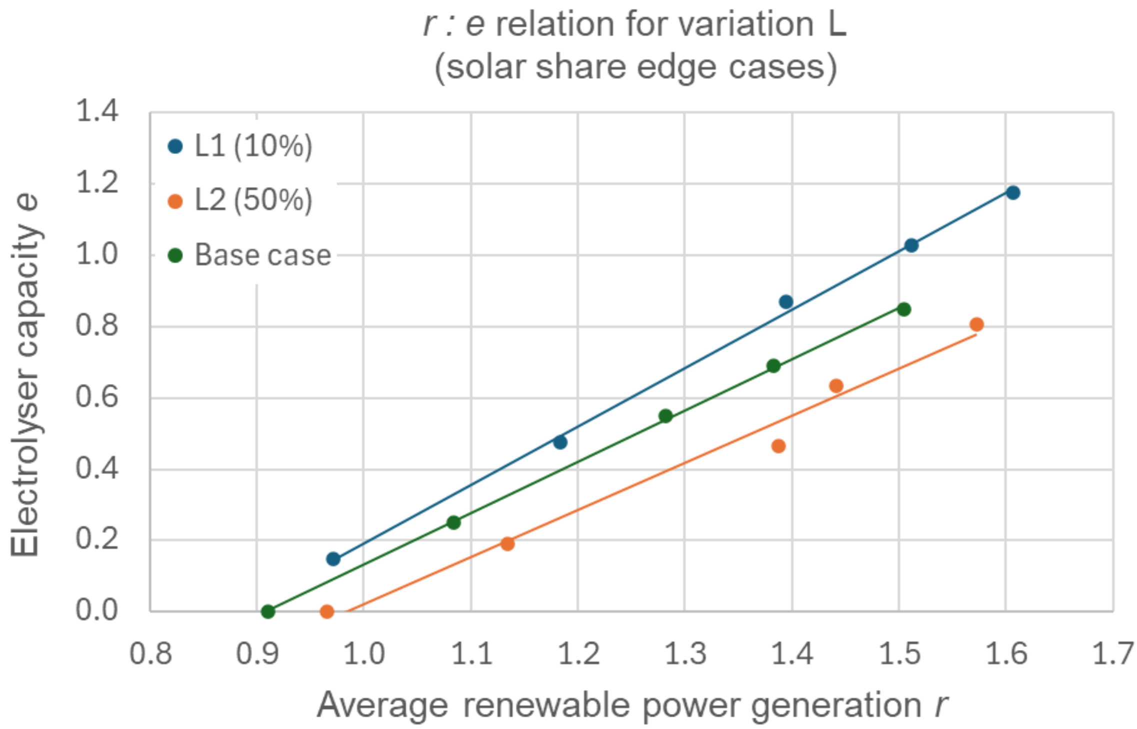
B4. Plots of Robustness Analysis Runs



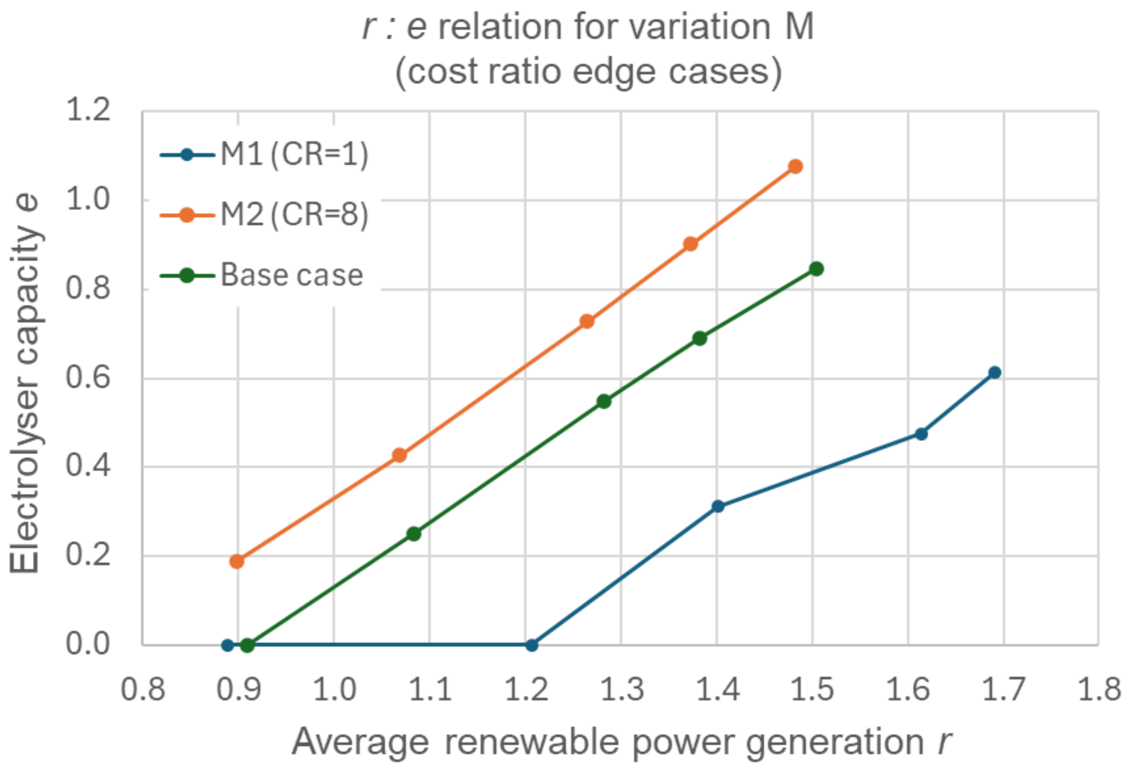
Appendix B4: r : e plot for variation