Evaluating investment performance under uncertainty for Battolyser Systems

A Value Driver Tree-Based Simulation Model

Master's thesis

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Evaluating investment performance under uncertainty for Battolyser Systems

A Value Driver Tree-Based Simulation Model

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Preface

This thesis marks the end of my Master's in Engineering and Policy Analysis at Delft University of Technology. Looking back, it has been a truly valuable and challenging journey. The last years, I dove into the world of solving complex challenges where technology and policy come together. With my bachelor's background in Life Science and Technology, I did not have the perfect knowledge and foundation. However, together with my friends, I dove into all the challenging and interesting topics

In the last part of my master programme, I decided to conduct an internship with Invest-NL. I want to thank Invest-NL for giving me the chance to do my research within their organisation. Looking back, it was the most valuable experience and I loved all the people I met there. I learned a lot about you as an inspiring group that works hard with the right passion. I really appreciated their support, openness and helpful feedback. A special thank you to Clayton at Invest-NL, who challenged me to think abstract and critically towards my work.

Then I want to say some words to my thesis committee members of TU Delft Rudi Hakvoort and Aad Correljé. First I want to thank Rudi who began the journey with me for my internship at the start. His experience and guidance helped me grow and focus on what was needed. In the begin our biweekly calls, became later weekly calls where you not only helped me content-wise but also with the whole project along. And then Aad, thank you for your guidance, knowledge and clear advice helped me grow during this project. I am very thankful for the critical but positive notes to guide me along. I hope to conduct a better insight in my chicken-or-egg story.

And of course to all my friends and family: thank you for always being there for me. Along the way, your support, laughter and care helped me stay positive, even during the difficult moments. Even the little moments or motivating phone calls and texts helped me more than you would know.

And finally, a special thank you to my mom and dad. You were always there when needed with a lot of love and support. I will not easily forget the days behind my laptop at the dinner table. Your belief in me made this possible. I couldn't have done it without you.

To the reader, have fun reading my research! In the end, it is a work I have become very proud of after all. It has taught me a lot and also about myself. I have delved into subjects I did not yet understand a lot about and hope the work will further contribute and inspire. :)

F.E. Adriaansens
Delft, June 2025

Summary

Context and relevance

There is an urgent need to develop flexibility in the electricity grid due to the increasing implementation of renewable energy, due to climate targets, which introduce greater variability and uncertainty in supply and demand. Current developments provide potential for the hydrogen market and the Netherlands is faced with the challenge of realising this on a large scale.

Despite national ambitions, choices about policies and investments in developing the technologies are lagging due to remaining uncertainties and risks. Many projects face delays due to technical, financial and regulatory barriers, risking stagnation in the broader energy transition. Invest-NL plays a catalytic role by investing at-risk capital in early-stage technologies aligned with societal and policy goals. One investment is made in Battolyser Systems, a dual-purpose technology that integrates electricity storage with hydrogen production. The technology addresses key grid challenges by dynamically responding to intermittent renewable availability.

However, further deployment is constrained by systemic barriers, highlighting the need for integrated, multi-actor strategies to unlock the full potential of such innovations. Instead of seeking a single optimal solution, policymakers facing uncertainty aim to develop policies that perform effectively across a range of conditions in early-stage markets.

Gap and research question

Due to uncertainties and risks, there is a barrier in investment decisions, underlining the need for structured analytical simulation model frameworks that support robust decision-making. The current literature shows the potential for exploratory model-based policy analysis with respect to the Value Driver Tree (VDT) model. This framework comes from value-based management theory to decompose the value drivers of a performance indicator. The research studies the coping with uncertainty through the use of simulation decision modelling to eventually implement these in VDTs that contain metrics of investment decisions.

This creates the main research question of:

> How can a value driver tree-based simulation model be designed and applied for investment performance of Battolyser Systems under uncertainty in the Dutch green hydrogen market?

Research approach

The research approach and objective are to obtain a VDT as a visual and causal framework with a techno-economic perspective toward the metric of the investment performance of the Economic Value Added (EVA). This makes it possible to explicitly and transparently link technical parameters, policy and economic value creation and eventually with environmental uncertainties. After the identification of the value drivers, the second part of the analysis is focused on the determination of the uncertainty factors. This is investigated through desk research and is linked to stakeholder analysis and the value drivers. Then the focus turns to a practical application as a simulation decision tool. Here, the requirements are created for the software implementations. Then the experiments are set up to test the model. This is done in three parts. First, the baseline analysis is conducted and supported by a sensitivity analysis to give insights into the influences of input parameters. Second, the uncertainty implementation is done using Monte Carlo simulations to create distributions within the model. And last, policy interventions are tested by implementing them into the adaptable VDT framework. Eventually, this facilitates data-driven decision-making that aligns technical feasibility with financial performance and societal objectives, to balance multiple objectives with overarching system goals.

Findings Value Driver Tree simulation model

The VDT approach provides a structured techno-economic framework that connects investment performance to system behaviour. It decomposes Economic Value Added into a hierarchical structure consisting of revenue, cost, and capital sub-trees. This allows for a transparent mapping of how technical, operational, and financial variables contribute to investment outcomes. These elements are integrated into a coherent simulation model that supports the causal interpretation of value creation in emerging technologies.

Based on a combination of policy review, literature insights and stakeholder analysis, five core uncertainties have been selected for further modelling. These include the electricity price, hydrogen price, unit capital costs, operating hours, and conversion efficiency of the Battolyser. Their relevance and variability across policy and investment concerns have made them suitable candidates for simulation under uncertainty.

The model formalises this structure computationally using a Monte Carlo simulation to quantify the impact of uncertain input parameters. Each element in the VDT is assigned to a mathematical operation or relationship, creating a replicable logic that generates distributions of Economic Value Added. The baseline results reveal a negative value, suggesting low investment viability under current assumptions. Sensitivity analysis shows that hydrogen price and operating hours have the highest influence, indicating areas where policy and market interventions can be most effective. The entropic analysis has added an important layer to the simulation by revealing not only which parameters drive the expected investment value but also which scenarios exhibit greater vulnerability or robustness under uncertainty.

Discussion

The model demonstrates that a VDT is a useful approach for evaluating investment feasibility in complex, uncertain systems with probabilistic and entropic metrics. It enables decision-makers to trace value creation through a clear causal hierarchy and explores the effects of uncertainty on project outcomes. However, the analysis remains limited by the availability and accuracy of data input. Parameters such as hydrogen price projections and utilisation rates are based on scenarios and benchmarks, rather than historical data, which limits the precision and the predictive capacity of the model.

Although the model successfully captures economic dynamics, it has not yet addressed social or environmental impacts. In addition, institutional dynamics such as evolving regulations, policy feedback or stakeholder negotiation processes are not incorporated. It would benefit from integration with dynamic and participatory modelling approaches.

Conclusion

This research shows that a simulation model based on a VDT offers a structured and transparent method for assessing the investment performance of Battolyser Systems in the Dutch green hydrogen sector. It identifies key value drivers under uncertainty, with hydrogen price, electricity costs, and operating hours emerging as decisive factors for investment viability.

To increase policy relevance and decision-making support, future development should integrate broader sustainability metrics, improve the quality of the input data and include dynamic institutional factors. These steps would improve the contribution of the model to support systemic innovation and adaptive policy design in energy transition contexts.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
CAPEX	Capital Expenditure
DCF	Discounted Cash Flow
EBIT	Earnings Before Interest and Taxes
EPA	Engineering and Policy Analysis
EVA	Economic Value Added
FID	Final Investment Decision
FLH	Full Load Hours
HNS	Hydrogen Network Services
H2	Hydrogen
CO2	Carbon dioxide
COGS	Cost Of Goods Sold
LCOH	Levelized Cost of Hydrogen
MCS	Monte Carlo Simulation
NPV	Net Present Value
NWC	Net Working Capital
NOPAT	Net Operating Profit After Taxes
O&M	Operation and Maintenance
OPEX	Operational Expenditure
R&D	Research and Development
ROIC	Return on Invested Capital
TSO	Transmission System Operator
UCC	Unit Capital Cost
VDD	Value Driven Design
VDT	Value Driver Tree
WACC	Weighted Average Cost of Capital

Symbol	Definition	Unit
P_{batt}	Installed battery system capacity	MW
P_{el}	Installed electrolyser system capacity	MW
η_{bat}	Battery round-trip efficiency	[–]
η_{el}	Electrolyser conversion efficiency (electricity per kg H_2)	MWh/kg
E_{total}	Total electricity consumption	MWh
p_{elec}	Electricity market price (excluding fees)	€/MWh
p_{H_2}	Hydrogen selling price	€/kg
τ_{TSO}	Transmission system operator tariff	€/MWh
τ_{HNS}	Hydrogen network tariff	€/kg
$C_{\text{unit,el}}$	Unit CAPEX for electrolyser system	€/MW
$C_{\text{unit,batt}}$	Unit CAPEX for battery system	€/MW
$C_{\text{O\&M}}$	Fixed operation and maintenance cost	€/year
$c^{\text{unit}}_{\text{O\&M}}$	O&M cost per MW per year	€/MW/year
γ_{stack}	Stack replacement cost (fraction of CAPEX)	[–]
δ	Annual performance degradation	%/year
τ	Corporate income tax rate	%
ϕ_{rev}	Revenue-based fee or system cost	% of revenue
R_{total}	Total annual revenue	€/year
R_E	Electricity storage revenue	€/year
R_{H_2}	Hydrogen electrolysis revenue	€/year
q_E	Electricity sold to grid	MWh/year
q_{H_2}	Hydrogen production	kg/year
C_{elec}	Electricity cost	€/year
C_{grid}	Grid cost (electricity + hydrogen)	€/year
C_{el}	Electricity grid cost component	€/year
C_{H_2}	Hydrogen network cost component	€/year
E_{bat}	Electricity output from battery	MWh/year
m_{H_2}	Mass of hydrogen produced	kg/year
C_{depr}	Depreciation cost	€/year
r_{deg}	Annual degradation rate	[–]
f_{rep}	Stack replacement fraction	[–]
K_{invested}	Total invested capital	€
K_{fixed}	Fixed capital investment	€
K_{working}	Working capital	€
c_{CAPEX}	Specific capital cost	€/MW
α	Working capital ratio (share of revenue)	[–]
r_{WACC}	Cost of capital applied in simulation	%/year

List of Figures

List of Tables

1 Introduction

This chapter introduces the societal and academic context in which the research is situated. It outlines the central problem and highlights the relevance to establish the direction of the study. The purpose of this chapter is to provide a coherent foundation that justifies the need for research and frames the subsequent chapters.

1.1. Background to the research

The global energy market is undergoing a rapid transformation, driven by climate targets, international commitments and policy mandates that aim to mitigate climate change. This transition requires profound systemic changes. Renewable energy sources such as solar and wind have immense potential to decarbonise the electricity sector in the Netherlands (Invest-NL, 2024). However, their inherent variability depends on weather conditions and creates significant fluctuations in the electricity grid, posing challenges to stability and efficiency (Alam et al., 2020).

Hydrogen offers a promising solution to balance the volatility of renewable electricity generation. As a flexible energy carrier, hydrogen enables the decoupling of electricity production and consumption through storage or conversion. In particular, electrolysers create potential as they can convert excess renewable electricity into hydrogen to support grid stability and sector coupling (Mulder et al., 2017). According to the Draghi report on the future of European competitiveness, hydrogen is essential to Europe's industrial decarbonization strategy (Draghi, 2024). The report emphasises the importance of large-scale investments in green hydrogen production, which is critical to reduce the dependence of Europe on imported fossil fuels and improve long-term energy resilience (Draghi, 2024). In line with this strategy, by 2030 the Netherlands has committed to developing a 3 to 4 GW electrolyser capacity under the Dutch Climate Agreement (Invest-NL, 2024).

Despite these ambitions, implementation towards this goal lags. To date, only one major Final Investment Decision (FID) has been reached in the Netherlands, while many other projects face delays (Invest-NL, 2024). Without decisive action, the country risks missing its targets, which can reflect broader stagnation in the energy transition and its supporting market mechanisms (Mulder et al., 2017).

Invest-NL, a national Dutch investment institution, plays an essential role in overcoming these barriers by combining financial instruments with strategic alignment with social and policy goals (Invest-NL, 2024). As part of its mission to stimulate innovation-driven transitions, Invest-NL acts as a market-shaping intermediary by deploying derisking capital in areas where private financial markets have yet to mature. Such interventions are critical in bridging the gap for high-potential but unproven technologies. Consequently, they support system innovations that may offer significant long-term societal and environmental benefits.

Concerning the trust and interest in the potential of the Dutch hydrogen market. Invest-NL has invested in Battolyser Systems (Origins, 2024). Battolyser Systems is an emerging dual-purpose technology that integrates electricity storage and hydrogen production. Battolyser Systems secured €30 million in Series A funding from investors such as Global Cleantech Capital, Innovation Industries and Invest-NL (Origins, 2024). This substantial financial backing underscores the confidence in Battolyser technology as a viable solution for green hydrogen production. Furthermore, the company has a €40 million financing agreement with the European Investment Bank (EIB), further solidifying its role in the Dutch hydrogen transition (Origins, 2024).

Battolysers offer a solution to important grid problems, such as the limited storage capacity of low-voltage networks, high reinforcement costs and the instability caused by distributed renewable generation. (Tomar et al., 2021). Battolyser technology is designed to dynamically switch on and off following intermittent renewable energy availability. This flexibility allows for optimised hydrogen production while mitigating the risk associated with fluctuating energy prices. So, the combination can reduce the pressure on the electricity grid by enabling a more flexible and localised energy management (Mulder et al., 2017). Moreover, in contrast to separate battery and electrolyser units, such systems can operate more continuously over time, which is often used less consistently.

However, their deployment is hindered by technical, financial and regulatory barriers, underscoring the need for a systemic and multi-actor approach (Mulder et al., 2017). One of the core barriers is the economic viability. Electrolysers remain capital-intensive, with current capital expenditures ranging from €800 to €1200 per kW for PEM and alkaline technologies (International Renewable Energy Agency, 2022). In addition, electricity costs often consist of 50–70% of the total costs of hydrogen production, making profitability highly sensitive to market dynamics (Vartiainen et al., 2020). The Levelized Cost of Hydrogen (LCOH) for green hydrogen is still higher than that for grey (fossil-based) hydrogen, which limits competitiveness in the absence of strong carbon pricing or specific subsidy mechanisms. (Hydrogen Council, 2021).

Moreover, coordination of the hydrogen policy network is a key challenge in the hydrogen economy. Ensuring the participation and commitment of key actors as the industry, investors and regulators is difficult. Many policy dialogues have the potential to foster iterative learning and strengthen credibility and decision making, but lack continuity and institutional grounding (Lee, 2023). The development of this flexibility in the grid and large-scale engineered systems involves complex coordination of objectives across stakeholders. An effective intervention design must reduce investor risk in the short term while fostering long-term cost reductions through learning effects and economies of scale (BloombergNEF, 2023). Conventional approaches, which decompose stakeholder requirements into isolated components, often fail to capture systemic interdependencies and lead to misalignment between local and global objectives.

As with any new market, the value chain for green hydrogen is not fully structured. Building a robust hydrogen value chain in Europe is not only important for reducing greenhouse gas emissions here, but also for ensuring European energy security and preserving European competence within clean energy technologies (Jensen, 2024). Adopting a transdisciplinary approach is critical to aligning local initiatives with broader sustainability objectives. Such approaches reveal synergies and trade-offs between localised and system-wide actions, enabling informed and coordinated efforts towards grid stability and market development (Bandari et al., 2024).

The successful implementation of green hydrogen technologies requires navigating through multiple barriers, which underscores the current uncertain operational environment. To address these limitations, a value-driven design (VDD) approach is necessary, which integrates decomposable value functions to represent stakeholder preferences and system-level trade-offs (Sherafat & Elahi, 2018). This facilitates decision-making that aligns technical feasibility with financial performance and societal objectives. The underlying influence and impact can be measured by indicating the value drivers of a system performance (Matthies, 2024). The goal is to balance individual objectives with the overall system goals (Sherafat & Elahi, 2018).

1.2. Research gap

The transition to a low-carbon economy in the Netherlands requires a large-scale deployment of green hydrogen, a critical energy carrier produced by electrolysis. However, the widespread adoption of electrolyser technologies faces significant barriers, including high capital costs, fluctuating external factors such as electricity prices and uncertain policy incentives.

Existing policy frameworks aim to support the transition, but their effectiveness is uncertain in the face of volatile market conditions and evolving technological environments. The lack of robust policy design that accounts for uncertainty in future energy markets, demand for hydrogen and the stability of subsidies raises the risk of suboptimal investments and inefficient use of public funds. This uncertainty and risk continue to hinder investment decisions, underlining the need for structured analytical frameworks that support robust decision-making in early-stage markets. The proposed research question is therefore:

How can a value driver tree-based simulation model be designed and applied to the investment performance of Battolyser Systems under uncertainty in the Dutch green hydrogen market?

1.3. Research objective

This research uses the Value Driver Tree (VDT) methodology to structure the analysis of how key business and technical drivers influence system performance, financial viability and energy system resilience. The VDT model provides a transparent and hierarchical framework to quantify relationships between variables and assess trade-offs between complex socio-technical systems (Cheung et al., 2010). By structuring these drivers, the VDT allows for a clearer understanding of the direct and indirect relationships among cost culture, generation of revenue and external market conditions. This helps identify which drivers require intervention to optimise the overall profitability (Matthies, 2024).

Through a VDT framework, this study investigates the systemic value proposition of such technologies and explores the conditions under which they can contribute to an efficient, scalable and resilient energy transition. Through this alignment of individual and systemic value creation, the study seeks to enhance the integration of renewable energy technologies, improve grid resilience and accelerate the energy transition in the Netherlands. This approach underscores the importance of balancing innovation with risk management to achieve a sustainable and robust energy future.

1.4. Relevance

From a societal perspective, the rapid deployment of renewables is necessary to meet international climate agreements such as the Paris Agreement. However, the inherent intermittent and decentralised nature of wind and solar power poses significant challenges to the stability, reliability and affordability of future energy systems (Alam et al., 2020). These challenges are not only technical but also socio-economic, affecting energy justice, industry competitiveness and public confidence in the transition (International Renewable Energy Agency, 2020). Supporting technologies, such as electrolysers, Battolysers and smart grid integration, play an important role in mitigating these risks, but require targeted, inclusive and timely investment strategies.

From a scientific perspective, this research contributes to a better understanding of how value is created, transferred and transformed within socio-technical energy systems. Existing research often focuses on techno-economic optimisation or policy alignment in isolation. This study fills a knowledge gap by operationalising Value-Driven Design (VDD) within a Value Driver Tree (VDT) framework, which enables the structured decomposition and quantification of value creation pathways. This extends recent work on causal modelling and systemic value trade-offs in uncertain multi-actor environments, such as Akkiraju and Zhou, 2012; Collopy and Hollingsworth, 2011; Matthies, 2024.

The research is specifically aimed at uncovering the dynamic interaction between the underlying technical, financial, infrastructural and regulatory value drivers in the deployment of green hydrogen technologies. By simulating and analysing these interactions, the research supports the development of more robust and adaptive decision-making models for policymakers, investors and technology developers.

This approach aligns closely with the objective of the Engineering and Policy Analysis (EPA) programme to address 'wicked problems': complex societal challenges characterised by dynamic feedbacks, stakeholder conflicts and high uncertainty. The empirical focus on the Dutch hydrogen sector and Battolyser Systems provides a current example of a socio-technical innovation caught between high system relevance and institutional misalignment. Understanding how such technologies can be better supported through integrated value modelling contributes directly to both policy learning and transition management.

Finally, this research improves the ability of the modelling system to generate insightful and stakeholder-relevant results. By combining system dynamics with value-based analysis, the VDT model developed in this research enables users to visualise, quantify and simulate how value flows and bottlenecks arise across technological, economic and regulatory layers. As a result, it supports more transparent and evidence-based designs of investment and policy strategies in emerging markets with high levels of uncertainty.

1.5. Structure of the report

Now that the research statement has been established, the report is structured to provide comprehensive answers to the central question. It begins with the theoretical framework (chapter 2), which introduces the value driver tree approach and reviews the relevant literature on investment decisions and specifics of Battolyser Systems. This is followed by the methodology section (chapter 3), which states the subquestions and outlines the research design, data and explicitly defines the research boundaries.

Then, the report transitions to applied analysis, which begins with the identification of the value drivers (chapter 4) and states the conceptualisation of the value driver tree and explores key concepts and relationships. This is followed by the declaration of the uncertainty and boundary conditions (chapter 5), development of the simulation model (chapter 6) and then by the results (chapter 7). The report ends with the discussion of the findings (chapter 8) and conclusions (chapter 9), to ensure that each side of the research is addressed. Finally, the overall research is reflected (chapter 10)

2

Theoretical framework

This chapter reviews the relevant academic literature to define key concepts, explore theoretical discussions and identify knowledge gaps. Based on this critical review, it develops a conceptual or analytical framework that informs the research design and guides the analysis. The theoretical foundation serves as a lens through which the research problem is understood and interpreted.

2.1. Defining key concepts

For theoretical understanding, the specifications of the concepts in the system context need to be clarified. A concept-based search strategy was used to ensure a comprehensive and focused review of the literature. Four main concept clusters were defined based on the theoretical focus of the study: value modelling, investment in uncertainty, simulation for decision support and green hydrogen systems. For each cluster, relevant keywords were identified and combined using Boolean operators (AND, OR) to balance breadth and specificity. The concepts with the corresponding keywords for the search words are stated in Table 2.1.

Table 2.1: Search strings per concept cluster

Concept cluster	Search string (Boolean logic)
Value driver modelling	(”value driver tree” OR ”value driver analysis” OR ”causal value modelling”) AND (”investment” OR ”performance analysis” OR ”simulation model”)
Simulation for decision support	(”simulation-based decision making” OR ”decision support model” OR ”system dynamics” OR ”stakeholder-informed simulation”) AND (”policy analysis” OR ”technology investment” OR ”hydrogen market”)
Investment under uncertainty	(”investment decision-making” OR ”strategic investment”) AND (”uncertainty” OR ”risk assessment” OR ”market volatility” OR ”sensitivity analysis”)
Green hydrogen systems	(”green hydrogen” OR ”renewable hydrogen”) AND (”Battolyser” OR ”electrolyser investment” OR ”Dutch hydrogen market” OR ”hydrogen technologies”)

This approach allowed interdisciplinary literature searches while maintaining relevance to the research question, further specifications are given in Appendix A. The frequency of key indicators within the title and abstract demonstrates that this is an emerging but increasingly relevant topic in research. Its relevance is determined based on three criteria: the year of publication, the utilisation of published academic articles that are peer-reviewed and the volume of citations and references.

This literature review synthesises research contributions related to the Value Driver Tree (VDT) model, its applications and role in optimising performance. The VDT has gained significant attention as a tool for enhancing business data analysis, performance measurement and decision-making. In addition, it explores the integration of robustness in decision-making with VDTs to address uncertainty in investment planning. The foundation is laid for the uncertain environment within the investment performance in the hydrogen sector. Last, this is specified towards the technological development of Battolyser

Systems.

2.2. Value Driver Tree model

VDTs in systems engineering have evolved from the concept of Value-Driven Design (VDD), which emerged as a movement to enhance systems engineering processes, such as in the aerospace sector (Collopy & Hollingsworth, 2011). VDD employs economic theory to enable rational decision-making and optimise large system designs (Cheung et al., 2010).

VDTs serve as conceptual models for structuring causal relationships among business performance indicators. Akkiraju and Zhou (2012) describes VDTs as abstract, indicator-based frameworks that facilitate financial and operational assessments. By mapping key value drivers and their interdependencies, VDTs enable businesses to visualise and quantify performance metrics effectively (Matthies, 2024). Grimaldi et al. (2013) emphasises the importance of selecting relevant value drivers, defining strategic importance and interrelationships when constructing VDTs and constructing indices to monitor performance. VDTs provide a structure for modelling accounting and financial data in the form of a logical system by enabling a strong data-driven statistical mapping of the systemic cause-and-effect relationships of business models (Wobst et al., 2023).

2.2.1. Current developments VDT in performance management

Some selected studies are examined to develop a Value Driver Tree framework to measure financial performance in complex systems. The studies cover multiple industries and methods, offering perspectives on how value is created and measured in complex technological systems. The literature trend of the framework is analysed with the papers chosen to be relevant for the scope of this research.

VDTs have been applied in outsourcing Information Technology services, to measure the quality of service solutions using ten dimensions and associated metrics (Akkiraju & Zhou, 2012) and manufacturing performance evaluations (Waldron, 2010). Despite their widespread use, there is a lack of systematic and unified approaches to VDT modelling (Matthies, 2024). Recent research has been focused on developing a unified approach to VDT modelling, proposing a classification system with 34 model constructs across three dimensions. Furthermore, researchers have explored the integration of VDTs with optimisation techniques to enhance decision support in areas such as sales and operations planning, emphasising the importance of working capital management as a key value driver (Hahn & Kuhn, 2011b).

In addition, the concept has been adapted to evaluate the engagement of stakeholders in mining projects through the development of a Value Analysis Tree framework, which quantitatively combines factors affecting the perceptions of stakeholders (Manjengwa et al., 2023). Analysis of value drivers' strength is crucial for understanding their influence on free cash flow generation, with research indicating that operating costs and interest expenses have a more significant impact than sales revenue (Akalu, 2002).

The value driver tree in performance management has its roots in the evolution of strategic management frameworks. The Balanced Scorecard, introduced by Kaplan and Norton in 1992, addressed the limitations of only financial measures by incorporating non-financial indicators to provide a more comprehensive view of organisational performance (Kaplan & Norton, 2001). This approach has emphasised the importance of intangible assets and their role in value creation. Building on this concept, the knowledge value chain framework has emerged, linking knowledge management initiatives to business performance through strategic, managerial and operational dimensions (Carlucci et al., 2004). The value creation map further refined this approach by visualising both direct and indirect dependencies among organisational resources, particularly intangible assets, in the value creation process (Marr et al., 2004). These innovations in performance measurement, including economic value measures and non-financial indicators, have become increasingly prevalent in both the private and public sectors.

2.2.2. Theoretical hierarchy of value drivers

The VDT offers a systematic framework for organising and analysing factors that influence the key performance indicators to be analysed. This crucial part of building the model guides the construction of the VDT. Figure 2.1 shows the conceptual construction of a tree illustrating the causal relationships obtained from Matthies, 2024.

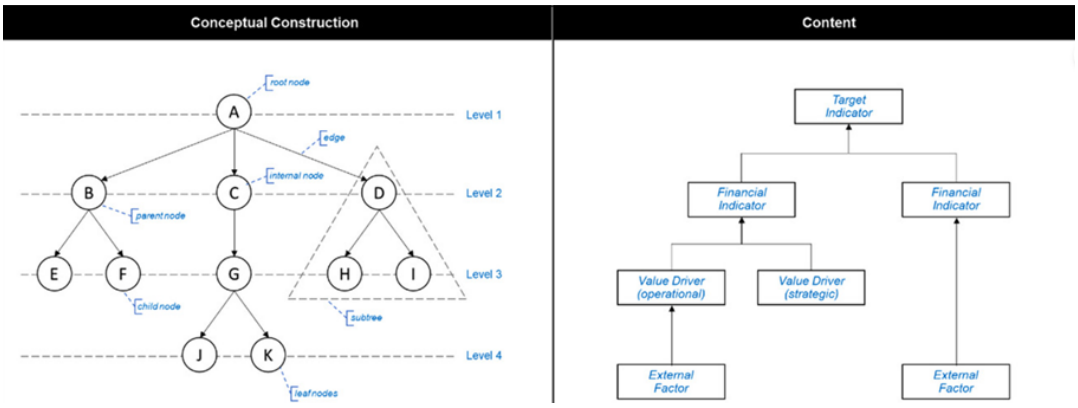

Figure 2.1: Conceptual construction of the VDT framework (Matthies, 2024)

In the conceptual framework, a tree with sub-trees is illustrated, which contains the standardised notation of elements by Matthies, 2024, containing nodes connected with edges. The VDT is represented as a weighted directed graph $G = (N, E)$, where N is the set of value drivers (nodes) and $E \subseteq N \times N$ is the set of directed edges linking these drivers (Matthies, 2024).

An edge $e(n_c, n_p)$, where $n_c, n_p \in N$, is directed from n_c (child) to n_p (parent), indicating that the metric at n_c influences n_p. Each edge $e(n_c, n_p)$ is associated with a weight $w(e)$, which represents the degree of influence n_c has on n_p. This weight quantifies the performance improvement in n_p resulting from a unit improvement in n_c, assuming that other factors remain constant (ceteris paribus) (Matthies, 2024).

The hierarchy of the tree is stated with different levels. The top element is called the root node, intermediate stated nodes are internal nodes and the bottom are called the leaf nodes. The objective of the VDT is to map the impact of lower-level operational metrics (near leaf nodes) on key performance indicators (near the root of the tree).

The VDT methodology has been widely used to examine the key factors that influence shareholder value, which branch out into primary drivers such as revenues, costs and capital efficiencies (Akkiraju & Zhou, 2012). Each of these drivers is further broken down into operational levers that influence them. Although this is the most common application of a VDT, the root can be positioned at any level and can extend as deep as needed to generate insights for a given strategic scenario (Akkiraju & Zhou, 2012).

2.2.3. VDT as decision making model

With the hierarchical theory, the literature has demonstrated the role of VDTs in the structuring of complex relationships between financial and operational drivers. Horak et al. (2017) explored enhancements in VDTs for business data analysis, focusing on their application in decision making. Matthies (2024) developed a classification framework to standardise VDT modelling, improving its usability in business environments. Klauck (2015) applied VDTs in enterprise simulations, showcasing their effectiveness in predictive analytics and scenario planning.

Korovkina and Fay (2014) justified IT investments using business driver trees, highlighting their role in aligning technology decisions with strategic goals. Similarly, Butzmann et al. (2015) discussed the use of in-memory column stores to support generic business simulations based on VDTs, showcasing improvements in computational efficiency. Hahn and Kuhn (2011a) optimised value-based performance indicators within mid-term sales and operations planning, underscoring the importance of linking VDTs to strategic objectives. Walters et al. (2020) elaborated on the concept of strategic value builders in performance management, emphasising VDTs as a core analytical tool.

Yüksel et al. (2016) applied performance driver analysis to determine competitive power, reinforcing the use of VDTs in benchmarking and business intelligence. Visani et al. (2023) utilised machine learning to identify key business value drivers, advancing data-driven performance measurement techniques.

A value driver is a variable or determinant that influences the value of a performance metric that is to be analysed (Akkiraju & Zhou, 2012). VDTs are typically modelled as a directed network to have a systematic framework with a formal representation mechanism that allows for capturing the correlation relationships among metrics. This enables simulation analysis, allowing decision makers to predict outcomes as a function of the underlying measures in the network. The modelling dimensions following the classification of the VDT modelling of Matthies, 2024 are:

- Structural dimension that defines the hierarchical arrangement of value drivers
- Behavioural dimension that captures the dynamic relationships and dependencies among drivers
- Contextual dimension that incorporates the external factors influencing the value drivers.

2.3. Decision making under uncertainty

Decision-making within grand challenges is critically shaped by how uncertainty is conceptualised and addressed. The capacity to quantify and manage uncertainty significantly improves the robustness of analytical models and the effectiveness of derived strategies (Walker et al., 2003).

2.3.1. Framing uncertainty

Decision-making under uncertainty is a central theme in both techno-economic theory and systems modelling. Uncertainty affects the robustness of analytical models, together with the operation and effectiveness of the resulting decisions (Kwakkel et al., 2016). A fundamental distinction is made by Knights et al. (2009), who differentiates between risk and uncertainty. Risk refers to situations where probability distributions over outcomes are known and quantifiable, while uncertainty describes contexts where such distributions are unknown or unknowable. However, this strict dichotomy has been increasingly criticised for its limited practical applicability, particularly in complex, real-world systems.

Therefore, Bayesian probability theory offers a more flexible framework for conceptualising uncertainty. Rather than relying on observed frequencies, it interprets probability as a degree of belief, which can be continuously updated with new information (Caticha et al., 2011). Within this perspective, uncertainty is not excluded from formal modelling but reframed as a characteristic of limited knowledge that can be expressed as *information entropy*. Following Shannon's definition, entropy quantifies the spread or diffuseness of a belief distribution (Lesne, 2014). This means that the greater the entropy, the less confidence in any specific outcome. High-entropy results reveal structural uncertainty, helping investors identify when further research or de-risking is required before committing capital. In this sense, entropy becomes a measurable form of epistemic uncertainty.

This research applies the entropic lens within a VDT modelling framework. Each node in the VDT captures a probabilistic dependency, and the uncertainty propagates through the system using a Monte Carlo simulation (Papadopoulos & Yeung, 2001). The entropy of the distribution of the resulting outcomes reflects the degree of epistemic fragility: a narrow distribution suggests a strong confidence in the expected outcomes, while a broad distribution indicates greater uncertainty (Caticha et al., 2011). This interpretation aligns with theoretical work connecting the Shannon and Boltzmann entropy, where the number of logically consistent microstates (or simulated futures) reflects the robustness of inference (Chakrabarti & Chakrabarty, 2007). Thus, uncertainty is not only acknowledged but actively measured and embedded in the modelling architecture.

2.3.2. Uncertainty simulation

So, building towards uncertainty simulation, there are more characterisations of uncertainty for simulation. Ascough et al. (2008) defined the context of uncertainty in environmental decision-making. This is used to distinguish between knowledge uncertainty, variability and linguistic uncertainty. These categories are visualised in Figure 2.2.

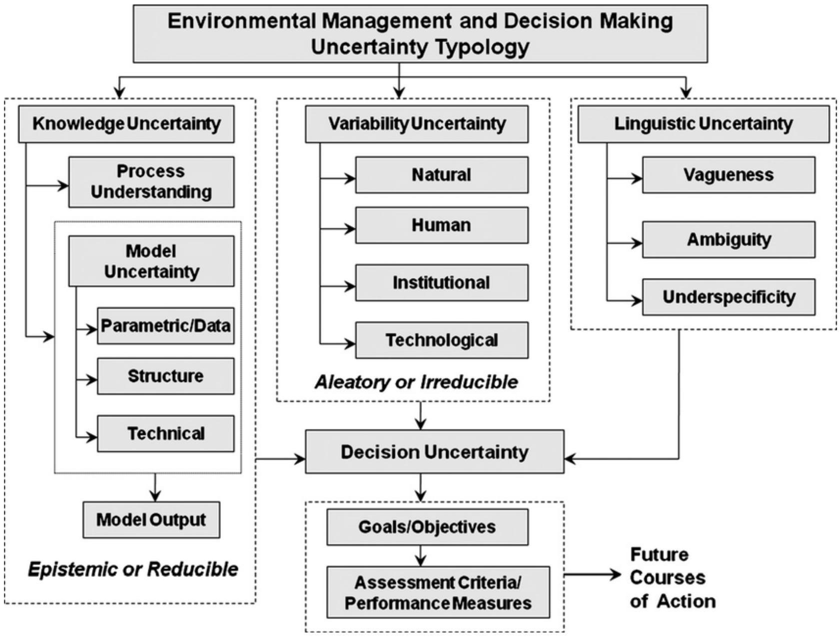

Figure 2.2: Description of the uncertainty in environmental management and decision making by Ascough et al., 2008

Within this framework, knowledge and linguistic uncertainties are classified as epistemic and are often difficult to translate directly into simulation input. Variability, on the other hand, refers to aleatory uncertainty, which can be expressed as probability distributions and is therefore well suited for formal modelling techniques such as Monte Carlo simulation (MCS) (Metropolis & Ulam, 1949). MCS is a widely adopted probabilistic method that uses repeated random sampling to approximate distributions of outcomes (Papadopoulos & Yeung, 2001). It enables the exploration of a wide range of future scenarios, rather than relying on fixed-point forecasts, and offers insight into expected values, variances, tail risks and confidence intervals.

Despite its established utility, the integration of MCS within causal system representations remains limited. This research addresses this gap by embedding MCS in a causal VDT structure. By assigning distributions to uncertain drivers and simulating numerous iterations, decision makers are provided not only with a projection of expected outcomes but with a structured representation of uncertainty itself.

By implementing the entropic layer in the simulation as an indicator of decision confidence, this can be a justification for further policy or data intervention. Combined with the transparency of the VDT framework, this approach enhances both interpretability and decision support under uncertainty. The entropic approach to uncertainty treats entropy as a measure of confidence concentration rather than outcome distribution (Williams, 2025). In this context, scenarios with similar expected value but different entropy levels reveal varying levels of epistemic robustness. This insight can be critical for sensitive public and private investment decisions.

2.4. Investment decisions in green hydrogen market

Investment decisions in the energy sector face significant uncertainties and risks (International Energy Agency, 2022). Traditional valuation methods, such as Net Present Value (NPV), real options and Discounted Cash Flow (DCF), often struggle to accommodate such uncertainties (Knights et al., 2009). On the other hand, Levelized Cost of Hydrogen (LCOH) is a measurement metric mainly used (International Energy Agency, 2022), which lacks direct use of policy interventions or market uncertainties. Techno-economic analysis uses deterministic input and needs clearly stated scenarios (Pfenninger, Staffel, 2015).

Uncertainty is an inherent feature of complex systems and investment analysis, especially in emerging energy technologies. The transition to green hydrogen as the cornerstone of future energy systems has attracted growing interest in both academic and industrial spheres. However, the path to large-scale adoption remains uncertain, with multiple challenges identified in the literature. Battolyser has been highlighted as a potentially transformative solution for flexible energy management and hydrogen production has been stated in the broader green hydrogen uncertainties. Because the study focuses on providing insight into what policy instruments and value drivers need to adapt to make the investment performance interesting, the focus is on uncertain parameters that restrict investments. In Figure 2.3, a visualisation is made of the results of uncertainties in the hydrogen market itself.

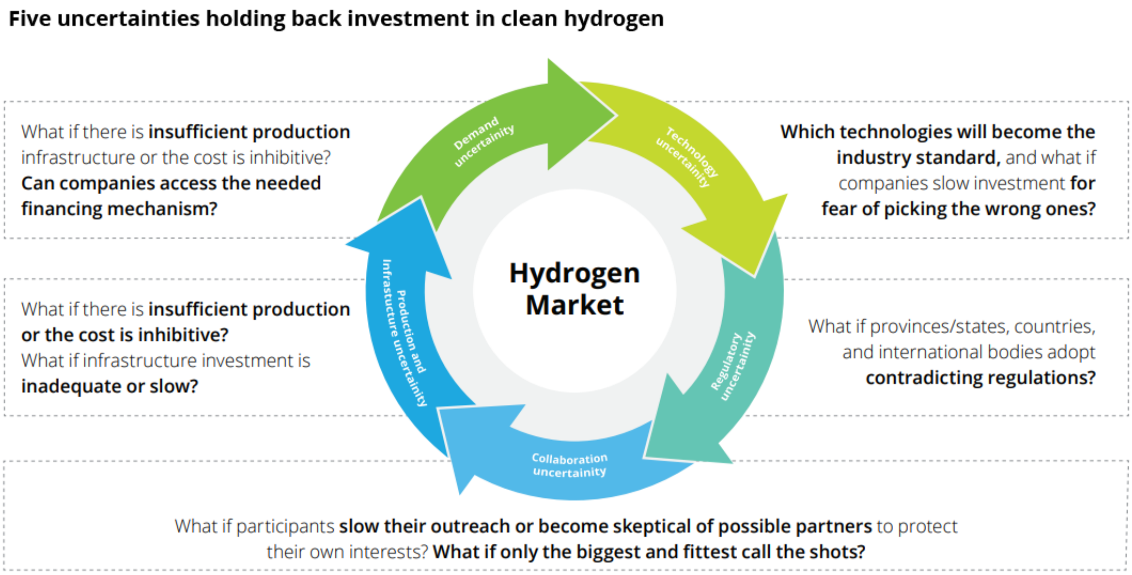

Figure 2.3: Uncertainties holding back investments in green hydrogen (Tuff, G. et al., 2023)

The figure highlights the five uncertainties categorised by demand, technology, regulatory, collaboration and lastly, production and infrastructure (Tuff, G. et al., 2023). These categories reflect the multidimensional nature of the investment environment, capturing both market-driven variability and systemic dependencies that influence the performance and viability. In a future powered by renewable energy, the storage of electricity in batteries and the production of hydrogen fuels will be essential to ensure sufficient energy availability on both daily and seasonal timescales (Invest-NL, 2024). This functionality is critical for a successful energy transition.

2.4.1. Specification of Battolyser Systems investment

As introduced in chapter 1, Battolyser Systems integrates an iron-nickel (Ni-Fe) battery with an alkaline electrolyser in a single device (Mulder et al., 2017). A schematic overview is given in Figure 2.4. The dual-use combination can reduce the pressure on the electricity grid by enabling a more flexible and localised energy management.

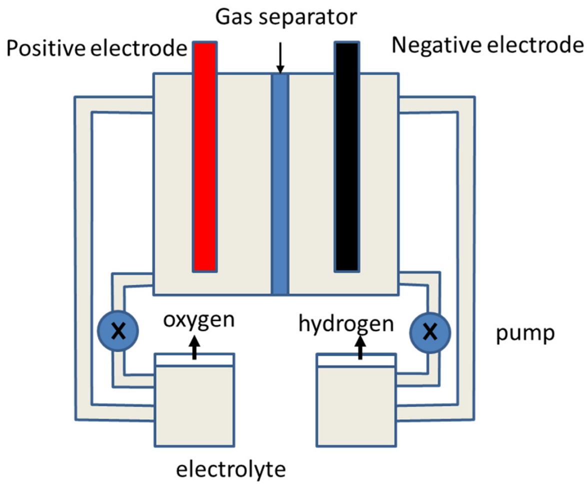

Figure 2.4: Schematic overview of functionality of a Battolyser System by Jenkins et al., 2022

Despite the relatively new technology, literature shows some attention towards the Battolyser functionality. Mulder et al., 2017 gives a detailed analysis of the charge products, which simultaneously serve as catalysts for the evolution of oxygen and hydrogen. Continuous storage is possible up to battery capacity, and beyond that, direct electrolysis occurs. To bring the technology into a broader perspective, the revenue model of Battolyser systems is stated in Figure 2.5. This hybrid capability is particularly relevant in the context of an energy system dominated by variable renewable sources, where flexibility across multiple timescales becomes critical.

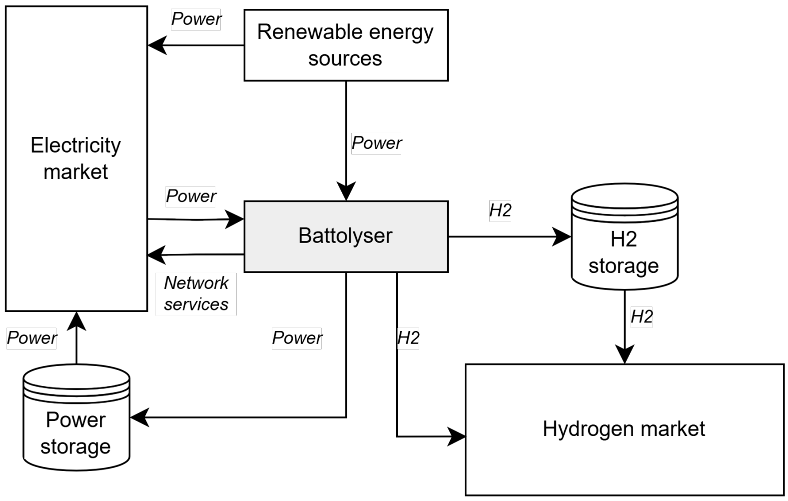

Figure 2.5: Revenue model of Battolyser Systems made by the author

As the energy transition accelerates, investments increasingly target innovations that operate at the intersection of multiple value streams such as electricity markets, hydrogen supply chains and system balancing services, as shown in Figure 2.5. The Battolyser is explicitly identified as a promising hybrid solution in the European battery strategy, especially for stationary storage (European Commission, n.d.). The technology fits the system's needs in the energy transition. The combination of a battery (more short-term) and hydrogen production (long-term) offers a unique value of a system for renewable energy grids. The intermittent production from solar and wind demands flexible, scalable storage solutions that can extract economic value from overproduction. A single system that replaces both the battery and electrolyser reduces costs and footprint.

2.4.2. Financial performance metric

Jenkins et al., 2022 shows with a techno-economic analysis that Battolyser Systems can be more profitable than the standalone electrolysers when integrated with offshore wind farms. Assessing the financial viability of integrated energy technologies such as the Battolyser requires more than conventional techno-economic analysis. Regarding many financial analyses of the battery and electrolyser performance, CE Delft used the calculation for the battery business case, given in Figure 2.6. This is translated into the commonly used metric Economic Value Added (EVA) in performance management (Patel & Patel, 2012). The calculation focuses on the parameters that eventually determine profitability.

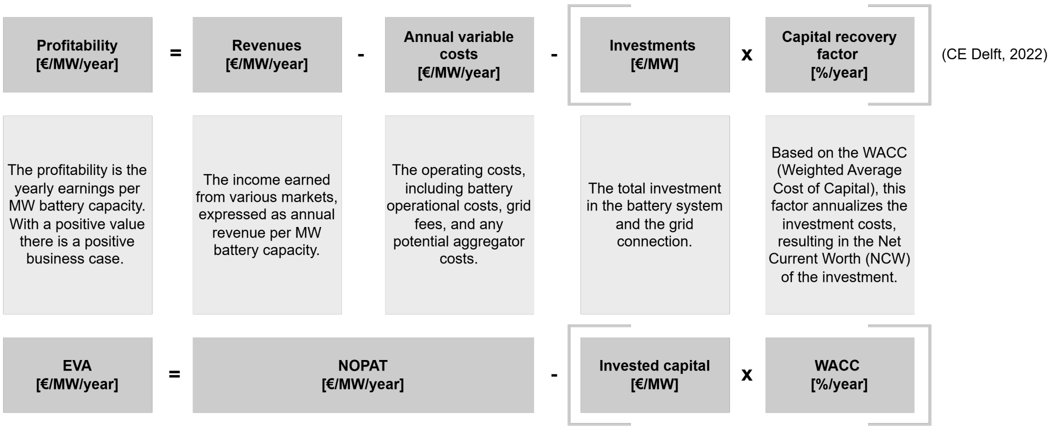

Figure 2.6: Business case of battery based on CE Delft, 2022

As mentioned, this kind of technology often faces elevated uncertainty due to evolving policy frameworks, market immaturity and infrastructural dependencies (Tuff, G. et al., 2023). Consequently, recent research has emphasised the need for investment evaluation methods that account for dynamic system interactions and policy-sensitive drivers. Within this broader perspective, financial viability is not only a function of cost and efficiency, but also adaptable to uncertain and emerging market structures (Delft, 2023).

In addition, the technology remains in a Technology Readiness Level 6 (mid-TLR) stage, which requires further validation of system and market levels (Mulder et al., 2017). Current policies do not include Battolysers as a distinct technology class. To inform policy development related to strategies, the focus is on economic modelling of incentives under uncertainties of the emerging market in the future. So, the next section focuses on the current policy developments related to the market.

2.4.3. Dutch policy instruments for Battolyser Systems innovation

In the Netherlands, the policy framework for energy transition technologies towards particularly green hydrogen and electricity storage is based on a complex combination of subsidy instruments, regulatory structures and long-term infrastructure initiatives. These instruments have been introduced to facilitate cost-effective decarbonisation and scale up green hydrogen production. As noted in Agora Energiewende (2021) and Hydrogen Europe (2022), many national and EU-level instruments are designed around the logic of cost competitiveness and large-scale deployment, prioritising CAPEX reduction and Levelized Cost of Hydrogen (LCOH) benchmarks. Instruments such as the SDE++ scheme (Stimulering Duurzame Energieproductie en Klimaattransitie (RVO), 2024 and OWE (Scaling up fully renewable hydrogen production (RVO), 2022) reflect this logic, with strict eligibility criteria based on cost-effectiveness (€/ton CO2 avoided) and continuous, standardised hydrogen production at scale.

However, this linear policy logic presents significant limitations when applied to emerging, integrated system innovations such as Battolyser Systems. The Battolyser uniquely combines battery storage and electrolysis in a single device, allowing it to flexibly alternate between storing electricity and producing hydrogen based on market conditions (Barton et al., 2020; Mulder et al., 2017). This hybrid functionality allows the Battolyser to deliver not only hydrogen output, but also system services such as load balance, congestion relief, and renewable energy integration (Jenkins et al., 2022). However, these contributions remain largely invisible to instruments focused solely on LCOH or CO2 abatement costs.

This misalignment between technology characteristics and policy logic leads to structural policy frictions. From a regulatory perspective, grid access fees and role definitions in the Dutch electricity market are based on capped actor categories in consumer, producer or storage. The Battolyser performs all three roles simultaneously, resulting in ambiguous classifications, double-grid charges or the inability to access balancing market compensation (Swarts et al., 2025). Moreover, the delayed rollout of the Dutch Hydrogen Backbone as infrastructural uncertainty combined with volatile WACC estimates ranging from 6.4% to 24%, further raises the investment risk profile of such hybrid technologies (Capgemini, 2024; Detz et al., 2022; PBL Netherlands Environmental Assessment Agency, 2022).

These challenges exemplify what Woolthuis et al. (2005) conceptualise as a system failure. This is a policy environment that cannot accommodate innovations that deviate from established, linear models of development. Moreover, they indicate an instrument misfit in which the design of policy tools (e.g., subsidies or regulations) is not aligned with the operational characteristics or innovation logic of the technologies they are meant to support (Borrás & Edler, 2014). As the literature on system innovation has argued, such instruments often fail to stimulate transformative change unless they are designed to account for multifunctionality, uncertainty and cross-sectoral value creation (Mazzucato, 2018).

Some policy mechanisms are aimed at bridging innovation and market deployment. However, these remain fragmented, often underscaled and poorly aligned with technologies that do not fit a single policy domain. An example is the HER+ with competitive grants (voor Ondernemend Nederland, 2025). This results in missed opportunities for technologies like Battolyser, whose systemic value could contribute directly to energy transition goals but lacks an institutional standardisation in current policy design.

The following Table 2.2 provides an overview of how current Dutch policy instruments are structured and how they relate to the needs of Battolyser Systems.

Table 2.2: Dutch policy instruments and their compatibility with Battolyser Systems

Instrument	Policy objective	Mechanism	Implications for Battolyser Systems
SDE++	Cost-effective CO_2 reduction via mature technologies	Operating subsidy (€/ton CO_2 avoided) ((RVO), 2024)	Ignores multifunctionality and system services. The selection is based only on LCOH integrated technologies
OWE	Scale-up of renewable hydrogen production capacity	CAPEX subsidy up to 80% + optional OPEX support ((RVO), 2022)	Strong preference for large-scale, single-purpose electrolysers.
HER+	Innovation support within SDE++ context	Competitive grant (€300/ton CO_2 avoided) (voor Ondernemend Nederland, 2025)	Focused on cost-reduction potential. This has limited relevance for system integration or hybrid business models
Grid tariffs	Access and enable demand-responsive electricity use and grid stability	Tariff discounts, curtailment compensation, non-firm contracts	Triple role (producer, consumer, storage) leads to regulatory ambiguity and potentially double charges
WACC regulation	Ensure fair returns for infrastructure investments	Weighted capital cost estimation (Swarts et al., 2025)	High risk perception of novel tech increases capital cost and undermines sustainability
Hydrogen backbone	Strategic national hydrogen transport and storage network	Public infrastructure investment, spatial planning (PBL Netherlands Environmental Assessment Agency, 2022)	Long-term timeline (2030+) misaligned with short-term deployment potential of Battolyser Systems

This misalignment reveals a broader policy gap of mismatch between policy goals (accelerating the energy transition) and policy instruments (cost-oriented subsidies). This study looks at how this policy framework can be applied and what gives the desired effects. The deployment in the Dutch market remains limited, and the potential for targeted research development also remains underused. Therefore, investigate what instrument design features may enable a more inclusive and effective innovation environment for system-oriented solutions.

2.5. Knowledge gap from literature

The literature underscores the variety of uses of VDT and its potential in value-based performance management. VDTs are recognised as effective tools to break down business value into measurable components (Hahn & Kuhn, 2011b). For this use, VDTs are commonly used in corporate finance to break down high-level financial performance indicators such as EVA and ROIC. However, this framework is rarely used in combination with simulation or uncertainty analysis in the energy investment context. The method is strongly focused on understanding the value drivers. This can be applied by linking investment decision factors to operational, technical and market drivers in uncertain developing sectors, like hydrogen technology.

Existing studies on green hydrogen economics (Hydrogen Council, 2021; International Energy Agency, 2022) are often based on static scenario analysis or deterministic techno-economic models. These approaches fall short in capturing systematic uncertainty and the interdependence of boundary conditions that determine investment performance. It is very valuable to create the logic structure of value creation and systematically prioritise which uncertainties are most important.

Moreover, metrics as LCOH and NPV are unable to support interactive, decision-oriented analyses

(International Energy Agency, 2022; Knights et al., 2009). The current literature offers tools for uncertainty analysis and financial modelling separately. An integrated approach that combines the intuitive structure of VDT with formal simulation and prioritisation techniques is largely missing.

This knowledge gap is seen as a potential approach to VDT integration with decision support, especially in the context of emerging technologies such as Battolyser Systems that operate in dynamic policy and market environments. So, this research aims to explore their integration with an advanced decision-making framework for a novel approach to creating insights on value drivers. This allows decision-makers to link strategic objectives with concrete levers for improvement.

3 Research approach

This chapter represents the approach to conducting the research, together with the formulation of the sub-questions. The formulated sub-questions will each contribute to eventually answering the main research question. For answering the questions, the selected methods and tools are listed. The selection is based on the knowledge of what data, simulation model and analysis are needed to perform adequate research.

3.1. Research questions

As contextual explained in the previous chapter 1 and further revealed in chapter 2, the study prioritises improving the model system to generate insights that support evidence-based decision making. Therefore, it will not be a mysterious black-box system but will create transparent insights into relevant causal relations that create value. This is highly relevant for policy making. The aim is to demonstrate that a comprehensive understanding of the system's uncertainties and value drivers, along with their appropriate modelling, can significantly enhance decision-making processes by breaking down the value creation process into its underlying operational and financial drivers. Thereby, the focus relies on interdisciplinary insights from different dimensions such as the technical, economic and operational sides. Using VDT models, the study aims to visualise and quantify relationships in a complex system with multiple variables and stakeholders.

The main research question is stated as:

How can a value driver tree-based simulation model be designed and applied to the investment performance of Battolyser Systems under uncertainty in the Dutch green hydrogen market?

From the main question, the following sub-questions have been devised to answer every part of the main question.

- **SQ 1**. What are the key value drivers influencing investment decisions of Battolyser Systems and how can they be structured in a value driver tree?
- **SQ 2**. What are the uncertainties that affect the behaviour of these value drivers?
- **SQ 3**. How can a simulation model be designed based on the value driver tree to capture investment performance under uncertainty?
- **SQ 4.** What insights does the simulation model provide about the most influential and uncertainty-sensitive value drivers?

3.2. Research design

To obtain the research objective, a model-based design approach is created that consists of six sequential phases: problem formulation, value driver tree formulation, uncertainty identification, model design and formalisation, model experimentation and analysis, and model evaluation and reflection.

Phase 1: Problem formulation

To begin, the research is focused on problem formulation. This initial step ensures that the research is grounded in the current academic field and that existing methodologies, frameworks and studies are considered for the development of the new research. The results are shown in Chapter 2. Literature review and desk research are used to gather existing knowledge, insights and theoretical foundations relevant to the study.

Phase 2: Value driver tree formulation (SQ1)

To go from theory to modelling, it is necessary to first understand and structure the system. The second phase of the research consists of identifying the variables that influence the key indicator of investment decisions. It combines the identification and decomposition of value drivers into the value driver tree structure. This sets the foundation for further research analysis.

This phase aims to answer the question: *SQ 1. What are the key value drivers influencing investment decisions of Battolyser Systems and how can they be structured in a value driver tree?*

This is where the Value Driver Tree is constructed by using the principles of systems thinking, decomposing the investment environment into causal relationships. Followed by the method constructed by Matthies, 2024. It starts with the conceptualisation of the performance metrics and output of the VDT tree. The structured visualisation tool breaks down high-level financial outcomes into their underlying drivers, helping to understand how specific variables influence value creation. By linking operational metrics with financial performance, it enables strategic decision-making and prioritisation of key levers (Kaplan & Norton, 2004). Next, the mechanisms of the relationships of the drivers are obtained. In this step, the operation of the model is described with logic, equations and mechanisms. The main focus is on the mathematical relationships.

The tools used for this question are Draw.io to visualise the relationships and then the spreadsheet of Microsoft Excel to further specify the statistics, operators and quantification of the variables and relationships between them. Sensitivity analysis is performed on the value driver tree model to find critical parameters.

Phase 3: Uncertainty specification (SQ2)

In line with the literature on decision-making modelling in an uncertain environment, the external conditions need to be identified. The key uncertainties related to the identified value drivers and that fall within the scope are defined (Gassmann et al., 2014). The system scoping phase is focused on the key uncertainties, boundary conditions, strategies, relationships and objectives. This is crucial to the research as it ensures that relevant factors are identified.

With this, the phase aims to answer: *SQ 2. What are the uncertainties that affect the behaviour of these value drivers?* This sub-question focuses on identifying external conditions and sources of uncertainty and risks that influence the value drivers that will be used in the analysis. The conditions are structured with suitable framing.

It starts with identifying these factors on the basis of relevance and plausibility, forming input for the simulation. Through stakeholder analysis, the research aims to incorporate multiple perspectives and objectives and come to an uncertainty classification. Uncertainties towards the model are classified and gathered using desk research.

Phase 4: Model design and implementation (SQ3)

Building on the structure of the system stated in phase 2 and combining with the uncertainties defined in phase 3, this phase translates the VDT into a computational model. The logic followed from value-based management theory to build the financial backbone of the model.

This phase results in a functioning simulation tool that can be used to explore the impact of uncertainty on investment performance to answer the question: *SQ 3. How can a simulation model be designed based on the value driver tree to capture investment performance under uncertainty?*

The objective is to build a simulation model that integrates the value driver tree with uncertainty modelling to assess investment outcomes. It explains the modelling, integration of the tree and how uncertainty is implemented. The model is created into an exploratory system tool based on the XLRM framework by Jafino et al., 2021 given in Figure 3.1. This structure allows for the explicit identification of exogenous uncertainties (X), policy levers (L), modelling relationships (R) and performance metrics (M), creating a coherent interface between stakeholder input, policy instruments and model outputs. To eventually be able to quantify it into the model mechanisms.

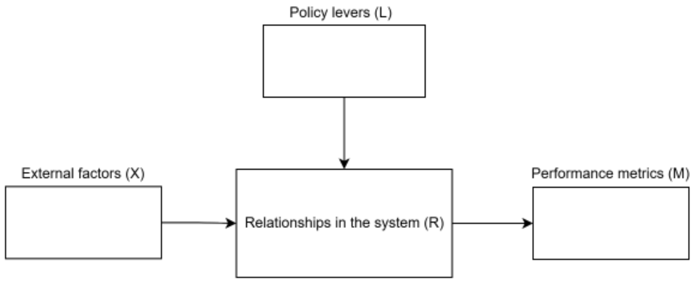

Figure 3.1: XLRM framework based on Jafino et al., 2021

This is where the combination of the structure mechanisms based on phase 2 is combined into the uncertainty environment stated in phase 3. Then, the uncertain factors of the policy framework are stated for the policy analysis.

An important part of the model implementation step is all about the implementation of the software. The model is implemented in Python, due to its flexibility, reproducibility and availability of scientific computing libraries. The modularity of the code supports transparency and future reuse.

Phase 5: Model experimentation and analysis (SQ4)

This part of the analysis focuses on visualisation and analysing the results of the experiments done with the model. The analysis is done in three sub-phases: baseline analysis, uncertainty integration and policy lever integration. The final statement on data input and outputs with fixed or distributed data is stated and also the ranges or probability distributions are defined.

Baseline analysis

The baseline analysis is to ensure that the model is reliable and ready for scenario exploration and decision support. Verification ensures that the model works as intended, both logically and technically. Using sensitivity analysis, the model is tested to identify which input variables have the greatest influence on the outcomes. This helps confirm the validity of the value driver relationships and prioritises areas where accurate data collection is most critical.

Structural validation is performed to check whether the value driver tree accurately reflects the causal relationships and hierarchy of variables that drive investment performance. The logic follows guidelines from systems modelling, ensuring that no key elements are left out and that relationships between drivers are theoretically grounded.

Sensitivity analysis evaluates how the variation in input variables affects a particular outcome, helping to identify which assumptions have the greatest influence on model results. It is especially useful in early-stage or uncertain projects to prioritise data collection and risk mitigation efforts (Saltelli et al., 2008). In the context of energy systems, sensitivity analysis can reveal the most influential parameters and therefore the main drivers. For example, what the effect of electricity prices or electrolyser efficiency is on the financial viability of hydrogen production (Pfenninger & Keirstead, 2015). The goal is not only to test robustness but also to inform policymakers and investors where leverage points exist.

Uncertainty integration

Simulation runs are done to identify patterns or trends in the performance based on various inputs and outputs of the model. Different ranges of uncertainties are simulated as input data. The resulting spread in performance outcomes reveals under which conditions the investment is viable, resilient or fragile. The data distributions model dynamic and realistic scenarios for the strategies, enriching the robustness of the simulations.

The distribution based on relevant studies is taken into account where possible. With the use of Monte Carlo simulations, different runs across combinations of uncertain inputs are executed, and then the distributions of the outcomes are analysed.

Monte Carlo simulation is a probabilistic method that uses random sampling to account for uncertainty in input variables, producing a distribution of possible outcomes rather than a single point estimate. By including uncertainty, the risks of the drivers can be examined. This approach is particularly valuable in complex systems with multiple interacting uncertainties (Metropolis & Ulam, 1949). In energy investment projects, Monte Carlo simulations can quantify the probability of achieving desired financial returns under variable market and policy conditions (Trück et al., 2011). Figure 3.2 shows the steps for the Monte Carlo simulation.