J (electrolyser efficiency edge cases).



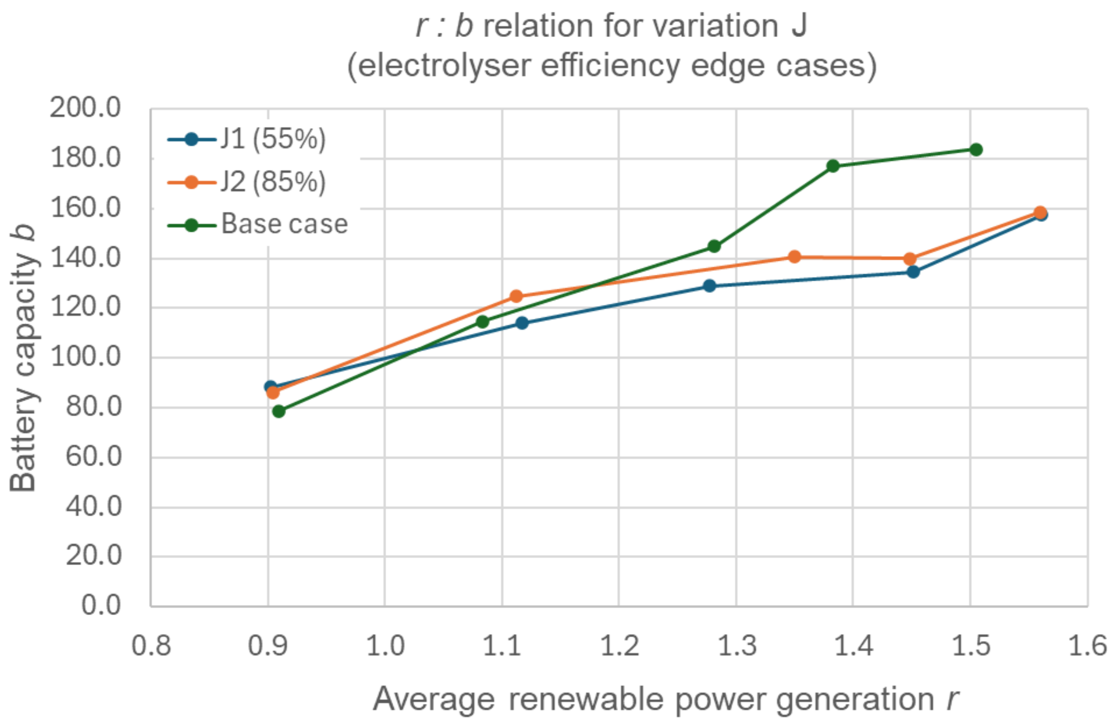
Appendix B4: r : e plot for variation K (demand flexibility edge case).