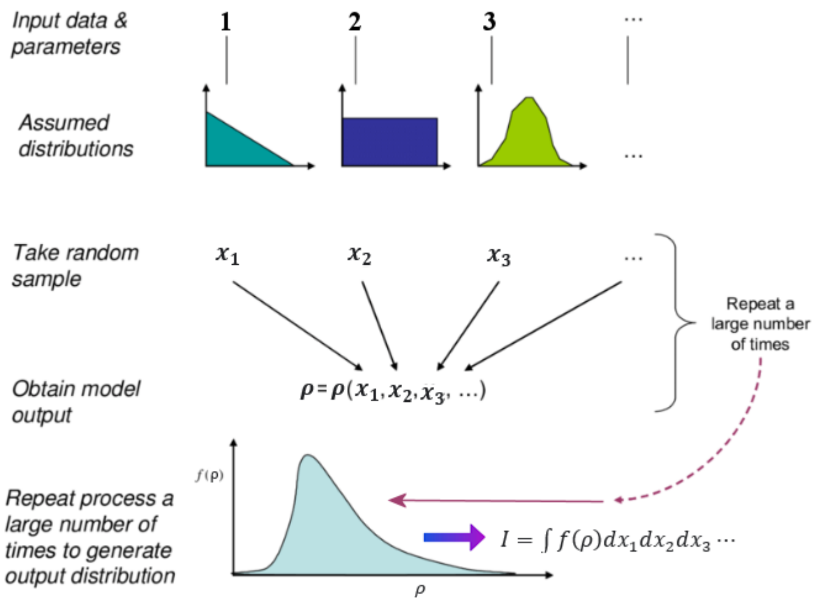

Figure 3.2: Monte Carlo Simulation method by Johnson, 2022.

First, the input data and parameters are defined, which is done by building on the previous phases and are structured in the uncertainty environment of the system. For each uncertain input, an appropriate probability distribution was assigned. This can be normal, triangular or uniform distributions. This depends on the availability of the data and the nature of the variable. For the simulation execution, random sampling techniques are used. The resulting output distributions can be analysed using descriptive statistics (mean, median and ranges) and visualised through box plots and cumulative distribution functions.

Policy levers

At last, as designed in phase 3, policy interventions are implemented in the model. The robustness of policies is compared across the stated uncertainty space to eventually answer the sub-question *SQ 4. What insights does the simulation model provide regarding the most influential and uncertainty-sensitive value drivers?* This simulation supports the understanding of how to consider the outcomes in the wide range of uncertainties included. The analysis is done using the Python 3.11 programming tool in Visual Studio Code.

Phase 6: Model evaluation and reflection

This phase closes the research loop by evaluating what the model adds and what it leaves open, in theory and practice.

Model evaluation

The final phase critically evaluates whether the simulation model, built around the VDT and the indicators expressed as value drivers, is valid, relevant and usable within the context of investment decision making in the Dutch green hydrogen sector. The model is evaluated not only as an analytical artifact, but also as a decision-support tool. The evaluation begins with a high-level assessment of whether the model meets its intended purpose: to support investment decisions under uncertainty by providing insight into the influence of key boundary conditions on value creation.

Limitation analysis and future recommendations

A critical reflection on the limitations of the model is essential to transparently communicate its scope and boundaries. The insights are categorised by empirical, conceptual and technical limitations. Recommendations are made for future improvements, including integration of other methods, dynamics or participatory decision applications.

The methodology can be seen in the overview given in Figure 3.3. Each phase is stated with the corresponding step, method and research question.

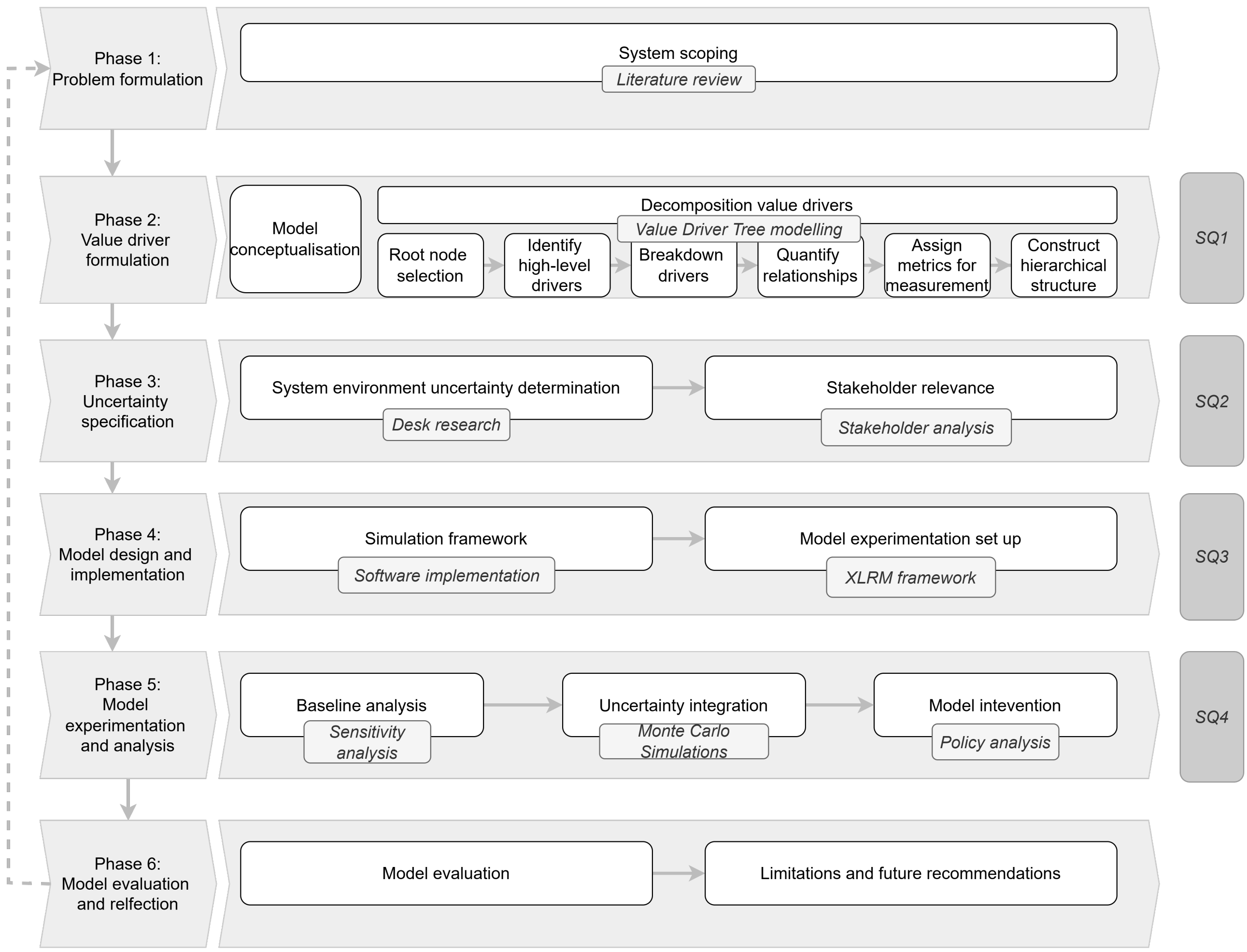

Figure 3.3: Research flow diagram

3.3. Criteria of the research approach

To ensure both analytical quality and practical relevance, this research applies a structured set of evaluation criteria that align with established practices in system modelling and policy analysis. These criteria serve as guiding principles throughout the modelling process. This provides a foundation for later evaluation from conceptual design to simulation and interpretation.

First, the design should be scientifically built and make use of established frameworks in systems thinking, value-driven management and decision-making under uncertainty. Second, the research phases should have a clear and logical structure. This ensures methodological transparency and coherence between the modelling steps. Also, reproducibility is prioritised through the use of documented assumptions, data structures and modular Python code.

The ability of the simulation to model uncertainty using sensitivity analyses and Monte Carlo techniques is crucial to capture realistic variability in outcomes. Expected contributions of the research include identifying critical value drivers, quantifying their sensitivity to uncertainty and supporting strategic decision making. Furthermore, the approach will be assessed on its ability to communicate results effectively, both visually (value drivers and simulation output) and statistically. These criteria are followed throughout the development of the model and contribute to reflecting the final evaluation phase.

A key requirement is that the model must explicitly integrate three core dimensions of the model: the structural, behavioural and contextual dimensions (Matthies, 2024). These dimensions reflect specific sources of uncertainty and influence on policy performance.

- The model must accurately reflect the causal architecture of the system, including the interdependencies between technical components and value drivers. This is implemented through the use of a VDT, where all output variables are decomposed into their underlying causes.
- The model must include behavioural assumptions regarding stakeholder responses, technology adoption or investment decisions. These are incorporated as probabilistic or policy elements.
- External conditions such as regulatory frameworks, market volatility or policy misalignment are treated as contextual scenario uncertainties. These influence the feasibility and performance of the system.

To operationalise these dimensions and ensure methodological robustness, the following evaluation criteria are applied in Table 3.1.

Table 3.1: Evaluation criteria for the research approach

Criterion	Description
Theoretical grounding	The model builds on established frameworks from systems thinking, value-based modelling and decision-making under uncertainty.
Dimensional completeness	Structural, behavioural and contextual elements are explicitly represented to capture complexity.
Methodological structure	The research follows a logically phased process from problem framing to simulation and policy testing, with transparent transitions.
Reproducibility	All assumptions, data structures and modelling steps are documented and implemented in modular Python code.
Uncertainty modelling	The model applies Monte Carlo simulation and sensitivity analysis to propagate and explore input variability and epistemic fragility.
Interpretability	Results are communicated through value driver visualisations, statistical summaries (e.g., percentiles, entropy) and scenario descriptions.

These criteria not only ensure scientific and technical quality but also improve the relevance of the model for strategic and policy decision-making. They are applied iteratively during the research process and provide a foundation to reflect on the robustness, generalisability and communication value of the model in the final evaluation phase.

3.4. Limitations of the research approach

When stating the research method, some limitations need to be taken into consideration. First, the research relies on simulations and data distributions, which assume that the underlying data is accurate, complete and representative. However, the availability of up-to-date and high-quality data can be constrained. If data inputs are unreliable or incomplete, the results of simulations and trade-off analysis may be biased or less reflective of real-world conditions.

Also, while Monte Carlo simulations and sensitivity analyses are valuable for exploring future uncertainties, they often rely on certain assumptions about the distributions and behaviour of key variables. This can oversimplify or bias real-world processes. The assumptions made in the construction of the value driver tree model could limit the model's ability to capture all relevant variables, especially those that could be less quantifiable or more context-specific. Similarly, defining relationships between variables might miss emergent properties that only become apparent in more nuanced models.

Biases in stakeholder selection could limit the comprehensiveness of the scoping phase, potentially leaving out key uncertainties or strategic considerations that might be important for a full understanding of the problem. That is why the participatory scoping is mainly focused on research of literature and current reports to include a broader perspective on the scoping phase.

Modelling with uncertainty and data distributions may still fully capture the dynamic nature of the systems, especially in fast-evolving areas like technology and policy. Thus, the research is limited by its ability to account for unexpected developments or sudden changes that could significantly alter the effectiveness of the proposed strategies.

Monte Carlo simulations and large-scale data analysis require substantial computational resources. If the resources available for the research are limited, the scope of the simulations may be constrained, or the models may be simplified in ways that reduce their precision or accuracy. Larger and more complex simulations could potentially improve the robustness of the results, but this requires significant computational power and time.

Finally, the assumptions underlying both the sensitivity and trade-off analyses may become outdated as policies and technologies evolve. For example, new government regulations or technological advancements can shift the balance of trade-offs or change the effectiveness of certain strategies over time. Thus, the research might be limited by the speed of change in policy or technological landscapes.

Recognising these limitations at the beginning has shaped the research design in meaningful ways. Rather than seeking to eliminate uncertainty, this study embraces it as a fundamental characteristic of complexity-based strategic decision making. By explicitly incorporating assumptions, data constraints and evolving policy conditions into the modelling framework, the research aims to build a flexible and transparent foundation for analysis.

The integration of Monte Carlo simulation, a causally structured Value Driver Tree and the framing of structural, behavioural and contextual into the model enables it to remain adaptable and relevant. In doing so, this research does not claim predictive precision, but rather seeks to enhance the quality of reasoning and support robust decision making in uncertain and fast-evolving domains.

4

Model value driver identification

This chapter aims to answer the first sub-question *'What are the key value drivers influencing investment decisions of Battolyser Systems and how can they be structured in a value driver tree?'*. To obtain the answer, it identifies and structures the key variables that affect investment performance. First, a theoretical decomposition of the value drivers influencing investment performance and the operational context is given. Then, the hierarchical structure is further specified in decomposing the system into value-creating mechanisms and financial relations. The technological and business characteristics of the selected Battolyser Systems technology provide an empirical basis for the value factors and assumptions used in later simulation phases.

4.1. Model conceptualization

One of the first and most essential steps of a simulation study is the creation of a conceptual model. There is only limited literature on this aspect, as conceptual models are often seen more as a creative task than a science. Yet in recent years, more attention has been drawn to the importance of conceptualisation (Robinson, 2014). As shown in the research design, the research consists of initiating the conceptual VDT model that follows the initial problem understanding and is an essential preparatory step to develop the model design and, eventually, the simulation model.

To establish a conceptual model, one must define the model objectives, followed by the model scope, and the content of inputs and outputs. These aspects are supported by the system boundaries, assumptions and simplifications to provide a complete picture (Robinson, 2015).

4.1.1. Model objective

This model aims to explore how key uncertainties affect the investment performance of Battolyser Systems on the Dutch green hydrogen market. The model aims to investigate how engineering innovations, such as a Battolyser in the energy grid interact with public policy to influence the economic performance of systems. Rather than predicting outcomes, the model is intended to support strategic thinking and scenario exploration by structuring the key value drivers and their interactions within a socio-technical system.

The tree offers a transparent breakdown of financial value drivers and aligns with the principles of value-based management (Young & O'Byrne, 2001). This promises a practical tool for strategic decision making and performance monitoring. The structure seeks to obtain the foundation for both empirical validation and dynamic simulation, so it provides pathways for further analysis in both academic and applied settings.

VDT models are currently being developed to measure Economic Value Added (EVA) (Stern et al., 1995). This is a widely recognised metric for assessing value creation within firms. The tree offers a structured decomposition towards generating the value a company gives beyond the cost of capital. To obtain a perspective on the actors in the system, the Return on Invested Capital (ROIC) gives investors how efficiently profitability is earned per company capital (Koller et al., 2010).

4.1.2. Model scope and boundary conditions

The model focuses on a single deployment case of Battolyser Systems in the Netherlands, covering the year 2030 as the time horizon. The core system includes the Battolyser unit (hybrid battery - electrolyser as given in Figure 2.5), grid connection and sales facility. External drivers such as electricity market dynamics, technology cost trends and national subsidy regimes that have a direct effect are explicitly included. The model excludes environmental externalities, detailed balance sheet modelling and international hydrogen trade.

Technological description

Battolyser Systems is a Dutch company developing an integrated dual-use electrolyser and battery system (Origins, 2024). This technology enables the production of green hydrogen through electrolysis while storing and delivering electricity from its integrated battery module at the same time. This combination offers flexibility to respond to fluctuating electricity prices and grid needs to improve asset utilisation and revenue diversification.

Business model

The VDT explicitly links technical performance metrics to financial indicators, allowing the model to simulate the cascading impact of uncertainty across the system (Collopy & Hollingsworth, 2011; Matthies, 2024). Battolyser's business model is built on two main revenue streams: first, hydrogen production and sales, targeted at industrial users and the mobility sectors (Origins, 2024) and second, energy arbitrage, storing electricity when cheap and selling when prices peak (Barton et al., 2020). Investment costs, stack efficiency, electricity sourcing and regulatory incentives define the financial viability of the technology. These parameters are used as input ranges in the simulation model.

4.1.3. Model outcomes

For conceptual development, it is important to clarify how the model is designed to deliver useful, actionable insights for investment decisions for integrated battery-electrolyser systems. Measures are defined that can be grouped into perspectives to provide concrete answers to the model objectives of the outcome. The output indicators collectively serve to evaluate the techno-economic viability and value creation potential of integrated battery-electrolyser systems. These outputs are organised into four analytical layers: financial performance, operational effectiveness, strategic interpretation and decision support (Koller et al., 2010). This structure enables both a quantitative assessment and an interpretation aligned with investment logic and policy relevance.

At this stage, the key indicators to define are the EVA calculated from ROIC (Stern et al., 1995). Technical measures such as electricity demand and hydrogen output are also included. These indicators are explicitly linked through the VDT structure, ensuring that the effects of changing input variables, such as electrolyser size, power use or market prices, can be traced throughout the system. Together, the model outputs enable a structured interpretation of system performance in multiple decision dimensions.

The outcome metric EVA shows the shareholder value (Stern et al., 1995). When EVA is positive, the company creates value, and if negative, it decreases the value. EVA is focused on long-term profitability and creates decision-making to enhance long-term alignment rather than only short-term gains (Young & O'Byrne, 2001). This metric can serve as a standard benchmark for comparison between design configurations or investment options.

Importantly, this setup incorporates the logic of robust decision-making. This means that the model is not built around one fixed scenario, but rather tests the outcomes on a range of future conditions (Kwakkel et al., 2016; Saltelli et al., 2008). This ensures that the insights produced remain valid and useful under real-world uncertainty and not only under ideal circumstances.

4.2. Decomposition value drivers

Now the conceptualisation helps to understand the goal and content of the model, the next step is the formalisation. A systematic approach is adopted to identify the core variables that impact the investment attractiveness of Battolyser Systems. To translate the objectives of the model into a formal simulation structure, a decomposition is performed based on value-based investment metrics. Starting from a theoretical basis, the value drivers are organised into a hierarchical structure that captures the relationships between operational mechanisms and financial outcomes (Matthies, 2024).

The research aims to understand the value creation under uncertainties related to the financial performance in the system. A realistic and related VDT model is essential for visualising the underlying revenue and costs. As stated in chapter 2, the theoretical framework of the VDT is used based on the current literature. The methodology is grounded in performance mapping frameworks such as those introduced by Kaplan and Norton, 2004 and Gassmann et al., 2014, which emphasise linking financial goals with operational actions.

A top-down approach can be used to design a VDT (Valjanow et al., 2019a). The modelling is based on the result item, so it is broken down in alignment with the drivers. The steps followed to decompose the value drivers into a VDT are given in Figure 4.1. This is based on the classification by (Matthies, 2024).

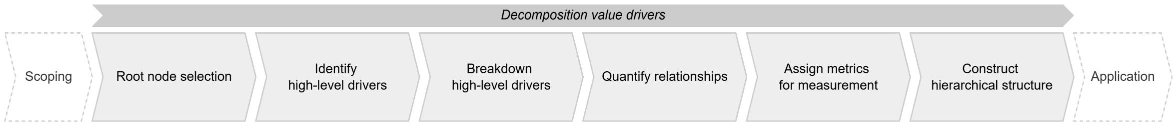

Figure 4.1: Methodology to systematically decompose the value drivers towards a VDT model made by the author

The steps given in Figure 4.1 are followed in the next sections to obtain the VDT related to the scoping of the study.

4.2.1. Justification of root node selection

To initiate the top-down modelling approach, it is essential to identify the root node that covers the primary performance objective. Continuing from the scope, Tortella and Brusco, 2003 states that the measurement of value creation according to EVA has been used as a guide for investment decisions. Therefore, this study uses ROIC and EVA as foundational performance indicators (Koller et al., 2010). These metrics are particularly suitable for the evaluation of long-term capital-intensive projects characterised by significant uncertainty, compared to simpler metrics such as Internal Rate of Return (IRR) or Net Present Value (NPV) (Stern et al., 1995). ROIC and EVA provide information on both operational efficiency and capital productivity (Koller et al., 2010), while allowing integration with uncertainty modelling through probabilistic inputs (Kwakkel et al., 2016), which fits the empirical study of Battolyser Systems.

Return on Invested Capital (ROIC)
The focus on ROIC serves as a comprehensive measure of a system's ability to generate returns relative to the capital invested. By evaluating the efficiency with which capital is invested to produce net operating profit, ROIC provides insight into the effectiveness of resource utilisation (Koller et al., 2010).

Economic Value Added (EVA)
EVA shows how much value a company creates for shareholders after covering the cost of capital. The EVA extends this analysis by quantifying the value created beyond the required return on capital (Stern et al., 1995).

Understanding and applying ROIC and EVA are crucial for evaluating performance, enhancing profitability, assessing risk, informing investment decisions and achieving competitive advantage. Moreover, adopting these metrics supports the principles of value-driven design, a system engineering strategy that prioritises maximising system value over simply meeting performance requirements (Collopy & Hollingsworth, 2011). By focusing on value creation, systems engineers can make more informed trade-offs during the design process, leading to solutions that are both technically sound and economically beneficial.

4.2.2. Identify high-level drivers

The first step for value creation logic is to identify high-level drivers. Concerning the key target indicator, the key drivers that directly impact the chosen objective need to be identified. The value creation logic is derived from financial theory. Based on Patel and Patel, 2012, the following equations are stated.

The fundamental work of Stern et al., 1995 EVA is conceptualized as the residual income after accounting for the cost of capital, formally defined as the difference between Net Operating Profit After Taxes (NOPAT) and the capital charge, which is the product of the Weighted Average Cost of Capital (WACC) and Invested Capital. As stated in Figure 2.6, the calculation for EVA can be obtained by:

$$\text{EVA} = \text{NOPAT} - (\text{Invested Capital} \cdot \text{WACC}) \tag{4.1}$$

Where:

- EVA: Economic Value Added [€/year]
- NOPAT: Net Operating Profit After Taxes [€/year]
- Invested capital: Total capital employed [€]
- WACC: Weighted Average Cost of Capital [%/year]

Invested capital, defined as the sum of fixed capital and net working capital, is consistent with the definitions used in the corporate finance literature (Koller et al., 2010). This enables the calculation of ROIC, a central indicator of capital productivity. A firm creates value when ROIC > WACC (Stern et al., 1995). By stating ROIC as the driver towards EVA, the equation becomes:

$$\text{EVA [\%]} = \text{ROIC} - \text{WACC} \tag{4.2}$$

$$\text{ROIC} = \frac{\text{NOPAT}}{\text{Invested capital}} \cdot 100\% \tag{4.3}$$

4.2.3. Breakdown high-level drivers

Then, each of the high-level drivers can be broken down into underlying sub-drivers. This hierarchical decomposition is instrumental in identifying and is essential to understand what factors can be influenced or optimised in practice (Akkiraju & Zhou, 2012). It allows for the systematic tracing of how changes at the operational or tactical level affect the performance metric (Matthies, 2024).

Drawing on the given standard ROIC formulation, the metric can be disaggregated into two main components: Net Operating Profit After Tax (NOPAT) and invested capital. On the operational side, Net Operating Profit After Tax (NOPAT) is derived from Earnings Before Interest and Taxes (EBIT), adjusted for applicable tax rates (Young & O'Byrne, 2001). EBIT itself can be further broken down into gross profit, operating cost structures and depreciation. Gross profit, in turn, results from the difference between revenue and variable costs.

This layered breakdown reveals how firm performance is shaped by distinct, measurable components, which can be grouped into three main categories of value drivers:

- **Revenue drivers**: Revenue is fundamentally determined by price and sales volume, both of which are subject to market dynamics, competitive strategy and customer demand (Gassmann et al., 2014). Understanding the elasticity of both variables is key to assessing a company's growth potential and pricing power (Tuff, G. et al., 2023).
- **Operating costs drivers**: Operating costs are split into
  - *The operating expenses (OPEX)* are the recurring costs required for the daily functioning of a business that are not directly tied to the production of goods or services (Cheung et al., 2010). This includes both fixed and variable expenses necessary for operations, but excludes capital expenditures (Carlucci et al., 2004).

  - *Depreciation* is the systematic allocation of capital expenditures throughout the life of tangible fixed assets. It is non-cash but affects EBIT and is vital to understand asset intensity and capital recovery (Koller et al., 2010).
  - *Variable costs* are expenses that fluctuate directly with the level of production or sales volume. Variable costs are directly proportional to the output (Walters et al., 2020).
- **Capital drivers**: These refer to efficient allocation and use of both working and fixed capital (Koller et al., 2010). Capital efficiency impacts the ROIC denominator and thus determines the productivity of each euro invested. Understanding how capital is invested and distributed is crucial to assessing the long-term sustainability of value creation (Valjanow et al., 2019b).

4.2.4. Quantify relationships and assign metrics for measurement

After this, the following is to quantify the relationships, where the relationships between the drivers can be determined by analysing data and conducting research on equations and assigning weight coefficients to reflect the strength and direction of these relationships. Connecting with this step is to assign metrics for measurement. Each driver must consist of a specific measurable metric, allowing for quantifiable assessment and tracking for analysis. The results are shown in Table 4.1. Further specifications on the mathematical formulation of the key relationships of these value drivers are provided in Appendix B.

Table 4.1: Model variables overview

Variable	Abbreviation	Unit	Description
Economic Value Added	EVA	%	ROIC - WACC
Return on Invested Capital	ROIC	%	NOPAT / Invested capital
Weighted Average Cost of Capital	WACC	%	Average cost of capital weighted by debt and equity proportions
Net Operating Profit After Taxes	NOPAT	€	EBIT $\times$ (1 - Tax rate)
Invested capital	$K_{invested}$	€	Net working capital + fixed assets
Net working capital	K_{nwc}	€	Current assets - current liabilities
Fixed capital	K_{fixed}	€	Long-term tangible assets used in operations
Earnings Before Interest and Tax	EBIT	€	Revenue - COGS - Operating expenses
Tax rate	-	%	Effective corporate tax rate
Revenue	R_{total}	€	Sales volume $\times$ price
Sales volume	Q	Units	Number of units sold
Price	p	€/unit	Selling price per unit
Cost of Goods Sold	COGS	€	Direct cost of producing goods sold
Operating costs	OpEx	€	Indirect operational costs excluding COGS

4.2.5. Construct the hierarchical structure

The drivers are organised in a flow of cause-and-effect relationships with high-level drivers at the top and sub-drivers at the bottom. Each node should represent a driver, with links showing their influence path. This ensures a well-constructed VDT that serves as both a conceptual map (as clear communication of how value is created and identification of leverage points for interventions) and a computational model (as the foundation for integration with simulation tools), recommended by Kaplan and Norton, 2004.

The basis structure of the VDT from current knowledge in the literature is therefore given in Figure 4.2. This can be seen as a high-level, standardised conceptual model which is not specific to a case description and can be used in different contexts.

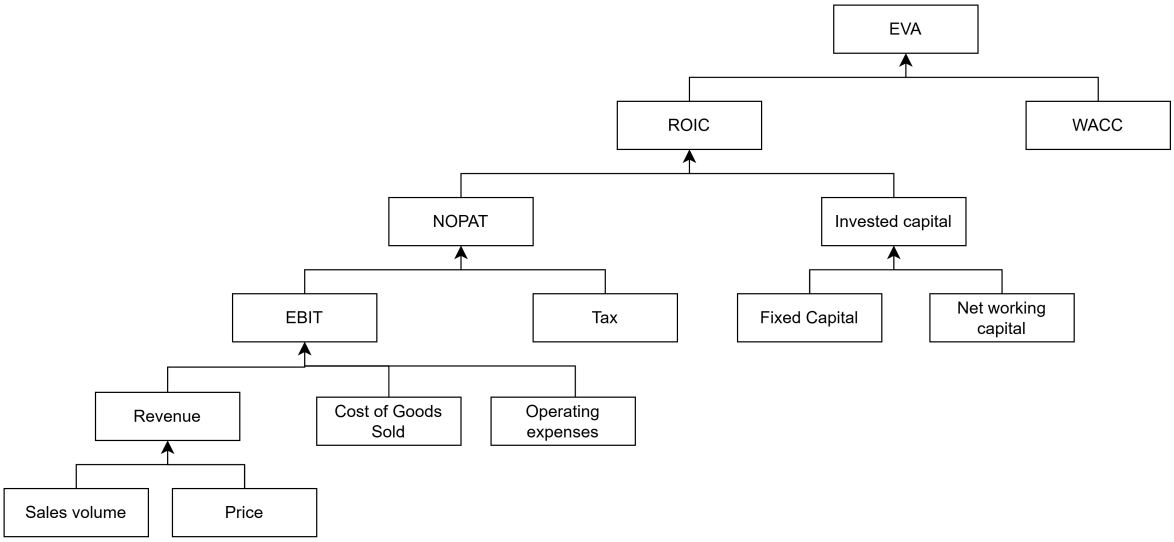

Figure 4.2: Value Driver Tree Jafino et al., 2021

With the high-level conceptual VDT and key value drivers, the next step is to map those drivers specific to the context. This part of the research supports the applicability and guarantees that the assumptions reflect the conditions in the Dutch green hydrogen market. So, to evaluate the economic performance of the integrated battery-electrolyser of Battolyser Systems, the EVA high-level conceptual VDT can be used as a central value-based performance metric. This model captures both revenue-generating capabilities and capital efficiency, reflecting value creation beyond the cost of capital.

4.3. Sub-tree specification

The model structure specifications follow the layers displayed in Figure 4.2: *revenue drivers*, *cost drivers* and *invested capital*. These drivers are now specified in sub-trees of the VDT and are further decomposed in the next sections. For this decomposition, the same methodology is followed as given in Figure 4.1.

4.3.1. Revenue drivers

Revenue drivers define the potential income streams from the implementation of Battolyser Systems, primarily through hydrogen production and electricity system services such as energy arbitrage and grid balancing (Jenkins et al., 2022; Origins, 2024; Tuff, G. et al., 2023). These revenue streams are influenced by market demand, regulatory incentives, and the flexibility offered by the dual-use system that integrates electrolyser and battery components (Capgemini, 2024; HyChain, 2024).

The numerator in the ROIC formula, Net Operating Profit After Tax (NOPAT), is selected as a key financial performance indicator. It can be calculated as follows:

$$\text{NOPAT} = \text{EBIT} \cdot (1 - \text{Tax rate}) = (R_{\text{total}} - C_{\text{operational}}) \cdot (1 - \tau) \tag{4.4}$$

with τ representing the corporate tax rate. EBIT, the Earnings Before Interest and Taxes, consists of the total revenue minus the operational costs. In this section, the focus is placed on what drives the total revenue from the income statement: price per unit and quantity sold, both of which are influenced by external market dynamics, system performance and strategic pricing decisions (Gassmann et al., 2014; Tuff, G. et al., 2023).

As defined in Figure 2.5, the revenue is generated through multiple output streams: hydrogen production and battery operation. This is followed in the model by the calculation of the total revenue by:

$$R_{\text{total}} = R_{\text{H}_2} + R_{\text{battery}} \tag{4.5}$$

Due to the high technological complexity of this technology, simplification is needed to get the revenue into the drivers of the separate revenue streams. The breakdown of this is given in Table 4.2.

Hydrogen production is a primary value proposition for electrolysis systems (International Energy Agency, 2022). It can be calculated based on technological parameters such as system capacity, stack efficiency and conversion rates (Detz et al., 2022). On the operational side, the number of full-load operating hours per year is a major determinant of output and cost per kilogram of hydrogen produced (Agora Energiewende, 2021; HyChain, 2024).

The values of these parameters are largely dependent on the scale and stability of green hydrogen demand in both industrial and mobility sectors (Hydrogen Europe, 2022). In particular, offtake agreements and sector-specific decarbonization targets influence long-term deployment feasibility (Azadnia et al., 2023). On the revenue side, the hydrogen price emerges as a central value driver. Due to market immaturity, pricing remains volatile and subject to uncertainty in both short-term spot markets and long-term contracts (Delft, 2023). These fluctuations represent critical boundary conditions for investment viability and impact return profiles.