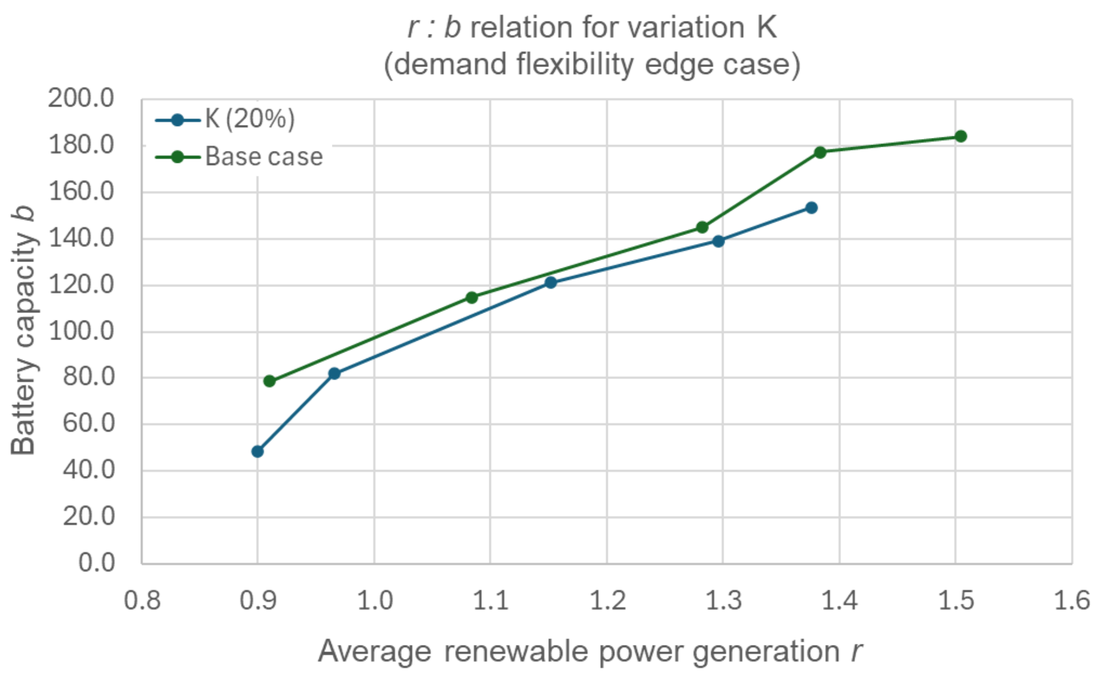
Appendix B4: r : e plot for variation L (solar share edge cases).



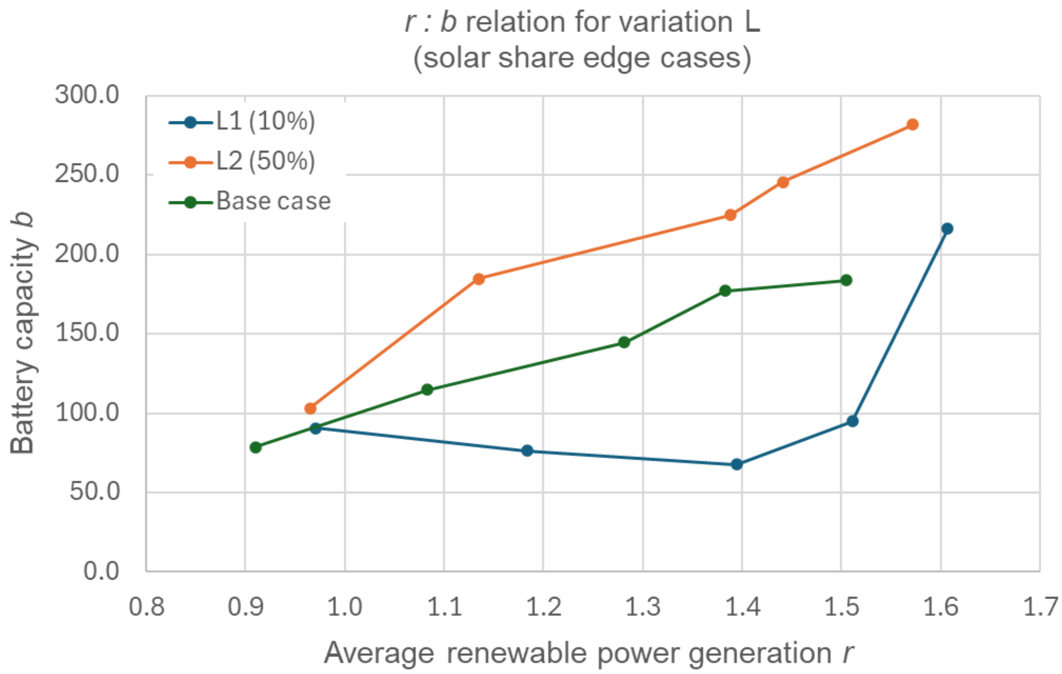
Appendix B4: r : e plot for variation M (cost ratio edge cases).