Given the dual function of an electrolyser and battery, the other part of the revenue is derived from arbitrage revenue. This is considered crucial in flexible energy models (Pfenninger & Keirstead, 2015). Battery-related income, denoted R_{battery}, depends on the operational strategy and uncertainty about the price spread in the electricity market (TNO, 2022).

Table 4.2: Revenue drivers overview by system function

Variable	Abbreviation	Unit	Description
Electrolyser			
Hydrogen sales revenue	R_{H_2}	€	Revenue from selling produced green hydrogen to industry or mobility markets
Hydrogen price	p_{H_2}	€/kg	Average market price per kilogram of hydrogen
Hydrogen output	q_{H_2}	kg/year	Total annual hydrogen production volume
Electrolyser electricity use	H_{annual}	kWh/year	Total annual electricity input to the electrolyser
Specific energy demand	s_{H_2}	kWh/kg	Electricity required to produce 1 kg of hydrogen
Full load hours (electrolyser)	FLH_{elec}	hours/year	Annual full load hours assumed for electrolyser operation
Electrolyser capacity	P_{elec}	kW	Installed electrolyser capacity
Battery			
Battery arbitrage revenue	R_{battery}	€	Income from electricity market arbitrage using battery storage
Battery discharge volume	Q_E	kWh/year	Net electricity delivered after round-trip efficiency and losses
Battery efficiency	η_{batt}	%	Round-trip efficiency of the battery
Battery capacity	P_{batt}	kW	Installed battery power rating
Full load hours (battery)	FLH_{batt}	hours/year	Operating hours at full load for the battery
Parasitic losses	C_{loss}	kWh/year	Losses due to standby, conversion, and thermal management

Further specifications on the mathematical formulation of the key relationships of these value drivers are provided in Appendix B. Given the identified drivers, the sub-tree of the revenue drivers is given in Figure 4.3.

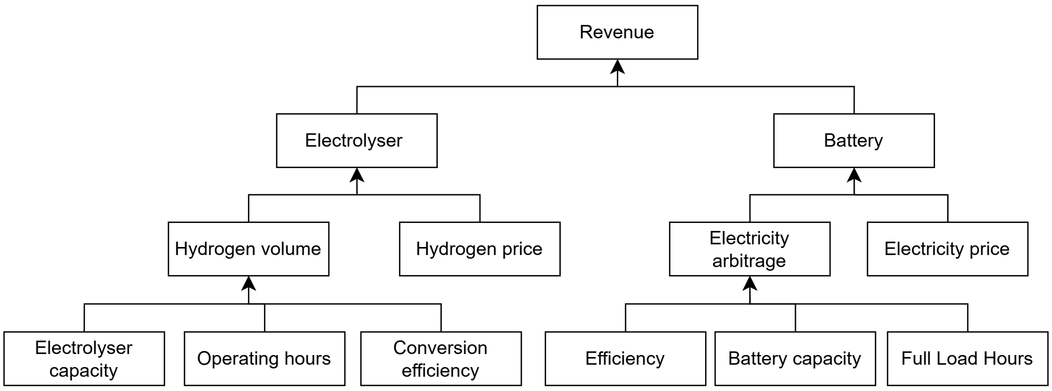

Figure 4.3: Sub-tree of the revenue drivers for Battolyser Systems

The sub-tree on revenue value drivers in Figure 4.3 shows a clear two-fold division into the electrolyser and battery function. This ensures a conceptual view of the operation of the Battolyser and the value drivers essential for each part. The tree shows where input data is needed and also includes parameters that are stated as important uncertainties in the market.

4.3.2. Operating cost drivers

The second focus of the model concerns the operating cost drivers, which are critical in evaluating the financial feasibility of Battolyser Systems. In financial management, there are various ways to group or display cost parameters depending on the level of granularity and purpose of analysis (Carlucci et al., 2004; Koller et al., 2010). For this techno-economic model, the cost structure is linked to EBIT, where the operational cost components are decomposed into two categories: Cost of Goods Sold (COGS) and Operating Expenses (OpEx). These categories reflect the distinction between volume-dependent costs and fixed recurring expenditures and provide a clear basis for structured financial evaluation (Kaplan & Norton, 2004).

The operating cost function is defined as:

$$C_{\text{operating}} = C_{\text{COGS}} + C_{\text{OpEx}} \tag{4.6}$$

An overview of the cost-related model variables is provided in Table 4.3. COGS includes expenditures that scale directly with system usage, such as electricity costs for electrolyser and battery operation, grid tariffs and hydrogen production inputs (Detz et al., 2022; TNO, 2022). Since electricity prices are highly volatile and represent the largest share of marginal costs, this cost component introduces significant uncertainty into the model (Delft, 2023; Institute for Energy Economics and Financial Analysis (IEEFA), 2023).

Operating Expenses (OpEx) consist of system-level maintenance, stack replacements, auxiliary systems and overheads. For modelling purposes, OpEx is assumed to scale linearly with installed capacity, based on benchmarks from similar electrolyser technologies (Hydrogen Europe, 2022; International Energy Agency, 2022). This assumption is consistent with findings from techno-economic assessments of integrated hydrogen systems (Jenkins et al., 2022). OpEx is considered a long-term value driver, affecting both EBIT and EVA through its influence on recurring cost loads (Walters et al., 2020).

Table 4.3: Cost drivers overview by system function

Variable	Abbreviation	Unit	Description
COGS			
Electricity price	p_{elec}	€/MWh	Price of electricity used by operation
Battery energy consumption	H_{bat}	MWh/year	Annual energy consumption by battery system
Battery electricity cost	$C_{\text{elec, batt}}$	€	Energy consumed for battery charging
Electrolyser energy consumption	H_{el}	MWh/year	Annual energy consumption by electrolyser
Electrolyser electricity cost	$C_{\text{elec, el}}$	€	Energy consumed for hydrogen production
Grid tariff	τ_{grid}	€/MWh	Cost paid per MWh to grid operator
Total electricity consumption	E_{total}	MWh/year	Total electricity consumed by the system
Grid cost	$\tau_{\text{grid}} \cdot E_{\text{total}}$	€	Grid usage cost
OpEx			
Stack replacement cost	C_{stack}	€	Annualized cost of stack degradation
Stack lifetime	L_{stack}	Years	Average operational life of an electrolyser stack
Stack cost fraction	γ_{stack}	-	Fraction of CapEx related to the stack
Electrolyser CapEx per MW	$C_{\text{el}}^{\text{cap}}$	€/MW	Investment cost per MW of electrolyser capacity
Electrolyser capacity	$P_{\text{electrolyser}}$	MW	Installed power capacity of electrolyser
O&M cost coefficient (electrolyser)	β_e	€/MW	Annual O&M cost per MW electrolyser capacity
O&M cost (electrolyser)	$C_{\text{o\&m, el}}$	€	Annual maintenance cost for electrolyser
Battery capacity	E_{battery}	MWh	Installed battery energy storage capacity
O&M cost coefficient (battery)	β_b	€/MWh	Annual O&M cost per MWh battery capacity
O&M cost (battery)	$C_{\text{o\&m, batt}}$	€	Maintenance cost for battery system

Further specifications on the mathematical formulation of the key relationships of these value drivers are provided in Appendix B.. The related sub-tree of the cost drivers is shown in Figure 4.4.

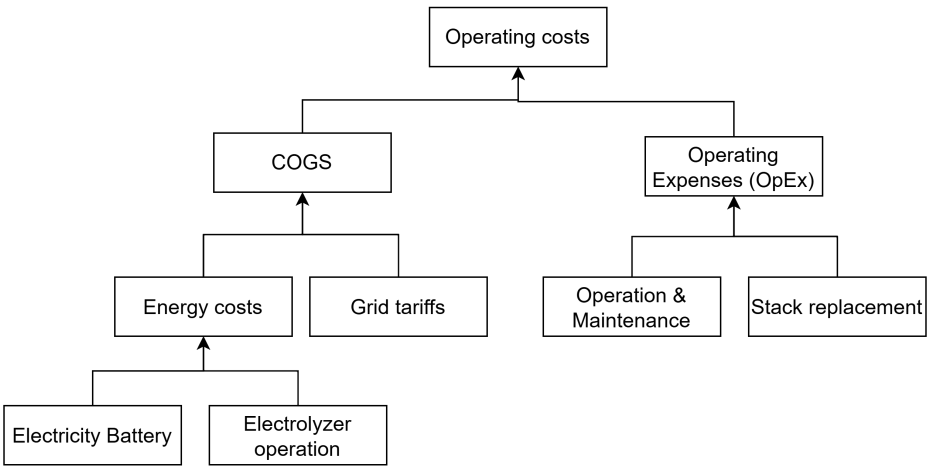

Figure 4.4: Sub-tree of the cost drivers for Battolyser Systems

Figure 4.4 illustrates the conceptual sub-tree on the drivers creating the value of the operating costs for Battolyser Systems in total. On one hand, the focus is more on the direct costs associated with producing goods sold and second on all other (indirect) expenses. This separation creates an illustration of relevance and details for the technological and broader system inputs of these costs.

4.3.3. Invested Capital

Next to the operational cost drivers, another key dimension in investment performance is the capital base, which directly influences the calculation of ROIC and EVA (Stern et al., 1995). This stream of the model focuses on invested capital, consisting of both net fixed capital and net working capital (NWC). These components are essential to accurately assess the financial requirements for generating returns and are highly relevant in the context of capital-intensive technologies such as hydrogen production systems (Koller et al., 2010).

The total invested capital is formally expressed as:

$$K_{\text{invested}} = K_{\text{fixed}} + K_{\text{nwc}} \tag{4.7}$$

Net fixed capital reflects long-term capital expenditures (CapEx) associated with the deployment of Battolyser Systems. It includes upfront investments in system hardware, adjusted for depreciation throughout the lifetime of a project (Detz et al., 2022; Jenkins et al., 2022). CapEx refers to one-time expenditures incurred during the design, acquisition and commissioning phases, which are capitalised and depreciated over time (Koller et al., 2010). As green hydrogen infrastructure typically requires high upfront investments and long asset lifetimes, fixed capital becomes a dominant factor in determining the required return on capital (International Energy Agency, 2022).

Fixed capital is also sensitive to external influences, such as CapEx subsidies, innovation incentives or technology learning effects. These policy mechanisms can significantly reduce capital requirements and are therefore treated as important boundary conditions in the model (Capgemini, 2024; Hydrogen Europe, 2022).

In contrast, Net Working Capital (NWC) captures short-term capital requirements within the operating cycle. This includes outstanding receivables from hydrogen customers, unpaid bills for electricity inputs or services and inventories of hydrogen or system components (Hydrogen Council, 2021). In rapidly growing energy ventures, NWC often scale with revenue and depends heavily on contract structures and billing cycles (BloombergNEF, 2023). For modelling purposes, NWC is expressed as a percentage of total revenue, reflecting its proportional behaviour with growth (Carlucci et al., 2004).

Efficient management of working capital is critical (Vartiainen et al., 2020). When not properly optimised, NWC can absorb large amounts of operational liquidity and lead to reduced ROIC (Walters et al., 2020). Therefore, this parameter is highly relevant when identifying boundary conditions of financial materials under uncertainty.

An overview of the key variables that influence invested capital is presented in Table 4.4. This table includes both fixed asset expenditures and the short-term liquidity required to support operations and market engagement.

Table 4.4: Invested capital drivers overview

Variable	Abbreviation	Unit	Description
Fixed capital			
Net fixed capital	K_{fixed}	€	Long-term capital expenditures for deployment and commissioning
Electrolyser capital cost	$C_{\text{electrolyser}}$	€/kW	Specific CapEx of electrolyser system
Installed electrolyser capacity	$P_{\text{electrolyser}}$	kW	Total installed power capacity of the electrolyser
Battery capital cost	C_{battery}	€/kWh	Specific CapEx of battery system
Installed battery capacity	E_{battery}	kWh	Total installed energy capacity of the battery
Net working capital			
Net working capital	K_{nwc}	€	Short-term capital tied up in receivables, payables and buffers
Working capital coefficient	α	–	Proportionality factor for net working capital estimation

Further specifications on the mathematical formulation of the key relationships of these value drivers are provided in Appendix B. How these drivers are stated in the tree is visualised in Figure 4.5. Important to acknowledge the revenue driver for net working capital. This is linked to the sub-tree stated in Figure 4.3. So, this makes it important to be consistent in determining this driver.

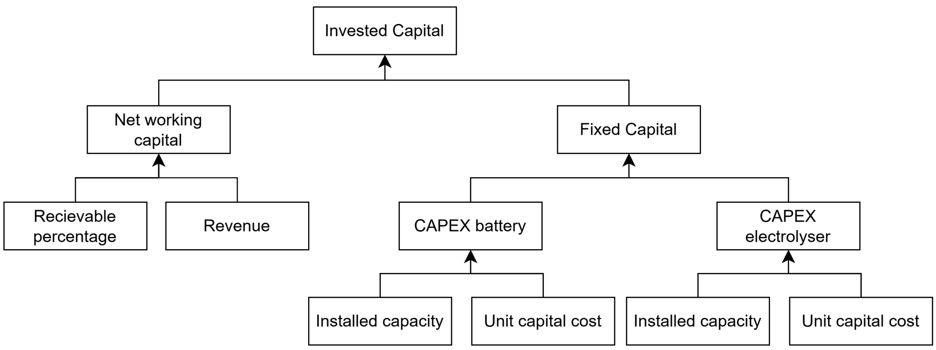

Figure 4.5: Sub-tree of the invested capital drivers for Battolyser Systems

The sub-trees enable dynamic modelling of the value drivers essential for the systems calculating financial indicators. Combining these trees into one, the resulting conceptual model for simulation is obtained. The details of how this looks are given in Appendix C. The figure provides a foundation for analysis by linking all the technical, operational and financial choices. The tree aligns with techno-economic modelling and sets the structure by connecting every value towards a system.

5
Uncertainty specification

This chapter identifies, classifies and quantifies the uncertainties and boundary conditions that influence the behaviour of value drivers within the investment simulation model. It provides the foundation for stochastic experimentation in later chapters and answers sub-question 2 *'What are the key boundary conditions and uncertainties that affect the behaviour of these value drivers?'*. First, the system uncertainties as stated in the literature have been analysed and defined, then with a stakeholder analysis, the most relevant uncertainties have been selected on their relevance across stakeholder concerns, specified to the system boundary for further implementation into the model.

5.1. System environment uncertainty

Uncertainty plays a central role in investment decisions for emerging technologies like green hydrogen. This section identifies and classifies the key uncertainties relevant to the system used in this research, based on chapter 2. To systematically determine which uncertainties are relevant for inclusion in the simulation model, this study is based upon the uncertainty typology presented in Ascough et al. (2008), as introduced in chapter 2. This typology categorises variability uncertainty into four overarching types: natural, human, institutional and technological. These uncertainties are characterised by their dynamic and often probabilistic nature and inclusion in the simulation model (Kwakkel et al., 2016).

Focusing specifically on the Battolyser concept, uncertainties are scoped based on electrolyser and battery domain-specific literature addressing the key challenges within the Dutch hydrogen and energy storage markets. Based on Tuff, G. et al. (2023) and Azadnia et al. (2023), seven primary uncertainty domains are identified: (1) market dynamics, (2) environmental changes, (3) social perception, (4) policy and regulatory risk, (5) economic volatility, (6) infrastructure constraints and grid integration and (7) technological and cost uncertainties. These categories are visualised in Figure 5.1, linked to the variability types of the uncertainty framework.

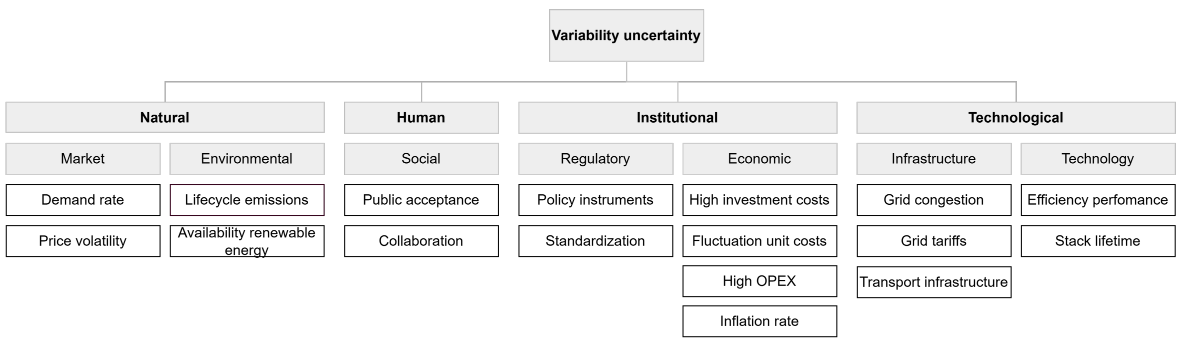

Figure 5.1: Variability uncertainty in categories made by the author

Following this categorisation, each domain of uncertainty is further specified in the subsequent sections to operationalise its relevance. In line with the framework of Ascough et al. (2008), the uncertainties are not treated as abstract concepts but are made actionable by linking them to concrete system elements, and where possible, making modelling assumptions. The aim is to clarify how the different types of natural, technical, behavioural and institutional uncertainty display within the context of the Battolyser investment case and how they are addressed. Following this categorisation, each uncertainty domain is specified further in the following sections.

5.1.1. Natural uncertainty

The first domain considered is natural uncertainty, which is related to environmental variability and external market conditions beyond the control of the system (Ascough et al., 2008). The domain is linked towards the market and environmental uncertainty.

Market dynamics

One of the biggest questions is whether there will be enough demand for green hydrogen in the future to justify large-scale investments. Forecasts for hydrogen use in the Netherlands vary widely between different sectors (mainly industry, transport and electricity). The Hydrogen Outlook by TNO (2022) shows where hydrogen demand is likely to grow, especially near industrial clusters, but these projections heavily rely on policy choices that are still uncertain. Similar EU-level forecasts from Hydrogen Europe (2022) and European Commission Joint Research Centre (2021) can help to benchmark the Dutch outlook and show different perceptions.

Another critical factor is the volatility of the electricity price. Since hydrogen is produced using electricity, fluctuations in electricity costs have a huge impact on the Levelized Cost of Hydrogen (LCOH). Reports by Institute for Energy Economics and Financial Analysis (IEEFA) (2023) and TNO (2022) show that regional grid congestion, sourcing strategies and locational tariffs can cause significant differences in hydrogen production costs. Most financial models assume stable average electricity prices, but Agora Energiewende (2021) points out that it is essential to also consider price volatility. Especially with the congested and renewable heavy electricity grid in the Netherlands.

Environmental changes

Environmental factors, such as the variability of renewable resources, can cause fluctuations in the amount of hydrogen that a Battolyser system can produce. Because these systems rely on wind or solar energy, variations in wind speed or solar radiation over seasons or years can significantly affect performance. For example, Dutch offshore wind patterns can vary by up to 15–20% annually, which would change the capacity factor of the electrolyser. Climate change could also introduce more extreme weather events, such as storms or heat waves, which could affect both the energy supply and the reliability of the equipment. These factors introduce operational uncertainty, especially on long-term investment horizons.

5.1.2. Human uncertainty

Human uncertainty refers to the variability and unpredictability arising from social behaviour, preferences and stakeholder interactions. These uncertainties are epistemic. Unlike natural uncertainty, which is often externally assessed, human uncertainty originates from the decisions, perceptions and adaptive behaviour of actors within the system (Ascough et al., 2008).

Social perception

The human aspect of decision-making is based on social acceptance. Although hydrogen is generally seen as a clean energy solution, the public may resist projects that involve large-scale infrastructure near residential areas. Concerns can include safety, noise, visual impact or even a general mistrust of new technologies. Studies such as Wolsink (2000) and data from PBL Netherlands Environmental Assessment Agency, 2022 show that gaining social agreement on operationalisation is not a given. It depends on transparent planning, fair compensation and meaningful community involvement. If local opposition arises, it could cause serious delays or even the cancellation of projects.

5.1.3. Institutional uncertainty

Institutional uncertainty emerges from the structures, rules and dynamics of governance, regulation and policy design. These uncertainties are particularly relevant in rapidly evolving technological and policy environments, where institutional responses often lag behind innovation. Institutional uncertainty is typically epistemic, as it is related to limited knowledge about how policies will evolve, how regulatory decisions will be implemented or how governance actors will interpret and apply rules (Ascough et al., 2008).

Policy and regulatory risk

The development of Battolyser systems in the Netherlands is strongly influenced by current regulatory uncertainties and policy developments in the flexibility of the electricity grid and the hydrogen market. These systems, which combine batteries and electrolysers, are at the intersection of several policy domains, leading to complex challenges and opportunities. Despite the hope and view of policies and regulations as the most powerful drivers of hydrogen project success, they are also very unpredictable.

Adding up the Dutch policy architecture given in chapter 2, the following section zooms into important instruments that are designed to reduce investment risks or improve market opportunities. Delays or changes in support schemes directly affect project timelines and returns.

Subsidies

The SDE++ (Stimulering Duurzame Energieproductie en Klimaattransitie) is the main Dutch subsidy instrument for emission reduction and is an operating subsidy payable during the operational period of a project ((RVO), 2024). In 2024, the budget was set at €11.5 billion. Subsidies are awarded based on cost-effectiveness per ton of CO2 avoided (voor Ondernemend Nederland, 2025). For electrolysis projects, the subsidy intensity is significant, with amounts up to €1,500 per ton of CO2 avoided. This amounts to about €9 per kilogram of green hydrogen produced (Eggink & Elzenga, 2024). As ECN part of TNO (2020) shows, the level of subsidies and carbon dioxide pricing has a major impact on financial viability. Moreover, large infrastructure plans like the Dutch Hydrogen Backbone are still in planning stages and could take years to implement, adding more uncertainty to infrastructure availability.

The second is the OWE (Scaling Up Fully Renewable Hydrogen Production), a scheme that specifically focuses on scaling up electrolysis projects ((RVO), 2022). By 2024, projects could be subsidised up to 80% of investment costs, supplemented by an operating subsidy for the unprofitable top for 5 to 10 years. The maximum amount of subsidy per project was €499 million ((RVO), 2022).

The Dutch government has committed €2.1 billion to green hydrogen production, introducing subsidies to boost domestic hydrogen production (voor Ondernemend Nederland (RVO), 2021). The scheme is intended for projects that improve the cost-effectiveness of technologies within SDE++. The HER+ grant supports innovative projects that lead to cost-effective CO2 reductions. In 2024, the budget was €30 million, with a subsidy intensity of up to €300 per ton of CO2 avoided.

Although these subsidies provide significant financial support, there is uncertainty about the continuity and exact terms of these schemes. The complexity of application procedures and competition between projects can limit accessibility for innovative systems such as the Battolyser.

Grid charges and access

Battery energy storage systems (BESS) face high grid charges in the Netherlands. Recently, changes have been made to mitigate these charges, such as the introduction of non-firm grid connections with lower fixed tariffs. Flexible off-takers, such as electrolyser projects, can reduce their grid fees on contracted capacity (Swarts et al., 2025). These agreements allow for consumer curtailment in exchange for grid tariff discounts or per-MW compensation, enhancing the profitability of flexible hydrogen production.

While these changes are positive steps, there is uncertainty about their implementation and effectiveness. For Battolyser systems, which both store electricity and produce hydrogen, it is essential to have clarity on applicable grid tariffs and grid connection conditions.

Financing conditions and WACC

The WACC is a critical component in the evaluation of investment projects, representing the minimum expected return required by investors. In the Netherlands, the WACC for new capital investments in electricity and gas distribution has been established for the period 2022-2026, with an average increase of 20.92% in the regulated asset base (Harris & Figurelli, 2021). In the context of green hydrogen projects, WACC values between 6.4% and 24% are used as proxy values for perceived risk and investment climate, influencing the levelized cost of hydrogen production (Capgemini, 2024). Rising WACC values may affect the fundability of capital-intensive projects such as Battolyser systems. It is important to explore ways to optimise these financing costs, for example by using helpful financing instruments or mitigating risks through long-term contracts.

These insights into the policy uncertainties of the two markets briefly outline the policy options being considered. However, current regulatory frameworks for batteries and electrolysers are often separate, leading to uncertainty about applicable regulations and subsidies for integrated systems. Battolyser systems are combining battery storage with hydrogen production, offering unique opportunities for grid flexibility and green hydrogen production ((RVO), 2022).

There is a clear need for the policy integration of energy storage and hydrogen production schemes. The lack of a holistic approach may hinder the development and implementation of innovative systems such as the Battolyser. However, this also presents multiple opportunities to implement in Battolyser. Looking at how these policy instruments fit into the model, it is possible to see what the particular impact is. It is included as a full operational uncertainty, but rather as interventions to see what results from this.

Economic conditions

Recent years have shown that macroeconomic conditions, such as inflation, interest rates and global material prices, can change quickly and are unpredictable. Electrolysers are based on materials like nickel and platinum, which are subject to international supply chain risks and geopolitical tensions. At the same time, inflation and rising interest rates increase the overall cost of financing projects.

According to Institute for Energy Economics and Financial Analysis (IEEFA) (2023), capital costs for clean energy projects increased significantly in 2022–2023, and these trends could continue. For modelling purposes, it is important to include ranges of uncertainties in economic variables. The discount rates used in financial calculations should also reflect this increased uncertainty.

5.1.4. Technological uncertainty

And last, technological uncertainties include development, adoption, performance and cost evolution of emerging technologies (Jenkins et al., 2022). Here, the focus relies on the infrastructure and technological uncertainty towards Battolyser.

Infrastructure and grid integration

In the Netherlands, there are still major gaps between where hydrogen can be produced and where it is needed. Studies by TNO (2022) and PBL Netherlands Environmental Assessment Agency (2022) highlight the risk of stranded assets if electrolysers are not properly connected to the grid or hydrogen transport networks. Grid congestion, in particular, is already a serious issue in many parts of the Netherlands. It could get worse as more renewable capacity is added.

Technological performance and cost

Finally, the technology itself still involves a lot of uncertainty. Electrolyser and battery technologies are improving rapidly, but the costs and performance levels vary widely depending on the manufacturer, project location and regulatory context. EU-level reports by Hydrogen Europe (2022) and Institute for Energy Economics and Financial Analysis (IEEFA) (2023) suggest that costs will reduce over time. However, Dutch-specific challenges like permitting delays and higher system integration costs (especially with offshore wind) might limit these gains.

The seven uncertainty areas identified above are relevant for the Battolyser simulation but vary in how much they affect investment decisions and system performance outcomes.

5.2. Stakeholder analysis

Having identified the key uncertainties that shape the development and deployment of Battolyser systems in the Dutch hydrogen sector, it is crucial to examine how these uncertainties affect the various stakeholders involved (Bandari et al., 2024). This step ensures that the simulation model reflects not only technological or economic dynamics, but also the perspectives, incentives and constraints of the actors who either drive or are impacted by system changes (Woolthuis et al., 2005).

There are eight stakeholders identified that have relevance to the system:

- Technology developers and manufacturers, who design and produce Battolyser components
- Investors and project developers, who fund and develop projects
- Battolyser plant owner and operator, who deploy and manage Battolyser systems
- Policymakers, who create enabling frameworks towards long-term targets
- Regulators, who translate the goals into rules and mechanisms
- Grid operators, who ensure infrastructure connectivity and balance
- Industrial end-users, who create demand and adoption of the technology
- Local communities and NGOs, who influence acceptance

5.2.1. Stakeholder objectives

Stakeholder relevance is essential for identifying which uncertainties matter most in practice (Borrás & Edler, 2014). While some actors, such as technology developers, directly influence cost and performance parameters, others, such as policymakers or regulators, play a critical role in shaping institutional and infrastructure types of uncertainties. Therefore, the next phase of the stakeholder analysis is focused on how the objectives and connections of the actors are related to each uncertainty domain.

Technology developers and manufacturers play an essential role in navigating technological and infrastructure uncertainties. Their ability to reduce capital costs depends on stack efficiency, scale effects and integration with grid dynamics (Jenkins et al., 2022). Cost reductions depend on learning-by-doing and economies of scale, but are also exposed to material shortages, supply chain disruptions and uncertain demand signals (Detz et al., 2022).

These actors are exposed to innovation risks, certification challenges and potential regulatory lag on safety or technical regulations (Hydrogen Europe, 2022). Material scarcity and supply chain instability further contribute to the uncertainty of the infrastructure (International Energy Agency, 2022). These actors are critical drivers of the technology cost curve, but are themselves constrained by market feedback and policy alignment.

Investors and project developers are among the most exposed actors, as they are directly influenced by multi-dimensional uncertainty: fluctuations in demand, policy consistency, infrastructure availability and technology performance. Demand fluctuations influence projected demand agreements and long-term profitability, while evolving technologies impact capital and operation expenditure risks (Hydrogen Council, 2021). Regulatory instability introduces vagueness around subsidy access, carbon pricing and eligibility for public-private partnerships (Swarts et al., 2025). Fluctuating electricity prices and subsidy access complicate ROIC estimates ((RVO), 2022). In addition, market volatility can significantly alter the Levelized Cost of Hydrogen (LCOH) (Institute for Energy Economics and Financial Analysis (IEEFA), 2023). From an investor's perspective, uncertainty directly affects investment decisions.

Battolyser plant owners and operators are at the centre of deployment. They must align project development timelines with evolving infrastructure plans, integrate uncertain technologies like Battolyser units into their systems and adapt to dynamic policy frameworks. These actors also face social and local acceptance issues, particularly if the system is deployed at bigger scale or in industrial clusters near residential zones (Eggink & Elzenga, 2024). Operational planning must account for both production-side uncertainty (e.g., variability in renewable input) and demand-side variability, requiring flexible, robust infrastructure and business models (TNO, 2022).

Policymakers play a strategic and agenda-setting role in the deployment of Battolyser systems. They influence uncertainty by defining long-term climate targets, allocating subsidies such as HER+ or SDE++, and directing public investments in hydrogen infrastructure (Mazzucato, 2018). Governments also promote innovation through R&D funding and pilot programs, shaping both technological progress and market readiness. Their decisions determine the institutional environment in which private actors operate, including the availability of financial support, spatial planning conditions and the credibility of long-term demand. Although they are not passive recipients of uncertainty, they must respond to social pressure and environmental imperatives (Draghi, 2024). As such, government actions can either reduce or reinforce uncertainty across economic, infrastructure and market domains for all stakeholders.

Regulators, by contrast, have the task to operationalise government policy through market rules, safety standards and oversight mechanisms (Borrás & Edler, 2014). They influence uncertainty primarily through the timing and clarity of implementation. For example, regulators define tariff structures, grid access conditions, and safety criteria for financial instruments. Inconsistent or delayed regulatory updates create uncertainty, especially in emerging sectors where sometimes innovation outdrives legislation (Hydrogen Europe, 2022). Their influence is therefore critical in reducing institutional and operational uncertainty during system deployment.

Grid operators actually experience infrastructure risks (Alam et al., 2020). However, they require coordination with regulators and project developers to enable timely connections and balancing of the grid. Electricity grid operators are indirectly involved in Battolyser deployment through infrastructure planning, connection approval and balancing operations (TenneT, 2024). They face significant regulatory uncertainty due to changing policies around congestion management, locational tariffs and curtailment rules. Market uncertainty is also relevant, as high renewables penetration increases price volatility (Swarts et al., 2025). These actors require clear long-term planning signals to align grid investments with decentralised hydrogen production.

Industrial end-users are highly dependent on market and cost dynamics, which influence adoption of feasibility and competitiveness in energy sectors (Hydrogen Europe, 2022). Hydrogen users can be indicated as industrial producers, owners of transport fleets or users of energy utilities (Azadnia et al., 2023). They face demand and supply uncertainty from a consumption perspective. Their long-term purchase contracts are shaped by cost competitiveness and energy transition alignment (International Energy Agency, 2022). These actors must assess whether hydrogen will be available at competitive prices, with reliable delivery and quality.

Technological uncertainty determines how easily hydrogen can be integrated into existing operations. Although consumers have less direct influence on market shaping than system designers, purchasing decisions create the demand signals that influence upstream investment (BloombergNEF, 2023).

Local communities and NGOs, while not involved in technical implementation, can delay or reshape project trajectories through resistance, safety or environmental concerns. Communities can have significant indirect influence on deployment outcomes, design and operation through public acceptance or resistance (Eggink & Elzenga, 2024). Infrastructure development with visible structures, land use or safety concerns gets push-back (Wolsink, 2000). Therefore, social perception uncertainty becomes a potential source of delay. Early stakeholder engagement and participatory design processes can mitigate this risk (Bandari et al., 2024).

5.2.2. Stakeholder map

How these stakeholders are positioned with corresponding interactions is shown in Figure 5.2. The stakeholder map reveals a highly interconnected ecosystem. The connections show information flows, regulatory dynamics, investment signals and social influences. The Battolyser owner and operator are connected to all other actors and serve as integrators at the deployment level. Policymakers and regulators influence nearly all actors.

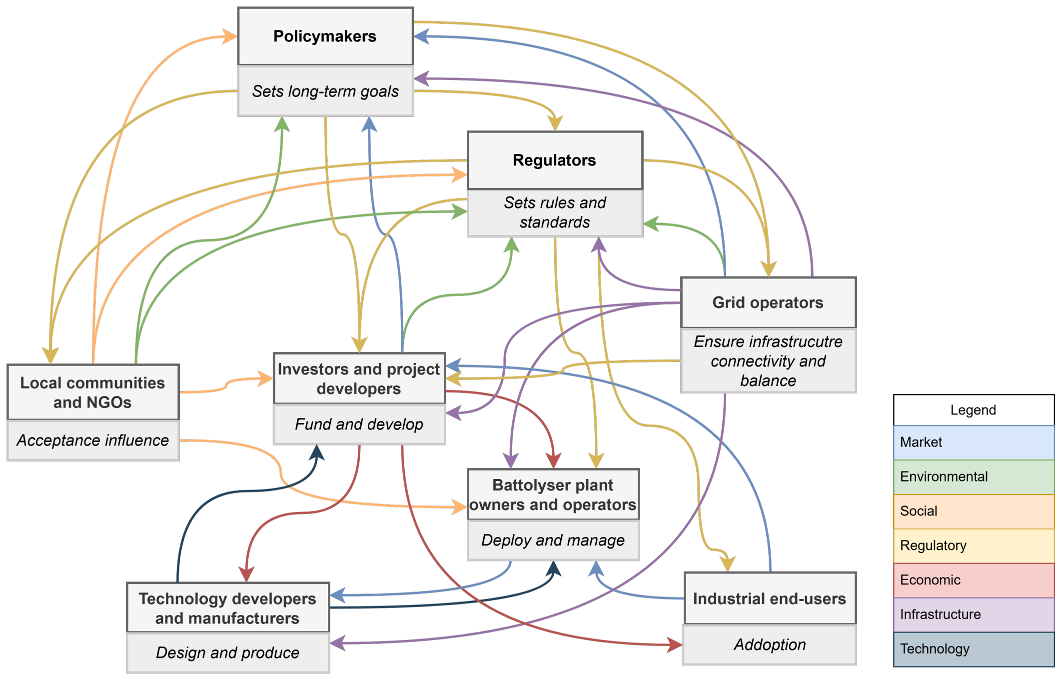

Figure 5.2: Stakeholder overview related to uncertainty domains made by the author

5.2.3. Stakeholder relevance towards uncertainties

To conclude, Table 5.1 presents a mapping of stakeholder relevance across key uncertainty domains in the Battolyser system. By linking each uncertainty category to its most affected stakeholders, we can better understand the decision-making environment around Battolyser deployment and construct simulation modelling that reflects the complexity and influences for specific stakeholders.

Table 5.1: Stakeholder influence across key uncertainty domains in the Battolyser system

Stakeholder Group	Market	Environmental	Social	Regulatory	Economic	Infrastructure	Technological
Technology developers	○			○	○	●	●
Investors	●	○	○	●	●	●	●
Plant owners	●	○	●	○	●	●	●
Policymakers	○	○	○	●	○	●	○
Regulators	○	○	○	●	○	●	○
Grid operators	○	○		○	○	●	○
Industrial end-users	●		○	○	●	○	○
Local communities	○	●	●	●		○	

Legend: ● = High influence or exposure; ○ = Moderate or indirect influence

To understand the relevance of each uncertainty per stakeholder, a more actor-sensitive model design not only supports but also ensures that the simulation captures the socio-technical dynamics of Battolyser deployment. The matrix highlights that uncertainty is not experienced uniformly by stakeholders. Some actors (e.g., investors, plant operators) are highly exposed and reactive, while others (e.g., policymakers, regulators) actively shape the conditions under which uncertainty unfolds. This confirms that uncertainty should not be treated as an exogenous input but as the result of multi-actor interaction and adaptive decision-making.

5.3. Model variables for simulation

The next step is the translation of relevant uncertainty domains into specific model variables. to be consistent in the criteria for the modelling analysis based on Table 3.1, these variables:

- Affects system behaviour or investment feasibility directly.
- Are viewed as critical by relevant stakeholders.
- Are feasible by quantification and/or traceability in empirical or literature-based sources and can be supported with data, expert studies, or modelling assumptions.

The variables for simulation are divided into uncertainty by external factors and by related policy interventions in the system.

5.3.1. Uncertain parameters in system

Based on this, the boundaries are kept to the project and technology-focused related to the Battolyser Systems on purpose. However, the scope is crucial for the economic performance of integrated systems. The social and environmental uncertainties can be seen as uncertainties, but are out of scope for quantifying in the model. In this way, a manageable modelling scoping is maintained while capturing critical techno-economic relationships. Also, this is done to ensure that financial metrics can be calculated based on project-specific data without the need to simulate entire market ecosystems. Due to subjectivity or lack of data and uncertainty domains, such as public perception, policy delay or macroeconomic instability, these data are excluded from the core simulation model.

The five uncertain variables presented in Table 5.2 were selected based on their dual relevance to both stakeholder concerns and the economic performance of Battolyser System. Each variable directly influences a core value driver in the model: cost, revenue, efficiency or utilisation. Also, they can be quantified through empirical data or by expert-derived distributions.

Variation of the electricity and hydrogen prices reflect market volatility and revenue risk, particularly for investors and end-users. CAPEX captures investment uncertainty and technological maturity, while operating hours and conversion efficiency determine the operational feasibility and yield of the system. Together, these parameters form a coherent and tractable set of inputs for Monte Carlo simulation within the value driver tree framework, enabling scenario analysis with real-world uncertainties.

Table 5.2: Integration of stakeholder-relevant uncertainties into the simulation model and VDT framework

Model variable	Uncertainty factor	Category	Stakeholders concerned	Justification
p_{elec}	Electricity price volatility	Market	Investors, end-users, policymakers	Primary cost component of hydrogen production. This parameter varies hourly and data available
p_{H_2}	Hydrogen selling price	Market	Investors, end-users	Key determinant of revenue, which is sector-dependent on demand and price structures
C_{CAPEX}	CAPEX variability due to learning curves, supply chain, scale-up	Infrastructure and Technological	Developers, investors and regulators	Affects total investment. Input informed by HydrogenEurope, ECN and experts
FLH_{elec}	Operating hours (Full Load Hours)	Infrastructure	Grid operators, plant operators	Reflects renewable availability, curtailment, grid capacity and affects utilisation
η_{conv}	Conversion efficiency of Battolyser	Technological	Developers	Influences electricity-to-H2 ratio. Input is based on technological specification with moderate variability

With the analyses and definitions of the system uncertainties and together with the stakeholder analyses, the most relevant uncertainties have been selected on their relevance across stakeholder concerns, electricity price, hydrogen selling price, CAPEX, operating hours and conversion efficiency of the Battolyser, which will be specified to the system boundaries for further implementation in the model.

5.3.2. Policy uncertainty as intervention

As mentioned in chapter 2, a major source of structural uncertainty within this study is the misalignment between the functional characteristics of the Battolyser technology and the existing Dutch policy framework. The Battolyser combines battery storage and electrolysis in one integrated system, offering both operational flexibility and the possibility of decentralised hydrogen production (Origins, 2024). This hybrid usage makes the technology potentially very valuable for balancing the grid load and stabilising the variable renewable energy. However, current policy and market design are insufficiently aligned to this kind of new multifunctional technology, making economic valuation uncertain.

Current subsidy mechanisms, such as the SDE++, focuses on continuous hydrogen production under fixed full-load hours and do not take into account technologies that operate cyclically or market-driven. At the same time, existing regulations around grid connection count on structures of flexibility and system services. The pricing of electricity imports and exports are based on a separation of roles between generation, storage and consumption. The Battolyser exceeds this separation, leading to policy ambiguity, like the double allocation of network fees or network charges.

This policy context introduces a form of epistemic uncertainty into the model. The technology itself is not unreliable, but it is because it remains unclear to what extent the policy incentives facilitate or hinder its operation. Within the Value Driver Tree model, this institutional uncertainty is explicitly included in the modelling of the value creation. Based on this identification, three policy interventions have been selected that are theoretically and modelling relevant for lowering the barriers.

- Operational Working Expenditure (OWE) subsidy: a subsidy on operational costs specifically targeted at market-based hydrogen production with variable load profiles.
- Reduction of network tariffs: as a measure to compensate for the cost of double connection or feed-in.
- Weighted Average Cost of Capital (WACC) adjustment: as a representation of risk reduction through targeted policy certainty or investment instruments.

These interventions are simulated within the probabilistic VDT model by analysing the impact on both the EVA and the entropy of outcome distributions. In this way, not only the potential policy impact is evaluated, but also the extent to which different interventions contribute to epistemic robustness and investment security. Thereby, this approach forms a bridge between uncertainty identification and policy design grounded in structured system simulation.

6 Simulation model development

This chapter focuses on how to build the model from a theoretical foundation to an empirical tool. The aim is to instantiate theoretical constructs into a robust simulation environment, capable of analysing various uncertainties and giving answers on the third sub-question of the research: *'How can a simulation model be designed based on the value driver tree to capture investment performance under uncertainty?'* The objective is to formalise the input-output relationships that enable scenario-based performance assessment and support strategic decision-making.

6.1. Conceptual framework for simulation design

To systematically integrate the complexity of the energy system into the techno-economic modelling of Battolyser systems, this study adopts the XLRM framework Jafino et al., 2021. The framework offers a structured and theory-based approach to distinguish and organise key elements necessary for robust simulation-based policy analysis: Exogenous uncertainties (X), Policy levers (L), Model relationships (R), and Performance metrics (M). Its adoption ensures conceptual consistency and enables a transparent translation from theory to simulation.

6.1.1. External factors

As follow-up from the uncertainty analysis in chapter 5, the full uncertainty space is defined as a multi-dimensional configuration of key variables. The focus is on quantification and operationalisation as input for simulation. These factors include electricity and hydrogen prices, CAPEX, operating hours and conversion efficiency. The variable values are driven by external influences on the system, but will fundamentally shape the investment performance. They are treated as stochastic variables, with appropriate probabilistic distributions and are defined to reflect aleatory uncertainty as inherent variability. This distinction enables a more nuanced simulation setup, where both randomness and data limitations are taken into account. Table 6.1 provides an overview. These ranges enable to test the robustness and sensitivity analysis. The experimental defined setup directly feeds the simulation phase.

Table 6.1: Key uncertainties [X] as external factors in the system with corresponding distributions

Uncertainty	Unit	Range	Description	Source
Electricity price (p_{elec})	€/MWh	Determined by kEV 2024 data input	Hourly electricity price for 2030	KEV Climate and Energy Outlook 2024 Intelligence, 2025
Hydrogen price (p_{H_2})	€/kg H_2	3 – 14	Aleatory uncertainty for Monte Carlo distribution	Detz et al. (2022)
CAPEX (Unit capital cost electrolyser)	€/MW	370,000 - 1,666,000	Aleatory uncertainty for Monte Carlo distribution	Rouwenhorst et al. (2019), Hydrogen Europe (2022)
Operating hours (FLH)	h/year	2500 - 8000	Aleatory uncertainty for Monte Carlo distribution	
Conversion efficiency (s_{H_2})	kWh/kg H_2	50 - 65	Aleatory uncertainty for Monte Carlo distribution	Hydrogen Europe (2022)

6.1.2. Policy levers

Policy levers represent the available instruments to regulators and public authorities how they will influence the system performance. Their inclusion ensures that the simulation not only reflects external constraints but also captures the effect of targeted interventions. The selected levers reflect real-world instruments as have been found in Dutch and European hydrogen policy contexts and are grouped into three categories: financial support instruments (OWE subsidy), infrastructure and cost regulations (grid tariff reductions) and market-based financial incentives (adjustments to WACC). Table 6.2 details the selected policy levers, their ranges, and sources.

Table 6.2: Policy levers [L] used in the simulation

Policy	Unit	Range	Description	Source
Operational subsidy	€/MWh	0 – 60	Compensation for the unprofitable component of renewable hydrogen production under the OWE scheme	(RVO) (2024)
Grid tariff reduction	%	–20 – 0	Tariff reductions for flexible hydrogen producers	Swarts et al. (2025)
WACC	%	6 – 24	Proxy for perceived risk and investment climate	Capgemini (2024)

6.1.3. Model relationships

The internal relationships (R) are structured via a value driver tree by linking technical inputs and policy variables to financial outputs. As given in chapter 4, the relationships define the internal logic of the model and have been made operational through a value driver tree. This tree captures the causal and financial relationships between technical characteristics, investment decisions and value creation. Each node in the tree is translated into equations and conditional logic in the simulation code. The core modelling relationships in this study have been made operational through the value-based financial framework that calculates the EVA.

6.1.4. Performance metric

Finally, to complete the framework, the criteria, which are evaluated against the system performance, are defined. As stated in the value driver identification in chapter 4, EVA serves as the primary metric, offering a comprehensive measure of value creation beyond the cost of capital.

The model evaluates system viability using a structured set of performance metrics that combines financial, operational and institutional criteria. These metrics are used to compare system configurations, assess sensitivity to external conditions and eventually evaluate the effectiveness of policy levers. The concluding XLRM framework is given in Figure 6.1.

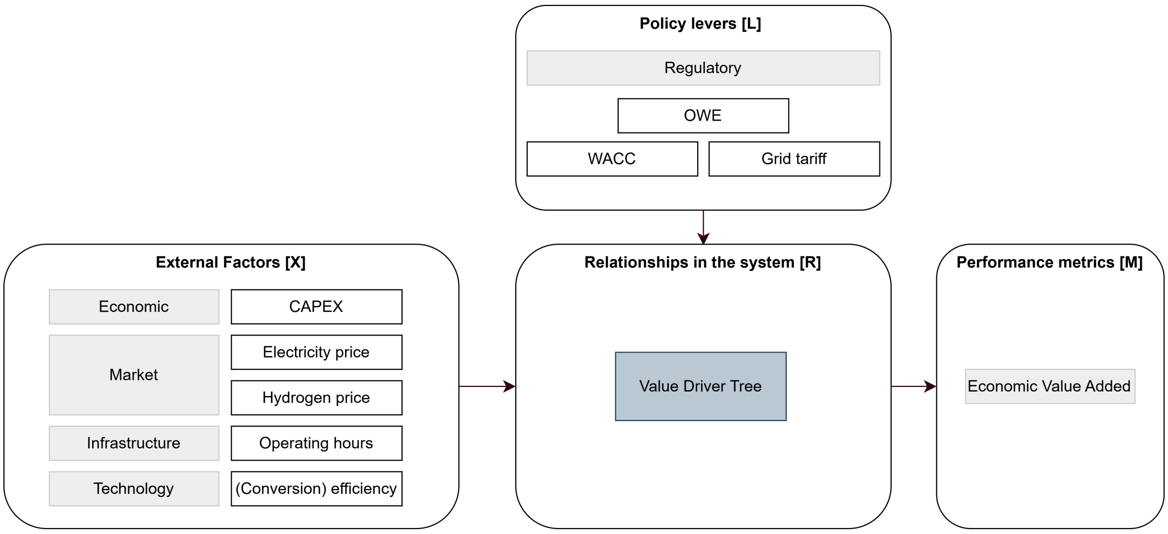

Figure 6.1: XLRM framework based on Jafino et al., 2021

6.2. Software implementation

The simulation framework has been developed in Python using a modular and extensible architecture that reflects the causal structure of the VDT. This implementation reflects the modelling criteria established in Table 3.1, particularly to transparency, reproducibility and uncertainty implementation. The workflow is structured to enable both deterministic and stochastic simulation processes, depending on the input configuration. An overview of the core simulation architecture is presented in Figure 6.2.

The simulation process begins with an initialisation phase, during which relevant libraries are imported, configuration settings are established and the structural definition of the VDT is imported via a structured Excel spreadsheet interface. This ensures that the system designs or stakeholder priorities can be easily adjusted.

Each node in the VDT corresponds to a specific value driver, as detailed in Appendix C. These nodes are defined according to a consistent scheme, enabling flexible integration of both fixed values and probabilistic uncertainties. The key attributes of each node include:

- **Level**: Indicates the depth of the node within the VDT hierarchy and determines the computation sequence. For instance, high-level performance indicators such as EVA are assigned to a top-level index, while base inputs (e.g., cost parameters) are located at the lowest level.
- **Unit**: Specifies the measurement unit of the node output, ensuring consistency in aggregation and interpretation across the tree.
- **Operator**: Defines the mathematical relationship between the node and its direct inputs. Supported operations include summation (+), subtraction (−), multiplication (*) and division (/), facilitating algebraic expression of value logic.
- **Fixed value**: Nodes at the lowest hierarchical level that are purely input-driven and can be assigned to deterministic fixed values, suitable for scenario testing or baseline calibration.
- **Distribution characteristics**: For nodes subjected to uncertainty, probability distributions are defined via parameters such as mean, minimum, and maximum values. This enables stochastic simulation using random sampling techniques.

Once the nodes are defined and structured, the simulation engine constructs a directed acyclic graph (DAG), in which each node is represented as a function of its immediate upstream inputs. This facilitates recursive computation through the hierarchy and ensures logical coherence in value propagation.

During execution, inputs are processed in a level-wise manner, starting from base values and proceeding upwards through the tree. This structure enables dynamic updating. When changes in input values or distributions are made, they automatically propagate through the model, ensuring consistency in output calculation.

The simulation results are stored in structured data formats, allowing for direct visualisation, statistical summarisation and sensitivity analysis. This modular architecture supports a clear analytical pathway from raw input to actionable insights.

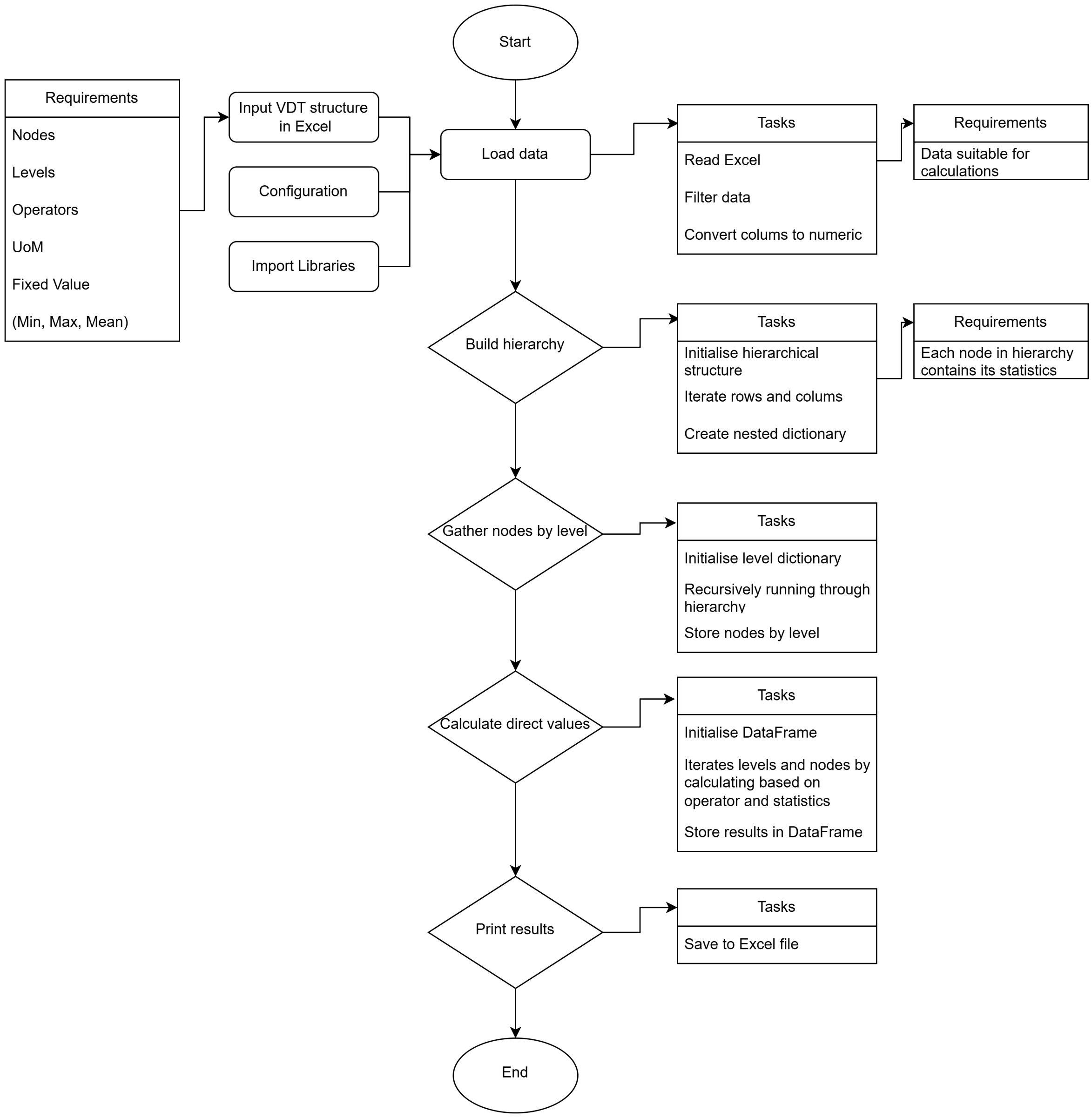

Figure 6.2: VDT modelling structure with fixed values

To extend the applicability of the model to uncertainty analysis, the simulation structure is enhanced with a Monte Carlo simulation step, as illustrated in Figure 6.3. In this extended structure, uncertain input nodes are characterised by probability distributions. The simulation engine samples from these distributions across a specified number of iterations, generating ensembles of outcome scenarios. These iterations are used to derive probabilistic indicators such as mean values, standard deviations, percentiles and entropy levels.

The Monte Carlo calculations also support different scenarios and policy testing by modifying input configurations across the runs. Another important part is the implementation of real-time data distribution when available. By checking whether the data points are consistent with the Monte Carlo simulations, the data can be implemented in the node.

This enables the comparison of output distributions under alternative policy interventions and enhances the capability of the model to assess robustness and sensitivity. The results are stored in structured arrays, which facilitate efficient post-processing, aggregation, and graphical presentation.

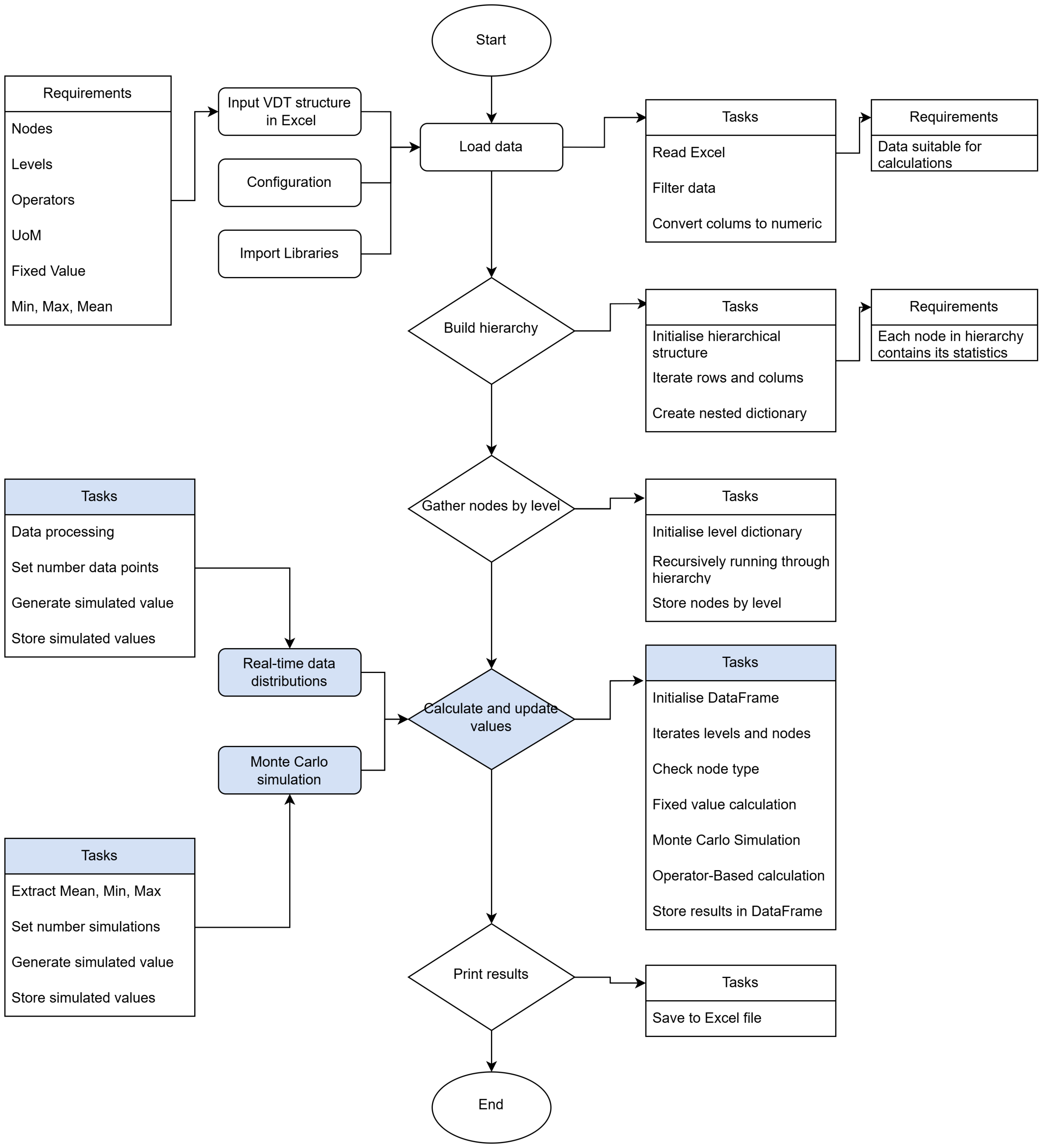

Figure 6.3: VDT modelling structure with Monte Carlo Simulations and real-time data distributions

Through this implementation, the model meets key methodological objectives. The model remains transparent, reproducible and modular, while performing structured uncertainty analysis. To fully implement the given frameworks, the Python code of the core modelling is given in Appendix F. These features support the role of the model as a decision-support tool in complex, policy-sensitive investment environments.

6.3. Simulation experiment set up

The experiments are designed to incrementally introduce complexity. Starting with fixed input values, the model proceeds to single-variable sensitivity tests and ultimately Monte Carlo simulations across multiple uncertainties. The simulation is structured in three experimental phases:

- Phase I: Baseline run with fixed parameter values
- Phase II: Uncertainty integration
- Phase III: Integration of policy levers into the model

Phase I: Fixed data inputs

The techno-economic model relies on a set of independent input variables that define the physical, operational and financial characteristics of the hydrogen production system. These variables are exogenous to the model and serve as foundational assumptions that remain constant throughout the analysis, unless otherwise specified in sensitivity or scenario assessment. All input variables are given in Appendix D. The model first runs under fixed assumptions to validate internal consistency and to establish a reference case. These inputs represent a deterministic scenario that can be compared with an uncertainty-based experiment.

Before the full uncertainty propagation, single-variable sensitivity experiments are conducted. These reveal the marginal impact of each input on investment outcomes and help to prioritise further analysis.

Phase II: Uncertainty integration

Each exogenous uncertainty is assigned a probability distribution as retrieved from literature or input from experts. Aleatory (inherent variability) and epistemic (lack of knowledge) uncertainties are explicitly categorised. Table 6.1 summarises these inputs.

The uncertainty space is explored using Latin Hypercube Sampling to ensure stratified coverage. A total of 8760 samples are drawn for each simulation batch to assess robustness. Additionally, the simulation is based on a Monte Carlo approach using 8760 iterations, based on 8760 hours in one year. In each run, the samples from the distributions, as defined in Table 6.1, cover both aleatory and epistemic uncertainties.

All uncertainties are varied simultaneously in a full Monte Carlo experiment. This captures system-wide interactions and variations in outcomes under plausible future conditions.

Phase III: Policy lever integration

Relevant policy levers include subsidies (OWE), WACC adjustment and grid tariff reforms. These levers are grounded in real-world policy mechanisms and cover both market-based and regulatory interventions. Policy levers are introduced as scenario parameters, as given in Table 6.2. Each lever modifies one or more model inputs and is included in the design matrix to test policy impacts under uncertainty.

Performance metrics are calculated for each scenario based on the simulation outputs. EVA is computed as:

$$\text{EVA [\%]} = \text{ROIC} - \text{WACC} \tag{6.1}$$

All metrics are stored for post-simulation evaluation and comparative analysis.

This chapter has outlined the modelling logic, software implementation, and experimental setup needed to simulate the Battolyser value driver tree under uncertainty. It formalises the computational backbone of the research and prepares the ground for quantitative analysis in the subsequent chapter.

7

Model application and findings

This chapter presents the outcomes of the simulation experiments, which were designed based on the identified uncertainty and boundary conditions. The objective is to present the results of the developed simulation model as explained in the previous chapter, to answer sub-question 4: *”What insights do the simulation model provide to identify and prioritise boundary conditions that have the highest impact on value creation?”*. The results are organized according to the three main phases of the experimental setup: (1) fixed baseline input with sensitivity analysis of key value drivers, (2) full uncertainty propagation through Monte Carlo simulation with resulting performance distribution and (3) final evaluation of the roles and effectiveness of policy levers in shifting system performance. For each phase, the key financial performance metric EVA is analysed. The aim is to provide a structured interpretation of value drivers subject to uncertainty and guide to strategic prioritisation of conditions for Battolyser investment viability.

Phase I: Fixed parameter values

This section determines the baseline performance of the Battolyser system, using fixed central input values based on current market estimates. It provides a reference point for interpreting the results of subsequent uncertainty and policy-based simulations.