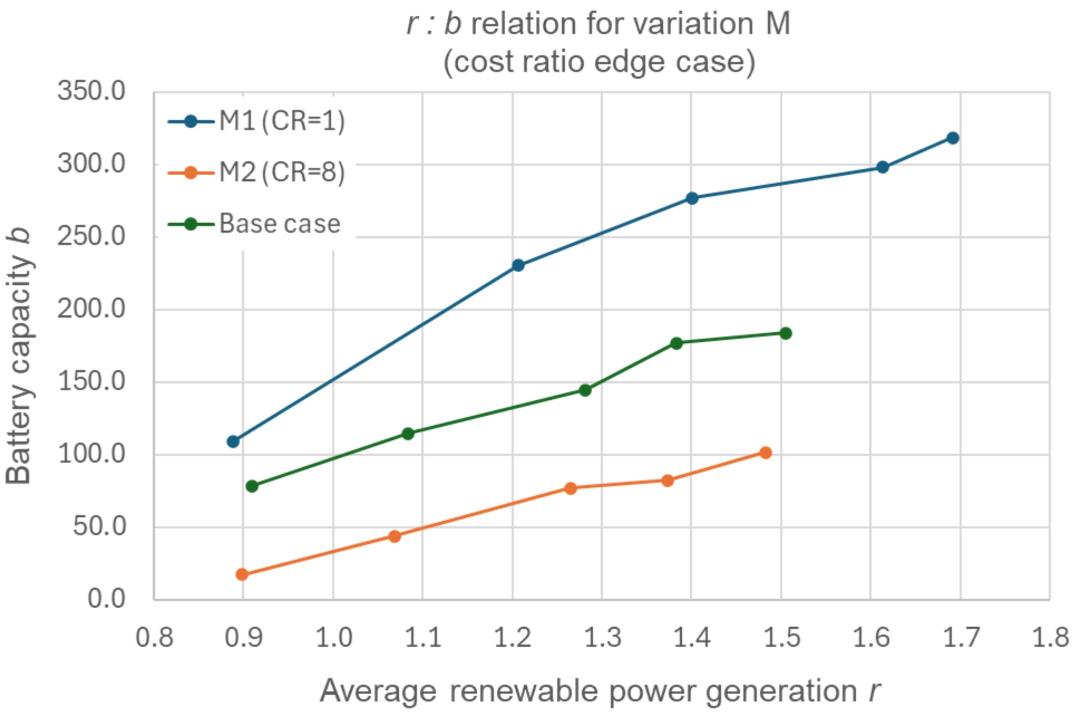
Appendix B4: r : b plot for variation J (electrolyser efficiency edge cases).