7.1. Baseline case

The selected input values represent a plausible central baseline scenario, without incorporating stochastic variation or policy interventions. All detailed input assumptions are given in Appendix D. This scenario serves as a reference to evaluate whether the Battolyser Systems can create economic value under assumed market and technical conditions. It also highlights initial economic bottlenecks and clarifies which components contribute most to cost or revenue. Key output metrics include EVA, ROIC and several operational performance indicators.

The baseline analysis results in an EVA of -8.5%, indicating insufficient value generation under current market conditions. The project does not meet the required return threshold defined by the assumed WACC of 11%. Although the system achieves a positive ROIC of 2.5%, it remains substantially below the capital cost benchmark, resulting in a negative net value contribution. These results confirm that, without support measures or improved market conditions, the system remains economically unprofitable.

As given in Table 7.1, NOPAT is limited to €222,112 per year, driven by relatively low EBIT (€296,150) and high operational expenditures. The system generates an annual revenue of €4.17 million, of which €3.64 million is derived from hydrogen sales and €534,375 from electricity arbitrage. However, this revenue is largely absorbed by operational costs, particularly by the electricity input cost (€2.44 million) and grid tariffs (€1.21 million), which together account for 88% of total COGS.

Table 7.1: Output parameters baseline analysis

Metric	Unit	Value	Description
EVA	€	-8.52	Economic Value Added
ROIC	%	2.48	Return on Invested Capital
NOPAT	€/year	222,112	Net Operating Profit After Taxes
EBIT	€/year	296,150	Earnings Before Interest and Taxes
Revenue	€/year	4,170,739	Total revenues from electricity and hydrogen sales
Electricity sales	€/year	534,375	Revenues from electricity sales
Hydrogen sales	€/year	3,636,364	Revenues from hydrogen sales
COGS	€/year	3,651,259	Cost of Goods Sold
Electricity costs	€/year	2,437,500	Costs for purchased electricity
Grid tariffs	€/year	1,213,759	Grid access fees
OPEX	€/year	223,330	Operational expenditures
Operation and maintenance costs	€/year	215,000	O&M of electrolyser system
Stack replacement costs	€/year	8,330	Annualised electrolyser stack replacements
Invested capital	€	8,954,574	Total capital invested
Net working capital	€	417,074	Liquid assets tied up in operations
Fixed capital	€	8,537,500	Long-term capital investments
WACC	%	11	Weighted Average Cost of Capital

A deeper breakdown reveals two main bottlenecks. First, the high energy-related costs (electricity and grid access) compress the gross margin, despite the healthy revenue. And second, the capital intensity, with €8.95 million in invested capital, mostly in fixed assets, is pushing down the ROIC, even in the presence of positive NOPAT.

The basis structure as given in Figure 4.1 can be indicated with the results of the baseline as shown in Figure 7.1. The nodes that contribute negatively are shown with edges in red, and those with positive contributions in green. What can be observed is that there is a slightly positive but low ROIC. The visualisation confirms that while the revenue base is relatively strong, the negative impact of high COGS and capital costs dominates the financial result. This highlights a mismatch between the technical potential of the Battolyser and its financial viability without further interventions.

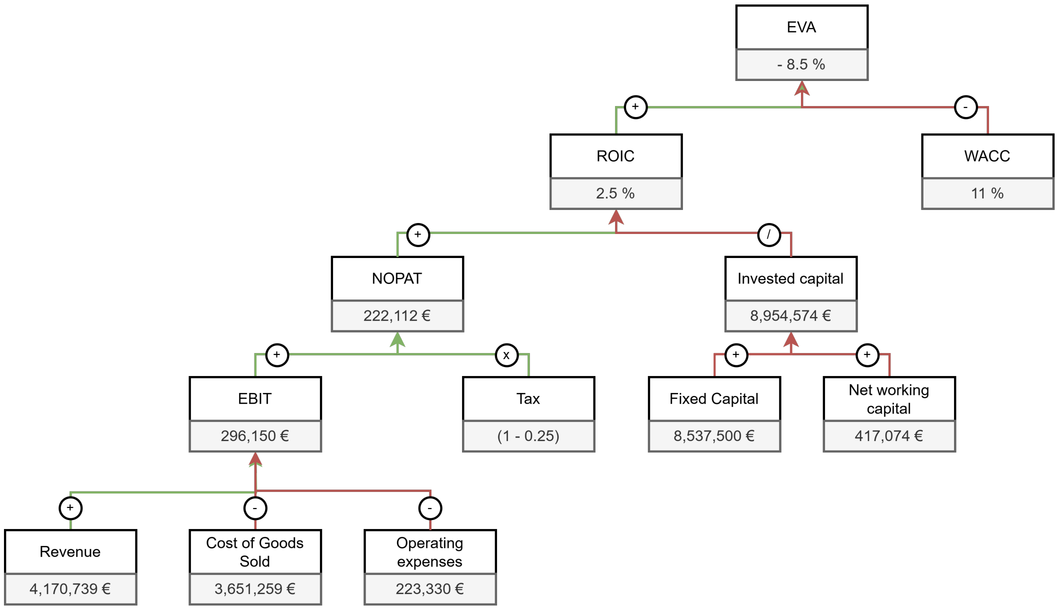

Figure 7.1: Result of the baseline analysis in the VDT structure

This step suggests that the Battolyser, in its current configuration, is sensitive to electricity price volatility, grid cost structures and investment scale. Without adjustments in parameters or policy incentives, the system is unlikely to meet return expectations. Thereby, the baseline serves as a critical benchmark for evaluating the effectiveness of design improvements or policy interventions in subsequent analyses.

7.2. Impact of value drivers

Before running stochastic simulations, a series of deterministic tests have been conducted to examine the individual effect of each value driver on EVA. This analysis isolates each input parameter while keeping others constant, providing clear insight into their marginal impact on value creation.

As part of factor prioritisation, sensitivity analysis is performed for the interpretation of the effect in the model. Figure 7.2 presents a tornado chart of EVA outcomes across fixed parameter changes (20%) of the lowest nodes as input variables. Further details are provided in Appendix E, showing an overview of the specific values.

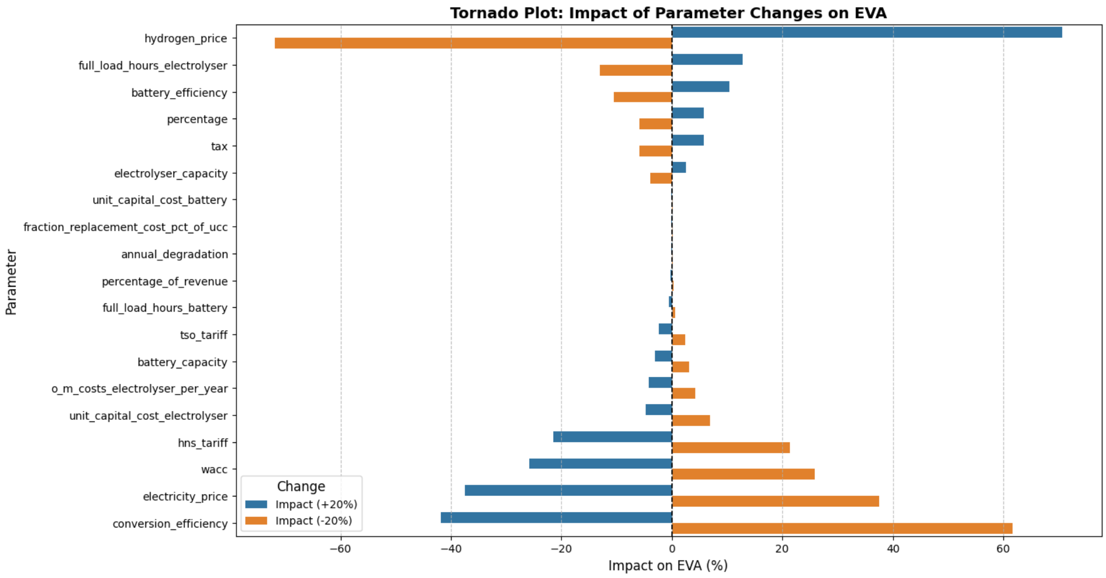

Figure 7.2: Sensitivity analysis of the VDT

From the sensitivity analysis, EVA is most sensitive to changes in hydrogen price, full load hours of the electrolyser and battery efficiency. More specifically, a ± 20% change in the hydrogen price has the highest identified impact on EVA. A positive change leads to an increase of more than 70% and a negative change results in an equally large decrease. This suggests that the economic viability of the project is highly exposed to hydrogen market dynamics. Also, increasing the full-load hours of the electrolyser or improving battery efficiency significantly improves the EVA. This highlights the importance of operational optimisation and technological performance.

On the other hand, parameters such as conversion efficiency, electricity price, WACC and unit capital cost of the electrolyser also have a significant impact. They show a negative impact when they decline by 20%. In particular, conversion efficiency shows an asymmetric effect. If there is a negative change (-20%), this causes a significant drop in EVA (more than 60%), while a positive change improves EVA only slightly. This indicates a critical vulnerability where a performance drop implies a high cost.

Parameters such as operation and maintenance (O&M) costs, battery capacity and TSO tariffs have moderate effects, while others, such as capital cost per battery unit, annual degradation and revenue rate, have relatively small effects, suggesting that they have a lower priority in strategic or design decisions. It underscores that managing input cost volatility and ensuring high system efficiency are key to maximising economic value subject to uncertainty.

This sensitivity analysis reveals that boundary conditions with small changes in inputs lead to large shifts in the outcome. These tipping points highlight where the system becomes economically fragile and creates the potential for policy or strategic interventions. These results are used to select variables to focus on in later uncertainty analysis.

Phase II: Uncertainty integration

In this phase, uncertainty is explicitly integrated into the simulation model using Monte Carlo techniques as stated in chapter 3. The factorial sampling method allows for assessing how variations in key input parameters propagate through the system and affect investment outcomes. This is primarily measured via the performance metric EVA. This provides insight not only into the expected performance but also into the distributional risk profile of the Battolyser Systems under variability. As discussed in chapter 6, experiments have been set up for this simulation.

7.3. Impact of uncertainty space

The following subsections give the detailed results of the uncertainty simulations for five critical parameters as stated in Table 6.1: electricity price, hydrogen price, unit capital cost, operating hours and electrolysis efficiency. Each scenario includes 8,760 iterations (1 per hour, 8,760 hours per year) to represent a full operational year. Distributions are presented using boxplots and histograms. The baseline EVA of -8.5% is used as a benchmark to interpret deviations caused by uncertainties. The probability distribution with descriptive statistics provides insight into system performance subject to realistic variation.

7.3.1. Electricity price

The first framed uncertainty factor is the electricity price. The input of this variable has been retrieved from the Climate Energy Outlook KEV 2024 scenario, with the data of electricity prices [€/MWh] in 2030. Figure 7.3 shows two plots, on the left the boxplot of the EVA values and on the right the histogram visualising the distribution of EVA as a result of variations in electricity price.

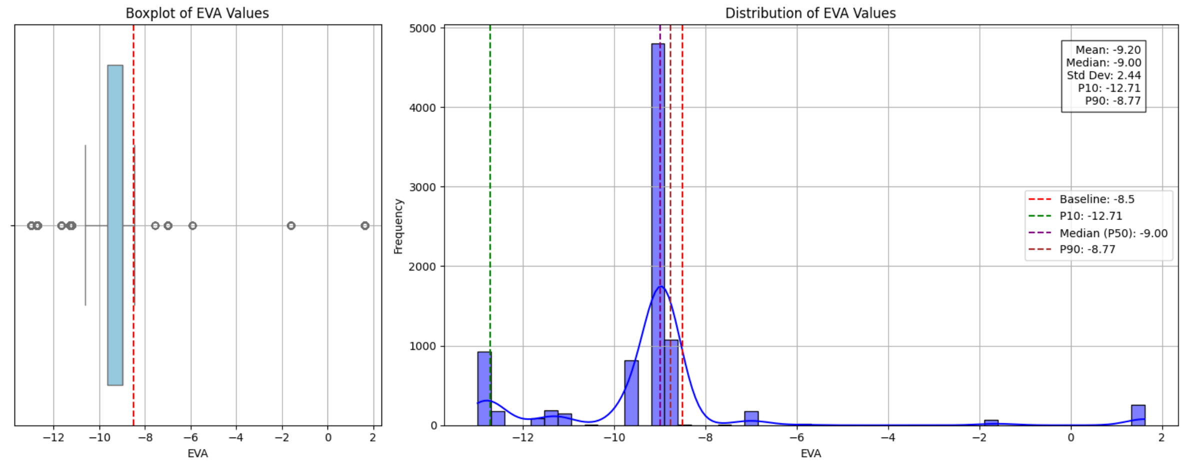

Figure 7.3: Impact of electricity price on EVA [%]

Figure 7.3 shows that variations in electricity price, derived from the KEV 2024 2030 projection, lead to a negatively skewed EVA distribution, with most outcomes below the baseline. The mean EVA is -9.2%, and the median is -9.0%, indicating a systematic underperformance with a price uncertainty. The standard deviation of 2.4 indicates moderate variability. Although the 10th percentile drops to -12.7%, the narrow spread suggests consistent underperformance, with limited upside.

With this narrow range, electricity price is a highly sensitive driver of economic performance. The conclusion is that with these variations of data, there is a high probability of decreased EVA compared to the base case and can be named as downside-oriented risk.

7.3.2. Hydrogen price

The second uncertainty factor is the hydrogen price. As given in the sensitivity analysis in Figure 7.2, this variable shows a big influence on the outperformance of EVA. The EVA results of a Monte Carlo simulation of 8,760 iterations with the hydrogen price range of 3 - 14 €/kg and a mean of 8 €/kg are shown in Figure 7.4.

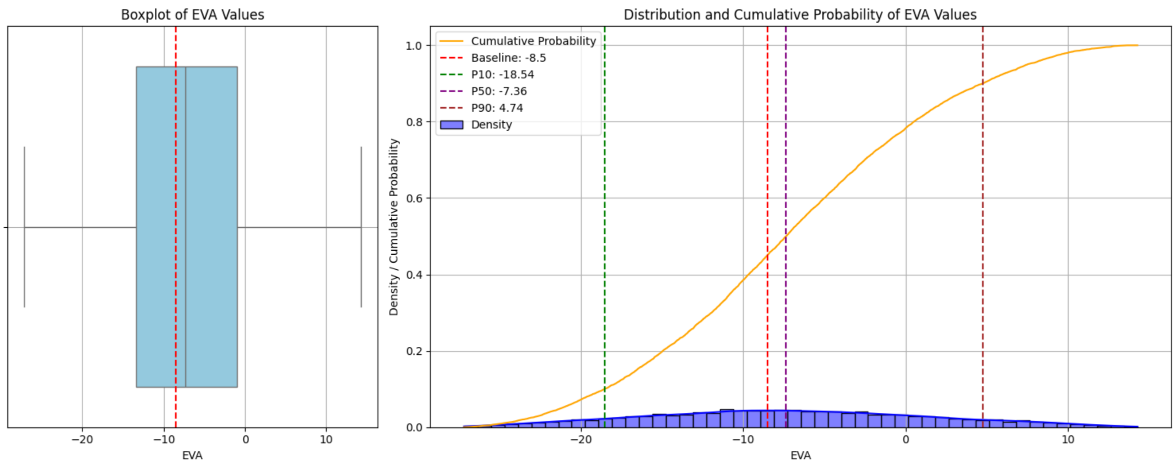

Figure 7.4: Impact of hydrogen price on EVA[%]

Figure 7.4 shows that the EVA distribution is largely symmetric and normal, with a median value just above the baseline. The result shows that the median EVA is negative with -7.4%. Most EVA values cluster around the negative range, stating that negative outcomes are most probable. The results show that with a slightly higher median, this uncertainty is somewhat increasing for most values. Shown with the box plot, about 80% of the values are in the range of -18.5 and 4.7 €/kg with the 10 and 90th percentiles. This wide range shows a high impact of the hydrogen price on the EVA.

So, hydrogen price introduces a significant uncertainty but with a balanced risk profile, offering both downside and upside potential. This emphasises the importance of market development, long-term offtake agreements and floor price mechanisms for investor confidence.

7.3.3. Unit capital cost

The third uncertainty parameter is the unit capital cost of the electrolyser. The results of a Monte Carlo simulation of 8,760 iterations with the range of 370 - 1,666 €/kW and a mean of 1,000 €/kW are shown in Figure 7.5.

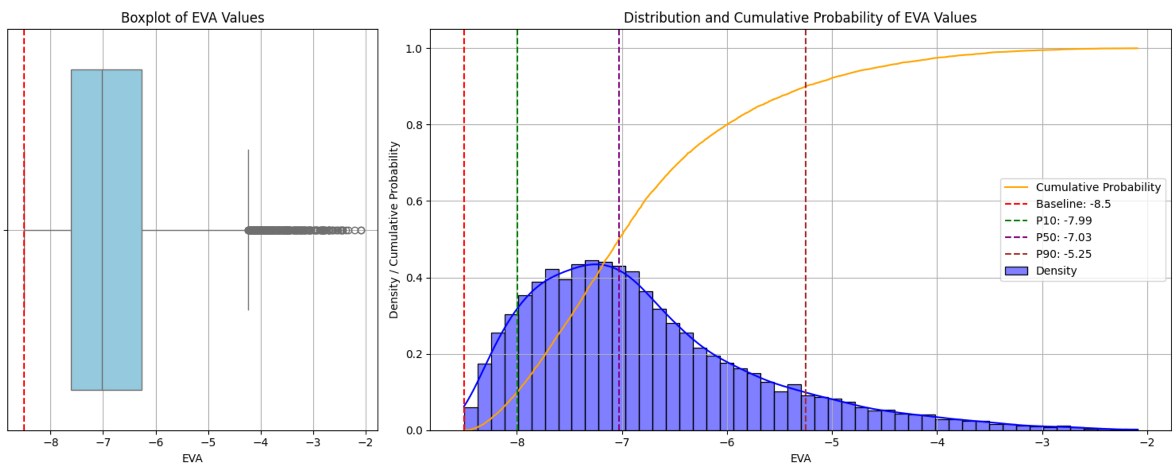

Figure 7.5: Impact of unit capital costs on EVA

The EVA distribution in Figure 7.5 significantly shows a difference from the baseline of -8.5%. Approximately 95% of the EVA values lie above this threshold, implying that the modelled values create higher yields and a consistent improvement over the baseline. A significant right skew suggests potential for even higher performance.

This logic is based on the fact that the new uncertainty price gives the baseline value as the maximum value of the distribution. However, the range of the EVA still shows a negative outcome, indicating that it does not give enough improvements for creating value. Capital cost reductions present a transformative opportunity for improving investment viability. This reinforces the importance of learning curves, scaling effects and CAPEX subsidies in early-stage deployment.

7.3.4. Operating hours

The fourth uncertainty parameter implemented is the operating hours. The results of a Monte Carlo simulation of 8,760 iterations with the range of 2500 - 8000 hours and a mean of 5000 hours are shown in Figure 7.6.

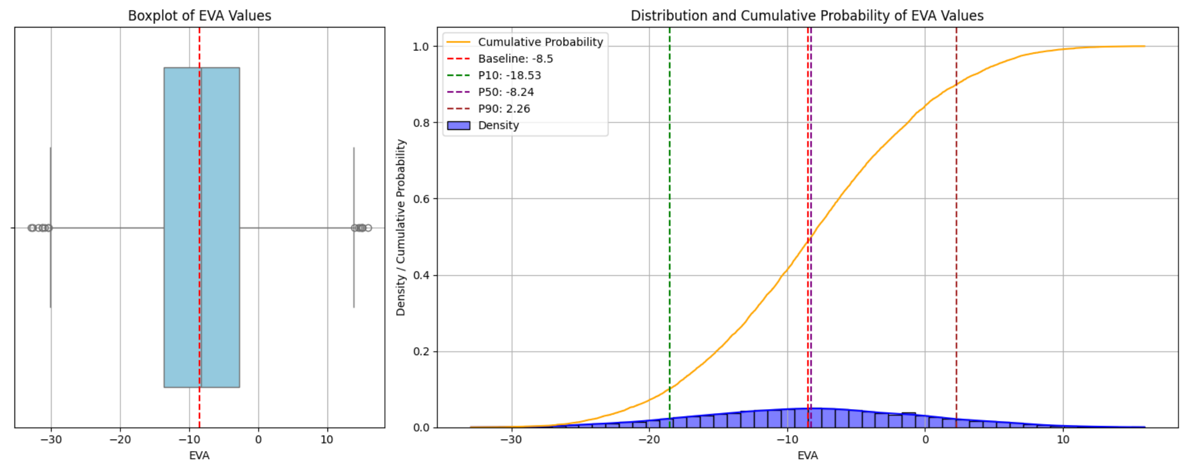

Figure 7.6: Impact of operating hours on EVA [%]

Figure 7.6 shows the impact of the operating hours on EVA. The median of -8.2 shows a very slight change from the baseline at -8.5. The range is very wide, suggesting the substantial variability within the central 50% of the input values. Also, several outliers on both sides are visible. The 10th and 90th percentiles are from -18.5 to 2.3% suggesting possible EVA outcomes, but tend to give no value with a negative EVA. Utilisation rate is a key uncertainty dimension with substantial influence on investment outcome.

7.3.5. Conversion efficiency electrolysis

The last uncertainty parameter is the conversion efficiency of the electrolysis. The results of a Monte Carlo simulation of 8,760 iterations with the range of 50 - 65 kWh/kg and a mean of 1,000 kWh/kg are shown in Figure 7.7.

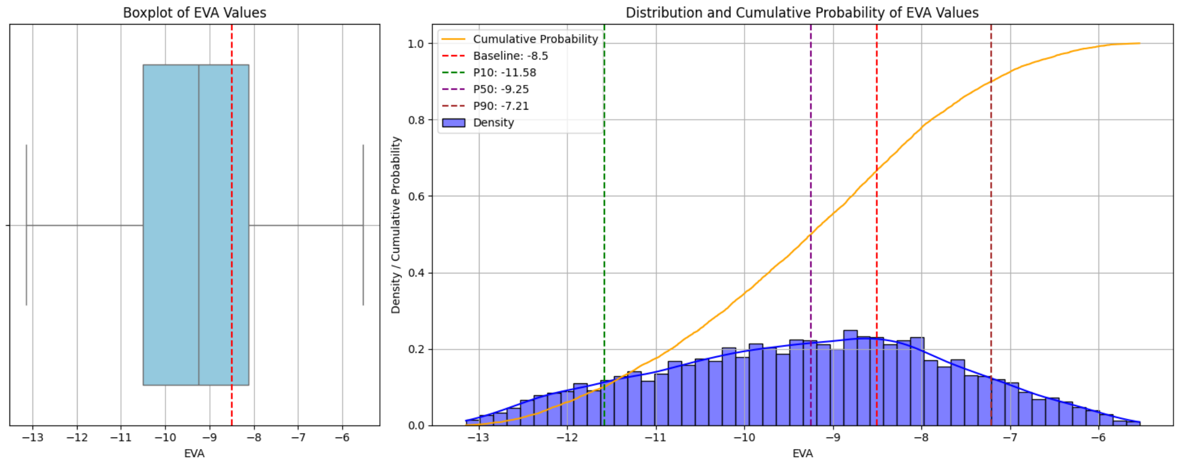

Figure 7.7: Impact of conversion efficiency of electrolyser on EVA [%]

On the left of Figure 7.7, the boxplot illustrates the spread of the EVA values with the range, median and outliers. The median is -9.3%, just below the baseline analysis. The distribution shows a central estimate where the 10th and 90th percentiles are from -11.6 to -7.2 % shows that EVA remains negative. The narrow range shows moderate variability and influence on EVA outcomes.

Although efficiency affects operational costs, its relative influence is moderate compared to price and capital cost variables. Technological efficiency improvements are desirable but not critical for this metric.

7.4. Synthesis of uncertainty space

As continued, every uncertainty is plotted separately to obtain the individual influence. The next phase is to create the total uncertainty space. Figure 7.8 shows the distribution of EVA across all uncertainty ranges taken into the simulations in the same format as the previous plots.

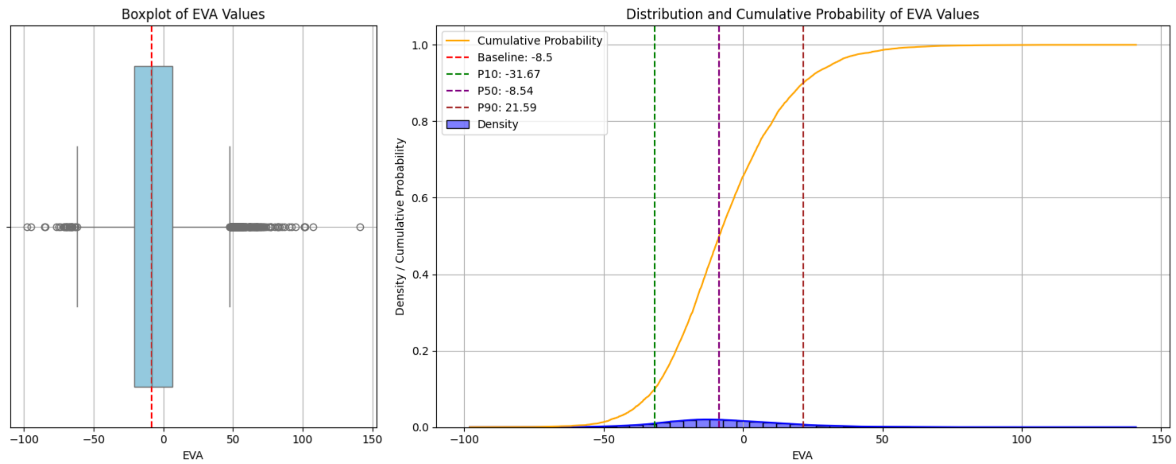

Figure 7.8: The EVA distribution under the whole uncertainty space

The results indicate a centre-skewed distribution with a median of -8.5% just as the baseline case. However, the wide range of outcomes shows a big uncertainty space with the 10th and 90th percentiles of -31.7 and 21.6 %.

With this uncertainty space given by the Monte Carlo simulation, an indication of the possible influences are established. The results can somewhat change due to the iterative approach behind the simulation.

The ranges indicate how much impact these input variabilities have on the estimation of the EVA. Not only the values, but also the switch of the EVA from negative to positive is presented.

The full uncertainty simulation underscores that Battolyser deployment under current market conditions is structurally risky, but targeted improvements in hydrogen pricing, CAPEX and electricity cost management can shift the probability space towards positive value creation.

Phase III: Policy lever integration

This phase explores how targeted policy interventions can influence the investment viability of Battolyser Systems, subject to uncertainty. Three levers were selected based on their practical relevance, model sensitivity and stakeholder influence: (1) operational subsidy (OWE), (2) grid tariff reduction and (3) weighted average cost of capital (WACC) adjustment. These levers are independently integrated into the simulation framework, allowing for controlled impact assessment. The overarching goal is to identify which instruments most effectively improve value creation under techno-economic constraints.

7.5. Impact of policy levers

Table 6.2 summarises the policy interventions and their assumed ranges. The results of each intervention are discussed below, with a focus on EVA performance as a proxy for investment attractiveness.

7.5.1. Operational subsidy

The first policy intervention targets operational expenditure, especially by subsidising the electricity cost input. This is stated as a dominant cost driver in the baseline analysis. As shown in Figure 7.9, increasing the subsidy from 0 to 80 €/MWh significantly improves EVA outcomes. A turning point is observed around 60 €/MWh, where EVA shifts from negative to strongly positive values (>80% of the simulations). This illustrates the high leverage of the electricity cost relief on investment performance.

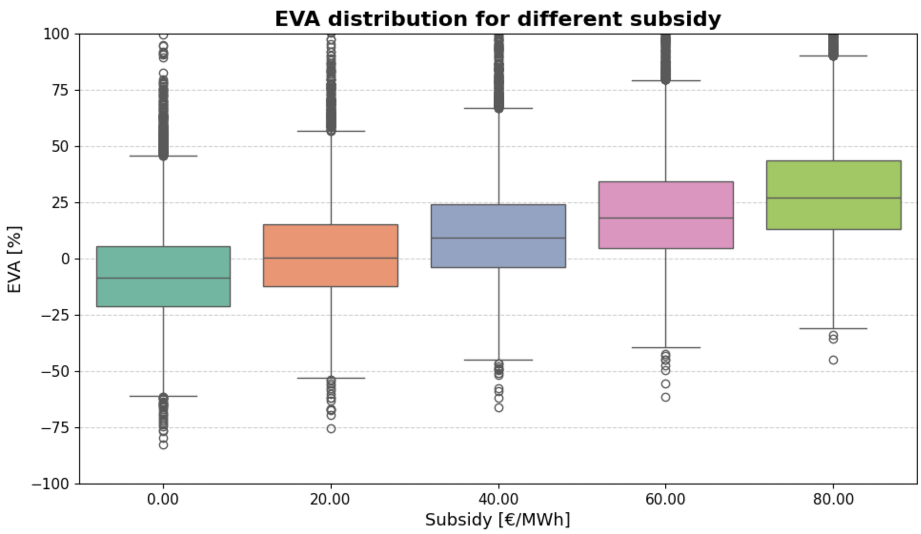

Figure 7.9: Subsidy influence on EVA [%]

These findings confirm that affordable electricity is the most influential value driver in the current system. Subsidies of this nature can help to mitigate price volatility, reduce exposure to grid costs and improve financial resilience, particularly in early project stages. From a policy perspective, this aligns with existing operational support schemes (e.g. SDE++), yet indicates that more targeted compensation may be needed for (dual-use) electrolysis technologies.

7.5.2. Grid tariff reduction

The second lever addresses fixed grid access costs. This is another contributor to operational expenditure and is seen as a possible policy intervention into the improvement of investment decisions. Grid tariff reductions between 20% and 80% were modelled, as shown in Figure 7.10. Unlike the electricity subsidy, the impact on EVA is relatively marginal, even under substantial tariff cuts.

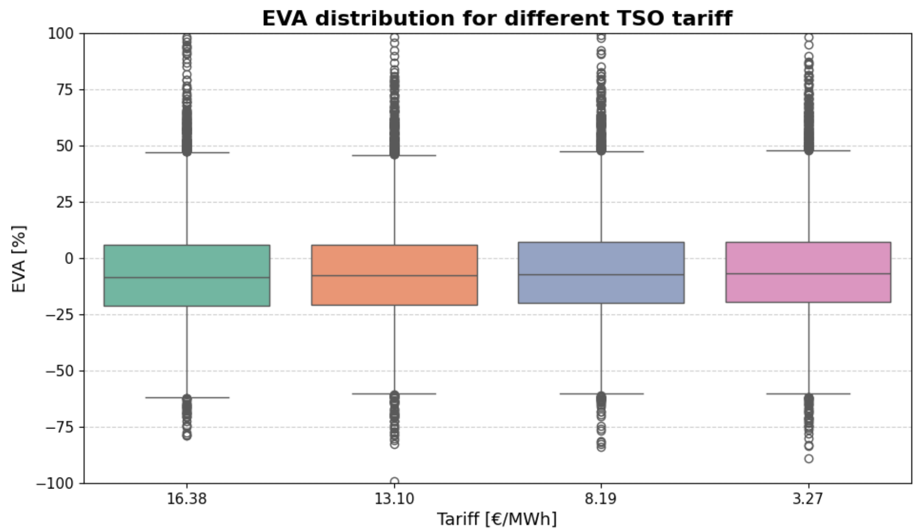

Figure 7.10: TSO tariff reduction influence on EVA [%]

This result suggests that although grid tariffs are non-negligible, they do not constitute to the core bottleneck in system viability. Their effect is diluted due to their smaller proportion in total COGS compared to electricity procurement. While tariff reduction could still serve as a supporting measure, its standalone effect is unlikely to shift investment outcomes substantially. This aligns with regulatory discussions around locational pricing and capacity scarcity, but suggests limited standalone policy payoff.

7.5.3. WACC

At last, the WACC is treated as a structural financial lever reflecting investor risk perception and financing conditions. As shown in Figure 7.11, lowering the WACC from 11% to values around 3 – 7% substantially increases EVA. This illustrates the tight coupling between financing conditions and value creation in capital-intensive systems.

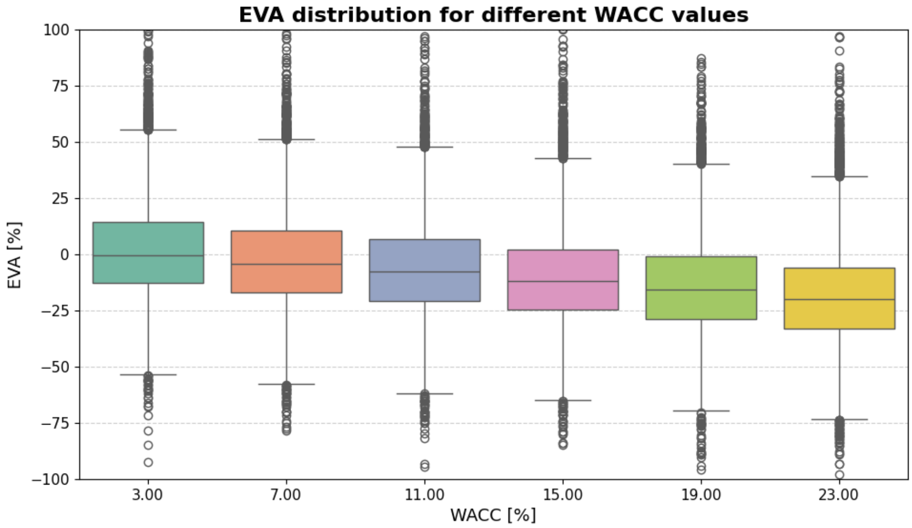

Figure 7.11: WACC change of influence on EVA [%]

This also confirms that de-risking mechanisms can have a decisive effect on the system metric. Some of those mechanisms could be credit guarantees, blended finance or public-private partnerships. Given the capital intensity of Battolyser deployment, WACC should be seen as a pivotal boundary condition rather than a passive parameter. Policy can influence this through clear regulatory signals, investment support instruments and long-term guarantees of hydrogen offtake.

7.6. Synthesis of policy effects

These last findings demonstrate how policy interventions affect the ability of the system to create economic value subject to uncertainty. Despite a slightly positive ROIC, the baseline EVA of -8.5% reflects a structurally unprofitable project without support. Among the tested levers, the following findings were obtained. First, electricity cost subsidies have the strongest positive effect, validating the importance of reducing OPEX volatility. Second, lowering WACC is also highly effective, confirming the sensitivity of EVA to financing conditions. Last, grid tariff reductions, while beneficial, have a limited standalone effect.

Additionally, the analysis reinforces that EVA is not a static measure but responds nonlinearly to changes in upstream policy and system conditions. As visualised in Figure 7.1, the policy levers affect different branches of the VDT. The operational subsidy boosts revenue margin, WACC reduces capital cost pressure and grid tariffs affect a smaller operational cost node.

This analysis underscores that targeted interventions on the most elastic and uncertain drivers, such as electricity and financing parameters, should be prioritised. Prioritising these levers can help to align policy with the most influential factors shaping project success. Doing so will not only improve financial viability but also strengthen the alignment between technology deployment and eventually systemic decarbonization success goals.

8

Discussion

This chapter reflects on the main findings, implications and limitations of this research. Previous chapters (4, 5, 6 and 7) addressed the specific sub-questions through the eventual model's value drivers and uncertainty specifications. This chapter situates those findings within a broader academic and social reflection. It discusses the relevance of value-driven investment modelling for emerging energy technologies, highlights key insights gained from applying the method to Battolyser Systems and reflects on the methodological strengths and limitations encountered. In addition, it examines the implications for interdisciplinary integration and policy design under uncertainty. This sets the foundation for the concluding chapter 9.

8.1. Insights from applying the VDT model to Battolyser Systems

In this research, a VDT-based simulation model has been designed and applied to investigate the investment performance of Battolyser Systems in the emerging Dutch green hydrogen market. By combining a structured decomposition of value drivers with Monte Carlo simulations, the model enables uncertainty-driven identification of boundary conditions which are critical in investment performance. This has offered a quantitative framework to assess how technical, financial and institutional drivers interact under volatile policy conditions.

8.1.1. Technology selection

The selection of Battolyser Systems, which combines battery storage and hydrogen production, has been proven to be methodologically valuable. Unlike single-purpose technologies, the hybrid nature is exposed to policy mismatches, such as double grid charges and inadequate existing subsidies. The visible limitations of subsidy instruments, such as SDE++ and OWE, remain tailored to linear, single-function technologies (Agora Energiewende, 2021; Invest-NL, 2024). However, despite the potential improvements in the model implementation of the technology related to the flexibility in the storage and production calculations, the technology enables to capture of structural uncertainty in the model.

The critical blind spots revealed in the current policy design for conventional cases would probably have been hidden (Woolthuis et al., 2005). Beyond this, the technology enables the modelling of both internal technological uncertainty and broader system uncertainties, such as infrastructure rollout, market design and regulatory direction. These uncertainties, often overlooked in standard techno-economic assessments, are crucial to understand the investment conditions for at-risk innovations.

The Battolyser case thus served as an entry point to reflect on how emerging system-integrated technologies interact with fragmented institutional structures. It helped operationalise to have a view of the system that moves beyond static metrics, connecting micro-level design objectives with macro-level sustainability goals across stakeholder domains. In doing so, it allowed the model to simulate the effects of policy interventions not only on financial viability but also on systemic fit, addressing a critical blind spot in how policy currently assesses multifunctional technologies.

8.1.2. Implications in approach

By applying the VDT approach to such a systemic innovation, it highlighted both its strengths and its boundaries. The method effectively unpacks operational and financial drivers beyond the Levelized Cost of Hydrogen, including flexibility and system services that are often underrated in policy metrics (Hydrogen Europe, 2022; Jenkins et al., 2022). Yet, it also revealed the challenge of modelling institutional uncertainty and non-linear policy impacts within a deterministic framework. Although Monte Carlo methods simulate outcome variability, they could not fully reflect how regulatory shifts or delayed infrastructure would influence strategic feasibility over time (Kwakkel et al., 2016).

8.1.3. Systemic value and model performance

So, this research functioned as a stress test. It confirmed the utility of VDT for visualising value interactions, while demonstrating the need to complement it with adaptive tools and broader system thinking. The multifunctionality of the Battolyser allowed the model to surface insights into the mismatch between technological potential and existing governance structures. More broadly, it underscores that robust support for the integration of technologies in the system requires policy instruments that recognise multifunctional value (Borrás & Edler, 2014; Mazzucato, 2018). This insight has direct implications for both model development and policy design, particularly for technologies navigating institutional complexity and market emergence.

8.2. Policy relevance and practical usefulness

This section interprets the results of the modelling concerning the Dutch policy landscape and reflects on how the findings inform investment support mechanisms, risk governance and innovation policy design for emerging energy technologies.

8.2.1. Translation to policy context

The modelling approach developed in this study aligns with key elements of Dutch and European hydrogen strategies, which increasingly rely on targeted subsidy schemes, infrastructure coordination, and regulatory reform to catalyse the deployment of green hydrogen (Agora Energiewende, 2021; Hydrogen Europe, 2022). By including variables such as subsidies, electricity costs, grid fees and WACC adjustments, the model reflects concrete, real-world policy levers. Battolyser Systems technology, serving as a reference case, enabled a grounded calibration of technical and financial input assumptions while also exposing information gaps arising from the hybrid and novel nature of the technology (Mulder et al., 2017).

Crucially, the integration of the VDT approach with Monte Carlo simulations offers a quantitative structure for assessing the financial consequences of policy scenarios under uncertainty. This structure enables policymakers to simulate the impact of interventions such as HER+ grants or grid tariff exemptions on investor expectations. The model design has prioritised transparency, modularity and scenario adaptability. This supports its application in capital-intensive dynamic decision environments. However, its static formulation and scarcity of feedback loops or learning effects limit its relevance for long-term strategic or adaptive policymaking. This limitation is commonly discussed in the literature on energy modelling, which can still be improved by research (Kwakkel et al., 2016).

8.2.2. Visualising uncertainty and sensitivity

The simulation results highlight the complex risk profile of investments in Battolyser Systems. The sensitivity analysis revealed the hydrogen price as the most influential and uncertain parameter, underscoring the high exposure of electrolysis technologies to the volatile market and policy factors (Capgemini, 2024). This price is market-driven and policy-mediated, making it a representative of deeper uncertainties about future energy governance and demand formation (Institute for Energy Economics and Financial Analysis (IEEFA), 2023). An interesting finding is that despite the relevance, electricity prices exhibit narrower variance in their effect on EVA, suggesting that policy interventions focused on electricity cost relief (e.g., through grid support or exemption mechanisms) offer less impact than expected.

Operational efficiency parameters, such as conversion rates and unit capital costs, have shown moderate sensitivity to innovation and scaling potential. Notably, full-load hours have emerged as a policy-sensitive variable linking infrastructure, market signals and grid access. This finding is reflected in recent literature on electrolyser utilisation risk (Azadnia et al., 2023). In the baseline scenario, EVA has remained negative. Under most uncertainty conditions, the model tends towards increasingly negative values. This underscores the systemic misalignment between investment incentives and multifunctional technologies. Subsidies lowering electricity costs and de-risking instruments (e.g., WACC reduction through guarantees) have shown to improve outcomes most significantly. However, it is important to consider the bounds conditioned by the broader dynamics of the system.

8.2.3. Limitations of current policy structures

This research underscores a critical gap in the current policy design of hydrogen and energy storage. There is a structural lack of recognition of system innovations that deliver cross-functional value. Battolyser Systems combines multiple value contributions of flexibility, storage and production (Mulder et al., 2017). However, the regulatory and subsidy regimes are still rooted in technological categorisation (Swarts et al., 2025; Woolthuis et al., 2005). This results in systemic blind spots.

The findings of the model make a case for shifting towards more adaptive, mission-oriented innovation policies as stated by Mazzucato, 2018. By identifying not only key value drivers but also their uncertainty profiles, the model supports a form of policy design that focuses on intervention leverage where impact meets risk. For instance, expanding load hour certainty through co-location strategies or integrated system design offers more robust returns than only focusing on CAPEX reductions.

In sum, the model offers policy applicability not by predicting outcomes but by illustrating the range and sources of investment risks. This allows policymakers to focus their dialogues on those variables where uncertainty is highest and policy leverage is most impactful. As such, the tool contributes to policy making by being more reactive and aware of risks. This is particularly required in early-stage markets characterised by high capital exposure and low regulatory maturity.

8.3. Methodological reflection

This research applies a structured value-based modelling framework to explore how external uncertainties affect the creation of investment value in the deployment of Battolyser Systems. Rather than providing deterministic forecasts, the methodology aims to support exploratory decision-making by integrating uncertainty in a transparent and quantifiable way.

8.3.1. Strengths of the VDT approach

The VDT offers a systematic way to understand complex socio-technical systems. It deconstructs value creation across technical, economic and policy domains. By integrating causal logic and system decomposition, it enables a clear link between policy levers and financial outcomes. While the model assumes rational investor behaviour and simplifies behavioural or institutional complexity, its transparent structure allows critical system dynamics to be visualised and simulated. This includes energy prices, grid access and capital costs.

A significant academic contribution lies in translating a conceptual VDT into a computational model. Each value driver has been defined mathematically, substantiated by literature and has been validated through unit consistency and logical coherence. This formalisation allows for simulation, sensitivity analysis and policy scenario evaluation. The VDT becomes a powerful analytical tool by being qualitative and adaptable to decision-making under deep uncertainty.

Monte Carlo simulation allows for probabilistic outcome distributions, enabling the identification of boundary conditions and exposure to extreme risks, building from other literature (Johnson, 2022). EVA has been selected as the core metric for investment performance, combining operational results (ROIC) and financing conditions (WACC). Although EVA frames the value in financial terms (Patel & Patel, 2012), the broader driver structure invites future integration of non-financial or societal indicators. Importantly, the model supports robustness orientation but stops at prescriptive or adaptive policy evaluation.

8.3.2. Evaluation of the entropic approach to uncertainty

Integrating of an entropic lens has improved the capacity of the model to assess not only the expected value results, but also their epistemic robustness. Entropy metrics revealed which scenarios has produced different forms of distributions, adding a second dimension of decision quality. This aligns with principles from value-of-information theory, enabling users to prioritise both policy interventions and data collection efforts. In stakeholder settings, entropy also serves as an intuitive indicator of decision confidence, improving the communicability of uncertainty in policy design.

8.3.3. Constraints and assumptions

The model makes several deliberate abstractions. First, the causal structure overlooks endogenous feedbacks, behavioural adaptation or temporal policy co-evolution. Second, parameter values do often rely on expert assumptions or sectoral reports due to data scarcity, particularly for emerging technologies. Third, static logic around investment (e.g., fixed WACC, linear scaling) limits the realism of dynamic capital flows or learning effects. In addition, policy and stakeholder interactions are treated exogenously. These limitations do not reject the utility of the model, but instead frame it as an exploratory tool best suited to early-stage assessments or scenario stress testing. Its academic strength lies in its transparency, traceability and transferability across innovation contexts with the follow-up of the stated criteria in Table 3.1 for the approach.

8.3.4. Passing to other applications

Beyond its application to Battolyser Systems, the VDT framework offers a replicable methodology for other capital-intensive systemic innovations. The three-step structure for decision support is stated as (1) decomposition of the value target via Fermi estimation, (2) causal structuring through a VDT and (3) simulation of uncertainty via stochastic sampling. This is grounded in theory and adaptable to practical cases. It addresses a growing academic demand for explainable, causal and uncertainty policy models. Together, these elements demonstrate that the methodological contribution of this research lies not only in producing results but in enabling a structured, transparent and uncertainty-aware way of thinking about early-stage investments in socio-technical transitions.

8.4. Interdisciplinary integration

This research responds to the societal and academic need for integrative tools that can navigate the complexity of the wicked problems of energy transitions. However, the impact of such modelling depends on how effectively it bridges disciplinary perspectives and aligns with societal objectives.

8.4.1. Interdisciplinary dimensions

The research incorporates engineering, economics and policy into a unified framework that captures key challenges in the hydrogen sector. Although embedded in financial metrics, the model allows exploration of systemic conditions and policy interventions. However, it abstracts from social, ethical and political dynamics that shape technology adoption in practice. The limited attention to grid governance and institutional coordination limits its value in infrastructure planning. Future work should broaden this scope by embedding the model into deliberative or co-creation contexts, where qualitative dimensions of the transition can be better represented.

8.4.2. Stakeholder integration

Although stakeholders are conceptually acknowledged within the experimentation design, their strategic behaviour and interactions are not explicitly modelled. Participatory modelling or agent-based approaches could enrich the framework and improve its capacity to inform governance under competing interests and institutional constraints.

8.4.3. Translation of complexity into actionable insights

The model simplifies investment complexity into structured outputs such as sensitivity rankings and EVA distributions, which clarify key uncertainties and leverage points. Yet, the financial framing may constrain its accessibility for non-experts, and the abstraction level may obscure real-world conditions. There is also a risk of overconfidence in probabilistic outputs derived from assumptions with limited empirical grounding. Increasing communication tools will enhance the usability of the model for policy and decision-making under uncertainty.

9 Conclusion

In conclusion of this research, the study employs a value driver tree-based simulation approach to explore the influence of key uncertainties on the attractiveness of Battolyser Systems investments in the Dutch green hydrogen market. First, relevant value drivers have been identified through the literature and expert consultation. Next, a model has been set up to structure these drivers in a hierarchical tree, mapping how upstream uncertainties propagate to investment-level outcomes. Then, an uncertainty analysis has been conducted with distributions by Monte Carlo simulation. This is applied to reproduce uncertainty through the model, allowing for the assessment of probabilistic outcomes and sensitivity. The final step involves a robustness and relevance analysis, identifying which uncertainties are most critical and affect performance.

9.1. Answers to research questions

This research has aimed to answer the main question:

> How can a value driver tree-based simulation model be designed and applied to the investment performance of Battolyser Systems under uncertainty in the Dutch green hydrogen market?

In conclusion, the value driver tree simulation model has been used in this study as a structured modelling approach to decompose investment outcomes into their associated causal drivers. The VDT provides both a conceptual and a computational framework to trace how uncertainties at different nodes are transmitted through the system and affect outcomes. The hierarchical, dependency-based structure aligns well with the entropy-based uncertainty framework introduced in this research. Each node represents a potential location of informational, epistemic or strategic entropy. The VDT enables simulation of complex interactions under uncertainty, while maintaining an understandable outcome, which is essential for strategic prioritisation in emerging markets such as green hydrogen.

Compared to black-box approaches such as neural networks or purely statistical models, the VDT provides a semi-transparent structure where uncertainty is not only detected post-hoc but also has been built into the model architecture itself. This transparency is particularly valuable in highly supported, but data-lacking domains such as emerging green technologies.

Value Driver Tree models enhance strategic planning by organising complex, uncertain or a lack of information into manageable components and aligns technical decisions with investment performance. Specific contributions to the method are given.

- First, visualising value creation relationships. The VDT allows for the visualisation of how various factors influence the desired outcome. In this way, it builds on the understanding of a chosen key performance indicator. By mapping out the interrelationships, clarity helps to pinpoint the most critical factors.

- Second, the potential of hierarchical structuring in system modelling. The VDT enables a hierarchical organisation of all the variables that are defined as factors that affect the top node. The problem involves multiple uncertain variables at different levels and the structure enables implementation. It breaks down complex systems into manageable parts, ensuring that each uncertainty is systematically addressed and its potential impact is understood in relation to the overall goal. The flexibility and adaptability of the model is a highly positive result.
- Third, a very important contribution is the quantification of uncertainties. The combination of the VDT with the probabilistic method of Monte Carlo simulation can quantify the impact of uncertainty on investment performance. By assigning probability distributions to key variables, the VDT helps to simulate different scenarios and understand their potential impact on performance.
- Fourth, one of the most valuable aspects of using the VDT method is its ability to prioritise the drivers of investment performance based on their relative importance and influence. This is crucial in decision-making, especially when resources are limited and investment strategies need to be tailored to address the most significant risks and opportunities in the market.
- Finally, this method can serve as a structured decision support tool. For stakeholders, the VDT provides a structured and transparent way to communicate complex relationships and uncertainties in investment performance. This method not only identifies the most critical factors but also allows decision-makers to visualise potential outcomes and their associated risks.

To further specify the answer, the sub-questions are answered from the insights gained in the research.

SQ 1. What are the key value drivers influencing investment decisions of Battolyser Systems and how can they be structured in a value driver tree?

Based on value-based management theory, the performance metric for an investment decision is the Economic Value Added, based on Return on Invested Capital and the Weighted Average Cost of Capital. Based on the Value Driver Tree framework, the structure of the drivers, every value is connected towards the system based on a techno-economic perspective. The systematic causal relations have been built into the structure and are divided into three sub-trees: revenue, costs and capital drivers. The sub-trees enable dynamic modelling of the value drivers, which are essential for the systems calculating financial indicators. By combining these trees into one, the resulting conceptual model for simulation is obtained.

All drivers can be structured in a value driver tree rooted from EVA, with branches reflecting the components of revenue, cost and capital efficiency. This structure links all the technical, operational and financial choices. By making the variables measurable, it can be clarified how uncertainties and interventions propagate through the system, and supports more targeted and effective policy and investment decisions.

SQ 2. What are the uncertainties that affect the behaviour of these value drivers?

By focusing on the VDT, the value creation of the system is embedded in a dynamic context of technological, market and policy uncertainties. The stakeholder analysis confirms that these uncertainties are widely recognised, but also differ in perception and priority. Key value drivers such as revenue, efficiency, costs and capital expenditures are sensitive to multiple factors simultaneously. The uncertainties are therefore stated as variable uncertainties, which are input variables for the modelling. Evaluating the robustness, sensitivity and adaptivity of the system is essential for reliable decision-making.

SQ 3. How can a simulation model be designed based on the value driver tree to capture investment performance under uncertainty?

A simulation model which is based on the value driver tree can effectively analyse investment performance under uncertainties by systematically modelling the underlying economic structure. This is done through a hierarchical structure in which value drivers are organised in multiple levels: from basic input parameters (such as price, volume and efficiency) to aggregated output (such as NOPAT, ROIC and EVA). The model works from bottom to top, whereby variables at lower levels are read and combined to higher levels via a structured dictionary approach. Operators are defined for each node in the tree (such as sum, product, quotient) that make the quantitative relationships explicit.

Crucial in this design is the distinction between input parameters with fixed values (such as investment costs or efficiency with technical assumptions) and parameters that are modelled as distributions (such as energy and hydrogen prices). This allows the model to represent uncertainty using Monte Carlo simulations, whereby the spread of results such as EVA and ROIC becomes visible. This combination of structure, calculation system and probabilistic inputs makes the model suitable for robust investment analysis under realistic uncertainty conditions.

SQ 4. What insights does the simulation model provide regarding the most influential and uncertainty-sensitive value drivers?

The simulation model provides valuable insights into which value drivers are most significant and most sensitive to uncertainty within the investment profile. The simulation shows that variables such as hydrogen price, electricity costs and electrolyser efficiency have the greatest influence on top-level parameters such as EVA. The hydrogen price in particular proves to be a crucial lever, where small variations lead to large shifts in value creation. The endogenous technical parameter of the conversion efficiency also shows a high impact on the EVA. WACC and network tariffs also show high sensitivity, underlining the importance of stable policies and reliable financing.

By placing EVA at the heart of the model, the focus shifts from short-term profit to long-term value creation, contributing to more sustainable investment choices. This is relevant for emerging markets and different stakeholders. The value driver tree makes the value chain visual and transparent. The logic connects key performance indicators and makes it clear how value flows through the system. With the use of combined policy interventions and uncertainty analyses, the effects of policies or market interventions can be directly evaluated, making the model a powerful tool for strategic planning.

9.2. Contribution to informed policy and strategic decision-making

The analysis reveals specific conditions under which alignment between individual incentives and collective interaction is achievable, for example, through targeted policy interventions or design. These findings underscore the relevance of individual-level modelling in understanding macro-level policy effectiveness and contribute to the broader discourse on the governance of complex adaptive systems.

This research makes a contribution to policymaking and strategic decision-making by developing a simulation-oriented decision-making framework that is suitable for use in contexts with considerable uncertainty. Instead of a conventional valuation model, a VDT is constructed that structures causal relationships between policy measures, technological developments and economic outcomes in a transparent manner. By applying a Monte Carlo simulation uncertainties in the input variables are systematically calculated, leading to a broad spectrum of possible outcomes. As such, the model does not just provide a single prediction, but a simulated overview of plausible scenarios.

A distinctive added value of this framework is the possibility to evaluate policy and strategic decisions both ex-ante and ex-post. Ex-ante provides support in anticipating possible effects of policy measures, while ex-post enables an evaluation based on the information that was available at the time of decision-making. This prevents decisions from being judged solely on outcomes and allows honest reflection on the quality of the decision-making process. This approach is particularly relevant for policy areas where the future is fundamentally uncertain, such as energy transitions, climate policy or innovation-oriented investment policy.

9.3. Contribution to academic methodology

In addition to its policy relevance, this research makes a methodological contribution to the academic field of decision-making under uncertainty. The approach used is built on the foundation of first principles and consists of three integrated steps. First, the target variable, for example, creation of economic value, is deconstructed via a Fermi approach, in which it is divided into estimable components. Second, a causal structure is constructed via a Value Driver Tree, in which the relationships between variables are explicitly and traceably recorded. Third, the effects of uncertainty on this structure are calculated using a Monte Carlo simulation, resulting in probability distributions of outcomes instead of just fixed, single point estimates.

This methodological approach results in a model that is replicable and explainable due to the transparency it offers. Thus, it offers an alternative to black-box models that are often based on correlations without structural substantiation. The methodology is in line with a growing academic approach in which simulation and causality are central to the analysis of complex policy issues. Moreover, it provides a solid starting point for further research, for example, on the effectiveness of policy instruments within the EU Green Deal, the resilience of innovative companies in volatile markets, or predicting system behaviour within the energy transition.

The integration of an entropic uncertainty lens within the VDT modelling framework has proven to be both analytically valuable and decision-relevant in this research. Most importantly, it enables a more nuanced comparison of policy scenarios by considering not only their expected performance but also the structure and dispersion of their outcome distributions. This distinction has become particularly meaningful in cases where scenarios yielded similar expected economic value with EVA but diverged in the breadth of their outcome ranges. High-entropy scenarios, as revealed through Monte Carlo simulation, have indicated greater epistemic fragility and reduced decision confidence. In contrast, low-entropy scenarios have reflected a concentration of belief, suggesting that the underlying assumptions and data input have offered more robust inferential ground. This has allowed decision quality to be evaluated not only in terms of average performance but also in terms of how resilient the decision remained across a range of plausible futures.

Furthermore, using entropy as a measurable indicator of uncertainty allows the model to assess where improving input data would be most valuable. By examining how output entropy changes when the uncertainty of specific inputs is reduced, the model highlights which variables contribute most to epistemic uncertainty. This helps identify where additional data collection or research would have the greatest impact in increasing decision confidence. This approach aligns with value-of-information principles in Bayesian decision theory, reinforcing the model's usefulness not only for guiding actions but also for prioritising future knowledge acquisition.

Beyond analytical precision, the entropic framing has also improved the interpretability of uncertainty for stakeholders. Rather than presenting risks in abstract statistical terms, the concept of entropy has offered an intuitive metric for understanding the confidence level behind each policy outcome. This added communicative value is particularly important in high-stakes or emerging policy domains, such as climate mitigation, energy transitions, or infrastructure investment, where decisions must be made under deep uncertainty and with limited historical precedent.

So, the entropic approach has facilitated a more comprehensive understanding of uncertainty by embedding it into both the modelling logic and the evaluation process. It has moved beyond the comparison of deterministic scenarios by explicitly quantifying the confidence associated with each result. This has improved both the transparency and robustness of the policy assessment and represents a methodological advance in simulation-based decision support under uncertainty.

9.4. Future research

Future research should increase the methodological depth and practical relevance of VDT models by integrating other emerging analytical tools and broadening the scope of value conceptualisation. First, this can be done by extending the model from purely economic indicators to broader social and ecological dimensions of value, such as social equity, ecological impact and institutional legitimacy. This would bring the model closer to comprehensive frameworks such as Total Value Added (TVA) and integrate reporting towards sustainability goals. However, this requires the inclusion of alternative performance measures and the quantification of socio-ecological externalities. Second, predictive analytics or artificial intelligence could be integrated to enhance the dynamic capabilities of VDTs. This can show results for real-time sensitivity assessments and adaptive forecasting under volatile conditions.

What may be seen as a limitation of the study can also be seen as an opportunity to further improve the model. Therefore, future studies should focus on improving the robustness and granularity of the input data used, for example, by using longitudinal datasets, high-frequency operational data and participatory data collection. By determining the most influential drivers, the most important data to obtain can be determined. This transparency of data could show high improvements in decision-making by stakeholders in the market.

Also, the role of institutional dynamics, including regulatory stability, policy feedback loops and governance structures, deserves further investigation. This can be a mediating layer that influences the behaviour of critical value drivers. Finally, future research should investigate the development of scenarios based on diverse uncertainty typologies, validated by structured stakeholder interactions, such as Delphi studies or co-creation workshops. This would increase both the explanatory power and stakeholder legitimacy of VDT-based investment models in complex socio-technical systems.

10
Reflection

Now after framing the scientific discussion and conclusion, a broader reflection of the research is given. Throughout this project, I shifted my perspective on what it means to model investment decisions in complex socio-technical systems. I initially viewed the task as primarily a technical challenge. So, trying to collect the right equations, calibrate the parameters and simulate data inputs. However, the deeper I was into the research, the more I realised that the true challenge was in structuring uncertainty in a way that exposed systemic influence and strategic blind spots. This was also the opportunity in the methodology where current research is still lacking some knowledge.

This concludes that designing a value driver tree was not just a modelling technique. It also became a method to clarify thinking, both for myself and for potential use by stakeholders. It helped me separate what drives value, what introduces noise and where assumptions are introduced or are secretly hidden during the process. More importantly, it made me recognise that even the best-structured model is only as useful as the scenarios, input and questions it is built to explore.

I also learned that models are never neutral. Each boundary I drew, each uncertainty I included or excluded, reflects a perspective on what matters in the energy transition. This highlighted for me, the impact on policy and institutional dimensions of investment decision-making is far deeper than I had expected at the start. This was an extra layer, adding to the uncertainty in data, than I expected at the forefront. This created continuous shifts in scoping and the intended approach for modelling.

Finally, this process taught me to embrace imperfection and iteration. Instead of striving for predictive accuracy, I began focusing on usefulness. Can the model inform a conversation, shape a decision or highlight a risk? In that sense, this project has given me not just technical skills but a mindset for navigating complexity. That is important to carry in future work when working on this problem statement or the framework used. The eventual result focuses on exploratory insights in the environment of engineering, policy and systems change. A lot of abstraction steps are needed to give results in such new and uncertain environments.

One of the most difficult things I encountered in this research design was scoping. In systems engineering quite an important concept because once quantified analysis is performed, it requires both data and a defined system and problem statement. Normally, from the study, you choose a research topic that has a lot of data available on it, so even though the research method provides transparency, one of the limitations is mainly data availability. The method helped counterproductively in the beginning to demarcate, because by completely breaking parameters down into value drivers, it causes more complexity and the realisation of even more relevant uncertainties. At the same time, this specifying approach makes it a relevant and well-founded method. But looking through this lens of problem scoping made it difficult to get a grip on the complexity of uncertainty.

As I reflect on the use of Artificial Intelligence (AI) tools for research, the following can be concluded. To support the research process in a structured, transparent and efficient manner, AI tools were employed in different stages.

In the literature review phase, AI was used to assist in identifying and structuring relevant academic papers and concepts. For academic writing, AI supports drafting and rephrasing of text passages. This was always followed by manual editing and critical review to ensure originality and clarity.

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A

Literature review methodology

The methodology behind the literature study consists of five steps given in Figure A.1.