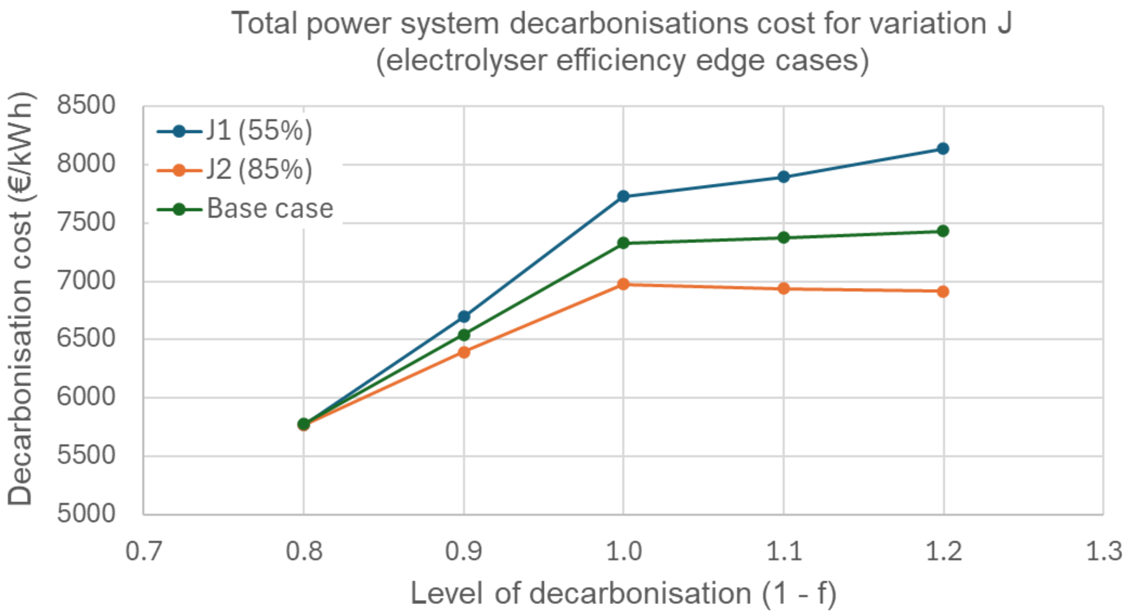
Appendix B4: r : b plot for variation K (demand flexibility edge cases).



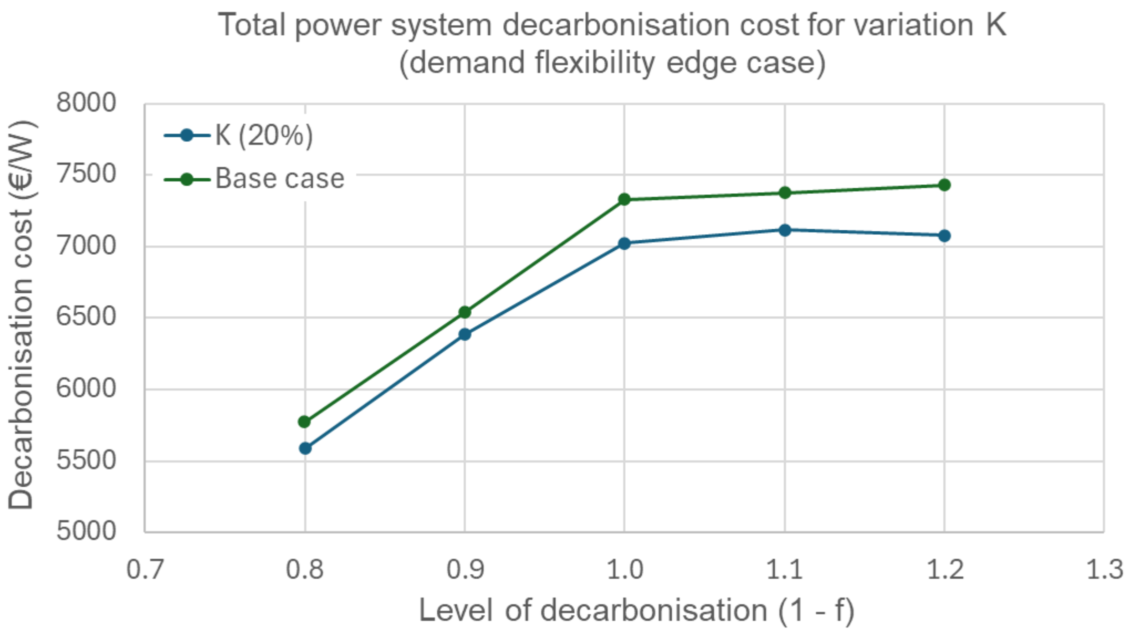
Appendix B4: r : b plot for variation L (solar share edge cases).