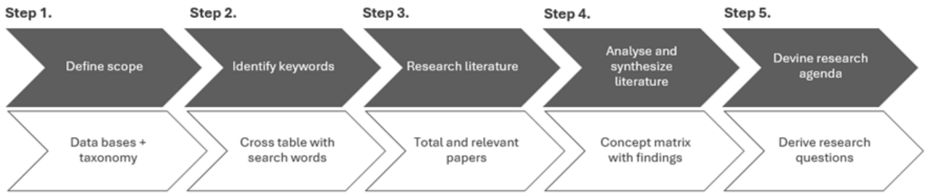

Figure A.1: Literature analysis methodology framework (Brocke et al., 2009)

To clearly define the scope of the research the taxonomy with six characteristics is applied (Brocke et al., 2009). To start, the research focuses on research methods for evaluating business characteristics and the relation towards the global system. The goal is integration to ensure structured approach to align technological advancements with policy and market mechanisms. The study is conceptually organized using Value Driver Tree (VDT) model to asses financial and performance impacts. It adopts a neutral representation perspective on decision-making frameworks. The primary audience includes general scholars, practitioners and politicians, providing insights that support both academic research and policymaking. The coverage is exhaustive and selective to explore the key value creation metrics.

Research findings and applications of value drivers and metrics are searched from [Number] databases (Google Scholar, Web of Science, Semantic Scholar, Mendeley, ScienceDirect, Elicit, Scopus), to conceptualize the findings. Only articles in English were included. Other criteria selecting literature are based on publishing date between 2014 - 2025, relevance to European or Dutch context and peer-reviewed or produced by a credible institutional source.

B

Economic Value Added calculation in Value Driver Tree structure

Economic Value Added (EVA) is calculated by:

$$\text{EVA} = \text{ROIC} - \text{WACC} \tag{B.1}$$

- ROIC: Return on Invested Capital [%]
- WACC: Weighted Average Cost of Capital [%]

B.1. Return on Invested Capital (ROIC)

Return on Invested Capital (ROIC) measures the efficiency of a company in generating returns from its capital employed:

$$\text{ROIC} = \frac{\text{NOPAT}}{\text{Invested Capital}} \cdot 100\% \tag{B.2}$$

Where:

- NOPAT: Net Operating Profit After Taxes [€/year]
- Invested Capital: Total capital employed [€]

B.1.1. Net Operating Profit After Taxes (NOPAT)

$$\text{NOPAT} = \text{EBIT} \cdot (1 - t) \tag{B.3}$$

Where:

- EBIT: Earnings Before Interest and Taxes [€/year]
- t: Corporate income tax rate [–]

EBIT

$$\text{EBIT} = R_{\text{total}} - C_{\text{COGS}} - C_{\text{OPEX}} \tag{B.4}$$

Where:

- R_{total}: Total annual revenue [€/year]
- C_{COGS}: Cost of goods sold [€/year]
- C_{OPEX}: Operating expenses [€/year]

Total Revenue

$$R_{\text{total}} = R_E + R_{\text{H}_2} \tag{B.5}$$

Where:

- R_E: Electricity storage revenue [€/year]
- R_{H_2}: Hydrogen electrolysis revenue [€/year]

Electricity storage revenue

$$R_E = p_E \cdot q_E \tag{B.6}$$

$$q_E = P_{\text{batt}} \cdot t_{\text{FLH,b}} \cdot \eta_{\text{batt}} \tag{B.7}$$

Where:

- p_E: Electricity price [€/MWh]
- q_E: Electricity sold [MWh/year]
- P_{batt}: Storage capacity [MWh]
- $t_{\text{FLH,b}}$: Full load hours per year [h/year]
- η_{batt}: Battery round-trip efficiency [–]

Hydrogen electrolysis revenue

$$R_{\text{H}_2} = p_{\text{H}_2} \cdot q_{\text{H}_2} \tag{B.8}$$

$$q_{\text{H}_2} = \frac{P_{\text{el}} \cdot t_{\text{FLH,e}}}{e_{\text{conv}}} \tag{B.9}$$

Where:

- p_{H_2}: Hydrogen price [€/kg]
- q_{H_2}: Hydrogen production [kg/year]
- P_{el}: Electrolyser capacity [MW]
- $t_{\text{FLH,e}}$: Full load hours per year [h/year]
- e_{conv}: Conversion efficiency [MWh/kg]

B.1.2. Cost of Goods Sold (COGS)

$$C_{\text{COGS}} = C_{\text{elec}} + C_{\text{grid}} \tag{B.10}$$

Where:

- C_{elec}: Electricity costs [€/year]
- C_{grid}: Grid tariffs [€/year]

Electricity cost

$$C_{\text{elec}} = (P_{\text{batt}} \cdot t_{\text{FLH,b}} + P_{\text{el}} \cdot t_{\text{FLH,e}}) \cdot p_{\text{elec}} \tag{B.11}$$

Where:

- p_{elec}: Electricity price [€/MWh]

Grid tariffs The total cost related to grid tariffs consists of two components: (1) electricity export to the grid via battery storage, and (2) hydrogen distribution via the hydrogen network.

$$C_{\text{grid}} = C_{\text{el}} + C_{\text{H}_2} \tag{B.12}$$

Where:

- C_{el}: Electricity grid network cost [€/year]
- C_{H_2}: Hydrogen network tariff cost [€/year]

$$C_{\text{el}} = \tau_{\text{TSO}} \cdot E_{\text{bat}} \tag{B.13}$$

$$E_{\text{bat}} = P_{\text{bat}} \cdot t_{\text{bat}} \cdot \eta_{\text{bat}} \tag{B.14}$$

Where:

- τ_{TSO}: Electricity grid tariff [€/MWh]
- E_{bat}: Electricity sold to the grid via battery [MWh/year]
- P_{bat}: Battery capacity [MW]
- t_{bat}: Full load hours battery [h/year]
- η_{bat}: Battery round-trip efficiency [–]

$$C_{\text{H}_2} = \tau_{\text{HNS}} \cdot m_{\text{H}_2} \tag{B.15}$$

$$m_{\text{H}_2} = \frac{P_{\text{el}} \cdot t_{\text{el}}}{\eta_{\text{el}}} \tag{B.16}$$

Where:

- τ_{HNS}: Hydrogen network tariff [€/kg]
- m_{H_2}: Hydrogen production volume [kg/year]
- P_{el}: Electrolyser capacity [MW]
- t_{el}: Full load hours electrolyser [h/year]
- η_{el}: Energy consumption per kg H_2 [MWh/kg]

$$C_{\text{grid}} = \tau \cdot E_{\text{total}} \tag{B.17}$$

B.1.3. Operating expenses (OPEX)

$$C_{\text{OPEX}} = C_{\text{O\&M}} + C_{\text{depr}} \tag{B.18}$$

Where:

- $C_{\text{O\&M}}$: Operation and maintenance costs [€/year]
- C_{depr}: Depreciation costs [€/year]

O&M cost

$$C_{\text{O\&M}} = P_{\text{el}} \cdot c_{\text{O\&M}}^{\text{unit}} \tag{B.19}$$

Where:

- $P_{\text{el}}^{\text{kW}}$: Electrolyser capacity [MW]
- $c_{\text{O\&M}}^{\text{unit}}$: O&M cost per MW per year [€/kW/year]

Depreciation costs

$$C_{\text{depr}} = \text{P}_{\text{el}} \cdot \text{CAPEX}_{\text{el}} \cdot r_{\text{deg}} \cdot f_{\text{rep}} \tag{B.20}$$

- P_{el}: Electrolyser capacity [MW]
- CAPEX_{el}: Unit capital cost electrolyser [€/MW]
- r_{deg}: Annual degradation rate [–]
- f_{rep}: Stack replacement cost fraction of unit CAPEX [–]

B.1.4. Invested capital

$$\text{Invested capital} = \text{Fixed capital} + \text{Working capital} \tag{B.21}$$

Where:

- Fixed capital: Capital expenditure on infrastructure [€]
- Working capital: Liquid capital tied to operations [€]

Fixed capital

$$\text{Fixed capital} = P_{\text{el}} \cdot c_{\text{CAPEX}_{\text{el}}} + P_{\text{batt}} \cdot c_{\text{CAPEX}_{\text{batt}}} \tag{B.22}$$

Where:

- P_{el}: Electrolyser capacity [MW]
- c_{CAPEX}: Specific capital cost [€/MW]

Working capital

$$\text{Working capital} = \alpha \cdot R_{\text{total}} \tag{B.23}$$

Where:

- α: Working capital coefficient [–]
- R_{total}: Total annual revenue [€/year]

B.2. Weighted Average Cost of Capital (WACC)

$$\text{WACC} = r_{\text{WACC}} \tag{B.24}$$

Where:

- r_{WACC}: Weighted average cost of capital [%/year]

C
VDT structure

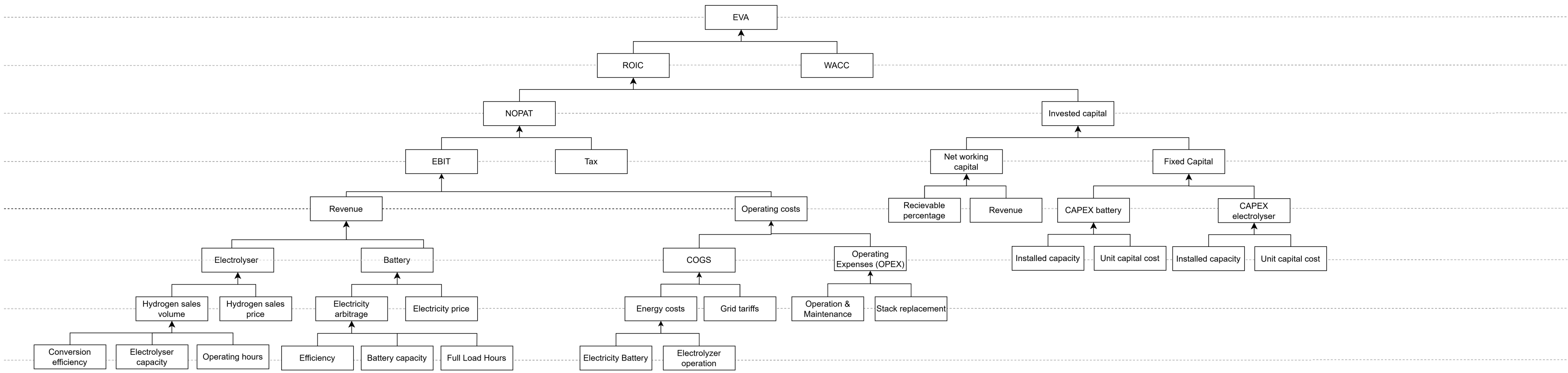

Figure C.1: Total VDT structure

D

Data input variables

Table D.1: Financial parameters

Input name	Normal name	Description	Symbol	Unit
eva	Economic Value Added	Value created above cost of capital	EVA	€
roic	Return on Invested Capital	Efficiency of capital use	ROIC	%
nopat	Net Operating Profit After Tax	Operating profit net of tax	NOPAT	€
operating_profit_ebit	EBIT	Earnings before interest and tax	EBIT	€
gross_profit	Gross Profit	Revenue - COGS	GP	€
revenue	Revenue	Total income from operations	R	€
tax	Tax	Corporate tax on profits	T	€
invested_capital	Invested Capital	Capital employed in operations	IC	€
net_working_capital_pct	NWC as % of revenue	Short-term capital usage	NWC	% of revenue
wacc	Weighted Avg. Cost of Capital	Discount rate for EVA/DCF	WACC	%

Table D.2: Electricity parameters

Input name	Normal name	Description	Symbol	Unit
electricity_sales_mwh	Electricity Sales	Amount sold	E_s	MWh
electricity_sales_price_eur_per_mwh	Electricity Sales Price	Sales price per MWh	P_e	€/MWh
electricity_costs_total_eur	Electricity Costs	Total cost of electricity purchased	C_e	€
electricity_consumption_total_mwh	Electricity Consumption	Total energy consumed	E_c	MWh
electricity_grid_tariff_eur_per_mwh	Grid Tariff	Electricity grid access cost	τ_g	€/MWh
grid_service_revenue	Grid Service Revenue	Revenue from grid services	R_g	€
contracted_capacity_mw	Contracted Capacity	Grid contracted power	C_g	MW
availability_rate	Availability Rate	Availability of the system	A	%

Table D.3: Battery parameters

Input name	Normal name	Description	Symbol	Unit
battery_output_mwh	Battery Output	Annual discharged energy	E_b	MWh
battery_capacity_mwh	Battery Capacity	Installed storage capacity	C_b	MWh
flh_battery_hours	Battery FLH	Full load hours of battery	FLH_b	hours

Table D.4: Electrolyser parameters

Input name	Normal name	Description	Symbol	Unit
hydrogen_sales_kg	Hydrogen Sales	Total hydrogen sold	H_s	kg
hydrogen_sales_price_eur_per_kg	Hydrogen Sales Price	Price per kg sold	P_h	€/kg
hydrogen_production_volume_kg	Hydrogen Production	Annual production volume	H_p	kg
electrolyser_output_kg_per_hour	Electrolyser Output	Hydrogen output per hour	O_e	kg/hr
electrolyser_capacity_mw	Electrolyser Capacity	Electrolyser installed power	C_e	MW
flh_electrolyser_hours	Electrolyser FLH	Annual full load hours	FLH_e	hours
conversion_efficiency_pct	Conversion Efficiency	Electrical to H2 efficiency	η_e	%
electrolyser_energy_consumption_kwh_per_kg	Specific Energy Use	Electricity use per kg H2	SEC	kWh/kg

Table D.5: costs parameters

Input name	Normal name	Description	Symbol	Unit
opex_total_eur	OPEX	Operating expenditures	$OPEX$	€
om_costs_per_kw_year	O&M Cost	Annual O&M per kW	C_{om}	€/kW/year
stack_replacement_cost_pct_ucc	Stack Replacement Cost	Cost as % of UCC	SRC	%
annual_degradation_pct	Annual Degradation	Performance loss per year	D_a	%
degradation_rate_pct_per_1000h	Degradation Rate	Per 1,000 FLH degradation	D_{1000}	%/1,000 h
annual_stack_replacement_cost	Stack Cost	Yearly stack replacement cost	C_{stack}	€
unit_capital_cost_eur_per_kw	CAPEX/unit	Capital cost per kW	UCC	€/kW
fixed_capital_eur	Fixed Capital	Long-term capital assets	FC	€
total_capex_eur	Total CAPEX	Total capital investment	$CAPEX$	€
annual_depreciation_eur	Annual Depreciation	Annual write-off	Dep_a	€
accumulated_depreciation_eur	Accumulated Depreciation	Total write-off over time	Dep_{acc}	€

Table D.6: Other parameters

Input name	Normal name	Description	Symbol	Unit
asset_lifetime_years	Asset Lifetime	Economic asset lifetime	L	years
years_in_service	Years in Service	Years used since start	Y	years

D.1. Input data baseline analysis

All independent variables are selected based on empirical data, literature references and industry benchmarks to ensure consistency and correctness in the modeling framework. The values and descriptions of these variables are summarized in Table D.7.

Table D.7: Independent input parameters for baseline, including assumed values and sources

Variable	Unit	Value	Description	Source
System configuration				
P_{batt}	MW	2,5	[battery_capacity] Installed capacity of the battery system	Case input based on HyChain, 2024
P_{el}	MW	5	[electrolyser_capacity] Installed capacity of the electrolyser system	Case input based on HyChain, 2024
FLH_{battery}	h/year	3,000	[full_load_hours_battery] Battery full load hours	Case input based on historical balancing use
η_{battery}	–	0.95	[battery_efficiency] Round-trip battery efficiency	Case input based on IRENA, 2023
E_{total}	MWh	500	[energy_consumption] Electricity consumption	Case input (model balance)
$FLH_{\text{electrolyser}}$	h/year	5,000	[full_load_hours_electrolyser] Electrolyser full load hours	Case input based on utilization targets
η_{conv}	MWh/kg	0.055	[conversion_efficiency] Electricity consumption per kg H_2	Case input based on TNO, 2023
Costs and prices				
p_{elec}	€/MWh	75	[electricity_price] Electricity market price (excl. fees)	Case input based on TenneT, 2024
p_{H_2}	€/kg	8	[hydrogen_price] Hydrogen selling price	Case input based on Delft, 2023
$\text{Tariff}_{\text{TSO}}$	€/MWh	16,38	[tso_tariff] Transmission system operator tariff	Eblé and Weeda, 2024
$\text{Tariff}_{\text{HNS}}$	€/kg	2,4	[hn_tariff] Hydrogen network service fee	Eblé and Weeda, 2024
CAPEX and OPEX				
$C_{\text{unit,el}}$	€/MW	1,666,000	[unit_capital_cost] Unit capital cost of battolyser system	Case input based on Delft, 2023
$C_{\text{unit,batt}}$	€/MW	83,000	[unit_capital_cost] Unit capital cost of battolyser system	Case input based on Delft, 2023
$O\&M_{\text{battolyser}}$	€/MW/year	43,000	[o_m_costs_per_year] Fixed O&M cost per MW battolyser	Case input based on Delft, 2023
γ_{stack}	% of UCC	5	[stack_replacement_cost] Stack replacement cost (as share of CAPEX)	Case input based on manufacturer guidance
δ	%/year	2	[annual_degradation] Annual performance degradation	Case input based on technical literature
Financial assumptions				
τ	%	25	[tax] Corporate income tax (Netherlands)	Rijksoverheid, 2024
ϕ_{rev}	%	10	[percentage_of_revenue] Revenue-based fee or system cost	Assumption (case input, system O&M proxy)
WACC	%	11	[wacc] Weighted average cost of capital	Eblé and Weeda, 2024

D.1.1. Distributed data input

KEV electricity price simulation 2030 (Intelligence, 2025).

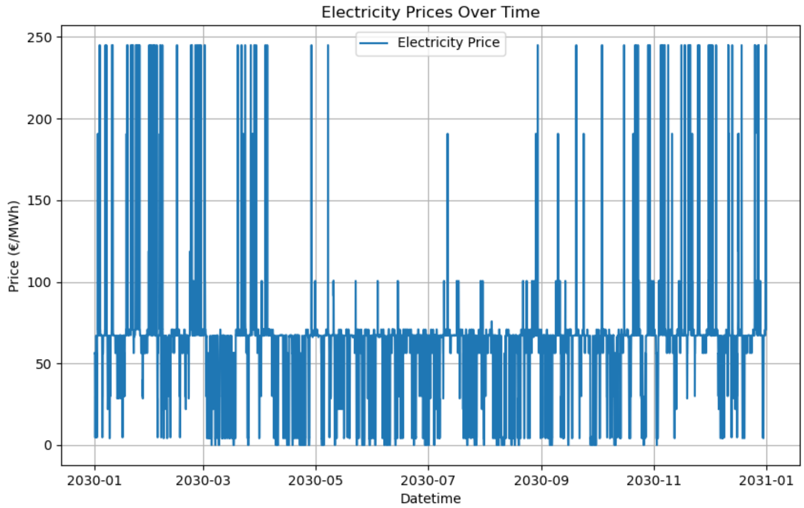

Figure D.1: Electricity price over time [€/MWh]

E

Sensitivity analysis

Table E.1: Sensitivity analysis on fixed values in the VDT model on EVA

Parameter	Code name	Original EVA	EVA (+20%)	EVA (-20%)	Impact (± 20%)
Weighted Average Cost of Capital	wacc	-8.52	-10.72	-6.32	±25.82
Percentage	percentage	-8.52	-8.02	-9.02	±5.82
Tax rate	tax	-8.52	-8.02	-9.02	±5.82
Revenue percentage	percentage_of_revenue	-8.52	-8.54	-8.50	±0.27
Battery capacity	battery_capacity	-8.52	-8.79	-8.25	±3.14
Battery capital cost	unit_capital_cost_battery	-8.52	-8.53	-8.51	±0.13
Electrolyser capacity	electrolyser_capacity	-8.52	-8.30	-8.85	±3.26
Electrolyser capital cost	unit_capital_cost_electrolyser	-8.52	-8.92	-7.94	±5.78
Electricity price	electricity_price	-8.52	-11.71	-5.32	±37.45
Hydrogen price	hydrogen_price	-8.52	-2.50	-14.64	±71.27
Conversion efficiency	conversion_efficiency	-8.52	-12.08	-3.27	±51.72
Battery efficiency	battery_efficiency	-8.52	-7.63	-9.41	±10.47
Battery full load hours	full_load_hours_battery	-8.52	-8.57	-8.47	±0.59
Electrolyser full load hours	full_load_hours_electrolyser	-8.52	-7.43	-9.63	±12.95
Annual degradation	annual_degradation	-8.52	-8.53	-8.51	±0.16
Replacement cost fraction	fraction_replacement_cost_pct_of_ucc	-8.52	-8.53	-8.51	±0.16
Electrolyser O&M costs	o_m_costs_electrolyser_per_year	-8.52	-8.88	-8.16	±4.23
TSO tariff	tso_tariff	-8.52	-8.73	-8.31	±2.42
HNS tariff	hns_tariff	-8.52	-10.35	-6.69	±21.45

F

Python code modelling framework

F.1. Load Data

The code starts with the data loading part, which is split into three parts: import libraries, configuration and function for data loading.

The imported libraries are for data manipulation (pandas, numpy), visualisation (matplotlib, networkx) and Excel file handling (openpyxl). These libraries are essential for loading data, building the hierarchical structure, performing calculations and visualising results later in the code.

Configuration specifies the Excel file and sheet name to load data from. The data for the hierarchical structure is stored in an Excel file. These variables are passed to the *load_data* function to load the data.

```python
# Importing required libraries
import pandas as pd
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
import networkx as nx
import openpyxl

# Configuration
excel_file = 'VDT_input_model_2.xlsx'
sheet_name = 'VDT_EVA_FV_copy'

# Load data
def load_data(excel_file, sheet_name):
    '''
    Load data from an Excel file and preprocess it by converting relevant columns to numeric.

    Parameters:
    - excel_file: Path to the Excel file.
    - sheet_name: Name of the sheet to load.

    Returns:
    - data: Preprocessed DataFrame.
    '''
    data = pd.read_excel(excel_file, sheet_name=sheet_name)
    data = data[data['Ignore?'] != 'yes']
    data['Min'] = pd.to_numeric(data['Min'])
    data['Max'] = pd.to_numeric(data['Max'])
    data['Mean'] = pd.to_numeric(data['Mean'])
    data['Fixed␣Value'] = pd.to_numeric(data['Fixed␣Value'])
    data['Delay'] = pd.to_numeric(data['Delay'])
    print('data␣loaded')
    return data
```

F.2. Hierarchical structure

This part of the code converts the flat data into a hierarchical structure as a nested dictionary. The hierarchical structure is required for calculations and sensitivity analysis. It iterates through the rows and columns of the data, creating nested dictionaries for each level.

```python
# Hierarchical structure
def build_hierarchy(data):
    '''
    Build a hierarchical structure from the input data.

    Parameters:
    - data: Preprocessed DataFrame.

    Returns:
    - hierarchy: Nested dictionary representing the hierarchical structure.
    '''
    hierarchy = {}
    current_level = hierarchy
    path_tracker = []
    name_count = {}
    previous_index = -1

    for _, row in data.iterrows():
        for col_index, item in enumerate(row):
            if pd.notna(item):
                item_str = str(item).strip()

                if item_str in {'+', 'x', '-', '/'}:
                    continue

                name_count[item_str] = name_count.get(item_str, 0) + 1
                if name_count[item_str] != 1:
                    unique_item_str = f"{item_str}_{name_count[item_str]}"
                else:
                    unique_item_str = f"{item_str}"

                stats = {'Level': col_index}
                if pd.notna(row['Operator']):
                    stats['Operator'] = row['Operator']
                if pd.notna(row['Fixed Value']):
                    stats['Fixed Value'] = row['Fixed Value']
                if pd.notna(row['Mean']):
                    stats['Mean'] = row['Mean']
                if pd.notna(row['Min']):
                    stats['Min'] = row['Min']
                if pd.notna(row['Max']):
                    stats['Max'] = row['Max']
                if pd.notna(row['Delay']):
                    stats['Delay'] = row['Delay']

                if col_index > previous_index:
                    current_level[unique_item_str] = {'stats': stats}
                    path_tracker = path_tracker[:col_index] + [unique_item_str]
                    current_level = current_level[unique_item_str]
                else:
                    current_level = hierarchy
                    path_tracker = path_tracker[:col_index]
                    for node in path_tracker:
                        current_level = current_level[node]
                    current_level[unique_item_str] = {'stats': stats}
                    path_tracker.append(unique_item_str)
                    current_level = current_level[unique_item_str]

                previous_index = col_index
                break
    print('hierarchy built')
    return hierarchy
```

F.3. Group nodes

Next, the code groups nodes by their hierarchical level into a dictionary *level_dict*. This allows processing nodes level by level, starting from the deepest level. Recursively traverses the hierarchy and appends nodes to *level_dict*.

```python
# Group nodes
def gather_nodes_by_level(node, level_dict, path=''):
    '''
    Gather nodes by their hierarchical level.

    Parameters:
    - node: Current node in the hierarchy.
    - level_dict: Dictionary to store nodes by level.
    - path: Current path in the hierarchy.
    '''
    if 'stats' in node and 'Level' in node['stats']:
        level = node['stats']['Level']
        level_dict.setdefault(level, []).append((path, node))

    for key, child in node.items():
        if key != 'stats':
            gather_nodes_by_level(child, level_dict, f'{path}/{key}' if path else key)

    print('nodes gathered')
```

F.4. Values calculation

Then the values are calculated for each node based on its Fixed Value, Mean, or Operator. It propagates values through the hierarchy to compute results for higher-level nodes. For process nodes, level by level, child node values are used for calculations.

```python
def calculate_direct_values(hierarchy, level_dict):
    """
    Computes hierarchical values using only direct calculations without Monte Carlo simulations.

    Parameters:
    - hierarchy: Hierarchical structure.
    - level_dict: Dictionary of nodes by level.

    Returns:
    - df_results: DataFrame containing calculated values.
    """

    df_results = pd.DataFrame()
    sorted_levels = sorted(level_dict.keys(), reverse=True)

    for level in sorted_levels:
        for path, node in level_dict[level]:
            stats = node['stats']

            # Case 1: Fixed Value
            if 'Fixed Value' in stats:
                stats['calculated_values'] = stats['Fixed Value']

            # Case 2: Mean-based calculation (No randomness)
            elif all(k in stats for k in ('Mean', 'Min', 'Max')):
                stats['calculated_values'] = stats['Mean']

            # Case 3: Compute based on Operator and Children Nodes
            elif 'Operator' in stats:
                operator = stats['Operator']
                children_values = [child['stats']['calculated_values']
                                   for child in node.values()
                                   if isinstance(child, dict) and 'stats' in child and 'calculated_values' in child['stats']]

                if children_values:
                    if operator == '+':
```

```
                        stats['calculated_values'] = sum(children_values)
                    elif operator == '-':
                        stats['calculated_values'] = children_values[0] - sum(children_values[1:])
                    elif operator == '/':
                        stats['calculated_values'] = children_values[0] / children_values[1] if children_values[1] != 0 else 0
                    elif operator == 'x':
                        stats['calculated_values'] = np.prod(children_values)
                    elif operator == '=':
                        stats['calculated_values'] = children_values[0]

            # Default case: Assign zero if no valid computation
            else:
                stats['calculated_values'] = 0

            # Store result in DataFrame
            df_results[path.split("/")[-1]] = [stats['calculated_values']]
            # df_results[path.split("/")[-1] + '_UoM'] = [stats.get('UoM', '')]  # Add UOM if available

    return df_results
```

F.5. Monte Carlo simulation

```
# Monte Carlo simulation
def monte_carlo_simulation(mean, min_val, max_val, num_simulations=8760):
    '''
    Perform Monte Carlo simulation using a triangular distribution.

    Parameters:
    - mean: Mean value for the distribution.
    - min_val: Minimum value for the distribution.
    - max_val: Maximum value for the distribution.
    - num_simulations: Number of simulations to run.

    Returns:
    - simulations: Array of simulated values.
    '''
    sims = np.random.triangular(min_val, mean, max_val, num_simulations)
    print('monte␣carlo␣calculations')
    return sims
```

F.6. Statistics

```
# Calculate statistics
def calculate_statistics(values):
    '''
    Calculate statistical metrics (mean, 1th percentile, 99th percentile) for an array of values.

    Parameters:
    - values: Array of values.

    Returns:
    - calculated_mean: Mean of the values.
    - calculated_min: 10th percentile of the values.
    - calculated_max: 90th percentile of the values.
    '''
    calculated_mean = np.mean(values)
    calculated_min = np.percentile(values, 1)
    calculated_max = np.percentile(values, 99)

    print('statistics␣calculated')
    return calculated_mean, calculated_min, calculated_max
```

F.7. Calculate values with simulation

```python
def calculate_and_update_values_with_real_data(hierarchy, level_dict, real_prices):
    """
    Calculate and update values in the hierarchy using real electricity prices or Monte Carlo simulations.

    Parameters:
    - hierarchy: Hierarchical structure.
    - level_dict: Dictionary of nodes by level.
    - real_prices: Array of real electricity prices from the data_input file.

    Returns:
    - df_results: DataFrame containing calculated values.
    """
    df_results = pd.DataFrame()
    sorted_levels = sorted(level_dict.keys(), reverse=True)

    for level in sorted_levels:
        for path, node in level_dict[level]:
            if 'Fixed Value' in node['stats']:
                fixed_value = node['stats']['Fixed Value']
                node['stats']['calculated_values'] = np.full(len(real_prices), fixed_value)
            elif all(k in node['stats'] for k in ('Mean', 'Min', 'Max')):
                # Replace Monte Carlo simulation with real electricity prices
                if path.split("/")[-1] == 'Electricity price':
                    node['stats']['calculated_values'] = real_prices
                    df_results['Electricity price'] = real_prices
                else:
                    mean, min_val, max_val = node['stats']['Mean'], node['stats']['Min'], node['stats']['Max']
                    # Perform Monte Carlo simulation
                    node['stats']['calculated_values'] = monte_carlo_simulation(mean, min_val, max_val, len(real_prices))
            elif 'Operator' in node['stats']:
                operator = node['stats']['Operator']
                children_values = [child['stats']['calculated_values'] for child in node.values() if 'stats' in child and 'calculated_values' in child['stats']]

                if children_values:
                    children_values = np.array(children_values)
                    if operator == '+':
                        node['stats']['calculated_values'] = np.sum(children_values, axis=0)
                    elif operator == '-':
                        node['stats']['calculated_values'] = children_values[0] - children_values[1]
                    elif operator == '/':
                        node['stats']['calculated_values'] = children_values[0] / children_values[1]
                    elif operator == 'x':
                        node['stats']['calculated_values'] = np.prod(children_values, axis=0)
                    elif operator == '=':
                        node['stats']['calculated_values'] = children_values[0]

                if path.split("/")[-1] == 'EVA':
                    df_results[path.split("/")[-1]] = node['stats']['calculated_values'].flatten()
            else:
                node['stats']['calculated_values'] = np.zeros(len(real_prices))

            calculated_mean, calculated_min, calculated_max = calculate_statistics(node['stats']['calculated_values'])
            node['stats']['calculated_mean'] = calculated_mean
            node['stats']['calculated_min'] = calculated_min
            node['stats']['calculated_max'] = calculated_max

    df_results = df_results[df_results.columns[::-1]]
    return df_results
```

F.8. Impact on EVA

```python
def get_values_for_eva(hierarchy):
```

```
    '''
    Extract the EVA values from the hierarchy.

    Parameters:
    - hierarchy: Hierarchical structure.

    Returns:
    - eva_values: Array of EVA values from the simulations.
    '''
    for key, node in hierarchy.items():
        if key == 'EVA':
            return node['stats']['calculated_values']
        else:
            result = get_values_for_eva(node)
            if result is not None:
                return result
    return None
```