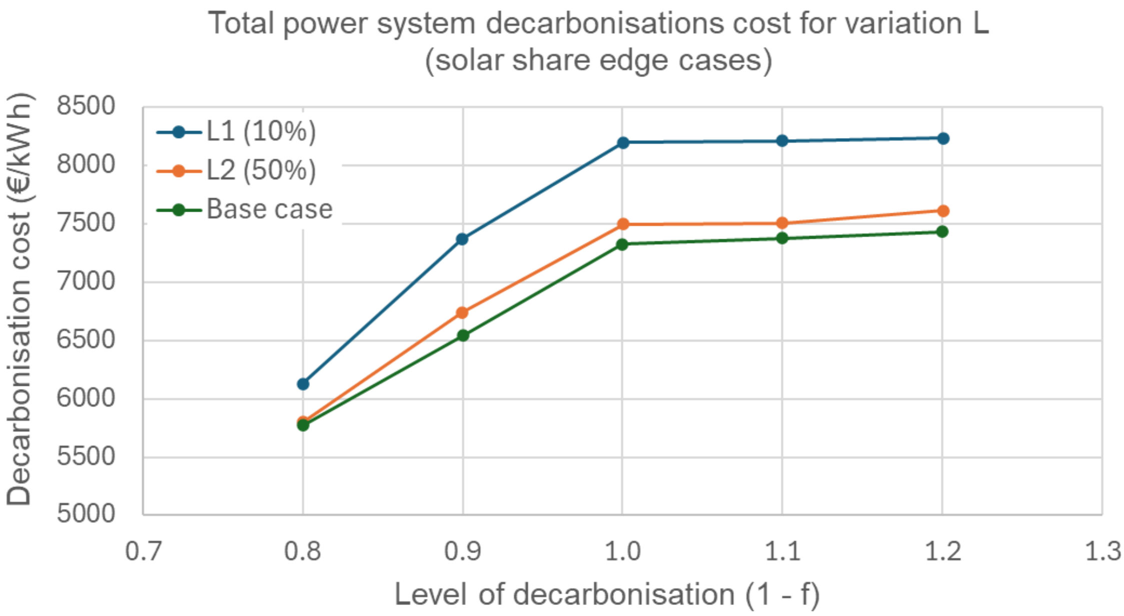
Appendix B4: r : b plot for variation M (cost ratio edge cases).



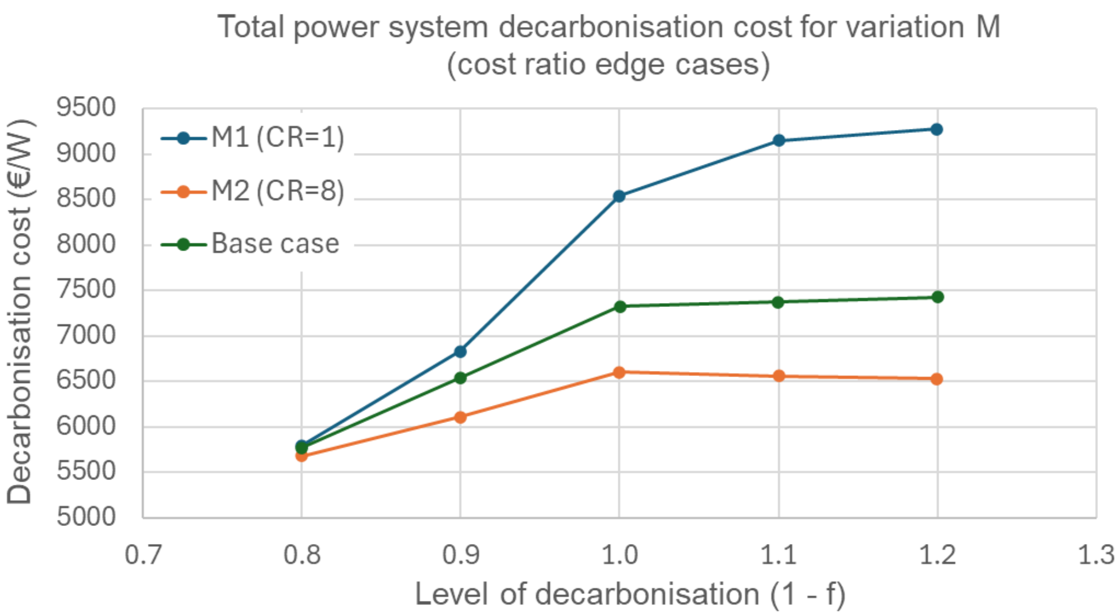
Appendix B4: Total power system decarbonisation cost for variation J (electrolyser efficiency edge cases).



Appendix B4: Total power system decarbonisation cost for variation K (demand flexibility edge cases).



Appendix B4: Total power system decarbonisation cost for variation L (solar share edge cases).



Appendix B4: Total power system decarbonisation cost for variation M (cost ratio edge cases).

C. Comparative Model Analysis

C1. MCA Longlist

Nr.	Name study	Author and year
1	Assessment for Connection Concepts for DE Far Out NS	E-Bridge (2024)
2	Floating Offshore Wind Outlook	IRENA (2024)
3	Global Offshore Wind Report	Global Wind Energy Council (2024)
4	Infrastructure and Financing of the North Sea	Energy and Climate Policy and Innovation Council (2024)
5	Integral Infrastructure 3050	Netbeheer Nederland (2023)
6	Integration of Renewable Energy Sources in future power systems: the role of storage	Weitemeyer et al. (2014)
7	Key Insights from the North Sea Integration Model	Fluxys (2024)
8	More Wind at Sea for Climate Neutrality	Agora Energiewende (2024)
9	Offshore Power and Hydrogen Networks for Europe's North Sea	Glaum et al. (2024)
10	Optimal hydrogen production in a wind-dominated zero-emission energy system	Weimann et al. (2021)
11	Pathway 2.0 Study	North Sea Wind Power Hub (2024)
12	Power sector effects of green hydrogen production in Germany	Kirchem & Schill (2023)
13	Role of Long-Duration Energy Storage in Variable Renewable Electricity Systems	Dowling et al. (2020)
14	Synergies of sector coupling and transmission reinforcement in a cost optimised, highly renewable European energy system	Brown et al. (2018)
15	System Integration Analysis for Programme VAWOZ	CE-Delft (2024)
16	Ten Year Network Development Plan	ENTSO-E & ENTSOG (2022)

C2. INT Scenario Description from the CE-Delft Study

“In this scenario, the Netherlands aims to develop its own economy by fully engaging with global energy and raw materials supply chains. The country acts as a 'multinational', strategically leveraging international energy and resource markets. Consequently, it seeks the lowest-cost options on the global market, with international free trade playing a key role. The market is supported through general incentives, subsidies, and carbon pricing — which also encourages Dutch companies to contribute to the sustainability of the supply chain.

Hydrogen and other climate-neutral energy carriers are imported from countries where they can be produced relatively cost-effectively. The Netherlands becomes a transit hub for hydrogen. In the built environment, the focus is on individual transition pathways, with less reliance on green gas and greater use of hybrid heating systems in combination with hydrogen.

The industrial sector decarbonizes through electrification and the use of hydrogen (also as a feedstock). As a result of global trade flows, some energy-intensive industries relocate abroad. Instead, the Netherlands imports more semi-finished products, which are further processed domestically. In addition, the country invests in the domestic production of green hydrogen, directly linked to offshore wind. (Netbeheer Nederland, 2023)”

C3. MET Scenario Description from the E-Bridge Study

“The scenario "Molecule-based energy transition" (MET) achieves the decarbonization until 2045 in line with the German policy targets by a strong(er) use of green gases (in comparison to CN). In line with the forecast of this transition scenario, a decisive share of current CH4 demand within the industry- and heating sector get substituted. Yet, the increased use of H2, especially in industry beyond material utilisation but also in some regions in the heating sector (e.g., heating networks) and in some parts of the heavy-duty transport sector leads to an overall higher level of hydrogen utilisation.

This development is also driven since limitations in acceptance of RES extension and a stronger push from society in the direction of (green-)gas applications for diversification, whole system efficiency, and cost reasons. The scenario has consequently a higher level of energy (hydrogen) import in the long run but therefore can manage to decrease the final onshore RES extension level (while maintaining it at a high level). A coal phase-out is reached latest by 2038.”

C4. DE Free Offshore Scenario Description from the NSWPH Study

The DE Free Offshore scenario expands on the Distributed Energy storyline by optimally scaling renewable and hydrogen infrastructure out to 2050. It endogenously determines offshore wind capacity, electrolysers, power and hydrogen transmission networks, and storage solutions to meet predefined annual electricity and hydrogen demand targets for 2030, 2040, and 2050. A modular, hub-and-spoke design is central to this scenario: multiple offshore hubs capture large-scale wind potential in the North Sea, convert surplus electricity into hydrogen near these sites, and transport both electricity and hydrogen via optimized HVDC and pipeline networks to shore. This layout enhances system integration by using electrolysers as flexible demand, improving offshore infrastructure utilization compared to more centralized alternatives